2^{nd} Reviewer

The study examines the sensitivity of GPP and NEP parameters to fluctuations in the rate of increase in global CO_2 concentrations in the East Asian region, aiming to improve the accuracy of predictive dynamic models of atmospheric CO_2 concentrations that account for carbon cycle feedbacks. While the authors acknowledge the significant influence of regional factors on carbon balance, these factors were not integrated into the methodology used to assess the sensitivity of ecosystem productivity. The methodology section requires significant expansion. Currently, there is insufficient justification for the chosen approach and insufficient detail on the specific data processing steps.

→ Thank you for the reviewer's valuable and constructive comments, which greatly contributed to improve the quality of the earlier version of the manuscript. According to the reviewer's comments, the manuscript has been revised accordingly.

Major comments

1. From the paper, it is unclear which detrending methods were applied to each parameter explored. It is important due to the different robustness of the existing methods and, therefore, for the accuracy of the final results.

→ Helpful comment! In the revised manuscript, the detrending procedure applied in the sensitivity analysis has been clearly explained in the method section. The same detrending method was consistently applied when calculating the sensitivity of ACGR and all ecosystem variables (e.g. NEP, GPP and associated fluxes). Detrending was performed using the LOWESS method, following the detrending approach of Li et al., (2024). Consistent with their approach, a smoothing span of 0.25 was used and three robustness iterations were applied in this study. This method was selected to effectively remove long-term trends, as LOWESS captures nonlinear variations by fitting a smoothing curve through locally weighted regressions, which differs from conventional linear detrending method. Responding to the reviewer's comments, we add the following sentences in the revised manuscript:

"We used the LOWESS method to remove a trend. This method differs from conventional linear trend removal and it captures nonlinear variations by fitting a smoothing curve through locally weighted regressions (smoothing span (f) = 0.25, robustness iterations = 3)."

2. Using a 20-year sliding window can introduce significant distortions in the final result due to potential cyclic fluctuations or extreme events. Therefore, it is necessary to either select a shorter window - with the length justified in advance based on additional analysis - or use other methods to calculate interannual differences.

→ Insightful comment! Responding to the reviewer's comment, we performed additional sensitivity analyses using a 15-year moving window to assess the impact of window length on the results. The results indicate that the overall pattern of sensitivity remains robust regardless of the moving window length (please see Figure R1, and R2 below). The major patterns - including overall increases and decreases as well as shifts between positive and negative values - are maintained for the NEP, GPP and R_a sensitivities (Fig. R1). However, in the monsoon region, sensitivities have shown a slight upward trend since 2010, and the overall range of sensitivity changes appears to have increased slightly. In addition, most relationships are consistent with those obtained using the 20-year window, which supports the main conclusions of this study (Fig. R2). In particular, the dominant role of soil moisture sensitivity in the non-monsoon region and PAR in the monsoon region remain consistent. Overall, the results based on the 15-year window show a highly similar pattern to those obtained using a 20-year window, and the main interpretations remain unchanged. Therefore, the results of this study can be considered robust to the length of moving window. Responding to the reviewer's comments, we add the following sentences in the revised manuscript:

"In addition, a 15-year moving window was applied to examine whether sensitivity trends were influenced by the length of the moving window (figure not shown) and it is found that the overall temporal patterns and trends were generally consistent with those observed using 20-year moving window. Therefore, the main interpretation of this study is not significantly dependent on the length of the moving window and is considered to be relatively robust."

"Additionally, the relationships presented in Figure 4 were reanalyzed using a 15-year moving window (figure not shown), and the main results were generally consistent with the results obtained using a 20-year moving window. This implies that the key finding of this study-that the regional factors contributing to GPP sensitivity vary by region-is not strongly dependent on of the length of the moving window."

