DEVELOPMENT OF CARBON STORAGE MODEL FOR ABOVEGROUND VEGETATION IN CHINA

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Abstract. Aboveground vegetation is an important component of the terrestrial ecosystem carbon storage, with a significant role in maintaining the global carbon cycle and balance. At present, the estimation method of aboveground vegetation carbon storage was concerned by people. Based on the national data of major trees, forest sample plots and major crops, the carbon storage models of 13 species of tree and 9 types of stands were established through regression analysis, and the carbon storage factors of main crops per unit area was calculated, Moreover, the carbon storage of forest in China was estimated. The results of model fitting showed that the fitting determination coefficients (R^2) were all above 0.9. Evaluation indicators of five regression models were selected to conduct model verification. And the verification results showed that the variation range of total relative error (TRE) of tree regression model is -6.03~4.76%, and that of forest classification regression model is -3.24~7.43%. The China forest carbon storage calculated by regression model is 8.999 Pg, considering that forest inventory is carried out based on a certain degree of canopy density, so the error between the results 8.427 Pg of regression model and forest inventory is within the permit range. Therefore, the aboveground vegetation carbon storage models established in this study can be used to estimate the carbon storage of China's main vegetation types.
Keywords: *forest type, tree, crop, carbon storage, regression model*

Introduction

Global climate change is a scientific problem that mankind has to deal with together, particularly climate warming is widely concerned by the scientific community (Canadell et al., 2000; Zeng et al., 2010). The vegetation ecosystem is an important part of the terrestrial ecosystem, the carbon sinks in vegetation ecosystem plays an important role in the global carbon cycle, it is a key factor in the study of global carbon cycle and carbon balance, it also plays an indispensable role in regulating climate change, absorbing greenhouse gases and mitigating the greenhouse effect (Cao and Woodward, 1998; Li et al., 2011). The quality and dynamics of regional forest cover, including afforestation, deforestation and forest protection, are important factors in mitigating climate change in the context of sustainable development (Koh and Ghazoul, 2010; Aryal et al., 2014; Edenhofer et al., 2014). The aboveground vegetation carbon storage, especially annual carbon increment, is a reliable index to measure the ecological function of vegetation, so how to determine the carbon storage of aboveground vegetation with high efficiency is a hot and important issue in scientific research.

Since the 1960s, many scholars have estimated and predicted the carbon storage of different types of forest (Nunery and Keeton, 2010; Popescu, 2007), many people has been well recognized that forest carbon pools are affected by forest management methods (Berbés-Blázquez, 2012), and they believe that it is a more accurate and feasible method to establish the carbon storage model of individual tree and then make scale transformation (Chave et al., 2005; Navar, 2009). Yangliu using Landsat 8, built a variety

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of forest accumulation prediction models by the method of machine learning information extraction and realized the measurement of coniferous forest, broad-leaved forest and mingled forest (Yang et al., 2017). Kurz, Heath and Holly K had respectively studied the northern forest, temperate forest and tropical forest and update prominent forest biomass carbon databases to create the Abies fabri Craibt complete set of national-level forest carbon stock estimates (Woodbury et al., 2007; Gibbs et al., 2007). Gilabert had conducted a research which is explored the relationships between crop canopy leaf area index, biomass and normalized differential vegetation index (NDVI) used by the method of remote sensing (Martínez and Gilabert, 2009). Chao Zhang were analyzed the forest carbon storage and their spatial distribution in China's small (2,300 km^2) liuxi river basin a, and determined the different contributors of carbon storage (Zhang et al., 2016). Rengtang Chen and Zhongke Feng established regression equations of each organ for Quercus acutidentata and other 7 tree species based on 1259 standard plots and 836 standard trees, measured and studied the biomass of 8 types of forest stands at Xiaolong Mountain (Cheng et al., 2007). Wensheng Cheng established binary volume models and form factor models of the main tree species in China which are based on the single volume tables of each province, and improved efficiency and reduced the workload of large area scale measurement of standing wood volume (Wensheng et al., 2017). The main method to calculate the carbon storage of forest ecosystem at large scale is based on the forest resource inventory data and there are increasing number of studies have been conducted on the application of forest resource inventory data and remote sensing data to the calculation of carbon storage of forest ecosystem (Zolkos et al., 2017; Jenkins et al., 2003). Although it is of high precision to estimate carbon storage of sample plots using forest resource inventory data, there are still some problems when predicting large scale carbon storage of sample plots, such as it is easy to ignore the sparse forest with less than 20% crown density. Moreover, large-scale forest resource inventory takes a lot of manpower and material resources and lasts for a long time, such as China's latest forest inventory took five years which has seriously affected the timeliness of forest carbon storage research. The calculation of regional scale carbon storage based on remote sensing data also has many defects, such as there is great uncertainty in the calculation of various remote sensing vegetation indexes (Moncada Rojas and Botero, 2013; Trishchenko et al., 2002). On the other hand, NDVI and other vegetation indexes always reflect the status of vegetation productivity, and it is quite different from the carbon storage of vegetation.

