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Review

A review of forest biomass assessments based on remote sensing reveals progress in methodological quality—but major challenges remain

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Abstract

Reliable forest biomass assessments are becoming increasingly important, as Parties to the Climate Convention are required to report changes in multiple carbon pools, including both above- and belowground biomass. In some regions, use of remote sensing is the only viable option for obtaining such estimates, whereas in other regions it bears potential to improve the accuracy of ground inventory-based biomass estimates. However, statistically rigorous estimation through remote sensing poses several challenges. This study systematically and comprehensively reviews the methodological quality of large-area biomass assessment studies from 1992 to 2022, based on core survey elements for successful biomass surveying assisted by remote sensing. For each element, we reviewed the studies in relation to "ideal standards" derived from the literature, which served as evaluation criteria. Our review revealed an increasing trend in use of remote sensing for biomass surveys, coupled with gradual improvements in methodological quality for all survey elements evaluated. For example, advances in remote sensing techniques, particularly the increased use of Light Detection and Ranging, Radio Detection and Ranging, and digital aerial photogrammetry, all technologies able to capture information on forest structure, have enhanced the reliability of biomass estimates. However, several problems remain, such as field data scarcity for model calibration, signal saturation in high-biomass regions, and misconceptions about the use of statistical methods. We identified five remaining key challenges for improving remote sensing assisted large-area biomass assessments. These include (i) obtaining sensor data that correlate stronger with biomass, (ii) acquiring larger sets of harmonized field data at the level of trees and plots for calibrating models, (iii) adequate use of statistical principles, (iv) developing methods for domain estimation, and (v) improved quality assurance and quality control. While upcoming new airborne technologies and satellite missions may mitigate some challenges, continued methodological innovation and further enhancement of the rigor of statistical and other procedures will remain essential for advancing remote sensing-based biomass assessments.

Keywords forest biomass, forest domains, statistical inference, remote sensing, LiDAR, RADAR

Introduction

Forests provide several essential ecosystem services, such as carbon sequestration (e.g. Pan *et al.* 2024), securing water resources, and sustainable provision of materials (Canadell and Raupach 2008). However, forests face threats such as deforestation and degradation. From 1990 to 2015, 129 million hectares of forest were lost (FAO 2015), mainly as a result of agricultural expansion (e.g. Curtis *et al.* 2018, Santos *et al.* 2020).

The importance of forests coupled with the threats they face have increased the demands for accurate forest information, spurred by global agreements like the United Nations' Framework Convention on Climate Change (UNFCCC 1992, Hunka *et al.* 2024) and the related Reducing Emissions from Deforestation and forest Degradation (REDD+) mechanism (Langner *et al.* 2014), which aims to mitigate climate change by reducing deforestation and forest degradation. Detailed information about changes in forest carbon pools is required from all Parties to the UNFCCC (Achard *et al.* 2002, Bonan 2008, Hansen *et al.* 2013), as well as from Parties that make agreements under the REDD+ mechanism (Angelsen 2009, Langner *et al.* 2014).

Forest biomass often serves as a proxy for several ecosystem services (Bonan 2008, Pan *et al.* 2011) and change in biomass is closely related to change in the biomass carbon pool. This has driven advancements in inventory methods to improve the reliability and cost-efficiency of biomass surveys (e.g. Asner *et al.* 2013). Although field-based national forest inventories (NFIs) provide the needed information in many countries, such inventories are lacking in several regions worldwide and updates may be infrequent in countries where they are conducted. Thus, NFIs alone cannot provide global level information about forest biomass (Tomppo *et al.* 2010,

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FAO 2015). On the other hand, remote sensing (RS) technologies, such as LiDAR (Light Detection and Ranging), RADAR (Radio Detection and Ranging) and optical sensors, offer standardized data for large-area forest assessments (e.g. Asner *et al.* 2003, Saatchi *et al.* 2011, Baccini *et al.* 2012). As a result, several biomass and carbon maps have been developed from RS data during the last decades (e.g. Chen *et al.* 2016, Giannetti *et al.* 2022). However, even when RS data are used, field data remain essential for model calibration (e.g. Woodwell *et al.* 1978, Dixon *et al.* 1994, Brown 2002, Kangas and Maltamo 2006, Henry *et al.* 2011).

The quality and availability of RS data have improved significantly over recent decades, driven by advancements in sensor technologies, new missions, and efforts to simplify access to data (e.g. Lu 2005, Viana *et al.* 2012, Dwyer *et al.* 2018, Dubayah *et al.* 2022). Global-scale RS data for civil applications began with the Landsat mission in the 1970s (Williams *et al.* 2006). Today, various missions provide spaceborne data across different spatial resolutions, ranging from coarse, such as MODIS, AVHRR and VIIRS (e.g. Yamaguchi *et al.* 1998, Cao *et al.* 2014, Kalluri *et al.* 2021), to intermediate or high, such as ASTER, Sentinel-2 and Landsat (Justice *et al.* 2002, Williams *et al.* 2006, Drusch *et al.* 2012), and to very high/fine resolution, such as QuickBird, PlanetScope, and WorldView (Bang *et al.* 2003, Anderson and Marchisio 2012, Sousa *et al.* 2015, Ahmad *et al.* 2021), among others. At the turn of the millennium, active RS techniques such as LiDAR and RADAR emerged as relevant tools for forest biomass surveys (e.g. Næsset 1997, Krieger *et al.* 2007, Narine *et al.* 2020), later supported by satellite missions including ICESat, GEDI, TanDEM-X, and Sentinel-1. In addition, several new space-borne sources have recently been launched or are about to be launched, such as Synthetic Aperture Radar (SAR) missions NISAR (Kellogg *et al.* 2020) and BIOMASS (Quegan *et al.* 2019), and the multi-footprint LiDAR and imager MOLI (Mitsuhashi *et al.* 2023), which will further expand the available data sources for RS-assisted estimation of biomass. Complementing these spaceborne sources, recent years have seen advances in RS data acquisition at smaller scales through UAV systems (Guimarães *et al.* 2020) and airborne platforms (e.g. helicopters and light aircraft, Boudreau *et al.* 2008). Systems such as airborne LiDAR, multispectral/hyperspectral optical sensors, and SAR have been extensively used to derive detailed information on forest structure, canopy height, and vegetation condition in the last decades (e.g. Zhao *et al.* 2009, Heiskanen *et al.* 2019, Hernando *et al.* 2019, Ramachandran *et al.* 2023).

A central approach to RS of forests is to link reference information on biophysical features from field plots with RS data through statistical models (e.g. Saatchi *et al.* 2011). The models can be parametric, as in the case of linear or non-linear regression analysis (e.g. Hudak *et al.* 2002), or non-parametric, using methods such as random forests or neural networks (e.g. Zaki Mohd and Latif 2017). Thapa *et al.* (2025) provide a detailed review of modelling approaches, highlighting differences among studies applying regression analysis, machine learning, deep learning, and Bayesian statistics. Their results showed that deep learning may lead to improved prediction accuracy but such methods may also be prone to overfitting, which must be carefully controlled (e.g. Valbuena *et al.* 2017). Once a model has been fitted, it is typically applied across the study area of interest to obtain a map of the biophysical feature of interest. The reliability of such maps depends on several factors, especially the goodness-of-fit of the model used to derive it (e.g. Kangas *et al.* 2023).

In many forest assessments, the interest is not only to produce a map but also to infer population means and totals (e.g. of biomass) across some larger area, such as a project area, a country, or an entire continent. In such upscaling, it is important to choose an appropriate statistical inference framework. Two main frameworks exist: design-based inference, also known as the fixed population approach, and model-based inference, also known as the superpopulation approach (e.g. Cassel *et al.* 1977, Gregoire 1998). Design-based inference can make efficient use of model predictions in terms of maps within the framework of model-assisted estimation (e.g. Särndal *et al.* 1992) but requires a probability sample of reference data from the entire target area of interest (e.g. Gregoire *et al.* 2011). Model-based inference, on the other hand, does not require probability sampling, but assumes at least approximate knowledge of the random process that has generated the true values for the variable of interest for all population units, often gained from a non-random sample. Most forest assessments that aim at producing maps and aggregating pixel-level values to obtain estimates for some larger area implicitly apply model-based inference, although this is not always clearly expressed (e.g. Gregoire *et al.* 2016). However, recently techniques for mapping under design-based inference have emerged as well (e.g. Fattorini *et al.* 2018, Fattorini *et al.* 2023).

