Referee #2

We thank the anonymous referee for his/her valuable comments and constructive suggestions. We have made changes according to the referee's suggestions and replied to all comments point by point. All the page and line number for corrections are referred to the revised manuscript, while the page and line number from original reviews are kept intact. The references related to the responses are listed in the end of this document.

General comments:

In this study, Jiang et al. upgraded the Global Carbon Assimilation System (GCAS) with new assimilation algorithms, a localization scheme, and a higher assimilation parameter resolution, namely GCASv2. The global terrestrial ecosystem (BIO) and ocean (OCN) carbon fluxes from 2009 to 2015 were constrained by the GOSAT ACOS XCO2 retrievals. Following this, the posterior carbon fluxes from 2010 to 2015 were evaluated using 52 surface flask observations. The errors in the posterior carbon fluxes in the new inversion system were compared to those in a previous version. The authors indicated that the pattern of regional carbon sinks was significantly different from previous studies (CT2017). The inter-annual variations of carbon fluxes in most land regions, and the relationship with the changes of severe drought area the plant indexes, and drought were re-visited. These results are interesting. However, the improvement of the inversion methodology is not presented, and the reduction of the uncertainty by the inversions remains unclear (Figure 3) in the current paper. I, therefore, recommend that this work cannot be published before the following comments are addressed.

Specific comments:

Figure 3: What is the source for error bars in these two plots? Are they coming from the uncertainty in the prior and posterior estimates? If yes, it seems that the uncertainty is not reduced from the prior estimates to the posterior estimates. One main purpose of inversion is to reduce the uncertainty in the prior estimates. If the uncertainty is not reduced, the effectiveness of the inversions should be evaluated.

Response: Thank you for this suggestion. The error bars represent the standard deviations of all biases at each latitude and each site, respectively. Indeed, the uncertainty reduction is very important for an inversion study. We analyzed the uncertainty reduction rate (UR), and added a section of "4.2 Uncertainty reduction" in the revised manuscript (see Lines 663 – 705, Pages 21 - 23). The annual mean URs of the BIO fluxes over different TRANSCOM regions are in the range of 6% ~ 27%, with global mean of 17%. The highest monthly UR is 51% in temperate South America.

Figures 4/5: Evaluation of the reduction of the uncertainty from the prior estimates to the posterior estimates is more important than evaluation of the bias itself for an inversion system.

Response: Thank you for this suggestion. We have analyzed the reductions of the uncertainties from the prior estimates to the posterior estimates and added a section of “4.2 Uncertainty reduction” in the revised manuscript (see Lines 663 – 705, Pages 21 - 23).

Tables 2/3: What is the uncertainty for the prior and posterior estimates?
Response: Thank you! We have added the uncertainties of the prior and posterior estimates in the revised manuscript (see Lines 719 – 723, Page 24 and Line 828, Page 28).

Line 473-488: What is the uncertainty for the estimates from this study? To evaluate the effectiveness of an inversion system, the uncertainty of the posterior estimates is more important than the central value. Such information is missing in the current manuscript, which is better considered / discussed in previous studies (e.g. the literature cited in line 586).
Response: Thank you for this suggestion! As shown above, we have analyzed the uncertainty reductions and added a section of “4.2 Uncertainty reduction” in the revised manuscript (see Lines 663 – 705, Pages 21 - 23).

Figures 7/9/10: What is the uncertainty for the prior and posterior estimates?
Response: Thank you for this suggestion. We have added the prior and posterior uncertainties in Figures 7, 9 and 10, which are named as Figure 8, 10 and 11 in the revised manuscript (see Lines 893-896, Page 31; Lines 934-937, Page 33; and Lines 1045-1049, Page 37).

Figure 1: The authors suggested that a new assimilation scheme is developed in this paper. Why not directly compare the flow charts between the GCAS and GCASv2 systems and show the difference?
Response: Many thanks for this suggestion. We have modified Figure 1 and given the differences in the flow charts between GCASv1 and GCASv2 (see Lines 147-148, Page 6).

