

Article

Can Stereoscopic Density Replace Planar Density for Forest Aboveground Biomass Estimation? A Case Study Using Airborne LiDAR and Landsat Data in Daxing'anling, China

Xuan Mu ^{1,2}, Dan Zhao ^{1,2,*}, Zhaoju Zheng ¹, Cong Xu ¹, Jinchen Wu ^{1,2}, Ping Zhao ^{1,2}, Xiaomin Li ^{1,2}, Yong Pang ³ , Yujin Zhao ⁴, Tianyu An ⁵, Yuan Zeng ^{1,2} and Bingfang Wu ^{1,2} 

¹ State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100101, China; muxuan22@mails.ucas.ac.cn (X.M.); zhengzhaoju@aircas.ac.cn (Z.Z.); xucong@aircas.ac.cn (C.X.); wujinchen22@mails.ucas.ac.cn (J.W.); zhaoping22@mails.ucas.ac.cn (P.Z.); lixiaomin231@mails.ucas.ac.cn (X.L.); zengyuan@aircas.ac.cn (Y.Z.); wubf@radi.ac.cn (B.W.)

² University of Chinese Academy of Sciences, Beijing 100049, China

³ Institute of Forest Resource Information Techniques, Chinese Academy of Forestry, Beijing 100091, China; pangy@ifrit.ac.cn

⁴ State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing 100093, China; zhaoyj@ibcas.ac.cn

⁵ Academy of Inventory and Planning, National Forestry and Grassland Administration, Beijing 100013, China; antianyu@forestry.gov.cn

* Correspondence: zhaodan@aircas.ac.cn; Tel.: +86-186-1162-2725

Abstract: Forest aboveground biomass (AGB) is a key indicator for evaluating carbon sequestration capacity and forest productivity. Accurate regional-scale AGB estimation is crucial for advancing research on global climate change, ecosystem carbon cycles, and ecological conservation. Traditional methods, whether based on LiDAR or optical remote sensing, estimate AGB using planar density (t/ha) multiplied by pixel area, which fails to account for vertical forest structure variability. This study proposes a novel “stereoscopic (stereo) density $\times$ volume” approach, upgrading planar density to stereo density (t/ha/m) by integrating canopy height information, thereby improving estimation accuracy and exploring the feasibility of this new method. In the Daxing'anling region, plot-scale AGB estimation models were developed using stepwise linear regression (SLR) for both “planar density $\times$ area” and “stereo density $\times$ volume” methods. Results indicated that the stereo model using arithmetic mean height (H_{AM}) achieved comparable accuracy ($R^2 = 0.83$, RMSE = 2.77 t) with the planar model ($R^2 = 0.83$, RMSE = 2.52 t). At the regional scale, high-precision AGB estimates derived from airborne LiDAR were combined with vegetation indices from the Landsat Thematic Mapper (TM), and topographic factors from DEM to develop regional-scale AGB estimation models, using SLR and random forest (RF) algorithms. The results of 10-fold cross-validation demonstrated the superiority of the stereo method over the planar method, with RF outperforming SLR. The optimal RF-based stereo model of H_{AM} ($R^2 = 0.65$, rRMSE = 26.05%) significantly improved AGB estimation compared to the planar model ($R^2 = 0.59$, rRMSE = 30.41%). Independent accuracy validation using 75 field plots demonstrated that the stereo model achieved a higher validation R^2 of 0.45 compared to the planar model's R^2 of 0.35. These findings suggest that the stereo approach mitigates the underestimation of AGB caused by forest height variability in planar methods, with no significant differences observed across forest types. In conclusion, the use of the stereo method to estimate forest AGB is superior to the planar method in optical remote sensing. This approach offers a scalable solution for forest AGB estimation and carbon stock assessment.



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Keywords: forest aboveground biomass; airborne LiDAR; Landsat; canopy height; stereoscopic density $\times$ volume estimation; Daxing'anling region

1. Introduction

Forests are a vital component of terrestrial ecosystems, covering approximately 30% of the Earth's land surface. Through photosynthesis, they sequester carbon dioxide and accumulate biomass, playing a crucial role in maintaining the Earth's carbon balance [1]. As the largest vegetation carbon reservoir, forests store approximately 80% of aboveground carbon and 40% of belowground carbon [2], making them a critical pathway to achieving carbon neutrality. Forest aboveground biomass (AGB) is a key metric for assessing both carbon sequestration capacity and forest productivity. It is of significant value for advancing research on global climate change, ecosystem carbon cycling, and ecological conservation [3]. Consequently, the accurate and efficient monitoring and estimating of forest AGB has become a central focus in remote sensing research [4,5].

Traditional ground-based methods for measuring forest AGB require cutting sample trees to construct allometric equations, which can accurately capture individual tree and plot-level data. But these methods require significant labor and resources, are costly and inefficient, and may cause varying degrees of disturbance to forest ecosystems. As a result, they are suitable only for small-scale measurements and sampling, falling short of the requirements for large-scale forest resource monitoring. In contrast, remote sensing offers several advantages, including minimal environmental disturbance, high efficiency, extensive coverage, and relatively high accuracy. Remote sensing-based AGB estimation effectively addresses the limitations of traditional field surveys, reducing the need for labor and resources while significantly improving efficiency. As a result, it has thus become a key approach for estimating forest AGB [6,7].

Optical remote sensing is widely applied to large-scale and long-term forest AGB estimation due to its extensive coverage and multi-temporal capabilities. The primary approach involves deriving forest feature indices based on spectral data, texture information, and vegetation indices, which are then used to establish linear or nonlinear relationships with measured biomass data [8,9]. This enables dynamic forest resource monitoring at various scales. However, optical remote sensing is prone to saturation effects in dense vegetation and is sensitive to environmental factors such as cloud cover and atmospheric conditions, which can lead to AGB underestimation [10–12]. To reduce these limitations, researchers have explored multi-seasonal data and spatial regression models, which have shown promise in mitigating saturation and improving accuracy [9,13].

Microwave remote sensing, particularly synthetic aperture radar (SAR), offers advantages such as weather independence and canopy penetration, making it suitable for capturing forest structural information [14]. However, SAR data are sensitive to topography and often require complex processing, limiting their widespread application [15]. Recent studies have demonstrated the potential of integrating SAR with optical data to combine spectral and structural information, thereby improving AGB estimation accuracy [16,17].

Light Detection and Ranging (LiDAR) actively emits laser pulses and receives return signals to measure distances with high precision. Compared to optical remote sensing, LiDAR is capable of operating effectively under a wider range of weather conditions. It has penetration abilities that make it particularly advantageous for acquiring forest height and detailed vertical vegetation structure information [18–20]. As one of the most widely used techniques for high-accuracy AGB estimation, LiDAR offers exceptional potential at both tree- and plot-level scales, especially when deployed via UAVs [20,21]. Furthermore,

the integration of LiDAR with optical data has been shown to enhance AGB estimation by combining structural and spectral information [22]. Satellite-based LiDAR systems, such as ICESat-2 and GEDI, have also contributed to regional and global AGB mapping, although they face challenges related to spatial coverage and terrain effects [23,24].

The Daxing'anling region, a critical component of China's northeastern temperate coniferous–broadleaf mixed forests, holds significant ecological importance and has been a focal area for advancing AGB estimation methodologies. Ground-based allometric equations developed through destructive sampling ($R^2 > 0.90$) for dominant species have provided essential biomass references for the region [25,26]. However, scaling these models to regional levels using remote sensing remains challenging. Liu et al. (2017) compared stepwise regression (SR), support vector regression (SVR), and random forest (RF) models for AGB estimation using Landsat Thematic Mapper (TM) and Geoscience Laser Altimeter System (GLAS) data. The RF model with Landsat data achieved high accuracy ($R^2 = 0.95$, RMSE = 17.73 Mg/ha), with reliable cross-validation ($R^2 = 0.71$, RMSE = 39.60 Mg/ha), while integrating GLAS data slightly enhanced SR and SVR performance [27]. This underscores the utility of machine learning methods for handling spectral data in remote sensing applications. Fusing airborne LiDAR metrics with Landsat and hyperspectral data [28] has further improved AGB estimation precision ($R^2 = 0.85$, RMSE = 18.17 Mg/ha), highlighting the potential of integrated approaches. Despite these advancements, optical remote sensing data still face limitations in capturing vertical structural variations, which can affect biomass estimation accuracy in forests.

