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Article

Planted forest is catching up with natural forest in China in terms of carbon density and carbon storage

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ABSTRACT

Over the last several decades, China has taken multiple measures for afforestation and natural forest protection, including setting the goal of carbon neutrality by the middle of 21th century. In order to support the practice of relevant policies from the scientific perspective, it is essential to precisely estimate the carbon storage of arbor forest, as it plays an important role in the carbon cycle of ecosystems. In this study, we first used the latest four phases of national forest inventory data to investigate the variation of carbon storage for both natural and planted arbor forest in China during the covered period (1999-2018). Then we used machine leaning methods to simulate the carbon density based on various kinds of environmental factors and analyzed the contribution of each influencing factor. Our results demonstrate that the total carbon storage for arbor forest in China kept increasing over the last two decades, but this increment was mainly brought about by the continuous expansion of forest land. The gap of carbon sequestration between natural forest and planted forest showed a significant trend of reduction. Additionally, tree age was identified as the dominant factor for influencing the spatiotemporal variation of carbon density among all the independent variables while the impact of climatic factor was limited. Therefore, the future improvement of carbon sequestration of arbor forest in should mainly rely on additional projects of afforestation, reforestation, green space conservation and reduction of emissions in China. Conclusions of this study have important implications for policy makers and other stakeholders to evaluate the previous achievement of environmental projects and can also help to set future plans and finally realize the goals of carbon neutrality.

1. Introduction

Climate change driven by over emission of GHG (Greenhouse Gas) is inducing long-lasting influence on human welfare [1]. In 2015, the United Nations launched the 2030 Agenda for Sustainable Development to protect the planet and ensure the prosperity of human beings [2]. Among all the 17 items, the SDG (Sustainable Development Goal) 13 stated specific vision of taking actions to combat climate change and its impacts [3]. At Paris in 2015, world leaders pledged to try to keep the world from warming by more than between 1.5 °C to 2 °C through sweeping emissions cuts [4]. China, as one of the top emitters of carbon dioxide in the world, has taken lots of measures to realize energy saving and emission reduction in recent years [5]. In 2020, Chinese government further announced that China's carbon dioxide emissions would peak before 2030, and reach neutrality, or net-zero emission by the year of 2060 [6].

Forests are one of the richest resource pools in nature and play an important role in the global carbon cycle [7]. The carbon storage of forest arbor layers occupies a dominant part of the carbon storage of forest ecosystems [8]. It is not only an important indicator reflecting the ecological structure and functionality of forest, but also a basic parameter for evaluating forest quality and carbon budget [9]. Accurately estimating the carbon storage of arbor forests at the regional scale is of great significance for understanding the productivity, process of carbon cycle, carbon sink capacity of terrestrial ecosystems, the distribution pattern of nutrient elements, and the accumulation of biomass energy [10]. It is also useful for studying the carbon cycle of the entire biosphere and regional carbon sinks. Research on carbon storage can reveal the relationship between ecosystems and the environment, providing countermeasures to excessive emissions of GHG.

Over the past decades, the Chinese government has initiated many projects for planting more trees and improving the natural environment

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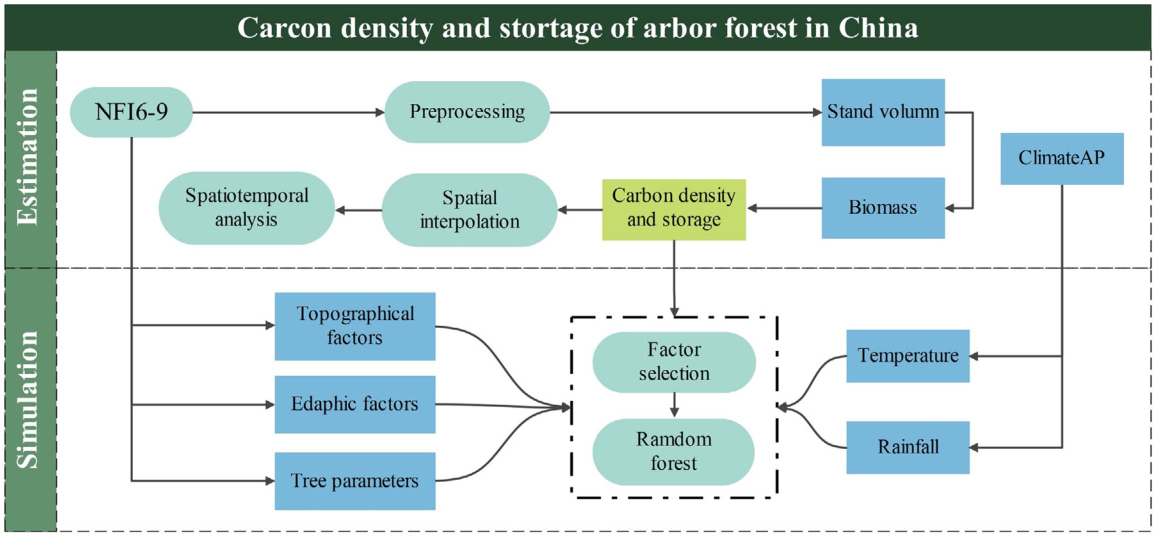

Fig. 1. Roadmap of the research.

since last century, such as "Grain for Green" (GFG) and Three-North Shelter Forest Program, which has been extended to the whole territory [11]. According to relevant statistics, China alone accounts for 25% of the global net increase in the leaf area with only 6.6% of the global vegetated area [12]. While the great potential of forest ecosystem in China has been widely recognized, some other challenges like the predominance of very few tree species in the plantations, uneven spatial distribution, skewed age-class distribution, and low volumes in growing stock, coupled with increasing complexity of multiple purpose forestry management under a changing environment, have also given rise to big concern [13,14]. Therefore, reliable evaluation of forest carbon storage distribution is essential for environmental protection and achievement of carbon emission goals.

