Authors' Response to Referee 2 (ESDD esd-2018-71)

March 19, 2019

The authors explore the robustness of the "emerging constraint" (EC) method by using vegetation changes in the Northern High Latitudes as a case study. As the authors discuss, the EC method has gained increasing popularity and is being applied to a wide range of climate change studies, including reducing uncertainty in the carbon cycle. Overall the paper is well-written and easy to follow. The authors identify and analyse a number of caveats that may influence results from the EC method that are likely relevant to the wider community.

We thank the reviewer for her/his constructive comments and for acknowledging the relevance of our study to a wider scientific community. All revisions done in response to the reviewer's comments has resulted in an improved manuscript.

1 General Comments

1.1 *My main criticism is the use of LAI to predict GPP changes and stating that these two variables possess a strong causal relationship (indeed the authors state that the predictor and predictand should be causally related). Yes, LAI and GPP are likely related, but there are many assumptions in models regarding how much GPP becomes NPP (i.e. how much GPP is respired) and how this carbon is then allocated into leaves, as opposed to other plant tissues.*

We agree with the referee, that the current manuscript lacks an in-depth discussion on the causal link between predictor and predictand. However, this aspect is discussed in more detail in the recently published companion paper by Winkler et al. (2019) and illustrated in Supplementary Figure 1 - *Schematic of the Emergent Constraint concept* (see Fig. R2-1). In our responses to Referee 1, we present a comprehensive analysis of the causal relationship of LAI and GPP in observations on the basis of upscaled eddy covariance flux measurements of GPP (FluxNet and FLUXCOM) and satellite observations of LAI (AVHRR and MODIS). For more details, please see Fig. R1-1 and comment 1.7 in our responses to Referee 1. In the model world, as the referee correctly states, there are many, possibly diverging, assumptions on carbon allocation to various plant organs. But overall, the CMIP5 model ensemble agrees on a tight relationship between concurrent changes in LAI and annual mean GPP for the historical period (1860 to 2005) in the NHL ($60°$ N - $90°$ N; see Fig. R2-2). This strong link between the predictand GPP and the predictor LAI in NHL, as shown for observations and models alike, is the baseline for the EC study in hand. We discuss this aspect in more detail in the revised manuscript.

1.2 *Furthermore, in the ESMs, allocation and respiration etc. can change with increased CO_2 forcing, influencing the GPP-LAI relationship over time. The authors should at the very least discuss the caveats of this approach and how this might affect their conclusions.*

Yes, the evolution of the predictand-predictor relationship in the course of the forcing is an essential aspect in the EC method. We already address this issue in the manuscript and is at the very core of the *Gedankenexperiment* discussed in Sect. 3.4 (P11, L2- P12, L33) and Fig. 5, 6, A1, and A2. The GPP-LAI relationship likely changes with increasing CO_2 as predicted by CMIP5 models (saturation of GPP to LAI allocation above $2\times CO_2$, Fig. 5). In the *Gedankenexperiment*, we conceive four possible scenarios of how the system might behave with increasing forcing. We show that changes in predictor and predictand relate linearly within the model ensemble (the basis for an EC) given the models agree on the occurrence and "timing" of saturation. At very high CO_2
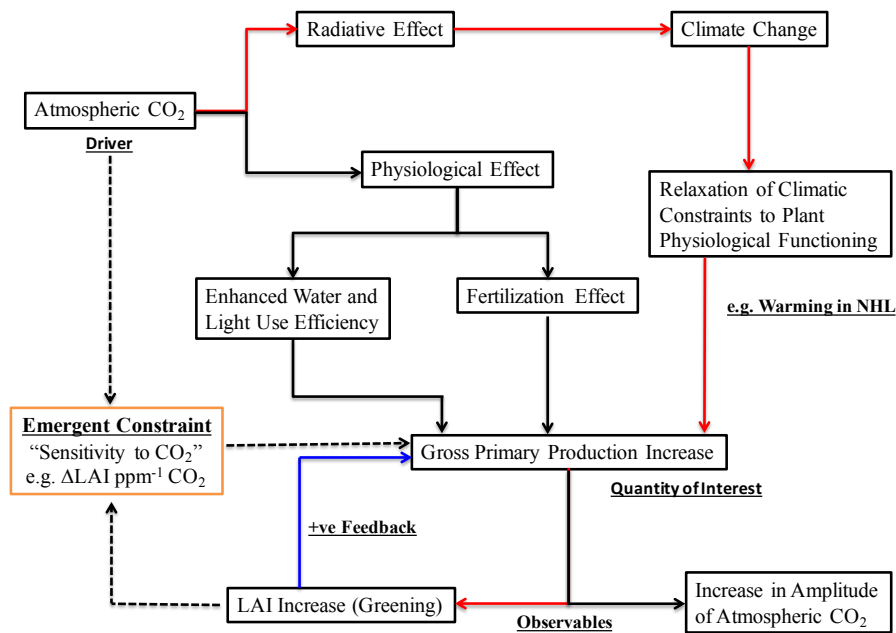
Figure R2- 1: Schematic of the Emergent Constraint concept. The radiative and physiological effects of increasing atmospheric CO_2 concentration, in the range 280 to 560 ppm, are thought to increase GPP. This is indirectly observed as changes in LAI or the amplitude of the seasonal cycle of atmospheric CO_2. The sensitivity of changes in observables to historical increase in CO_2 concentration (e.g., 280 to 400 ppm) can be thought of as an Emergent Constraint on model-projected changes in carbon cycle quantities (e.g., ΔGPP for CO_2 change from 280 to 560 ppm), if the inter-model variation of projections is linear, or nearly so, with respect to modelled historical sensitivities. GPP enhancement from the positive feedback effect (blue arrow) is thought to be small relative to the physiological and radiative effects (Keenan et al., 2016). Supplementary Figure 1 in Winkler et al. (2019).

