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REVIEW

Forest Aboveground Biomass Estimation Using Airborne LiDAR: A Systematic Review and Meta-Analysis

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Abstract

Forest aboveground biomass (AGB) estimation is crucial for understanding carbon dynamics and supporting Reducing Emissions from Deforestation and Forest Degradation (REDD +) initiatives. It has gained significant research interest, evident in the skyrocketing number of peer-reviewed journal articles over the past decade alone. The availability of free and open-access airborne light detection and ranging (LiDAR) data has further accelerated the development of advanced AGB modeling approaches. However, a comprehensive summary of milestones achieved in AGB estimation using airborne LiDAR is still lacking. Our study aims to fill this gap by summarizing AGB model errors with respect to different data sources, forest biomes, and methods used. The overall objective of the study was to conduct a systematic review and meta-analysis of peer-reviewed journal articles on AGB estimation using airborne LiDAR published between 2013 and 2023. We followed the Preferred Reporting Items for Systematic Reviews and Meta- Analysis (PRISMA) framework to select 52 articles. Results indicate that most studies on AGB using airborne LiDAR were carried out in tropical biomes and employed multiple linear regression analysis as the modeling method. Results also show Root Mean Square Error as the most preferred model evaluation metric. Additionally, we concluded that meta-analysis of studies with a controlled predictor variable and modeling method produced less heterogeneous results (I^2 = 91.67% and Q = 399.97) as compared to the overall meta-analysis (I^2 = 96.38% and Q = 6648.28). The findings provide new insights to researchers for advancing AGB estimation accuracy using airborne LiDAR.

Keywords AGB · Carbon · PRISMA · Modeling · Biomes

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Introduction

Background

Forest aboveground biomass (AGB) refers to the dry weight of tree components that are located above the ground surface (Popescu 2007). Accurate AGB monitoring is essential for implementing climate-smart forestry practices, such as reduced deforestation, reforestation prospects, and enhanced management for carbon sequestration to increase forest carbon storage (Johnson et al. 2022; Shen et al. 2016; Shephard et al. 2022). In the past, AGB estimation focused solely on timber production; however, policymakers are now also concerned about forest carbon sequestration and the forest carbon cycle (Hughes et al. 2018; Kristensen et al. 2015). Forest aboveground biomass is a prominent measure to track progress towards Sustainable Development Goals of the United Nations and the Paris Agreement on Climate Change (Herold et al. 2019). Additionally, the reporting of forest carbon stocks is a requirement for countries ratifying the Kyoto protocol to the United Nations Framework Convention on Climate Change (UNFCCC) (Secretariat 2016). Based on the protocol, industrialized countries have limits on greenhouse gas emissions. These countries promote sustainable forestry development to help mitigate climate change in the long term by preventing the introduction of carbon into the atmosphere and enhancing carbon sequestration. Hence, accurate AGB estimation has gained significant interest due to the growing need for carbon monitoring.

Traditional field inventory methods can provide accurate AGB. However, such methods are generally labor-intensive, time-consuming and cost-prohibitive, (Cao 2022), and may lack sufficient spatio-temporal coverage (Su et al. 2020). Remote sensing offers a non-destructive and continuous approach for estimating and monitoring AGB. Remotely sensed data can supplement field data, due to the wide availability of open-source, multi-temporal, and multi-scale resolution sources (Cao 2022). For example, studies have used different temporal and spatial resolutions of remote sensing data, such as Landsat, Sentinel- 2, PALSAR (Hudak et al. 2020; Tamiminia et al. 2022; Y. Zhang et al. 2023a, b), MODIS (Nelson et al. 2017), Ice, Cloud, and land Elevation Satellite (ICESat- 2), and Global Ecosystem Dynamics Investigation (GEDI) (Duncanson et al. 2020; Narine et al. 2020; Silva et al. 2021) for AGB mapping. Data, such as SPOT, QuickBird, IKONOS, WorldView, ASTER, AVHRR, and Radarsat, are also available for exploration (Lu et al. 2016).

Airborne LiDAR, its Advantages, and Early History in Forestry with Associated Challenges

Among the remote sensing techniques used, manned airborne light detection and ranging (LiDAR hereafter) has revolutionized the acquisition of forest structure information by providing highly accurate three-dimensional data (Wehr & Lohr 1999). LiDAR is an active remote sensing technique that measures the distance traveled by a laser light between a sensor and a target on the surface of the earth, acquiring detailed information about vertical vegetation structure and terrain morphology (Popescu 2007; Thapa et al. 2023). LiDAR has gained popularity among the scientific research community for AGB modeling for three key reasons. First, the availability of cost-reduced data from the United States Geological Survey 3-Dimensional Elevation Program and National Ecological Observatory Network, the National Forest Inventory of Finland, and the Canadian Consortium for LiDAR Environmental Applications Research. Second, the use of LiDAR derived variables for accurate AGB modeling can reduce the amount of laborious fieldwork, as field inventory data is necessary primarily for model training and evaluation. For example, a study found that airborne LiDAR can produce estimates with a level of precision that was similar to those obtained by traditional inventory methods (Næsset et al. 2004). Third, airborne LiDAR-derived information may be used to address the issue of spatial misalignment between spaceborne data and plot-level measurements, offering continuous spatial coverage across study sites. For instance, studies have developed spatially incontiguous AGB reference products using airborne LiDAR and field plots to calibrate the AGB estimates from GEDI (Duncanson et al. 2022; Pascual et al. 2023) and assess the accuracy of AGB products from ICESat- 2 and GEDI (Rodda et al. 2023).

The application of airborne LiDAR in forestry dates back to 1960 s when Rempel and Parker (1964) introduced an airborne laser terrain profiler for measuring tree heights at the University of Michigan. However, it took another 15 years for airborne lasers to be used for forest measurements. In 1975, a workshop on hydrography held in Maryland, USA, led to the development of a laser scanning system for studying oceanic and terrestrial vegetation (Goodman 1975). Following this, Solodukhin et al. (1976) utilized a He–Ne laser with a wavelength of 0.63 mm to study the vertical structure of a tree. Their findings advocated that a laser can be mounted on an aircraft for remotely measuring forest canopies, thus inspiring other researchers to explore the application of airborne LiDAR in forest vegetation studies. By the 1980s, the potential of airborne LiDAR for studies based on forest vegetation became apparent. In 1984, Maclean and Martin (1984) proposed that future research should investigate the potential of canopy profile metrics derived from airborne LiDAR for estimating AGB. Building upon that, Nelson et al. (1988) conducted a study using airborne LiDAR in a pure pine forest in Georgia, USA, to predict AGB and volume. The resulting model successfully explained 65% variability of AGB measured in ground measurements. Further, Nelson et al. (1997) applied the technique to mixed forest stands in Costa Rica achieving a coefficient of determination (R^2) of 0.54 and a relative Root Mean Squared Error (rRMSE) of 65%. The moderate accuracy was attributed to discrepancies between LiDAR and field measurements in capturing key variables, like canopy height and density. Dubayah and Drake (2000) later confirmed that intermediary variables, such as canopy height and density, significantly impact the accuracy of AGB estimation. Additionally, multiple studies have demonstrated a strong correlation between canopy height derived from airborne LiDAR and AGB (Maclean & Martin 1984; Means et al. 1999; Nelson et al. 1988, 1997). Nelson et al. (1997) also hypothesized that species variability within mixed forest stands might have contributed to the errors in AGB predictions. In contrast, a study in more homogenous stands demonstrated higher accuracy. For instance, Means et al.

