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Interactive comment on "Spatially resolved evaluation of Earth system models with satellite column averaged CO_2" *by* Bettina K. Gier et al.

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Response to Anonymous Referee #2

We thank the reviewer for the helpful comments. We have revised the manuscript according to all review comments we have received. A pointwise reply is given below, with the original comments in **bold**, and our answers in red.

This study used satellite-observed column-average CO_2 (XCO_2) to evaluate how well the current generation of earth system models reproduces atmospheric CO_2 variability. The authors compared spatially resolved model simulations of XCO2 with observed XCO_2 in terms of biases, growth rates,

seasonal cycle amplitudes (SCA), and trends in SCA. They found that most models overestimate XCO_2 and the growth rates of XCO_2, but underestimate the seasonal amplitudes of XCO_2. The study is novel and interesting, and could be considered for publication after concerns are addressed.

We thank Referee #2 for the constructive comments which helped to improve the manuscript.

General comments

1. The apparent "trend reversal" of SCA in satellite XCO_2 caused by the sampling coverage bias raises an important question whether other characteristics of the observed XCO_2 were subject to the same bias. It seems that the "sampled" vs. "unsampled" comparison was done only for the trend in SCA. Would this comparison give different results for the growth rate of XCO2?

As mentioned in section 5.2. the spatial variability of the growth rate is small. We did analyze the sampling on the other considered quantities, but found no significant sampling impact on the growth rate. We have also added a panel to Figure 3 which depicts the mean monthly growth rate, and while the change from the satellites is visible in these monthly rates in 2009, this is due to the way in which it is calculated and averaged out in the annual values. The annual growth rates of the satellite dataset have been found to correlate well (correlation coefficient of 0.82) with the NOAA global growth rates (Buchwitz et al., 2018). We have added the sentence "No significant changes to the annual growth rates due to the satellite spatial coverage have been found." in section 5.2 to clarify this.

2. Although the effect of different spatial coverage between the two instruments has been addressed in Figs. 9 and 10, there has been no mention of whether the measurement scales of XCO_2 were calibrated between the two

instruments. This could be another source of bias. During the overlapping period, did SCIAMACHY and GOSAT measurements agree well with each other?
The joint time series is computed using the Ensemble Median Algorithm (EMMA, Reuter et al. (2013); Reuter et al. (2020)), which includes a bias correction to all products during overlap phases, resulting in a good agreement during the overlap period. This bias correction is shown in Figure 5 of Reuter et al. (2020).

3. In addition to the spatial distribution of SCA shown in Fig. 6, it would also be interesting to compare the simulated latitudinal gradients (i.e., the zonal mean) of SCA from different models on the same plot.

We have added zonal mean panels to the map plots in Figure 6. They show the increase of SCA with increasing latitude for all models, with growth spurts around the equator and in the midlatitudes for most models.

4. Given that there was no correlation between the growth rate and the growing-season temperature anomaly in the observations (Fig. 5), I'm not convinced that a robust emergent constraint relationship can be established for the period of 2003–2014. Note that this is different from Fig. 2 in Cox et al. (2013) Nature in which a clear correlation is seen in the observations. In the absence of a relationship of the same kind in the observations, one could not distinguish a real emergent constraint from an artifact of model assumptions. It may as well exist for a longer period with more data, but we couldn't tell. I suggest moving the paragraph of P8L248–P9L263 as well as Fig. 5 to the supplement.

We agree with this assessment, as discussed in ll. 257-259 - "This shows that the time period 2003–2014 is not sufficient to reproduce the emergent constraint, but it might be feasible once CMIP6 emission driven future simulations are available for a longer time overlap between models and observations". We have moved this

paragraph and its accompanying Figure to Appendix C.

5. In all figures that show a regression line, it would be better to show both the Pearson correlation and the p-value.

p-values have been added next to the Pearson correlation coefficient in the bottom right of the panels.

6. The study would benefit from a more structured discussion of lessons learned from model evaluation, for example, what the likely causes of model biases in XCO_2 and the SCA of XCO_2 would be. There are some good points made in section 5.3 and the summary, which could be better organized.

Following a suggestion from Referee #1 we have added a paragraph devoted to the discussion on the limitations and future directions, which should include some of these points.
"There are several ways to improve on this analysis in the future. With more available future scenario simulations, the analysis can be extended for a longer time series, making use of longer observational timeseries, such as the one introduced in Reuter et al. (2020). Higher temporal resolution of the models would enable studies on the effect of the diurnal cycle of CO_2 on the monthly mean and also allow for the construction of a co-located time series with the Level 2 satellite data. This could help highlight some of the causes of model biases by being able to pinpoint time and space where they occur more precisely. Model biases may also result from the CMIP experimental design, such as requiring the climate state to be in equilibrium in 1850 while the real world may not have been (Bronselaer et al., 2017), or the parameterizations of biological and physical processes not allowing the system to change rapidly enough (Hoffman et al., 2014). Along with a longer time series, newer satellites, such as OCO-2 or the planned Sentinel 7 bring higher resolutions and more data, potentially helping

to fill in the gaps and reduce the impact of the sampling we discussed in Section 5.3.2.".

Specific comments

âĂć Abstract: The abstract is quite long and technical. Describe the major findings concisely and leave nonessential details to the main text.

We have shortened the abstract by removing several of the technical sentences which are not required to understand the results.

âĂć P1L20: The multi-model means give a feeling that CMIP6 models had a great improvement relative to CMIP5 models. But a closer look at Fig. 3 would tell that this was mainly because negative biases canceled positive biases. I suggest adding the multi-model standard deviations of the bias (or other statistics that characterize the spread) in parentheses.

