Re-estimating the changes and ranges of forest biomass carbon in China during the past 40 years

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Abstract

Background: In recent decades the future of global forests has been a matter of increasing concern, particularly in relation to the threat of forest ecosystem responses under potential climate change. To the future predictions of these responses, the current forest biomass carbon storage (FCS) should first be clarified as much as possible, especially at national scales. However, few studies have introduced how to verify an FCS estimate by delimiting the reasonable ranges. This paper addresses an estimation of national FCS and its verification using two-step process to narrow the uncertainty. Our study focuses on a methodology for reducing the uncertainty resulted by converting from growing stock volume to above- and below-ground biomass (AB biomass), so as to eliminate the significant bias in national scale estimations.

Methods: We recommend splitting the estimation into two parts, one part for stem and the other part for AB biomass to preclude possible significant bias. Our method estimates the stem biomass from volume and wood density (WD), and converts the AB biomass from stem biomass by using allometric relationships.

Results: Based on the presented two-step process, the estimation of China's FCS is performed as an example to explicate how to infer the ranges of national FCS. The experimental results demonstrate a national FCS estimation within the reasonable ranges (relative errors: + 4.46% and − 4.44%), e.g., 5.6–6.1 PgC for China's forest ecosystem at the beginning of the 2010s. These ranges are less than 0.52 PgC for confirming each FCS estimate of different periods during the last 40 years. In addition, our results suggest the upper-limits by specifying a highly impractical value of WD (0.7 t·m^{-3}) on the national scale. As a control reference, this value decides what estimate is impossible to achieve for the FCS estimates.

Conclusions: Presented methodological analysis highlights the possibility to determine a range that the true value could be located in. The two-step process will help to verify national FCS and also to reduce uncertainty in related studies. While the true value of national FCS is immeasurable, our work should motivate future studies that explore new estimations to approach the true value by narrowing the uncertainty in FCS estimations on national and global scales.

Keywords: Allometric equation, Forest carbon, Stem-biomass proportion, Volume-derived method, Wood density

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Introduction

Over the last two decades, research on terrestrial plant ecosystems has been expanding from field experimental sites to national or global scales for addressing global change issues (Bellassen and Luyssaert 2014). Accurately quantifying carbon stocks is one of the critical components to assessing potential impacts of climate change (Temesgen et al. 2015). Many researchers have extensively studied the estimation of forest carbon storage (FCS), and provided much knowledge and information (Ciais et al. 2008; Luyssaert et al. 2008; Keith et al. 2009; Gustafson et al. 2010) for understanding large-scale forest resources (Petrescu et al. 2012; Crowther et al. 2015; Kohl et al. 2015). However, when globally assessing forest resources, the accuracies are different between countries (MacDicken 2015). The results for certain countries (in Europe, North America, etc) have relatively high accuracies, which were statistically analyzed based on detailed information (Jenkins et al. 2003; Lambert et al. 2005; Breidenbach et al. 2014; Berger et al. 2014; Neumann et al. 2016), such as diameter at breast height (DBH) and tree height data. Collecting this information at a national scale has been difficult for other countries because the details of data are scarce (Mather 2005). This has generated criticisms on global-level forest resource assessments (Grainger 2008; Harris et al. 2012; Hansen et al. 2013; Achard et al. 2014; Ussiri and Lal 2017; Avitabile and Camia 2018). Actually, in many countries only the volume information is released in their national forest inventory (NFI) reports (Mather 2005), which requires the volume-based method to convert forest volumes to AB biomass. In practice, most countries in the world use volume-based models and biomass expansion factors (BEF) to estimate national forest biomass (FAO 2010).

Using volume-based methods would lead to uncertainty in national FCS estimates (Jenkins et al. 2003; Henry et al. 2015), and on certain conditions, could generate apparent inconsistency between the estimates for the same area (Ni 2013). This is particularly noticeable for monitoring dynamics of the biomass in those countries, in which the promotions of afforestation and reforestation programs have continued for decades and increasingly affect world FCS. For instance, as the third largest country by landmass (SFA 2013), China currently has the largest area of artificial forest (approximately 62 million ha) and the fifth largest total forested area (approximately 165 million ha) in the world. Over the past 40 years, forest volume has increased continuously at an average of 2% per year (SFA 1977, 1982, 1989, 1994, 1999, 2004, 2009, 2013). However, the uncertainties in FCS estimates are hard to remove on the national scale. Based on a partial literature review (Zhou et al. 2016), existing studies suggest large differences between China's FCS estimates. It is necessary to explore a way to reduce such gaps that could appear in FCS estimates of some regions or countries, as the gaps may influence understanding for the FCS itself as well as many study results associated with the FCS on national or global scales.

National forest inventory and the first uncertainty

There are primarily two sources of uncertainties, the uncertainty in volume prediction and the uncertainty from volume to biomass conversion. Usually, the volume data extensively published in most countries are available in NFI reports, with the minimum scale being the average provincial or regional mean volumes and areas. The first uncertainty in NFI would be caused by many factors (Berger et al. 2014), such as volume prediction models and measurement errors (Suty et al. 2013; Breidenbach et al. 2014; McRoberts and Westfall 2014), as well as be impacted by different survey designs in different eras (Stahl et al. 2013). The continuous improvement of sampling design and remote sensing application made significant advantages, so that the earlier NFIs have larger uncertainty than later NFIs. However, this kind of data, as a compilation of national resource statistics, has typically undergone rational sampling design and rigorous statistical tests, and as such it is considered reliable (Fang et al. 2001) despite the possible errors that exist. For example, systematic sampling was adapted in Chinese national forest inventory, which provides valuable statistics on forest area, volume, and their changes with periods of 5 years for strategic decision making (Lei et al. 2009). For decades, the Food and Agriculture Organization of the United Nations (FAO) and also Intergovernmental Panel on Climate Change (IPCC) have relied on those country NFI reports to publish their forest resources assessment reports (FAO 2010, 2016).

National forest biomass and the second uncertainty

While using the volume information provided by NFI reports, the successful conversion from the volume estimates to accurate biomass estimates is still an arduous process. The choice of methods could result in different results. Generally, the volume-based method is called the indirect method (Somogyi et al. 2007) which is a realistic method based on building the relationships between volume and biomass (Brown and Lugo 1984; Brown 1997). These relationships have been expressed in different definitions, such as BEFs and allometric equations of the biomass with volume predictor(s) (Henry et al. 2015). These equations can be derived empirically from tree sampling as well as from estimates per unit area. Based on the latter, as long as the volume per unit area ($m^3 \cdot ha^{-1}$) of a forested land is known, the corresponding biomass ($t \cdot ha^{-1}$) can be calculated using an appropriate factor or equation.

Currently the allometric equations are widely applied in FCS estimation of China's forest ecosystems (Fang et al. 2007; Xu et al. 2007; Guo et al. 2010; Li et al. 2011; Zhou et al. 2016). Previous studies have reported their methods, which include mean biomass density (MBD), volume-derived, and remote sensing methods. These are three commonly applied approaches in China's FCS estimation. Table 1 summarized the features of the approach and the main results of the estimations. Guo et al. (2010), Ni (2013), and Tang et al. (2018) have discussed the difference between the estimates for China's FCS, and suggested that various estimates may be resulted from different methods and models. As the researchers pointed out, when we estimate forest biomass using field data of biomass measurements, an important issue is how to find an allometric relationship that can suitably be applied to forest conditions encountered (Sileshi 2014). This is rather troublesome. Through the graphical analysis of volume-based biomass equations listed in Table 1, we found that it is hard to observe and test a physiological relationship between volume and AB biomass. These approaches converted volume to AB biomass directly, and they seem to lack an obvious causal relationship of volume and AB biomass. In addition to the difference between results of volume-derived methods themselves, there are also larger differences between volume-derived and other methods (Table 1). In general, the MBD and remote sensing methods frequently introduce a larger estimate than volume-derived methods for China's forest ecosystems. The reason for this remains unclear. One potential reason is likely due to the uses of multiple data sources, limited sample size, and data representativeness (Tang et al. 2018). Previous comparisons have also indicated that MBD may result in overestimates because of possible bias of field measurements (Dixon et al. 1994; Guo et al. 2010). The inconsistency of these estimates implies that we may need to demarcate the range of forest carbon. This range should be understandable for practical applications at the national scale.

