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

Dear Reviewer and Editor,

We would like to thank the reviewer for his 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. 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 #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, Figures 1, 2, 9 and 10 are the most important and 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:** Yes. 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.

"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 for describing the spread of temperature.

"The average annual temperature normally increases from the northwest toward the southeast, and the average annual temperature is about 15.5°C."

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.

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 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:

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

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.

$$A_c = V_m \frac{C_i - \Gamma}{C_i + K} \tag{S2}$$

$$A_j = J \frac{C_i - \Gamma}{4.5C_i + 10.5\Gamma} \tag{S3}$$

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; $\Gamma$ 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:

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

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

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

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, 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 factors of the relationship between SIF-GPP at present. For example, the GPP-SIF relationship is 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) Currently, available GPP and SIF products are both known to have large systematic biases, particularly when the resolution is coarse (Frankenberg et al., 2014). Such biases could affect the observed SIF-GPP relationship, which in turn will affect the accuracy and quality of GPP products. Although 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). However, the sparse coverage and coarse spatial resolution (~1°) of OCO-2 may also lead to large uncertainty in GOSIF GPP products.

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 confusing sentence 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 catching the mistake. 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:** Thank you for the good suggestion. 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. We have listed the validation results of NEP 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 produced using 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 BEPS GPP are all based on 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. So, 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 have 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.

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 the 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 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. In addition, the effect of topography also leads 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 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 leads to generally low fluxes in the southerly direction (Li et al., 2021). Despite the presence of lower observations at the DHS, the small bias is 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.

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).

"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 catching an error in the description. For more clarification, 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:** True. 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, in this study, our simulated GPP is mainly compared with other GPP products 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 model, remote sensing-based models, machine-learning-based model, and some terrestrial ecosystem 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, including solar radiation, air temperature, water availability, and vegetation indexes (e.g., EVI or NDVI). Current LUE-based models do not completely integrate the other key environmental regulations to vegetation productivity, such as the effect of atmospheric $CO_2$ concentration, canopy structure (e.g., LAI), diffuse radiation, etc. 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 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. S8). 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.

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 represents the GPP in the actual situation, i.e. under the interactive influence 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:

"Spatially, 90.4% of forest areas in the study area showed an increasing trend in GPP, while 9.6% of forest areas 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:

"Based on the ESA CCI land cover data, it showed the area of gains or losses for different forest types between 2001 and 2018 (Fig. 5a). We found that FCC positively affected the entire forest GPP at a rate of 1.35 TgC year$^{-1}$ ($p = 0.000$) (Fig. 5b), mainly driven by EBF GPP (1.17 TgC year$^{-1}$, $p = 0.001$) and MXF GPP (2.15 TgC year$^{-1}$, $p = 0.000$). However, the FCC had a negative effect on the DBF GPP and ENF GPP variations at the rate of -0.05 TgC year$^{-1}$ ($p = 0.195$) and -1.92 TgC year$^{-1}$ ($p = 0.000$), respectively. Spatially, 92.2% of the total forest GPP showed a stable state, and only 7.8% of GPP exhibited an increase or decrease under the effect of FCC (Fig. 5c). Among them, 3.9% of the forest GPP increased significantly, mainly located in the western region (e.g., the south slope of the Qinling mountains, the southwest karst region), while 2.6% of the forest GPP was significantly reduced in the eastern regions, which belong to the ENF (Fig. 5)."

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 significantly higher than in other regions because temperature, precipitation, and radiation all contribute to GPP increase in this region (Fig. 6). Although the area of GPP reduction due to climate change is relatively large, its impact magnitude 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, land cover change, 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.

