

GFOI Rapid Response Module: Guidance to inform the use of space-based forest biomass-related data in MRV procedures

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Chapter 1. Introduction

In recent years, a series of space-based missions targeted at improving forest biomass estimates have been launched, providing global forest biomass density maps[1]. Space-based forest biomass-related data have been produced through dedicated projects, such as ESA's CCI BIOMASS, and missions such as NASA's GEDI, and JAXA's ALOS satellite series[2]. New satellite missions in operation from 2024 and 2025 include the ESA BIOMASS, JAXA ALOS-4, and the NASA/ISRO SAR (NISAR) missions, which have dedicated forest and biomass mission goals. Biomass estimates derived from data from these missions offer new possibilities for enhancing national forest monitoring systems and improving the accuracy and completeness of National Greenhouse Gas Inventory (NGHGs) and Reducing Emissions from Deforestation and Forest Degradation (REDD+) reporting. There is growing interest in the use of this data to improve NGHGs including REDD+ reporting[3], [4] and other related monitoring and reporting priorities.

Despite the potential of space-based forest biomass-related datasets, their adoption within national systems remains limited. Key barriers include technical challenges in integrating space-based data with ground-based data, concerns about uncertainty and validation, and a lack of clear guidance on operational use. Many countries are unsure how to assess the readiness of space-based biomass products or apply them in a way that meets good practice for reporting estimates from space. The publication of *the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*[5], hereafter referred to as the *2019 Refinement*, focused on general warnings to avoid potential misuse, however guidance on operational application has been limited to date. This rapid



response module aims to support informed decision-making related to operational uses of space-based forest biomass-related datasets and products within multipurpose National Forest Monitoring Systems.

Chapter 2. Biomass maps created with Earth Observation

Biomass maps created with space-based data can provide a representation of forest aboveground biomass density (AGBD), that is forest AGB stock per unit area for a point in time. While no space-based technology *directly* measures forest AGB stocks or stock-changes, satellite sensors are sensitive to various biophysical properties of vegetation (Figure 2.1). Such biophysical properties (tree heights, greenness, water content, vegetation structure and density) are often closely related to the biomass content of vegetation, thereby allowing its indirect estimation with space-based data.

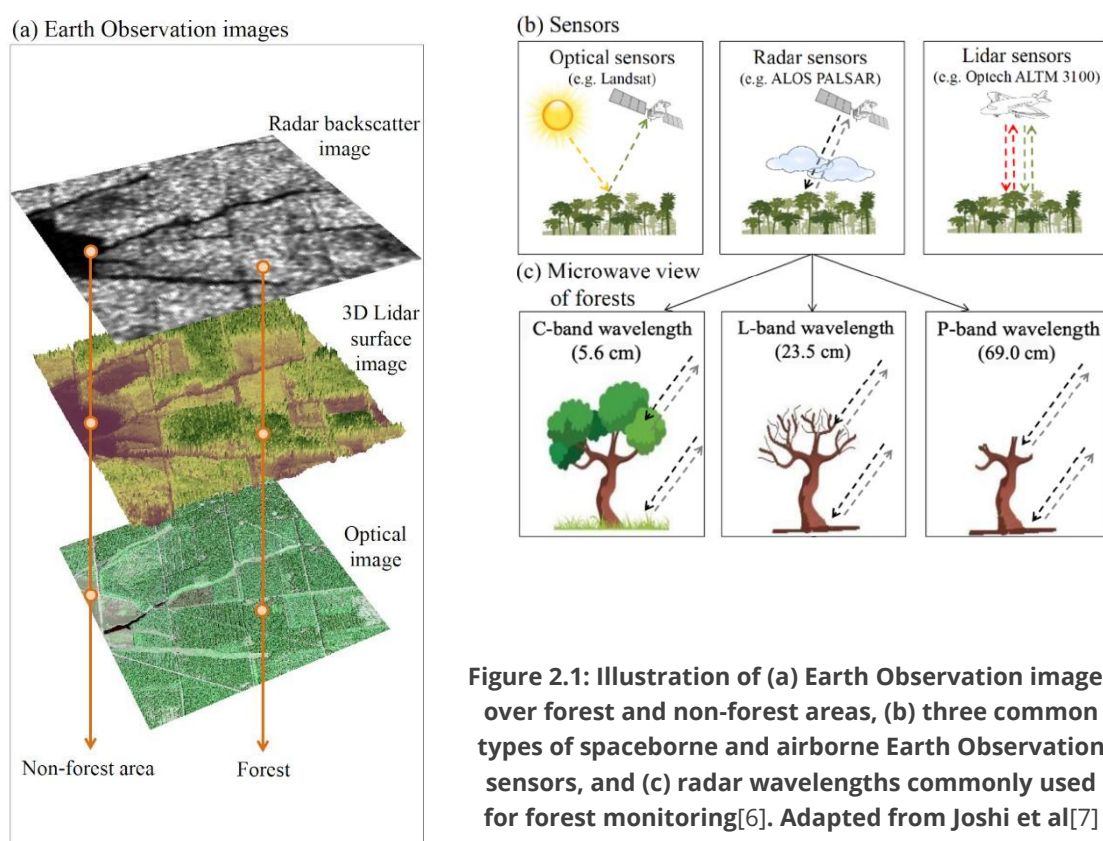


Figure 2.1: Illustration of (a) Earth Observation images over forest and non-forest areas, (b) three common types of spaceborne and airborne Earth Observation sensors, and (c) radar wavelengths commonly used for forest monitoring[6]. Adapted from Joshi et al[7]

The type of biophysical properties of vegetation sensed by space-based technologies is dependent on the wavelengths of electromagnetic energy used and/or detected by the satellite. Typically, optical sensors are sensitive to the spectral characteristics of the vegetation, while radar and lidar sensors collect data related to vegetation structural parameters. The different sensor types are thus complementary and are therefore commonly used in combination. The fundamental principle underlying the creation of AGBD maps from any sensor, or combination of sensors, is the calibration of the space-



based measurements with forest-type-specific ground inventory data. Most commonly, the carbon pool estimated through Earth Observation (EO) is AGBD.

Accurate ground inventories are necessary for the calibration and validation of any model, including those linking space-based data to forest AGBD. Space-based datasets serve simply as auxiliary data to the ground inventories for estimation of forest biomass. Therefore, the validity of models relating space-based and ground data are important to achieve accurate estimates for use in National GHG Inventories. The Committee of Earth Observations Satellite (CEOS) Aboveground Woody Biomass Product Validation[8] provides a synthesis of scientific consensus on good practices in biomass mapping and validation.

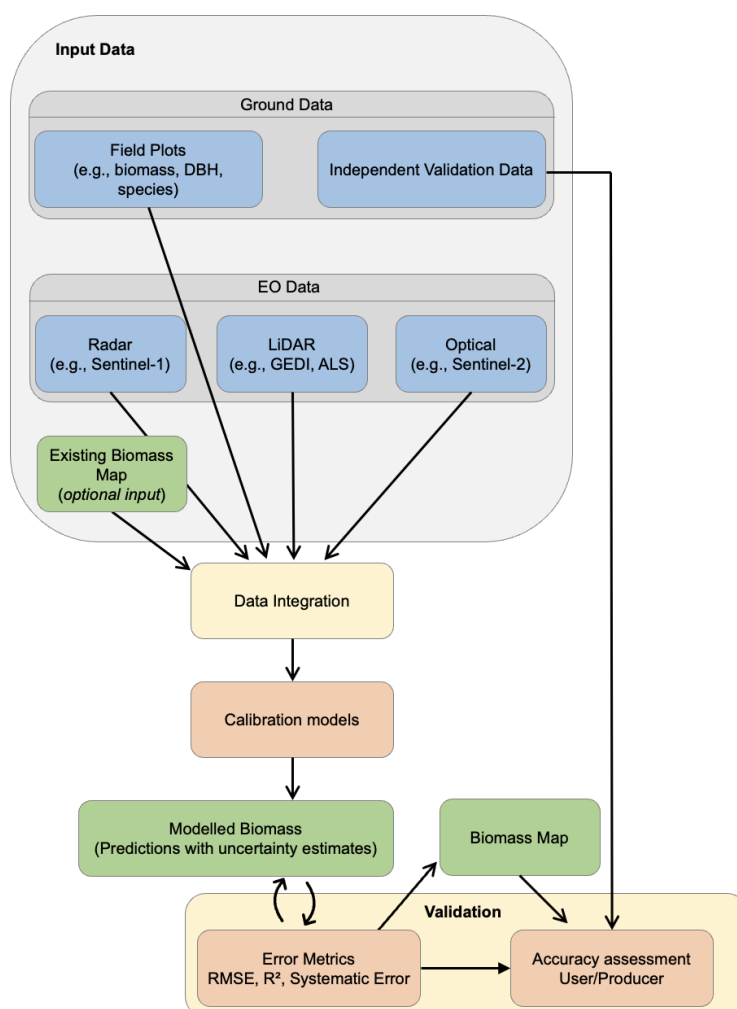


Figure 2.2: Integration in-situ/EO for generation of modelled biomass and biomass maps. Input data, model-related processes and products are depicted in blue, orange, and green boxes, respectively

Figure 2.2 outlines a generic process that results in space-based forest biomass-related data being appropriate for application in National GHG inventories. In the figure, optical (e.g., Landsat, Sentinel-2), radar (e.g., ALOS PALSAR, Sentinel-1), and/or lidar (e.g., GEDI, ICESat-2) are combined with ground reference data (field plots) to calibrate models that are used to predict biomass. Model diagnostics are assessed with commonly used error



metrics. Thereafter, predictions of biomass are made on a regular grid, represented visually as a biomass map.

Challenges and limitations in creating AGBD maps exist for both space-based sensors and ground-based data. For example, optical sensors are affected by the complexity of forest crown layers and rely on cloud-free weather conditions. Radar signals transmitted at long wavelengths (L-band, P-band) are unaffected by cloud particles, but ground-topographic distortions can constitute possible limitations. Furthermore, both optical and radar sensors are susceptible to signal saturation at high AGBD levels. Similarly, lidar-predicted height used to develop AGBD estimates of one forest type may not be representative of vegetation with different structure and wood density. The availability of suitable and high-quality ground-based data, or lack thereof, to calibrate models from space-based data can substantially affect both the estimates of forest AGBD and their associated uncertainty. Therefore, the validation of biomass maps is needed before their direct use in forest biomass estimation. Furthermore, global- or large-coverage biomass maps may be re-calibrated, and re-validated with independently collected local datasets, for a more complete and accurate representation of AGBD across the domain of interest.