Table 1 Different methods for estimating carbon storages of China's forest (PgC). The first period is the start of the Returning Farmland to Forest Program

Method	Feature	Period			Reference
		1999–2003	2004–2008	2009–2013	
Volume-derived	Stand-level linear volume-biomass equations, or continuous biomass expansion factor (CBEF), using variables of total area, volume per unit area. Data: NFIs.	5.9	6.2		Fang et al. (2007; 2014); Guo et al. (2010)
Volume-derived	Age-grouped, stand-level linear volume-biomass equations based. Data: 6th NFI.	5.5			Xu et al. (2007)
Volume-derived	Mean ratio method, using variables of total volume and mean BEF. Data: 6th NFI.	6.2			Guo et al. (2010)
Volume-derived	Tree-level allometric biomass equations with DBH and height predictors. Provincial BEFs were calculated based on DBH and height information of plots (660,000 permanent plots established in 7th NFI). Data: 7th NFI.		6.7		Li et al. (2011)
Volume-derived	Stand-level allometric volume-biomass equations (power functions); removing upscaling error. Data: NFIs.	4.9	5.4	6.0	Zhou et al. (2016)
Carbon density	Mean biomass density method, using variables of total area and mean biomass density. Data: 6th NFI.	7.7			Guo et al. (2010)
Carbon density	Deriving carbon density from site measurements, and average carbon density from the provincial area-weighted average and its corresponding area; using Random Forest model to detail spatial patterns of carbon density. Data: Independent investigation, establishing total 7800 sites for field measurements in forests.			10.4	Tang et al. (2018)
Remote sensing	Multiple spectral bands of MODIS and forest inventory data with an empirical statistical model.	6.3		6.8	Sun et al. (2015)
Remote sensing	A development of AGBmapping. Data: Geoscience Laser Altimeter System (GLAS)/Ice, Cloud, Land Elevation Satellite (ICESat) data, optical imagery, climate surfaces, and topographic data.		10.2[a]		Su et al. (2016)

[a]Total biomass carbon, estimated from the reported AGB (7.5 Pg)

At the current stage, we are trying to find whether there is any relationship that can be applied other than the relationship between volume and AB biomass. If a relationship can express AB biomass and its predictor biologically or physically, it will be possible to place complete reliance on the range of FCS estimates on the national scale. Hence, several basic issues have to be considered when performing an estimation of national FCS, such as the national average WD for each species, the ratios of stem to AB biomass for each species, and the estimates of TB for each species across the country. Although numerous studies have presented approaches to estimate national FCS, very few studies have addressed how to recognize whether those estimates are beyond their possible upper and lower limits. Poor understanding of reasonable ranges of national FCS will limit our ability to raise the accuracy in FCS estimations.

Study objective

Our study addresses the second uncertainty. To address the above issues, it is necessary to find an applicable method,

which can supplement or improve conventional approaches. Given this, we divided the uncertainty into two parts as stem and AB biomass, and correspondingly built two relationships, "volume to stem biomass" and "stem biomass to AB biomass". Then we tested the relationships by two steps. Depending on possible error of WD, the range of FCS can be predicted on the national scale. This is to avoid systematic error by utilizing trees' physical and physiological properties. We hypothesize that the percent error of WD is close to the percent error of the AB biomass estimate, i.e., the range of WD error on average primarily affects the ranges of national FCS estimates. As an application, we estimate China's FCSs using a two-step process to avoid significant bias on the national scale.

Methods

Two parts of FCS estimation

The AB biomass is divided into two parts, i.e. stem biomass and non-stem biomass, to be calculated separately for each tree species (Fig. 1). Here, ρ is the ratio of dry
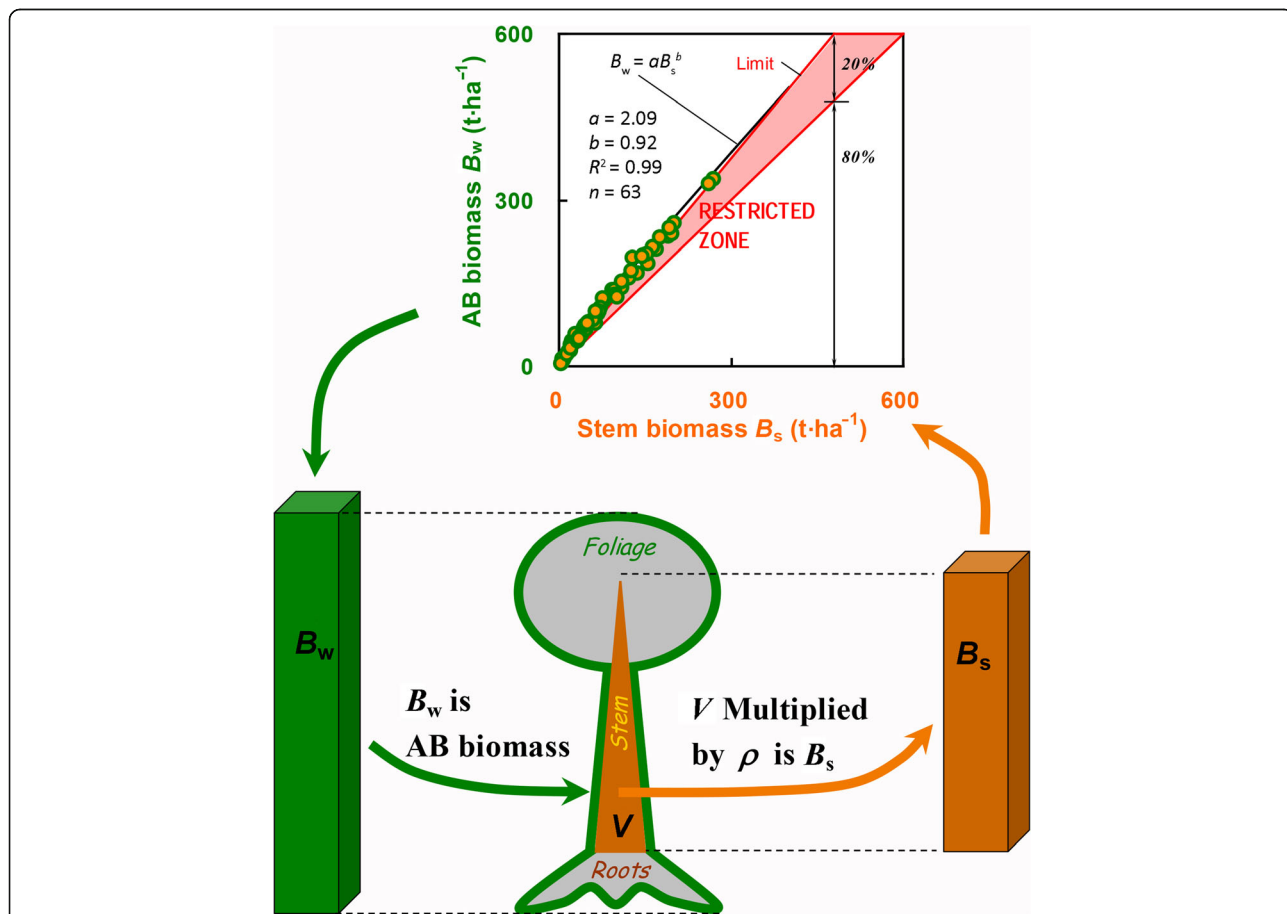

Fig. 1 An example (*Pinus massoniana* in China) to convert stem volume (V, $m^3 \cdot ha^{-1}$) to AB biomass (B_w, $t \cdot ha^{-1}$) via WD (ρ) and allometric equation for the species. The stem biomass (B_s, $t \cdot ha^{-1}$) is an intermediate variable in the calculation. A restricted zone is designed ranging from the limit line of B_w (showing a proportion of 80% stem and 20% other parts of the tree) to the 45 degree line. Parameters a and b (plot 8) refer to Fig. 4. Note that the restricted zone may change for different species or forest types in realistic forests

mass to stem volume per unit area. The ρ might not be strictly defined as WD in forest or wood science. To develop an approach for national-scale estimation, we tentatively refer to the ρ as WD. As Fig. 1 illustrated, we firstly convert stem biomass from the volume multiplied by estimated WDs (ρ). Second, we estimated AB biomass by converting stem biomass using widely used allometric equations with a simple power-law form (West et al. 1999; Gillooly et al. 2001; Zianis et al. 2005; Sileshi 2014), which expresses the relationship between biomasses of an organ (stem) and entire organism (whole tree).