This study attempts to establish aboveground vegetation carbon storage measurement models to solve the problem of carbon storage estimation in large scale vegetation ecosystem. This paper aims to establish models with high precision and timeliness and partly relies on sample plot inventory data. This study using the national permanent sample plot data and the binary volume table as basic materials, the study was based on the national fixed sample land data and the measured forest sample land data in various regions of the country, using the SPSS software to regression analysis, and establishing 13 types of trees binary carbon storage models, 9 types of forest stands carbon storage models and staple crops carbon storage models.

Materials and methods

Tree data

The data of forest biomass in this study are derived from the eighth national forest inventory data and the measured data of different forest types in different regions of

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China (Department of Forest Resources, 2014). Mainly including place names, longitude and latitude, altitude, annual average temperature, annual average rainfall, forest origin, tree species, composition, age, average DBH, average height, forest density, standing stock volume, arbor biomass (trunk, branch, leaf, ground, etc.) (Wang et al., 2001; Zhao and Zhou, 2004; Fang, 2001). In this study, forest biomass was measured by standard plot method. Standard plot is the miniature of the whole stand. Standard plot is only different from the whole stand in area, but not in quality. The data used in this study include dominant tree species, research area, stand origin, age, stand volume and tree biomass. Some of the data are shown in *Table 1*. Based on the analysis of 160 million sets of forest inventory data in China, the inventory data of dominant tree species in various provinces and cities were selected, and the volume of individual tree was calculated. Then the biomass of sample plot was estimated according to dominant tree species in forest sample plot. National forest data are divided into nine categories, such as: coniferous forest, hardwood broad-leaved forest, soft leaf broad-leaved forest, miscellaneous wood forest, coniferous and broad-leaved mixed forest ecosystem, Coniferous mixed forest, Broad-leaved mixed forest, Chinese fir forest, Mongolica forest, and Tthirteen tree species such as: Pinus tabuliformis, Picea asperata Mast, Cryptomeria fortune, Cunninghamia Lanceolata, Quercus, Abies fabri, Pinus yunnanensis, Pinus massoniana, schima superba, Betula, Pinus elliottii, Larix gmelinii, Liquidambar formosana Hance.

Table 1. *Forest biomass data (part of the data)*

Dominant species	**Research area**	**Stand origin**	**Stand age (a)**	**Standing stock (m^3/ha)**	**Biomass (Mg/ha)**
Spruce	Ebian County, Sichuan Province	Planted forest	35	337.8	173.08
Spruce	Heishui County, Sichuan Province	Planted forest	32	125.2	107.82
Larix olgensis Henry	Fengcheng City, Liaoning Province	Planted forest	32	357.63	283.61
Larix principis-rupprechtii Mayr	Quangou Nature Reserve in Shanxi Province	Natural forest	35	287	189.99
Larix gmelinii	Shangzhi City, Heilongjiang Province	Planted forest	24	173.58	168.79
Pinus	Tianshui City, Gansu Province	Planted forest	42	92.94	60.7
Pinus	Zhengning County, Gansu Province	Secondary forest	26	89.41	89.44
Platycladus orientalis	Yongshou County, Shaanxi Province	Planted forest	17	18.53	35.43

Crop data

The crop data in this study mainly include rice, wheat, maize, beans, potato, cotton, oil, sugar, tobacco, vegetables, total of ten species. The yield of sown area of crops originated from the National Statistical Yearbook (2014). Through the method of sample plot investigation and experimental analysis, the sample plot of 1 m × 1 m was randomly selected from the selected experimental observation farmland sample plot before the crop was mature, After the collection of plant samples, the samples were put

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into a constant temperature oven (100 constant temperature) to bake to constant weight according to different organs. After being taken out, the dry matter weight of each organ was weighed, and the biological quantity of crops was calculated by adding, so as to obtain the economic coefficient of crops.

Model selection

Carbon storage model of forest stand

In order to ensure the application value of the model, this paper uses SPSS software to analyze the correlation of the carbon storage between tree species, and generates the scatter plots. According to the data point distribution, it is found that power function is more consistent with data rules, and combined with the results of previous carbon storage models, the model is obtained by nonlinear regression:

Forest stand carbon storage model:

$$C = aV^{b} \tag{Eq.1}$$

C is forest stand carbon storage (Mg), V stands for forest stand volume (m^3), a and b are estimated parameters.

