Science of the Total Environment 850 (2022) 157788

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Exploring characteristics of national forest inventories for integration with global space-based forest biomass data

Karimon Nesha [a,*], Martin Herold [a,b], Veronique De Sy [a], Sytze de Bruin [a], Arnan Araza [a], Natalia Málaga [a], Javier G.P. Gamarra [c], Kristell Hergoualc'h [d], Anssi Pekkarinen [c], Carla Ramirez [c], David Morales-Hidalgo [c], Rebecca Tavani [c]

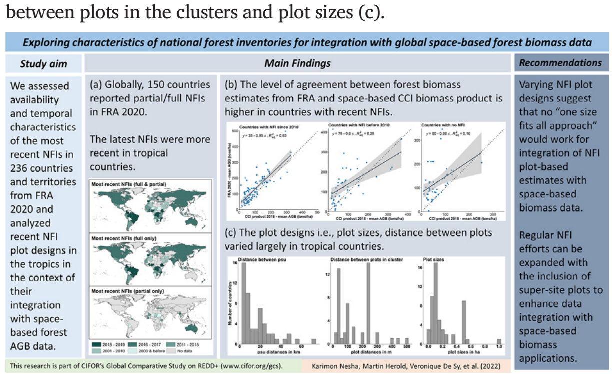
[a] Laboratory of Geo-Information Science and Remote Sensing, Wageningen University and Research, Droevendaalsesteeg 3, 6708 PB Wageningen, the Netherlands
[b] Helmholtz GeoResearch Center Potsdam (GFZ), Potsdam, Germany
[c] Food and Agriculture Organization of the United Nations, Viale delle Terme di Caracalla, 00153 Rome, Italy
[d] Center for International Forestry Research (CIFOR) c/o Centro Internacional de la Papa (CIP), Av. La Molina 1895, La Molina, Apdo Postal 1558, 15024 Lima, Peru

HIGHLIGHTS

- Tropical NFIs are increasing and mostly one-time efforts; however plans for continuity exists for many countries.
- There is higher agreement between FRA and space-based forest biomass estimates in countries with recent NFIs.
- NFI design characteristics (i.e. sampling design, plot size/shape, plot distances) vary across the countries.
- No "one size fits all approach" suits the integration of NFI and space-based biomass data: various (statistical) approaches needed.
- Super-site NFI plots are an opportunity for better integration with space-based data and collaboration with global community.

GRAPHICAL ABSTRACT

NFI characteristics relating to integration with space-based forest biomass data - temporality of the most recent NFIs (a), intercomparison of national forest biomass estimates for the year 2018 from FRA and space-based CCI biomass data (b), and NFI plot designs e.g., distances between primary sampling units (cluster and single plots), distances between plots in the clusters and plot sizes (c).



ARTICLE INFO

Editor: Elena Paoletti

Keywords:
National Forest Inventory (NFI)
NFI plot design
Aboveground biomass (AGB)
CCI biomass
Forest Resources Assessment (FRA)
NFI and space-based data integration

ABSTRACT

National forest inventories (NFIs) are a reliable source for national forest measurements. However, they are usually not developed for linking with remotely sensed (RS) biomass information. There are increasing needs and opportunities to facilitate this link towards better global and national biomass estimation. Thus, it is important to study and understand NFI characteristics relating to their integration with space-based products; in particular for the tropics where NFIs are quite recent, less frequent, and partially incomplete in several countries. Here, we (1) assessed NFIs in terms of their availability, temporal distribution, and extent in 236 countries from FAO's Global Forest Resources Assessment (FRA) 2020; (2) compared national forest biomass estimates in 2018 from FRA and global space-based Climate Change Initiative (CCI) product in 182 countries considering NFI availability and temporality; and (3) analyzed the latest NFI design characteristics in 46 tropical countries relating to their integration with space-based biomass datasets. We observed significant NFI availability globally and multiple NFIs were mostly found in temperate and boreal countries while most of the single NFI countries (94 %) were in the tropics. The latest NFIs were more recent in the tropics and many countries (35) implemented NFIs from 2016 onwards. The increasing availability and update of NFIs create new opportunities for integration with space-based data at the national level. This is supported by the agreement we

* Corresponding author.
E-mail addresses: karimon.nesha@wur.nl, karimonnesha@gmail.com (K. Nesha).

http://dx.doi.org/10.1016/j.scitotenv.2022.157788
Received 16 May 2022; Received in revised form 21 July 2022; Accepted 29 July 2022
Available online 2 August 2022

found between country biomass estimates for 2018 from FRA and CCI product, with a significantly higher correlation in countries with recent NFIs. We observed that NFI designs varied greatly in tropical countries. For example, the size of the plots ranged from 0.01 to 1 ha and more than three-quarters of the countries had smaller plots of ≤0.25 ha. The existing NFI designs could pose specific challenges for statistical integration with RS data in the tropics. Future NFI and space-based efforts should aim towards a more integrated approach taking advantage of both data streams to improve national estimates and help future data harmonization efforts. Regular NFI efforts can be expanded with the inclusion of some super-site plots to enhance data integration with currently available space-based applications. Issues related to cost implications versus improvements in the accuracy, timeliness, and sustainability of national forest biomass estimation should be further explored.

1. Introduction

Forests harbor most of the world's terrestrial biodiversity and provide vital ecosystem services and resources that are critical to upholding the sustainability of the environment and humankind. To maintain and enhance forest biodiversity and services, informed forest management decision-making at the national and international levels needs consistent and up-to-date forest information. Traditionally, many countries use national forest inventories (NFIs) as the main sources of forest information for meeting (inter)national needs (Tomppo et al., 2010). Forest inventories dated back to the end of the Middle Ages and until the mid-1970, the primary focus of NFIs was on timber resources (Davis et al., 2001; Tomppo et al., 2010). Over time, the information needs have expanded to the ecological, economic, and social roles of forests (Davis et al., 2001; Tomppo et al., 2010). This has broadened the scope of NFIs and consequently, included new NFI variables to meet increasing information needs (Tomppo et al., 2010). Now, NFIs are multifunctional and provide information on many important ecosystem services and biodiversity variables (Mononen et al., 2016). In addition, remote sensing (RS) techniques have been deployed in recent decades for producing consistent forest information on a national to global scale (Pekkarinen et al., 2009; Saatchi et al., 2011a, 2011b; Hansen et al., 2013).

Forest information on aboveground biomass (AGB) is central for forest management and policy processes at local, national, and global levels for many reasons. Apart from being the direct sources of food, fiber, and fuelwood, AGB has a critical role in the functioning of terrestrial ecosystems and thus, the earth system as a whole (Houghton et al., 2009; Patel and Majumdar, 2011; Reichstein et al., 2019). Particularly, being an important source and sink in the terrestrial carbon cycle, AGB has a crucial role in maintaining the global climate balance (Houghton, 2005; Houghton et al., 2009). For this critical role, the Global Climate Observing System (GCOS) in 2003 included AGB in the list of Terrestrial Essential Climate Variables (ECVs) (Bojinski et al., 2014). Being an ECV, AGB is a key input to the United Nations Reducing Emissions from Deforestation and Forest Degradation (REDD+) and is crucial to model the Earth system (Herold et al., 2019). Inspired by ECV, AGB was further included in the measurements of Essential Biodiversity Variables (EBV), particularly ecosystem vertical profile, live cover fraction, and primary productivity by the Group on Earth Observations Biodiversity Observation Network to monitor ecosystem structure and ecosystem functioning (Pereira et al., 2013; GEO BON, 2022).

The most accurate forest AGB information is obtained from the field measurements (Saatchi et al., 2007; Guitet et al., 2015). Field AGB measurements could be obtained from several sources such as research plots, concession or commercial plots, management plots, and NFI plots. NFI plots are a systematic and reliable source of accurate field AGB measurements at the subnational and national levels (Fang et al., 2014; Guitet et al., 2015). Therefore, NFI-based AGB estimates are used as the official data for national forest planning and management, and international reporting to the Food and Agriculture Organization of the United Nations (FAO), United Nations Framework Convention on Climate Change (UNFCCC), and United Nations Economic Commission for Europe (Herold et al., 2019).

Although NFI field plots provide the most accurate AGB measurements, they are sometimes impractical and often cost-inefficient for frequent (e.g. bi-annual) and wall-to-wall spatially explicit (sub)national AGB reporting. Such information is increasingly required for national and international climate actions in the context of the UNFCCC Global Stocktake, Paris Agreement, and REDD+ implementation programme (Herold et al., 2019). A recent study by Nesha et al. (2021) found that globally, remeasurement cycles of NFIs vary from 5 to 10 years in most of the countries having multi-date NFIs. Field plot measurements are labor-intensive, expensive, and time-demanding (Gollob et al., 2021; Liang et al., 2018; Wittke et al., 2019) and this explains why NFIs are not frequently available. Moreover, NFI plot data are aggregated to derive average estimates for a region or the whole country (Tomppo et al., 2010), and thus, do not provide spatially-detailed AGB information.

Alternatively, earth observation (EO) techniques can help overcome the abovementioned problems related to spatial and temporal detail with in-situ AGB measurements. RS community has produced several AGB maps at regional to global scales using either stand-alone or a combination of optical, radar, or LiDAR data in the recent decade (Gallaun et al., 2010; Santoro et al., 2021; Saatchi et al., 2011a, 2011b; Baccini et al., 2012; Huang et al., 2013; Thurner et al., 2014; Avitabile et al., 2016; Hu et al., 2016; Avitabile and Camia, 2018). Currently, there are targeted biomass missions that produce the next generation of regional and global AGB maps with improved accuracy. One of them is the European Space Agency's (ESA) Climate Change Initiative (CCI) BIOMASS mission which has produced 100 m global AGB maps for 2010, 2017, and 2018 by integrating optical, LiDAR, and Synthetic Aperture Radar (SAR) data for the first time (Quegan and Lucas, 2021). While boreal forest AGB estimation with NASA's Ice, Cloud, and Land Elevation Satellite-2 has been made available in 2021 (Duncanson et al., 2021a, 2021b), 1 km gridded AGB data for tropical and temperate forests are available in the year 2021 from NASA Global Ecosystem Dynamics Investigation (GEDI) mission (Dubayah et al., 2020). Upon completion of the GEDI mission in 2021, Japan Aerospace Exploration Agency's (JAXA) forthcoming Multi-footprint Observation Lidar and Imager will continue to provide the gridded AGB data (Daisuke et al., 2020). Moreover, the upcoming NASA-ISRO SAR mission in 2023 will provide global biomass datasets using L-band SAR at the temporal resolution twice every twelve days (NASA, 2021). Further, ESA plans to launch a new BIOMASS mission in 2023 using the first space-based P-band SAR that will produce more accurate global biomass maps (ESA, 2021).

Current EO technologies do not provide direct AGB estimation from space (Woodhouse et al., 2012). Space-based AGB products profoundly hinge on models that convert RS observations to AGB estimates (Santoro et al., 2021). Furthermore, RS signals saturate at high AGB areas resulting in underestimation beyond the saturation level (Rodríguez-Veiga et al., 2019). Likewise, AGB overestimation occurs in low forest cover areas because open surfaces and non-woody vegetation contribute to RS signals (Avitabile et al., 2012; Avitabile and Camia, 2018). Therefore, space-based AGB maps need to be calibrated and validated by adequate AGB reference datasets from field measurements (Chave et al., 2019). Nonetheless, global or regional AGB product validation is challenging as there are no representative reference datasets at these levels (Duncanson et al., 2019). Validation is further hindered by the lack of well-tested methods flexible to the spatial extent and spatial resolution of the AGB products (Duncanson et al., 2019). Such validation challenges limit the application of existing global space-based AGB products for national estimation and reporting.

As recommended by the CCI BIOMASS, biomass harmonization team, and Global Stocktake, a potential way forward to make use of global space-based AGB products in national estimation involves the integration of NFI field AGB measurements with global products at the national level (Herold et al., 2019; Herold et al., 2021; Santoro et al., 2021). This is primarily because NFI plot measurements are sources of independent reference data for calibration and validation of global products at the national level. The validated space-based AGB product at the (sub)national level could make a dedicated contribution to detailed spatially explicit data needs for the UNFCCC Global Stocktake, Paris Agreement, and UN-REDD + Programme (Herold et al., 2019). Furthermore, if NFI has missing samples in certain regions, e.g., inaccessible and undersampled areas, or if NFI is incomplete/partial, space-based data could be used to add sampling plots in those regions and thereby, complement the NFI (Herold et al., 2019). Further, a combination of the space-based and NFI data could be used to improve the precision of biomass estimation at the sub-national or local level (Næsset et al., 2020). In case NFI is older, space-based data could be used to update NFI and improve the comparability of global space-based and national datasets which is useful for UNFCCC Global Stocktake (Herold et al., 2019). The space-based data could also be used to add detailed spatial information to NFI biomass estimates which could be interesting for different policy purposes (Herold et al., 2019). In Nordic countries, e.g., Sweden and Finland, national biomass mapping has been done using a combination of NFI and RS data (Kangas et al., 2018). In this way, the integration of RS data can help in the harmonization process of NFIs. This would also help understand if global AGB map products aggregated at the national level can be used to meet more frequent international reporting needs (annual/biennial).

However, the integration of NFIs and space-based data is challenging since the availability and characteristics of NFIs differ by country. Out of 150 countries with NFI in FRA 2020, 41 countries reported nationwide regular, multi-date NFIs while others have not regularly updated them or not updated them at all (Nesha et al., 2021). Also, several countries (86) have no NFI to date (Nesha et al., 2021). Further, NFI years refer to different periods across the countries, and the latest NFIs were relatively old (i.e. implemented before 2010) in 56 countries (Nesha et al., 2021). This raises questions about how varying NFI availability and temporality influence the integration of NFI estimates with the global space-based AGB products at the national level.