Assessing uncertainties in forest biomass assessments is becoming increasingly important for applications such as reporting linked to the Climate Convention (UNFCCC 2014). The choice of inference framework significantly influences the uncertainty assessment methods and the interpretation of measures such as "bias" and "variance" (e.g. Ståhl *et al.* 2024). Depending on what assumptions are made, and what statistical framework is applied, substantial differences in magnitudes of uncertainties may be obtained (e.g. Gregoire *et al.* 2016). Many studies fail to state what statistical principles underpin their uncertainty assessments (ibid.), which complicates evaluations.

Forest surveys face multiple sources of uncertainty, such as model specification errors, poor model fit, RS data noise, field reference errors, and mismatches between field and RS data due to positioning inaccuracies (Fassnacht *et al.* 2014, Picard *et al.* 2015, Lu *et al.* 2016, Persson and Ståhl 2020, Persson *et al.* 2022). Effective uncertainty assessment requires identifying and quantifying these sources and evaluating their contributions using methods appropriate for the chosen statistical framework (e.g. Tian *et al.* 2016, Saarela *et al.* 2020, Ståhl *et al.* 2024).

Given the many challenges arising in connection with large-area biomass assessments, it is not surprising that studies sometimes yield different results for the same region (e.g. Saatchi *et al.* 2011, Baccini *et al.* 2012, Hu *et al.* 2016, Santoro *et al.* 2021), and comparisons with national statistics often reveal large differences (e.g. Gallaun *et al.* 2010, Breidenbach *et al.* 2022). As a result, initiatives such as the Global Earth Observation System (GEOSS 2016) have emerged to improve procedures for making best use of RS data, in some cases in connection with harmonized direct carbon flux estimates (e.g. Heinrich *et al.* 2023). For biomass mapping, NASA and the European Space Agency have created a platform for harmonization of global biomass maps, the Multi-Mission Algorithm and Analysis Platform (Albinet *et al.* 2019).

Due to the global interest in biomass mapping, several review articles have assessed the related developments. Many authors reviewed RS-based approaches for aboveground biomass (AGB) estimation, highlighting key sensors, modelling techniques, and challenges (e.g. Lu 2006, Zaki Mohd and Latif 2017, Ahmad *et al.* 2021). Coops *et al.* (2021) reviewed studies that utilized modelling approaches to extend airborne and spaceborne LiDAR data for forest attribute estimation, highlighting their effectiveness across different spatial scales and the importance of applying appropriate statistical methods. Recently, Ma *et al.* (2024) and Tian *et al.* (2023) addressed uncertainty in statistical modelling, RS data quality, field data uncertainty, and the challenge of matching field data with RS data, while Chen *et al.* (2015) identified several error sources and their propagation throughout biomass estimation procedures. Furthermore, Man *et al.* (2014) reviewed LiDAR-hyperspectral data fusion for forest biomass estimation, highlighting advancements, challenges, and future research directions. Lister *et al.* (2020) went through the history of integrating RS data into the US National Forest Inventory (FIA), while Knott *et al.* (2023) investigated sources of outliers in RS-assisted biomass predictions. Finally, Sileshi (2014) focused on common pitfalls in biomass modelling, highlighting methodological errors and proposing corrective measures. Thus, previous reviews have highlighted several critical aspects of large-area biomass assessments using a combination of RS and field data, emphasizing the need for identifying and reducing major sources of error. However, as pointed out by, e.g. Mitchard *et al.* (2013), Gregoire *et al.* (2016), and Kangas *et al.* (2023), large-area biomass assessments remain associated with a high level of uncertainty.

The objective of the current study was to conduct a systematic and comprehensive review of the developments of large-area biomass assessments based on combinations of RS and field data between 1992 and 2022. In this study, "large-area assessment" refers to forest biomass surveys covering more than 1000 hectares. We identified key elements (as explained below) involved in this type of biomass surveying from the literature and assessed each study and element using a system with criteria for high-quality biomass assessment. Examples of key elements are RS data quality, field data availability, statistical methods applied, methods applied for quality assurance and quality control (QA/QC), and workflow transparency. This approach provided quantitative scores for large-area biomass assessments across three decades of progress. Lastly, we identified major remaining challenges for making large-area biomass assessments more reliable, which is urgently needed given their importance for guiding decisions related to climate change mitigation, transition to bio-based economies, and providing information for ecosystem management and biodiversity conservation.

Material and methods

We conducted a comprehensive and systematic review of the scholarly literature on large-area forest biomass assessment and mapping. A structured search of studies was carried out using the databases Web of Sciences Core Collection, Scopus, and Google Scholar. We then analyzed the selected articles using the software Rayyan (website: https://rayyan.ai). Rayyan expedited the paper selection process through assessing titles, abstracts, and critical metadata, e.g. year of publication and number of citations, associated with each study. The workflow for the paper selection process is shown in Fig. 1.

In total, 4258 articles were initially selected based on the articles' objectives, which had to be related to RS-based forest biomass assessment and/or mapping. The screening process involved the use of specific search terms within the titles and abstracts. Terms related to the topic of interest, such as "AGB," "estimation," "satellite," and "forest" were marked as higher interest, while terms outside the scope, such as "grasslands" and "wetlands," were marked as lower interest. Importantly, the presence of negative terms did not automatically exclude a paper; instead, these terms were used to assess the overall context, allowing for a thorough evaluation before deciding on in- or exclusion. Based on the gross list of scientific articles identified through this process, we applied further filters in Rayyan, as described in bullets (i–v) below, i.e. a paper had to fulfil each of these inclusion criteria for being selected.

(i) The article was published during the period from 1992 to 2022.
(ii) The study has been moderately or largely influential in this field of research, which we specified by requiring at least a mean of 1.8 citations per year during the period from its publication to the end of 2022, which we retrieved from (Web of Science Core Collection 2025)
(iii) The study area was at least 1000 ha. No maximum area limit was applied.
(iv) RS data was part of the assessment scheme. These studies were identified through search terms such as "remote sensing," "satellite," "RADAR," "LiDAR," "imagery," and "multispectral" in Rayyan, and checking manually the actual application of RS data in those papers.
(v) Field data was part of the assessment scheme, at least for calibrating biomass prediction models based on RS data. However, we also included studies where "pseudo-field" data obtained from high-resolution airborne laser scanning were used. This search was achieved through using search terms such as "field," "sampling," and "ground data," and checking manually all studies that preliminarily passed this filter.

Respecting the filters and the manual checking described above, our selection process reduced the number of studies from an initial 4258 down to 80. To some extent, our inclusion criterion in bullet (ii) was chosen from the point of view of ending up with a manageable number of papers for the review. Information about the final cohort of 80 articles selected for this study is presented in the Supplementary Material A.

The review methodology, outlined in Fig. 2, aimed at conducting a comprehensive analysis of the selected articles, structured into two main phases. The first phase involved collecting basic information about each study, including location of the study area, study area size, sources of RS data applied, field sample size, statistical inference framework applied, etc. These descriptive data were used in the subsequent analyses, mainly for displaying results by groups of similar studies.

We classified the RS sensors into five broad categories, namely (i) airborne optical, (ii) airborne LiDAR, (iii) space-borne optical, (iv) space-borne RADAR, and (v) space-borne LiDAR. Each category includes several different missions, as shown in Supplementary Material B, Fig. S1. Further, we categorized the papers into four groups based on what inference approach was applied, i.e.: (i) design-based (model-assisted estimation), (ii) model-based, (iii) hybrid between design-based and model-based, and (iv) non-inferential. The latter category (non-inferential) included studies that focused on predicting spatially explicit biomass maps (i.e. generating pixel-level predictions or testing new mapping approaches), without extending the analysis to infer aggregated values such as mean or total biomass for the study area. Finally, the reviewed papers were categorized according to study area size (Sub-Regional = 10 to 40 000 km^2; Regional = 40 000 to 250 000 km^2; Sub-Global = 250 000 km^2 to Continent size; Global = Multiple Continent to Global scale).

