Increased forest coverage will induce more carbon fixation in vegetation than in soil during 2015–2060 in China based on CMIP6

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Abstract

As components of terrestrial carbon sinks, vegetation and soil carbon pools are important for offsetting CO₂ emissions. However, differences in their carbon sequestration capacities and their responses to global change in the future are poorly understood. This study assessed the changes in vegetation and soil carbon and their ratios and drivers under the SSP126 scenario from 2015 to 2060, using Coupled Model Intercomparison Project phase 6 simulations in China, a major carbon sink region in global terrestrial ecosystems. The content of vegetation carbon (29 ± 1 PgC) was observed to be lower than that of soil carbon (113 ± 23 PgC), and the ratio of vegetation to soil carbon was the highest in the subtropical-tropical monsoon climatic region (0.55 ± 0.12). Moreover, the total stock of vegetation and soil carbon increased by 10 ± 1 PgC during the study period, and the increase in vegetation carbon was 4.31 times that of soil carbon, because the responses of vegetation carbon stocks to increased forest coverage and atmospheric CO₂ were greater than that of soil carbon stocks, especially in the subtropical-tropical and temperate monsoonal climatic regions. However, bare land encroachment on grasslands reduced their increments in the temperate monsoonal and high-cold Tibetan Plateau climatic regions. Furthermore, compared with SSP245 and SSP585 scenarios, vegetation and soil carbon sinks can offset a greater amount of carbon emissions in 2060 under the SSP126 scenario, accounting for 53% of all carbon emissions, offsetting 60%–79% of carbon emissions from China under its policy of increasing forest coverage. The study revealed the important role of afforestation in increasing ecosystem carbon stocks, additionally, grassland conservation and deep reductions in carbon emissions cannot be ignored in the future. This study provides a basis for determining the response of vegetation and soil carbon to environmental factors and the realization of net-zero emissions globally.

1. Introduction

Terrestrial ecosystems absorb approximately 31% of total anthropogenic carbon emissions annually (Friedlingstein et al 2020). Therefore, enhancing carbon sinks in these ecosystems is necessary to achieve net-zero emissions and curb global warming (Schimel et al 2015, Windisch et al 2021). Changes in vegetation and soil carbon stocks are important carbon sinks (Friedlingstein et al 2020), and several studies have investigated their combined carbon sequestration benefits and roles in offsetting carbon emissions...
that influence variations in vegetation and soil carbon stocks in the future.

As a region with plans for extensive afforestation (Chen et al 2019a), China has experienced a substantial increase in vegetation and soil carbon stocks in recent years. Ecological restoration projects, such as the national project (Lu et al 2018), and those in the northeast (Hong et al 2020), southwest (Tong et al 2018), and semi-arid and semi-humid (Niu et al 2019) areas, have made substantial contributions to the global carbon sink and absorption of CO₂ emissions (Piao et al 2009, Wang et al 2020, 2022). Recently, estimations were made of future ecosystem carbon sinks in all of China (Huang et al 2022) and only forests (Cai et al 2022). However, the assessment of these carbon sinks only relied on simple empirical equations related to forest age or atmospheric CO₂ concentration, and the responses of changes in vegetation and soil carbon stocks in China to environmental factors remain poorly understood.

Based on an ensemble average of nine ESM simulations under the SSP126 scenario, this study aimed to evaluate the magnitude and ratio of vegetation and soil carbon stocks (a) and carbon sinks (b) and their variations across different climatic regions. The main contributors (c) to changes in vegetation and soil carbon stocks were also analyzed in China during 2015–2060. This study not only provides a knowledge base for clarifying the dynamic changes in vegetation and soil carbon stocks, and their potential responses to environmental factors under a warming of below 2 °C scenario but also provides a basis for enhancing ecosystem carbon sinks and achieving carbon neutrality.

2. Data and methods

2.1. Data

2.1.1. Carbon density and carbon flux data

Monthly vegetation and soil carbon densities (cVeg and cSoil) during 2015–2060 from nine publicly accessible ESMs with climate change and land use change modules (i.e. ACCESS-ESM1-5, BCC-CSM2-MR, CanESM5, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, IPSL-CM6A-LR, MPI-ESM1-2-LR, and NorESM2-LM) participating in CMIP6 were obtained from https://esgf-node.llnl.gov/search/cmip6/ under SSP126 scenario, and the same variant label ‘r1i1p1f1’ was used for all data. Moreover, the historical vegetation and soil carbon data were also downloaded during 1980–2009 of these ESMs for comparison with previous studies. Additionally, total anthropogenic CO₂ emission data were used for the auxiliary analysis of the mitigation capacity of vegetation and soil to achieve carbon neutrality under different scenarios (SSP126, SSP245, and SSP585), which was summed by the anthropogenic CO₂ emissions from all sectors, including agriculture; energy; industrial; transportation; residential, commercial,
other; solvents production and application; waste; international shipping; negative CO₂ emissions, and was obtained from https://esgf-node.llnl.gov/search/input4mips/.

Although the models considered different soil depths (table 1), the resulting analysis of the dynamics of soil carbon stocks was only slightly impacted, and most of these dynamics occurred in the surface layer considering the typically stable deep soil (Hou et al 2019). Factors considered by the models were climate and land use changes. However, not all models had nitrogen cycle modules (table 1); therefore, nitrogen deposition data were excluded from the attribution analysis.

2.1.2. Environment variables
To analyze the factors influencing carbon stock changes during 2015–2060, monthly climate data (including temperature and precipitation) of nine ESMs under the SSP126 scenario were downloaded from https://esgf-node.llnl.gov/search/cmip6. Annual atmospheric CO₂ data under the SSP126 scenario were obtained from the website of forcing datasets needed for Model Intercomparison Projects in CMIP6 (https://esgf-node.llnl.gov/search/input4mips). Additionally, the percentage coverages (%) of different land types (including forests, croplands, farmland, cities, and bare land) during 2015–2060 under the SSP126 scenario were obtained from the LUH2 (Hurtt et al 2020), which was used as the land use forcing for CMIP6.