Carbon storage model of tree species

Measuring DBH is usually fast, convenient and accurate, but measuring tree height is time-consuming and laborious. In forest survey, only part of dominant tree height is usually measured, and the missing tree height is often predicted by tree height curve model of different tree species (McRoberts et al., 2013). Therefore, the H index coefficient of tree height in tree species biomass model is set to 1, and the expression of tree species carbon storage model is as follows.

$$C = aD^{b}H \tag{Eq.2}$$

C is the carbon storage of single tree species (kg/tree), D is diameter at breast height (DBH) (cm), H is the tree height (m), a and b are estimated parameters.

Carbon storage model of crop

The economic yield and economic coefficient of crop production carbon coefficient are selected as independent variables in the crop carbon storage model. Through the model, the crop vegetation carbon storage per unit area can be calculated.

$$C = C_f * D_w = C_f * Y_w / H_t \tag{Eq.3}$$

C is Crop carbon storage (unit: t/ha), D_w is crop production, Cf is carbon coefficient, Y_w is economic output, H_t is economic coefficient.

Model evaluation standard

The last and most important step of regression analysis is to verify the model. It is not appropriate to evaluate the predictive ability of the sample calculation model only

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by using the fitting or test indicators, the test sample which means that samples not involved in the fitting model also need to be used in fitting or test indicators. Zeng et al. (2011) believed that the applicability test could not reflect the prediction accuracy of the model, and suggested to combine the test sample and modeling sample for modeling in order to make full use of the sample information The statistical indicators of model test and evaluation include the following five items: Coefficients of determination (R2), Standard error of estimated (SEE), Total relative error (TRE), Mean systematic error (MSE) and Mean prediction error (MPE) (Tang et al., 2008), the specific calculation formula was shown in (*Eqs. 4–8*). In the formula: y_i Is the actual observed value; $\hat{y}_i$ is the estimation; $\bar{y}_i$ is the mean of the reference values; n is the number of estimation, and p is number of parameters. R2 and SEE are the most common evaluation indicators which are reflect the goodness of the fit of models. TRE and MSE are the important indexes to reflect the fitting effects which are should be within ± 3% or ± 5% and it works best when close to zero. MPE is a precision index which reflecting average carbon storage valuation. In addition, the good fitted model should also have the characteristics of parameter stability and residual (symmetric random distribution with 0 as the base).

$$R^2 = 1 - \sum (\hat{y}_i - y_i)^2 / \sum (y_i - \bar{y}_i)^2 \tag{Eq.4}$$

$$SEE = \sqrt{\sum (y_i - \hat{y}_i)^2 / (n-p)} \tag{Eq.5}$$

$$TRE = \sum (y_i - \hat{y}_i) / \sum \hat{y}_i \times 100 \tag{Eq.6}$$

$$MSE = \sum (y_i - \hat{y}_i) / \hat{y}_i / n \times 100 \tag{Eq.7}$$

$$MPE = t_\alpha (SEE / \bar{y}) / \sqrt{n} \times 100 \tag{Eq.8}$$

Results

Carbon storage model of stands

Based on the sample data of each forest tree species, Carbon storage model was processed by SPSS 23 software with nonlinear regression analysis method. And the generated carbon storage model of 9 stand types were evaluated by 4 indicators. The results of the indicators evaluation and parameters estimation are shown in *Table 2*.

As shown in *Table 2*, TRE and MPE of carbon storage model in each stand were low, which indicated that the parameters of each model were very accurate. Accurate prediction of model parameters is the basis for the accuracy of model prediction capability. R2 values were over 0.9, which indicated that the fitting precision was perfect. Meanwhile, MSE was also lower, which indicated that the model had a better accuracy in estimating carbon storage. In general, the regression model had an excellent fitting performance on different forest types.

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Table 2. *Results of the regression analyses of carbon storage in 9 types of stand*

No.	Stand type	a	b	R^2	SEE (%)	MPE (%)	TRE (%)	MSE (%)
1	Coniferous forest	2.221	0.647	0.913	43.41	1.27	1.87	5.89
2	Chinese fir forest	3.453	0.635	0.992	32.63	1.86	2.31	6.75
3	Mongolica forest	2.019	0.991	0.993	27.58	1.29	3.37	7.38
4	Hardwood broad-leaved	1.826	0.903	0.982	39.52	2.18	4.96	11.59
5	Soft leaf broad-leaved	5.006	0.603	0.991	41.25	1.65	1.58	6.18
6	Miscellaneous wood	1.329	0.902	0.991	34.66	1.73	1.86	9.46
7	Coniferous and broad-leaved mixed	2.373	0.816	0.987	18.36	1.03	1.28	5.73
8	Broad-leaved mixed forest	1.285	0.875	0.981	10.45	1.41	0.68	5.38
9	Coniferous mixed forest	5.434	0.603	0.973	24.47	1.31	1.23	6.81

Carbon storage model of individual tree

Through process and analysis, the regression model of carbon storage model of 13 types of tree species in China was established, and the sample data were non-linearly fitted, and the fitting results of the model were calculated by evaluation indexes respectively. The parameter estimation and fitting evaluation are shown in *Table 3*.