A graph is imbedded in Fig. 1 illustrating several key points in judging the relationships between stem and AB biomass. Obviously, the curve of allometric equation is always above the 45° line. This means that AB biomass is larger by some percentage than stem biomass on either observed data or regressed curve. The percentages for non-stem parts are different for each species, but not less than a lowest limit. Our analysis suggests a range of 20% to 30% for this limit, which is estimated as the minimum ratio of the non-stem parts depending on the observed data of mature stands (Fig. 2). The graph in
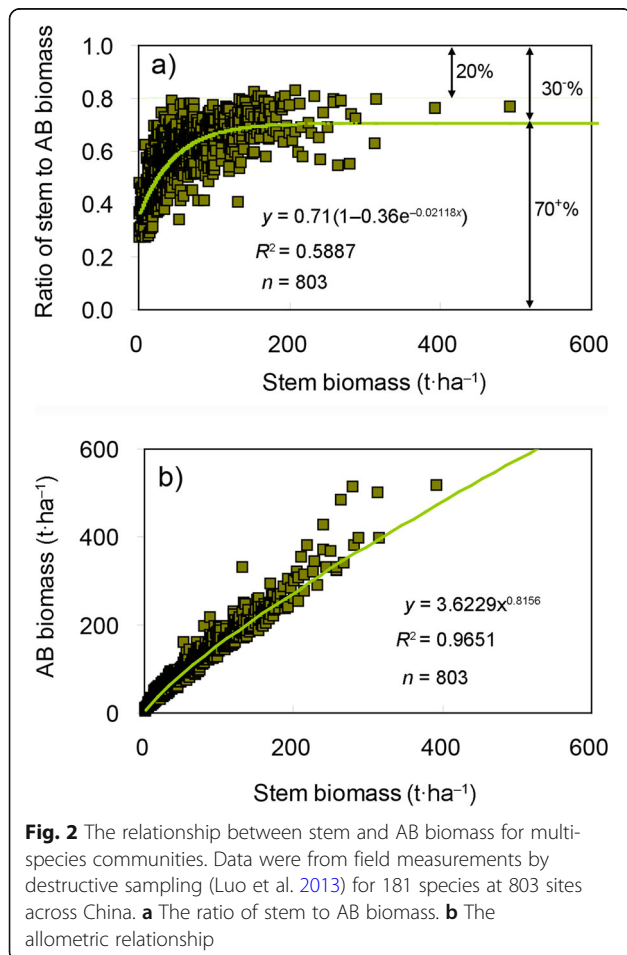

Fig. 2 The relationship between stem and AB biomass for multi-species communities. Data were from field measurements by destructive sampling (Luo et al. 2013) for 181 species at 803 sites across China. **a** The ratio of stem to AB biomass. **b** The allometric relationship

Fig. 1 shows an example of the ratio with 20% for *Pinus massoniana*. Furthermore, the minimum ratio of non-stem part forms an area existing between the limit line and 45° line. It can be called the "restricted zone" where the regression curve should not lie unless there are errors or anomalies in the data. Similarly, the curve cannot be too far from the 45° line as this curve is only decided by the dynamics of the non-stem part ratio. The concept of restricted zone helps to test systematic error depending on trees' physiological properties. Reducing this error is advantageous in diagnosing a range that will possibly enclose the true value of the FCS.

Data and measurements

The field observations include both measured mean diameter at breast height (DBH), mean tree height, volume per hectare, and biomass per hectare of each tree organ (foliage, flower, fruit, branch, stem, and root) for 261 species at 1607 sites over the country (Fig. 3). The reference (Luo et al. 2013) provided detailed information on site description, species introduction, measurement methods, and brief data analyses. We screened all available 1056 measurements for calculating WDs, and 803 measurements for building allometric equations. These measurements were based on destructively sampled trees. All tree-level observations have been initially scaled to area-based values (per hectare) by data measurers and providers (Luo et al. 2013; Additional file 1. Therefore, our analysis is based on unit area rather than plot or single tree because of the data source. The subsequently used allometric relationships employed refer to area-based quantities. It means that certain patterns that are observed on an area basis, such as the amount of whole-tree or stem biomass per hectare, might differ from those observed in individual trees. On the national scale, we directly applied the area-based data (biomass and volume).

Equations and estimations

Stem biomass estimation. The species surveyed in the inventories were classified into 15 general tree types or species. We calculated stem biomass based on volume multiplied by WD corresponding to each species, i.e., $B_s = \rho V$ (V-to-B_s equation), where B_s denotes stem biomass (oven dry, $t \cdot ha^{-1}$); ρ represents WD ($t \cdot m^{-3}$); V expresses volume ($m^3 \cdot ha^{-1}$).

AB biomass estimation. This was estimated using allometric equations of stem vs AB biomass, i.e., $B_w = aB_s^b$ (B_s-to-B_w equation), where B_w is AB biomass (oven dry, $t \cdot ha^{-1}$), a and b are parameters. To determine these parameters, a nonlinear regression was conducted.

National FCS estimation. National FCSs of China are estimated by accumulating the biomass carbon of all combinations of each species and province in each period, e.g.,
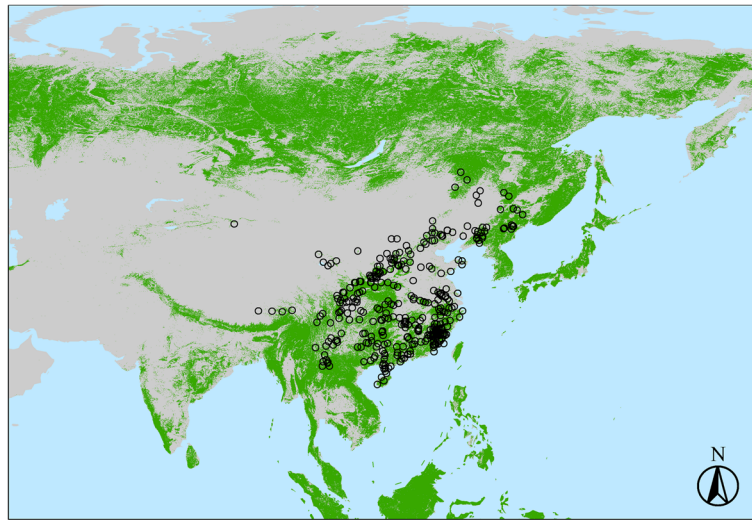
Fig. 3 1607 plots at 623 study sites across mainland China (Latitude: 18.7°–50.87°N; Longitude: 87.13°–130.88°E). The forest species and types were reclassified and grouped into 15 categories

the inventory (2008–2013) provides 15 grouped species or forest types distributed in 31 provinces. Carbon content is converted from biomass using a factor of 0.5. The correspondence between the tree species classified in forest inventories and the tree species described by B_s-to-B_w equations are listed in Additional file 1: Table SI_1. In our experiment, the species surveyed in the inventories were classified as 15 species, for which the WDs (ρ) were also classified as such species. The national forest stem carbon was calculated by the equation $0.5 \times (\sum_{i=1}^{31} \sum_{s=1}^{15} B_s)$; the national FCS was calculated by the equation $0.5 \times (\sum_{i=1}^{31} \sum_{s=1}^{15} B_w)$, where i represents the number of provinces in China, and s denotes the number of species, B_s and B_w express stem biomass and AB biomass, and 0.5 is the carbon fraction to convert dry biomass.

Results

Estimates of ratio of stem biomass to AB biomass and WD for different species

The ratios of stem to AB biomass exhibit nonlinear variations, expressed by 15 allometric equations in Fig. 4. The parameters of these equations have prediction precisions that are high for all species (coefficient of determination R^2 ranges from 0.81 to 0.99). The field data were measured at various locations for each species. They are consistent with regression curves. All the parameters of equations are summarized in Additional file 2: Table SI_1 and Table SI_2. The WDs (ρ) are the ratios of stem biomass to volume for each species (see the slopes in Fig. 4b). Field measurements exhibited macroscopic homogeneity of the ratio of stem biomass to AB biomass (B_s-to-B_w) under different growth conditions. The standard deviation

of relative error (RE) of the mean values is approximately 5% based on our analysis. This is the range for "Wood density estimates" in Table 2.

