RC1: 'Comment on bg-2023-140', Anonymous Referee #1, 29 Oct 2023

Dear Reviewer and Editor,

We would like to thank the reviewer and you for your interest in our study, and for the feedback provided. We appreciate these constructive and specific comments, which will help improve the quality of the manuscript. We have carefully inspected all reviewer comments. We also streamlined the results, figures and text as suggested by reviewers. Below, you will find our responses to the comments (responses in blue).

We hope that you will find the result satisfying.

Sincerely,

Tao Chen, Félicien Meunier, Marc Peaucelle, Guoping Tang, Ye Yuan, Hans Verbeeck

Reviewer #1

In their study, the authors investigate the influence of different drivers on changes in GPP in subtropical forests in China. The considered drivers were climate change, forest cover change, change in vegetation structure, and changes in CO_2 concentrations.

The authors use the BEPS model and run multiple simulations to disentangle the impact of the different drivers and find that atmospheric CO_2 and vegetation structure play the most important roles.

This is an interesting and well-conducted study and the manuscript is decently written. In my opinion, this study can be published in Biogeosciences after it went through some major revisions.

I mainly find that there needs to be some more model evaluation. Furthermore, some results need to be explained better. Also, the discussion has some points that need to be made clearer or added (see details below).

I'd further suggest some streamlining of results, figures, and text. There are 10 Figures, often with 6 panels. I believe this could be made more concise.

Further detailed comments follow below.

Response: Thank you very much for the valuable comments and suggestions. Below we go through point-by-point our answers to the comments, and our responses are in blue. Moreover, we have also streamlined the results, figures and text as suggested. Especially, six most important Figures remain in the main text. The rest do not necessarily need to be placed in the main text and have been moved to the supplementary.

Abstract:

Why call it VSC and not just LAI?

Response: Thank you for this comment. LAI is one of the most important parameters representing vegetation structure, which can influence the carbon cycle and is widely used in models (e.g., LUE-based models and process-based models) to simulate carbon and water fluxes (Chen et al., 2019; Zhang, X. et al., 2022). Thus, the VSC was adopted in our study to represent LAI. Indeed, LAI does not represent all vegetation structure changes. As suggested, we use LAI directly in the revised version.

References:

Chen, J.M. et al., 2019. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nature Communications, 10(1): 4259.

Zhang, X. et al., 2022. Land cover change instead of solar radiation change dominates the forest GPP increase during the recent phase of the Shelterbelt Program for Pearl River. Ecological Indicators, 136: 108664.

Introduction

l. 39: the statement about the 30% is not a result of the cited study and is also not cited there... Please find a better reference

Response: Thank you for this suggestion. We added the new reference in the revised version (see below).

"Giovanni Forzieri, et al, 2022. Emerging signals of declining forest resilience under climate change. Nature, 608, 534–539."

l. 55: should be 0.82 billion I guess.

Response: Agree! The 8.2 billion has been changed to 0.82 billion.

l. 59: is this compared to global surface temp or temp over land?

Response: Thanks. It is compared to the global surface temperature. We have rewritten the sentence as follows (see Page 3, Lines 87-89).

"the annual mean temperature in the Chinese subtropical monsoon region has increased by more than 1.0 °C over the past 30 years (Fang et al., 2018), which was higher than the global surface temperature increase (Sun et al., 2019)."

References:

Sun, C., et al, 2019. Changes in extreme temperature over China when global warming stabilized at 1.5 °C and 2.0 °C. Scientific Reports, 9:14982.

Fang, J., et., 2018. Climate change, human impacts, and carbon sequestration in China. Proceedings of the National Academy of Sciences, 115(16): 4015-4020.

Methods:

l. 103: what about the spread of temperature as you mention for precipitation?

Response: Thanks for this comment. We added the following sentence to the revised version to describe the spread of temperature (see Page 5, Lines 152-153).

"The mean annual temperature of the study area is about 15.5°C, and it normally increases from the northwest toward the southeast."

l. 115: NEP was not introduced. Generally, a glossary with abbreviations would be helpful.

Response: We have added the full name of the NEP (i.e., net ecosystem productivity) in the revised text. As suggested, we also added the following glossary of acronyms in the revised text to show abbreviations for other terms (see Page 2, Lines 39-43).

List of Abbreviations

Abbreviation	Definition
BEPS	The Boreal Ecosystem Productivity Simulator
GPP	Gross primary productivity
FCC	Forest cover change
LAI	Leaf area index
CC	Climate change
CO_2	Carbon dioxide
EBF	Evergreen broadleaved forest
ENF	Evergreen needle-leaved forest
DBF	Deciduous broadleaved forest
MXF	Mixed forest
QYZ	Qianyanzhou station
DHS	Dinghushan station
ALS	Ailaoshan station
V_{cmax}	The maximum carboxylation rate
NEP	Net ecosystem productivity
ER	Ecosystem respiration

l. 116: some more text on the model is necessary to allow the reader to get a basic understanding of it. It may go into the supplements.

Response: Thank you for the constructive suggestion. Following your suggestion, we have added more descriptions (please see below) about the model in the supplementary (see also Text S1).

“Text S1 (description of the BEPS model)

The BEPS model was originally developed at the Canada Centre for Remote Sensing to assist in natural resources management (Liu et al., 1997). Compared with 15 prognostic models that participated in the Global Carbon Project (GCP) (Le Quere et al., 2018), BEPS results are mostly better in terms of the Pearson regression coefficient (R^2), root mean square error (RMSE), accumulated total sink, and trend against the residual land sink reported by Le Quere et al (2018). The BEPS model was mainly driven by remotely sensed datasets, which can be used for simulating the key carbon (e.g., GPP, NPP and NEP) and water (e.g., ET) fluxes of the terrestrial ecosystems at the yearly, daily and hourly scales. In the BEPS model, there are 8 plant functional types (PFTs), including shrubland, grassland, cropland, and four forest types (the evergreen needleleaf forests (ENF), deciduous needleleaf forests (DNF), deciduous broadleaf forests (DBF), evergreen broadleaf forests (EBF), mixed forests (MXF)).

At the daily scale, the BEPS model was driven by the daily leaf area index (LAI), daily meteorological data, etc. Daily carbon fixation in the BEPS model is calculated by scaling Farquhar's leaf biochemical model (Farquhar et al., 1980) up to canopy-level implemented with a spatial and temporal scaling scheme (Chen et al., 1999). Daily gross primary productivity (GPP) is calculated separately for sunlit and shaded leaves (see Eq. (1-3) and Eq. (S1-S6)). The photosynthesis of sunlit and shaded leaves A (i.e., A_{sun} (unit: $\mu mol\ m^{-2}\ s^{-1}$) and A_{shade} (unit: $\mu mol\ m^{-2}\ s^{-1}$)) can be calculated as follows:

$$A = min(A_c, A_j) - 0.015 \times V_m \quad \text{(S1)}$$

where A_c denotes the Rubisco-limited gross photosynthesis rate ($\mu mol\ m^{-2}\ s^{-1}$) and is computed as Eq. S2; A_j is the RuBP-limited gross photosynthesis rate ($\mu mol\ m^{-2}\ s^{-1}$) and is calculated as Eq. S3.

$$A_c = V_m \frac{C_i - \Gamma}{C_i + K} \quad \text{(S2)}$$

$$A_j = J \frac{C_i - \Gamma}{4.5C_i + 10.5\Gamma} \quad \text{(S3)}$$

where C_i is the intercellular CO_2 (Pa); K is a function of enzyme kinetics (Pa) and is calculated as $K = K_C \times \left(1 + \frac{O_2}{K_O}\right)$; O_2 is oxygen concentrations in the atmosphere (Pa); K_C and K_O are the Michaelis-Menten constants for CO_2 (Pa) and O_2 (Pa), respectively; Γ denotes the CO_2 compensation point without dark respiration (Pa) and is calculated as $\Gamma = 4.04 \times 1.75^{(T_a - 25)/10}$; V_{cmax} is the maximum carboxylation rate ($\mu mol\ m^{-2}\ s^{-1}$) and J represents the electron transport rate ($\mu mol\ m^{-2}\ s^{-1}$). The corresponding formulas for V_m and J are as follows:

$$V_m = V_{cmax25} \times 2.4^{\frac{T_a - 25}{10}} f(T_a) f(N) \quad \text{(S4)}$$

$$f(T_a) = \left\{1 + exp\left[\frac{-220000 + 710 \times (T_a + 273)}{8.314 \times (T_a + 273)}\right]\right\}^{-1} \quad \text{(S5)}$$

$$J = (29.1 + 1.64V_m) \times PPFD/\left(PPFD + 2.1 \times (29.1 + 1.64V_m)\right) \quad \text{(S6)}$$

where V_{cmax25} is the maximum carboxylation rate at 25°C ($\mu molm^{-2}s^{-1}$); Ta is air temperature (°C); $f(N)$ is the function of nitrogen (N) and is usually set to 0.5 in BEPS model (Liu et al., 1999; Zhang et al., 2018), which can adjust the photosynthesis rate for foliage nitrogen (Bonan, 1995). The $PPFD$ is the photosynthesis photon flux density ($\mu mol\ m^{-2}\ s^{-1}$).

When BEPS modelled the dynamics of carbon pools beyond the GPP, it stratified soil carbon stocks into 9 pools (i.e., surface structural litter, surface metabolic litter, soil structural litter, soil metabolic litter, coarse woody litter, surface microbe, soil microbe, slow, and passive carbon pools). These 9 carbon pools were used to calculate heterotrophic respiration (R_h) and autotrophic respiration (R_a). Eventually, the net ecosystem productivity (NEP) is calculated as the difference between GPP and R_h and R_a.

$$NEP = GPP - R_h - R_a \quad \text{(S7)}$$

References:

Liu, J., et al., 1997. A process-based boreal ecosystem productivity simulator using remote sensing inputs. Remote Sensing Environment, 62, 158-175.

Le Quere, C., 2018. Global carbon budget 2017. Earth System Science Data, 10, 405-448.

Farquhar, G.D., et al., 1980. A biochemical-model of photosynthetic CO_2 assimilation in leaves of C-3 Species. Planta, 149, 78-90.

Chen, J.M., et al., 1999. Daily canopy photosynthesis model through temporal and spatial scaling for remote sensing applications. Ecological Modelling, 124, 99-119.

Bonan, G.B., 1995. Land-atmosphere CO_2 exchange simulated by a land surface process model coupled to an atmospheric general circulation model. Journal of Geophysical Research, 100(D2): 2817-2831.

l. 148: flux partitioning is not quality control.

Response: Thanks. We have removed this inappropriate description from the text.

l. 151: ER not introduced

Response: The full name of ER has been added in the text (see list of abbreviations), namely ecosystem respiration (ER).

l. 170: I am not an expert on this. Any reason why GOSIF was not used? I thought this would be the state-of-the-art GPP product.

Response: Yes, the Sun-induced chlorophyll *a* fluorescence (SIF) retrieved from satellites has shown potential as a remote sensing proxy for gross primary productivity

(GPP), such as GOSIF GPP. Generally, there are two approaches to estimating GPP based on SIF: one is to establish a direct empirical linear model of the two, and the other is based on the models, such as Soil-Canopy-Observation of Photosynthesis and the Energy Balance (SCOPE) model. The GOSIF GPP was not used in this study, mainly considering the following reasons:

(1) Most previous studies have shown that SIF and GPP can be characterized by linear relationships (Smith et al., 2018; Li et al., 2018; Li et al., 2019). However, some studies recently indicated a non-linear relationship between SIF and GPP (Kim et al., 2021; Liu et al., 2022), and the relationship between SIF-GPP varies across different climatic zones and biomes (Chen et al., 2021). All these results suggested that the relationship between SIF and GPP remains highly uncertain across space and time. This is mainly due to an insufficient understanding of the influencing mechanism of the relationship between SIF-GPP at present. For example, the GPP-SIF relationship is strongly influenced by environmental factors and has a high sensitivity to precipitation. Especially, there will be differences in the trend of changes in SIF and GPP under drought stress conditions, and SIF offers limited potential for quantitatively monitoring GPP during heat waves (Wohlfahrt et al., 2018). However, most of the SIF-based GPP products including the GOSIF GPP were generated by the linear relationships between SIF and GPP to map GPP globally. Therefore, the current GPP products retrieved from SIF may have significant uncertainty and controversy due to insufficient understanding of the mechanism of the relationship between SIF-GPP (Chen et al., 2021; Liao et al., 2023).