(1999) estimated AGB in pure pine stands in Oregon, USA, using airborne LiDAR and achieved a good accuracy ($R^2 = 0.96$, Root Mean Squared Error (RMSE) = 88 Mg/ha), explaining more than 90% of the variation in AGB. This study provides evidence that AGB estimation carried out in pure forest stands provides higher accuracies compared to mixed forest stands, as initially recognized by Nelson et al. (1997).

To improve AGB estimation in mixed forests, Jenkins et al. (2003) developed species-specific allometric equations based on field measurements. These equations often serve as response variables in LiDAR-based AGB models, enabling the development of models for specific forest types, such as pines and mixed hardwoods (Campbell et al. 2024). Throughout the 2000 s, researchers experimented with LiDAR-based AGB models using field-measured, species-specific allometric data (Kim et al. 2009; Popescu 2007; Zhao et al. 2009). This approach somewhat resolved the inaccuracies in mixed forest AGB modeling. For instance, Zhao et al. (2009) estimated AGB for a mixed forest in Texas (48 km^2), achieving an R^2 of 0.80 with an RMSE of 237 kg for pines, and an R^2 of 0.88 with an RMSE of 138 kg for deciduous trees. Insights gained from the local-scale perspective of airborne LiDAR regarding AGB estimation in different forest types are vital for enhancing our understanding of AGB dynamics across different biomes at a broader scale.

Summary of Statistical Methods and Machine Learning Algorithms for AGB Modeling over Past Decade

In the past decade, there has been an increase in the number of studies using regression analysis (for example, linear regression, multiple linear regression, ordinary least square regression, partial least square regression, and generalized linear mixed regression) (Cao et al. 2014; Cushman et al. 2023; Luo et al. 2017; Nelson et al. 2017; Rodda et al. 2023; Sheridan et al. 2014), and Random Forest (RF) (Feng et al. 2017; Hudak et al. 2020; Queinnec et al. 2022; Rana et al. 2023) for AGB estimation. Other commonly used machine learning algorithms consist of Support Vector Machine (SVM), Gradient Boosting (GB), support vector regression, extreme learning machine, extremely randomized tree, k-nearest neighbor, and cubist. Deep learning algorithms include backpropagation neural networks, convolutional neural networks, artificial neural networks, multilayer perception neural networks, and deep learning stacked autoencoder (Cao et al. 2018; Rana et al. 2023; Schuh et al. 2020). In Bayesian statistics, studies have utilized Gaussian processes and sparse Bayesian regression (Babcock et al. 2016; Li et al. 2016; Rana et al. 2016). Similarly, geostatistical approaches are comprised of ordinary kriging, regression co-kriging, and regression kriging (Li et al. 2015).

Current Limitations and Aim of the Review

The skyrocketing number of peer-reviewed journal articles on AGB estimation using airborne LiDAR in the past decade reflects increasing research interest. Despite this surge, a meta-analysis using standardized rRMSE or R^2 is still missing. This intellectual gap highlights a need to analyze available evidence related to AGB modeling with airborne LiDAR in forest ecosystems. While several studies have summarized LiDAR applications for biomass estimation in savanna grasslands (Maake et al. 2023; Muumbe et al. 2021), mangrove forests (Pillodar et al. 2023), and agricultural crops (Bahrami et al. 2022), they primarily rely on quantitative summaries or non-standardized R^2. Zolkos et al. (2013) aggregated studies related to terrestrial AGB estimation using airborne and spaceborne LiDAR remote sensing, with standardized error as the effect size for meta-analysis. Additionally, they observed an inverse relationship between the standardized error and plot size, concluding that spatial averaging of error for large plot sizes leads to a negative relationship. To overcome this, we analyzed AGB estimates based on the standardized error calculated using relative plot level mean AGB. This approach reduces the spatial averaging error and enables a fair comparison of results. We also conducted a meta-analysis following the fundamentals of meta-analysis by calculating an effect size after assessing the data quality. We used standardized R^2 for effect size calculation, addressed heterogeneity, and publication bias across different sample sizes. This example differs from narrative reviews or systematic reviews, and existing meta-analysis approaches in that it requires calculation of the effect size and variance using defined measures (Israel & Richter 2011) and necessitates uniformity across studies (Harrer et al. 2022).

The overall goal of this study was to conduct a systematic review and meta-analysis of peer-reviewed journal articles on AGB estimation using airborne LiDAR for forest ecosystems, published between 2013–2023. The systematic review consisted of two parts: (1) a quantitative summary of studies by geographical region and AGB model evaluation metrics, and (2) an analysis of plot-level standardized error, categorized by data source (three groups), forest biome (five groups), and modeling method (five groups) (see Sect. 2.1). We then used the Kruskal-Wallis test to assess significant differences between these groups. For the meta-analysis, we applied two approaches:

(1) An overall meta-analysis of all observations, and (2) a meta-analysis using observations with the same predictor (mean canopy height) and modeling method (regression analysis). Next, we compared the results of both approaches to evaluate differences in heterogeneity and publication bias.