National wood densities

The WD in average does not change significantly during 40 years. It ranges from 0.429 to 0.502 t·m^{-3} (Table 2). The upper limit of WD is specified as 0.7 t·m^{-3}. This value can be utilized to assess whether a FCS estimate is realistic or not. In fact, WD cannot reach a national average of 0.7 t·m^{-3} in non-tropical regions. This value is the wood basic density (WBD, oven-dry mass divided by green volume) of rosewood, which is much heavier than most tree species. According to our analysis of China's NFI (the period of 2008–2013), 12 out of the 15 species have low WDs ($\rho < 0.49$) (see Additional file 2), and occupied over 81.6% of volume in the country (Fig. 5). This percentage implies that the WD should not be higher than an average of 0.49 t·m^{-3} on the national scale. Our analysis reports that the national WD was 0.469 t·m^{-3} on average in present.

China's FCS estimates and its future trend

China's FCSs are estimated in periods over a 40 year span (1973–2013, Table 2, Fig. 6). The results demonstrate a national FCS estimation within the reasonable ranges, e.g., 5.6–6.1 PgC at the beginning of the 2010s. These ranges are less than 0.52 PgC (relative errors: + 4.46% and − 4.44%) for confirming each FCS estimate of different periods. The possible ranges of the errors for FCS estimates are ranked depending on the errors of WD. The ratio of B_s-to-B_w ranges from 57.4% to 59.2%. We assessed the status of forest maturity depending on
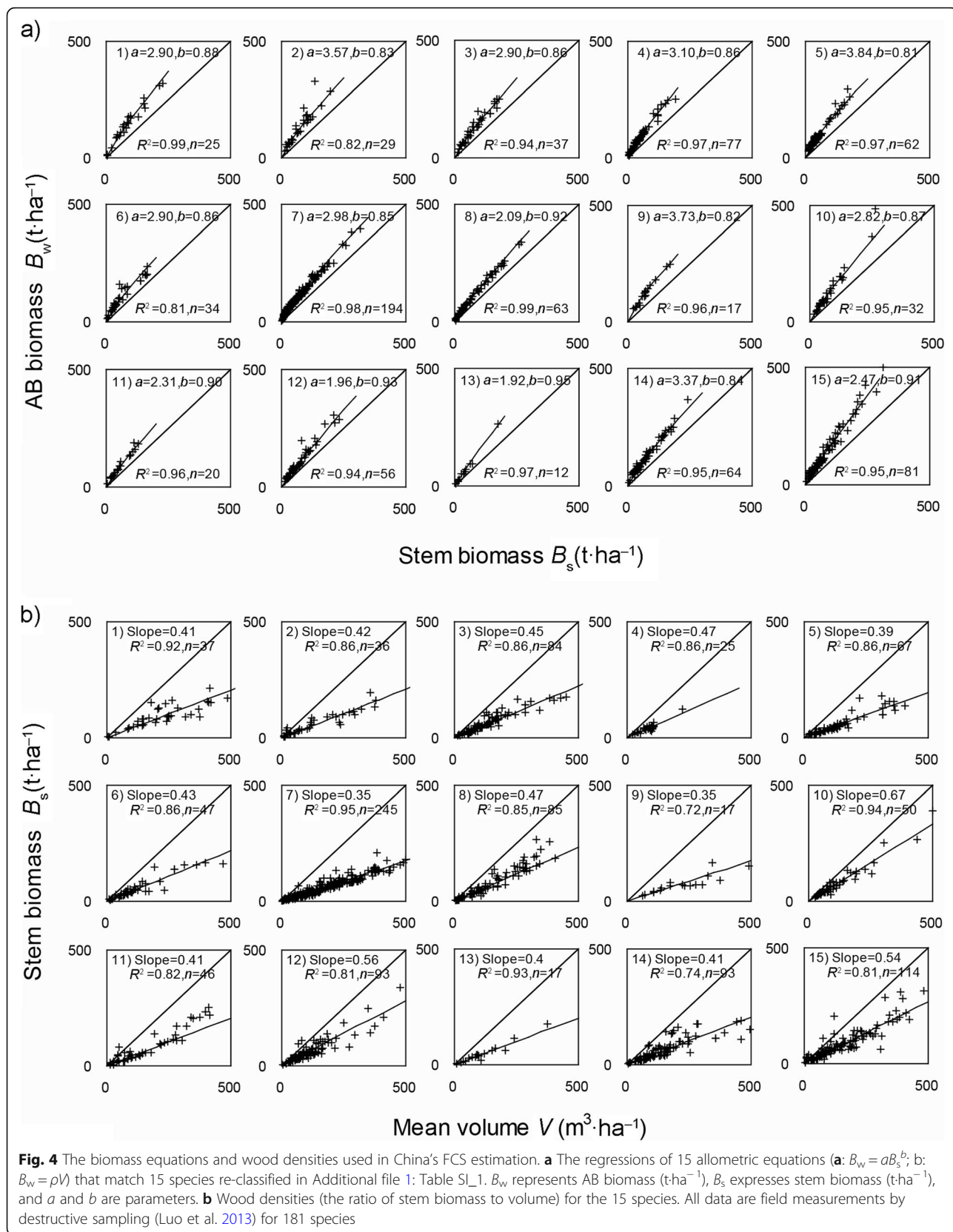
Fig. 4 The biomass equations and wood densities used in China's FCS estimation. **a** The regressions of 15 allometric equations (**a**: $B_w = aB_s{}^b$; b: $B_w = \rho V$) that match 15 species re-classified in Additional file 1: Table SI_1. B_w represents AB biomass (t·ha^{-1}), B_s expresses stem biomass (t·ha^{-1}), and a and b are parameters. **b** Wood densities (the ratio of stem biomass to volume) for the 15 species. All data are field measurements by destructive sampling (Luo et al. 2013) for 181 species

Table 2 Forested land area, volume, converted stem C, and estimated total C with different WDs for all forests for eight inventory periods from 1973 to 2013 in China. Estimated total C is based on AB biomass, Estimated forest contains primarily timber forests and do not contain economic, bamboo, under storey, and shrub forests

No.	Period	Area (10^6 ha)	Volume (10^9 m^3)	Volume per hectare (m^3·ha^{-1})	Wood density[a] estimates, ρ (t·m^{-3})	Stem C (PgC)	Total C (PgC)	Mean ratio[b] of stem to whole tree	C density (tC·ha^{-1})	Total C[c] (PgC) (other studies)
1st	1973–1976	101.68	7.78	76.1	0.451 (average)	1.7	3.0	58.3%	29.5	3.5–4.4
					0.429 (average, −5%)	1.7	2.9		28.1	
					0.474 (average, +5%)	1.8	3.1		30.8	
					0.700 (upper limit)	2.7	4.4		43.4	
2nd	1977–1981	95.62	7.98	83.4	0.465 (average)	1.9	3.2	57.7%	33.6	3.6–4.7
					0.442 (average, −5%)	1.8	3.1		32.1	
					0.488 (average, +5%)	1.9	3.4		35.1	
					0.700 (upper limit)	2.8	4.6		48.1	
3rd	1984–1988	102.19	8.09	79.2	0.470 (average)	1.9	3.3	57.4%	32.4	3.2–5.0
					0.447 (average, −5%)	1.8	3.2		31.0	
					0.494 (average, +5%)	2.0	3.5		33.9	
					0.700 (upper limit)	2.8	4.7		46.0	
4th	1989–1993	108.64	9.09	83.6	0.469 (average)	2.1	3.6	58.6%	33.5	3.8–9.1
					0.446 (average, −5%)	2.0	3.5		32.0	
					0.493 (average, +5%)	2.2	3.8		35.0	
					0.700 (upper limit)	3.2	5.2		47.5	
5th	1994–1998	129.20	10.09	78.0	0.478 (average)	2.4	4.1	58.4%	31.9	4.6–5.7
					0.454 (average, −5%)	2.3	3.9		30.5	
					0.502 (average, +5%)	2.5	4.3		33.3	
					0.700 (upper limit)	3.5	5.8		44.6	
6th	1999–2003	142.79	12.10	84.7	0.473 (average)	2.9	4.9	58.9%	34.0	5.2–7.7
					0.450 (average, −5%)	2.7	4.6		32.5	
					0.497 (average, +5%)	3.0	5.1		35.5	
					0.700 (upper limit)	4.2	6.8		47.9	
7th	2004–2008	155.59	13.36	85.9	0.468 (average)	3.1	5.3	58.9%	34.1	5.8–6.7
					0.444 (average, −5%)	3.0	5.1		32.6	
					0.491 (average, +5%)	3.3	5.5		35.6	
					0.700 (upper limit)	4.7	7.6		48.5	
8th	2009–2013	164.60	14.78	89.7	0.469 (average)	3.5	5.9	59.2%	35.5	6.2–8.4