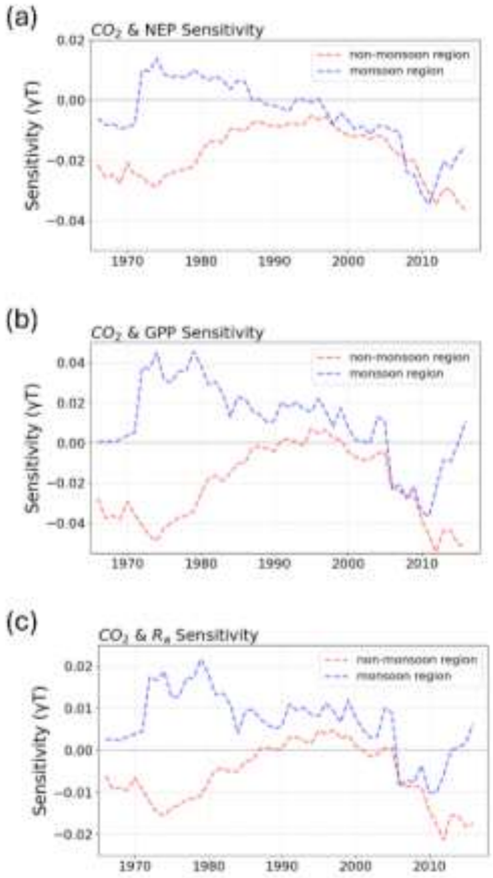

Figure R1. Time series of the sensitivity between atmospheric CO_2 growth and (a) NEP, (b) GPP, (c) R_a over 15-year moving window in 1959-2023. Lines show the ensemble mean of nine TRENDY models for the non-monsoon (red) and monsoon (blue) regions.