Line 124: It seems that a major advance of GCASv2 against GCAS is that “In the second step, the MOZART-4 model is run again using the optimized fluxes of Xa, to generate new CO2 concentrations for the initial field of the next DA window. This DA flow chart is different from the previous version of GCAS, which runs the MOZART-4 model only once, and optimizes the fluxes and the initial field of the next window synchronously.” However, I do not understand how this improves the inversion system. The old GCAS system produces the posterior global gridded carbon fluxes, which were used as prior fluxes as input to any other forward models to simulate the CO2 field. If the difference of GCASv2 was just that the posterior global gridded carbon fluxes were used by MOZART-4 to simulate the CO2 field, I cannot see how and why the inversing methodology is improved.
Response: Thank you for this comment. Indeed, as you said, the descriptions of the differences between GCASv2 and GCASv1 are rather vague. We have revised Section 2.1 to further clarify their differences. The main differences between GCASv2 and GCASv1 are as follows:

1) Optimization of the initial field of each window. In GCASv1, it is directly optimized using the observations, while in GCASv2, it is simulated using the posterior fluxes of the previous window. The advantage of this method in GCASv2 is that the assimilation errors could be

transported from one window to the next. If the fluxes are overestimated in one window because of some reasons, by this method, they will affect the concentrations of the next window, thereby the posterior fluxes of the next window will compensate the overestimations. While in GCASv1, since the initial field of each window is directly optimized using the observations, which means in each window, there are relatively perfect initial fields, the inversions of each window are independent, and the amount of overestimation or underestimation in one window will continue to accumulate until the end, leading to an overall overestimation or underestimation. In addition, due to the perfect initial field, the differences between the simulated and observed concentrations are only contributed by the errors in the prior fluxes of current window, resulting in a relatively smaller model – data mismatch, so as to weaken the assimilation benefits on fluxes. This difference is given in Lines 128 – 143, Page 5 in the revised manuscript.

2) State vector. In GCASv1, only BIO is state vector, while in GCASv2, we set 4 state vector schemes for different applications: 1) only the BIO flux is state vector; 2) both BIO and OCN fluxes are treated as state vectors; 3) the BIO, OCN and FOSSIL fluxes are optimized at the same time; and 4) only net flux is optimized. This difference is given in Lines 172 – 178, Page 7 in the revised manuscript.

3) Resolution of the state vectors. In GCASv1, the scaling factor λ is defined in different land and ocean areas based on 22 TRANSCOM regions (Gurney et al., 2002) and 19 Olson ecosystem types, as in CarbonTracker (Peters et al., 2007), while in GCASv2, we change to use a λ in each grid, meaning that for each grid, the perturbations of prior fluxes are independent, and the grid cell of λ could be set freely. This difference is given in Lines 154-161, Page 6 in the revised manuscript.

4) observation data. In GCASv1, only flask/in situ observations were assimilated, while in GCASv2, we added a module to assimilate the satellite XCO_2 retrievals, and allow users to simultaneously or separately assimilate the flask/in situ concentrations and the XCO_2 retrievals. See Lines 186 – 201, Pages 7 -8 in the revised manuscript. Besides, a 'super-observation' approach is also adopted in GCASv2, See Lines 202-215, Page 8 in the revised manuscript.

5) assimilation algorithm, in GCASv2, we added another EnKF algorithm, i.e., EnSRF. See Lines 223-227, Page 9.

Line 143: It seems that the carbon emission from cement production, a large part of CO2 source, is missed in this inversion system. This could be a big weakness of the current system.
Response: Sorry, that description is not accurate enough. The carbon emission from cement production has been included in this study. The fossil fuel carbon emissions are obtained from NOAA's CarbonTracker, version CT2017, which is an average of the Carbon Dioxide Information Analysis Center (CDIAC) product (Andres et al., 2011) and the Open-source Data Inventory of Anthropogenic CO2 (ODIAC) emission product (Oda et al., 2018). We have checked the document of CT2017 and the introduction of CDIAC database, compared the annual global fossil fuel emissions in our system with the global emissions from the CDIAC website (https://cdiac.ess-dive.lbl.gov/), and confirmed that the carbon emission from

cement production has been included in this study. We have changed the sentence of "… atmosphere and ocean (OCN) carbon exchange, fossil fuel (FOSSIL) carbon emission and biomass burning (FIRE) carbon emission…" to "*… atmosphere and ocean (OCN) carbon exchange, fossil fuel* ***and cement production*** *(FOSSIL) carbon emission and biomass burning (FIRE) carbon emission…*" (see Lines 166-167, Page 7)