Table 2 Forested land area, volume, converted stem C, and estimated total C with different WDs for all forests for eight inventory periods from 1973 to 2013 in China. Estimated total C is based on AB biomass, Estimated forest contains primarily timber forests and do not contain economic, bamboo, under storey, and shrub forests (Continued)

Forest inventories					Wood density[a] estimates. ρ (t·m^{-3})	Carbon estimates (this study)				Total C[c] (PgC) (other studies)
No.	Period	Area (10^6 ha)	Volume (10^9 m^3)	Volume per hectare (m^3·ha^{-1})		Stem C (PgC)	Total C (PgC)	Mean ratio[b] of stem to whole tree	C density (tC·ha^{-1})	
					0.446 (average, −5%)	3.3	5.6		34.0	
					0.493 (average, +5%)	3.6	6.1		37.1	
					0.700 (upper limit)	5.2	8.3		50.5	
Projecting future biomass carbon for 2050:										
The timber forests:		220.61[d]	23.00[d]	104.3	0.469 (?)	5.4	9.1	59.2% (?)	41.3	
Potential plantation and its age effect:					–	–	1.5	–	–	
Climate change effects:					–	–	3.0	–	–	
Total FCS (the lower limit for 2050; total volume = 23.00 +?):					–	–	12.6	–	–	

[a]The values of volume per hectare are weighted by amount volume of each species. The ratios are weighted by the volume of each species. The ratio in 2050 is assumed to be the same as the current value for each species. The WD in 2050 is assumed to be the same as the current value for each species. The reference ρ (0.7) can be used to test whether an estimate is proper. [b]The ratios are weighted by the volume of each species. [c]Existing studies refer to (Fang et al. 2001; Pan et al. 2004; Xu et al. 2007; Guo et al. 2010; Li et al. 2011; Ni 2013; SFA-CFN 2013). [d]The area and volume in 2050 refer to (SFA-CFN 2016). Note: 1) the ranges of Total C are less than 0.52 PgC; 2) the relative errors of Total C are +4.46% and −4.44%; 3) the question marks indicate possible uncertain offsets
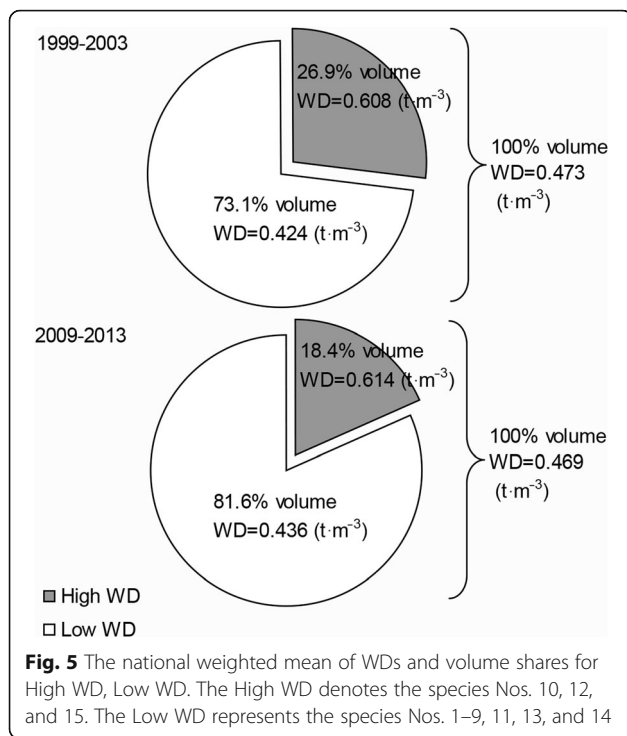
Fig. 5 The national weighted mean of WDs and volume shares for High WD, Low WD. The High WD denotes the species Nos. 10, 12, and 15. The Low WD represents the species Nos. 1–9, 11, 13, and 14
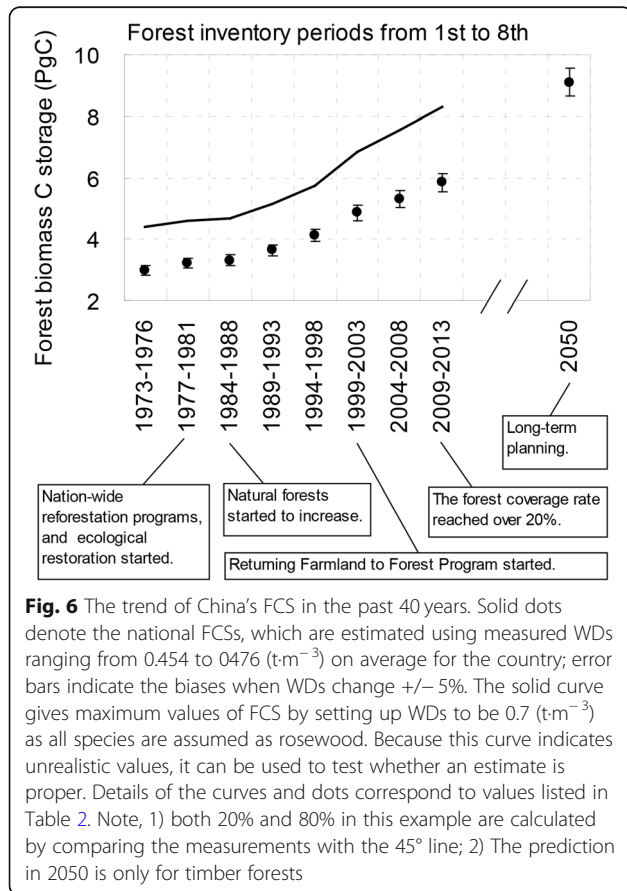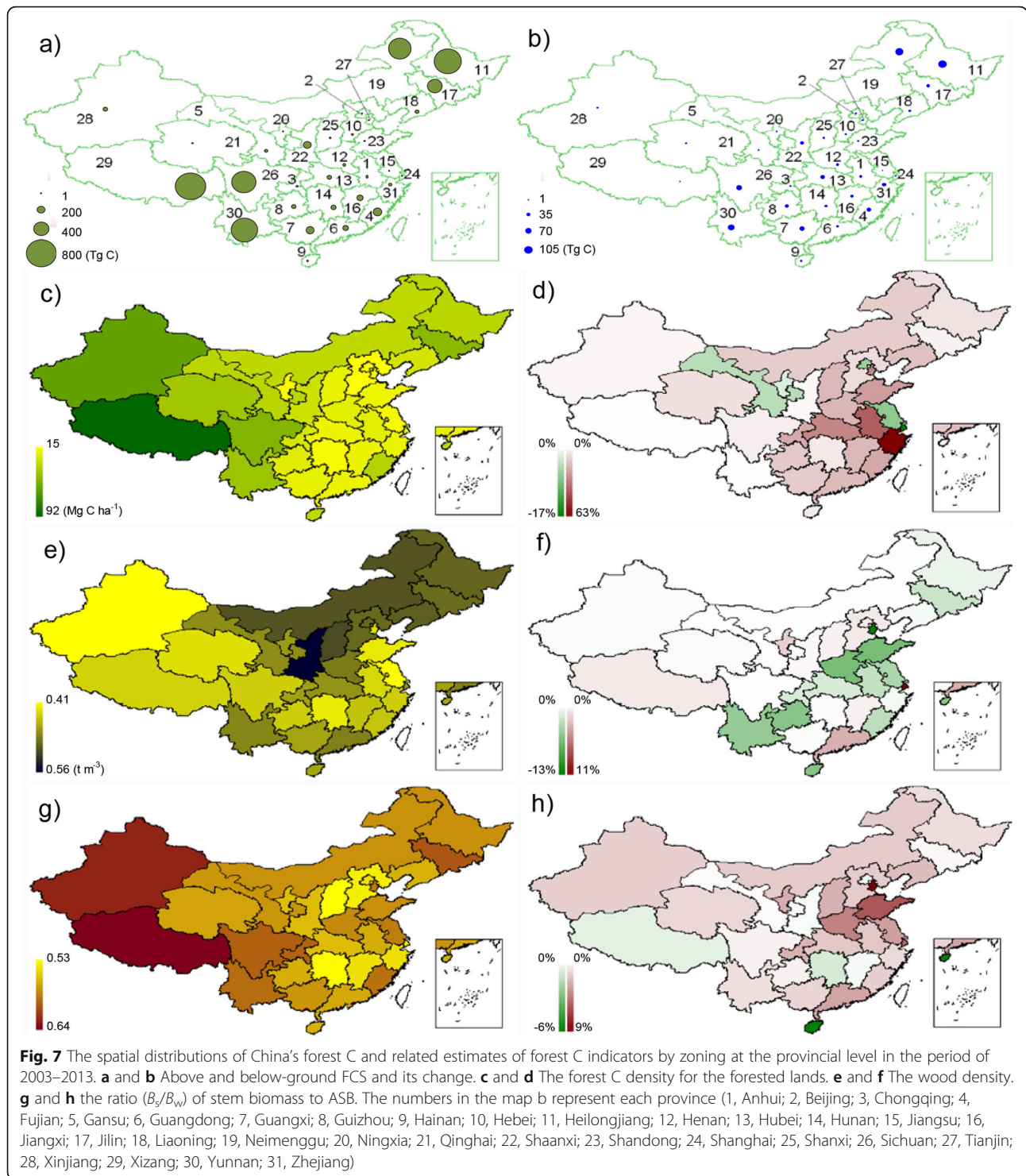