When an NFI is available, there are technical challenges for integration linked to varying NFI design characteristics across the countries. The most relevant NFI design characteristics pertaining to integration are plot size, and distance between plots when cluster plots are used as sampling units. The smaller field plots, even when the ratio between field plots and RS pixels is the same, can produce large sampling errors due to local AGB variability and spatial mismatches between the field plots and RS footprints leading to high uncertainty in AGB maps (Réjou-Méchain et al., 2014). Noticeably, spatial AGB variations at the local scale tend to be high in the tropics (Wagner et al., 2010; Réjou-Méchain et al., 2014; Guitet et al., 2015). Therefore, field plots smaller than RS pixels in the tropics could cause considerable sampling errors resulting in dilution biases, i.e. systematic underestimation of calibration slopes (Réjou-Méchain et al., 2014). Dilution bias has been reported on average by 54 % with 0.1 ha plots and by 37 % with 0.25 ha plots (Réjou-Méchain et al., 2014). Further, small plots are linked to edge effects that can cause a mismatch in tree representation between RS footprints and field plots (Mascaro et al., 2011). Moreover, the distance between plots in the cluster influences the integration of NFI plot data with space-based biomass products, and this is linked to spatial autocorrelation (Zhang et al., 2008, 2009; Réjou-Méchain et al., 2014; Yim et al., 2015). Also, other design characteristics such as plot shape (i.e., more border trees appear in square/rectangular plots) and distance between clusters (interpolation effects) could pose challenges for the integration of NFI data with space-based biomass datasets (Kershaw et al., 2016; Hajj et al., 2017; Picard et al., 2018).

A fundamental reason why NFI characteristics have major implications on integration is that NFIs are designed on a sample basis for data collection purposes other than integration with space-based biomass products (Næsset et al., 2020; Araza et al., 2022). Hence, it is essential to understand the NFI characteristics and the potential implications for their integration with space-based products at the national level. Until now, NFI characteristics and related implications have not yet been systematically studied across the countries globally. This gap is even more pronounced in the tropics as countries have mostly started to implement NFIs in the last decade (Nesha et al., 2021). There are significant improvements in NFI availability in the tropics where the good to very good use of NFIs increased from 21 countries in FRA 2005 to 57 countries in FRA 2020 (Nesha et al., 2021). However, little is known about NFI designs in the tropics. Despite the improvements in NFI availability, several tropical countries struggle to complete or update their NFIs on a regular basis (Nesha et al., 2021). It is particularly important to explore the use of space-based products with the existing NFI field data for complementing national estimation and reporting in these countries.

In this paper, we systematically assess the global availability and characteristics of the most recent NFIs in the context of their integration with space-based forest AGB data. This includes the first global analysis of NFI characteristics in relation to their temporal distribution and extent. In addition, we analyze the recent NFI plot designs first-ever in the (sub)tropics (henceforth referred to as tropical countries) pertaining to their integration with space-based forest AGB data. Here, our aim is not to investigate how NFI plot designs affect national AGB estimation. Rather, we build on earlier research on the integration implications of NFI plot designs and evaluations of the relationships between plot design characteristics and RS-based AGB estimations (e.g., Réjou-Méchain et al., 2014; Picard et al., 2018). More specifically, we:

1. Assess the characteristics of the latest NFIs globally in 236 countries and territories from FRA 2020 in terms of their availability, temporal distribution, and extent.
2. Compare national forest biomass data for 2018 between FRA estimates and a recent global space-based ESA CCI biomass product taking into account the NFI availability and temporal characteristics.
3. Analyze the latest NFI plot design characteristics in tropical countries relating to integration with space-based biomass datasets.

2. Methods

2.1. NFI availability, temporal and extent characteristics

We assessed the availability and characteristics of NFIs globally in 236 countries and territories (hereafter referred to as countries). We evaluated NFI availability based on the total number of NFIs in a country. We analyzed NFI characteristics in a country in terms of their extent and temporal distribution. The latest NFI was included in the analysis of NFI characteristics. The data on NFI availability, temporal and extent characteristics were compiled from FRA 2020 country reports (Table 1). The FRA 2020 country reports are publicly available on the FAO website (https://www.fao.org/forest-resources-assessment/fra-2020/country-reports/en/).

For assessment of NFI availability, we classified the countries into the following groups based on the number of existing NFIs per country.

- countries with no NFI
- countries with a single NFI
- countries with multiple NFIs

Table 1
Dataset used in the analysis of NFI availability and characteristics across the countries.

Dataset description	Purpose of use	Data sources
Total number of NFIs per country	NFI availability analysis	FRA 2020 country reports, section 2c
Extent of the latest NFIs	Analysis of NFI characteristics in terms of NFI country coverage	FRA 2020 country reports, section 2c
Years of the latest NFIs	Analysis of NFI characteristics in terms of NFI temporal distribution	FRA 2020 country reports, section 2c

Here, a single NFI means only one NFI measurement and multiple NFIs imply at least two or more measurements. We further categorized the countries with multiple NFIs into the following classes:

- countries with 2–3 NFIs
- countries with 4–5 NFIs
- countries with >5 NFIs

For evaluating NFI extent over a country, we categorized the NFI into partial or full NFI. If an NFI was implemented nationwide, it was categorized as a full NFI. Similarly, if NFI covered only parts of the country, it was classified as partial NFI. To assess the temporal characteristics of NFIs, we defined the year 2010 as the threshold year to distinguish whether the NFIs are recent or old. Accordingly, if the latest NFIs were implemented in countries from 2010 onwards, they were considered recent NFIs. Conversely, the latest NFIs implemented in countries before 2010 were considered old NFIs. The years used in the analysis of NFI temporal characteristics usually referred to the years of data collection (see FRA 2020 guidelines and specifications).

2.2. Intercomparison of national forest AGB estimates from a global space-based biomass product and FRA 2020

The integration of NFI field estimates with space-based global biomass products is essential for using the products at the national level. A key step towards this process is the intercomparison of the global AGB products at the national level with NFI field AGB estimates (Herold et al., 2021). Intercomparison is crucial to assess the usefulness of space-based global AGB products at the national level as it shows the agreement of space-based products with the field reference datasets and identifies the areas with underestimation and overestimation (Herold et al., 2021). We performed an intercomparison analysis between two national forest AGB estimates for the year 2018 – one estimate from a space-based global biomass product and another from FRA AGB estimates. We performed this analysis for both country mean (tons/ha) and country total (Gigaton i.e., Gt) forest biomass estimates. We applied linear regression between these two datasets for intercomparison.

We compiled FRA forest AGB estimates for the year 2018 for individual countries from section 2c, FRA 2020 country reports. FRA forest AGB estimates are generally derived from NFI field data in countries with NFI (see FRA 2020 country reports, section 2c). AGB estimates in FRA reporting vary among the countries due to a wide array of country reporting circumstances and limitations. We used the country biomass data from FRA reporting because FRA is the only worldwide database constituting a benchmark for comparison with RS data on forest resources due to its scale and comprehensiveness (Santoro et al., 2021). Although discrepancies between FRA and RS-based AGB estimates have been highlighted earlier (Hill et al., 2013), there is a large fraction of the current literature establishing these comparisons where FRA estimates are used as a benchmark for comparison (Hill et al., 2013; Mitchard et al., 2013; Santoro et al., 2021; Araza et al., 2022).

We used the latest ESA CCI global biomass product 2018 version 3.0 (v3.0) (see Santoro and Cartus, 2021) to obtain the space-based national forest AGB estimates. A brief overview of datasets used in this analysis is given in Table 2. We performed this analysis globally in 182 countries. We excluded 54 countries from the analysis as forest AGB data from FRA 2020 or CCI biomass product was not available. The ESA CCI global biomass product provides space-based AGB estimates for all types of vegetation covers (ESA, 2021). Therefore, we extracted forest AGB from the CCI biomass product using a forest mask and then calculated the forest AGB statistics per country. The forest mask was created following FAO's forest definition i.e. tree cover >10 % (FAO, 2018). For this purpose, we used the space-based global tree cover dataset for 2018 from the Copernicus Global Land Service (Buchhorn et al., 2020). The spatial resolution of the CCI global biomass product and global tree cover dataset was 100 m.

Noticeably, the availability and temporal distribution of NFIs vary across the countries. An earlier study showed that globally 150 countries had NFI and out of them, 94 countries implemented their latest NFI in the 2010s (Nesha et al., 2021). Out of 182 countries included in the intercomparison analysis, NFIs were data sources for national forest AGB estimates in 137 countries in FRA 2020. NFIs have not yet been implemented in other countries included in the analysis. In the absence of NFI, FRA AGB estimates mainly relied on forest area data derived from RS observations (see FRA 2020 country reports).

The availability and varying temporal characteristics of the NFIs could influence the national AGB estimates, and thus, their integration with the space-based biomass product. Considering this, we performed an intercomparison analysis taking into account the NFI availability and temporal characteristics. This involved intercomparison analysis in three groups of countries viz. countries with NFI since 2010, countries with NFI before 2010, and countries with no NFI. This would provide a clear overview of how intercomparison results vary with the NFI availability and temporal characteristics, and thus, a better understanding of the potential link of the corresponding agreement and disagreement between the two national forest AGB estimates. This is also important to identify the areas for improvement on both national estimates. Thus, the findings of this analysis have great significance in the context of integration of NFI-based AGB estimates with the global space-based AGB estimates at the national level.

2.3. NFI plot design characteristics in the tropics

We analyzed the design characteristics of the most recent NFIs in 46 tropical countries (Fig. 1). The countries were chosen based on data availability. The data were compiled from the country NFI field manual and NFI report. In this study, we analyzed the key NFI design characteristics related to sampling and plot designs (see Appendix 1 for the variables list). We investigated the NFI design characteristics that have significant implications on NFI integration with space-based biomass datasets.

3. Results

3.1. NFI availability, temporal and extent characteristics

Globally, 150 countries reported partial or full NFIs in FRA 2020 (Fig. 2a), with 120 countries reporting full NFIs (Fig. 2b). Partial NFIs mainly occurred in tropical countries (Fig. 2c). Almost half of the countries (~46 %) with either partial or full NFIs reported only a single NFI in FRA 2020. Notably, most of these single NFI countries (94 %) were found in tropical nations, particularly in South America, Africa, and Asia. On the other hand, most of the temperate and boreal countries had 4 to 5 full NFIs with Russia, Canada, Denmark, and the US implementing >5 full NFIs. The multiple and full NFIs were also implemented in some tropical

Table 2
Datasets used in the intercomparison analysis of national forest AGB estimates between global space-based CCI biomass product and FRA 2020.

Dataset used	Dataset description	Purpose of use	Data sources
ESA CCI biomass product 2018 version3.0	The latest global space-based biomass dataset for the year 2018 at 100 m resolution	Obtained space-based AGB estimates for 182 countries	ESA CCI BIOMASS Mission (Santoro and Cartus, 2021)
Global tree cover dataset 2018 version3.0.1	Global space-based tree cover dataset for the year 2018 at 100 m resolution	Created a forest mask layer to extract space-based forest AGB from ESA CCI biomass product for 182 countries	Copernicus Global Land Service (Buchhorn et al., 2020)
Country forest AGB dataset 2018 from FRA 2020	Country forest AGB from FRA 2020– total and mean statistics for the year 2018	Obtained NFI-based (and from other sources in the absence of NFI) forest AGB estimates by country from FRA 2020	FRA 2020 country reports, section 2c

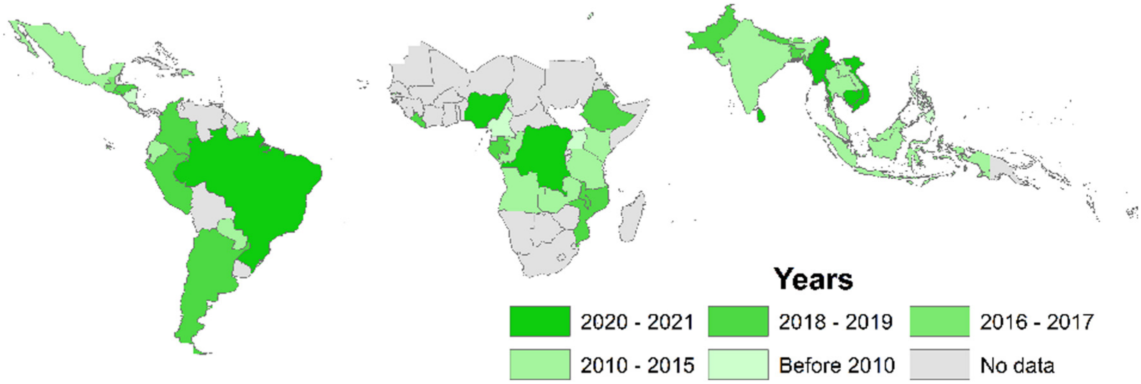


Fig. 1. Tropical countries (46) for the analysis of the latest NFI design characteristics. The years of the latest NFI by country are shown in green colors. Years were compiled from the latest country NFI design manual or NFI report (both ongoing and completed NFI). The years generally refer to the last years of data collection. No data means that either some countries didn't implement NFI yet, or data sources i.e. NFI design manuals/NFI reports were not available in others.

nations but the number of NFIs mostly ranged between 2 and 3. The highest number of full NFIs accounted for 4 to 5 in a few tropical countries including India, Ghana, Panama, and Viet Nam.

The latest NFIs were more recent in the tropics compared to temperate and boreal countries (Fig. 2d, e & f). In many tropical countries (35), NFIs were implemented in the last five years starting from 2016. Among them, more than half of the countries implemented full NFIs in the year 2018–2019 for the first time, including DRC and Brazil. The NFIs implemented since 2016 were nationwide (i.e., full) in 86 % of the tropical countries. Partial NFIs in tropical countries were mostly implemented before 2000. The temperate and boreal countries, on the other hand, implemented their latest NFIs largely between 2011 and 2017. While the US and Canada implemented their last NFI in 2016–2017, most of the European countries had their latest NFIs between 2011 and 2015.

