Reply to Reviewers for the manuscript egusphere-2022-96:" Inter–annual global carbon cycle variations linked to atmospheric circulation variability":

Na Li, Sebastian Sippel, Alexander Winkler, Miguel D. Mahecha, Markus Reichstein, Ana Bastos

Reply to Reviewer #1

Na Li and co-authors relate the inter-annual variability (IAV) of de-trended global observed atmospheric CO_2 growth rates and the modelled global land sink from 1959 to 2017 with spatio- temporal sea level pressure (SLP) anomaly fields. They use a regularised linear regression method (Ridge Regression, RR) combined with a statistical learning technique to predict the IAV of the observed and model-simulated global CO_2 growth rates. They compare these results with a similar regression that is based on 15 classical global and hemispheric teleconnection indices, as well as with a regression that is solely based on Southern Oscillation index (SOI). They find very good predictability (Pearson R > 0.7) with boreal winter SLP anomalies, that is comparable or even better than with classical teleconnection indices. They show that CO_2 IAV is most sensitive to tropical and southern hemisphere SLP anomalies (a finding, which was already observed by Bacastow in 1976 and attributed to the influence of ENSO on the land biosphere sink by Keeling et al. in 1995).

We thank the reviewer for the positive evaluation of our study and the constructive comments. We provide in-depth replies to each comment below.

This is an interesting and careful analysis, with the results being well presented in the manuscript. However, I would have appreciated some more discussions of the results. For example, it would be nice to gain some direct insight, which land regions dominate the globally observed atmospheric CO_2 growth rates. The biosphere models obviously reproduce the IAV very well so that this information should be available from these models.

We thank the reviewer for this suggestion to improve the manuscript. In the revised version of the manuscript, we now provide a more in-depth discussion about processes and how this study can contribute to improved understanding of IAV in the carbon cycle.

Specific comments:

Abstract

Line 6: Please add "global" in "...from the **global** de-trended ...", "... and from different datasets ...": Please be more specific which datasets have been evaluated.

Thanks, we corrected this phrase in line 6, which now reads: "CO2 variability is diagnosed from the **global** detrended atmospheric CO_2 growth rate and the land CO_2 sink from **16 dynamic global vegetation models and two atmospheric inversions** ~~different datasets~~ in the global carbon budget **2018**."

1. Introduction

Line 23: "Quantifying and understanding the patterns of variability in the C-cycle and their drivers is crucial to better understand the drivers of C-cycle dynamics and better constrain future climate projections." I fully agree to this statement, however, in the current study solely the SLP anomaly is correlated with the CO_2 IAV, which, at least to my understanding, serves as a place-holder for the real drivers, which are e.g. temperature, water and radiation availability, for CO_2 exchange with the land biosphere (as correctly stated in line 39). Do the correlations presented here really help "process understanding of C-cycle dynamics"? This needs to be explained to the reader or, alternatively, such rather strong statements should be a bit de-emphasised throughout the manuscript.

We thank the reviewer for pointing this out, and we agree that the relevance for process understanding was overemphasized. Still, we believe that our results have important implications for the analysis of drivers of variability of C–cycle processes, given the short nature of observational records compared to the time–scales of natural climate variability modes. We explain our reasoning below and have updated the manuscript accordingly.

Indeed, temperature, water, and radiation availability, etc. are the direct drivers of ecosystem processes that control C fluxes (photosynthesis, growth, decomposition, fires, …). These drivers, however, show strong covariations in time and space, for example due to land–atmosphere feedbacks (Seneviratne et al., 2012), but also because they are influenced to a large extent by atmospheric circulation patterns that affect anomalies in multiple variables at the same time, leading to spatio–temporal co–variability. For example, persistent anticyclonic conditions promote both warm, sunny, and dry conditions at the surface in summer. Likewise, ENSO variability controls anomalies in both temperature and water/radiation availability over the tropics and in the extratropics through large–scale teleconnections. As already observed by Bacastow (1976), ENSO explains a large fraction of variability in the global carbon cycle. It has been argued that indices reflecting atmospheric circulation patterns might be more useful predictors of variability in ecosystem activity than the direct drivers themselves because these indices aggregate information about the range of climatic conditions experienced by ecosystems at a particular time and place, so that they can be used as a way to reduce dimensionality of the space of climatic drivers (Hallet et al., 2004; Bastos et al., 2016; 2017; Zhu et al., 2017).