Box 2.1: Open source global-scale biomass datasets

Estimating forest AGBD for use in climate change mitigation efforts, including NGHGI, is a priority for several new and upcoming space agency missions, including the GEDI[9], NISAR[10], BIOMASS[11], ALOS-4[12] and MOLI[13]. One of the primary goals of the missions is the uptake of their products for forest monitoring toward climate mitigation. Space agencies (such as NASA and ESA) have released a series of global or near-global coverage biomass datasets, with prediction techniques calibrated either directly with ground-plot data, airborne lidar datasets, and/or with AGBD compiled from various National Forest Inventory (NFI) reports (see Table 2.1; Hunka et al[14] describes the background approaches used in the generation of the datasets). This rapid response module provides a few country-case examples (see Appendix) where existing NFIs have been augmented with the use of these global space-based biomass datasets as auxiliary data sources.

Table 2.1: Summary of two of open-source global-scale biomass datasets and their attributes

	Sensor	Spatial resolution	Geographic coverage	Temporal Coverage	Uncertainty	Reference	Access
NASA Global Ecosystem Dynamics Investigation (GEDI)	LiDAR (GEDI)	25-m footprints that are 60 m apart along-track and 600 m apart across tracks. A gridded 1-km map product from GEDI is also available.	Between 52° N and 52° S	April 2019 – March 2023 and April 2024 - to date	Standard error of the predicted aboveground biomass at each 25-m footprint. The 1km gridded product has an uncertainty layer associated with it (based on hybrid inference)	Dubayah et al[15]	Available through Creative Commons Attribution 4.0 International (CC-BY-4.0)
ESA Climate Change Initiative (CCI) Biomass	SAR (ALOS-1/-2, Sentinel-1, ASAR) and LiDAR (GEDI, ICESat)	100 m	Global	2007, 2010, 2015-2022	Standard deviations (SDs) available as separate map products.	Santoro et al[16]	Available at ESA's Open Data Portal[17]



Chapter 3. Application of space-based forest biomass-related estimates

Considerations for the use of space-based forest biomass-related data in National GHG Inventories were first introduced in [Chapter 2, Volume 4 of the 2019 Refinement](#)[5]. The 2019 Refinement was then complemented by the GFOI Methods and Guidance (MGD) v 3.0[18], which elaborates on the use of these datasets in [Section 4.3.1.2](#). Both the 2019 Refinement and the MGD v 3.0 suggest possible applications and general considerations to improve the estimation of carbon emissions at higher Tier levels using space-based forest biomass-related estimates.

Initially, exploratory uses considered pixel-level biomass values to estimate overall forest biomass in areas of interest, with emissions thereafter estimated when combined with activity data. However, to reduce uncertainties, for the most part, current applications aim to produce stratum-specific mean estimates and associated uncertainties of aboveground carbon stock, and in some cases emissions factors for land-use, land cover transitions including activities under REDD+.

Here, we expand on the possible applications (Table 3.1), including the associated opportunities, challenges, and current level of maturity, as defined by the [GFOI CALM criteria](#)[19]. Guidance provided in this Module focuses only on applications that are considered Pre-Operational to Operational applying the CALM Criteria.

Table 3.1: Opportunities, Challenges and Levels of Maturity of applications of space-based forest biomass-related estimates in NGHGs

Application	Opportunities	Challenges	Corresponding GFOI CALM Phase
Enhancing NFI sampling designs through defining strata, or defining strata for reporting purposes	- EO-based biomass information (e.g., biomass maps) can support the design of new National Forest Inventories (NFIs) or enhance existing NFI sampling schemes. Furthermore, stratified estimation for reporting purposes using sub-populations defined through space-based estimates can increase the precision of sample-based estimates. - For a country-case example, see Appendix 1, Example 5 (Zambia)	- Using biomass maps for constructing NFI sampling designs should take into consideration objectives/variables beyond biomass estimation. - Post-stratification for reporting purposes requires an expertise to define sub-populations that adequately represent local biomass variations. - Using forest biomass-related data for stratification presents challenges if/when forest conditions change over time. This reflects a trade-off between achieving high short-term precision and ensuring long-term robustness and flexibility in survey design.	Operational



Application	Opportunities	Challenges	Corresponding GFOI CALM Phase
As auxiliary data for increasing the precision of aboveground carbon stock estimates in Forest Land derived primarily from ground data	- Countries facing challenges in the implementation of their NFIs can consider the use of EO-based datasets as an auxiliary source of information to report at greater levels of precision than with exclusively NFI data. This is in line with IPCC good practice guidelines for NGHGs, where it is good practice to reduce uncertainties as far as practicable (IPCC [20], Section 1.2). - Implementation challenges that can be addressed include but are not limited to: incomplete NFIs, inaccessible areas (i.e., gaps), limited funding for implementation. - Improved forest carbon stock estimates provide more precise pre-deforestation values for calculating emission factors. - For country-case examples, see Appendix 1, Examples 1 (Peru, Guyana, Mozambique and Tanzania), 2 (Sudan), and 3 (Mexico)	- Consistency is required between the activity data and biomass maps including definitions, geolocation, and spatial and temporal data characteristics. - Furthermore, the integration method should be fully supported by the initial conditions of the ground data, as specified in Chapter 5.	Pre-operational/ Operational
Basis for directly estimating carbon stock values in Forest Land	- EO-based biomass estimates could provide an initial assessment of carbon stock levels in forest land for reporting purposes. - Aggregating estimates at the regional level can help reduce the impact of pixel-level uncertainties in EO-based biomass products. Mean estimates from pixel values result in more stable and reliable biomass estimates at larger scales are produced. - Estimates derived from EO-based biomass information can provide pre-deforestation values for calculating emission factors. - For a country-case example, see Appendix 1, Example 4 (Paraguay)	- Ensuring compliance with good practice (see Chapter 4) can be challenging, which may hamper verification processes. - Enough reliable ground data will be necessary for validation. - Additionally, ground data used for calibration and validations of EO-based estimates must accurately represent the area for which direct estimation is conducted. - Post-deforestation carbon stock values cannot be inferred directly from EO-based forest biomass datasets.	Pre-operational/ Operational
For comparison-verification purposes	- Earth Observation (EO)-based biomass estimates can serve as an independent and complementary data source to support a wide range of stakeholders in assessing reported forest biomass estimates. For example, Validation and Verification Bodies (VVBs) can use EO-based estimates to independently evaluate and verify the accuracy of biomass data reported in forest projects.	- EO-based estimates used for comparison or verification need to be validated with high-quality reference data representative of the reported area. Note that the reference data used in the calibration and validation of these estimates should not consist of the same reference data used in reporting. - The quality of EO-based estimates needs to be	Operational



Application	Opportunities	Challenges	Corresponding GFOI CALM Phase
	- For a country-case example, see Appendix 1, Example 6 (Nepal)	comparable to the quality of reference data used for reporting. Good practice considerations in selecting EO-based datasets or products are elaborated in Chapter 4.	
Basis for directly estimating biomass change through multi-temporal EO-based biomass estimates	- Directly estimating biomass change would allow the monitoring of carbon stock changes from land cover change as well as Forest land remaining Forest land, considering processes such as degradation, regrowth, planting and harvest, as well as natural disturbances.	- Requires an established time series of EO-based estimates. Though research advances in this field are promising, the use of multi-temporal EO-based biomass estimates is not recommended for reporting purposes due to requirements of consistent and well-validated biomass maps to accurately estimate biomass changes and their associated uncertainties, as well as of verification of estimated biomass stock changes - Systematic errors from multi-temporal biomass estimates propagate and can cause significant errors if uncorrected. - Limited availability of ground reference data on biomass changes hamper the verification of this approach at national and subnational scales.	Research
Integrating EO-based biomass estimates with time series of land use change and/or with Tier 3 models.	- In combination with EO-based land cover time series, using space-for-time substitution, where spatial differences between forests of different ages or conditions are used as a proxy for temporal change, EO-based biomass estimates could be used to estimate different spatial variations of forest carbon stocks. This use has potential for improved representations of complex forest-related carbon fluxes.	- This requires consistency between the various data sources including forest definitions and spatial and temporal data characteristics, as well as an established time series of EO-based land cover change, or knowledge of the forest age/management status at a scale consistent with the EO-based biomass estimates. - Systematic errors from multi-temporal biomass estimates propagate and can cause significant errors if uncorrected. - Limited availability of reference biomass stock changes ground estimates impede this approach from being verified over large areas and thus used for reporting purposes.	Research



Box 3.1. Non-MRV uses for EO-based biomass estimation

EO-based biomass estimation has proliferated as a tool to support management of natural resources not directly associated with climate change mitigation. While the purpose of this guidance is limited to the uses of these datasets for NGHGs, here we highlight a few non-MRV uses:

- In **Peru**, requests for forest removal follow guidelines[21] which consist of a regulatory framework to be assessed by forest and wildlife authorities. The objective of these guidelines is to ensure that the environmental impact of forest cover removal is minimized. To achieve this, a standardized methodology has been established for calculating the payment required for authorized deforestation. The calculation incorporates economic and biophysical variables to create a bioeconomic model that determines the payment amount for deforestation authorization. This model incorporates the quantification of forest carbon stocks, which is calculated using a national carbon stock map.
- In **Bolivia**, timely information on forest fire prevention and management is a crucial resource for society. SATRIFO[22], the country's wildfire monitoring and early warning system, provides data for fire prevention and control. Among its resources is an interactive tool that allows users to explore forest burn areas and fire risk zones, which can be overlaid with forest biomass estimates developed specifically for Bolivia[23]. By integrating these data sources into a visualization platform, SATRIFO enables broad public access to information on forest fire prevalence and the associated biomass content in affected areas.
- The **Congo Basin** is the largest forest ecosystem tract in Africa, storing a vast amount of biodiversity, while at the same time being inhabited by over 30 million inhabitants. Quantifying the ecological condition of forests is thus important for its sustainable management. Shapiro et al[24] mapped Forest Condition (FC), a metric aimed to quantify the degree of forest degradation, by integrating mainly EO-derived datasets ecological, physical and forest characteristics in the region, including a national forest biomass dataset derived from airborne lidar and satellite imagery for the Democratic Republic of the Congo[25]. This exercise provided a methodological approach for assessing the condition of forests, which can be used for assessing ecosystem risk under the IUCN Red List of Ecosystems framework.

