~~High~~1 km-resolution maps reveal increases in ~~woody~~ above- and belowground forest biomass carbon pools in China ~~from 2003 to 2020~~over the past 20 years

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样式定义: 正文

样式定义: EndNote Bibliography Title: 不检查拼写或语法

样式定义: EndNote Bibliography: 不检查拼写或语法

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Abstract

To quantify the ecological consequences of recent ~~nation-wide~~nationwide restoration efforts in China, spatially-explicit information on ~~woody~~forest biomass carbon stock changes over the ~~21st century~~past 20 years is critical. However, long-term biomass tracking at the national scale remains challenging as it requires continuous and high-resolution monitoring. Here, we characterize the changes in forests' above- and belowground biomass ~~(AGB~~carbon (AGBC and ~~BGB) for woody vegetation~~BGBC) in China between ~~2003~~2002 and ~~2020~~2021 at ~1 km spatial resolution by integrating multiple types of remote sensing observations with intensive field ~~plot~~ measurements through regression and machine learning ~~and mixed-pixel decomposition methods.~~approaches. On average, ~~11.~~8.6 ± 0~~ ± 0.7~~.6 and 2.~~8 ± 0.~~2 ± 0.1 PgC ~~are~~were stored in above- and belowground live ~~woody biomass~~forests in China. Over the last ~~18~~20 years, the total ~~woody~~forest biomass carbon pool in China has increased at a rate of ~~163.8~~114.5 ± 16.3 TgC/yr (~~0.5~~approximately 1.1%/yr). The most pronounced forest biomass carbon stock gains occurred in central to southern China, including the southern Loess Plateau, Qinling Mountains, southwest ~~karst~~karsts and southeast forests. ~~The~~While the combined use of ~~low-frequency microwaves and advanced laser~~multi-source remote sensing data provides a powerful tool to assess the forest biomass ~~trends, minimizing under- or overestimation of biomass variation in space and time. Future~~carbon changes, future research is also needed to explore the drivers of the observed woody biomass trends, and to evaluate the degree to which biomass gains will translate into biodiverse, healthy ecosystems and thus are sustainable.

Key words: Aboveground biomass carbon pool; Belowground biomass carbon; Long-term continuous mapping~~; Hotspot of amount and trend~~; China

1 Introduction

~~Woody (forest and shrubland) biomass contributes to over 90% of global vegetation biomass (Ma et al. 2021). As a net outcome of carbon gains from photosynthesis and carbon losses from respiration, mortality and disturbances, woody biomass is a critical indicator of ecosystem function and services, such as carbon sequestration, wood production and resource allocation (Kumar and Mutanga 2017). Accurate biomass monitoring over space and time is thus essential for assessing ecosystem management strategies and mitigation policies (Kumar and Mutanga 2017).~~

~~In recent decades, remote sensing tools have been integral in our efforts to map aboveground biomass (AGB).~~Forest biomass carbon stock contributes to over 90% of the global vegetation biomass carbon pool (Ma et al., 2021). As a net outcome of carbon gains from photosynthesis and carbon losses from respiration, mortality and disturbances, forest biomass carbon stock (approximately 50% of biomass) is a critical indicator of ecosystem function ~~hereinafter SVCmean r~~and ecosystem services, such as carbon sequestration, wood production and resource allocation (Kumar and Mutanga, 2017). Accurate forest biomass carbon stock monitoring over space and time is thus essential for assessing ecosystem management strategies and mitigation policies (Kumar and Mutanga, 2017).

In recent decades, remote sensing tools have been integral in our efforts to map aboveground biomass (AGB) or carbon stock (AGBC). By combining satellite imagery (e.g., MODIS) and airborne LiDAR signals, forest cover and canopy height can be mapped across large spatial scales (Hu et al~~.~~., 2016; Saatchi et al~~.~~., 2011; Su et al~~.~~., 2016; Tong et al~~.~~., 2020; Xu et al~~.~~., 2021). Apart from ~~imageries~~optical images and LiDAR signals, microwaves can provide more detailed insights into ~~sub-canopy~~subcanopy forest structure and ~~AGB~~AGBC due to their ability to penetrate the canopy. Active microwave techniques, i.e., Synthetic Aperture Radar (SAR) backscatters, facilitate high-resolution (e.g., 100 m) AGB mapping, but the temporal coverage is limited (~~Bouvet et al. 2018;~~ Cartus et al~~.~~., 2012; Bouvet et al., 2018). Conversely, vegetation optical depth (VOD) retrieved from multiple passive microwave sensors can be used to produce long-term continuous AGB maps (Frappart et al~~.~~., 2020; Liu et al~~.~~., 2011; Liu et al~~.~~., 2015), yet at a coarse spatial resolution (e.g., 0.25°). Because ~~optical, LiDAR and microwave (both active and passive)~~different remote sensing techniques ~~all~~ have ~~different~~their advantages and pitfalls, combining these techniques and complementing them with direct ground measurements is integral to maximizing the accuracy and precision of biomass carbon estimations across space and time.

Another source of uncertainty in vegetation biomass carbon stocks is the extent of biomass that is stored belowground as roots. While ~~AGB~~AGBC mapping is facilitated by ~~the~~a suite of emerging remote sensing techniques, investigating the spatiotemporal variation in belowground biomass ~~(BGB~~carbon pool (BGBC) remains challenging despite the large contribution of ~~root biomass~~roots to total carbon storage (Huang et al~~.~~., 2021; Ma et al~~.~~., 2021). To map ~~BGB~~BGBC, the commonly-used approach is to combine aboveground biomass information with vegetation type-specific ratios of BGB to AGB (i.e., root-shoot ratio, or RSR) (Xu et al., 2021; Saatchi et al~~.~~., 2011~~; Xu et al. 2021~~)~~. Because field studies indicate a near-linear relationship between log-transformed BGB and AGB (Enquist Brian and Niklas Karl 2002), BGB variations at large scales have often been approximated using this relationship (Spawn et al. 2020). To capture the complex relationship between BGB and biotic or abiotic variables (e.g., stand age, heat and water availability), machine learning algorithms have been applied to map BGB (Huang et al. 2021) and root mass fractions (Ma et al. 2021) globally. In mixed pixels with multiple plant functional types, BGB mapping relying on satellite-based AGB and plot-based models is expected to be less accurate. In addition, the existing woody plots are unevenly distributed across the world, with limited plots in developing countries, leading to large uncertainties in BGB estimation within those regions (Huang et al. 2021).~~

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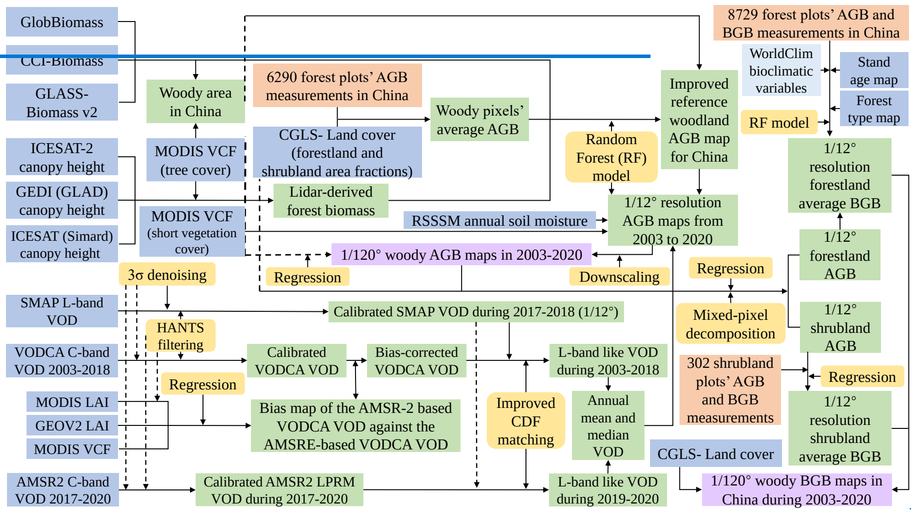
China has been implementing national-scale afforestation and reforestation programs since the late 1990s ~~(Lu et al. 2018)~~(Lu et al., 2018), promoting vegetation cover and carbon storage in the Loess Plateau and the southwest karst regions, etc. (Chen et al~~.~~., 2019a; Niu et al~~.~~., 2019; Tong et al~~.~~., 2018). A spatial understanding of ~~woody~~forest biomass trends can help evaluate the efficiency of ecological restoration programs. High quality, high resolution and long-term continuous woody biomass monitoring in China has remained challenging~~, due to difficulties in integrating different remote sensing techniques with ground-sourced measurements~~ (Zhang et al., 2019; Huang et al~~. 2019; Zhang et al.~~., 2019).

In this study, ~~we integrate different~~by integrating multi-source remote sensing ~~tools (optical, active/passive microwave and LiDAR)~~data with large quantities of plot measurements~~ through random forest approach to produce high-~~, we produced 1 km resolution ~~(1 km)~~ above- and belowground ~~woody~~forest biomass carbon pool maps ~~in~~for China during ~~2003–2020.~~the past 20 years (2002–2021). This dataset could provide new insights into ~~the spatial hotspots of woody biomass and its interannual~~forest carbon stock changes in China over the past two decades.

2 Materials and methods

~~To map above- and belowground woody biomass in China during 2003–2020, we 1) integrated state-of-the-art satellite-derived forest AGB and canopy height information with ground-sourced plot data; 2) developed an improved vegetation water content (VWC) dataset covering~~

~~2003–2020 based on the intercalibration of vegetation optical depth retrieved from various microwave sensors; 3) combined multiple sources of remote sensing and in-situ observations simultaneously allowing for both high-resolution and long-term mapping; 4) built a plot data-based random forest or regression model to estimate BGB based on AGB information; and 5) harmonized scale differences existing between plot measurements and satellite observations. The basic procedure is shown in Figure 1 and described in sections 2.1–2.5.~~



~~**Figure 1.** Workflow of woody AGB and BGB monitoring in China during 2003–2020. The blue rectangles are remote sensing-based data inputs; orange rectangles are plot-level measurements; yellow rectangles represent the key methods; while the purple rectangles represent the final output products of this study. 'GlobBiomass', 'CCI', etc. are data products' names; 'CDF' = 'cumulative distribution function'; 'HANTS' = 'harmonic analysis of time series'; 'VCF' = vegetation continuous fields. Locations of forest plots are shown in Figure S1a.~~

~~2.1 An improved benchmark map of aboveground biomass (AGB) in China~~

~~We used the three latest and highest quality global-scale AGB datasets (GlobBiomass, CCI-Biomass and GLASS-Biomass v2) to derive our benchmark map. Using SAR, LiDAR and optical images, the first global high resolution (100 m) forest AGB dataset for the year 2018, GlobBiomass, was published through the European Space Agency (ESA)'s Data User Element (DUE) project (Santoro et al. 2021). The relative root mean square error (RMSE) was below 30%, although biomass tends to be underestimated in dense forests (Mialon et al. 2020). Subsequently, ESA's Climate Change Initiative (CCI) published a global AGB map for all vegetation in 2017 using a slightly different algorithm, followed by AGB maps for 2010, 2018 and 2019 (Santoro and Cartus 2019, 2021). Datasets derived from different methods have their advantages in different regions. By referring to adequate in situ data, we may combine the advantages of different datasets. Accordingly, integration of several high-quality AGB maps has become popular. The Global Land Surface Satellite (GLASS) AGB v2 was developed by fusing the AGB maps in (Hu et al. 2016), (Su et al. 2016) and (Thurner et al. 2014), etc., through the linear combination method. GLASS-Biomass v2 roughly represents the AGB status in the year 2000, the median period of the collected woody plots' data (Zhang and Liang 2020).~~

~~We aggregated the GlobBiomass and CCI-Biomass maps from 1/1125° resolution to 1/120° (approximately 1 km) and resampled the GLASS-Biomass product from 0.01° to 1/120°. The study area, i.e., woody areas in China, was determined as all the 1/120° pixels (note: the 1/120°~~

~~resolution is referred to as a pixel hereinafter) for which AGB data are available from each of these three biomass datasets.~~

