

Contributions of ecological restoration policies to China's land carbon balance



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REVIEWER COMMENTS

Reviewer #2 (Remarks to the Author):

China ranks 1st in forest plantations, contributing significantly to carbon uptake and offsetting CO₂ emissions. Although the pivotal role of land carbon sequestration is well-acknowledged, the contributions of different management practices to the carbon sink remain unclear. This study examines the historical impacts of land management on the carbon sink in China, focusing on the recent two decades (2001–2020). Results indicate that land management changes were the dominant contributors to the land sink, with afforestation and reforestation being the largest driving forces. Overall, this study provides crucial insights into the impacts of different ecological restoration policies on the carbon sink. The experimental design is clear, and the results are easy to follow. However, I have a few suggestions for improvement:

1. In Line 201–202, why warming leading to a decline of the carbon sink? The authors explained that "The annual temperatures remained higher during 1981–2020 than the cycled ones of 1961–1980 but warming was more pronounced during 2001–2020 with less precipitation". Does warming exceed a threshold, causing a reduction in the carbon sink? This is intriguing as warming typically stimulates forest growth.

2. Regarding the uncertainty analysis, I found that the author focused majorly on parameter uncertainties. I believe that the spatial uncertainties are also important, but I didn't find such information. For example, the reconstruction of the land use change data, the allocation of the land management practices, such as wood harvest, fuelwood extraction, etc. Moreover, how these practices have been implemented spatially is unknown. It seems that these data were at national scale, but how were they determined in each grid?

3. Forest age is essential in forest growth simulations, but it is unclear how forest age was represented in the modeling. As shown in Figure 14 in the supplement file, forest age classes were shown. Was the forest age represented by the specific number of years or age class in modeling? If forest age class was used, how the forest growth was affected by age class in the simulation? The author mentioned that forest age structure was accounted at subgrid scales, but how? More information should be provided. This is important because the average age at grid/subgrid level for a specific PFT could lead to bias. For example, a grid comprised of 50% of both the youngest and oldest age classes may have the same average age as a grid fully covered by mid-age trees, but their carbon sequestration capabilities differ significantly.

4. Cropland change might be biased. In this study, the cropland area data was reconstructed using the cropland map of 2015 as the base year and using temporal change information from HYDE3.2. However, the cropland change signals in HYDE data have been reported as unreliable (See Yu et al 2021). This uncertainty should be discussed.

5. Correct the duplicate references (15 and 38).

Reference:

Yu, Z., Jin, X., Miao, L., & Yang, X. (2021). A historical reconstruction of cropland in China from 1900 to 2016. *Earth System Science Data*, 13(7), 3203-3218.

Reviewer #3 (Remarks to the Author):

The study examines the impact of changes in land management policies on China's terrestrial carbon balance and assesses the contribution of ecological restoration policies to the global and regional carbon cycle since 1980. The study provides new perspectives for understanding the impact of land management policies on the carbon cycle, and the findings highlight the importance of achieving carbon neutrality targets through active land management. Here are some suggestions that could improve the paper.

Lines 78-80 Most management activities, including forest management, grassland grazing and fire management, were ignored in the majority of DGVMs used for large-scale assessments of carbon budgets. Only one example is given here, and others should be added to support it.

Lines 130-131 No-policy scenarios start at different times for different land management policies. "The no-policy scenario assumes that all timber demand has been met by domestic production since 1981" means that the Reduced Timber Harvest no-policy scenarios start in 1981? But the "Reduced Timber Harvest" no-policy scenarios in Figure 1c start in 1990?

The land management policies in the second and third parts of the results do not correspond exactly to the results in the first part. Reduced wood extraction, including reductions in both timber harvesting and fuelwood extraction. The above explanations should be given in the methods or in the notes to Figures 2 and 3.

The colors in Figure 2c are so similar that it is difficult to distinguish between "grassland grazing exclusion" and "forest fire suppression".

The extent of the Middle, South and Southeast of the seven regions on the map in Figure 4 is not clearly labelled.

This study should provide new insights into modelling and parameter selection by illustrating uncertainties and implications.

Response to reviewer comments

We sincerely thank both referees for their efforts in reviewing our paper and for their valuable comments that have helped us greatly improve the robustness of our findings and the quality of our manuscript. Please find below our point-by-point responses to the referees' comments. To make it easy to track our revisions, all substantially modified text has been marked in blue in the revised manuscript.

Reviewer #2 (Remarks to the Author):

[Comment 1] China ranks 1st in forest plantations, contributing significantly to carbon uptake and offsetting CO₂ emissions. Although the pivotal role of land carbon sequestration is well-acknowledged, the contributions of different management practices to the carbon sink remain unclear. This study examines the historical impacts of land management on the carbon sink in China, focusing on the recent two decades (2001–2020). Results indicate that land management changes were the dominant contributors to the land sink, with afforestation and reforestation being the largest driving forces. Overall, this study provides crucial insights into the impacts of different ecological restoration policies on the carbon sink. The experimental design is clear, and the results are easy to follow. However, I have a few suggestions for improvement:

[Response 1] We deeply appreciate the referee's efforts in reviewing our paper and the overall positive comments. In particular, we highly appreciate the referee's constructive comments that have helped greatly improve the manuscript quality. Please find below our point-by-point responses to your comments.

[Comment 2] In Line 201–202, why warming leading to a decline of the carbon sink? The authors explained that "The annual temperatures remained higher during 1981–2020 than the cycled ones of 1961–1980 but warming was more pronounced during 2001–2020 with less precipitation". Does warming exceed a threshold, causing a reduction in the carbon sink? This is intriguing as warming typically stimulates forest growth.

[Response 2] We are sorry for the confusion in the original lines 201–202 and the sentence that follows. In fact, the decadal variations in the contribution of climate change to China's terrestrial carbon sink over 1981–2020, compared to the cycling climate of 1961–1980, seem to be more driven by changes in precipitation and surface air humidity, rather than by changes in temperature. This is because the change in annual temperature (ΔT) remained positive for almost all years of 1981–2020, whereas the change in annual precipitation (ΔP) and surface air humidity showed great temporal variations (Supplementary Fig. 6). During 1981–2000, the temperature increases also played a role, which is mostly negative (detailed below), but the increases in precipitation and surface air humidity seem to outweigh the negative effect of ΔT , leading to an overall positive contribution of climate change. For 2001–2020, the reverse was true, as explained fully in our original manuscript (lines 220–236 of the original manuscript).

We agree with the referee that warming typically stimulates vegetation growth but this seems to be valid only for northern boreal regions. Piao et al.¹ analyzed the partial relationship between satellite-derived vegetation greenness (NDVI), which can be considered as a proxy for vegetation productivity, and growing-season temperature over northern land ($> 30^{\circ}\text{N}$). They found a positive relationship between NDVI and temperature but only for northern boreal regions ($> 50^{\circ}\text{N}$). For temperate regions (30°N – 50°N), a negative relationship between NDVI and temperature was found. This indicates that, on an interannual basis (similar to our analysis which investigated the effect of climate difference between two periods), the stimulative effect of temperature increase (warming) on forest growth is mainly limited to boreal forests, while for temperate forests, warming has a negative impact on forest growth. In addition, Piao et al.¹ also showed that such satellite-derived contrasting NDVI-temperature (or productivity-temperature) relationships between boreal and temperate regions were successfully captured by dynamic global vegetation models (DGVMs).