Chapter 4. Good practice considerations

Adopting Tier 2 Methods

The adoption of aboveground carbon stock values (for the stock difference method) can be at a Tiered level as defined in the IPCC Guidelines. The 2006 IPCC Guidelines[26] Volume 1, Section 2.2.4 highlights what constitutes a Tier 1 and Tier 2 estimation. Specifically, Tier 1 is the application of the default methods and supporting carbon-stock-change values / emissions factors in the Guidelines. Tier 2 is defined as the use, together with the default or an enhanced method, of carbon stock change values or emission factors that better reflect national circumstances, derived from (a) literature values, (b) the IPCC Emission Factor Database values, or (c) nationally obtained measurement data.

Tier 2 methods involve consideration of country-relevant or specific data and greater disaggregation to reflect national circumstances. As a result, Tier 2 methods are typically more accurate when compared to Tier 1. Space-based data and modelling tools are acceptable Tier 2 methods if they are calibrated and validated with nationally-relevant ground data (2019 Refinement[5] [Volume 4, Chapter 2](#)). Jurisdictional programme



requirements for REDD+ can take on a more defined approach when it comes to what constitutes Tier 2 values, with higher requirements for demonstration of National relevance and a focus on data obtained from measurements[27], [28].

Developing or Selecting Models

The generation of AGBD estimates from space-based datasets rely on models. The use of a model does not replace the need to collect ground data for calibration or validation (see 2019 Refinement[5] [Volume 4, Chapter 2](#)). The *2019 Refinement* also notes the difficulties of aligning space-based biomass products with national definitions and that these datasets can display significant systematic errors in estimation of carbon stock. When developing or selecting any model for inclusion in NGHGI reporting, the *2019 Refinement* notes the following is good practice:

- **adequate representation of the range of land uses, ecosystems and management practices in the region or country for which the model will be used**

In opting to use AGBD values derived from space-based data the following considerations should be made:

- data availability through time and space, resolution, and limitations of the method/product (e.g., saturation issues in dense forests).
- consistency with the National Forest definition.
- consistency with activity data characteristics such as land use classes, ecozones, among others, to enable integration and the generation of consistent, emissions/removals estimates; specifically, the 2019 Refinement notes: it is *“good practice to demonstrate how the (biomass density) maps are consistent with national land-use classification system, in particular how they are integrated with the land-use data chosen by the country”*.
- representative of the range of AGBD values within the area of interest. In line with IPCC Guidelines, seeking local expert judgement is desirable, in this case on AGBD values of the region’s biomes and vegetation types.

Validation of any data, including space-based forest biomass-related data, at the relevant scale is strongly recommended before their direct use in forest biomass estimation. Such validation can contribute to the assessment of whether such data meet user needs before relying on these for estimation.

Furthermore, these data may be re-calibrated with local datasets to develop Tier 2 estimates that more accurately predict forest biomass in the domain of interest. It is good practice to ensure that models are calibrated and modelled predictions are assessed for accuracy against ground measurements aimed at reducing uncertainties as far as practicable.

- **allow for the estimation of uncertainty**

The uncertainty of the estimates inferred from the model predictions, as well as the inherent uncertainties of the model itself, should be characterized and reported



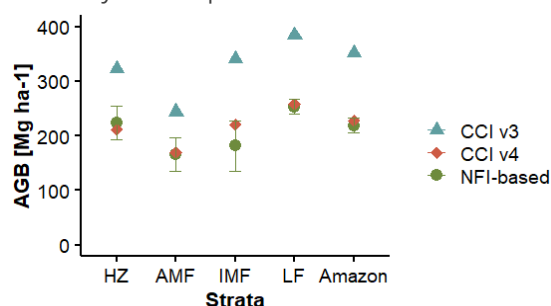
transparently. This includes how the estimates are produced. The following information is to be provided by the model producer:

- documentation describing ground data used in the model calibration and validation, including means of any quality assessment
- description of how bias was/can be assessed and removed
- any systematic prediction errors within areas of interest identified using available ground data (systematic over- or under estimation) (Box 4.1)
- documented assumptions (inclusions and exclusions) and explanations/justifications for them
- description of how the model could be used to improve estimates from ground data.

Box 4.1: Comparing (sub)national NFI-based estimates to a global biomass map

In Peru, Málaga et al[29] compared AGBD estimates from the 2017 European Space Agency Climate Change Initiative (CCI) biomass map (v3) to the country's ground data across four strata in the Peruvian Amazon: hydromorphic zone (HZ), accessible montane forest (AMF), inaccessible montane forest (IMF), and lowland forest (LF). The study assessed the extent to which the global map, used as auxiliary information, could enhance the precision of (sub)national forest AGBD estimates. When comparing stratum-wise AGBD estimates from the uncalibrated version of the map (i.e. more specifically, the synthetic estimator) with NFI-based direct estimates, results showed systematic overestimation by the global map. While NFI-based means ranged from 218–254 Mg ha⁻¹, map estimates ranged from 243–385 Mg ha⁻¹. As shown in the figure below, stratum-wise v3 map AGBD estimates were always greater than NFI-based AGBD mean estimates and their corresponding confidence intervals.

The CCI biomass map showed improvements in version (V4), which were observed in a later study[30]. Across all four strata, no systematic error was observed between the 2017 CCI v4 map estimates and NFI-based AGBD estimates. Such examples highlight the importance of comparing and calibrating biomass map predictions with ground-based estimates, while also helping map producers identify product limitations and improve the accuracy of their products.



- **can be maintained in an operational context with available time and resources (e.g., input data is readily available, staff have sufficient experience and knowledge, suitable compute infrastructure is available)**

Developing biomass models can be data processing and resource/skills heavy, especially for annual reporting cycles required for National GHG Inventories. If using EO based biomass density estimates for various forest types (e.g., open and closed forest), it may be that generating new models is not something that needs to be repeated in each inventory cycle, while instead repeated periodically as for NFIs.



Other use cases may require deeper consideration if such processes are to be repeated every GHG inventory cycle.

- **produce outputs that can be used for reporting emissions and removals by relevant land-use categories**

When using data from biomass density maps in a NGHGI, it is important to ensure spatial alignment between biomass datasets and national land-use classifications. Reporting of biomass C stock change estimates from forest land, and forest land conversions, requires gain and loss or stock change factors. Stock change factors (as generated by NFI data) rely on carbon stock being measured at least two points in time. Carrying out a comparable process using exclusively biomass density maps is not considered operational (Table 3.1). However, where there is a land use change from forest land to non-forest land, enhanced estimates from or with biomass maps can inform the pre-deforestation carbon stock. This applied with Tier 1 stocks from the post land use can generate the emissions factor required which is aligned with the gain and loss method; noting that the direct generation of removals factors from exclusively EO based biomass data are not yet considered operational.

- **are well documented and tested**

Documentation leads to ownership, control, consideration of trustworthy data and transparency which is core to consistency and continuity in National GHG Inventories. It is also fundamental to third party review.

Depending on the application, the *2019 Refinement* highlights that additional metadata from models and parameters used to generate biomass maps may be required to characterise and fully report how bias and precision are addressed.

The following should be considered to achieve the principles of transparency:

- document the qualities of the model to demonstrate that it is fit for purpose.
- document the calibration procedure and results.
- provide clear metadata on data sources, methodologies, and assumptions (exclusions and inclusion).
- document bias correction procedures and assessment of uncertainty.



Chapter 5. How to meet good practice for operational use cases

Ensuring compliance with good practice implies obtaining an accurate estimate of forest biomass/carbon *while* minimizing uncertainties as far as practical. The manner in which space-based biomass maps can be used for obtaining biomass estimates is dictated by the availability (or lack thereof) and quality of reference data, and the sampling designs by which these data were collected. Ground reference data from NFIs, for example, may be augmented with biomass maps as auxiliary data sources, but the approach taken to the statistical inference will vary based on the completeness and representativeness of the reference data and the sampling design used to acquire it.

This chapter presents a decision tree (Figure 5.1) to guide countries in ways of enhancing biomass/carbon estimates based on the availability and quality of their reference data (e.g., from an NFI, and referred to as ‘observations’ in the following text), reflected in different scenarios. The following paragraphs first describe the inferential methodological **scenarios**. They are then followed by descriptions of the **actions** and **decisions** (Figure 5.1) needed to be made before using a recommended inferential technique. In support of the decision tree, Figure 5.2 illustrates a geographical distribution of observations and ways in which the sample units may be missing.