Currently, the staple methods of estimating forest carbon include ground observation, remote sensing inversion, UAV (unmanned aerial vehicle) image extraction, model estimation, etc. [15–17]. As an important part of national information infrastructure, NFI (National Forest Inventory) assessments provide an essential service, reconciling available resources with national priorities related to timeliness, precision, and forest values of interest [18]. Starting from the 1950s, China has carried out 9 phases of NFI. This nation-wide assessment presented a general overview of forest resources in China. In recent years, NFI system has been greatly refined in regard of sampling design, survey methods, and technical standards, based on fast development of Chinese ecology and technology [19]. Now the national inventory has a stable 5-year cycle, and approximately 1/5 of provinces conduct inventories each year during the period, based on a systematic sampling design and permanent field plots [20].

Here, we first used the latest four phases of NFI (NFI6-9, covering 1999-2018) data to evaluate the spatiotemporal distribution of carbon storage of arbor forest in China for the past two decades (Fig. 1). Then we built up the machine learning models (using random forest) to establish the quantitative relationship between vegetation carbon reserve and environmental factors. Last, we evaluated the contribution of each influencing factor on carbon density and imported the algorithm of spatial interpolation to show the spatial patterns for all the forest region in China (introduced in Supplementary materials).

2. Material and methods

2.1. National forest inventory data

The four phases of forest inventory data used in this study cover more than 8000 permanent sample plots in China, which are widely distributed all across the country. For the step of preprocessing this dataset, we first excluded the plots which involved outliers for the specific parameters or had data scarcity (e.g., the plots with records for less than four phases of NFI). In addition, some plots containing multiple dominant tree species were also deleted. Finally, we kept 7029 permanent sample plots (Fig. 2a) for the subsequent work (totally, 28,196 groups of data for combining the four phases of NFI). Each sample plot is comprised of environment dataset (e.g., coordinates, altitude, slope, aspect, soil depth) and forest dataset (e.g., average diameter at breast height – DBH, average tree height, average tree age, origin, dominant tree species, total stand volume), of which some key parameters was shown in Table S1. Considering the spatial heterogeneity of climatic conditions and administrative unit for NFI in China, we grouped all the provinces into 6 different subregions (Fig. 2b), in order to reduce the climatic disturbance on simulating carbon storage.

2.2. Calculation of carbon density

The estimation of carbon density can be divided into two steps. First, aboveground biomass density (referred as biomass density hereinafter) of each plot is calculated by empirical equations (Eq. 1) based on its quantitative relationship with the corresponding stand volume (M, unit: m^3/ha):

$$B_j = p_j M + q_j \tag{1}$$

Where B_j is the biomass density of forest species j (Mg/ha), p_j and q_j represent the slope and intercept for each species, detailed in the supplementary materials (Table S2). Then the aboveground carbon density (referred as carbon density hereinafter) C_j is obtained by multiplying biomass density with percent of carbon content (C_c) for each forest species. C_c was shown in supplementary material (Table S3). In mixed forest sample plots, where no dominant tree species was given, the forest species of the sample plot were defined as coniferous or broad-leaved forest by referring to the vegetation types of the sample plot:

$$C_j = B_j C_c \tag{2}$$

For the two equations, all relative coefficients (C_c, p_j and q_j) for each forest species were defined in the previous research [21].

2.3. Random forest

We first tested the inter correlations among different variables (Fig. S1) and finally selected 11 variables for simulating carbon density in random forest (methodology introduced and detailed in Supplementary

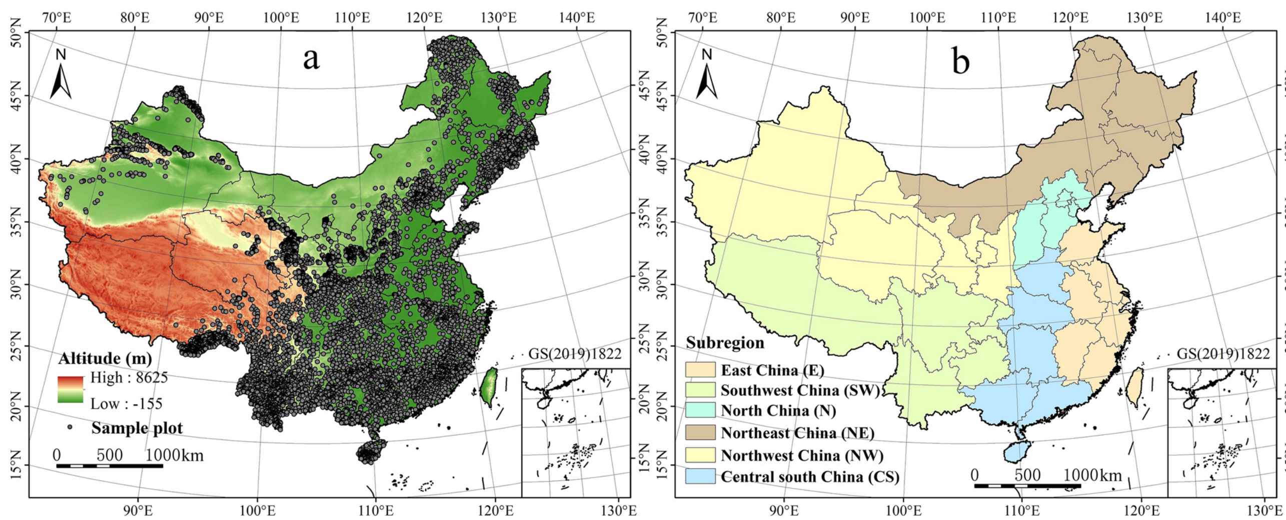

Fig. 2. Sample plots of NFI (a) and subregions of China (b).

