

The authors thank the reviewer 1 for a thoughtful review of the manuscript. The responses for the reviewer's specific comments are as follows.

Comment:

This study evaluates the influence of CO₂ observations on the analysis of CO₂ surface fluxes. The influence matrix concept, which is routinely used within the NWP community, has been employed to assess the benefit of different surface observation sites within the CarbonTracker framework. The novelty of this study is in its application to carbon science since the specific tools/methods discussed here are well established.

General Comment:

It seems that a few choices and assumptions (and accordingly the final results) are very much tied to the CarbonTracker setup that the authors have used. Hence, the conclusions may not be reflective of the performance of a generic ensemble Kalman Filter in which the lag window size, localization, inflation parameters etc. can be tuned. In fact there is no discussion of inflation in Section 2.2. The following comments are intended to provide the authors with a few starting points that can make the study more appealing to the general carbon data assimilation, and not just the CarbonTracker, community.

Author's response: The purpose of this work is to estimate the effect of CO₂ observations on the analysis of surface CO₂ flux in the globe. Until now, no studies have investigated how CO₂ observations are used to optimize the surface CO₂ flux using the influence matrix analysis in the real carbon data assimilation. We think that this work is the first step to diagnose the impact of specific CO₂ observations to the estimated CO₂ flux using any CO₂ inversion technique.

The lag window was set to 5 weeks because several previous studies have already shown that the 5 weeks of window are appropriate to estimate the surface CO₂ flux for the globe in CarbonTracker. Recently, we are investigating which window size and localization are appropriate for the analysis of surface CO₂ flux in Asia using CarbonTracker. The results will be presented in another paper. Again, this study is to investigate the impact of CO₂ observations in the globe not just in local region (e.g., Asia). Therefore, it is reasonable to use 5 weeks of lag window because the 5 weeks lag window have been used and found to be appropriate for the Globe, North America, and Europe in previous studies.

In addition, we have added a discussion of inflation in Section 2.2 as follows.

"Many inflation techniques (e.g., Wang and Bishop, 2003; Bowler et al., 2008; Whitaker et al., 2008; Li et al., 2009; Anderson, 2009; Miyoshi, 2011; Kang et al., 2012) have been used to maintain proper ensemble spread and to improve the performance of EnKF data assimilation. Although the EnSRF in CarbonTracker does not use the inflation method, Kim et al. (2012) demonstrated that the ensemble spread measured by rank histograms is maintained properly."

Specific Comments:

1) By the authors' own admission, a lag window of 5 weeks may not be sufficient to optimize the surface CO₂ flux in Asia (Section 3.3.3). This raises two main questions: a) Why didn't the authors use a lag window of more than 5 weeks? Bruhwiler et al. [2005] (Figure 1 in their paper) showed that for some of the remote sites, the lag window might need to be in the order of months. 5 weeks is suboptimal in that respect, and may very well be the reason why the SH (and a few of the MBL) sites seem to provide little to no information (Figure 8). Can the authors show some sensitivity tests when the lag window is increased beyond 5 weeks? Or is this not feasible given the CarbonTracker setup? If the latter assumption is true, then this drawback needs to be clarified early in Section 1. b) The authors repeatedly claim that the cumulative impact over five weeks would be greater than the average self-sensitivity of 4.8%, which is calculated over the most recent assimilation cycle (i.e., one week). But no quantitative value is provided for this 'cumulative impact'. In general, an ensemble Kalman filter is designed to propagate the covariances in time, and hence the cumulative impact can be calculated over the entire analysis period and not just the most recent assimilation cycle. Again if this is an artifact of the Carbon Tracker setup, then this needs to be clearly stated. Or else the authors need to provide magnitudes for the cumulative impact of the observations.

Author's response: Specific answers for the reviewer's questions are as follows.

a) In CarbonTracker framework, it's possible to change the length of assimilation lag window. We have used a lag window of 5 weeks not because it cannot be changed in CarbonTracker, but because several previous studies using CarbonTracker have reported the lag window of 5 weeks is appropriate to estimate the surface CO₂ flux. Both CarbonTracker North America (Peters et al. 2007) and CarbonTracker Europe (Peters et al. 2010) have used the lag window of 5 weeks. Peters et al. (2007) mentioned that the lag window of 5 weeks is appropriate for North America. In addition, Kim et al. (2012, 2014) and Zhang et al. (2014a and b) have shown that the lag window of 5 weeks could produce realistic surface carbon fluxes in Asia and the globe in CarbonTracker. Because of these many previous studies, we have used the lag window of 5 weeks. As mentioned earlier, the purpose of this study is to estimate the impact of individual observations on a particular CO₂ flux analysis in the globe

using CarbonTracker. Therefore it was necessary to use an appropriate length of lag window for the entire globe not just for Asia.

