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Which Provinces Will Be the Beneficiaries of Forestry Carbon Sink Trade? A Study on the Carbon Intensity–Carbon Sink Assessment Model in China

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Abstract: Carbon emissions pose a significant challenge to sustainable development, particularly for China, which is the world's largest emerging economy and is under pressure to achieve carbon neutrality and reduce emissions amid escalating human activities. The variation in economic development levels and carbon sequestration capacities among its provinces poses a significant hurdle. However, previous research has not adequately examined this dual discrepancy from the perspective of spatial heterogeneity, resulting in a lack of differentiated management of forest carbon sinks across diverse regions. Therefore, to mitigate this discrepancy, this study presents an assessment methodology that analyzes over 100 types of natural and plantation forests using forest age and biomass expansion factors. This study presents a model that can significantly support the efforts of both China and the whole world to achieve carbon neutrality through the improved management of forest carbon sinks. This approach facilitates the assessment of carbon offsets required to meet reduction targets, the development of a provincial framework for carbon intensity and sequestration, and the exploration of their potential for trading markets. Analysis is conducted using MATLAB. Key achievements of this study include the following: (1) The collection of a comprehensive carbon stock dataset for 50 natural and 57 plantation forest types in 31 provinces from 2009 to 2018, highlighting the significant role of new forests in carbon sequestration. (2) The development of a provincial carbon status scoring system that categorizes provinces as carbon-negative, carbon-balancing, or carbon-positive based on local forest sink data and carbon credit demand. (3) The formulation of the carbon intensity–carbon sink assessment (CISA) model, which suggests that provinces with middle- to upper-middle-level economies may have a prolonged need for carbon sink credits during their peak carbon phase. Furthermore, the results show that carbon trading may benefit Guangxi and Yunnan, but may also bring opportunities and risks to Hunan and Hubei. To address regional imbalances, this study advocates tailored policies: carbon-negative and carbon-balancing provinces should enhance carbon sink management, while carbon-positive provinces must focus on energy structure transformation to achieve sustainable development goals.

Keywords: forest carbon sink; sustainable development; green economy; carbon sequestration trading; China

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1. Introduction

Global warming—a consequence of climate change—has emerged as a focal issue worldwide, significantly affecting the economies and societies of all nations [1]. As the world's largest carbon dioxide emitter, China's commitment to achieving carbon neutrality by 2060 is pivotal to global climate mitigation efforts [2–4]. Attaining this ambitious goal necessitates extensive actions in both reducing CO_2 emissions and removing atmospheric CO_2 [5–7]. Forest carbon projects, which involve planting trees and managing forests to store atmospheric CO_2 in forest biomass (according to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) [8], biomass may refer to the mass of organic matter in a specific area) and ecosystems, offer substantial carbon sequestration potential [9–11]. They are a crucial component of climate strategies in numerous countries and a key element in international climate agreements [12,13].

Expanding forest carbon sinks is a vital part of China's climate change mitigation strategy, which is frequently highlighted in the country's national plans to increase forest cover [11]. However, due to China's vast geographical area and diverse hydrothermal conditions and socio-economic environments across its provinces [14,15], there is a conflict between the development of forest carbon projects and economic growth objectives, which is a common problem in other parts of the world as well [16,17]. Furthermore, it is hard to retain a sustained supply of forest carbon credits due to the inherent flaws and inefficiencies in the pricing mechanism. This raises feasibility concerns regarding the economic benefit of forest carbon sequestration. The national emission trading scheme (ETS) offers a market-based solution to this issue. By compensating for the mitigation function through carbon trading, it can effectively increase the supply of forest carbon sinks [18–20].

In addition, conducting a thorough assessment of the carbon sequestration potential of forest ecosystems can assist provinces in understanding their forest carbon sink status and formulating customized forest management policies. This can also create opportunities for carbon sink trading between provinces based on differences in their economic development levels and carbon sequestration potentials. Previous research has primarily focused on national-level studies or a limited number of provinces [21–24]. This may result in a lack of consideration for the spatial diversity of a country with over thirty provinces, such as China. Consequently, this may limit the ability to gain a complete understanding of the forest carbon sequestration potentials in varied regions, which is crucial for achieving China's 2060 carbon neutrality goal. Therefore, it is essential to conduct comprehensive research that encompasses all provinces and accounts for their distinctive economic and environmental characteristics in order to gain a full understanding of and enhance China's forest carbon sequestration capabilities.

Recent research has led to improved methods and data, including updated forest inventory data, such as those included in the eighth and ninth *China's National Forest Inventory (NFI) Report* (NFI Reports are produced by the National Forestry and Grassland Administration (NFGA) of China. The NFGA and its predecessors have published nine NFI reports since 1973. After 1984, the inventory has been conducted once every 5 years [25]) [26], enhanced biomass conversion factor models [27], and carbon sink simulations using dynamic forest age models [28]. These advancements enable the integration of various methodologies to establish an index system connecting carbon intensity and carbon sinks. This system facilitates the identification of beneficiaries in China's provincial forest carbon sink trade and offers solutions to address the imbalance between carbon intensity and carbon sink volumes across different provinces.

This study makes three key contributions to the existing body of knowledge in the field: (1) It adopts a detailed, granular approach to distinguish between natural and plantation forests, categorizing the diversity of over 100 tree species within five distinct forest age groups at the provincial scale. It meticulously accounts for the spatial heterogeneity of identical tree species across various regions, significantly improving the accuracy of data and the precision of predictions related to carbon storage and carbon sequestration capabilities for each province in China. (2) Moreover, it develops a practical model for predicting carbon storage and sinks at the provincial level in China, performing spatial and temporal comparisons across 31 provinces. (3) Lastly, it links provincial carbon intensity reduction targets to forest carbon sink offsets by simulating changes in the carbon sink volumes of provincial forest ecosystems. It establishes a coupled index system for provincial carbon emission intensity and carbon sinks influenced by carbon offset factors, categorizing provinces into carbon-negative, carbon-positive, and carbon-balancing provinces in China's forest carbon sink trade. Through quantifying and identifying primary stakeholders and consumers of provincial forest carbon credits, the research clarifies the supply–demand relationship in forest carbon trading, offering data support for integrating forest carbon sinks into compliance carbon markets (CCMs), especially in China's national ETS.

The paper is structured as follows: Section 2 reviews the contemporary literature, focusing on carbon sink measurement and trading, and emphasizes the importance of coupling provincial economic development levels with carbon sequestration potential. Forest carbon offset mechanisms are categorized and challenges related to compensating forest carbon sinks are addressed. Section 3 describes the selection of models and scenario assumptions, detailing the process of estimating provincial forest carbon storage, predicting carbon sinks, and studying the coupling of carbon intensity and sinks in China. Section 4 presents the findings for the three models and identifies the future roles of various provinces in carbon trading. Finally, Section 5 provides a comprehensive overview of the implications for future studies and Section 6 offers policy recommendations based on the conclusions of empirical research.

In conclusion, existing research has predominantly focused on global or national scales. This leaves a significant gap in dynamic carbon accounting at the regional level, particularly between different regions. This study aims to bridge this gap by exploring the disparities in regional socio-economic development and carbon storage capacities. These are analyzed through the lens of carbon intensity and carbon sequestration. Through the contributions of this research—refined data accuracy, an innovative predictive model, and a comprehensive index system—this study proposes a provincial carbon intensity–carbon sink framework. It aims to synchronize forest carbon sinks with economic development goals, thereby facilitating the creation of an effective carbon trading market.

2. Literature Review of Forest Carbon Sink Trading

Forest carbon sink trading significantly contributes to the harmonizing of economic development with ecological protection, thereby serving as a crucial mechanism for aligning ecological and economic benefits [18]. This strategy has captured the attention of governments and the global research community, reflecting its importance in addressing climate change and promoting sustainable development. Present studies in this field primarily encompass three key areas: analysis of the supply side of the carbon trading market, economic evaluations of carbon sink trading, and the exploration of the mechanisms and institutional structures that facilitate forest carbon sink trading.

(1) The models for estimating carbon sinks: This area of research focuses on models for estimating forest carbon sinks, methods for valuing carbon sinks, and strategies for enhancing carbon sink growth efficiency. Significant progress has been made in global and national carbon storage studies [29,30], with an expansion into provincial and regional levels [15,31,32]. These studies commonly identify data acquisition methods, forest management, and forest age structure as crucial factors affecting carbon storage estimates. Through improved biomass expansion factors (BEFs) (according to IPCC Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG-LULUCF) [33], biomass expansion factor is a multiplication factor that expands growing stock, or commercial round-wood harvest volume, or growing stock volume increment data, to account for non-merchantable biomass components such as branches, foliage, and non-commercial trees) and the biomass density–forest age model, some scholars have estimated changes in China's arboreal biomass carbon pools [27,34]. Others have discussed the impact of different estimation methods on the spatiotemporal dynamics of arboreal carbon pools, highlighting the importance of forest age structure in carbon storage estimates and proposing a biomass storage model to calculate forest carbon storage [35]. Additionally, the role of afforestation and reforestation in enhancing carbon sequestration has gained prominence. With advancements in technologies such as sensing satellites, researchers are using high-precision remote sensing to analyze the dynamic changes in the carbon storage of plantation forests in different regions, finding that regenerating forests possess high carbon sequestration potential [36–38].

(2) Economic analysis of carbon sink trading: This includes theoretical discussions on the negative externalities of environmental pollution [39,40], studies on the mechanisms of carbon sink trading [41,42], and analyses of the impacts of carbon sink trading on the economic development of enterprises and countries [43,44]. Empirical studies have illustrated that integrating carbon sink trading into broader environmental and economic strategies can substantially lower the costs associated with emission reductions while offering both economic and ecological benefits to less developed regions [45,46].

(3) Mechanisms and institutional design of forest carbon sink trading: Natural climate solutions have become key to achieving carbon neutrality [47,48], with forest carbon sink offsets playing a crucial role [1,15,49]. However, the carbon market faces issues of oversupply and low prices, mainly due to insufficient demand and imperfect pricing mechanisms [50]. Moreover, the sustainability of forest carbon credit projects, characterized by their temporality and cyclical nature, has also been a subject of extensive debate [51–53]. Subsequent research has improved the assessment model of forest carbon trading by incorporating carbon flows in harvested wood products and harvesting volumes. This enhancement has provided a more accurate assessment of the impact of forest carbon trading [20,54].

Scholars have conducted in-depth studies on carbon sink trading pricing and trading methods, comparing the advantages and disadvantages of different policy tools from the perspectives of cost and risk control [55–57]. The various carbon offset trading mechanisms in international and Chinese markets, distinguishing between on-exchange and off-exchange carbon offset trading mechanisms, are summarized in Table 1. Carbon market trading mechanisms can be classified in a way that mirrors the organization of securities markets, which are typically divided into on-exchange and off-exchange (over the counter, OTC) transactions.

Table 1. Comparison of forest carbon sink trading mechanisms.

Market Level	International Market	National Level in China	Provincial Level in China	Carbon Sink Products
Off-Exchange Carbon Trading Mechanisms	Verified Carbon Standard (VCS Projects); Gold Standard Projects	China Green Carbon Foundation forestry projects; Large-Scale Event Carbon Neutrality	Independent carbon credit trading; provincial forest carbon credit projects (e.g., Fujian)	VCU [1]
On-Exchange Carbon Trading Mechanisms	Clean Development Mechanism (CDM); Joint Implementation (JI); Emission Trading Mechanism	Chinese Certified Emission Reductions (CCER)	Local CCER trading; carbon-inclusive forestry projects;	CCER, CER, EUR, AAU, RMU [2]

Note: The authors compiled this table based on the relevant literature and reports [2,19,58]. [1] VCU (verified carbon unit). [2] CER (certified emission reduction), ERU (emission reduction unit), AAU (assigned amount unit), RMU (removal unit).

In summary, although significant strides have been made in carbon storage and sink quantification, discussions on the economic valuation of forest carbon sinks as ecological goods remain relatively nascent. Moreover, while existing studies have focused on global or national scales, there is a noticeable gap in dynamic carbon accounting research at regional levels and between regions. Research covering the supply and demand sides of carbon credit trading, as well as its regulatory and institutional frameworks, has been extensive. However, investigations into effective strategies for addressing the dual challenges of sustainable economic development goals (this study uses "carbon intensity" as a proxy variable) and carbon sink imbalances are just beginning.

3. Materials and Methods

3.1. Data Sources

The forest inventory data used in this study, including forest area and stock volume, were obtained from the *China Forest Resources Report*; the GDP growth data were obtained from the national data in the National Bureau of Statistics of China (NBSC); and the carbon intensity data were obtained from the research reports of China's central government and local governments. Three main models were designed in this study: a biomass-storage model to estimate the carbon stock of Chinese arbor forests, a biomass density–forest age model (according to IPCC GPG-LULUCF, biomass density is the ratio between oven dry mass and fresh stem-wood volume without bark. It allows the calculation of woody biomass in dry matter mass) to estimate the carbon sink of Chinese arbor forest, and a carbon intensity–carbon sink assessment model to quantify and identify the carbon sink resources endowment in each province of China. The different data used in each model are described below.

For the biomass-storage model, we collected data on arbor forests from China's eighth (2009–2013) and ninth (2014–2018) forest inventories, including the area and storage of each forest type and the age group in 31 provincial administrative regions of China (excluding data from Taiwan and Hong Kong and Macao (due to the lack of disaggregated data on forest resources in Taiwan Province and Hong Kong and Macao Special Administrative Regions, the data for Taiwan Province and Hong Kong and Macao Special Administrative Regions are not included in the subsequent data from this paper unless otherwise noted.)). These data serve as the basis for the measurement and comparative analysis of carbon stocks and sinks in arbor forests. The forest resource inventory data in China are divided into those concerning arbor forests, bamboo forests, and special shrub forests, where quantitative indicators include area and storage volume [26]; the arbor forest data are further divided into natural forests and planted forests, according to the dominant species. In the ninth China Forest Inventory, only arbor forests are included in the forest stock. Therefore, the data collected for these types of study are primarily from arbor forests unless specified, and the focus is on the biomass carbon pool of arbor forests in the forest carbon pool, including both above-ground and below-ground biomass carbon pools. Notably, litter, dead wood, and soil organic matter carbon pools are not included in this study.

Furthermore, this study included more categories of dominant tree species and a more subdivided stand age structure. The eighth China Forest Inventory categorized trees into 84 dominant tree species in different provinces. The ninth China Forest Inventory classified every province's forest in China into natural forests and planted forests and specified 50 dominant tree species in natural forests and 57 dominant tree species in planted forests. Moreover, the two forest inventories divided the forests into five forest age groups according to growth and development stages, namely, young forest, middle-aged forest, near-mature forest, mature forest, and over-mature forest.

After excluding outliers, the eighth forest inventory contains 924 national data and 8448 provincial data, and the ninth National Forest Inventory contains 600 national data and 6024 provincial data for natural forests and 684 national data and 8100 inter-provincial data for planted forests.

This study employed the biomass density–forest age model to estimate the future carbon sink for each province in China. This was achieved by classifying the dominant tree species and forest age groups, utilizing data from the ninth National Forest Inventory (2014–2018). The analysis also incorporated provincial biomass carbon stock data, which were derived from the aforementioned biomass-storage model.

