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Simultaneous Models for the Estimation of Main Forest Parameters Based on Airborne LiDAR Data

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Abstract: This study aimed to develop simultaneous models with universal applicability for the estimation of the main factors of forest stands based on airborne LiDAR data and to provide a reference for standardizing the approach and evaluation indices of main forest factor modeling. Using airborne LiDAR and field survey data from 190 sample plots in spruce (*Picea* spp.), fir (*Abies* spp.), and spruce–fir mixed forests in Northeast China, the simultaneous models for estimating the main factors of forest stands were developed. To develop the models, the relationships between mean tree height, stand basal area, stand volume, and the main metrics of the LiDAR data and the correlations between eight quantitative factors of forest stands were considered, and the error-in-variable simultaneous equations approach was employed to fit the models. The results showed that the mean prediction errors (MPEs) of eight forest stand factors estimated by the simultaneous models were mostly within 5%, and only the MPE of the number of trees per hectare exceeded 5%. The mean percentage standard errors (MPSEs) of the estimates, including the mean diameter at the breast height (DBH), mean tree height, and mean dominant tree height, were within 15%; the MPSEs of the estimates of the stand basal area, volume, biomass, and carbon stock per hectare were within 25%; and only the MPSE of the estimated number of trees per hectare exceeded 30%. The coefficients of determination (R^2) of the core prediction models for the volume, biomass, and carbon storage were all greater than 0.7. It can be concluded that estimating the main factors of forest stands based on the combination of LiDAR and field survey data is technically feasible, and the simultaneous models developed in this study for the estimation of the eight main stand factors of spruce–fir forests can meet the precision requirements of forest resource inventory, except for the number of trees, indicating that the models can be applied in practice.

Keywords: airborne LiDAR data; forest stand factors; error-in-variable; simultaneous models

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1. Introduction

Light detection and ranging (LiDAR) is an active laser measuring technology that combines laser scanning and position and orientation systems (POSs) in imaging for the generation of accurate and dense 3D point clouds, digital elevation models (DEMs), digital surface models (DSMs), and tree heights estimated from the 3D point cloud products [1]. LiDAR can be divided into four categories: space-borne, airborne, unmanned aerial systems (UAS), and ground-based according to the method of sensor mounting. Airborne LiDAR is widely used to obtain three-dimensional forest scanning data at different scales to estimate major forest parameters such as average stand height, basal area, volume, and biomass [2–5].

Research on forest stock estimation based on LiDAR data can be traced back to the 1980s [6]. After nearly 40 years of research and practice, LiDAR technology, especially airborne LiDAR data, has been widely used for estimating forest volume and has achieved fruitful and successful research results [7–15]. LiDAR technology has significant advantages in estimating tree height and forest spatial structure. Existing case studies that estimate major forest parameters based on LiDAR data have revealed new approaches for the application of remote sensing technology in forest resource surveys [16–19].

In recent years, the emergence of new laser scanning forms, such as Terrestrial Laser Scanning (TLS) and Unoccupied Aerial Vehicle Laser Scanning (UAV-LS), accompanied by innovative data fusion and other data processing algorithms have further improved the accuracy of models based on LiDAR data for forest parameters estimation. In a recent study, Panagiotidis et al. [20] created a 3D point cloud from fusion of the UAV-LS and TLS data to assess several tree metrics, such as the diameter at breast height (DBH), total tree height (HT), crown projection area (PAC), crown width (WC), crown length (LC), 3D crown surface (SC), and 3D crown volume (VC). Their results showed that LiDAR fusion can significantly improve the estimation accuracy of DBH and HT, and these estimations for broadleaves reach an accuracy of 97.8%. Terryn's research also proved that fusion from the TLS and UAV-LS opens up new avenues for obtaining accurate and detailed forest structural information [21].

Research on the application of LiDAR technology in forestry field surveys in China is relatively lagging compared with that in other countries, and most of these methods have been used only for forest stock estimation for research purposes [22–26]. Additionally, pilot studies attempting to use LiDAR technology for forest resource inventories are relatively rare [27–31]. Traditional forest resource planning and design inventories are time-consuming and labor-intensive [32], and these shortcomings provide opportunities for the application of remote sensing. Existing pilot results show that the accuracy of the estimation of core parameters such as forest stock based on LiDAR can meet the requirements of forest resource inventories [27–30]. It has been proposed that key small-scale factors of forest stands can be identified via remote sensing technologies such as LiDAR [33]. However, there is currently no clear conclusion on whether the major parameters of forest stands, such as the stand volume, biomass, carbon stock, mean diameter at breast height (MD), mean tree height (MH), mean dominant tree height (DH), number of trees (NT), and stand basal area (BA) can be estimated simultaneously based on LiDAR data, and the joint estimation of these major forest stand factors based on LiDAR has not yet been reported.