Here we took a step forward and adopted the approach proposed by Sippel et al., (2019), where SLP anomaly fields are used directly as a proxy of atmospheric circulation variability. The advantage of this approach is that it allows for a more flexible definition of the relevant atmospheric circulation patterns that influence interannual CO_2 variability, since it does not require the use of predefined teleconnection indices. This allows, for example, identifying relevant domains that are affected by more than one mode of atmospheric variability, such as the west Pacific domain in MAM (Fig. 3), or by variations in the importance of different atmospheric domains over time (Fig. 4). Nevertheless, we agree that for interpretation of the correlations found, it is important to understand how the identified SLP patterns influence the direct climatic drivers of CO_2 sinks and sources. For this, we evaluated the Pearson correlations between global SLP predicted AGR_R (i.e. the component of AGR_R that is driven by the atmospheric circulation patterns in Fig. 3) to global land temperature and precipitation anomaly, both from CRU_TS4.05 monthly data, over the period 1980–2017. The corresponding maps are shown in Fig. R1:

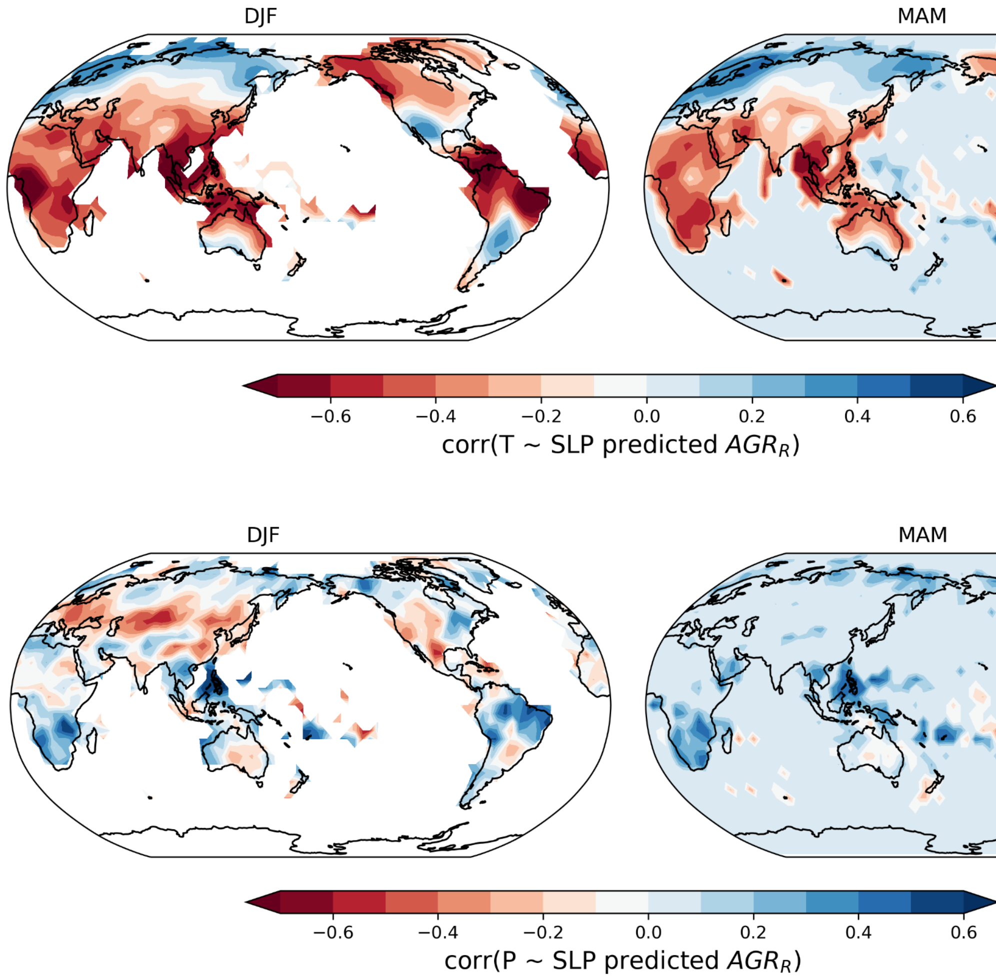

Figure R1. The spatial distribution of Pearson correlations between global SLP predicted AGR_R (one time–series) to global pixel–based land temperature/precipitation anomalies (both from CRU_TS4.05 monthly dataset, aggregated to annual mean temperature/annual sum precipitation, and detrended by LOWESS), in the period 1980–2017. The top panel shows the spatial distribution of correlations between pixel–based land temperature anomalies to global SLP predicted AGR_R for DJF (left) and MAM (right), and the bottom panel shows correlations of land precipitation anomalies.