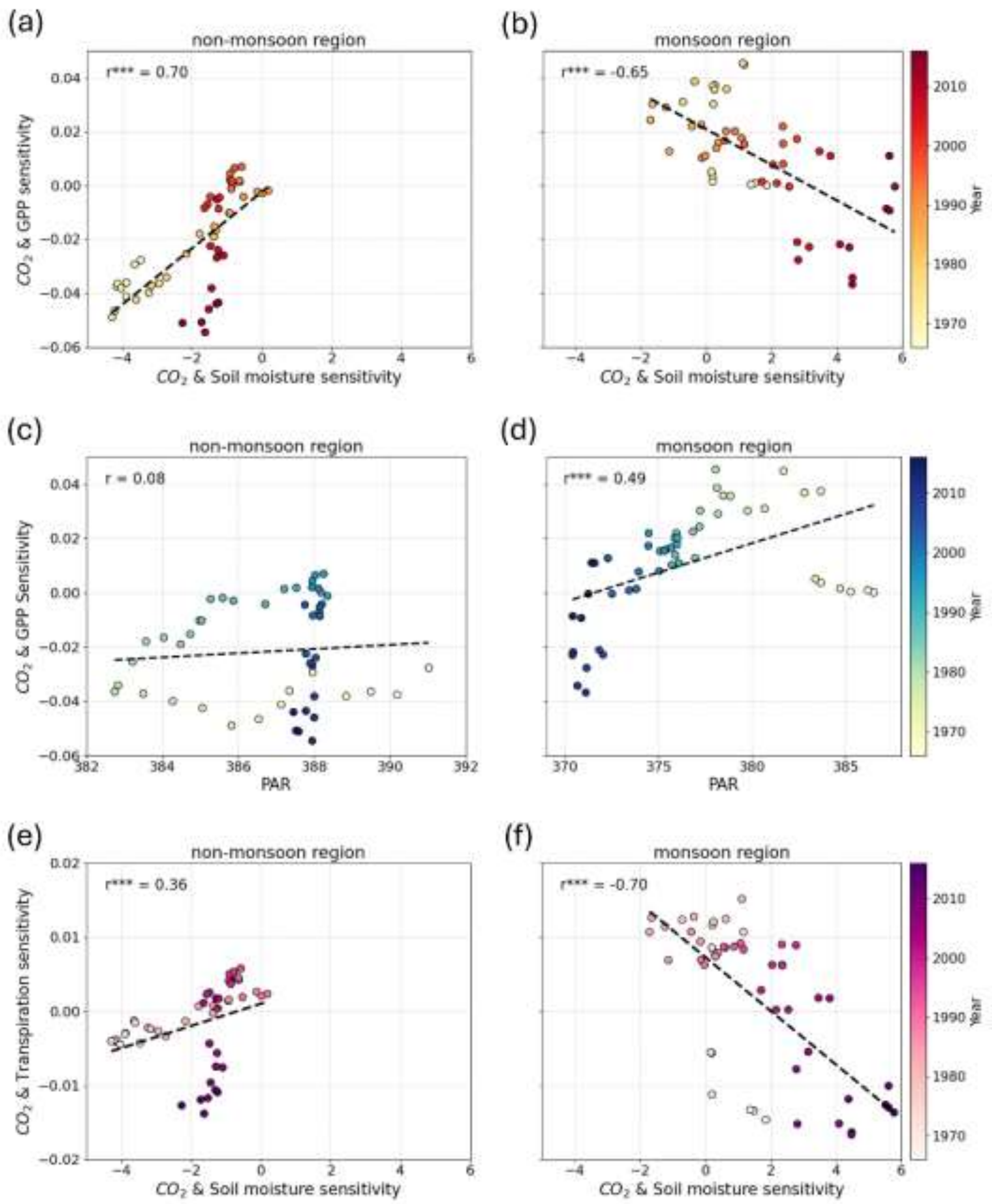

Figure R2. Correlation between (a, b) CO_2&GPP sensitivity (y-axis) and CO_2&SM sensitivity (x-axis), (c, d) CO_2&GPP sensitivity (y-axis) and PAR (x-axis), and (e, f) CO_2&transpiration sensitivity (y-axis) and CO_2&SM sensitivity (x-axis) for the non-monsoon (left) and monsoon (right) region during 1959-2023. Each scatter represents a 15-year moving window, with color changes representing the time period. Asterisks (*) indicate statistical significance levels where applicable: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; not significant, $p > 0.1$.

3. The behaviour of the data presented in Fig. 4 (specifically b, c, f, and, in particular, e) suggests that the used linear approximations (likely based on linear correlation analysis) are incorrect. An exploratory data analysis is required before linear correlation can be applied. Furthermore, transitions between samples in the year-ordered sequence demonstrate different *directions across various time periods. This factor also calls into question the applicability of linear regression analysis.*

→ Valuable comment! We agree that, because Pearson's correlation was used in Figure 4, the analysis primarily assessed the linear relationship between the two variables. Accordingly, we additionally applied Spearman's correlation, which can evaluate monotonic relationships. Table R1 compares the results of Pearson and Spearman correlations for the relationships between GPP sensitivity and SM sensitivity (Fig. 4a, b), GPP sensitivity and PAR (Fig. 4c, d), and transpiration sensitivity and SM sensitivity (Fig. 4e, f).

Table R1. Comparison of Pearson and Spearman correlation coefficients for the relationships shown in Figure 4.

Relationship	Region	Pearson correlation coefficient (significance)	Spearman correlation coefficient (significance)
Figure 4a, b	non-monsoon	0.85 (***)	0.87 (***)
	monsoon	-0.65 (***)	-0.66 (***)
Figure 4c, d	non-monsoon	0.07	0.15
	monsoon	0.72 (***)	0.85 (***)
Figure 4e, f	non-monsoon	0.59 (***)	0.77 (***)
	monsoon	-0.66 (***)	-0.60 (***)

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; not significant, $p > 0.1$.