3.2. Intercomparison of national forest AGB estimates from global space-based CCI biomass product 2018 and FRA 2020

Overall, national forest AGB estimates from the CCI product and FRA 2020 had a strong positive relationship at the country level, however, country mean AGB estimates (tons/ha) showed a weaker agreement than country total AGB estimates (Gt) (Fig. 3). For country total AGB statistics, the

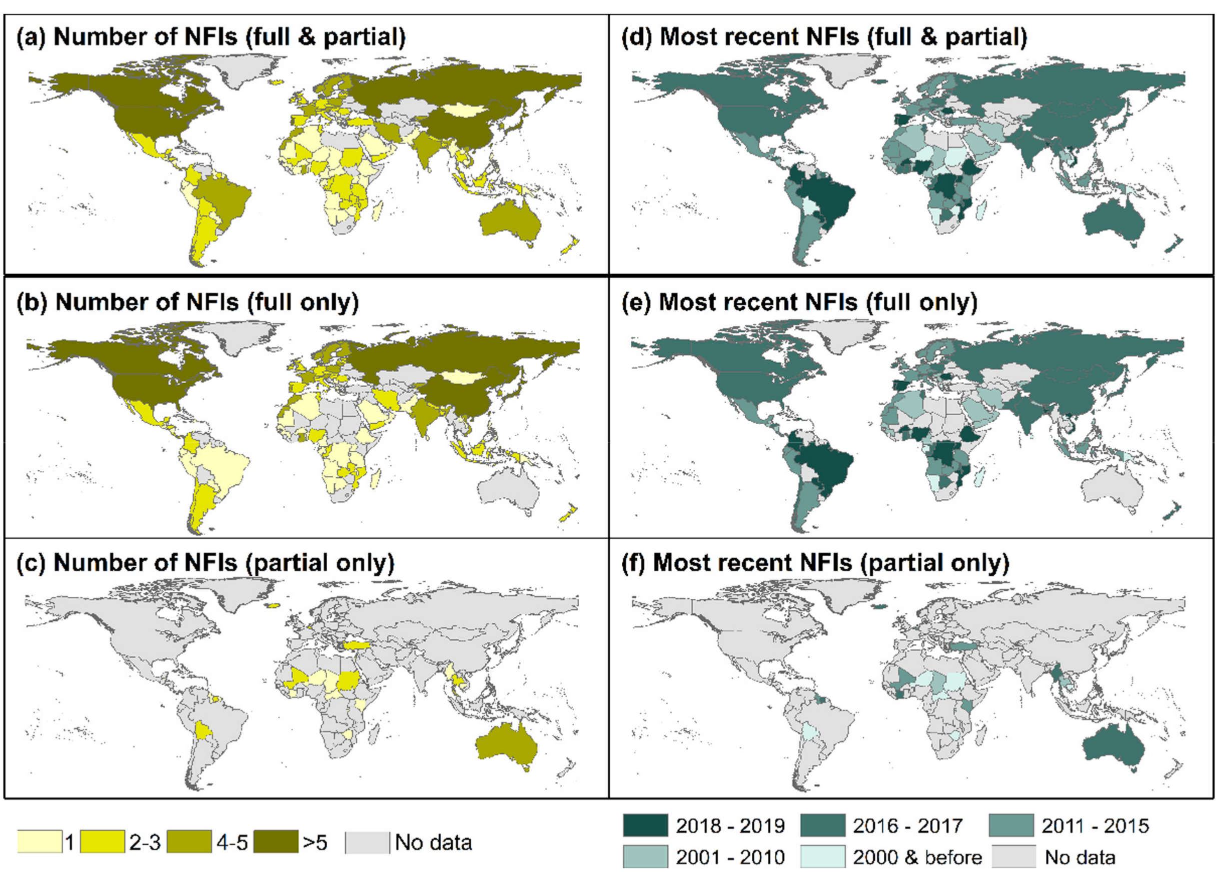


Fig. 2. The total number of NFIs and the extent and temporality of the latest NFIs in 236 countries and territories in FRA 2020 (both ongoing and completed NFI). (2a) the number of full and partial NFIs; (2b) the number of full NFIs only; (2c) the number of partial NFIs only; (2d) most recent NFIs - both full and partial; (2e) most recent NFIs - full only; and (2f) most recent NFIs – partial only. No data means that countries didn't implement any NFI up to the FRA 2020 report.

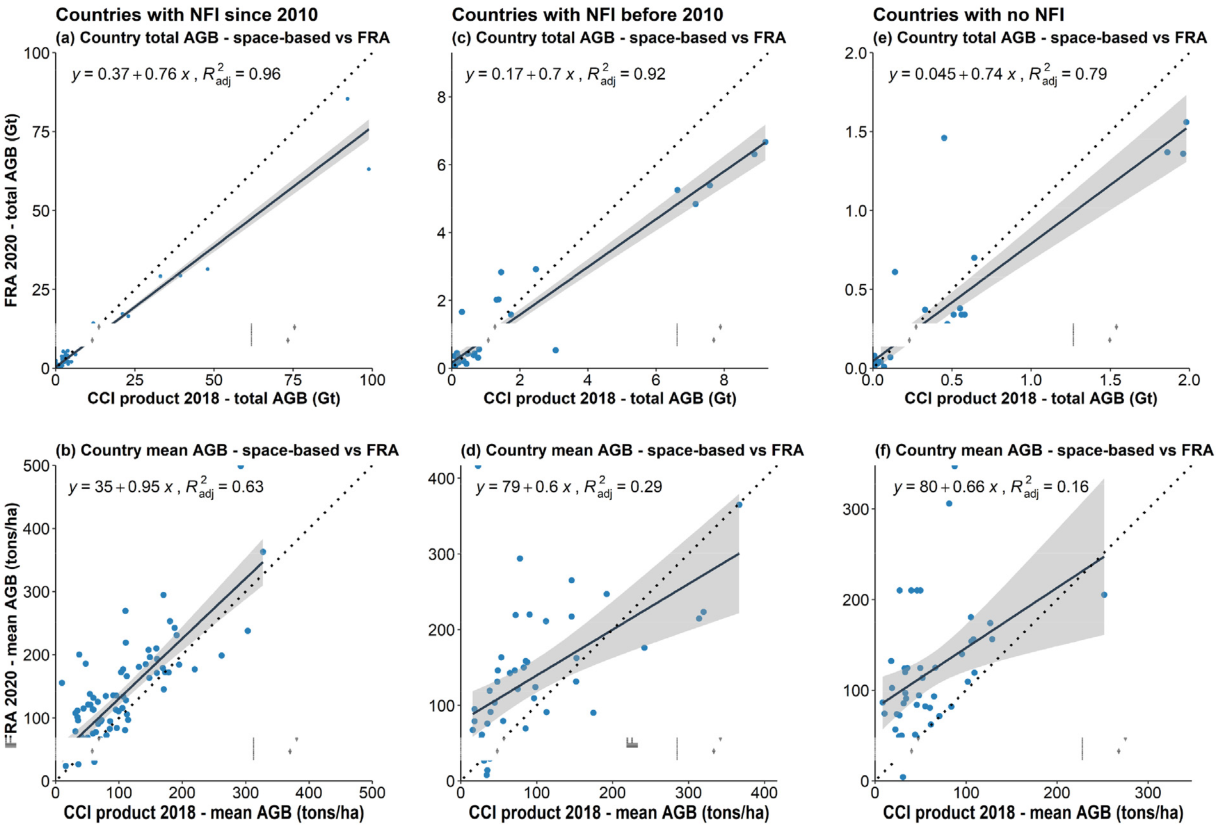


Fig. 3. An intercomparison of national forest AGB estimates in the year 2018 from global space-based CCI biomass product and FRA 2020. The intercomparison is performed considering NFI availability and temporal characteristics across the countries. Intercomparison in countries with NFI since 2010 – total AGB in Gt (MSE: 7.7, bias: 6.17, variance: 1.60) (a), mean AGB in tons/ha (MSE: 2341.34, bias: 2253.98, variance: 87.36) (b). Intercomparison in countries with NFI before 2010 – total AGB in Gt (MSE: 0.28, bias: 0.26, variance: 0.02) (c), mean AGB in tons/ha (MSE: 5675.28, bias: 5476.03, variance: 199.25) (d). Intercomparison in countries without NFI - total AGB in Gt (MSE: 0.038, bias: 0.036, variance: 0.002) (e), mean AGB in tons/ha (MSE: 3870.03, bias: 3714.93, variance: 155.10) (f). The black dotted line is a 1:1 line. Grey bands depict 95 % confidence interval. The range of the x and y values are highly different in three groups of countries i.e., countries with NFI since 2010 (e.g., <1 to 100 Gt), countries with NFI before 2010 (e.g., <1 to 8 Gt), and countries with no NFI (e.g., <1 to 2 Gt). Therefore, the MSE values are not comparable between the groups.

two datasets matched very well ($R^2_{adj} = 0.96$) in countries with recent NFIs (Fig. 3a). The agreement was relatively lower ($R^2_{adj} = 0.92$) in countries with old NFIs (Fig. 3c) and it was much lower ($R^2_{adj} = 0.79$) in countries without NFI (Fig. 3e). The stronger relationships for total estimates can be expected since they are related to the size and the forest area of the country. We also observed much higher agreement ($R^2_{adj} = 0.63$) between FRA and space-based mean AGB estimates in countries with recent NFIs compared to countries with old NFIs ($R^2_{adj} = 0.29$) and it was poorest ($R^2_{adj} = 0.16$) in countries without NFI (Fig. 3b, d & f). Although there was still a fair amount of scattering in graph 3b, the relationship was along the 1:1 line, while FRA AGB estimates tended to be higher in low biomass ranges in countries with old or no NFIs (Fig. 3d & f).

3.3. NFI design characteristics in tropical countries

Our findings on the most recent NFI design characteristics in 46 tropical countries revealed that all countries except two implemented NFIs nationwide i.e. full NFIs. Further, 61 % of the countries included both forests and trees outside forests in their NFIs while others included only forests. All countries implemented sample-based NFIs, mainly using three types of sampling designs, namely systematic, stratified systematic, and stratified random (Fig. 4a). About half of the countries used systematic sampling designs. Among the other half, the majority of the countries (18) used a stratified systematic sampling design. In stratified sampling, ecozones (i.e., ecological zones) were the most common sampling strata used in both stratified systematic ($n = 9$) and stratified random design ($n = 2$). Other sampling strata were forest types, vegetation types, and integrated land use assessment (ILUA).

Overall, two types of sampling units were established across the countries for NFI field data collection: primary sampling unit (PSU) and secondary sampling unit (SSU). Forty-two countries established PSU as clusters while four countries used single plots. The clusters consisted of multiple SSU or plots (hereafter cluster plots and single plots are referred to as plots if not specified otherwise). Within the clusters, the number of plots varied between 3 and 10 across the countries. A large number of countries (48 %) had clusters with 4 plots, followed by 3 plots in 21 % of the countries and 5 plots in 19 % of the countries.

The shape of the PSU (clusters) varied by country and most of the countries (43 %) implemented square shape clusters, followed by L-shape at 24 % of the countries (Fig. 4b). Regarding PSU single plots and SSU plots, most countries (54 %) had circular plots, followed by rectangular plots in several countries (43 %), and square plots in others (13 %) (Fig. 4c). Some examples of these different clusters and plot shapes are shown in Fig. 5. All countries employed the fixed-area SSU plots and PSU single plots with a concentric or nested design. A nested plot consisted of multiple smaller subplots for measuring trees of different sizes or other elements in the multipurpose NFI. Around 44 % of countries measured trees in the largest outer subplot with a minimum DBH ≥20 cm, followed by 36 % with ≥10 cm, 10 % with ≥30 cm, 5 % with ≥40 cm, and 5 % with ≥5 cm. Trees with smaller DBH in the respective countries were measured in the inner nested subplots. In many countries (43 %), smaller trees measured in the inner subplot were ≤10 cm in DBH, followed by trees with ≤5 cm DBH in 17 % of countries. Some countries measured trees as small as 0.5 cm DBH in the inner subplots. The smallest subplots were used for measuring regeneration trees, seedlings, samplings, litter, and soil samples.

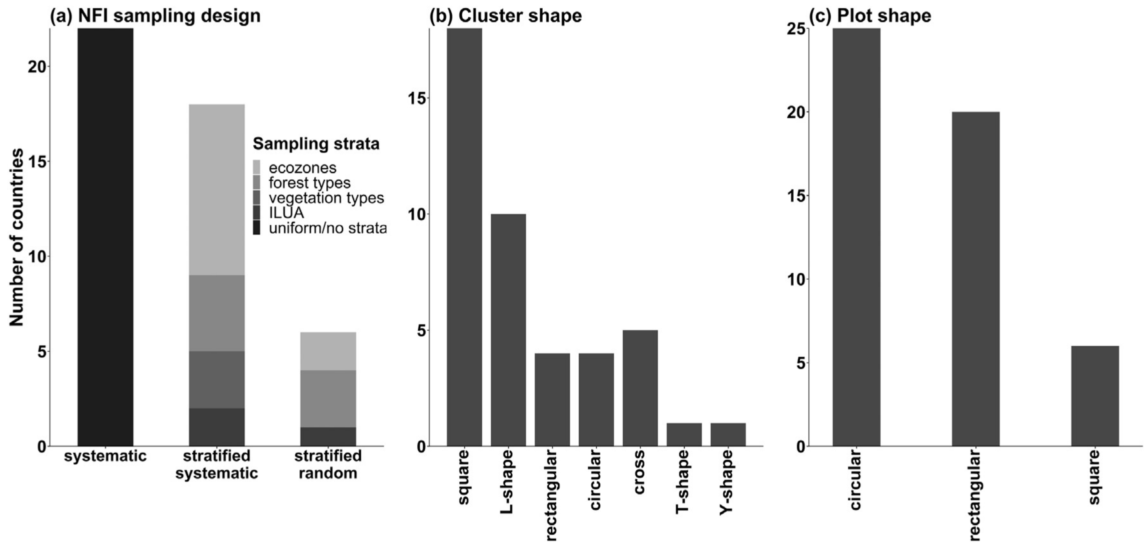


Fig. 4. NFI sampling design in tropical countries. (a) Three types of sampling designs were employed in NFIs in 46 countries-systematic, stratified systematic, and stratified random. Stratification includes pre-stratification in some countries while post-stratification in others. The sampling intensity differs in stratified sampling among the strata in a country. Five types of strata were used with stratified sampling. (b) The shape of the primary sampling unit (cluster) in 42 countries. The total number of responses for this variable was 43 as Kenya used two types of cluster shapes in different strata. (c) The shape of the secondary sampling unit (SSU plots) and PSU single plots in 46 countries. The total number of responses for this variable was 51 as 5 countries (Mozambique, Nigeria, Mexico, Peru, and Ecuador) used multiple plot shapes in different strata.