materials), including Longitude, Latitude, Elevation, Aspect, Slope position, Slope, Soil thickness, Dominant tree, Mean age, MAT (Mean annual temperature), MAP (Mean annual precipitation). Climatic factors of MAT and MAP was obtained by ClimateAP (Detailed in Supplementary materials) and others were recorded in NFI. Excluded variables are Mean diameter, Average tree height, Shrub coverage, Average shrub height, Herbage coverage, Average herb height, Total vegetation cover, and Closure, which are either vegetation parameters or highly correlated with other explanatory variables (Fig. S1). In case of data deficiency, we used the approach of temporal-spatial fusion to recombine all the data for the four phases of NFIs in advance (28,196 groups of data, as described in Section 2.1). We tested dozens of grouping strategies for training the random forest. After comparing the simulation accuracy and time cost, we grouped the forest data into 1) natural forest, 2) planted coniferous forest, 3) planted broad-leaved forest and mixed forest, and each group was spatially divided into East China (group 1), Northwest China (group 2), Southwest, Central and South China (group 3), and North and Northeast China (group 4). All the steps were taken in the Pycharm operating environment, mainly using the package of scikit-learn for building random forests. The range of parameter n (number of trees) and m (number of tree features) in each random forest was manually set as 500-2000 and 0-30, respectively, which was further automatically optimized by the program (Introduction of random forest detailed in Supplementary materials).

During the process of simulating forest carbon storage, the relative importance of each influencing factor is estimated based on the following steps [22]: (1) every single tree in the model has its simulation error, denoted as B1; (2) add permutation for specific influencing factor X and recalculate the simulation error B2; (3) assume the total number of tree is n, then the RI (relative importance) is calculated by Eq. 3:

$$RI(X) = \frac{\sum (B2 - B1)}{n} \tag{3}$$

For accuracy evaluation, we first randomly separated the dataset into training group and validation group, which account for 90% and 10%, respectively. Then R^2 (determination coefficient), RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) between true value group (a) and simulated value group (b) are chosen as accuracy index and calculated by the following equations, based on the validation group:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(b_i - a\right)^2}{\sum_{i=1}^{n} \left(a_i - \bar{a}\right)^2} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(a_i - b_i\right)^2}{n}} \tag{5}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left|a_i - b_i\right| \tag{6}$$

Where n stands for the number of simulated/true value.

3. Results

3.1. Variation of arbor forest growth conditions over the four phases of NFI

The environmental and vegetation parameters are shown in Table S4. In terms of tree age, DBH, tree height, canopy density, stand volume, the increase for six subregions in China has been significantly identified since 1999 when the 6th NFI started. For example, the average stand volume for each sample plot in China is 9.32 m^3 for the 9th NFI, compared with the value of 6.87 m^3 for the 6th NFI. In contrast, the environmental parameters including temperature, precipitation and soil thickness were relatively stable during the covered period.

3.2. Carbon density and biomass density

Over the four phases of NFI, the rank of carbon density and biomass density in each subregion of China kept relatively stable (Fig. 3). Particularly, Southwest, Northwest, and Northeast always had the greatest value of these two parameters over the period, because the forests in these three subregions are mostly distributed in the vertical natural zone of temperate mountains where the tree species are mainly coniferous. Subalpine coniferous forest is a higher-level forest community with more biomass. Although there are few forests in the Northwest, most of them are mature forests and over-mature forests. Therefore, the accumulation per unit area is large, and the carbon density is high. By contrast, the carbon density and biomass density were the least in North China, where the vegetation was dominantly influenced by either arid climate or human activities like urbanization and afforestation projects. In addition, carbon density and biomass density increased significantly in all subregions for the past two decades. For example, the carbon density increases from 33.9 Mg/ha (6th NFI) to 45.4 Mg/ha (9th NFI) in North China, with the proportional increment of 33.9%.

