Referee #2:

General comments

The authors applied a flux inversion system based on LETKF algorithm to estimate the global and regional CO_2 fluxes based on OCO-2 satellite observations. They obtained useful results indicating ability to reconstruct the regional surface fluxes fitting within a spread of the recent global inverse modelling results by other modelling systems. On the other hand, there are deficiencies of the method that authors could not overcome and hope to improve in further developments. Paper is well written and illustrated and can be accepted after minor revisions.

Response:

We thank the referee for the constructive comments on our paper. We have provided our point-by-point responses as follows and revised the manuscript accordingly.

Detailed comments.

The length of optimization window of 1 week limits the power of the remote observations to constrain the fluxes. One can see a difference between fluxes retrieved with Kalman smoother when applying 1-month and 3-month assimilation window (Bruhwiler et al, 2005). The deficiency has been noted in the abstract as 'Four sensitivity experiments are performed herein to vary the prior fluxes and uncertainties in our inversion system, suggesting that regions that lack OCO-2 coverage are sensitive to the priors, especially over the tropics and high latitudes', which authors hope to address in future.

Response:

Thanks for your comments. We agree that the 1-week assimilation window may limit the power of remote observations to constrain fluxes. We adopt such a short window because the OCO-2 satellite provides spatially dense observations of XCO_2 per week over most regions, which is already sufficient to drive the 4D-LETKF algorithm to optimize fluxes. We also tested a 2-week window in the experiment S_exp4, which gave broadly consistent estimates of global and regional fluxes with the 1-week window inversions. These results have suggested that the OCO-2 provides similar constraints on fluxes despite the length of the assimilation window being doubled. However, we still observed that a few regions without sufficient OCO-2 coverage (e.g., the tropics and high latitudes) tended to be sensitive to the priors in carbon flux estimates, which could be further improved based on an assimilation window longer than 2 weeks. We will address this issue as the referee suggested in the future.

There are visible problems with posterior fluxes, as shown on Fig. 4, the range of annual mean grid fluxes occasionally goes out of reasonable range, exceeding 100 $gC/m^2/year$, pointing to a poor balance between large scale and grid scale uncertainties, lack of a spatial correlation constraint on flux correction gradients. The results with the presumably similar algorithm in Liu et al (2019) do not show such noise, which pint to having some important differences that must be documented. Similar flux noise problem was encountered by Miyazaki et al, (2011) and later studies. Can authors isolate the cause of the problem? Could it be a result of using random grid fields as ensemble flux perturbations, while there is an alternative of using smoother random fields?

Response:

Thanks for pointing out this problem, which is related to the configuration of prior flux fields and their ensemble perturbations. Liu et al. (2019) did not present the noise of posterior grid fluxes like our study, probably because they sampled the ensemble perturbations based on the prior flux model instead of random grid fluxes as in our study, which better represents the spatial variations of both prior and posterior fluxes. According to our new experiment S_exp5, using a better prior flux field, we can reduce the uncertainties of prior fluxes in inversions and suppresses the noise of posterior fluxes (Fig. R1). Miyazaki et al (2011), which encountered a similar flux noise problem to our study, suggested that setting a high spatial correlation of grid flux uncertainties and doubling the ensemble size from 48 to 96 substantially reduced the noise of posterior fluxes and provided smoother posterior fields. Based on these discussions above, the methods to constrain grid-scale uncertainties include using a reasonable prior flux associated with small uncertainties, constraining the spatial correlation of grid flux uncertainties, and increasing the ensemble size.