(2) The SIF signal of vegetation is very weak, and it is only 1% of the incident radiation. However, current satellites for SIF detection typically have coarse spatial resolution, which could result in a large systematic bias in both the available SIF and SIF-based GPP products, particularly when the resolution is coarse (Frankenberg et al., 2014). Indeed, Li et al., (2019) have produced relatively high-resolution GOSIF GPP products on a global scale. The raw data used for the GOSIF GPP production stems from SIF observed by the Orbiting Carbon Observatory-2 (OCO-2). The sparse coverage and coarse spatial resolution (~1°) of OCO-2 may also lead to large uncertainty in the production of GOSIF GPP. Additionally, the GOSIF is not fully independent from MODIS greenness indices, since its derivation relies on both solar-induced fluorescence measurements from OCO-2 and MODIS reflectance measurements.

Actually, we recognize that SIF brings major advancements in measuring terrestrial photosynthesis, especially in estimating GPP. We will consider SIF-based GPP in our future research.

References:

Smith, W.K., et al., 2018. Chlorophyll Fluorescence Better Captures Seasonal and Interannual Gross Primary Productivity Dynamics Across Dryland Ecosystems of Southwestern North America. Geophysical Research Letters, 45, 748–757.

Li, X., et al., 2018. Solar-induced chlorophyll fluorescence is strongly correlated with terrestrial photosynthesis for a wide variety of biomes: First global analysis based on OCO-2 and flux tower observations. Global Change Biology, 24, 3990–4008.

Li, X., Xiao, J., 2019. Mapping photosynthesis solely from solar-induced chlorophyll fluorescence: A global, fine-resolution dataset of gross primary production derived from OCO-2. Remote Sensing, 11(21), 2563.

Kim et al., 2021. Solar-induced chlorophyll fluorescence is non-linearly related to canopy photosynthesis in a temperate evergreen needleleaf forest during the fall transition. Remote Sensing of Environment, 258, 112362.

Liu et al., 2022. Non-linearity between gross primary productivity and far-red solar-induced chlorophyll fluorescence emitted from canopies of major biomes. Remote Sensing of Environment, 271, 112896.

Chen et al., 2021. Moisture availability mediates the relationship between terrestrial gross primary production and solar-induced chlorophyll fluorescence: Insights from global-scale variations. Global Change Biology, 27:1144–1156.

Miao, G., et al, 2018. Sun-induced chlorophyll fluorescence, photosynthesis, and light use efficiency of a soybean field from seasonally continuous measurements. Journal of Geophysical Research, 123, 610-623.

Wohlfahrt, G., et al., 2018. Sun-induced fluorescence and gross primary productivity during a heat wave. Scientific Reports, 8,14169.

Liao, Z., et al., 2023. A critical review of methods, principles and progress for estimating the gross primary productivity of terrestrial ecosystems. Frontiers in Environmental Science,11, 1093095.

Frankenberg, C., et al., 2014. Prospects for chlorophyll fluorescence remote sensing from the Orbiting Carbon Observatory-2. Remote Sensing of Environment, 147, 1–12.

l. 210: this reads strange. In S1 the land cover is fixed. But then you write that "in this scenario, LCC may lead to changes..."

Response: Thanks for catching the inappropriate description. We have removed the unnecessary and confusing sentences from the revised text.

l. 212: this is confusing. You talk about the conversion of forest to non-forest, and then about forest cover change. Is that not the same thing?

Response: Thanks again for pointing out the inappropriate description. To avoid confusion, we have also removed the statement from the revised text where there are unnecessary.

Improve Table S3, explain more. What is remote sensing, what is modeled, etc.

Response: Following your suggestion, we have modified the Table S3 as follows:

Table S3 Details of the published GPP products were used for model comparison.

Dataset	Time Range	Spatial Resolution	Description	Source	References
MODIS GPP	2000-2022	500 m	MODIS GPP product derived from satellite observations	https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/6/MOD17A2H/	Running et al. (2015)
EC-LUE GPP	1982–2018	0.05°	EC-LUE GPP product derived from the light use efficiency model	https://doi.org/10.6084/m9.figshare.8942336.v3.	Zheng et al. (2020)
NIRv GPP	1982–2018	0.05°	NIRv GPP product derived from satellite observations	https://doi.org/10.6084/m9.figshare.12981977.v2.	Wang et al. (2021)
VPM GPP	2000-2016	0.05°	VPM GPP product derived from satellite observations and NCEP Reanalysis II climate data	https://figshare.com/articles/dataset/Annual_GPP_at_0_5_degree/5048005	Zhang et al. (2017)
$BEPS_g$ GPP	1982–2019	0.072727°	$BEPS_g$ GPP product derived from the process-based model	http://www.nesdc.org.cn/sdo/detail?id=612f42ee7e28172cbed3d809	Chen et al. (2019); He et al. (2021)

Results:

The model performance section is very good. But only GPP is evaluated. What about other model outputs?

Response: Thank you very much for this positive comment. In this study, we aim to understand how different drivers affect GPP changes. Therefore, we mainly focus on the validation and evaluation of GPP. In order to further validate the simulation results from the BEPS model, we also validated the simulated NEP at the three flux sites. The validation results of NEP have listed in the supplementary (please see Table S5 and Figure S4-S6).

Also, Fig 3 does not really convince me. Can you discuss why the GPPs are so different?

Response: Thank you for this comment. We agree that there are relative differences between these GPP products. This stems mainly from the fact that different products are generated by different methods, data sources, etc, which may lead to differences in the GPPs produced. For example, the MODIS GPP product was mainly generated by the Terra/Aqua satellite observations. The newly released NIRv GPP was produced by near-infrared reflectance (i.e., the AVHRR reflectance from LTDR (Land Long Term Data Record v4) product). Thus, the data sources derived from divergent satellite observations may result in the differences between the two GPPs. Additionally, the EC-LUE GPP, VPM GPP, and the published BEPS GPP are all model outputs, where

EC-LUE GPP and VPM GPP are simulated based on different light use efficiency (LUE) models, respectively, and the BEPS GPP is produced based on a process model. Current LUE-based models do not completely integrate other key environmental regulations to vegetation productivity, such as the effect of atmospheric CO_2 concentration. Thus, the underestimation in other GPP products is possibly due to the failure to assess the CO_2 fertilizer effects, because almost no apparent response to the rising atmospheric CO_2 concentration in the LUE models leads to an underestimated trend (Anav et al., 2015). In our study, the GPP was estimated by a process-based model (i.e., BEPS) that considered the effects of these important factors on GPP, especially the CO_2 fertilization effect, which may lead to a higher GPP when compared to other GPP products. Overall, the parameters, inputs, and model structure of different models are inconsistent, which may also lead to differences in GPP production.

Although these products have differences and were used for comparison in this study, we mainly consider that these GPP products have been widely used in previous studies (NIRv GPP: Zhang et al., 2022; MODIS GPP: Yao et al., 2020; VPM GPP: Zhang et al., 2016; BEPS GPP: Chen et al., 2019; EC-LUE GPP: Wang et al., 2020). Especially, Xing et al., (2023) also adopted the same global GPP products for comparison with the GPP simulated by BEPS over China. Moreover, these products are produced from different data sources and methods, and it would be more reasonable and reliable to use them for comparing the simulated GPP in our study.

To respond to your question, we added these discussion in the revised manuscript (see Pages 11, Lines 347-361). We also moved Figure 3 to the supplementary, mainly because Figure 3 is relatively less important for the understanding of the main text, and on the other hand, it also can reduce the number of figures in the main text.

References:

Zhang et al., 2022. Revisiting the cumulative effects of drought on global gross primary productivity based on new long-term series data (1982–2018). Global Change Biology, 28, 3620–3635.

Yao et al., 2020. Accelerated dryland expansion regulates future variability in dryland gross primary production. Nature Communications, 11, 1665.

Zhang et al., 2016. Consistency between sun-induced chlorophyll fluorescence and gross primary production of vegetation in North America. Remote Sensing of Environment, 183, 154-169.

Chen, J.M. et al., 2019. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nature Communications, 10(1): 4259.

Wang et al., 2020. Recent global decline of CO_2 fertilization effects on vegetation photosynthesis. Science, 370, 1295-1300.

Xing et al., 2023. Modeling China's terrestrial ecosystem gross primary productivity with BEPS model: Parameter sensitivity analysis and model calibration. Agricultural and Forest Meteorology, 343, 15, 109789.

Anav, A., et al., 2015. Spatiotemporal patterns of terrestrial gross primary production: a review. Reviews of Geophysics, 53(3), 785-818.

l. 242: typo: "203-2010"

Response: The “203-2010” has been changed to “2003-2010”.

l. 240-245: any explanation as to why some of the sites are performing much better? R2 as low as 0.43 in one site, up to 0.85 in another

Response: Thanks for this comment. Yes, our validation results show that the performance of the model in simulating GPP at the three flux sites is different. This may be due to the following reasons:

(1) On the one hand, it may be due to differences in geographic location, topographic features, climate and water variability, complex structure and composition of community, and soil types at different flux sites, leading to inconsistent performance of the model in simulating GPP. Generally, there are a large number of parameters were set as constants in the model, even for the same PFT. Thus not considering the spatial and temporal variability of these parameters, which may cause differences in the accuracy of the simulation results at different sites. For example, the elevations of the three flux sites are 100 m for QYZ, 300 m for DHS, and 2400 m for ALS, respectively. The mean annual temperature and (°C) and annual precipitation (mm) of these sites are also different. Therefore, these factors may result in variability in simulation results.
(2) On the other hand, the quality and accuracy of the flux observations vary from site to site due to differences in observation equipment (e.g., the eddy covariance technique), topography, data quality controls, etc., which may also affect our validation results. For example, as reported by Wang et al., (2006), the low observed values of CO_2 flux are mainly caused by a CO_2 leak during the nighttime at the DHS station. In addition, the effect of topography also led to generally low fluxes in the southerly direction at DHS site (Li et al., 2021).

We also reviewed previous studies and found similar results to our study. For example, Muhammad et al., (2022) simulated the GPP at the DHS station based on an improved process model and it had an R^2 of only 0.38. He et al., (2013) also reported the R^2 between the BEPS-simulated GPP and EC-based GPP for the same site (DHS) was 0.48, but the R^2 was 0.78 for the QYZ. Zeng et al., (2020) used the Random forest model to simulate global GPP and showed that there was a relatively low R^2 (< 0.5) in the DHS site when comparing their simulated results with global flux data sets. These results indicate that there may be relatively low-quality issues with observed flux data from DHS.

References:

Muhammad A., et al., 2021. Reflectance and chlorophyll fluorescence-based retrieval of photosynthetic parameters improves the estimation of subtropical forest productivity. Ecological Indicators, 131, 108133.

He, M., et al., 2013. Development of a two-leaf light use efficiency model for improving the calculation of terrestrial gross primary productivity. Agricultural and Forest Meteorology,173, 28–39.

Zeng et al., 2020. Global terrestrial carbon fluxes of 1999–2019 estimated by upscaling eddy covariance data with a random forest. Scientific Data, 7, 313.

Wang et al., 2006. CO_2 flux evaluation over the evergreen coniferous and broad-leaved mixed forest in Dinghushan, China. Science in China Series D: Earth Sciences, 49, 127–138.

Li et al., 2021. An observation dataset of carbon and water fluxes in a mixed coniferous broad-leaved forest at Dinghushan, Southern China (2003 – 2010). China Scientific Data, 6(1), DOI: 10.11922/csdata. 2020. 0046.zh.

Fig 2: do you have any explanation about the small bias in DHS at low observed values? This is also visible in all years in the supplements.

Response: Thanks. As mentioned above, the small bias may be caused by the observations of the flux tower itself. As reported by Wang et al., (2006), the low observed values of CO_2 flux are mainly caused by a CO_2 leak during the nighttime at the site. In addition, the effect of topography also led to generally low fluxes in the southerly direction at this site (Li et al., 2021). We also reviewed previous studies and found similar results to our study. For example, Muhammad et al., (2022) simulated the GPP at the DHS station based on an improved process model and it had an R^2 of only 0.38. He et al., (2013) also reported the R^2 between the BEPS-simulated GPP and EC-based GPP for the same site (DHS) was 0.48, but the R^2 was 0.78 for the QYZ. Zeng et al., (2020) used the Random forest model to simulate global GPP and showed that there was a relatively low R^2 (< 0.5) in the DHS site when comparing their simulated results with global flux data sets. These results indicate that there may be relatively low-quality issues with observed flux data from DHS. Despite the presence of lower observations at the DHS, the small bias is the systematic errors and it may not affect the validation of our model. Besides, at the other two stations (e.g., QYZ and ALS), our validation results confirmed the good performance of the model used in this study.