All data were aggregated to annual values, resampled to 0.5° × 0.5°, and clipped using China’s border map.

2.2. Method
2.2.1. Calculation of carbon stocks
The carbon stocks of vegetation (cVeg) and soil (cSoil) in China were calculated according to the weighted sum of their carbon density and area and subsequently, converted to a unit of ‘PgC’ (1 PgC = 10¹⁵ gC). Additionally, equation (1) was also used to calculate the carbon stocks in four climatic regions (He et al 2019; supplementary figure 1): temperate continental, temperate monsoonal, high-cold Tibetan Plateau, and subtropical-tropical monsoonal:

\[ C_{\text{stock}} = \sum_{i=1}^{N} C_{\text{density}}^i \times A_i \times 10^{-15} \]  

where \( C_{\text{stock}} \) is the carbon stock (cVeg or cSoil; PgC) in China or the four climatic regions, \( C_{\text{density}}^i \) and \( A_i \) are the carbon density (gC m⁻²) and area (m²) of pixel \( i \), respectively.

2.2.2. Carbon sink ratios of vegetation to soil
Vegetation to soil carbon stock ratios (\( \text{Ratio}_{\text{stock}} \); equation (2)) were calculated for China and each climate region to compare variations. For further comparisons of the carbon sequestration capacities of vegetation and soil during the study period, carbon sink ratios (\( \text{Ratio}_{\text{sink}} \); equation (3)) were estimated:

\[ \text{Ratio}_{\text{stock}} = \frac{c\text{Veg}}{c\text{Soil}} \]  

\[ \text{Ratio}_{\text{sink}} = \frac{c\text{Veg slope}}{c\text{Soil slope}} \]  

where \( \text{Ratio}_{\text{stock}} \) and \( \text{Ratio}_{\text{sink}} \) are the ratios of vegetation to soil carbon stocks and carbon sinks, respectively, and \( c\text{Veg} \) slope and \( c\text{Soil} \) slope are the temporal trends of vegetation and soil carbon stocks from 2015 to 2060.

2.2.3. Effect of environmental factors on carbon stock modifications
Before conducting attribution analysis, the LUH2 dataset was reclassified into the land use types (forest, grassland, cropland, city, and bare land) analyzed in this paper according to the classification scheme of supplementary table 1. The average coverage (%) of LUH2 land use has relatively small differences with MODIS observations, and forests increased and grasslands declined from 2015 to 2020, which is consistent with MODIS (supplementary table 2). The annual changes in the average coverage (%) of each land use type in China and the four climatic regions were observed (supplementary figure 2). The results showed that the main land use change characteristics in China and the four climatic regions were: conversion of grasslands to forests and bare lands (occurring in China and the high-cold Tibetan Plateau climatic region), conversion of grasslands to forests (occurring in the subtropical-tropical monsoonal climatic region), conversion of grasslands to bare lands (occurring in the temperate continental climatic region), and conversion of grasslands and croplands to forests and bare lands (occurring in the temperate monsoonal climatic region) under the SSP126 scenario (supplementary figure 2).

Consequently, to avoid collinearity, the percentage coverages of target land use type (i.e. forests or bare lands) (supplementary figure 2(f)) were used to represent land use change factors (\( X_{\text{LC}k}, \ k = 1 \) or 2) in the attribution analysis. A map of their changes from 2015 to 2060 was shown in supplementary figure 3.

Major contributors to carbon stock changes in China under the SSP126 scenario were identified using equation (4) (He et al 2019) to calculate the contribution (\( C_i \)) of precipitation (\( X_{\text{PRE}} \)), temperature (\( X_{\text{TEM}} \)), \( \text{CO}_2 \) (\( X_{\text{CO}_2} \)), and land use change factors (\( X_{\text{LC}k} \)) on the trend of carbon stocks (\( Y \)), expressed as the rate of the product of the standardized environmental factors (\( X \)) and its regression
Table 1. Introduction of CMIP6 ESMs analyzed in this study, including the number of cells (resolution), land sub-models, soil layers and depth, and whether climate change, land use change, and nitrogen cycling processes were considered.

| Models           | Number of cells | Land sub-model | Soil pools or layers (no bedrock) | Soil depth (no bedrock) | Climate change | Land use change | Nitrogen cycle | References                          |
|------------------|-----------------|----------------|-----------------------------------|-------------------------|----------------|----------------|---------------|-------------------------------------|
| ACCESS-ESM1-5    | 145 × 192       | CABLE2.4       | Microbial, slow, passive Surface structural material; soil structural material; soil microbes; surface microbes; surface metabolic material; slow SOM; passive SOM | Unknown                | √              | √              |               | Ziehn et al (2020)                  |
| BCC-CSM2-MR      | 160 × 320       | BCC-AVIM2      | Unknown                           | √                       | √              |                 |               | Wu et al (2019), (2021)             |
| CanESM5          | 64 × 128        | CLASS-CTEM     | Three permeable soil layers 5 (0.4 m)–20 (8 m) layers | 4.1 m                  | √              | √              |               | Lawrence et al (2019)               |
| CESM2-WACCM      | 192 × 288       | CLM5           | Spatially variable soil depth (0.4–8.5 m) | 3.8 m                  | √              | √              |               | Cherchi et al (2019), Oleson et al (2013) |
| CMCC-CM2-SR5     | 192 × 288       | CLM4.5         | 10 layers                         | 3.8 m                  | √              | √              |               | Cherchi et al (2019), Oleson et al (2013) |
| CMCC-ESM2        | 192 × 288       | CLM4.5         | 10 layers                         | 3.8 m                  | √              | √              |               | Cherchi et al (2019), Oleson et al (2013) |
| IPSL-CM6A-LR     | 143 × 144       | ORCHIDEE       | 11 layers                         | 2 m                    | √              | √              |               | Boucher et al (2020)                |
| MPI-ESM1-2-LR    | 96 × 192        | JSBACH 3.20    | 4 layers                          | 4.1 m                  | √              | √              |               | Hagemann and Stacke (2015), Mauritsen et al (2019) |
| NorESM2-LM       | 96 × 144        | CLM5           | 5 (0.4 m)–20 (8 m) layers         | Spatially variable soil depth (0.4–8.5 m) | √              | √              |               | Seland et al (2020)                |

a The ESMs participating in CMIP6 have a strong ability to simulate the ecosystem carbon cycle. To analyze the impact of land use change and climate change on vegetation and soil carbon storage, we have chosen the nine ESMs that included climate change and land use change processes and had publicly available data on vegetation and soil carbon densities and climate variables during 2015–2060.