The second phase of the review involved assessments of the core elements of each study, using a set of evaluation criteria that we

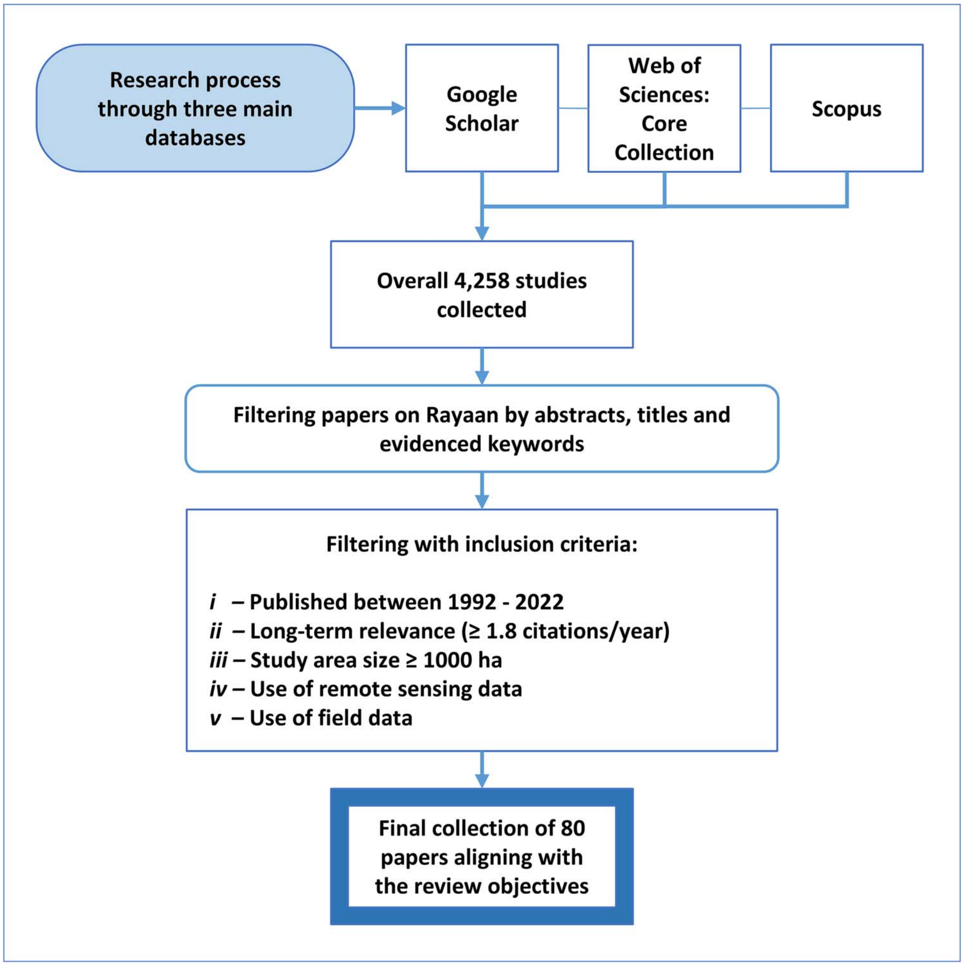

Figure 1 An overview of the systematic approach applied for including articles to the review.

termed "ideal standards" for large-area biomass assessment. We employed these standards as benchmarks for evaluating the quality of the reviewed studies and assigned numerical values to each criterion during the evaluation, aiming at a quantitative analysis. While the ideal standards are largely based on frameworks proposed in previous studies (e.g. Penman *et al.* 2003, Houghton *et al.* 2009, Mitchard *et al.* 2013, FAO 2015, Gregoire *et al.* 2016, Lu *et al.* 2016, Ståhl *et al.* 2016, Apostol *et al.* 2018, Claverie *et al.* 2018, FAO 2020), we synthesized and structured them to serve the purpose of this review study.

It is important to stress that our ideal standards should be considered "ideal" only in the context of ensuring reliable results for large-area biomass assessment based on our current knowledge and resources. We recognize that all forest surveys are constrained by economic and time limitations, as highlighted in, e.g. McRoberts and Tomppo (2007), making it close to impossible for any single study to completely satisfy all criteria of our survey elements. However, several identified shortcomings were not attributable to resource constraints but rather to adoption of suboptimal practices or misconceptions of methodologies.

The standards comprise six elements: (i) RS data properties, (ii) field data properties, (iii) auxiliary data for the target area and domains ("Domains of interest" refer to specific thematic or spatial categories within forests. Examples include distinguishing between forest and non-forest areas, or between different forest or ecosystem types, generically termed "domains.") of interest, (iv) statistical procedures applied, (v) QA/QC, and (vi) workflow transparency. Each element was evaluated using multiple criteria. The details are shown in Table 1, and further motivations for the selected elements and criteria are given in Supplementary Material C.

A low score for a component implies low quality, perhaps due to mistakes and errors, while a high score implies good compliance with the ideal standards. For example, the QA/QC component includes three criteria that underscore the importance of independent review and quality verification of field data, RS data, and methods used in the study. These criteria represent important aspects, which, if neglected, could compromise the rigor of the study.

Each element was assessed in an ordinal scale from 0 to 5 (representing "not addressed," "poor," "fair," "good," "excellent," and "outstanding"). The score for an element was derived from scores assigned to its associated criteria, each of which was based on a scale from 0 to 1, with the steps 0.0, 0.25, 0.5, 0.75, and 1 to provide nuances (further description in Supplementary Material C). These values, while subjective, reflect the level of fulfilment of a certain criterion. If a criterion was entirely overlooked, the score received was 0. The final score for an element was normalized by summing the scores for the associated criteria, dividing by the number of criteria, and multiplying with 5 to obtain a final score for the element in the range from 0 to 5. Although subjective, we suggest that this semi-quantitative methodology facilitates comprehensive evaluations adaptable to a wide range of studies, making it possible

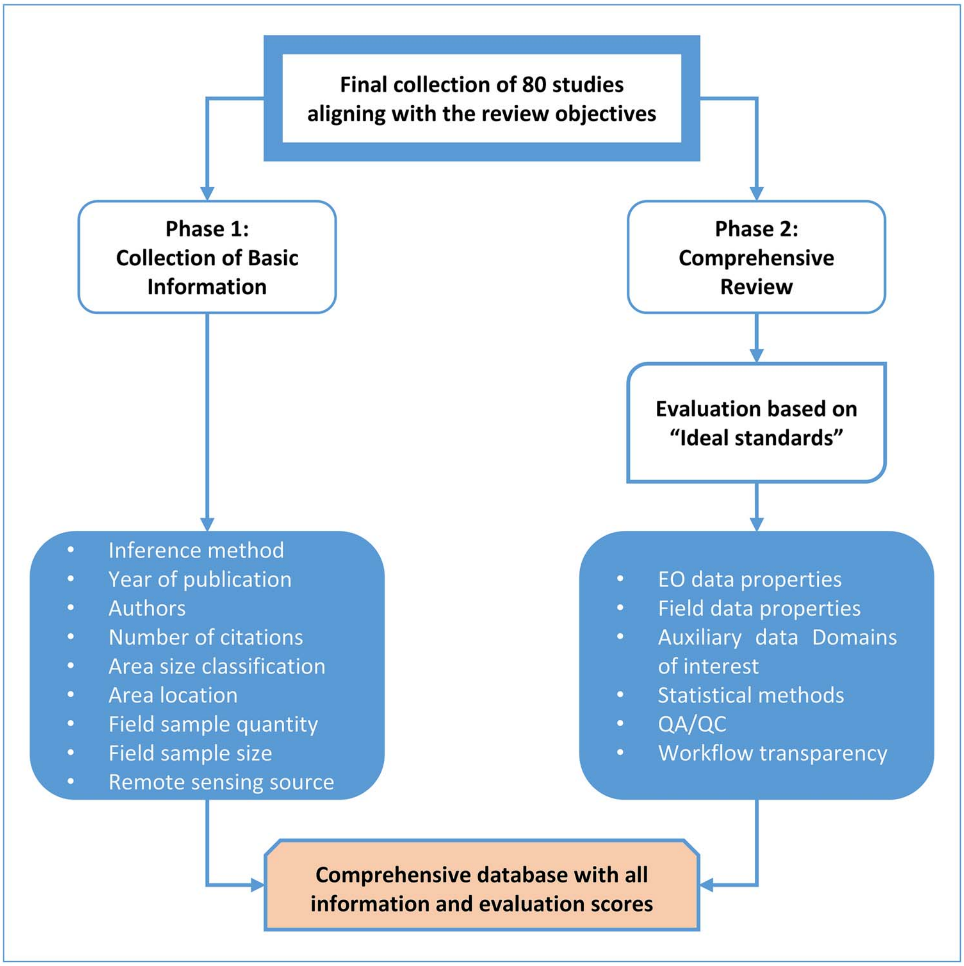

Figure 2 An overview of the review process for the selected articles.

to assess overall adherence to our defined baseline, i.e. our ideal standards.

As shown in Table 1, we used slightly different criteria for model-based studies compared to design-based studies (hybrid and non-inferential studies were grouped into the model-based category due to their methodological similarities). This distinction arose from differences between the frameworks with regard to the degree of reliance on features related to RS and field data, and models derived from such data. For example, design-based inference relies on an adequate probability sampling design and an appropriate estimator for this design, whereas model-based inference relies on the correctness of the specified and estimated model, but not on probability sampling of field reference data (e.g. Gregoire 1998).