References

Wang et al., 2006. CO_2 flux evaluation over the evergreen coniferous and broad-leaved mixed forest in Dinghushan, China. Science in China Series D: Earth Sciences, 49, 127–138.

Li et al., 2021. An observation dataset of carbon and water fluxes in a mixed coniferous broad-leaved forest at Dinghushan, Southern China (2003 – 2010). China Scientific Data, 6(1), DOI: 10.11922/csdata.2020.0046.zh.

Muhammad A., et al., 2021. Reflectance and chlorophyll fluorescence-based retrieval of photosynthetic parameters improves the estimation of subtropical forest productivity. Ecological Indicators, 131, 108133.

He, M., et al., 2013. Development of a two-leaf light use efficiency model for improving the calculation of terrestrial gross primary productivity. Agricultural and Forest Meteorology,173, 28–39.

Zeng et al., 2020. Global terrestrial carbon fluxes of 1999–2019 estimated by upscaling eddy covariance data with a random forest. Scientific Data, 7, 313.

Fig 2: The caption misses that the dots are observations

Response: Thanks. The dark circles represent the observations. We added the description of the green lines and dark circles in the Figure caption (see below and Page 10, Lines 326-327).

"Figure 2 Comparison of simulated GPP with measured GPP from three flux tower stations at daily (a-c) and annual (d-f) scales. The green lines and dark circles represent the simulated GPP and observed GPP, respectively."

l. 266: This is an issue: obviously the increase in GPP is similar in a study with the same model. The next data product has a much lower increase, 0.017, compared to this study's 0.026.

Response: Thank you very much for pointing out the inappropriate description. To avoid confusion, we have removed this sentence from the revised text.

BEPS simulates a higher GPP compared to all the other products, and a higher trend, too. This needs to be discussed further.

Response: Agree. Our simulated GPP is slightly higher than other products. Firstly, there are some uncertainties and substantial differences in the simulated interannual variability in GPP from various ecosystem models due to many differences in model structure, parameterization and driving data (Cai et al., 2014; Lin et al., 2023). Secondly, the other GPP products used in this study were mainly generated by the LUE model-based and remote sensing-based models. However, previous studies (Zhu et al., 2018; O'Sullivan et al., 2020; Wang et al., 2023) reported that LUE-based models, remote sensing-based models, machine-learning-based models, etc., may underestimate the GPP at an annual scale. For example, the GPP estimates by the LUE models mainly depend on a few important factors, including solar radiation, air temperature, water availability, and vegetation indexes (e.g., EVI or NDVI). Current LUE-based models do not completely integrate other key environmental regulations to vegetation productivity, such as the effect of atmospheric CO_2 concentration on GPP.

Therefore, one cause of the underestimation in other GPP products is possibly failure to assess the CO_2 fertilizer effects, because almost no apparent response to the rising atmospheric CO_2 concentration in the LUE models leads to an underestimated trend (Anav et al., 2015). In our study, the GPP was estimated by a process-based model (i.e., BEPS) that considers the effects of these important factors on GPP, especially the CO_2 fertilization effect, which may lead to a higher GPP compared to other GPP products.

For what it's worth, the results of our comparisons showed that the interannual trends of our simulated results were in line with other GPP products (Fig. S9). Despite possible overestimation, the purpose of this study mainly focuses on the trends and explains the driving mechanism behind them, thus it may not affect our results and conclusions. The above discussion has been added to the revised version (see Page 11, Lines 344-361).

References

Cai, W., et al., 2014. Large differences in terrestrial vegetation production derived from satellite-based light use efficiency models. Remote Sensing, 6(9), 8945–8965.

Lin et al., 2023. Underestimated Interannual Variability of Terrestrial Vegetation Production by Terrestrial Ecosystem Models. Global Biogeochemical Cycles, 34(4), e2023GB007696.

Zhu et al., 2018. Underestimates of Grassland Gross Primary Production in MODIS Standard Products. Remote Sensing, 2018, 10(11), 1771.

Wang et al., 2023. Assessment of Six Machine Learning Methods for Predicting Gross Primary Productivity in Grassland. Remote sensing, 15(14), 3475.

O'Sullivan, M., et al. 2020. Climate-driven variability and trends in plant productivity over recent decades based on three global products. Global Biogeochemical Cycles, 34(12), e2020GB006613.

Anav, A., et al., 2015. Spatiotemporal patterns of terrestrial gross primary production: a review. Reviews of Geophysics, 53(3), 785-818.

l. 276: what do you mean by simulated actual GPP?

Response: Thanks for the comment. Here, the simulated actual GPP is used to represent the GPP in the real situation, i.e., under the interactive effects of different drivers (e.g., climate change, vegetation change, etc.), which is different from the GPP under other scenario simulations, such as the climate change-induced GPP.

l. 280: grammar

Response: Thanks for catching this error. Revised text to (see below and see Page 12, 372-373):

“Spatially, 90.4% of forested land in the study area showed an increasing trend in GPP, while 9.6% of forested land exhibited a decreasing trend in GPP.”

l. 290s: streamline this section to make clear that the change in GPP comes from the increasing/decreasing areas

Response: Thanks for the suggestion. We have streamlined this paragraph as follows (see Page 13, Lines 378-387):

“We investigated the area of gains or losses for different subtropical forest types between 2001 and 2018 using the ESA CCI land cover data (Fig. S10). We found that FCC increased the entire subtropical forest GPP at a rate of 0.52 gC/m^2/year (p = 0.000) (Fig. 4a), and the increase mainly driven by EBF GPP (0.39 gC/m^2/year, p = 0.011) and MXF GPP (1.14 gC/m^2/year, p = 0.000). However, the FCC had a negative effect on the DBF GPP and ENF GPP variations at the rate of -0.06 gC/m^2/year (p = 0.632) and -0.19 gC/m^2/year (p = 0.002), respectively. Spatially, 92.2% of the total GPP were relatively stable, and only 7.8% of GPP exhibited an increase or decrease under the effect of FCC (Fig. 4b). Among them, 3.9% of the GPP increased significantly and the increased were mainly located in the western region (e.g., the south slope of the Qinling mountains, the southwest karst region), while 2.6% of the GPP was significantly reduced in the eastern regions where the ENF is dominated (Fig. 4b).”

l. 305: In section 3.3.2, the point needs to be better explained that although climate change contributes to a 1.11 TgC/year most of the area has a decreasing trend. This increase seems to stem from a small region in the west. What is happening in this region? E.g. Fig 6b

Response: Thanks for the comment. The main vegetation types in the small regions (the area you mentioned) located in the south of Tibet are natural broad-leaved evergreen forests (Cheng et al.,2023), and they are in middle age and in range of 40-60 years old, which has a strong carbon sequestration potential (Zhang et al.,2017; Zhang et al.,2014). The magnitude of GPP increase (see the legend in Fig. 6) in the small areas is also significantly higher than in other regions because temperature, precipitation, and radiation all contribute to GPP increase in this region (Fig. 6). Despite the relatively large area of GPP reduction due to climate change, the magnitude of its impact is relatively small, resulting in smaller areas with higher magnitude offsetting the larger area of GPP decrease.

References:

Cheng, K., Chen, Y., Xiang, T., Yang, H., Liu, W., Ren, Y., Guan, H., Hu, T., Ma, Q., and Guo, Q.: 2020 forest age map for China with 30 m resolution, Earth Syst. Sci. Data Discuss. [preprint], https://doi.org/10.5194/essd-2023-385, in review, 2023.

Zhang, Y., et al., 2017. Mapping spatial distribution of forest age in China. Earth and Space Science,4, 108–116.

Zhang, C., et al., 2014. Mapping forest stand age in China using remotely sensed forest height and observation data. Journal of Geophysical Research: Biogeosciences,119,1163–1179.

l. 346: why is LAI increasing at all?

Response: Thanks. The LAI indeed shows the increasing trend for the different subtropical forests in our study during 2001-2018. This is in line with many previous studies that reported the greening (using LAI as an indicator) of our Earth due to different driving factors (e.g., climate change, human activities, etc.) during the past 30 years (Zhu et al., 2016; Tong et al., 2018; Chen et al., 2019; Tong et al., 2020; Chen et al., 2020). Especially in the southern region of China, there is a significant increase in forest LAI, and the main driving factors for the increase in LAI are climate change (Zhu et al., 2016) and ecological engineering projects (e.g., afforestation and reforestation projects) (Tong et al., 2018; Chen et al., 2019; Tong et al., 2020; Chen et al., 2020).

References:

Zhu et al., 2016. Greening of the Earth and its drivers. Nature Climate Change, 6, 791–795.

Tong et al., 2018. Increased vegetation growth and carbon stock in China karst via ecological engineering. Nature Sustainability, 1, 44–50.

Chen et al., 2019. China and India lead in greening of the world through land-use management. Nature Sustainability, 2, 122–129.

Tong et al., 2020. Forest management in southern China generates short term extensive carbon sequestration. Nature Communications, 11, 129.

Chen et al., 2020. Afforestation promotes the enhancement of forest LAI and NPP in China. Forest Ecology and Management, 462, 117990.

l. 349 and in general: The wording "Especially, the positive effect of VSC on EBF" is strange. I mean, the VSC change inside the EBF and that led to a change in GPP in those forests.

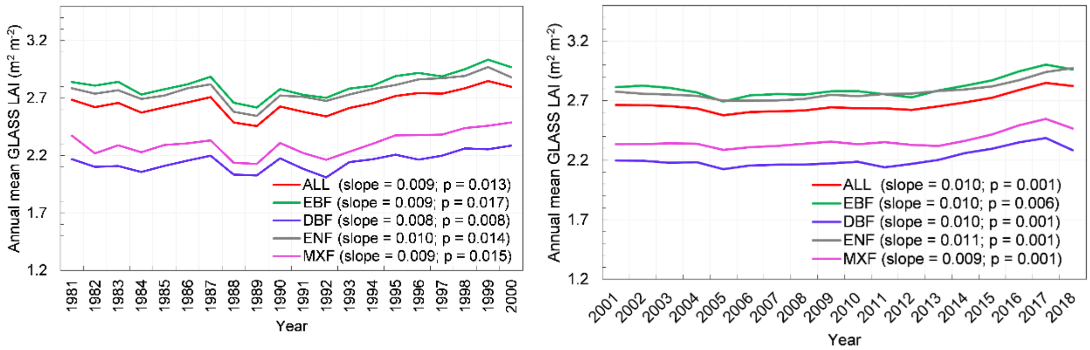
Response: We are sorry for the confusion. We have removed the unnecessary and confusing sentence from the revised text.

Fig S10: There is a rapid increase in trend around 2011. Why is that? Also, how does LAI look in the model pre-2000?

Response: As reported by many studies (Zhu et al., 2016; Tong et al., 2018; Chen et al., 2019; Tong et al., 2020; Chen et al., 2020), the LAI showed a significant increase over the past two decades. Especially, the Chinese government has made an enormous investment to implement some key ecological restoration programs since

2000. Lu et al., (2015) indicated that the vegetation had a relatively stable status from 2000 to 2010. After 2010, the vegetation may begin to show significant growth. This may be due to the lagged response of vegetation to these measures. Therefore, there was a rapid increase in trend around 2011. Based on different vegetation indices (e.g., LAI), Chen et al. (2021b) also demonstrated a turning point in vegetation change in China around 2010. They also found that the GPP and LAI increased significantly after 2010 mainly driven by the climatic factors and ecological restoration programs.

Considering that the available time periods for different driving data are inconsistent, we can not run the model to simulate GPP of our study area before 2001. Here, based on your suggestion, we compared the changes in LAI before and after 2001. It shows that there is also a significant upward trend in LAI before 2001 (see figure on the left). The increase in LAI prior to 2001 could also lead to an increase in GPP under the scenario S_3 simulation (i.e., the effect of LAI on GPP).



Figures showing annual changes of GLASS LAI for entire forest region and different forest types before and after 2001. EBF: evergreen needleleaf forest; DBF: deciduous broadleaf forest; ENF: evergreen needleleaf forest; MF: mixed forest.

References:

Zhu et al., 2016. Greening of the Earth and its drivers. Nature Climate Change, 6, 791–795.

Tong et al., 2018. Increased vegetation growth and carbon stock in China karst via ecological engineering. Nature Sustainability, 1, 44–50.

Chen et al., 2019. China and India lead in greening of the world through land-use management. Nature Sustainability, 2, 122–129.

Tong et al., 2020. Forest management in southern China generates short term extensive carbon sequestration. Nature Communications, 11, 129.

