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Atmospheric Chemistry and Physics Discussions

Interactive comment on "Contrasting effects of CO_2 fertilisation, land-use change and warming on seasonal amplitude of northern hemisphere CO_2 exchange" *by* A. Bastos et al.

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RC1: This paper investigated the relative importance of individual contributors to trends and drivers of the seasonal-cycle amplitude (SCA) in northern high latitudes using two atmospheric inversions and land-surface models. They found the most likely explanation of the trend of SCA at high latitudes is the CO2 fertilization of photosynthesis, rather than LULCC. Although I see the value of publishing, I am concerned about the definition of SCA and reliability of results. The SCA of atmospheric CO2 should be the difference between the peak and trough values of the cumulative CO2 in a year. But the definition of SCA in this manuscript is the difference between peak uptake and

trough of NBP. The sum of NBP during the growing season is related to the SCA of atmospheric CO2 while the difference between peak uptake and trough of NBP may be not.

AR: Most previous studies indeed have analyzed trends in SCA of atmospheric CO2 concentrations (Graven et al., 2013; Forkel et al., 2016; Thomas et al., 2016; Zhu et al., 2016; Piao et al., 2017; Yin et al., 2018). However, to attribute changes in the seasonal amplitude of atmospheric CO2 to specific processes it is necessary to look at net surface fluxes as a function of changes in primary productivity and respiration. Moreover, quantifying bias in CO2 concentration at a given site from a bias in land-surface model (LSM) simulated fluxes is difficult, since the biases can be affected by many other factors such as transport model characteristics, forcing data used, etc. As discussed in the Introduction (P2 L 29 to P3 L2), atmospheric inversions might partly tackle this issue by limiting the space of surface fluxes that are consistent with the atmospheric CO2 concentration measured at several sites. Moreover, when aggregated at large spatial scales, the annual amplitude of NBP is related with the amplitude of the concentration (although this relationship is complicated by atmospheric transport, to the first order, the SCA of concentration should roughly be the integral of the flux). Such an approach has for example been used by Welp et al. (2016) for boreal ecosystems. Finally, here we compare results from two inversion systems and results from sensitivity runs from CarboScope forced with different inputs and using different parameters. This allows further insight about the range of SCANBP values that can still be compatible with in-situ atmospheric CO2 measurements. By doing this, we believe we can provide a fair evaluation of the ability of LSMs to capture changes in the seasonal amplitude of NBP (and CO2) in the Northern Hemisphere.

Welp, L. R., Patra, P. K., Rödenbeck, C., Nemani, R., Bi, J., Piper, S. C., and Keeling, R. F.: Increasing summer net CO2 uptake in high northern ecosystems inferred from atmospheric inversions and comparisons to remote-sensing NDVI, Atmos. Chem. Phys., 16, 9047-9066, https://doi.org/10.5194/acp-16-9047-2016, 2016.

RC2: It will be clearer if the Result and discussion can be separated into two part alone. The key finding is CO2 fertilization drive the SCA trend, but more discussion and speculation focused on warming.

AR: The results and discussion sections will be separated in the revised version. We believe that our finding that warming has a negative effect on SCANBP is also a key finding of this study, and the one deserving more explanation. The effect of CO2 fertilization in increasing CO2 uptake is well understood from a physiological point of view, while the effects of temperature on SCANBP are complex and, in this case, counter-intuitive. In fact, earlier studies pointed for a positive effect of warming on SCA because of earlier onset of the growing-season or increase growth at higher latitudes (Keeling et al., 1996; Forkel et al. 2016). The negative effect of warming we find seems though to be supported by studies covering a more recent period (Schneising et al., 2014; Peñuelas et al., 2017; Yin et al., 2018), although the mechanisms behind were not discussed. Here we try to understand this by analyzing the link between T and GPP and TER simulated by models. The fact that models show biases in their simulated sensitivity of SCA and TER to T indicates that certain processes might be missing. We point to some processes that might explain these biases, based on published research, rather than speculation. To evaluate whether these processes can or cannot explain the biases, these would need to be included in model simulations, which is beyond the goals of our study.

RC3: Page 2 Line 8, how many are the relative effects of CO2 fertilization and warming in SCA, respectively?

AR: This is discussed in the following paragraphs of the introduction.

RC4: Page 5 line 8 and line 28 typos

AR: Corrected.

RC5: Page 5, why did you use ESA-CCI Land-Cover data set for the analysis of

satellite-based vegetation data sets? What are the problems if LUH2 was used for the analysis of satellite-based vegetation data sets?

AR: We used ESA-CCI Land-Cover because it is a purely remote-sensing based land-cover dataset, while LUH2v2h is partly based on HYDE3.1, which in turn uses FAO data for cropland extent. However, since LUH2v2h is used to force the LSMs, it is true that a comparison with this dataset should also be made. We have now compared the results in Fig. S6 using LUH2v2h. We compare trends in LAI, NPP and AGB for the LUH2v2h classes cropland, forest and non-forest natural vegetation (which should include shrublands and natural grasslands), for the period 1982-2015, for latitudes north of 40oN. As in our results with ESA-CCI Land-Cover, forests contribute the most to LAI, NPP and AGB increase.