~~In September 2018, ICESat-2 provided an Advanced Topographic Laser Altimeter System (ATLAS) that provides more accurate and denser measurements of canopy height than GLAS (Markus et al. 2017). However, the application of ICESAT-2 data in canopy height estimation at large scales is currently limited (Liu et al. 2022). This study selected the ATL08 land and vegetation V004 product, and the 98% height retrievals of all canopy photons in each 100 m segment can best represent the mean top canopy height (Neuenschwander et al. 2020). All ATLAS records acquired in China's woody areas during 2018~2020 were incorporated. ATLAS has three strong and three weak beams. According to previous studies, the canopy heights retrieved using strong beams are generally more accurate than those retrieved by weak beams (Neuenschwander et al. 2020). Hence, in each 1/120° resolution pixel, we counted the numbers of valid strong beam and weak beam observations within the pixel during 2018~2020. If the number of strong beam records exceeded 5, then only those higher quality data were used. Otherwise, if there were at least 5 valid observations, but the number of strong beam retrievals was not enough, all data in the pixel were incorporated. Afterwards, we adopted the median absolute deviation (MAD) method to detect and eliminate outliers (Leys et al. 2013). For the remaining reliable canopy height retrievals in each pixel, we took the average weighted by the corresponding canopy cover fractions. Here, the top canopy cover fraction was estimated as the ratio of canopy photons to the number of all photons in the 100 m segment. By following the~~

~~above steps, we mapped forest height over China using ATLAS data. Because gaps remain between the tracks of ICESAT-2, although ATLAS's six beams enable a larger spatial coverage than any other LiDAR instrument, the derived forest height map provides values in only 42% of all woody pixels in China. Because of the potentially bad LiDAR estimates, the highest 2.5% extreme values were further excluded.~~

~~Another new LiDAR instrument is NASA's Global Ecosystem Dynamics Investigation (GEDI). It is optimized for global canopy height estimation, and has been collecting data in China since April 2019 (Dubayah et al. 2020). However, the orbital gaps of GEDI are much larger than that of ICESAT-2, resulting in limited spatial coverage by direct observation. Therefore, this study adopted the Global Forest Canopy Height 2019 dataset provided by the Global Land Analysis and Discover (GLAD). GLAD's canopy height was mapped by integrating the GEDI's forest structure measurements globally with Landsat maps through machine learning (Potapov et al. 2020). The original 30 m resolution data were averaged to 1/120°. GEDI does not collect data in north of 51.6°N (Dubayah et al. 2020), but the highest latitude of China is about 53.56°N. Therefore, we used an alternative global gridded forest height map that was developed earlier through machine learning, yet based on the ICESAT GLAS retrievals (Simard et al. 2011).~~

~~Because AGB is more related to the forest volume rather than just the canopy height, we further multiplied the three different LiDAR-based canopy height maps with the percent of tree cover (hereinafter TC) acquired from MOD44B v006 dataset. The products of multiplications are~~

~~hereinafter ATLAS-derived volume, GEDI-derived volume and GLAS-derived volume. None of these LiDAR-based timber volumes cover all woodland pixels in China. Specifically, without spatial interpolation using optical remote sensing, the ATLAS-derived volume inherited the orbital gaps of ICESAT-2, although the quality is expected higher than that of the other two machine learning-derived canopy heights and volumes. Thus, we designed three random forests for AGB estimation. Each of these three random forests (RFs) have four input predictors. GlobBiomass, CCI-Biomass and GLASS-Biomass v2, are incorporated as the predictors of each RF, while the use of which LiDAR-derived volume as the 4th input predictor makes the difference among the three RFs. Moreover, to reduce uncertainties in LiDAR-derived timber volumes, the pixels with tree cover below 5% are classified as nonwoody areas and excluded.~~

~~The training target should be a large number of high-quality 1/120° pixel-scale AGB data in China. This study collated forest or shrubland plots' AGB calculated using allometric equations or clear-cutting methods from various published papers, including (Luo 1996), (Luo et al. 2014), (Guo and Ren 2014), (Peng et al. 2016), (Wang et al. 2014), (Guo et al. 2021), (Yang et al. 2017), (Liu et al. 2020) and (Nie et al. 2016). In addition to AGB, we recorded the BGB, stand age, vegetation species or type and location information. The spatial distributions of all these woody plots are shown in Figure S1a. Some records were measured in 1990–2000, whereas others were acquired during 2000–2010. Because plots smaller than 0.05 ha are not comparable to satellite observations (Su et al. 2016), 10 m×10 m plots (Guo and Ren 2014) were not included as the training target here, but were applicable in determining the biomass allocation~~

~~rule later in section 2.5. Moreover, the understory shrub AGB was excluded, since SAR and LiDAR can observe only the canopy. The extreme values (the highest and lowest 1%) were excluded as well. These filters resulted in 6290 woody plots remaining. Because the plots are mainly located in woodlands, yet the corresponding pixel usually contains cropland, urban, waters or bare ground, whose AGB are much lower than those in the plots, we converted the plot-level AGB into the pixel-scale AGB by multiplying the area fraction of forestland in the pixel, as long as the forestland area fraction exceeds 20% and is larger than the shrubland area fraction. Here, land cover type comes from the Copernicus Global Land Service: Land Cover 100m (CGLS-LC) - epoch 2017: v3.0.1 product (Buchhorn et al. 2020). It includes not only discrete land cover classification but also the fractions of forestland, shrubland, grassland and cropland at 100 m resolution. We aggregated these high-resolution land cover fractions to 1/120° to reduce the uncertainties. It should be noted that VCF data cannot be applied here because they indicate the fractions of pure tree cover and short vegetation cover, yet a forestland contains bare ground or herbs among trees.~~

~~The RF model trainings were conducted in MATLAB R2021a software. After the RF trainings, three sets of simulations were performed using the corresponding RF model in woody pixels where all four predictors (three existing AGB products and one LiDAR-derived volume) have valid data. In addition, we performed ten-fold cross-validation to assess the performance of each RF model, and took the averages of ten times of simulations. Finally, we combined the three sets of simulations by averaging that is weighted by the mean R^2 of the corresponding RF~~

~~model. Using above methods, we produced a spatially-continuous 1/120° benchmark AGB map for China. Because most of these measurements refer to the vegetation biomass status in around 2000, we expect our AGB map to represent the AGB in around 2000. Therefore, our improved benchmark AGB map is hereinafter named 'AGBbenchmark-2000s'.~~

~~In addition, we exported the importance of each predictor variable in the RF models. For any variable, the measure is the increase in prediction error if the values of that variable are permuted across the out-of-bag observations. This measure is computed for every tree, then averaged over the entire ensemble and divided by the standard deviation of the entire ensemble.~~

~~2.2 An improved vegetation optical depth dataset covering 2003–2020~~

~~To derive a long time series of AGB, long-term continuous microwave VOD (i.e., vegetation opacity) data is useful (Jackson and Schmugge 1991; O'Neill et al. 2021). Through cumulative distribution function (CDF) matching among different VOD products, the vegetation optical depth climate archive (VODCA) was developed (Moesinger et al. 2020). The 'C-band' product which was retrieved using several C-band microwave sensors including AMSR-E, WindSat and AMSR2 and covers 2003~2018, is a better indicator of the whole woody plants' biomass than those retrieved using higher frequency microwave bands (i.e., X-band and Ku-band). However, compared to the VOD retrieved from L-band sensors such as SMOS (Wigneron et al. 2021) and SMAP (Konings et al. 2017), C-band VODs are still less sensitive to the biomass of trunks and branches, which contribute most to the AGB (Li et al. 2021). Therefore, C-band VODs usually~~

~~have high-frequency variations due to the strong variation in leaf water content per biomass under rainfall or drought events (Li et al. 2021). In addition, VODCA's C-band product is not perfectly continuous. Because the AMSR2 sensor does not share any temporal overlap with AMSR-E, the rescaling of AMSR2 data towards AMSR-E was based on the assumption that VOD remained stable over 2010~2013, i.e., the last and first two years of both sensors. For China where land use cover changes were prevalent, this assumption may lead to a bias of AMSR2-based VODCA data during 2013~2018 compared to the values in this period if the retrievals from AMSR-E were available. Theoretically, this bias is spatially variable, and is positively correlated with local VOD changes from 2010 to 2013. Thus, to develop an improved VOD dataset covering 2003–2020 for China, we focused on 1) filtering out the high-frequency fluctuations in VODCA's product and other C-band VOD products; 2) mapping and correcting the bias of AMSR2-based VODCA data during 2013~2018 compared to the AMSR-E-based VODCA VOD; 3) rescaling the C-band VODs against L-band VOD data to make their spatial patterns more correlated with that of woody plants' AGB; 4) extending the VODCA dataset to 2020 by using AMSR2 observations. Details are as follows.~~

~~Due to a very high level of radio frequency interference (RFI), SMOS data are noisy and even missing in China, especially in eastern China (Wigneron et al. 2021), making it inapplicable to this study despite its longer time series than SMAP. SMAP observations have been available since April 2015, so this study utilized the data from 2016 to 2020. The dual channel algorithm (DCA) derived VOD data included in the SMAP Enhanced L3 v5 product (O'Neill et al. 2021)~~

~~were resampled from 9 km resolution to 1/12°. For each 1/12° grid cell (note: 1/12° resolution is hereinafter called a grid cell) where at least 609 (i.e., 1/3 of 1827 daily maps in 5 years) valid VOD retrievals are available, we first filtered the abnormal values using '3σ denoising' (Chen et al. 2021). Second, we virtually filled in the data in 2015 and 2021 by using those in 2016 and 2020. Subsequently, the no-data values resulting from orbital gaps or frozen states were filled by linear interpolation, while the outputs during 2016~2020 were supposedly valid. Moreover, we also determined the average annual number of VOD peaks for each grid after setting the thresholds of minimum distance between two peaks, peak height and dominance of peaks to reasonable values. Specifically, for grid cells where woody plants exist yet without VOD data, the values were filled by sequentially searching and averaging nearby valid values (Chen et al. 2019b). For VODCA's C-band VOD during 2003~2018, after filtering out the abnormal values and virtually filling the data in 2002 and 2019, we performed the Harmonic Analysis of Time Series (HANTS) filtering (Menenti et al. 1993; Roerink et al. 2000). Either high or low outliers were excluded, while the number of frequencies to be considered above zero frequency in the Fourier function was set to the product of the mean annual peak number detected by SMAP VOD and the number of years.~~

~~We then mapped the bias of AMSR2-based VODCA's VOD compared to the AMSR-E based VODCA VOD data in 2003~2011. Because annual VOD is closely related to the leaf area index (LAI), and is clearly affected by percent tree cover and percent nontree vegetation (i.e., crops, grass and shrubs) cover, we performed a multiple linear regression between annual medians of~~

~~adjusted VODCA VOD data during the period of 2003~2011 and annual LAI values as well as VCF retrievals. This study employed LAI from two sources. First, we processed the potential cloud-affected values within the MODIS LAI product (MCD15A2H v006) by masking the values flagged by clouds and then performing HANTS filtering, with low outliers excluded and the number of frequencies set to 3 times the number of years. Second, for the LAI developed by the ESA- Copernicus Global Land Service (GEOV2 LAI) (Baret et al. 2013; Verger et al. 2014), we harmonized the retrievals from the SPOT-VGT sensor during 2003~2013 and those from the PROBA-V sensor after 2014 using CDF matching with MODIS data applied as the reference (Cammalleri et al. 2019). The MODIS LAI, VCF and GEOV2 LAI were all averaged from their original spatial resolutions (250m~1km) to 0.25° to match the resolution of VODCA. As shown in Figure S2a~b, after the regression, the R^2 values of 90% grids exceeded 0.3, and the grid-specific regression coefficients were exported. Therefore, the mean bias of AMSR2-based VODCA data during 2013~2018 compared to that before 2012 could be estimated as the difference between the mean annual VOD calculated based on the above regression coefficients as well as LAI and VCF data during 2013~2018 and the mean value of the adjusted VODCA's medians over that period. This bias was positive in most areas of China, especially afforested areas, such as northern Beijing (Figure S2c~d). Accordingly, by adding this bias to the VODCA VOD data after 2013, we improved its temporal continuity.~~

~~Using SMAP's 1/12° VOD data during 2017~2018 as the reference, we calibrated the spatial pattern of the adjusted VODCA VOD by rescaling. Notably, we revised the CDF matching~~