Chen et al., 2020. Afforestation promotes the enhancement of forest LAI and NPP in China. Forest Ecology and Management, 462, 117990.

Lu et al., 2015. Recent ecological transitions in China: greening, browning, and influential factors. Scientific Reports, 5, 8732.

Chen, Y. et al., 2021b. Accelerated increase in vegetation carbon sequestration in China after 2010: A turning point resulting from climate and human interaction. Global Change Biology, 27(22), 5848-5864.

l. 355: You write:

"results showed that most GPP increases in China's subtropical forests due to the increase of LAI, which also offset the negative effects of VSC on GPP, thus allowing VSC to play a key driving factor in promoting GPP increases throughout the forest area."

This is confusing. Did you mean FSC maybe instead of VSC at the first mention? LAI is the same as VSC, right? So how does the effect of change in LAI on GPP offset the effect of change in LAI on GPP? They are the same thing? Or do you mean, there is more positive change that heavily offsets the negative changes?

Response: We are sorry for the confusion. FSC in this study represents forest cover changes, while VSC indicates vegetation structure changes. In this study, LAI is the same as VSC. As you suggested above, we have changed VSC to LAI to avoid confusion. Yes, there is the more positive change that heavily offsets the negative changes. Because not all pixels show the same changes in space (see previous Figure 7 and the updated Figure 4f), some pixels have a positive trend in GPP due to the influence of LAI, while others may have a negative trend. Meanwhile, the magnitude of the pixels with positive trends is larger than that of the pixels with negative trends, which results in these pixels cancelling each other out.

For clear understanding, revised text to (see Page 17, Lines 465-467):

"Overall, there are more positive changes in GPP due to the effect of LAI that heavily offsets the negative changes in GPP, ultimately making LAI the main factor in GPP increases throughout China's subtropical forests."

l. 361: verb is missing

Response: As suggested, we have revised this sentence as follows (see Page 19, Line 483):

"The annual mean CO_2 concentration increased from 371.3 ppm to 408.7 ppm during 2001-2018."

Fig. 9: This is a nice figure that shows the main results.

Response: Thank you very much for this encouraging comment.

Fig 9: I am puzzled that, e.g., in b) CC-ALL is nowhere near the sum of the three. I understand that there will be interactions, but I find it quite strange that the interactions are quite strongly positive but each of the components is almost 0. Maybe these cancel each other out over the entire region.

Response: We are sorry for the confusion. We agree with your comment that the impact of each climatic factor is almost 0, while the interactions seem to be strong. However, the overall effects of different factors may not be able to be simply added together. Although their individual effects may be small, their interactive effects may become relatively large, because their interactions are not simply linear relationships in our model. This is where we differ from previous studies (Zhang et al., 2014; Zhang et al., 2022) that used relatively simple models to detect single or interactive effects of different factors. In this study, the effects of these factors are analysed using a process-based model in which the different factors are nonlinearly related to each other. Actually, this is also the purpose of this study, which is to try to unravel the possible effects of different drivers on GPP changes individually and interactively based on a process model.

References:

Zhang et al., 2014. Effects of land use/land cover and climate changes on terrestrial net primary productivity in the Yangtze River Basin, China, from 2001 to 2010. Journal of Geophysical Research: Biogeosciences, 119, 1092–1109.

Zhang, X. et al., 2022. Land cover change instead of solar radiation change dominates the forest GPP increase during the recent phase of the Shelterbelt Program for Pearl River. Ecological Indicators, 136: 108664.

Results: when you describe the changes for each of the forest types, I believe the results stem solely from the changing areas. It would be better to show the changes on a per-area basis or in the simulations even keep the forest cover stable...

Response: Thank you for the suggestion! Following your suggestion, we have changed the total GPP (TgC/year) to GPP per unit area (gC/m^2/year) for a specific forest area throughout the revised manuscript to make the results comparable. All of these changes did not alter the conclusions of our study.

Discussion:

l. 416: "which is mainly converted from cropland". You need to elaborate here. Croplands can be highly productive. A few models even indicate that in some regions in China, cropland could potentially be more productive than forests in terms of GPP (Fig. 3 in https://doi.org/10.1038/s41598-022-23120-0). To back your claim, can you provide some numbers here on GPP values of the crops that have been reforested?

Response: Thank you very much for the suggestion. Yes, Krause et al., (2022) suggested that cropland could potentially be more productive than forests in terms of GPP, while the suitable area was mostly in Central Africa, Indonesia and northern Australia, western North America, and parts of the Amazon. Indeed, the findings derived from 3 models of Krause et al. (2022) (Figure 3) indicated that some regions of China have higher productivity of cropland. However, the results derived from the other 4 models also showed that the forests were the most productive land cover when compared with grasslands and croplands in the subtropical region of China. Therefore, there may be some uncertainties in their study.

As suggested, we have provided some numbers here on the GPP values of the crops that have been reforested. Here, we take the conversion of cropland to MXF as an example, we counted the changes in GPP resulting from the conversion of cropland to MXF. We found that the GPP value in the changed area was 7.48 TgC in 2001 and increased to 7.64 TgC in 2018 due to the conversion of cropland to MXF. Revised text to (see Page 23, Lines 552-553):

"For example, after the conversion of cropland to MXF in the study area, GPP in the converted area increased by 0.16 Tg C between 2001 and 2018."

l. 419: what do you mean by the negative effect of a specific forest type on forest GPP variations? That the planting of a certain forest type may result in a lower GPP than the previous land cover? Or something else?

Generally in this section, you need to be careful with the wording as you refer to "forest GPP" most of the time, but sometimes you mean the GPP of the entire area.

Response: Thank you very much for the comment and suggestion. Here, we mean that the changes in the area of a specific forest type may lead to changes in the total GPP of a certain forest type. For example, an increase in the EBF area leads to an increase in its GPP in our study, while a decrease in the ENF area results in a decrease in its GPP. We are sorry for the confusion. We have reworded the statement to revised text: “which may ignore the different effects of a specific forest type on forest GPP variations.” (see Page 24, Lines 556-557). As you mentioned in a previous study (Krause et al., 2022), the planting of a certain forest type may result in a lower GPP than the previous land cover at the global scale. However, Krause et al., 2022 indicated that croplands are most productive in 21% of the suitable area, mostly in Central Africa, Indonesia and northern Australia, western North America, and parts of the Amazon. In our study, we also found that a decrease in ENF area led to a decrease in GPP, while an increase in EBF and MXF area led to an increase in GPP. This implies that the conversion of other land cover types to forests improved the productivity, and the forests in the study area have a higher GPP, which is consistent with the findings of Krause et al., (2022), who also showed that forests are more productive in the subtropical region of China. Moreover, we have harmonized the description of forest GPP as subtropical forest GPP, and removed the statement “the GPP of the entire area” from the revised text.

References:

Krause et al., 2022. Quantifying the impacts of land cover change on gross primary productivity globally. Scientific Reports, 12, 18398.

l. 447ff: citations for the claim? Also, drought relates more to precipitation, maybe you can instead mention increased VPD as a result of a high temp increase.

Response: Thank you again for the suggestion. Following your suggestions, we have added some citations in the revised text (see below and Page 23, Lines 586-589). We also reworded this sentence to mention increased VPD as a result of a high temperature increase.

"Many studies suggested that an increment in temperature can benefit vegetation productivity (Myneni, et al., 1997; Nemani, et al., 2003; Song et al., 2022), or could reduce vegetation productivity due to increased VPD as a result of a high temperature increase (Yuan et al., 2019; Lopez et al., 2021)."

References:

Myneni, R. B., et al., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. Nature, 386, 698–702.

Nemani, R. R., et al., 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. Science, 300, 1560–1563.

Song, Y., et al., 2022. Increased global vegetation productivity despite rising atmospheric dryness over the last two decades. Earth's Future, 10, e2021EF002634.

Yuan, W. P., et al., 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. Science Advances, 5, eaax1396.

Lopez, J., et al., 2021. Systemic effects of rising atmospheric vapor pressure deficit on plant physiology and productivity. Global Change Biology, 27, 1704–1720.

l. 450 mention again the magnitudes. They should explain that the smaller area of increase outweighs the larger area of decrease

Response: Thank you very much for the suggestion. As the same responses mentioned above. We also added the following explanation to the revised text (Page 25, Lines 595-599):

"The magnitude of GPP increase in the small areas is significantly higher than in other regions because temperature, precipitation and radiation all contribute to GPP increase in these areas (Fig. S12). Although the area of GPP reduction due to climate change is relatively large, the magnitude of its impact is relatively small, resulting in smaller areas with higher magnitude offsetting the larger area of GPP decrease."

l. 461: why is that?

Response: Thanks for the comment. As shown in Fig. 1, ENF is mainly distributed in the eastern and western regions of the subtropics. Our results also showed that climatic factors (e.g., temperature, precipitation, and solar radiation) in these regions have negative effects on the GPP of ENF (Fig. 6), and particularly the solar radiation declined significantly in the eastern region, which led to a decrease in the GPP of ENF in the east. For EBF, it is mainly distributed in the central and western regions where climate change mainly contributes to the increase of GPP of EBF.

For clear understanding, revised text to (Page 25, Lines 606-614):

"climate change has a positive effect on the GPP of EBF, but a negative effect on the GPP of ENF. The main reason is that ENF is predominantly located in the eastern and western parts of the subtropics (Fig. 1). In these areas, individual climatic factors (e.g., temperature, precipitation, and solar radiation) or their interactions caused the GPP of ENF to decrease (Fig. 4c-4d), and particularly the solar radiation declined significantly in the eastern region, which led to a decrease in the GPP of ENF in the east. The EBF is mainly distributed in the central and western regions (Fig. 1) where climate change mainly contributes to the increase of EBF GPP (Fig. 4c-4d)."

l. 488: Forest protection has greater carbon uptake potential than what? This also relates to my comment on l. 416. Also, you only refer to GPP. Can you make any claims on NPP?

Response: Thanks again for your comment and suggestion. We are sorry for the confusion. Considering this sentence is not necessary, we have removed the confusing sentence from the revised text. As suggested, we also added some claims on NPP to the revised text as follows (Page 26, Lines 642-648).

"Consistent with our study period (2001–2018), Chen et al. (2021b) also reported an increase in vegetation carbon sequestration in China based on the two indicators of GPP and NPP, especially with an accelerated increase in carbon sequestration potential after 2010. They showed that GPP and NPP in China increased obviously at the rate of 49.1–53.1 TgC/yr^2 and 22.4–24.9 TgC/yr^2, respectively. The significant increase of subtropical forest GPP and NPP was highly attributed to human activities (e.g., ecological restoration projects) in southern and eastern China, especially the human-induced NPP gains can offset the climate-induced NPP losses in southern China."

References:

Chen, Y. et al., 2021b. Accelerated increase in vegetation carbon sequestration in China after 2010: A turning point resulting from climate and human interaction. Global Change Biology, 27(22), 5848-5864.

section 4.1.4: here I also find that some discussion on the relation of GPP to carbon sequestration is missing.

Response: Following your suggestion, we have added the following discussion to the revised text (see Page 26, Lines 650-656):

"The carbon sequestered by vegetation through photosynthesis in a given unit of space and time, i.e., GPP, forms the fundamental part of the carbon cycle (Monteith 1972). GPP is a crucial indicator for estimating the carbon sequestration capacity of ecosystems (Chen et al., 2021b; Ma et al., 2019), which reflects the largest carbon sequestered by plant photosynthesis (Christian et al., 2010; Xu et al., 2019). Moreover, GPP drives land carbon sequestration and partly offsets anthropogenic CO_2 emission, which significantly affects global carbon balance and climate change (Running et al., 2008)."

References:

Monteith, J. L., 1972. Solar-radiation and productivity in tropical ecosystems. Journal of Applied Ecology, 9(3), 747-766.

Chen, Y. et al., 2021b. Accelerated increase in vegetation carbon sequestration in China after 2010: A turning point resulting from climate and human interaction. Global Change Biology, 27(22), 5848-5864.

Ma, J., 2019. Trends and controls of terrestrial gross primary productivity of China during 2000–2016. Environmental Research Letters, 14, 084032.

Christian, B., et al., 2010. Terrestrial gross carbon dioxide uptake: Global distribution and covariation with climate. Science, 329 (5993), 834–838.

Xu, C. et al., 2019. Increasing impacts of extreme droughts on vegetation productivity under climate change. Nature Climate Change, 9, 948–953.

Running, S.T., 2008. Ecosystem Disturbance, Carbon, and Climate. Science, 321 (5889), 652-653.