concentrations (above 3xCO_2), this is not the case anymore in the CMIP5 ensemble resulting in a weakening of the relationship between GPP and LAI.

1.3 *I would also like the authors to consider in more detail what aspects of their findings might be specific to their case study (for example the idealised experiments where the effects of radiation and fertilisation effects are rather straightforward and increase GPP)*

Each Emergent Constraint is somewhat unique in its mechanistic relationship under a strengthening forcing. However, in theory, the results presented in this study are qualitatively transmissive to other sets of predictors and predictands. Of course, the aspect related to idealized setups of disentangling radiative and fertilizing effects of CO_2 is rather specific for carbon cycle research. Other aspects, such as the the influence of the observational estimate (dependence on observational source), predictor comparability between models and observations (especially within the temporal domain), or uncertainty based on spatial aggregation of gridded data are more general. We included a short paragraph discussing general and more specific findings in the revised manuscript.

2 Specific comments:

2.1 *P5, L21: Should this say 0.005 deg (500m) instead of 0.05 deg (5km)?*

MODIS LAI products (Collection 6, Aqua and Terra) are provided as 8-day composites with a 500m sinusoidal projection covering the whole globe. To minimize contamination from clouds, aerosols, snow and shadow, careful quality assurance and filtering techniques are applied to obtain highest quality MODIS LAI observations. The 16-day composite LAI dataset is then derived by taking the
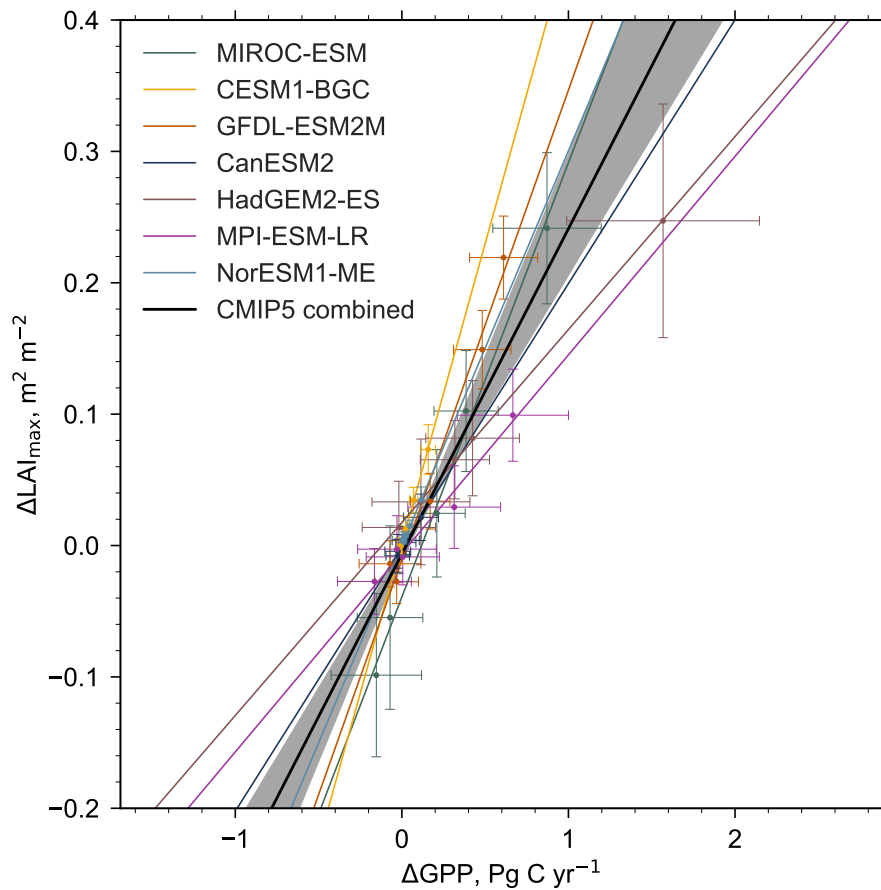
Figure R2- 2: Linear relationship between concurrent changes in LAI_{max} and annual mean GPP. Comparison of changes in LAI_{max} and annual mean GPP for the historical period (1860 to 2005) for the NHL (60° N - 90° N) in the CMIP5 ensemble. The colored dots show values for 30 year chunks of the total time series (error bars denote one standard deviation). The colored lines represent the best linear fit for each model, while the black line indicates the best linear fit for all models. The 68% confidence interval estimated by bootstrapping is shown by the grey shading. Supplementary Figure 2 in Winkler et al. (2019).