b The recorded soil depths were measured from the soil surface to the upper boundary of the bedrock. Soil depth information was not reported for ACCESS-ESM1-5 and BCC-CSM2-MR models, and the soils in these models were divided into several pools based on turnover rates.
coefficient \( b_i \) in the multiple linear regression equation (5):

\[
C_i = \frac{d (b_i \times X_i)}{dt}, \quad i = \text{PRE, TEM, CO}_2, \text{LC}_k, \\
k = 1 \text{ or } 2
\]

where \( t \) is the study period, i.e. 2015–2060, \( d/dt \) is the time derivative, \( X_i \) are the annual standardized values of environmental factors, i.e. precipitation \((X_{\text{PRE}})\), air temperature \((X_{\text{TEM}})\), atmospheric \ CO\(_2\) \( (X_{\text{CO}_2})\), and land use change factors \((X_{\text{LC}})\) in China or the four climatic regions during 2015–2060 on average. The land use change factors represent the percentage coverages (%) of different land use types in different regions: forest and bare land in China and the temperate monsoonal and high-cold Tibetan Plateau climatic regions, forest in the subtropical-tropical monsoonal climatic region, and bare land in the temperate continental climatic region (supplementary figure 2(f)). Other environmental factors have historical simulations consistent with observations (supplementary figure 4), and their annual changes during 2015–2060 were shown in supplementary figure 5. \( b_i \) represents the response coefficient of carbon stocks to each factor, which was calculated using equation (5):

\[
Y = b_0 + \sum b_i X_i + \varepsilon, \quad i = \text{PRE, TEM, CO}_2, \text{LC}_k, \\
k = 1 \text{ or } 2
\]

where \( b_0 \) is a constant and \( \varepsilon \) is the residual. \( Y \) represents the carbon stocks. \( b_{\text{PRE}}, b_{\text{TEM}}, b_{\text{CO}_2}, \text{and } b_{\text{LC}} \) are the responses of carbon stocks to standardized annual precipitation, annual average temperature, atmospheric \ CO\(_2\), and land use change factors, respectively, during the study period.

2.2.4. Uncertainty between simulations of ESMs

All calculations were performed not only in the ensemble average of multiple ESMs simulations, but also in each ESM simulation. Furthermore, we used the standard error (SE; equation (6); McHugh 2008) of the statistical results of the nine ESMs to characterize the uncertainty between multi-model simulations:

\[
\text{SE} = \frac{\text{SD}}{\sqrt{n}}
\]

where SD and \( n \) are the standard deviation and count of a set of numbers, respectively.

3. Results

3.1. Spatial patterns and ratios of vegetation and soil carbon stocks in China from 2015 to 2060

The vegetation carbon stock was lower than soil carbon stock in China for all pixels \( (\text{Ratio}_{\text{stock}} < 1; \) figures 1(a)–(c)), and the average vegetation carbon stock was 29 ± 1 PgC from 2015 to 2060, accounting for approximately 26 ± 6% of the soil carbon stock \( (113 ± 23 \text{ PgC}; \) figure 1(f)). Initially, the \( \text{Ratio}_{\text{stock}} \) decreased rapidly and then increased slightly with increasing latitude, whereas it first increased and then decreased with increasing longitude (figures 1(d) and (e)). The \( \text{Ratio}_{\text{stock}} \) values above 0.5 were mainly observed at 21–29° N (figure 1(d)).

The highest \( \text{Ratio}_{\text{stock}} \) were observed in the subtropical-tropical monsoonal \( (0.55 ± 0.12) \) and temperate monsoonal \( (0.21 ± 0.06) \) climatic regions, with high vegetation carbon stocks of 17 ± 1 PgC and 8 ± 1 PgC, respectively (figure 1(f)). However, in the high-cold Tibetan Plateau and temperate monsoonal climatic regions, carbon was mostly stored in the soil, and the ratio of vegetation to soil carbon was 0.11 ± 0.02 and 0.08 ± 0.02, respectively (figure 1(f)).

3.2. Vegetation and soil carbon trends and ratios in China from 2015 to 2060

Vegetation and soil carbon in China showed increasing trends from 2015 to 2060, with a total carbon sequestration of 10 ± 1 PgC (figure 2(a)). Specifically, the carbon sequestration rate of vegetation \( (0.19 ± 0.01 \text{ PgC yr}^{-1}) \) was approximately 4.31 times greater than that of soil \( (0.04 ± 0.01 \text{ PgC yr}^{-1}; \) figure 2(e)). The temperate monsoon climatic region’s \( \text{Ratio}_{\text{sink}} \) \( (9 ± 1) \) was the highest (figures 2(d) and (e)) among the climatic regions because the growth rate of vegetation carbon was relatively high \( (0.067 ± 0.006 \text{ PgC yr}^{-1}) \), while that of soil carbon was low \( (0.007 ± 0.003 \text{ PgC yr}^{-1}) \) (figures 2(b), (c) and (e)). The greatest increase in vegetation carbon stocks was observed in the subtropical-tropical monsoonal climatic region \( (0.097 ± 0.008 \text{ PgC yr}^{-1}) \), which was approximately 5.52 ± 2.05 times the soil carbon stock (figure 2(e)). Conversely, \( \text{Ratio}_{\text{sink}} \) was low in the high-cold Tibetan Plateau \( (1.66 ± 0.38) \) and temperate continental \( (1.04 ± 0.77) \) climatic regions, which presented relatively high soil carbon sequestration potential (figures 2(b), (c) and (e)).