Results and discussion

General trends

The number of articles that passed our selection criteria reveals a notable increase from 1992 to 2022, peaking in recent years (Fig. 3). Among the different inference methods, the model-based approach dominates. Although this increasing trend indicates an increasing interest in large-area biomass assessment, such interpretation must be done with caution because during recent decades an exponential growth of the number of publications has been observed in several research fields (Fire and Guestrin 2019, Hanson *et al.* 2024). However, growing awareness about the importance of biomass assessments has been affirmed in earlier studies (Busch and Ferretti-Gallon 2023).

Almost all of the studies focus on AGB, with a single exception where belowground biomass was included as well (Næsset and Gobakken 2008). Approximately 15% of reviewed studies focus solely on mapping, without extending the analysis to estimating totals or means for the study area.

Space-borne optical and RADAR data were the most frequently used RS sources across the reviewed studies, often combined, with clear geographic clustering in their application (Fig. 4b). Airborne and space-borne LiDAR data were also commonly used, and recently space-borne LiDAR data from the ICESat2 and GEDI missions have become more popular. With the latter types of data, three-dimensional data about the height distribution of forests are obtained, enabling the extraction of forest features such as canopy height and vegetation structure (Drake *et al.* 2002, Duncanson *et al.* 2020), which are strongly correlated with biomass. Unfortunately, due to the time constraint of this study, we could not include many GEDI-related papers released after 2022 (e.g. Bullock *et al.* 2023, Nazir *et al.* 2025).

Space-borne optical data, such as from Sentinel-2 and Landsat, have seen a sharp increase in usage in recent years (Fig. 4a). These freely available datasets have partially replaced more expensive high-resolution optical data (e.g. from the QuickBird satellite mission), despite offering lower spatial detail. Their accessibility has made them particularly valuable in remote areas, where logistical challenges

Table 1 A summary of elements and associated criteria applied as ideal standards during the review. Note the differences between studies applying model-based inference (including hybrid and non-inferential approaches) and design-based inference.

Core element	**Evaluation criteria for design-based inference**	**Evaluation criteria for model-based inference**	**References**
RS data properties	• Strong correlation with biomass • Available wall-to-wall or as a probability sample • Appropriate spatial and temporal resolution	• Strong correlation with biomass • RS data adequate pre-processing • Available wall-to-wall or as a probability sample (hybrid inference in the latter case) • Appropriate spatial and temporal resolution	Claverie *et al.* 2018 Coops *et al.* 2021 Lu *et al.* 2016 Saarela *et al.* 2016 Ståhl *et al.* 2016
Field data properties	• Adequate sampling design • Harmonized across the study area • Adequate allometric biomass models	• Data available from all different ecosystem types • Harmonized across the study area • First-order balanced data • Adequate allometric biomass models	Apostol *et al.* 2018 Grafström *et al.* 2014 Magnussen *et al.* 2016 McRoberts *et al.* 2010 Næsset *et al.* 2011 Persson and Ståhl 2020 Sileshi 2014 Ståhl *et al.* 2024
Auxiliary data for the target area and domains of interest	• Strict definition of the study area • Availability of thematic maps • Use of clear forest definition (e.g. the FAO definition)	• Strict definition of the study area • Availability of thematic maps • Map information for all domains of interest • Use of clear forest definition (e.g. the FAO definition)	Grafström *et al.* 2014 Næsset *et al.* 2011 Mitchard *et al.* 2013 Lu *et al.* 2016 Duncanson *et al.* 2020 FAO 2020 Coops *et al.* 2021
Statistical procedures	• Design-based statistical rigor	• Model-based statistical rigor • Managing shrinkage towards the mean for fixed populations	Cassel *et al.* 1979 Sileshi 2014 Chen *et al.* 2015 Picard *et al.* 2015 Gregoire *et al.* 2016 Saarela *et al.* 2020 Kangas *et al.* 2023 Ståhl *et al.* 2024
Quality assurance and quality control	• Independent control of field survey data • Independent control of RS data	• Independent control of field survey data • Independent control of RS data • Control of model performance in all ecosystem types	Penman *et al.* 2003 FAO 2015 FAO 2020
Workflow transparency	• Clearly specified inference framework • Workflow description and replicability	• Clearly specified inference framework • Workflow description and replicability	Sileshi 2014 Gregoire *et al.* 2016

may pose constraints to other techniques (e.g. Navarro *et al.* 2019, Puliti *et al.* 2021). Likewise, a marked increasing trend appeared after 2016 in the use of multiple RS sources, spanning optical, RADAR, and LiDAR data, highlighting the growing trend toward their combined and hierarchical application in biomass modelling (Fig. 4a).

For smaller study areas, use of airborne LiDAR data has advanced substantially over the past decades, particularly in Europe and North America (Fig. 4b), while airborne optical data (e.g. drone and airplane optical imagery) remain only marginally used in large-area surveys. The high-resolution data provided by airborne LiDAR sensors enable accurate biomass assessments, but the associated high costs make the technique infeasible for large-area applications, where freely available space-borne data are preferred (Fig. S2). Despite these costs, airborne LiDAR is frequently used to collect data for model calibration in multi-phase surveys or combined with other multisource RS data (Qi *et al.* 2019, Mäkinen *et al.* 2024).

Most studies covered North America, Asia and Africa, whereas South American, European and Global studies were fewer. The composition of RS data used in the different regions highlights variations in the use of high-resolution optical and LiDAR data between more localized studies and global biomass assessments (Fig. 4b). Most of the studies from all regions employed multiple RS sources, as previously mentioned. Among those based on a single RS source, most relied on one dataset for model metrics, while others incorporated additional RS sources for specific purposes such as modelling, validation, or comparative analysis of approaches (Fig. 4b).

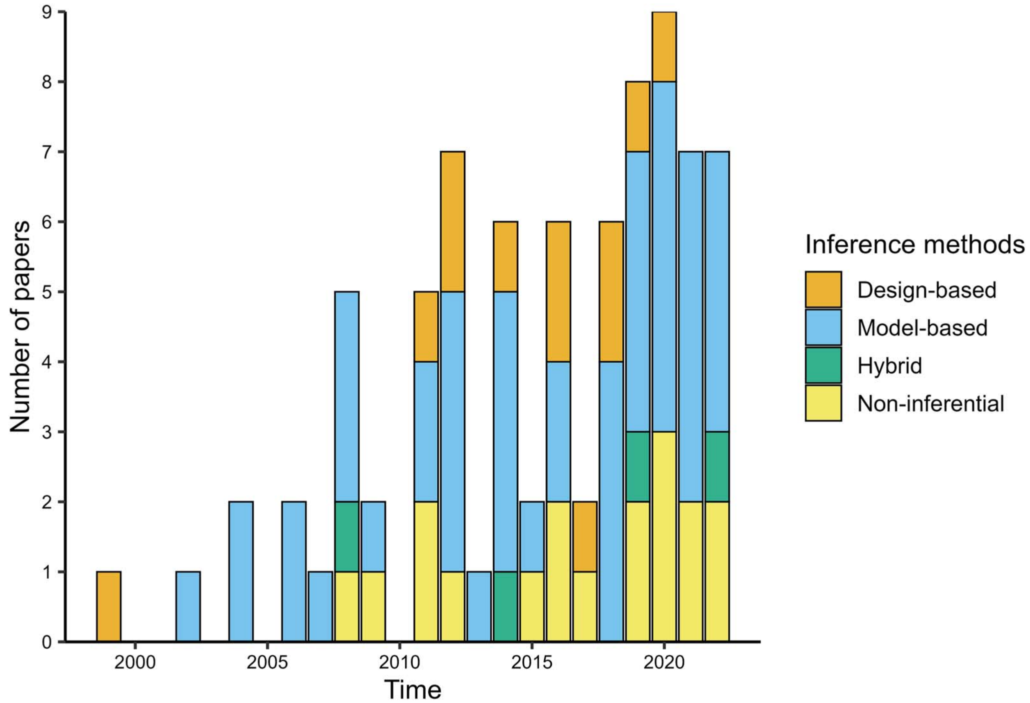

Figure 3 The number of articles that passed our selection criteria, by inference categories.