Line 143: What is the relationship between BIO and FIRE? Biomass sequestrates carbon from the atmosphere, and releases CO2 in biomass burning. Should FIRE be a part of BIO?
Response: Yes, biomass burning carbon emission is a part of terrestrial ecosystem carbon flux. Terrestrial ecosystems uptake carbon through photosynthesis (GPP) and release carbon through respiration (ER) and biomass combustion (FIRE). The BIO flux defined in this study is the net flux of GPP and ER (ER-GPP). In many previous inversion studies, it is directly defined as net ecosystem exchange [NEE = ecosystem respiration (ER) − gross primary production (GPP)] (e.g., Hu et al., 2019; Peters et al., 2007, 2010), and the sum of NEE and FIRE is defined as net biosphere exchange (NBE, Liu et al., 2017). In the revised manuscript, we have changed the sentence of "… name terrestrial ecosystem (BIO) carbon flux, …" to "*namely terrestrial ecosystem (BIO) carbon flux (i.e., net ecosystem exchange (NEE) = ecosystem respiration (ER) − gross primary production (GPP)), …*" (see Lines 163-166, Pages 6-7)

Line 147: "FOSSIL and FIRE fluxes are assumed to have no errors, only BIO and OCN fluxes are optimized in an assimilation system". I do not think that this is the case in other inversion systems: (1) It needs clear justification by summarizing and tabulating the methodology in the literature. (2) The difference relative to a system with errors considered for FOSSIL and FIRE need to be calculated to show how much the conclusion of the present study are sensitive to this assumption.
Response: Thank you for this comment. Yes, there are considerable uncertainties for the fossil fuel and biomass burning carbon emissions, which are about 6% and 20% for global mean, respectively. Ideally, we would like the inversion to partition the deviations from the a-priori fluxes among all the four type of carbon fluxes. NEE and ocean fluxes can, since they are geographically separated, readily be accounted for in statistically independent deviation terms. However, the inversion cannot be expected to distinguish between land biosphere fluxes and fossil fuel emissions, because both are inextricably localized on land, and the CO_2 data alone do not discern fossil and non-fossil carbon (Rödenbeck et al., 2003). Therefore, most inversion studies for surface carbon fluxes focused on the NEE and ocean fluxes, and the fossil fuel and biomass burning were prescribed (e.g., Gurney et al., 2002, 2003; Peters et al., 2007; Nassar et al., 2011; Feng et al., 2009; Monteil et al., 2020). As shown in Table 1, we have reviewed a lot of studies, in which only Deng et al. (2014, 2015) considered the uncertainties of fossil fuel and biomass burning carbon emissions, Liu et al. (2019) and Kang et al. (2012) directly optimized the net carbon flux, and Some studies (Monteil et al., 2020, Scholze et al., 2019) only optimized the NEE. Although Deng et al. (2014)'s state vector includes emissions of CO_2 from fossil fuel combustion, when they reported their posteriori flux estimates, they removed the a priori fossil fuel estimate from the reported total land flux.

As shown in section 2.1, we have added a scheme to simultaneously the fossil fuel and cement production carbon emissions in GCASv2. We have tried to use it to optimize the fossil fuel emissions in China. We tested different emission inventories, but GCASv2 did not make them converge, but only made the emissions of each inventory slightly lower. Therefore, we think that under the current resolution of atmospheric transport model, spatial coverage of observational data, and the assimilation settings, GCASv2 cannot optimize it well.

According to your suggestion, we added a sensitivity test for optimizing fossil fuel carbon emissions, using the same localization scheme as BIO and OCN, giving fossil fuels a global uncertainty of 5%. The results showed that the impact on both the inverted global and regional scale BIO fluxes are very small (Table 2).

The following sentences has been added in the revised manuscript:

"… and the FOSSIL and FIRE carbon emissions are kept intact *(the impact of this assumption on both the inverted global and regional BIO fluxes are very small (Table S4))*. Following Wang et al. (2019), …" (see Lines 558-560, Pages 16-17)

Table 1. a summary of the inversion methodology in the literature.

System Name	**Transport model/Res.**	**Assimilation method**	**Obs.**	**State Vector***	**Reference**
CT/CTE/CT-China	TM5,global 3x2, region, 1x1	EnSRF	obspack	NEE, OCN	Peters et al., 2007; Peters et al., 2010; Zhang et al., 2014
UoE	GEOS-Chem,4x5	EnKF	in situ or GOSAT	NEE, OCN	Feng et al., 2009, 2016, 2017
CAMS CO2 inversion system	LMDz,3.75x1.875	variational	surface observations, GOSAT, OCO-2	NEE, OCN	Chevallier, et al., 2019
CCDAS	TM3,4x5	4D-Var	in situ CO2, SM, and L-VOD	NEE	Scholze et al., 2019
Jena CarboScope	TM3,4x5	time-independent Bayesian inversion	surface observations	NBE, OCN	Rödenbeck, 2005; Rödenbeck et al., 2003
TransCom 3 inversions	16 Atmospheric Transport Models,2.0x2.5 to 7.5x7.5	Bayesian synthesis inversion	GLOBALVIEW data	NEE, OCN	Baker et al., 2006; Gurney et al., 2002, 2003

