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Atmospheric Chemistry and Physics
Discussions

Interactive comment on "The potential for regional-scale bias in top-down CO_2 flux estimates due to atmospheric transport errors" *by* S. M. Miller et al.

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We would like to thank the reviewer for suggestions and comments on the manuscript. The reviewer's detailed suggestions have been very helpful in improving the manuscript. Below, we have included the reviewers comments (in bold) along with our reply and the associated changes/updates to the manuscript.

- **These uncertainties are calculated based on a coarse resolution meteorological model, which has a spatial resolution of 2.5o longitude x 1.9o latitude. In the reality, there are other additional error terms introduced due to**

fine-scale variations that cannot be captured by the coarse model. These additional terms will be more significant depending on the regions and/or periods you sample.

Uncertainties in the posterior meteorology estimate include uncertainties in the model, uncertainties due to measurement errors, and uncertainties due to meteorological patterns that are smaller in scale than the model resolution. The latter two uncertainties are incorporated into the posterior estimate via the $\mathbf{R}$ covariance matrix (e.g., Hunt et al. 2007). This matrix, often referred to as the nugget covariance matrix, is used as an input into the meteorology model-data assimilation and the posterior uncertainty calculation. We estimate the elements of the $\mathbf{R}$ matrix directly from the meteorological data using an adaptive approach outlined by Li et. al. (2009). This adaptive approach estimates the collective variance due to measurement error and uncertainties due to meteorological processes that occur at scales smaller than the model resolution. Hence, errors due to small-scale processes are a component of the posterior meteorology and CO_2 estimates. However, we cannot resolve the spatial distribution of these fine-scale errors at sub-grid scale.

In addition, one goal of this study is to run simulations that are analogous to commonly-used, top-down global CO_2 flux estimates like CarbonTracker. The grid used in this study is comparable, if not smaller, than many existing global CO_2 inversion studies. For example, CarbonTracker has a 2° latitude by 3° longitude global resolution (Peters et al., 2007, http://www.esrl.noaa.gov/gmd/ccgg/carbontracker/). Other global inversion studies, like Mueller et al. (2008) and Gourdji et al. (2008) used a resolution of 3.75° by 5°, and Basu et al. (2013) used a 4° by 6° resolution. One could argue that there are advantages to estimating global CO_2 fluxes using a model with finer spatial resolution. With that said, the resolution used here is analogous to that used by common top-down CO_2 flux products like CarbonTracker and would be able to speak more directly to the types of transport errors that would be encountered in those efforts.

- **The mentioned model ensemble method cannot account for these fine-scale spatial variations, given that the weights (to match the meteorological observations) are estimated for each grid box using observations within a radius about 1500 km.**

  We do not compare the model estimate in one grid box against wind or temperature observations taken 1500km away. As the reviewer points out, that approach would be ill-advised. We have added text to the supplement (section S1) to clarify and further explain this point.

  In the LETKF, we estimate a set of weighting factors for the 64 ensemble members such that the weighted ensemble best matches the meteorological observations. To achieve this, we first interpolate the gridded model output to the observation locations and times. We then estimate a unique weighting factor for each individual grid box. If we estimated the weights using only model-measurement pairs in the grid box of interest, several problems could arise. First, there may not be many relevant observations that are sensitive to that specific grid box, particularly over the open ocean or near the poles. In those circumstances, the estimated weights could be inaccurate. Second, that approach could produce vastly different weights in adjacent grid boxes, a result that is unlikely to be physically realistic. For example, the estimated weights for one model grid box over eastern North Dakota should look somewhat similar to the weights for a grid box over western North Dakota. If the two sets of weights were completely unrelated, one could argue that the optimization would be an over-fit.