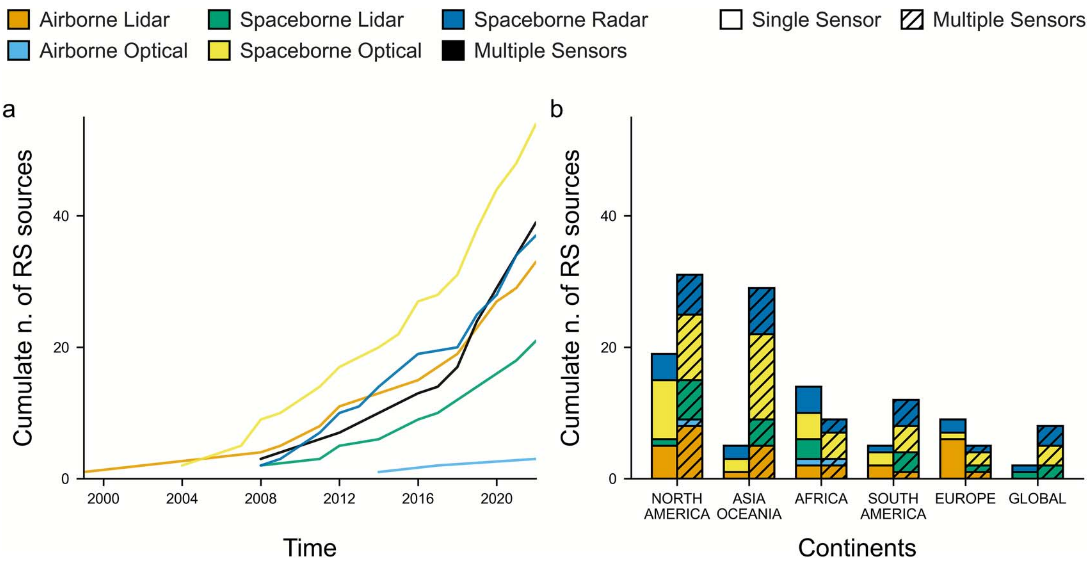

Figure 4 Trends in the use of RS sources across the reviewed studies. RS sources are counted cumulatively, accounting for studies that employed more than one RS data type. (a) Temporal evolution of the cumulative number of different RS data sources. (b) Distribution of RS data sources by study area location. RS sources are classified according to whether they are used individually or in combination.

Overall compliance with ideal standards

Compliance with ideal standards tended to increase slightly over time, but with high variation among studies (Fig. 5). Among the inferential methods, the studies based on design-based inference tended to score higher. The average endpoint score was 3.3, increasing from 2.5 at the start of the period.

Unsurprisingly, compliance with ideal standards tended to decline with increasing study area size, from sub-regional to global scales (Fig. 6b). Studies such as Saatchi *et al.* (2011) and Santoro *et al.* (2021) underscore the difficulties of achieving reliable results at the global scale. The challenges involve large uncertainties at the level of map elements, inconsistent spatial resolutions, and limited and sometimes outdated field reference data.

A notable proportion of studies employed purposive sampling (32.5%), meaning that samples were deliberately selected based on accessibility for measurements or specific objectives, rather than through a formal sampling design. An additional 23.8% of studies did not clearly define their field data collection method (Fig. 6a). The overall compliance with the standards was lower for those categories compared to the category "sampling design." Common problems

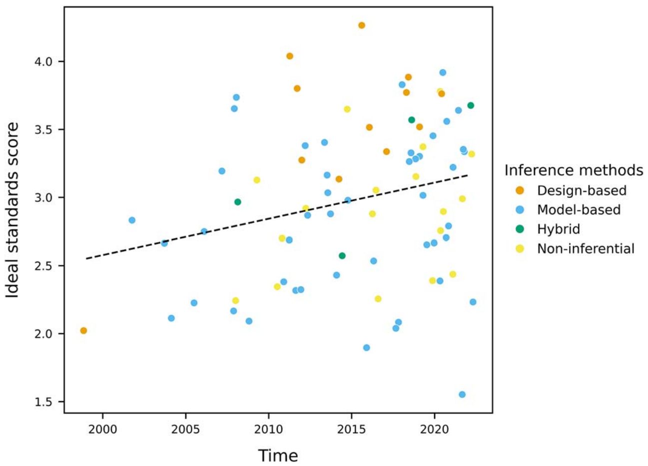

Figure 5 Trend for the overall compliance with ideal standards across the study period; the black dashed line represents the overall trend.

included small sample sizes, missing data from some ecosystem types, and lack of standardized or harmonized methods for the data collection across the study area. Even within NFIs, harmonization of methods across regions and over time may be a challenge, but essential for ensuring comparability (Qin *et al.* 2021).

Results by survey elements

Positive developments were observed for all core elements considered in the review, but our mean scores were only weakly increasing and accompanied by substantial variability (Fig. 7). Different inferential methods show slightly contrasting trends, with design-based studies increasing over time and model-based studies remaining stable, although the limited sample warrants cautious interpretation.

Compliance with the ideal standards for “RS data properties” improved only slightly across time, with mean scores increasing from 3.7 to 3.9, with substantial variation (Fig. 7a). This element assesses the quality, coverage, resolution, preprocessing, and correlation of RS data with forest biomass. While the evaluation checklist may have been insensitive to incremental advances, as many studies already scored fairly high in the early years of the study period, we did observe increasing experimentation with vegetation indices, spectral bands, and forest structural attributes, as well as integration of multiple RS sources (e.g. imagery, Radar, LiDAR) with rigorous pre-processing (Zhang *et al.* 2014, Navarro *et al.* 2019, Nandy *et al.* 2021, David *et al.* 2022). Despite these advancements in techniques, key challenges remain, such as processing complexities and limited access to high-resolution data for large-area assessments (e.g. Navarro *et al.* 2019, Fararoda *et al.* 2021).

Alignment with the ideal standards for “field data properties” improved slightly over time, with mean scores increasing from 3.0 to 3.6 (Fig. 7b). This element evaluates the collection methods, sampling design, harmonization, and allometric models related to field data. Although there is progress, substantial scope for improvement remains in data harmonization, field collection methods and the spatial coverage of field data. Varying measurement protocols (e.g. 500 vs. 1000 m^2 plots or DBH $\geq$ 5 cm vs. $\geq$ 10 cm) create problems when combining data from multiple inventories or when combining NFI datasets with *ad hoc* research plots, as shown by Mauya *et al.* (2015) and Searle and Chen (2017). Such inconsistencies may bias biomass prediction models unless explicitly accounted for. Harmonization frameworks and empirical studies may be used to quantify the magnitude of such effects and provide approaches to reconcile disparate protocols (e.g. Ståhl *et al.* 2012). Increased use of probability sampling designs and greater attention to ecological heterogeneity (e.g. Chirici *et al.* 2016, Puliti *et al.* 2020) could yield more spatially representative data and enhance the reliability of biomass assessments.

Compliance with the element “auxiliary data for the target area and domains of interest” improved markedly across time, with mean scores rising from 2.2 to 3.5 (Fig. 7c). This element highlights the value of structured datasets based on specific forest definitions and the usefulness of novel maps of features such as topography and ecosystem type. For instance, improvements include the integration of slope and terrain indices (e.g. López-Serrano *et al.* 2016) as well as other environmental-related details (e.g. Enquist 2002, Chave *et al.* 2014), the adoption of explicit forest definitions to ensure data consistency (e.g. Næsset *et al.* 2016), and clearer descriptions and delineations of study areas. Together, these developments illustrate a move towards more rigorous integration of auxiliary data in the studies. Nevertheless, challenges remain, particularly in the definition and delineation of forest domains for which separate estimates are of interest. Many studies rely on crude domain maps with unknown map errors, which undermine the reliability of the reported estimates.

Scores for the element “statistical procedures” increased from 1.8 to 3.4, indicating growing use of more rigorous approaches (Fig. 7d). This element evaluates the rigor of design-based and model-based inference, including sampling clarity, model validation, bias control, and uncertainty quantification. The observed improvement at least to some extent reflects the growing use of model-assisted estimation frameworks (e.g. Strunk *et al.* 2012), while model-based approaches still struggle with adequate uncertainty assessment (Gregoire *et al.* 2016, Ståhl *et al.* 2024). Nonetheless, some model-based studies have advanced by propagating uncertainty across prediction layers, such as the hierarchical prediction framework of Saarela *et al.* (2020), and the propagation of uncertainty from allometric models to RS predictions by Vorster *et al.* (2020).