Nasser et al., 2011	GEOS-Chem,2x2.5	time-independent Bayesian inversion	TES and surface flask measurements	NEE, OCN	Nassar et al., 2011
EUROCOM (include 6 systems)	CHIMERE, FLEXPART, STILT, TM5, NAME/0.5x0.5 ~1x1	Variational, EnKF, MCMC	flask	NEE OCN (4 prescribed)	Monteil et al., 2020
Deng et al., 2007	NIES,2.5x2.5	Time-dependent Bayesian synthesis	GLOBALVIEW data	NEE, OCN	Deng et al., 2007
Niwa et al., 2012	NICAM-TM,~240 km	Time-dependent Bayesian synthesis	GLOBALVIEW, CONTRAIL	NEE, OCN	Niwa et al., 2012
Miyazaki et al., 2011	AGCM,2.8x2.8	LETKF	OSSEs (GOSAT, CONTRAIL, and surface sites)	NEE, OCN	Miyazaki et al., 2011
TM5-4DVAR inversion system	TM5,6x4	4D-Var	GOSAT	NEE, OCN	Basu et al., 2013
GEOS-Chem-4DVAR inversion system	GEOS-Chem,4x5	4D-Var	GOSAT, Flask	NEE, OCN, FOSSIL, FIRE	Deng et al., 2014; 2016
CMS-Flux inversion framework	GEOS-Chem,4x5	4D-Var	GOSAT, OCO-2, SIF	NBE, OCN	Liu et al., 2017
LETKF_C	GEOS-Chem,4x5	LETKF	OSSEs (GOSAT, CONTRAIL, and surface sites)	Net flux	Liu et al., 2019; Kang et al., 2012

*NEE: net ecosystem exchange, ecosystem respiration (ER) − gross primary production (GPP); NBE: net biosphere exchange, NEE + biomass burning carbon emission (FIRE); OCN: atmosphere - ocean carbon exchange; FOSSIL: fossil fuel and cement production carbon emission; Net flux: NEE + OCN + FOSSIL+ FIRE

Table 2. Results of sensitivity tests in the year of 2010 (Wfossil is an experiment with the

FOSSIL carbon emissions being synchronously optimized) (This Table has been added in the revised Supporting Information)

		Prior	1 week	Wfossil
Super Obs. Num. per window	Total	-	730	730
	Each grid could use	-	4	4
Global Flux (PgC/yr)	BIO	-2.07	-4.16	-4.15
	OCN	-2.08	-2.33	-2.31
	FOSSIL	9.07	9.07	9.05
	AGR	7.25	4.91	4.92
Regional Flux (PgC/yr)	North America Boreal	-0.29	-0.43	-0.44
	North America Temperate	-0.42	-1.25	-1.21
	Tropical South America	-0.17	-0.26	-0.27
	Temperate South America	-0.24	-0.4	-0.41
	Northern Afirca	0.21	0.32	0.34
	Southern Africa	0.22	-0.3	-0.29
	Boreal Asia	-0.4	-0.46	-0.48
	Temperate Asia	-0.3	-0.29	-0.27
	Southeast Asia	-0.29	-0.23	-0.24
	Australia	-0.17	-0.4	-0.4
	Europe	-0.19	-0.41	-0.43
independent evaluation	BIAS	1.43	-0.44	-0.43
	MAE	1.92	1.37	1.35
	RMSE	2.36	2.11	2.08
Deviation from the observed AGR (PgC yr^{-1})		2.08	-0.26	-0.25

Line 209: How does GCASv2 consider the spatial representativeness errors in the inversion system?