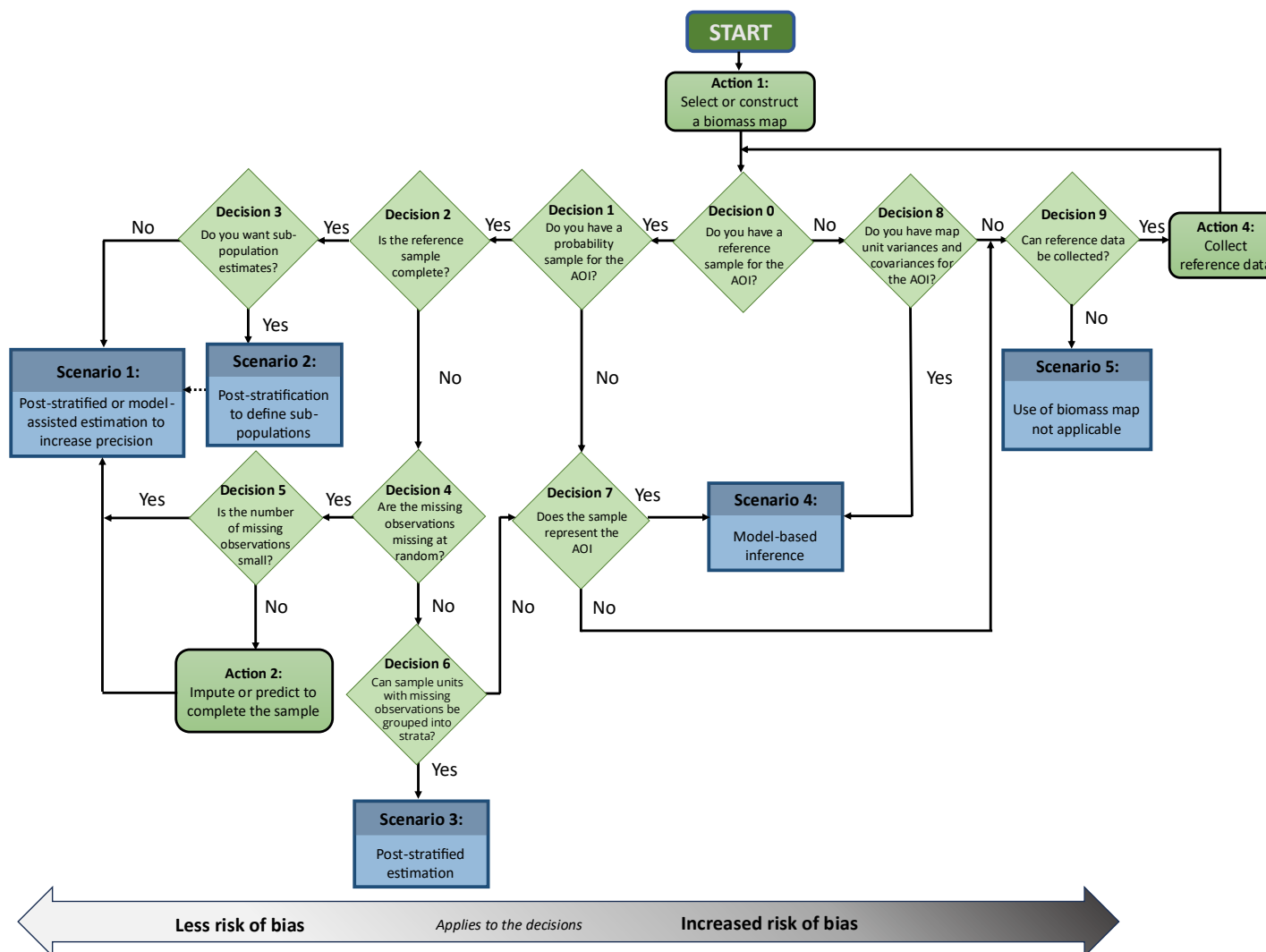


Figure 5.1: Decision tree showing the process of selection of a method to enhance estimates of forest biomass across an Area of interest (AOI). The “risk of bias” arrow bar applies to the “Decisions” (e.g., Decision 3 carries less risk of bias in comparison to Decision 8).

Box 5.1 - Scenarios: Methodological approaches for enhancing biomass estimates with the use of space-based biomass maps

Scenario 1: With this scenario, the primary purpose is to use the biomass map as auxiliary data to increase the precision of the estimate of the population mean. The model-assisted estimator uses the map unit values as the model-predictions and the reference data as the observations. The post-stratified estimator uses the biomass map as the source of auxiliary stratification data.

- A **post-stratified** estimator. A common approach is to divide the biomass map values into a small number (3-6) of groups or strata. Each map unit is assigned to the stratum corresponding to the map unit value, and each sample unit is assigned to the stratum of the map unit containing the sample unit center. Possible stratifications include constructing strata so that each represents the same proportion of the sample or so that each represents an equal division of the range of map values. Post-stratified estimators can improve precision when the variability of the population within each stratum is less than the total variability of the population. In the case of a stratified random sample, post-stratification should take place within strata. Key constraints are that each post-stratum (the final strata) should have at least 10 and preferably 20 sample units and that the sampling intensity within each post-stratum is constant. Most often, the **simple expansion estimators** are used for within-stratum estimation, but the model-assisted estimators could also be used.
- A **model-assisted** estimator of the population mean consists of the sum of a prediction-based term (the synthetic estimator) and a residual-based adjustment term (based on the differences between the reference data and their location-corresponding map predictions). The model-assisted *difference* estimator uses the map unit values directly as the model predictions and the reference data as the observations. In addition, uncertainty in the model-assisted and post-stratified estimates resulting from uncertainty in the map could be reduced by calibrating the map, i.e., by constructing a model of the relationship between the reference data as the dependent variable and the map values as the independent variable and then applying the model to predict a new value for each map unit. Model assisted estimators can improve precision when the variance of the residuals (the difference between the reference data and predictions) is less than the variance of the reference data.

References: Cochran, 1977[31, p. 198], pp. 134; Westfall et al, 2011[32]; Næsset et al, 2011[33]; McRoberts et al., 2022[34], Málaga et al., 2022[29].

Scenario 2 : Use a spatial layer as a source of auxiliary data to divide the population into relevant sub-populations. Examples include use of a layer representing administrative regions, a land cover layer, a forest type layer, or climatic or



topographic layers. As for Scenario 1, the model-assisted difference estimator could be used within strata to further increase the precision of estimates and/or the map could be calibrated before application of the post-stratified or model-assisted estimators (see dashed line to *Scenario 1*).

Scenario 3: This scenario groups the sample units with incomplete observations into a single or small number of strata. Estimates for the strata without missing observations can be calculated using the **simple-expansion** or **model-assisted estimators**, as described above. Estimates for strata with incomplete observations must be calculated independently from the other strata. A general approach would be to enter the decision tree at **Start** (see Figure 5.1), following the recommended inference techniques just for the stratum with incomplete observations. If a model-based approach is taken, only existing observations within the strata of interest must be used to obtain estimates of the strata means and variances. Once estimates for all strata are obtained, estimates are combined to produce the population mean estimate through post-stratified estimators.

References: Cochran, 1977[31], p. 134; Westfall et al, 2011[32].

Scenario 4: In this scenario, model-based inference is recommended when either the reference data are not available (Decision 8), or if available, the reference data are not a probability sample (Decision 7). The population mean is estimated using the standard model-based synthetic estimator, expressed as the mean over all map unit predictions. To estimate the variance of the mean estimate, the user requires map unit variances and pairwise map unit covariances throughout the population.

- When reference data are available (Decision 7): In the context where the reference data may not constitute a probability sample, but the sample is nevertheless fairly balanced across the whole area of interest, or adequately represents the whole range of the distribution of AGBD expected, the population mean and variance are estimated using **model-based** estimators. Under the model-based approach, a model is fitted using the reference data as the dependent variable and auxiliary variables (such as space-based biomass maps) as the independent variables. The fitted model is then used to predict biomass values for each map unit within the area of interest. Here, rather than relying on the underlying probability-based sample of reference data, the validity of inference is determined by the model's distributional assumptions. Several studies have investigated parametric and non-parametric approaches, used hierarchical, mixed-effects or geostatistical models, conducted inference in frequentist or Bayesian domains, hybrid inference, amongst others. For simpler models, such as linear regression, explicit formulas may be available for the estimation of map unit variances and pairwise map unit covariances. For more complex models where explicit formulas are not available, simulation based approaches such as bootstrap and Monte Carlo methods, amongst others, can be a viable option to



estimate the (co)variances. Model-based inference is considered conditional on the reference data - the risk of bias is lesser when reference data of suitable quality and distribution are available.

- When reference data are not available or not being used (Decision 8): the risk of bias increases. In such a case, (co)variances provided by the map maker or estimated during the construction of the map at Action 1, could be used for estimating the variance of the estimate of the mean.

References: Ståhl et al, 2011[35]; Brus and de Gruijter, 1997[36]; Babcock, 2015[37]; Babcock, 2018[38]; McRoberts et al, 2018[39]; McRoberts et al, 2022[40]; Emick, 2023[41]; May, 2023[42]

Scenario 5: With this scenario, the use of biomass maps is not considered appropriate because reference data cannot be used to assess the validity of the map or used to calibrate it. Alternative methods should be investigated, such as the 2006 IPCC guidelines guidance on Tier 1 and Tier 2 methods[26].

Actions and **Decisions**, as detailed in Figure 5.1, required prior to implementing a recommended inferential method.

Action 1: The user either selects an existing biomass map or constructs a new map based on user-acquired reference and auxiliary data. In the latter case, map unit variances and covariances are estimated directly when constructing the map. When relying on existing maps, the decision of *which* space-based biomass map to select for the described approaches must be made by the user. It is recommended that several existing maps be tested by the user, before selecting one that best meets the user's requirements (e.g. selecting the map that most increases precision of estimates, the accuracy of model-based predictions, etc.).

Decision 0: Do you have and want to use a reference sample for the area of interest?

A reference sample is usually a set of observations with negligible uncertainty used for training prediction techniques, uncertainty estimation, resampling, or map calibration. For design-based inference (including post-stratified and model-assisted estimators), reference samples are required. For model-based inference, reference samples are preferred but not strictly required, with the requirement that map unit variances and pairwise covariances estimated using data for the AOI are available.

Decision 1: Do you have a probability sample for the AOI?

Probability samples are required for design-based inference whose primary advantages are twofold. First, *estimators of the population mean are unbiased*,



meaning that over all possible samples that could be realized with the sampling design, the average of estimates of the mean equals the true value. However, even with an unbiased estimator the estimate of the mean for any particular sample may still deviate substantially from the true value, thus the role of the confidence interval. The second advantage is that *estimators of the variance are usually less complex and less computationally intensive than for model-based inference*. In general, design-based inference is preferred. This is illustrated by the gradient-coloured arrow in Figure 5.1, where the risk of bias decreases toward the left side of the tree, corresponding to decisions where a probability sample is available and design-based inference is prioritized. Probability sample designs include simple random sampling, systematic sampling, and variations of cluster or two-stage sampling with simple random or systematic sampling in the first stage. If the area of interest is a sub-region of the complete map region, design-based inference requires a probability sample of sufficient size for the area of interest, not just the complete map region.

Decision 2: Is the reference sample complete?

For a variety of reasons, probability samples may be missing observations. The key issue is whether the missing observations compromise the probability nature of the sample and whether the realized sample size is sufficient to achieve the desired precision of the estimate. Figure 5.2 illustrates a complete probability sample alongside subsequent cases with missing observations

Decision 3: Do you want sub-population estimates?

Often, estimates for sub-populations may be desired. These may often be activity classes and administrative regions, but also specific land cover, climatic, topographic, or forest type classes. If so, a digital geo-spatial layer that depicts the boundaries of the sub-populations must be available to intersect with the biomass map.

Decision 4: Are the missing observations missing at random?

A probability sample with observations missing at random still is considered a probability sample. In this context, missing 'at random' means that the missing observations are unrelated to any observed or unobserved data and/or have no systematic relationship with any other relevant factors such as map values, climatic or topographic variables, land cover types etc.

Decision 5: Is the number of missing observations relatively small?

In some cases, the number of missing observations is small in comparison to the total sample size (Figure 5.2). The key issue is whether the reduced sample size is still sufficient to achieve the desired precision, even when the post-stratified or



model-assisted estimators that use the map as auxiliary data are used to increase precision.