Currently, forest AGB estimation, whether based on optical remote sensing data or LiDAR data, primarily relies on AGB planar density. This approach expresses AGB density in units such as “tons per hectare (t/ha)” or “grams per square meter (g/m^2)” and multiplies these values by pixel area to estimate pixel-level AGB [22,29]. Such planar density models are widely used for ground plot observations and pixel-by-pixel regional monitoring. However, they only reflect AGB distribution differences on a two-dimensional plane, failing to account for variations in vertical structure. Consequently, this limitation hinders further improvements in the accuracy of forest AGB estimation. To address this issue, this study introduces a novel AGB estimation method based on the concept of “stereoscopic (stereo) density $\times$ volume”. By incorporating measurable canopy height information—such as arithmetic mean height, basal area-weighted mean height, and canopy area-weighted mean height [30–32]—the planar AGB density unit of “t/ha” is transformed into a stereo density unit of “t/ha/m”. This adjustment supplements AGB information in the vertical dimension, mitigating the underestimation of AGB caused by height variations in optical remote sensing data. This study aims to evaluate the feasibility of this new method and its potential for improving regional AGB estimation and carbon stock assessment.

2. Materials and Methods

2.1. Study Area

The study area consists of two parts: the LiDAR airborne survey area and the optical remote sensing coverage area. The optical remote sensing area corresponds to the Daxing'anling region, which forms the western part of the Greater Hinggan Mountains in China (Figure 1b), located at longitude $118^\circ 46'$ to $127^\circ 08'E$ and latitude $43^\circ 51'$ to $53^\circ 33'N$. It is situated in the northwestern part of Heilongjiang Province and the northeastern part of the Inner Mongolia Autonomous Region, acting as a watershed between the Inner Mongolia Plateau and the Songliao Plain. This region connects Inner Mongolia, Heilongjiang, and Jilin provinces, extending in a continuous line from the Taihang and Xuefeng mountains. The terrain of the Daxing'anling region trends southwest and is characterized by low hills, with elevations ranging from 1100 to 1400 m. The climate is classified as cold temperate

continental monsoon, with an annual average temperature of $-2.8\text{ }^{\circ}\text{C}$ and a record low of $-52.3\text{ }^{\circ}\text{C}$. The region receives an annual average precipitation of 746 mm.

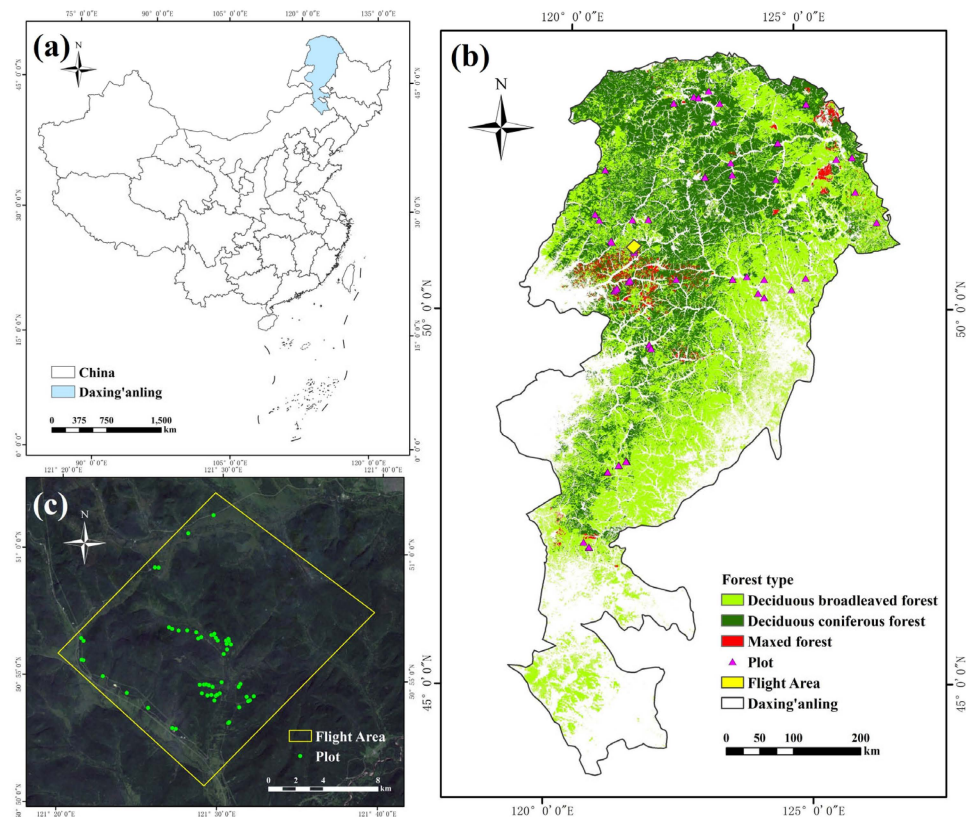


Figure 1. Study area location map. (a) Geographic location of the study area. (b) Study area with ChinaLandCover data. (c) Flight study area with Landsat 5 TM data (Red: 660 nm, Green: 560 nm, Blue: 485 nm).

The LiDAR airborne survey area is located in the Genhe Experimental Research Area of the Daxing'anling region (Figure 1c), in the northwestern part of Genhe City, Hulunbuir, Inner Mongolia Autonomous Region, China. This area spans from $121^{\circ}20'$ to $121^{\circ}39'E$ and from $50^{\circ}50'$ to $51^{\circ}02'N$. This area encompasses the main forest types of the Daxing'anling and the Genhe Ecological Station of Inner Mongolia Agricultural University, which include *Larix gmelinii*, *Betula platyphylla*, and *Populus davidiana*.

2.2. LiDAR Data

The airborne LiDAR data for the study area were collected in September 2012, covering an area of approximately 200 km^2 (Figure 1c). The airborne LiDAR system used was the ALS60, with a maximum pulse frequency of 200 kHz and a maximum field of view of 75° . At a flight altitude of 750 m, the system achieved horizontal and vertical accuracy of 8 cm. A total of 32 flight strips of LiDAR data were obtained, yielding point cloud data with a point density exceeding 4 points per m^2 . The LiDAR data were pre-processed to remove noise, classify ground points, and normalize the data. A high-resolution digital elevation model (DEM) and canopy height model (CHM) were produced for the study area. Subsequently, forest feature parameters were extracted based on a $30\text{ m} \times 30\text{ m}$ grid, including height variables, canopy closure, leaf area index, and gap fraction [33–35], as shown in Table 1.

Table 1. Forest feature parameters derived from LiDAR data.

Feature Variable	Description
Canopy Closure (CC)	$CC = n_{vegfirst}/n_{first}$, the ratio of vegetation points in the first return to the total first return points.
Gap Fraction (GF)	$GF = n_{ground}/n$, the ratio of ground points to total points.
Leaf Area Index (LAI)	$LAI = -\cos(ang) \times \ln(GF)/k$, where ang is the average scan angle, GF is the gap fraction, and k is the extinction coefficient.
Canopy Relief Ratio (CRR)	$V = (mean - min)/(max - min)$, where $mean$, min , and max are height values of all points within a unit.
Accumulated Height Percentile (AIH)	Cumulative height of X% of points in a statistical unit based on normalized LiDAR data.
Interquartile Range of AIH (IQ)	Difference between the 75% and 25% percentiles of accumulated height.
Kurtosis	Coefficient of variation in Z-values within a statistical unit.
Coefficient of Variation (cv_z)	Measure of the flatness of Z-value distribution in a unit.
Density	Proportion of echoes in each of ten equally distributed height slices.
Median	Median Z-value of all points within a unit.
Max	Maximum Z-value of all points within a unit.
Min	Minimum Z-value of all points within a unit.
Mean	Mean Z-value of all points within a unit.
Height Percentile (Elev)	Height at the X% percentile of normalized LiDAR data within a unit.
Skewness	Symmetry of Z-value distribution in a unit.
Stddev	Standard deviation of Z-values within a unit.
Variance	Variance of Z-values within a unit.