  Instead, we use model-measurement pairs within a certain geographic radius to compute each set of weights. This approach ensures coherence among adjacent grid boxes and ensures that the optimization is not an over-fit to the data. We further taper the influence of model-observation pairs on the optimization depending on their distance from the grid box in question (using a Blackman window

function as described by Oppenheim and Schafer (1989) and Liu et al. (2012)). Hence, model-measurement pairs located within the model grid box of interest will influence the optimization much more strongly than model-observation pairs located 1000km away. A radius of 1500km for the Blackman window function is comparable to values used throughout the meteorological literature. For example, Liu et al. (2011) and Liu et al. (2012) also used a 1500km radius. Furthermore, Miyoshi (2011) set a 1825 km radius of influence, Miyoshi and Kunii (2012) used a 1460km radius, and Szunyogh et al. (2008) used an 800km radius.

- **I am not sure how nugget variance (R) is constructed and whether it necessarily represents all errors due to these fine-scale variations.**

  Many existing meteorology studies that implement an ensemble Kalman filter have used the published measurement error for $\mathbf{R}$ (e.g., Szunyogh et al., 2008; Liu et al., 2012). In reality, $\mathbf{R}$ also includes a number of other errors, including errors due to meteorological features that are smaller than the model resolution (as discussed above). To capture this entire spectrum of errors, we estimate these errors directly from the meteorological data, an advance over previous efforts that used only the published measurement error. These calculations for $\mathbf{R}$, by definition, will capture any variability in the measurements that cannot be incorporated into the model ensemble. This variability includes both measurement errors and errors due to fine-scale meteorological processes. This approach is detailed in Eq. S11 and in Li et al. (2009).

- **Moreover, I am not much convinced how a single inflation factor for each model grid box works fine for all model parameters.**

  The use of a single inflation factor per grid box has been a common practice in ensemble Kalman filters applied to weather models (e.g., Szunyogh et al., 2008; Liu et al., 2011, 2012; Miyoshi and Kunii, 2012; Kang et al., 2012). In our study, we use a relatively new technique known as adaptive inflation to estimate the inflation factors. This approach estimates inflation factors based upon actual model-data residuals (Miyoshi, 2011). The traditional approach has been to choose inflation factors subjectively based upon 'expert knowledge.' In fact, previous studies used zonally-constant inflation factors (e.g., Szunyogh et al., 2008; Saito et al., 2011; Liu et al., 2011, 2012; Yang et al., 2012). Miyoshi (2011), in contrast, argues that this zonally-constant approach is not ideal because it cannot differentiate between ocean and terrestrial regions. The statistical approach implemented here is therefore an advancement over previous efforts because we estimate spatially- and temporally-variable inflation factors directly from the data.

In practice, adaptive inflation can be very challenging to implement; the inflation factors that best match the model-data residuals can, in some cases, cause instabilities in meteorological model that result in incompatible combinations of meteorological parameters. These instabilities often crash one or more of the ensemble members. Furthermore, the approach performs poorly when observations are sparse (e.g., Miyoshi, 2011). When we estimate a single inflation factor per box, we can leverage more observations to make a more stable inflation estimate. Hence, we felt that this framework would require more development before we could reliably estimate unique, grid-scale inflation factors for many different meteorological parameters.

The meteorological data-assimilation community is moving toward adaptive inflation techniques that can accomplish this task (e.g., Zheng et al., 2013). However, this kind of in-depth methodological development is beyond the scope of our study.

- **Hence I fear that the values reported for CO2 transport uncertainty (globally) can be far away from reality. This could be one of the reasons why Fig. 2 does not generally show high transport related uncertainties in the coastal sides (sea/land breeze effects?).**

  We do see larger uncertainties in zonal winds along many coastal regions, pre-

sumably related to sea breezes. We have added a new plot to the supplement that illustrates these features (Fig. S17). These uncertainties are particularly prominent across the west coast of North America where sea breezes are an important component of coastal weather. In our simulations, uncertainties in zonal winds at the coastline do not always translate into large uncertainties in modeled CO_2 concentrations. For example, uncertainties in both zonal and meridional winds are high along the coast of British Columbia and Alaska in February (Fig. S17). Since those regions have small CO_2 fluxes in winter, large uncertainties in the winds do not translate into large uncertainties in 6-hourly modeled atmospheric CO_2 (Fig. 2a).