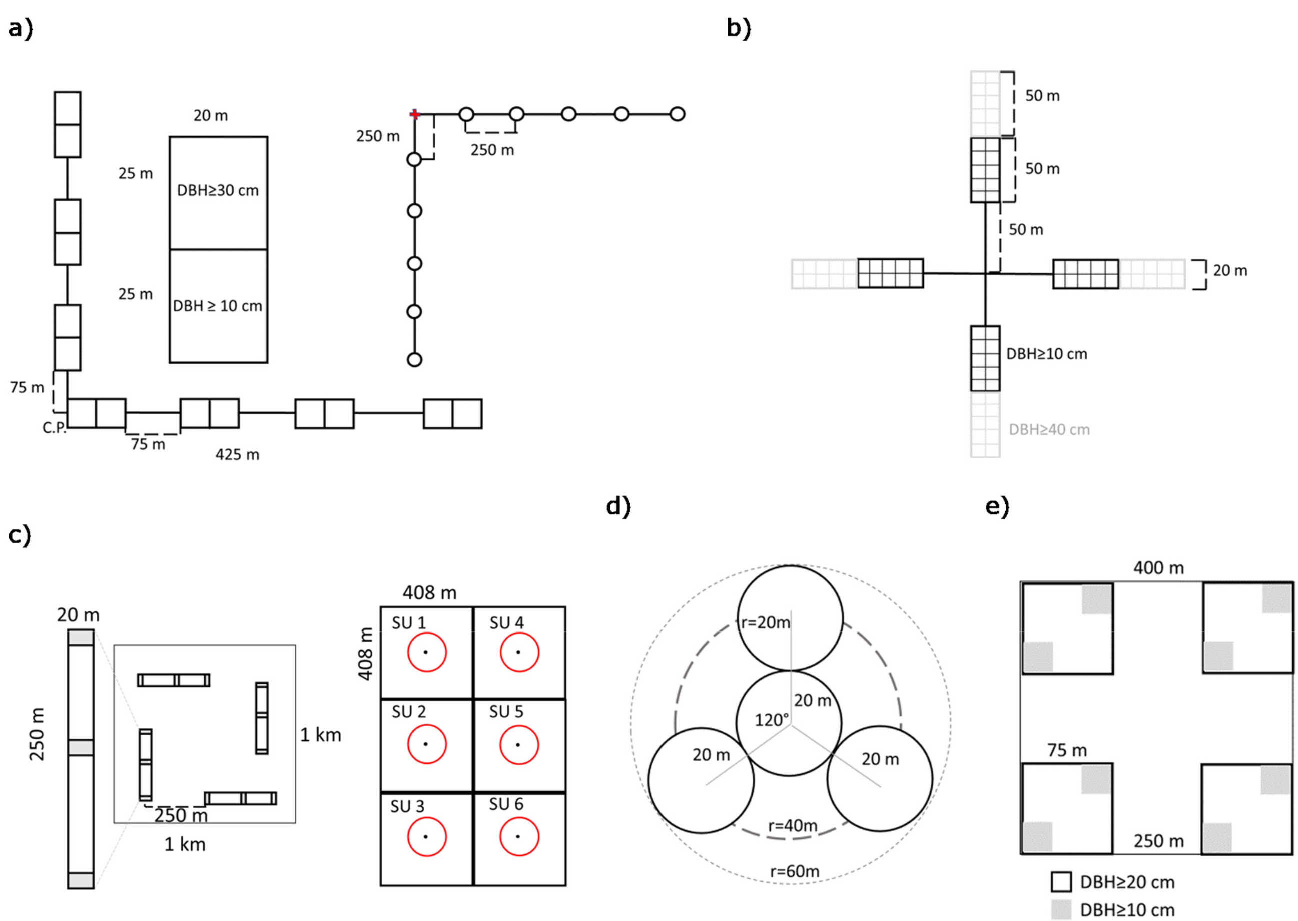


Fig. 5. The different shapes of clusters and plots used the latest NFIs in some tropical countries. a) L-shape cluster – Peru on the left and Tanzania on the right. b) Cross shape cluster – Brazil. c) Rectangular shape cluster - Angola, Ethiopia, Gambia, and Nicaragua on the left and Timor Leste on the right. d) Circular shape cluster – India. e) Square shape cluster – DRC. The figures are taken from country NFI manuals. A list of the available manuals consulted in this study is provided in Appendix 2.

In countries with systematic and stratified systematic sampling, the distance between PSUs (clusters and single plots) varied widely and the largest distance was >70 km (in one stratum with arid and semi-arid shrublands in Ethiopia) (Fig. 6a). Some countries (10) established PSU within a distance of 5 km which is considered a reasonably high sampling intensity in NFI design. Most countries (67 %) established PSU at distances above 5 km and up to 20 km. The distances between PSU were much greater (>20 km) in some countries.

Similarly, the distances between SSU plots (i.e. plots within clusters) across the countries varied largely ranging from 10 m to 500 m (Fig. 6b). Most countries (50 %) established plots at relatively short distances (≤100 m). Also, a large number of countries (40 %) established plots at comparatively large distances between 200 and 300 m. These countries include the Philippines, DRC, Republic of Congo, Tanzania, Kenya, Gambia, Ethiopia, and Nicaragua among others. Indonesia maintained the largest distance (500 m) between the plots.

Further, the size of the plots (SSU plots and PSU single plots) varied greatly extending from 0.01 to 1 ha (Fig. 6c). More than three-quarters (78 %) of the countries had smaller plots of ≤0.25 ha. These countries included Bangladesh, Brazil, India, Malaysia, Gabon, Kenya, Myanmar, Mexico, and Peru, among others. Several countries (9) had relatively large plots of around 0.5 ha. Among others, these countries included Cameroon, Republic of Congo, and DRC mostly covering the Congo basin forests. Indonesia had the largest plots of 1 ha.

A large number of countries (37) established continuous NFI by using permanent sample plots for periodic measurements of the same sampling units. Several countries (~57 %) implemented only permanent plots while other countries implemented both permanent and temporary plots within a sampling unit. Information on permanent or temporary sample plots was not available for 9 countries. Among 37 countries with continuous NFI, the information on remeasurement cycles was available for 16 countries. The remeasurement cycles varied between 5 and 10 years and most of the countries (11) used a 5-year remeasurement cycle. Few countries such as India, Sri Lanka, the Philippines, Vietnam, Peru, Honduras, and Mexico implemented a 5-year NFI cycle in a panel system where 20 % of the plots were sampled each year.

4. Discussion

4.1. NFI availability, temporal and extent characteristics

The findings on the NFI availability show that 94 % of the single NFI countries are in the tropics. This is not surprising given the fact that NFIs are fairly recent in the tropics where several countries have established NFIs in the year 2018–2019 for the first time. This is a positive development given that many tropical countries have now better data underpinning the national and international monitoring and reporting obligations. Also, having recent NFI data provides an important opportunity to better link NFI field plots and space-based global biomass products together, and explore complementary aspects of both data sources. The one-time nature of most tropical NFIs, however, limits the countries' ability to systematically track biomass changes using field plot remeasurements. Field remeasurements through permanent sample plots are also needed for the validation of space-based products for estimating detailed spatially explicit forest biomass distribution and their changes over time (Avitabile et al., 2016). Notably, many tropical countries have established permanent sample plots in their NFIs with 5–10 years' remeasurement plans. This means that NFIs in the tropics would be updated in the future using the same field plots in 5–10 year windows. In theory, tropical countries could make use of the space-based biomass estimates for regular annual/biennial and more rapid updating of the estimates in the coming years and expand biomass estimation towards the sub-national levels. Even though tropical countries have a 5–10 year remeasurement plan, there could be practical hurdles with remeasuring NFI regularly in some countries, and evidence is found in some countries where the completion of the first NFI cycle is already delayed. Further, the use of NFI field plots for integration with space-based global products is still a challenge in 86 countries as they have no NFI to date and most of these countries are in the tropics. In these cases, space-based biomass estimates are the only up-to-date data sources at the national level.

For countries with multiple full NFIs, several countries only have 2 to 3 NFIs as they do not update them regularly. NFIs in about 45 % of the European countries were last updated in the period 2011–2015. The timely and regular update of NFIs is also an issue in several tropical countries with repeated NFIs. In ~50 % of those tropical countries in Asia, Africa and South America, the NFIs were last updated before 2015. In such cases, the need for up-to-date field data for integration with the current space-based datasets can underpin a more timely update of the NFI field data.

4.2. Intercomparison of national forest AGB estimates from global space-based CCI biomass product 2018 and FRA 2020

Our findings reveal the importance of availability and timely updates of NFIs for better integration of NFI plot data with the recent space-based global AGB estimates at the national level. The intercomparison results showed that FRA AGB estimates and space-based CCI biomass products had a better agreement in countries with NFIs and the agreement was much higher in countries with recent NFIs (i.e., NFI since 2010). This highlights the need to synchronize both NFI field AGB estimates and space-based global biomass data to optimize their common use at the national level. Such understanding helps to develop strategies to use both data sources together for improving estimations at national and sub-national levels. Having an NFI, in the first place, allows for independent

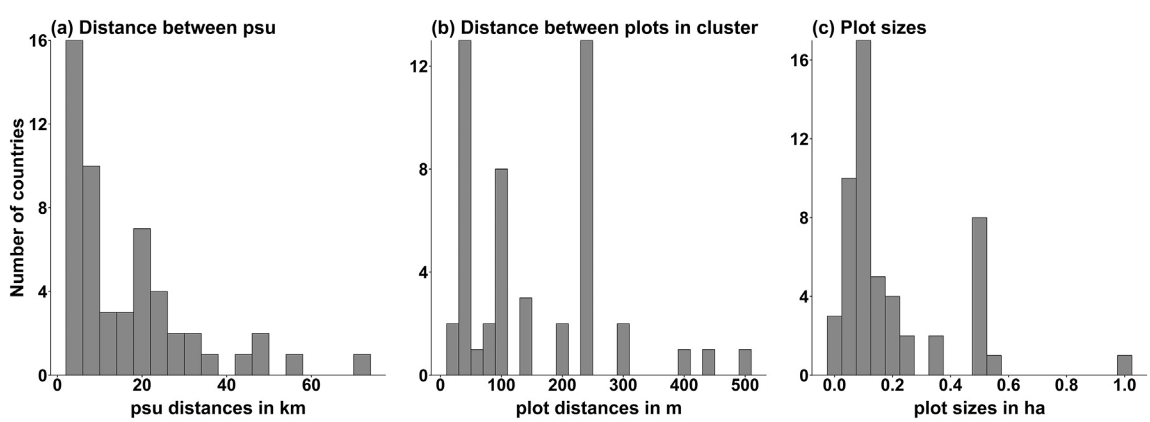


Fig. 6. The design characteristics of the PSU and SSU in tropical countries. (a) The distances between PSU (clusters and single plots) in 30 countries with available data. The total number of responses for this variable was 52 as 10 countries used multiple PSU distances in different strata.(5b) The distances between SSU plots (within clusters) in 42 countries. The total number of responses for this variable was 49 as 7 countries used multiple plot distances in different strata. (5c) The size of the SSU plots and PSU single plots in hectare (ha) in 46 countries. The total number of responses for this variable was 53 as 7 countries used multiple plot sizes in different strata.

comparison and validation, calibration, and integration with space-based biomass maps. Furthermore, timely updates of NFIs allow countries to reduce temporal mismatches of NFI data with contemporary space-based biomass data and thus, provide opportunities for better integration of the two datasets at the national level.

It is important to note that countries without NFI commonly use RS data for their national AGB estimations. This involves the use of RS data for forest area estimation that are combined with the average biomass (default) factor in the FRA biomass calculator (see FRA 2020 country reports and Nesha et al., 2021). In some cases, FRA estimates are combined from different sources including expert opinion. We found that this tends to produce higher average FRA biomass estimates compared to the space-based CCI biomass product in countries without NFIs. This is an encouragement for countries without NFI to refine their national biomass estimates and explore opportunities to eventually enhance the current approach of using biomass default factors combining available space-based biomass data.

We understand the limitations behind the FRA estimates and have been careful to use them to qualitatively contrast with RS-based estimates based on different conditions. Our aim was not to directly assess the quality or reliability of FRA data sources or look into FRA data to estimate possible biases in RS-derived AGB estimates. We used the country biomass data behind FRA reporting as they are established and recognized national reference AGB estimates for comparison.