A recent review study of climate change impacts on the land carbon cycle² indicates that, according to multiple DGVMs of the TRENDY project, climate change during the last two decades (2001–2019) compared to the beginning of the 20th century (1901–1920), which was dominated by temperature increase, has reduced global and continental terrestrial net ecosystem productivities or NEPs (Fig. 4 in Ruehr et al.²). The global reduction in NEP caused by climate warming is a result of an increase in NEP in boreal regions being offset by extensive NEP reductions in temperate and tropical regions. For China, the climate change effect has been dominated by reductions in NEP even in northeastern China (Fig. 5a in Ruehr et al.²). The NEP reductions in response to temperature increase, even in southern parts of the boreal regions, are due to greater increases in ecosystem respiration than those in ecosystem productivity, with both having been stimulated by temperature increase. Such a greater stimulation of national ecosystem respiration (RE) than national GPP by temperature increase was also confirmed by Zhang et al.³ using six ecosystem models over China. Zhang et al.³ showed that, on an interannual basis, while both GPP and RE are positively correlated with temperature over China, NEP is negatively correlated with temperature, suggesting a greater stimulation of RE than GPP by temperature increase.

Likewise, our simulation showed that warming combined with a slight increase in precipitation in northeastern China in 2001–2020 compared to 1961–1980 led to increases in GPP, but NEP in this region showed mostly decreases (with very limited increases), largely because warming and wetting also simulated ecosystem respiration (Fig. R1). This result is consistent with the findings derived using multiple DGVMs of the TRENDY project² and using six ecosystem models in China as mentioned above³.

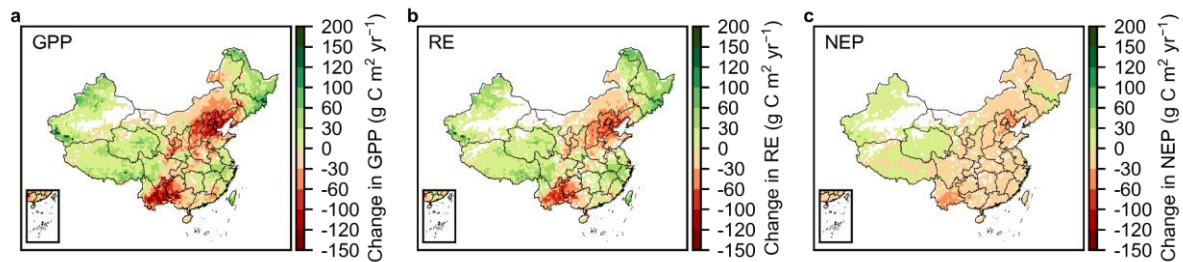


Fig. R1 The spatial patterns of changes in GPP (a), RE (b), and NEP (c) contributed by climate change over 2001–2020 in contrast to 1961–1980. This is a copy of the revised Supplementary Fig. 8.

Based on our own simulation results (northeastern and southeastern China as shown in Fig. R1a) and the results of Zhang et al.³ obtained using six ecosystem models over China, climate warming in China largely stimulated ecosystem photosynthetic uptake (GPP), which means that current temperature has not yet substantially exceeded the optimal temperature for photosynthesis, which would result in a decrease in plant photosynthesis. This is also consistent with the results of field warming experiments (mainly in temperate regions), which largely show a stimulative effect of warming on plant photosynthesis⁴. We are not aware of any studies showing that the current level of warming has exceeded the optimal temperature for photosynthesis and caused substantial reductions in vegetation GPP in China. Instead, the asymmetric effects of warming on photosynthesis and ecosystem respiration, which lead to reduced NEP with warming, seems more widely accepted.

In response to the referee's comment, the original text in lines 200–206 has been substantially expanded and revised to incorporate the above discussion. To avoid repetition, please refer to lines 205–230 in the revised manuscript for the revisions. In addition, the detailed discussions on the spatial pattern of changes in China's terrestrial carbon sink attributed to the difference in climate between 2001–2020 and 1961–1980, and their underlying climate drivers, have also been substantially enhanced (lines 248–263). In particular, the asymmetric warming effects on photosynthesis and ecosystem respiration have been explained (lines 253–263). Fig. R1, shown above, has replaced the original Supplementary Fig. 10, which is now Supplementary Fig. 8 in the revised manuscript.

[Comment 3] Regarding the uncertainty analysis, I found that the author focused majorly on parameter uncertainties. I believe that the spatial uncertainties are also important, but I didn't find such information. For example, the reconstruction of the land use change data, the allocation of the land management practices, such as wood harvest, fuelwood extraction, etc. Moreover, how these practices have been implemented spatially is unknown. It seems that these data were at national scale, but how were they determined in each grid?

[Response 3] We thank the referee for raising this important point. The spatial allocation of national (or provincial) total values of land use and land management data onto grid cells is described in the original Supplementary Method 2 (Supplementary Method 1 in the Supplementary Material of the revised manuscript), but was only summarized as one sentence in the

main text for brevity (Line 548 of the original manuscript): “*Detailed information on spatial disaggregation from national to grid scale is provided in Supplementary Method 2.*”

We understand that this line is easy to miss and we are sorry for this. In response to the referee’s comment, the following revisions have been made:

(1) The text block that deals with the spatial allocation of national land use data and its associated uncertainties has been expanded (lines 818–826 in the revised manuscript) as below: “*Information on the spatial disaggregation of land use and land management data from national to grid cell scales is provided in detail in Supplementary Method 1 and summarized in Supplementary Table 6. The spatial allocation of prefectural, provincial or national total values of land use and land management to grid cells either follows satellite observations and state-of-the-art land use products, or, when no such observation-based datasets are available, is based on reasonable assumptions. Often, there are no alternative more reliable datasets which allow quantitative investigation of spatial allocation errors and uncertainties (with the exception of cropland areas, see Supplementary Discussion 1). Hence, we deem it adequate to provide a qualitative assessment of the uncertainty (Supplementary Table 6) in the spatial pattern of land use and land management.*”

This text block has been inserted into section 4.3 of the main text, whose title has also been revised as “*Uncertainties in land use forcing data and **their spatial allocation to grid cells***”. This revised title explicitly addresses the spatial allocation of national values to grid cells to make it easier for readers to find such information.

(2) Supplementary Method 1 has been extensively improved to ensure accurate and adequate descriptions of the spatial allocation of national or provincial values of land use and land management to grid cells. The revisions include: a) a description of how national grazing exclusion area was spatially allocated (lines 42–46 and 64–66 of the Supplementary Material); b) an updated description of cropland data for 2016–2019 obtained from the China Statistical Yearbook (lines 60–62 of the Supplementary Material); c) an updated description of stocking rates for 2013–2020 (lines 80–83 of the Supplementary Material).