Action 2: The user applies an imputation technique to obtain biomass estimates or predictions for the missing observations. Imputation in this setting may involve methods such as substituting missing values with averages or values from comparable plots, or techniques that rely on models or external information from EO data. For example, regression can make use of known tree or stand attributes to fill in gaps in biomass data, and nearest neighbor methods select values based on similarities to other observed plots. For more complex cases, hierarchical or multiple imputation approaches may incorporate extra sources of information and allow for better characterization of uncertainty (see, e.g., Little & Rubin 2019). Further guidance on imputation techniques and the use of model-based approaches (e.g., those resulting from Scenario 4) to generate predictions when dealing with nonresponse can be found in the GFOI Methods and Guidance (MGD) v3.0¹⁷. Following the imputation step, either the post-stratified or model-assisted estimator as described in Scenario 1 can be used. However, the uncertainty of the imputations must be incorporated into the overall estimate of the variance of the estimate of the population mean, though operational examples on the subject still need to be explored. If the uncertainty of the imputations is small, the increase in sample size achieved by imputing for the missing observations may decrease the variance and increase the precision of the estimate of the mean. If the uncertainty of the imputations is large, no increase in precision may be realized; in fact, the precision could be less than for estimates obtained without imputing for the missing observations. *References: Rubin, 1987[45]; Eskelson et al., 2009[46]; McRoberts, 2001[47]; Little & Rubin, 2020[48].*

Decision 6: Can sample units with missing observations be grouped into strata?

In some cases, the missing observations can be confined to some specific areas. The key issue is whether the missing observations can be confined to portions of the population that can be readily geographically delineated such as administrative, topographic or climatic regions, or land cover or forest type classes (see Figure 5.2). If so, then estimates can be obtained as described in Scenario 3.

Decision 7: Does the sample represent the area of interest?

If the missing observations severely compromise the probability nature of the sample (Figure 5.2), then model-based inference, which does not rely on probability samples, may be suitable. An important consideration of model-based inference is that the estimator of the mean is not necessarily unbiased. Sample balance (characterized by means and variances of the independent variables in the sample that are comparable to the means and variances in the population) assures that the sample represents the area of interest and provides a measure of protection against such bias. Local expert knowledge of the biomes and vegetation types in the region may assist to assess the representativeness of the



sample in the area of interest. If the area of interest is a sub-region of the complete map region, model-based inference requires a sample that is representative of the area of interest and/or map unit prediction variance and pairwise covariance estimates for the area of interest, not just the complete map region.

Decision 8: Did the map-maker provide map unit variances and covariances?

The 2006 IPCC guidelines[26] advises that estimates be accurate in the sense that they are neither over- nor underestimated as far as can be judged, and precise in the sense that uncertainties are reduced as far as practicable. To do so, uncertainty in the form of variance must first be correctly estimated. With model-based inference, correct estimation of the variance of the population mean requires the variances of the predictions for all individual map units and the covariances of the predictions for all pairwise combinations of map units. To reduce the risk of bias, the data used to estimate the map unit variances and covariances must represent the particular area of interest, rather than just the complete map region or an entirely different region altogether.

Decision 9: Can reference data be collected?

When all possible options of calibrating or validating biomass maps using the recommendations of the decision tree are exhausted, the user is encouraged to collect ground reference data. As ground data is obtained, the approach would be to enter the decision tree at **Start** (see Figure 5.1) and follow the recommendations as needed.

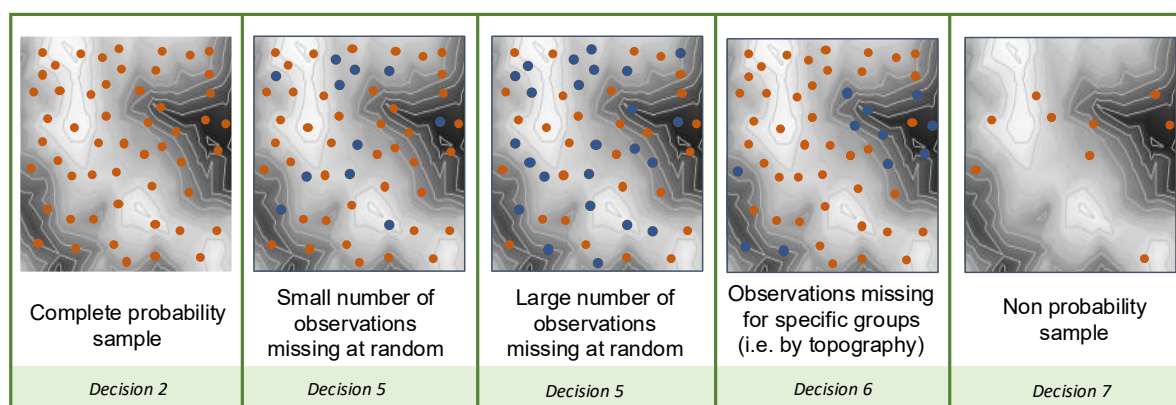


Figure 5.2: Visual representation of observations completeness and missingness at decision points in the tree. Orange dots show available observations, blue dots represent missing observations, overlaid on a topographic layer.



Chapter 6. Summary

Recent advances in space-based technologies have enabled the generation of large-area biomass maps that offer potential to enhance national forest monitoring systems to produce NGHGI, including REDD+ reporting. These products can improve spatial coverage of biomass estimates, particularly in remote or under-sampled areas, and support improved stratification and independent validation of forest biomass assessments.

Biomass maps developed from space-based data can:

support the design and enhancement of National Forest Inventories (NFIs).

- improve estimation accuracy in regions lacking sufficient ground data.
- serve as an independent reference in support of verification of biomass estimates where the map-based estimates are of comparable quality with the estimate being verified.
- contribute to broader forest and ecosystem monitoring beyond climate mitigation frameworks.

However, limitations and constraints to consider include:

- pixel-level biomass estimates are **not recommended** for reporting purposes.
- ground data are required for calibration and validation, as well as for verification of biomass stock change estimates, and for evaluating model performance over time.
- global and regional biomass products may require re-calibration at the national or subnational level to be fit-for-purpose.

To ensure alignment with IPCC good practice and to enable robust integration into national systems, the following requires consideration:

- **Consistency** with national forest definitions, land-use categories, and stratifications.
- **Calibration, validation and verification** with locally representative ground data.
- **Transparent documentation** of modelling assumptions, calibration datasets, and processing methodologies.
- **Characterisation of bias and uncertainty**, including documentation of how systematic errors are assessed and corrected.
- **Alignment with national emissions/removals reporting structures**, including compatibility with Tier approaches and spatial alignment with land-use classifications.
- **Sustainability of operational use**, in terms of institutional capacity, space-based data availability and mission continuity, and technical infrastructure.

While space-based biomass estimation is not yet universally operational across all contexts, it holds promise. Countries are encouraged to take a cautious, scientifically grounded approach, leveraging space-based data where appropriate, while upholding the principles of good practice, transparency, and national relevance.



Version	Change Log	Date
V1.0	Initial release	19 th October 2025
V1.1	Author list updated.	22 nd October 2025



Appendix: Country case examples

The following Appendix presents selected country case studies that illustrate how space-based forest biomass-related datasets have been applied to enhance aboveground biomass (AGB) estimation and reporting. These examples reflect a range of contexts, from peer-reviewed scientific studies to official national reports, and demonstrate different ways countries have integrated remote sensing products with National Forest Inventory (NFI) data. Each case is linked to a specific Scenario from Chapter 5, or an application discussed in Chapter 3. While these cases provide practical insights, this compilation is not exhaustive, acknowledging that additional country efforts are ongoing or in development.

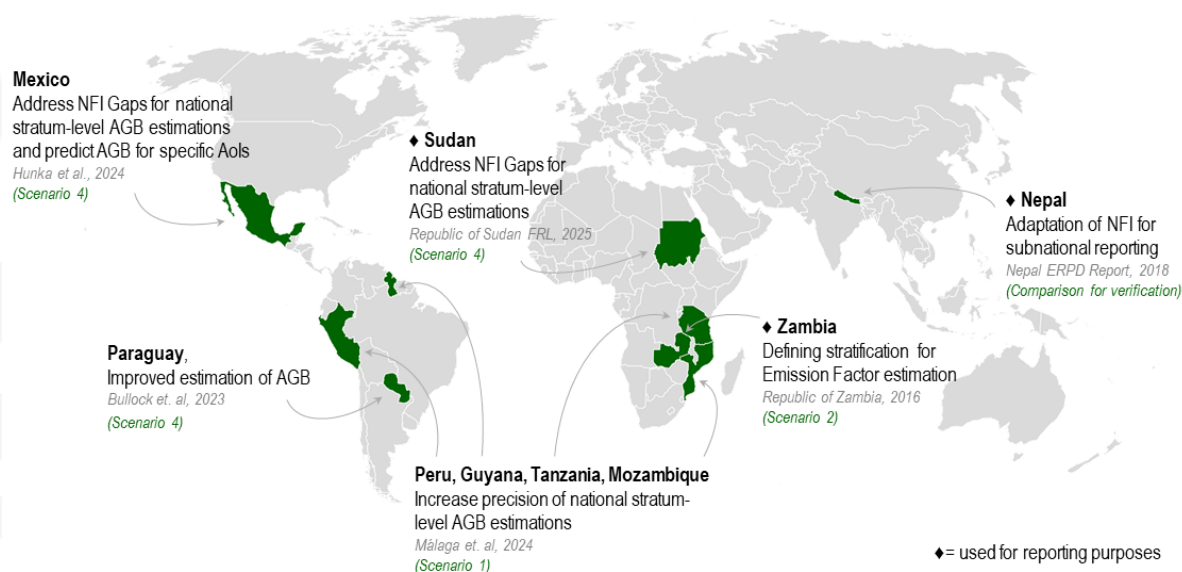


Figure A.1. Summary of key operational and research examples for the use of space-based forest biomass-related data as auxiliary information for reporting purposes.

1. Peru, Guyana, Mozambique and Tanzania: Increasing the precision of subnational AGBD estimates through model-assisted estimation (Scenario 1, Chapter 5)

Context: Many countries within the tropics struggle to complete or update their NFIs, thereby limiting the quality of their (sub)national forest-related AGBD estimates and corresponding emission factors. In a cross-country study, the complexities around the integration of a global biomass map with NFI data under model-assisted estimation across four tropical country-cases (Peru, Guyana, Mozambique, and Tanzania) were investigated. These countries represent a range of NFI sampling designs and biomass densities. The study focused on how best to associate frequent NFI cluster plot configurations (here defined as two or more plots arranged in some kind of fixed spatial configuration) with space-based biomass map units. The study aimed to demonstrate the practical application of model-assisted approaches when using biomass maps in addition to NFI information and their potential to enhance the precision of AGBD estimates.