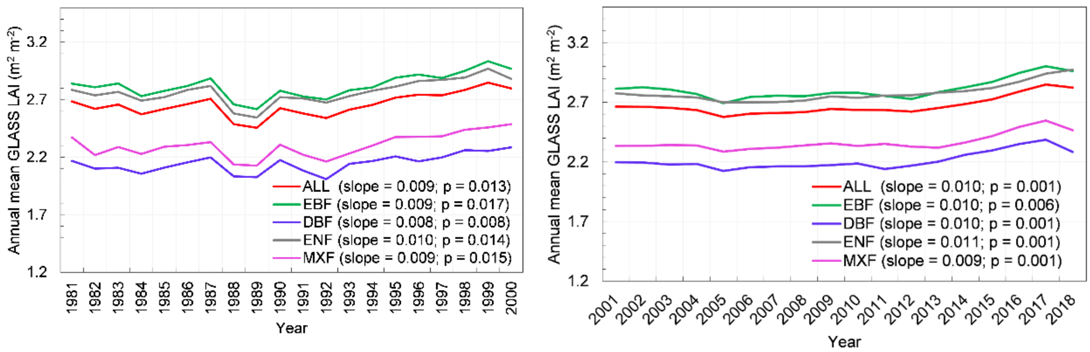
**Response:** We are sorry for the confusion. We have reworded the following sentence to make it clear in the revised text.

“Especially, the LAI change significantly promotes EBF GPP increase at a rate of 1.64 TgC $year^{-1}$ ($p = 0.025$).”

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.

Based on your suggestion, we also compared the changes in LAI before and after 2001. It indicates that there is also an upward trend in LAI before 2001 (see figure on the left and right).




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. 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 Figure 7), some pixels have a positive GPP trend 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:

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

l. 361: verb is missing

**Response:** As suggested, we have revised this sentence as follows:

"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 comment! Yes, when we investigated the impact of forest cover changes on GPP variations, the results stem solely from the changing areas of different forest types. In other simulations, we do keep different forest cover unchanged, and it would not be influenced by forest cover change.

**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:

"For example, after the conversion of cropland to MXF, GPP in this changed 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.”. 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 forests have higher productivity, 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, 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). 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 the vegetation productivity (Myneni, et al., 1997; Nemani, et al., 2003; Song et al., 2022), or could reduce the 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:

"The main vegetation types in the small regions are natural broad-leaved evergreen forests (Cheng et al.,2023), and they are in middle age and in the 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 significantly higher than in other regions because temperature, precipitation and radiation all contribute to GPP increase in this region (see Fig. 6). Although the area of GPP reduction due to climate change is relatively large, its impact magnitude 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. 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. Moreover, 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:

"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 decrease (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. 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. 6)."

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.

"Consistent with our study period (2001–2018), Chen et al. (2021b) 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, and the significant increase of 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. Based on the Carnegie-Ames-Stanford (CASA) model, Li et al. (2021) stated that NPP in China showed an increasing trend of 15.2 TgC/yr, and that the humid region (i.e., most of southern China) dominated the interannual variation of the NPP. Using NPP as an indicator, many previous studies have also reported similar results that the carbon sequestration potential of the tropical and subtropical forests has increased over the past few decades (Wang et al., 2008; Shang et al., 2023)."

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.

Li et al., 2021. Regional contributions to interannual variability of net primary production and climatic attributions. Agricultural and Forest Meteorology, 303, 108384.

Wang et al., 2008. Spatiotemporal dynamics of forest net primary production in China over the past two decades. Global and Planetary Change, 61(3–4), 267-274.

Shang et al., 2023. China’s current forest age structure will lead to weakened carbon sinks in the near future. The Innovation, 4 (6), 100515.

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:

“The carbon sequestered by vegetation through photosynthesis in a given unit of space and time, i.e., gross primary productivity (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 photosynthesis in carbon budget (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 (Lan et al., 2021; Running et al., 2008). However, the distribution and dynamics of terrestrial GPP are significantly affected by global environmental changes (Piao et al., 2015; Chen et al., 2021b). Even minor changes in GPP may have a significant effect on regional and global carbon balance (Yao et al., 2018). Investigating the variations of GPP and their drivers at the spatial-temporal scale is crucial for human beings to understand the changes in carbon sequestration in terrestrial ecosystems and are conducive to making appropriate ecological and environmental management decisions (Andersson et al., 2009).”

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.

Piao et al., 2015. Detection and attribution of vegetation greening trend in China over the last 30 years. Global Change Biology, 21 (4), 1601-1609.

Yao, Y., et al. 2018. Spatiotemporal pattern of gross primary productivity and its covariation with climate in China over the last thirty years. Global Change Biology, 24, 184–196.

Andersson, K., 2009. National forest carbon inventories: policy needs and assessment capacity. Climatic Change, 93, 69–101.

**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.