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Spatial and Temporal Patterns of Forest Biomass Carbon Sink in China from 1990 to 2021

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Abstract: China's forests act as a large carbon sink and play a vital role in achieving the carbon neutrality goal by the 2060s. To achieve this goal, the magnitude and spatial patterns of forest carbon sinks must be accurately quantified. In this study, we aim to provide the longest estimate of forest biomass carbon storage and sinks in China at a 1 km spatial resolution from 1990 to 2021 by merging long-term observations from optical and microwave remote sensing datasets with a field-validated benchmark map. We explored the spatial characteristics of aboveground biomass (AGB) and belowground biomass (BGB) carbon in China's forests, as well as variations in AGB carbon sinks. The average AGB and BGB carbon storage from 1990 to 2021 in China's forests were 8.42 ± 0.96 Pg C and 1.9 ± 0.21 Pg C, respectively. The average annual AGB carbon sink during this period was approximately 0.083 ± 0.023 Pg C yr⁻¹. Forests in the southwest region contributed 31.15% of the forest AGB carbon sink in China and contributed 41.01% of the forest AGB carbon storage. Our study presents an effective tool for assessing changes in forest biomass carbon by leveraging comprehensive multi-source remote sensing data and highlights the importance of obtaining large-scale, high-quality, consistent, and accessible plot survey data to validate the earth observation of biomass.

Keywords: carbon sink; forest biomass; spatial and temporal patterns; machine learning; remote sensing



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1. Introduction

The terrestrial ecosystem is estimated to absorb approximately 32% of the carbon dioxide (CO₂) emitted by burning fossil fuels and industrial activities, with the majority of this uptake occurring in forests [1,2]. Forests thus play a crucial role in mitigating climate change and are considered a key component of nature-based climate solutions. However, large uncertainties still exist in understanding the spatial patterns, magnitude, and trends in forest carbon flux. For example, the National Greenhouse Gas Inventories (NGHGs) submitted to the United Nations Framework Convention on Climate Change (UNFCCC) indicate that forests act as a net carbon sink, absorbing approximately 1.9 ± 1.0 GtCO₂ yr⁻¹, while data from FAOSTAT suggest forest-related land use activities emitted 1.1 GtCO₂ yr⁻¹ from 2000 to 2020. Concurrently, earth-observation-based assessments estimate a substantial CO₂ sink of 7.6 GtCO₂ e yr⁻¹ in forests [3]. These significant uncertainties in estimating forest carbon stock and sink could severely undermine their role in climate mitigation. Therefore, reducing uncertainties in global forest carbon flux estimates is critical to meeting climate targets for carbon storage and emission reductions [4].

Previous studies have indicated that temperate forests contributed the most to the uncertainty in estimating forest carbon flux. This uncertainty likely arises from the complex interactions among land use history, environment changes, and forest demography [3]. As a

major component of the global temperate forest biome, China's forests are critical to understanding the temperate forest carbon cycle. Since the 1990s, China has experienced intensive afforestation, potentially positioning its forests as significant carbon sink [5,6]. Yet, quantifying the magnitude and spatial patterns of this sink remains challenging. Despite significant efforts, the forest ecosystem carbon sink (ranging from 0.08 to 0.59 Pg C yr⁻¹) [7–10] and forest biomass carbon sink (ranging between 0.02 and 0.23 Pg C yr⁻¹) [7,11–14] varied widely among studies. Such considerable variability in these estimates highlights the complexity of accurately measuring the carbon sequestration potential of China's forests. Addressing these inconsistencies is essential for refining our understanding of forests' role as land carbon sink in China and for providing a more straightforward path towards leveraging forest carbon sinks to achieve China's carbon neutrality target by 2060.

There are many methods to quantify a forest carbon sink, each with advantages and constraints. The atmospheric CO₂ inversion method provides near-real-time estimates of carbon flux, yet it suffers from low spatial resolution and limitations tied to the sparse distribution of observation stations. In contrast, bottom-up approaches, such as field-based inventories or eddy covariance, offer more localized insights but are often geographically biased because of their limited spatial coverage. The rapid development of the remote sensing technique makes it a viable method to map carbon stock changes across large areas, harnessing the power of satellite data to penetrate previously inaccessible dimensions of carbon sink estimation. This technology facilitates a more comprehensive understanding of the spatial variability in carbon sequestration.

Utilizing remote sensing data to map forest carbon storage and sinks represents a shift in our ability to monitor the earth's carbon cycle and forests' role in mitigating climate change. Ref. [15] used optical satellite data to map carbon stocks in global forests. Later, the integration of lidar with optical satellite imagery, the fusion of multiple data sources, and the gradual refinement of methodologies significantly enhanced the spatial resolution and accuracy of forest biomass estimates [16–19]. More recently, refs. [20,21] integrated long-term satellite observations with dynamic stock change methods, offering nuanced insights into the spatiotemporal patterns of biomass carbon sinks. This progression towards integrating multiple data sources and advanced computational methods has significantly enhanced our understanding of forest carbon dynamics. However, several challenges remain, such as saturation issues in high-biomass areas, spatial resolution mismatches between active and passive satellite-based sensors, inaccuracies brought by sparse survey data with high uncertainty, and difficulties in accounting for land use changes and disturbances in aboveground biomass (AGB) estimates, making forest carbon stock and sink estimates uncertain.

In this study, we aim to estimate forest biomass carbon storage and sinks across China at a 1 km spatial resolution from 1990 to 2021. By integrating medium-resolution optical and microwave remote sensing data with a field-validated AGB benchmark map and annual forest cover, this study, to our knowledge, provides the first longest continuous estimates of forest biomass carbon storage in China. Using the stock change method, we provided annual forest carbon sink maps that are otherwise not available when using other methods. Our study also revealed the complex interaction between forest biomass and environmental controls and explained the uncertainties associated with these estimations. In bridging these methodological gaps, our research refined our understanding of forest carbon dynamics and its drivers in China.

2. Materials and Methods

2.1. Overall Study Design

We developed a framework for generating an annual forest AGB dataset at 1 km resolution spanning 1990 to 2021 in China using a Machine Learning (ML) method (i.e., the random forest (RF) model in this study) and estimating forest carbon sink based on the stock change approach (Figure 1).