2.3. Field Data

The ground survey data (Figure 1c) was collected from mid-August to early September 2012, synchronized with the airborne LiDAR data acquisition. A total of 37 ground survey plots, each measuring 30 m × 30 m, were established. The field inventory measured individual trees with a minimum breast height diameter (DBH) of 5 cm. Data collected included DBH, tree height, height to the first branch, and crown diameter for each tree. Using the survey data, we applied additive biomass models to calculate the AGB for each plot [26]. We also calculated five types of canopy height information, which were used to obtain the stereo density: maximum height, geometric mean height, arithmetic mean height, DBH-weighted mean height, and canopy area-weighted mean height, as shown in Table 2.

Table 2. Canopy Height information.

Height Type	Calculation Formula
Maximum Height	$H_{Max} = MAX(H_1, H_2, \dots, H_n)$
Geometric Mean Height	$H_{GM} = \sqrt[n]{H_1 H_2 \dots H_n}$
Arithmetic Mean Height	$H_{AM} = (H_1 + H_2 + \dots + H_n)/n$
DBH-weighted Mean Height	$H_{Lor} = (\sum_{i=1}^n H_i G_i) / (\sum_{i=1}^n G_i)$
Canopy Area-weighted Mean Height	$H_{CW} = (\sum_{i=1}^n H_i A_i) / (\sum_{i=1}^n A_i)$

Note: $H_1, H_2, \dots, H_n$ represent the individual tree heights; n is the total number of trees in the sample plot; G_i is DBH weighted average height of the i -th tree, calculated as: $G_i = \pi \times d^2/4$, where d is the DBH of the tree; A_i is the crown area of the i -th tree, calculated by approximating the crown shape to a circle, with the formula: $A = \pi \times C^2/4$, where A is the crown area and C is the crown diameter, representing the tree crown's width.

The independent validation plots data for the Daxing'anling (Figure 1b) were collected in August 2011 and August 2012, with a total of 75 samples of plot ground survey data. The survey recorded plot location, area, slope and aspect, vegetation type, canopy cover, stand height, and forest AGB (t/ha).

2.4. Landsat5 TM Data

The multispectral data used in this study were Landsat 5 TM (<https://earthexplorer.usgs.gov/>, accessed on 9 May 2024). Launched on 1 March 1984, Landsat 5 was a key component of the U.S. Landsat series until its decommissioning in 2013. The TM sensor ceased operation in November 2011 due to rapid degradation of its electronic components. Landsat 5 provided global coverage every 16 days and featured a total of seven bands. The TM sensor had a spatial resolution of 30 m for most bands, except for Band 6, which had a resolution of 120 m. This resolution aligns with the scale of LiDAR data in this study.

The study acquired multiple Landsat 5 TM Collection 2 Level-2 T1 products, provided by the United States Geological Survey (USGS), Reston, VA, USA, from July to August between 2010 and 2011, covering the Daxing'anling region. These images were processed through cloud removal, image fusion, and other preprocessing steps using Google Earth Engine (GEE, <https://code.earthengine.google.com/>, accessed on 9 May 2024). Vegetation indices, derived from different band reflectance combinations, are widely used in land cover classification and biomass estimation research [36,37], as they enhance vegetation information while reducing the influence of non-vegetation elements. Numerous vegetation indices have been studied by researchers worldwide. In this study, the following 15 vegetation indices [38,39] were selected to construct the biomass inversion model, as shown in Table 3.

Table 3. Common vegetation indices.

Vegetation Index	Calculation Formula
Normalized Difference Vegetation Index	$NDVI = (NIR - Red) / (NIR + Red)$
Enhanced Vegetation Index	$EVI = 2.5(NIR - Red) / (NIR + 6Red - 7.5Blue + 1)$
Soil-Adjusted Vegetation Index	$SAVI = (1 + L)(NIR - Red) / (NIR + Red + L) (L = 0.5)$
Simple Leaf Area Vegetation Index	$SLAVI = NIR / (Red + SWIR2)$
Simple Ratio Vegetation Index	$RVI = NIR / Red$
Difference Vegetation Index	$DVI = NIR - Red$
Mid-Infrared Vegetation Index	$VI3 = (NIR - SWIR1) / (NIR + SWIR1)$
Perpendicular Vegetation Index	$PVI = \sqrt{(0.355NIR - 0.149Red)^2 + (0.355Red - 0.852NIR)^2}$
Transformed Normalized Difference Vegetation Index	$TNDVI = \sqrt{NDVI + 0.5}$
Red-Edge Vegetation Index	$RDVI = (NIR - Red) / \sqrt{NIR + Red}$
Leaf Area Index	$LAI = 3.618 \times EVI - 0.118$
Green Difference Vegetation Index	$GDVI = NIR - Green$
Green Normalized Difference Vegetation Index	$GNDVI = (NIR - Green) / (NIR + Green)$
Nonlinear Vegetation Index	$NLI = (NIR^2 - Red) / (NIR^2 + Red)$
Red-Green Ratio Index	$RGRI = Red / Green$

2.5. Auxiliary Data

This study also collected auxiliary data including the 30 m spatial resolution ChinaLandCover data (ChinaCover2015) [40], ASTER GDEM digital elevation data (https://lpdaac.usgs.gov, accessed on 28 May 2024), and 1 m resolution global tree canopy height data (<https://registry.opendata.aws/dataforgood-fb-forests>, accessed on 6 June 2024) [41]. The GDEM data were used to extract four topographic factors for AGB modeling: Elevation, Slope, Aspect, and the Topographic Solar Radiation Index (TSRI) [23]. The equation of TSRI can be expressed as:

$$TSRI = 1 - \cos\left(\left(\frac{\pi}{180}\right)(Aspect - 30)\right)/2. \quad (1)$$

ChinaCover2015 is a 30 m spatial resolution national-scale land cover dataset for 2015, constructed using multi-source domestic satellite data (HJ-1A/B, ZY-3, GF-1/2, etc.) and Landsat TM data. The dataset was generated through an automated remote sensing monitoring system based on object-oriented decision tree classification and support vector machine-based change detection techniques. It includes six primary classes and

40 secondary classes. In this study, the ChinaCover2015 dataset was employed for forest masking and forest type analysis.

The 1 m resolution global tree canopy height data, developed using the self-supervised model DIONv2 and fine-tuned with 0.59 m Maxar imagery (2017–2020), exhibits an average error of 0.6 m and a mean absolute error of 2.8 m. This dataset was utilized as the basis for calculating average height information at the regional scale in this study. Given the relatively slow vegetation growth in the study area, the scarcity of large-scale height data, and the primary goal of exploring the feasibility of stereo methods, phase inconsistencies in the survey data were deemed negligible and thus excluded from the analysis.

2.6. Methods

The method used for this research is briefly outlined in Figure 2. At the plot scale, stepwise linear regression (SLR) was selected to construct AGB models because forest feature parameters derived from LiDAR show strong linear relationships with ground-measured AGB. First, a stereo density $\times$ volume estimation method for forest AGB was proposed. Forest feature parameters and five canopy height metrics, extracted from LiDAR and ground survey data, were used to construct the models using SLR. The applicability of different canopy height metrics was then evaluated. These models were compared with the planar regression model to explore the potential of stereo density monitoring to improve estimation accuracy by using airborne LiDAR data.