Materials and Methods

Study Selection and Data Extraction

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) to select articles from 787 peer-reviewed journal articles focusing on AGB and airborne LiDAR (Page et al. 2021) (Fig. 1). Articles published between the years 2013–2023 and in English language were searched from two databases, i.e., Web of Science ($n = 419$) and Scopus ($n = 368$). Articles selected from 2013 to 2023 prevented data duplication with studies used in Zolkos et al. (2013). First,

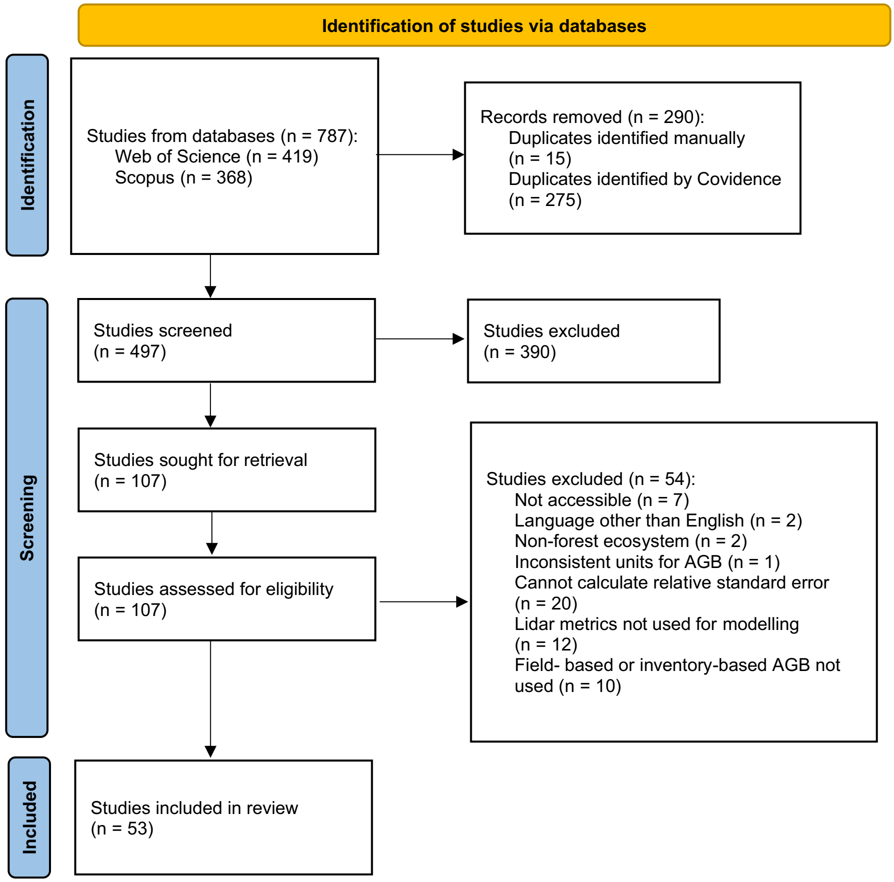


Fig. 1 PRISMA flowchart showing study selection steps

we searched keywords relevant to our study objective, such as airborne LiDAR, aerial laser scanning, AGB, and forest ecosystem. Our article search strategy involved using all possible synonyms for the keywords, utilizing Boolean operators, and implementing quotation marks for increased efficiency. Second, the searched articles from two databases were imported from Endnote to Covidence. Third, the articles underwent duplicate removal, title, and abstract screening. Those articles that passed the title and abstract screening were subjected to full-text review in Covidence. Articles related to airborne LiDAR-based AGB model, forest ecosystems, and reported AGB model evaluation in terms of R^2 or adjusted R^2 and RMSE or rRMSE were the key inclusion criteria. Whereas articles that focused on carbon density, change in

AGB, and ecosystems other than forest were excluded by a single reviewer following PRISMA guidelines.

Out of 787 total articles, Covidence removed 275 duplicates and an additional 15 articles were manually identified and excluded (Fig. 1). After title and abstract screening, a total of 390 irrelevant articles were removed and 54 articles were excluded based on defined exclusion criteria. Finally, 53 articles were selected for data extraction after the screening process (Fig. 1). One among the 53 articles was a review paper and the remaining 52 were published journal articles. We collected data from 15 variables, namely R^2, adjusted R^2, RMSE, rRMSE, number of predictors used to build the model, sample size, plot size, data sources, forest biome, method used to build the model, authors, title, study location, area of study, and publication year (Supplementary Table 1), when available. Data sources were categorized into two groups, i.e., airborne LiDAR data alone and airborne LiDAR combined with multi-source data. Forest biomes were classified into five groups i.e., Boreal, Temperate Coniferous, Temperate Deciduous, Temperate Mixed, and Tropical/Subtropical, as defined by Zolkos et al. (2013). The methods used were also differentiated into five groups i.e., Bayesian statistics, deep learning, geostatistical approaches, machine learning, and regression analysis. We used Web Plot Digitizer to extract data from bar and line charts when values were not available in the text or tables (Rohatgi 2019).

Data Analysis

The data analysis section has two parts, i.e., Systematic Review and Meta-Analysis. We conducted a Systematic Review using data collected from 52 articles. We selected RMSE or rRMSE for analysis because it allowed us to standardize results based on mean AGB and was the most favored AGB model evaluation metric (Fig. 4). For meta- analysis, we used R^2 for obtaining results as there is no defined measure for calculating effect sizes and variances using RMSE or rRMSE. R^2 measures how well a model's predicted values fit the observed values, while the adjusted R^2 accounts for the number of predictors to indicate whether adding variables improves model performance.

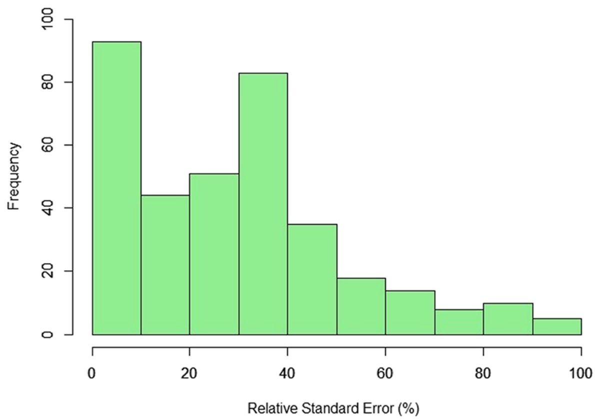
Systematic Review

We evaluated the model error across different data sources, forest biomes, and methods used for AGB modeling using rRMSE. For observations where rRMSE was not reported, we calculated this by dividing RMSE by mean AGB. To compare different observations, we standardized rRMSE by plot level mean AGB and defined it as a percentage Relative Standard Error (RSE). The primary reason for using standardized RSE was to adjust variation in biomass magnitude, with the error controlled by plot size. For instance, we removed observations that reported a single mean AGB for different plot sizes (Nelson et al. 2017), mean AGB for different forest types (Hirata et al. 2018; Li et al. 2022; Ota et al. 2015), did not use training and validation data from the same study area (Hayashi et al. 2015), or did not report mean AGB and RMSE (Brovkina et al. 2017; Chirici et al. 2016; Hernández-Stefanoni et al. 2014; Wang et al. 2019). Additionally, we excluded the outlier observations that did not provide sufficient information to calculate RSE.