The results showed that the signs and statistical significance of the Pearson and Spearman correlations were generally consistent. This indicates that the relationships shown in Figure 4 are not solely the result of linear correlation analysis. However, to avoid any misunderstanding in the interpretation, we have mentioned in the discussion section of the revised manuscript that non-linear relationships between variables may exist. We also clarified in the results section that the correlations shown in Figure 4 used the Pearson analysis method. Responding to the reviewer's comments, we add the following sentences in the revised manuscript:

"To identify how these structural differences influence ecosystem productivities, we examined the relationships between GPP sensitivity and key environmental factors in each region using Pearson correlation analysis (Fig. 4)."

"In addition, Spearman correlation analysis was performed to verify the influence of non-linearity in the relationships shown in Figure 4. The Spearman correlation results were generally consistent with the direction and significance observed in Figure 4, suggesting that the identified relationships were not solely dependent on linear correlation (results not shown). However, these results should still be interpreted as statistical associations, because correlation analysis alone cannot fully establish causality."

4. The correlation analysis between pairs of sensitivities used in Section 3.2 raises doubts about its advisability from a mathematical standpoint, since ultimately the dACGR terms drop out of the ratio, leaving only the relation of the increment Asians of the studied parameters, for example, [dGPP/dACGR] <-> [dSoilMoisture/dACGR] => dGPP <-> dSoilMoisture (Fig. 4.a,b,e,f), i.e., it will not affect the correlation.

→ Thoughtful comment! In response to this comment, we re-examined the sensitivity calculation method used in this study and clarified that sensitivity is defined not simply as dGPP/dACGR but as the slope β of the linear regression performed on each 20-year moving window. In linear regression, the slope β is calculated as follows:

$$\beta = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sum(X_i - \bar{X})^2}$$

where X denotes the detrended ACGR, Y denotes the detrended ecosystem variables, and $\bar{X}$ and $\bar{Y}$ represent the mean values of X and Y, respectively. Consequently, the GPP sensitivity and SM sensitivity are calculated by dividing the covariance between ACGR and GPP, and the covariance between ACGR and SM, respectively, by the variance of ACGR. In other words, both sensitivities have the same ACGR variance as their denominator, but the covariance values in the numerator differ. Therefore, the correlation between the two sensitivities is not simply a result of the dACGR term being eliminated, reducing the relationship to that between dGPP and dSM alone. To clarify this point, we have added the calculation equation for slope β to the data and methods section of the revised manuscript as follows:

"The calculation for the slope β is as follows:

$$\beta = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sum(X_i - \bar{X})^2}$$

(3)

,where $\bar{X}$ *and* $\bar{Y}$ denote the mean values of variable X and Y, respectively."

5. The analysis presented in this study does not account for factors related to ecosystem evolution, assuming that the ecosystem of the selected area is stable, even though ecosystems can both develop and degrade over such a long period, which in turn leads to changes in productivity characteristics.

→ Insightful comment. We agree that ecosystem evolution may change over long time periods through vegetation changes, degradation, and land-cover change, which can affect productivities characteristics. However, this study does not assume that ecosystems are completely unchanged over the analysis period. The TRENDY S3 simulations used in this study include changes in CO_2, climate, and land use, and therefore partially account for changes in ecosystem conditions. The main purpose of this study is to quantify regional difference in ecosystem productivity sensitivity to ACGR during the historical period, rather than to assess or predict ecosystem evolutionary processes. Responding to the reviewer's comments, we add the following sentences in the revised manuscript:

"Although ecosystem evolutionary processes were not explicitly assessed in this study, the use of TRENDY S3 simulations partially accounts for changes in ecosystem conditions through changes in CO_2, climate and land use."

Minor comments

1. Table 1 lacks relevant study parameters. Consider moving it to the appendix and updating it with a detailed description of DVGM's characteristics pertinent to the study.