3.3. Effects of environmental factors on vegetation and soil carbon stock variations in China from 2015 to 2060

This study also explored the impacts of environmental factors on the dynamics of vegetation and soil carbon stocks in China. Vegetation and soil carbon responded positively to temperature and precipitation (figures 3(a) and (b)), while their contributions to stocks were small owing to the low response coefficients (figures 3(a)–(d)). Compared with temperature and precipitation, major contributions to the increased vegetation and soil carbon stocks of China were observed from increased forest coverage during the study period, with a contribution of up to 81 ± 0.4% and 82 ± 3% in vegetation and soil, respectively (figures 3(c) and (d)). Carbon stocks were highly correlated with the normalized forest coverage (figures 3(a) and (b)), and
with increasing forest coverage, more carbon was stored in vegetation than in soil (figure 2(e)) due to a higher response coefficient of vegetation carbon (2.10 ± 0.28) than that of soil carbon (0.49 ± 0.15) (figures 3(a) and (b)). Moreover, the substantial increase in forest coverage (supplementary figure 2) promoted an expansion in vegetation carbon stocks in the subtropical-tropical monsoonal and temperate monsoonal climatic regions from 2015 to 2060 (figures 2(e) and 3(c), (d)).

Rising CO$_2$ concentrations were a secondary factor in the increase in China’s vegetation and soil carbon stocks, contributing 65 ± 1% and 60 ± 6%, respectively; presenting a similar response in the high-cold Tibetan Plateau climatic region, but playing a role as important as the forest in two monsoon climatic regions (figures 3(c) and (d)).

The increase in China’s vegetation and soil carbon was impacted by bare land expansion (response coefficients: −1.43 ± 0.53 and −0.30 ± 0.17; figures 3(a) and (b)) that encroached on grasslands in the temperate continental, high-cold Tibetan Plateau, and temperate monsoon climatic regions, contributing −55 ± 4% and −50 ± 12% to the increase in China’s vegetation and soil carbon, respectively (figures 3(c) and (d)).

4. Discussion

4.1. Magnitude of China’s vegetation and soil carbon stocks and sinks

The ensemble average of the CMIP6 simulations revealed that China’s vegetation and soil carbon stocks will increase from 2015 to 2060 under the SSP126 scenario, and the magnitude of vegetation and soil carbon sinks were approximately consistent among most ESMs of CMIP6 (supplementary table 3). Furthermore, the ensemble average of the vegetation carbon sink of the nine models in the 1990s (0.049 ± 0.009; table 2) was similar to that of the process-based model of Cao et al (2003) but lower than that of the Ground survey during the same
period (Fang et al. 2007, 2018). The soil carbon sink (table 2) was close to that of the inventory-satellite-based estimation and process-based models of Piao et al. (2009) in the same period. Moreover, the ratios (1.258 ± 0.585–1.443 ± 0.459) of vegetation to soil carbon sinks in China of CMIP6 during 1990–2010 were consistent with most studies (table 2, Piao et al. 2009, Jiang et al. 2016, Fang et al. 2018). Furthermore, the CMIP6 simulations revealed that the Ratio\textsubscript{sink} will increase to 2.344 ± 2.227 in 2015–2020 and 4.776 ± 2.300 in 2055–2060, indicating an enhancement in vegetation carbon sinks, with a magnitude of approximately 0.209 ± 0.031 Pg C yr\textsuperscript{−1} by 2060 (table 2). Additionally, the CMIP6-based vegetation and soil carbon sinks in China during 2015–2060 were lower than those reported by Huang et al. (2022) and Cai et al. (2022), which may be caused by the following reasons. On the one hand, several parameter-sparse empirical models do not take into account nutrient limitations and carbon losses caused by climate change, especially extreme climates, compared with ESMs of CMIP6. On the other hand, carbon sinks are generally lower under the SSP126 scenario with low forcing used in this study than under the SSP245 and SSP585 scenarios with high forcing (Cai et al. 2022, Huang et al. 2022).

However, China’s vegetation carbon stock in CMIP6 was higher than that in previous studies (table 3), especially in the ACCESS-ESM1-5 model (supplementary table 3), with magnitudes of 25 ± 2 Pg C during 1980s, 24 ± 2 Pg C during 1990s, and 25 ± 2 Pg C during 2000s (table 3), whereas that in the ground survey and process-based model was only 13–15 Pg C in previous decades (table 3, Li et al. 2004, Xu et al. 2018). Compared with vegetation, the soil carbon estimation from CMIP6 (around 111–112 Pg C) during 1980–2010 was relatively reasonable, although slightly higher than that in previous studies (75–90 Pg C, Xie et al. 2007, Tang et al. 2018), because the soil depth of ESMs in CMIP6 was greater than the 1 m depth commonly used in these studies (table 1). However, the uncertainty of soil carbon size among ESMs was large, for example, the China’s soil carbon in CMCC-CM2-SR5 or CMCC-ESM2 model was
Figure 3. Effects of environmental factors on variations in vegetation and soil carbon stocks across China's climatic regions from 2015 to 2060 under the SSP126 scenario. Standardized response coefficients of (a) vegetation and (b) soil carbon stocks to variations in precipitation (Pre), temperature (Tem), CO$_2$, forest coverage (Forest), and bare land coverage (Bare); contributions of these environmental factors to changes in (c) vegetation and (d) soil carbon stocks; (e) trends in the normalized environmental factors across climatic regions. The trends in the normalized factors are the slopes of standardized values of annual average environmental factors in China or the four climatic regions during 2015–2060 (supplementary figures 2 and 5). The error bars are the standard errors between the simulations of the nine earth system models. The map of the change in percent coverage (%) of forest (a) and bare land (b) from 2015 to 2060 was shown in supplementary figure 3.