In previous Section 3.3.3 (3.2.3 in the revised manuscript), we mentioned “In addition, the five-week assimilation lag is effective in optimizing the surface CO₂ flux in this region.” Therefore we mentioned the effectiveness of the five-week lag window in Asia, but at the same time we were interested in some possibilities to use a longer lag window for Asia. To investigate which lag window is more appropriate for Asia, we are now testing several different assimilation parameters (e.g., ensemble size, length of lag window, etc.) for Asia using CarbonTracker. Therefore, we have added the following texts at the end of previous Section 3.3.3 (3.2.3 in the revised manuscript).

“A study on the effect of various assimilation window and ensemble size on the estimation of the surface CO₂ flux in Asia is under way to investigate which lag window and ensemble size are appropriate for Asia in CarbonTracker.”

In addition, a discussion on the lag window of MBL sites is shown in the response for the reviewer question 2).

- b) First of all, the impact can be calculated either in the most recent assimilation cycle or in the length of lag window (or even in the entire analysis period). It is not related with CarbonTracker setup, but related with which one is more appropriate.

Even though Liu et al. (2009) has used an ensemble Kalman Filter, Liu et al. (2009) has calculated the observation impact at each assimilation cycle because there was no lag window in Liu et al. (2009) which is associated with NWP. For the same reason, Cardinali et al. (2004) has calculated the observation impact at each assimilation cycle. There have been no studies on the cumulative observation impact yet. Because we have applied the influence matrix concept to carbon science for the first time and the lagged assimilation window is used in CarbonTracker, we had to consider the cumulative impact as well as the impact in the most recent assimilation cycle.

Following the reviewer’s suggestion, we have provided magnitudes for the cumulative impact of the observations in the abstract and Section 3.2.1 as follows.

“Because the surface CO₂ flux in each week is optimized by five weeks of observations, the cumulative impact over five weeks is 19.1%, much greater than 4.8%.”

The cumulative impact considers the previous observation effect which is included in the previous analysis. Therefore the forecast from the previous analysis already includes some percentage of previous observation impact. This kind of concept can also be applied to the observation impact calculation for NWP which does not use the lagged assimilation cycle. Because the cumulative observation impact is used for the first time in this study, we have added a schematic (Fig. 2) and texts in Section 2.3 as

follows.

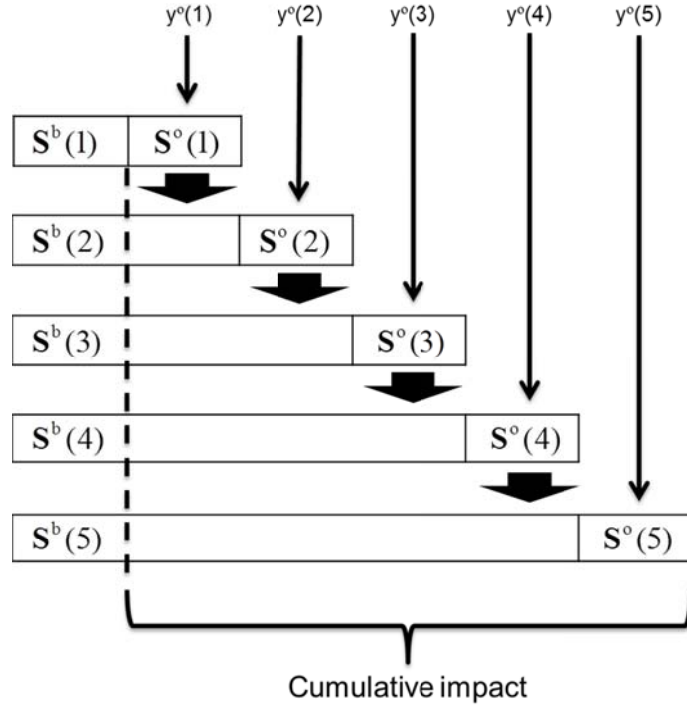


Figure 2. Schematic diagram of calculating cumulative impact in CarbonTraker. $S^b(\bullet)$ indicates the analysis sensitivity to background at each analysis cycle within five weeks of lag, where \bullet denotes each week from 1 to 5. $S^o(\bullet)$ indicates the analysis sensitivity to observation at each analysis cycle.

“The influence matrix is calculated for the most recent week of each cycle because the background at the most recent week of each cycle is updated once by observations.