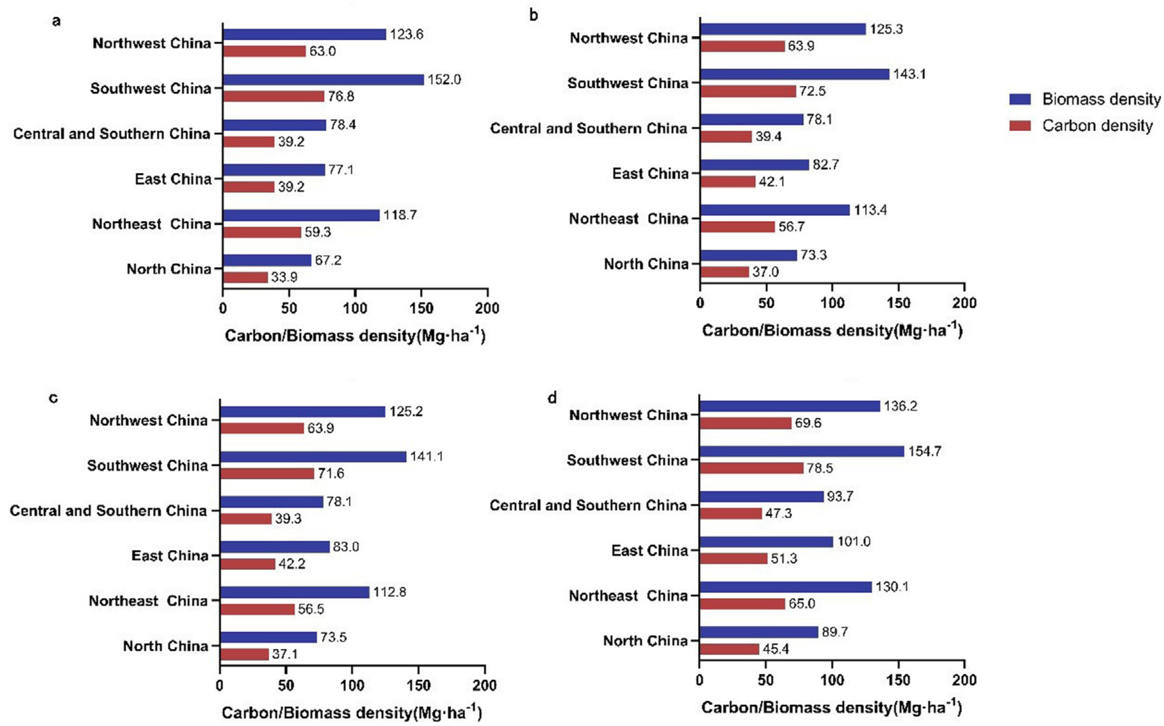

Fig. 3. Statistics of carbon density and biomass density in the six subregions in China (result derived from 6th, 7th 8th and 9th inventory data were shown by subplot a, b, c and d, respectively).

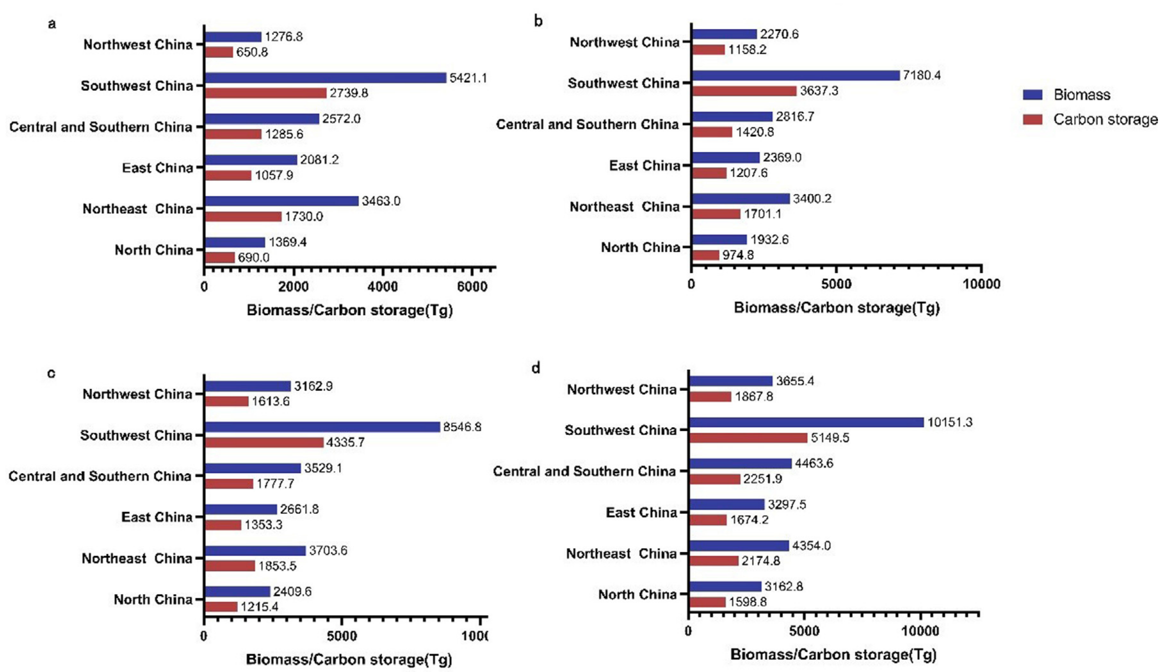

Fig. 4. Statistics of carbon storage and biomass in the six subregions in China (result derived from 6th, 7th 8th and 9th inventory data were shown by subplot a, b, c and d, respectively).

3.3. Carbon storage and total biomass

We further calculated the total carbon storage and biomass by multiplying the carbon and biomass density with the corresponding forest area (Fig. 4, forest areas were referred to in the concurrent documents of China Forestry and Grassland Statistical Yearbook). On the whole, six subregions ranked differently from that of density values, due to the limit of natural growing conditions or fast urban sprawl. This was illustrated by the slow increment of carbon storage in East China and Central south China, where some large cities and populations are mainly concentrated. However, the change of these two parameters for the covered period in some subregions of China was much more remarkable than that of density values. For example, the latest carbon storage in northwest China was roughly three times that in the sixth NFI (increases from 605.8 Tg for the 6th NFI, to 1867.8 Tg for the 9th NFI).