We examined 361 observations from 52 articles to determine the distribution of RSE and found that it was not normally distributed (Fig. 2). Therefore, we conducted a non-parametric Kruskal–Wallis test in R Studio. This test is suitable for analyzing environmental data due to its ability to handle deviations from normality. However, the Kruskal-Wallis test only informs if there are significant differences among groups without specifying which pairs of groups differ significantly. To identify those differences, the post hoc pairwise Wilcoxon test was conducted with Bonferroni correction. This allowed us to determine which pair of groups present within different variables, such as data source, forest biomes, and methods used, had statistically significant differences in terms of RSE.

We conducted a quality assessment and risk of bias evaluation for individual studies using the Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modeling Studies, sourced from the Quality Assessment and Risk of Bias Tool Repository (Ledbetter & Hendren 2021). This tool is designed to support the evaluation of prediction modeling studies, including those employing regression, neural networks, and machine learning techniques. The assessment focused on 10 relevant domains, such as AGB definition, data sources, number of predictors, missing data, sample size, model development, model performance, model evaluation, results, and interpretation and discussion. For the risk of bias assessment, studies were classified into two categories, i.e., low bias and high bias. Studies that met all criteria outlined in the checklist were categorized as low bias, while those that did not meet the criteria were classified as high bias (Cramer et al. 2015). The domains and checklist used to evaluate the included studies are available in Supplementary Table 2.

Fig. 2 Histogram of RSE (%) for 361 observations



Meta-Analysis

We conducted meta-analysis using two approaches. The first approach involved an overall meta-analysis of 288 observations, while the second approach focused on meta-analysis using 42 observations that used the same LiDAR derived predictor (mean canopy height) and modeling method (regression analysis). The significance of selecting 42 observations over 288 observations is to investigate the heterogeneity and publication bias across studies when a conventional meta-analysis framework is followed. This novel approach examines whether uniformity across studies helps reduce uncertainty in the findings, offering insights into how consistent data source and method influence the reliability of results.

We used the correlation coefficient (r) to calculate the effect size and variance using the *escalc* function in the Metafor package (Viechtbauer 2010). We first converted R^2 to the correlation coefficient (r) and then transformed r to Fisher's z for statistical analysis. The correlation coefficient is a metric that measures the strength of a linear relationship between field measured AGB and model predicted AGB. We transformed r to z using Fischer's transformation given that the latter has strong statistical properties including normalizing r distributions. The calculated effect sizes and variance measures were used to conduct meta-analysis using the *rma* function in Metafor package. Deliverables for the test of heterogeneity were reported in terms of I^2 and Q statistics. I^2 statistics is a measure of heterogeneity that gives the percentage of inconsistency across the findings. The ratio ranges from 0—100%. The Q statistic is another standardized measure of heterogeneity. It can have positive or negative values. The values less than or equal to 0 indicate all variation is due to within study error and values greater than 0 indicate heterogeneity across studies that could be further tested with moderator analysis.

Additionally, data from 52 articles were evaluated for the consistency of results in terms of the same LiDAR-derived predictor and method used to build the model. Evaluation results revealed mean canopy height as the dominant airborne LiDAR-derived predictor and regression analysis as the most used modeling method. Therefore, we selected 7 articles with 42 observations that used mean canopy height as the predictor and regression analysis as the modeling method for meta-analysis. Similar to the meta-analysis of 288 observations, we calculated the effect size using transformed r and then performed a meta-analysis for 42 observations. We reported all results of the meta-analysis using test statistics to comprehend heterogeneity and funnel plots to discern publication bias. A funnel plot is a meta-analysis tool used to assess publication bias and examine the distribution of effect sizes across studies, with the x-axis representing the measured effect size and the y-axis indicating study precision (standard error, for this study). The publication bias is studied with the help of an inverted funnel shape, where more precise studies cluster near the top and less precise studies spread out toward the bottom. Publication bias is identified through asymmetry in the plot with a hollowed funnel (often the lower left side). Moreover, a narrow funnel suggests lower variability among studies and minimal bias, while a wider funnel indicates selective reporting or differences across studies. We conducted all analysis in R Studio (R Core Team 2021).

Results

Systematic Review Results

We report three key findings. First, we present the total number of articles conducted per country on a map (Sect. 3.1.1). Second, we report a quantitative summary of the evaluation metrics for AGB model using a bar plot (Sect. 3.1.2). Third, we analyzed the articles based on three different variables, namely data source, forest biomes, and method used for AGB modeling (Section. 3.1.3).

Number of Studies by Geographical Region

The articles selected according to the PRISMA workflow are dispersed across 19 different countries (Fig. 3). Out of those 19 countries, the highest number of selected articles are from USA (11 out of 52 studies) and China (9 out of 52 studies) followed by Tanzania and Malaysia. Nine studies were conducted in China, with 6 in temperate forests and 3 in tropical forest biome, while 11 studies were conducted in the USA, including 9 in temperate, 1 in boreal, and 1 in tropical forest biome.