~~algorithm (Moesinger et al. 2020). For either the lowest or the highest 10% of the time series, a linear fitting model was designed and applied, to eliminate abnormally low or high values. Finally, to ensure a temporally consistent VOD time series from 2003 to 2020, for 2019 and 2020, we adopted the AMSR2 C-band VOD and converted it into L-band-like VOD by referring to SMAP data. Here, we chose the AMSR2/GCOM-W1 surface soil moisture (LPRM) L3 1 day 10 km x 10 km descending V001 dataset, and resampled it to 1/12° resolution. Upon noticing sharp changes in AMSR2 VOD at the beginning of 2016 in many grid cells in China, this study selected the records from only 2017~2020, which were calibrated and rescaled later through improved CDF matching by referring to the SMAP's VOD during 2017~2018.~~

~~Using the temporally-continuous and spatially L-band-like VOD dataset from 2003 to 2020, we calculated both annual mean and median VOD values as two robust indicators of annual AGB.~~

~~2.3 High-resolution woodland AGB mapping in China from 2003 to 2020~~

~~We performed two steps to map woodland AGB in China during 2003–2020. For the first step, AGBbenchmark-2000s and VCF data in 2003 were all resampled to 1/12° resolution, the same as VOD data. Specifically, for grid cells in which less than 50% of pixels were without valid AGBbenchmark-2000s values due to limited forest cover, resampling was not performed. Because VOD is influenced by the soil water availability, we built a random forest in which the predictors include: mean and median VOD values, VCF data (i.e., TC and all vegetation cover, hereinafter denoted as VC) and the mean surface soil moisture (SSM) in 2003. Here, SSM was~~

~~derived from a long-term remote sensing-based surface soil moisture (RSSSM) developed in our previous study (Chen et al. 2021). The training target is the resampled AGBbenchmark-2000s. More than 80000 grids all across China were available for the training of this RF model. Afterwards, using VOD, VCF and SSM in each year, we performed 1/12° resolution AGB simulations over 2003–2020 along with ten-fold cross-validations, and adopted the mean of ten independent simulations. We also calculated the 'calibration factor' which is defined as the ratio of resampled AGBbenchmark-2000 (i.e., the training target) to the simulated AGB in 2003 in every grid. Then, we multiplied the annual 1/12° resolution AGB in China during 2003–2020 with the grid-specific 'calibration factor'.~~

~~For the next step, we downscaled the 1/12° resolution AGB to 1/120°. Here, it is assumed that within a grid cell, the heights of trees are similar, while the short vegetation's heights are also similar. So, within a 1/12° grid cell, the AGB per tree cover (TC) and AGB per short vegetation cover (SC) can both be considered constants. Hence, we performed a binary linear regression between the AGBbenchmark-2000s value in each 1/120° pixel within the grid cell and the corresponding VCF (TC and SC) values. The intercept (i.e., constant term) was excluded, so the derived two regression coefficients can represent the mean values of AGB per TC and per SC in the grid cell. For more than 75% of all grid cells, the regression~~ $\cancel{R^2}$ ~~exceed 0.5. Since VCF indicates the coverage of pure tree and non-tree vegetation, AGB per TC should be higher than that per SC. Therefore, for grid cells where the derived AGB per TC was smaller than the AGB per SC, grids where either one of the regression coefficients was negative, or those~~

~~without very significant regressions (i.e., $p>0.01$ or $R^2<0.1$), the regression was considered invalid. The AGB per TC and AGB per SC in those grid cells were filled later by searching for nearby valid regression results, while the R^2 values of those valid regressions were applied as the weights in averaging the nearby valid values. The maps of AGB per TC and per SC in 2003 are shown in Figure S3. By integrating these data with pixel-scale VCF, we calculated the AGB of all woody vegetation in each 1/120° pixel, which was averaged to the AGB at 1/12° resolution. Accordingly, the ratio of the grid-scale AGB calculated in the first step to the aggregated AGB derived in this step can be used to further calibrate the high-resolution AGB data. Finally, by repeating the procedures, we mapped woody AGB in China at 1/120° resolution from 2003 to 2020.~~

~~2.4 Mixed-pixel AGB decomposition- towards scale matching~~

~~We mapped AGB in China at 1/120° pixel resolution, which is quite larger than the scale of plot measurements. The collected plot-level data usually represent the AGB and BGB per area in a forest or shrubland with basically uniform landscapes (i.e., the density of trees/shrubs is even in the plot, which can be either low or high). However, within a pixel, forests, shrubs, crops, herbs and bare ground may coexist. It is known that the relationship between BGB and AGB in forests differs from that in shrublands. Generally, shrub species have a much higher RSR than trees (Qi et al. 2019; Tang et al. 2018). Hence, we tried to solve that 'mixed-pixel problem' by decomposing the simulated AGB in woody regions into the AGB per forestland area and the~~

~~AGB per shrubland area. Then, we applied the respective relationships between BGB and AGB to transform the decomposed per-area AGBs into per-area BGBs for different types of forests and shrublands. Afterwards, we multiplied the per-area BGBs with the corresponding area and summed the products (i.e., all forestlands' BGB and shrublands' BGB). By this method, we basically achieved scale matching between remote sensing and plot-level observations.~~

~~AGB decomposition generally followed the idea we proposed in a previous article (Chen et al. 2019b). Specifically, in woody grids, we counted the numbers of pixels with forests (i.e., pixels in which the forestland area percentage was >10% according to the CGLS-LC) and those with shrublands (shrubland area percentage >10%). For grid cells where there were at least 50 pixels with forestland and 50 pixels with shrubland, we performed a binary linear regression without intercept between all these pixel-scale AGB data and the area percentages of forestland and shrubland in every woody pixel. Afterwards, the average per-area BGB for forestland and shrubland in woody grid cells can be estimated as the corresponding regression coefficients. However, the regression was supposed invalid when either regression coefficient was negative, or the significance p-value exceeded 0.05, or R^2 was below 0 (R^2 can be negative for regressions without constants due to the potential significant bias in AGB data). For these grids, a constant term was further added to the regression if a valid result could be derived under this situation. Specifically, for 1/12° grids with less than 50 pixels with forests, but the pixels with shrubland are sufficient, we can reliably estimate the AGB per area shrubland as the ratio of grid average AGB to the mean shrubland area percentage in the grid. Similarly, the forestland per area AGB~~

~~in grids with only enough pixels with forests can be estimated by simply neglecting the few shrubs. According to Figure S4a–b, complete AGB decomposition was achieved in 36% of all grids with enough woody pixels, and the grid cells with reliable AGB estimates accounted for 61%. The invalid decompositions composed only 3%, which were filled later by sequentially searching and averaging nearby valid results (88% of the valid regressions are with~~ R^2 ~~higher than 0.5, see Figure S4c–d). Subsequently, we deleted both the highest and lowest 2.5% values of all gridded per area AGB estimates in China, and then filled those values. Finally, a mean filter with a window size of 3×3 was applied for spatial smoothing. The final maps of AGB per area forestland and that per shrubland area in around 2017 (note: CGLS-LC data represent the land cover around 2017) are shown in Figure S5. Within a grid cell, the per-area forestland's AGB is usually (71% in China) higher than the corresponding per-area shrubland AGB, except in mountains around the Sichuan Basin and some karst regions in southwestern China where shrubs are probably much denser than trees. Because the average forestland area percentage in woody grids in China (55%) is greater than the CGLS-LC's mean shrubland area percentage (13%), the average forestlands' AGB calculated based on the decomposition result (63.4 t/ha) is much larger than the mean shrublands' AGB (11.6 t/ha in around 2017), which is reasonable.~~

~~After the decomposition, some per-area AGBs were filled-in values, while some were derived from linear regressions with intercepts. Therefore, the sum of forestland AGB and shrubland AGB in approximately 2017 may not be equal to the total grid AGB at the same time before decomposition. In addition, the sum of the decomposed AGBs in 2017 was obviously different~~

~~from the pre-decomposed AGB in other years. To solve this problem, we defined and calculated another 'calibration factor' as the ratio of the simulated grid-scale AGB in any year from 2003 to 2020 before mixed-pixel decomposition to the grid's AGB in 2017 after the decomposition. Accordingly, by referring to the per-area forestland/shrubland AGB in 2017 and this 'calibration factor' in each separate year, we could decompose the annual simulated pixel-scale AGB into the 1/120° resolution AGBs of forests and shrublands and the per-area forestland/shrubland's AGB over the whole study period.~~

~~2.5 BGB mapping in China during 2003–2020 based on its relationship with AGB~~

~~In this study, we collected 8729 and 302 records of both AGB and BGB in forest and shrubland plots, respectively, throughout China (section 2.1). For forest plots, the BGB~AGB relationship follows: log (BGB)=0.93×log (AGB)−0.51, while the relationship for shrubland plots follows: log (BGB)=0.96×log (AGB)−0.20, and the regression~~ ~~R^2~~ ~~are 0.92 and 0.85, respectively (Figure S6). The number of forest plots is large enough, and the forest type and stand age information are both available at 8182 plots (~94% of all forest plots). Therefore, we trained an RF model for estimating per-area forestland's BGB annually.~~

~~In the RF model, the training target is the per-area BGB at 8182 forest plots, while the predictors included not only forest plots' per-area AGB, forest type (hereinafter FOR_T), stand age, but also mean annual temperature (MAT), temperature seasonality (standard deviation of monthly temperature×100, abbreviated as Tsea), mean annual precipitation (MAP) and precipitation~~

~~seasonality (coefficient of variation of monthly precipitation, Psea). These climatic factors can be obtained from the corresponding papers, or estimated from the WorldClim v2.1 dataset (Fick and Hijmans 2017). In this study, FOR_T includes evergreen broadleaf forest (EBF), deciduous broadleaf forest (DBF), evergreen needleleaf forest (ENF), deciduous needleleaf forest (DNF), and mixed forest (MF), and was determined based on the major tree species in the plot. After the RF training, to simulate grid-scale per-area forestland's BGB annually, apart from importing WorldClim v2.1's MAT, Tsea, MAP, Psea and the decomposed per-area forestland AGB in each year into the RF model, we also inputted the forest stand age map for China (Zhang et al. 2017) and the annual forest type map during 2003–2020, which was determined from the ESA CCI's global 300 m resolution annual land cover classification v2.0.7cds~v2.1.1 (Li et al. 2018).~~

~~Because shrubland plots are relatively limited, and the species and stand age information was hardly provided, we directly converted the decomposed shrublands' per-area AGB into the per-area BGB during 2003–2020 using the above regression relationship. Finally, by referring to the forestland and shrubland area percentages in the CGLS-LC dataset, we mapped the annual woody BGB in China at 1/120° resolution.~~

~~In addition, we also calculated the relative errors and uncertainties of AGB and BGB in each year during 2003–2020 (see section 3.4).~~

~~2.6 Data comparison and verifications~~

~~Apart from cross-validations based on woody plots' AGB and BGB measurements over China,~~

~~we further verified our AGB and BGB estimates by referring to the results of Tang et al., who established 7800 forest plots and 1200 shrubland plots throughout China and then utilized the random forest approach to spatially map AGB and BGB (Tang et al. 2018). Various statistics were reported, e.g., the AGB, BGB and RSR for each woody vegetation type. Therefore, using the discrete land cover classification map in the CGLS-LC dataset, we classified China's woody ecosystems into six woody ecosystem types, i.e., EBF, DBF, ENF, DNF, MF and shrubland (SHR) ecosystems, according to the majority in every pixel (Figure S7). The EBF, DBF, ENF, DNF, MF and SHR ecosystems account for 59.6%, 18.4%, 15.3%, 6.1%, 0.1% and 0.5%, respectively, of the total woody area in China. Because the MF and SHR ecosystems both have very limited areas, this study just compares the AGB and BGB per area among the four major forest ecosystems in China. Similarly, the change in woody biomass or carbon stock in China can be verified by several measurements and remote sensing-based studies (Fang et al. 2018; Qiu et al. 2020; Xu et al. 2018).~~

~~We also compared the calculated spatial pattern of woody biomass and its trend against that of existing global/regional long-term woody biomass datasets, including the well-received global long-term AGB between 1993~2012 (Liu et al. 2015) and an updated woody biomass dataset covering 2001~2019 (Xu et al. 2021).~~

~~Finally, to~~To map above- and belowground forest biomass carbon stock in China during 2002–2021, we 1) calibrated a SAR-based high-resolution forest aboveground biomass map in China based on massive field measurements of AGBC during 2011–2015; 2) extended the AGBC time series to 2002–2021 by referring to the tree and short vegetation cover retrieved from optical remote sensing; 3) calibrated the AGBC time series in some specific areas using a long-term integrated microwave-based VOD dataset; and 4) mapped forestlands' BGBC through a random forest model developed based on the in-situ records in published literature. The basic procedure is shown in Figure 1 and described below.