(3) The spatial allocation of national total values of land use to grid cells either follows satellite observations and state-of-the-art land use products, or, when no such observation-based datasets are available, is based on reasonable assumptions. There are often no alternative more reliable datasets which allow quantitative evaluation of spatial allocation errors and uncertainties (with the exception of cropland areas, see below). Hence, we deem it adequate to provide a qualitative assessment of the uncertainty in spatial pattern of land use and land management. This qualitative assessment information has been provided in Supplementary Table 6 (reproduced as Table R1 below).

(4) The spatial uncertainty arising from using national cropland areas and their spatial distribution in this study versus using the more reliable data sources of Yu et al.⁵, as suggested by the referee in Comment 5, has been explicitly addressed. Please see row 3 of Table R1 (a copy of Supplementary Table 6) and our response to Comment 5 below.

(5) The spatial allocation of land use and land management and its associated uncertainties has been expanded in the results section “**Spatial patterns of management and environmental contributions**” (lines 302–328 in the revised manuscript) as below:

“The land use and land management datasets were well constrained on prefectural (rural fuelwood extraction), provincial (afforestation and reforestation, cropland area) and national (timber harvest, grazing exclusion, and forest fire burned area) scales (see Methods). The spatial allocation of prefectural, provincial or national total values of land use and land management to grid cells either follows satellite observations and state-of-the-art land use products, or, when no such observation-based datasets are available, is based on reasonable assumptions (Supplementary Method 1, Supplementary Table 6). Often, there are no alternative more reliable datasets which would allow quantification of spatial allocation errors and uncertainties (with the exception of cropland, see Supplementary Discussion 1). Hence, a qualitative assessment of the uncertainty in the spatial pattern of land use and land management is provided as Supplementary Table 6. Small uncertainties were assigned to the spatial pattern of the carbon sink contributions of afforestation/reforestation and forest fire suppression. For the contribution of reduced wood extraction, a small uncertainty was assigned to rural fuelwood extraction, which dominates the total reduction in wood extraction due to ecological restoration (Fig. 1c, d), while a large uncertainty was assigned to timber production. A medium level of uncertainty was assigned to the contribution of grazing exclusion.

The impacts on the simulated terrestrial NBP by the S_{actual} simulation over 2001–2020 and its spatial distribution resulting from the uncertainties in cropland spatial distribution were additionally investigated through adjusting the cropland distribution in this study to match that provided by a reconstruction of China’s cropland distribution over 1900–2016. This reconstruction integrated datasets from multiple sources and is considered to be more reliable over China than HYDE3.2 (Supplementary Discussion 1). The results show that, for 90% of grid cells, the uncertainties in the simulated NBP over 2001–2016 were less than $0.01 \text{ Tg C yr}^{-1}$ — a relatively small value (Supplementary Fig. 14). The national NBP, on average, 2.2 Tg C yr^{-1} lower after the adjustment for 2001–2016, well within the uncertainty range of $(-33.2, +31.1) \text{ Tg C yr}^{-1}$ of the initially estimated value (Fig. 2a, Supplementary Fig. 14). These results illustrate a small impact of the uncertainty in the spatial distribution of cropland on the simulated national NBP. Furthermore, as the influences of cropland distribution will be filtered out when comparing simulated NBP between S_{actual} and $S_{baseline}$, the contributions of different land management changes shown in Fig. 3 are expected to be little impacted by any uncertainty in cropland distribution.”

Table R1 (a copy of Supplementary Table 6) Qualitative assessment of the uncertainties of the spatial patterns of land use and land management datasets for 1981–2020.

Type of land use or land management	Constraint of national, provincial or	Spatial allocation method	Uncertainty assessment of spatial pattern
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	prefectural total value		
Forest area change	Provincial forest areas were constrained by government statistics.	Allocation of provincial areas to grid cells followed satellite observation (CLUD-A).	<u>Small uncertainty.</u> (1) provincial distribution is highly robust. (2) grid cell distribution within each province is highly robust because it is based on satellite observation.
Cropland	Provincial cropland areas for 2015–2019 were constrained by data from the China Statistical Yearbook. For 1981–2014, annual changes in spatial cropland distribution were mainly derived from HYDE3.2.	Allocation of provincial cropland areas to grid cells follows the spatial distribution of cropland according to CLUD-A ⁶ (satellite observation) and HYDE3.2 ⁷ (hybrid approach of satellite observation and algorithmic allocation).	<u>Medium uncertainty.</u> (1) provincial distribution is highly robust. (2) grid cell distribution has medium uncertainty given algorithmic allocation was used in HYDE3.2. (3) The additional analysis incorporating alternative, more reliable spatial maps of cropland in China for 1980–2016 indicates an uncertainty in NBP by S_{actual} simulation about one order magnitude lower than the absolute value of NBP_{actual} over 2001–2016 (see Supplementary Discussion 1, Supplementary Figs. 14 and 23).
Timber harvest	National timber harvest volumes were derived from FAO.	Allocation of national timber harvested carbon to grid cells follows the spatial pattern of forest coverage.	<u>Large uncertainty.</u> It makes sense that larger amounts of timber wood harvest can only occur in places with more abundant

			forest resources as indicated by a greater forest coverage. However, timber production also depends on forest age and regulation status such as forest protection. Therefore a large uncertainty was assigned to the spatial distribution of timber harvest.
Rural fuelwood extraction	Annual rural fuelwood extraction at the prefecture level was estimated based on systematic field surveys, linear regressions, rural population and fuelwood consumption per capita. This dataset has been peer reviewed ⁸ and, to our knowledge, is the most reliable dataset of fuelwood extraction in China.	The spatial distribution of rural fuelwood extraction was based on the distribution of rural population from HYDE3.2 within each of the 346 prefectures in China.	<u>Small uncertainty.</u> The rural fuelwood extraction was primarily constrained on the prefecture level (346 prefectures in China). Given the relatively coarse spatial resolution of this study (0.5°), the spatial distribution of fuelwood extraction is considered robust.
Grazing exclusion	The national area of grazed grassland was derived from HYDE3.2, following adjustments based on the area of grazing exclusion from China's national grassland monitoring report for 2003–2020.	The spatial pattern of grazing exclusion followed that of grazed grassland in the exclusion regions. The map of grazing exclusion region was derived from several previous studies which showed consistent locations of grazing exclusion mainly distributed in Inner Mongolia, Liao-	<u>Medium uncertainty.</u> The map of grazing exclusion regions used to distribute the national total area of grazing exclusion was consistent with several previous studies and congruent with China's national grassland monitoring reports.

		ning, Jilin, Heilongjiang, Sichuan, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang ⁹⁻¹¹ (http://www.moa.gov.cn/nybgb/2017/dyiq/201712/t20171227_6129885.htm).	
Forest fire burned area	The actual annual national areas of forest fire were derived from official statistics. The annual national burned areas under the ‘no-policy’ scenario were derived from multiple DGVMs with corrections based on government statistics.	The spatial patterns of both actual and ‘no-policy’ forest burned areas follows the satellite product of Global Fire Emissions Database (GFED4).	<u>Small uncertainty.</u> The government-reported national forest burned area shows a good agreement with GFED4 for their overlapping period of 1995–2016. The spatial allocation follows satellite observation hence it has a small spatial uncertainty.