seven times higher than that in the IPSL-CM6A-LR model (supplementary table 3). Conclusively, vegetation carbon sinks of the CMIP6 ESMs were higher than soil carbon sinks, and the ratio of vegetation to soil carbon sinks will continue to increase in the future, although estimates of vegetation carbon stocks were higher than previous studies over the same period. Therefore, the prior calibration of the carbon pool size using the uniformly standardized vegetation and soil carbon data from ground surveys is necessary before biogeochemical model simulation in China. Initial calibration can also improve the representation of the processes related to vegetation and soil carbon changes, such as turnover loss of carbon pool (Koven et al 2013, Wu et al 2019, Boucher et al 2020, Ziehn et al 2020).

4.2. Influencing factors of changes in China’s vegetation and soil carbon stocks in the future

Increases in China’s vegetation and soil carbon are mainly affected by the combined effects of increased forest coverage and CO$_2$ concentrations from 2015 to 2060 under the SSP126 scenario, with regional differences. Increased forest coverage will promote a greater increase in vegetation carbon stocks than that soil carbon stocks in the subtropical-tropical and temperate monsoonal climatic regions because of the difference in response coefficients to an increase in forest coverage. Similarly, a previous study reported that ecological restoration projects such as afforestation contributed more than half of the contribution to the enhancement of China’s carbon stocks in project areas (Lu et al 2018). Moreover, the two monsoonal climatic regions are appropriate for potential afforestation (Zhang et al 2021). CO$_2$ had an effect equivalent to forest coverage in two monsoonal climatic regions but has a weaker contribution in the high-cold Tibetan Plateau with a high soil carbon sequestration potential as indicated by the relatively low Ratio$_{sink}$. However, grassland encroachment by bare land will weaken the increases in vegetation and soil carbon stocks in the high-cold Tibetan Plateau and temperate monsoonal climatic regions, which has experienced significant grassland degradation over
Ground survey — 89.14 — — — Yu

Process-based scenarios, the contribution of vegetation and soil emissions under various scenarios to offset anthropogenic CO$_2$ emissions (0.61 PgC yr$^{-1}$; supplementary figure 12) was the greatest in 2060 under the SSP126 scenario (53%; figure 4(a)), and the total carbon sequestration rate of vegetation and soil was 0.33 ± 0.07 PgC yr$^{-1}$.

China’s actual forest coverage was 23.2% in 2020 (Central People’s Government of the People’s Republic of China 2021a), and the Chinese government has set a phased target to increase forest coverage (24.1% in 2025; 25% in 2030; and 26% in 2035) (National Development and orm Commission of the People's

4.3. Contribution of China’s vegetation and soil carbon sinks to offset anthropogenic CO$_2$ emissions under various scenarios

Compared with the SSP245 (23%) and SSP585 (6%) scenarios, the contribution of vegetation and soil to the absorption of anthropogenic CO$_2$ emissions (0.61 PgC yr$^{-1}$; supplementary figure 12) was the greatest in 2060 under the SSP126 scenario (53%; figure 4(a)), and the total carbon sequestration rate of vegetation and soil was 0.33 ± 0.07 PgC yr$^{-1}$.

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Table 2. Comparisons with the magnitude of China’s vegetation and soil carbon sinks in previous studies.

| Methods | cVeg sink (PgC yr$^{-1}$) | cSoil sink (PgC yr$^{-1}$) | (cVeg sink + cSoil sink) or NEP | Ratio$_{sink}$ | Period | References |
|---------|---------------------------|---------------------------|--------------------------------|---------------|--------|------------|
| CMIP6 mean$^a$ | -0.150 ± 0.020 | 0.059 ± 0.015 | -0.094 ± 0.029 | -2.688 ± 1.339 | 1980–1989 | In this study |
| CMIP6 mean$^a$ | 0.049 ± 0.009 | 0.039 ± 0.014 | 0.089 ± 0.019 | 1.258 ± 0.585 | 1990–1999 | In this study |
| CMIP6 mean$^a$ | 0.048 ± 0.012 | 0.034 ± 0.013 | 0.082 ± 0.021 | 1.443 ± 0.459 | 2000–2009 | In this study |
| CMIP6 mean$^a$ | 0.081 ± 0.027 | 0.034 ± 0.014 | 0.115 ± 0.016 | 2.344 ± 2.227 | 2015–2020 | In this study |
| CMIP6 mean$^a$ | 0.209 ± 0.031 | 0.044 ± 0.010 | 0.252 ± 0.029 | 4.776 ± 2.300 | 2055–2060 | In this study |
| Inventory-satellite-based estimation | 0.105 | 0.075 | 0.180 | | | |

$c_{\text{Veg}}$ sink and $c_{\text{Soil}}$ sink denote vegetation and soil carbon sinks, respectively. Ratio$_{sink}$ is the ratio of vegetation to soil carbon sinks.

$^a$ In the rows of ‘CMIP6 mean’, the ensemble average ± standard error of the simulations between the nine ESMs is shown.