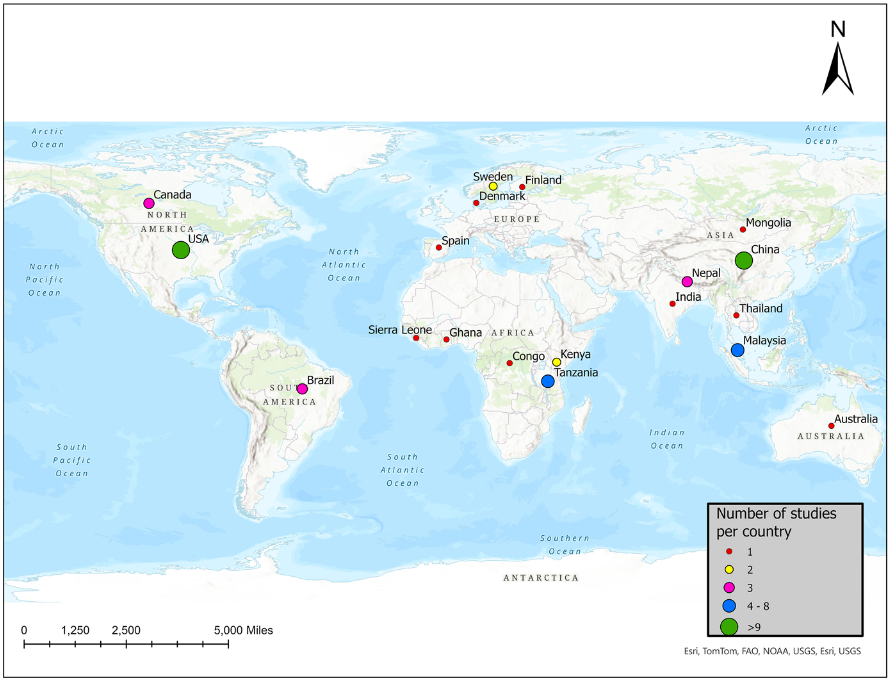


Fig. 3 Location of selected studies per country

AGB Model Evaluation Metrics

Among the AGB model evaluation metrics extracted from the selected studies, we observed that RMSE had the most occurrences (48 studies, 313 observations), followed by rRMSE (39 studies, 292 observations), R^2 (43 studies, 288 observations), and adjusted R^2 (15 studies, 87 observations) (Fig. 4). The number of observations reporting model evaluation in RMSE (313) and rRMSE (292) is comparatively higher as compared to R^2 and adjusted R^2.

Analysis of the Articles Based on Data Source, Forest Biomes, and Method Used for AGB Modeling

We observed distinct patterns in the data sources, biome types, and modeling approaches used in the selected studies. Airborne LiDAR-derived predictors were the most used data source for AGB modeling (42), followed by airborne LiDAR integrated with multi-source data (24) (Fig. 5). In terms of forest biomes, the highest number of studies were conducted in tropical forests (27), followed by temperate mixed (11), temperate coniferous (9), boreal (8), and temperate deciduous (4) (Fig. 5). Regarding modeling approaches, regression analysis was the most employed method (41). Machine learning techniques were also quite popular (19) followed by deep learning (5 studies), Bayesian statistics (3 studies), and geostatistical approaches (2 studies) (Fig. 5).

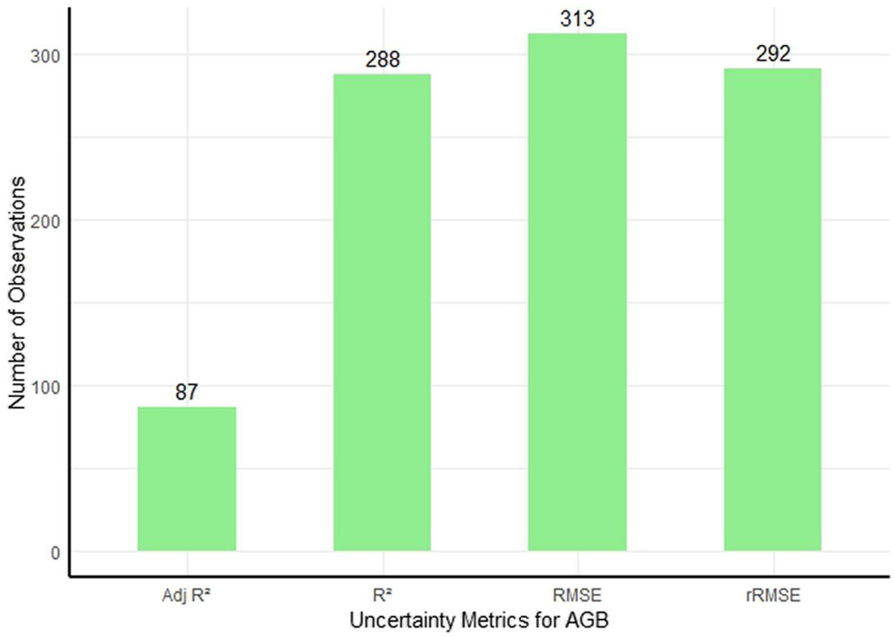


Fig. 4 Quantitative summary of model evaluation metrics. Adj R^2 = Adjusted coefficient of determination, R^2 = coefficient of determination, RMSE = Root Mean Squared Error, and rRMSE = relative Root Mean Squared ErrorAnalysis of variables for AGB modeling

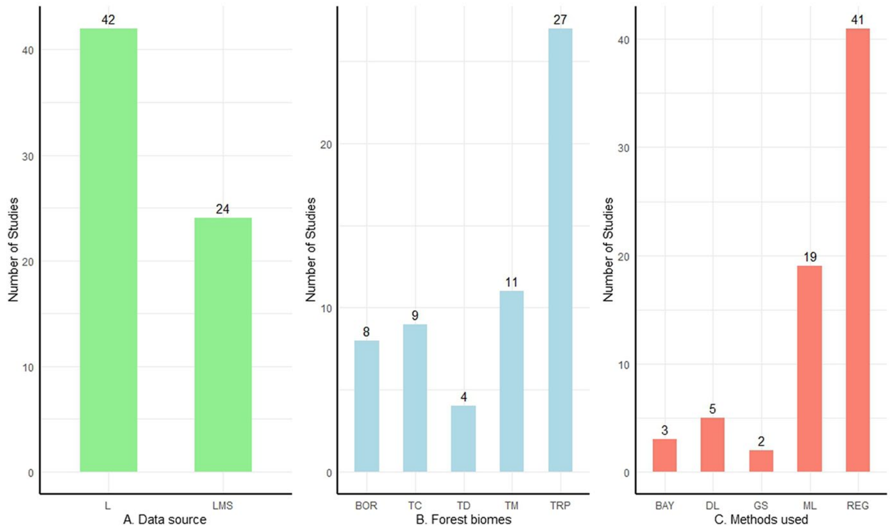


Fig. 5 Quantitative summary of variables. **A** Data source for AGB modeling. L= Airborne LiDAR data only and LMS = Airborne LiDAR and multi-source data. **B** Forest biomes. BOR = Boreal, TC = Temperate Coniferous, TD = Temperate Deciduous, TM = Temperate Mixed, and TRP = Tropical/Sub tropical. **C** Methods used for AGB modeling. BAY = Bayesian statistics, DL = deep learning, GS = geostatistical approaches, ML = machine learning, and REG = regression analysis

The results of the Kruskal–Wallis test indicated significant variation in RSE across groups for different variables, including data sources, forest biomes, and methods used ($p < 0.05$) (Table 1). Pairwise Wilcoxon test results identified specific groups within variables with statistically significant errors. The findings from the Pairwise Wilcoxon rank sum test are presented below in three different sections.

In terms of data source, post hoc multiple comparisons using the pairwise Wilcoxon rank sum test reported a statistically significant difference between studies using airborne LiDAR data only and those using airborne LiDAR in combination with multi-source data ($7.8* 10^{-5}$) (Table 2). AGB model based on airborne LiDAR alone had the highest mean RSE (33.86%), implying that AGB estimates were not closer to the field estimates, compared to airborne LiDAR combined with multi-source data (20.46%) (Table 6).