According to the data of the ninth National Forest Inventory, the forest area is 218,220,500 hectares and the arboreal forest area is 179,888,500 hectares [26]. The percentage of existing arboreal forest area of the total forest area in China is 82.43%. If the percentage remains unchanged, the new forest area in China can be projected from 2021 to 2035 based on future forest coverage.

For the carbon intensity–carbon sink assessment model, provincial carbon emission data were obtained from the 2019 provincial carbon emission inventory of China's carbon accounting database CEADs [59–62], which contains the total annual provincial CO_2 emissions of 30 provincial administrative regions of China (excluding Tibet, as data were unavailable). These data derive from the apparent emissions auditing method, which includes carbon emissions from fossil energy consumption and industrial processes and can better reflect the changes in carbon emissions brought by economic development in each province. In addition, the National Bureau of Statistics has provided detailed information on each province's GDP. Furthermore, the forecast data on the national GDP growth rate were from *The 14th Five-Year Plan of National Economic and Social Development of the People's Republic of China and the Outline of Vision 2035.* If China expects to double its GDP per capita in 15 years, it must maintain an annual GDP growth rate of at least 4.7%. The data related to China's national ETS originate from the public database of the Ministry of Ecology and Environment (MEE), and the regulation of a 5% carbon sink offsetting of total carbon emissions originates from the "Measures for the Administration of Carbon Emission Trading (Trial)" issued by the MEE. Furthermore, this research operates under the assumption that all CCERs are sourced exclusively from forest carbon sink initiatives.

3.2. Selection of Models and Scenario

In the realm of forest carbon measurement, international researchers primarily concentrate on two approaches: vegetation carbon measurement methods based on plot surveys and model-based carbon measurement strategies [63–65]. These methodologies are categorized as follows (Table 2).

Table 2. Comparison of forest carbon accounting research methods.

Method	Main Content	Premise	Limitations
Carbon Accounting Based on Plot Surveys	Harvesting method; biomass method; accumulation method; biomass inventory method; eddy covariance method.	Accurate forest resource inventory data	Excessive cost; long time cycle; data lag
Carbon Accounting Based on Spatial Technologies	Satellite remote sensing method.	Relevant technology and measurement methods are required	High technical difficulty; excessive cost

Note: The authors compiled this table based on the relevant literature and reports [65–67].

This research adopts the biomass approach from the carbon accounting techniques based on plot surveys. Figure 1 presents the methodology for assessing China's carbon intensity and sink capacities through an integrated approach involving three models. Initially, a biomass-storage model calculates current forest carbon stocks (according to the IPCC AR6, carbon stock is identified as "The quantity of carbon in a carbon pool") per province. Subsequently, future stocks are estimated using a biomass density–forest age model, classifying provinces as 'sinks' (according to the IPCC AR6, sink is identified as "Any process, activity or mechanism which removes CO_2 from the atmosphere") if future stocks exceed current ones, or 'sources' (according to the IPCC AR6, source is identified as "Any process or activity which releases a greenhouse gas") otherwise. Furthermore, a carbon intensity–sink assessment model projects future emissions and the required offsetting volume for each province. This leads to a determination of carbon surplus or deficit, culminating in a scoring system that categorizes provinces as carbon-negative, carbon-balancing, or carbon-positive based on forest sink data and carbon credit demand.

The merit of this approach lies in leveraging models integrated with on-the-ground data to offer more precise forest carbon storage estimates. When contrasted with newer satellite and remote sensing methods, it stands out for its lower technical complexity, higher practicality, and data availability. Recent studies utilizing remote sensing and other modern technologies have revealed the significant potential of China's terrestrial carbon sinks [66]. The acknowledgement of this potential has initiated new discussions about the accuracy of remote sensing technology in the field of carbon sink estimation [68].

The biomass-storage model, part of the BEF methodology [34], is a globally accepted approach for estimating forest carbon storage. Its strengths include being straightforward and reliable, and it has demonstrated considerable credibility in China's carbon sink measurement studies. This method is frequently employed in the forest carbon sink reports of the Intergovernmental Panel on Climate Change (IPCC) and the carbon sink measurement analyses of China's National Forestry and Grassland Administration. The biomass density–forest age model employs the logistic growth model, which is a kind of allometric model using non-linear regression techniques. This model is adept at fitting plant growth curves and estimating the carbon sequestration rate of forest ecosystems using age-related data, which are prevalent in forestry studies [23,27].

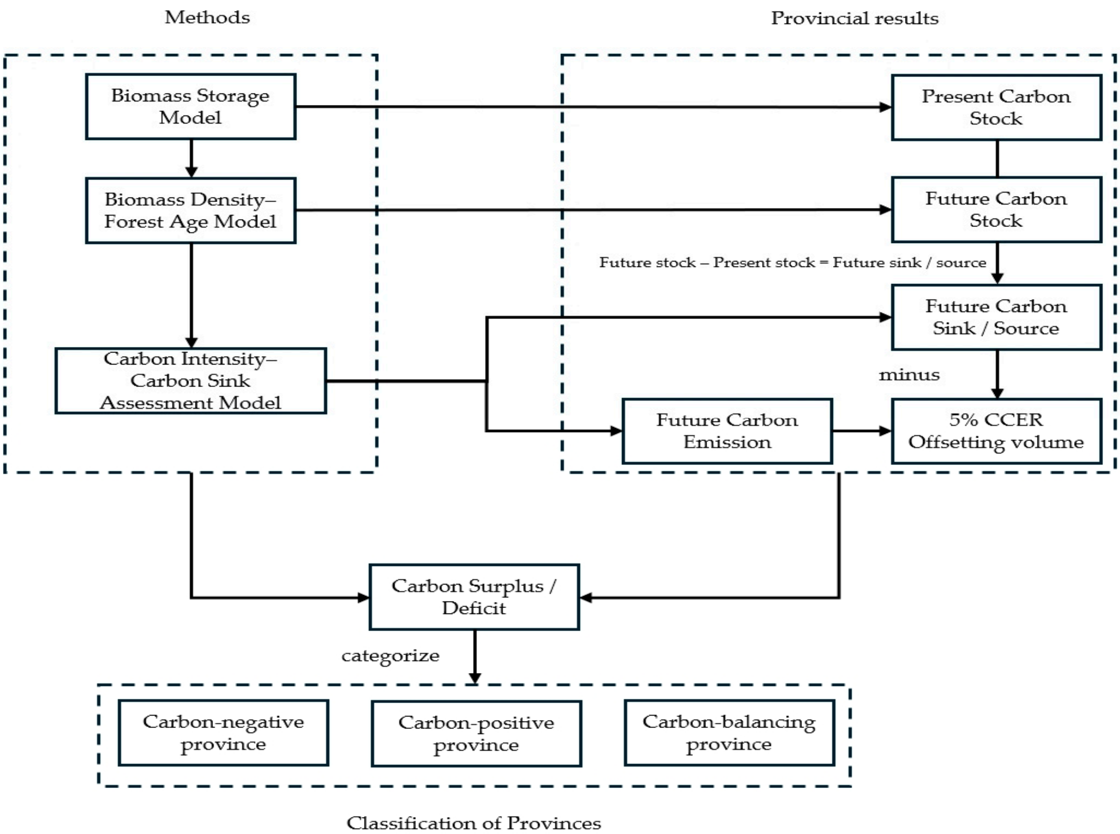


Figure 1. Analytical framework of the study on the carbon intensity–sink assessment model in China.

Due to the advantages of plot surveys and BEFs methodology we mentioned, this study calculates forest carbon storage using the biomass-storage model and forest carbon sink volume using the biomass density–forest age model. Coupled with annual provincial carbon emission data from China, the carbon intensity–carbon sink coupling model is employed to assess the carbon sink balance in various provinces.

Based on these models, the following scenario assumptions were considered. In terms of the timeframe and research project, this study focuses on the carbon emission absorption issues during China's carbon neutrality period. The carbon emissions during China's carbon neutrality period are those that cannot be further mitigated through technological advancements in industrial processes and energy consumption, representing "inevitable CO_2 emissions." According to Ding Zhongli of the Chinese Academy of Sciences, chief of the China Carbon Neutrality Roadmap Research Project, China will still emit approximately 2 to 2.5 billion tons of CO_2 in 2060 [69]. These emissions require removal through ecological construction, engineering sequestration, etc., to achieve carbon neutrality.

The research scope centers on the provincial scale, addressing mismatches in carbon sink/carbon emission ratios and discrepancies between production and consumption-end carbon emissions. The research subject is the critical aspect of ecosystem carbon sequestration, and specifically forest ecosystem carbon sequestration, encompassing both forest carbon storage and carbon sink volume.

3.3. Methods for Carbon Stock Measurement

In calculating carbon sequestration using the biomass-storage model, tree species and stand age are crucial components of the fitting equations. This section categorizes the different tree species for each province and further differentiates stand age according to tree species and region, referencing the forest carbon stock measurement method proposed by previous research [35] to categorize the species of the eighth and ninth National Forest Inventory data according to 13 forest types, and further specifies the forest age groups from three groups to five. The provincial forest biomass density and carbon stock were estimated by fitting the biomass-storage model (the equation fitting parameters are shown in Table A1), respectively.

$$Bij = a + b * Vij \tag{1}$$

In this equation, B_{ij} is the unit biomass of forest type i and forest age group j (Mgha^{-1}), V_{ij} is the unit stock volume of forest age group j of forest type (m^3 ha^{-1}), i is a forest type (i = 1, 2, . . ., 13), and j is a forest age group (j = 1, 2, 3, 4, 5); a and b are constants to adjust forest growth.

Based on the provincial data of the eighth forest inventory, the unit stock volume of each forest age group of 84 dominant tree species was calculated and applied into Equation (2) to calculate the total biomass of different forest types separately. Furthermore, the unit biomass density and unit carbon density were calculated based on the area of each forest type.

$$C_p = \left[\sum_{i=1}^{84}\sum_{j=1}^{5} A_{ij} \times B_{ij}\right] \times C_c \tag{2}$$

Applying Equation (1) to Equation (2) provides the forest carbon stock (2009–2013) in each province:

$$C_p = \left[\sum_{i=1}^{84}\sum_{j=1}^{5} A_{ij} \times \left(a + b * V_{ij}\right)\right] * C_c \tag{3}$$

where C_p is the forest carbon stock (Tg C) of provincial administrative region P, C_c is the carbon content of forest vegetation, and 0.5 is often used (The Intergovernmental Panel on Climate Change (IPCC) suggests a default value of 0.5 for the carbon fraction of dry matter to estimate carbon stock changes in biomass, based on the GPG-LULUCF.

Based on the data from the ninth National Forest Inventory, it is evident that applying Equations (1)–(3) provides more accurate data regarding the stock volume and carbon unit density of the 50 natural forests and 57 planted forests in question, demonstrating the 2014–2018 provincial forest carbon stock volume.

3.4. Methods for Carbon Sink Prediction

Forest age and tree species are typically used as key explanatory variables for estimating forest carbon sequestration through BEFs; however, effective extrapolation of the stand age presents certain challenges. Based on the forest inventory criteria for classifying the age classes of different forest types (Table A2), this study used the forest age segmentation method (the method used in this study was compiled from the forestry industry standard 'Classification of age classes and age groups of major tree species' (LY/T 2908-2017)) for 50 natural forests and 57 planted forests in the ninth National Forest Inventory, and we used the median value of the forest age segment to represent the average forest age of the forest age group. This method predicts the future carbon stock and carbon sink in each province of China with the premise that the future forest coverage and stand structure will remain unchanged and that there will be no large-scale deforestation or mortality in the future.

We adapted the method of Xu Bing et al. [27] and optimized data collection on the age group values of natural and planted forests (see Table A2). The relationship between biomass density and forest age for each forest type was fitted based on the logistic growth equation to form the equation for predicting future forest carbon sink growth (biomass density–forest age).

$$B = \frac{\omega}{1 + ke^{-at}} \tag{4}$$

where B is the biomass density (Mgha^{-1}), t is the stand age (a), e is the base of the natural logarithm, and ω, k, and a are constants.

In this research, we used MATLAB R2022a (Natick, MA, USA: The MathWorks Inc.) to demonstrate the curve-fitted results of a non-linear regression code, according to the categories of natural and planted forests and each tree species' biomass density and stand age. Furthermore, adding Equation (4) into the calculation produced the equation coefficients of the carbon sink growth of each tree species.

For example, based on the data provided by the ninth National Forest Inventory (covering 2014–2018) and the area and stock distribution of each age group for each type of forest, and assuming there is no large-scale deforestation and mortality in the next 5 years, then the size of the biomass carbon pool of this part of the existing forest in a future year can be calculated with the following equation, using planted forests as an example:

$$C_{\Delta t} = \sum_{i=1}^{57}\sum_{j=1}^{5} c \times A_{ij} \times B_{ij} = \sum_{i=1}^{57}\sum_{j=1}^{5} c \times A_{ij} \times \frac{\omega_i}{1 + k_i e^{-a_i(t_{ij}+\Delta t)}} \quad (5)$$

where $C_{\Delta t}$ is the total carbon pool of the existing forest at Δt years later (Tg C); i is the total carbon pool of a forest type (i = 1, 2, . . ., 57); j is a forest age group (j = 1, 2, 3, 4, 5); c is the carbon content of forest vegetation, often using 0.5; A_{ij} is the area (ha) of forest age group j of forest type i in a provincial administrative region; B_{ij} is the biomass density of forest age group j of forest type i (Mgha^{-1}); ω_i, k_i, and a_i are the logistic curve constants of biomass density versus forest age for forest type i; t_{ij} is the mean stand age (a) for age group j of forest type i; and Δt is the time span between the prediction period and the baseline time period.

The predicted total biomass carbon pool of the natural forest at year N is equal to the sum of the size of the biomass carbon pool of the existing forest at year t + N and the size of the biomass carbon pool of the newly created forest at year N.

The future total forest carbon pool projection relies on the future forest coverage data. According to the outline of the 14th Five-Year Plan (the Five-Year Plans are a series of social and economic development initiatives issued by the Chinese Communist Party (CCP) in the People's Republic of China. The 14th Five-Year Plan covers the years 2021–2025), the forest coverage rate will increase to 24.1% by 2025. According to *The Master Plan of Major Projects of National Important Ecosystem Protection and Restoration (2021–2035)* [70], forest coverage will reach 26% in 2035. Assuming that China's forest coverage is considered as a simple linear growth to reduce uncertainties, such as those related to deforestation and wildfires, the forest coverage during 2026–2030 will reach around 25.05%.

In this study, the growth curves of each dominant species were calculated based on the data of 62 forest types (50 natural forests and 57 planted forests) from the ninth National Forest Inventory. Moreover, based on the ratio of the area of each dominant species in planted forests (Table A3), the new forest area was assigned to 57 forest types according to the abovementioned newly planted forest area in China. Finally, the carbon pool of the new forest area was obtained by adding the new forest area of each dominant species to Equation (5).

3.5. Methodology for Carbon Intensity–Carbon Sink Assessment Analysis

The main function of the carbon intensity–carbon sink assessment model is to predict the carbon credit market capacity of each province in China based on the annual carbon emission data of that province in the past to a certain point in the future calculation period.