4.3. NFI design characteristics in the tropics

Our findings on the latest NFI designs in 46 tropical countries show that most of the countries (57 %) had comparatively small field plots of ≤0.1 ha. When such small field plots are used, spatial mismatches between the field plots and RS footprints can occur even after maintaining the same ratio between field/RS footprints (Réjou-Méchain et al., 2014). About two-thirds of these small plots (≤0.1 ha) were circular and others were rectangular or square. Spatial mismatches could even be higher from circular small plots resulting from plot circles vs pixel squares (Réjou-Méchain et al., 2014). Furthermore, edge effects i.e., mismatches between circular plots vs. square RS footprints could lead to considerable calibration and validation errors (Réjou-Méchain et al., 2014). The edge effects and spatial mismatches between field plots and RS footprints might cause bias in forest AGB and its change estimation using NFI plots and space-based measurements (Réjou-Méchain et al., 2015). In addition, the integration can be affected by dilution bias in the tropics, because countries mostly had NFI field plots much smaller than the resolution of the current space-based global products. For example, currently, ESA CCI provides biomass products with 1-ha pixels (ESA, 2021; Santoro et al., 2021). The use of biomass estimates at cluster level instead of individual plot level is one way to reduce this effect. However, very large clusters can capture data from different land uses that could affect the forest biomass estimation. We suggest that future NFI plot designs or RS-based product approaches should consider the issues mentioned above to better integrate these two data sources as complementary rather than independent streams. This has also been recommended in the FAO's Voluntary Guidelines on National Forest Monitoring System (FAO, 2017).

One proposed option is to include some “super-site” plots using LIDAR that are larger and provide more detailed forest measurements to better integrate the information. Related concepts have been proposed by the GEO-TREES initiative and CEOS Forest Biomass Reference System in country NFI efforts (Chave et al., 2021; Duncanson et al., 2021a, 2021b). The use of supersites (i.e., larger plots) in combination with traditional NFI plots could help derive the biomass estimation while reducing bias as supersites have been previously shown to more closely depict “reality” in regards to AGB. Such super-site plots are prioritized in the tropics and optimized for use in EO applications following the CEOS LPV biomass protocol that particularly includes larger plots (1 ha) for accurate calibration and validation of space-based products (Chave et al., 2021). Therefore, nesting super-site plots within traditional NFI plots design would benefit plot data integration with currently available space-based applications, and help improve space-based estimations at global and national levels to better meet the data needs for reporting to the UNFCCC, the FRA, and for climate-smart and sustainable forest and land-use management. While there are examples of incorporating super-site monitoring concepts in NFIs (i.e., in Europe or the USA), implementing super-site measurements requires additional resources. The number of such plots, the related efforts, and costs needs to be investigated in the context of their benefits for in-situ/space-based biomass data integration towards enhancing accuracy, timeliness, and sustainability of national and sub-national biomass estimation.

Most tropical countries (50 %) established NFI field plots within 100 m distances in the cluster. Plots within such distances could be affected by spatial autocorrelation (Réjou-Méchain et al., 2014; Yim et al., 2015). The use of field-based estimates from spatially autocorrelated plots could cause uncertainties and spatial overfitting to model calibration and validation of RS observations (Zhang et al., 2008, 2009; Parmentier et al., 2011; Réjou-Méchain et al., 2014; Roberts et al., 2017; Meyer et al., 2018, 2019). Several studies recommended the use of recently developed spatial validation methods to address spatial overfitting in RS-based model validations (Roberts et al., 2017; Meyer et al., 2018, 2019). However, a recent study opposed spatial cross-validation methods for assessing map accuracy and suggested the use of probability sampling and design-based inference since this method does not need to account for spatial autocorrelation (Wadoux et al., 2021). All tropical countries used probability sampling in their latest NFIs which allows countries to choose either method for AGB estimation using field and RS observations.

In many countries, PSUs including clusters and single plots were established at large distances. AGB estimations from PSUs in large distances could induce bias even when the sampling designs exclusively deal with the forest as population targets (Fisher et al., 2008; Guitet et al., 2015; Hajj et al., 2017). We found that the distances between PSUs are considerably larger in some particular forest types (e.g., in mangroves and open forest or shrubland). Countries having PSUs separated by large distances could consider increasing NFI sampling intensity to improve the precision of AGB estimates. However, increasing sampling intensity implies a significant increase in cost and time to complete an NFI which might not be practical in many countries.

Most tropical countries took around 5 years to complete an NFI cycle which means that NFI data representation for a single year spans over the entire NFI cycle of 5 years. This could result in an error in field biomass estimation due to processes associated with tree recruitment, re/growth, and mortality over that period (Poorter et al., 2016). There are also evolving demands for increasing reporting cycles e.g., biennial transparency reporting for the UNFCCC Paris Agreement (Herold et al., 2019). The issues of the temporal gap in NFI data could be addressed by applying predictive models of biomass changes over time (Chazdon et al., 2006) or by integrating more timely data streams. Some countries such as India, Sri Lanka, the Philippines, and Viet Nam have a panel design where about 20 % of the field plots are updated every year to complete a 5-year NFI cycle. Combining yearly NFI plot measurements from the panel system with RS data can offer an effective way to address the temporal gap between the field and space-based biomass data at the national level that could help meet annual/biennial reporting needs as required by the UNFCCC. Further, using annual data from the panel system with RS data also leverages the power of an NFI to be used to assess forest disturbances at the (sub)national level, and forest managers may be able to respond rapidly (Vogeler et al., 2020). Such approaches for combined usage of annual NFI panel data with RS including their practicalities, related efforts, and cost considerations should be investigated in the context of a specific country's circumstances.

Tropical countries used forest definitions in their NFIs with canopy cover varying from 10 to 30 % which can be an issue for integration with space-based global biomass data. Earlier studies showed that total national forest biomass varied by 31–44 % when different forest definitions were applied (Cartus et al., 2014; Rodríguez-Veiga et al., 2016; Mermoz et al., 2018). Careful consideration of the national forest definition is essential when comparing the national forest AGB estimates from NFI and space-based biomass data across the countries. The most recent NFIs in tropical countries are mostly full NFIs. This allows validation of space-based biomass data for all forest extent in a country. Further, a large number of tropical countries include both forests and trees outside forests in their NFIs. Therefore, there are opportunities to integrate space-based biomass products in areas outside forests in those tropical countries. A couple of tropical countries e.g., Sri Lanka and Costa Rica, where NFIs currently only include forests, have a plan to include trees outside forests in future NFIs. In addition, tropical countries included smaller trees by establishing concentric/nested plots in NFIs. This indicates that NFI-based biomass estimates may not be potentially affected by underestimation and bias which have been reported from the exclusion of smaller trees in NFIs (Searle and Chen, 2017).

The large variations in the tropical NFI designs observed in our study highlight some of the limits in the international comparability for large-area forest monitoring and reporting. Therefore, efforts aiming at the harmonization of the NFI-based estimates to improve the comparability of tropical NFIs could be one objective for future activities. The use of space-based data could help to overcome gaps and incompatibilities and support any future harmonization process of NFIs in the tropics. Also, processes of harmonization followed in the European NFI Network (ENFIN) could provide examples on how harmonization of NFIs can be performed in other biomes (Tomppo et al., 2010; Bosela et al., 2016; Gschwantner et al., 2016, 2019, 2022). FAO and ENFIN already provide direct support for the harmonization of NFIs in Latin America and the Caribbean (Ramírez et al., 2022). At the same time, cost and other related considerations should be investigated in the context of harmonization efforts in the tropical region as many countries still depend on external resources to implement NFIs.

5. Conclusions

Our study shows that most of the single NFI countries (~94 %) were in the tropical nations. The latest NFIs were more recent in the tropics, mostly implemented from 2016 onwards. While, the temperate and boreal countries implemented their latest NFIs largely between 2011 and 2017. The intercomparison results for the year 2018 showed that recent NFI data availability had a positive effect on the relationship between country AGB estimates from a space-based CCI biomass product versus FRA data. This highlights the importance of having a recent NFI to better link field data and space-based biomass products at the national level.

Our findings in 46 tropical countries revealed that different NFI designs are persisting in the tropics. For instance, about half of the countries used systematic sampling designs to establish field plots. The size of the plots varied between 0.01 and 1 ha, and more than three-quarters of the countries had smaller plots of ≤0.25 ha. Further, the distances between plots in the cluster varied largely from 10 to 500 m and most of the countries (50 %) had plots within 100 m distances. These varying NFI plot designs suggest that no "one size fits all approach" would work for the statistical integration of NFI plot data with space-based biomass estimates. Rather, different approaches and inference methods are required. We suggest that issues related to small plots such as dilution biases, edge effects, and spatial mismatches between the field plots and RS footprints need to be taken into account for better integration of NFI data with space-based biomass products.

Future NFI plot designs and RS-based estimation approaches should aim to better integrate these two data sources at the national level. Complementing NFI efforts and super-site plots (as proposed by GEO-TREES, CEOS) would benefit plot data integration with currently available space-based applications, help improve biomass estimations at the global and national levels to better meet the data needs for reporting to the UNFCCC, FRA, and for climate-smart and sustainable forest and land-use management. Super-site designs have been developed but their implementation requires additional resources. There is an urgent need to assess the related efforts and costs needed in the context of the benefits for combining in-situ/space-based biomass data towards enhancing the accuracy and timeliness of national and sub-national biomass estimation.

One key motivation for developing in-situ and satellite data streams for biomass estimation is to support sustainability and reduce temporal gaps in monitoring systems. Many tropical countries have recent NFIs but some have data gaps and some struggles to complete the current cycle and/or to secure the cyclic NFI updates where space-based data can serve as an additional, complementary data stream if well integrated. The integration of space-based data can also help in processes of NFI harmonization and international comparability. Many countries established NFIs with a 5-year remeasurement plan using permanent sample plots; few through a panel system where 20 % of the plots are measured every year in some tropical countries. Using the yearly plot measurements from a panel system with (sub)annual remote sensing data can offer an effective way to address the temporal differences between the field and space-based data at the national level towards annual/biennial updates as required for the reporting to the UNFCCC and other applications.

CRediT authorship contribution statement

Karimon Nesha: Conceptualisation, Methodology, Data curation, Software, Analysis, Investigation, Visualisation, Writing- Original Draft, Writing – Revising and Editing.

Martin Herold: Funding acquisition; Conceptualisation, Methodology, Supervision, Writing – Reviewing and Editing.

Veronique De Sy: Conceptualisation, Methodology, Supervision, Writing – Reviewing and Editing.

Sytze de Bruin: Methodology, Writing – Reviewing and Editing.

Arnan Araza: Writing – Reviewing and Editing.

Natalia Málaga: Writing – Reviewing and Editing.

Javier G P Gamarra: Writing – Reviewing and Editing.

Kristell Hergoualc'h: Writing – Reviewing and Editing.

Anssi Pekkarinen: Writing – Reviewing and Editing.

Carla Ramirez: Writing – Reviewing and Editing.

David Morales-Hidalgo: Writing – Reviewing and Editing.

Rebecca Tavani: Writing – Reviewing and Editing.

Disclaimer

The designations employed and the presentation of the material in the maps do not imply the expression of any opinion whatsoever on the part of the authors concerning the legal or constitutional status of any country, territory, or sea area, or concerning the delimitation of frontiers.

Data availability

Data are publicly available on Zenodo under a CC BY 4.0 license at the following DOI: 10.5281/zenodo.6992943.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is part of CIFOR's Global Comparative Study on REDD+ (www.cifor.org/gcs). The funding partners of this research include the International Climate Initiative (IKI) of the German Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB), the Norwegian Agency for Development Cooperation (Norad), and the CGIAR Research Programme on Forests, Trees, and Agroforestry (CRP-FTA) and the MITIGATE+ initiative with financial support from the CGIAR Fund Donors. The work was further supported by the European Commission Horizon Europe project OpenEarthMonitor.org (Grant agreement number 101056875) and Forest Navigator (Grant agreement number 101059548), and the ESA funded projects CCI-Biomass phase 2 and ForestCarbon. Further, FAO provided access to NFI manuals of some tropical countries at the unpublished stage which enabled us to perform analysis for objective 3 in this research.

Appendix 1

List of key variables for analysis of NFI design characteristics related to NFI sampling and plot designs in 46 tropical countries. PSU refers to Primary Sampling Unit. Plot shape and plot size include both plots in cluster and single plots. Sampling strata 'uniform' means no strata.