In this study, we used LiDAR data and synchronous ground survey data from 190 sample plots in spruce (*Picea* spp.), fir (*Abies* spp.), and spruce–fir mixed forests distributed in the forest region of northeastern China and estimated eight major stand factors, including the mean diameter at breast height, mean tree height, mean dominant tree height, number of trees, basal area, volume, biomass, and carbon storage per hectare based on the error-in-variable simultaneous equations method [34]. Then, we comprehensively evaluated the various errors of the model [35] to provide a scientific basis for standardizing the estimation methods of the major stand factors and advancing the application of LiDAR technology in forest resource inventory and monitoring.

2. Data and Methods

2.1. Study Area

The study areas involved eight Forestry Bureaus, which were distributed in five forest regions in Northeast China, including Tahe and Xinlin in the Daxinganling region, Zhanhe and Nancha in the Xiaoxinganling region, Fangzheng in the Songhuajiang region, Weihe in the Mudanjiang region, and Dunhua and Bajiazi in the Changbaishan region. The five forest regions are located between 41°29′–53°21′ N, 123°19′–129°25′ E (Figure 1). The spruce (*Picea* spp.), fir (*Abies* spp.), and spruce–fir mixed forests selected in our study were also the typical coniferous forest types that are widely distributed in northeastern China.

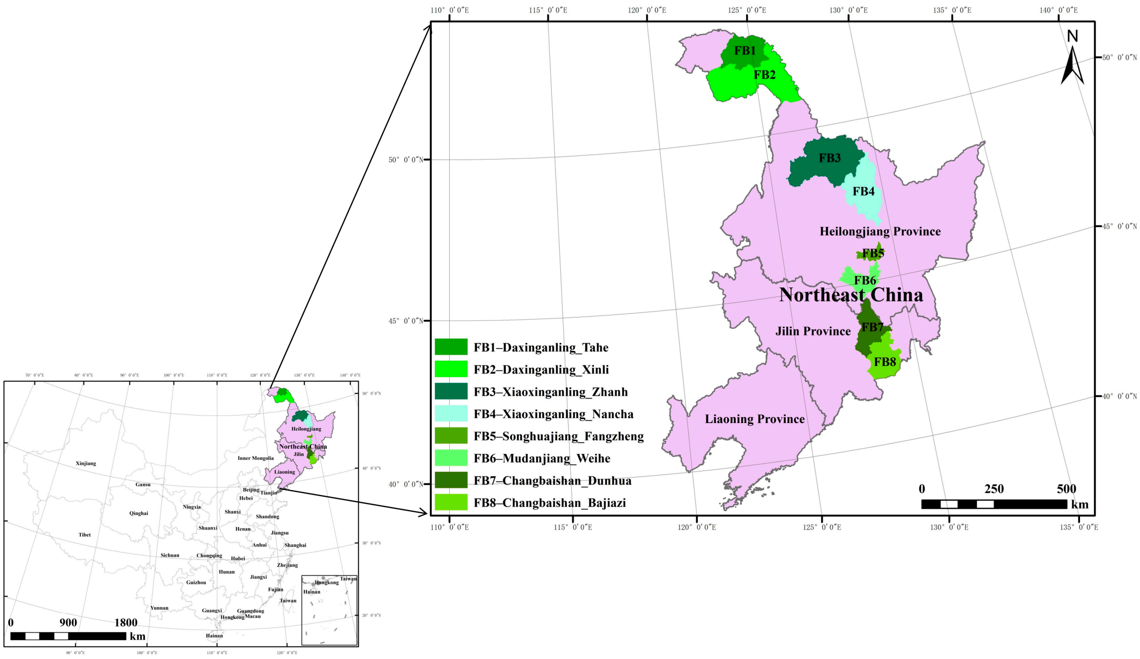

Figure 1. Locations of the eight Forest Bureaus in which 199 sample plots were distributed.