Based on the CCER offsetting ratio and China's carbon intensity reduction target, the carbon intensity reduction and forest carbon sink of each province are calculated, where the GDP growth rate is used as the national average growth rate value, and, finally, the carbon credit market capacity of each province is derived to distinguish carbon sink, carbon balance, and carbon-positive provinces; the equation is derived as follows:

$$V_P = C_i \times \alpha \quad (6)$$

$$C_i = G_i \times CI_i \quad (7)$$

$$G_i = G_t \times (1+R)^{(i-t)} \quad (8)$$

$$CI_i = C_t / G_t \times (1 - T_P) \quad (9)$$

Bringing Equations (8) and (9) into Equation (7) yields the following:

$$C_i = \left[G_t \times (1+R)^{(i-t)} \right] \times (C_t / G_t \times (1 - T_P)) \quad (10)$$

Bringing Equation (10) into Equation (6) yields the following:

$$V_P = C_t \times (1+R)^{(i-t)} \times (1 - T_P) - C_t \times \alpha = C_t \times \left[(1+R)^{(i-t)} \times (1 - T_P) \right] \times \alpha \quad (11)$$

where V_P is the carbon credit market capacity of provincial administrative region P during the period (million tons), C is carbon emissions (million tons), G is total GDP (million CNY), α is the CCER offset ratio (%), CI is the carbon intensity (CO_2/GDP), R is the GDP growth rate (%), T_P is carbon intensity reduction target (%) in the provincial administrative region P, i is the end year of the calculation period, and t is the beginning year of the calculation period.

From Equation (11), it follows that C_t, R, and α are constants, the carbon intensity reduction percentage T_P and CCER market capacity V_P have a linear relationship, and the carbon intensity reduction target T_P and CCER market capacity V_P are inversely proportional to the CCER market capacity. Furthermore, the CCER market capacity has a maximum limit when T_P is zero.

Therefore, considering the forest carbon sink data from 2019 to 2025 as an example, it is evident that incorporating China's GDP and the carbon intensity control target of each province in the period of the 13th Five-Year Plan (13th Five-Year Plan covers the years 2016–2020) (Table A4) into the calculation of China's provincial carbon intensity index in 2019 and the 14th Five-Year Plan period would yield the desired information on carbon intensity emission target reduction in each province in China for 2019–2025 and the carbon credit market capacity of each province. Furthermore, according to additional data sources of this study, it was assumed that R is 4.7%, α is 5%, and i and t are 2019 and 2025, respectively. Using these data in Equation (11) yields the carbon sink demand of each province:

$$V_P = 0.0659 C_t \times (1 - T_P) \quad (12)$$

There are two assumptions in this calculation: (1) the total carbon emissions of each province in 2025 depend on the carbon sinks of newly planted forests in each province from 2019 to 2025 to complete the carbon intensity reduction target in the 14th Five-Year Plan period. (2) The forest carbon sinks' calculation assumes that only the carbon sinks of newly planted forests can enter the CCER circulation market, and the carbon sink growth of existing forests is not considered, for the time being, when using Equation (5).

The carbon balance of each province can be obtained by subtracting the demand for carbon sinks in each province from Equation (12) and by subtracting the carbon sinks of newly planted forests from Equation (5); the result will demonstrate either a carbon surplus or a deficit:

$$CB = V_P - C_{\Delta t} = 0.0659 C_t \times (1 - T_P) - \sum_{i=1}^{57} \sum_{j=1}^{5} c \times A_{ij} \times \frac{\omega_i}{1 + k_i e^{-a_i (t_{ij} + 8)}} \quad (13)$$

According to the ninth National Forest Inventory's data on the total percentage of planted forest, the newly planted forest area from 2019 to 2025 is distributed into 57 forest categories (Table A3). These data were incorporated into Equation (13) to calculate the carbon sink of the new forest area.

4. Results

4.1. Provincial Carbon Stock Model

The calculation based on the data of the biomass-storage model estimates the total biomass, biomass density, carbon stock, and carbon density of 31 provinces in China, as shown in Table 3. According to the ninth Forest Inventory (China's National Forest Inventory based on continuous forest inventory principles with permanent plots and statistical sampling. The national statistics were obtained from the summation of all provincial statistics completed in a 5-year cycle [25]. The results of carbon stock and carbon density in the study reflect a rolling average picture of conditions over a 5 year period) (2014–2018), the carbon stock of arbor forests was 7575.38 Tg C. The data difference is 1.29% when comparing the result to the carbon stock model; this shows that the model has good robustness. The comprehensive environmental protection policies and afforestation since the early years of the 21st century have benefited the growth of China's forest area, forest stock volume, carbon stock, and carbon intensity from 2009 to 2018.

Table 3. Forest carbon pools in China, 2009–2018.

Periods	Arbor Forest Area (10^4 ha)	Forest Stock Volume (10^6 m^3)	Biomass (Tg)	Carbon Stock (Tg C)	Carbon Density $(Mgha)^{-1}$
2009–2013	16,460.35	14,779.09	13,462.27	6731.14	40.89
2014–2018	17,988.85	17,058.20	15,347.64	7673.82	42.66

According to the distribution of carbon stocks and carbon density by province in China (Figures 2–4, Table A5), there are apparent gradient and spatial differences in the regional distribution of carbon stocks and carbon density in China. The data divide the provinces into three different levels of carbon resources. The first level contains provinces which registered a carbon-rich inventory from 2014 to 2018: Heilongjiang, Yunnan, Tibet, Inner Mongolia, and Sichuan. These account for 50.8% of China's carbon inventory. The second level includes Jilin, Guangxi Fujian, Guangdong, Jiangxi, Shaanxi, Hunan, Hubei, Guizhou, and Liaoning, with a cumulative proportion of 85.4% of China's total carbon inventory; the remaining provinces are the third level, with a combined proportion of 14.4% of China's total carbon inventory. The national average of forest carbon density in China from 2014 to 2018 was 42.66 $Mgha^{-1}$, with 10 provinces above the national average (Figure 5). The top provinces in terms of carbon density were Tibet, Xinjiang, and Jilin.

There is a significant carbon stock imbalance problem in each province, according to carbon stock changes (Figure 3). The total volume shows that northeast, southwest, and south China have excessive carbon stock, whereas northwest and east China have insufficient carbon stock. The growth volume is higher in southwest, northeast, and south China and lower in east and north China.

In terms of carbon density change, the same challenge of large carbon density imbalance exists in all provinces (Figure 4); however, the total volume is higher in the southwest and northeast than in the south and middle China. On the other hand, the growth volume is faster in east, south, and middle China than in the southwest and northwest. Meanwhile, it is evident that there is a fundamental imbalance between the forest carbon stock-rich regions and economically developed regions in China, and most of the economically developed regions are the regions with lower forest carbon stocks.

In conclusion, according to the distribution maps (Figures 2 and 3), China's carbon reserves are concentrated in the northeastern and southwestern regions. Moreover, the carbon reserves in the southwest and southeast regions have a higher growth rate, especially those on the southeast coast. Therefore, the southeast coast needs to purchase carbon sinks to offset in the short term. However, the demand gap for carbon sinks in provinces such as Fujian and Guangdong will gradually decrease in the long term. There will also be demand for carbon sink purchases that will become less critical. Therefore, Guangdong and Fujian may not become the focus of carbon sink trading based on the supply–demand relationship of China's national ETS. However, given the slow growth rate of carbon sink volume in central China, which overlaps with the development demand of the central rising strategy, provinces such as Hubei and Hunan may require a substantial carbon sink purchase, creating a gap in their trading.

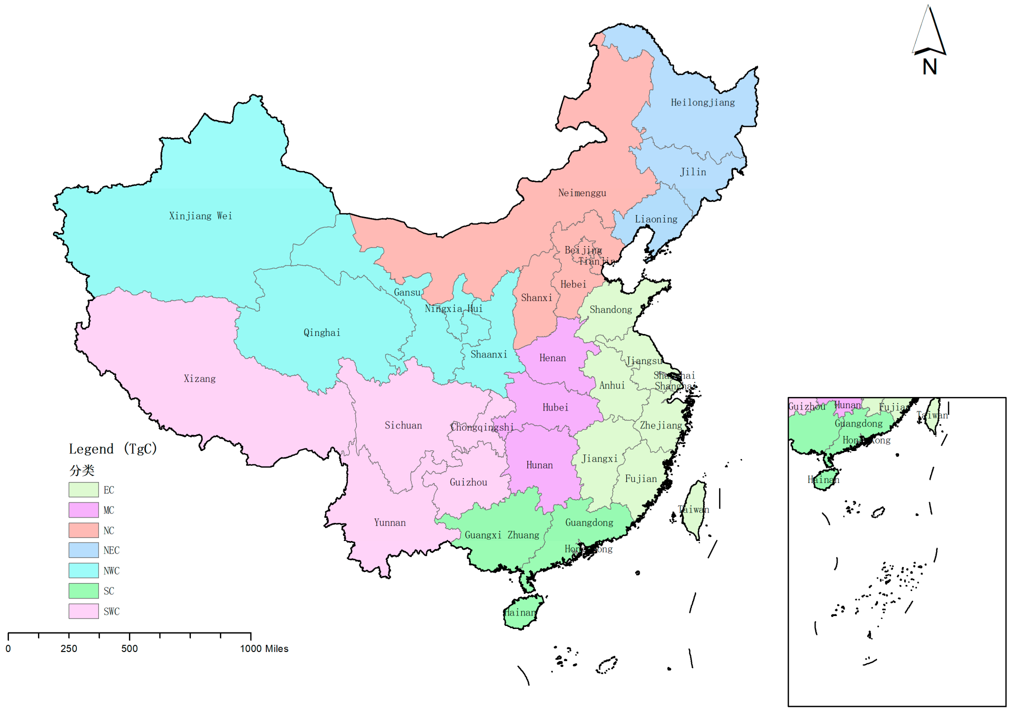
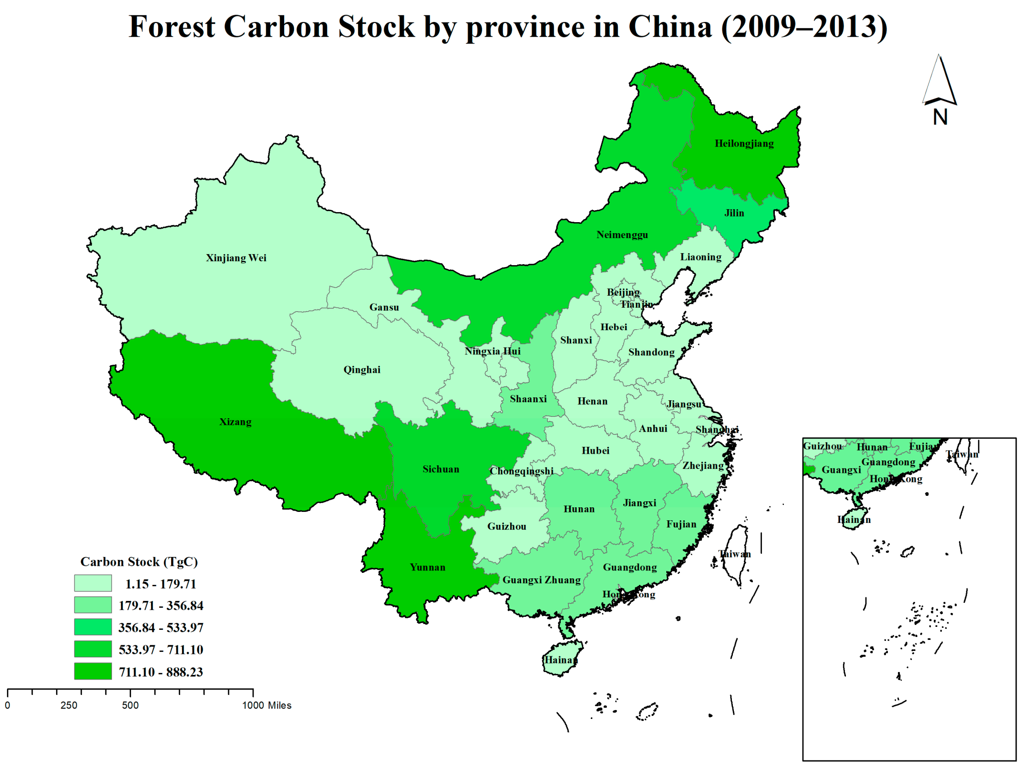


Figure 2. The seven regions in Chinese geography [71]. EC: east China, MC: middle China, NC: north China, NEC: northeast China, NWC: northwest China, SC: south China, and SWC: southwest China.



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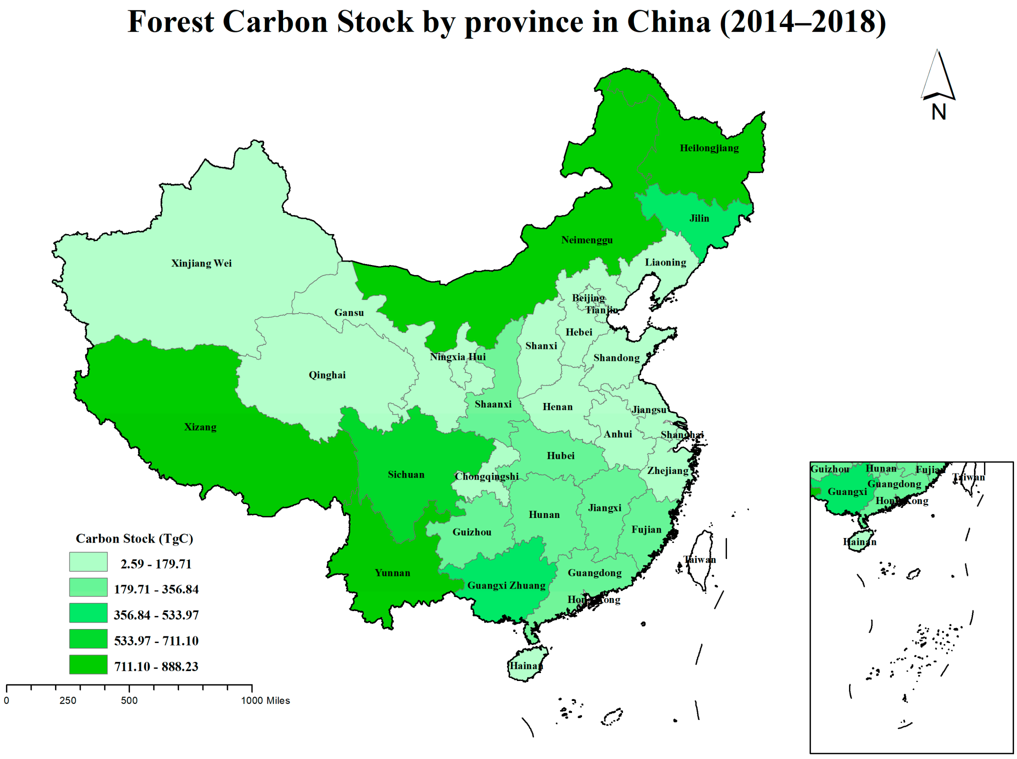
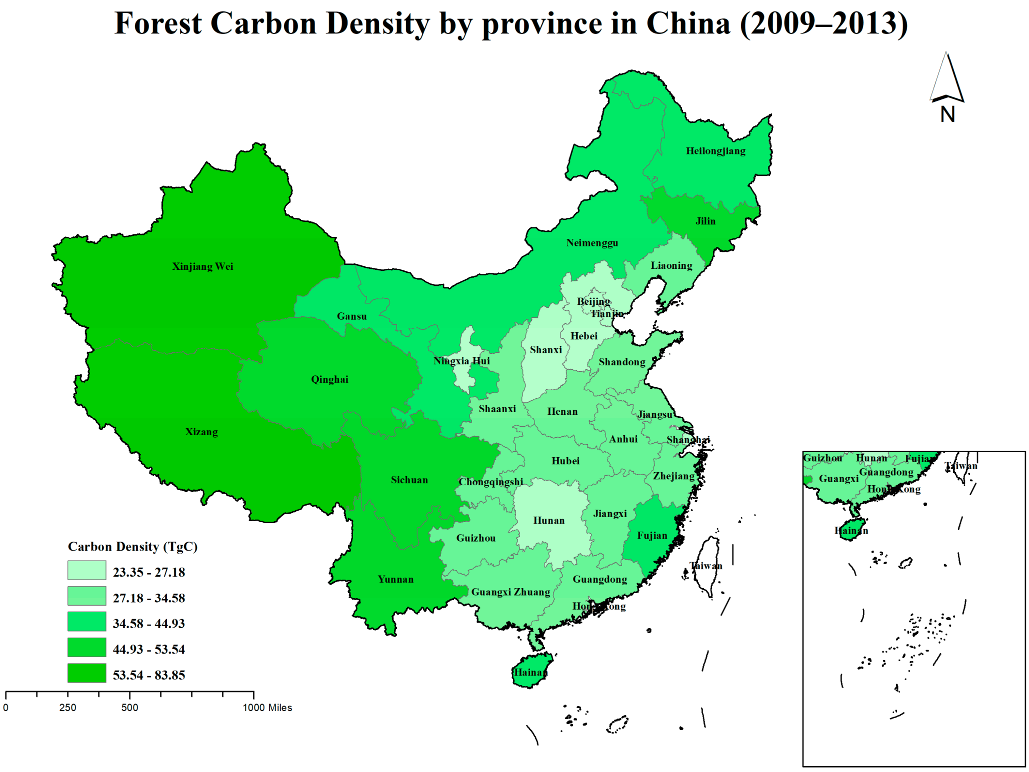


Figure 3. Provincial forest carbon stocks in China, 2009–2018 (TgC).