Fig. 6 The trend of China's FCS in the past 40 years. Solid dots denote the national FCSs, which are estimated using measured WDs ranging from 0.454 to 0476 (t·m^{-3}) on average for the country; error bars indicate the biases when WDs change +/− 5%. The solid curve gives maximum values of FCS by setting up WDs to be 0.7 (t·m^{-3}) as all species are assumed as rosewood. Because this curve indicates unrealistic values, it can be used to test whether an estimate is proper. Details of the curves and dots correspond to values listed in Table 2. Note, 1) both 20% and 80% in this example are calculated by comparing the measurements with the 45° line; 2) the prediction in 2050 is only for timber forests

the ratios of B_s-to-B_w in different periods. For example, both of these ratios and the volumes per hectare increased from 1994 to 2013 (Table 2). This implies that stem biomass is growing faster than AB biomass while the entire national forest is trending towards maturity. But the average ratio (59.2%) and carbon density average (35.5 tC·ha^{-1}) is still relatively low in the 8th period (2009–2013). These low values agree with our investigation on the forest age composition. Presently, the most forested lands are the young and middle-aged (approximately 65%) (SFA-CFN 2013), the remaining is near mature, mature, and over-mature forests.

Figure 6 summarized notes for understanding the national forest development and the influence of forestry policy in the country during the 40 years. The results indicate that China's forests have continually functioned as a carbon sink in the past 40 years. The national FCS increased approximately 2.4% per year on average during the period, in which it exhibited a 1.7% increase per year in the first 30 years and accelerated to 3.1% per year in the last 10 years. We projected the FCS to be 9.1 PgC by the 2050s for the primarily timber forests according to the target of 23 billion m^3 scheduled by China's forest planners in 2013 (SFA-CFN 2016). The biomass carbon of potential plantation forests was estimated as 1.5 PgC using the C sequestration rate (0.94 MgC·ha^{-1}·yr^{-1}) suggested by Lu et al. (2018), which has reflected their growth during the term. Adopting an estimate of the effect of CO_2 fertilization and climate change as 3.0 PgC in the 2040s (Yao et al. 2018), China's FCS may be 12.6 PgC for 2050 (Table 2). Notice that this value is a lower limit that might be surpassed depending on different strategies of forest plantation. We do not predict either an upper limit or total volume for the future.

Temporal and spatial patterns of forest biomass carbon

We selected 10 year period from 2003 to 2013 for depicting the change of spatial patterns. At the start of this period, the Returning Farmland to Forest program began, which has profoundly influenced China's forest development. The provincial forest C stock, wood density, and the ratio of stem biomass to AB biomass are illustrated in Fig. 7 for imaging the changes of China's forests between the early 2000s (1999–2003) and the early 2010s (2009–2013). The forest C in all provinces has functioned as C sinks during the period (Fig. 7a and b). The largest C sink was in Heilongjiang (102.1 TgC, 10.2% of total forest C sink in China), followed by Inner Mongolia (98.8 TgC, 9.8%), and Yunnan (80.0 TgC, 8.0%). The average wood densities decreased in most areas (18 provinces) (Fig. 7c and d), which made the wood density national average decrease slightly during the decade (Fig. 5b). The ratio of stem biomass to AB biomass increased widely in 25 provinces. The ratio in national average was also increased from 58.9% to 59.2% in the period.

Fig. 7 The spatial distributions of China's forest C and related estimates of forest C indicators by zoning at the provincial level in the period of 2003–2013. **a** and **b** Above and below-ground FCS and its change. **c** and **d** The forest C density for the forested lands. **e** and **f** The wood density. **g** and **h** the ratio (B_s/B_w) of stem biomass to ASB. The numbers in the map b represent each province (1, Anhui; 2, Beijing; 3, Chongqing; 4, Fujian; 5, Gansu; 6, Guangdong; 7, Guangxi; 8, Guizhou; 9, Hainan; 10, Hebei; 11, Heilongjiang; 12, Henan; 13, Hubei; 14, Hunan; 15, Jiangsu; 16, Jiangxi; 17, Jilin; 18, Liaoning; 19, Neimenggu; 20, Ningxia; 21, Qinghai; 22, Shaanxi; 23, Shandong; 24, Shanghai; 25, Shanxi; 26, Sichuan; 27, Tianjin; 28, Xinjiang; 29, Xizang; 30, Yunnan; 31, Zhejiang)

Discussions

Effects of two relationships on national FCS estimation

Confirming our hypothesis, generally we found that each of the species, whether conifer or deciduous, has the observed data appear to be in good agreement with the allometric equations, whereas each of the species has

relatively low correlation between stem biomass and volume. The difference of R^2 on average is 0.09 lower for the equations of V-to-B_s than B_s-to-B_w (Fig. 4). The slopes (p) for V-to-B_s can be regarded as measured WDs for each species. When the slope (p) changes, it results in a larger difference on final carbon estimate than the

allometric equation to AB biomass does. For example, on average ± 5% modification of slope (p) resulted in approximate percentage change (4.43% and – 4.46%, Table 2) of AB biomass estimates. The possibility of significant total effects of WD on forest biomass estimation is also supported by the findings of previous analyses (Baker 2004; Chave et al. 2004; Nogueira et al. 2005; Swenson and Enquist 2007; Henry et al. 2010). In their papers, the variance of WD and its effects were deeply discussed, and are further discussed in this study (see next section). Although these previous analyses mainly focused on AG biomass or plot-level measurements, they indicated four critical issues, i.e., WDs may vary between trees (Stegen et al. 2009), between different parts in a tree (Hytonen et al. 2018), on soil fertility (ter Steege et al. 2006), and in time or under climate change (Slik et al. 2010; Bouriaud et al. 2015). It means that observed WD would be discrepant depending on measurement design. This variance is consistent with our analysis of field measurements for the relationship of V-to-B_s.

In addition to the effect of WD, the relationship between stem and AB biomass also influences the final FCS estimate. Nonetheless, it is limited by robustness of the relationship. Our results illustrate that stem biomass can explain an average of 94.3% of AB biomass via allometric equations (Fig. 3a). This partly confirms that WD has major effects on FCS estimation. A high correlation of the two variables (B_s and B_w) implies that the robust relationship individual organ and whole-tree organism reflects, in tree physiology, how the different net primary production (NPP) was allocated at different locations (Falster et al. 2011; Hytonen et al. 2018). This finding is also concordant with the results of the recent study (Luo et al. 2013) which compared biomass measurements of tree components for 17 species at 1607 plots across China, and indicated that the correlations are higher between B_s and B_w ($R^2 > 0.927$) than other correlations (e.g., root-mass and B_w, $R^2 = 0.883$, SEE = 0.115; foliage-mass and B_w, $R^2 = 0.203$, SEE = 0.275). These imply that the disparity of allometric relationship between stem- and AB biomass is not large for the same species. This low dispersion is consistent with a pattern analysis in forest biomass partition (Zhang et al. 2015). At the present stage, we suggest that the allometric relationships are utilizable at large scales.