Over time, a range of modelling approaches have been applied, including linear and non-linear regression (e.g. Mermoz *et al.* 2014, López-Serrano *et al.* 2016), machine learning methods such as support vector machines and random forests (e.g. Navarro *et al.* 2019, Guerra-Hernández *et al.* 2022), Neural Networks (e.g. Zhu and Liu 2015), and deep learning (e.g. Ghosh and Behera 2021). Consistent with Thapa *et al.* (2025), machine learning emerged as the most frequently applied approach. Unlike their review, which ranked deep learning second, we found non-linear regression in this position, with deep learning barely represented. This difference likely reflects the exclusion of studies from recent years (2023–2025) from our analysis, during which the use of deep learning has expanded considerably. Results indicate a gradual shift towards advanced modelling with greater attention to validation and reporting. However, our analysis addressed validation strategies and statistical rigor rather than the performance of individual modelling methods (cf. Thapa *et al.* 2025).

Results for the QA/QC element show consistently low scores, with almost no positive trend over time (Fig. 7e), indicating that rigorous QA/QC remain difficult to achieve in practice. In this case, the element evaluates the rigor of QA/QC procedures applied to field and RS data, including independent verification, adherence to recognized standards, and comprehensive assessment of model performance across

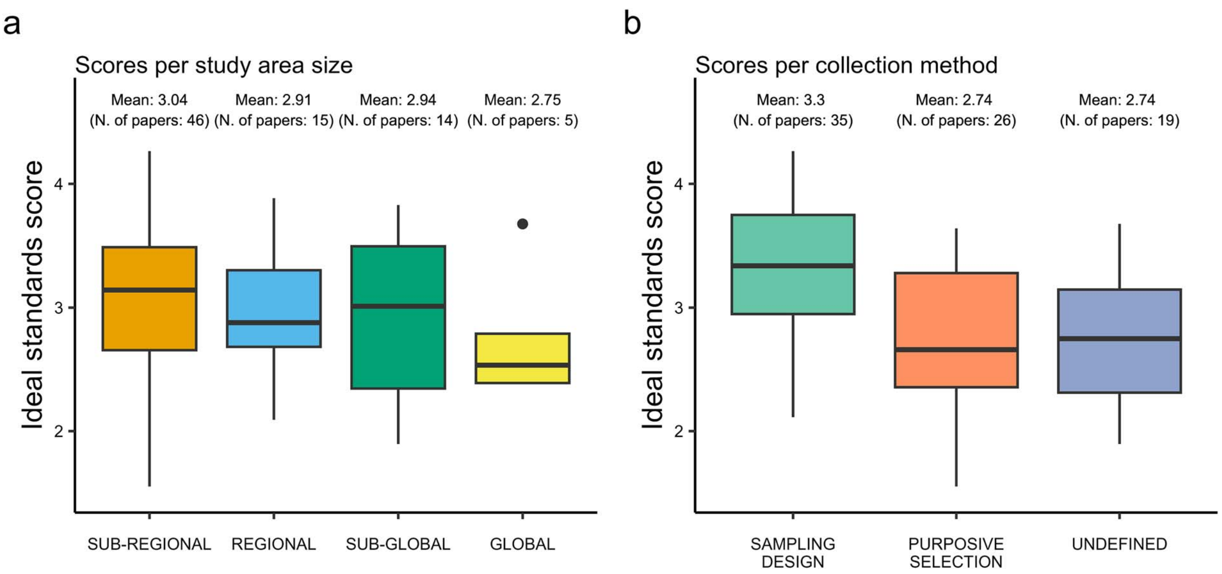

Figure 6 Ideal standard scores for studies having different study area sizes (a) and applying different field data collection methods (b).

ecosystems. Effective QA/QC mostly require independent validations, as outlined by Pearson *et al.* (2007) and FAO (2015). This may involve substantial time and extra resources, which may be a reason why external quality control is usually not a part of assessments. Many studies rely on pre-processed datasets, such as those from satellite missions or NFIs with established standards and protocols, offering high-quality internalized validation (e.g. Healey and Berrett 2017). However, in large-area studies the possibility to use existing national forest statistics for independent validation is often not considered, and most studies do not explicitly report any structured or standardized QA/QC procedure. Consequently, QA/QC score assignment was primarily driven by data provenance rather than by study-specific validation, leading to a limited spread and clustering of values in Fig. 7e.

Results for the "workflow transparency" element show substantial improvement, with mean scores increasing from 2.0 to 3.6 over time (Fig. 7f). This reflects the clarity and reproducibility of the biomass estimation process, including framework description, methodological detail, and data/code accessibility. The observed improvement corresponds to a shift toward more detailed methodological reporting, as seen in studies such as Magdon *et al.* (2018) and Saarela *et al.* (2020), which enhance transparency and reproducibility of their studies. Model-assisted and hybrid approaches generally achieved the highest scores for this element. Despite the overall improvement, important shortcomings remain regarding open access to data and codes. Only ∼10% of the reviewed studies shared at least part of their datasets or algorithms, and never both together. Data sharing was often limited, with studies providing processed RS layers but not the corresponding field measurements. While restrictions on NFI permanent plot data are understandable, sharing self-collected data would mostly be less problematic. Some studies provided data upon request or shared datasets of aggregated features or estimates (e.g. at state or regional level), which fall short of true open access. Algorithm sharing was even rarer.

Remaining challenges

Across all survey elements evaluated in this review, we observed modest but consistent improvements of methodological quality across time. This is an important and reassuring finding, given existing concerns about a decline in overall research quality, driven by the increasing incentives for scientists to increase their amounts of publications during recent years (e.g. Fire and Guestrin 2019, Hanson *et al.* 2024). Our analyses did not reveal any relationship between paper quality and citation impact, suggesting that citations often reflect specific contributions, such as the introduction of novel methods (e.g. Silva *et al.* 2021), rather than overall quality under our assessment criteria. Despite the progress, the average endpoint scores for the core elements were not always high, indicating further room for improvement.

We identified five areas within which we suggest that improvements would be relevant for making future large-area biomass assessments more reliable. These are (3.4.1) properties of RS data, (3.4.2) properties of field data, (3.4.3) use of statistical principles, (3.4.4) methods for domain assessment, and (3.4.5) QA/QC. Whereas the first two aspects have been identified in several previous review studies (e.g. Duncanson *et al.* 2019, Réjou-Méchain *et al.* 2019, Radočaj *et al.* 2020), the last three are rarely pointed out as important areas for improvement, although addressed by, e.g. Avitabile *et al.* (2016), Gregoire *et al.* (2016), and Penman *et al.* (2003). Each of these five areas is discussed below.

Properties of remotely sensed data

Optical satellite data have been used for a long time for biomass assessments (e.g. Zheng *et al.* 2004, Karlson *et al.* 2015, Ehlers *et al.* 2022), but the goodness-of-fit of prediction models based solely on optical data is typically poor (e.g. Wang *et al.* 2020, Ehlers *et al.* 2022) even when multispectral or hyperspectral data are involved (e.g. Clevers *et al.* 2007, Laurin *et al.* 2014). Further, in heterogeneous landscapes mixed pixels could complicate predictions (Hall *et al.* 2006, Lu 2006). Recent innovations such as the composite-to-change approach (Hermosilla *et al.* 2015) and enhanced atmospheric and radiometric corrections (Mauya *et al.* 2015) have improved the usefulness of optical data in specific circumstances.

When RS data are strongly correlated with biomass, maps tend to capture the actual variability across the landscape. In contrast, when