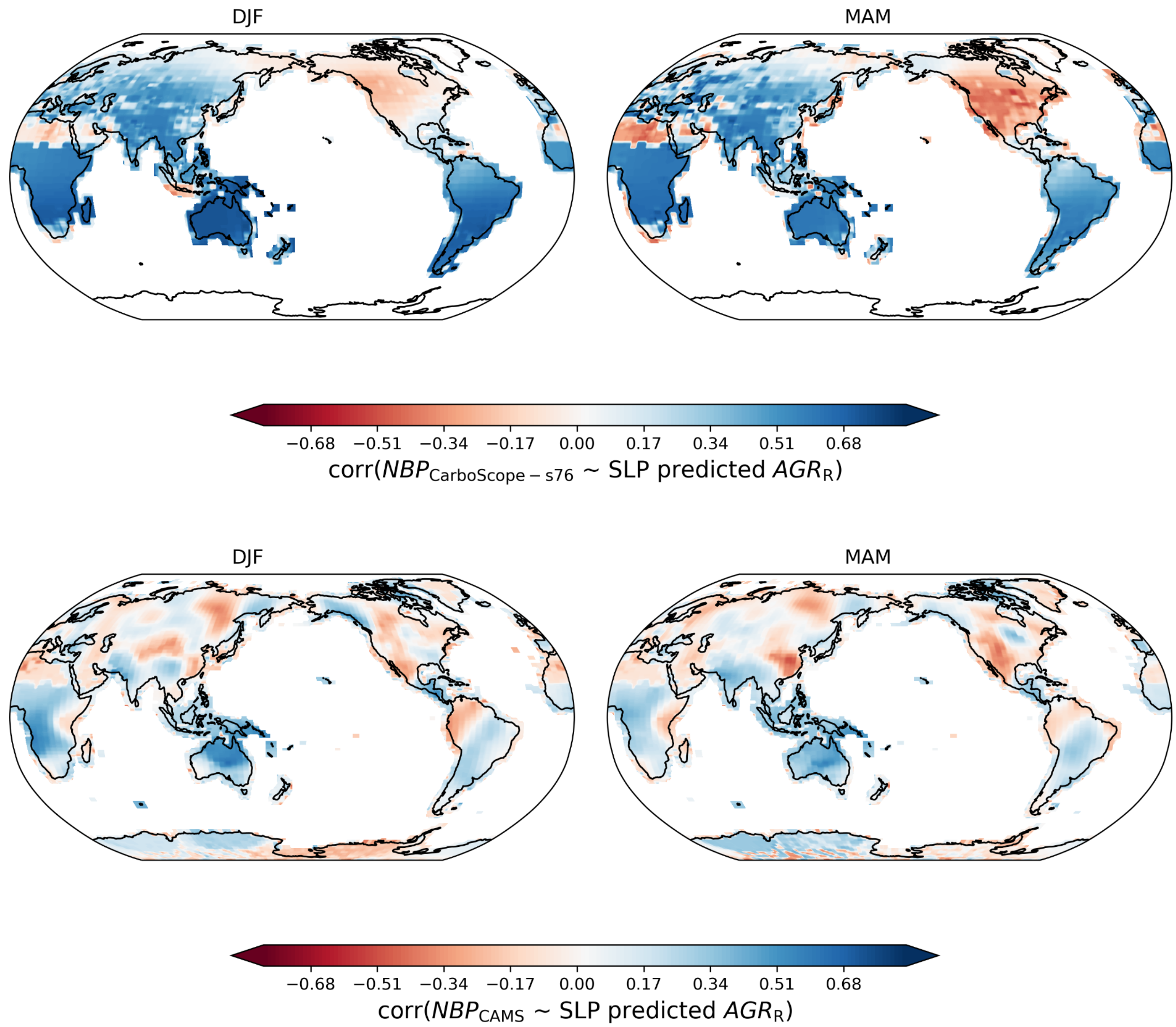

Figure R2. The spatial distribution of correlations between global DJF/MAM SLP predicted AGR_R (one time–series) with pixel–based annual sum NBP variation (LOWESS detrended) from atmospheric inversion CarboScope s76 (upper panel) and CAMS (lower panel), in the period 1980–2017.

Generally, the annual mean temperature anomaly over the tropics shows negative correlation to land sink (SLP driven AGR_R) in both DJF (as high as -0.85) and MAM (as high as -0.71), while weaker but positive correlations are found in Eurasia. Tropical annual sum precipitation anomaly shows roughly positive correlation in DJF (as high as 0.68) and in MAM (as high as 0.65). This pattern indicates that AGR_R is generally higher for cooler and wetter conditions over the tropics and SH semi-arid regions, which result in increased NBP (Fig. R2), and cooler but also predominantly drier conditions over Eurasia, which result in a complex pattern of NBP anomalies (Fig. R2). These results are consistent with the strong ENSO fingerprint on global CO_2 variability, e.g. as pointed out by Piao et al. (2020) and with the importance of southern semi-arid ecosystems (Ahlström et al., 2015). The patterns of anomalies in the northern extratropics are more complex and strongly season dependent (Wang et al., 2022) so we do not expect these to contribute strongly to the global relationships found here.

In our manuscript, we find in DJF, the AGR_R is largely positively driven by SLP in the east Pacific area, and negatively driven in southeast Asia to Australia (Fig. 3), roughly corresponding to the dynamics of El Niño/La Niña. El Niño normally induces a negative SLP anomaly in the east Pacific (King et al., 2020). We could infer that in DJF, enhanced El Niño – reduced SLP anomaly in eastern Pacific – reduced land sink (SLP driven AGR_R), and enhanced La Niña, enhanced SLP anomaly in eastern Pacific – enhanced land sink (SLP driven AGR_R). This matches the general finding that strong El Niño relates to reduced land sink, and strong La Niña relates to increased land sink (Bonan 2016, P567). It is found that El Niño induces increased temperature (Chiang and Lintner 2005) and decreased precipitation on tropical land (Gu et al. 2007; Miralles et al. 2014; Bosilovich et al., 2022).