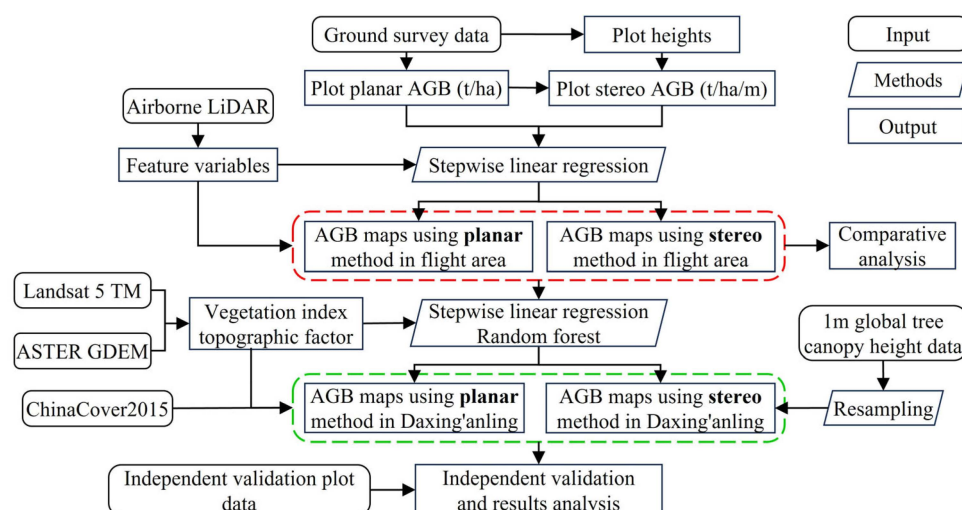


Figure 2. Method flowchart of the study. Red dashed box: results of the flight area; green dashed box: results of the Daxing'anling region.

At the regional scale, RF algorithm was applied to account for potential nonlinear relationships between AGB and topographic variables. High-resolution AGB for the flight area obtained from different average height models was combined with Landsat 5 and DEM to construct a regional-scale forest AGB stereo density model using SLR and RF methods. By comparing AGB density models based on different average heights, the optimal estimation model was identified. This model was integrated with forest canopy height data, which was derived by resampling the 1 m global tree canopy height dataset, to derive the regional-scale AGB distribution. Finally, independent accuracy validation was conducted to analyze the feasibility and applicability of the stereo AGB estimation approach.

2.6.1. AGB Monitoring Model Based on Planar Density $\times$ Area for the Plot Scale

Following the conventional methodology [42], forest AGB for each sample plot was first calculated using allometric equations based on tree species, DBH, and tree height from

ground survey data. The AGB was divided by the plot area to obtain planar AGB density (t/ha). Forest feature parameters were extracted from LiDAR data for each plot area and used as independent variables in SLR to construct a planar AGB density model at the plot scale. Forest feature parameters were extracted at 30 m × 30 m grid scale from airborne LiDAR data. Planar AGB density was calculated using the regression model, and the total AGB was obtained by multiplying the density by the pixel area. Finally, AGB mapping for the flight area was generated based on the planar method.

2.6.2. AGB Monitoring Model Based on Stereo Density × Volume for the Plot Scale

Building on the planar AGB density derived in Section 2.6.1, the stereo AGB density (t/ha/m) for each plot was calculated by dividing the planar density by five canopy height metrics from Table 2. SLR was then performed to establish relationships between the stereo AGB density and forest feature parameters at the plot scale. Simultaneously, canopy height metrics were also regressed against forest feature parameters. The stereo AGB density regression model was applied to calculate the stereo AGB density (t/ha/m) across the flight area. This was then multiplied by canopy height metrics predicted from the regression models (m) and pixel area (ha) to generate AGB mappings for the flight area. The applicability of planar and stereo methods, along with the suitability of five canopy height metrics, was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m, \quad (2)$$

$$R^2 = 1 - \sum_{i=1}^n (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2, \quad (3)$$

$$RMSE = \sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2 / n}. \quad (4)$$

In these contexts: Y , AGB density (t/ha for planar; t/ha/m for stereo); $X_1 \cdots X_m$, independent variables; $\beta_0 \cdots \beta_m$, regression coefficients; y_i , observed AGB values; $\hat{y}_i$, predicted AGB values; $\bar{y}$, mean observed AGB values; n , sample size.

2.6.3. Planar and Stereo AGB Estimation with Landsat Data in the Daxing'anling

High-precision AGB planar and stereo density maps derived from the flight area were combined with Landsat 5 TM and GDEM data to develop regional-scale estimation models. First, forest masks for the Daxing'anling region were generated using the China-Cover2015 dataset. Landsat 5 TM spectral bands and vegetation indices, along with four topographic factors derived from GDEM data were extracted as model parameters. A total of 839 random samples were then selected using the AGB planar/stereo density results from the flight area as reference values. We employed SLR and RF algorithms to construct regional-scale AGB planar density estimation model and stereo density estimation models for five average heights. Model performance was rigorously evaluated through 10-fold cross-validation, and the optimal average height and its corresponding stereo density model were selected based on key metrics: R^2 , RMSE, and relative RMSE (rRMSE).

$$rRMSE = RMSE / \bar{y} \times 100. \quad (5)$$

The selected stereo density map was multiplied by canopy height data—derived by resampling the 1 m global tree canopy height dataset—and by the pixel area to generate AGB distribution maps. For comparison, planar AGB maps were derived by multiplying planar density by pixel area. Finally, the optimal stereo method was compared with the planar method through independent validation to assess its effectiveness.

3. Results

3.1. AGB Monitoring Results Based on Planar and Stereo Methods at the Plot Scale

The plot-scale AGB monitoring results (Figure 3) show that the planar method achieved a performance of $R^2 = 0.83$ and $RMSE = 2.52$ t. Except for the H_{Lor} -based stereo model, which had lower performance ($R^2 = 0.67$), the other four stereo methods matched or exceeded the planar method's performance. Among them, the H_{GM} -based stereo method achieved the highest performance ($R^2 = 0.91$, $RMSE = 2.03$ t), followed by the H_{CW} -based method ($R^2 = 0.84$, $RMSE = 2.52$ t), and the H_{AM} -based method ($R^2 = 0.84$, $RMSE = 2.77$ t). The paired t -test also indicated that there were no significant differences ($p > 0.05$) between the planar method and stereo methods.

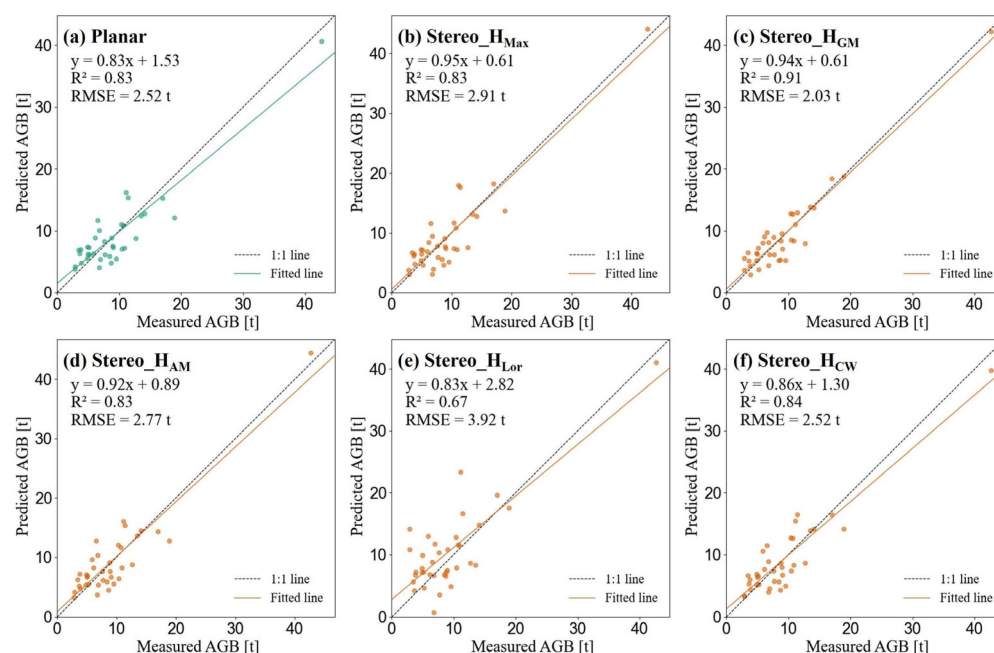


Figure 3. Scatterplots of SLR of AGB monitoring at the plot scale. (a) Planar method. (b–f) Stereo methods based on H_{Max} , H_{GM} , H_{AM} , H_{Lor} , and H_{CW} , respectively.