→ Thank you for the reviewer's comment. We have revised Table 1 by adding the spatial resolution of each DGVM in order to provide specific information on the model datasets used in this study. With this additional information, we retained Table 1 in the main text to summarize the model datasets used in this study. Responding to the reviewer's comments, we have revised Table 1 by adding the resolution in the revised manuscript:

Table 1. Information on the TRENDY v13 model list used in this study.

	Model	Modeling center	Resolution	Reference
1	CLASSIC	Environment and Climate Change Canada	1° x 1°	(Asaadi and Arora, 2021)
2	CLM6.0	National Center for Atmospheric Research NCAR	1.25° x 0.94°	(Lawrence et al., 2019)
3	E3SM	US Department of Energy	1.25° x 0.94°	(Tang et al., 2023)
4	EDv3	University of Maryland	0.5° x 0.5°	(Ma et al., 2021)
5	IBIS	McGill University	0.5° x 0.5°	(Landry et al., 2016)
6	ISBA-CTRIP	Météo-France, French national meteorological centre	1° x 1°	(Decharme et al., 2019)
7	JULES	UK Met Office, Centre for Ecology & Hydrology, University of Reading, University of Exeter	0.5° x 0.5°	(Burton et al., 2019)
8	LPJmL	Potsdam Institute for Climate Impact Research	0.5° x 0.5°	(Beer et al., 2007; Rolinski et al., 2018)
9	LPX-Bern	University of Bern	0.5° x 0.5°	(Lienert and Joos, 2018)
10	ORCHIDEE	Institut Pierre-Simon Laplace, IPSL	0.5° x 0.5°	(Krinner et al., 2005)
11	SDGVM	University of Sheffield	1° x 1°	(Walker et al., 2017)
12	VISIT	The University of Tokyo, NIES, and JAMSTEC	0.5° x 0.5°	(Ito, 2019)

2. Lines 83-85: It is stated that the spatial resolution of the Land Cover data has been changed to 0.5° × 0.5°, whereas the rest of the data uses 1.0° × 1.0°. The use of a different resolution requires an explanation of why this was done and how it affects the estimation methods. It is also noted that when changing the resolution, the most frequent land cover type is used; however, no estimates or background information are provided for this concept.

→ Important comments! Considering that using different spatial resolutions may compromise the consistency of the analysis results, this study standardized the spatial resolution of the land cover data to 1.0° × 1.0°, in line with the other variables. Furthermore, additional information regarding the method of selecting the most frequent land cover type during resolution changes is provided in the method section. Consequently, figure 7 has been updated in the revised manuscript to reflect the 1.0° × 1.0° resolution (see Fig. R3 below). However, land cover data is categorized into different classes (such as forest, savanna and grassland); using low resolution can result in high mixing of different vegetation types, which may disrupt meaningful classification and prevent detailed-scale heterogeneity from being clearly revealed. To ensure the robustness of the findings, this study additionally compared the analysis results based on 0.5° × 0.5° land cover data (Fig. R4) with Fig. R3, and the findings were included in the discussion section of the revised manuscript.

A comparison of the results at 0.5° × 0.5° and 1.0° × 1.0° resolutions shows that the dominant vegetation types in both regions remain consistent regardless of resolution. However, slight differences are observed in the minor vegetation types in the monsoon region: at 0.5° × 0.5° resolution, Evergreen Broadleaf Forests (7.8%) and Grasslands (6.1%) are replaced by Grasslands (6.3%) and mixed Forests (4.7%) at 1.0° × 1.0° resolution. Although there are slight variations in the proportion of minor vegetation types, these differences are relatively small, indicating that the overall results remain consistent.