2.2. Data Collection

2.2.1. Field Data

The data used in this study were collected from 199 sample plots in spruce, fir, and spruce–fir mixed forests distributed in the eight Forest Bureaus mentioned above. The ground survey was conducted from September to November 2019. The sample plot was circular with an area of 600 m^2, and the coordinates of the center point were positioned with RTK equipment with a positioning accuracy of 0.2 m. In addition to measuring the diameter at the breast height of each tree with a tape meter, the heights of 15 sample trees distributed in five different diameter classes/groups were also measured with a Blume-Leiss altimeter or laser altimeter. Based on these, a tree height–diameter at breast height curve model was established to estimate the height of each tree on a plot and combined with the two-variable tree volume model [36], the biomass model, and the carbon content coefficient [37,38]; the volume, biomass and carbon stock of trees and plots were calculated. The mean diameter at breast height, mean tree height (the height corresponding to the mean DBH), mean dominant tree height (the mean height of the three tallest trees in a plot), number of trees, and basal area per hectare were also calculated for each sample plot. These eight key quantitative factors of stands, including the mean diameter at breast height, mean tree height, mean dominant tree height, number of trees per hectare, basal area per hectare, volume per hectare, biomass per hectare, and carbon storage per hectare, were defined as the target variables in the modeling process.

2.2.2. Aerial Data

The coverage range and acquisition time of the LiDAR data are the same as those of the field survey, which was conducted from September to October 2019. A vertical take-off and landing fixed-wing UAV modeled YC–02 was selected to carry out the flight missions. A total of 49 sorties with a flight altitude of 350 m, covering 695 square kilometers, were conducted in the mentioned eight Forest Bureaus. The flight weather required avoiding strong winds, rain, and snow. The RIEGL-VUX-1UAV laser scanning system was used to obtain LiDAR point cloud data, and the main parameters of the LiDAR system were as follows: a measurement accuracy of 10 mm, a maximum distance measurement range of 920 m, a maximum transmission frequency of 550 kHz, a maximum effective measurement rate of 500,000 times per second, a point cloud density greater than 4 points per square meter, and on-site positioning accuracy of 0.11 m. After completing the raw data prepossessing, classification, and adjustment, the digital elevation model (DEM), digital surface model (DSM), and canopy height model (CHM) were applied to process the point cloud data, and 98 metrics reflecting the height, density, and structure of the forest stands were extracted as the explanatory variables for modeling [29].

2.2.3. Data Screening

Before modeling, abnormal data or outliers were determined and eliminated by drawing scatter plots between core target variables and key explanatory variables. A total of 9 sample plots were eliminated, and the remained 190 sample plots ultimately constitute the modeling data. Table 1 shows the statistical parameters of the eight main forest stand factors.

Table 1. Statistical parameters of eight forest stand factors used for modeling plots.

Forest Stand Factors	Mean	Min	Max	Standard Deviation (SD)	Coefficient of Variation (CV)/%
Mean diameter at breast height D (cm)	16.8	7.6	30.6	4.8	28.3
Mean tree height H (m)	14.13	4.59	24.85	3.93	27.8
Mean dominant tree height H_d (m)	18.71	5.15	28.23	4.10	21.9
Number of trees per hectare N (ha^{-1})	1097	400	3133	461	42.0
Basal area per hectare G (m^2/ha)	23.02	1.93	45.22	9.16	39.8
Volume per hectare V (m^3/ha)	185.8	5.3	491.8	100.7	54.2
Biomass per hectare B (t/ha)	140.1	6.7	326.2	67.1	47.9
Carbon storage per hectare C (t/ha)	68.5	3.3	156.3	32.7	47.7

2.3. Modeling Method

Based on the screened airborne LiDAR data and ground survey data of 190 spruce–fir forest plots, independent regression models for the estimation of the main stand factors were established according to the correlations between the mean tree height, basal area, and volume of stands, and the main metrics were extracted from the LiDAR data and the relationships between eight quantitative factors of forest stands. Then, the error-in-variable simultaneous equations approach was employed to fit the models.