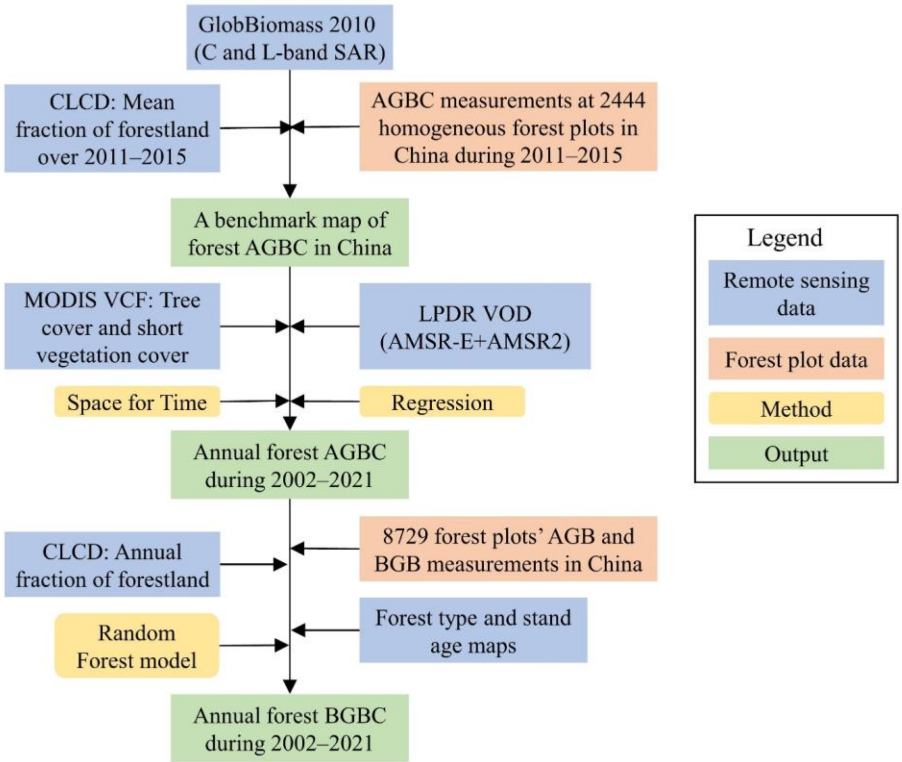


Figure 1. Workflow of forest biomass carbon pool monitoring in China during 2002–2021. AGBC, BGBC: aboveground and belowground biomass carbon; VCF: vegetation continuous

fields; LPDR VOD: global land parameter data record- vegetation optical depth; CLCD: China Land Cover Dataset

2.1 A benchmark map of forest aboveground biomass carbon (AGBC) in China

By combining multiple satellite observations of SAR backscatter, including the L-band ALOS PALSAR and C-band Envisat ASAR around the year 2010, the first global high-resolution (100 m) forest AGB dataset, GlobBiomass 2010, was published through the European Space Agency (ESA)'s Data User Element project (Santoro et al., 2021), whose relative root mean square error (RMSE) was below 30% (Mialon et al., 2020). Apart from GlobBiomass 2010, another high-resolution (30 m) forest AGB for China was produced by relating the ICESat GLAS (LiDAR)-derived footprint AGB to various variables derived from Landsat optical images (Huang et al., 2019). Because the ICESat data in 2006 were applied as the training target of the random forest model, Huang's dataset refers to the AGB status in 2006. According to a recent validation study, GlobBiomass and Huang's AGB performed the best among all existing AGB datasets in China (Chang et al., 2021). Mean forest canopy heights and tree coverage are also good indicators of the spatial pattern of forest biomass. The high-resolution (30 m) forest canopy height map for China was developed by interpolating the ICESat-2 and GEDI data in 2019 through a neural network (Liu et al., 2022), while the tree cover map at the same resolution was derived from cloud-free growing season composite Landsat 7 data in around 2010 (Hansen et al., 2013). We resampled GlobBiomass from 100 m resolution (1/1125°) to 1/1200° (approximately 90 m), and averaged Huang's AGB map, canopy height map and tree cover map to the same resolution.

A reviewable, consistent ecosystem carbon stock inventory was conducted in China between 2011 and 2015 (Tang et al., 2018). We requested the AGB carbon stock (AGBC) data at more than 5,000 30×30 m sized forest plots from the authors. Due to the scale mismatch between the maps of biomass, canopy height or tree cover and the field measurements, we dropped out the data within the 1/1200° resolution grids in which the standard deviation of tree cover was greater than 15%, according to (Chang et al., 2021), leaving 2444 homogeneous forest plots remaining (see Figure 2 for the spatial distribution of these forest plots and Figure S1a~b for the cumulative frequency curve and histogram of the AGBC records). The AGBC records in these forest plots were further multiplied by the mean fraction of forestland over 2011–2015 in the corresponding grid, which was computed from the annual 30 m resolution China Land Cover Dataset (CLCD) (Yang and Huang, 2021). By comparison, GlobBiomass 2010 AGB matches the best with the grid-scale forest AGBC derived from plot measurements, with a correlation coefficient (CC) of 0.50, followed by tree cover (CC=0.42), the product of canopy height and tree cover (CC=0.38), and finally the canopy height (0.27) and Huang's AGB (0.25). Therefore, to obtain an improved benchmark map of forest AGBC in China for the period of 2011–2015, we chose the GlobBiomass 2010 dataset as our basis, and calibrated it against the in-situ observation-based grid-scale forest AGBC. To build an equation for the calibration, we divided the grid-scale AGBC values into 16 equidistant subranges (0~15, 15~30, …, 225~240 tC/ha), calculated the median of grid-scale AGBC values that are within each subrange, and then the median of GlobBiomass AGB values in the corresponding grids. According to previous studies, an exponential function would be suitable for calibrating the GlobBiomass map in a region such as China (Mialon et al., 2020). After the calibration, we averaged the benchmark AGBC map from 1/1200° to 1/120° (approximately 1 km) to further reduce the uncertainties.

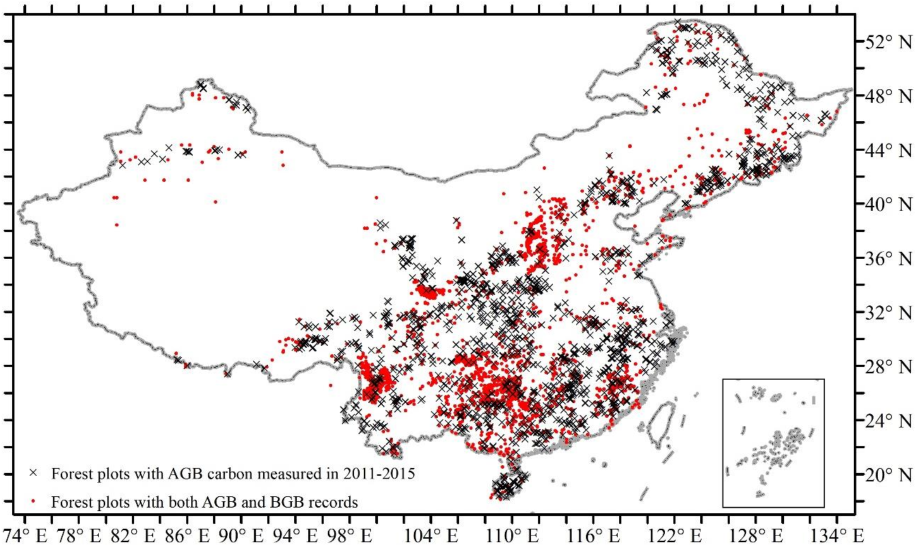


Figure 2. The spatial distribution of 1) 2444 homogeneous forest plots with aboveground ground biomass carbon stock measured between 2011 and 2015; and 2) 8182 forest plots with both above- and belowground biomass records collated in this study.

2.2 Temporally continuous forest AGBC mapping during 2002–2021

Because the benchmark AGBC was mapped based on SAR data, the spatial pattern accuracy is guaranteed, but the temporal coverage is limited to just a few years. Hence, to create a forest AGBC time series over the past 20 years, we integrated the benchmark AGBC with long-term continuous optical and passive microwave remote sensing data.

The spatial resolution of optical remote sensing is higher, and is thus preferred in this study. By adopting the MODIS vegetation continuous fields (VCF) data (MOD44B v061) which includes three ground cover components: percent tree cover, percent non-tree vegetation (i.e., short vegetation) cover, and percent non-vegetated (Dimiceli et al., 2022), we first calculated the mean tree cover (hereinafter, TC_{mean}) and short vegetation cover (hereinafter SVC_{mean}) during 2011–2015, and resampled them from 250 m to 1/120°, the same resolution as the benchmark AGBC map for 2011–2015. Because the canopy heights of trees are usually similar within a small area, the regional AGBC per TC_{mean} can be assumed as the same, which is referred to as the 'homogeneous assumption' hereinafter. Accordingly, for each grid, we searched the TC_{mean}, SVC_{mean} and AGBC within a 3×3 window (1/40°×1/40°), and then regressed the AGBC values in 9 grids against both TC_{mean} (the primary, or key predictor of AGBC) and SVC_{mean} (assumed as a supplementary predictor) linearly. Specifically, when the regression coefficient of SVC_{mean} was negative or the fitting efficiency was low (R^2<0.5; significance p-value>0.05), we excluded the supplementary predictor from the regression, only exploring the linear relationship between TC_{mean} and AGBC. Afterwards, if the regression between TC_{mean} and AGBC was still invalid, we enlarged the searching window size to 5×5, then 7×7, and finally 9×9, until the regression as well as the coefficients became valid. Then, the grid annual AGBC from 2002 to 2021 can be estimated from the TC or both TC and SVC in each year, following the regression results. If the regression failed even if the window size reached 9×9, we stopped expanding the searching window to avoid the 'homogeneous assumption' being invalid. In those grids, following a previous study (Xu et al., 2021), we divided the estimated AGBC by the TC_{mean} during 2011–2015 and then multiplied the TC in each year to obtain the AGBC time series. The above method utilized spatial information to estimate the temporal variation, and can thus be referred to as the 'space for time' method.

Long-term continuous microwave VOD can also reflect forest biomass changes, although the relationship was nonlinear (Jackson and Schmugge, 1991; O'neill et al., 2021; Liu et al., 2015; Wigneron et al., 1995). We selected the global land parameter data record (LPDR) v3 0.25° resolution VOD product, which was generated using similar calibrated, X-band brightness temperature retrieved from the Advanced Microwave Scanning Radiometer (AMSR-E) and the Advanced Microwave Scanning Radiometer 2 (AMSR2) (Du et al., 2017). As revealed by a recent evaluation study, LPDR VOD is better correlated with AGB than other long-term VOD products, especially in less-vegetated areas (Li et al., 2021). Because X-band VODs are still more sensitive to canopy cover than stem biomass and there is a data gap between October 2010 and June 2011, while the plot investigations were all conducted in summers (Tang et al., 2018), we averaged the VOD data from mid-July (the 206th day) until the end of September (the 274th day) in each year to represent the annual AGB status. We also aggregated the benchmark AGBC map as well as the VCF data (TC_{mean} and SVC_{mean}) to 0.25° resolution. After each round of searching, we applied the shape language modelling algorithm (D'errico, 2022) to fit the nonlinear but monotonous relationship between AGBC and VOD values within the searching window, and then fitted the bivariate linear regression between AGBC and VCF. If the nonlinear regression between AGBC and VOD is valid and the R^2 is superior to the regression between AGBC and VCF data, LPDR VOD data is expected to outperform VCF in predicting the inter-annual AGBC changes in the corresponding 0.25° grid. Therefore, in these areas, we calibrated the VCF-derived high (1/120°) resolution annual AGBC by incorporating the ratio between the VOD-derived 0.25° AGBC and the aggregated VCF-derived AGBC in that year.