[Comment 4] Forest age is essential in forest growth simulations, but it is unclear how forest age was represented in the modeling. As shown in Figure 14 in the supplement file, forest age classes were shown. (1) Was the forest age represented by the specific number of years or age class in modeling? (2) If forest age class was used, how the forest growth was affected by age class in the simulation? (3) The author mentioned that forest age structure was accounted at subgrid scales, but how? More information should be provided. This is important because the average age at grid/subgrid level for a specific PFT could lead to bias. For example, a grid comprised of 50% of both the youngest and oldest age classes may have the same average age as a grid fully covered by mid-age trees, but their carbon sequestration capabilities differ significantly.

[Response 4] We thank the referee for this question and apologize for neglecting this aspect in our manuscript. We have responded below to each of the three elements of the referee’s comment.

(1) In ORCHIDEE, forest age is expressed as age class rather than as a specific number of years since forest establishment or regeneration. The number of age classes is a parameter in the model whose value can be customized. Assigning this parameter an extremely large value (e.g., 100) would make ‘age class’ very close to the continuous ‘age’ but would explode the demand for computational resources. In this study, six age classes were used for each forest PFT (young

to old, denoted as Age 1 to Age 6; see Supplementary Figs. 1–3) giving an acceptable discretization of age class while maintaining a reasonable computational-resource demand.

(2) The ORCHIDEE model can faithfully simulate forest biomass growth with age (Fig. R2), which can be typically described by a Richard growth function in the form of:

$$B=B_{\max} \times (1-e^{-k \times \text{Age}}) \quad \text{Eq. (R1)}$$

where $B_{\max}$ indicates the maximum (saturated) biomass when forest reaches a mature stage close to equilibrium, Age denotes forest age, and k is a factor that governs the speed with which biomass reaches its maximum value. According to this equation, the growth in biomass carbon stock, i.e., biomass carbon sink, will decrease with age, hence representing the age effect on forest biomass carbon sink. Although in this case the biomass carbon sink reaches its maximum at the young forest age, the increase in soil respiration due to, for example, the decomposition of the wood harvest residual shortly after harvest-induced forest regeneration, will lead to a small net ecosystem productivity (NEP) at the young forest age. The NEP then increases to a maximum value at an intermediate forest age and decreases again at the old age. In Fig. R2, wood mass, which includes both above- and below-ground sapwood and heartwood, and dominates forest biomass, was used.

Eq. (R1) was then fitted for each of the eight forest PFTs by averaging simulated wood mass of all grid cells where a given PFT was present and was at the same age. Rather than explicitly tracking ‘forest age’ in terms of years in ORCHIDEE, we used the fraction, $B/B_{\max}$, as a proxy to represent age class, as Age can be derived as a function of $B/B_{\max}$ by inverting Eq. (R1):

$$\text{Age}=\log(1-B/B_{\max})/(-k) \quad \text{Eq. (R2)}$$

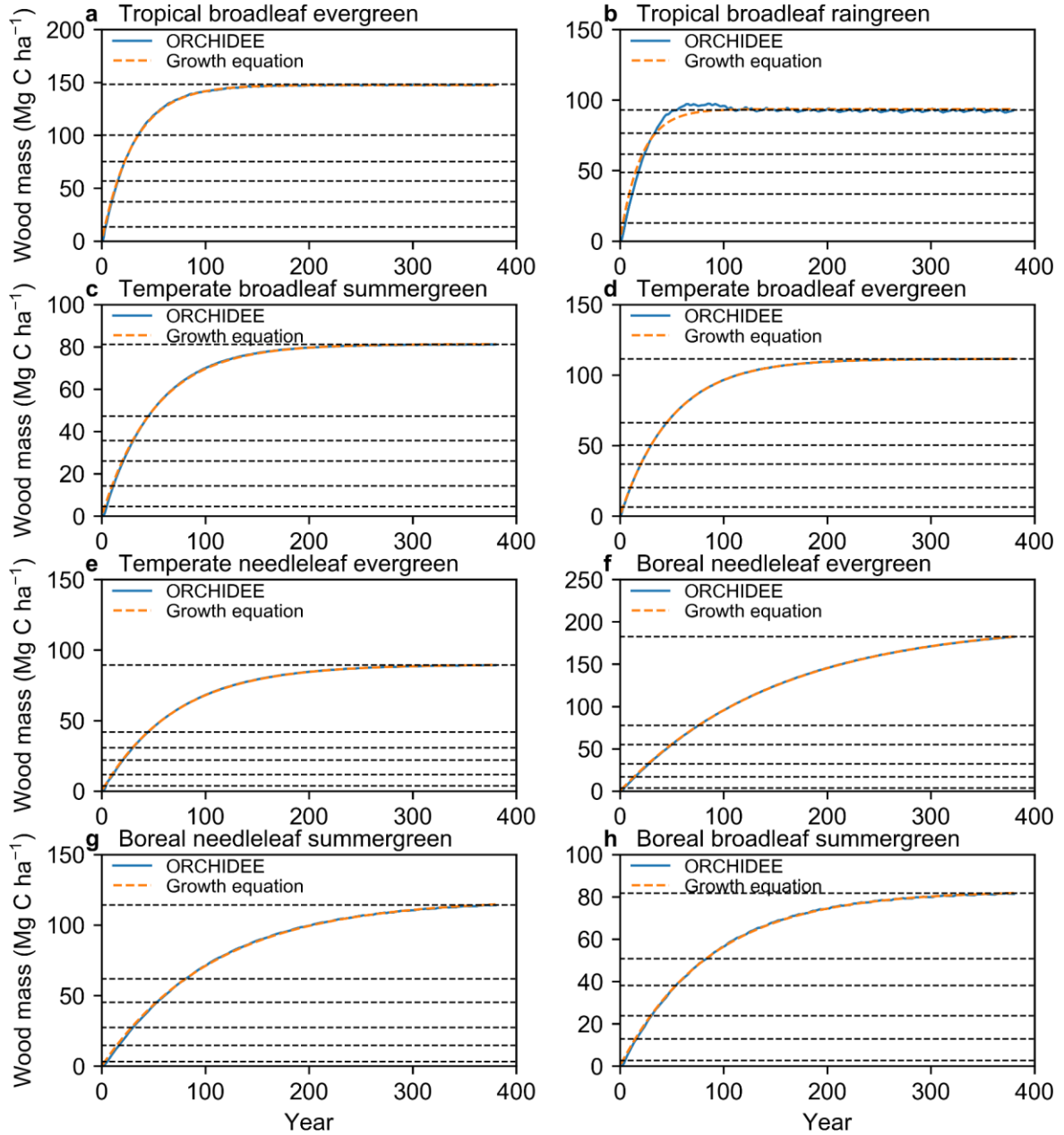


Fig. R2 (a copy of Supplementary Fig. 22) Simulated wood mass as a function of forest age by the ORCHIDEE model for eight forest PFTs. Wood mass includes both above- and below-ground sapwood and heartwood. The eight forest PFTs are tropical broadleaf evergreen forest (a), tropical broadleaf raingreen forest (b), temperate broadleaf summergreen forest (c), temperate broadleaf evergreen forest (d), temperate needleleaf evergreen forest (e), boreal needleleaf evergreen forest (f), boreal needleleaf summergreen forest (g), and boreal broadleaf summergreen forest (h). The horizontal black dashed lines indicate wood mass thresholds corresponding to age thresholds (Table R2) based on the fitted wood mass growth equation (Eq. (R1)).