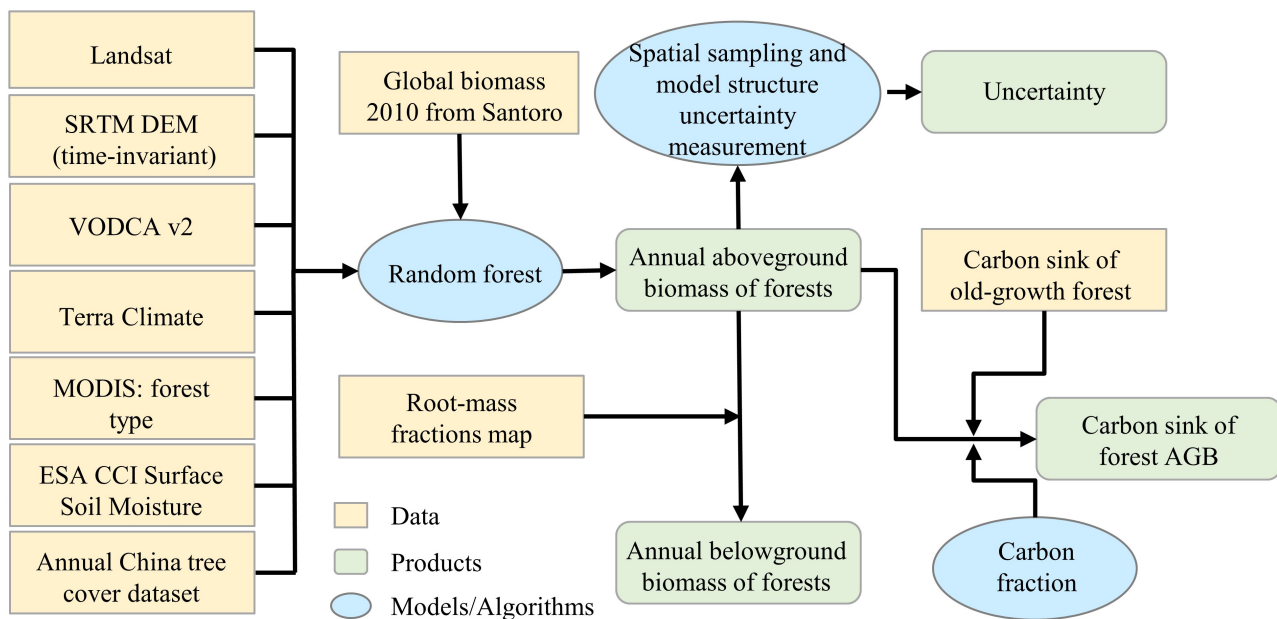


Figure 1. Flowchart of the process used to estimate forest biomass carbon stocks and carbon sink in this study.

2.2. Data Collection

2.2.1. Benchmark Map of Forest AGB

A global 100 m resolution forest AGB dataset in 2010, produced by the European Space Agency (ESA)'s Climate Change Initiative (CCI) BIOMASS project, was selected as the benchmark map for our study [22]. We resampled the AGB dataset to 1 km resolution and randomly selected 82,348 sample points, representing 1.5% of the total biomass pixels, to serve as training and validation data for the RF model. This method enabled us to extend the forest biomass dataset into a gridded long-term time series using annually varying environmental predictors (Table 1).

Table 1. Predictor variables used for RF AGB modeling.

Variables	Description	Dataset	Original Spatial Resolution
NDVI	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$, NDVI was processed to annual growing season (May–October) averages	Landsat5, 7, 8	~30 m
NBR	$(\text{NIR} - \text{SWIR2}) / (\text{NIR} + \text{SWIR2})$, annual growing season averages	Landsat5, 7, 8	~30 m
NDMI	$(\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$, annual growing season averages	Landsat5, 7, 8	~30 m
NIRv	$\text{NDVI} * \text{NIR}$, annual growing season averages	Landsat5, 7, 8	~30 m
KNDVI	$\tanh(\text{NDVI}^2)$, annual growing season averages	Landsat5, 7, 8	~30 m
TCB, TCG, TCW	Tasseled-Cap Brightness, Greenness, and Wetness, annual growing season averages	Landsat5, 7, 8	~30 m
B1, B2, B3, B4, B5, B7	Band of blue, green, red, NIR, SWIR1, and SWIR2, annual growing season averages	Landsat	~30 m

Table 1. Cont.

Variables	Description	Dataset	Original Spatial Resolution
Elevation	Elevation (m), time-invariant	SRTM DEM	~30 m
Aspect	Aspect index (−1, 1), higher value receives more potential solar radiation, time-invariant	SRTM DEM	~30 m
Slope	Slope (degrees), time-invariant	SRTM DEM	~30 m
VODCA	Ku-Band	VODCA	0.25 degree
Growing season precipitation	Annual growing season (May–October) precipitation (mm).	Terra Climate	1/24 degree
Annual precipitation	Total annual precipitation (mm)	Terra Climate	1/24 degree
Annual average temperature	Annual average temperature	Terra Climate	1/24 degree
Growing season average temperature	Annual growing season (May–October) average temperature	Terra Climate	1/24 degree
Annual VPD	Annual average VPD	Terra Climate	1/24 degree
Growing season VPD	Growing season average VPD	Terra Climate	1/24 degree
Landcover type	Forest type based on MODIS IGBP land cover.	MODIS (MCD12Q1)	~500 m
Surface soil moisture	Growing season soil moisture	ESA CCI Surface Soil Moisture	0.25 degree

2.2.2. Environmental Predictors

We prepared a series of environmental predictors related to forest biomass for RF modeling (Table 1). Multiple satellite observations from optical and microwave sensors were processed to obtain annual time series variables. All these wall-to-wall variables were resampled to 1 km resolution. Further details are available in the supplemental information. Here, we briefly describe the procedures used to obtain the annual environmental predictors.

We utilized Landsat’s land surface observations to derive a range of spectral indices for detecting vegetation changes. Landsat images from 1990 to 2021 were collected from Google Earth Engine’s surface reflectance products of Landsat5, Landsat7, and Landsat8 [23]. We applied masking techniques to eliminate low-quantity pixels (e.g., cloud and cloud shadow) from the images. To mitigate differences among the Landsat satellite sensors, we harmonized Landsat Operational Land Imager (OLI) surface reflectance data with Enhanced Thematic Mapper Plus (ETM+) surface reflectance data [24]. The spectral indices we employed have different advantages in quantifying vegetation growth and representing vegetation structural information; they are also sensitive to plant biophysical parameters, as well as to fire and other factors [25–28]. Finally, we used the median values during the growing season (May to October) to create annual composites of spectral indices.

To quantify topographical effects, we derived topographical variables, including elevation, slope, and aspect from the Shuttle Radar Topography Mission (SRTM) digital elevation dataset [29]. To indicate the potential solar radiation exposure, we transformed the aspect into an aspect index using the following formula [30]:

$$\text{Aspect index} = -\cos(\theta \times 2 \times \pi / 360)$$

where θ represents the original aspect values, ranging from 0 to 360 degrees. This transformation allows for a more nuanced assessment of solar radiation exposure across varied topographies.

We used TerraClimate to estimate total precipitation at both the annual and growing season scales, along with the mean temperature and vapor pressure deficit (VPD) from 1990 to 2021 [31].

We estimated soil moisture using the ESA CCI Soil Moisture product (SM, version 7.1). The SM product integrates satellite-derived active and passive microwave remote sensing observations and specifically targets surface soil moisture content within the top 0–5 cm layer of soil [32–34]. In instances where pixels lacked values in some years, we filled these gaps by using multi-year average values.

Microwave-based Vegetation Optical Depth (VOD) is sensitive to both woody and leafy AGB, providing complementary information to vegetation indices such as NDVI [35]. To facilitate a comprehensive long-term analysis, we utilized the global long-term microwave Vegetation Optical Depth Climate Archive (VODCA v2) [36]. We used monthly Ku-band VODCA data and then aggregated it to growing season composites from 1990 to 2021. For pixels that lacked values in certain years, we employed a gap-filling technique that utilized multi-year average values to ensure continuity and completeness of the dataset.