2.3.1. Independent Models

According to the conclusions of existing studies, forest volume is mainly related to the variable with the largest positive correlation (the mean height of the point cloud) and the largest negative correlation (the mean intensity of the point cloud) among the 98 LiDAR metrics [29]. Since volume is the most important target variable for forest resource inventories and mainly depends on the mean tree height and basal area of the stands [27], our research utilized the key LiDAR metrics, the mean height (X_1) and mean intensity (X_2) of the point cloud, to establish prediction models for the direct estimation of the main factors of stands, including the mean tree height, basal area, and stand volume.

$$H = a_0 {X_1}^{a1} {X_2}^{a2} + \varepsilon_H \tag{1}$$

$$G = b_0 {X_1}^{b1} {X_2}^{b2} + \varepsilon_G \tag{2}$$

$$V = c_0 {X_1}^{c1} {X_2}^{c2} + \varepsilon_V \tag{3}$$

In these equations, H is the mean tree height of the stand (m), G is the basal area per hectare (m^2/ha), V is the volume per hectare (m^3/ha), X_1 is the mean height of the point cloud, X_2 is the mean intensity of the point cloud, a_i, b_i, and c_i are the model parameters, and ε_H, ε_G, and ε_V are the error terms, which are assumed to follow a normal distribution with a mean of zero.

According to the correlations between biomass, carbon storage, and volume, as well as the correlations between the mean diameter at breast height, the mean dominant tree height, and the mean tree height [34], the following regression model can be developed:

$$B = d_0 + d_1 V + \varepsilon_B \tag{4}$$

$$C = e_0 B + \varepsilon_C \tag{5}$$

$$D = f_0 H^{f1} + \varepsilon_D \tag{6}$$

$$H_d = g_0 + g_1 H + \varepsilon_{Hd} \tag{7}$$

where B is the biomass per hectare (t/ha), C is the carbon storage per hectare (t/ha), D is the mean diameter at breast height (cm), H_d is the mean dominant tree height (m), d_i, e_i, f_i, and g_i are model parameters, and ε_B, ε_C, ε_D, and ε_{Hd} are error terms, which are assumed to follow a normal distribution with a mean of zero. The other symbols in the equations are the same as those mentioned above.

In addition, the number of trees per hectare N can be directly calculated from the basal area per hectare G and the mean diameter at breast height D. The calculation formula is as follows:

$$N = G/(\pi D^2/40000) \tag{8}$$

Models (1) to (7) can be independently fitted based on the data from the 190 sample plots. Except for Equations (1), (6), and (7), which can be fitted by the ordinary regression method due to insignificant heteroscedasticity, the other four models from (2) to (5) should be fitted by the weighted regression method [35].

2.3.2. Simultaneous Models

Due to the correlations between models for the estimation of the eight forest stand factors mentioned above, if they are all fitted independently, there will be two deficiencies. On the one hand, the compatibility between the parameter estimates cannot be guaranteed. For example, the independent fitting of Equations (2) and (6) cannot satisfy the establishment of Equation (8). On the other hand, the transmission of errors cannot be taken into account in the models with progressive relationships. For example, the estimation of Equations (4) and (5) do not consider the estimation errors of the volume and biomass, respectively. Therefore, only by transforming the eight independent models mentioned above into a set of equations and solving the parameters via the error-in-variable simultaneous equations method [27,34], can we ensure the compatibility between parameters and consider the impact of error transmission in order to objectively evaluate the accuracy of forest stand factors based on LiDAR data. The simultaneous equations are as follows:

$$\begin{cases} \hat{H} = a_0 X_1^{a_1} X_2^{a_2} \\ \hat{G} = b_0 X_1^{b_1} X_2^{b_2} \\ \hat{V} = c_0 X_1^{c_1} X_2^{c_2} \\ \hat{B} = d_0 + d_1 \hat{V} \\ \hat{C} = e_0 \hat{B} \\ \hat{D} = f_0 \hat{H}^{f_1} \\ \hat{H}_d = g_0 + g_1 \hat{H} \\ \hat{N} = \hat{G}/(\pi \hat{D}^2/40000) \end{cases} \tag{9}$$

In these equations, $\hat{H}, \hat{G}, \hat{V}, \hat{B}, \hat{C}, \hat{D}, \hat{H}_d, \hat{N}$ are the estimates of the mean tree height, basal area per hectare, volume per hectare, biomass per hectare, carbon storage per hectare, mean diameter at breast height, mean dominant tree height, and number of trees per hectare, respectively. The parameters are the same as those mentioned above.