Conclusion

l. 560ff: I am not sure about this last concluding statement. You basically show that changes in the vegetation structure have a strong impact on GPP. You don't show anything about NPP or NEE. I would doubt that the growth of an entire new forest would have a lower impact on the carbon balance than improving the current ones. At least this claim cannot be made based on your work.

Response: Thank you again for the suggestion. We agree that there is some confusion in this statement. To avoid confusion, we have removed the statement where there are unnecessary.

RC2: 'Comment on bg-2023-140', Anonymous Referee #2, 30 Oct 2023

Dear Reviewer and Editor,

We would like to thank the reviewer and you for your interest in our study, and for the feedback provided. We appreciate these constructive and specific comments, which will help improve the quality of the manuscript. We have carefully inspected all reviewer comments. Moreover, the English writing in the revised manuscript has been carefully checked and improved. Below, you will find our responses to the comments (responses in blue). Please find the response to each comment below.

We hope that you will find the result satisfying.

Sincerely,

Tao Chen, Félicien Meunier, Marc Peaucelle, Guoping Tang, Ye Yuan, Hans Verbeeck

Reviewer #2

Review of "Elevated atmospheric CO_2 and vegetation structural changes contributed to GPP increase more than climate and forest cover changes in subtropical forests of China" by Chen et al.

The manuscript by Chen et al. investigates drivers of subtropical forest GPP trends in China using a process-based model that runs to provide causal attribution. The study concludes that the primary drivers of GPP change are the CO_2 fertilization effect and increased LAI. While the study conducts comprehensive model experiments and maintains a well-organized structure, it lacks a convincing theoretical framework for designing the experiments and conducting the analysis, which is essential for consideration in publication. Additionally, the manuscript requires careful revision for the English language and logical syntax. Please refer to my comments for further details.

<u>Response:</u> Thank you very much for your valuable and thoughtful comments and suggestions. Below we go through point-by-point our answers to the comments, and our responses are in blue. Based on your suggestion, in the introduction, we added relevant theories and statements explaining why we designed the experiments and conducted our analysis. We also streamlined the results, figures and text as suggested. Moreover, we have carefully checked and improved the English writing in the revised manuscript.

General comments:

1. Introduction: In the second paragraph, several relevant drivers are listed, followed by the research question “the relative contributions of these factors…not clear” in the next paragraph. It does not adequately explain to the reader why these factors are crucial to GPP or provide mechanistic expectations. For instance, in Line 60, rather than stating the increased temperature “has also influenced the forest carbon uptake”, it would be beneficial to summarize the specific mechanisms and reasons behind this influence. Is the influence positive or negative? Some clarifications would be helpful.

Response: Thank you very much for the valuable suggestions. To make the possible mechanisms behind the GPP changes clearer, we have added the following sentences to the revised text (see Pages 2-3, Lines 71-114).

“Previous studies also reported that LAI was the important biotic driver of carbon sink increase in China’s forest ecosystems (Chen et al., 2019a; Chen et al., 2019b). Especially, LAI is a critical parameter for depicting vegetation canopy structure, which can influence some important photosynthetic parameters (e.g., quantum yield (α), diurnal ecosystem respiration rate (R_d), etc.), and in particular, it can determine the amount of photosynthetically active sunlight that is absorbed by vegetation and thus influence photosynthetic assimilation rate (Piao et al., 2020). In addition, LAI can influence the annual productivity of vegetation by ruling the length of the growing season (i.e., phenology). Meanwhile, the annual mean atmospheric CO_2 concentration in China has reached new highs due to large anthropogenic emissions (e.g., 407 ppm in 2017) (CMA, 2018). Elevated CO_2 concentrations may enrich the intercellular CO_2 content and thus enhance the photosynthetic rates and plant productivity (i.e., GPP) at the ecosystem scale, which is known as the CO_2 fertilization effect (Piao et al 2020). CO_2 fertilization was also identified as the pivotal driver for enhancing carbon sink in terrestrial ecosystems, and some studies even reported that the southern region of China was more affected by the CO_2 fertilization effect than other Chinese regions (Chen et al., 2019b; Zhu et al., 2016).

In addition to these drivers, the annual mean temperature in the Chinese subtropical monsoon region has increased by more than 1.0 °C over the past 30 years (Fang et al., 2018), which was higher than the global surface temperature increase (Sun et al., 2019) and also influenced the forest carbon uptake (Gao et al., 2017; Yuan et al., 2016). Recently, several studies investigated the roles of climate factors in regulating the changes of forest GPP at the site or global scales (Barman et al., 2014; Ma et al., 2015), as well as in some regions of China (Ma et al., 2019; Yao et al., 2018b). For instance, previous studies showed that temperature was the major factor influencing GPP variations in the Yangtze River Basin of southern China (Nie et al., 2023), as well as in other southern parts of China (Ma et al., 2019). Generally, a proper increasing temperature can promote enzyme activity and CO_2 fixation (Siddik et al., 2019; Moore, et al., 2021). However, when the temperature increases exceed the optimal temperature, the activity of enzymes in plants will decrease, thereby affecting the photosynthetic rate and carbon sequestration. Climate warming can also increase the vapor pressure deficit (VPD), leading to more drought stress on plants (Yuan et al., 2019). However, when atmospheric moisture is insufficient, plants tend to inhibit photosynthesis by reducing stomatal conductance, thereby significantly reducing GPP (Yuan et al., 2019; Grossiord et al., 2020). Moreover, Li et al., (2022) highlighted that precipitation dominated the interannual changes in the forest GPP of Southwest China, while vegetation productivity response to the precipitation variations shows large spatial heterogeneity (Camberlin et al., 2007), which largely depends on topographic attributes, vegetation types, and even soil texture. Additionally, a previous study also indicated that the GPP changes were more affected by solar radiation than by precipitation and temperature in humid regions of China (Chen et al., 2021a). Therefore, the dominant factors affecting GPP varied a lot depending on regions and different time scales, and thus these studies in identifying the drivers of changes in GPP led to divergent conclusions."

References:

Chen, C. et al., 2019a. China and India lead in greening of the world through land-use management. Nature Sustainability, 2: 122-129.

Chen, J.M., Ju, W., Ciais, P., Viovy, N. and Lu, X., 2019b. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nature Communications, 10(1): 4259.

CMA, 2018. China Greenhouse Gas Bulletin: The State of Greenhouse Gases in the Atmosphere Based on Chinese and Global Observations before 2017. http://www.cma.gov.cn/en2014/news/News/201901/P020190122575481732415.pdf).

Piao, S. et al., 2020. Characteristics, drivers and feedbacks of global greening. Nature Reviews Earth & Environment, 1: 14-27.

Zhu, et al., 2016. Greening of the Earth and Its Drivers. Nature Climate Change, 6 (8), 791–795.

Fang, J., Yu, G., Liu, L., Hu, S. and Chapin, F.S., 2018. Climate change, human impacts, and carbon sequestration in China. Proceedings of the National Academy of Sciences, 115(16): 4015-4020.

Sun, C., Jiang, Z., Li, W., Hou, Q. and Li, L., 2019. Changes in extreme temperature over China when global warming stabilized at 1.5 degrees C and 2.0 degrees C. Scientific Reports, 9(1): 14982.

Gao, T., Wang, H.J. and Zhou, T., 2017. Changes of extreme precipitation and nonlinear influence of climate variables over monsoon region in China. Atmospheric Research, 197: 379-389.

Yuan, W. et al., 2016. Severe summer heatwave and drought strongly reduced carbon uptake in Southern China. Scientific Reports, 6(1): 18813.

Ma, J., Yan, X., Dong, W. and Chou, J., 2015. Gross primary production of global forest ecosystems has been overestimated. Scientific Reports, 5(1): 10820.

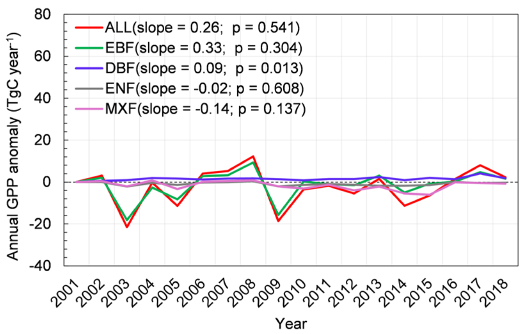
Barman, R., Jain, A.K. and Liang, M., 2014. Climate-driven uncertainties in modeling terrestrial gross primary production: a site level to global-scale analysis. Global Change Biology, 20(5): 1394-1411.

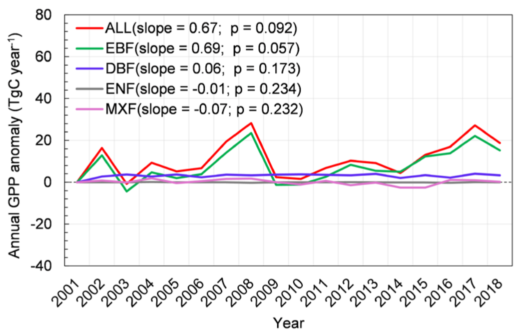
Ma, J. et al., 2019. Trends and controls of terrestrial gross primary productivity of China during 2000–2016. Environmental Research Letters, 14(8): 084032.

Yao, Y. et al., 2018b. Spatiotemporal pattern of gross primary productivity and its covariation with climate in China over the last thirty years. Global Change Biology, 24(1): 184-196.
Nie, C., et al., 2023. The Spatio-Temporal Variations of GPP and Its Climatic Driving Factors in the Yangtze River Basin during 2000–2018. Forests, 14(9):1898.
Li, Y., et al., 2022. Interannual variations in GPP in forest ecosystems in Southwest China and regional differences in the climatic contributions. Ecological Informatics, 69: 101591.
Chen, S. et al., 2021a. Vegetation structural change and CO_2 fertilization more than offset gross primary production decline caused by reduced solar radiation in China. Agricultural and Forest Meteorology, 296: 108207.
Siddik, M.A., et al., 2019. Responses of indica rice yield and quality to extreme high and low temperatures during the reproductive period. European Journal of Agronomy, 106, 30-38.
Moore, C.E., et al., 2021. The effect of increasing temperature on crop photosynthesis: from enzymes to ecosystems. Journal of Experimental Botany, 72 (8), 2822-2844.
Yuan, W. P., et al., 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. Science Advances, 5, eaax1396.
Grossiord, C., et al., 2020. Plant responses to rising vapor pressure deficit. New Phytologist, 226(6), 1550–1566.
Camberlin, P., et al., 20007. Determinants of the interannual relationships between remote sensed photosynthetic activity and rainfall in tropical Africa. Remote sensing of environment, 106, 199–216.

2. Experiment design: I have two main concerns concerning the experiment design in Table 1. A) When assessing the effect of climate variables on GPP, one of the climate variables (e.g., precipitation) is fixed as the value in 2001 in the forcing for the S2 scenario. As I understand it, that means in the S2 scenario there is no climatological cycle at all. The difference in GPP between S2 and the control run should include the effect of both the long-term trend and short-term variabilities of climate. This means, by design, the trend of GPP driven by climate is overshadowed by the shorter-term variabilities (Figure 6). However, when designing the CO_2 and LAI scenarios, the difference of CO_2 or LAI forcings are less variable (Figure S10, S11), thus a “clear” trend of GPP can be observed in both Figure 7 (a) and 8 (a). There is no surprise when the authors find that CO_2 and LAI are the most prominent drivers, when they are comparing the effect of “trend” (e.g., CO_2) and “trend + variabilities” (e.g., precipitation). One may need to test to which extent the way of prescribing climate forcings influences the conclusion, e.g., by removing the trend of climate variables but keeping variabilities. B) Is the GLASS LAI also sensitive to climate change and increasing CO_2? With an increased carbon uptake due to increasing CO_2, more carbon can be allocated to leaf growth. I wonder if the authors have some thoughts about the causal link when discussing the effect of LAI on GPP.

Response: Thank you very much for the comment and suggestion. As suggested, we used the mean value of each climate variable, including the precipitation, temperature, and solar radiation rather than the initial (2001) value for the different variables to redo the simulation. Here, taking the precipitation as an example, we compared the simulated results based on the mean value of the precipitation over the study periods (see below right figure) with the simulations in the first year (2001) (see below left figure), and found that there are no significant differences between them. Although there are relative differences in the magnitude of the slopes (i.e., compared the present simulations with previous simulations) under the effect of precipitation changes on GPP, they are not significant and show a similar effect, suggesting that the effect of precipitation on GPP changes in different forests is less influenced by trends. As shown in Fig. S11, our results also indicated that the annual variations of the climate variables have insignificant trends from 2001 to 2018. From Fig. S11 and Fig. S12, the results also suggested that the year 2001 was not an extreme year for any of those variables. Therefore, the initial year (2001) used in this study may be reasonable. The same experiment designs were also adopted in previous studies (Chen et al., 2021a; Sun et al., 2022). Overall, considering that there are no obvious trends in these climate variables and the low effects of these variables when compared to the CO_2 and LAI, whatever the experimental design it wouldn't change our findings.