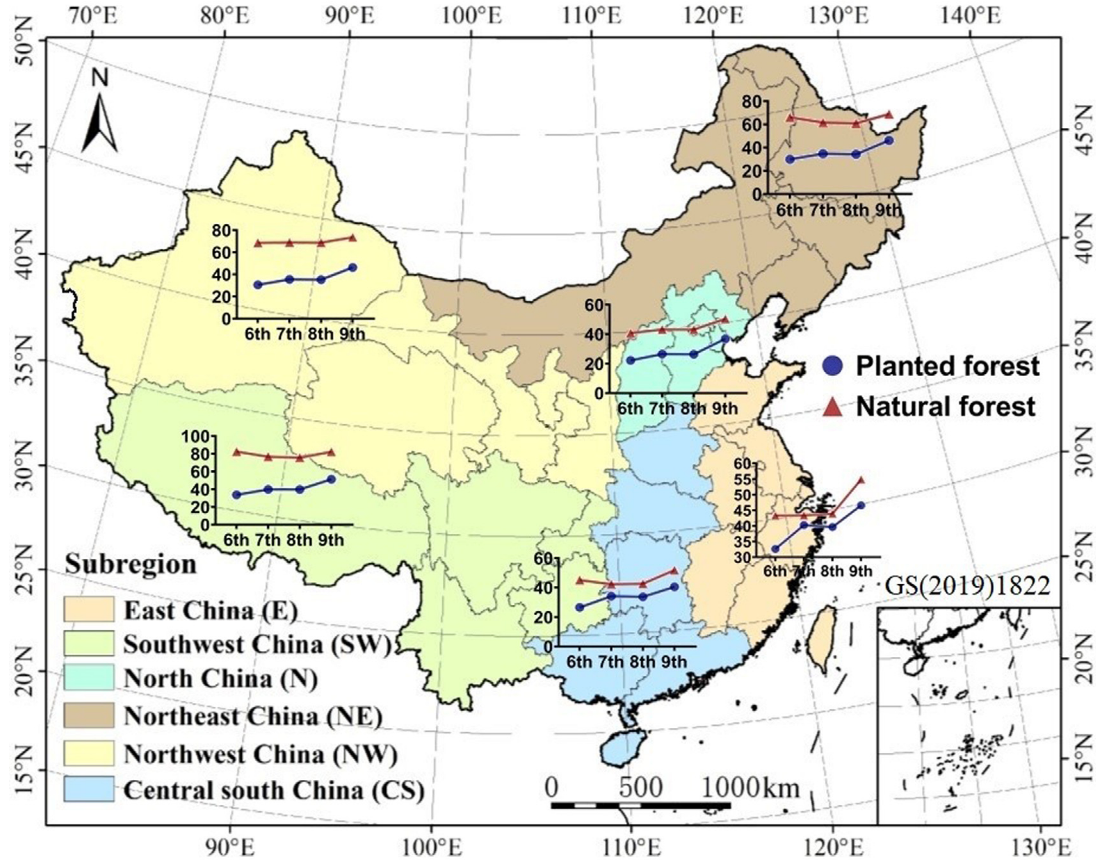

Fig. 5. Variation of carbon density across the four phases of NFI in the six subregions of China.

3.4. Carbon density and storage for natural and planted forest

According to Fig. 5, the carbon density of both planted forest and natural forest went through a clear increasing trend. However, the increase from the 8^{th} to 9^{th} NFI accounted for the most change over the period. On the other hand, the carbon density of planted forest is still much lower than that of natural forest, although the gap was gradually closing for the past two decades. For example, the carbon density of planted forest was about 58.8% of that in natural forest in the 6^{th} NFI, while the percentage had increased to 78.2% in the 9^{th} NFI. Additionally, in the 7^{th} and 8^{th} NFI, the carbon density of natural forest in some subregions like Northeast and Southwest China decreased slightly. Details of the statistics are shown in supplementary materials (Fig. S2).

From the perspective of carbon storage (Fig. 6), the gap between planted forest and natural forest was spatially heterogeneous. For example, in North China, natural forest contributed more than 75% of the total stored forest carbon, while the carbon storage of planted forest was close to that of natural forest in Central south China, especially in recent years. From the 6^{th} to 9^{th} NFI, the absolute increase of all the selected plots for carbon storage was 2286.6Tg in planted forest and 4276.1Tg in natural forest, but the relative increase was 145.0% and 65.0%, respectively. Details of the statistics were shown in supplementary materials (Fig. S3).

3.5. Simulation of forest carbon density

The simulation of carbon density for natural forest is better than that for planted forest, using the selected independent variables (Table S5). For natural forest, R^2 of the validation set were greater than 0.8 for group 2,3 and 4, while the value of R^2 for the group one is greater than 0.7. By contrast, the accuracy for planted forest (including coniferous forest, broad-leaved forest and mixed forest) is relatively lower. Although R^2 of the training set for planted forest is all greater than 0.85, but the value for the validation set is not as strong, as shown by only half of the groups of planted forest (group 2 and 4) having an R^2 greater than 0.6.

We illustrated the relative importance for the 11 independent variables (Fig. 7, error bar indicates the standard error of mean for each variable). For all natural forests and planted forests, tree age was dominant for simulating carbon density, having the highest importance (0.25) in the case of natural forest. Some parameters of large-scale location like latitude, longitude and altitude have more influence on variation of carbon density than small-scale parameters (e.g., aspect and slope). In addition, the impact of the dominant tree species on the carbon density of planted coniferous forest (0.18) was second only to tree age, which ranked in fourth place in natural forest. It is also notable that the carbon density of forests was less influenced by climatic variables like temperature and rainfall, which accounted for 0.1 to 0.2 combined. We further divided the data of natural and planted forest into different groups based on the value of tree age and altitude, and tested the variation in carbon density among each group. We also calculated the linear relationships between carbon density and climate factors (precipitation and temperature). For natural forest, the carbon density has an increasing trend, supported by significant difference among the first three age groups (0-50, 50-100, 100-200 y). Comparatively, if the tree age is older than 200 y, the density would quickly decrease, which is even significantly less than that of 50-100 y group (Fig. S4a). Therefore, the optimal carbon sequestration period of natural forest is generally in the age interval of 100-200 y. For planted forest, the carbon density kept increasing with the increase of tree age (Fig. S5a). However, it is worth noticing that the gap between group 25-50 y and 10-20 y is more significant than the