2.3.3. Model Evaluation

The coefficients of determination (R^2), standard error of estimates (SEE), total relative error (TRE), average systematic error (ASE), mean prediction error (MPE), and mean percentage standard error (MPSE) are the indices widely used for models evaluation [34,35], and the key indices for evaluating whether models are applicable in forest inventory are the MPE and MPSE. For the simultaneous prediction models of eight forest stand factors, the six evaluation indices mentioned above were calculated to assess the models. In addition, the residual plot is also an important reference for the evaluation of models, and the residuals are generally required to be distributed randomly.

3. Results and Analysis

The eight forest stand factors from the field survey and LiDAR data collected from 190 spruce–fir forest sample plots were used to simultaneously fit the independent models from (1) to (8) and, simultaneously, model (9), respectively. The parameter estimates and six evaluation indices for the models are shown in Table 2, and the estimated effects of the simultaneous models are shown in Figure 2.

Table 2. Estimates and evaluation indices of independent and simultaneous models.

Type	Factors	Parameter Estimates			Evaluation Indices					
		a_0~g_0	a_1~f_1	a_2~c_2	R^2	SEE	TRE/%	ASE/%	MPE/%	MPSE/%
Independent model	H	8.17	0.6618	−0.3226	0.696	2.19	0.07	0.33	2.21	12.55
	G	10.50	1.0234	−0.5259	0.699	5.07	−0.03	−0.21	3.15	18.86
	V	65.38	1.5221	−0.8354	0.743	51.49	−0.11	−0.25	3.97	21.68
	B	9.330	0.7050	/	0.888	22.63	−0.15	0.86	2.31	10.99
	C	0.4886	/	/	0.899	10.40	−0.09	0.91	2.17	10.54
	D	1.780	0.8491	/	0.695	2.64	0.07	0.34	2.25	12.03
	H_d	7.34	0.8048	/	0.596	2.62	0.00	−0.17	2.00	12.39
	N	/	/	/	0.115	442	2.83	5.90	5.77	31.24
Simultaneous model	H	3.46	0.6052	/	0.664	2.29	−1.37	−1.97	2.32	13.00
	G	31.85	1.0331	−0.8960	0.672	5.29	1.84	2.93	3.29	19.92
	V	71.47	1.4719	−0.8316	0.742	51.61	2.21	1.27	3.98	22.07
	B	5.085	0.7334	/	0.709	36.67	1.24	2.67	3.75	21.84
	C	0.4890	/	/	0.712	17.82	1.22	2.65	3.72	21.61
	D	0.7256	1.1810	/	0.692	2.67	−0.67	−0.07	2.28	12.69
	H_d	5.80	0.8968	/	0.551	2.78	0.35	−0.22	2.12	12.29
	N	/	/	/	0.060	456	10.42	10.59	5.94	32.79

As shown in Table 2, differences existed between the estimation results of the independent models and the simultaneous models for the eight forest stand factors. Since the simultaneous models are affected by both the correlation between equations and error transmission, most of its evaluation indices are slightly worse than those of the independent models, among which R^2 decreases, while SEE and the other four error indices increase. The MPEs of the eight forest stand factors estimated by the simultaneous models were mostly within 5%, and only the MPE of the number of trees per hectare exceeded 5%. The MPSEs of the estimates for the mean diameter at breast height, mean tree height, and mean dominant tree height were within 15%; the MPSEs of the estimates for the basal area, volume, biomass, and carbon stock per hectare were approximately 20%; and only that of the estimated number of trees per hectare exceeded 30%. The R^2 values of the core prediction models for volume, biomass, and carbon storage per hectare were all greater than 0.7, and the R^2 of the models for the stand basal area, mean DBH, and mean tree height (H) were more than 0.66. We noticed that two models for mean dominant height (H_d) and number of trees per hectare (N) performed worse. The first reason is that spruce–fir forests are close to uneven-aged but regarded as even-aged stands, resulting in a decrease in relationships between stand factors, such as H_d, H, D, and N. The second reason is the error propagation; that is, the error in the H_d estimate includes both errors in the H estimate and the H_d–H model. Similarly, the error in the N estimate includes both errors in the D estimate and the stand basal area estimate (G).