In MAM, AGR_R is largely negatively driven by SLP in the Western pacific, and positively driven by central pacific, possibly a mix of different modes, such as the ENSO, West Pacific teleconnection and the Interdecadal Pacific Oscillation, all showing strong RR coefficients in Fig. 3b (SOI, WP and TPI indices). This still requires further study.

We have made small changes accordingly in the line 263-269, and we will add Fig. R1 and R2 as supplementary Figures in the manuscript (since we still need to arrange the order of these two added figures, the figure No. listed below now still use “R1” and “R2”, we will change accordingly in the manuscript later):

“In DJF the negative coefficients over the eastern tropical Pacific are higher than in other regions, ~~while in MAM the area over the central and western tropical Pacific shows higher sensitivity~~, which are influenced by El Niño and La Niña respectively (Monahan, 2001; Hsieh, 2004; Rodgers et al., 2004; Schopf and Burgman, 2006; Sun and Yu, 2009; Yu and Kim, 2011): El Niño induces negative SLP anomalies over the East Pacific and positive SLP anomalies over the west Pacific (see (King et al. (2020), Fig. 5). We infer that the land sink is negatively driven by El Niño in winter (strong El Niño, decreased land sink) and positively driven by La Niña in ~~spring~~ **winter** (strong La Niña, increased land sink). **While in MAM the area over the central and western tropical Pacific shows higher sensitivity, possibly a mix of different modes, such as the ENSO, West Pacific teleconnection and the Interdecadal Pacific Oscillation, both showing strong RR coefficients in Fig. 3b (SOI, WP and TPI indices). In Fig. R1 we show the anomalies in temperature and precipitation associated to these patterns, as well as those in NBP from the two atmospheric inversions. Generally, the temperature anomaly over the tropics shows negative correlation to land sink (SLP driven AGR_R) in both DJF (as high as -0.85) and MAM (as high as -0.71), while weaker but positive correlations are found in Eurasia. Tropical precipitation anomaly shows roughly positive correlation in DJF (as high as 0.68) and in MAM (as high as 0.65). This pattern indicates that AGR_R is generally higher for cooler and wetter conditions over the tropics and SH semi-arid regions in both seasons, which result in increased NBP (Fig. R2), and cooler but also predominantly drier conditions over Eurasia, which result in a complex pattern of NBP anomalies (Fig. R2). These results are consistent with the strong ENSO fingerprint on global CO_2 variability, e.g. as pointed out by Piao et al. (2020) and with the importance of southern semi-arid ecosystems (Ahlström et al., 2015)."**

Line 30: “(e.g., carbon uptake by photosynthesis)” Isn’t heterotrophic respiration even less well observable?

We agree with the reviewer that “heterotrophic respiration is even less well observable”, we have changed it to “(e.g. photosynthesis **or heterotrophic respiration**)”.

Line 72: Please add again “... **global** atmospheric CO_2 ...”

Thanks, added: “We use observation–based time–series of **global** atmospheric CO_2 growth rate”

Line 74: “We additionally compare results with...” which results?

We thank the reviewer for pointing this out, we have corrected it as follows: “We additionally compare results **(the fraction of C–cycle IAV that can be explained by atmospheric variability)** with a very…”

Line 77: Please make sure that the reader understands this sentence correctly, i.e. that the latitudinal domains only refer to SLP, not to the biosphere land sink. See my general remark above.

We thank the reviewer for pointing out this aspect, modified and specified as: “Next, we analyze and discuss how the **global** C–cycle sensitivity to atmospheric circulation changes from various latitudinal domains of **SLP anomaly fields**”.

2. Data and methods 2.1 CO_2 data sets:

As an “atmospheric observations person”, I was a bit confused that not only the AGR but also the modelled land sinks etc. were named “CO2 data sets” (see my comment on lines 225ff below). Also, please have a look at Le Quéré et al. (2018) how the different components of the carbon budget listed in Eq. (1) shall be cited (see their Table 2).

Thanks for pointing out, the land sinks will be referred to as modeled in the revised version of the manuscript. The citations for Equation 1 have been added.

Lines 135-136: What are the consequences that “dynamic vegetation” is not included?

This means that the land–cover composition is prescribed, rather than be prognostically simulated by the model in response to climate (which is rarely the case in global climate models). If dynamic vegetation would be included, this would mean that the distribution of the different plant functional types would be allowed to change over the 2000 years. The CESM control run uses a prescribed land-cover map from Lawrence and Chase (2007), fixed to the year 1850, and is hence only thought to represent internal variability in the atmosphere, and the response to it in terms of net biome productivity. The CESM control run is therefore only used to determine the degree of predictability we would achieve as a function of the length of the training sample.