2.3 Forest belowground biomass carbon (BGBC) mapping during 2002–2021

This study mapped belowground forest biomass carbon (BGBC) following the random forest (RF) model approach (Huang et al., 2021). To reveal forests' above- and belowground biomass allocation rules in China, this study collated both AGB and BGB records at 8729 forest plots throughout China, which were obtained using allometric equations or clear-cutting methods from published papers, including (Luo, 1996), (Luo et al., 2014), (Guo and Ren, 2014), (Wang et al., 2014). Because forest stand age and tree species (forest type) information are also available at 8182 plots, while the climatic backgrounds are available from the WorldClim v2.1 dataset (Fick and Hijmans, 2017), forest plots' AGB, forest type (hereinafter FOR_T), stand age, mean annual temperature (MAT), temperature seasonality (standard deviation of monthly temperature×100, abbreviated as Tsea), mean annual precipitation (MAP) and precipitation seasonality (coefficient of variation of monthly precipitation, Psea) were applied as predictors of forest plots' BGB. For simplicity, we distinguished all forests into 5 types: evergreen broadleaf forest (EBF), deciduous broadleaf forest (DBF), evergreen needleleaf forest (ENF), deciduous needleleaf forest (DNF), and mixed forest (MF). Using the data records at these 8182 plots (see Figure 2 for the locations of these forest plots and Figure S1c~f for the cumulative frequency curves and histograms of the AGB and BGB data), we trained ten-fold RF models using MATLAB R2021a®. The number of regression trees was set to 500.

Because the 1/120° resolution grids where forest AGBC data were available are often mixed with forestland and some other land cover types, e.g., water bodies, bare ground, croplands, we converted the annual grid-average AGBC into the AGBC per area forestland by incorporating the annual fraction of forestland computed from the CLCD at 30 m resolution. Considering the potential uncertainties in the forestland fraction as well as the inclusion of shrub or herbaceous plant AGB in the SAR-derived AGB, we only calculated the annual AGBC per area forestland in grids that were dominated by forestland (forestland fractions were consistently over 50%). In these forestland grids, we simulated the forest BGBC per area forestland during 2002–2021 by inputting the estimated annual AGB (approximately 2 times of the AGBC) per forestland, annual forest type map derived from ESA CCI's land cover classification dataset (Li et al., 2018), forest stand age (Besnard et al., 2021) and climatic background variables into the RF model. Afterwards, we multiplied the simulation results in every forestland grid with the annual forestland fractions to obtain the forests' BGB and BGBC (0.5×BGB) time series. Finally, for grids with forests but are not dominated by forestlands, we sequentially searched for at least five valid RSR values (the ratio of forests' BGBC to AGBC) nearby (Chen et al., 2019b), and then multiplied the annual forest AGBC in the grid with the median of nearby RSR values in each year to estimate the annual forest BGBC.

2.4 Evaluation and assessment

We compared the inter-annual trend of forest biomass carbon calculated in this study against that of existing global/regional long-term woody biomass datasets, including the well-received global long-term terrestrial biomass data between 1993–2012, which was developed mainly based on a long-term integrated VOD dataset (Liu et al., 2015), as well as an updated woody biomass dataset covering 2001–2019 whose long time series was derived from optical remote sensing data (i.e., MODIS VCF dataset) (Xu et al., 2021).

To justify the random forest models for ~~biomass and allocation~~BGBC predictions, we drew partial dependence plots (PDPs) in MATLAB R2021a® to show the marginal effect that one predictor has on the training target (e.g., BGB at forest plots)~~ from a machine learning model (Hastie et al. 2009).~~(Hastie et al., 2009). Here, for each predictor, we excluded the extreme values (the lowest 1% and the highest 1%) before calculating the corresponding PDP to ~~ensure its robustness.~~avoid roughly extending the PDP lines to data-scarce areas. Ten-fold RF trainings were also performed to derive the mean PDP values as well as the standard deviations.

3 Results and discussion

3.1 ~~Model development and~~ Evaluation of forests' AGBC and BGBC estimation

~~In the first step, i.e., the benchmark woodland AGB mapping, when ATLAS data derived canopy height was applied as an additional predictor in the RF model apart from the three biomass datasets (see section 2.1), the number of data points available for training was 1392, and the predicted R-square (R^2) according to the ten-fold cross validation was 0.49±0.06 (mean ± standard deviation). The training efficiency is limited by the potential errors in plot-level AGB records as well as the CGLS-LC's land cover fraction maps, and the scale difference between satellite and plot-level observations. Although introducing climatic and topographic variables as predictors could increase the R^2 of ten-fold cross validation, these variables contain high spatial autocorrelation, and thus even an elevated R^2 cannot indicate a higher predictive performance (Ploton et al. 2020). According to a test addressing the relative contribution of the four predictors, GLASS-Biomass dataset contributed most to the woody AGB mapping (35%), followed by GlobBiomass (24%), CCI-Biomass (22%) and ATLAS-derived tree volume (19%). When GEDI-derived and GLAS-derived wood volumes were respectively used, the available data points increased to 3842 and 2286, but the mean R^2 values were both reduced to 0.36. After combining these three sets of AGB simulations, the R^2 between the resulting benchmark AGB map for China (Figure S1c) and the upscaled plots' AGB was 0.56 (Figure S1b).~~

~~In the second step, i.e., long-term continuous AGB mapping (see section 2.3), with a ten-fold~~

~~cross-validation, the RF model's predictive R^2 and RMSE were 0.79±0.01 and 16.7±0.33 t/ha, respectively. Vegetation continuous fields (VCF) contributed most to the training efficiency (tree cover and all vegetation cover contributed 39% and 17%, respectively). Mean and median vegetation optical depth (VOD) values both contributed 17% to the training efficiency, whereas mean surface soil moisture accounted for 10% (methods are in section 2.3).~~

First, according to Figure 3a, an exponential function: $y=1.63 \times x^{0.73}$ can fit the relationship between the actual grid-scale forest AGBC over 2011–2015 (y) and the AGB values predicted by GlobBiomass 2010 (x). Hence, this function was applied to derive the benchmark map of forest AGBC across China.

Second, when using the spatial information of tree cover and short vegetation cover to estimate the temporal variation of AGBC in each grid, the spatial searching window was at its minimum of 3×3 in most (53%) grids with forests. Across China, the temporal extension of AGBC in only 15% of all grids with forest cannot be achieved even when the searching window was enlarged to 9×9 (Figure 3b).

Next, as shown in Figure 3c and 3d, the grids where LPDR X-band VOD performed better than MODIS VCF in predicting the temporal change in forest AGBC are usually located in regions with low tree cover. These grids account for just 10.4% of all grids with forests, and may suffer from high uncertainty within the optical-based variation in tree cover. Therefore, microwave-based VOD is supposed to be more suitable for estimating the forests' AGBC changes in these regions.

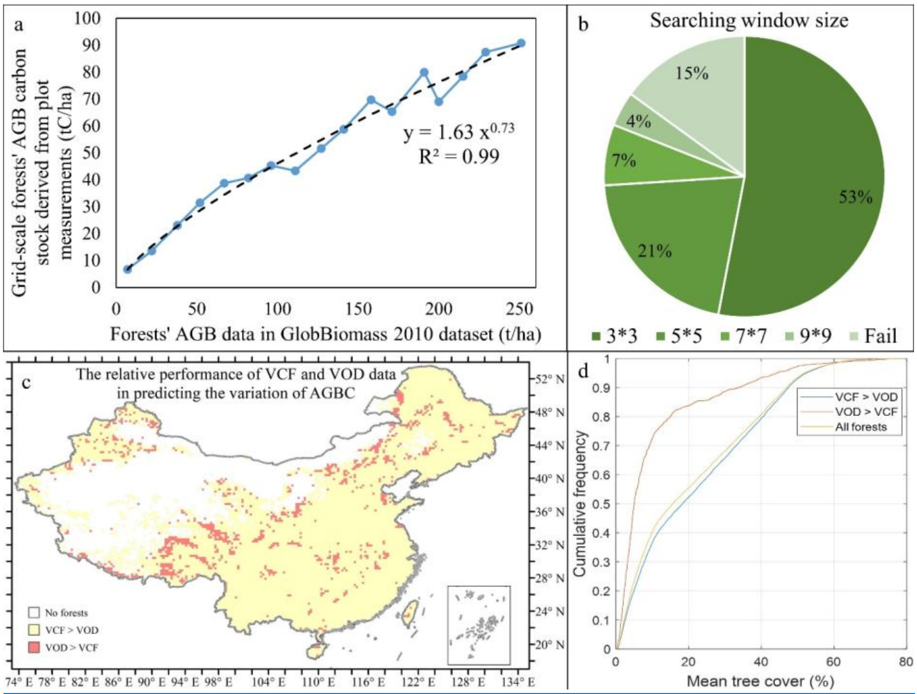


Figure 3. Evaluation of the forest AGBC and BGBC mapping in this study. (a) The regression relationship between the grid-scale forest AGB carbon stock derived from plot measurements during 2011–2015 and the GlobBiomass AGB dataset for 2010; (b) the minimum searching window sizes of every 1/120° grid when the spatial variation in MODIS VCF was applied as the predictor of AGBC changes; (c) the spatial pattern of the relative performances of MODIS VCF and LPDR VOD data in predicting the variation in AGBC; (d) comparison of the mean tree cover between the grids where VOD data were more suitable for predicting the variation

of AGBC and the grids where VCF data were the better predictor.

The RF model designed for ~~woody plots'~~forest plot BGB estimation (see section 2.~~5~~3) achieved a predictive R^2 of 0.89±0.02, while the RMSE was 6.3±0.5 t/ha. AGB explained 53% of the variation in BGB~~'s variation~~ among different ~~woody~~ plots. Long-term climate backgrounds, i.e., mean annual temperature, temperature seasonality, annual precipitation and precipitation seasonality accounted for 8%, 6%, 8% and 7%, respectively. Forest type and stand age also contributed 12% and 8% to the training efficiency, indicating that the effects of these factors are nonnegligible. The selection of predictors of BGB basically followed the existing knowledge ~~(Huang et al. 2021)~~(Huang et al., 2021), and the seasonality of temperature and precipitation made sense in the prediction (see Text S1). On the other hand, although previous studies incorporated many edaphic factors as predictors of BGB ~~(Huang et al. 2021), by comparing the training efficiencies when whether these edaphic factors are incorporated~~(Huang et al., 2021), by comparing the training efficiencies when whether these edaphic factors are incorporated or not, we could justify the reasonability of our simplified set of predictors (Text S1).