The variable importance ranking of LiDAR features for the planar density model and the H_{GM} -based stereo density model is shown in Figure 4. Height percentiles (Elev 1%) and accumulated height percentiles (AIH 1%, AIH 10%) are key predictors for both models. Additionally, LiDAR density variables exhibited a notable correlation with stereo density.

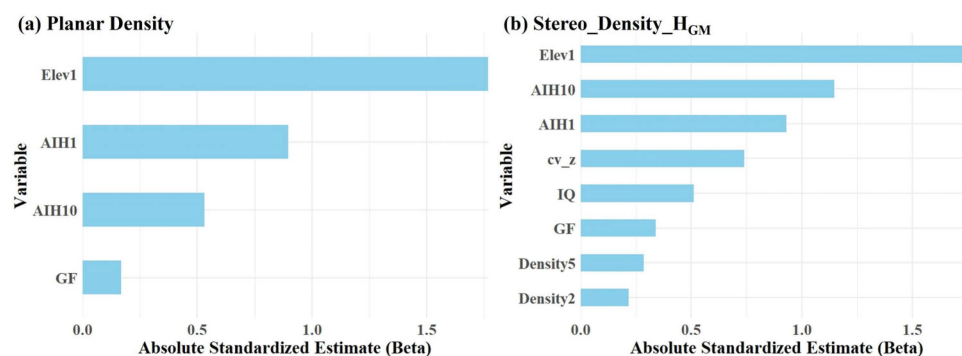


Figure 4. Variable importance ranking of LiDAR features. (a) Planar density model. (b) H_{GM} -based stereo density model.

Using the ChinaCover2015 dataset, a forest mask was applied to the flight area. AGB results were obtained using both planar and stereo monitoring models based on LiDAR-derived forest feature parameters, as shown in the following maps (Figure 5).

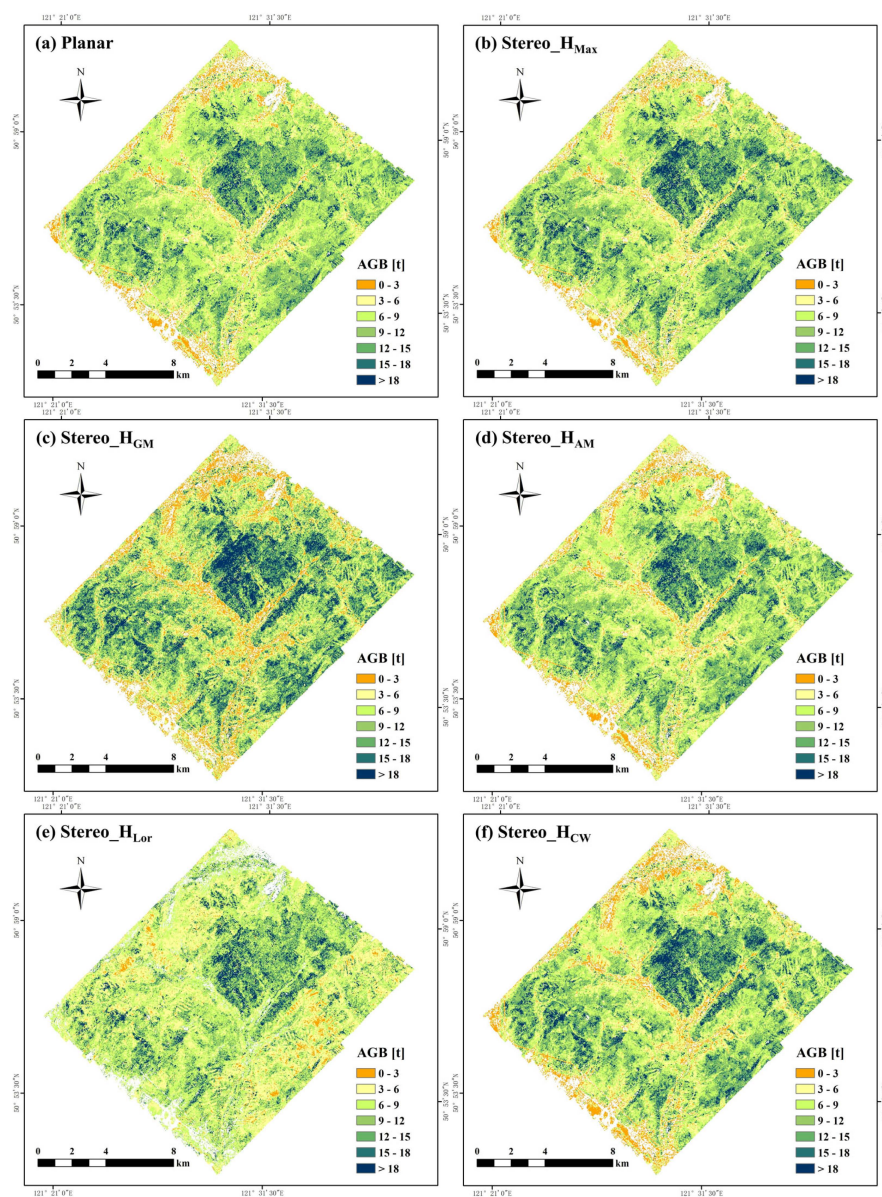


Figure 5. AGB monitoring maps of the flight area. (a) Results based on planar method. (b–f) Results based on stereo methods with H_{Max} , H_{GM} , H_{AM} , H_{Lor} , and H_{CW} , respectively.

3.2. AGB Density Estimation Model at the Flight Area Scale

The AGB density estimation models were constructed using SLR and RF algorithms. Model robustness was evaluated through 10-fold cross-validation, with performance metrics averaged across folds. Among the stereo models, those based on H_{Max} , H_{GM} , and H_{Lor} were excluded due to poor performance ($R^2 < 0.40$), indicating their unsuitability as canopy height metrics. The results showed (Table 4 and Figure 6) the following. We found that RF had slightly higher performance and less error than SLR. Stereo methods also demonstrated superior performance compared to planar methods. Specifically, the RF-based H_{AM} stereo model achieved an average $R^2 = 0.52$, average RMSE = 1.95 t/ha/m, average rRMSE = 24.57%, while the planar model yielded an average $R^2 = 0.46$, average RMSE = 24.87 t/ha, average rRMSE = 28.86%. Among them, the optimal models were

obtained at the 10th cross-validation. The optimal RF-based stereo model of H_{AM} ($R^2 = 0.65$, $rRMSE = 26.05\%$) significantly improved AGB estimation compared to the planar model ($R^2 = 0.59$, $rRMSE = 30.41\%$). The paired t -test revealed significant differences ($p < 0.05$) among all these methods.

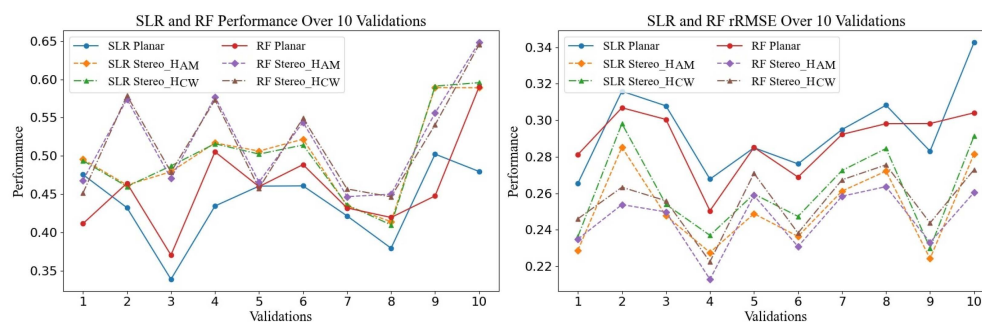


Figure 6. R^2 (left) and $rRMSE$ (right) of SLR and RF algorithms based on 10-fold cross-validation.