Assessment of wood densities at the national scale

Unlike the relationship between stem and AB biomass, the collected data of WD are usually over wide ranges with a relatively high dispersion. Previous studies found that WD varies not only in a region (Crowther et al. 2015) but also in a stand at tree level. For instance, the lighter species can change in life cycle (Visser et al. 2016) due to their initial fast growth with low-density

and later high-density wood for structural support (Rueda and Williamson 1992). In addition, different periods in life cycle determine tree size that is related with different densities, because smaller young trees have higher ratio of sapwood to heartwood than larger trees (Adu-Bredu and Hagihara 1996). Amongst different species, there is great variation in WD (Chave et al. 2003; Baker 2004; Chave et al. 2009). Fast growing species generally have low densities (Kojima et al. 2009; Pretzsch et al. 2018) in their juvenile wood, especially for the first one or two decades. Denslow (1980) also reported that WD is lower for pioneer trees in succession. However, in our study we found that these differences did not remarkably influence national estimates of WD, which locate between the values of dominant and non-dominant species (Fig. 5). This may be attributed to following processes.

The first is regression analysis. Its results were not largely impacted by a few possible outliers in field measurements. Most of all, some outliers of juvenile stand illustrated that their WDs exceed 1.0 (t·m^{-3}) (Fig. 4b), but their impact was weakened on calculating average WDs (slope of regression lines) because of their low biomasses. The regression indicates that standard error of the parameter (slope p) is 5% approximately on average. The robustness of the ranges could be explained by the measurements used in the study. The stem biomass and volume were measured across the country and over 30 years, which contain locational, regional, and climate impacts (Luo et al. 2013). It is to say, WD correlates with environmental factors and presents a variety of endemic feature (Swenson and Enquist 2007). Based on such a large area and long time period, WDs are expected to contain influences of different regions and climates, and to provide an integrated assessment of average value with less systematic bias at the large scale.

Second, the weighted-average treatment counteracted the single effect of each species on the national level. In practice, these effects cannot be easily assessed as lacking data may result in WD changing in different ways (Chave et al. 2006) or only representing a part of trees or species (Lewis et al. 2009). We noticed that a prior study reported China's WDs being 0.56 (Chave et al. 2009), which are estimated based on a global WD dataset (Zanne et al. 2009) and higher than our estimates of 19%. The possible reason could be that those measurements compiled in the database are normally associated with different study objectives for specified species or commercial importance, for which the wood is normally denser (Henry et al. 2010). In terms of data, Flores and Coomes (2011) suggested building more data into the dataset for improvement. Considering the large scale of the study area, our estimation adopts the national mean value calculated by weighting volume amounts of each species, instead of mixing and averaging the sample

values reported by literatures. We found that the volume share of dominant species is decisive to estimate average WD at the national scale, therefore a comparison of average WDs between dominant, non-dominant, and all species, is advantageous to demonstrate the effects of species in combination. Depending on our analysis, the averaged WD is very different from what their WDs were observed in isolation. For example, although some non-dominant species have high (e.g., 0.56 for *Eucalyptus*, weight: 1.2%) or low (e.g., 0.35 for *Cunninghamia lanceolata*, weight: 4.9%) WDs, they cannot represent national WD. Accordingly, the volume-weighted WD and its range should be close to realistic conditions.

Furthermore, we compared WD with another dataset (RIWI 1982) to avoid systematic errors in WDs at the national scale. This dataset provides WBD and contains 426 measurements for 283 tree species in 28 provinces across the country. The comparison between two different estimates indicates that ρ values are very close on the national scale. For example, during 2009–2013, ρ is 0.461 (±5%) using field biomass measurements, and 0.460 (±8%) using WBD dataset. It confirms statistical consistency without systematic errors. In short, our analysis suggests that a regional or national WD can be estimated by resulting regression line for the relationship between measured volume and stem biomass, and calculated by weighting the volume amount of each species, to ensure that the national WD becomes a mathematical expectation lest a bias occurs in the FCS estimates.

National FCS estimate based on the two-step process

According to our hypothesis, the two-step process separates the uncertainty as two parts that are caused by assessments of WD and allometric relationship. The first step aims at stem biomass. To convert stem biomass from the volume is straightforward (Neumann and Jandl 2005). It is the way to exclude possible systematic errors using WD. Many studies suggested adding a factor of WD in the biomass equation (Henry et al. 2010; Domke et al. 2012; Chave et al. 2004, 2014; Weiskittel et al. 2015) because biomass estimation is a complex process (Temesgen et al. 2015), in which some aspects may not necessarily be considered or processed well. We found that it is effective to infer a range for AB biomass using WD. For example, the ±5% bias of WD keeps estimates of AB biomass to range from 5.6 to 6.1 (PgC) for 2009–2013 (Table 2). This implies that the maximum AB biomass can be predicted using an upper limit of WD. We suggest using 0.7 (t·m^{-3}) as an upper limit of WD, which is common for rose-wood and impossible for temperate forests located in much of China. Thus, our estimation acquired limitations of AB biomass that should not be exceeded for each period (Table 2). We suggest predicting the potential error within an expected range around a central value, named averaged

WD for all species. In the second step, the AB biomass is calculated by allometric equations, which are reliable with high coefficients of determination. The approach of two-step is general and can be applied to estimate FCS from local to national scales. In the case of wood density estimation, our analysis suggests a possibility to estimate FCS based on a reference of reasonable ranges. Figure 6 and Table 2 summarized the dynamics of China's FCS in the past 40 years and future year up to 2050, and compared FCS estimates with earlier estimates. Although most of which are within the ranges (Table 2), to propose an upper limit of FCS is feasible and meaningful at the national level. In short, the two-step process demonstrates that the estimate of growing stock volume and stem biomass is a cornerstone in the estimation using volume-derived methodology.

Temporal and spatial changes

Geographically, forested area, volume, and FCSs are mainly accumulated in the northeast and southwest in China, because of the moderate precipitation and temperature. These two regions contain the largest growing volumes in six provinces (Nos. 11, 17, 19, 26, 29, and 30 in Fig. 7a). The province No. 29 has the greatest amount of FCS amongst these provinces. But the spatial pattern of forest C sink is different. Two other provinces (Nos. 11 and 19) in northeast China have the largest carbon sequestration (Fig. 7b). Comparing the C changes of these two regions, the forests in the northeast area functioned as the larger carbon sink at the end of the first decade in the twenty-first century. Furthermore, we found that the spatial pattern did not change significantly since 2000 after comparing with a comprehensive analysis (Fang et al. 2001). It implies that the policies of forest conservation and protecting forests have entirely influenced most forested lands in the country.

The spatial pattern of forest C density is similar to FCS (Fig. 7c) during the period. But the pattern of the dynamic density change became notably different (Fig. 7d). The higher C density was distributed in the southeast area, in which increased C densities have offset the decreased C densities in a few provinces. At the national level, forest C density had increased from 2000 to 2013. Our results of both FCS and forest C density are consistent with previous studies (Xu et al. 2007; Li et al. 2011; Guo et al. 2013).

The distributions of wood density (Fig. 7e) influences stem biomass by multiplying growing stock volume (see Fig. 1), and explains approximately 60% China's FCS at the end of the 8th period of NFI (59.2% for the year of 2013, Table 2). The remaining 40% FCS can be explained by the ratio (B_s/B_w) of stem biomass to AB biomass (Fig. 7g, Table 2). Graphical analysis illustrates that the ratios range from 53% to 64% for all forested lands across the country. We have conformed that this ratio is stable (Laiho and Laine 1997) and similar to different

species using the field measurements (Fig. 2). This indicates that stem biomass is a dominating part in whole forest biomass, and the estimate of stem biomass should be the foundation in national FSC estimation.