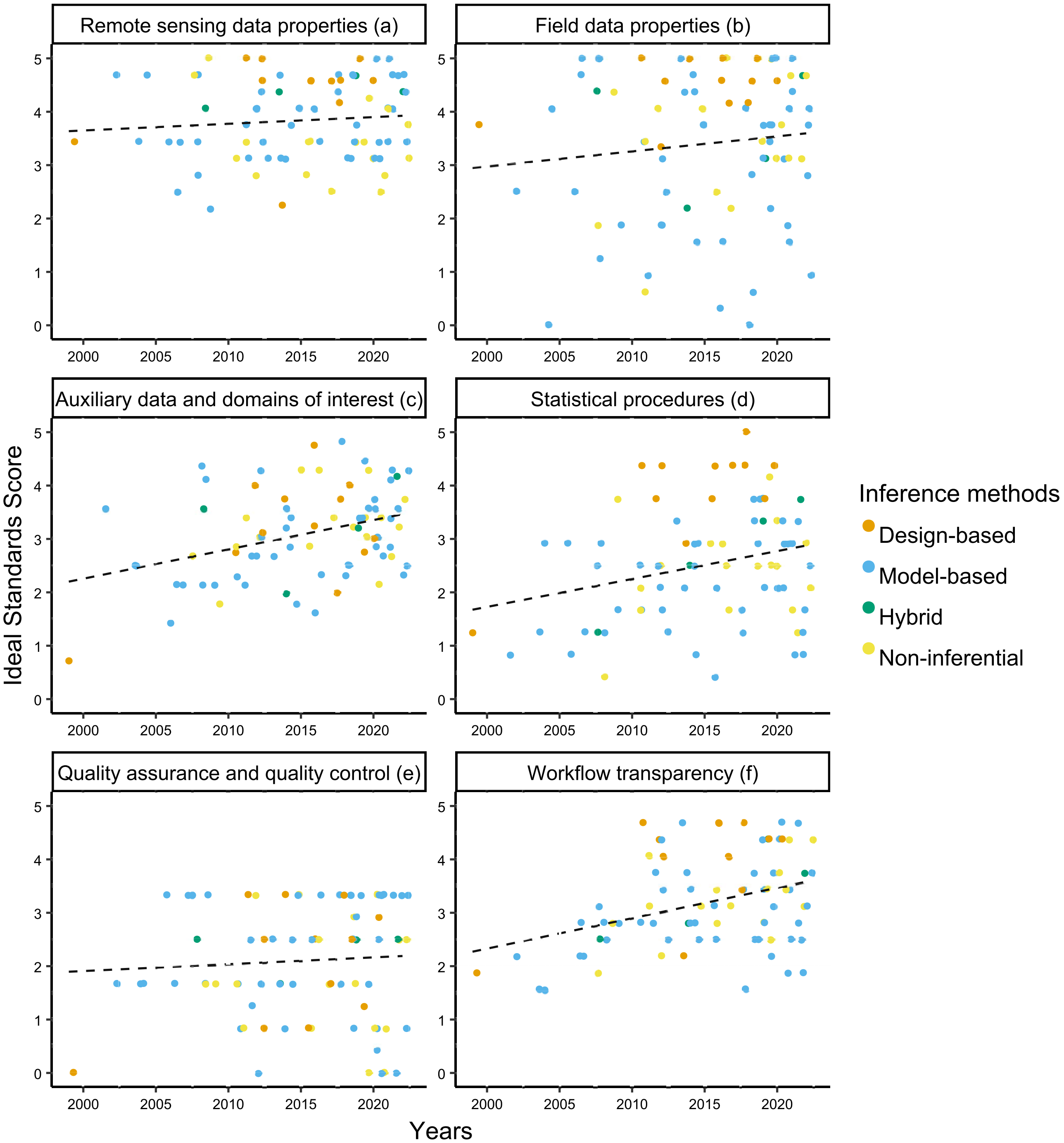

Figure 7 Trends in compliance with the ideal standards for the six different core survey elements. The panels show results for (a) RS data properties, (b) field data properties, (c) auxiliary data for the target area and domains of interest, (d) statistical procedures, (e) QA/QC, and (f) workflow transparency. The colors refer to inference method used (design-based, model-based, hybrid, or non-inferential), while the black dashed line represents the overall trend.

weakly correlated data are used, the resulting maps substantially underestimate biomass variability (e.g. Saarela *et al.* 2023).

Adding information about the height structure (obtained from sources such as LiDAR, RADAR, or aerial photogrammetry) of forest vegetation substantially improves the goodness-of-fit of biomass prediction models, as demonstrated in several studies (e.g. Chen *et al.* 2002, 2019, Clark *et al.* 2011, Laurin *et al.* 2014, Brovkina *et al.* 2017, Guerra-Hernández *et al.* 2022). However, airborne LiDAR data are costly (e.g. Clark *et al.* 2011, Gregoire *et al.* 2011) and hence challenging to collect and apply across large areas. The same holds true for digital aerial photogrammetry. While data from space-borne sensors have (almost) global coverage, to date, space-borne LiDAR data have only been available as relatively sparse samples, often coupled with inexact positioning, large footprints, and instruments that may not penetrate dense forest vegetation (e.g. Tang *et al.* 2019, Aguilar *et al.* 2024). Similarly, for RADAR data, saturation effects reduce the efficacy of C- and L-bands in high-biomass regions, limiting their overall applicability. For instance, saturation typically occurs at biomass levels of 50–70 Mg ha^{-1} for C-band and 100–150 Mg ha^{-1} for L-band in RADAR data (Kasischke *et al.* 1997, Luckman *et al.* 1997, Saatchi *et al.* 2011, Navarro *et al.* 2019, Fararoda *et al.* 2021). X-band wavelength is constrained by limited penetration of dense canopies (e.g. Schlund *et al.* 2015). However, the Interferometric synthetic aperture RADAR (InSAR or ifSAR) technique has proven more effective in mapping forest structure and predicting biomass compared to backscatter approaches. It addresses issues of saturation in biomass prediction and provides high-resolution data on canopy height and topography (Santos *et al.* 2004, Treuhaft *et al.* 2004, Santoro *et al.* 2015, Sinha and Schuster 2015, Persson and Fransson 2017).

Although our endpoint score for the survey element "RS data properties" was relatively high, we suggest that stable provision of RS data that provide reliable information about the height structure of forests with relatively fine spatial resolution and accurate geo-localization remains as a challenge for large-area biomass surveys. While provision and use of spaceborne LiDAR data have advanced significantly over the past decades (e.g. Coops *et al.* 2021, Dubayah *et al.* 2022), for several reasons mentioned above, these data are not yet as strongly related to biomass as the corresponding data from airborne LiDAR.

Field data properties

A persistent limitation of large-scale biomass assessments is the scarcity of ground observations for model calibration (e.g. Saatchi *et al.* 2011, Laurin *et al.* 2014, Yu *et al.* 2022). As a result, biomass models are often extrapolated to areas lacking corresponding field measurements, even though the consequences remain poorly understood and may introduce substantial bias (e.g. Schlund *et al.* 2015, Yu *et al.* 2022). In several countries, data access policies impose additional constraints on the use of NFIs information: plot locations are often perturbed for confidentiality, and unaltered data are generally restricted to NFI staff, affecting external research (e.g. US FIA, Sabor *et al.* 2007; U.S. Forest Service 2023). Further, field data from different countries typically are acquired using different definitions and protocols, and thus field data are far from well-aligned across all regions of the world, although harmonization efforts are ongoing (e.g. Vidal *et al.* 2016, Herold *et al.* 2019). Further, in case field data are very sparse, pseudo-field data obtained from, e.g. airborne laser scanning is sometimes used in hierarchical modelling approaches (e.g. Saarela *et al.* 2018, Wang *et al.* 2019).

Another important limitation concerns the severe shortage of data for allometric biomass modelling from destructive sampling, at the level of single trees and plots. This is mainly due to the labor-intensive and thus costly work required to acquire such data (Sileshi 2014). As a consequence, the few models available (e.g. Alvarez *et al.* 2012, Yuen *et al.* 2016, Aabeyir *et al.* 2020, Mulatu *et al.* 2024) are typically extrapolated across large areas, with unknown errors (e.g. Temesgen *et al.* 2015). For instance, an equation developed from trees in moist tropical forests most likely is unreliable in dry forests, where differences in wood density and tree architecture may introduce substantial errors (Ngomanda *et al.* 2014). The problem is even greater for belowground biomass, which is typically modelled from aboveground attributes. The reliability of allometric equations may also be affected by choices of analytical methods (Sileshi 2014). Thus, newly developed allometric models may markedly alter biomass estimates and their relation to remotely sensed metrics, whereby model substitution may lead to complications for interpreting trends and formal reporting (e.g. Johnson *et al.* 2025).

Overall, as pointed out by Lu (2006) the shortage of field data is a substantial limiting factor for large-area biomass surveys. Initiatives to compile field data sets from different biomes across the globe (e.g. Winter *et al.* 2008, Duncanson *et al.* 2019) are to be commended, but it is likely that limited access to field data will remain a substantial challenge for a long time.

Potentially, advances in terrestrial laser scanning (TLS) and mobile laser scanning (MLS) may offer new opportunities for the supply of inexpensive field data (e.g. Pires *et al.* 2024, Holvoet *et al.* 2025, Molina-Valero *et al.* 2025). TLS and MLS could be used for detailed digital tree reconstruction through quantitative structural models, which may limit the need for destructive sampling (e.g. Enquist *et al.* 2009, Torresan *et al.* 2018).

Use of statistical principles

Most biomass surveys aim to provide not only maps, but also biomass densities and totals for the target area. In deriving such statistics, there is a need for a framework for the statistical inference. As previously noted, the two main statistical frameworks in this context are design-based inference and model-based inference (e.g. Gregoire 1998). It has already been pointed out that there are substantial differences between them regarding what assumptions are made and how uncertainty metrics should be interpreted.