We used annual land cover data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) product MCD12Q1 (v6.1) at 500 m using the IGBP classification standard [37]. This dataset categorizes forests into evergreen needleleaf forests, deciduous needleleaf forests, evergreen broadleaf forests, deciduous broadleaf forests, and mixed forests. Because of the absence of data prior to the year 2000, land cover data from 2001 were used as a surrogate for the decade 1990–2000.

2.3. Geospatial Modeling of Forest AGB

2.3.1. Random Forest Model

To develop prediction models for forest AGB, we employed an RF model utilizing the R package h2o (R version 4.3.1; h2o version 3.30.0.1) [38]. We implemented a grid-search procedure to explore multiple RF models for each region. We developed 160 models by selecting a range of hyperparameters for the grid-search procedure. The hyperparameters included the number of RF trees (100, 150, 170, or 200), the variables number selected at each split (6 to 13), and the minimum number of observations per leaf node (2 to 6). We evaluated each model's performance using randomized ten-fold cross-validation and utilized the coefficient of determination (R^2) as an evaluation metric for model cross-validation. We finally selected the top 10 AGB models with the highest R^2 values.

We averaged predictions from the 10 most effective RF models to generate the final AGB maps at a 1 km resolution for each year. Averaging across multiple models mitigates the impact of any single model's prediction, enhancing stability in estimations and reducing biases often associated with extrapolation or overfitting in individual models [39]. At the same time, we used a Landsat-derived annual land cover dataset to update the annual forest extension of the AGB maps [40].

Furthermore, we estimated annual belowground biomass (BGB) using pixel-level root mass fractions (spatially explicit map of the index of forest belowground versus aboveground biomass distribution) [41]. Forest stand biomass was then defined as the sum of AGB and BGB. With these estimates, we estimated the total carbon stock of live forest as follows:

$$\text{Carbon} = (\text{AGB} + \text{BGB}) \times 0.476$$

where the factor 0.476 is the average fraction of carbon in the dry biomass [42].

2.3.2. Uncertainty Analysis

We evaluate the effects of spatial sampling bias on the mean AGB by implementing a stratified bootstrapping procedure. This involved 100 iterations of bootstrapping, where 75% of the 82,348 samples were randomly selected with replacement in each iteration, and the RF model was repeated. Using each of the 100 bootstrap samples, we generated annual AGB maps from 1990 to 2021, as described above. This procedure finally produced 100 AGB averaged maps for the same timeframe.

We also evaluated the impact of model structure uncertainty on average AGB. To accomplish this, we randomly chose one prediction from each year's top ten performing RF models, covering 32 years, resulting in a series of potential combinations of time-series gridded AGB maps. From these, 100 combinations were selected to create a composite of predicted mean AGB layers for 1990 to 2021.

We integrated the above 200 averaged AGB maps and calculated spatial patterns for the mean, lower (2.5% quantile), and upper (97.5% quantile) AGB prediction intervals and summarized the latitudinal trends in mean AGB from 1990 to 2021 [43]. The coefficient of variation (standard deviation divided by the mean predicted value) (CV) was calculated as an overall measure of uncertainty, offering a comprehensive understanding of spatial and model-related variabilities in predicting AGB.

2.4. Forest Biomass Carbon Sink

The annual wall-to-wall forest biomass carbon sink was determined by the “stock change” method, that is, the difference in forest biomass carbon between consecutive years. This approach simplifies the analysis by focusing on the net change in carbon stock without requiring a detailed examination of various underlying processes. Nonetheless, two significant sources of uncertainty emerged in our approach. First, the bias inherent in the RF methodology skews estimates towards the mean, potentially resulting in systematic underestimation of the carbon sink. Secondly, the optical remote sensing data faced limitations in penetrating dense vegetation, causing a saturation effect. Although microwave remote sensing data were used, the Ku-band VOD also suffers from a saturation effect in detecting forests because of tradeoffs in long-term data acquisition [35]. Consequently, these biases result in an overall underestimation of the carbon sink, particularly in regions with dense canopy cover and high biomass, typically found in mature and old-growth forests. Given that these forests contribute significantly to the overall forest carbon sink, we adopted a correction method similar to [19] by adding the carbon sink to these forests. The mature and old-growth forests were identified by biomass exceeding 50 Mg ha⁻¹, and the carbon sink added was determined based on the literature [44].

We further investigated the temporal trends in the AGB carbon sink and compared our findings with those of other studies. To perform this investigation, we collected studies (Table S1) that reported forest carbon sink estimates using forest resource inventory data. To facilitate a comparison with our results, we converted the carbon sink from these studies into AGB carbon sink values based on the ratio of aboveground to belowground carbon storage derived from our study's average AGB and BGB calculations.

2.5. Environmental Drivers of AGB Mean and Trends

RF models were also employed to assess the relative significance of each predictor in estimating mean AGB. We utilized RF-based Partial Dependency Plots (PDPs) to elucidate the relationship between environmental variables and mean AGB while controlling for the influence of other predictors. This methodological approach enabled us to discern the marginal impacts of individual variables on mean AGB rather than their absolute values. Such an analysis provides deeper insights into the dynamics of AGB estimation, enhancing our understanding of the factors influencing its variability.

3. Results

3.1. Mapping of Forest AGB and Model Performance

A gridded annual forest AGB dataset was constructed by RF models (see Section 2). The cross-validation results demonstrated that the models achieved high accuracy for AGB prediction. Specifically, the models explained 57–82% of the spatial variance in forest AGB ($R^2 = 0.82, 0.68, 0.68$, and 0.57 for II, IV, I, and III, respectively; Figure 2b–e). However, there was a systematic bias in overestimating AGB at lower values and underestimating higher values for all four regions (Figure 2b–e), which is a common issue with statistically based ML approaches. This suggests that while RF models accurately predict central AGB values,

they may not fully capture the range of AGB variability, potentially leading to smaller interannual variability in AGB, and consequently, a lower trend in forest carbon sinks.