The cumulative impact of the influence matrix for the five weeks of lag can be calculated because the background in the lagged window already includes the effect from previous observations. For example, Fig. 2 shows that $S^b(5)$ is affected by $S^o(1)$, $S^o(2)$, $S^o(3)$, and $S^o(4)$, where the number inside of parenthesis represent the week of the five-week assimilation lag. If $S^o(\bullet)$ has a value between 0 and 1, $S^b(1)$, the analysis sensitivity to background at the first week, represents an information from previous analysis cycle and is calculated as

$$S^b(1) = (1 - S^o(1))(1 - S^o(2))(1 - S^o(3))(1 - S^o(4))(1 - S^o(5)), \quad (17)$$

Using Eq. (13), the cumulative impact of the influence matrix is

$$\mathbf{S}_{\text{cum}}^{\circ} = 1 - \mathbf{S}^{\circ}(1) = 1 - (1 - \mathbf{S}^{\circ}(1))(1 - \mathbf{S}^{\circ}(2))(1 - \mathbf{S}^{\circ}(3))(1 - \mathbf{S}^{\circ}(4))(1 - \mathbf{S}^{\circ}(5)), \quad (18)$$

where $\mathbf{S}_{\text{cum}}^{\circ}$ is the cumulative impact of observations during the lagged window. The cumulative impact was defined within the five-week assimilation lag and calculated when $\mathbf{S}^{\circ}(5)$ exists.”

2) *Figure 4a – it is particularly curious that the self-sensitivity of the MBL sites are the same as the self-sensitivity of the Difficult sites. In Section 3.2.1, the authors argue that the spread of the analysis CO₂ concentrations is small at the MBL sites. But they have to be an order of magnitude lower to compensate for the fact that the model-data mismatch values at the MBL sites are 10 times lower than the model-data mismatch values at the Difficult sites (based on Table 2). Can the authors show a time-series of how the spread in the analysis CO₂ concentrations compare between these two sets of sites? Are the spread in the analysis CO₂ concentrations that different during the NH winter months? Or is it because that the assimilation system is unable to use the information from the MBL sites, given the constraints on the lag window size?*

Author’s response: The time-series of the spread of analysis CO₂ concentration [ppm²] for MBL and Difficult site are shown in Fig. rev_1. As we have denoted in Section 3.2.1, the spread of the analysis CO₂ concentration is much smaller at the MBL sites than that at the Difficult sites.

As denoted in Section 2.2, the observations at MBL sites affects globally because they are considered to include information on large footprints of flux signals as mentioned in Peters et al. (2007). Therefore, regardless of the lag window size, the information from the MBL sites is used well in CarbonTracker. The small spread of analysis CO₂ concentration in the MBL sites are caused by small CO₂ flux spread in Antarctica because most MBL sites are located in Antarctica.