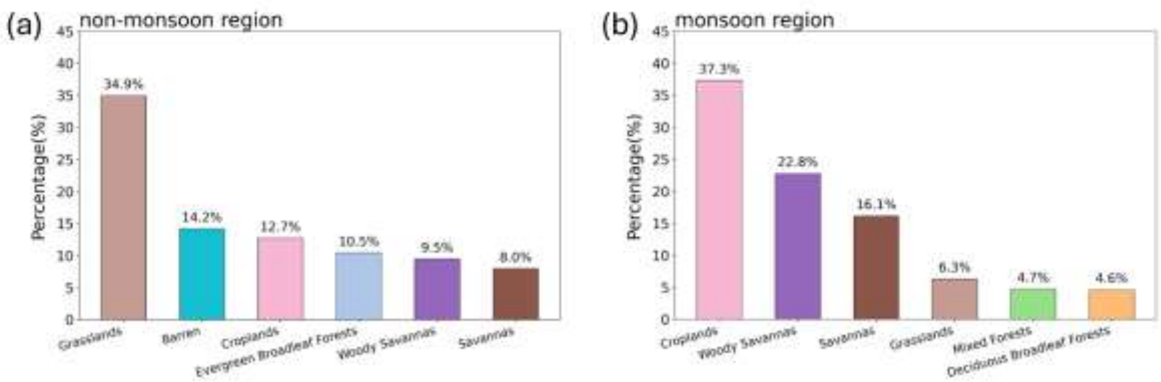

Figure R3. East Asian land cover distribution based on IGBP classification. MODIS land cover averaged during 2001-2023, regridded to 1.0° × 1.0° spatial resolution, showing the percentage distribution of land cover types in the (a) non-monsoon and (b) monsoon region.

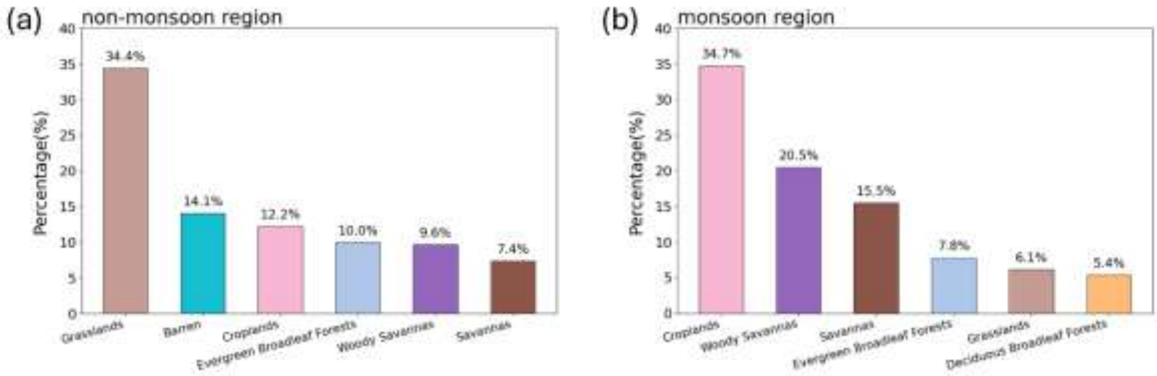

Figure R4. East Asian land cover distribution based on IGBP classification. MODIS land cover averaged during 2001-2023, regridded to 0.5° × 0.5° spatial resolution, showing the percentage distribution of land cover types in (a) non-monsoon and (b) monsoon region.

Responding to the reviewer's comments, we add the following sentences with a new figure (Fig. 7) in the revised manuscript:

"The dataset was regridded to a 1.0° × 1.0° spatial resolution. Specifically, the most frequently occurring land cover type within each grid cell was defined as the representative land cover type; no cases were found where the frequency of multiple land cover types was identical. This regridding procedure was used solely to describe regional land cover characteristics and therefore had no impact on the sensitivity estimates."

"In the analysis of land cover types using MODIS, on the other hand, a comparison at a higher resolution (0.5° × 0.5°) revealed that, although some differences are observed in minor vegetation types, the main vegetation patterns generally remain consistent; consequently, the overall sensitivity patterns appear robust and are not strongly influenced by such minor variations."