For question B, we acknowledge that LAI may be affected by climatic factors and CO_2 fertilization. We added the following discussion to the revised manuscript as suggested.

Revised text to (see Page 27, Lines 697-710):

"It should be noted that changes in LAI could be influenced by both climatic factors and elevated atmospheric CO_2 concentration (Chen et al., 2019; Chen et al., 2021a; Sun et al., 2022). Previous studies reported that the elevated atmospheric CO_2 concentration was the dominant driver of global LAI increase, and there are also regional differences in the impact mechanism of climate factors on LAI changes (Zhu et al., 2016; Zhu et al., 2017), thereby influencing the GPP dynamics. Moreover, the interactions between these driving factors can also influence the LAI, and even the interactive impacts of these factors on LAI may offset each other. For instance, rising CO_2 concentration and solar radiation can affect temperature and VPD (Chen et al., 2021a). High VPD leads to plants to close their stomata, resulting in lower intercellular CO_2 concentrations in the leaves, which reduces the rate of photosynthesis (Yuan et al., 2019). Additionally, changes in LAI can feed back to the climate through biogeochemical and biogeophysical processes (Li et al., 2023).

There is a bidirectional interaction between vegetation and the atmosphere, and the relationship between vegetation dynamics and driving factors is complicated. The current methods used in this study cannot elucidate the complex interactions of the climate factors and elevated CO_2 concentration on LAI changes, which may bring some uncertainties to our results."

References:

Chen, S. et al., 2021a. Vegetation structural change and CO_2 fertilization more than offset gross primary production decline caused by reduced solar radiation in China. Agricultural and Forest Meteorology, 296: 108207.

Sun et al., 2022. Causes for the increases in both evapotranspiration and water yield over vegetated mainland China during the last two decades. Agricultural and Forest Meteorology, 324, 109118.

Chen, C., et al., 2019. China and India Lead in Greening of the World through Land-Use Management. Nature Sustainability, 2 (2), 122–129.

Zhu, et al., 2016. Greening of the Earth and Its Drivers. Nature Climate Change, 6 (8), 791–795.

Zhu et al., 2017. Attribution of seasonal leaf area index trends in the northern latitudes with "optimally" integrated ecosystem models. Global Change Biology, 23, 4798–4813.

Yuan, W. P., et al., 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. Science Advances, 5, eaax1396.

Li, Y., et al., 2023. Biophysical impacts of earth greening can substantially mitigate regional land surface temperature warming. Nature Communications,14, 121.

3. Results: This study compares the contribution of different drivers to GPP in the unit of TgC/year (e.g., Figure 9). It is not introduced in the method section how the total GPP is calculated. If I assume GPP in TgC/year is the sum of GPP from all regions or the sum for each PFT, then it is highly related to the specific regions. Figure 1 shows the study region is mostly occupied by EBF and ENF, there is no wonder GPP is higher in TgC/year in EBF. In addition to that, the title indicates that CO_2 and LAI contribute more to GPP than forest cover changes. However, only very few regions are affected by forest cover change (Figure 5c), by contrast, all of the regions are under increasing CO_2 in the model experiment. It is unfair to compare the relative impact between these two drivers when looking at the total GPP. Or one has to make it clear in the beginning, that only total GPP in this specific region is considered.

Response: Thanks for the comments and suggestions. The total GPP (TgC/year) for the entire forest area or a specific forest area (e.g., EBF, ENF, etc.) was calculated based on the regional mean value of GPP (gC/m^2/year) multiplied by the total area (m^2) of a certain forest type (1TgC = 1x10^{12} gC). Following your suggestion, we have changed the total GPP (TgC/year) to GPP per unit area (gC/m^2/year) for a specific forest area throughout the revised manuscript to make the results comparable. All of these changes did not alter the conclusions of our study.

4. Discussion: I like they discuss the model uncertainties. Most of the model discussion is about the input data, though it is important, the inherent model structure and underlying assumptions and how would these possibly affect the attribution is not so well discussed. For instance, it is not clear how the model simulates plants' response to CO_2. It would greatly enhance the understanding of the contribution results if the authors included more discussion on these elements.

Response: Thanks. As suggested, we added the following discussion about the BEPS model to the revised manuscript (see Page 27, Lines 677-696).

"In the BEPS model, the LAI is separated into two parts including the LAI of sunlit and shaded leaves, which are adopted to calculate the photosynthesis at leaf level (sunlit and shaded leaves) based on the FvCB photosynthesis model (Farquhar et al., 1980), and further compute the GPP at canopy level by adding the photosynthesis rates of sunlit and shaded leaves. Moreover, the Ball-Berry equation (Ball et al., 1987) was used in the model to calculate the stomatal conductance of sunlit and shaded leaves, which influenced the intercellular CO_2, the photosynthetic rate, and evapotranspiration (ET). Therefore, the LAI directly determined the allocation of light and water availability and influenced the gross photosynthesis rate of the sunlit and shaded leaves. The LAI may impact its contribution to GPP variations through these processes. The atmospheric CO_2 concentration affects the intercellular CO_2 through the stomatal conductance, which, together with temperature and maximum carboxylation rate (V_{cmax}), determines the Rubisco-limited (A_c) and RuBP-limited (A_j) gross photosynthesis rate in the model. Over the past few decades, the CO_2 concentrations continuously increased and reached the current level of over 400 ppm. Elevated atmospheric CO_2 concentration can increase photosynthesis by accelerating the rate of carboxylation, thereby influencing the GPP changes. Additionally, solar radiation variability would directly influence the potential electron transport rate and thus regulate the RuBP-limited (A_j) gross photosynthesis rate. The temperature in the model directly impacts the V_{cmax} and the CO_2 compensation point without dark respiration (Γ), thereby determining the gross photosynthesis rate. The temperature positively affects the V_{cmax} when it is below the optimal temperature. However, when the temperature exceeds the optimal temperature, V_{cmax} will not continue to increase with the temperature. Therefore, changes in temperature in the model may have a positive or negative impact on GPP."

References:

Farquhar, et al., 1980. A biochemical model of photosynthetic CO_2 assimilation in leaves of C3 species. Planta 149, 78–90.

Ball, J.T., et., 1987. A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions. J. Biggins (Ed.). Progress in Photosynthesis Research: Volume 4 Proceedings of the VIIth International Congress On Photosynthesis Providence, Rhode Island, USA, August 10–15, 1986. Springer Netherlands, Dordrecht, pp. 221–224.

Specific comments:

1. L16: If you only use LAI to represent vegetation structural change, it might not be necessary to mention "VSC" explicitly.

   Response: Thanks for the suggestion. Yes, LAI does not represent all vegetation structure changes. As suggested, we use LAI directly in the revised version instead of VSC.

2. L29: Please be consistent with abbreviations.

   Response: Thanks. As suggested, the LAI and FCC were adopted here to be consistent with the abbreviations mentioned above.

3. L30: What do you mean by "overlooked"?

   Response: We are sorry for the confusion. Here we are trying to emphasize the importance of LAI. For clear understanding, the "overlooked" was changed to "essential".

4. L32: How might these findings inform climate change mitigation efforts or forest management strategies?

   Response: Thank you for the comment. GPP is a crucial indicator for estimating the carbon sequestration capacity of ecosystems (Chen et al., 2021b; Ma et al., 2019). Firstly, estimation of the GPP in the subtropical forests is important for people to understand how much carbon sequestration capacity it offers. For example, in this study, we have estimated the GPP of different forests, thus providing forest managers with basic reference on the carbon sequestration potential of different Chinese subtropical forests. Secondly, we investigated the dynamics of GPP and their dominant driving factors in the study area. This information is crucial for decision-makers to adjust and optimize forest management policies promptly, so as to ensure that forests can provide the best ecological services for humans (Fang et al., 2010).

   Additionally, China is still one of the world's top emitters of greenhouse gases that directly contribute to global warming (Chen et al., 2021). In September 2020, China announced the plan to achieve carbon neutrality by 2060 (Dong et al., 2021). This target closely aligns with the Intergovernmental Panel on Climate Change (IPCC) Special Report on 1.5 °C (SR15), which states that global CO_2 emissions must decline well before 2050 to curb the anticipated 1.5 °C global warming. Vegetation carbon uptake could significantly regulate the inter-annual variability of atmospheric CO_2 concentration and mitigate climate change. Developing forest carbon sinks is very important for China to achieve carbon neutrality. The Chinese government implemented several large-scale forestation programs since the 2000s, especially in the subtropical regions. Therefore, quantification of China's subtropical forest GPP and understanding of its driving mechanisms in this study can provide policy makers with a basic reference to answer the question: (1) How has the carbon sequestration potential of subtropical forests changed over the past decades? (2) Does the region have the potential to achieve carbon neutrality and mitigate climate change?

References:

Chen, Y. et al., 2021. Accelerated increase in vegetation carbon sequestration in China after 2010: A turning point resulting from climate and human interaction. Global Change Biology, 27(22), 5848-5864.

Ma, J., 2019. Trends and controls of terrestrial gross primary productivity of China during 2000–2016. Environmental Research Letters, 14, 084032.

Zhao et al., 2023. Toward the carbon neutrality: Forest carbon sinks and its spatial spillover effect in China. Ecological Economics, 209, 107837.

Dong, L., et al., 2021.China's carbon neutrality policy: objectives, impacts and paths. East Asian Policy, 13, 5-18.

Beer, C., et al., 2010. Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. Science, 329 (5993), 834–838.

Fang, J., et al, 2010. Why are East Asian ecosystems important for carbon cycle research? Science China Life Sciences, 53(7): 753–756.

5. L37: Carbon emissions?

Response: Sorry for the confusion. We have reworded the sentence as follows (see Page 2, Lines 45-48):

"Terrestrial ecosystems can capture carbon dioxide (CO_2) from the atmosphere through photosynthesis, which is regarded as a potential solution for slowing down the increase in global CO_2 concentration (Keenan et al., 2016) and mitigating global warming (Fang et al., 2018; Shevliakova et al., 2013)."

References:

Keenan, T.F., et al., 2016. Recent pause in the growth rate of atmospheric CO_2 due to enhanced terrestrial carbon uptake. Nature Communications, 7, 13428.

Fang, J., Yu, G., Liu, L., Hu, S. and Chapin, F.S., 2018. Climate change, human impacts, and carbon sequestration in China. Proceedings of the National Academy of Sciences, 115(16): 4015-4020.

Shevliakova E., et al., 2013. Historical warming reduced due to enhanced land carbon uptake. Proceedings of the National Academy of Sciences, 110,16730–16735.

6. L66-68: Which regions are they looking at? The major drivers on GPP vary a lot depending on regions and even seasons. Please be precise here.

Response: Thanks. As suggested, we added the specific regions to the revised text as follows (see Page 3, Lines 94-108):

"For instance, previous studies showed that temperature is the major factor influencing GPP variations in the Yangtze River Basin of southern China (Nie et al., 2023), as well as in other southern parts of China (Ma et al., 2019). Li et al., (2022) highlighted that precipitation dominated the interannual changes in forest GPP in Southwest China, while the GPP changes were more affected by solar radiation than by precipitation and temperature in humid region of China (Chen et al., 2021a). Therefore, the dominant factors affecting GPP varied a lot depending on regions and different time scales…"

References:

Nie, C., et al., 2023. The Spatio-Temporal Variations of GPP and Its Climatic Driving Factors in the Yangtze River Basin during 2000–2018. Forests, 14(9):1898.

Li, Y., et al., 2022. Interannual variations in GPP in forest ecosystems in Southwest China and regional differences in the climatic contributions. Ecological Informatics, 69: 101591.

Ma et al., 2019. Trends and controls of terrestrial gross primary productivity of China during 2000–2016. Environmental Research Letters, 14(8): 084032.

Chen, S. et al., 2021a. Vegetation structural change and CO_2 fertilization more than offset gross primary production decline caused by reduced solar radiation in China. Agricultural and Forest Meteorology, 296: 108207.

7. L70-71: The term "CO_2 fertilization" has not been introduced. Do you mean the CO_2 fertilization effect is stronger in China than in other regions, or the CO_2 effect is stronger in forest ecosystems than in other ecosystems?