Like Gregoire *et al.* (2016), we found substantial confusion around statistical concepts in many of the articles reviewed. A common approach is to apply model-based principles during the compilation of results, and then switch to design-based principles for their evaluation, without reflecting on the inconsistency created when mixing the two frameworks (e.g. Ståhl *et al.* 2024). This often leads to observing that small true values are overestimated and large true values are underestimated, which follows from evaluating predictions that are model-unbiased in fixed populations (ibid.). In fact, contrary to what is often assumed, model-based predictions are not unbiased for biomass values of individual map units in real forests, but only across hypothetical population realizations under a superpopulation model (Cassel *et al.* 1977). Sometimes, predictions from regression models are treated as observations and population totals and means, and their corresponding uncertainties, are estimated following fully design-based principles, overlooking how the models affect uncertainties.

Overall, there is considerable room for improving the statistical practices in large-area biomass assessments. We found that the main problems seem to be confined to studies applying model-based inference, whereas studies relying on design-based inference (typically model-assisted estimation) normally manage the statistics correctly. Limited teaching of these concepts at university level probably means that early-career researchers often struggle in engaging with specialized literature. Targeted courses or R/Python packages with tutorials could enhance understanding and uptake of methods. Moreover, some key limitations of model-based inference remain to be addressed, including its bias in fixed populations and the challenge of quantifying it without extensive field data (Ståhl *et al.* 2024).

Methods for domain assessment

Although domain assessment is a part of statistical inference (treated in the previous section), we address domain level assessment separately due to the unique challenge it presents in large-area surveys. Typically, both model-based and design-based approaches rely on maps for delineating domains. This works well for domains with clear boundaries, such as administrative units. However, difficulties arise when areas belonging to the domain occur scattered across the study area, such as the domain "forest," or domains formed by different forest types (e.g. Duncanson *et al.* 2020, Vorster *et al.* 2020). In such cases, maps are typically still used to identify domains, assuming the maps are error-free, and methods specific for a certain domain are then applied based on the mapped information. However, maps are rarely perfect (e.g. Avitabile *et al.* 2016), and errors in domain maps introduce additional uncertainties, which are often overlooked (e.g. McRoberts *et al.* 2010).

Design-based inference (model-assisted estimation) methods for domain assessments have evolved over time, and in principle domain level estimation is not a problem (e.g. Andersen *et al.* 2024), even in the absence of domain maps. However, to our knowledge, no practical solutions currently exist for domain-level estimation in model-based inference that avoid the use of domain maps. Moreover, the lack of uncertainty information associated with these maps highlights an area requiring further attention. As a result, domain-level inference remains a substantial challenge.

A rigorous procedure in model-based inference might involve two-step modelling, where a first model predicts the domain category whereas in the second step biomass is predicted. Uncertainty assessment would then need to account for errors in both steps. While none of the reviewed articles explicitly implemented this kind of methodology, several studies have developed procedures that move in this direction. In specific cases, biomass prediction has been carried out using models developed separately for distinct forest ecosystem types (e.g. Qi *et al.* 2019). Other studies have produced wall-to-wall biomass maps that account for forest type variability during model development by using stratified or balanced field sampling across forest conditions, without explicitly delineating forest domain maps (e.g. Guerra-Hernández *et al.* 2022). These contributions provide valuable steps towards tackling the problem, even though the main challenge remain, particularly with regard to assessing uncertainties, which is central for adequate interpretation of results from surveys applying model-based inference.

Quality assurance and quality control

Principles of QA/QC are important in all types of surveys (e.g. Penman *et al.* 2003, FAO 2015). Based on our review, this element remains a challenge for most surveys, especially in the case of studies covering very large areas. In such cases, it is important to define clear quality requirements and maintain consistency across field and RS data (Avitabile *et al.* 2016, Ma *et al.* 2021). It was also noted that a lack of standardized measurement protocols or proper instrument calibration may introduce systematic errors that undermine comparability across field plots (e.g. McRoberts *et al.* 2011). Therefore, we suggest that a specific and tailored benchmark methodology for QA/QC in biomass surveys should be developed to strengthen the reliability of the results (e.g. Penman *et al.* 2003). Independent validation or cross-checking of procedures would also enhance survey's reliability, but such practices remain rare due to resource limitations and institutional barriers.

An interesting practice is to make comparisons with available national statistics (e.g. Blackard *et al.* 2008, Liu *et al.* 2017, Bispo *et al.* 2020). However, such comparisons raise the question of whether discrepancies stem from inaccuracies in national statistics, methodological differences, or limitations in the large-area biomass survey. Considering the numerous uncertainties involved in large-area biomass surveys, we suggest that great caution should be exercised before claiming that national statistics are incorrect. Thus, country-level statistics from countries that apply field-based forest surveys offer great potential for quality control of results. However, this is not the case in many tropical regions, where NFIs are often incomplete, irregular, or absent, limiting comparisons of biomass estimates with national statistics (FAO 2020). Where possible, reliability can be improved by establishing transparent *ad hoc* QA/QC procedures, comparing results with local or independent datasets, and following established validation frameworks such as the IPCC QA/QC and uncertainty guidance (Maksyutov *et al.* 2019), GFOI MGD validation steps (Espejo *et al.* 2020), or CEOS LPV biomass product validation practices (Duncanson *et al.* 2021), while applying an internationally recognized forest definition (e.g. FAO FRA).

About the criteria applied and the selection of articles for the review

As most literature reviews, our study was influenced by perceptions, in our case about how large-area biomass assessments ought to be performed. To clarify these perceptions, and to structure the review, we specified ideal standards for high-quality biomass surveying, for six core survey elements. To each element, we linked a number of criteria for high-quality biomass surveying (further description given in Supplementary Materials C and D).

However, our criteria were formulated in general terms and furthermore we might have misinterpreted parts of articles during the review, which makes the scores only approximate. Thus, we suggest that the broad patterns observed are more important than the scores for individual articles.

The scoring was mainly conducted by the first author through the checklist presented in Supplementary Material D. Cross-evaluations were performed in challenging cases or when clarification was required based on specific co-author expertise. To minimize potential conflicts of interest or bias, articles involving other co-authors were not cross-evaluated in this way.

The method used to select articles for the review also entails potential limitations that should be acknowledged. We included highly cited studies from 1992 to 2022, by requiring a certain number of citations per year. However, certain types of articles may be more cited than other regardless of quality, such as articles from research groups with large networks. Certain kinds of articles may also be more easily accessed than other and may thus obtain more citations. Due to the increasing amounts of publications, and thus citations, during recent years, articles published during later years may have been favored for selection over articles published during the early phase of our study period. In contrast, it may also take some time for a study to be recognized, and thus articles from the last years (2021 and 2022) of our study period may be underrepresented.

Despite the potential limitations outlined above, we suggest that the method we applied for selecting articles was a means to maintain objectivity throughout the selection process, while at least approximately ensuring that the most influential papers were included in the study. The temporal distribution of the selected studies reflects the overall increase in publication volume over time (see Figure 3S).

Conclusions

This review revealed gradual improvements of the methodological quality of large-area biomass assessments over the study period, from 1992 to 2022. The methods applied have improved during this time, but several challenges remain for making biomass assessments more reliable. These include potential launching of new space missions for providing global data about the height structure of forests, acquiring larger datasets of harmonized field data for model calibration, correct use of statistical principles, developing novel methods for domain estimation, and improving QA/QC of surveys. Currently, many efforts are underway to address these challenges.

At the same time, national-scale mapping efforts integrating RS and field data are contributing to more detailed forest type and tree species information, thereby partially addressing some of these challenges. Thus, although we conclude that the current scientific state-of-the-art of large-area biomass assessment is fair, there remains room for substantial further improvement.

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Author contributions

Emanuele Papucci (Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing—original draft), Ruben Valbuena (Conceptualization, Methodology, Writing—review & editing), Cornelia Roberge (Conceptualization, Methodology, Writing—review & editing), Alex Appiah Mensah (Conceptualization, Methodology, Writing—review & editing), and Göran Ståhl (Conceptualization, Funding acquisition, Methodology, Resources, Supervision, Writing—review & editing)

Supplementary material

Supplementary material are available at *Forestry: An International Journal of Forest Research* online.

Conflict of interest

The authors declare that they have no conflicts of interest related to this work.

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Data availability

The data underlying this article cannot be shared publicly in order to avoid highlighting or potentially identifying specific articles or authors included in the analysis. The data will be shared on reasonable request to the corresponding author. All the articles analyzed in this paper are present in Supplementary Material A.

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