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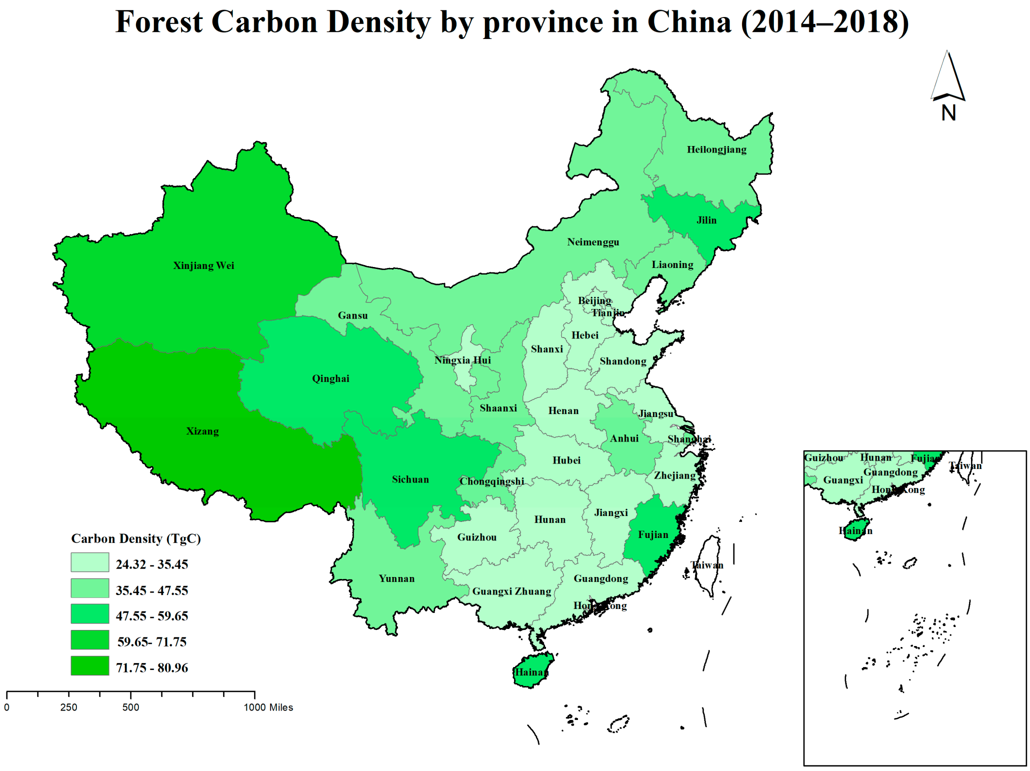
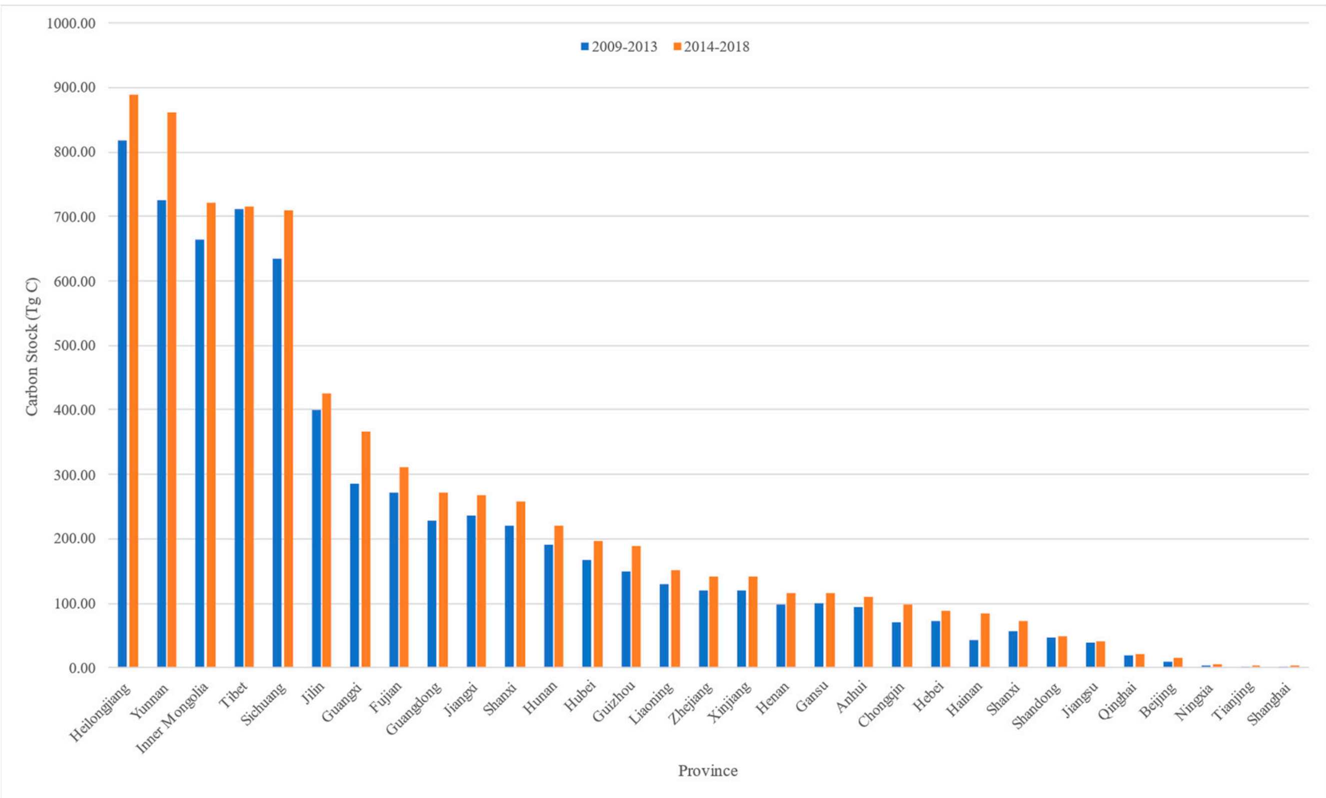


Figure 4. Provincial forest carbon density in China, 2009–2018 (TgC).



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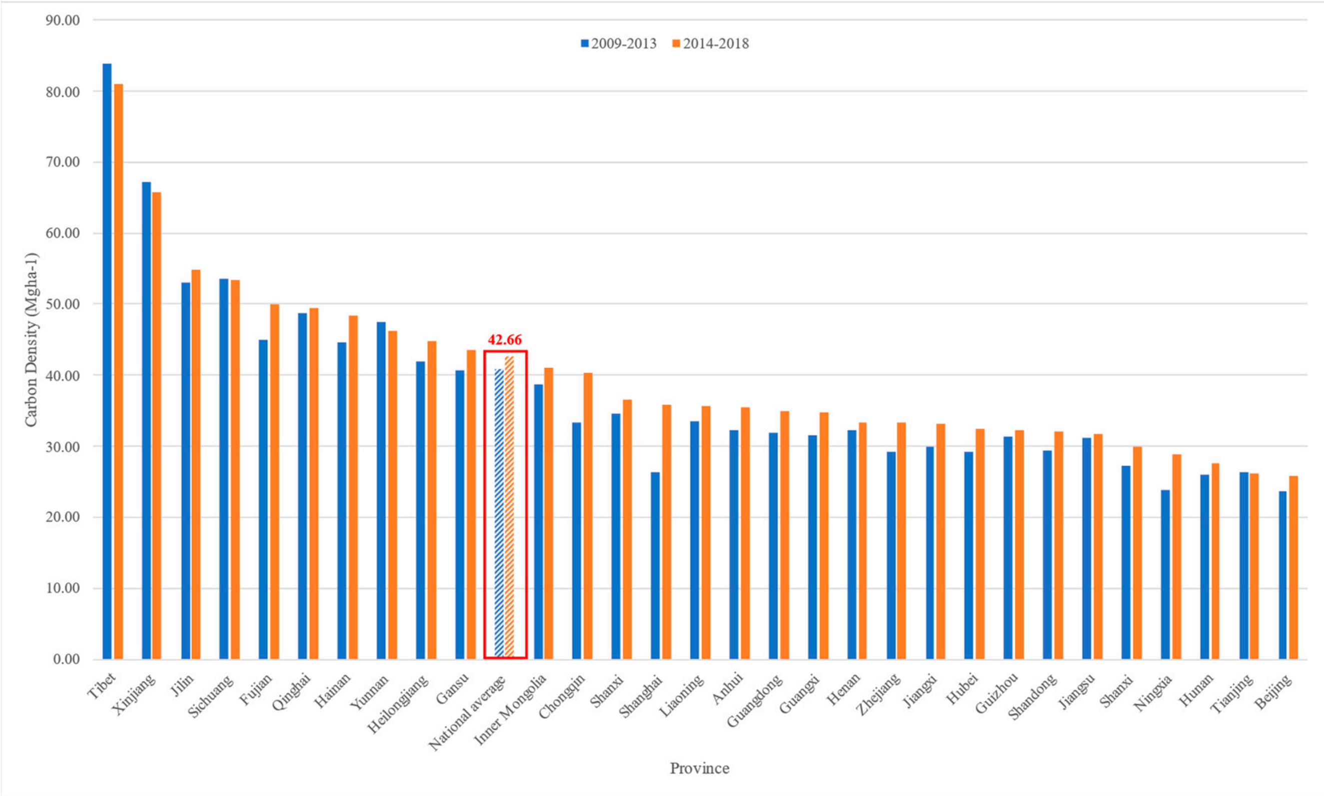

Figure 5. Carbon stock and carbon intensity ranking of China's provinces and their changes.

4.2. Provincial Carbon Sink Model

The biomass density–forest age relationship was fitted for 50 natural forest species and 57 planted species by the biomass density–forest age model in the ninth National Forest Inventory, and the results are shown in Appendix B Tables A6 and A7. This table is arranged in descending order according to the area of dominant tree species. After excluding the species with invalid data, 41 species were calculated in natural forests. Of these, 36 species had R^2 greater than 0.8, accounting for 97.27% of the total area of natural forests, and 51 species were registered in planted forests (among them, the data quality of Siemian pine, maple, fir, and cork oak in planted forest was characterized by poor fit, and natural forest fitting parameters were used instead) (of these species, 35 had an R^2 greater than 0.8, accounting for 97.20% of the total area of planted forests). The calculated results present optimistic data, using reliable evidence, regarding the natural growth process of each forest type. As shown in the figure, the fitted curve effects of both the natural forests and planted forests with the top six land areas also better reflected the natural growth process of trees (Figures A1 and A2).

Based on the logistic growth equation (in the biomass density–forest age model) using the forest inventory data from 2014 to 2018, the changes in carbon pools of existing forests in the 14th, 15th, and 16th Five-Year Plans were predicted. The results are shown in Table A8. In terms of carbon stock, the carbon stock of existing forests steadily increased to 9.8 billion tons C after three Five-Year Plans. It increased by 2.203 billion tons C compared with 2014–2018, with an average annual increase of 120 million tons C. In terms of carbon density, the carbon density of existing forests increased from 42.66 Mgha^{-1} to 54.9 Mgha^{-1}, with an average annual increase of 0.72 Mgha^{-1}.

Table A8 in Appendix B shows the prediction of newly planted forests' carbon inventory changes in China's next Five-Year Plan. The carbon inventories will increase to 892 million tons C, with an average annual growth rate of 52 million tons. Furthermore, the proportion of increased carbon inventories grew from 2.38% in the 14th Five-Year Plan to 9.05% in the 16th Five-Year Plan. In terms of carbon density, it will reach 37.45 Mgha^{-1}.

Combining every change in the carbon stock and carbon intensity of existing and newly planted forests (see Figure 6), it can be observed that newly planted forest is gradually becoming the main source of the carbon pool increase. The proportion of newly planted forest's carbon pool went up from 2.38% in the 14th Five-Year Plan to 9.05% in the 16th Five-Year Plan.

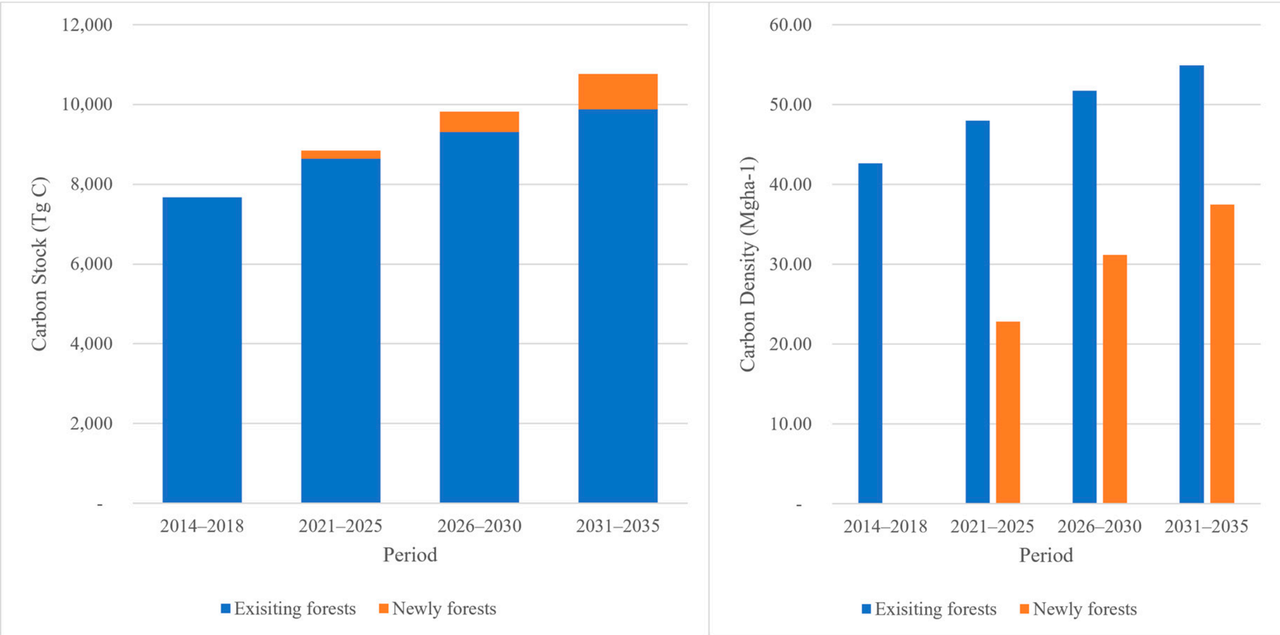

Figure 6. Projected carbon stock and carbon density of existing and newly created forests in China, 2014–2035.