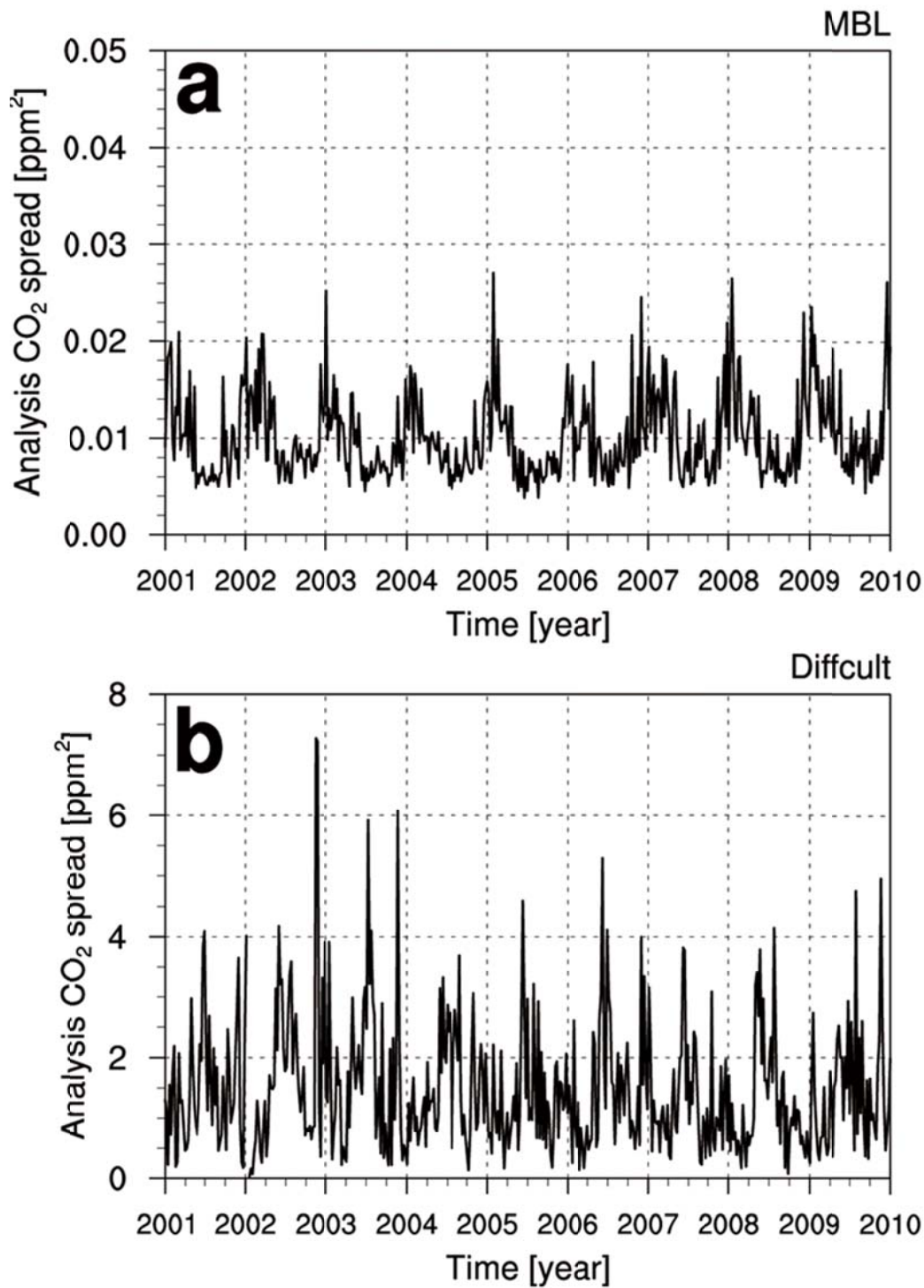


Figure rev_1. The spread of analysis CO₂ concentration [ppm²] for (a) MBL and (b) Difficult category.

3) Does the calculation of the influence matrix take into account systematic errors in the observations? Or are the authors implicitly assuming that the observations do not have systematic errors? If so, why is this a valid assumption?

Author’s response: Including Cardinali et al. (2004) and Liu et al. (2009), no previous observation impact studies have taken into account systematic errors in the observations. The observations used in this study are the same as the observations used in previous studies on CarbonTracker. As shown in Table 1, these observations are collected and managed by NOAA-ESRL. Therefore, we have considered that the quality of the observations is good. These observations are disseminated as ObsPACK (Observation Package; <http://www.esrl.noaa.gov/gmd/ccgg/obspack>) after CT2011_oi which is the current release of CarbonTracker.

4) Section 2.3 – This section mirrors Section 2 in Liu et al. [2009] very closely. But it skips an important assumption, i.e., Equations 16 and 17 assume that observation errors are not correlated. This needs to be added in the text.

Author’s response: Following the reviewer’s suggestion, we have revised the texts to read, “More specifically, if the observation errors are not correlated, the diagonal elements of the influence matrix (i.e., self-sensitivity) are calculated as~”.

5) Section 3.1 is called ‘validation’ but it is unclear what is being ‘validated’ in this sections. Liu et al. [2009] had a similar section titled ‘validation’ but in that study different data-denial experiments were proposed. Have the authors considered data-denial experiments to better demonstrate the applicability/utility of this influence matrix approach for the carbon flux estimation problem? The authors should show some sensitivity experiments using the data-denial approach, especially to bring out the value of MBL vs Difficult sites.

Author’s response: We agree with the reviewer’s opinion on the unclear title of previous Section 3.1. Therefore we have removed the previous Section 3.1 and have moved the content in the previous Section 3.1 to the first paragraph in new Section 3.1.1. While Liu et al. (2009) used an ideal model (Lorenz 40-variable model) to perform data-denial experiments, our study applied the influence matrix analysis in the real carbon data assimilation using CarbonTracker and real CO₂ observations, as the reviewer has indicated. The computational cost of this study is much expensive compared with Liu et al. (2009). Therefore, we think that this work is the first step to diagnose the impact of specific CO₂ observations to the estimated CO₂ flux. The data-denial experiments are out of scope of this study and would be considered in the future. In addition, the value of MBL and Difficult sites are already shown in the above response to the reviewer question 2).

6) Section 3.1 – Why do the authors claim that the self-sensitivity in EnKF should have a value less than one? Can the authors justify this statement? Further, Lines 15-18 need to be rephrased as it currently gives the impression that when the analysis error covariance in

4DVAR is calculated using the inverse of the Hessian matrix of the cost function, then this being an approximate method will result in self-sensitivity values greater than one.