~~We also explored how different factors influence AGB and BGB among woody plots in China. Of the biotic and abiotic factors included in our model, partial dependence plots (PDPs, Figure 2a~c) show that stand age is the main driver of AGB. However, with forest aging, forest growth gradually stops, conforming with common knowledge (Xu et al. 2010). Woody AGB also~~

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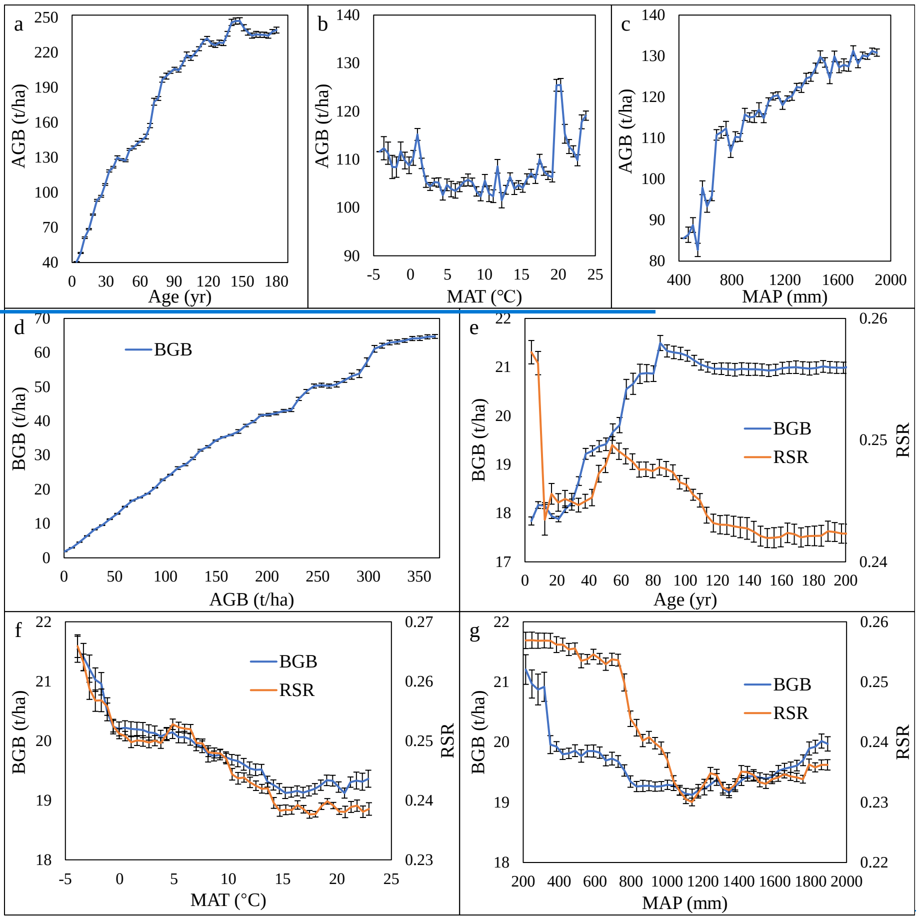
~~increases significantly with precipitation, but water availability does not constrain biomass in humid regions with annual precipitation above 1500 mm, and temperature did not significantly affect AGB at large scales. These findings are in line with previous studies (Stegen et al. 2011).~~

According to the collected woody plots' data, AGB is a key driver of BGB (Figure ~~2d~g~~4). Yet, RSR changes among different forest growth stages, decreasing in general as reported ~~(Mokany et al. 2006).~~(Mokany et al., 2006). The overall negative impact of mean temperature on BGB or RSR agrees with the mechanism that higher heat promotes nutrient accessibility (Luo et al~~.~~., 2012; Ma et al~~.~~., 2021), and increases the turnover rates of roots at a higher magnitude than stems ~~(Reich et al. 2014).~~(Reich et al., 2014). The 'U-shaped' relationship between precipitation and belowground biomass allocation follows the 'optimal biomass allocation' theory, because arid climates promote root extension, yet too heavy rainfall reduces nutrient availability through leaching and dilution ~~effect~~effects ~~(Luo et al. 2012).~~(Luo et al., 2012). Other factors, including temperature seasonality, precipitation seasonality and forest type, have supplementary effects on ~~the~~ biomass allocation (Figure ~~S8~~S2).



a
b
c
d
e
f
g
AGB (t/ha)
Age (yr)
MAT (°C)
MAP (mm)
BGB (t/ha)
AGB (t/ha)
BGB
RSR

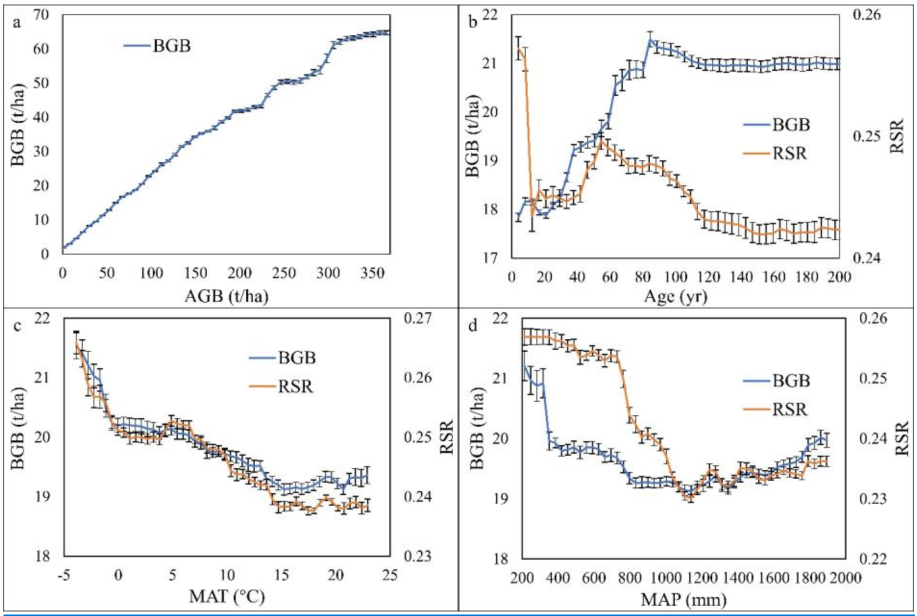


Figure ~~2~~4. Influence of key factors on ~~woody plots' above- and~~ forest belowground ~~woody~~ biomass (BGB) and root-shoot ratio (RSR) in China. Subfigures (a~~~c) Partial effects of (a) forest age; (b) mean annual temperature (MAT) and (c) mean annual precipitation (MAP) on AGB in all qualified woody plots; (~~d~~~g)) show partial influences of (a) AGB; (b) stand age; (c) MAT and (d) ~~AGB; (e) stand age; (f) MAT and (g)~~ MAP on BGB and RSR values of all ~~qualified woody~~forest plots. The error bars represent the standard deviations of the ten-fold trainings. We did not draw the PDP for the impact of AGB on RSR, since the dividend of RSR calculation is AGB.

3.2 ~~Total woody~~Forest biomass carbon pool, allocation and change in China

~~Between 2003 to 2020, the total woody biomass in forestlands and shrublands in China were 28.4±1.8 Pg and 2.3±0.2 Pg, respectively (Table 1), while the total woody AGB and BGB were 24.4±1.6 Pg and 6.2±0.4 Pg. The mean RSR for forests (0.24) and that of all woody areas in~~

~~China (0.26) are both slightly lower than the global average values of approximately 0.25 and 0.3, respectively (Huang et al. 2021; Ma et al. 2021). Separated by forest types, evergreen conifer forest (ENF) occupies the highest woody biomass per unit area (143.5 t/ha), followed by 109.5 t/ha in the evergreen broadleaf forest (EBF), whereas deciduous forests (DBF & DNF) harbor 92 t/ha (Figure 3a). By contrast, deciduous forests in northern China (see Figure S7 for the distribution of forest ecosystems) occupy higher mean RSR values (Figure 3a).~~

~~Woody biomass across China increased by an average rate of 363.9±11.2 Tg/yr during 2003–2020, equaling a vegetation carbon sink of approximately 163.8±5.9 TgC/yr (assuming a carbon density to biomass ratio of 0.45 (Xu et al. 2018)). Changes in forestland AGB, forestland BGB, shrubland AGB and shrubland BGB account for 73.8%, 7.1%, 15.5% and 3.6%, respectively, of the total woody biomass trend. Apart from visible declines from 2010 to 2011 and from 2016 to 2017, China has undergone a continuous increase in woody biomass (p<0.01) during 2003–2020, and the biomass gains were the greatest from 2014 to 2016 (Figure 3b).~~

~~Our estimates of woody biomass and its trend are generally consistent with previous results in China obtained using both satellite observation and massive field measurements (Table 1). Yet, differences occur in some aspects. For example, as the grass-dominated pixels are excluded in this study, the mean RSR for Chinese shrubs (including those in grass-dominated pixels) was reported as 0.71 (Tang et al. 2018), slightly higher than our estimate of 0.53 for shrubland ecosystems in China. Moreover, regarding trees' occurrence in shrublands, the shrublands'~~

~~woody biomass and RSR values in this study refer to a mosaic of shrubs and some trees.~~

~~**Table 1.** Basic statistics of the calculated woody biomass in China and the agreement with those reported previously (the ratio of carbon density to biomass is set to 0.45 (Xu et al. 2018)).~~

Between 2002 to 2021, the forest above- and belowground biomass carbon (AGBC and BGBC) pools in China were 8.6 ± 0.6 and 2.2 ± 0.1 PgC, respectively (Table 1). The mean RSR for all forests was 0.25, basically equal to the global average (Huang et al., 2021). Separated by forest type, evergreen conifer forests (ENF) occupy the highest biomass carbon pool per unit area, mainly because ENF are mainly located in southwestern China and are more mature and natural (Yu et al., 2020; Zhang et al., 2017). Deciduous forests (DBF & DNF) in northern China (see Figure S3 for the distribution of different forest ecosystems) harbor less biomass carbon but higher BGBC (Figure 5a), which can be attributed to the higher RSR values (Table 1).

The forest biomass carbon stock in China increased at an average rate of 114.5±16.3 TgC/yr ($p<0.01$) during 2002–2021, and the annual biomass carbon gains were the greatest from 2014 to 2015, reaching 736 TgC (Figure 5b). Changes in AGB and BGB accounted for 81.9% and 18.1%, respectively, of the forest carbon stock gains over the past 20 years.

Our estimates of the forest biomass carbon pool, forest RSR and the recent inter-annual trend of forest biomass carbon are generally consistent with previous estimates based on massive field investigations (Table 1).

Table 1. Agreement of the estimated various forest RSR and the trend of forest biomass carbon in China with existing studies.

Variables ~~related to woody biomass~~	Our estimate ~~(mean value in 2003–2020)~~	Previous ~~high-quality~~ estimates	Reference
~~Forestland AGB in China~~	~~22.9 Pg~~	~~18.7 Pg~~	~~(Tang et al. 2018)~~
~~Forestland BGB in China~~	~~5.5 Pg~~	~~4.6 Pg~~	
~~Shrubland AGB in China~~	~~1.5 Pg~~	~~0.9 Pg~~	
~~Shrubland BGB in China~~Forests' AGBC	~~0.8 Pg~~8.6 ± 0.6 (2002–2021) 8.7 ± 0.3 (2011–2015)	~~0.7 Pg~~8.4 ± 1.6 (2011–2015)	(Tang et al., 2018)
~~Woody biomass in China~~	~~30.7 Pg~~	~~24.9–26.4 Pg~~	~~(Tang et al. 2018; Xu et al. 2018)~~
~~Forestland RSR in China~~Forests' BGBC	~~0.24~~2.2 ± 0.1 (2002–2021) 2.2 ± 0.1 (2011–2015)	~~0.23–0.25~~2.1 ± 0.4 (2011–2015)	~~(Jiang and Wang 2017; Tang et al. 2018)~~
~~Shrubland RSR in China~~	~~0.53~~	~~0.71~~	
~~ENF's per-area AGB~~	~~143.5 t/ha~~	~~~122 t/ha~~	~~(Tang et al. 2018)~~
~~EBF's per-area AGB~~	~~109.5 t/ha~~	~~~109 t/ha~~	
~~DBF's per-area AGB~~	~~92.2 t/ha~~	~~~87 t/ha~~	
~~DNF's per-area AGB~~	~~91.5 t/ha~~	~~~98 t/ha~~	
~~All forests' per-area AGB~~	~~109.3 t/ha~~	~~99–112 t/ha~~	~~(Tang et al. 2018; Yin et al. 2015)~~
~~Forests' per-area total biomass~~	~~137.3 t/ha~~	~~124–144 t/ha~~	~~(Tang et al. 2018; Yao et al. 2018)~~
~~ENF's~~EBF's RSR	0.~~22~~27±0.~~03~~07	0.~~24~~22±0.11	~~(Tang et al. 2018)~~(Tang et al., 2018)
~~EBF's~~DBF's RSR	0.~~25~~31±0.~~04~~05	0.~~22~~28±0.15	
~~DBF's~~ENF's RSR	0.~~30~~22±0.~~03~~04	0.~~28~~24±0.11	
DNF's RSR	0.~~34~~29±0.~~04~~10	0.31±0.13	
Annual ~~woody~~forest carbon stock increase	~~163.8±~~114.5~~.9~~ ± 16.3 TgC/yr (2002–2021) 105.1 ± 42.2 TgC/yr (2002–2010)	~~120.2~~116.7 TgC/yr (2000~~–~~–2010)	~~(Fang et al. 2018)~~(Fang et al., 2018)
		~~178 TgC/yr (2020–2030)~~	~~(Tang et al. 2018)~~
		~~170 TgC/yr (2000s–2040s)~~	~~(Yao et al. 2018)~~
~~Annual forests' carbon stock increase~~	~~146.2–163.8 TgC/yr~~	~~153.6 TgC/yr (2003–2020)~~	~~(Qiu et al. 2020)~~