Response: Thank you. As suggested, we have added a brief introduction to CO_2 fertilization as follows (Page 3, Lines 80-82).

"Elevated CO_2 concentrations may enhance the plant productivity, i.e., GPP, at the ecosystem scale, which is known as the CO_2 fertilization effect (Piao et al, 2020)."

Here, we mean that the southern region of China is more affected by the carbon dioxide fertilization effect than other regions of China. Revised text to (Page 3, Lines 82-85):

"The CO_2 fertilization was also identified as the pivotal driver for enhancing carbon sink in terrestrial ecosystems, and some studies even reported that the southern region of China was more affected by the CO_2 fertilization effect than other Chinese regions (Chen et al., 2019b; Zhu et al., 2016)."

References:

Piao, S. et al., 2020. Characteristics, drivers and feedbacks of global greening. Nature Reviews Earth & Environment, 1: 14-27.

Chen et al., 2019b. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nature Communications, 10(1): 4259.

Zhu et al., 2016. Greening of the Earth and its drivers. Nature Climate Change, 6, 791–795.

8. L73-74: "…most of the current studies…", really? At least different PFTs are represented in land surface or earth system models.

Response: We agree that different PFTs are represented in land surface or earth system models. We apologize for the misleading description. We have changed the statement "most of the current studies" to "some of the recent studies".

9. L86: How "better-performed" is BEPS? It seems unusual to encounter the conclusion without having reviewed the results, where the performance of the BEPS model has been tested.

Response: Thanks. Actually, the BEPS model has been tested and validated at the regional and global scales in previous studies. Considering the statement "better-performed" is inappropriate, we have removed the confusing sentence from the revised text (see Page 4, Lines 127-131).

Revised text to: "Recently, the BEPS model has been widely used to simulate carbon fluxes at the regional and global scales (Chen et al., 2019b; Chen et al., 2012; Liu et al., 1997; Luo et al., 2019; Wang et al., 2021a), especially it has been well evaluated and validated in China (Feng et al., 2007; Liu et al., 2018; Peng et al., 2021; Wang et al., 2018)."

References:

Chen, J.M., 2019b. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nature Communications, 10(1): 4259.

Chen, J.M. et al., 2012. Effects of foliage clumping on the estimation of global terrestrial gross primary productivity. Global Biogeochemical Cycles, 26(1): GB1019.

Liu, J., et al., 1997. A process-based boreal ecosystem productivity simulator using remote sensing inputs. Remote Sensing of Environment, 62(2): 158-175.

Luo, X., et al., 2019. Improved estimates of global terrestrial photosynthesis using information on leaf chlorophyll content. Global Change Biology, 25(7): 2499-2514.

Wang, M., Wang, S., Zhao, J., Ju, W. and Hao, Z., 2021a. Global positive gross primary productivity extremes and climate contributions during 1982-2016. Science of the Total Environment, 774: 145703.

Feng, X. et al., 2007. Net primary productivity of China's terrestrial ecosystems from a process model driven by remote sensing. Journal of Environmental Management, 85(3): 563-573.

Liu, Y. et al., 2018. Satellite-derived LAI products exhibit large discrepancies and can lead to substantial uncertainty in simulated carbon and water fluxes. Remote Sensing of Environment, 206: 174-188.

Peng, J. et al., 2021. Incorporating water availability into autumn phenological model improved China's terrestrial gross primary productivity (GPP) simulation. Environmental Research Letters, 16(9): 094012.

Wang, M. et al., 2018. Detection of Positive Gross Primary Production Extremes in Terrestrial Ecosystems of China During 1982-2015 and Analysis of Climate Contribution. Journal of Geophysical Research: Biogeosciences, 123(9): 2807-2823.

10. L93: Do you mean different GPP products?

Response: Thanks for catching the error in the description. Here we want to express the GPP of different forest types. We reworded the sentence as follows (see Page 4, Line 137):

"to quantify the spatiotemporal trends in GPP of different forest types across the subtropics."

11. L95-96: I find this statement not specific. Also, see my comment before.

Response: To make it clearer, we have added the following sentences to the revised manuscript (see Page 4, Lines 141-145).

"The results of this study can provide forest managers with basic reference on the carbon sequestration potential of different Chinese subtropical forests. Moreover, investigating the dynamics of GPP and their dominant driving factors in the study area is crucial for decision-makers to adjust and optimize forest management policies promptly, so as to ensure that forests can provide the best ecological services for humans."

12. L139: What are "the other parameters"?

Response: The other important parameters mainly include the clumping index, maximum stomatal conductance, specific leaf area, respiration coefficient for leaf, stem, coarse root, and fine root, as well as the Q10 for leaf, stem, and root. We have added this information to the revised text. Revised text to (see Page 6, Lines 189-191):

"The other important parameters, including the clumping index, maximum stomatal conductance, specific leaf area, respiration coefficient for leaf, stem, coarse root, and fine root, and Q10 for leaf, stem, and root, used in the BEPS model for each plant functional type can be found in Liu et al. (2018)."

References:

Liu, Y. et al., 2018. Satellite-derived LAI products exhibit large discrepancies and can lead to substantial uncertainty in simulated carbon and water fluxes. Remote Sensing of Environment, 206: 174-188.

13. L147-149: How is the "nighttime flux correction" done? Gap filling and flux partitioning are not data quality control.

Response: According to the flux dataset processing standards developed by ChinaFLUX (Zhang et al.), the nighttime flux correction mainly includes removing outliers when there is precipitation, CO_2 concentration exceeds the instrument's measurement range, insufficient turbulence (e.g., u* <0.2 m/s), and less than 15,000 valid samples. We have added this information to the revised text (see Page 6, Lines 203-207). As suggested, we also removed the statement "gap filling and flux partitioning" from the revised text.

References:

Zhang et al., 2019. Carbon and water fluxes observed by the Chinese Flux Observation and Research Network (2003–2005). China Scientific Data, 4(1), DOI: 10.11922/csdata.2018.0028.zh.

14. L150: Which u* is used for each site?

Response: Thanks. We have added the specific values of u* for each site, namely the threshold of u* < 0.2 m s^{-1} was used for the QYZ and ALS stations, while the threshold of u* < 0.05 m s^{-1} was used for the DHS station. We have added this information to the revised version (see Page 6, Lines 205-206).

15. L167: Vague statement. What does “robust enough” mean?

Response: We apologize for the vague statement. Revised text to (see Page 7, Lines 229-230):

"It has been shown that this can effectively reduce the uncertainty in the simulations of the BEPS model."

16. L195: You mean “original vegetation classes”?

Response: Yes, the “original classes” has been changed to “original vegetation classes” (see Page 8, Line 257).

17. L210-213: The sentence is not clear.

Response: Sorry for the inappropriate description. To avoid confusion, we have removed the statement from the revised text where there are unnecessary.

18. L244: “reasonably well” is not an accurate phrasing, notably considering that all R^2 values are below 0.5. Why is NEP only used for testing model performance? Why is NEP exclusively used for testing the model's performance? There seems to be a lack of additional results or discussion regarding NEP thereafter.

Response: Thank you very much for the comment. As suggested, we have removed the “reasonably” from the revised text. Yes, we also used the NEP for testing the model performance, because NEP (i.e., -NEE) is a direct measurement of carbon fluxes between the atmosphere and ecosystems, while the ecosystem GPP cannot be measured directly and is derived from the partitioning of NEE from flux measurements. Therefore, we not only used the observed GPP from the flux sites to validate our model, but also the NEP. We recognized that the validation of model performance based on measured NEP was relatively lower than that of GPP. One reason for this is that the simulation of NEP in the model is affected not only by the accuracy of simulated GPP, but also by the accuracy of simulated heterotrophic respiration (R_h) and autotrophic respiration (R_a). Therefore, a relatively poor performance of the simulated NEP was observed in this study.

However, the purpose of this is to disentangle how different drivers affect GPP changes in China’s subtropical forests. Therefore, we mainly focus on the GPP in our study area. Our findings also showed that the validation of the simulated GPP at three flux sites performed well. We have added the explanations to the revised manuscript. Revised text to (see Pages 10, Lines 317-323):

“In this study, we used the NEP for testing the model performance, because NEP (i.e., -NEE (net ecosystem exchange)) is a direct measurement of carbon fluxes between the atmosphere and ecosystems. Therefore, we not only used the observed GPP from the flux sites to validate our model, but also the NEP. The validation of model performance based on measured NEP was relatively lower than that of GPP. One cause is that the simulation of NEP in the model is influenced not only by the accuracy of simulated GPP, but also by the accuracy of simulated heterotrophic respiration (R_h) and autotrophic respiration (R_a)."

19. What do the green lines and circles represent in Figure 2?

    Response: Thanks. The green lines represent the simulated GPP, and the dark circles represent the observations. We added the description of the green lines and dark circles in the Figure caption (see below and Page 10, Lines 326-327).

    "Figure 2 Comparison of simulated GPP with measured GPP from three flux tower stations at daily (a-c) and annual (d-f) scales. The green lines and dark circles represent the simulated GPP and observed GPP, respectively."

20. L254-255: It is not clear how the spatial correlation is calculated.

    Response: Thanks. Here the spatial correlation is calculated pixel by pixel at the annual scale. For example, we obtained the MODIS GPP from a certain pixel, and our simulated GPP was also derived from the same pixel during the same period. Then, the correlation between the two GPPs was computed. Similarly, we can calculate the correlation coefficients of different pixels to obtain their spatial distribution. We added the following description of the methodology for calculating spatial correlation in the revised manuscript. Revised text to (see Page 9, Lines 296-300):

    "Moreover, the spatial correlation was adopted in this study to compare the spatial consistency of our simulated GPP with other GPP products. The spatial correlation was calculated pixel by pixel at the annual scale. First, two GPP time series for a certain pixel were obtained in the same period, and then the correlation between the two GPPs was calculated. By analogy, the spatial distribution of the correlation coefficients can be achieved."

21. L261-264: The number does not align within the range of all five GPP products as mentioned. Additionally, the reference to 'another BEPS' requires clarification. How to interpret the difference between "another BEPS" and "this BEPS" in Figure S7d?

    Response: Thanks. We acknowledge that our simulated GPP is slightly higher than other products. Although our estimated GPP is slightly higher for the entire subtropical forests, our modeled GPP is very close to other GPP products for a specific forest type, such as the DBF and MXF (Fig. S9). In fact, other GPP products (e.g., MODIS GPP, EC-LUE GPP, NIRv GPP, and VPM GPP) also have significant differences when compared to each other (Fig. S9). The results indicate there are still significant differences in simulating GPP to date. The possible reasons are:

(1) there are some substantial differences in the simulated GPP from various ecosystem models due to many differences in model structure, parameterization, and driving data (Cai et al., 2014; Lin et al., 2023).
(2) other GPP products used in this study were mainly generated by the LUE model-based and remote sensing-based models. However, previous studies (Zhu et al., 2018; O'Sullivan et al., 2020; Wang et al., 2023) also reported that LUE-based models, remote sensing-based models, and machine-learning-based models may underestimate the GPP at an annual scale. For example, the GPP estimates by the LUE models mainly depend on a few important factors, such as solar radiation, air temperature, water availability, and vegetation indexes (e.g., EVI or NDVI). Current LUE-based models do not completely integrate other key environmental regulations to vegetation productivity, such as the effect of atmospheric CO_2 concentration. Thus, the underestimation in other GPP products is possibly due to the failure to assess the CO_2 fertilizer effects, because almost no apparent response to the rising atmospheric CO_2 concentration in the LUE models leads to an underestimated trend (Anav et al., 2015). In our study, the GPP was estimated by a process-based model (i.e., BEPS) that considers the effects of these important factors on GPP, especially the CO_2 fertilization effect, which may lead to a higher GPP compared to all the other products.

For what it's worth, the results of our comparisons showed that the interannual trends of our simulated results were in line with other GPP products (Fig. S9). Despite possible overestimation, the purpose of this study mainly focuses on the trends and explains the driving mechanism behind them, thus it may not affect our results and conclusions.

We added the discussion to the revised version (see Page 11, Lines 344-361). We also reworded the statement "…, which falled in the range of the five GPP products… " to "…, closing to the magnitudes of the three GPP products… ".

In order to distinguish it from the GPP we simulated, the reference (i.e., $BEPS_g$ GPP) to 'another BEPS' has been added to the revised text (see Page 7, Line 239) and Table S3. Actually, the $BEPS_g$ GPP product was also produced by a similar BEPS model. However, this model is driven by the global datasets, and the parameters in the model are also calibrated for the global GPP mapping. Therefore, It is different from our simulated GPP and can be used for comparison with our simulated GPP.