Table 3. Comparisons with the magnitude of China’s vegetation and soil carbon stocks in previous studies.

| Methods | cVeg (PgC) | cSoil (PgC) | cVeg + cSoil | Ratio$_{stock}$ | Period | References |
|---------|------------|------------|--------------|----------------|--------|------------|
| CMIP6 mean$^a$ | 25 ± 2 | 111 ± 22 | 136 ± 22 | 0.225 ± 0.050 | 1980–1989 | In this study |
| CMIP6 mean$^a$ | 24 ± 2 | 112 ± 22 | 136 ± 22 | 0.219 ± 0.048 | 1990–1999 | In this study |
| CMIP6 mean$^a$ | 25 ± 2 | 112 ± 22 | 137 ± 22 | 0.222 ± 0.047 | 2000–2009 | In this study |
| CMIP6 mean$^a$ | 26 ± 2 | 113 ± 22 | 138 ± 22 | 0.228 ± 0.047 | 2015–2020 | In this study |
| CMIP6 mean$^a$ | 33 ± 3 | 114 ± 22 | 147 ± 22 | 0.290 ± 0.060 | 2055–2060 | In this study |
| Ground survey | 14.29 | 74.98 | 89.27 | 0.191 | 2010–2015 | Tang et al (2018) |
| Ground survey | 14.60 | 84.55 | 99.15 | 0.173 | 2004–2014 | Xu et al (2018) |
| Process-based model | 13.33 | 82.65 | 95.98 | 0.161 | — | Li et al (2004) |
| Process-based model | 13.74 | 82.77 | 96.51 | 0.166 | 1981–2000 | Ji et al (2008) |
| Ground survey | — | 89.61 | — | — | Early 1980s | Xie et al (2007) |
| Ground survey | — | 89.14 | — | — | — | Yu et al (2007) |
| Ground survey | — | 69.10 | — | — | — | Yang et al (2007) |

$c_{\text{Veg}}$ and $c_{\text{Soil}}$ denote vegetation and soil carbon stocks, respectively. Ratio$_{stock}$ is the ratio of vegetation to soil carbon stocks.

$^a$ In the rows of ‘CMIP6 mean’, the ensemble average ± standard error of the simulations between the nine ESMs is shown.
Republic of China 2020, Central People's Government of the People's Republic of China 2021a, 2021b). Assuming that the response coefficients of vegetation and soil carbon stocks to individual factors remain unchanged (or changed within ±15%), the total carbon sink potential in China will reach 0.42 Pg C yr⁻¹ (0.37–0.48 Pg C yr⁻¹) in 2060 under the planned policies (figures 4(b) and (c)), which can absorb approximately 69% (60%–79%) of the projected anthropogenic CO₂ emissions from China in 2060. Note that we only provided a potential vegetation and soil carbon sink in the future using China's average forest coverage of the planned policies. However, the unknown spatial location of these afforestation sites may introduce uncertainty into the predicted carbon sinks. Based on the increased forest map of LUH2 (supplementary figure 3(a)), modeling carbon sinks in different spatial distribution schemes of afforestation is needed in future work, which may bring additional carbon sink increments over the SSP126 scenario.

Therefore, China’s ecosystem will generate a major carbon sink under China’s planned policies. This can contribute to the achievement of China’s carbon neutrality goal by 2060. Additionally, it provides strong support and broad implications for carbon sink improvement and net-zero emission achievement globally.

4.4. Uncertainty and limitations

There were large differences in China’s soil carbon between the nine ESMs analyzed in this study, with a maximum (227 Pg C) in the CMCC-ESM2 model and a minimum (32 Pg C) in the IPSL-CM6A-LR models, respectively (supplementary table 3), both of which deviated greatly from the results of the Ground survey (table 3). Although the magnitudes of China’s vegetation carbon were similar among most ESMs (BCC-CSM2-MR, CanESM5, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, NorESM2-LM, MPI-ESM1-2-LR), which was much higher than the results of the ground survey (table 3). Fortunately, the uncertainty of vegetation carbon sinks among the nine ESMs was small, and soil carbon sinks were similar among most ESMs (supplementary table 3). Moreover, changes in vegetation and soil carbon stocks were positive for all ESMs (supplementary table 3), which improved the confidence of our results. Nonetheless, the effects of the high uncertainty in the magnitude of soil carbon between the models and the relatively high vegetation carbon on the carbon cycle are unclear and need to be assessed in future work.

In this study, we used multiple linear regression to analyze the responses of vegetation and soil carbon to precipitation, air temperature, and CO₂, as well as land use change, but did not consider the nonlinear effects of multiple factors. Actually, the interaction between these factors has an impact on carbon dynamics (Garten et al 2009, Wolf et al 2011, Sui et al 2013). Although we have modeled differential responses across four climatic regions, this rough consideration of interactions between climatic conditions and environmental factors may not be sufficient. An in-depth analysis of the impact of nonlinear relationships between different factors on the carbon cycle is required in the future.
5. Conclusion

Changes in vegetation and soil carbon stocks and their ratios and drivers in China were assessed under the SSP126 scenario from 2015 to 2060 using the ensemble average of simulations from nine ESMs in CMIP6. Results presented a lower vegetation carbon stock than soil carbon stock, with the Ratio$_{soil}$ being high in the southeast and low in the northwest. In contrast, vegetation carbon increased more than soil carbon during the period, with the highest Ratio$_{veg}$ in subtropical-tropical and temperate monsoonal climatic regions mainly because of increased forest coverage and CO$_2$ concentrations. Conversely, Ratio$_{soil}$ was low in the other two climatic regions. Moreover, bare land encroachment on grassland decreased the vegetation and soil carbon stocks. Additionally, under the SSP126 scenario with deep reductions in CO$_2$ emissions, the vegetation and soil carbon sinks will show an increasing trend and absorb the most carbon emissions in 2060, when compared with the SSP245 and SSP585 scenarios, at approximately half of the total anthropogenic carbon emissions. Exceptionally, under the afforestation scenario planned by China’s policies, vegetation, soil carbon sinks may offset 69% of carbon emissions. Therefore, afforestation in monsoonal regions and the protection of grasslands are recommended to improve carbon sinks, and deep reductions in fossil fuel emissions are also necessary, providing a basis for adjusting the response of vegetation and soil carbon stocks to environmental factors and achieving net-zero emissions.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/search/cmip6/, https://esgf-node.llnl.gov/search/input4mips/, and https://luh.umd.edu/data.shtml.