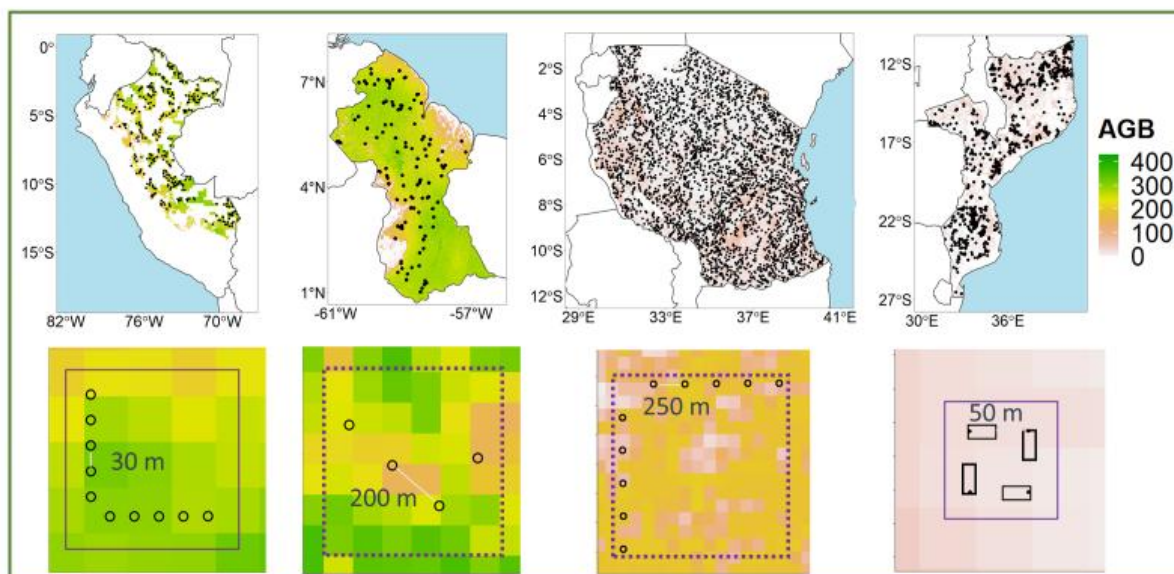


Figure A.2: NFI reference data and the biomass map, to the extent of the population as defined for Peru, Guyana, Tanzania and Mozambique, in that order. The bottom row details examples of these countries' plot configurations along with the defined polygons encompassing the clusters (in purple). Adapted from Málaga et al, 2024[30]

Methodological Approach: To evaluate the contribution of biomass maps to reduce uncertainty of (sub)national AGBD estimates, model-assisted regression estimators accommodating each country's NFI sampling design were implemented and compared to a baseline approach using only NFI field data. For the purpose of model-assisted estimation, linear regression models were developed per country and stratum to locally calibrate the biomass map. Given the widespread use of clustered plots in NFIs, a two-stage model-assisted estimation framework[49], [50] was followed, considering two different strategies. In Peru and Mozambique, where plot distances were shorter than a CCI map unit (~100 m), regression models were fitted at the aggregated level, using mean AGBD values per cluster as the dependent variable and mean map values within polygons encompassing those same clusters as the independent variables. In contrast, for Guyana and Tanzania, where plot distances exceeded the biomass map unit size, models were fitted at the individual level, relating AGBD plot values to spatially corresponding biomass map unit values. Additionally, harmonization procedures were implemented to ensure consistency across field-based and model-assisted estimates, for instance, by accommodating the map to each country's stratification layer and forest definition (when necessary). The study shows that upon calibration, introducing openly available biomass products into (sub)national AGBD estimates resulted in a fair gain of precision of 10% to 50% at country-level, aligning with 2006 IPCC Guidelines of reducing uncertainties as far as practicable[20].

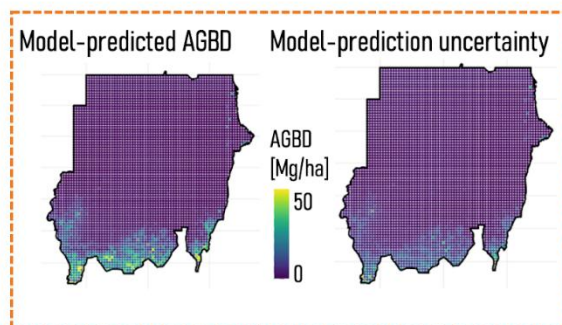
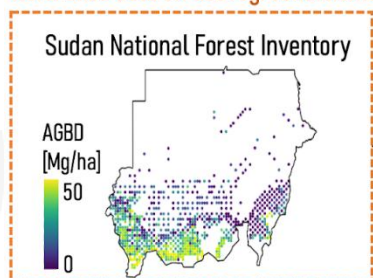
Further resources: Methodological details can be found in Málaga et al, 2024[30].



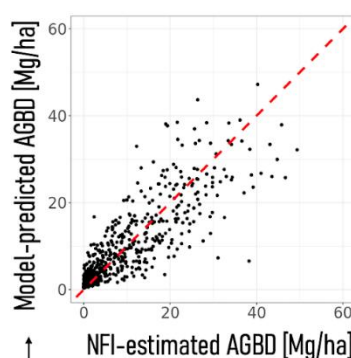
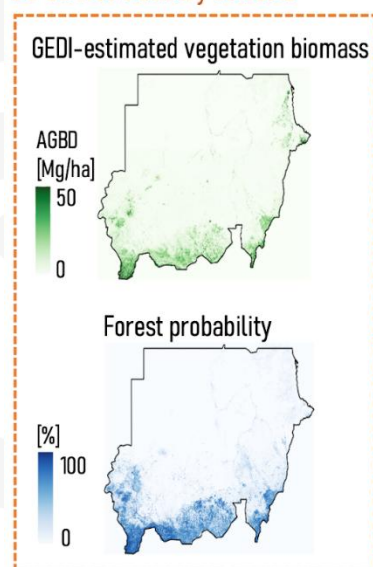
2. Sudan: Using the Geostatistical Model-based Estimator to fill gaps in NFI (Scenario 4, Chapter 5)

Context: Sudan's NFI offers estimates for vegetation and forest assessments, such as volume and AGB density (AGBD). The NFI uses a systematic grid sampling design, with its density adjusted based on ecological strata throughout the country. However, large spatial gaps exist due to the inaccessibility of certain regions, leading to entire sections of unvisited inventory plots. These gaps violate the intended sampling design of the NFI, complicating assessments at the stratum, state, or national level.

Reference data on aboveground biomass



EO-derived auxiliary datasets



Geostatistical
model predictions
of aboveground
biomass

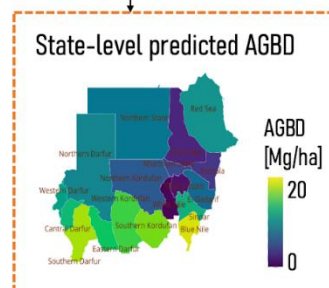


Figure A.3: Schematic representation of the integration of EO-derived auxiliary datasets with an incomplete probability sample of ground reference data that is missing entire areas. Reproduced from Sudan FRL (in review).

Methodological Approach: To overcome this challenge, EO-derived datasets were used to provide auxiliary data to augment the NFI. Geostatistical model-based inference was chosen (Scenario 4, Figure 5.1), wherein a linear relation between (a) forest volume and biomass estimated at the NFI plots, and (b) auxiliary EO datasets, was developed. The auxiliary EO datasets, individually, were selected based on their moderately strong relationship with the NFI-estimated biomass (where available). The developed linear geostatistical model accounts for the underlying spatial autocorrelation observed in NFI-estimated biomass across the domain of interest. Fundamentally, the assumption behind



the inference technique is that observations of a spatially continuous phenomenon (i.e. AGBD at the reference plot locations) in close proximity will tend to exhibit similar values. Hence, geostatistical techniques are employed, relating biomass estimated at reference plots with auxiliary EO datasets in a model while accounting for the underlying spatial autocorrelation in biomass across the area of interest. The three important considerations for the technique are (1) the auxiliary EO datasets used capture spatial variations across the domain of the country, (2) the visited ground reference plots cover the range of vegetation types, and their biomass, found over the area of interest, and (3) any auxiliary EO datasets are acquired or created independent of the ground reference data. The results of this approach allow “gap-filling”, i.e., the prediction of biomass/carbon in locations of unvisited NFI plots, and in undersampled areas. This provides a spatially-dense and spatially-complete set of predictions for the nation, thereby allowing state-level and national-level estimates to be generated.

Further Resources: Details of the model fitting procedure and source code can be accessed at Sudan FRL (currently under review).

3. Mexico: Using the Geostatistical Model-based Estimator to fill gaps in NFI and biomass predictions over specific project sites (Scenario 4, Chapter 5)

Context: Mexico has an advanced forest inventorying system in place, with a nationwide systematic gridded network of permanent plots as a part of the Inventario Nacional Forestal y de Suelos (INFiS). Grid sizes vary across forest strata, but are continuous over vegetated and non-vegetated areas.

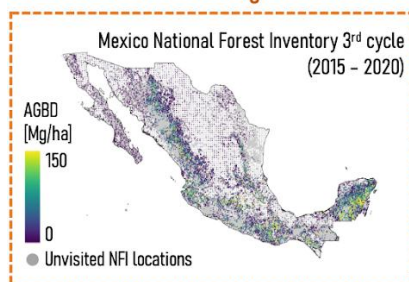
Due to various financial and logistical constraints, the third NFI cycle remains incomplete, leading to spatially irregular, non-random gaps in the probability design across the country. Besides gap-filling locations of unvisited NFI plots with vegetation biomass predictions, the country was also interested in predicting biomass over arbitrary regions, such as nationally demarcated protected areas, terrestrial ecological strata, and community forest management projects and payment for environmental services.

Methodological Approach: Similar to the case of Sudan, a geostatistical model-based approach (Scenario 4, Figure 5.1) was developed for Mexico using auxiliary datasets of forest height and biomass estimates derived from EO. The model is a linear regression that uses spatially varying regression coefficients to account for the spatial autocorrelation in the model residuals and model parameter nonstationarity. Therefore, for any desired prediction location, values of the regression coefficients can be inferred while accounting for spatial effects. The results enable the prediction of biomass in any area of interest - single-location or area-wide spatial scales - with traceable uncertainty analyses. They, hence, fill a gap between national, design-based NFI efforts and the need for more regional-level to project-level assessments of biomass.