2.2 Data pre-treatment:

Line 145: “grid points”? Do you mean “months”?

We thank the reviewer for pointing this out. Here the “grid points” refers to the number of pixel-based SLP time series (predictors) selected, corrected in the manuscript as: “so the number of ~~grid points~~ **pixel–based time–series (predictors)** in DJF+MAM is double of DJF.”

Line 146: “... LOESS as for the SLP fields.” Do you mean “as for the CO_2 time series”? There is no mentioning of a smoothing of the SLP fields.

Indeed, we chose not to detrend the SLP data. The reason for this is that while the trend in AGR and the other CO_2 datasets has clearly an anthropogenic fingerprint (through emissions of CO_2 and CO_2 fertilization effect of the land–sink), forced trends in SLP are much less pronounced relative to internal variability (although they exist in certain regions; Knutson and Ploshay (2021)). Therefore, SLP is often used in so–called dynamical adjustment studies as a proxy for atmospheric circulation, thus reflecting variability due to atmospheric dynamics (Deser et al., 2016 Journal of Climate), which can to a large extent be thought as reflecting internal climate variability. For records of 60 years, as used here, we cannot exclude the possibility that some trends may be a result of slow modes of internal climate variability.

For this reason, we refrained from explicitly stating whether our results relate to internal only or internal+forced atmospheric circulation variability. Nevertheless, we agree that results might be sensitive to this decision. Therefore, we first conducted a Mann Kendall trend test (Fig. R3) to the SLP anomalies in DJF and MAM. About 75% of the pixels show no significant trend (at 0.05 % significance level). The results indicate that significant trends can be found in the Southern Hemisphere extra–tropics and in the North Atlantic Ocean. To evaluate how these trends affect our results, we then used SLP anomalies detrended using LOWESS to predict AGR_R in the period 1959–2017. We use detrended SLP anomalies with different spatial domains: global, tropical (18° N–18° S), and tropical to SH (18° N–72° S). Generally, the spatial coefficient trend shows no large differences (Fig. R4), while the predictability is only slightly improved by about 0.04–0.05 (Fig. R5).

We also compared the AGR_R with DJF SLP (LOWESS detrended) over various latitude domains (Fig. R6) in a 30–yr sliding window. We still find enhanced predictability in the domains of tropical extend to SH mid-high latitude, but this enhancement occurs earlier compared with the results without SLP detrending (the enhanced period starts in the period 1972–2005, but with non–detrended SLP, it starts in the period 1978–2011). Also, the domains with the highest predictability with detrended SLP are generally smaller than by using non–detrended SLP, and the predictability enhanced in most other domains. This might be influenced by the decadal trend we found in Fig. R3 after removing the long–term trend from SLP. This decadal trend of SLP in high–latitude SH has some influence in the global CO_2 IAV.

Since the differences between SLP detrending/non detrending are small, and given the reasoning explained above, we keep the analysis of SLP anomaly with no LOWESS detrending. However, we add a sentence in the section 2.2 Data–pretreatment to indicate the possible influences of SLP trends:

"**Note that a large fraction of the pixel–based time–series of seasonal SLP anomalies show no long–term trend, and the predicted differences between LOWESS detrended and no detrended SLP are small. Here we keep the analysis of SLP anomaly with no LOWESS detrending.**"

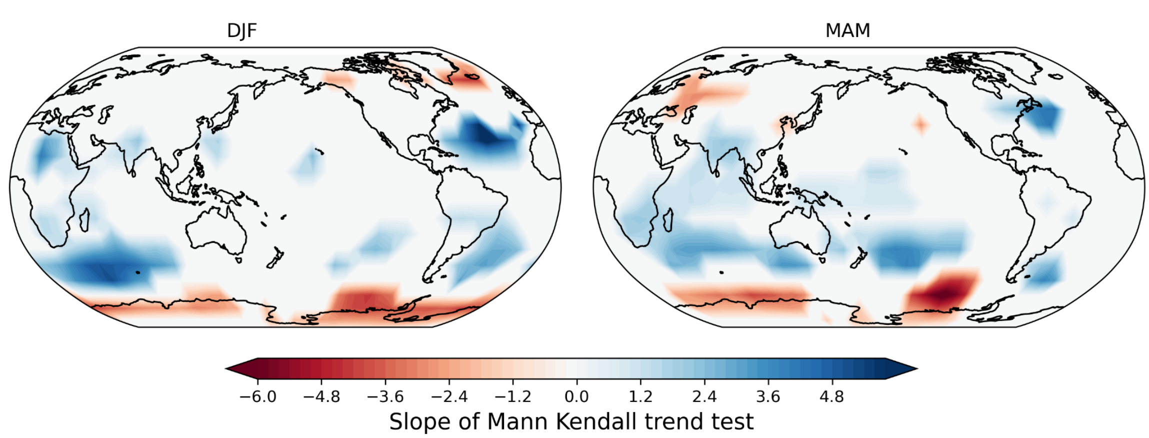

Figure R3. Spatial distribution of Mann Kendall trend test slope, the dataset used is the pre–treated SLP anomalies in DJF and MAM, in the period 1959–2017.