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References

Aparicio S, Carvalhais N and Seixas J 2015 Climate change impacts on the vegetation carbon cycle of the Iberian Peninsula—intercomparison of CMIP5 results J. Geophys. Res. Biogeosci. 120 641–60

Baccini A, Walker W, Carvalho L, Farina M, Sulla-Menashe D and Houghton R A 2017 Tropical forests are a net carbon source based on aboveground measurements of gain and loss Science 358 230–4

Bardgett R D et al 2021 Combating global grassland degradation Nat. Rev. Earth Environ. 2 720–35

Boucher O et al 2020 Presentation and evaluation of the IPSL-CM6A-LR climate model J. Adv. Model. Earth Syst. 12 e2019MS002010

Cai W et al 2022 Carbon sequestration of Chinese forests from 2010 to 2060: spatiotemporal dynamics and its regulatory strategies Sci. Bull. 67 836–43

Cao M K, Prince S D, Li K R, Tao B, Small J and Shao X M 2003 Response of terrestrial carbon uptake to climate interannual variability in China Glob. Change Biol. 9 536–46

Central People’s Government of the People’s Republic of China 2021a Fourteenth Five-Year Plan for National Economic and Social Development of the People’s Republic of China and the outline of long-term goals for 2035 (available at: www.gov.cn/xinwen/2021-03/13/content_5592681.htm)

Central People’s Government of the People’s Republic of China 2021b Carbon peak action plan by 2030 (available at: www.gov.cn/zhuanti/2021-10/content_5644984.htm)

Chen C et al 2019a China and India lead in greening of the world through land-use management Nat. Sustain. 2 122–9

Chen J M, Ju W M, Ciais P, Viovy N, Liu R G, Liu Y and Lu X H 2019b Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink Nat. Commun. 10 4259

Cherchi A et al 2019 Global mean climate and main patterns of variability in the CMCC–CM2 coupled model J. Adv. Model. Earth Syst. 11 185–209

Dusenge M E, Duarte A G and Way D A 2019 Plant carbon metabolism and climate change: elevated CO$_2$ and temperature impacts on photosynthesis, photosrespiration and respiration New Phytol. 221 32–49

Fang J Y, Guo Z D, Piao S L and Chen A P 2007 Terrestrial vegetation carbon sinks in China, 1981–2000 Sci. China-Earth Sc. 50 1341–50

Fang J Y, Yu G R, Liu L L, Hu S J and Chapin F S 2018 Climate change, human impacts, and carbon sequestration in China introduction Proc. Natl. Acad. Sci. USA 115 4013–20

Feng Y et al 2022 Doubling of annual forest carbon loss over the tropics during the early twenty-first century Nat. Sustain. 5 444–51

Friedlingstein P et al 2020 Global Carbon Budget 2020 Earth Syst. Sci. Data 12 3269–340

Garten C T, Classen A T and Norby R J 2009 Soil moisture surpluses elevated CO$_2$ and temperature as a control on soil carbon dynamics in a multi-factor climate change experiment Plant Soil 319 85–94

Hagemann S and Stacke T 2015 Impact of the soil hydrology scheme on simulated soil moisture memory Clim. Dyn. 44 1731–50

He H L et al 2019 Altered trends in carbon uptake in China’s terrestrial ecosystems under the enhanced summer monsoon and warming hiatus Natl Sci. Rev. 6 505–14

Hong S B, Yin G, Piao S, Dybzinski R, Cong N, Li X, Wang K, Peñuelas J, Zeng H and Chen A E 2020 Divergent responses of soil organic carbon to afforestation Nat. Sustain. 3 694–700

Hou Y H, Chen Y, Chen X, He K Y and Zhu B 2019 Changes in soil organic matter stability with depth in two alpine ecosystems on the Tibetan Plateau Geoderma 351 153–62

Huang Y et al 2022 The role of China’s terrestrial carbon sequestration 2010–2060 in offsetting energy-related CO$_2$ emissions Natl Sci. Rev. 9 nwac057

Hurtt G C et al 2020 Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6 Geosci. Model Dev. 13 5425–64