Table 3. *Results of the regression analyses of carbon storage in 13 types of tree species*

No.	Tree types	a	b	R^2	SEE (%)	MPE (%)	TRE (%)	MSE (%)
1	Pinus tabuliformis	0.00497	2.267	0.924	12.37	2.34	4.93	17.52
2	Picea asperata Mast	0.00408	2.343	0.861	41.17	3.14	1.13	3.07
3	Cryptomeria fortunei	0.00914	2.010	0.925	14.38	2.24	6.41	10.19
4	Cunninghamia Lanceolata	0.00597	2.109	0.926	13.85	2.04	-1.98	-3.91
5	Quercus	0.00507	2.375	0.876	35.36	3.01	4.71	6.65
6	Abies fabri Craib	0.00713	2.130	0.924	25.87	1.73	-3.24	-4.36
7	Pinus yunnanensis	0.00621	2.121	0.928	9.76	1.52	6.15	5.37
8	Pinus massoniana	0.00591	2.201	0.933	13.87	1.68	3.53	9.69
9	Schima superba	0.01012	2.115	0.894	27.85	3.27	-2.24	-6.87
10	Betula	0.01009	2.101	0.948	42.15	2.56	6.42	8.53
11	Pinus elliottii	0.00914	2.104	0.966	12.08	1.98	3.12	7.15
12	Larix gmelinii	0.00897	2.113	0.935	7.75	1.84	5.34	4.58
13	Liquidambar formosana Hance	0.00632	2.292	0.902	34.32	2.58	7.43	8.17

As can be seen from the evaluation results in *Table 3*, the overall fitting degree of the regression model of carbon storage of 9 types of tree species was over 0.9. Among them, only Picea asperata Mast, Quercus, schima superba and Liquidambar formosana Hance trees were slightly less than 0.9. And MPE was an important index in the calculation of carbon storage. It can be seen from the table that the mean square error was controlled within 5%, and the overall influence was small, which was in line with the calculation of carbon storage of major tree species.

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Carbon storage model of crop

We collected and sorted out the crop economic output, economic coefficient, carbon absorption and other related factors in the Statistic Yearbook of China, the biomass per hectare and carbon storage per hectare were obtained by regression model analysis. The parameters were shown in *Table 4*. If the aboveground vegetation density stays the same, the calculated parameters can be used to calculate the carbon storage of crops directly by multiplying the planting area of agricultural crops by the carbon storage per unit area.

Table 4. *Coefficient of crop carbon storage*

No.	Crop	Carbon storage per hectare (t/ha)	Absorptivity of carbon (%)	Carbon sink per hectare (t/ha)
1	Rice	7.60	0.41	6.24
2	Wheat	6.65	0.49	6.52
3	Maize	7.45	0.47	7.01
4	Beans	2.61	0.45	2.34
5	Potato	2.70	0.42	2.27
6	Cotton	7.90	0.45	7.11
7	Oil plants	5.15	0.45	4.63
8	Sugar plant	51.95	0.43	44.68
9	Tobacco	1.95	0.45	1.75
10	Vegetables	2.75	0.41	2.25

Model evaluation and analysis

Model evaluation and analysis of stand carbon storage

We tested the applicability of each aboveground vegetation carbon storage model with data not involved in the model fitting. The evaluation indexes of TRE and MSE were respectively calculated by the regression model of 9 types of forest stand, and the test results were shown in *Table 5*. The range of TRE in the table varied from -4.72% to 2.64%, and MSE variation range was -4.12%~3.25%. The absolute value of the predicted error of all indexes was less than 5%, which meets the requirements of the model method of biomass and the industry standards (Tang et al., 2008). In order to verify the accuracy of the stand carbon storage model, a set of reserved data was used to verify the accuracy of the model. The results of analysis and comparison between the predicted and measured values were shown in *Figure 1*. The above results show that the model can effectively convert forest carbon reserves.