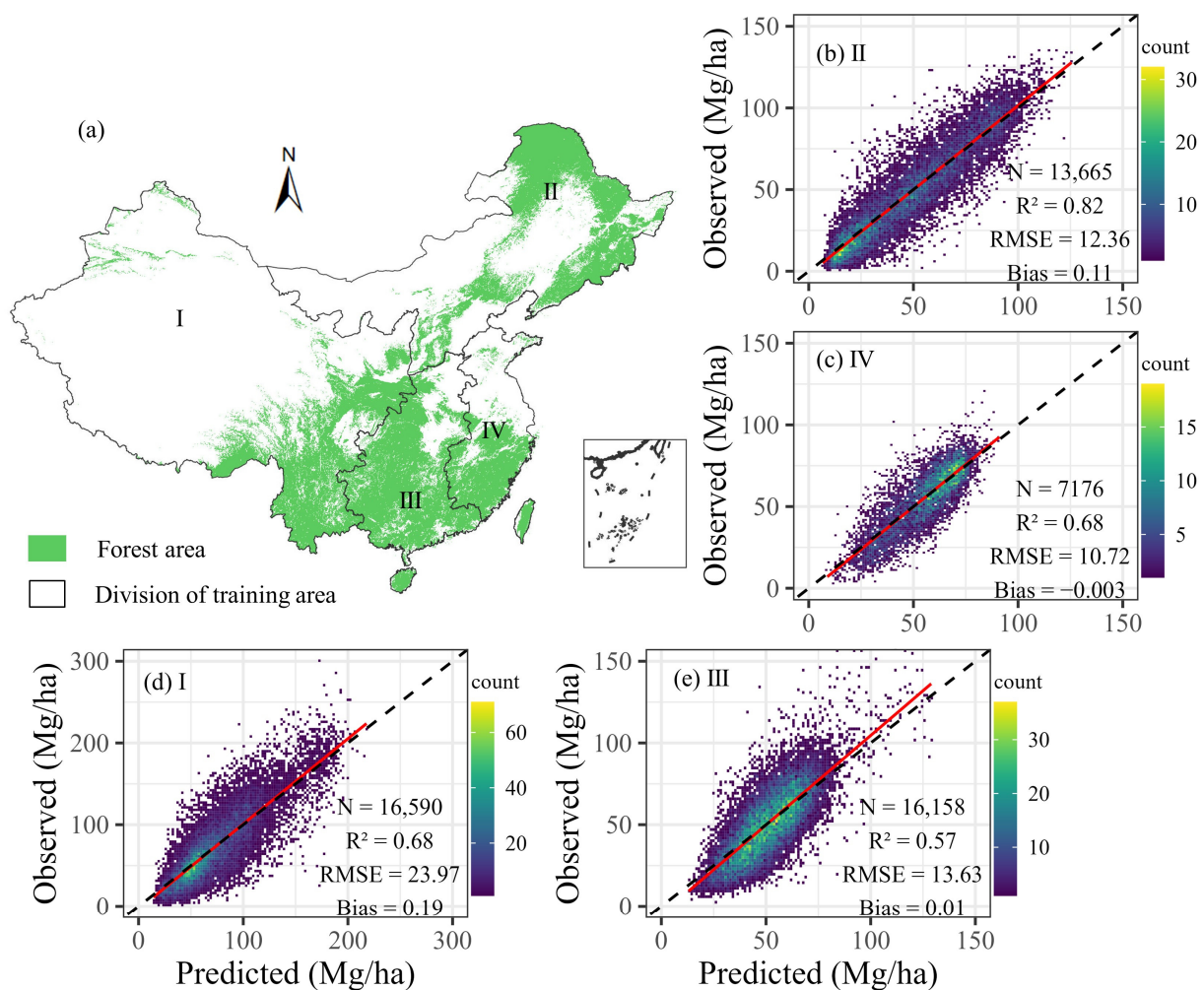


Figure 2. Validation of RF models for different areas. The study area was divided into four regions (a) to assess the model's accuracy across different regions (b–e). Heat plots show the relationships between the AGB of the predicted and sampling points in forests. The red lines represent the best-fit linear models, and the dashed lines represent 1:1 relationships. N represents the number of points in this area used for validation.

The carbon stock of China's forest stand biomass (AGB + BGB) averaged 10.32 ± 1.17 Pg C from 1990 to 2021, with 8.42 ± 0.96 Pg C in AGB and 1.90 ± 0.21 Pg C in BGB (Table 2). The spatial pattern in long-term mean forest AGB and BGB from 1990 to 2021 across China revealed substantial variability (Figures 3 and S2). The highest AGB densities were recorded in the southwestern region and the Changbai Mountains, peaking at over 150 Mg ha^{-1} . In contrast, the lowest densities were observed near 40°N latitude. Regionally, the southwestern region has the highest AGB carbon stocks, comprising approximately one-third of the nation's total, followed by the southern and northeastern regions (Figure 3a,b). On the provincial level, Yunnan topped carbon storage at 1.37 Pg C (Table S2). Figure 3c–f display the average AGB maps for a specific region during the 1990s, 2000s, 2010s, and 2020s, revealing varying degrees of land use and biomass density alterations over the decades. Figure 3g highlights the overall increase in total AGB carbon in this area from 1990 to 2021, despite some fluctuations.

Table 2. Comparison forest AGB and BGB with existing studies.

	Carbon Stock	Period	Reference
Forest AGB carbon storage	8.42 ± 0.96	1990–2021	This study
	8.6 ± 0.6	2002–2021	Chen et al. [21]
	8.4 ± 1.6	2011–2015	Tang et al. [45]
	8.3	2007	Liu et al. [46]
	11.06	2019	Yang et al. [47]
	5.54	around 2000	Huang et al. [17]
Forest BGB carbon storage	1.9 ± 0.21	1990–2021	This study
	2.2 ± 0.1	2002–2021	Chen et al. [21]
	2.1 ± 0.4	2011–2015	Tang et al. [45]