Response: Many thanks for this question. GCASv2 do not consider the spatial representativeness errors for the GOSAT XCO_2 retrievals in this study. Generally, the spatial representation error must be considered when the resolution of the model grid is inconsistent with the spatial range represented by the observation data. In this study, we only use the XCO_2 retrievals. The reason of why we do not consider the spatial representativeness errors is that, first, the XCO_2 retrieval is a column averaged atmospheric CO_2 concentration, which is the result of full atmosphere mixing; 2) before we use the GOSAT data in GCASv2, it has been averaged within the grid cell of 1°×1°. 3) a 'super-observation' approach is adopted based on the optimal estimation theory (Miyazaki et al., 2012). A super-observation is generated by averaging all observations located within the same model grid within a DA window. Therefore, we believe that the spatial representation of the re-grided and averaged XCO_2 data can match the grid of the model. In addition, the model-data mismatch error of XCO_2 is constructed using the GOSAT retrieval error, which has been uniformly inflated by a factor of 1.9 with lowest error fixed as 1 ppm. Therefore, we did not consider the spatial representation error in this study.

Line 238: How many sites are subject to this spurious noise? Are these sites excluded from the inversion system? How much does removing data at these sites influence the inversion fluxes?

Response: We have conducted an additional assimilation for the year of 2010, in which we do not remove the spurious signals, namely all the data with the correlation coefficient with the perturbed fluxes greater than zero were used for assimilation. As shown in Table 3, on average, 87% of the observations were spurious noise and removed in this study. The spurious observations will increase the inverted global land sink and enlarge the deviation of the simulated and observed atmospheric CO_2 growth rate. For different TRANSCOM regions, the impact for the BIO fluxes could be in the range of -32% to 40%. We have added the following sentences in the revised manuscript (see Lines 351-355, Page 12) and added Table 3 in the revised Supporting Information.

"…Otherwise, the relationship is assumed to be spurious noise. *On average, 87% of the observations were spurious noise and removed in this study. The spurious observations will increase the inverted global land sink and enlarge the deviation of the simulated and observed AGR. For different TRANSCOM regions, the impact for the BIO fluxes could be in the range of -32% to 40% (Table S4)*. The scale of 3000 km …"

Table 3. Results of sensitivity tests in the year of 2010 (Wnoise is the experiment with spurious signals included)

		Prior	Posterior	Wnoise
Super Obs. Num. per window	Total	-	730	730
	Each grid could use	-	4	28
Global Flux (PgC/yr)	BIO	-2.07	-4.16	-4.31
	OCN	-2.08	-2.33	-2.42
	AGR	7.25	4.91	4.67
Regional Flux (PgC/yr)	North America Boreal	-0.29	-0.43	-0.42
	North America Temperate	-0.42	-1.25	-1.41
	Tropical South America	-0.17	-0.26	-0.3
	Temperate South America	-0.24	-0.4	-0.37
	Northern Afirca	0.21	0.32	0.28
	Southern Africa	0.22	-0.3	-0.42
	Boreal Asia	-0.4	-0.46	-0.33
	Temperate Asia	-0.3	-0.29	-0.31
	Southeast Asia	-0.29	-0.23	-0.27
	Australia	-0.17	-0.4	-0.4
	Europe	-0.19	-0.41	-0.28
independent evaluation	BIAS	1.43	-0.44	-0.41
	MAE	1.92	1.37	1.4
	RMSE	2.36	2.11	2.2
Deviation from the observed AGR (PgC yr^{-1})		2.08	-0.26	-0.5

Technical corrections:

Line 38: “BIAS” is not defined before it is used.

Response: Thanks! We have changed “BIAS” to “bias” in the revised manuscript (see Line 38, Page 2).

Line 63: “However, their carbon uptakes have significant spatial differences and interannual variations.” References are needed.

Response: Thanks for this suggestion. We have added three references, namely *Bousquet et al. (2000)*, *Takahashi et al. (2009)* and *Piao et al. (2020)*. (see Lines 65-66, Page 3)

Line 95: “However, so far, on the one hand, most studies focused on the impact of GOAST XCO 2 retrievals on the inversion of surface carbon fluxes, but in many regions, there are still large divergences for carbon sinks between different inversions with the same GOSAT data or between inversions with GOSAT and in situ observations (Chevallier et al., 2014)”. Is only one study considered and cited?

Response: Many thanks for this suggestion. We have added two references in the revised manuscript, i.e., Wang et al. (2018) and Feng et al. (2016). The sentence has been revised as follows (see Line 102, page 4 in the revised manuscript):

“…between inversions with GOSAT and in situ observations (e.g., Chevallier et al., 2014; Feng et al., 2016; Wang et al., 2018), on the other hand, …”

Line 102. References are needed.

Response: Thank you! We have added two references, namely Feng et al. (2017) and Byrne et al., (2019). See Line 106, Page 4 in the revised manuscript.