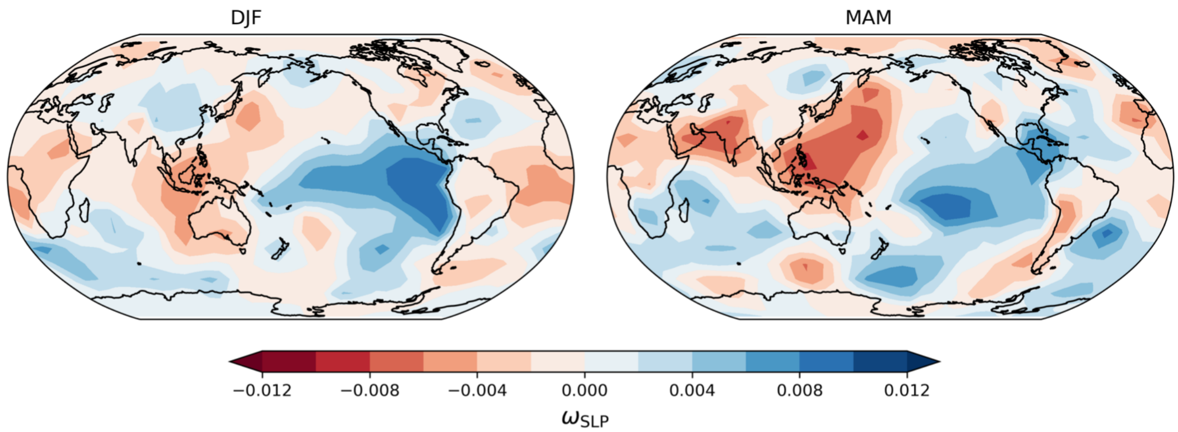

Figure R4. Distribution of RR coefficient with the time–series of AGR_R in DJF (left column) and MAM (right column) based on LOWESS detrended SLP fields in the period 1959–2017.

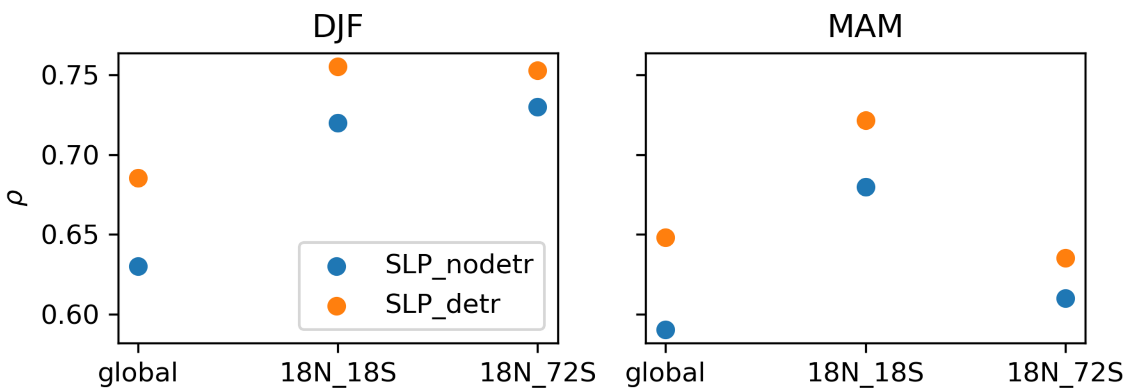

Figure R5. The comparison of predictability with SLP detrended (SLP_detr) vs no detrended (SLP_nodetr) in DJF and MAM, the x axis with different spatial domain (global, 18° N–18° S and 18° N–72° S) of SLP to predict AGR_R, in the period of 1959–2017.