mean of all valid LAI estimates from the 8-day composites. The final dataset is provided at a spatially aggregated 0.05° climate-modelling grid (CMG; Chen et al., 2019).

2.2 *P5, L32: why averaged and not taking the max (to further reduce cloud contamination)?*

Comparability between models and observations are key in the EC method. CMIP5 models provide LAI as monthly means. Averaging the 16-day composites for each month is the closest we get to a monthly mean estimate from observations.

2.3 *P6, L26-28: Not very clear*

Yes, we agree. The description of the idealized CMIP5 simulations is somewhat confusing. We rewrote this section in the revised manuscript.

2.4 *P7, L7: Can you provide a few more details for "ω" and how it was derived? Is it the time series for PC1?*

We agree, that a more detailed description of the derivation of ω needs to be provided. We perform a PCA of the time-series of CO_2 and GDD0 on large-scale aggregated values as well as on pixel level to investigate on spatial variations. We only retain the first principal component (denoted ω), which explains a large fraction of the variance, ranging approximately from 70% ot 90% in models and observations (for more details see Table R1-1 in our responses to Referee 1). Figure R2-3 depicts the temporal development of CO_2 and GDD0 as well as the principal component ω for observations. Please see also our responses to comment 1.2 and 1.5 of Referee 1. In the

revised manuscript, we make abundantly clear how ω is derived and describe its characteristics for models and observations. Figure R2-3, with some modifications, has been included in the appendix of the revised manuscript.
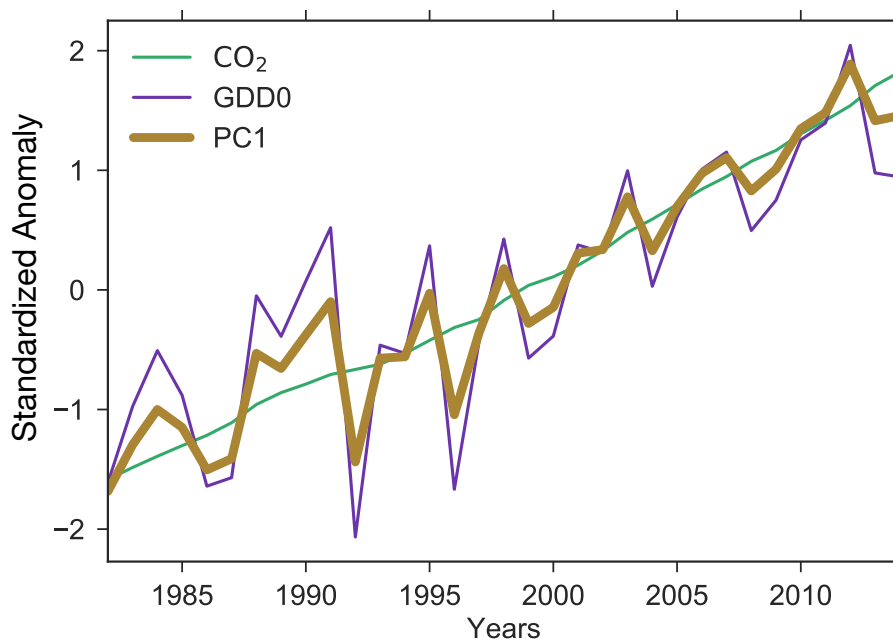

Figure R2- 3: Standardized temporal anomalies of annual averaged atmospheric CO_2 concentration, area-weighted averaged GDD0 for NHL, and their leading principal component ω in observations.

2.5 *P8, L15: Where do the vegetation classes come from?*

We provide the reference (Olson et al., 2001) in Sect. 2.3 **Estimation of greening sensitivities** (P6, L32) and in the caption of Figure 2.