4.3. Provincial Carbon Intensity–Carbon Sink Assessment Model

The calculations of the carbon intensity for 30 Chinese provinces in 2019 are based on the carbon intensity–carbon sink assessment model, which projects the target carbon intensity and carbon emissions in 2025. In addition, the calculation based on the 5% CCER offset principle provides the demand volume of carbon credit from sink projects in 30 provinces. The difference between the demand of carbon credits and the supply of forest carbon credits in each province is the carbon balance data of the province. Therefore, a positive result represents a carbon surplus, while a negative result represents a carbon deficit.

The total volume data (Table 4) predict that China's total carbon emissions in 2025 will be about 13.22 billion tons C, and the demand for carbon sink credits, according to the 5% CCER offset principle, will be about 661 million tons C. The amount of carbon sinks in the newly planted area of planted forests in the 14th Five-Year Plan period will be about 203 million tons C. The supply to-demand ratio is about 1:3, which aligns with the total emission control target of tightening the carbon market and is conducive to carbon emission regulation.

At the provincial level, regions are affected by natural conditions and resource endowments, and there are spatial imbalances in both carbon sink growth and emissions (Table 5). Regarding carbon emissions, socio-economic development conditions heavily influence the provinces. Carbon emissions are mainly concentrated in the traditional energy generation provinces such as Shanxi, Shandong, and Inner Mongolia, leading carbon emissions in 2025 and making up 31.89% of the country's carbon emission. However, provinces with lower carbon emissions are typically either economically developed areas with a strong tertiary sector or economically lagging regions. Qinghai, Beijing, Hainan, Chongqing, Tianjin, Shanghai, and Yunnan are among the provinces with the lowest carbon emissions, contributing to only 6.3% of the national total.

Table 4. Projected total provincial carbon emissions in China in 2025 and forest carbon sinks in 2019–2025 (million tons).

Province	Carbon Intensity	Carbon Emissions	5% CCER Offsetting Volume	Carbon Sink	Carbon Surplus/Deficit
Beijing	0.16	73.95	3.70	0.96	(2.74)
Tianjin	0.78	144.22	7.21	0.37	(6.85)
Hebei	1.35	621.47	31.07	5.80	(25.27)
Shanxi	8.22	1836.34	91.82	3.29	(88.53)
Inner Mongolia	4.75	1076.41	53.18	12.97	(40.21)
Liaoning	2.07	678.38	33.92	6.57	(27.34)
Jilin	1.38	213.62	10.68	6.14	(4.54)
Heilongjiang	2.12	377.48	18.65	8.49	(10.15)
Shanghai	0.33	167.03	8.35	0.15	(8.20)
Jiangsu	0.51	666.66	33.33	4.65	(28.68)
Zhejiang	0.53	438.95	21.95	3.69	(18.26)
Anhui	0.89	430.95	21.55	5.56	(15.99)
Fujian	0.52	292.65	14.63	10.08	(4.55)
Jiangxi	0.61	197.43	9.87	9.56	(0.31)
Shandong	1.40	1303.51	65.18	5.55	(59.62)
Henan	0.70	492.03	24.60	7.35	(17.25)
Hubei	0.50	301.28	14.97	4.76	(10.21)
Hunan	0.50	261.47	13.07	12.10	(0.98)
Guangdong	0.42	595.86	29.79	19.55	(10.25)
Guangxi	0.90	250.73	12.39	22.86	10.47
Hainan	1.09	76.62	3.83	5.36	1.53
Chongqing	0.43	133.26	6.66	2.31	(4.36)
Sichuan	0.48	293.27	14.66	11.85	(2.81)
Guizhou	1.41	312.42	15.62	8.58	(7.04)
Yunnan	0.61	185.91	9.30	14.82	5.53
Shaanxi	1.94	660.63	33.03	4.69	(28.34)
Gansu	1.79	205.19	10.14	2.88	(7.26)
Qinghai	1.35	52.49	2.62	0.29	(2.33)
Ningxia	5.64	278.73	13.77	0.37	(13.40)
Xinjiang	3.36	601.98	30.10	1.97	(28.13)

Table 5. China's total provincial carbon emissions in 2025 and the proportion of forest carbon sinks in China during 2019–2025.

Province	Proportion of Carbon Emissions	Proportion of Carbon Sinks
National	100%	100%
Shanxi	13.89%	1.62%
Shandong	9.86%	2.73%
Inner Mongolia	8.14%	6.37%
Liaoning	5.13%	3.23%
Jiangsu	5.04%	2.28%
Shaanxi	5.00%	2.30%
Hebei	4.70%	2.85%
Xinjiang	4.55%	0.97%
Guangdong	4.51%	9.60%
Henan	3.72%	3.61%
Zhejiang	3.32%	1.81%
Anhui	3.26%	2.73%
Heilongjiang	2.86%	4.17%
Guizhou	2.36%	4.22%
Hubei	2.28%	2.34%
Sichuan	2.22%	5.82%
Fujian	2.21%	4.95%
Ningxia	2.11%	0.18%
Hunan	1.98%	5.94%
Guangxi	1.90%	11.23%
Jilin	1.62%	3.02%
Gansu	1.55%	1.42%
Jiangxi	1.49%	4.70%

Table 5. *Cont.*

Province	Proportion of Carbon Emissions	Proportion of Carbon Sinks
Yunnan	1.41%	7.28%
Shanghai	1.26%	0.07%
Tianjin	1.09%	0.18%
Chongqing	1.01%	1.13%
Hainan	0.58%	2.63%
Beijing	0.56%	0.47%
Qinghai	0.40%	0.14%

The regions mentioned above only generate 10.72% of the nation's electricity, and China's seven lowest-ranking provinces generate only 11.92% of the total carbon sink. Therefore, it is evident that a spatial imbalance exists in the proportion of carbon emissions and carbon sinks among Chinese provinces. For example, Shanxi accounts for 13.89% of carbon emissions and only 1.62% of carbon sinks, and Guangxi accounts for 1.9% of carbon emissions and 11.23% of carbon sinks. In total, the provinces mentioned above include 13 provinces that have imbalanced carbon emissions and carbon sinks.

According to the data from the study on carbon sink offset in each province, we compared the proportions of provincial carbon emissions (Figure 7) and carbon sinks (Figure 8) in China. We used three different labels to categorize 30 provinces (Table 6): carbon-negative, carbon-balancing, and carbon-positive. The definition of each category was determined by the relationship between carbon sink and carbon emissions. A "carbon-negative province" sequesters more carbon than it emits, reaching a threshold where the carbon sequestered is greater than 5% of its emissions. A "carbon-balancing province" does not reach the 5% absorption threshold but stands out because its contribution to national carbon absorption is greater than its share of national emissions. Finally, a "carbon-positive province" also falls below the 5% sequestration threshold and also contributes less to national carbon sequestration than it does to emissions, indicating that it releases more carbon than it sequesters.

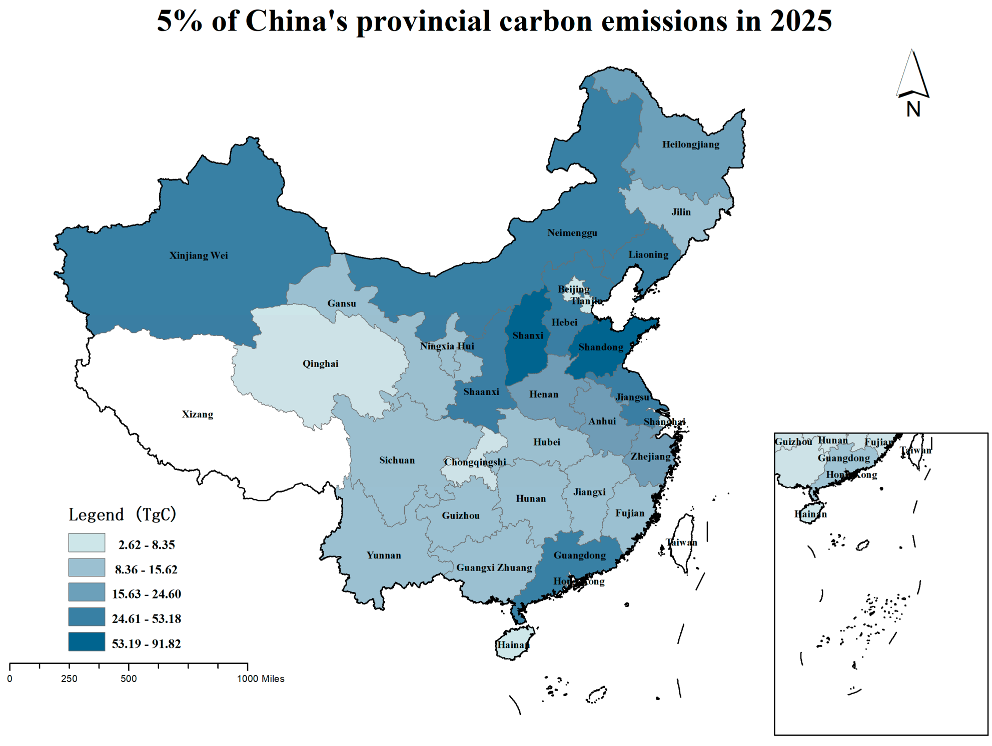

Figure 7. This figure shows 5% of China's provincial carbon emissions in 2025 (TgC).

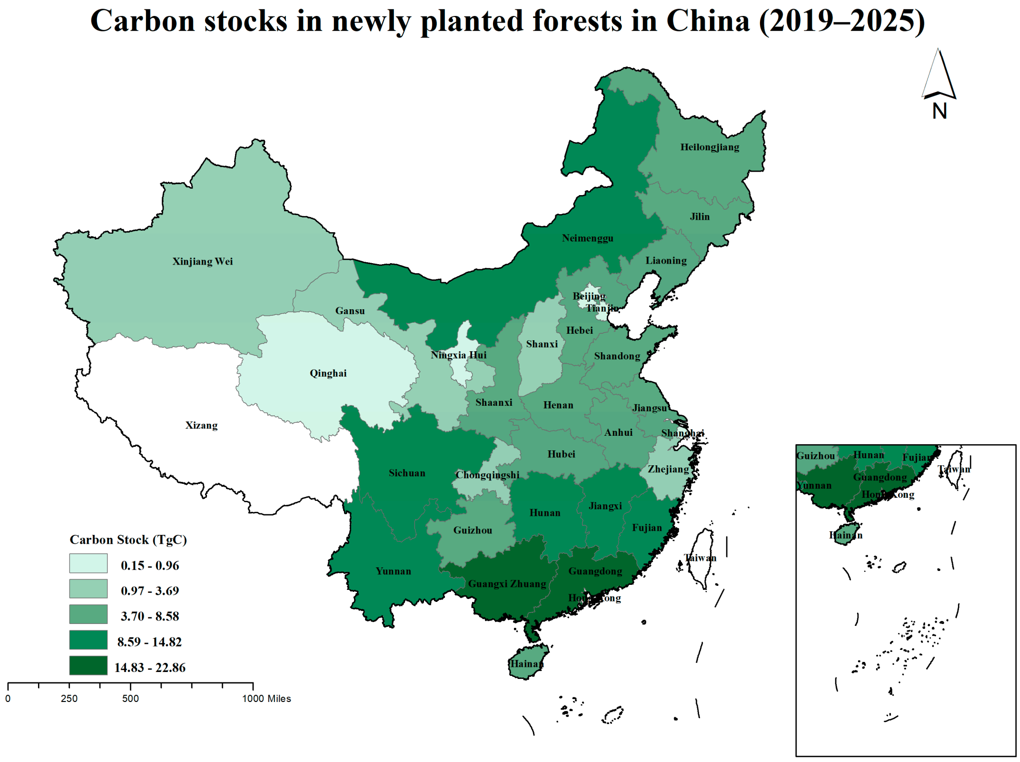

Figure 8. Carbon stocks in newly planted forests in China (2019–2025) (TgC).

Table 6. Classification of carbon sinks by province.

Classification	Province
Carbon-negative province	Guangxi, Yunnan, Hainan
Carbon-balancing province	Jiangxi, Hunan, Sichuan, Chongqing, Fujian, Jilin, Guizhou, Heilongjiang, Hubei, Guangdong
Carbon-positive province	Shanxi, Shandong, Inner Mongolia, Jiangsu, Shaanxi, Xinjiang, Liaoning, Hebei, Zhejiang, Henan, Anhui, Ningxia, Shanghai, Gansu, Tianjin, Qinghai, Beijing

Figures 7 and 8 serve as the foundation for this classification. The categorization into carbon-negative, carbon-positive, and carbon-balancing provinces is then visually represented in Figure 9, which synthesizes the data from Figures 7 and 8 to map out the provinces according to their net carbon impact. This approach ensures a nuanced understanding of each province's role in China's broader carbon dynamics, with Table 7 offering further clarity on the specific criteria and definitions applied in this analytical framework.

Table 7. The definition of each category in different provinces.

Classification	Rule	Roles
Carbon-negative province	**Provincial carbon sinks > 5% of provincial carbon emissions**	Carbon asset holders
Carbon-balancing province	Provincial carbon sinks < 5% of provincial carbon emissions **Percentage of carbon sinks in China > percentage of carbon emissions in China**	Carbon-balancing traders
Carbon-positive province	Provincial carbon sinks < 5% of provincial carbon emissions **Percentage of carbon sinks in China < percentage of carbon emissions in China**	Carbon sink buyers

In the carbon trading market, carbon-negative provinces serve as suppliers of carbon credit, such as CCER. Their roles are as traders who hold carbon sink assets and provide carbon sink allowances for the market; carbon-balancing provinces are the speculative side of the market that balance carbon emissions by buying or selling carbon sinks to provide liquidity for the carbon credit market. In addition, carbon-positive provinces are on the demand side of the carbon trading market, which needs to buy carbon sinks to reduce carbon emissions while increasing carbon sink demand. In conclusion, the provinces comprise three categories: asset holders, traders, and buyers.