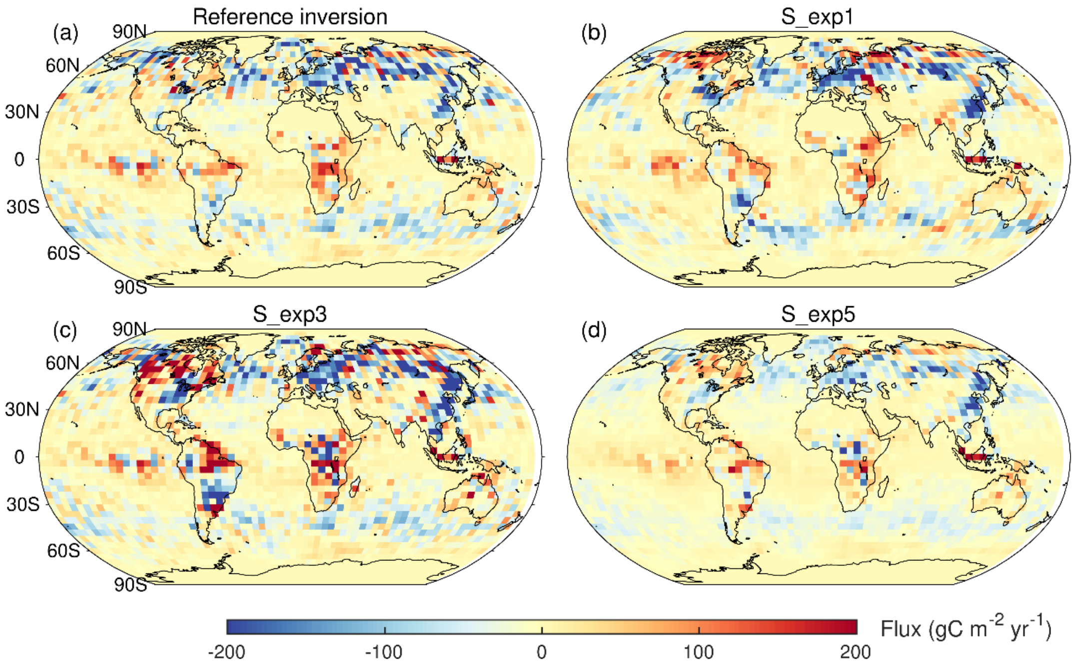

Figure R1. The global natural carbon fluxes in 2015 derived from four inversions. The reference inversion (a), S_exp1 (b), and S_exp3 (c) are described in Tables 1 and 2 of the main text. S_exp5 (d) used the same configurations as S_exp3 except for the uncertainty of prior fluxes set as a normal distribution with standard deviation of 1.0.

Another issue related to the grid flux noise is the ensemble size. As shown by Chatterjee et al (2012), Chatterjee and Michalak, (2013) the inversion results are sensitive to ensemble size, and useful improvement are archived by increasing the ensemble size beyond 100. Miyazaki et al (2011) also obtained visible improvement of flux constraint by increasing the ensemble size from 48 to 96. Compared to those designs a system presented in this study relies on rather small ensemble size.

Response:

We agree that increasing the ensemble size can reduce grid flux noises. We have used an ensemble size of 24 because the LETKF performs well with a small ensemble size (e.g., Miyoshi and Yamane, 2007; Liu et al., 2019). The LETKF adopts the explicit localization schemes and the analysis is done in a much lower-dimensional space spanned by ensemble perturbations (Hunt et al., 2007). We will try larger ensemble sizes in the future development of our inversion system to constrain grid flux noises.

Despite of the visible success in weather forecast applications, LETKF use in carbon flux inversion has been tried in several studies but did not become widely used due to limitations, presumably not providing a better computational efficiency over adjoint-based variational or low rank inversion algorithms. In a revised manuscript it is advisable to mention the deficiencies of the LETKF system: limitations of small ensemble size and short window length (which may be reasonable for coupled weather-carbon cycle assimilation) and provide better arguments in support of this direction in comparison to other settings, for example Kalman filter approaches formulated by Feng et al, (2009).

Response:

Thanks for this good suggestion. We have added a short discussion in Lines 399-419.

Lines 399-419:

"The ensemble methods such as 4D-LETKF used in this study have a major advantage over the variational methods (e.g., 4D-Var) in system development simplification, but the limited ensemble size and the short spatial-temporal localization window could reduce the estimation accuracy when there is a lack of sufficient CO_2 observations (Chatterjee and Michalak, 2013; Liu et al., 2016). The 4D-Var method uses an adjoint model to compute the sensitivity of CO_2 concentrations to surface fluxes, typically associated with a long assimilation window of years (e.g., Chevallier et al., 2005; Baker et al., 2006; Liu et al., 2016), which is accurate but computationally expensive. The 4D-LETKF algorithm relates surface carbon fluxes to CO_2 observations through ensemble simulations upon a short assimilation window of hours to months (e.g., Kang et al., 2011; Peters et al., 2005; Bruhwiler et al., 2005). The 4D-LETKF algorithm was designed for easy implementation and computational efficiency (Hunt et al., 2007), making it easier and faster to use in high-dimensional assimilation systems than the 4D-Var method.

The explicit localization scheme in space and time for 4D-LETKF ensures the accuracy and efficiency of flux estimation based on a moderate size of ensemble members (Miyoshi and Yamane, 2007), especially over regions with sufficient observations. For example, the 4D-LETKF algorithm can achieve comparable carbon fluxes to 4D-Var over regions with dense CO_2 observations (Liu et al., 2016). However, over observation-sparse regions, the localization scheme of 4D-LETKF makes it difficult to optimize fluxes effectively, while the 4D-Var method can optimize carbon fluxes based on observations over a broad region where CO_2 concentrations are sensitive to fluxes. Increasing the duration of the assimilation window and localization length can improve 4D-LETKF performance in this case, however, impose a heavy computational burden. Alternatively, several ensemble Kalman filter studies estimated carbon fluxes for ecoregions, which reduced the system dimensions to minimize the impacts of sampling errors and the lack of observational constraints on inversions (Peters et al., 2005; Feng et al., 2009). In the future, with the increased availability of satellite CO_2 observations, the 4D-LETKF algorithm has the potential to play a more important role in grid-scale inversions."