- **The authors may wish to provide more detailed discussion regarding this aspect and it is worthwhile to mention explicitly the significant limitations of this approach.**

  We have added text to the methods section 2.2 that describes both the advantages and limitations of the meteorology model-data assimilation (e.g., the model cannot resolve the spatial patterns of meteorological features at sub-grid scale).

- **In the given design and set up, I would certainly consider that the flux bias estimations in the case study 1 are overestimated values, because of unrealistically "too strict" constraints.**

  We have reformulated case study #1 in a way that no longer uses a hypothesis test, and we no longer make definitive statements on whether the observations would be able to 'see' biases in a CO_2 flux estimate. Instead, we visually display the 95% confidence intervals in modeled atmospheric CO_2 and compare those uncertainties against the afternoon boundary layer enhancement in CO_2 at various observation sites.

- **The current inversion approaches followed by many modeling groups take into account the transport uncertainties to some extent and the method is**

not as simplified as the approach given here.

We have clarified this point in the revised manuscript. Most current inversion approaches do account for transport uncertainties. However, the majority of existing inversion studies assume that the transport uncertainties are uncorrelated in space and time. In other words, existing studies typically use a diagonal covariance matrix to describe errors due to atmospheric transport, measurements, and model resolution, etc. A central question in our paper is to understand how transport errors are correlated in both space and in time, and we find that these correlations or covariances are substantial. An inversion study that ignores these covariances could either underestimate uncertainties in the CO_2 fluxes or propagate transport errors into the estimated fluxes. We have revised the setup for case study #1 to make this point clearer within the manuscript.

- **I am a bit surprised to see totally different patterns between these two mean values. I could not find very direct and convincing reasons for these differences from the manuscript. Perhaps I missed some details. In that case, the authors may wish to bring this point clearly in the discussion part.**

  Monthly-scale error patterns depend upon error covariances in the 6-hourly model output. Different regions will have greater temporal error covariances than others. These differences in the covariances will result in different error patterns at the 6-hourly versus monthly scale. The underlying question is why the error covariances are so much higher over the oceans and Arctic than over regions with large fluxes (Fig. 2).

  Uncertainties in the month-long mean concentrations (Fig. 2) are most influenced by transport errors that occur over sustained time periods. When CO_2 is transported from source/sink regions to remote regions, that transport is likely to be associated with synoptic time scales, and any transport errors would likely be sustained over multi-day time periods. At these longer time scales, the surface

fluxes are transported away from the surface grid box where they occurred and can manifest as transport errors in regions that are remote from large fluxes.

In regions with large fluxes, surface concentrations will additionally be influenced by grid-scale winds or boundary layer mixing. Transport errors at this grid-scale may have a shorter decorrelation time compared to errors in large-scale flow. In addition, sustained transport errors over regions of large biosphere flux would be more likely to cancel out at longer time scales – due to the diurnal cycle of biosphere CO_2 uptake and release (i.e., transport errors times of CO_2 uptake and release will have opposite sign.). Hence, transport errors in regions with large fluxes would likely average out or cancel to a greater degree than those in remote areas.

We have added additional explanation on this point to section 3.2 in the revised manuscript.

- **p.23692, line 13: ".. from surface sources is strong" - ".. from surface sources and sinks is strong"**

  We have updated the manuscript accordingly.

- **p. 23696, line 9: "At marine sites, in contrast, the minimum detectable bias is far larger". Why? transport uncertainties are comparatively shown lower over coastal areas!?**

  Marine sites are often located relatively far from regions with large CO_2 fluxes. At these marine sites, the signal-to-noise ratio is therefore smaller. We have added a similar explanation to this section of the revised manuscript.

- **p. 23696, line 11: ".. large sources are better .." - ".. large sources and sinks are better .."**

  We have changed this text accordingly.

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