In the revised version of the manuscript we can add these results as a second panel in Figure S6 (Fig. 1 below).

RC6: Page7 line4, figure S was missed

AR: It should read S5, it has been accordingly corrected.

RC7: The size of Fig1.a is too small to see them clearly. Also for figure 4.

AR: The figures will be improved.

RC8: Page 7 line 15, how did you know the breakpoint in the north of40âŮęN?

AR: It is the point north of which the two inversions agree on a significant sign of SCANBP trends. This will be clarified in the text in a revision of the manuscript.

RC9: Page 8, The patterns of SCA NBP trends from the LSM were not consistent with that of CAMS at the pixel scale.

AR: Inversion fluxes are highly uncertain at pixel-scale (discussed in P6 L12, P8 L30-31) and should not be directly compared with pixel-scale LSM fluxes, especially in regions where there are sparse atmospheric CO2 measurements. The large-scale spatial distribution of SCANBP is shown in Fig. 1 to illustrate the distinct results from the two observation-based datasets (which underlines the problems of relying on single atmospheric-transport models to forward-transport fluxes). The sentence will be reformulated in a future revision of the MS.

RC10: The attribution analysis based on LSMs is not very convincing.

AR: We do not necessarily agree with the reviewer, especially because the reviewer has not identified specific weaknesses in our analysis or conclusions. Attribution of changes in SCA (or NBP) to CO2, climate and LUC can be made using statistical methods or performing modelling experiments. For observation-based data, statistical attribution is the only option, and we try to do disentangle the effect of each term from the others by fitting statistical models with different numbers and combinations of predictors. Process-based models, on the other hand, allow us to evaluate individual processes that may be contributing to the observed patters by running simulations in which the LSMs are forced with only one, two or more factors. The effect of CO2, climate and LUC can then be diagnosed by the differences in resulting SCA between experiments. We would like to note that model-based attribution is actually the approach followed by most studies analyzing trends in NBP or in SCA (Graven et al., 2013; Forkel et al., 2016; Thomas et al., 2016; Zhu et al., 2016; Piao et al., 2017). The difficulty with the attribution by models is that it cannot easily be validated, as discussed in the manuscript. Therefore, we compare: (i) the process attribution from factorial simulations, (ii) the regional statistical attribution based on inversion fluxes, (iii) the statistical attribution based on LSMs fluxes from S3 and (iv) the statistical attribution based on the differences between factorial simulations. This allows testing the statistical attribution, and allows comparing the results from observation-based data with simulated data. To the best of our knowledge this is the most robust way to perform such attribution, and it has not been done in other studies (which have relied mainly on factorial simulations and did not compare with observation-based data). While each attribution approach may have their respective limitations, the fact that our regional attribution identifies the

Eurasian Boreal forest as a major contributor to SCA, and our process attribution identifies CO2 fertilization of Eurasian Forests as the mechanism, provides more support for the natural vegetation hypothesis than the agricultural intensification hypothesis.

RC11: Page 9 line 29-34, these sentences should be moved into Method

AR: The sentences were redundant as this was already discussed in the Methods, so they were removed.

Please find a PDF version of this reply attached.

Please also note the supplement to this comment:
https://www.atmos-chem-phys-discuss.net/acp-2019-252/acp-2019-252-AC1-supplement.pdf

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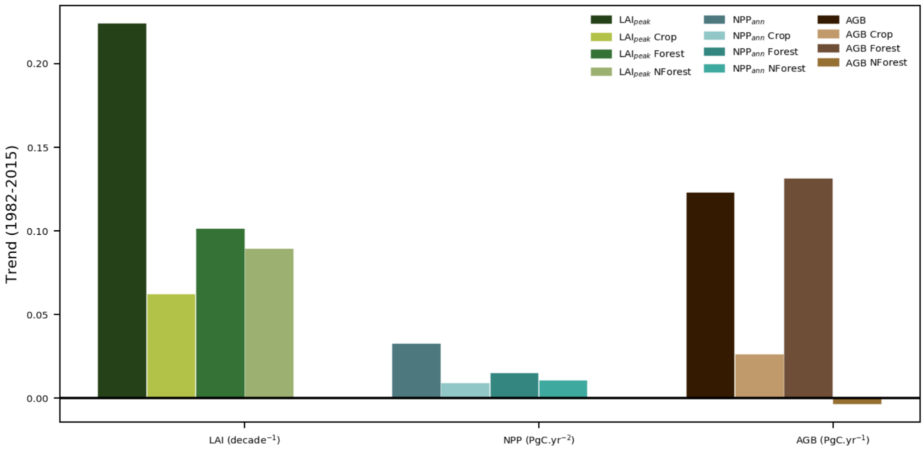

LAI_{peak}
LAI_{peak} Crop
LAI_{peak} Forest
LAI_{peak} NForest
NPP_{ann}
NPP_{ann} Crop
NPP_{ann} Forest
NPP_{ann} NForest
AGB
AGB Crop
AGB Forest
AGB NForest
Trend (1982-2015)
0.20
0.15
0.10
0.05
0.00
LAI ($decade^{-1}$)
NPP ($PgC.yr^{-2}$)
AGB ($PgC.yr^{-1}$)

Fig. 1.