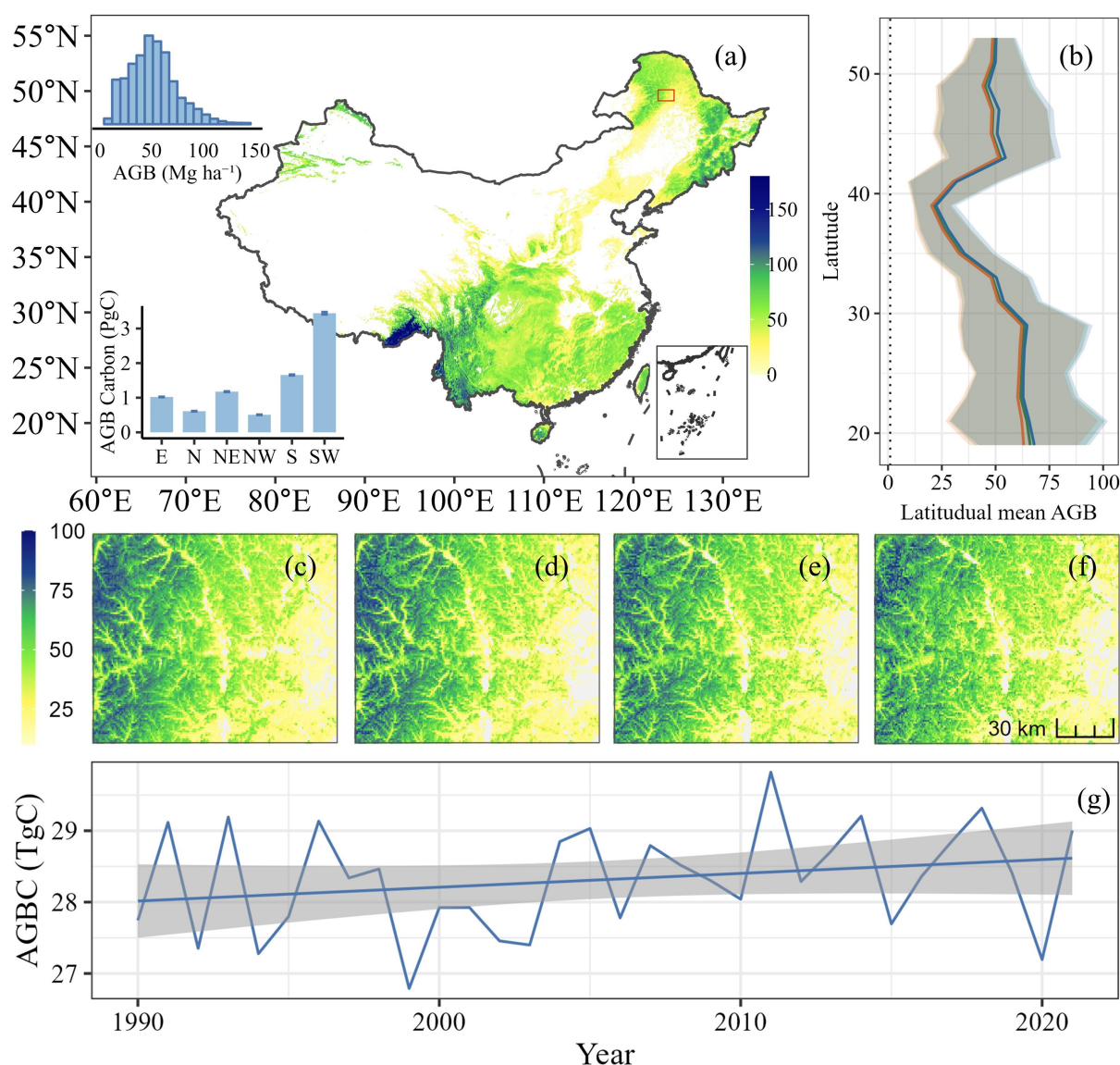


Figure 3. Spatial patterns of forest AGB. (a) Spatial patterns of averaged forest AGB from 1990 to 2021. (b) Latitudinal gradient summary of averaged forest AGB from 1990 to 2021. The three orange green and blue lines represent the lower, mean, and upper predictions. (c–f) Averaged AGB of the areas indicated in the red boxes during the 1990s, 2000s, 2010s, and 2020s. (g) The total annual AGB carbon for the region is indicated in the red box. The blue solid line represents the temporal trend of AGBC over time, while the gray shading indicates the confidence interval of the linear regression trend line.

The CV of AGB shows that uncertainty in spatial sampling and model structure is generally low (<0.1), indicating relatively low between-model variation. However, regions with the highest and lowest AGB densities exhibited higher CV values, suggesting lower accuracy in these areas (Figure S3). Our estimates of AGB carbon storage aligned closely with those of similar studies, while the estimates of BGB carbon storage were slightly lower than those previously reported (Table 2). We further randomly selected approximately 5000 points from our AGB map and compared them with the values from several existing AGB products. The AGB values from Chen's map [21] correlated best with our predictions, yielding an R^2 of 0.77 and an RMSE of 15.25 Mg ha^{-1} , followed by Su's [18] and Yang's maps [47]. Notably, compared with our AGB estimates, Su's map and the Global Ecosystem Dynamics Investigation (GEDI) Level 4A data tended to overestimate forest AGB, with most sampling points lying above the 1:1 line. Yang's map also overestimated AGB, but these overestimations were primarily in areas with AGB less than 125 Mg ha^{-1} (Figure 4).

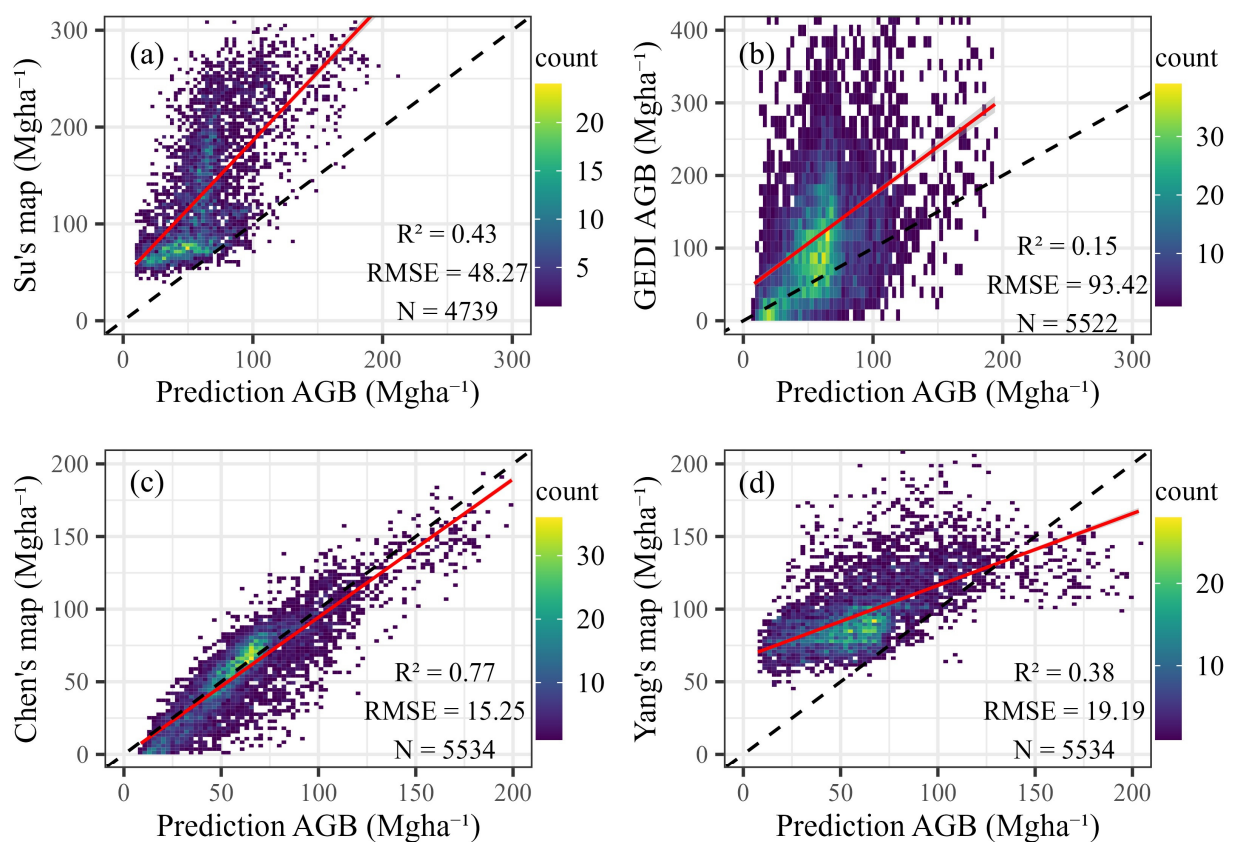


Figure 4. Predicted AGB in this study versus the estimates from other products. (a–d) Predicted AGB in this study versus the estimates from Su's map, GEDI AGB, Chen's map and Yang's map. The red lines represent the best-fit linear models, and the dashed lines represent 1:1 relationships.

3.2. Spatial and Temporal Patterns of Forest Biomass Carbon Sinks

From 1990 to 2020, the average AGB carbon sink in China's forests was $0.083 \pm 0.023 \text{ Pg C yr}^{-1}$. The total forest live biomass (AGB + BGB) carbon sink was estimated at $0.098 \pm 0.027 \text{ Pg C yr}^{-1}$. At the regional level, the southwest region was the predominant contributor to the total carbon sink, followed by the southern region (Figure 5). At the pixel scale, approximately 89% of the forested areas acted as carbon sinks, with the majority of these sinks ranging from 0 to $1 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$. Only a few forest pixels in the northwest region exceed $1 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ (Figure 5).