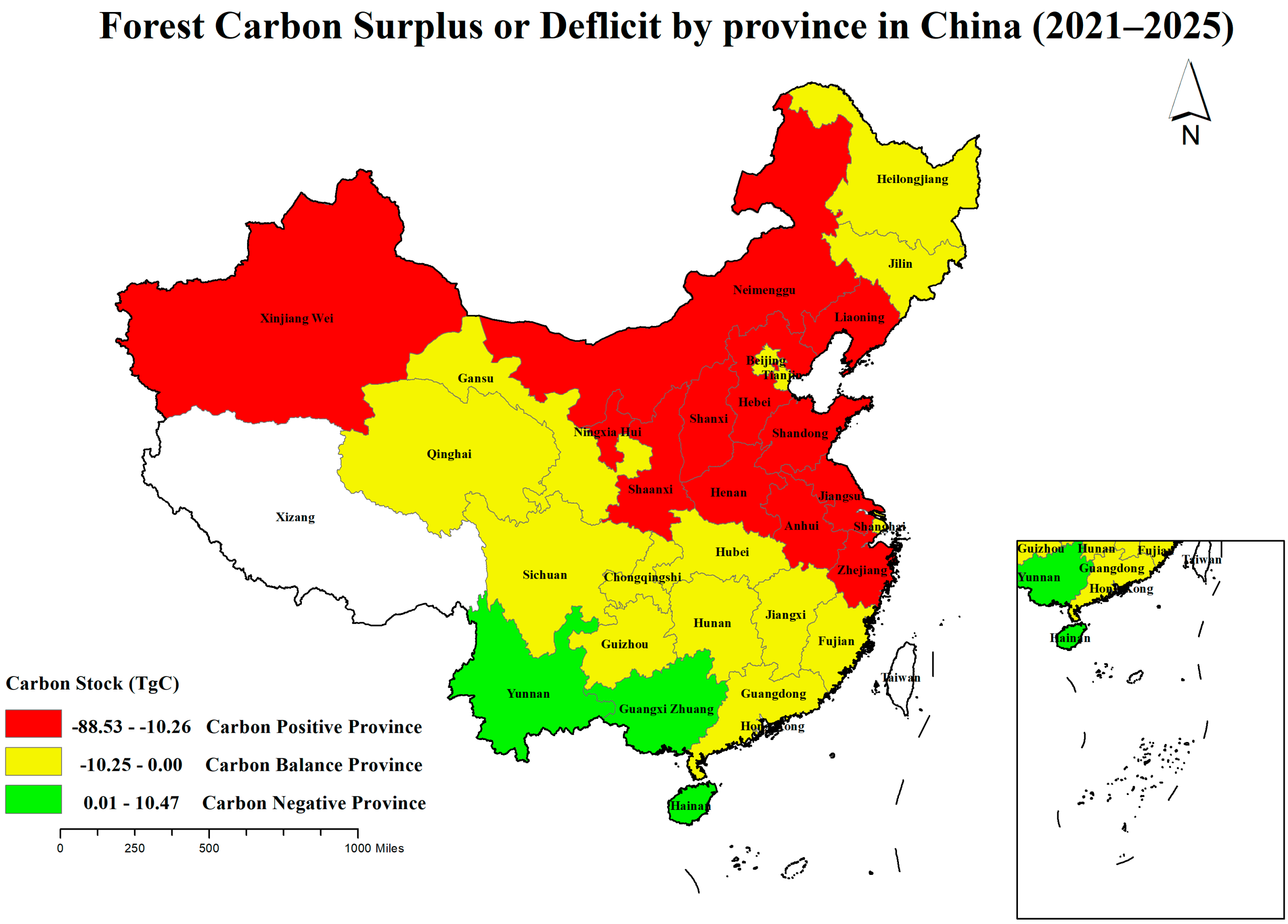

Figure 9. Provincial carbon surplus/deficit during the 14th Five-Year Plan period (TgC).

Carbon-negative provinces, carbon-balancing provinces, and carbon-positive provinces in the carbon credit market are carbon asset holders, carbon balancing traders, and carbon sink buyers, respectively.

Although some provinces, such as Guangdong and Fujian, have higher carbon emissions and their carbon balances are currently in deficit, they are likely to become the next group of carbon-negative provinces because their carbon sinks are rapidly growing, and purchasing demand is diminishing in the long run. However, these economically developed provinces with more oversized carbon sinks will play an active role in positively affecting the carbon credit market in supply and demand.

On the other hand, provinces such as Shanxi and Shandong will become significant purchasing powers in the future carbon credit market. This consequence is the result of two factors. First, they do not have enough forest recourse for carbon offsetting. Second, they are constantly under immense pressure to offset their carbon emissions during their economic development, which generates an enormous amount of carbon emissions. In addition, the current carbon-negative provinces, such as Guangxi and Yunnan, will become the major suppliers in the carbon credit market, and carbon sink trading will generate additional revenue for the local government.

In conclusion, it is evident that the carbon sink deficit in the market will occur regularly, as there are fewer carbon-negative provinces than carbon-positive provinces, which may cause a carbon price surge in the future. Therefore, introducing market principles will help to promote the green development strategies of all provinces, increase recognition of forest carbon sink values, and expedite the process of reaching carbon neutrality.

In the long run, the number of carbon-negative provinces will increase, and the tension currently existing between suppliers and buyers will reduce. As a result—and to further strengthen the outcome of green development and stabilize carbon prices in the market—it may be necessary to periodically adjust the ratio of carbon offset credits according to the current supply and demand relationship in the market.

5. Discussion

5.1. Superiority and Innovations of the Models

For this study, we utilized carbon accounting methods based on plot surveys, employing three distinct approaches to estimate the 2019 carbon storage and the carbon sink volume from 2019 to 2035 in Chinese provincial forests. This analysis also discerned the future carbon sink surplus and deficit scenarios for different provinces in light of their economic development. Compared to other methodologies, such as satellite remote sensing and simulation models [31,32,66,72], our study's carbon sink estimates showed high similarity with results found in most of the literature while providing more precise identification of the spatiotemporal heterogeneity of provincial carbon sinks. This increased accuracy was achieved by including comprehensive data on natural and plantation forests categorized by dominant tree species in each province. It can also assist regions in proactively reducing carbon emissions if they find themselves in a carbon deficit, which has also been referred to as a carbon-positive province in this study. Such detailed analysis is vitally important for policymakers to formulate proactive policies based on the carbon sequestration surplus or deficit across different regions, thereby providing a strategic advantage in addressing regional and national carbon management objectives effectively.

5.2. Robustness of the Models

Regarding model robustness, the carbon storage calculations from this research show a minimal statistical discrepancy of only 1.29% compared to the arboreal carbon storage figures reported in the ninth National Forest Inventory. Within the carbon sequestration model, 97.27% of total natural forest species and 97.2% of total plantation forest species demonstrate a model fit (R^2) greater than 0.8. The fitted curves for the six most extensive natural and plantation forests accurately reflect the natural growth process of trees (as detailed in Figures A1 and A2).

5.3. Limitations and Future Research

There are several limitations to the model's prediction in this study, in terms of carbon intensity and carbon sink. Although we cannot predict technological advancements, the process guarantees that progress in achieving the carbon intensity reduction target will occur, leading to a substantial carbon intensity reduction in the carbon-emission-heavy provinces in the future, ultimately resulting in a change in carbon-positive provinces. On the other hand, the growth of forest carbon sinks may be limited. This is because forest growth has specific natural law characteristics and requires a longer cycle to reach maturity. At the same time, the natural conditions, including drought, fire, and other climatic anomalies, will also limit the growth of forest carbon sinks, especially for forest resources in the central and western regions.

In summary, future coupled carbon intensity–carbon sink studies need to consider both the limits of forest carbon sink growth and the decrease in carbon intensity due to technological progress. If this method is appropriate, combined with China's efforts in natural forest cultivation and low- and medium-yield forest renovation, the carbon sink limit may also be further increased; therefore, the number of provinces in carbon balance and carbon sink may be larger than the model predicts, and the carbon surplus will be more significant.

In the following stages of the carbon intensity–carbon sink study, carbon sink data with a more extensive range of periods can also be considered for inclusion. In this study, the carbon sinks in the coupled carbon intensity–carbon sink assessment model are considered only for the forest area that is newly planted from 2019 to 2025. Due to uncertainties, such as those related to deforestation and wildfires, and the lack of data, we did not include carbon sinks from the existing forests under forest management in the model. However, it is required that data from all forest newly planted in China since 2005 are included in the carbon sink calculation. It may be more realistic to include the above carbon sinks, and the carbon-balanced and carbon-negative provinces should have more carbon surplus than the current model predicts. It is also important to consider the reduction in forest carbon stocks due to timber harvesting and natural disasters such as wildfires [18,20].

6. Conclusions

Utilizing the carbon intensity–carbon sink assessment (CISA) model in conjunction with the biomass-storage model and biomass density–forest age model, this study conducts a comprehensive analysis of carbon dynamics and forest carbon sinks across Chinese provinces. The findings highlight several key insights.

First, the study reveals that high levels of economic development do not invariably lead to increased demand for carbon credit purchases. Instead, regions with middle to upper-middle levels of economic development may exhibit sustained demand for carbon credits. Specifically, central China is projected to become the region with the highest demand for carbon credits in the future, while demand in southeast China is expected to decline over time.

Furthermore, the research demonstrates a significant imbalance between carbon stock-rich and economically developed regions in China. Economically developed regions typically exhibit lower forest carbon stocks, presenting challenges regarding carbon stock changes across different regions. The results indicate that 17 carbon-positive provinces account for 73.86% of carbon emissions, while 10 carbon-balancing provinces account for 22.26%, and three carbon-negative provinces account for 3.88%. In terms of forest carbon sinks, the corresponding shares are 37.19%, 30.58%, and 21.14%, respectively.

In light of these findings, the study offers policy recommendations to address the imbalance between regional economic development and forest carbon sequestration capacity in China. Carbon-negative provinces are encouraged to refine the management of forest carbon sink markets to act as "purifiers," cleansing the economy of carbon emissions. Meanwhile, carbon-balancing provinces should prioritize energy conservation, carbon reduction, and afforestation to become "engines" of China's green economy. Carbon-positive provinces are advised to focus on sustainable development through transforming their energy structures and promoting research and development in energy technologies, thereby stabilizing China's transition towards sustainability.

In conclusion, this research underscores the significance of understanding the regional disparities in carbon dynamics and forest carbon sinks in China. By shedding light on these imbalances, the study provides valuable insights for policymakers and stakeholders seeking to promote sustainable development and mitigate climate change impacts.

Author Contributions: All authors contributed to the design and development of this manuscript. C.L. and J.H. designed the study methods; C.L. and E.X. were responsible for language proofreading; C.L. analyzed the data and created the tables and figures. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Publicly available data sets were analyzed in this study. These data can be found here: https://data.stats.gov.cn/ (accessed on 28 April 2024). The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

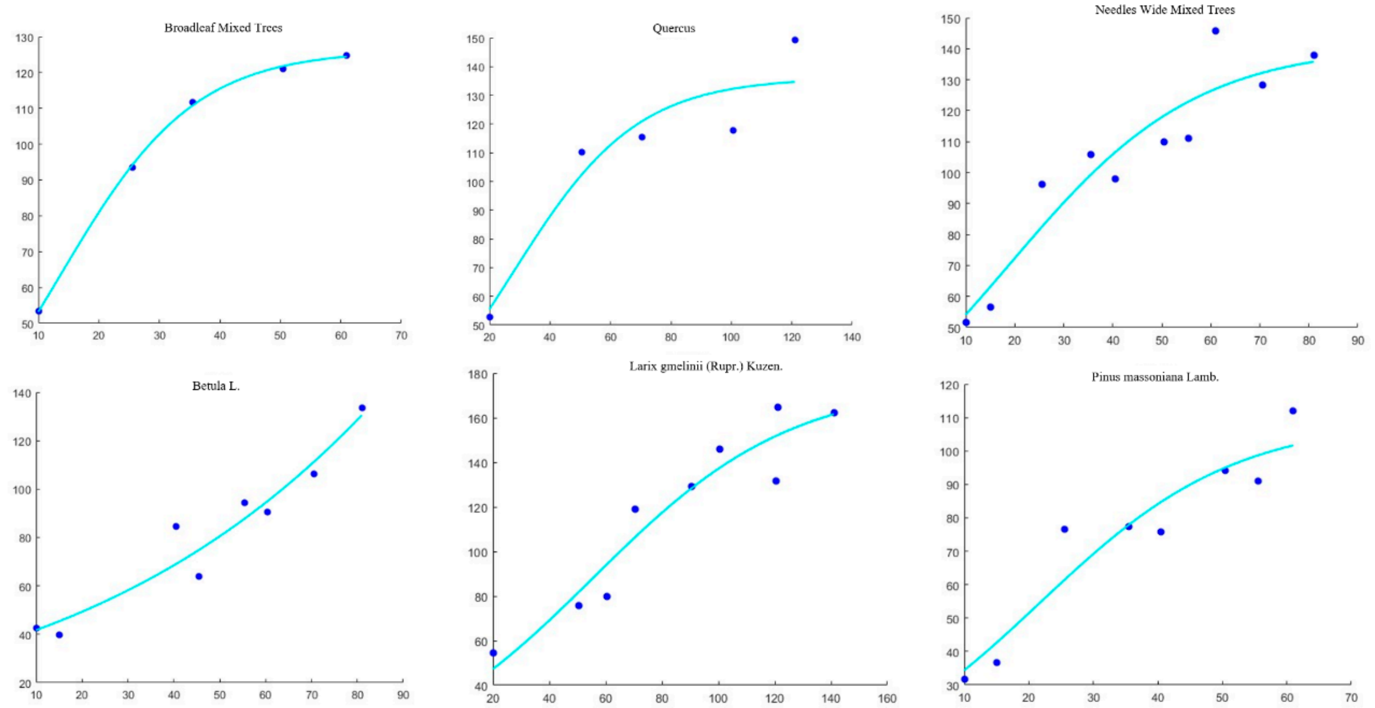

Figure A1. Logistic growth models for natural forests in the top six areas.