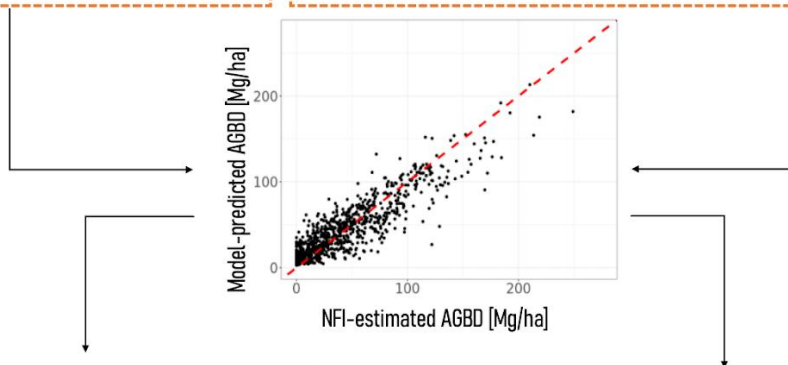
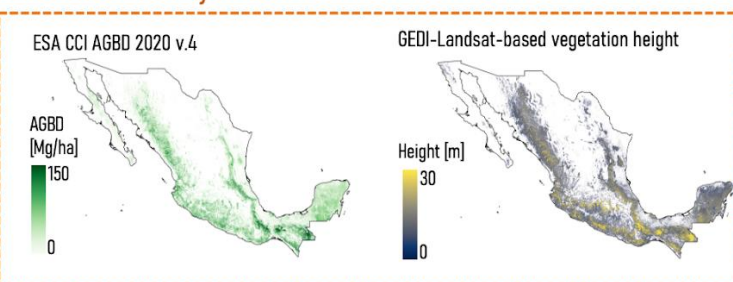
Further Resources: Details of the model fitting procedure and source code can be accessed at Hunka et al, 2025[44].



Reference data on aboveground biomass



EO-derived auxiliary datasets



Geostatistical model predictions of aboveground biomass

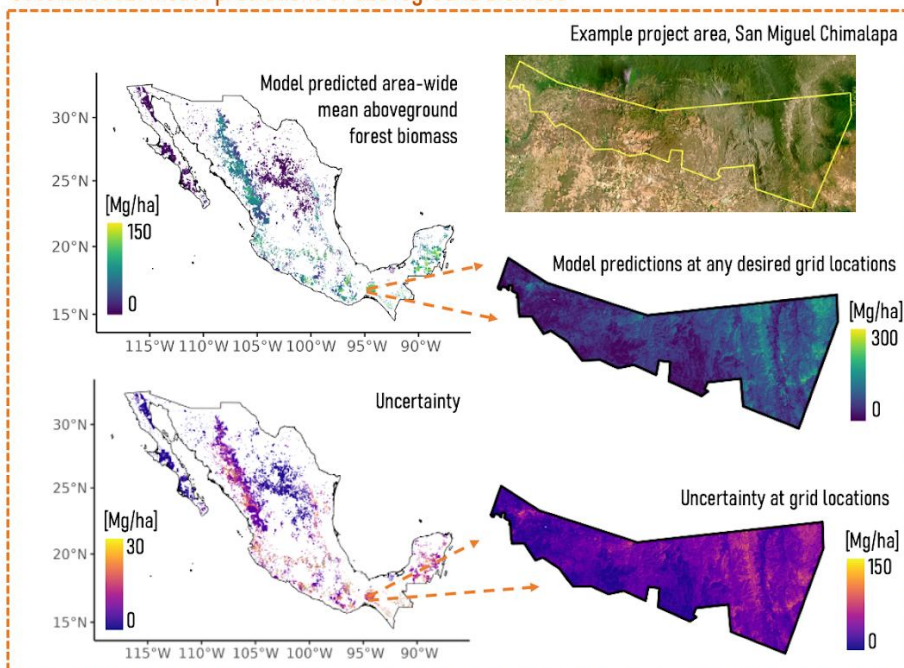


Figure A.4: Schematic representation of the integration of EO-derived auxiliary datasets with an incomplete probability sample of ground reference data that is missing entire areas. Reproduced from Hunka et al, 2025[44]



4. Paraguay: direct estimation of biomass density (Scenario 4, Chapter 5)

Context: Paraguay's forests, particularly within the Chaco region, are globally significant yet are threatened by high deforestation rates, making the accurate estimation of its forest biomass critical for national climate reporting and mitigation efforts. To estimate AGBD for their GHG reporting, Paraguay has undergone one round of their National Forest Inventory (NFI), and are now challenged with updating their NFI as well as improving their coverage. A research study explored whether and how EO-based information could improve the coverage of biomass data and thus the country's stratum-level biomass estimates. Current available information from spaceborne-lidar might not accurately represent structural characteristics of Paraguay's dry forests, therefore off-the-shelf spaceborne-lidar estimates are not ideal for estimating biomass in Paraguay's territory. Hence, the study developed a country-specific biomass map by combining Paraguay's NFI data with GEDI spaceborne-lidar information, and then applied model-based inference to produce stratum-wise biomass estimates with improved precision. Once the biomass map was created, the use of map-unit variances and covariances under model-based estimation was explored. Model based inference can be pursued when, for example, map units are very large and spatial co-registration with small reference sample plots can introduce large additional uncertainty in the relation between AGBD on the plot and the map unit AGBD.

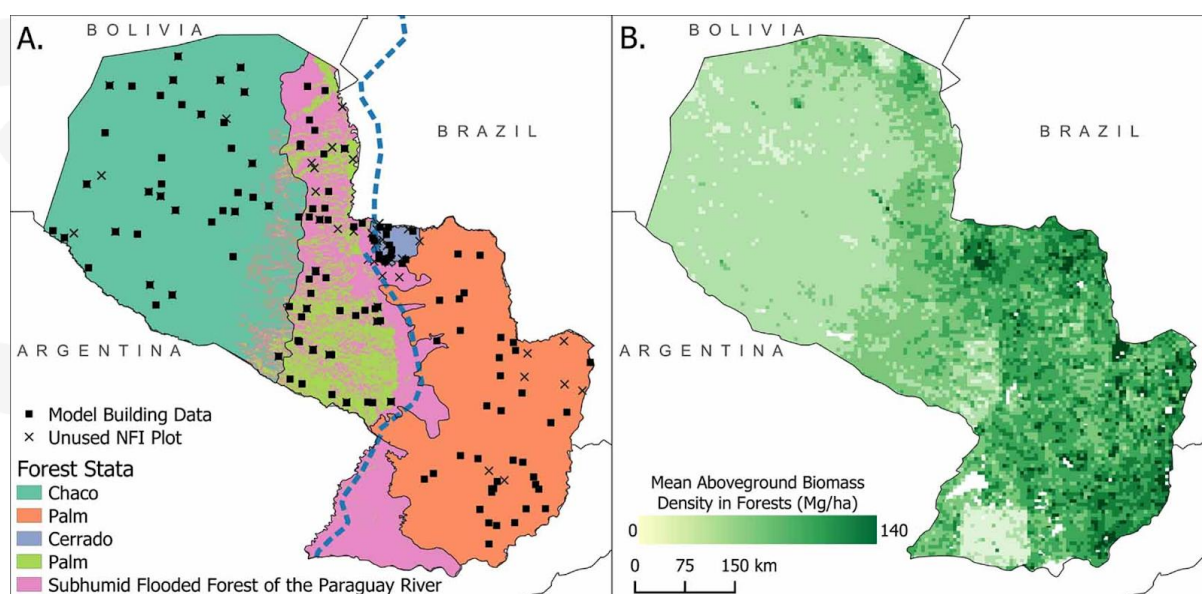


Figure A.5: (A) NFI plots either used for the model development or excluded from the analysis, as well as the forest strata within the country, and Paraguay River presented as a blue dashed line. (B) Predicted AGBD values using the prediction model. Reproduced from Bullock et al, 2023[51]

Methodological approach: A country-specific biomass mapping model (at 6 km by 6 km) was developed for Paraguay by matching NFI plots with high-quality spaceborne-lidar shots (GEDI) within 200 m of each other, to ensure consistency in elevation, forest types and conditions, including disturbance (Action 1, Chapter 5). The study used GEDI's hybrid statistical framework (Dubayah et al, 2022[52]) to estimate mean AGBD at the 6 km tiles, along with the associated variances and pairwise covariances for those tiles. Finally,



stratum- and national-level biomass means and corresponding standard errors were estimated using a model-based approach. Standard errors for model-based stratum-level estimates were, on average, 47% smaller than those estimated with the NFI data alone, reflecting a substantial gain in precision.

Further Resources: Details of the study can be accessed at Bullock et al, 2023[51].

5. Zambia: post-stratification for emission factors (Scenario 2, Chapter 5)

Context: Zambia's Forest Reference Emission Level (FREL)[53] emphasizes the need for reporting forest carbon stock estimates representative of their diverse forests. Zambia's forests, including miombo woodlands and wetlands, exhibit significant variability in carbon stocks across ecological zones, which are represented in the ILUA II National Forest Inventory. To improve the estimation of their deforestation based-emissions, Zambia post-stratified the country into five strata using a spatially explicit carbon map estimated from a combination of their NFI data and remotely sensed information.