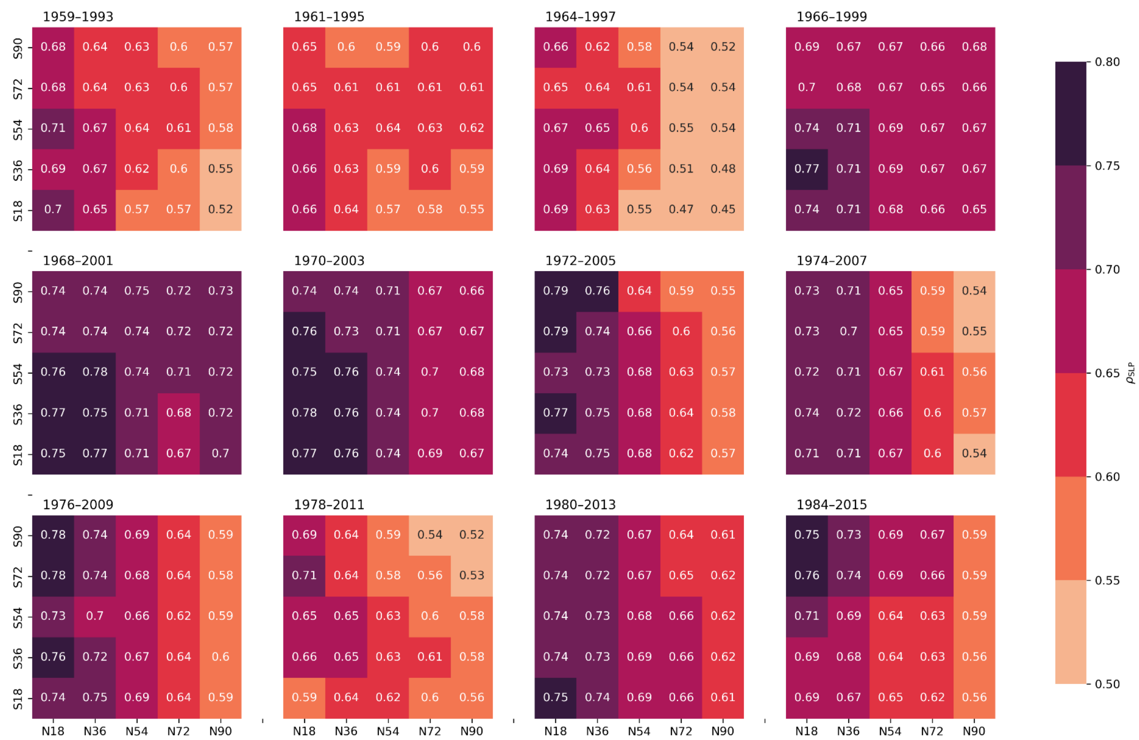

Figure R6. Heat map of r of AGR_R with DJF SLP (LOWESS detrended) over various latitude domains. A 30–yr sliding window in the period of 1959–2017 with a one–year step is created. The starting and end year of each interval is labeled on the top of each heat map. Here we only show the results of every second starting year, as in Fig. 5 of the manuscript.

2.4 Experimental design:

Line 206: "... from 1 to 53 years". Do you mean "1 to 35 years".

Corrected to: "the temporal auto–correlation of all CO_2 time–series is mostly less than 0.4 with lag ranging from 1 to ~~53~~ **35** years"

Lines 221-222: Verb is missing in the last sentence.

Thanks, the sentence has now been corrected:

"The error rate is calculated by the number of invalid predictions that ~~with are~~ **have** significance $P > 0.05$ in ρ_{SLP} divided by the number of total predictions within a given window."

3. Results and discussion

3.1 Global IAV patterns:

Lines 225-227: See my earlier comment on the confusion about "observed" CO_2 time series (sec. 2.1). It would be easier for the reader if only the AGR is called an observed CO_2 time series and the biosphere model based IAV records are called differently. In this manuscript I had a hard time to get used to the many different terms and abbreviations. A few more explanatory words here and there may help to digest the text.

Line 233: include "... LOO correlation of **SLP-**predicted and observed**/modelled** CO_2 time series ..."

We agree with the reviewer and have added accordingly: "the LOO correlation of **SLP–**predicted and observed/**modeled** CO_2 time–series ~~based on RR and with SLP anomalies as predictors~~."

Figure 2: It is a bit confusing that the y-Axis title is called r_{SLP}. I guess simply r would be correct.

"SLP" is now removed.

Figure 2 caption Line 1: insert "... annual **measured and modelled** CO_2 time-series..."

For consistence with the addition above, we correct to: "Standardized annual **observed/modeled** CO_2 time–series over period 1959–2017"

Line 4: insert "...de-trended **data** based ....predicted vs. observed **and modelled** CO_2 time ..." Line 5: "Additionally ..." Verb is missing in this sentence.

Added, thanks. The corrected lines: "in period 1980–2017 are detrended **data** based on their relevant period, and compared with detrended **data** based on 1959–2017, the difference is negligible. (b) LOO correlation of predicted vs observed/**modeled** CO_2 time–series by linear regression **is** based on the single predictor of SOI index."

Lines 258-259: "2) SL_{Resid} implicitly includes the variability from land use changes as well as ocean sink variations" Any idea which one contributed more?

According to Le Quéré et al. (2018), they consider the uncertainty in the land and ocean sink constitute the main part of the budget imbalance. They pointed out that the variability of ocean sink flux which are estimated by GOBMs models are underestimated globally (DeVries et al., 2017; Landschützer et al., 2015), and the amount of underestimation could explain part of the C-cycle budget imbalance (Le Quéré et al., 2018). They also pointed out that "at least a 68% chance that the true land–use changes emission lies within the given change" (Le Quéré et al. (2018)). So possibly the ocean sink variations contribute more to the imbalance, and then to the SL_{Resid}, but this still requires further study.