We have added the full model spread alongside the means.

âĂć P1L25–32: The "trend reversal" in SCA caused by sampling bias is not clear on a first reading. It would be helpful to write this in a way that is less entangled.

We have rewritten this part as follows to make it clearer: "While the combined satellite product shows a strong negative trend of decreasing effective SCA with increasing XCO_2 in the northern midlatitudes, both CMIP ensembles instead show a non-significant positive trend in the multi-model mean. The negative trend is reproduced by the models when sampling them as the observations, attributing it to sampling characteristics. Applying a mask of the mean data coverage of each satellite to the models, the effective SCA is higher for the SCIAMACHY/ENVISAT mask than when using the TANSO-FTS/GOSAT mask. This induces an artificial negative trend when using observational sampling over the full period, as SCIAMACHY/ENVISAT covers the early period until 2012, with TANSO-FTS/GOSAT measurements starting in 2009."

âĂć P2L46–60: If the purpose of this paragraph is to introduce SCA, then the first few sentences seem quite redundant. Better get to the point straight away.

We have rewritten this part to be a more concise introduction of SCA: "Photosynthesis causes a net uptake of atmospheric CO_2 and thus declining atmospheric CO_2 concentrations in the growing season. Conversely, atmospheric CO_2 concentrations rise throughout the dormant season when there is a net release of CO_2 from the land due to decomposition of organic matter in soils. This uptake and release of carbon by the terrestrial biosphere throughout the year causes a seasonal cycle of atmospheric CO_2 (Keeling et al., 1989)."

âĂć P2L64: Missing Ciais et al., 2013 in the References.

Fixed issue which resulted in reference not showing in the bibliography, thank you for spotting this.

âĂć P3L65: "downlooking" $\longrightarrow$ "downward-looking"

Changed.

âĂć P3L89–90: "such as a general overestimation of photosynthesis [relative to datadriven models]." We don't know the magnitude of the global photosynthesis with certainty. The number could range from 112 to 169 PgC yr^{-1} (Ryu et al., 2019, RSE). The MTE GPP data product (Jung et al., 2011, JGR) that was used to evaluate the CMIP models would sit near the lower end of this range.

We have added this as a caveat and added the example of the overestimated leaf area index. "... such as a general overestimation leaf area index and photosynthesis. However, the magnitude of the global photosynthesis is not well constrained by observations, with estimates ranging between 112 and 169 PgC yr^{-1} (Ryu et al., 2019), with the dataset used by Anav et al. (2013) on the lower end of this range."

P5L131: Missing Dlugokencky et al., 2018 in the References.
Updated this reference to newer version and solved issue preventing it from showing in bibliography, thank you for spotting this.

âĂć P7L203: "parameters" ⟶ "variables"
Changed.

âĂć P7L205: Surface observations sample the air within or closer to the boundary layer, and therefore may have a larger seasonal swing.
The larger seasonal swing and thus higher seasonal cycle amplitude at the surface is discussed in the next paragraph. L205 was referring to the total offset of the mean, as evident most clearly in the Cape Grim and Hegyhatsal stations, comparing the blue (station) and red (model surface) curves.

âĂć P8L241: What is the correlation between the observed GR and the multi-model mean GR?
The correlation between the observed and multi-model mean annual GR is 0.48 in CMIP6 and 0.07 in CMIP5, which is higher than most the models. We have added this to the paragraph.

âĂć P9L256: The increase of GR sensitivity to temperature after including 2015 and 2016 data could have been due to El Niño.
This is true and has been added as a note in this sentence (now in the Appendix), as well as mentioned as a reason for suggesting that the timeseries is not long enough to support trying to reproduce this emergent constraint.

âĂć Table 1: Use whole numbers in the "Altitude" column.
Changed to whole numbers.

âĂć Figure 2: I suggest lightening the gray background to prevent it from interfering with the reading of the curves.
Changed the color of the land areas of the underlaying map plot to a very light grey.

âĂć Figure 3: It seems that after detrending, the seasonal variability in the multimodel mean XCO_2 would match quite well with that in the observed XCO_2, and better than the seasonal variability in any individual models. I wonder what the correlation coefficients would be.
We have extended this figure with panels showing the calculated monthly growth rate and the detrended seasonal cycle. The correlation between the detrended seasonal cycle of the multi-model mean to the observations is 0.98 in CMIP6 and 0.93 in CMIP5. in CMIP6 this is the best correlation, the closest models have a correlation of 0.96 (MRI-ESM2-0 and GFDL-ESM4). For CMIP6 a few models are close and a bit higher than the multi-model mean with 0.93 for NorESM1-ME and MIROC-ESM, 0.94 for MRI-ESM1 and 0.95 for MPI-ESM-LR. So the multi-model mean in CMIP6 indeed captures the seasonal variability better than any individual model.

âĂć Figure 4: I think ranking the models by their average growth rates, from low to high, would make the figure clearer.
Models are now ranked from low to high in the barplot.

âĂć Figures 6a and 6b: Why not use the same scale? One could reserve the purple region of the colormap for the high SCA values from MPI-ESM-LR. This would not affect other models that have values represented in colors from blue to red.
We have adjusted the scale to be the same for both figures. We have furthermore changed the colormap to a non-diverging one, which was requested by Referee #1 for the top panels in figure 6 (formerly 7) to contrast the bottom panels showing the

differences. This colormap has been adapted for Figure 5 (formerly 6) as well for consistency.

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