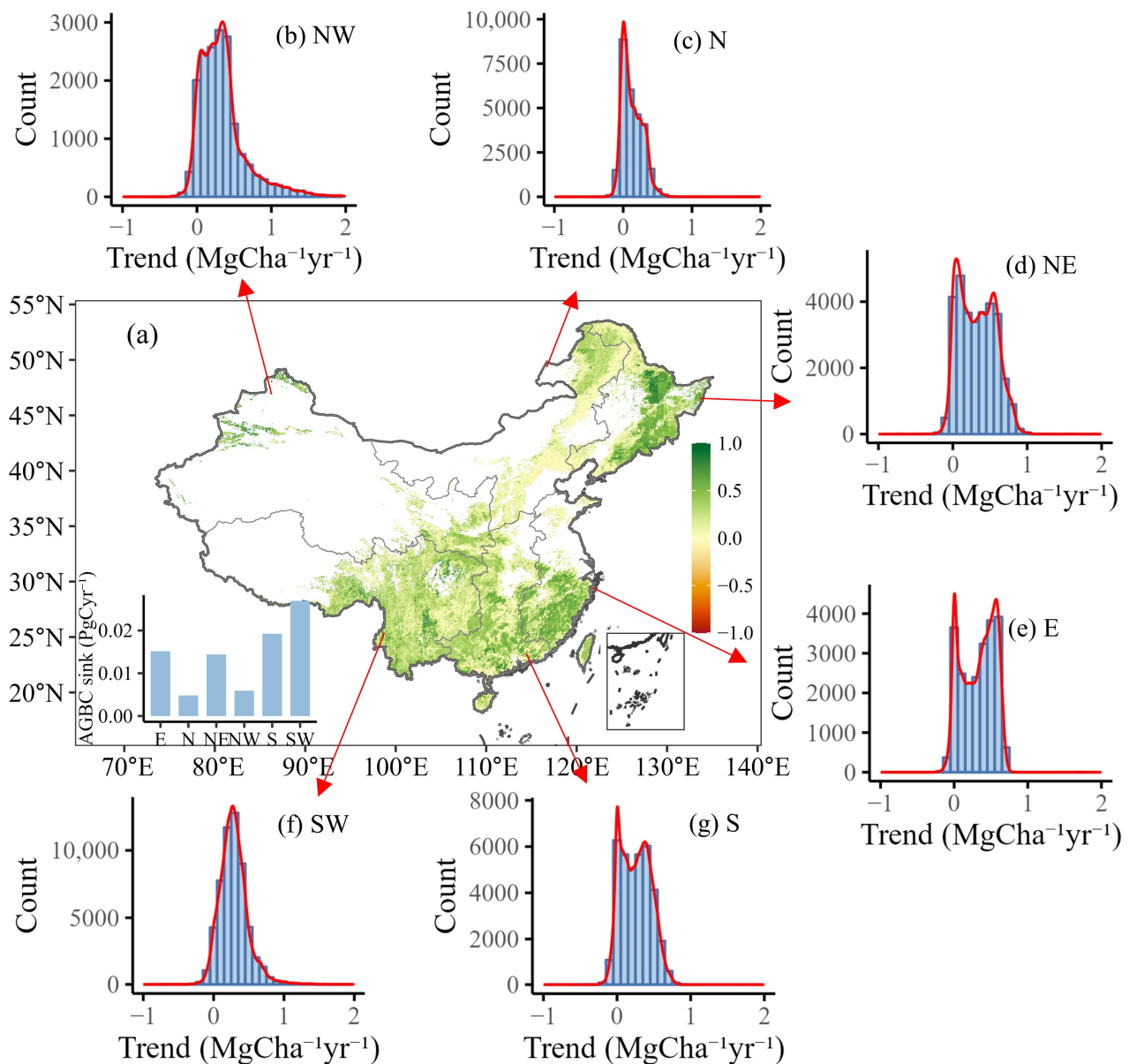


Figure 5. Spatial patterns of the forest AGB carbon sink. (a) Spatial patterns of the forest AGB carbon sink and the AGB carbon sink by regions. (b–g) Frequency distribution of the AGB carbon sink in different regions of China.

China's forest AGB carbon sink increased from $66.7 \pm 25.6 \text{ Tg C yr}^{-1}$ in the 1990s to $85.7 \pm 6.3 \text{ Tg C yr}^{-1}$ in the 2000s and $95.7 \pm 22.6 \text{ Tg C yr}^{-1}$ in the 2010s (Figure S4). Regional analyses indicated significant increases in forest AGB carbon sink across China, except in the southwest region (Figure 6). During the 2000s and 2010s, despite remaining carbon sinks, the strength of the sink decreased, with the southwest and northeast regions contributing most significantly to this decrease (Figure S4). Compared with previous research, the findings of this study indicated a more modest trend of an increasing carbon sink in AGB. The outcomes of concurrent studies have a significant disparity, suggesting a level of uncertainty even when employing similar methodologies (Figure 6, Table S1). One source of uncertainty is the varying definitions of forests. For instance, ref. [13] included live tree biomass but excluded woodlands and bamboo forests, while ref. [48] adopted a broader definition including forests, sparse woods, scattered trees, and roadside trees.