As shown in Figure 7, Landsat spectral bands and vegetation indices were identified as significant predictors for regional-scale AGB density, particularly B5, B6, and SLAVI. Additionally, elevation and slope also contributed notably to model performance. Compared to the planar density model, VI3 and PVI are identified as key predictors for the stereo density models.

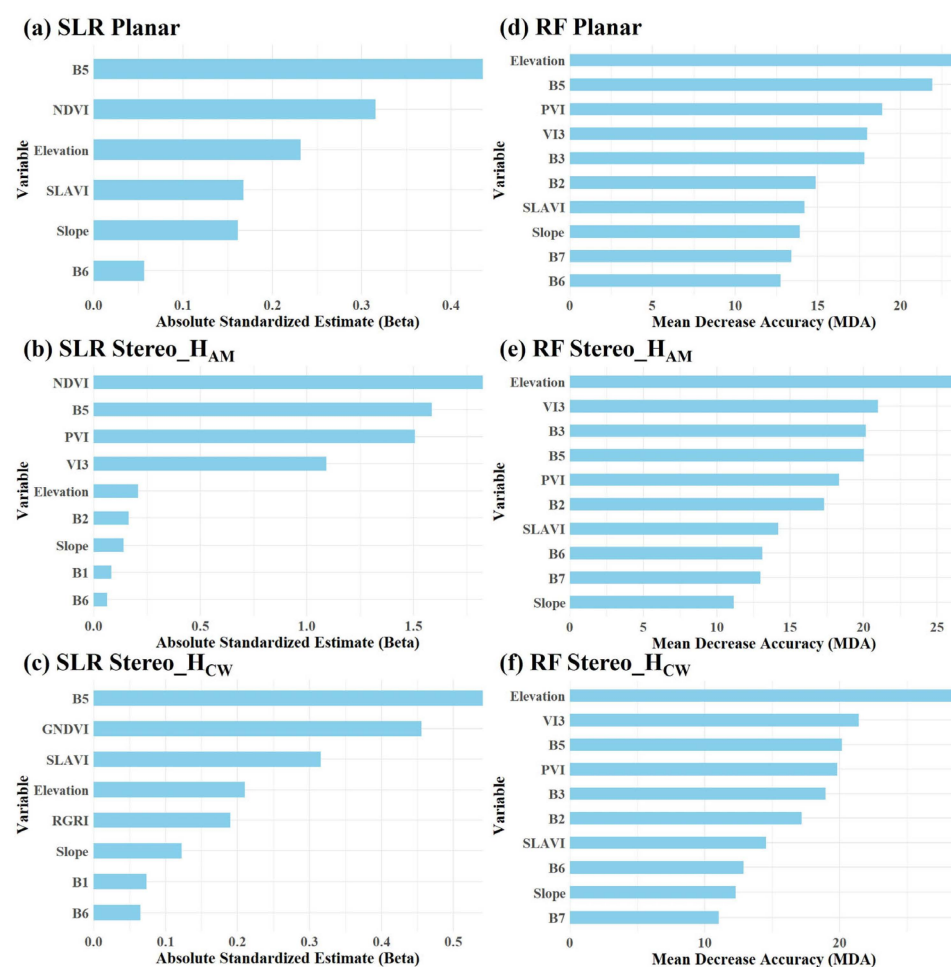


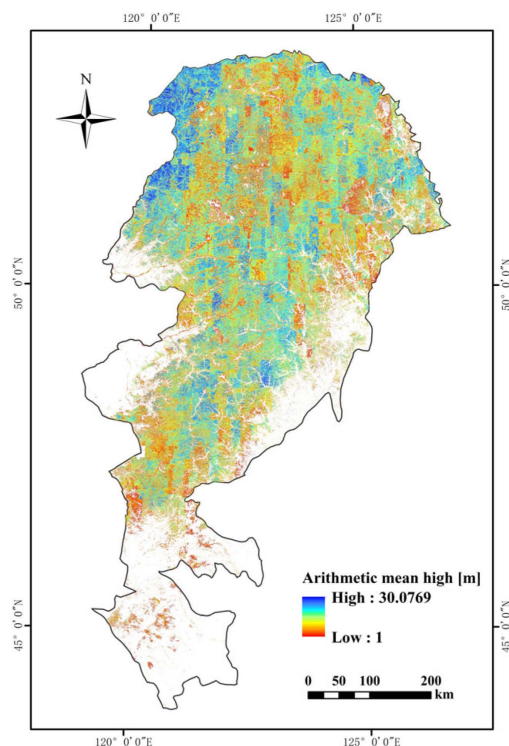
Figure 7. The feature's variable importance ranking for planar and stereo density models with H_{AM} and H_{CW} , respectively. (a–c) Based on SLR; (d–f) Based on RF.

Table 4. The 10-fold cross-validation results (average) for SLR and RF algorithms.

Metrics \ Methods	SLR			RF		
	Planar	Stereo_H _{AM}	Stereo_H _{CW}	Planar	Stereo_H _{AM}	Stereo_H _{CW}
R ²	0.44	0.50	0.50	0.46	0.52	0.52
RMSE	25.37 t/ha	1.99 t/ha/m	1.78 t/ha/m	24.87 t/ha	1.95 t/ha/m	1.74 t/ha/m
rRMSE	29.47%	25.14%	26.11%	28.86%	24.57%	25.57%

3.3. AGB Estimation Results in the Daxing'anling

In the Daxing'anling region, considering both model performance and the practical feasibility of obtaining canopy height at the plot and regional scales, we selected H_{AM} as the optimal mean height. Then, we used the 1 m resolution global tree canopy height data to calculate H_{AM}, which was obtained by computing the arithmetic mean values, within a 30 m × 30 m grid through resampling, as shown in Figure 8.

**Figure 8.** Spatial distribution of arithmetic mean height in the Daxing'anling region.

Using the optimal AGB density models from the RF algorithm, we generated maps for both planar and H_{AM}-based stereo forest AGB, as shown in Figure 9.

The linear relationship between the measured AGB from 75 ground survey plots in the Daxing'anling and the two predicted AGB values is shown in Figure 10. The validation results show that planar AGB estimation achieved $R^2 = 0.35$, $RMSE = 0.99$ t, while the H_{AM}-based stereo AGB estimation achieved $R^2 = 0.45$, $RMSE = 2.34$ t. This stereo method demonstrates a better linear fit and explains the variability in the measured AGB to a greater extent. Despite a marginally higher RMSE, it reflects the method's robustness against data outliers. The coefficients of the stereo method's equation further confirm its accuracy in representing the measured AGB. In the Daxing'anling, the stereo method shows a significant improvement over the planar method in both model performance and independent validation accuracy.