Author's response: Cardinali et al. (2004) demonstrated that the self-sensitivity is theoretically between 0 and 1 if observations are not correlated. Liu et al. (2009) also mentioned that the calculation of the self-sensitivity requires no approximations when the observation errors are not correlated, so that the self-sensitivity satisfies the theoretical limits between 0 and 1. Even though there is the theoretical limit, the calculation of the analysis error covariance in 4D-VAR can introduce spurious values larger than 1 because it is based on a truncated eigenvector expansion with the vectors obtained through the Lanczos algorithm, as denoted by Cardinali et al. (2004). Therefore, we have revised the sentences of previous Section 3.1 as follows. In the revised manuscript, the sentences are in Section 3.1.1.

“Cardinali et al. (2004) demonstrated that the self-sensitivity is theoretically between 0 and 1 if observations are not correlated. In 4D-VAR, Cardinali et al. (2004) denoted that analysis error covariance based on the Hessian representation with truncated eigenvector expansion can introduce the self-sensitivities greater than 1 for only a small percentage of the cases. In contrast, the self-sensitivity in EnKF theoretically has a value lesser than 1 (Liu et al. 2009). Nevertheless, the self-sensitivity in this study shows a value greater than one because the sparse observations cause insufficient reduction of the background and observation operator used has nonlinearity in calculating the transport of CO₂ concentrations. In this study, 13 observations from the total of 76,801 observations used for data assimilation present a value greater than one. This is only 0.02% of the total number of observations, which implies that the calculated self-sensitivity is generally valid.”

7) My biggest disappointment is that the quality of the optimized CO₂ fluxes has not been assessed. Some robust ways of evaluating the posterior CO₂ fluxes (i.e., comparison to biosphere model output, comparison of posterior CO₂ concentrations to independent datasets like aircraft observations etc.) would have been beneficial for the reader. Only the uncertainty reductions are presented in Figure 7. Additionally, the color bar should be different for JJA and DJF to bring out the uncertainty reductions for DJF. The same recommendation applies for Figure 12.

Author's response: Kim et al. (2012) already showed the high quality of the optimized CO₂ flux compared with independent aircraft observations using CarbonTracker. To avoid redundancy, we have not shown the quality of the optimized CO₂ flux.

However, following the reviewer's suggestion, we have compared the optimized CO₂ flux of this study with that of other previous studies (Tables rev_1 and rev_2). Results from CT2010 (CarbonTracker 2010) used in this study, CT2013 (CarbonTracker-NOAA; <http://www.esrl.noaa.gov/gmd/ccgg/carbontracker/>), CTE2013 (CarbonTracker-EU;

<http://www.carbontracker.eu>) (Peylin et al., 2013), and Zhang et al. (2014b) using CONTRAIL data (CarbonTracker-China; <http://www.carbontracker.net>) were compared. Saeki et al. (2013) used NIES-TM transport model and NOAA observations and JR-STATION data. Niwa et al. (2012) used NICAM-TM transport model and GLOBALVIEW-CO₂ observations and CONTRAIL data. In contrast, Pan et al. (2011) used bottom-up method to estimate global net forest sink from forest inventory data and long term ecosystem studies.

We have compared biosphere, ocean, and biomass burning emission (fire flux in CarbonTracker) except fossil fuel emission because biosphere, ocean, and biomass burning emission were used in previous studies. Because the study period of each study is different, we have shown two tables which are for a longer period (Table rev_1) and for a shorter period (Table rev_2). As shown in Tables, the optimized CO₂ flux of this study is similar to those of other previous studies in the globe, land, and ocean. Therefore, we think the quality of the optimized CO₂ flux of this study is good enough to investigate the purpose of this study which is estimating the effect of CO₂ observations on the analysis of surface CO₂ flux in the globe.

Table rev_1. Global annual average optimized CO₂ fluxes (including biomass burning emission and without fossil fuel emission) of each study for globe, land, and ocean. Unit is P g C yr⁻¹.

	This study	CT2010	CT2013	CTE2013 Peylin et al. (2013)	Saeki et al. (2013)	Pan et al. (2011)
Period	2001-2009				2000-2009	2000-2007
Globe	-3.71	-3.68	-3.82	-3.59	-3.51	
Land	-1.59	-1.78	-1.78	-1.85	-1.9	-1.2
Ocean	-2.12	-1.9	-2.01	-1.74	-1.61	

Table rev_2. Global annual average optimized CO₂ fluxes (including biomass burning emission and without fossil fuel emission) of each study for globe, land, and ocean. Unit is P g C yr⁻¹.