Table 5. *Results of forest carbon storage model test*

Forest stand	TRE (%)	MSE (%)	Forest stand	TRE (%)	MSE (%)
Coniferous forest	-4.72	-3.75	Miscellaneous wood forest	-.346	-2.27
Chinese fir forest	-3.87	-4.12	Coniferous mixed forest	-3.56	-4.08
Mongolica forest	-2.65	-3.42	Broad-leaved mixed forest	2.64	3.25
Hardwood broad-leaved forest	1.96	2.74	Coniferous and broad-leaved mixed forest	1.76	1.87
Soft leaf broad-leaved forest	-2.05	-1.89	-	-	-

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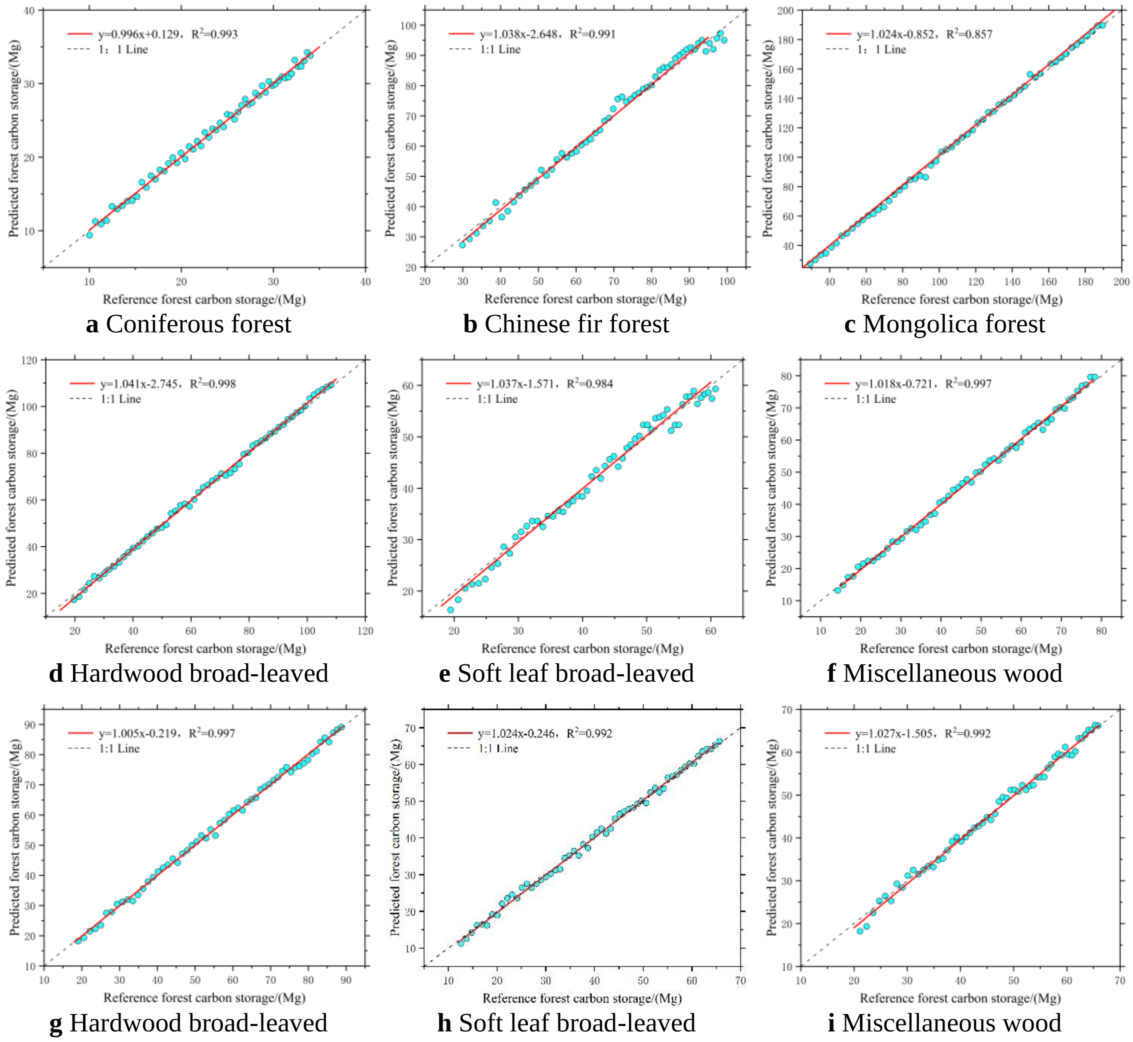

Figure 1. *Reference value and estimation value distribution of forest stand carbon storage*

Model evaluation and analysis of individual tree carbon storage

TRE and MSE were used to test the error of the carbon storage model of 13 species of individual tree. As shown in *Table 6*, experimental investigation showed that the relative TRE of individual tree carbon storage measurements is -6.03%, the relative TRE of hypsometrical measurements is 3.93%, MSE of individual tree carbon storage measurements is -4.72%, and the relative MSE of hypsometrical measurements is 4.37%, all of which are higher than the accuracy required for traditional forestry surveys. In order to verify the accuracy of the tree carbon storage model, a set of reserved data was used to verify the accuracy of the model. The results of analysis and comparison between the predicted and measured values were shown in *Figure 2*. The above results show that the model can effectively convert tree carbon reserves.