For each PFT, there are six age classes, and correspondingly six $B/B_{\max}$ threshold values, as shown in Fig. R2. The age class thresholds (Table R2) were determined for different climatic

zones (tropical, temperate, or boreal) according to the definitions of age classes of different forest species in the official Technical Regulations for Continuous Forest Inventory (<https://openstd.samr.gov.cn/bzgk/gb/>) used by the National Forestry and Grassland Administration in national forest inventories. For example, the six age-class thresholds for boreal forests were classified as 3, 15, 30, 55, 85 and >85 years, respectively (Table R2, Fig. R2).

Table R2 (a copy of Supplementary Table 14) Age thresholds of different forest age classes (unit: year).

Forest PFT name	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6
tropical broadleaf evergreen	< 3	9	15	22	35	>35
tropical broadleaf raingreen	< 3	9	15	22	35	>35
temperate needleleaf evergreen	< 3	10	20	30	45	>45
temperate broadleaf evergreen	< 3	10	20	30	45	>45
temperate broadleaf summergreen	< 3	10	20	30	45	>45
boreal needleleaf evergreen	< 3	15	30	55	85	>85
boreal broadleaf summergreen	< 3	15	30	55	85	>85
boreal needleleaf summergreen	< 3	15	30	55	85	>85

As $B_{\max}$ can be derived individually for each PFT and each grid cell from an ORCHIDEE simulation (the spinup simulation), the corresponding threshold values of $B/B_{\max}$ for different age classes can then be translated into spatial maps of threshold values in terms of wood mass, which can subsequently be used in ORCHIDEE simulations to segregate age classes.

After the spinup simulation, all forests are at their oldest age class (Age 6). When the transient simulations start, land-use changes including afforestation, wood harvest, and forest fire disturbances generate secondary forest, which is established as forest of the youngest age class. As the wood mass of each class grows and exceeds the wood mass threshold, the concerned age cohort will be moved into the next age class, with all the variables of the moving age class and the target age class being merged together (e.g., all biomass components, soil organic carbon, GPP, NPP, autotrophic respiration, heterotrophic respiration, leaf age, etc.). For details, please refer to Yue et al.¹². As afforestation, wood harvest and forest fire continue to generate new forests of the youngest age class, and different age cohorts grow and move to the next age class, a dynamic, sub-grid forest age structure becomes established during the transient simulations. Areas of different forest age classes impacted by different processes of land management can then be examined (Supplementary Figs. 1–3).

(3) For each grid cell, the ORCHIDEE model tracks the ground fraction of each age class of each forest PFT. In fact, all simulation variables are tracked for each age class of each forest PFT. This results in a total of 48 age cohorts (age classes) for all forest PFTs. In this way, ORCHIDEE can track the age structure of each forest PFT at a sub-grid scale.

We agree with the referee that the carbon sequestration capability differs among young and old age classes of forests (as described above). In our case, because the simulated variables (e.g., GPP, NPP, autotrophic respiration, heterotrophic respiration) are only merged for two consecutive age classes when there is a need (for instance, it is not possible for the youngest age class to be merged with the oldest age class), a discrete number of age classes (six age classes) is always maintained on the sub-grid scale to adequately represent the difference in biomass growth among age classes. We acknowledge that this is not as good as the perfect solution of tracking a continuous forest age in terms of years, but doing the latter in FORTRAN language would explode the computational resource demand for only a relatively small gain.

The above descriptions have been incorporated as Supplementary Method 2 (***Representing forest age class dynamics at sub-grid scale***) in the Supplementary Material of the revised manuscript. Fig. R2 is inserted as Supplementary Fig. 22. Table R2 is inserted as Supplementary Table 14. Both of them are cited in Supplementary Method 2. We have added the following sentence to lines 532–533 of the revised manuscript: “*For details on forest age class representation, please refer to Supplementary Method 2.*”

[Comment 5] Cropland change might be biased. In this study, the cropland area data was reconstructed using the cropland map of 2015 as the base year and using temporal change information from HYDE3.2. However, the cropland change signals in HYDE data have been reported as unreliable (See Yu et al 2021). This uncertainty should be discussed.

[Response 5] We appreciate the referee’s insightful comment on the differences in cropland area between our study and that of Yu et al.⁵. We are sorry to say that the original descriptions regarding cropland area dynamics in our study were not completely correct. The original text (Line 580 of the original main text and lines 62–63 of the original Supplementary Material)

says that national cropland areas remained unchanged for 2016–2020, which was not true. In fact, temporally varying national and provincial cropland areas from the China Statistical Yearbook were used for 2015–2019. The cropland area for 2020 was assumed to be the same as in 2019 as it was not provided in the China Statistical Yearbook. For 1800–2015, changes in cropland areas between two consecutive years from HYDE3.2 were used and applied on top of the 2015 cropland area to obtain a reconstructed time series. The relevant descriptions have been revised (lines 727–729 of the main text) as: “*The national cropland area for 2016–2019 was derived from the China Statistical Yearbook. Because the cropland area for 2020 was not available in the China Statistical Yearbook, it was assumed to be the same as in 2019.*”, and further in the Supplementary Information (lines 60–62) as: “*Cropland area in each province for 2016–2019 was obtained from the China Statistical Yearbook. For 2020, in the absence of data, cropland area was assumed to be the same as in 2019. Changes in cropland area from 2016 to 2020 were allocated in a manner similar to the process used for forest allocation.*”

We are grateful to the referee for referring us to Yu et al.⁵. Indeed, Yu et al.⁵ provide a highly reliable spatial reconstruction of cropland area in China for 1900–2016 through fusing multiple government statistics and satellite datasets. Following the referee’s suggestion, we compared the difference in cropland area between our study and Yu et al. and assessed its impact on the simulated terrestrial carbon balance (net biome production or NBP).

As shown in Fig. R3a, over our study period of 1980–2020, national cropland areas between our study and Yu et al.⁵ are very similar for 1990–2016, although there are large differences for 1980–1989, because, as pointed by Yu et al.⁵, an abrupt increase in cropland area between 1980 and 1989 in HYDE3.2 was inherited from the FAO data. Nonetheless, there is a remarkable agreement between our study and Yu et al.⁵ for 2001–2016, the period which dominates our key study window of 2001–2020 in the main text.