Regarding forest biomes, we observed a statistically significant difference in RSE between tropical and temperate mixed forest biomes (Table 3). The lowest RSE was reported in temperate deciduous forest biomes (17.93%) and the highest RSE was in

Table 1 Kruskal Wallis test for different variables

Kruskal Wallis test	Data sources	Forest biomes	Methods used
chi-squared	17.69	18.36	74.94
df	1	4	4
p-value	< 0.01	< 0.05	< 0.01

Table 2 *P*-values obtained from Pairwise Wilcoxon rank sum test for different data sources. (h0 = the error difference between the different groups of data source is zero, null hypothesis rejected at $p \leq 0.05$). L refers to airborne LiDAR data alone and LMS refers to airborne LiDAR used in combination with multi-source data

	L (42)
LMS (24)	$2.6 * 10^{-5*}$

$^{*}p \leq 0.05$

Table 3 *P*-values obtained from Pairwise Wilcoxon rank sum test for different forest biomes. (h0 = the error difference between the different groups of forest biome is zero, null hypothesis rejected at $p \leq 0.05$). The values in parenthesis represent the number of studies conducted in respective forest biomes

	Boreal (8)	Temperate Coniferous (9)	Temperate Deciduous (4)	TemperateMixed (11)
Temperate Coniferous (9)	1	-	-	-
Temperate Deciduous (4)	1	1	-	-
TemperateMixed (11)	1	0.26	1	-
Tropical (27)	0.73	0.88	0.47	0.0027*

$^{*}p \leq 0.05$

tropical (32.71%) (Fig. 6). The mean RSE for other forest biomes (temperate mixed, temperate coniferous, and boreal) ranged from 23.66% to 28.74%, but they were not significantly different. Model errors varied across different forest biomes, but the sample sizes were too small for the results to be statistically significant. In the discussion, we elaborate on the factors that might influence AGB model error for different forest biomes.

Model errors varied substantially for different methods used. We identified a significant difference in RSE across studies that employed deep learning ($3.4 * 10^{-10*}$) and machine learning ($6.6 * 10^{-8*}$) compared to those using regression analysis. Similarly, there was a significant difference in RSE between studies utilizing deep learning (0.00029) and Bayesian statistics (0.001) as compared to the studies using machine learning. Additionally, we observed a significant difference in RSE between studies employing Bayesian statistics and deep learning ($1.1 * 10^{-6*}$) (Table 4). The mean RSE using deep learning methods is significantly lower (6.56%) than the mean RSE obtained from Bayesian statistics (37.01%), machine learning (20.83%), and regression analysis (36.27%). However, the geostatistical approaches were not significantly different from other methods and had a mean RSE of 13%.

Table 5 provides an overview of the risk of bias assessment for the selected studies across 10 domains, such as the definition of AGB, data sources used, number of predictors, missing data, sample size, model development, model performance, model evaluation, results, and interpretation and discussion. Most studies

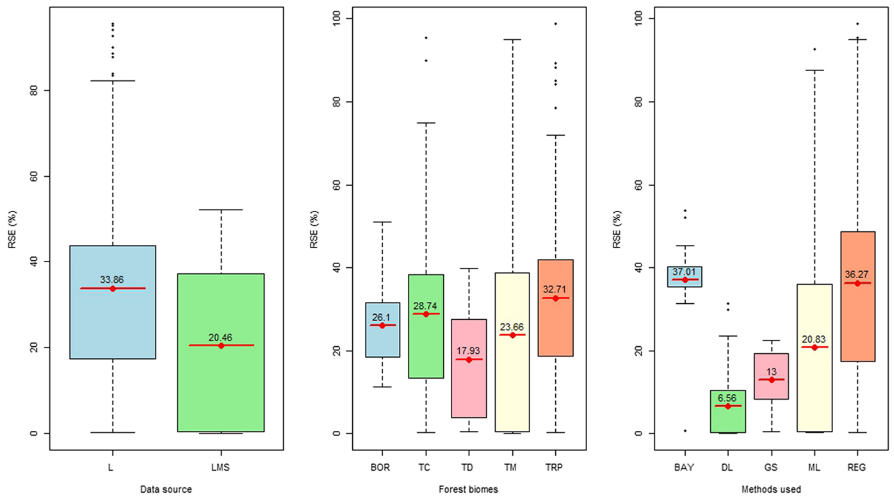


Fig. 6 RSE % standardized by mean AGB for three different categories, i.e., data source (left panel), forest biomes (middle panel), and methods used (right panel). Each boxplot represents the distribution of RSE values for each category, with the red horizontal lines and red dots indicating the mean RSE values. The colors distinguish different groups for better visualization

Table 4 *P*-values obtained from Pairwise Wilcoxon rank sum test for different methods used. (h0 = the error difference between the different groups of method used is zero, null hypothesis rejected at $p \leq 0.05$). The values in parenthesis represent the number of studies that used respective methods

	Bayesian (3)	Deep Learning (5)	Geostatistical (2)	Machine Learning (19)
Deep Learning (5)	$1.1 * 10^{-6*}$	-	-	-
Geostatistical (2)	0.07	1	-	-
Machine Learning (19)	0.001*	0.00029*	1	-
Regression (41)	1	$3.4 * 10^{-10*}$	0.58	$6.6 * 10^{-8*}$

$^{*}p \leq 0.05$

demonstrated a low risk of bias in domains such as AGB definition, selection of predictors, model development, model performance, and results reporting. However, concerns identified in the data sources and model evaluation domains highlight areas where the selected studies may face limitations or inconsistencies.

Meta-Analysis Results

We presented meta-analysis results based on two categories, i.e., 288 overall observations from 52 studies and 42 controlled observations from 7 studies. Controlled observations differ from overall observations because they come from studies that used the same predictor and modeling method. For the overall observations, the meta-analysis yielded an $I^2 = 96.38\%$ and $Q = 6648.28$ (Table 6). In comparison,

Table 5 Risk of Bias assessment for the studies included

Domains	Risk of Bias (number of studies)	
	High	Low
AGB definition	0	53
Data source	28	25
Predictors	0	53
Missing data	14	39
Sample size	3	50
Model development	0	53
Model performance	8	45
Model evaluation	28	25
Results	0	53
Interpretation and Discussion	8	45

Table 6 Results obtained from meta-analysis with overall and controlled observations

	Meta-Analysis Overall observations (288)	Meta-Analysis Controlled observations (42)
I^2 statistics (%)	96.38	91.67
Q statistics	6648.28 (df = 287) (*p*-value < 0.001)	399.97 (df = 41) (*p*-value < 0.001)
p-value	< 0.0001	< 0.0001

the controlled observations showed a slightly lower $I^2 = 91.67\%$ and a $Q = 399.97$ (Table 6). The higher values indicate significant inconsistency across study findings in both categories. While controlling for the predictor variable and modeling method reduced the heterogeneity, the difference between the two categories was not drastic.