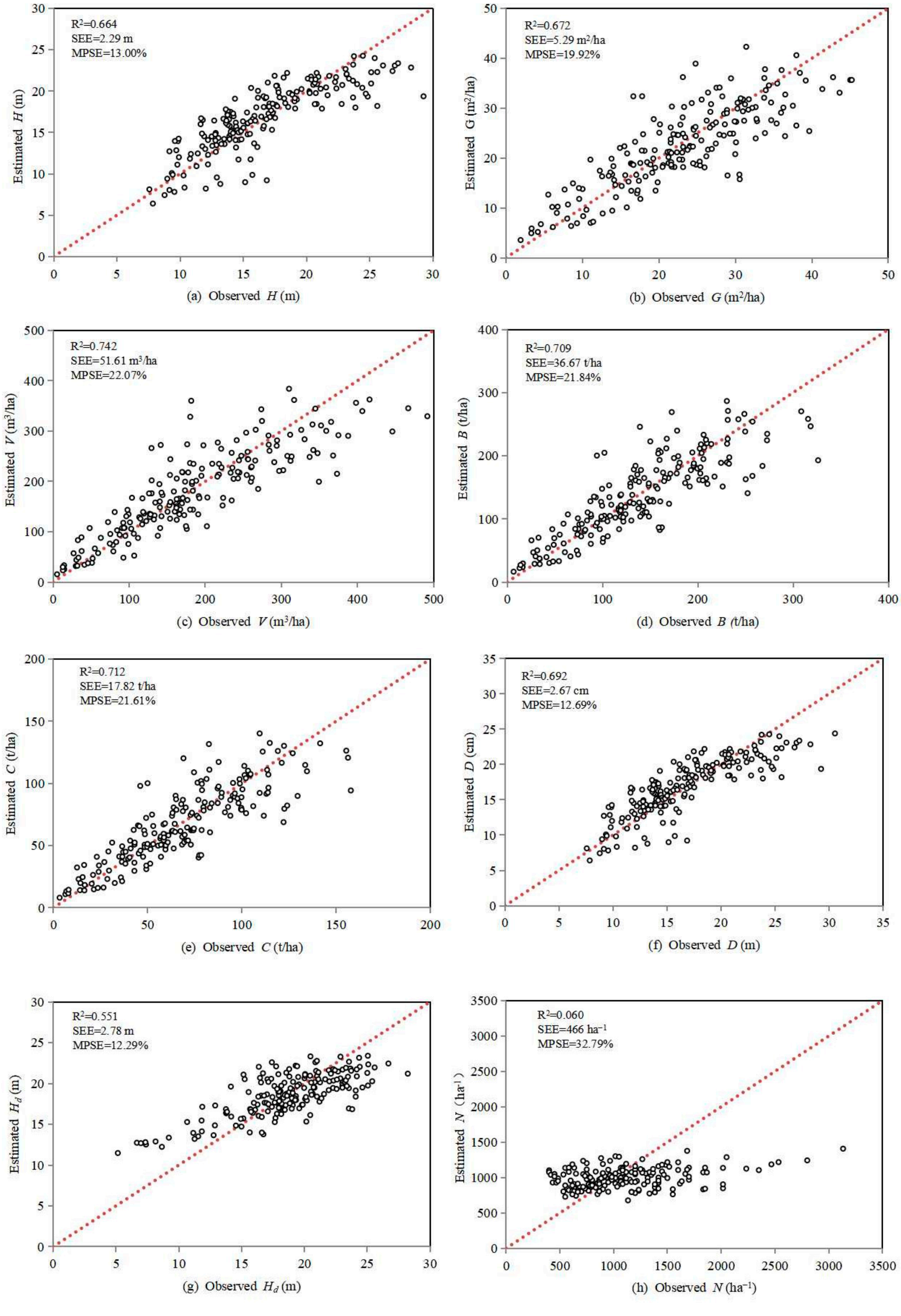

Figure 2. Fitting performance of simultaneous models for eight stand factors. (**a**) Mean tree height; (**b**) Basal area; (**c**) Volume; (**d**) Biomass; (**e**) Carbon storage; (**f**) Mean diameter at breast height; (**g**) Mean dominant tree height; (**h**) Number of trees. The red dashed line is y = x line.

In addition, the TRE and ASE of the main forest stand factors that were estimated by the simultaneous models were all within ±3%, with the exception of those for the number of trees, which had larger errors. This indicates a good estimation of the overall eigenvalues without a systematic bias. Figure 3 shows the distribution of the relative errors of the volume and carbon stock models with X_1 as the mean height of the point cloud, which can be considered a random distribution. Although the MPSEs of both the volume and carbon stock models are within 25%, the main distribution of the relative errors ranges by ±40%, and the errors of some sample plots even exceed 90%. The residual distributions of other factors are similar and were omitted here.