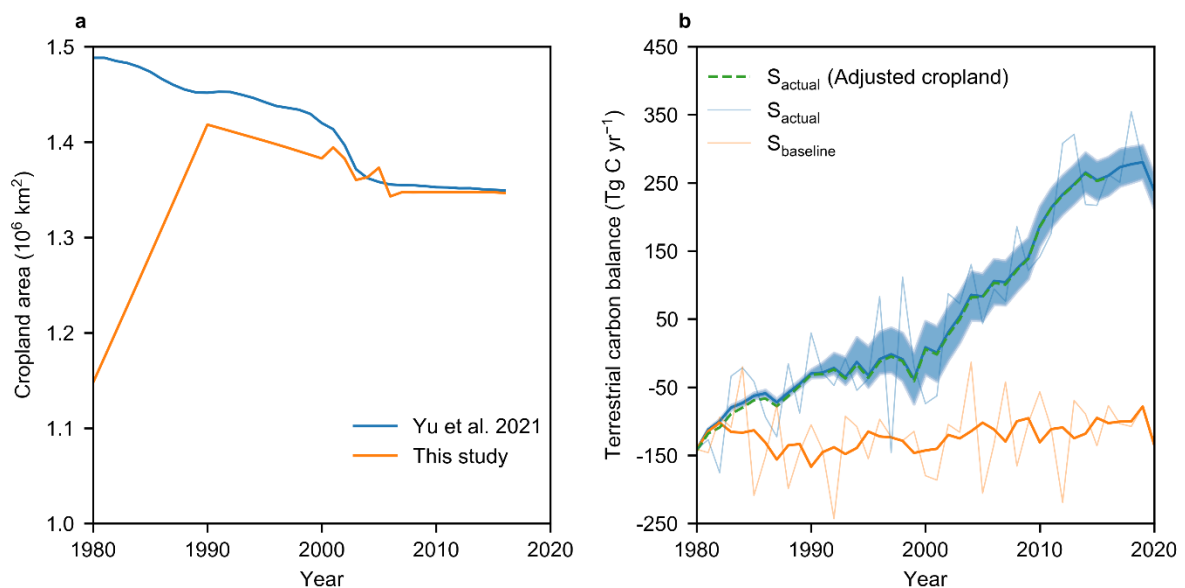


Fig. R3 (a copy of Supplementary Fig. 23) Difference in national cropland area between our study and Yu et al.⁵ and its influence on the simulated terrestrial carbon balance in China. (a) Comparing national cropland area in this study and that from Yu et al.⁵ for 1980–

2020. **(b)** The simulated terrestrial carbon balance for China over 1980–2020 using this study’s national cropland distribution (solid blue line) and after adjusting it to match that from Yu et al.⁵ (dashed green line).

In our reconstruction of the PFT map time series, annual changes in forest area and grazed grassland area were well constrained by information from the national forest inventory (for forest area), HYDE3.2 (for grazed grassland) and the National Grassland Monitoring Report (for areas of grazing exclusion). After changes in cropland area were additionally accounted for, changes in natural grassland were then derived as residuals (described in section 4.1 of Methods). Hence, using a new time series of cropland area mainly affects the national areas of natural grassland, as well as the spatial distribution of both land use types. As the annual maps of NBP per area for either cropland and natural grassland were available from our simulation, these NBP maps can be then combined with alternative spatial maps of both land use types (cropland and natural grassland) to estimate the simulated NBP when cropland areas and their spatial distribution were adjusted to match Yu et al.⁵. Such adjustment mainly influences the simulated NBP in the S_{actual} and S_{baseline} simulations, but the difference in NBP between these two simulations is unlikely to be affected, because any NBP effects of changes in cropland and natural grassland areas will be filtered out when taking the difference between the two simulations.

We first compared cropland areas at provincial scales between our study and Yu et al.⁵, before performing any adjustment at the grid cell level to make our spatial distribution of cropland area match that of Yu et al.⁵ (Figs. R4 and R5). The results show that provincial cropland areas for 2001–2016 in our study agree well with those given by Yu et al.⁵ ($R^2 = 0.99$, $p < 0.01$, Slope = 0.996, Fig. R5a), suggesting that cropland areas on provincial scales were highly robust in our study.

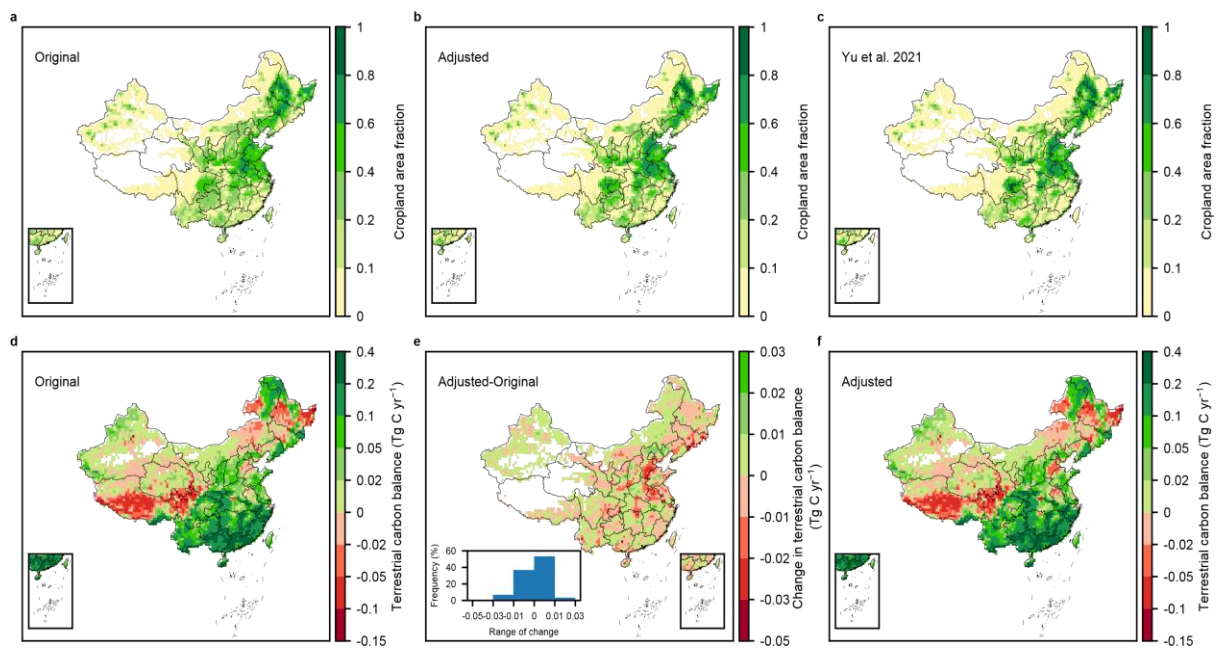


Fig. R4 (a copy of Supplementary Fig. 14) Spatial differences in cropland area between our study and Yu et al.⁵ and their impact on simulated terrestrial carbon balance in China during 2001-2016. **a–c**, Comparing spatial distribution of cropland area (as a percentage of grid cell land area) between our study (**a**), after adjustment to match Yu et al.⁵ (**b**), and Yu et al.⁵ (**c**). **d–f**, The spatial distribution of the terrestrial carbon balance using the original cropland distribution simulated in this study (**d**), the corresponding change in the terrestrial carbon balance due to spatial adjustment of cropland (**e**), and the terrestrial carbon balance adjusted for cropland distribution according to Yu et al.⁵ (**f**).