The funnel plot for the meta-analysis of overall observations (Fig. 7A) shows an asymmetrical distribution, indicating a high likelihood of publication bias. The wider funnel plot and numerous data points outside the 95% confidence interval suggest non-normal distribution or significant heterogeneity. In contrast, the funnel plot for controlled observations (Fig. 7B) is narrower and more symmetrical, indicating lower variability, reduced heterogeneity, and potentially less publication bias.

Discussion

Systematic Review

Forest aboveground biomass estimation using airborne LiDAR is a globally recognized research topic, as exemplified by the studies selected for review. The development of MRV (measuring, reporting, and verification) guidelines, to assess forest carbon stocks and implement REDD (Duncanson et al. 2021; Herold

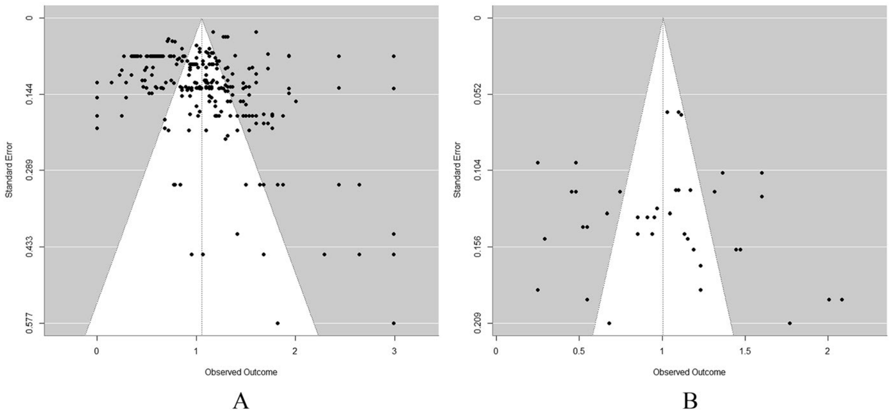


Fig. 7 Funnel plots obtained from the meta-analysis. **A** Obtained from 288 overall observations. **B** Obtained from 42 controlled observations (mean canopy height as the predictor and regression analysis as the AGB modeling method)

& Skutsch 2011) has further promoted studies in AGB estimation worldwide. Based on our results, the majority of selected studies are from USA and China (Fig. 3). Additionally, RMSE and rRMSE are reported more frequently than R^2 for AGB model evaluation (Fig. 4). However, some studies report only R^2 (Chirici et al. 2016; Hernández-Stefanoni et al. 2014; Wang et al. 2019) and some present relative error metrics analogous to rRMSE (Cushman et al. 2023; Du et al. 2021; Næsset et al. 2016; L. Zhang et al. 2023a, b). For example, Zolkos et al. (2013) defined RSE as the absolute model error, equivalent to RMSE, and RSE (%) as model performance standardized by mean biomass from field measurements, resembling rRMSE. We acknowledge that each model evaluation metric has its own strengths and weaknesses, our findings indicate that RMSE and rRMSE have been the most used model evaluation metrics over the past decade.

We recognize that various factors differ across the studies we reviewed, such as geographic location, forest biomes, number of variables used in model, and modeling methods used. However, isolating and measuring the impact of each variable is not feasible due to the risk of small sample sizes. Therefore, we selected three commonly used variables i.e., data source, forest biome, and methods used for AGB modeling to study how RSE varies within these variables. The quantitative summary of the selected studies indicates that airborne LiDAR data alone (42 studies), tropical forest biomes (27 studies), and regression analysis (41 studies) are most frequently examined (Fig. 5). As expected, our statistical results show a significant difference in RSE among the groups within the data source, forest biome, and methods used for AGB modeling (Table 1). To be specific, the chi-squared value obtained from the Kruskal Wallis test for RSE variation within methods used (74.94) is comparatively higher than the data source (17.69) and forest biomes (18.36). This indicates that the choice of method influences AGB estimation accuracy, highlighting the importance of selecting an appropriate modeling method.

We observed a significant difference in RSE between using airborne LiDAR data alone and using a combination of airborne LiDAR data with multi-source data (Table 2). The mean RSE is significantly higher using just airborne LiDAR (33.86%) compared to using a combination of airborne LiDAR with multi-source data (20.46%) (Fig. 6). Airborne LiDAR is a powerful tool for capturing the vertical structure of a forest including height and canopy characteristics (Hansen et al. 2015; Hayashi et al. 2015; Ma et al. 2023), however, it has limitations in capturing ecological features (Luo et al. 2017; Persson et al. 2013; Phua et al. 2017). Integrating multiple sources of data (e.g., LiDAR, satellite optical, radar, or environmental data) can complement airborne LiDAR by capturing the complexity of forest structure and environmental conditions to minimize errors in AGB estimation (Jha et al. 2021; Johnson et al. 2022). Our findings support that airborne LiDAR used in combination with multiple sources of data has significantly less AGB model error than using just airborne LiDAR. However, the reliance of a majority of selected studies solely on airborne LiDAR predictors for AGB estimation suggests a gap in the literature and current practices. It indicates that the potential advantages of integrating multiple sources of data in AGB modeling are not fully utilized. This could be due to various factors, such as limited access to data, challenges for suitable variable selection, and higher complexity of multi-source models. Future research should prioritize the integration of multiple sources of data with airborne LiDAR and investigate methods to minimize errors in AGB estimation across diverse ecosystems.