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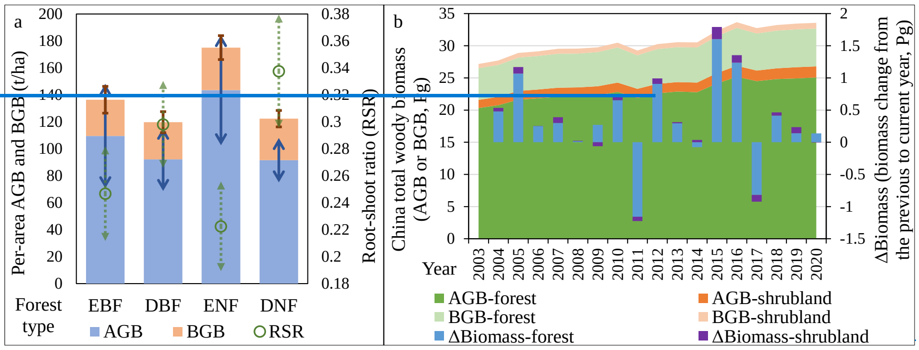

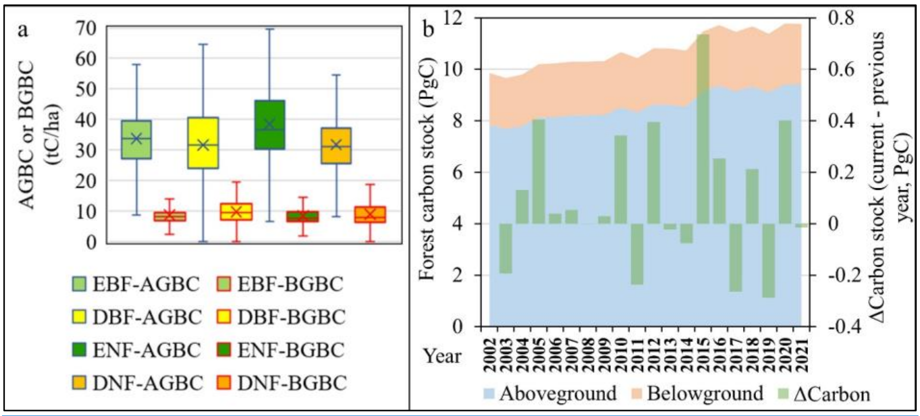

Figure ~~3. Woody~~5. Forest biomass allocation and biomass change in China during ~~2003–2020~~2002–2021: (a) ~~per-area AGB and BGB, as well as RSRs~~aboveground biomass carbon (AGBC) and belowground biomass carbon (BGBC) density of different forest ecosystems in China~~. The blue, red and green error bars are the standard deviations of AGB, BGB and RSR in China~~; (b) the ~~interannual~~inter-annual changes of ~~total forestland' AGB (AGB-~~forest~~), shrubland' AGB (AGB-shrubland), forestland' BGB (BGB-~~ AGBC and BGBC in China. Total forest~~), shrubland' BGB (BGB-shrubland). Biomass~~ biomass carbon stock changes ~~(ΔBiomass) in forests and shrublands~~ from the previous to the current year are represented by ~~blue and purple~~ green columns.

3.3 ~~Updated spatial hotspots~~Spatial pattern of ~~woody~~the forest biomass ~~amount and~~carbon stock trend in China

The highest ~~per-area woodland~~forest biomass ~~is~~carbon pools during 2002–2021 were observed in ~~the southwest of~~northeastern and southwestern China, especially ~~south~~southern Tibet. ~~Woody~~Forest biomass ~~is~~carbon stocks were also high in ~~parts of~~the natural or semi-natural forests in the Qinling Mountains, Hengduan Mountains, Hainan and Taiwan ~~islands~~ (Figure ~~4a). Hence, woody biomass was highest in the south < 34°N, followed by the northeast forests, and lowest in the mid-latitudes, 38–40°N (Figure 4b).~~6a). Above- and belowground ~~woody~~forest biomass allocation varies significantly among regions. RSR is highest in northeastern deciduous conifer forests and northern China's deciduous ~~forest. The southwest karsts also have higher RSR than its surroundings due to high shrubland biomass (Figure 4c and Figure S5b). Woody pixels' RSR ranges from 0.17 to 0.42 across China, with 67% of pixels having a RSR of 0.2–0.3 (Figure 4d).~~broadleaf forests but low in southern China (Figure 6b). The strongest forest biomass carbon increases were found in central to southern China, including the ~~southern part of the~~ Loess Plateau, ~~the~~ Qinling Mountains, ~~the~~ southwest karst region and southeastern forests. ~~Declines~~Slight declines in ~~woody~~forest biomass carbon only occurred in some mature and natural forests, e.g., those in the Greater Khingan Mountain, Hengduan Mountains and South Tibet (Figure ~~4e). 59.8%~~6c). A total of ~~woody areas~~40.3% of all forests in China showed significant biomass carbon stock gains ~~(Figure 4f~~over the past 20 years, whereas only 3.3% of forests experienced significant biomass carbon losses (Figure 6d).

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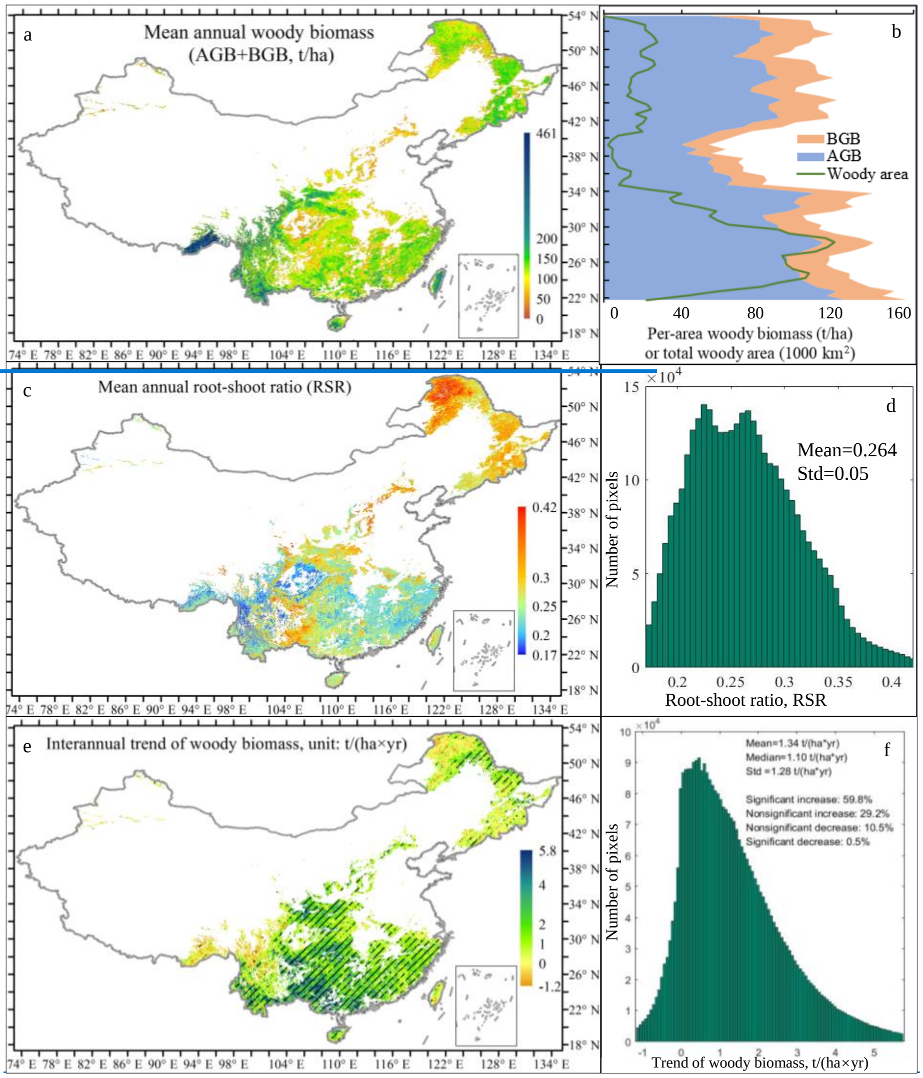
a
Mean annual woody biomass
(AGB+BGB, t/ha)
461
200
150
100
50
0
b
BGB
AGB
Woody area
Per-area woody biomass (t/ha)
or total woody area (1000 km²)
c
Mean annual root-shoot ratio (RSR)
0.42
0.3
0.25
0.2
0.17
d
Mean=0.264
Std=0.05
Number of pixels
Root-shoot ratio, RSR
e
Interannual trend of woody biomass, unit: t/(ha×yr)
5.8
4
2
1
0
-1.2
f
Mean=1.34 t/(ha*yr)
Median=1.10 t/(ha*yr)
Std =1.28 t/(ha*yr)
Significant increase: 59.8%
Nonsignificant increase: 29.2%
Nonsignificant decrease: 10.5%
Significant decrease: 0.5%
Number of pixels
Trend of woody biomass, t/(ha×yr)

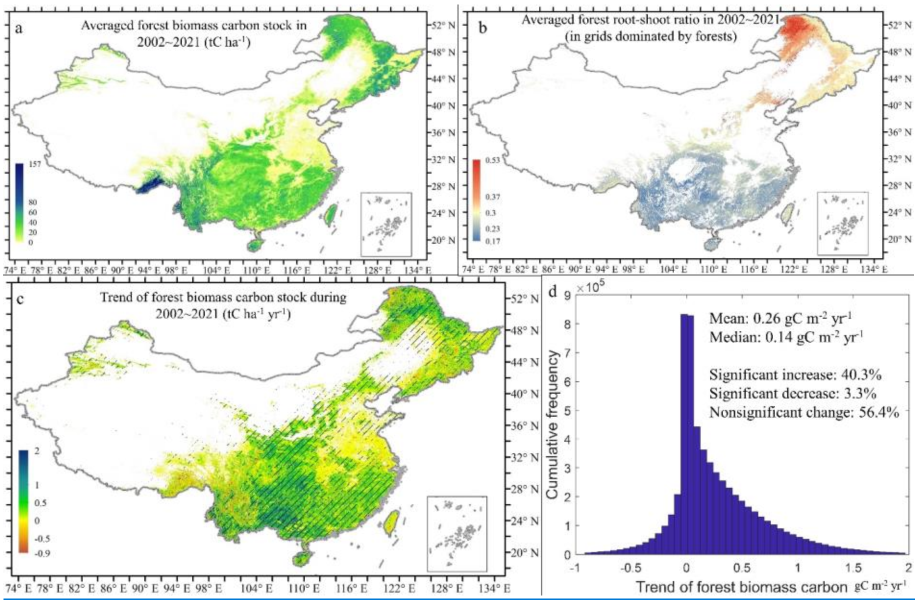

Figure ~~4~~6. Maps of ~~woody~~forest biomass ~~amount~~carbon pool, allocation and trend in China during ~~2003–2020~~2002–2021. (a) Spatial ~~pattern of woody total biomass in China; (b) the latitudinal~~ pattern of ~~per-area woody AGB, BGB and total woody area in China (woody areas below 22°N are limited); (c–d) map of woody vegetation's RSR and its histogram; (e–f) map of the woody biomass trend and its histogram. Shaded areas in trend maps indicate~~the forest biomass carbon pool in China; (b) all forestland pixels' RSR; (c) map of the forest biomass carbon stock trend from 2002 to 2021, with shaded areas representing statistically significant trends at the 95% confidence level~~, while the~~; (d) histogram and basic statistics of all ~~woody pixels'~~forest biomass ~~amount and~~carbon stock trend ~~are labelled in the subfigures with histograms~~.