Nonetheless, at the grid cell scale, our spatial distribution of cropland does still differ from Yu et al.⁵ To examine the impact of such a difference on the spatial distribution of the simulated terrestrial carbon balance, we made further adjustments in the spatial distribution of cropland to match it as closely as possible to Yu et al.⁵ (Fig. R4b and R4c). More specifically, we first attempted to adjust the cropland area for each grid cell for each year of 2001–2016 to match exactly the value given by Yu et al.⁵, making corresponding changes in natural grassland area while maintaining the areas of forest and grazed grassland unchanged. When this is not possible – for example, if the required increase in cropland area exceeds the current area of natural grassland – then the expansion in cropland area is set as the current area of natural grassland (i.e., the maximum allowable increase given that the areas of all land cover types cannot exceed the area of the grid cell), and the remaining unrealized increase is allocated to neighboring grid cells in which there is still natural grassland available to accommodate the needed change. Such spatial adjustment further enhanced the agreement in the provincial cropland area between our study and Yu et al.⁵ ($R^2 = 1.00$, $p < 0.01$, Slope = 1.000, Fig. R5b), leading to almost identical provincial cropland areas.

The adjustment in cropland area at the grid-cell level was made by displacing the natural grassland area. We then combined the simulated annual NBP maps for cropland and natural grassland per area with the changes in the spatial distribution of these two land cover maps to derive the corresponding change in terrestrial carbon balance caused by the spatial adjustment described above (Fig. R4e). This change was then added to the originally simulated spatial distribution of NBP (Fig. R4d) to obtain an adjusted NBP spatial distribution map (Fig. R4f). We found that 90% of the grid cells have an absolute error of $< 0.01 \text{ Tg C yr}^{-1}$, suggesting that, overall, the influence of the error in the spatial distribution of cropland on the simulated spatial distribution of NBP was small. On the national scale, adjusting the cropland distribution to match that of Yu et al.⁵ resulted in China's terrestrial carbon balance being on average 2.2 Tg C yr^{-1} smaller for 2001–2016: a small difference compared to the original value of $149.4 \text{ Tg C yr}^{-1}$.

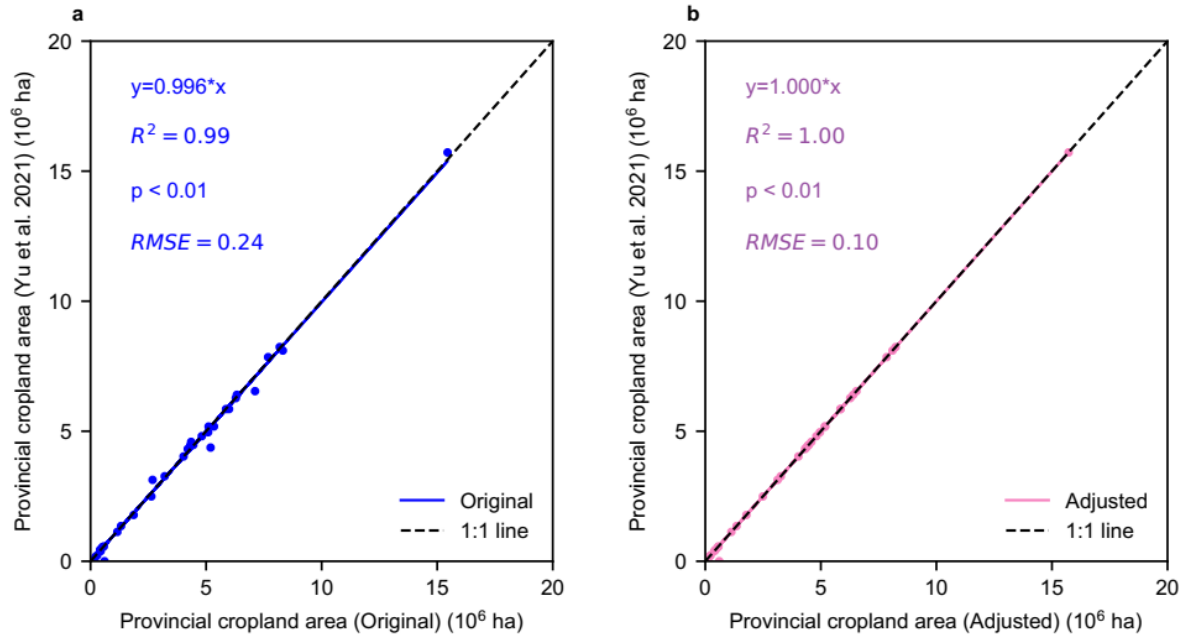


Fig. R5 (a copy of Supplementary Fig. 24) Comparing provincial cropland areas averaged over 2001–2016 between our study and Yu et al.⁵. The comparison is made between our study (i.e., the original cropland distribution) and Yu et al. (a), and after adjusting our original cropland map to match Yu et al.⁵ (i.e., adjusted) and Yu et al.⁵ (b).

Next, we applied the spatial adjustment method described above to adjust the cropland area and the simulated NBP for 1980–2000. Adjusting the spatial distribution of cropland rendered the simulated national NBP consistently smaller over 1980–2016 (Fig. R3b), by an amount ranging from -9.3 to -0.7 Tg C yr^{-1} for different years, with an average value of -3.5 Tg C yr^{-1} . For 1980–1989, when the difference in the decadal national cropland area between our study and Yu et al.⁵ reaches a maximum value of $0.21 \times 10^6 \text{ km}^2$ (the average value of the difference over 1980–1989), adjusting the cropland spatial distribution resulted in the simulated national NBP being smaller by 6.1 Tg C yr^{-1} (ranging from -9.3 Tg C yr^{-1} to -3.2 Tg C yr^{-1}), which is 8.7% of the original NBP over this decade (Fig. R3b). Moreover, the changes in simulated NBP due to cropland distribution adjustment remain within the uncertainty range of the originally estimated NBP over most time of the period of 1980–2016, except for the initial years of 1980–1988. However, the uncertainties in the originally simulated NBP for the initial years of 1980–2020 might be underestimated, because we assigned a relative uncertainty on the annual growth of forest areas rather than the existing forest area (the uncertainties in other land use types were handled in a similar way), which results in a small NBP uncertainty for the initial years of 1980–2020 given the small areas of forest growth during that time.

In summary, we explored the impacts of the simulated national terrestrial carbon balance and its spatial distribution by using the cropland dataset of Yu et al.⁵, through a simple approach of making spatial adjustment in combination with simulated NBP for cropland and natural grassland, rather than performing new simulations by natively incorporating the dataset of Yu et al.⁵

in the PFT map time series. The main reason for adopting this approach was to save the intensive computation demand of performing new simulations, because adopting the cropland distribution dataset of Yu et al.⁵ in a native way in our simulations requires all simulations, including the PFT map time series, to be completely re-performed. In general, we think this spatial adjustment method is sufficient for our purpose. However, if the referee deems it necessary to perform new simulations, we can do that.