Among the forest biomes studied, we found significantly higher RSE in tropical forests (32.71%) implying greater challenges for accurate AGB estimation. Model errors were different but not significant across other forest biomes, including boreal (26.1%), temperate conifer (28.74%), temperate mixed forests (23.66%), and temperate deciduous (17.93%) (Fig. 6). We suspect that factors related to forest structure, species diversity and genetics, stand density, environmental variability, phenology, soil characteristics, and disturbance regimes can influence model errors across forest biomes. Supporting this finding, earlier studies conducted by Nelson et al. (1997) and Nelson et al. (1988) demonstrated that model performance is notably enhanced in pure stands compared to mixed forest stands. This suggests that the high species diversity and structural complexity of tropical forests might contribute to the increased challenges in AGB estimation. However, it is important to note that the sample sizes across forest biomes were small to draw statistically significant conclusions about all the observed differences. We suspect that the relatively higher mean RSE for the temperate coniferous biome than the temperate mixed and temperate deciduous forest biome may be due to uneven sample sizes and outliers present in the data (Fig. 6). The outliers are obtained from the study by Cushman et al. (2023), which developed a general AGB model for temperate coniferous forests in North America. Their study compared the performance of general, ecosystem-specific, and site-specific aboveground biomass models based on airborne laser scanning. Additionally, our review revealed that the majority of selected studies were conducted in tropical forests followed by temperate mixed forests, with a maximum number of studies originating from the USA and China. The geographical dominance of USA and China in selected studies may influence the overall understanding of model errors across forest biomes.

Methods based on regression analysis and machine learning algorithms emerge as the most commonly used AGB modeling methods followed by deep learning, Bayesian statistics, and geostatistical approaches (Fig. 5). Our analysis revealed that deep learning had the lowest RSE (6.56%) compared to regression analysis (36.27%), machine learning (20.83%), Bayesian statistics (37.01%), and geostatistical approaches (13%) (Fig. 6). Despite having significantly lower RSE, deep learning has not been widely adopted for AGB estimation, most likely due to challenges related to small samples of ecological data, overfitting, and advanced computation. Additionally, we observed a small subset of studies, using Bayesian statistics and geostatistical approaches, selected following the PRISMA guideline based on predefined inclusion and exclusion criteria. It is important to acknowledge that the sample sizes obtained from these studies were too small to draw statistically significant conclusions, although having an abundance of AGB studies based on airborne LiDAR. Therefore, our findings highlight the need for further exploration of under-studied methods, like deep learning, Bayesian statistics, and geostatistical approaches. The small sample sizes observed may lead to increased variability, reduced generalizability, and sensitivity to outliers, which can result in biased or inconsistent results.

Meta-Analysis

When modeling AGB using airborne LiDAR in diverse forested ecosystems, a wide range of predictors is necessary to capture biome nuances. However, the variation in predictors and modeling methods across regions contributes to challenges in obtaining a sufficient sample size for meta-analysis. A meta-analysis requires uniformity across studies in terms of LiDAR sensor used, predictor used, modeling method used, and defined output, such as AGB. As a result, we ended up with 7 studies having 42 observations that employed airborne LiDAR-derived mean canopy height as the predictor variable and regression analysis as the modeling method for the controlled meta- analysis. Meta-analysis with both overall observations and controlled observations has their own limitations. Overall observations account for different predictors and modeling methods, while controlled observations have the same predictor and modeling approach but a smaller sample size of 42.

We compared the meta-analysis results of controlled observations, using a uniform data source, predictor, and AGB modeling method, with an overall 288 observations aiming to assess heterogeneity and bias in AGB model performance. As expected, the controlled observations produced less heterogeneous results than the overall observations (Table 6). This reduced heterogeneity is supported by the funnel plots showing less bias in controlled observations (Fig. 7B) compared to the overall observations (Fig. 7A), indicating greater consistency in results. These findings suggest that the observed heterogeneity in overall results may be due to varied data sources, predictors, and AGB modeling methods. We also recognize that additional factors, such as site conditions, nutrient availability, management practices, disturbances, climate, and topography can have an influential impact on AGB. A moderator analysis could be carried out to further investigate this. However, there are less observations across studies available with comparable results and filtering by individual variables may result in small sample sizes. Our findings highlight the need for standardized and comparable methodologies in meta-analysis to reduce heterogeneity and enhance comparability, particularly when dealing with complex environmental variables. This standardization supports greater reliability and consistent interpretation of results in meta-analysis outcomes.This study adheres to the fundamental principles of meta-analysis, distinct from narrative or systematic reviews and from prior studies labeled as meta-analysis (Maake et al. 2023; Muumbe et al. 2021; Pillodar et al. 2023), which did not account for effect size and variance in the same rigorous manner. Our study followed established guidelines (Harrer et al. 2022; Israel & Richter 2011) and emphasizes the importance of uniform study design and measurement types consistency. Due to the limitation of sample size, our study was unable to perform moderator analysis and highlight exact source of variation in data collected across studies. We also acknowledge the limitations of sample size since the data collected across variables were not the same. However, our findings infer that variations in predictor variables and modeling methods contribute substantially to heterogeneity, whereas methodological consistency across predictors and modeling approaches minimizes variability, resulting in more reliable outcomes.

Conclusion

We conducted a quantitative analysis to determine the number of studies conducted by country, evaluation metrics for AGB models, and a summary of variables used in AGB modeling. Additionally, we presented an analysis of RSE categorized by data source, forest biome, and AGB modeling method used. Our findings indicate that most studies favored airborne LiDAR-derived predictors alone, tropical forest biomes, and regression analysis methods. However, notable variations in results were observed within studies. We concluded that conducting a meta-analysis with controlled predictor variables and modeling methods resulted in less heterogeneous results. However, further investigation is needed to understand the sources of inconsistencies across studies. Additionally, researchers intending to estimate AGB using airborne LiDAR in mixed forests should be mindful of potential sources of inaccuracies in model performance.

Based on our findings, we realized a need for expanding research to underrepresented biomes, such as boreal and temperate, to capture a more comprehensive understanding of model errors across diverse ecosystems. Additionally, studies should prioritize data collection from regions beyond the USA and China to reduce geographical bias and enhance the global applicability of AGB models. Incorporating multiple sources of data (e.g., combining LiDAR, radar, and optical data) in diverse forest types can further increase accuracy across forest biomes. When using multi-source data, data sources with lower model error should be assigned in model building, enabling the model to rely heavily on high-accuracy sources. Developing region-specific allometric models and considering local disturbances and climate variations is expected to strengthen future AGB estimations. Researchers should also focus on expanding the application of underutilized methods, such as deep learning, Bayesian statistics, and geostatistical approaches, to improve AGB estimation. Addressing the challenges of small sample sizes through techniques that are robust to limited data, such as transfer learning, data augmentation, or ensemble methods, can be valuable. Interdisciplinary approaches integrating ecological and computational expertise are recommended to further refine AGB estimation models. Our study has limitations related to the screening and data collection process, as these tasks were performed by a single author. Furthermore, the search for grey literature was not comprehensive and may have excluded the bias assessment from unpublished studies.

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Data Availability Data is available within the article and supplementary materials.

Declarations

Competing Interests Authors declare no conflict of interest.

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