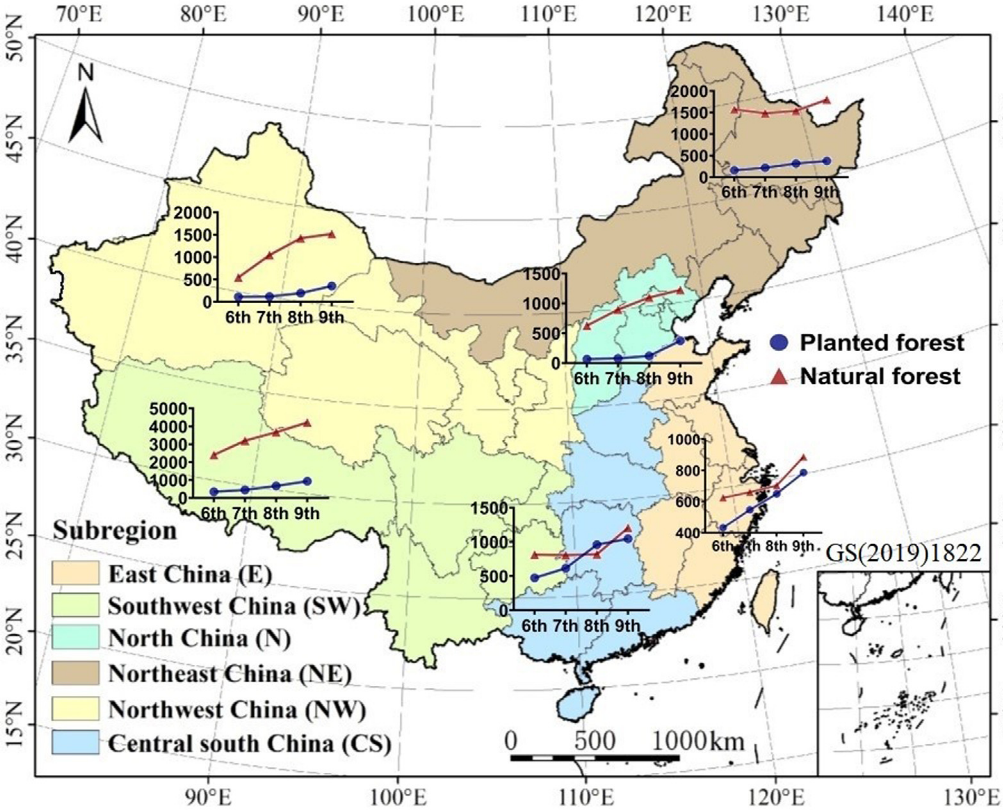

Fig. 6. Variation of carbon storage across the four phases of NFI in the six subregions of China.

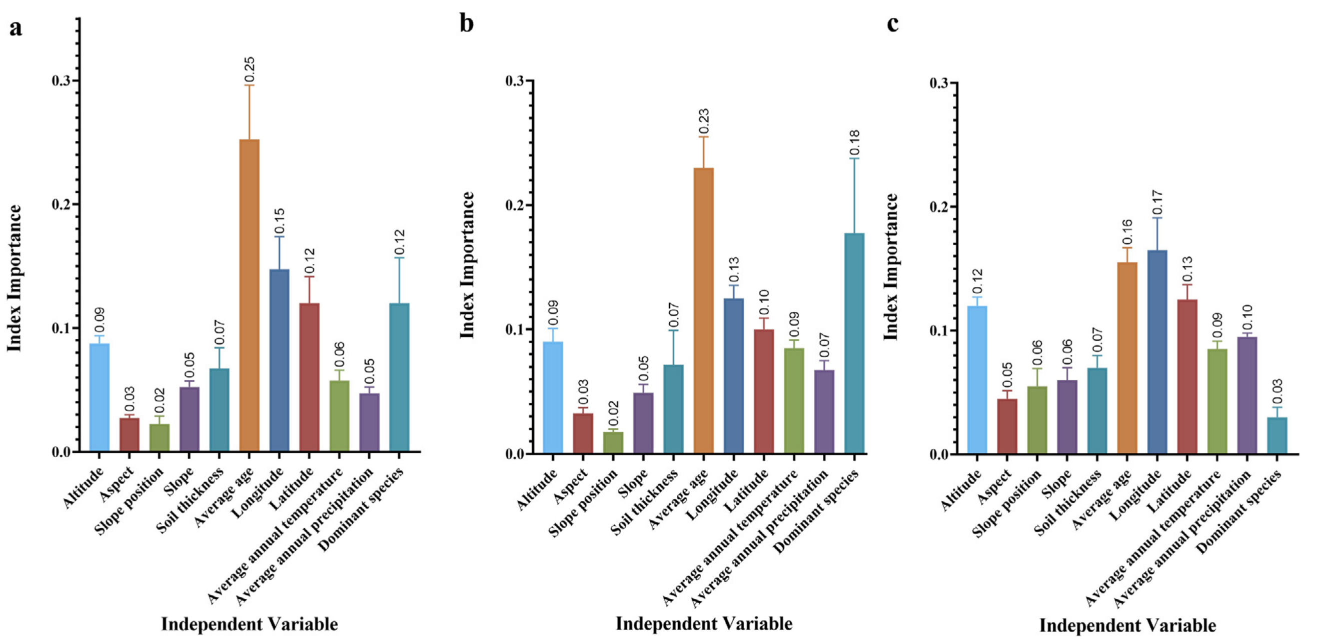

Fig. 7. Relative importance of explanatory variables to carbon density in different groups of forest (a. natural forest, b. planted coniferous forest, c. planted broad-leaved forest and mixed forest).

gap between group > 50 y and 25-50 y. We could infer that the carbon sequestration of planted forest might start to enter a period of plateau after the tree age exceeds 50 y, on average. Meanwhile, the history of planting projects in China is only about 50 y, therefore, it is hard to predict the future trend of carbon sequestration of planted forest for longer temporal scale at present. On the other hand, the carbon densities of planted forest and natural forest also show different patterns along with altitude gradient (Figs. S4b and S5b). Particularly, the carbon density of natural forest increases with the higher altitude while for planted forest the trend is not constant over the four altitude groups. Different from commonly studied large scale vegetation growth proxies (e.g., leaf area index, normalized difference vegetation index and enhanced vegetation index) [23–26], local climatic conditions of precipitation and temperature had little impact on carbon density (Figs. S4c, S4d, S5c, S5d). The impact for planted forest was even less than that for natural forest.