Ito A et al 2020 Soil carbon sequestration simulated in CMIP6-LMIP models; implications for climatic mitigation Environ. Res. Lett. 15 124061
Ji J J, Huang M and Li K R 2008 Prediction of carbon exchanges between China terrestrial ecosystem and atmosphere in 21st century Sci. China-Earth Sci. 51 885–98
Jiang F et al 2016 A comprehensive estimate of recent carbon sinks in China using both top-down and bottom-up approaches Sci. Rep. 6 22130
Keenan T F et al 2014 Net carbon uptake has increased through warming-induced changes in temperate forest phenology Nat. Clim. Change 4 598–604
Koven C D, Riley W J, Subin Z M, Tang J Y, Torn M S, Collins W D, Bonan G B, Lawrence D M and Swenson S C 2013 The effect of vertically resolved soil biogeochemistry and alternate soil C and N models on C dynamics of CLM4 Biogeosciences 10 7109–31
Lawrence D M et al 2016 The Land Use Model Intercomparison Project (LUMP) contribution to CMIP6: rationale and experimental design Geosci. Model Dev. 9 2973–98
Lawrence D M et al 2019 The Community Land Model version 5: description of new features benchmarking, and impact of forcing uncertainty J. Adv. Model. Earth Syst. 11 4245–87
Li K R, Wang S Q and Cao M K 2004 Vegetation and soil carbon storage in China Sci. China-Earth Sci. 47 49–57
Li S, Liu N, Liu Y, Sun S, Wang S, Pan Y and Yin Y 2021 Change in soil organic carbon and its climate drivers over the Tibetan Plateau in CMIP5 earth system models Theor. Appl. Climatol. 145 187–96
Li Y, Brando P M, Morton D C, Lawrence D M, Yang H and Randerson J T 2022 Deforestation-induced climate change reduces carbon storage in remaining tropical forests Nat. Commun. 13 1964
Lu F et al 2018 Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010 Prog. Natl. Acad. Sci. USA 115 6038–44
Mauritsen T et al 2019 Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and its response to increasing CO2 J. Adv. Model. Earth Syst. 11 998–1038
McHugh M I 2008 Standard error: meaning and interpretation Biochem. Med. 18 7–13
National Development and Reform Commission of the People's Republic of China 2020 National major ecosystem protection and restoration major project master plan (2021–2035) (available at: https://www.ndrc.gov.cn/xzbg/zcblzt/202006/20200611_1231112.html?code=8&state=123)
Niu Q F et al 2019 Ecological engineering projects increased vegetation cover, production, and biomass in semiarid and subhumid Northern China Land Degrad. Dev. 30 1620–31
O'Neill B C et al 2016 The scenario model intercomparison project (ScenarioMIP) for CMIP6 Geosci. Model Dev. 9 3461–82
Oleson K W et al 2013 Technical description of version 4.5 of the community land model (CLM) (No. NCAR/TN-503+STR) (National Center for Atmospheric Research) (https://doi.org/10.5065/D6RR1W7M)
Peng J, Dan L and Huang M 2014 Sensitivity of global and regional terrestrial carbon storage to the direct CO2 effect and climate change based on the CMIP5 model intercomparison PLoS One 9 e95282
Piao S L, Fang J Y, Ciais P, Peylin P, Huang Y, Sitch S and Wang T 2009 The carbon balance of terrestrial ecosystems in China Nature 458 1099–13
Riahi K et al 2017 The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview Glob. Environ. Change 42 153–68
Schimel D, Stephens B B and Fisher J B 2015 Effect of increasing CO2 on the terrestrial carbon cycle Proc. Natl. Acad. Sci. USA 112 436–41
Seland O et al 2020 Overview of the Norwegian earth system model (NorESM2) and key climate response of CMIP6 DECK, historical, and scenario simulations Geosci. Model Dev. 13 6165–200
Sui X H, Zhou G S and Zhuang Q L 2013 Sensitivity of carbon budget to historical climate variability and atmospheric CO2 concentration in temperate grassland ecosystems in China Clim. Change 117 259–72
Swart N C et al 2019 The Canadian earth system model version 5 (CanESM5.0.3) Geosci. Model Dev. 12 4823–73
Tang X L et al 2018 Carbon pools in China's terrestrial ecosystem: new estimates based on an intensive field survey Proc. Natl. Acad. Sci. USA 115 4021–6
Thurner M et al 2017 Evaluation of climate-related carbon turnover processes in global vegetation models for boreal and temperate forests Glob. Change Biol. 23 3076–91
Tong X W et al 2018 Increased vegetation growth and carbon stock in China karst via ecological engineering Nat. Sustain. 1 44–50
van Soest H L, den Elen M G J and van Vuuren D P 2021 Net-zero emission targets for major emitting countries consistent with the Paris Agreement Nat. Commun. 12 2140
van Vuuren D P, Edmonds J A, Kainuma M, Riahi K and Weyant J 2011 A special issue on the RCPs Clim. Change 109 1–4
Wang J et al 2020 Large Chinese land carbon sink estimated from atmospheric carbon dioxide data Nature 586 720–3
Wang Y L et al 2022 The size of the land carbon sink in China Nature 603 17–19
Winiwarter M G, Davin E L and Seneviratne S I 2021 Prioritizing forestation based on biogeochemical and local biogeochemical impacts Nat. Clim. Change 11 867–71
Wolf S, Eugster W, Potvin C and Buchmann N 2011 Strong seasonal variations in net ecosystem CO2 exchange of a tropical pasture and afforestation in Panama Agric. For. Meteorol. 151 1139–51
Wu D H, Piao S L, Liu Y W, Ciais P and Yao Y T 2018 Evaluation of CMIP5 earth system models for the spatial patterns of biomass and soil carbon turnover times and their linkage with climate J. Clim. 31 5947–60
Wu T W et al 2019 The Beijing Climate Center Climate System Model (BCC-CSM): the main progress from CMIP5 to CMIP6 Geosci. Model Dev. 12 1573–600
Wu T W et al 2021 BCC-CSM2-HR: a high-resolution version of the Beijing Climate Center Climate System Model Geosci. Model Dev. 14 2977–3006
Xie Z, Zhu J, Liu G, Cadisch G, Hasegawa T, Chen C, Sun H, Tang H and Zeng Q 2007 Soil organic carbon stocks in China and changes from 1980s to 2000s Glob. Change Biol. 13 1989–2007
Xu L, Yu G and He N 2019 Increased soil organic carbon storage in Chinese terrestrial ecosystems from the 1980s to the 2010s J. Geogr. Sci. 29 49–66
Xu L, Yu G, He N, Wang Q, Gao Y, Wen D, Li S, Niu S and Ge J 2018 Carbon storage in China's terrestrial ecosystems: a synthesis Sci. Rep. 8 2806
Yang Y H, Mohammat A, Feng J M, Zhou R and Fang J Y 2007 Storage, patterns and environmental controls of soil organic carbon in China Biogeochemistry 84 131–41
Yang Y et al 2022 Terrrestrial carbon sinks in China and around the world and their contribution to carbon neutrality Sci. China-Life Sci. 65 861–90
Yu D, Shi X, Z, Wang H J, Sun W X, Chen J M, Liu Q H and Zhao Y C 2007 Regional patterns of soil organic carbon stocks in China J. Environ. Manage. 85 680–9
Yukimoto S et al 2019 The meteorological research institute Earth System Model version 2.0, MRI-ESM2.0:description and basic evaluation of the physical component J. Meteorol. Soc. Japan 97 931–65
Zhang L, Sun B, Huettemann F and Liu S 2021 Where should China practice forestry in a warming world? Glob. Change Biol. 28 2461–75
Ziehn T, Chamberlain M A, Law R M, Lenton A, Bodman R W, Dix M, Stevens L, Wang Y P and Srbinovsky J 2020 The Dix M, Stevens L, Wang Y P and Srbinovsky J 2020 The