2.6 *P8, L17: I'm a little confused here. You talk about NHL but then go on to describe differences in tropical forests etc.*

In Sect. 3.1 **Uncertainty in Observed Sensitivity Due to Data Source** we present sensitivities in a global comparison for different climatic regimes, vegetation types, and latitudinal bands (e.g. comparing tropical, mid-latitude, and high-latitude sensitivities; Figure 2). Then, we show that LAI is only a meaningful predictor for changes in GPP in the northern high latitudes, which constitutes the focus of the study thereafter. We rewrote this section and provide better explanation for our approach.

2.7 *P11, L18: I admit I had to google the meaning of "Gedankenexperiment", perhaps a more common term is available?*

Yes, in the revised manuscript we now use the term "thought experiment".

2.8 *P12, L9: do you show this anywhere?*

Figure 4 and Table 2 in the manuscript illustrate that the CMIP5 models (3 models are shown) reveal saturation of the relationship between ΔLAI_{max} and ΔGPP with increasing CO_2 forcing. The slopes in Figure 4 (detailed estimates in Table 2) reveal that the strength and 'timing' of saturation (i.e. at what level of CO_2 concentration) differs among the models. In the revised manuscript, we implemented a more accurate description and references to tables and figures. Also, we generated an additional figure (shown in the appendix of the revised manuscript) which displays the results of the other 4 models analogous to Figure 4.

2.9 *P13, L14: Do these models simulate species composition changes?*

Yes, most of the models include dynamic vegetation. In the revised manuscript, we include a short description of the representation of dynamic vegetation in CMIP5 models. In general, the historical and idealized model setups of the CMIP5 land components are comprehensively explained in several studies, such as Wenzel et al. (2014); Mahowald et al. (2016); Arora et al. (2013); Winkler et al. (2019). This is why we refrain from providing a detailed overview of the CMIP5 models in this study.

2.10 *P16, L1 onward: These aren't really results presented in this study*

Yes, we agree, these are rather findings presented in the companion paper by Winkler et al. (2019). We rewrote this paragraph to sharpen the focus on the results discussed in this article.

2.11 *Figure 2: I don't quite follow why only NHL was analysed when boreal, temperate forests and grasslands all show good agreement between AVHRR and MODIS (if this was the premise of the authors' choice)?*

Ecosystems in NHL are barely influenced by human land use. Thus, the changes of vegetation greenness are natural responses to the forcing rather than agricultural artifacts. At high LAI regions, GPP might also increase due to CO_2 fertilization without an enhancement of LAI. In rural areas, the observed greening is mainly caused by direct drivers such irrigation, application of fertilizers, and double cropping as shown recently by Chen et al. (2019). Overall, we focus on the NHL, because there we obtain a clear LAI signal, i.e. a signal hardly being distorted by direct human interference.

References

Arora, V. K., Boer, G. J., Friedlingstein, P., Eby, M., Jones, C. D., Christian, J. R., Bonan, G., Bopp, L., Brovkin, V., Cadule, P., Hajima, T., Ilyina, T., Lindsay, K., Tjiputra, J. F., and Wu, T. (2013). Carbon–Concentration and Carbon–Climate Feedbacks in CMIP5 Earth System Models. *Journal of Climate*, 26:5289–5314.

Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R. K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R. R., and Myneni, R. B. (2019). China and India lead in greening of the world through land-use management. *Nature Sustainability*, 2(2):122.

Keenan, T. F., Prentice, I. C., Canadell, J. G., Williams, C. A., Wang, H., Raupach, M., and Collatz, G. J. (2016). Recent pause in the growth rate of atmospheric CO2 due to enhanced terrestrial carbon uptake. *Nature Communications*, 7:13428.

Mahowald, N., Lo, F., Zheng, Y., Harrison, L., Funk, C., Lombardozzi, D., and Goodale, C. (2016). Projections of leaf area index in earth system models. *Earth Syst. Dynam.*, 7:211–229.

Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'amico, J. A., Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W. W., Hedao, P., and Kassem, K. R. (2001). Terrestrial Ecoregions of the World: A New Map of Life on Earth. *BioScience*, 51(11):933–938.

Wenzel, S., Cox, P. M., Eyring, V., and Friedlingstein, P. (2014). Emergent constraints on climate-carbon cycle feedbacks in the CMIP5 Earth system models. *Journal of Geophysical Research: Biogeosciences*, 119(5):794–807.

Winkler, A. J., Myneni, R. B., Alexandrov, G. A., and Brovkin, V. (2019). Earth system models underestimate carbon fixation by plants in the high latitudes. *Nature Communications*, 10(1):885.