Spatial distribution of forest carbon storage in China

In order to quantitatively analyze the spatial distribution characteristics of forest carbon storage in China and verify the accuracy of research model, this paper divides China into six regions (the northeast, the north, the northwest, the southwest, the central

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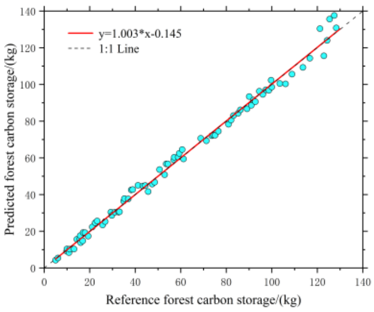
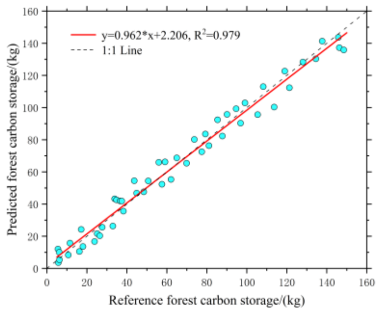
south and the eastern coasts) and separately estimates the regional carbon storage calculated from forest inventory and the results of carbon storage value obtained in this paper.

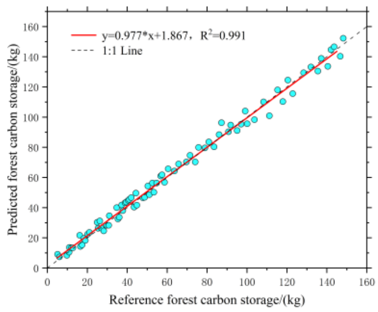
It can be seen from *Table 7*, the calculated value based on forest resource inventory is basically match the spatial distribution of carbon reserves value obtained by the simulation in this study. The specific distribution is: the largest is southwest and northeast, followed by central south and north, while northwest and east are relatively small, which is basically consistent with previous studies (Zhao et al., 2014). While there still has some differences between simulation results and results obtained from forest resource inventory, the main reason is the carbon reserve calculated based on forest resource inventory has error. Forest resource inventory is based on 20% crown density standard which means that sparse forests with crown density less than 20% and shrubs were not examined. This error cannot be ignored at the national scale. In addition, there might be some errors also in the process of forest resource inventory and carbon storage calculation. The difference between northeast and southwest is the largest, the reason should be these two areas are the main forest areas in China, and the forest area is large and the terrain is complex. However, the simulation method in this paper can take the calculation of carbon reserves of sparse forests and shrubs into account at the same time, the simulation results match the actual carbon reserves distributions.