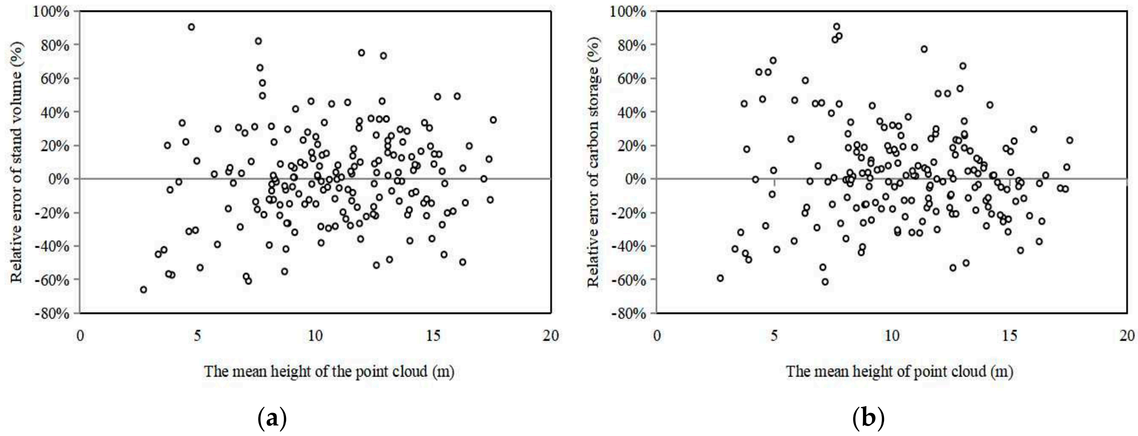

Figure 3. The distribution of relative errors of the stand volume and carbon storage models with the mean height of the point cloud: (**a**) stand volume, (**b**) carbon storage.

4. Discussion

Combining the actual data requirements of forest resource inventory and monitoring at present in China and referencing previous research results, our research used the error-in-variable simultaneous equations approach for estimating the eight main forest stand factors. This approach not only ensures the consistency of the estimates of forest stand factors but also solves the problem of error transmission between the estimation results of the related factors.

When applying LiDAR data combined with field survey data to construct prediction models of stand factors, our research utilized the key LiDAR metrics, namely, the mean height (X_1) and mean intensity (X_2) of the point cloud, to establish prediction models for the direct estimation of stand volume and other main factors. The two selected explanatory variables are also widely used in other related studies when constructing main forest stand factor prediction models. Bottalicoa et al. [39] extracted 49 metrics from LiDAR point cloud data as explanatory variables for the estimation of volume and other main stand factors, and their results showed that the mean height of the point cloud had the greatest correlation with the estimated stand volume. White et al. [40] also concluded that the mean height of the point cloud was one of the most important predictor variables in volume estimation based on ALS data. The variables selected in these studies are basically consistent with the explanatory variables employed in our study. Furthermore, the metrics, including different percentiles of normalized point heights and standard deviations of point heights, derived from the height of point cloud data were also used to establish prediction models for the top height, basal area, and total plot volume, and the R^2 values of the models were 0.76, 0.71, and 0.78, respectively [41]. The results indicate that the models can meet the needs of forest inventories. In the research conducted by Mariano García et al. [42] for biomass and carbon stock estimation based on LiDAR data, the mean height of the point cloud data was the explanatory variable selected for model estimation of above-ground biomass (AGB) and branch biomass (BB) modeling, which is consistent with the key variable X_1, used in our study for volume and biomass prediction. However, for the intensity-based models in their work, both the general models and species-specific models, the variables used for modeling were % int_P_i, CV_i, and DWCRS, among others, which were derived from the normalized intensity of the LiDAR data rather than X_2 (the mean intensity of the point cloud) directly, as used in our study. However, it is worth noting that the mean intensity of the point cloud data, used in our study for volume and biomass estimation, was also employed as a correction factor in their study. They calculated the density-weighted canopy reflection sum (DWCRS) based on the mean intensity of the point cloud data, and the DWCRS was the key explanatory variable for the estimation of the AGB and FB of holm oak. The R^2 values of the corresponding models were 0.98 and 0.96, respectively, indicating the best-fitting effects among the models mentioned in their study.