Line 293: insert "...number **of** predictors ..."

Added, thanks. The corrected line: "and the large number **of** predictors for RR training…"

3.2 Sensitivity to the SLP domains:

Lines 299-300 and 304-306: If I read the heat maps in Fig. 4 correctly, the predictability is largest if the domain includes high latitudes of the SH, i.e. not only the tropics.

We agree with the reviewer and have added the "high latitudes of the SH". The corrected line: "We find improved predictability in both seasons when selecting smaller **spatial** domains (particularly **including** the tropics **to high latitudes of the SH**)".

Lines 311-315: This explanation would be more convincing with some spatial information on the biosphere fluxes (see my general comment).

Please see the reply to the next comment.

Lines 316-317: "... is likely due to strong ..." here a more detailed inspection of the model results may give insight (see my general comment).

We agree with the reviewer that this is a very important question, and that this information can be obtained by global vegetation models.

We thank the reviewer for the advice. We calculated the spatial distribution of correlations between global DJF/MAM SLP predicted AGR_R (one time–series) with pixel–based annual sum NBP anomalies (LOWESS detrended) from atmospheric inversions CarboScope s76 and CAMS, in the period 1980–2017 (Fig. R2). This shows in each region, the higher the correlation, the stronger the relationship of variability in that region to that in the global land sink (SLP driven AGR_R or internal climatic variations driven AGR_R).

The figure shows that with both inversion datasets, the tropical to Southern Hemisphere have higher correlations (higher than 0.6), but the correlation tends to decrease Northwards. This suggests that tropical areas contribute most to the global land sink, the Northern hemisphere shows a decreasing contribution as we go north. A recent study by Wang et al. (2022) shows this is the case, and this might explain the general trend we found in Fig. 4 of the manuscript. Also, both datasets show negative correlations in North America, which shows these regions are dominated by land release instead of land sink. The correlations to CarboScope s76 are generally higher than to CAMS, and CarboScope s76 shows a more distinct pattern. The main differences of the correlation distribution between the two datasets lies in the Eurasia continent and northern South America. Here we focus on pixel–wise correlations, but to estimate the contribution to the global sink, one would need to consider spatial covariation of NBP, as well as the effect of seasonal variability in the relationships between local NBP and global CO_2. Such an analysis has just been published by Wang et al. (2022). Our results are in line with their conclusion that the tropical regions dominate the global land sink, so that we refrain from analyzing spatial variability in more detail.

3.3 Sensitivity to the temporal domains:

Lines 345-346 and Fig. 6: When increasing the time interval there are less possibilities to obtain different r_{SLP} and the correlated data become more and more similar. Doesn't this automatically decrease the variability of r_{SLP}?

The lower spread in the predicted correlations for longer periods can have physical reasons – the longer the interval, the more we can capture IAV due to slow modes of atmospheric variability (e.g. AMO) – but we agree that we cannot exclude that this can be due to statistical reasons, i.e. fewer possible combinations resulting in lower spread. These are difficult to tease apart in the short observation or modeled datasets where the sample sizes for AGR_R range from 40 for intervals of 15 years to 15, for intervals of 40 years. However, in the 4000–yr long simulation by CESM statistical effects should not strongly affect the spread for rSLP for periods of 15 or 40 years, since the corresponding sample sizes are large enough (3986 and 3961, respectively). Since the predictability is generally stable for time intervals longer than 100 years, for intervals of 100 years, the sample size is 79 (50 year step), and for intervals of 2000 years it is 5 (500 year step).

Lines 360 and 364: Perhaps better use the word “interval” instead of “scale”.

We thank the reviewer for pointing this out, we have changed accordingly: “We find that with different time ~~scales~~ intervals…”.

An explanation of Figure 6b is missing in the text.

We apologize, we realize the figure shows redundant information to that in panel (a) and have therefore deleted this panel.

Line 395: please include “... different **atmospheric** driving ...”

We have corrected the sentence to:

"This method allows quantifying the contribution of atmospheric dynamical processes in driving variability in CO_2 sources and sinks at global and regional scales, which may further be useful for attributing observed changes to internal variability versus anthropogenic climate change."

Lines 392-396: Please refer here to my comment that SLP is only a place-holder for atmospheric drivers influencing the C-cycle.

Please see reply to the respective comment above.

Figure A1: The x-axis scale and title should be degrees.

We thank the reviewer for pointing out this critical error, it is now corrected.

Figure A3: What are the light blue shaded areas?

The shaded areas are the 95% confidence interval of the calculated autocorrelation under different lags. We have now added this information in the Fig. A3 caption: “The shaded areas are the 95% confidence interval of the calculated autocorrelation under different lags”.

Figure A6 caption line 2: delete “extending” at the end of the line.

Thanks for pointing this out, “extending” is removed.