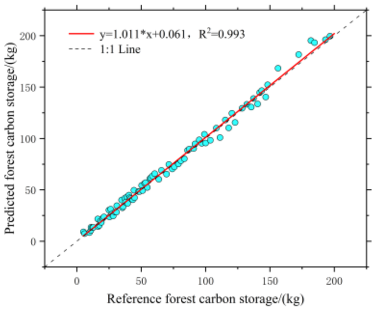
a Pinus tabuliformis



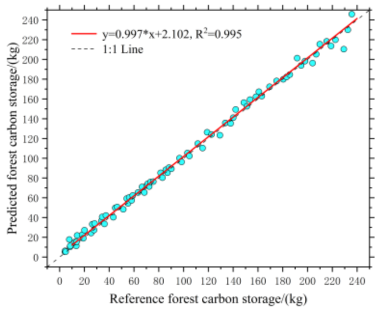
b Spruce



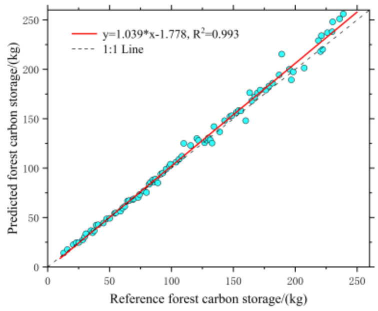
c Mongolica forest



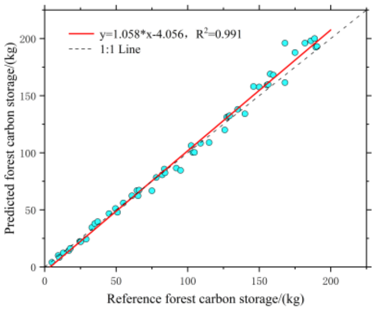
d Cunninghamia Lanceolata



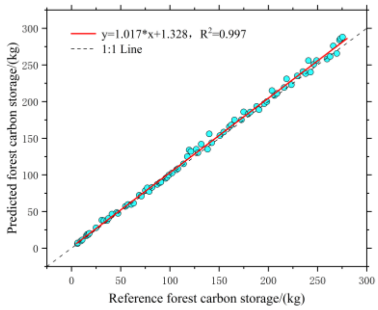
e Oaks



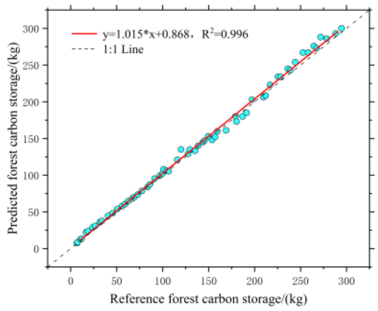
f Firs



g Pinus yunnanensis



h Pinus massoniana



i Schima superba

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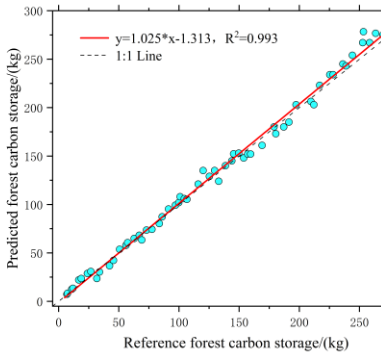
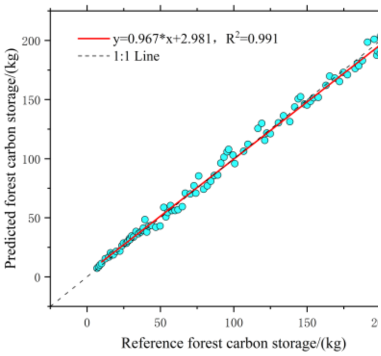
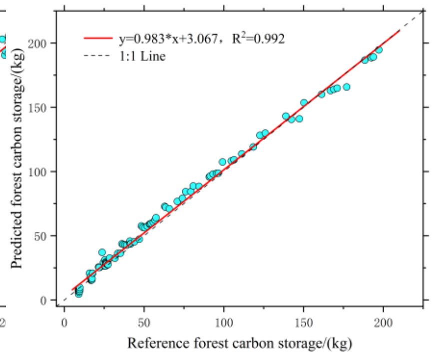


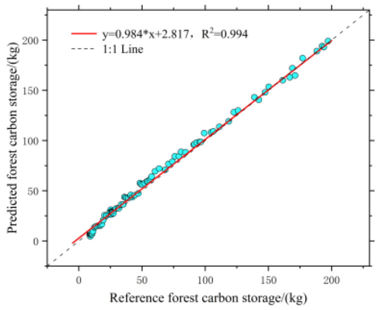
j Birch



k Slash pine



l Dahurian larch



m Sweetgum

Figure 2. *Reference value and estimation value distribution of tree carbon storage*

Table 6. *Results of tree carbon storage model test*

No.	Tree types	TRE (%)	MSE (%)	No.	tree types	TRE (%)	MSE (%)
1	Pinus tabuliformis	-4.18	-3.87	8	Pinus massoniana	3.87	4.04
2	Picea asperata Mast	-3.58	-3.56	9	Schima superba	2.63	3.28
3	Cryptomeria fortunei	-2.38	-2.28	10	Betula	1.98	2.97
4	Cunninghamia Lanceolata	2.67	2.19	11	Pinus elliottii	2.77	3.26
5	Quercus	-2.39	-2.54	12	Larix gmelinii	-2.76	-3.45
6	Abies fabri Craib	-6.03	-4.72	13	Liquidambar formosana Hance	-2.83	-1.87
7	Pinus yunnanensis	4.76	4.37		-	-	-

Table 7. *Forest carbon storage and density in China at large region level*

Regions	Data of forest resource monitoring (Pg)	Results of model estimates (Pg)	Difference (Pg)	Relative difference (%)
Northeast	1.746	1.923	0.177	10.137
North	0.923	0.867	-0.056	-6.067
Northwest	0.696	0.742	0.046	6.609
Southwest	2.913	3.212	0.299	10.264
Central south	1.145	1.224	-0.079	6.899
Southeast	1.004	1.031	0.027	2.689
total	8.427	8.999	0.572	6.788