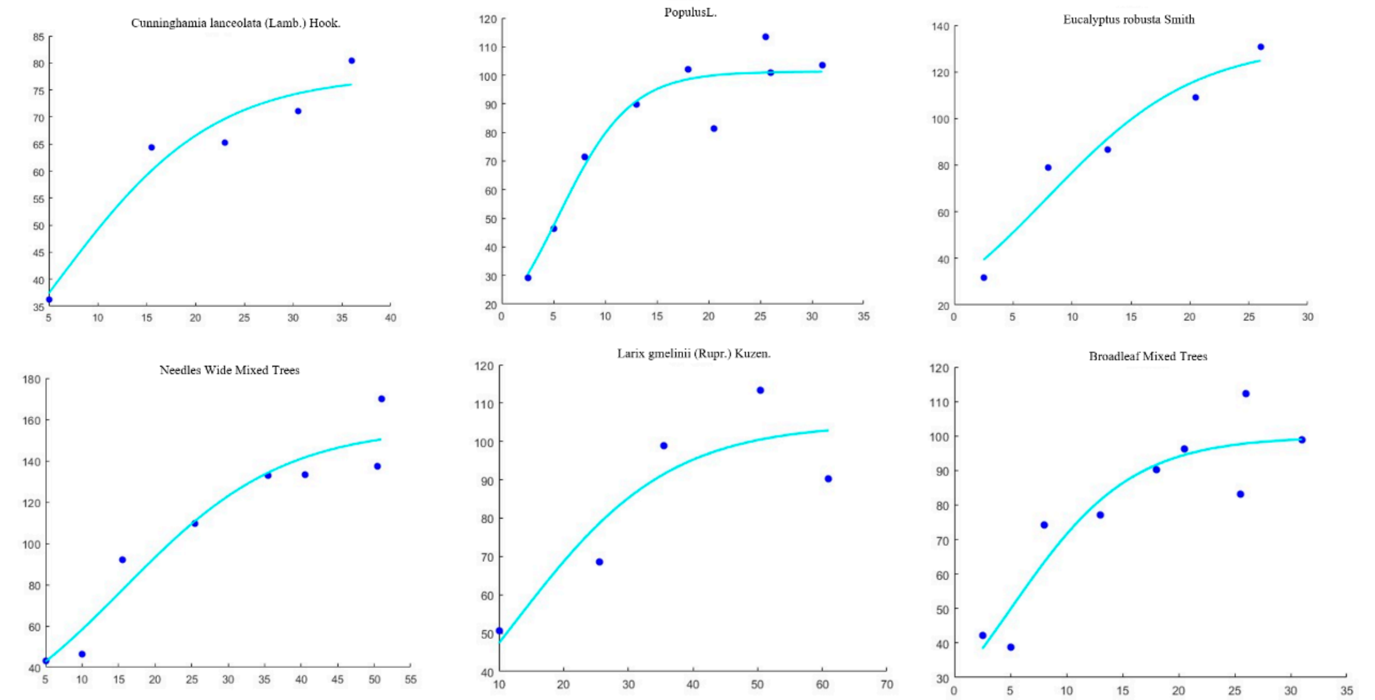

Figure A2. Logistic growth models for the top six planted areas.

Appendix B

Table A1. Fitting parameters for the biomass-storage model.

Forest Type	Age Group	a	b
Coniferous mixed trees, Cinnamomum camphora (L.) J. Presl, Abrus precatorius L., other broad-leaved softwood trees, Phoebe zhennan, Casuarina equisetifolia, Schima superba Gardner & Champ.	Young forest	17.5941	0.9501
	Middle-aged forest	39.3752	0.8593
	Near-mature forest	43.4173	0.8389
	Mature forest	43.4173	0.8389
	Over-ripe forest	43.4173	0.8389
Pinus koraiensis Siebold & Zucc.	Young forest	33.2049	0.4834
	Middle-aged forest	54.7293	0.4108
	Near-mature forest	54.7293	0.4108
	Mature Forest	54.7293	0.4108
	Over-ripe forest	54.7293	0.4108
Pinus wallichiana, other pine classes, Pinus taiwanensis Hayata, Pinus armandii Franch., Pinus densata Mast.	Young forest	15.6557	0.6333
	Middle-aged forest	45.5374	0.4139
	Near-mature forest	47.6751	0.4292
	Mature forest	47.6751	0.4292
	Over-ripe forest	47.6751	0.4292
PopulusL., Populus davidiana, Betula L.	Young forest	21.5600	0.5750
	Middle-aged forest	39.9348	0.5917
	Near-mature forest	29.6156	0.6257
	Mature forest	29.6156	0.6257
	Over-ripe forest	29.6156	0.6257
Taxus cuspidata Siebold & Zucc., Picea asperata Mast., Keteleeria fortunei, Tsuga chinensis, Abies fabri (Mast.) Craib	Young forest	49.0802	0.3422
	Middle-aged forests	29.3993	0.4952
	Near-mature forest	53.612	0.3917
	Mature forest	53.612	0.3917
	Over-ripe forest	53.612	0.3917
Cryptomeria fortunei Hooibr. ex Otto & Dietrich, Cupressus funebris Endl.	Young forest	35.2538	0.4741
	Middle-aged forests	47.6005	0.4741
	Near-mature forest	69.3512	0.393
	Mature forest	69.3512	0.393
	Over-ripe forest	69.3512	0.393
Wide-needled mixed trees, Ulmus pumila L., Phellodendron amurense Rupr., Quercus variabilis Bl., Other broad-leaved hardwood trees, other economic trees, Toxicodendron delavayi, Paulownia Sieb. et Zucc., Salix L., Melia azedarach L., Quercus, pinus massoniana, Juglans regia L., Liquidambar formosana Hance, Tilia, Robinia pseudoacacia L., Sassafras tzumu (Hemsl.) Hemsl., Castanea mollissima Bl., Fraxinus chinensis Roxb.	Young forest	21.8281	0.7084
	Middle-aged forests	22.2598	0.8398
	Near-mature forest	55.4361	0.4265
	Mature forest	55.4361	0.4265
	Over-ripe forest	55.4361	0.4265
Larix gmelinii	Young forest	30.4438	0.6194
	Middle-aged forest	14.3096	0.6425
	Near-mature Forest	33.7734	0.5558
	Mature forest	33.7734	0.5558
	Over-ripe forest	33.7734	0.5558
Pinus massoniana	Young forest	12.1063	0.5093
	Middle-aged forest	38.6436	0.4934
	Near-mature forest	21.2812	0.5497
	Mature forest	21.2812	0.5497
	Over-ripe forest	21.2812	0.5497
Cunninghamia lanceolata	Young forest	14.6212	0.6765
	Middle-aged forest	32.8777	0.3858
	Near-mature forest	0.5264	0.5115
	Mature forest	0.5264	0.5115
	Over-ripe forest	0.5264	0.5115
Pinus tabuliformis, Pinus densiflora	Young forest	14.4807	0.7106
	Middle-aged forest	4.9498	0.8115
	Near-mature forest	8.4727	0.6983
	Mature forest	8.4727	0.6983
	Over-ripe forest	8.4727	0.6983
Pinus yunnanensis, Pinus kesiya	Young forest	31.7207	0.507
	Middle-aged forest	4.2304	0.7185
	Near-mature forest	−10.0118	0.7892
	Mature forest	−10.0118	0.7892
	Over-ripe forest	−10.0118	0.7892
Pinus sylvestris var. mongholica Litv.	Young forest	1.1302	1.1034
	Middle-aged forest	55.795	0.2545
	Near-mature forest	55.795	0.2545
	Mature Forest	55.795	0.2545
	Over-ripe forest	55.795	0.2545

Note: In the equation $B_{ij} = a + b * V_{ij}$, B is the biomass density, V is the forest stock density, and a and b are constants to adjust forest growth.

Table A2. Age group division of each dominant tree species.

Tree Species	Region	Origins	Young Forest	Middle-Aged Forests	Near-Mature Forest	Mature Forest	Over-Ripe Forest
A	North	Natural	0–60	61–100	101–120	121–160	≥161
	North	Artificial	0–40	41–60	61–80	81–120	≥121
	South	Natural	0–40	41–60	61–80	81–120	≥121
	South	Artificial	0–30	31–50	51–60	61–80	≥81
B	North	Natural	0–60	61–100	101–120	121–160	≥161
	North	Artificial	0–30	31–50	51–60	61–80	≥81
	South	Natural	0–40	41–60	61–80	81–120	≥121
	South	Artificial	0–30	31–50	51–60	61–80	≥81
C	North	Natural	0–40	41–80	81–100	101–140	≥141
	North	Artificial	0–20	21–30	31–40	41–60	≥61
	South	Natural	0–40	41–60	61–80	81–120	≥121
	South	Artificial	0–20	21–30	31–40	41–60	≥61
D	North	Natural	0–30	31–50	51–60	61–80	≥81
	North	Artificial	0–20	21–30	31–40	41–60	≥61
	South	Natural	0–20	21–30	31–40	41–60	≥61
	South	Artificial	0–10	11–20	21–30	31–50	≥51
E	North	Natural	0–20	21–30	31–40	41–60	≥61
	North	Artificial	0–10	11–15	16–20	21–30	≥31
	South	Artificial	0–5	6–10	11–15	16–25	≥26
F	South	Natural	0–20	21–30	31–40	41–60	≥61
	South	Artificial	0–5	6–10	11–15	16–25	≥26
G	North	Natural/artificial	0–10	11–15	16–20	21–30	≥31
	South	Natural/artificial	0–5	6–10	11–15	16–25	≥26
H	South	Artificial	0–5	6–10	11–15	16–25	≥26
I	North	Natural	0–30	31–50	51–60	61–80	≥81
	North	Artificial	0–20	21–30	31–40	41–60	≥61
	South	Natural	0–20	21–40	41–50	51–70	≥71
	South	Artificial	0–10	11–20	21–30	31–50	≥51
J	North	Natural	0–40	41–60	61–80	81–120	≥121
	South	Artificial	0–20	21–40	41–50	51–70	≥71
K	South	Artificial	0–10	11–20	21–25	26–35	≥36

Notes: This table was compiled using data from the forestry industry standard "Classification of age classes and age groups of major tree species" (LY/T 2908-2017) and "China Forest Inventory (2005)" on the classification of forest age groups; these were combined with latest forest inventory data [73,74]. Tree species were replaced by the following capital letters: A: *Pinus koraiensis Siebold & Zucc., Picea asperata Mast., Tsuga chinensis, Taxus cuspidata Siebold & Zucc., Keteleeria fortunei, Cupressus funebris Endl.* B: *Cupressus funebris Endl.* C: *Larix gmelinii (Rupr.) Kuzen., Abies fabri (Mast.) Craib, Pinus sylvestris L. var. mongholica Litv., Pinus densiflora Siebold & Zucc., Pinus thunbergii Parl.* D: *Pinus tabuliformis Carrière, Pinus massoniana Lamb., Pinus yunnanensis Franch., Pinus kesiya, Pinus armandii Franch., Pinus densata Mast., coniferous mixed trees, mixed wide-needled trees, Pinus taiwanensis Hayata, Pinus wallichiana, Exotic pines, other pine classes.* E: *PopulusL., Salix L., Sassafras tzumu (Hemsl.) Hemsl., Paulownia Sieb. et Zucc., Illicium verum Hook.f., Hevea brasiliensis (Willd. ex A. Juss.) Müll. Arg., other broad-leaved softwood trees, pinus massoniana.* F: *Melia azedarach L.* G: *Robinia pseudoacacia L.* H: *Casuarina equisetifolia, Eucalyptus robusta Smith.* I: *Betula L., Ulmus pumila L., Schima superba Gardner & Champ., Liquidambar formosana Hance.* J: *Quercus, Cinnamomum camphora (L.) J. Presl, Phoebe zhennan, Tilia, other broad-leaved hardwood trees, Abrus precatorius L., Phellodendron amurense Rupr., Juglans regia L., Castanea mollissima Bl., Populus davidiana, Toxicodendron delavayi, Fraxinus chinensis Roxb., Quercus variabilis Bl., Magnolia officinalis Rehder & E. H. Wilson, Eucommia ulmoides Oliver, Ginkgo biloba L., Vernicia fordii (Hemsl.) Airy-Shaw, other economic trees.* K: *Cunninghamia lanceolata (Lamb.) Hook., Cryptomeria fortunei Hooibr. ex Otto & Dietrich, Metasequoia glyptostroboides, Taxodium ascendens Brongn., other fir species.*

Table A3. New forest area from 2021 to 2035 (unit: hectares).

Dominant Tree Species	Percentage	Existing Planted Forest Area	2021–2025	2026–2030	2031–2035
Total	100%	57,126,700	8,931,746	16,374,868	23,817,990
Abies fabri (Mast.) Craib	0.08%	48,100	7520	13,787	20,054
Picea asperata Mast.	0.72%	411,900	64,400	118,068	171,735
Larix gmelinii (Rupr.) Kuzen.	5.54%	3,162,900	494,519	906,618	1,318,716
Pinus koraiensis	0.54%	309,100	48,328	88,601	128,874
Pinus sylvestris	0.84%	478,900	74,876	137,272	199,669
Pinus densiflora	0.10%	58,300	9115	16,711	24,307
Pinus thunbergii Parl.	0.22%	123,200	19,262	35,314	51,366
Pinus tabuliformis Carrière	2.94%	1,677,600	262,292	480,869	699,446
Pinus armandii	0.92%	528,200	82,584	151,404	220,224
Pinus massoniana Lamb.	4.41%	2,519,200	393,876	722,107	1,050,337
Pinus yunnanensis	0.78%	445,400	69,638	127,670	185,702
Pinus kesiya	0.33%	187,200	29,269	53,659	78,050
Pinus densata Mast.	0.02%	9700	1517	2780	4044
Exotic pines	2.57%	1,465,700	229,162	420,130	611,098
Pinus taiwanensis Hayata	0.08%	44,600	6973	12,784	18,595
Other pine classes	0.09%	52,600	8224	15,077	21,931

Table A3. *Cont.*

Dominant Tree Species	Percentage	Existing Planted Forest Area	2021–2025	2026–2030	2031–2035
Cunninghamia lanceolata	17.33%	9,902,000	1,548,175	2,838,322	4,128,468
Cryptomeria fortunei Hooibr. ex Otto & Dietrich	1.15%	657,500	102,800	188,467	274,133
Metasequoia glyptostroboides Hu & W. C. Cheng	0.19%	109,000	17,042	31,244	45,446
Taxodium ascendens Brongn.	0.02%	10,900	1704	3124	4545
Cupressus funebris Endl.	2.82%	1,611,300	251,926	461,865	671,804
Taxus cuspidata Siebold & Zucc.	0.01%	4800	750	1376	2001
Other fir species	0.004%	2400	375	688	1001
Quercus	1.03%	588,800	92,059	168,774	245,490
Betula L.	0.19%	108,600	16,980	31,129	45,279
Phellodendron amurense Rupr.	0.04%	23,400	3659	6707	9756
Cinnamomum camphora (L.) J. Presl	0.52%	299,400	46,811	85,820	124,830
Phoebe zhennan S. K. Lee & F. N. Wei	0.003%	1600	250	459	667
Ulmus pumila L.	0.55%	312,600	48,875	89,604	130,333
Robinia pseudoacacia L.	3.11%	1,778,400	278,052	509,763	741,473
Schima superba Gardner & Champ.	0.24%	137,500	21,498	39,413	57,328
Liquidambar formosana Hance	0.19%	110,000	17,198	31,531	45,863
Other broad-leaved hardwood trees	1.90%	1,085,400	169,702	311,120	452,539
Sassafras tzumu (Hemsl.) Hemsl.	0.02%	14,100	2205	4042	5879
PopulusL.	13.25%	7,570,700	1,183,677	2,170,075	3,156,472
Salix L.	0.54%	309,300	48,359	88,658	128,957
Paulownia Sieb. et Zucc.	0.32%	181,100	28,315	51,911	75,507
Eucalyptus robusta Smith	9.57%	5,467,400	854,827	1,567,182	2,279,538
Abrus precatorius L.	0.34%	193,200	30,207	55,379	80,551
Casuarina equisetifolia J.R. Forst. & G. Forst.	0.04%	24,000	3752	6879	10,006
Melia azedarach L.	0.03%	17,900	2799	5131	7463
Other broad-leaved softwood trees	1.66%	946,300	147,954	271,249	394,543
Coniferous mixed trees	4.28%	2,446,800	382,557	701,354	1,020,151
Broadleaf mixed trees	4.65%	2,655,900	415,249	761,290	1,107,332
Wide-needled mixed trees	6.78%	3,873,600	605,636	1,110,333	1,615,031
Juglans regia L.	1.71%	974,900	152,425	279,447	406,468
Castanea mollissima Bl.	1.31%	746,700	116,746	214,035	311,324
Illicium verum Hook.f.	0.64%	365,000	57,068	104,624	152,180
Eucommia ulmoides Oliver	0.09%	51,800	8099	14,848	21,597
Magnolia officinalis Rehder & E. H. Wilson	0.23%	133,300	20,841	38,209	55,577
Ginkgo biloba L.	0.11%	61,200	9569	17,542	25,516
Toxicodendron delavayi	0.14%	80,500	12,586	23,075	33,563
Vernicia fordii (Hemsl.) Airy-Shaw	0.20%	111,800	17,480	32,046	46,613
Hevea brasiliensis (Willd. ex A. Juss.) Müll. Arg.	2.42%	1,382,800	216,200	396,367	576,535
Fraxinus chinensis Roxb.	0.08%	46,500	7270	13,329	19,387
Quercus variabilis Bl.	0.03%	19,100	2986	5475	7963
Other Economic Trees	2.08%	1,186,600	185,525	340,128	494,732

Notes: Data of new forest area for the periods 2021–2025, 2026–2030, and 2031–2035.