In order to objectively evaluate the estimation errors of different forest stand factors, conventional indices such as the coefficient of determination (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) were widely used for the evaluation of models in previous studies [24–26,31,32], but various relative error indices that can reflect the practicality of models, such as the TRE, ASE, MPE, and MPSE [34], were not selected for the model evaluation. There is no doubt that R^2 is one of the most important indices for model evaluation, but the quality of a model cannot be evaluated entirely by it. This can be supported by comparing the R^2 values of the simultaneous models of eight forest stand factors and the other four error indices in Table 2: the models with the highest R^2 values do not have better performance in the four error indices, while the models with the lowest R^2 values do not have the worst performance in the four error indices. Furthermore, the RMSE and SEE are basically equivalent, and the difference between them is similar to that between the coefficient of determination R^2 and the adjusted coefficient of determination R^2_{adj}. Since the RMSE or SEE of different research subjects varies greatly, these kinds of indices are not comparable. The model evaluation indices that can be used to compare models include a variety of relative error indices, such as the commonly used RRMSE and the four error indices used in this study.

The purpose of modeling is to find universal rules and apply them to various predictions or forecasts; hence, the determination of evaluation indices is highly important. Previous studies have established a comprehensive index framework that can be used to conduct model evaluation [35], which contains the six basic indices listed in Table 2. Except for the two conventional indices R^2 and SEE (which are similar to RMSE but related to MPE), the other four indices, namely, TRE, ASE, MPE, and MPSE, are all relative error indices. The practicality of the prediction models of forest stand factors mainly depends on the magnitude of two indicators, MPE and MPSE. The former can be used to assess the estimation error of the population, while the latter can be used to assess the estimation error of a single unit in the population, such as a plot, a stand, or a sub-compartment. The simultaneous models established for the estimation of the eight forest stand factors in this study had MPE values between 2.12% and 5.94%, with only the MPE of the model for the estimation of the number of trees per hectare exceeding 5%; the MPSE values ranged from 12.29% to 32.79%, with only that of the model for the number of trees per hectare exceeding 30%. In this study, we focused on the establishment of simultaneous models and did not pay much attention to the improvement of each model, such as the dominant tree height model. We would make further efforts to improve the performance of each model in a future study. One direction is to combine laser scanning metrics with derived canopy surface texture metrics [43].

We know that the Technical regulations for inventory for forest management planning and design [44] classified the accuracy of field surveys of volume per hectare into three levels—A, B, and C—and each level required that the errors do not exceed 15%, 20%, and 25%, respectively. As seen from the MPSE in Table 2, the estimations of the three core variables of forest stands (volume, biomass, and carbon storage) all met the C-level accuracy requirements. Traditional methods for conducting field surveys that can meet the accuracy requirements mentioned in the Technical regulations for inventory for forest management planning and design are time-consuming and labor-intensive. When LiDAR data are used to construct the prediction model, only the relevant metrics need to be extracted to obtain unbiased estimation values with guaranteed accuracy. This new approach not only improves work efficiency but also ensures the objectivity and authenticity of the results.

5. Conclusions

Based on the results of this study, the following conclusions can be drawn:

(1) It is technically feasible to estimate the main stand factors, such as the volume, biomass, carbon storage per hectare, mean diameter at breast height, average tree height, mean dominant tree height, number of trees, and basal area per hectare, using the error–in–variable simultaneous equations method based on airborne LiDAR and ground survey sample plot data.

(2) The MPE values of the eight main forest stand factor prediction models for spruce–fir forests in Northeast China were all less than 5%, with the exception of that of the number of trees. The MPSE values reflecting the accuracy of the models for a single unit of population were below 25%, indicating that the accuracy of the established models can meet the requirements of the Technical regulations for inventory for forest management planning and design and can be promoted and applied in practice.

(3) To increase the accuracy of the estimates of the main stand factors, especially the dominant height and tree number per hectare, it is necessary to improve the goodness–of–fit of each model in the simultaneous equations in future studies. One approach is to combine LiDAR data with other remote sensing data to enhance the potential of applications.

Author Contributions: W.Z. (Wentao Zou) jointly conceived the study with W.Z. (Weisheng Zeng); X.S. designed the experiments and collected data; W.Z. (Wentao Zou) and W.Z. (Weisheng Zeng) developed the models and wrote the manuscript. All authors have read and agreed to the published version of the manuscript.

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