	This study	CT2010	CT2013	CTE2013 Peylin et al. (2013)	CT-China Zhang et al. (2014b)	Niwa et al. (2012)
Period	2006-2009				2006-2010	2006-2008
Globe	-4.49	-3.68	-4.69	-4.44	-4.5	-4.46
Land	-2.09	-1.78	-2.63	-2.52	-2.43	-2.67
Ocean	-2.4	-1.9	-2.07	-1.93	-2.08	-1.79

As mentioned in the manuscript, we set the same color bar for both JJA and DJF in Figs.

7 and 12 because we compared the seasonal and regional characteristics of the uncertainty reduction. If we use different color bar for JJA and DJF, it is difficult to compare how the uncertainty reduction and root mean square difference are different in JJA and DJF and how they differ in Asia and North America. For the original purpose of two Figures, we kept the original Figures.

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Response to Reviewer 2

The authors thank the reviewer 2 for a thoughtful review of the manuscript. We agree with many of the reviewer's points and have made the necessary changes. The responses for the reviewer's specific comments are as follows.

Comment:

The manuscript has examined the contribution of CO₂ observations to the optimized CO₂ flux within Carbon Tracker EnKF assimilation system. Quantitative analysis of which observation data give more correction to the prior is indeed very interesting trial, and would give an essential feedback to the community of data providers. Especially in Carbon Tracker, it would not be very easy due to a special assimilation window, which is still remained as the non-resolved problem to the authors. However, based on the methodology introduced by Liu et al. (2009), authors have made very useful tool to estimate observation impact on the analyzed CO₂ fluxes. Although the paper was not written in a very exciting way, a revision focusing on the presentation would bring this manuscript qualified to the publication.

Specific Comment:

1) Abstract of the manuscript needs serious revision. Major reason may be because authors use several terminologies (e.g. self-sensitivity, analysis sensitivity, information content) which need their explanations or definitions, for general readers. The abstract of the manuscript contains too much detailed results that may not be appropriate for a general abstract. Thus, the current abstract does not concisely deliver what exactly you have done. This referee suggests to emphasize important findings of your research as a discerning summary.

Author's response: Following the reviewer's suggestion, we have revised the abstract. We have added definitions of some terminologies and tried to emphasize important findings.

2) Isn't there any way to estimate the cumulative impact? Any idea? As the authors pointed out, the posterior flux seems to be determined mostly by the prior flux, not by the assimilation of the observation based on the analysis of self-sensitivity. However, there is just a statement saying that the cumulative impact would be greater. Can you "prove" it? Figure 12 lets us guess roughly how the cumulative impact would be though. Still, the first week seems to give the largest correction to the prior, doesn't it? It would be quite important message for Carbon

Tracker users.

Author’s response: Following the reviewer’s suggestion, we have provided magnitudes for the cumulative impact of the observations in the abstract and Section 3.2.1 as follows.

“Because the surface CO₂ flux in each week is optimized by five weeks of observations, the cumulative impact over five weeks is 19.1%, much greater than 4.8%.”

The cumulative impact considers the previous observation effect which is included in the previous analysis. Therefore the forecast from the previous analysis already has some percentage of observation impact. This kind of concept can also be applied to the observation impact for NWP which does not use the lagged assimilation cycle. Because the cumulative observation impact is used for the first time in this study, we have added a schematic (Fig. 2) and texts in Section 2.3 as follows.

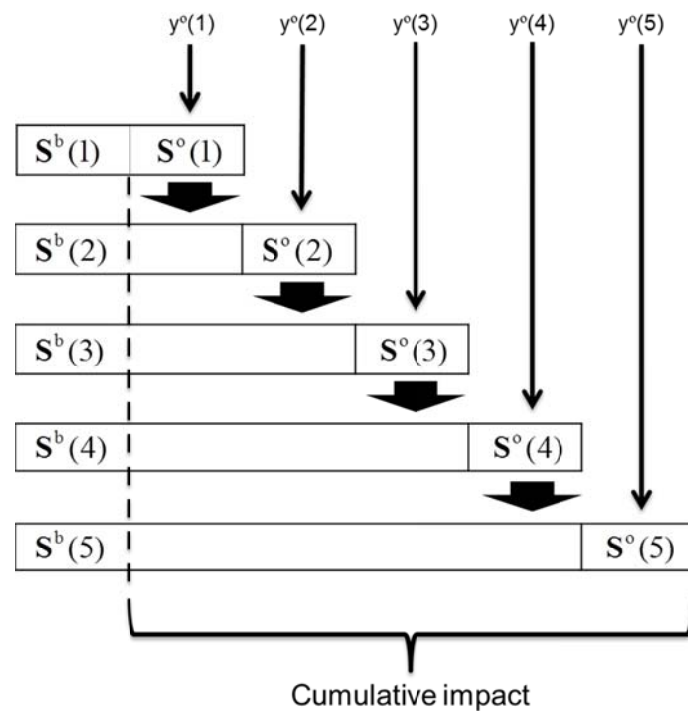


Figure 2. Schematic diagram of calculating cumulative impact in CarbonTracker. $S^b(\bullet)$ indicates the analysis sensitivity to background at each analysis cycle within five weeks of lag, where \bullet denotes each week from 1 to 5. $S^o(\bullet)$ indicates the analysis sensitivity to observation at each analysis cycle.