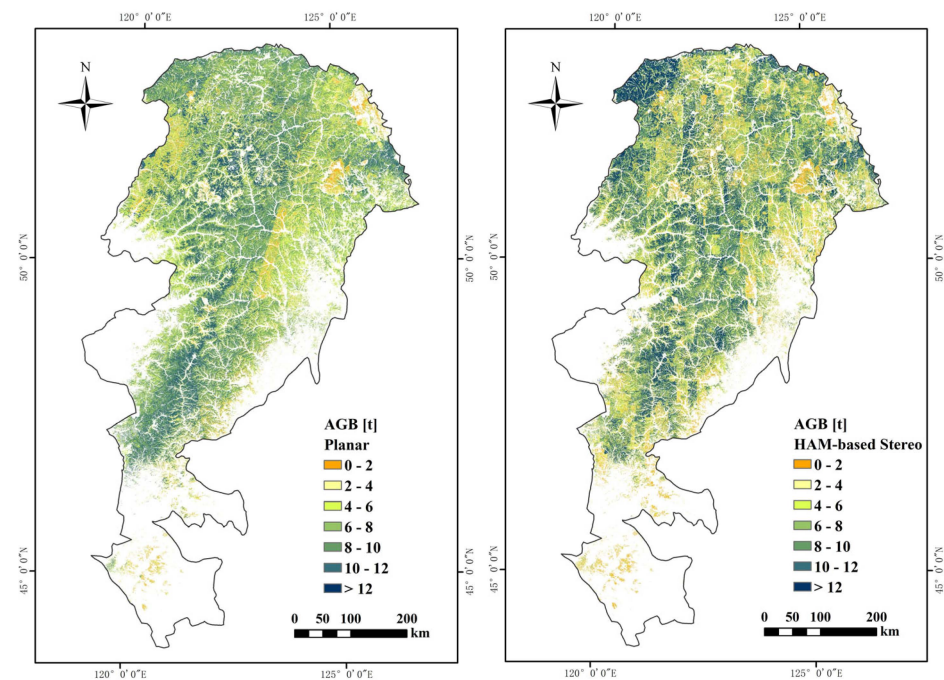


Figure 9. AGB distribution maps for the Daxing'anling region based on planar method (left) and the H_{AM} -based stereo method (right).

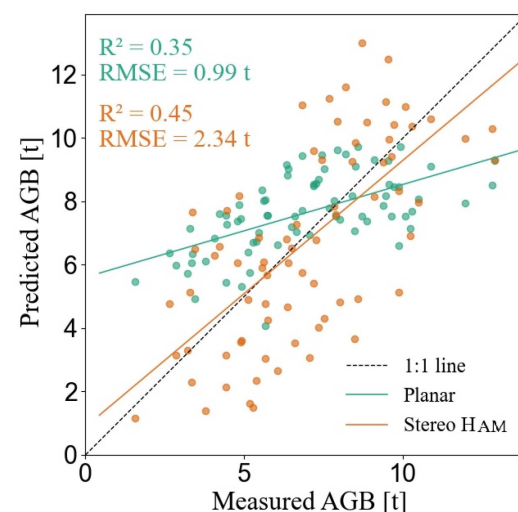


Figure 10. Scatterplots of independent accuracy validation for RF-based AGB results in the Daxing'anling region.

4. Discussion

4.1. Applicability of the AGB Stereo Method on Airborne LiDAR Data

Results from the planar and stereo AGB monitoring at the plot scale show a strong correlation between airborne LiDAR-derived forest feature parameters and AGB. Further analysis of the importance ranking of LiDAR-derived variables provides deeper insights into their contributions to AGB estimation. It was found that height percentile metrics such as Elev 1% and accumulated height percentiles like AIH 1% and AIH 10% are consistently identified as key predictors in both planar and stereo models. This highlights the importance of vertical distribution in biomass estimation. Furthermore, density variables exhibit a strong correlation with stereo density, indicating their additional value in enhancing the three-dimensional structural representation of forest stands. These findings underscore the complementary roles of height- and density-based metrics in improving AGB prediction.

performance across different modeling approaches. The AGB H_{AM} -based stereo method achieved a comparable performance to the AGB planar method, and introduced critical vertical structure information through the stereo density. The different performance of models based on five canopy height metrics indicated their differing abilities to capture height variation. All these methods can effectively monitor the sample plot AGB, therefore, the stereo monitoring method is applicable at the plot scale, and while it shows limited accuracy improvement, its equation coefficients suggest higher reliability.

To further quantify the differences methods, we calculated the differences by subtracting the AGB planar result from the H_{AM} -based stereo result and analyzed their distribution under H_{AM} -based stereo result (Figure 11). We found that in a very small number of areas with high AGB, the stereo result is higher than the planar result, but overall, the differences between the two estimation methods are minimal (mean absolute difference = 0.93 t). This indicates that LiDAR data inherently capture structural details sufficient for high-precision AGB estimation, regardless of whether the planar or the stereo method is used.

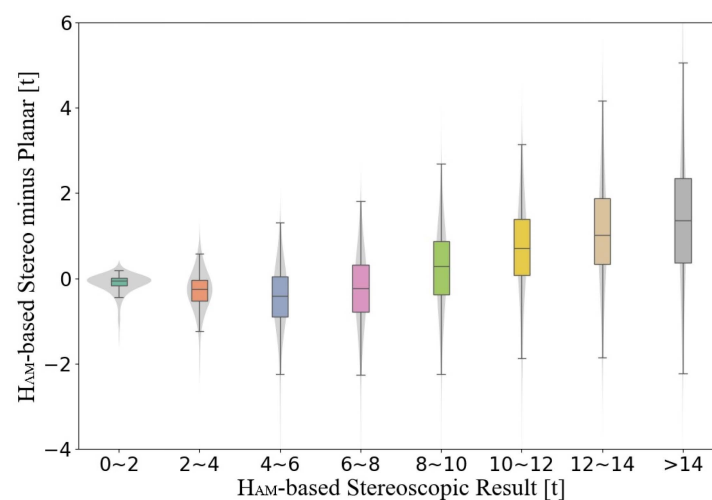


Figure 11. Distribution of “AGB H_{AM} -based Stereo Result Minus Planar Result” in stereo result at the flight area.

4.2. Applicability of the AGB Stereo Method at the Regional Scale

The AGB density estimation performance of the H_{AM} -based stereo model shows a significant improvement compared to the planar model, indicating that optical remote sensing data have a weak ability to reflect vertical structure information. The stereo method takes forest height information into account, converting planar density into stereo density. By incorporating vertical information, this method reduces AGB underestimation caused by height differences, thereby improving the AGB modeling performance. In addition, the comparison between SLR and RF algorithms showed only modest performance improvements from RF. This suggests that the linear relationships between canopy height and AGB dominate the variability, leaving limited nonlinearity for RF to exploit. Additionally, the low-dimensional feature space may constrain RF’s ability to outperform SLR. Nonetheless, both SLR and RF stereo models consistently surpassed their planar counterparts ($\Delta R^2 > 0.06$), highlighting that vertical structure integration drives the primary accuracy gains. Future studies could explore RF’s potential with higher-dimensional data to better leverage its nonlinear capabilities.

We calculated the differences by subtracting the AGB planar result from the H_{AM} -based stereo result in the Daxing’anling region, and analyzed their distribution under different perspectives, such as forest canopy height and forest type.

As shown in Figure 12, we observed that the stereo result gradually increased compared to the planar result as the forest AGB grew. Planar AGB methods cause underestimation errors, particularly in high-biomass forests.

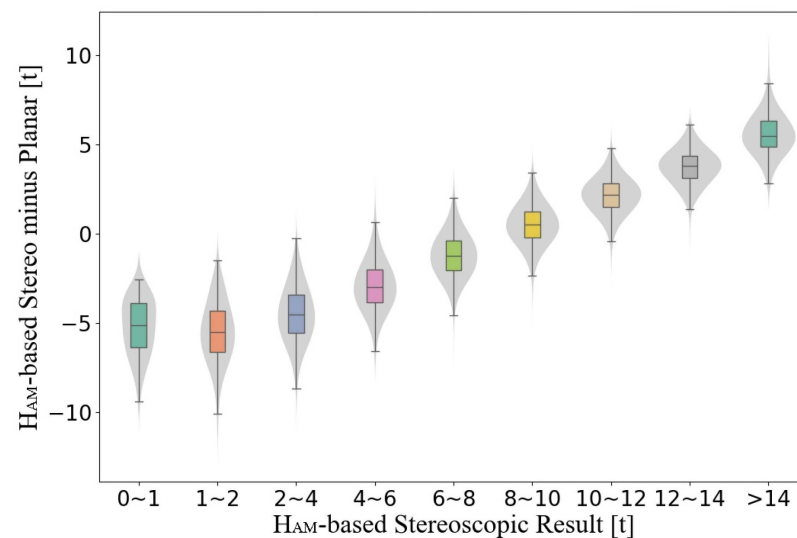


Figure 12. Distribution of “AGB H_{AM} -based Stereo Result Minus Planar Result” in stereo result in the Daxing'anling region.