References

Cai, W., et al., 2014. Large differences in terrestrial vegetation production derived from satellite-based light use efficiency models. Remote Sensing, 6(9), 8945–8965.

Lin et al., 2023. Underestimated Interannual Variability of Terrestrial Vegetation Production by Terrestrial Ecosystem Models. Global Biogeochemical Cycles, 34(4), e2023GB007696.

Zhu et al., 2018. Underestimates of Grassland Gross Primary Production in MODIS Standard Products. Remote Sensing, 2018, 10(11), 1771.

Wang et al., 2023. Assessment of Six Machine Learning Methods for Predicting Gross Primary Productivity in Grassland. Remote sensing, 15(14), 3475.

O'Sullivan, M., et al. 2020. Climate-driven variability and trends in plant productivity over recent decades based on three global products. Global Biogeochemical Cycles, 34(12), e2020GB006613.

Anav, A., et al., 2015. Spatiotemporal patterns of terrestrial gross primary production: a review. Reviews of Geophysics, 53(3), 785-818.

22. L268-269: Rather than a simple conclusion that BEPS-GPP aligns well with other GPP products, it would be more informative to delineate areas of agreement and disagreement between the models.

Response: Thank you for the constructive suggestion. We added the following sentences to the revised text (see Page 11, Lines 344-349):

"Although our simulated GPP is slightly higher for the entire subtropical forests, EBF and ENF than other GPP products, it is very close to other GPP products for specific forest types such as DBF and MXF (Fig. S9). Similarly, these commonly used GPP products also have large differences when compared to each other (Fig. S9). These results indicate that there is still a large discrepancy in modelling GPP to date, due to many differences in model structure, parameterization, and driving data."

23. L277: Please explain what is the "interactive effect".

Response: Here the "interactive effect" represents the combined effect of different drivers, namely, GPP is simultaneously influenced by different driving factors, such as changes in the climatic factors, vegetation status, rising CO_2 concentration, etc.

24. L281: "…of the forest GPP", do you mean forest areas showed increased and decreased GPP?

Response: Yes, We want to state that 90.4% of the forest areas in the study area exhibited an increasing trend in GPP, while 9.6% of the forest areas showed a decreasing trend in GPP. Sorry for the confusion. We have updated the sentence as follows (see Page 12, Lines 372-373):

"Spatially, 90.4% of forested land in the study area showed an increasing trend in GPP, while 9.6% of forested land exhibited a decreasing trend in GPP."

25. L297: What is "stable state"? No forest cover change? Or no significant effect of forest cover change?

Response: Thanks for the comment. True, here the stable state indicates no forest cover change.

26. In Figure 5 (b), the time series of GPP in MXF seems to be very symmetric with GPP in ENF, any explanations for that?

    Response: Thanks. Such results are mainly due to the inter-annual variability of the area of each forest type and the conversion between them. This is because in this section we only investigated the effect of changes in the area of each forest type on the GPP.

27. L307: Is the increasing trend significant?

    Response: Thanks. As shown in Fig. S11, the trends in annual precipitation and temperature of the entire study area showed increasing trends, but are not significant. However, the trends in annual precipitation and temperature varied spatially (Fig. S11b and Fig. S11d), with some areas showing significant increasing trends.

28. L334: "…58.2% of the…", but quite a lot of white spaces are shown up on the map. How is the 58.2% derived? Are you referring to Fig. 6h in this statement?

    Response: Thank you for the comment. The 58.2% was computed as the ratio of the pixels with a decreasing trend to the total number of pixels in the study area. This statement refers to Fig. 6h (see the updated Fig. 4d). A lot of white spaces mainly arise from the results of masking non-forested areas. To avoid confusion, we have updated the color of the mask area in the revised manuscript.

29. In Figure 6a, most of the variabilities are from EBF, any explanations?

    Response: Thanks. As shown in Figure 6a and 6b, the significant effects of precipitation on GPP mainly occurred in some parts of the West. Meanwhile, the predominant forest type in these areas is EBF (Fig. 1). However, precipitation is relatively stable in other forest areas (e.g., ENF, MXF, etc.) and has relatively little impact on the GPP of other forests. Therefore, changes in precipitation have a greater impact on EBF, leading to most of the variabilities being from EBF.

30. L381-383: Where does the conclusion "…EBF…has the highest carbon uptake potential" come from?

    Response: We are sorry for the confusion. We reworded the sentence as follows (see Page 21, 513-514):

    "Overall, the GPP of EBF in the subtropical region of China experienced the largest annual growth rate when compared with other forest types (Fig. 5b)."

31. L423-424: But in Table S6, the majority of the ENF has been observed to transition into MXF (19040 km^2).

Response: Thank you for pointing out this error. Yes, there were 19,040 km^2 of MXF was converted from ENF. As shown in Table S6, when ENF converts to non-forests, the ENF mainly converts to cropland (13,100 km^2). We are sorry for the confusion. We have reworded the sentence as follows (see Page 24, Lines 559-561):

"The total area of the ENF was lost obviously during the study period in eastern and southern regions, and the ENF was mainly converted to MXF (19,040 km^2) and cropland (13,100 km^2) (Table S6), causing large parts of GPP to decrease."

32. L450: Could you explain how climate warming negatively influences GPP in your study?

Response: Thanks. Our findings found that temperature induced the GPP decrease and mainly located in large parts of the eastern and the southwest (see Fig. S12d). In these areas, the temperature showed significant increasing trends (see Fig. S11d). The results indicated that increased temperature led to GPP reduction. Climate warming could increase the vapor pressure deficit (VPD), leading to more drought stress on plants (Yuan et al., 2019). Generally, when atmospheric moisture is insufficient, plants tend to inhibit photosynthesis by reducing stomatal conductance, thereby significantly reducing GPP (Yuan et al., 2019; Grossiord et al., 2020). Additionally, when the temperature increases exceed the optimal temperature, the activity of enzymes in plants will decrease, thereby affecting the photosynthesis rate and carbon sequestration.

References:

Yuan, W. P., et al., 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. Science Advances, 5, eaax1396.

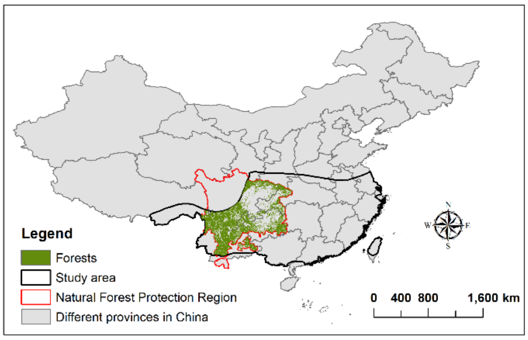
Grossiord, C., et al., 2020. Plant responses to rising vapor pressure deficit. New Phytologist, 226(6), 1550–1566.

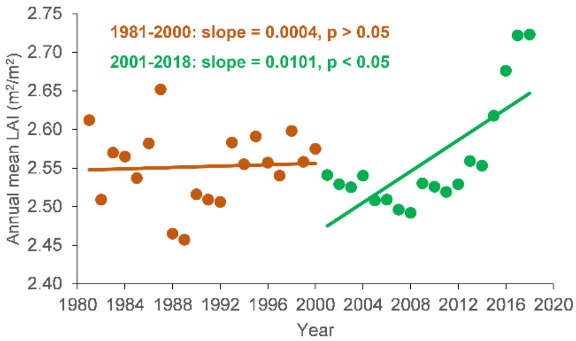
33. L460-462: Why do you observe different behaviors between EBF and ENF? Any hypothesis for that?

Response: Thanks for the comment. The cause of the observed different behaviors between EBF and ENF is that different forest types have different geographical distributions and are subject to different influences of climatic factors, etc. As shown in Fig. 1, ENF is mainly distributed in the eastern and western regions of the subtropics. Our results showed that climatic factors (e.g., temperature and solar radiation) in these regions have negative effects on the GPP of ENF (Fig. S12), particularly the solar radiation declined significantly in the eastern region, which led to a decrease in the GPP of ENF in the east. For EBF, it is mainly distributed in the central and some western regions where climate change mainly contributes to the increase of GPP of EBF, especially the precipitation and temperature in the small area of the west (see Fig. S12b and Fig. S12d) contribute significantly to EBF GPP increase.

34. L486-L488: How much increase in LAI is related to the forest protection projects?

Response: Thanks for the comment. The Chinese Natural Forest Protection Project (NFPP) has been implemented around 2000 and completed by the end of 2020. Therefore, we first obtained the natural forest protection region in our study area (see left figure) from the National Ecosystem Science Data Center (http://www.nesdc.org.cn/). Further, we calculated the annual average LAI for the region to compare the LAI changes over two phases (i.e., 1981-2000 and 2001-2018) (see right figure). Before 2000, the annual mean LAI showed a relatively stable state (slope = 0.0004 m^2/m^2/year, $p > 0.05$), and in the second phase (our study period), the annual mean LAI displayed a significant increasing trend (slope = 0.0101 m^2/m^2/year, $p < 0.05$), indicating that the implementation of NFPP may contribute to the increase in LAI.





35. L495: Chen et al. attribute drivers to GPP in gC/m2/year, which is not comparable with the GPP attribution in this study because of different regions and units as I mentioned in the general comments. The results in Zhan et al. stem from a land surface model instead of eddy covariance records.

Response: Thanks for the comment! As suggested, we first removed the references from the revised text. Besides, we also reworded the sentence in the revised version as follows (see Page 26, Lines 662-665):

"This was also confirmed by the results of free-air CO_2 enrichment (FACE) experiments (Norby et al., 2010) and a previous study using terrestrial biosphere models, remote sensing-based methods, ecological optimality theory and an emergent constraint based on global carbon budget estimates (Keenan, et al., 2023)."

References:

Keenan, T. F., et al., 2023. A constraint on historic growth in global photosynthesis due to rising CO_2. Nature Climate Change, 13: 1376–1381.

Norby, R. J., et al., 2010. CO_2 enhancement of forest productivity constrained by limited nitrogen availability. Proceedings of the National Academy of Sciences, 107, 19368–19373.

36. L515-517: "…still in the early developing stage…" Could you specify the limitations of using this V_{cmax25} product? Is the limitation about the theory or data quality?

Response: Thanks. It is possible that the limitation may derive from the data quality and the key parameters in the model. Following your suggestion, we added the following sentences to the revised text to specify the limitations of using this V_{cmax25} product (see Page 27, Lines 722-730).

"For example, the V_{cmax25} product used in this study was mainly generated by the MODIS surface reflectance, thus the data quality of the surface reflectance may cause uncertainty in V_{cmax25} product. The uncertainties in MODIS reflectance datasets can arise from sensor calibration issues, cloud contamination, atmospheric correction errors, etc. Changes in the reflectance could result in large changes in the modelled chlorophyll values, thereby affecting the V_{cmax25} product. Additionally, the V_{cmax25} was produced by a semi-mechanistic model (Friend., 1995), and the key parameter K_{cat}^{25} in the model (the Rubisco turnover rate at 25 °C) would bring uncertainties in modeling V_{cmax25}, because current ground-based data are still rarely used for calibration of this parameter and validation of the V_{cmax25} products (Lu et al., 2022; Chen et al., 2022b)."

References:

Friend, A., 1995. PGEN: an integrated model of leaf photosynthesis, transpiration, and conductance Ecologicl Modelling, 77: 233–55.

Lu, X., et al., 2022. Estimating photosynthetic capacity from optimized Rubisco–chlorophyll relationships among vegetation types and under global change. Environmental Research Letters, 17(1): 014028.

Chen, J.M. et al., 2022b. Global datasets of leaf photosynthetic capacity for ecological and earth system research. Earth System Science Data, 14(9): 4077-4093.

37. Kindly utilize diverging color schemes with the midpoint at 0 for clarity.

Response: Thanks for the suggestion. The diverging color scheme with the midpoint at 0 was adopted in the revised manuscript (e.g., the updated Fig. 3 and Fig. 4).

38. I suggest minimizing the use of abbreviations in the conclusion for better clarity. If necessary, they can be reintroduced.

Response: Thank you for the suggestion. The full name of different abbreviations was added to the conclusion section of the revised manuscript, as suggested.

Technical corrections:

1. L164: “yearly” means “from year to year”.

   Response: We changed the “yearly” to “annual”.

2. L470: “increase” instead of “improve”.

   Response: Thanks again! The “increase” has been changed to the revised manuscript.