Line 255: The references for the two emission inventories of FOSSIL and FIRE are out of date. ODIAC and GFEDv4 have been updated recently.

Response: We have revised the reference of ODIAC “Oda and Maksyutov (2011)” as “*Oda et al. (2018)*”, and the references of GFEDv4 “van der Werf et al. (2010) and Giglio et al. (2013)” as “*Randerson et al., 2017*” (see Lines 377 and 379, Page 13)

Line 270: “The BIO carbon flux, which is the most important prior carbon flux”. Why is the prior carbon flux of BIO more important than FOSSIL and FIRE to an inversion system?

Response: This statement is problematic. From the perspective of the carbon cycle, the carbon flux of terrestrial ecosystems is not more important than others. In fact, what we want to express is that because the carbon flux of terrestrial ecosystems has the greatest uncertainty and the most significant interannual variation, when using observational data to optimize surface carbon flux, the carbon flux of terrestrial ecosystems is the most concerned. We have modified that sentence to “*The BIO carbon flux, which is one of the most concerned prior carbon fluxes in an assimilation system*” in the revised manuscript. (see Line 389, Page 13)

Line 340: When the averages of the modeled and the observational values/retrievals are equal, BIAS is zero, even if all data are distant to the 1:1 line in the comparison. BIAS cannot effectively evaluate the performance of the model by showing how much the modeled values/retrievals agree with the observational values/retrievals. The average of absolute difference between the modeled and the observational values/retrievals is needed.

Response: Thank you! We have added the mean absolute error (MAE) between the modeled and the observational values/retrievals in the revised manuscript. (see Line 532, Page 15; Lines 577-579, Page 17; Lines 599-601, Page 18; and Lines 614 – 616, Page 19)

Line 360: Does the study of Wang et al. (2019) account for the uncertainty in FOSSIL and FIRE?

Response: No, Wang et al. (2019) only optimized the terrestrial ecosystem and ocean carbon fluxes.

Line 448: What is “impact of accumulation”?

Response: As shown in the following figure (Figure 1), we find that there is a significant increasing trend for the annual BIAS between the simulated CO_2 concentration with the posterior flux and the observed concentration. We believe that this increasing trend is due to the accumulation of errors in the assimilation system, which may be caused by the slight overestimates of land sink in each year.

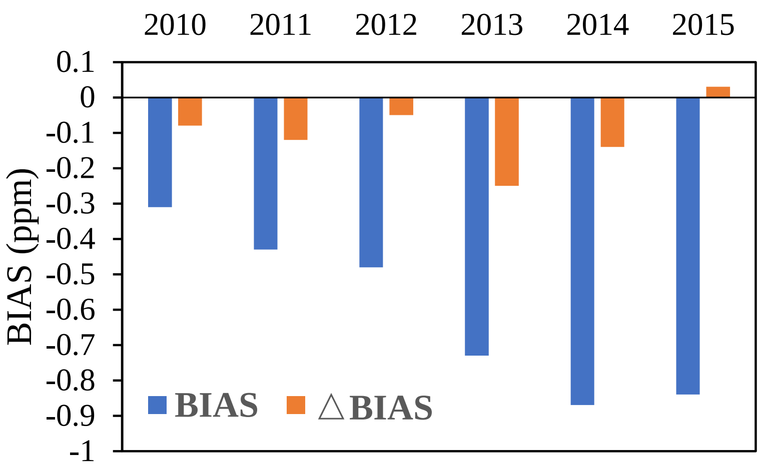

Figure 1. Annual mean BIAS between the surface flask observations and the simulations with posterior fluxes, the △BIAS means the difference in BIAS between two consecutive years, for example, the △BIAS in 2011 means the BIAS in 2011 minus the one of 2010.

Figures 3/4: “Biases” in the caption is easily confused with “BIAS” defined in equation 10.

Response: Thank you! We have modified the “Biases” in the caption Figures 3/4 to “BIAS”. (see Line 595, page 18 and Line 605, page 19)

Table 1: BIAS cannot evaluate the performance of the model by showing how much the modeled values/retrievals agree with the observed values/retrievals.

Response: Thank you for this suggestion! According to this suggestion, we have added the mean absolute error (MAE) in Table 1 in the revised manuscript. (see Line 532, Page 15; Lines 577-579, Page 17; Lines 599-601, Page 18; and Lines 614 – 616, Page 19)

Reference:

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