Detailed comments

Line 72 In addition to Liu et al 2019, it is useful to mention the results by Miyazaki et al. (2011) who also studied adding GOSAT satellite observations.

Response:

Done.

References

Miyazaki, K., Maki, T., Patra, P., and Nakazawa, T.: Assessing the impact of satellite, aircraft, and surface observations on CO_2 flux estimation using an ensemble based 4-D data assimilation system, J. Geophys. Res., 116, D16306, doi:10.1029/2010JD015366, 2011.

Liu, Y., Kalnay, E., Zeng, N., Asrar, G., Chen, Z., and Jia, B.: Estimating surface carbon fluxes based on a local ensemble transform Kalman filter with a short assimilation window and a long observation window: an observing system simulation experiment test in GEOS-Chem 10.1, Geosci. Model Dev., 12, 2899-2914, doi: 10.5194/gmd-12-2899-2019, 2019.

Hunt, B. R., Kostelich, E. J., and Szunyogh, I.: Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter, Physica D: Nonlinear Phenomena, 230, 112-126, doi: 10.1016/j.physd.2006.11.008, 2007.

Miyoshi, T. and Yamane, S.: Local Ensemble Transform Kalman Filtering with an AGCM at a T159/L48 Resolution, Mon. Weather Rev., 135, 3841-3861, doi:10.1175/2007MWR1873.1, 2007.

Chatterjee, A., Michalak, A. M., Anderson, J. L., Mueller, K. L., and Yadav, V.: Toward reliable ensemble Kalman filter estimates of CO_2 fluxes, J. Geophys. Res.-Atmos., 117, 1–17, doi: 10.1029/2012JD018176, 2012.

Chatterjee, A. and Michalak, A. M.: Technical Note: Comparison of ensemble Kalman filter and variational approaches for CO_2 data assimilation, Atmos. Chem. Phys., 13, 11643–11660, doi: 10.5194/acp-13-11643-2013, 2013.

Chevallier, F., Fisher, M., Peylin, P., Serrar, S., Bousquet, P., Bréon, F. M., Chédin, A., and Ciais, P.: Inferring CO_2 sources and sinks from satellite observations: Method and application to TOVS data, J. Geophys. Res. Atmos., 110, D24309, doi: 10.1029/2005JD006390, 2005.

Baker, D. F., Doney, S. C., and Schimel, D. S.: Variational data assimilation for atmospheric CO_2, Tellus Series B-Chemical and Physical Meteorology, 58, 359-365, doi:10.1111/j.1600-0889.2006.00218.x, 2006.

Liu, J., Bowman, K. W., and Lee, M.: Comparison between the Local Ensemble Transform Kalman Filter (LETKF) and 4D-Var in atmospheric CO_2 flux inversion with the Goddard Earth Observing System-Chem model and the observation impact diagnostics from the LETKF, J. Geophys. Res.-Atmos., 121, 13066-13087, doi: 10.1002/2016JD025100, 2016.

Kang, J.-S., Kalnay, E., Liu, J., Fung, I., Miyoshi, T., and Ide, K.: “Variable localization” in an ensemble Kalman filter: application to the carbon cycle data assimilation, J. Geophys. Res., 116, D09110, doi:10.1029/2010JD014673, 2011.

Peters, W., Miller, J., Whitaker, J., Denning, S., Hirsch, A., Krol, M., Zupanski, D., Bruhwiler, L., and Tans, P.: An ensemble data assimilation system to estimate CO_2 surface fluxes from atmospheric trace gas observations, J. Geophys. Res., 110, D24304, doi:10.1029/2005JD006157, 2005.

Bruhwiler, L. M. P., Michalak, A. M., Peters, W., Baker, D. F., and Tans, P.: An improved Kalman Smoother for atmospheric inversions, Atmos. Chem. Phys., 5, 2691-2702, doi: 10.5194/acp-5-2691-2005, 2005.

Feng, L., Palmer, P. I., Bösch, H., and Dance, S.: Estimating surface CO_2 fluxes from space-borne CO_2 dry air mole fraction observations using an ensemble Kalman Filter, Atmos. Chem. Phys., 9, 2619-2633, doi: 10.5194/acp-9-2619-2009, 2009.