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Discussion

The carbon storage conversion model was established by regression model in this study, problem of estimated the carbon storage of single wood level and stand level of each dominant tree species has been solved successfully, It is a less time consuming, lower cost and less laborious approach. Diameter at breast height was the main explanatory tree variable used to estimate the tree carbon storage components for all species. Several authors have noted that inclusion of total height does not usually lead to a substantial increase in the predictive ability of diameter-based biomass regressions, and they also assume that d is sufficient to yield a reliable tree carbon storage prediction (Johansson, 1999; Porté et al., 2002; Jenkins et al., 2003). However, other authors also found that when h was added as a factor, the fitting effect of the model was significantly improved (Reed and Tomé, 1998; Bartelink, 1996), and the accuracy of carbon storage estimation was improved (Menéndez-Miguélez et al., 2013). In this study, D was a good predictor of carbon storage, but the addition of h as the second variable improved the prediction of several species. Tang et al. compared 5 biomass estimation methods based on forest inventory data (Tang, 2016), four carbon storage assessment methods were compared by Gao et al. (2016). Feldpausch et al. (2012) reported that the mean relative error in biomass estimates when h was included was 50% lower than when h was excluded. There are two sets of carbon storage conversion models, one based on DBH and the other based on DBH and tree height, The model of binary was as, D and H are tree DBH and tree height respectively, a, b and c are parameters of the binary model. In the investigation of forest resources, usually only the average tree height of trees was measured, so the coefficient of the tree height parameter H was one in this study.

The combined variable D^2H is usually used in biomass equations (Chave, 2010), and the accuracy of carbon storage estimation has been found to increase significantly (measured as R^2) when h or D^2H was also included, in addition to H. In fact, tree biomass is closely correlated with D^2H, as shown by Parresol (1999) and Carvalho and Parresol (2003). In the models developed by Parresol (1999), height was a good predictor of stem wood but not of stem bark biomass, whereas Carvalho and Parresol (2003) obtained the best estimates for stem, crown and total tree biomass of Pyrenean oak by including the variable D^2H as the sole independent variable in the equation. Bi et al. (2004) reached a similar conclusion, reporting that D^2H performed better for predicting stem and bark components than diameter alone but not for branch and leaf components. In the present study, D、H yielded the best estimates of all biomass components and AGB for P. leiophylla, J. depeanna and Q. crassifolia. The results reported here suggest that the best equations for biomass estimation for most species are based on D and H.

In the total carbon storage of China’s forest vegetation, arbor forest accounts for more than 85%, which is the main part. According to the statistics of dominant tree species, the top 10 tree species in terms of area proportion are oak, birch, larch, Pinus massoniana, poplar, yunnan pine, eucalyptus, spruce and cypress, which accounts for 52.54% of the total area in China. In this paper, according to the proportion of dominant tree species in the area, 13 dominant tree species of trees in China were selected. At the same time, according to the composition of dominant tree species, the national arbor forest was divided into 9 categories. such as: coniferous forest, hardwood broad-leaved forest, soft leaf broad-leaved forest, miscellaneous wood forest, coniferous and broad-leaved mixed forest ecosystem, Coniferous mixed forest, Broad-leaved mixed forest, Chinese fir forest, Mongolica forest. Since the bamboo forest in China only accounts for

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1.98% of the national forest area, and the bamboo forest is mainly distributed in several southern provinces of China, the research on bamboo forest is not included in this paper. In future studies, special studies will be conducted on bamboo forest, grassland and shrub.

Conclusions

Based on the general volume table, national forest inventory data and national crop statistic yearbook, this paper proposed a regression modeling method to estimate the carbon storage of large-scale aboveground vegetation in China. The proposed method proved to be capable of reducing field work, evaluating contribution of forests to the global carbon cycle and to support international research on forest carbon and greenhouse gas exchange. According to the results of the modeling, the following conclusions can be drawn.

(1) For Stands and individual trees carbon storage regression model, MSE were within 10% and TRE were within 5%, and it has high fitting precision. Based on the established aboveground vegetation carbon storage model, the regional carbon storage would be directly calculated by using the survey original data. As this method avoids the conversion of tree material volume to biomass, so it has the advantage of high efficiency.

(2) In this study, the carbon storage coefficient of crops can be calculated by directly multiplying the area of crops with the corresponding carbon coefficient, which can be used to estimate carbon storage after UAV detection and the estimation of crop production in a large area.

(3) During the growth and development of aboveground vegetation, the environmental conditions such as water, light, soil characteristics and site conditions have a great influence on the growth and development of trees. Due to the difficulty in collecting and receiving some data, these factors are not considered in this study. Therefore, factors such as rainfall, altitude and site index should be introduced into the model in the future research of carbon storage model.

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Conflict of interests. Ziyu zhao, Zhongke Feng, Jincheng Liu, Yajun Shen declare that they have no conflict of interest or financial conflicts to disclose.

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