3. Lines 88-89: For their research, the authors adopted the methodology of Li et al. (2024). It is valuable to include this work in the outlook, explain the disadvantages of the existing approach, and clarify the relevance and sense of the proposed improvements.

→ Helpful comment. The moving-window linear regression method used in the previous study has the advantage of allowing us to observe changes in sensitivity over time across the entire analysis period; therefore, this study applied this method to analyze how the response of ecosystem productivity to changes in ACGR changes.

However, the results of this method may vary depending on the selected window length and may include the effects of extreme climate events or internal variability occurring during specific periods. Furthermore, the estimated sensitivity serves as an indicator of the statistical relationship between two variables, and its interpretation as a direct causal relationship between them requires caution. Therefore, this study evaluated sensitivity using both 15-year and 20-year moving windows, and the results were interpreted with caution, also considering differences in environmental conditions and related climate variables across regions.

4. Fig. 1: Correct dAGR to dACGR.

→ Corrected as follows:

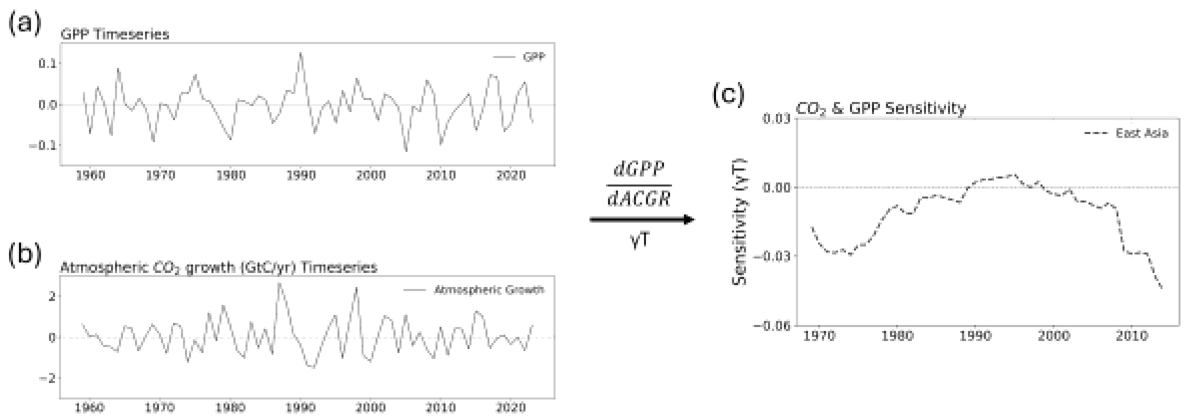

Figure R5. Methodological procedure for ecosystem productivity sensitivity to atmospheric CO_2 growth. (a) Detrended time series of GPP over East Asia from nine TRENDY v13 models. (b) Detrended atmospheric CO_2 growth from the Global Carbon Budget 2024. (c) Sensitivity of atmospheric CO_2 growth and GPP over 20-year moving windows in 1959-2023.

5. Lines 110-112: It is stated that the NEP sensitivity is examined for each DGVM model over the period 1959-2023; however, the results presented (Fig. 2a) show only a single value per model rather than a time series. There is no explanation of how the presented values were obtained.

→ Sorry for this confusion. We have clarified in the revised manuscript that the single value shown for each model in Fig. 2a represents the temporal mean of the 20-year moving window NEP sensitivities calculated for the period from 1959 to 2023. We add the following sentences in the revised manuscript:

"The value for each model in Figure 2a represents the temporal mean of the 20-year moving window NEP sensitivities calculated over the period of 1959-2023."

6. Lines 133-134: It is stated that spatial analysis uses average values of GPP sensitivity to increases in CO_2 concentration. Given the dynamics of the characteristics under study over the selected period, using an average value for the assessment is questionable. A justification should be provided, or the possibility of using secondary parameters should be analysed.