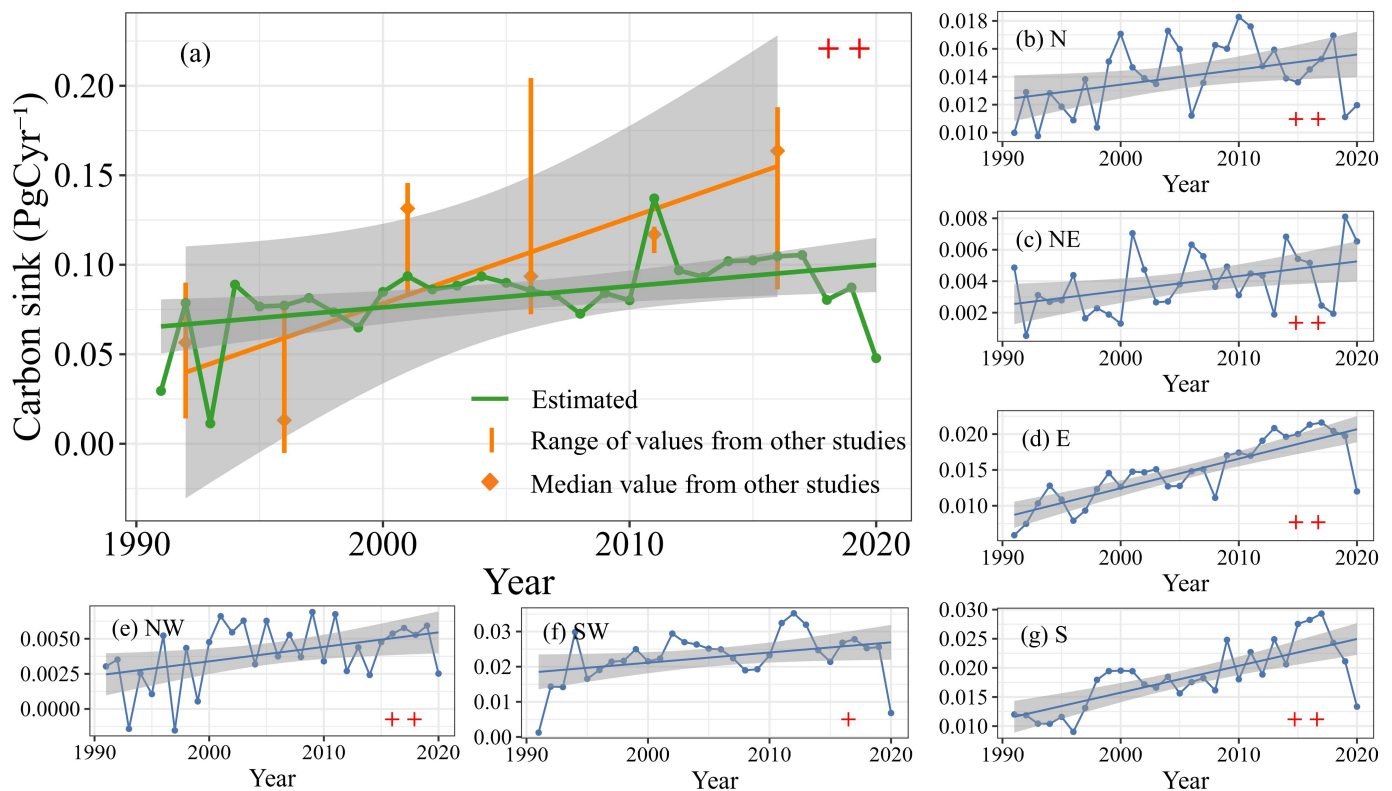


Figure 6. Temporal dynamics of the forest AGB carbon sink. The green lines in the main figure show the AGB carbon sink time dynamics estimated in this paper. The orange lines and points are the estimate of the forest AGB carbon sink from other studies, where the horizontal coordinate corresponding to the point is the median value of the study period, and the vertical coordinate corresponding to the point is the median value of the estimate from other studies. (a–g) Changes of carbon sink in different regions over time. The + in the figure represent upward trends, where ++ indicates a significant rise ($p < 0.05$). The blue solid line represents the temporal trend of carbon sink over time, while the gray shading indicates the confidence interval of the linear regression trend line.

3.3. Environmental Drivers of Forest AGB

The RF model indicated that forest AGB was impacted by a combination of factors, including forest type, topographic properties, vegetation characteristics, and climatic conditions. Among these predictor variables, landcover type was the most influential factor, with different categories representing various forest types (i.e., evergreen needleleaf forests, evergreen broadleaf forests, deciduous needleleaf forests, deciduous broadleaf forests, and mixed forests). Our study found that AGB was highest in evergreen needleleaf forests and lowest in mixed forests. Additionally, AGB demonstrated a gradual increase with elevation, growing season precipitation, and the TCW index, and then stabilized (Figure 7). The TCW index represented enhanced vegetation moisture information after tassle-cap transformation. The Landsat B7 band, a short-wave infrared band, showed that as its value increased, AGB exhibited a declining and then stable trend.

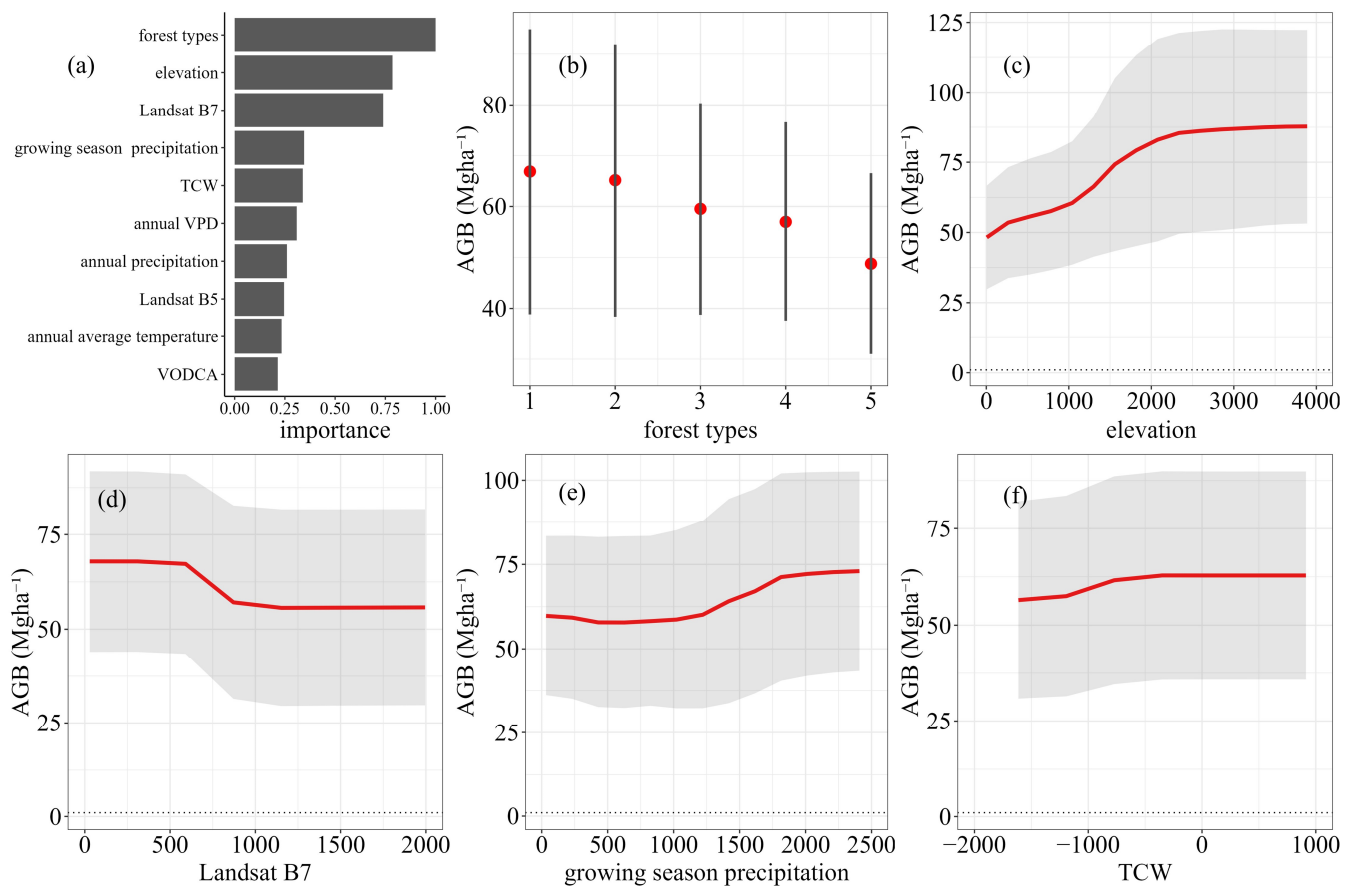


Figure 7. Environmental drivers of forest AGB. (a) Relative importance measure of the effect of predictors on forest AGB from RF models. Figure (b–f) show partial influences of (b) forest types, (c) elevation, (d) Landsat B7, (e) growing season precipitation, and (f) TCW on AGB values of all forests. Only the most important variables are shown.