~~**In agreement with our results (AGB: 24.4±1.6 Pg, total biomass: 30.7±2.0 Pg), previous studies estimated a total woody AGB in China of 23.4±0.6 Pg after 2003 (Liu et al. 2015) and a total woody biomass of 29.4±1.1 Pg during 2003~2019 (Xu et al. 2021). However, the spatial pattern inferred here markedly differ compared with these previous estimates. We predict higher woody biomass in the central-south and southwest China but lower biomass values in the northern and northwest regions (Figure S9a~f). The spatial pattern of our AGB map agrees well with that of recent high-quality China's forest AGB maps which were developed by integrating Lidar, P-band SAR and forest inventory data**~~

4 Discussion

4.1 Comparison of the estimated forest biomass carbon pool change in this study against the existing datasets

Although with potential overestimation, the inter-annual variation in forest AGBC in China according to Liu et al. (2015) and that of total biomass carbon according to Xu et al. (2021) are both highly correlated with our results (R^2= 0.65 and 0.88). Liu et al. predicted a forest AGBC increase rate of 102.2 ± 35.8 Tg/yr (p<0.01), slightly higher than our estimate of 80.8 ± 25.1 Tg/yr during 2002–2012; while Xu et al. indicated a biomass carbon stock trend of 99.4 ± 23.2 Tg/yr (p<0.01) from 2002 to 2019, slightly lower than the rate of 115.6 ± 20.2 Tg/yr in this study (Figure 7a~b). The spatial maps of the forest biomass carbon trends estimated by Xu et al. and Liu et al. were slightly patchy (Figure 7c~d). Compared to this study, the two existing datasets (i.e., Liu et al. (2015) and Xu et al. (2021)'s datasets) predicted higher biomass carbon stock trends in the Qinling Mountains and the mature deciduous conifer forests in northeast China. Meanwhile, they predicted lower carbon sinks in southern China (Figure 7c~f), where reforestation and forest management-induced short term extensive carbon uptake (Tong et al., 2020) have been confirmed by atmospheric inversions (Wang et al., 2020; Yang et al., 2021).

Finally, by comparing Figure 7e and 7f, we could also notice that the hotspot of forest biomass carbon gains has moved from the Loess Plateau over the first decade of our study period (2002–2012) to southern China (e.g., Guangxi Province) later. This change was probably due to the large-scale implementation of the 'Grain for Green' project on the Loess Plateau (~~Huang~~Liu et al~~. 2019; Su~~., 2020; Wu et al~~. 2016~~., 2019)~~, with the correlation coefficients both reaching 0.73. For Liu et al. (2015)'s and Xu et al. (2021)'s dataset, the spatial pattern correlations with those improved AGB maps are 0.35~0.50 and 0.27~0.37, respectively (Figure S10). The average woody AGB in eight provinces of southern China was 92~104 t/ha (Tong et al. 2020), close to our estimate of 85~110 t/ha. Forest inventory indicated a tree biomass of 1.92 Pg in Tibet (Sun et al. 2016) where our result was 1.86 Pg yet the two existing long-term datasets predicted 1.26~1.52 Pg.~~

~~The interannual variation in woody AGB in China according to Liu et al. (2015) and that of total woody biomass according to Xu et al. (2021) are both highly correlated with our results~~

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~~(r= 0.76 and 0.95). Liu et al. predicted a woody AGB increasing rate of 186±79.6 Tg/yr ($p<0.01$), similar to our estimate of 236±117 Tg/yr during 2003~2012; while Xu et al. indicated a biomass trend of 219.4±79.6 Tg/yr ($p<0.01$) from 2003 to 2019, lower than the rate of 368±69.9 Tg/yr in this study (Figure S11a, c). Spatially, this study predicted an obviously faster biomass increases in southern China than their datasets (Figure S11). Reforestation and forest management led to a short term extensive carbon sequestration in southern China, which was estimated as 220±100 Tg AGB/yr during 2002~2017 by developing a regional RF model between MODIS reflectance data and a global benchmark AGB map (Tong et al. 2020), close to our estimate of 200±58 Tg AGB/yr. The high ecosystem carbon sink in central to south China and southwestern China has been shown by atmospheric inversions as well (Wang et al. 2020; Yang et al. 2021).~~

~~Accordingly, by fusing low-frequency active, passive microwaves and the advanced LiDAR-derived canopy heights under the reference of extensive field measurements, this study could generate updated estimates on the spatial hotspots of woody biomass and its trends in China.~~

~~3.4 Uncertainties of the woody biomass dataset~~ before 2012, and the massive plantation of fast-growing trees in southern China after 2010 (Tong et al., 2020).

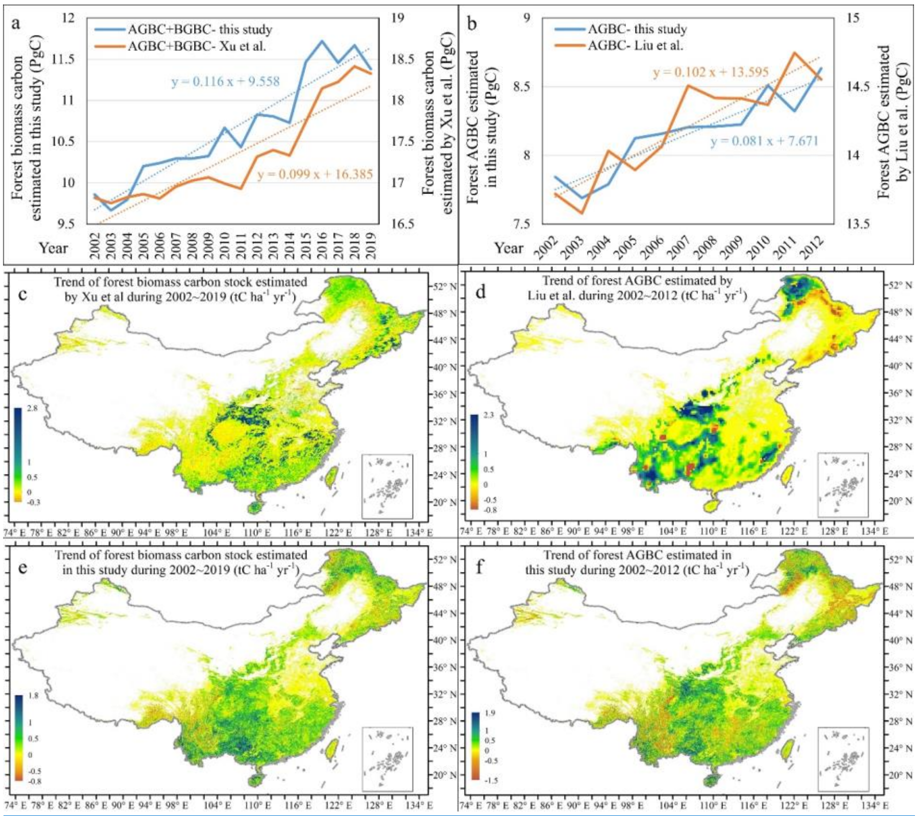

Figure 7. Comparison of the estimated forest biomass carbon pool change in this study against two existing datasets. (a) Comparison of the inter-annual variation of forest biomass carbon in this study against the estimate by Xu et al. during 2002–2019; (b) comparison of the inter-annual variation of forest AGBC calculated in this study against the estimate by Liu et al. over 2002–2012; (c) map of the inter-annual trend of forest biomass carbon stock in China during 2003–2019 according to Xu et al; (d) map of the forest AGBC trend in China during 2003–2012 according to Liu et al; (e) map of the estimated trend of forest biomass carbon stock over 2002–

2019 in this study; (f) map of the estimated forest AGBC trend over 2002–2012 in this study.

4.2 Some uncertainties of the forest biomass carbon dataset and future prospects

~~The uncertainties of AGB in this study came from four sources: 1) the improved benchmark AGB map for China; 2) the extension of AGB time series based on the long-term integrated VOD and high/short vegetation coverage datasets; 3) downscaling of coarse resolution AGB; and 4) the AGB decomposition process. The uncertainty in BGB was composed of the error within the AGB time series and the prediction uncertainty of the models that transform AGB to BGB. The details for the calculation of each source of error are in Text S2. Finally, the annual AGB and BGB's relative error can be calculated as the square root of the sum of squares of all relative errors, which is referred to as the 'error propagation rule' when assuming that each error is independent and random (Huang et al. 2021). By multiplying the annual AGB or BGB map with the corresponding relative error, we mapped the AGB and BGB's uncertainties in China annually during 2003–2020. As shown in Figure S12, the spatial patterns of the relative errors of AGB and BGB are similar. Relative errors were lower in the pure forests located in northeast China and the south Tibet, and high in the mixed forest and shrublands in the southwest karst regions and part of North China.~~

~~A recent study revealed that the variation in VODs is correlated with not only biomass, but also soil moisture availability (Konings et al. 2021). To alleviate this source of uncertainty as much as possible, we have incorporated the satellite-based surface soil moisture dataset to account~~

~~for the impact from the interannual variation in water content per biomass. In addition, we have included optical-based vegetation continuous fields in predicting the spatiotemporal variation in biomass, which turned out to be the variable with the highest contribution (56%). In fact, the interannual variation in Chinese woody biomass according to this study is highly correlated (r=0.95) with that calculated independent of microwave-based VOD (Xu et al. 2021).~~

~~Next, the~~ During benchmark AGBC mapping, we converted the in-situ AGBC data at forest plots into the grid-scale average AGBC by multiplying by the fraction of forestland during the time period of field investigation. Considering the overall high-quality of the China's land-use/cover datasets developed via human–computer interactive interpretation of Landsat images (Liu et al., 2014; Yang and Huang, 2021), and that the producer's accuracy (PA) and user's accuracy (UA) for forestland classification in the CLCD dataset used in this study were 73% and 85% respectively, the errors within the benchmark AGBC mapping induced by the scale conversion based on the forestland area fraction were generally limited.

The variation in climatic conditions in ~~a~~the short term may have subtle influences on that in the BGB, but explicit knowledge on this effect is lacking. Instead, woody vegetation BGB is much more driven by AGB (vegetation density), as indicated by the very strong relationship between BGB and AGB ($R^2 \geq 0.85$). Moreover, the long-term climatic background is expected to have a stronger influence on the RSR of perennial woody plants than the meteorological conditions in only a few years, since above- and belowground biomass allocation is the result of plants' long-

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term adjustment to the environment ~~(Qi et al. 2019). Accordingly~~(Qi et al., 2019). Therefore, it is reasonable not to consider the influence of the specific climatic conditions in a year on the variation in BGB.

In the near future, P-band microwave sensors, which have higher penetrability into the canopy than L-band microwaves, will further improve ~~the~~ AGB mapping. For example, BIOMASS, a fully polarimetric P-band SAR, is scheduled to be launched in 2022 ~~(Le Toan et al. 2011)~~(Le Toan et al., 2011). Therefore, in the future the relationship between P-band microwave retrievals and biomass should be addressed, as well as the calibration of historical AGB datasets (e.g., the long-term AGB dataset in this study) against the P-band SAR-based AGB benchmark map to extend the time series. In addition, an inter-calibration between the AMSR-E-based VOD and the AMSR2-based VOD will further reduce the potential bias within the long-term integrated VOD datasets (Wang et al., 2021a; Wang et al., 2021b). On the other hand, more in-situ AGB and BGB measurements in larger plots are needed to further improve the estimation of belowground biomass allocation.

Data availability

Annual forest above- and belowground biomass maps in China between 2002 and 2021 are now available at: https://doi.org/10.6084/m9.figshare.21931161.v1. This dataset will also be available on the National Tibetan Plateau/Third Pole Environment Data Center and PANGAEA soon (under checking now). ~~Annual AGB and BGB in China will be available on the National~~

~~Tibetan Plateau/Third Pole Environment Data Center and PANGAEA: .~~ Other open datasets that made this research possible and the related references are attached in Supplementary Information- Text ~~S3~~S2.

Funding and acknowledgements

This work was supported by the ~~National Key~~CAS Project for Young Scientists in Basic Research ~~and Development Program of China (2017YFA0604700), National Science Foundation of China (41991233) and the Chinese Academy of Sciences (QYZDY-SSW-DQC025).~~(YSBR-037). We are grateful to all the data contributors, especially ~~Yuan Zhang~~Xuli Tang for sharing in-situ measurements of forest aboveground biomass carbon stock across China, and Huabing Huang for sharing ~~the forest stand age map and~~his forest aboveground biomass map ~~in China to us~~.

Conflict of interests

The authors declare no conflict of interest.

Credit author statement

Y.C designed and conducted the research. B.F and X.F funded the research. Y.Z wrote the draft of the manuscript; X.F and all other authors read and revised the manuscript.

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