Table A4. China's carbon intensity reduction target for its 13th Five-Year Plan by province (excluding Tibet).

Region	Carbon Intensity Reduction Target (%)
Beijing	20.5
Tianjin	20.5
Hebei	20.5
Shanxi	18
Inner Mongolia	17
Liaoning	18
Jilin	18
Heilongjiang	17
Shanghai	20.5
Jiangsu	20.5
Zhejiang	20.5
Anhui	18
Fujian	19.5
Jiangxi	19.5
Shandong	20.5
Henan	19.5
Hubei	19.5
Hunan	18
Guangdong	20.5
Guangxi	17
Hainan	12

Table A4. *Cont.*

Region	Carbon Intensity Reduction Target (%)
Chongqing	19.5
Sichuan	19.5
Guizhou	18
Yunnan	18
Shanxi	18
Gansu	17
Qinghai	12
Ningxia	17
Xinjiang	12

Table A5. Carbon stocks and carbon density and their changes by province in China, 2009–2018.

Projects	Region	2009–2013	2014–2018	Amount of Change
Carbon stock (Tg C)	Beijing	10.17	16.00	5.83
	Tianjin	1.98	2.68	0.70
	Hebei	72.62	88.87	16.24
	Shanxi	57.20	73.33	16.13
	Inner Mongolia	663.96	722.09	58.14
	Liaoning	130.33	151.85	21.52
	Jilin	399.64	424.87	25.23
	Heilongjiang	817.35	888.23	70.88
	Shanghai	1.15	2.59	1.43
	Jiangsu	38.95	40.28	1.33
	Zhejiang	119.68	142.28	22.61
	Anhui	94.05	109.73	15.68
	Fujian	272.58	310.77	38.19
	Jiangxi	235.99	267.90	31.91
	Shandong	47.54	48.94	1.40
	Henan	98.40	116.11	17.71
	Hubei	167.13	196.39	29.26
	Hunan	189.95	221.04	31.09
	Guangdong	228.19	272.38	44.19
	Guangxi	285.66	365.68	80.01
	Hainan	43.26	83.74	40.48
	Chongqing	70.47	99.04	28.56
	Sichuan	633.80	710.43	76.64
	Guizhou	150.25	188.38	38.12
	Yunnan	725.15	861.03	135.88
	Tibet	711.48	715.39	3.90
	Shanxi	221.05	258.59	37.55
	Gansu	100.54	115.10	14.56
	Qinghai	18.46	20.82	2.36
	Ningxia	3.77	5.00	1.23
	Xinjiang	120.38	141.11	20.73
Carbon density (Mgha^{-1})	Beijing	23.71	25.73	2.03
	Tianjin	26.31	26.09	−0.22
	Hebei	23.35	24.32	0.97
	Shanxi	27.18	30.01	2.83
	Inner Mongolia	38.76	41.12	2.36
	Liaoning	33.45	35.68	2.23
	Jilin	53.04	54.85	1.80
	Heilongjiang	41.92	44.76	2.84
	Shanghai	26.43	35.77	9.34
	Jiangsu	31.12	31.77	0.66
	Zhejiang	29.18	33.33	4.15
	Anhui	32.24	35.55	3.31
	Fujian	44.93	50.02	5.09
	Jiangxi	29.88	33.14	3.26
	Shandong	29.45	32.06	2.61
	Henan	32.22	33.34	1.11
	Hubei	29.20	32.37	3.17
	Hunan	25.97	27.67	1.70
	Guangdong	31.93	34.88	2.95
	Guangxi	31.60	34.82	3.23
	Hainan	44.54	48.30	3.75

Table A5. *Cont.*

Projects	Region	2009–2013	2014–2018	Amount of Change
	Chongqing	33.42	40.28	6.87
	Sichuan	53.54	53.32	−0.22
	Guizhou	31.39	32.18	0.79
	Yunnan	47.49	46.22	−1.27
	Tibet	83.85	80.96	−2.89
	Shanxi	34.58	36.57	1.99
	Gansu	40.67	43.62	2.95
	Qinghai	48.78	49.41	0.63
	Ningxia	23.79	28.91	5.12
	Xinjiang	67.18	65.69	−1.49

Table A6. Logistic growth equation fitting parameters based on natural forest.

Number	Dominant Tree Species	w	k	a	R^2
1	*Pinus massoniana*	126.20	3.3635	0.0898	0.999
2	*Quercus*	136.12	3.8364	0.0486	0.893
3	*Needles wide mixed trees*	141.05	2.7176	0.0526	0.891
4	*Betula L.*	969.46	26.4673	0.0175	0.931
5	*Larix gmelinii (Rupr.) Kuzen.*	175.92	4.7963	0.0283	0.913
6	*Pinus massoniana Lamb.*	109.22	4.2193	0.0662	0.903
7	*Picea asperata Mast.*	393.62	4.6298	0.0079	0.845
8	*Pinus yunnanensis Franch.*	2618.06	74.6539	0.0287	0.853
9	*Abies fabri (Mast.) Craib*	263.98	3.0862	0.0154	0.888
10	*Other broad-leaved softwood trees*	183.91	5.5553	0.0647	0.952
11	*Coniferous mixed trees*	463.75	8.2634	0.0214	0.945
12	*Cupressus funebris Endl.*	100.73	3.8362	0.0659	0.506
13	*Other broad-leaved hardwood trees*	159.34	4.1043	0.0275	0.975
14	*Pinus densata Mast.*	597.28	9.4820	0.0182	0.951
15	*Cunninghamia lanceolata (Lamb.) Hook.*	82.13	3.6189	0.1440	0.978
16	*Populus davidiana*	128.38	3.4278	0.0415	0.992
17	*Ulmus pumila L.*	101.66	2.5524	0.0379	0.883
18	*Pinus tabuliformis Carrière*	135.75	4.0321	0.0384	0.776
19	*PopulusL.*	209.45	4.5446	0.0310	0.873
20	*Phellodendron amurense Rupr.*	113.99	3.3169	0.0470	0.906
21	*Quercus variabilis Bl.*	372.90	7.2828	0.0114	0.997
22	*Schima superba Gardner & Champ.*	150.83	6.6465	0.0945	0.844
23	*Pinus kesiya*	114.15	1.0033	0.0559	0.812
24	*Tilia*	123.08	2.5930	0.0411	0.944
25	*Pinus sylvestris L. var. mongholica Litv.*	110.83	3.9274	0.0356	0.980
26	*Pinus armandii Franch.*	111.37	3.8474	0.0683	0.931
27	*Keteleeria fortunei*	102.13	1.5248	0.0310	0.867
28	*Liquidambar formosana Hance*	112.51	7.8187	0.1140	0.752
29	*Tsuga chinensis*	264.45	23.9632	0.0361	0.918
30	*Salix L.*	139.00	2.9226	0.0331	0.964
31	*Phoebe zhennan*	191.58	11.4202	0.0636	0.997
32	*Pinus taiwanensis Hayata*	112.90	6.6056	0.1122	0.913
33	*Pinus densiflora Siebold & Zucc.*	114.93	13.5835	0.0836	0.315
34	*Castanea mollissima Bl.*	242.13	4.7340	0.0172	0.410
35	*Cinnamomum camphora (L.) J. Presl*	197.58	4.6505	0.0392	0.994
36	*Other pine classes*	68.43	5.4237	0.0891	0.998
37	*Pinus koraiensis Siebold & Zucc.*	244.68	2.7223	0.0139	1.000
38	*Pinus wallichiana*	/	/	/	/
39	*Other economic trees*	94.14	11.1035	0.0851	0.914
40	*Toxicodendron delavayi*	125.90	2.9024	0.0164	0.811
41	*Robinia pseudoacacia L.*	34.78	1.7564	0.6009	1.000
42	*Paulownia Sieb. et Zucc.*	68.76	190.3043	0.5568	0.945
43	*Fraxinus chinensis Roxb.*	/	/	/	/
44	*Melia azedarach L.*	/	/	/	/
45	*Cryptomeria fortunei Hooibr. ex Otto & Dietrich*	/	/	/	/
46	*Taxus cuspidata Siebold & Zucc.*	/	/	/	/
47	*Abrus precatorius L.*	/	/	/	/
48	*Sassafras tzumu (Hemsl.) Hemsl.*	/	/	/	/
49	*Casuarina equisetifolia*	/	/	/	/
50	*Juglans regia L.*	/	/	/	/

Table A7. Logistic growth equation fitting parameters based on planted forests.

Number	Dominant Tree Species	w	k	a	R^2
1	*Cunninghamia lanceolata (Lamb.) Hook.*	77.79	2.0005	0.1235	0.937
2	*PopulusL.*	101.29	4.7948	0.2874	0.917
3	*Eucalyptus robusta Smith*	131.98	3.4903	0.1582	0.942
4	*Wide-needled mixed trees*	156.42	4.1926	0.0911	0.932
5	*Larix gmelinii (Rupr.) Kuzen.*	104.66	2.7795	0.0834	0.801
6	*pinus massoniana*	99.79	2.5508	0.1862	0.860
7	*Pinus massoniana Lamb.*	70.96	13.8463	0.2998	0.878
8	*Coniferous mixed trees*	169.16	3.0879	0.0435	0.839
9	*Robinia pseudoacacia L.*	94.93	2.2815	0.1011	0.949
10	*Pinus tabuliformis Carrière*	107.32	4.8563	0.0458	0.970
11	*Cupressus funebris Endl.*	110.68	3.9664	0.0572	0.893
12	*Exotic pines*	92.35	6.0569	0.1874	0.987
13	*Hevea brasiliensis (Willd. ex A. Juss.) Müll. Arg.*	173.58	3.6690	0.1397	0.996
14	*Other economic trees*	94.81	4.6483	0.0486	0.971
15	*Other broad-leaved hardwood trees*	92.80	4.0680	0.0801	0.887
16	*Juglans regia L.*	87.59	3.7985	0.0436	0.914
17	*Other broad-leaved softwood trees*	222.63	6.1933	0.1061	0.935
18	*Castanea mollissima Bl.*	96.78	3.7204	0.0588	0.877
19	*Cryptomeria fortunei Hooibr. ex Otto & Dietrich*	162.53	4.0251	0.1277	0.999
20	*Quercus*	107.51	3.8135	0.0710	0.980
21	*Pinus armandii Franch.*	116.18	4.7543	0.0933	0.969
22	*Pinus sylvestris L. var. mongholica Litv.*	90.76	50.7269	0.2393	0.995
23	*Pinus yunnanensis Franch.*	276.57	6.9718	0.0244	0.991
24	*Picea asperata Mast.*	153.45	3.6541	0.0345	0.735
25	*Illicium verum Hook.f.*	150.08	5.1549	0.1606	0.992
26	*Ulmus pumila L.*	70.07	3.0878	0.1209	0.933
27	*Salix L.*	101.38	5.0435	0.1897	0.949
28	*Pinus koraiensis Siebold & Zucc.*	236.06	5.6602	0.0350	0.919
29	*Cinnamomum camphora (L.) J. Presl*	137.23	2247.4151	0.6887	0.893
30	*Phellodendron amurense Rupr.*	220.84	7.8430	0.0507	0.619
31	*Abrus precatorius L.*	119.08	12.8831	0.1698	0.968
32	*Pinus kesiya*	114.15	1.0033	0.0559	0.812
33	*Paulownia Sieb. et Zucc.*	88.99	3.6066	0.3367	0.785
34	*Schima superba Gardner & Champ.*	139.00	4.7506	0.1935	0.574
35	*Magnolia officinalis Rehder & E. H. Wilson*	82.28	2.6947	0.0462	0.982
36	*Pinus thunbergii Parl.*	68.62	5.6969	0.0915	0.844
37	*Vernicia fordii (Hemsl.) Airy-Shaw*	94.70	2.9632	0.0318	0.813
38	*Liquidambar formosana Hance*	112.51	7.8187	0.1140	0.752
39	*Metasequoia glyptostroboides*	403.62	15.5384	0.0518	0.929
40	*Betula L.*	63.70	19.5038	0.3215	0.569
41	*Toxicodendron delavayi*	162.18	9.9784	0.0409	0.909
42	*Ginkgo biloba L.*	117.94	3.1343	0.0485	0.556
43	*Pinus densiflora Siebold & Zucc.*	181.83	7.3057	0.0230	0.958
44	*Other pine classes*	76.39	6.3204	0.1843	0.761
45	*Eucommia ulmoides Oliver*	/	/	/	/
46	*Abies fabri (Mast.) Craib*	263.98	3.0862	0.0154	0.888
47	*Fraxinus chinensis Roxb.*	100.07	758.2827	0.6194	0.474
48	*Pinus taiwanensis Hayata*	112.53	18.6471	0.1864	0.451
49	*Casuarina equisetifolia*	155.13	5.4512	0.1799	0.891
50	*Quercus variabilis Bl.*	372.90	7.2828	0.0114	0.997
51	*Melia azedarach L.*	/	/	/	/
52	*Sassafras tzumu (Hemsl.) Hemsl.*	97.31	3.8786	0.3532	0.067
53	*Taxodium ascendens Brongn.*	75.15	3.2820	0.2485	0.296
54	*Pinus densata Mast.*	/	/	/	/
55	*Taxus cuspidata Siebold & Zucc.*	/	/	/	/
56	*Other fir species*	/	/	/	/
57	*Phoebe zhennan*	/	/	/	/

Table A8. Forecast of forest carbon pools in China, 2014–2035.

Forest Type		2014–2018	2021–2025	2026–2030	2031–2035
Existing forests	Area (10^4 ha)	7674	8635	9308	9877
	Carbon stock (Tg C)	42.66	48	51.75	54.9
	Carbon density (Mgha^{-1})	0	893	1637	2382
Newly created forests	Area (10^4 ha)	0	204	510	892
	Carbon stock (Tg C)	0	22.82	31.16	37.45
	Carbon density (Mgha^{-1})	17,989	18,882	19,626	20,371
Total	Area (10^4 ha)	7674	8839	9819	10,769
	Carbon stock (Tg C)	42.66	46.81	50.03	52.86
	Carbon density (Mgha^{-1})	7674	8635	9308	9877

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