→ Indeed, GPP sensitivity can vary over time during the study period. However, the purpose of the spatial analysis was not to assess temporal variations, but to provide a representative overview of the dominant spatial contrast in GPP sensitivity. In addition, the regional classification was not based solely on an average sensitivity map. Instead, it was determined by combining the monsoon region boundaries defined in previous study (Li and Zeng, 2002; Jianping and Qingcun, 2003) with the spatial distribution of GPP sensitivity obtained in this study. Therefore, the spatial distribution of GPP sensitivity was used as an indicator to summarize the average spatial characteristics during the analysis period, and temporal variations in sensitivity were subsequently examined through time series analysis (Figure 3 in the revised manuscript).

*7. Fig. 4-6: All captions include "***p<0.01; **p<0.05; *p<0.1; not significant p>0.1" part, but each figure does not include data relevant to all the probabilities.*

→ To avoid confusion, we have revised each caption to explicitly state that significance levels are indicated only where applicable as follows:

"Asterisks (*) indicate statistical significance levels where applicable: ***p < 0.01; **p < 0.05; *p < 0.1; not significant, p > 0.1."

Furthermore, the text has been revised to reflect this notation as follows:

"In the non-monsoon region, GPP sensitivity exhibited a strong positive correlation (r***=0.85; Fig. 4a) with SM sensitivity."

“However, the monsoon region shows a contrasting pattern, resulting in a significant negative correlation (r***=-0.65; Fig. 4b).”

“In the monsoon region, GPP sensitivity decreased from positive to negative, and PAR also showed a distinct decreasing trend (Fig. 4d); a significant positive correlation was shown (r***=0.72; Fig. 4d).”

“In the non-monsoon region, a significant positive correlation (r***=0.59; Fig. 4e) was observed between transpiration sensitivity and SM sensitivity.”

“In contrast, the monsoon region showed increasing SM sensitivity from negative to positive, whereas transpiration sensitivity exhibited a decreasing trend from positive to negative (r***=-0.66; Fig. 4f).”

“In the non-monsoon region, the correlation between GPP sensitivity and SM sensitivity exhibited a strong positive correlation in both periods (r***=0.92 for the early period; r***=0.87 for the late period), with high explanatory power (r^2=0.85 and r^2=0.76, respectively; Fig. 5a, b).”

“However, in the late period, a positive correlation emerged (r**=0.59 and r^2=0.35; Fig. 5d), with both PAR and GPP sensitivity decreasing, and GPP sensitivity having a negative value.”

“In addition, the relationship between transpiration sensitivity and SM sensitivity also remained consistently a positive correlation in both periods (r***=0.89 for the early period; r***=0.85 for the late period), with consistently high coefficients of determination (r^2=0.80 and r^2=0.73, respectively; Fig. 5e, f).”

“The relationship between GPP sensitivity and PAR exhibited a significant positive correlation in both periods (r**=0.46 for the early period; r***=0.77 for the late period), and its coefficients of determination strengthened over time (r^2=0.21 and r^2=0.59, respectively; Fig. 6c, d), emphasizing that the role of PAR in explaining GPP sensitivity enhanced during later period.”

"The relationship between transpiration sensitivity and SM sensitivity showed insignificant correlation during the early period ($r=0.13$, $p>0.1$; Fig. 6e), but became significantly negatively correlated during the later period ($r^{**}=-0.50$ and $r^2=0.25$; Fig. 6f), highlighting a pattern consistent with the full period analysis, in which changes in transpiration sensitivity are inversely associated with changes in SM sensitivity under ACGR related responses."

8. Line 192: the sign of the correlation coefficient in the text does not correspond to the one in Fig. 4f.

→ Thank you for the reviewer's detailed comment. Corrected as follows:
"In contrast, the monsoon region showed increasing SM sensitivity from negative to positive, whereas transpiration sensitivity exhibited a decreasing trend from positive to negative ($r^{***}=-0.66$; Fig. 4f)."