Country	NFI extent	NFI component	Sampling stratification	Sampling design	PSU unit	PSU distance in km	Cluster shape	Plot shape	Cluster plot distance in m	Plot size in ha
Angola	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster	37 50	Square	Rectangular	250	0.5
Argentina	Full	Forests	Uniform	Systematic sampling	Single plot	10		Circular		0.1
Bangladesh	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster	5.9 10.4	Circular	Circular	38	0.11
Bhutan	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	4	L-shape	Circular	50	0.05
Brazil	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	20	Cross	Rectangular	50	0.2 0.1
Cambodia	Full	Forests	Forest types	Stratified systematic sampling	Cluster	6 4 3	Square	Circular	100	0.13
Cameroon	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster	25 50	Square	Rectangular	250	0.5
Colombia	Full	Forests	Uniform	Systematic sampling	Cluster		Cross	Circular	80	0.07
Comoros	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster		Square	Rectangular	100	0.2
Costa Rica	Full	Forests	Vegetation types	Stratified systematic sampling	Single plot	23 15 5 11 2		Rectangular		0.1
Dominican Republic	Full	Forests	Forest types	Stratified systematic sampling	Single plot	7 6 5 2		Rectangular		0.1
DRC	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster		Square	Square	250	0.56
Ecuador	Full	Forests	Forest types	Stratified random sampling	Cluster		L-shape	Square Rectangular	250	0.36 0.24
EL Salvador	Full	Forests	Vegetation types	Stratified systematic sampling	Single plot			Rectangular		0.1
Ethiopia	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster	28 56 72	Square	Rectangular	250	0.5
Gabon	Full	Forests	Forest types	Stratified systematic sampling	Cluster		Cross	Circular	100	0.1
Gambia	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	9	Square	Rectangular	250	0.5
Guatemala	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster		Rectangular	Circular	40	0.07
Hondurus	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster		Rectangular	Circular	50	0.07
India	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	5	Circular	Circular	40	0.02
Indonesia	Full	Forests	Uniform	Systematic sampling	Cluster	10	Square	Square	500	1.0
Kenya	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster		Rectangular Square	Circular	250 150	0.13 0.07
Lao PDR	Full	Forests and trees outside forests	ILUA	Stratified random sampling	Cluster		L-shape	Circular	200	0.2
Lebanon	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	7.4	Square	Rectangular	250	0.5
Liberia	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	19.9	L-shape	Circular	60	0.1
Malawi	Full	Forests	Forest types	Stratified random sampling	Cluster		T-shape	Circular	100 50	0.13
Malaysia	Full	Forests	Forest types	Stratified random sampling	Cluster		Square	Circular	100	0.01

(continued on next page)

(*continued*)

Country	NFI extent	NFI component	Sampling stratification	Sampling design	PSU unit	PSU distance in km	Cluster shape	Plot shape	Cluster plot distance in m	Plot size in ha
										0.04
Mexico	Full	Forests and trees outside forests	Vegetation types	Stratified systematic sampling	Cluster	5	Y-shape	Circular	45.14	0.04
						10		Rectangular		
						20				
Mozambique	Full	Forests	Ecological zones	Stratified random sampling	Cluster		Square	Rectangular	50	0.1
								Circular		
Myanmar	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster	12	L-shape	Circular	100	0.1
						3			50	
Nepal	Full	Forests and trees outside forests	Ecological zones	Stratified systematic sampling	Cluster		Square	Circular	300	0.13
									150	
Nicaragua	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	18	Square	Rectangular	250	0.5
Nigeria	Full	Forests	Ecological zones	Stratified random sampling	Cluster		L-shape	Square	100	0.12
								Rectangular	10	0.02
Pakistan	Full	Forests	Ecological zones	Stratified systematic sampling	Cluster	16	Square	Circular	200	0.1
Paraguay	Full	Forests	Forest types	Stratified systematic sampling	Cluster		L-shape	Square	250	0.36
										0.16
Peru	Full	Forests	Ecological zones	Stratified systematic sampling	Cluster	19	L-shape	Circular	30	0.05
						8				
						31				
						20				
						34				
						24		Rectangular	75	0.1
Philippines	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	27.75	Square	Rectangular	250	0.5
Republic of Congo	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	25	Square	Rectangular	250	0.5
Sri Lanka	Full	Forests	Uniform	Systematic sampling	Cluster	2	Circular	Circular	40	0.03
Suriname	Partial	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	20	Cross	Rectangular	50	0.2
									100	
Tanzania	Full	Forests and trees outside forests	ILUA	Stratified systematic sampling	Cluster	10	L-shape	Circular	250	0.07
Thailand	Full	Forests	Uniform	Systematic sampling	Cluster	20	Circular	Circular	50	0.1
Timor-Leste	Partial	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	4	Rectangular	Circular	408	0.1
Uganda	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	5	Cross	Square	300	0.25
Viet Nam	Full	Forests and trees outside forests	Uniform	Systematic sampling	Cluster	8	L-shape	Circular	150	0.1
Zambia	Full	Forests and trees outside forests	ILUA	Stratified systematic sampling	Cluster	10	Square	Rectangular	450	0.1

Appendix 2

A list of the available NFI field manuals/NFI reports consulted in the analysis of NFI plot design characteristics in 46 tropical countries.

Country	References/citations of the NFI manuals and reports
Angola	FAO & IDF 2009. Inventário Florestal Nacional Guia de campo para recolha de dados. Monitorização e Avaliação de Recursos Florestais Nacionais de Angola – Guia para recolha de dados. National Forest Monitoring and Assessment Working Paper NFMA XX/P. Rome.
Argentina	Secretaría de Gobierno de Ambiente y Desarrollo Sustentable de la Nación. (2019). Segundo Inventario Nacional de Bosques Nativos: manual de campo. Buenos Aires: Secretaría de Gobierno de Ambiente y Desarrollo Sustentable de la Nación, Argentina.
Bangladesh	BFD (2016). Field Instructions for the Bangladesh Forest Inventory. Bangladesh Forest Department and Food and Agricultural Organization of the United Nations. Dhaka, Bangladesh.
	GoB (2019). Tree and forest resources of Bangladesh: Report on the Bangladesh Forest Inventory. Forest Department, Ministry of Environment, Forest and Climate Change, Government of the People's Republic of Bangladesh, Dhaka, Bangladesh.
	BFD 2016.The Bangladesh Forest Inventory Design. Dhaka, Bangladesh
Bhutan	Department of Forests and Park Services (DoFPS) 2012. National Forest Inventory Field Manual. Forest Resources Management Division (FRMD), DoFPS, Royal Government of Bhutan.
	DoFPS 2016. National Forest Inventory Report. Forest Resources Management Division (FRMD), DoFPS, Royal Government of Bhutan
Brazil	Serviço Florestal Brasileiro 2020. Manual de campo: Procedimentos Para Coleta De Dados Biofísicos E Socioambientais. Serviço Florestal Brasileiro, Ministério Do Meio Ambiente, Brasília.
Cambodia	MAFF 2015. National Forest Monitoring System of Cambodia. Ministry of Agriculture, Forestry and Fisheries (MAFF), The Royal Government of Cambodia.
Cameroon	FAO 2005. National Forest Assessment. Manual for Data Processing and Analysis. Forest Resources Assessment Programme Working Paper. Rome.
	FAO 2004. National Forest Inventory Field Manual. Forest Resources Assessment Programme Working Paper. Rome.

(*continued*)

Country	References/citations of the NFI manuals and reports
Colombia	Barbosa P, Herrera F., Goeking S., Nieto V., Peña M., Ortiz S. 2014. Manual de Control de Calidad del Inventario Forestal Nacional (IFN). IDEAM. Bogotá D.C., Colombia.
Comoros	FAO 2009. Appui au Programme forestier national projet. Rome.
Costa Rica	Sistema Nacional de Áreas de Conservación (Sinac) – Programa REDD-CCAD-GIZ, 2014. Manual de campo para el inventario forestal nacional de Costa Rica: Diseño de parcela y medición de variables de sitio y dasométricas. Preparado por Jorge Fallas – consultor para el Programa Reducción de Emisiones por Deforestación y Degradación Forestal en Centroamérica y la República Dominicana (REDD/CCAD/GIZ). San José, Costa Rica.
Dominic Republic	REDD/CCAD-GIZ 2014. Inventario Nacional Forestal Multipropósito de República Dominicana 2014–2015. Elementos de Planificación y Protocolo para las Operaciones de Medición. Integrando Esfuerzos Para Un Buen Manejo De Los Bosques Programa Regional. REDD/CCAD-GIZ. Ministerio de Ambiente, Republica Dominicana.
DRC	MEDD & FAO 2019. Manuel de terrain de l'Inventaire Forestier National de la République Démocratique du Congo. Ministère de l'Environnement et Développement Durable (MEDD), DRC.
El Salvador	MARN 2018. Inventario Nacional de Bosques de El Salvador (IBN) 2018. Ministerio de Medio Ambiente y Recursos Naturales (MARN), Centroamérica, El Salvador.
Ethiopia	Moges Y (2014). Ethiopia's National Forest Monitoring System (NFMS). Ministry of Environment, Forest and Climate Change Commission, Ethiopia. FREL (2016). Ethiopia's Forest Reference Level Submission to the UNFCCC. Ministry of Environment, Forest and Climate Change, Ethiopia.
Ecuador	Segura, D., Jiménez, D., Chinchero, M., Iglesias, J., & Sola, A. (2015). Evaluación Nacional Forestal Del Ecuador, Un Proceso En Contruccion Hacia El Monitoreo De Los Bosques Y La Biodiversidad. Segura, D., Digner, J., Iglesias, J., Augusto, S., Miguel, C., Casanoves, F., Mario, C., Cifuentes, M., & Rodrigo, T. (2016). The Ecuadorian National Forest Inventory (pp. 347–367).
Gabon	République Gabonaise (2018). Rapport Final du Projet de Développement d'un Système d'Inventaire des Ressources Forestières Nationales contribuant à la Gestion Durable des Forêts en République Gabonaise. Ministére de la Forêt, de la Mer et de I'Environment & Association Japonese de Technologie Forestière.
Gambia	DoF 2010. National Forest Assessment 2008–2010. Government of The Gambia – Ministry of Forestry and the Environment (MoFEN) & Food and Agriculture Organization of the United Nation (FAO).
Guatemala	Instituto Nacional de Bosques y Consejo Nacional de Áreas Protegidas. 2020. Manual de campo para el Inventario Forestal Nacional 2020, Grupo Interinstitucional de Monitoreo de Bosques y Uso de la Tierra. Guatemala.
Hondurus	ICF 2017. Manual Para La Colecta De Datos De Campo Para El Inventario Nacional Forestal De Honduras. Instituto Nacional de Conservación y Desarrollo Forestal, Áreas Protegidas y Vida Silvestre (ICF). Honduras.
India	FSI (2019). State of forest report. Forest Survey of India, Ministry of Environment Forest & Climate Change, Government of India. FSI (2021). National Forest Inventory of India. Ministry of Environment Forest & Climate Change, Government of India. https://fsi.nic.in/about-forest-inventory
Indonesia	MoF Indonesia 2014. Indonesia's National Forest Monitoring System. Forestry Planning & Forestry Resources Inventory and Monitoring, Ministry of Forestry (MoF). Jakarta, Indonesia.
Kenya	Kenya Forest Service (KFS) 2016. Field Manual for Biophysical Forest Resources Assessment in Kenya. The Project Improving Capacity in Forest Resources Assessment in Kenya (IC-FRA) implemented 2013–2015. Kenya Forest Service (KFS) 2016. Proposal for National Forest Resources Assessment in Kenya (NFRA). The Project Improving Capacity in Forest Resources Assessment in Kenya (IC-FRA) implemented 2013–2015.
Lao People's Democratic Republic (Lao PDR)	DoF 2016, The Capacity Development Project for Establishing National Forest Information System for Sustainable Forest Management and REDD+ (Phase II) Completion Report. Department of Forestry(DoF), Ministry of Agriculture and Forestry. Lao People's Democratic Republic.
Lebanon	FAO 2004. National Forest Inventory Field Manual. FAO Forestry Department, Rome. MOA/FAO 2005. National Forest and Tree Assessment and Inventory Final Report. FAO, Rome/Ministry of Agriculture (MOA), Republic of Lebanon.
Liberia	Forestry Development Authority (FDA) 2019. National Forest Inventory 2018. The Forestry Development Authority (FDA), Liberia and the National REDD+ Implementation Unit, Liberia.
Malawi	Government of Malawi 2018. National Forest Inventory Analysis Report. The Ministry of Natural Resources, Energy and Mining, Republic of Malawi.
Malaysia	PSM 2012. Inventori Hutan Nasional Kelima (IHN-5) 2011–2012. Perhutanan Semenanjung Malaysia (PSM), Malaysia.
Mexico	SEMARNAT & CONAFOR 2009. Inventario Nacional Forestal y de Suelos. Manual y procedimientos para el muestreo de campo. Secretaría de Medio Ambiente y Recursos Naturales (SEMARNAT) and Comisión Nacional Forestal (CONAFOR), Mexico.
Mozambique	Republic of Mozambique 2018. The Project for the Establishment of Sustainable Forest Resource Information Platform for Monitoring Redd+. Ministry of Land, Environment and Rural Development, Republic of Mozambique. Republic of Mozambique 2018. Mozambique's Forest Reference Emission Level for Reducing Emissions from Deforestation in Natural Forests. Ministry of Land, Environment and Rural Development, Republic of Mozambique.
Myanmar	FD & FAO 2021. National Forest Inventory Field Manual. Forest Department (FD), Ministry of Agriculture and Forests, Rangoon, Myanmar.
Nepal	FRTC, 2019. Forest Resource Assessment Field Manual, 2019 (Remeasurement of Permanent Sample Plot), Forest Resource Assessment (FRA), Forest Research & Training Center (FRTC), Nepal.
Nicaragua	INAFOR & FAO 2008. Inventario Nacional Forestal de Nicaragua 2007–2008 Manual de Campo. Instituto Nacional Forestal (INAFOR). Gobierno de Unidad y Reconciliación Nacional. Nicaragua.
Nigeria	FAO 2020. Nigeria – National Forest (Carbon) Inventory Field Manual. Abuja. https://doi.org/10.4060/cb2087en
Pakistan	Arbonaut Oy/WWF-Pakistan (2018). National Forest Monitoring System - Measurement, Reporting and Verification (MRV) System for Pakistan. MoCC/National REDD+ Office. Arbonaut Oy/WWF-Pakistan (2017). National Forest Inventory and Field Surveying Manual. MoCC/National REDD+ Office, Pakistan.
Paraguay	INFONA 2014. Manual de Campo: Procedimientos para la planificación, medición y registro de información del Inventario Forestal Nacional del Paraguay. Instituto Forestal Nacional (INFONA), Paraguay. INFONA & ONU-REDD 2015. Inventario Forestal Nacional (IFN). Dirección De Sistema Nacional De Información Forestal. Instituto Forestal Nacional (INFONA), Paraguay.
Peru	SERFOR 2016. Inventario Nacional Forestal - INF. Servicio Nacional Forestal y de Fauna Silvestre SERFOR. Rinconada Baja, La Molina, Lima, Perú
Philippines	FAO 2002. National Forest Inventory Field Manual. FAO Forestry Department, Rome, Italy.
Republic of Congo	MDLF 2020. Inventaire forestier national multiressource de la République du Congo 2009–2014. Tome 1: Méthodologie et mise en oeuvre, Ministère De L'economie Forestière (MDLF), Brazzaville, République du Congo.
Sri Lanka	FSI 2017. Methodology Document for National Forest Inventory of Sri Lanka. Forest Survey of India (FSI), Ministry of Environment, Forest and Climate Change, India.
Suriname	SBB and ANRICA 2014. National Forest Inventory Field Manual. Stichting Bosbeheer en Bostoezicht (SBB) Suriname.
Tanzania	Ministry of Natural Resources & Tourism 2010. National Forestry Resources Monitoring and Assessment of Tanzania (NAFORMA) - Field Manual and Biophysical Survey. Forestry and Beekeeping Division, Ministry of Natural Resources and Tourism, The United Republic of Tanzania.
Thailand	FAO 2007. Brief on National Forest Inventory. Forestry Department, FAO, Rome, Italy. Trisurat Y,Eiadthong W, Khunrattanasiri W, Saengnin S,Chitechote A, Maneerat S (2020). Systematic forest inventory plots and their contribution

(continued on next page)

(continued)

Country	References/citations of the NFI manuals and reports
	to plant distribution and climate change impact studies in Thailand. Ecological Research. 35:724–732. https://doi.org/:10.1111/1440-1703.12105
Timor Leste	Carlos Pacheco Marques (et al.) 2010. First forest inventory of Timor-Leste: districts of Bobonaro and Covalima: 2008–2009. Vila Real, Universidade de Trás-os-Montes e Alto Douro, Portugal.
Uganda	Elungat Odeke David 2004. Forest inventories in National Forestry Authority. Forest Department, Uganda.
Vietnam	FAO 2013. Overview of Improved NFIMAP Methodology - Support to National Assessment and Long Term Monitoring of The Forest and Tree Resources in Vietnam. Forestry Department, FAO, Rome, Italy.
	MARD 2015. Viet Nam's Submission on Reference Levels for REDD+ Results Based Payments. Ministry of Agriculture and Rural Development (MA & RD), Vietnam.
	Paul Silfverberg et al. 2015. Development of Management Information System for the Forestry Sector in Vietnam – Phase II (FORMIS) Final Report. FCG International Ltd. Presented to the Ministry for Foreign Affairs of Finland
Zambia	Forestry Department 2014. Integrated Land Use Assessment Phase II Zambia, Biophysical Field Manual. Forestry Department, Ministry of Lands, Natural Resources and Environmental Protection, Government of Zambia.