“The influence matrix is calculated for the most recent week of each cycle because the background at the most recent week of each cycle is updated once by observations.

The cumulative impact of the influence matrix for the five weeks of lag can be calculated because the background in the lagged window already includes the effect from previous observations. For example, Fig. 2 shows that $\mathbf{S}^b(5)$ is affected by $\mathbf{S}^o(1)$, $\mathbf{S}^o(2)$, $\mathbf{S}^o(3)$, and $\mathbf{S}^o(4)$, where the number inside of parenthesis represent the week of the five-week assimilation lag. If $\mathbf{S}^o(\bullet)$ has a value between 0 and 1, $\mathbf{S}^b(1)$, the analysis sensitivity to background at the first week, represents an information from previous analysis cycle and is calculated as

$$\mathbf{S}^b(1) = (1 - \mathbf{S}^o(1))(1 - \mathbf{S}^o(2))(1 - \mathbf{S}^o(3))(1 - \mathbf{S}^o(4))(1 - \mathbf{S}^o(5)), \quad (17)$$

Using Eq. (13), the cumulative impact of the influence matrix is

$$\mathbf{S}_{\text{cum}}^o = 1 - \mathbf{S}^b(1) = 1 - (1 - \mathbf{S}^o(1))(1 - \mathbf{S}^o(2))(1 - \mathbf{S}^o(3))(1 - \mathbf{S}^o(4))(1 - \mathbf{S}^o(5)), \quad (18)$$

where $\mathbf{S}_{\text{cum}}^o$ is the cumulative impact of observations during the lagged window. The cumulative impact was defined within the five-week assimilation lag and calculated when $\mathbf{S}^o(5)$ exists.”

3) *Lines 19-22 of p.13568: What about the computational cost of this process? Are the authors doing this process at every analysis step?*

Author’s response: We did the process at every analysis step. The computational cost of this process is not much. Most of the computational cost in CarbonTracker is used for TM5 transport model run to calculate model CO₂ concentration. Compared to the TM5 model run, the computational cost for the analysis procedure in CarbonTracker is much smaller.

4) *Equation (16) is just a case of $l=j$ in Equation (17). Any reason to write exactly same equation twice? Unnecessary repetition makes the manuscript a little boring.*

Author’s response: Following the reviewer’s opinion, we have deleted Eq. (17).

5) *Lines 19-22 of p.13572: Isn’t there any possible link with the prescribed Pb in EnKF of Carbon Tracker?*

Author’s response: The self-sensitivity value greater than 1 may be associated with the prescribed Pb in EnKF of CarbonTracker. However, we found that the greater self-sensitivity is more directly related with the sparse observations. We found that 7 of the

total 13 cases were occurred in Eurasian Boreal region with very sparse observations. Regardless of the prescribed Pb or non-prescribed Pb, the $\mathbf{HP}^a\mathbf{H}^T$ becomes large if there are few observations. In a different study, we found that the greater self-sensitivity in Eurasian Boreal region decreases from 7 to 2 cases when the additional observations in the region were assimilated.

The other reason of the greater self-sensitivity is associated with transport model mentioned already in the manuscript.

Therefore, we have revised the text to read, “Nevertheless, the self-sensitivity in this study shows a value greater than one because the sparse observations cause insufficient reduction of the background and observation operator used has nonlinearity in calculating the transport of CO₂ concentrations.”

6) The reason why the inverse relationship between the average self-sensitivity and the number of observations is not shown was not explained. Authors said that is due to the insufficient number of observations. It does not make sense. It is just denying the statement of inverse relationship, because it is not valid when the number of observation is few. Thus, please find another reasonable reason within your experimental settings.

Author’s response: As the number of observations increases, the average self-sensitivity decreases. The inverse relationship between the average self-sensitivity and the number of observations is not shown in the SH because the increase of the number of observations is not enough to cause the decrease of the average-self sensitivity. Therefore we have revised the text to read, “In the SH, an inverse relationship between the average self-sensitivity and the number of observations is not clearly shown (Fig. 6d), which is due to the insufficient increase of the number of observations assimilated in the SH compared with the other regions. However, the seasonal variability of the average self-sensitivity appears clearly in the SH. Therefore the inverse relationship is distinctly shown when the increase of the number of observations is enough to cause the decrease of the average self-sensitivity.”.