As shown in Figure 13, the trend is similar to that observed under stereo result (Figure 12). Planar estimates exceed stereoscopic values in low-stature forests ($H_{AM} < 9$ m), where vertical complexity is minimal, but significantly underestimate AGB in taller forests ($H_{AM} > 12$ m). These findings demonstrate a strong positive correlation between AGB and forest height.

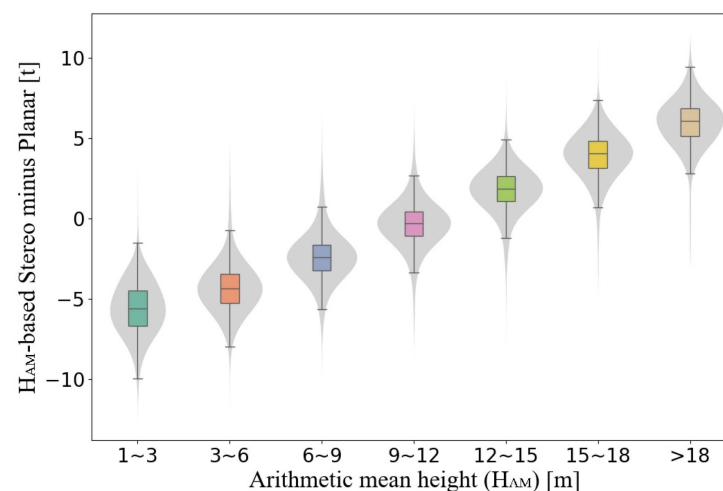


Figure 13. Distribution of “AGB H_{AM} -based Stereo Result Minus Planar Result” in H_{AM} in the Daxing'anling region.

As shown in Figure 14, there is no significant difference between the stereo result and planar result across different forest types. This confirms that, regardless of whether the forest is coniferous or broadleaf, forest height remains the primary factor affecting AGB.

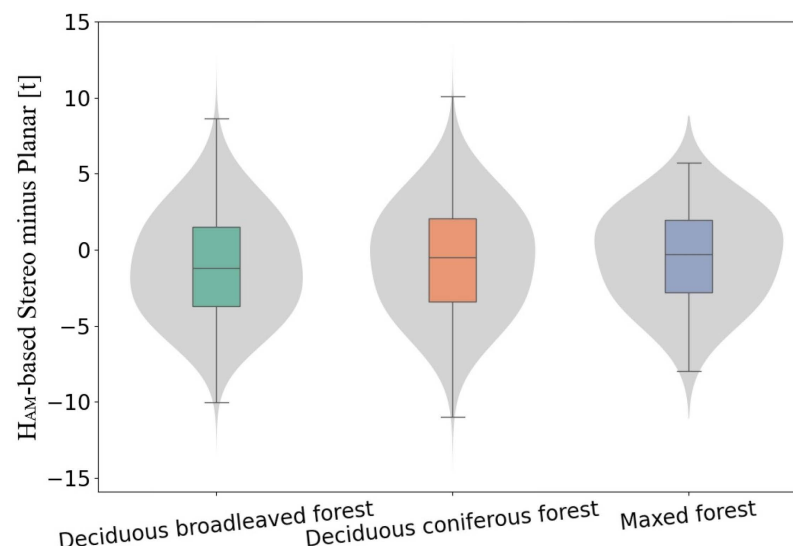


Figure 14. Distribution of “AGB H_{AM} -based Stereo Result Minus Planar Result” in different forest types in the Daxing’anling region.

From the above analysis, we found that as forest height increases, the planar estimation method tends to significantly underestimate the AGB, while the stereo estimation method provides higher AGB estimates, which helps reduce the underestimation caused by height differences. Moreover, the differences in AGB estimation results between stereo and planar methods show no significant correlation with forest type.

Additionally, it is worth mentioning that a major forest fire occurred in the northern part of the Daxing’anling region in 1987, which affected 1.01 million hectares of forest. This is also clearly reflected in the AGB estimation results, especially the stereo method, where the AGB is notably lower in this area, consistent with the actual situation.

4.3. Limitations

In terms of data selection and temporal consistency, due to the relatively simple vegetation and slow growth in the Daxing’anling region, Landsat 5 TM from 2010 to 2011 was selected for cloud removal processing to improve the quality of the fused imagery. However, the temporal mismatch between Landsat imagery and the global canopy height dataset (2017–2020) introduces potential biases in dynamic forest analyses. Additionally, the resampled $30\text{ m} \times 30\text{ m}$ H_{AM} , derived from the 1 m resolution global tree canopy height data (Figure 6), reveals that the dataset contains some stratification issues caused by the stitching of remote sensing images. As a result, using this dataset as the height input leads to small-scale stratification problems in the AGB stereo result. Future research should focus on acquiring more accurate and easily accessible canopy height information to further enhance the performance of the stereo method [43,44].

This study aims to explore the feasibility of the stereo method and whether it can be used instead of the planar method to improve the accuracy of AGB estimation. At the plot scale, where LiDAR inherently captures the 3D forest structure, stereo methods showed no significant advantage over planar models. At the regional scale, we investigated whether the addition of canopy height data to optical data can effectively reduce the underestimation of high-density biomass regions due to the absence of vertical structure. The model results showed that the stereo method can indeed obtain better estimates. Although the independent accuracy verification achieved a higher R^2 , there was also a larger RMSE, indicating the limitations and large errors of the stereo method. The method’s reliance on existing global height data further limits operational scalability.

The study did not address the saturation issue. Although forest height information was considered, saturation resulting from high vegetation density in densely forested areas remains the primary cause of AGB underestimation [45,46]. The applicability of this method to ecosystems with extreme vertical heterogeneity, such as tropical or subtropical forests, remains untested.

Despite these constraints, the stereo framework provides a transitional solution for regions lacking LiDAR coverage, bridging plot-level precision with optical remote sensing's broad-scale capabilities. Future integration of multi-temporal multispectral data and annually updated canopy height products could enable high-precision, long-term AGB monitoring. This approach highlights the potential to transform the planar view of optical data into a stereo perspective, advancing global carbon stock assessments.

5. Conclusions

This study proposed and validated a novel “stereo density $\times$ volume” method for forest AGB estimation, addressing the critical gap in capturing vertical structural variability within conventional planar approaches. We identified H_{AM} as the optimal height parameter, and we achieved AGB stereo estimation using RF algorithms in the Daxing'anling region. At the plot scale, the H_{AM} -based stereo method achieved comparable performance to the planar model ($R^2 \geq 0.83$, $RMSE \leq 2.77$ t), while at the regional scale, they significantly outperformed the planar method using RF algorithms in optical remote sensing areas (average $R^2 = 0.52$, average $rRMSE = 24.57\%$ vs. average $R^2 = 0.46$, average $rRMSE = 28.86\%$), proving stereo method viability in this region. Independent validation using 75 ground survey data points revealed that the H_{AM} -based stereo method ($R^2 = 0.45$, $RMSE = 2.34$ t) achieved better performance but higher error compared to the planar method ($R^2 = 0.35$, $RMSE = 0.99$ t). The study revealed that AGB increases with forest height, and the planar result was significantly lower than the stereo result, but no clear correlation with forest types was found. The stereo estimation method, based on the planar method, converts planar density to stereo density, thus incorporating vertical structural information of forests.

Despite these advances, the scalability of this method remains contingent on advancements in global canopy height mapping. Future work should prioritize the development of open-access, high-resolution canopy height products to enable stereo AGB estimation at continental scales, as well as testing the method in biomes with complex forest structures. In conclusion, this study confirms the feasibility of AGB stereo estimation as a scalable solution for bridging the gap between plot-level precision and regional-scale estimation, particularly in regions where LiDAR data are unavailable. It also provides new approaches for estimating forest dynamics and assessing forest carbon sequestration capacity.

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