References

Araza, A., de Bruin, S., Herold, M., Quegan, S., Labriere, N., Rodriguez-Veiga, P., Avitabile, V., Santoro, M., Mitchard, E.T.A., Ryan, C.M., Phillips, O.L., Willcock, S., Verbeeck, H., Carreiras, J., Hein, L., Schelhaas, M.J., Pacheco-Pascagaza, A.M., da Conceição Bispo, P., Laurin, G.V., Lucas, R., 2022. A comprehensive framework for assessing the accuracy and uncertainty of global above-ground biomass maps. Remote Sens. Environ. 272, 112917. https://doi.org/10.1016/J.RSE.2022.112917.

Avitabile, V., Camia, A., 2018. An assessment of forest biomass maps in Europe using harmonized national statistics and inventory plots. For. Ecol. Manag. 409, 489–498. https://doi.org/10.1016/J.FORECO.2017.11.047.

Avitabile, V., Baccini, A., Friedl, M.A., Schmullius, C., 2012. Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. Remote Sens. Environ. 117, 366–380. https://doi.org/10.1016/J.RSE.2011.10.012.

Avitabile, V., Herold, M., Heuvelink, G.B.M., Lewis, S.L., Phillips, O.L., Asner, G.P., Armston, J., Ashton, P.S., Banin, L., Bayol, N., Berry, N.J., Boeckx, P., de Jong, B.H.J., DeVries, B., Girardin, C.A.J., Kearsley, E., Lindsell, J.A., Lopez-Gonzalez, G., Lucas, R., Willcock, S., 2016. An integrated pan-tropical biomass map using multiple reference datasets. Glob. Chang. Biol. 22 (4), 1406–1420. https://doi.org/10.1111/GCB.13139.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., Samanta, S., Houghton, R.A., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Chang. 2 (3), 182–185. https://doi.org/10.1038/nclimate1354.

Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., 2014. The concept of essential climate variables in support of climate research, applications, and policy. Bull. Am. Meteorol. Soc. 95 (9), 1431–1443. https://doi.org/10.1175/BAMS-D-13-00047.1.

Bosela, M., Redmond, J., Kučera, M., Marin, G., Adolt, R., Gschwantner, T., Petráš, R., Korhonen, K., Kuliešis, A., Kulbokas, G., Fischer, C., Lanz, A., 2016. Stem quality assessment in European National Forest Inventories: an opportunity for harmonised reporting? Ann. For. Sci. 73 (3), 635–648. https://doi.org/10.1007/S13595-015-0503-8/TABLES/5.

Buchhorn, M., Smets, B., Bertels, L., Roo, B.De, Lesiv, M., Tsendbazar, N.-E., Herold, M., Fritz, S., 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2018: Globe (V3.0.1) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.3518038.

Cartus, O., Kellndorfer, J., Walker, W., Franco, C., Bishop, J., Santos, L., Fuentes, J.M.M., 2014. A national, detailed map of forest aboveground carbon stocks in Mexico. Remote Sens. 6 (6), 5559–5588. https://doi.org/10.3390/RS6065559.

Chave, Jérôme, Davies, S.J., Phillips, O.L., Lewis, S.L., Sist, P., Schepaschenko, D., Armston, J., Baker, T.R., Coomes, D., Disney, M., Duncanson, L., Hérault, B., Labrière, N., Meyer, V., Réjou-Méchain, M., Scipal, K., Saatchi, S., 2019. Ground data are essential for biomass remote sensing missions. Surv. Geophys. 40 (4), 863–880. https://doi.org/10.1007/S10712-019-09528-W.

Chave, Jerome, Davies, S., Disney, M., Duncanson, L., Herold, M., Labrière, N., Phillips, O., Quegan, S., Saatchi, S., Schepaschenko, D., Scipal, K., Sist, P., 2021. GEO-TREES: Forest Biomass Reference System from Tree-by-Tree Inventory Data. https://earthobservations.org/documents/gwp20_22/GEO-TREES.pdf.

Chazdon, R.L., Letcher, S.G., Van Breugel, M., Martínez-Ramos, M., Bongers, F., Finegan, B., 2006. Rates of change in tree communities of secondary Neotropical forests following major disturbances. Philos. Trans. R. Soc. BBiol. Sci. 362 (1478), 273–289. https://doi.org/10.1098/RSTB.2006.1990.

Daisuke, S., Trung, N.T., Rei, M., Yoshito, S., Tadashi, I., Toshiyoshi, K., 2020. Progress of the ISS based vegetation LiDAR mission, Moli - Japan's first space-based LiDAR. International Geoscience And Remote Sensing Symposium (IGARSS), pp. 3467–3470. https://doi.org/10.1109/IGARSS39084.2020.9323332.

Davis, L.S., Johnson, K.N., Bettinger, P., Howard, T.E., 2001. Forest Management: To Sustain Ecological, Economic, And Social Values. 4th ed. Waveland Press Inc.

Dubayah, R., Blair, J.B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., Hofton, M., Hurtt, G., Kellner, J., Luthcke, S., Armston, J., Tang, H., Duncanson, L., Hancock, S., Jantz, P., Marselis, S., Patterson, P.L., Qi, W., Silva, C., 2020. The Global Ecosystem Dynamics Investigation: high-resolution laser ranging of the Earth's forests and topography. Sci. Remote Sens. 1, 100002. https://doi.org/10.1016/J.SRS.2020.100002.

Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., Carter, S., Chave, J., Herold, M., Crowther, T.W., Falkowski, M., Kellner, J.R., Labrière, N., Lucas, R., MacBean, N., McRoberts, R.E., Meyer, V., Næsset, E., Nickeson, J.E., Williams, M., 2019. The importance of consistent global forest aboveground biomass product validation. Surv. Geophys. 40 (4), 979–999. https://doi.org/10.1007/S10712-019-09538-8.

Duncanson, Laura, Disney, M., Armston, J., Nickeson, J., Minor, D., Camacho, F., 2021. Committee on Earth Observation Satellites Working Group on Calibration And Validation Land Product Validation Subgroup Aboveground Woody Biomass Product Validation Good Practices Protocol Version 1.0-2021. https://doi.org/10.5067/doc/ceoswgcv/lpv/agb.001.

Duncanson, Laura, Neuenschwander, A., Silva, C.A., Montesano, P., Guenther, E., Thomas, N., Hancock, S., Minor, D., White, J., Wulder, M., Armston, J., 2021. Forest Aboveground Biomass Estimation With GEDI And ICESat-2 in Boreal Forests, pp. 670–672. https://doi.org/10.1109/IGARSS47720.2021.9553209.

ESA, 2021. ESA - introducing biomass. https://www.esa.int/Applications/Observing_the_Earth/Biomass/Introducing_Biomass.

Fang, J., Guo, Z., Hu, H., Kato, T., Muraoka, H., Son, Y., 2014. Forest biomass carbon sinks in East Asia, with special reference to the relative contributions of forest expansion and forest growth. Glob. Chang. Biol. 20 (6), 2019–2030. https://doi.org/10.1111/gcb.12512.

FAO, 2017. Voluntary Guidelines on National Forest Monitoring. https://doi.org/10.4060/i6767en.

FAO, 2018. FRA 2020 - terms and definitions. https://www.fao.org/3/I8661EN/i8661en.pdf.

Fisher, J.I., Hurtt, G.C., Thomas, R.Q., Chambers, J.Q., 2008. Clustered disturbances lead to bias in large-scale estimates based on forest sample plots. Ecol. Lett. 11 (6), 554–563. https://doi.org/10.1111/J.1461-0248.2008.01169.X.

Gallaun, H., Zanchi, G., Nabuurs, G.J., Hengeveld, G., Schardt, M., Verkerk, P.J., 2010. EU-wide maps of growing stock and above-ground biomass in forests based on remote sensing and field measurements. For. Ecol. Manag. 260 (3), 252–261. https://doi.org/10.1016/J.FORECO.2009.10.011.

GEO BON, 2022. Essential biodiversity variables. https://geobon.org/ebvs/what-are-ebvs/.

Gollob, C., Ritter, T., Kraßnitzer, R., Tockner, A., Nothdurft, A., 2021. Measurement of forest inventory parameters with Apple iPad Pro and integrated LiDAR technology. Remote Sens. 13 (16), 3129. https://doi.org/10.3390/RS13163129.

Gschwantner, T., Lanz, A., Vidal, C., Bosela, M., Di Cosmo, L., Fridman, J., Gasparini, P., Kuliešis, A., Tomter, S., Schadauer, K., 2016. Comparison of methods used in European National Forest Inventories for the estimation of volume increment: towards harmonisation. Ann. For. Sci. 73 (4), 807–821. https://doi.org/10.1007/S13595-016-0554-5/TABLES/11.

Gschwantner, T., Alberdi, I., Balázs, A., Bauwens, S., Bender, S., Borota, D., Bosela, M., Bouriaud, O., Cañellas, I., Donis, J., Freudenschuß, A., Hervé, J.C., Hladnik, D., Jansons, J., Kolozs, L., Korhonen, K.T., Kucera, M., Kulbokas, G., Kuliešis, A., Zell, J., 2019. Harmonisation of stem volume estimates in European National Forest Inventories. Ann. For. Sci. 76 (1), 1–23. https://doi.org/10.1007/S13595-019-0800-8/TABLES/10.

Gschwantner, T., Alberdi, I., Bauwens, S., Bender, S., Borota, D., Bosela, M., Bouriaud, O., Breidenbach, J., Donis, J., Fischer, C., Gasparini, P., Heffernan, L., Hervé, J.C., Kolozs, L., Korhonen, K.T., Koutsias, N., Kovácsevics, P., Kučera, M., Kulbokas, G., Tomter, S.M., 2022. Growing stock monitoring by European National Forest Inventories: historical origins, current methods and harmonisation. For. Ecol. Manag. 505, 119868. https://doi.org/10.1016/J.FORECO.2021.119868.

Guitet, S., Hérault, B., Molto, Q., Brunaux, O., Couteron, P., 2015. Spatial structure of above-ground biomass limits accuracy of carbon mapping in rainforest but large scale forest inventories can help to overcome. PLOS ONE 10 (9), e0138456. https://doi.org/10.1371/JOURNAL.PONE.0138456.

Hajj, M.El, Baghdadi, N., Fayad, I., Vieilledent, G., Bailly, J.-S., Minh, D.H.T., 2017. Interest of integrating spaceborne LiDAR data to improve the estimation of biomass in high biomass forested areas. Remote Sens. 9 (3), 213. https://doi.org/10.3390/RS9030213.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (6160), 850–853. https://doi.org/10.1126/science.1244693.

Herold, M., Carter, S., Avitabile, V., Espejo, A.B., Jonckheere, I., Lucas, R., McRoberts, R.E., Næsset, E., Nightingale, J., Petersen, R., Reiche, J., Romijn, E., Rosenqvist, A., Rozendaal, D.M.A., Seifert, F.M., Sanz, M.J., De Sy, V., 2019. The role and need for space-based forest biomass-related measurements in environmental management and policy. Surv. Geophys. 40 (4), 757–778. https://doi.org/10.1007/s10712-019-09510-6.