7) Explaining Figure 6, authors continue to mention the inversely proportional relationship between the number of observations and self-sensitivity even though the results do not show it consistently. It seems to this referee that it is just visible in Figure 6(d), because the increase rate of the number of Continuous observations is remarkable.

Author’s response: As the reviewer indicated, we have mentioned the inverse relationship only for Continuous site category when explaining the previous Fig. 6 (Fig. 7 in the revised manuscript).

8) *Figure 7: it would be better to plot the reduction of self-sensitivity rather than the reduced ones.*

Author's response: The self-sensitivity is calculated in observation space. Therefore the reduction of self-sensitivity is also calculated in observation space and cannot be shown as the form in previous Fig. 7 (Fig. 8 in the revised manuscript). In addition, the self-sensitivity was not calculated in every week in the 5-weeks of assimilation window. Instead of the reduction of self-sensitivity, the average standard deviations of background and posterior CO₂ fluxes in one- and five- week were shown to investigate the influence of the surface CO₂ flux uncertainties on the seasonal and regional characteristics of the self-sensitivities. In addition, the cumulative impact implies the overall observation impact during the lagged assimilation window.

9) *Lines 27-28 of p.13576: "and the seasonal variability of the surface . . . variation of the self-sensitivities" seems unnecessary repetition.*

Author's response: Following the reviewer's opinion, we have revised the text to read, "Therefore, the surface CO₂ flux uncertainty is one of the components to determine the magnitude and seasonal variation of the self-sensitivities."

10) *Lines 8-9 of p.13577: Do the authors indicate the temporal resolution of the station? Please rephrase it.*

Author's response: The number of observations at one station depends on the temporal resolution, missing rate, and total period of observations. Therefore we have revised the text to read, "Because the magnitude of the information content at one observation site is proportional to the self-sensitivity and the number of observations, the observation sites with a high average self-sensitivity or a large number of observations show high information content. The number of observations at one station depends on the temporal resolution, missing rate, and total period of observations. Therefore, the observation sites located in North America and Asia generally show high average information content."

11) *Some statements are so trivial, not worth pointing out: e.g. lines 21-22 of p.13577, lines 10-12 of p.13578.*

Author's response: For the lines 21-22 of p. 13577, even though they are trivial, we need a text to explain the previous Fig. 9b (Fig. 10b in the revised manuscript). Therefore we have revised the text to read, "As in the globe, the Continuous site category is the most informative in the NH (Fig. 10b)".

For the lines 10-12 of p. 13578, we have deleted the texts following the reviewer's

opinion.

12) Line 3 of p.13579: have the authors really assimilated only surface CO₂ concentration data? What's the criterion of surface layer? Carbon Tracker assimilates observations which are located up in the air either.

Author's response: To clarify the surface observations used in this study, at the first paragraph in Section 2.4, we have revised the text to read, "The observations used in this study are surface CO₂ mole fraction data observed at sites distributed around the globe (Table 1 and Fig. 3). As in Peters et al. (2007), the surface CO₂ mole fraction data used in this study includes surface air samples collected around the globe and from tall towers."

13) Lines 26-27 of p.13580: while statement needs to be rephrased.

Author's response: Following the reviewer's opinion, we have rephrased the text to read, "The self-sensitivity and spatial coverage of the observation sites are inversely correlated in the NH, whereas these factors are not apparently related in the Tropics and SH."

14) At the end of line 20 of p.13581, it would be better to mention a possible advanced data assimilation method which allows considering high-resolution data, because Carbon Tracker may not be able to assimilate those high-resolution data (such as remote sensing data) easily with the current algorithm.

Author's response: The sentence in line 20 of p. 13581 implies that new observation sites are necessary in regions with a low spatial density of observation sites (e.g., Asia) to obtain the beneficial effect of additional observations on the surface CO₂ flux analysis in the current CarbonTracker framework. We have not mention the reviewer's suggestion because we have mentioned that the use of high-resolution data (e.g., CONTRAIL, GOSAT etc.) in CarbonTracker is the future work at the last paragraph of Section 4. In fact, we plan to assimilate the GOSAT data in CarbonTracker in the future.

15) Unit of MDM should be presented in Table 1 rather than Table 2.

Author's response: We have revised the Tables following the reviewer's opinion.

16) When explaining Figure 9 (section 3.3.1), please make sure there is no Continuous data in SH.

Author's response: At the end of previous Section 3.3.1 (Section 3.2.1 in the revised manuscript), we have added the text to read, "In addition, the information from the Continuous site category is zero because there is no Continuous data in the SH."

References

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