4. Discussion

4.1. Comparisons with Other Dataset Estimates

The spatial distribution of forest AGB in China revealed the highest biomass densities along the southeastern edge of the Tibetan Plateau and in the northeast (Figure 3). This finding aligns with findings such as those in [16,17,21,47]. However, the histogram of AGB density values by [47] suggested higher numbers than our estimates, potentially because of differences in the study periods. In comparison with [19], their results did not show higher biomass density near the Hengduan Mountains. Ref. [18] indicated higher estimates in the southeast region of China. Given that the quantity and representativeness of training samples are crucial factors affecting the accuracy of forest AGB inversion [49], these discrepancies may arise from such differences. Our study estimated China's forest average AGB carbon storage at 8.42 ± 0.96 Pg C, closely aligning with the estimate by [21] of 8.6 Pg C from 2002 to 2021. Intensive field surveys by [45], which estimated AGB carbon storage in China between 2011 and 2015 at 8.4 Pg C, further corroborated the accuracy of our estimates.

The spatial distribution of carbon sinks is consistent with previous research, indicating the significant contribution of the southwest and northeast regions to the national forest carbon sink [50]. The strong carbon sink in these regions may be due to ecological restoration and forest protection projects, as well as decreasing forest disturbance. At the pixel level, our findings demonstrated that the southern region was a stronger carbon sink compared with the southwestern region (Figure 5). This is consistent with [51] but differs slightly from [21,50]. We estimated China's AGB carbon sink at 0.083 ± 0.023 Pg C yr^{-1} , and the

total biomass carbon sink approximated $0.098 \pm 0.027 \text{ Pg C yr}^{-1}$ from 1990 to 2021. This figure is lower than the figures reported by [7,21] but higher than the estimate provided by [19], which was $0.094 \text{ Pg C yr}^{-1}$ for the same period. Ref. [7] reported a total forest biomass carbon sink in China of $0.117 \text{ Pg C yr}^{-1}$ from 2001 to 2010, while [21] estimated the 21st century carbon sink at $0.114 \text{ Pg C yr}^{-1}$.

4.2. Uncertainty and Prospects

Our study's main contribution to this analysis is to provide the longest estimates of forest biomass carbon storage and sinks in China, and the results are generally consistent with previous findings. Nonetheless, a few limitations exist. We chose a benchmark map for training and validation, rather than relying on extensive field survey data, because of the lack of high-quality, publicly available, and representative data for large-scale training and validation in China. The forest AGB data obtained by [22] through microwave remote sensing observations, served as our benchmark map. Compared with other published spatially explicit datasets, the dataset was confirmed to perform the best in China by field data validation [16]. Nevertheless, the benchmark dataset is acknowledged to have regional uncertainties, particularly in high-biomass forests ($>250 \text{ Mg ha}^{-1}$) [22]. However, this region constitutes only a small portion of China, accounting for only 0.33% of the forest area. Using field survey data may improve our estimates, but field survey data suffer from the issues of representativeness, consistency, and uncertainties. Considering that this may be a potential problem that cannot be specifically evaluated, our novel methodology, utilizing the benchmark map, provides an alternative approach and offers the longest current time series estimate of forest AGB in China since 1990. Given this, collecting field data in a standardized and accessible manner remains essential for future research.

ML is an effective tool for predicting spatiotemporal patterns of forest biomass carbon and sinks over large areas. However, as mentioned earlier (refer to Materials and Methods 4), the inherent limitations of RF may underestimate the variability in estimates, and thus lead to an underestimation of the forest carbon sink in this study. Multiple-model ensemble has been proposed to mitigate this issue. To test this, we applied several different methods, including Adaptive Boosting (AdaBoost) [52], Gradient Boosting Decision Tree (GBDT) [53], Support Vector Machine (SVM) [54], and Multilayer Perceptron (MLP) [55] using the necessary standardization and optimal parameter selection. The results indicated that all the methods we tested had issues with underestimating or overestimating extreme biomass values. Among these methods, RF performed the best (Figures S5 and 2e). Therefore, we adopted a correction method similar to [19]. The combination of multi-source remote sensing data can leverage their strengths, and ML offers viable avenues for data integration. Nonetheless, caution is advised regarding the use of ML methods.

The environmental predictors for forest AGB mapping were primarily obtained from optical remote sensing and the Ku-band of VOD, both of which exhibit saturation effects to varying degrees. Consequently, these methods lack sufficient canopy penetration in densely forested areas, limiting our observations of understory vegetation, litter, humus, or soil carbon storage. These observations are essential for a comprehensive understanding of forest carbon storage. Additionally, our spatial resolution of 1 km may not adequately capture local variations, particularly in fragmented or mosaic forest areas. Therefore, it would be worthwhile to explore finer spatial resolutions in future studies. In addition, while our research includes carbon sinks resulting from land use changes, which were not examined in this study. Further investigation into the dynamics of carbon sinks by land use change over time would offer valuable insights.

5. Conclusions

In this study, we utilized an ML method to develop the longest (1990–2021) and most detailed spatiotemporal patterns of forest live biomass carbon storage and sinks across China by integrating a benchmark map with a range of observational variables. We used annual forest extension in stock change approach and obtained a more accurate

gridded forest carbon sink. Our ML-derived AGB estimates demonstrated high accuracy ($R^2 = 0.57\text{--}0.82$) with minimal bias. Between 1990 and 2021, China's average forest AGB carbon storage amounted to 8.42 ± 0.96 Pg C, with a total biomass carbon storage of 10.32 ± 1.17 Pg C. The AGB carbon sink was 0.083 ± 0.023 Pg C yr^{-1} , showing an increasing trend at a rate of 0.1 Tg C yr^{-2} . At the pixel scale, approximately 89% of the forested areas acted as carbon sinks. RF analyses indicated that forest AGB was predominantly influenced by forest type. This study provides crucial insight into the magnitude and trends of forest carbon sinks in China, highlighting the crucial role of forests in mitigating anthropogenic carbon emissions.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs16203811/s1>. Figure S1: Provinces and regions in China. NW: Northwest; N: North; NE: Northeast; SW: Southwest; S: South; E: East. Figure S2: Spatial patterns of mean BGB in forest area from 1990–2021 and AGB carbon stocks by region. Figure S3: Spatial patterns of coefficient of variation in forest area from 1990–2021. Figure S4: Temporal trends of forest AGB carbon sink in China and different regions over three 10-year periods. Figure S5: Model validation using (a–d) Adaptive Boosting (AdaBoost), Gradient Boosting Decision Tree (GBDT), support vector machine (SVM), and Multilayer Perceptron (MLP). Heat plots show the relationships between the AGB of the predicted and sampling points of Region III in forests. The solid line represents the best fit linear models and the dashed lines represent 1:1 relationships. Table S1: China's forest biomass carbon sink estimated by several articles. Table S2: Provinces in China and the forest carbon density, carbon storage and carbon sink value. References [11–13,48,56–59] are cited in the supplementary materials.

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