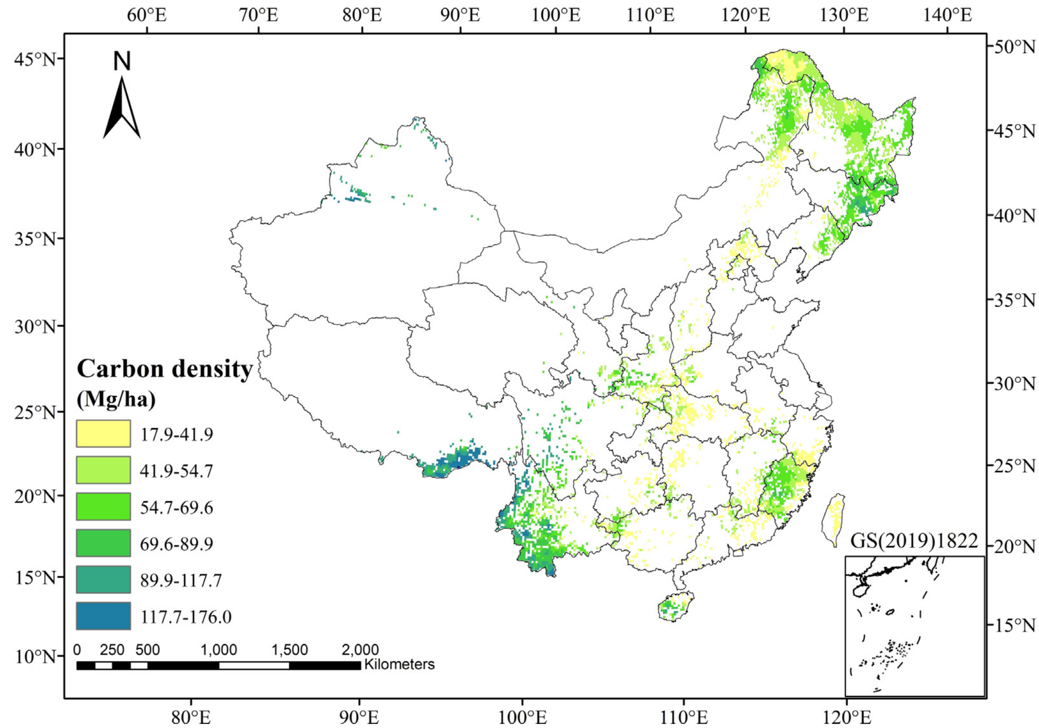

Fig. 8. Spatial distribution of average carbon density in forest region across the four phases of NFI.

3.6. Spatial distribution of carbon density in arbor forest of China

Based on result of carbon density for the four NFIs, we calculated the average value of the sample plots and then conducted 10 different interpolation methods to show the spatial distribution of carbon density in forest of China, masked by the forest land cover (IGBP DISCover map) [27]. 80% of all the plots were randomly selected for the interpolation and the remaining 20% were kept for precision validation. The result (Table S6) shows that IDW (Inverse Distance Weighted) with fourth power function and Ordinary kriging with circular function tended to have higher accuracy than others. Considering both accuracy indices, the performance of Ordinary kriging with circular function is more robust. Thus, we finally applied it to the whole region. Fig. 8 shows the spatial distribution of carbon density in the forest region of China. It is notable that the carbon density of forests in parts of northern, central and southeast China is the lowest (mostly less than 40 Mg/ha) nationwide during the period of the four NFIs. In contrast, southern and southwestern China were consistently the regions with the highest carbon density (over 110 Mg/ha). Meanwhile, the carbon density of northeast China also has relatively high value, where the mountains are widely distributed (mostly between 40 and 90 Mg/ha).

4. Discussion

The climate in southwest, central and south parts of China is relatively warm and humid, which is beneficial to the fast growth of trees and high biodiversity. Broad-leaved forest and mixed forest are widely distributed in this region, and the mature age for carbon sequestration is less than that of northern coniferous forest [28]. Therefore, the four indices of biomass, biomass density, carbon storage and carbon density always had the greatest values compared with other regions. In contrast, the northwest region of China contains large areas of Gobi Desert and Loess Plateau, where there are many valleys and fragmented forest. Severe soil and nutrient loss in this region impede forest growth and high carbon sequestration [29]. Meanwhile, urban areas in north and east China went through rapid expansion in recent years, occupying the original land of forest and other natural vegetations [30,31]. Although the urban forests and green spaces are built synchronously with urban construction, it is very hard to form the forest with rich species and high biomass density. Therefore, the carbon storage and density are smaller than the average level for the whole country. For example, analyses based on remote sensing technology demonstrated that the carbon density of Shanghai and Hangzhou was only 47.8 Mg/ha and 30.25 Mg/ha [32,33]. Over the four phases of NFI, the aboveground biomass and total carbon storage of arbor forest in China kept increasing for all the six subregions in China. However, the carbon density and biomass density over the last two decades were not significantly improved (Fig. 3 and Fig. S2). For example, in Southwest China, average carbon density for 9th NFI (82.2 Mg/ha) was even lower than that for 6th NFI 82.3 Mg/ha) representing 20 years ago. In this case, it can be inferred that the increment of total carbon storage was mainly driven by the fast extension of forest area, especially for planted forest. This conclusion was also supported by the evidence that the gap between natural forest and planted forest in terms of both carbon density and carbon storage reduced significantly for the last two decades, most prominently in Central south and East China.