Herold, M., Saatchi, S., Duncanson, L., 2021. Concept for a coordinated activity to provide refined global biomass and biomass change estimates in support of the UNFCCC Global

Stocktake Background. https://ceos.org/document_management/Meetings/SIT/SIT-36/Presentations/3.2_Biomass_GST_concept_v8.pdf.
Hill, T.C., Williams, M., Bloom, A.A., Mitchard, E.T.A., Ryan, C.M., 2013. Are inventory based and remotely sensed above-ground biomass estimates consistent? PLOS ONE 8 (9), e74170. https://doi.org/10.1371/JOURNAL.PONE.0074170.
Houghton, R.A., 2005. Aboveground forest biomass and the global carbon balance. Glob. Chang. Biol. 11 (6), 945–958. https://doi.org/10.1111/j.1365-2486.2005.00955.x.
Houghton, R.A., Hall, F., Goetz, S.J., 2009. Importance of biomass in the global carbon cycle. J. Geophys. Res. Biogeosci. 114 (3), 0–03. https://doi.org/10.1029/2009JG000935.
Hu, T., Su, Y., Xue, B., Liu, J., Zhao, X., Fang, J., Guo, Q., 2016. Mapping global forest aboveground biomass with spaceborne LiDAR, optical imagery, and forest inventory data. Remote Sens. 8 (7), 565. https://doi.org/10.3390/RS8070565.
Huang, W., Sun, G., Dubayah, R., Cook, B., Montesano, P., Ni, W., Zhang, Z., 2013. Mapping biomass change after forest disturbance: applying LiDAR footprint-derived models at key map scales. Remote Sens. Environ. 134, 319–332. https://doi.org/10.1016/J.RSE.2013.03.017.
Kangas, A., Astrup, R., Breidenbach, J., Fridman, J., Gobakken, T., Korhonen, K.T., Maltamo, M., Nilsson, M., Nord-Larsen, T., Næsset, E., Olsson, H., 2018. Remote sensing and forest inventories in Nordic countries – roadmap for the future. 33(4), pp. 397–412. https://doi.org/10.1080/02827581.2017.1416666.
Kershaw, J.A., Ducey, M.J., Beers, T.W., Husch, B., 2016. Forest Mensuration. 5th ed. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118902028.
Liang, X., Hyyppä, J., Kaartinen, H., Lehtomäki, M., Pyörälä, J., Pfeifer, N., Holopainen, M., Brolly, G., Francesco, P., Hackenberg, J., Huang, H., Jo, H.W., Katoh, M., Liu, L., Mokroš, M., Morel, J., Olofsson, K., Poveda-Lopez, J., Trochta, J., Wang, Y., 2018. International benchmarking of terrestrial laser scanning approaches for forest inventories. ISPRS J. Photogramm. Remote Sens. 144, 137–179. https://doi.org/10.1016/J.ISPRSJPRS.2018.06.021.
Mascaro, J., Detto, M., Asner, G.P., Muller-Landau, H.C., 2011. Evaluating uncertainty in mapping forest carbon with airborne LiDAR. Remote Sens. Environ. 115 (12), 3770–3774. https://doi.org/10.1016/J.RSE.2011.07.019.
Mermoz, S., Bouvet, A., Toan, T.Le, Herold, M., 2018. Impacts of the forest definitions adopted by African countries on carbon conservation. Environ. Res. Lett. 13 (10), 104014. https://doi.org/10.1088/1748-9326/AAE3B1.
Meyer, H., Reudenbach, C., Hengl, T., Katurji, M., Nauss, T., 2018. Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. Environ. Model Softw. 101, 1–9. https://doi.org/10.1016/j.envsoft.2017.12.001.
Meyer, H., Reudenbach, C., Wöllauer, S., Nauss, T., 2019. Importance of spatial predictor variable selection in machine learning applications – moving from data reproduction to spatial prediction. Ecol. Model. 411, 108815. https://doi.org/10.1016/J.ECOLMODEL.2019.108815.
Mitchard, E.T.A., Saatchi, S.S., Baccini, A., Asner, G.P., Goetz, S.J., Harris, N.L., Brown, S., 2013. Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-tropical maps. Carbon Balance Manag. 8 (1), 1–13. https://doi.org/10.1186/1750-0680-8-10/FIGURES/6.
Mononen, L., Auvinen, A.P., Ahokumpu, A.L., Rönkä, M., Aarras, N., Tolvanen, H., Kamppinen, M., Viirret, E., Kumpula, T., Vihervaara, P., 2016. National ecosystem service indicators: measures of social-ecological sustainability. Ecol. Indic. 61, 27–37. https://doi.org/10.1016/j.ecolind.2015.03.041.
Næsset, E., McRoberts, R.E., Pekkarinen, A., Saatchi, S., Santoro, M., Trier, Ø.D., Zahabu, E., Gobakken, T., 2020. Use of local and global maps of forest canopy height and above-ground biomass to enhance local estimates of biomass in miombo woodlands in Tanzania. Int. J. Appl. Earth Obs. Geoinf. 89, 102109. https://doi.org/10.1016/J.JAG.2020.102109.
NASA, 2021. Mission concept | Mission – NASA-ISRO SAR Mission (NISAR). https://nisar.jpl.nasa.gov/mission/mission-concept/.
Nesha, M.K., Herold, M., De Sy, V., Duchelle, A.E., Martius, C., Branthomme, A., Garzuglia, M., Jonsson, O., Pekkarinen, A., 2021. An assessment of data sources, data quality and changes in national forest monitoring capacities in the Global Forest Resources Assessment 2005-2020. Environ. Res. Lett. 16 (5). https://doi.org/10.1088/1748-9326/ABD81B.
Parmentier, I., Harrigan, R.J., Buermann, W., Mitchard, E.T.A., Saatchi, S., Malhi, Y., Bongers, F., Hawthorne, W.D., Leal, M.E., Lewis, S.L., Nusbaumer, L., Sheil, D., Sosef, M.S.M., Affum-Baffoe, K., Bakayoko, A., Chuyong, G.B., Chatelain, C., Comiskey, J.A., Dauby, G., Hardy, O.J., 2011. Predicting alpha diversity of African rain forests: models based on climate and satellite-derived data do not perform better than a purely spatial model. J. Biogeogr. 38 (6), 1164–1176. https://doi.org/10.1111/J.1365-2699.2010.02467.X.
Patel, N., Majumdar, A., 2011. Comparative assessment of the relationship of satellite data with the above ground biomass of Sal trees (Shorea robusta) determined from phenologically different time periods. Geo-Spat. Inf. Sci. 14 (3), 177–183. https://doi.org/10.1007/s11806-011-0492-1.
Pekkarinen, A., Reithmaier, L., Strobl, P., 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. ISPRS J. Photogramm. Remote Sens. 64 (2), 171–183. https://doi.org/10.1016/j.isprsjprs.2008.09.004.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C., Coops, N.C., Dulloo, E., Faith, D.P., Freyhof, J., Gregory, R.D., Heip, C., Höft, R., Hurtt, G., Jetz, W., Wegmann, M., 2013. Essential biodiversity variables. Science. Vol. 339. American Association for the Advancement of Science, pp. 277–278. https://doi.org/10.1126/science.1229931. Issue 6117.
Picard, N., Gamarra, J.G.P., Birigazzi, L., Branthomme, A., 2018. Plot-level variability in biomass for tropical forest inventory designs. For. Ecol. Manag. 430, 10–20. https://doi.org/10.1016/J.FORECO.2018.07.052.
Poorter, L., Bongers, F., Aide, T.M., Almeyda Zambrano, A.M., Balvanera, P., Becknell, J.M., Boukili, V., Brancalion, P.H.S., Broadbent, E.N., Chazdon, R.L., Craven, D., De Almeida-Cortez, J.S., Cabral, G.A.L., De Jong, B.H.J., Denslow, J.S., Dent, D.H., DeWalt, S.J., Dupuy, J.M., Durán, S.M., Rozendaal, D.M.A., 2016. Biomass resilience of Neotropical secondary forests. Nature 530 (7589), 211–214. https://doi.org/10.1038/nature16512.
Quegan, S., Lucas, R., 2021. CCI BIOMASS Product Specification Document Year 3 Version 3.0.
Ramírez, C., Alberdi, I., Bahamondez, C., Freitas, J., 2022. National forest inventories of Latin America and the Caribbean – towards the harmonization of forest information. National Forest Inventories of Latin America And the Caribbean. FAO. https://doi.org/10.4060/CB7791EN.
Reichstein, M., Carvalhais, N., De, M.-J.M., 2019. Aspects of forest biomass in the earth system: its role and major unknowns. Surv. Geophys. 40, 693–707. https://doi.org/10.1007/s10712-019-09551-x.
Réjou-Méchain, M., Muller-Landau, H.C., Detto, M., Thomas, S.C., Le Toan, T., Saatchi, S.S., Barreto-Silva, J.S., Bourg, N.A., Bunyavejchewin, S., Butt, N., Brockelman, W.Y., Cao, M., Cárdenas, D., Chiang, J.M., Chuyong, G.B., Clay, K., Condit, R., Dattaraja, H.S., Davies, S.J., Chave, J., 2014. Local spatial structure of forest biomass and its consequences for remote sensing of carbon stocks. Biogeosciences 11 (23), 6827–6840. https://doi.org/10.5194/BG-11-6827-2014.
Réjou-Méchain, M., Tymen, B., Blanc, L., Fauset, S., Feldpausch, T.R., Monteagudo, A., Phillips, O.L., Richard, H., Chave, J., 2015. Using repeated small-footprint LiDAR acquisitions to infer spatial and temporal variations of a high-biomass neotropical forest. Remote Sens. Environ. 169, 93–101. https://doi.org/10.1016/J.RSE.2015.08.001.
Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle, B.A., Hartig, F., Dormann, C.F., 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography 40 (8), 913–929. https://doi.org/10.1111/ecog.02881.
Rodríguez-Veiga, P., Saatchi, S., Tansey, K., Balzter, H., 2016. Magnitude, spatial distribution and uncertainty of forest biomass stocks in Mexico. Remote Sens. Environ. 183, 265–281. https://doi.org/10.1016/J.RSE.2016.06.004.
Rodríguez-Veiga, P., Quegan, S., Carreiras, J., Persson, H.J., Fransson, J.E.S., Hoscilo, A., Ziółkowski, D., Stereńczak, K., Lohberger, S., Stängel, M., Berninger, A., Siegert, F., Avitabile, V., Herold, M., Mermoz, S., Bouvet, A., Le Toan, T., Carvalhais, N., Santoro, M., Balzter, H., 2019. Forest biomass retrieval approaches from earth observation in different biomes. Int. J. Appl. Earth Obs. Geoinf. 77, 53–68. https://doi.org/10.1016/j.jag.2018.12.008.
Saatchi, S., Houghton, R.A., Dos Santos Alvalá, R.C., Soares, J.V., Yu, Y., 2007. Distribution of aboveground live biomass in the Amazon basin. Glob. Chang. Biol. 13 (4), 816–837. https://doi.org/10.1111/j.1365-2486.2007.01323.x.
Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011a. Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. U. S. A. 108 (24), 9899–9904. https://doi.org/10.1073/pnas.1019576108.
Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011b. Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. 108 (24), 9899–9904. https://doi.org/10.1073/PNAS.1019576108.
Santoro, Maurizio, Cartus, O., 2021. ESA Biomass Climate Change Initiative (Biomass_cci): Global Datasets of Forest Above-ground Biomass for the Years 2010, 2017 And 2018, v3. NERC EDS Centre for Environmental Data Analysis.
Santoro, M., Kay, H., Quegan, S., 2021. CCI Biomass Product User Guide, Year 3, Version 3.
Searle, E.B., Chen, H.Y.H., 2017. Tree size thresholds produce biased estimates of forest biomass dynamics. For. Ecol. Manag. 400, 468–474. https://doi.org/10.1016/J.FORECO.2017.06.042.
Thurner, M., Beer, C., Santoro, M., Carvalhais, N., Wutzler, T., Schepaschenko, D., Shvidenko, A., Kompter, E., Ahrens, B., Levick, S.R., Schmullius, C., 2014. Carbon stock and density of northern boreal and temperate forests. Glob. Ecol. Biogeogr. 23 (3), 297–310. https://doi.org/10.1111/GEB.12125.
Tomppo, E., Gschwantner, T., Lawrence, M., McRoberts, R.E., 2010. National forest inventories: pathways for common reporting. National Forest Inventories: Pathways for Common Reporting. Springer, Netherlands. https://doi.org/10.1007/978-90-481-3233-1.
Vogeler, J.C., Slesak, R.A., Fekety, P.A., Falkowski, M.J., 2020. Characterizing over four decades of forest disturbance in Minnesota, USA. Forests 11 (3), 362. https://doi.org/10.3390/F11030362.
Wadoux, A.M., Heuvelink, G.B., de Bruin, S., Brus, D.J., 2021. Spatial cross-validation is not the right way to evaluate map accuracy. Ecol. Model. 457, 109692. https://doi.org/10.1016/j.ecolmodel.2021.109692.
Wagner, F., Rutishauser, E., Blanc, L., Herault, B., 2010. Effects of plot size and census interval on descriptors of Forest structure and dynamics. Biotropica 42 (6), 664–671. https://doi.org/10.1111/J.1744-7429.2010.00644.X.
Wittke, S., Yu, X., Karjalainen, M., Hyyppä, J., Puttonen, E., 2019. Comparison of two-dimensional multitemporal Sentinel-2 data with three-dimensional remote sensing data sources for forest inventory parameter estimation over a boreal forest. Int. J. Appl. Earth Obs. Geoinf. 76, 167–178. https://doi.org/10.1016/j.jag.2018.11.009.
Woodhouse, I.H., Mitchard, E.T.A., Brolly, M., Maniatis, D., Ryan, C.M., 2012. Radar backscatter is not a “direct measure” of forest biomass. Nat. Clim. Chang. 2 (8), 556–557. https://doi.org/10.1038/nclimate1601.
Yim, J.-S., Shin, M.-Y., Son, Y., Kleinn, C., 2015. Cluster plot optimization for a large area forest resource inventory in Korea. https://doi.org/10.1080/21580103.2014.968222.
Zhang, L., Ma, Z., Guo, L., 2008. Spatially assessing model errors of four regression techniques for three types of forest stands. Forestry 81 (2), 209–225. https://doi.org/10.1093/FORESTRY/CPN014.
Zhang, L., Ma, Z., Guo, L., 2009. An evaluation of spatial autocorrelation and heterogeneity in the residuals of six regression models. For. Sci. 55 (6), 533–548. https://doi.org/10.1093/FORESTSCIENCE/55.6.533.