Finally, the methods and results presented above, including Figs. R3–R5, have been incorporated in detail as Supplementary Discussion 1 and Supplementary Figs 23, 14 and 24. These results have also been summarized in the main text (lines 316–328) due to the length limit of the main text.

[Comment 6] Correct the duplicate references (15 and 38).

[Response 6] We apologize for this error. We have corrected the references following the referee's suggestion.

Reviewer #3 (Remarks to the Author):

[Comment 7] The study examines the impact of changes in land management policies on China's terrestrial carbon balance and assesses the contribution of ecological restoration policies to the global and regional carbon cycle since 1980. The study provides new perspectives for understanding the impact of land management policies on the carbon cycle, and the findings highlight the importance of achieving carbon neutrality targets through active land management. Here are some suggestions that could improve the paper.

[Response 7] We appreciate the referee's efforts in reviewing our paper and the overall positive comments. Please find below our point-by-point responses to your comments.

[Comment 8] Lines 78-80 Most management activities, including forest management, grassland grazing and fire management, were ignored in the majority of DGVMs used for large-scale assessments of carbon budgets. Only one example is given here, and others should be added to support it.

[Response 8] Reference 3 (GCP Global Carbon Budget 2022) cited in the original lines 78–80 included 16 state-of-the-art DGVMs and therefore constitutes an overview of the representation of land management in current DGVMs. Following the referee's suggestion, information on the representation of forest demography, grassland grazing and litter raking in these DGVMs has been provided in the revised manuscript (lines 78–81) as: *“For example, out of a total of 16 DGVMs used in the Global Carbon Project (GCP) 2022 global carbon budget assessment, only 2 included forest demography and only 6 grassland grazing¹³. None of these DGVMs included active fire suppression or litter raking¹³.”*.

[**Comment 9**] Lines 130-131 No-policy scenarios start at different times for different land management policies. "The no-policy scenario assumes that all timber demand has been met by domestic production since 1981" means that the Reduced Timber Harvest no-policy scenarios start in 1981? But the "Reduced Timber Harvest" no-policy scenarios in Figure 1c start in 1990?

[**Response 9**] We are sorry for overlooking this. The starting years of the ‘no-policy’ scenarios for various land management types considered in our study are shown in Fig. 1. For timber harvest, the most pronounced surge in China’s timber net import did indeed start in 1998, the starting year of the Natural Forest Protection Program. However, the availability of data for China’s net timber import started in 1990 and the import amount before 1998 was relatively low. Therefore, as a rough approximation, we have assumed that under the ‘no-policy’ scenario, all timber demand would have been met by domestic production since 1990. This has been explained in the revised manuscript (lines 134–137) as: *“Given that data on China’s net timber import is only available from 1990 and the imported amount before 1998 was relatively low, for the ‘no-policy’ scenario, we make the rough approximation that all timber demand since 1990 would have been met by domestic production (Fig. 1c).”*

[**Comment 10**] The land management policies in the second and third parts of the results do not correspond exactly to the results in the first part. Reduced wood extraction, including reductions in both timber harvesting and fuelwood extraction. The above explanations should be given in the methods or in the notes to Figures 2 and 3.

[**Response 10**] Following the referee’s helpful suggestion, in the first part of the “Results” section, we have combined the two subsections “Reduced timber harvest” and “Reduced fuelwood extraction” into a single subsection: “Reduced wood extraction”. The revisions are in lines 124–125 of the revised manuscript: *“**Reduced wood extraction.** Human wood extraction considered in this study consists of timber harvest for industrial and household use, and rural fuelwood extraction.”* The same has also been noted in the Methods (line 584).

We have also inserted the following text in the captions of Figs. 1–4:

- (1) in the caption of Fig. 1: *“Timber harvest and rural fuelwood extraction were further combined as wood extraction.”*
- (2) in the caption of Fig. 2: *“Reduced wood extraction includes both timber harvest and fuelwood extraction.”*
- (3) in the caption of Fig. 3: *“reduced wood extraction, including both timber harvest and fuelwood extraction (g)”*
- (4) in the caption of Fig. 4: *“Reduced wood extraction includes both timber harvest and fuelwood extraction.”*

[**Comment 11**] The colors in Figure 2c are so similar that it is difficult to distinguish between “grassland grazing exclusion” and “forest fire suppression”.

[Response 11] Thank you for pointing out this issue. We have adjusted the colour scheme to provide a better visual distinction between the two categories of "Grassland grazing exclusion" and "Forest fire suppression" and changed the caption of Fig. 2c to “*Temporal patterns of the contributions of different driving factors stacked on top of each other (with individual contributions separately shown in Supplementary Fig. 5).*” We have also added Supplementary Fig. 5 to show the temporal pattern of the individual contributions of the different factors.

[Comment 12] The extent of the Middle, South and Southeast of the seven regions on the map in Figure 4 is not clearly labelled.

[Response 12] Thank you for highlighting this issue. We have revised the map by adding clearer boundaries to these regions to improve the readability.

[Comment 13] This study should provide new insights into modelling and parameter selection by illustrating uncertainties and implications.

[Response 13] Following the referee’s suggestion, the last section of the paper, ‘**Uncertainties and implications**’, has been substantially expanded to enhance the discussion of the uncertainties of our results and the associated implications. The newly added text consists of about 1200 words, in lines 357–375, 391–395, 401–447 and 450–463.

Below we provide a brief summary of the revisions:

- (1) The simulated sensitivities of the CO₂ fertilization effect on vegetation biomass and NPP by the ORCHIDEE model have been compared with field observations to discuss the quantified CO₂ effects on China’s terrestrial carbon sink found in this study, with a link to the need to explicitly represent the nitrogen cycle in future model development (lines 357–375).
- (2) Linked to ORCHIDEE’s capability to represent forest demography, the simulated changes in forest age structure and the associated implications on China’s current and future forest carbon sinks have been discussed in the context of existing studies (lines 391–395 and 401–412).
- (3) The quantified contributions of reduced wood extraction to China’s terrestrial carbon sink, linked to data availability, have been compared with other studies to aid understanding of the uncertainties in our results (lines 413–428).
- (4) The reductions in forest burned area due to fire suppression and their contributions to China’s terrestrial carbon sink have been discussed in view of similar reductions in the USA—the only country, to the best of our knowledge, for which detailed quantification of the carbon effects of fire management are available (lines 429–441).
- (5) Last, future perspectives on China’s terrestrial carbon sink are provided in view of past land management and forest age structure. General perspectives on how land management could further enhance the land carbon sink, the risk of carbon storage stability in view of potential increasing disturbances with future climate change, and the associated need for future model development, have been broadly discussed (lines 446–447 and 450–463). We believe these are part of the important implications of our study.

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REVIEWERS' COMMENTS

Reviewer #2 (Remarks to the Author):

The manuscript has been greatly improved and I have no more comments.