Since the 1970s, China has implemented several major projects of affectation, which helped to achieve a series of remarkable accomplishment for mitigating climate change [34,35]. For example, the public could easily participate in the Ant Forest Project for voluntary tree planting, by living a low-carbon life or taking other low-carbon activities like walking or bicycling for daily transportation [36,37]. The Three North Shelterbelt Project has produced 30.143 million hectares of forest, with the coverage increasing from 5.05% to 13.57%, and a 61% reduction in the area affected by soil erosion [38,39]. Other than the aspect of planted forest, China has also made a great contribution to the preservation of natural forest with hundreds of natural reserves and natural parks built successively, as natural forest has been proven to benefit more than planted forest from the comprehensive perspective of ecology [40]. According to relevant statistics, over 30 million hectares of natural forests in 18 out of 34 provincial regions had engaged in the Protection Project by 2016 [41]. However, if we neglect the site conditions like climate for forest growth, the carbon density in China still have potential to grow compared with other regions in the world, which is most notable for planted forest. Specifically, the average value of carbon density for the six subregions in the 9th NFI was 69.2 Mg/ha for natural forest and 44.0 Mg/ha for planted forest, compared with 40.4 Mg/ha for Russia [42,43], 58.8 Mg/ha for United States [44], 30.7 Mg/ha for Canada [45] and 57.1 Mg/ha for temperate zone [46]. Some countries in tropics have much higher values (Thailand with 98.8 Mg/ha, Malaysia with 100.0 Mg/ha and Philippines with 86.0 Mg/ha) [47]. Moreover, all of these estimations were conducted more than 20 years ago, excluding the carbon density growth promoted by natural and human factors in 21th century.

The usage of advanced machine learning method (random forest in this study) helps us to obtain high accuracy in terms of simulating the carbon density of arbor forest by various kinds of environmental factors. Besides, the higher accuracy for the training group than the validation group, the performance of random forest for simulating carbon density of natural forest is evidently better than that of planted forest. Two reasons could explain this phenomenon. First, the number of sample plots of natural forest (about 5700) is much more than planted forest (less than 1300 for each NFI), which would benefit the process of training models. Second, the growth of planted forest is more influenced or sometimes even controlled by anthropogenic forest management like fertilization, irrigation, and more frequent activities of pruning, disease and insect control, and stand thinning, of which the datasets are mostly unavailable. Therefore, the accuracy of simulating of carbon density of planted forest is less than that of natural forest.

However, the places where lots of afforestation projects were implemented tend to have lower carbon density, indicating lower overall carbon sequestration potential [48]. Similarly with previous studies which highlighted concerns from policy and practical perspectives [49], we infer that some researchers might have overestimated the potential of future carbon storage in these Chinese forest areas [50–53], especially if we fail to take active steps, and only rely on the impetus of climate warming and self-regeneration of the ecosystems for the improvement of carbon sequestration. We suggest that more afforestation projects and activities be focused in Southwest China, in order to maximize the total carbon sequestration potential for the goals of peak carbon dioxide emissions and carbon neutrality. Although the karst landform with its thin and infertile soil layer is widely distributed in this area, the arbor trees can still access the deep water inside the rock fractures, especially in the region where carbonates are well developed [54]. Some previous studies also demonstrated that the bonus of planted forest for carbon fixation seemed to plateau for older trees and some planted forests are less resilient and can suffer mortality when they encounter extreme climate events [55]. Therefore, we also advocate that we need to be aware of the potential bottleneck of carbon sequestration for planted forest and renew some of the old planted trees. In order to do so, we ought to carry out regular monitoring on planted forest from a carbon perspective and take effective actions like reforestation in time. The evaluation of the local environment on whether it is still suitable for planting specific tree species should be adopted in advance of planting, to encourage resilience. Meanwhile, refining the strategies of forest management for existing planted forests is better than blind afforestation.

Some other uncertainties of this study were mainly derived from three aspects. First, the deviation brought by the simulation of carbon density based on random forest model. We built up the model using the attainable environmental factors from each NFI. However, some factors like soil organic matter or other edaphic characteristics were not recorded in the dataset. To improve the model performance, relative remotely sensed dataset or more detailed records could be included in future studies. Second, the sample plots of NFI are not evenly distributed in China, some areas like the Gobi Desert and the Tibet Plateau have a lack of data resources. In this case, the spatial patterns had relatively low credibility in these regions. Third, this study only focused on the whole variation of carbon storage for arbor forest in China, future work could provide more focused information, such as, different tree species, shrublands, grasslands and soil carbon, combined with the policy blueprint, so as to refine the carbon research in China.

5. Conclusion

In this study, we utilized four phases of national forestry inventory data to 1) calculate and analyze the spatiotemporal patterns of carbon density and carbon storage of arbor forest in China over the last two decades, 2) simulate the carbon density using multiple environmental factors, and 3) investigate the dominant factors on variation of carbon density. Our results demonstrated that the carbon storage kept increasing for the study period. This increment was mainly due to the expansion of planted forest while the increase of carbon density was limited. Meanwhile, the gap between natural forest and planted forest has reduced due to a series of afforestation projects implemented by related organizations. However, as carbon density of arbor forest would not greatly benefit from global warming, future projects of afforestation, reforestation and environment protection still need to be rationally planned and reinforced to achieve future carbon goals. We suggest that more actions be taken in the areas of high carbon density like Southwest China.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest in this work.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.fmre.2022.04.008.

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