Overall, through reviewing the forestry development in China, our results are consistent with the policy influence on FCS in the country. The estimated dynamics of national FCS has portrayed an impressive trend (Fig. 6) since the 1970s. The continuous FCS increase has been facilitated by several large projects and programs (Lu et al. 2018). The initial policy concentrated on forest conservation and protecting forests against desertification and embankment damage (Zhang et al. 2000; Fang et al. 2001, 2018). After ten years of ecological restoration, the natural forests have started to increase. By 1999, the most influential program, Returning Farmland to Forest (Zhang et al. 2000; McNutt 2014), was implemented by compensating rural residents for the conversion of some farmland and barren mountainsides to forestland with financial support (Cao et al. 2011; Trac et al. 2013; McNutt 2014). This program has remarkably expanded forestland. Our results indicate that the national FCS exhibited a 1.7% increase per year in the first 30 years and accelerated to 3.1% per year in the last 10 years. In the long term, the policy-driven programs have contributed to a dramatic increase in forest cover from 8% in the 1960s to over 20% at the beginning of the 2010s.

In the prediction of future FCS, the temporal and spatial patterns could help to reason the possible dynamic changes. We found that wood densities have declined in most provinces (Fig. 7f). This means that both the area and volume have increased for the species that have low wood density. Our calculation has also proved this trend at the national level (Fig. 5), despite a very low decrease (− 0.4%, Table 2). This was probably because there were mainly plantation forests of fast growing species during the period (Cao et al. 2011; Xu 2011). Those species have relative low wood density (RIWI 1982). Choosing species for forest plantation will affect wood density pattern in the future. On the other hand, the spatiotemporal pattern of the ratio (B_s/B_w) shows an increasing trend from 2003 to 2013 (Fig. 7g and h). This was because of the growing years and stand ages (de-Miguel et al. 2014). We suggested that the ratio (B_s/B_w) will tend to increase and stabilize up to around 0.7 with the body weight increase of trees based on our analysis of field measurements (Fig. 2; Luo et al. 2013). In short, we tentatively propose that the wood density will not change largely, and the ratio (B_s/B_w) will not greater than 70% (Fig. 2) at the national scale in the 2040s. Using these rough estimates, we suggest that 9.1 PgC is a lower limit of China's FCS in the 2040s according to the volume target of 23 billion m³ predicted by China's forest planners (SFA-CFN 2016). Above this level of the FSC, there may be two extra increments, which are

caused by climate change and forest plantation in the future. These issues will be discussed in the following section.

Trend in the future

The first extra increment affected by CO_2 fertilization and climate change has been analyzed recently by Yao et al. (2018). It might further increase the total forest biomass C sequestration to 2.2 or 3.7 PgC (on average 3.0 PgC) according to the RCP scenarios in the 2040s. Another extra increment should come from forest plantation. Although it is difficult to quantify the contribution of low canopy cover to the increased area, we can assess the growing trends (Fang et al. 2018). Previous evaluations (Zhang et al. 2000; Lu et al. 2018) pointed out that extensive afforestation has been carried out for millions of hectares of open forested land, barren hillsides, and converted marginal farmland in the 1900s and 2000s. In these afforested lands, most open forests in the 1990s would have become closed forests in the 2010s, finally accumulating volume (SFA-CFN 2013). Our results support the increase of forest cover percentage. The cover percentage is consistent with volume increase. The total amounts of both area and volume have been rising continually with relative high rates. However, the total area of suitable lands for forest had been decreasing through expansive and continuous afforestation, because of limited total amount of lands. These lands have been reduced by approximately 10% from the 7th to 8th NFI (2008–2013) (SFA-CFN 2013). Assuming all suitable lands will be forested before 2050, their total area (39 × 10⁶ ha; SFA-CFN 2013) could produce around 1.5 PgC FCS from 2013 to 2050. This may be the second extra increment of China's FSC at the end of the 2040s. Thus, we reckon that the comprehensive lower limit of China's FSC might reach up to 12.6 PgC (Table 2) for the long term prediction, i.e., increase by a further 38% from the estimate (9.1 PgC) of current forests. In addition, over time the effect of low canopy cover on the national average level will be lighter in the future than present time. Hopefully, the FCS will rise steadily in the next few decades.

Uncertainty analyses

Our analysis demonstrates how the use of average WDs ensures the estimates of national FCS within a reasonable range, however, uncertainties still remain due to inherent limitations in measurements and the lack of large datasets. Some of species have small amounts of samples (e.g., species No. 9 and No. 13) (Fig. 4b), which may not well represent statistical population of those species. Thus, the regression could be questionable for a few species. Nevertheless, our comparison between WD and WBD suggests that this may not cause large biases in

this study. The average WBDs are 0.36 (species No. 9) and 0.395 (species No. 13). These values are only 0.01 higher and 0.005 lower than the WD measurements (0.35, species No. 9; 0.40, species No. 13). Additionally, these two species had very low volume weight, which was 3.1% of total volume during 2009–2013. We suggest that the over- or under-estimation of these two WDs may not be an issue in this study.

Another source of uncertainty may frequently come from field measurements. We noticed that a few sample points over the 45 degree line in Fig. 4b. It means that several ratios of stem biomass to volume (i.e., WD) become higher than $1.0 \, t \cdot m^{-3}$. Errors notwithstanding, our results show that these outliers do not have a great impact on the regression because they are younger stands with low biomass than most measurements. Moreover, the slopes express WDs as the values of mathematical expectation in a normal distribution, in other words, over- and under-estimated WDs actually canceled each other out. As for those outliers that usually represent younger stands with low biomass than most measurements, we suppose that the measurement issue may be found in the measurements of volume, rather than in biomass. This is because the stem biomass explained 94.3% of AB biomass on average through allometric equations. It implies that the relationships between biomasses of different tree organs are practical. Yet, it is difficult to confirm the results of volume measurements, since the data used in this study comes from a public dataset. The dataset provides biomass and volume per unit area that have been converted already by the observers from the measurements in field plots. Overall the lack of a sufficient number of high-quality measurements still reduces our ability to remove the uncertainty in national forest carbon estimation. From the present study, we suggest that: (1) More measurement experiments and studies are needed from principal species in different regions for better large scale estimations, and (2) well-designed measurement of stem volume and conversion from plots to unit area are needed for better understanding WD ranges to narrow the uncertainty in national forest carbon estimation.

At last, after considering the effects of forest plantation, CO_2 fertilization, and climate change, the FCS is projected to be further increased. However, there is still uncertainty on predicting the increment of total volume at the national level during the future long term. The future effects of the Returning Farmland to Forest program on FCS may be largely impacted by development of the national economy. Furthermore, forest growth rates are affected in very complicated ways by a number of factors, such as, planted species, site index, soil moisture, temperature and phenology, CO_2 concentration and acclimation, stand mortality, and forest management

practices. The target volume of national forest development (23 billion m^3) might be a conservative figure under climate change. Predicting the future volume remains a challenge.

Conclusions

By surveying, it is difficult to accurately estimate AB biomass and FCS at the national scale because the true value is unknown and impossible to measure directly. However, whether the estimates are appropriate or not can be deduced and verified with the suggested computation, which splits the processing of forest biomass estimation into two parts for stem and whole tree. This presented method will help us understand the relationship between these two parts, and conveniently confirm the results according to a general knowledge of tree and wood. Our study performs a robust estimation of FCS using this two-step processing, and recommends the ranges which should be used for China's FCSs. We suggest applying this approach to narrow uncertainty in the estimation that converts forest volume to biomass. The method presented helps to verify national FCS and to avoid significant biases in FCS estimates and related studies at the national scale. As a case study, the estimation results confirmed that China's forest ecosystems have functioned as a C sink in the past 40 years. The national FCS increased approximately 2.4% per year on average during the period, in which it exhibited a 1.7% increase per year in the first 30 years and accelerated to 3.1% per year in the last 10 years. This suggests that national forest restoration policies and projects could be an effective way to increase forest C sequestration.

Supplementary information

Authors' contributions
XZ, XL and CL conceived this study and performed mathematical analysis; CL, HH, CP and CZ discussed the algorithm and its explanations, data analysis, and manuscript preparation. All authors read and approved the final manuscript.

Zhou *et al. Forest Ecosystems*   (2019) 6:51

Page 16 of 18

Availability of data and materials
All data is available on request (see details in Supporting Information).

Ethics approval and consent to participate
Not applicable.

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Competing interests
The authors declare that they have no competing interests.

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Zhou *et al. Forest Ecosystems*   (2019) 6:51

Page 17 of 18

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