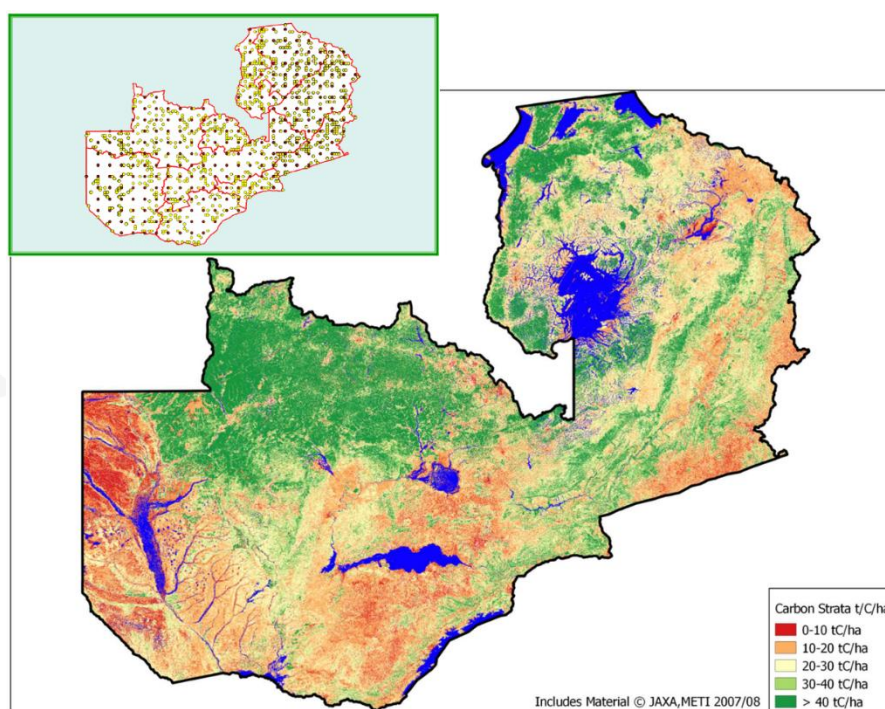


Fig. A.6: Zambia's AGC map, based on the CART approach using Landsat and SAR for post-stratification of estimates. Inset: Location of ILUA II and ILUA I field cluster plots (yellow and red circles, respectively). Adapted from Zambia's FREL Report[53]

Methodology: To address this, the country combined Zambia's ILUA II National Forest Inventory data with optical and Synthetic Aperture Radar (SAR) remotely sensed data to estimate an aboveground carbon (AGC) map. The methodology integrated field data, remote sensing, and classification and regression trees (CART) to come up with carbon predictions beyond NFI sampling locations. Plot-level carbon stocks were estimated from field data, collected through systematic sampling. Optical (e.g., Landsat) and SAR (e.g., ALOS PALSAR) data were used to map forest cover and structure. CART models were applied to predict AGBD by linking field data with remote sensing variables like spectral



indices and backscatter values. A wall-to-wall map of CART-predicted AGBD was then created, which was used for post-stratifying forest areas into five homogeneous classes based on per ha carbon stock values. Per-stratum emission factors were then estimated from the plot-level AGBD information within each stratum, improving accuracy by addressing spatial variability and reducing uncertainties.

Further resources: Further details can be found in Zambia's FREL Report[53].

6. Nepal: Independent comparison for the estimation of emission factors for Terai Arc Landscape (Application: comparison for verification, Chapter 3)

Context: Nepal's Emission Reduction Program (ERPD) is a key component of its National REDD+ Strategy. Aligned with multiple national policies, the ERPD targets the Terai Arc Landscape (TAL), a region of rich biodiversity and productive forests but facing deforestation and forest degradation pressures. In order to improve their mapping of forest-related activity data to include forest degradation, they currently make use of the Morphological Spatial Pattern Analysis Tool (MSPA), which classifies each pixel based on the surrounding landscape. This results in forest pixels being divided into Intact and Edge pixels, which are expected to store different amounts of biomass. The Programme wanted to have separate biomass estimates for both Intact and Edge classes (as defined by MSPA tool) using National Forest Inventory as input data. However, before adopting a post-stratification approach using the corresponding NFI data within TAL and the MSPA classification, additional verifications were needed to confirm different biomass estimates in their strata of interest (Intact and Edge).

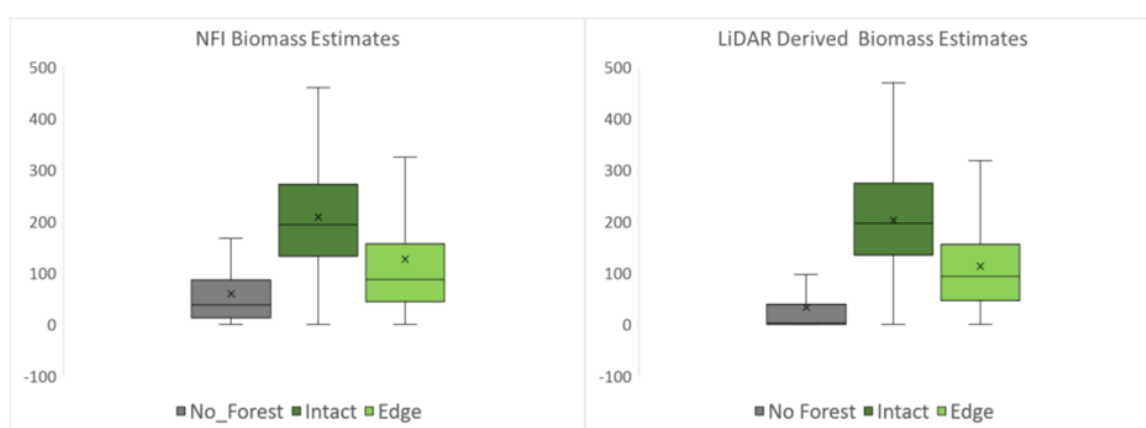


Figure A.7 Comparison of forest biomass estimates in the Terai Arc Landscape (TAL) for No Forest, Intact and Edge strata, using National Forest Inventory plots (left) and lidar-derived estimates (right).
Adapted from Nepal ERPD[54]

Methodology: To estimate forest biomass for Intact and Edge strata within TAL, total biomass stocks were recalculated into Intact and Edge classes, following Birigazzi et al[55]. Greater biomass values were observed in the Intact strata in comparison to the Edge strata (Figure A.7, left). However, to assess the likelihood of systematic errors in the estimates due to the adaptation of the NFI design into the ERPD area of interest, a comparison was made with lidar estimates. Lidar-based estimates were derived from an



airborne laser scanning (ALS) campaign covering 5% of the Terai Arc Landscape, with systematically sampled blocks and calibration plots used to model above-ground biomass (AGB)[56]. Lidar-based estimates showed a similar pattern as the NFI-based estimates of greater carbon in the Intact strata than those in the Edge strata (Figure A.7, right). This gave increased confidence in the use of NFI data for the EPRD forest strata.

Further Resources: Further details can be found in Birigazzi et al[55], Kauranne et al[56], and Nepal's ERPD report[54].



Contributors and acknowledgments

This guidance was developed following discussions at a workshop hosted by the GFOI R&D and MGD Components titled: **Informed use of space-based biomass data in MRV procedures**, held over October 23-25, 2024 in Potsdam, Germany.

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References

- [1] M. Herold *et al.*, "The Role and Need for Space-Based Forest Biomass-Related Measurements in Environmental Management and Policy," *Surv. Geophys.*, vol. 40, no. 4, pp. 757–778, Jul. 2019, doi: 10.1007/s10712-019-09510-6.
- [2] CEOS, "Above ground biomass products: NCEO Africa Biomass, IceSat-2 Boreal Biomass, JPL Global Biomass, GEDI Biomass, ESA CCI Biomass." Accessed: Aug. 15, 2025. [Online]. Available: <https://ceos.org/gst/biomass.html>
- [3] E. T. A. Mitchard *et al.*, "Markedly divergent estimates of Amazon forest carbon density from ground plots and satellites," *Glob. Ecol. Biogeogr.*, vol. 23, no. 8, pp. 935–946, Aug. 2014, doi: 10.1111/geb.12168.
- [4] V. Avitabile *et al.*, "An integrated pan-tropical biomass map using multiple reference datasets," *Glob. Change Biol.*, vol. 22, no. 4, pp. 1406–1420, Apr. 2016, doi: 10.1111/gcb.13139.
- [5] IPCC, *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Switzerland: IPCC, 2019.
- [6] CEOS, "A Layman's Interpretation Guide to L-band and C-band Synthetic Aperture Radar Data," Committee on Earth Observation Satellites (CEOS), 2023. Accessed: Aug. 13, 2025. [Online]. Available: https://ceos.org/ard/files/Laymans_SAR_Interpretation_Guide_3.0.pdf
- [7] N. Joshi, "Spaceborne Radar for Mapping Forest and Land Use Changes: An Empirical Synthesis Combining Local Knowledge, Field Inventories, Lidar and Optical Remote Sensing Data," PhD Thesis, Department of Geosciences and Natural Resource Management, Faculty of Science, University of Copenhagen, 2016. [Online]. Available: https://soeg.kb.dk/permalink/45KBDK_KGL/fbp0ps/alma99122260139205763
- [8] L. Duncanson *et al.*, "Aboveground woody biomass product validation good practices protocol," 2021, Accessed: Aug. 13, 2025. [Online]. Available: https://lpvs.gsfc.nasa.gov/PDF/CEOS_WGCV_LPV_Biomass_Protocol_2021_V1.0.pdf
- [9] R. Dubayah *et al.*, "The Global Ecosystem Dynamics Investigation: High-resolution laser ranging of the Earth's forests and topography," *Sci. Remote Sens.*, vol. 1, p. 100002, Jun. 2020, doi: 10.1016/j.srs.2020.100002.
- [10] NASA-JPL, *NASA-ISRO SAR (NISAR) Mission Science Users' Handbook*. 2019. [Online]. Available: https://assets.science.nasa.gov/content/dam/science/missions/nisar/nisar-jpl/pdf/NISAR_FINAL_9-6-19.pdf
- [11] S. Quegan *et al.*, "The European Space Agency BIOMASS mission: Measuring forest above-ground biomass from space," *Remote Sens. Environ.*, vol. 227, pp. 44–60, Jun. 2019, doi: 10.1016/j.rse.2019.03.032.
- [12] JAXA, "The Advanced Land Observing Satellite-4 (ALOS-4) PALSAR-3 Basic Observation Scenario," FTR-210002, Rev B, 2024. Accessed: Aug. 13, 2025. [Online]. Available: https://www.eorc.jaxa.jp/ALOS/en/alos-4/pdf/FTR-210002B_ALOS4PALSAR3_BasicObservationScenario.pdf
- [13] JAXA, "Multi-sensing Observation Lidar and Imager Demonstration (MOLI) Project." Accessed: Aug. 13, 2025. [Online]. Available: <https://www.kenkai.jaxa.jp/eng/research/moli/moli-index.html>



- [14] N. Hunka *et al.*, "On the NASA GEDI and ESA CCI biomass maps: aligning for uptake in the UNFCCC global stocktake," *Environ. Res. Lett.*, vol. 18, no. 12, p. 124042, Dec. 2023, doi: 10.1088/1748-9326/ad0b60.
- [15] "GEDI L4A Footprint Level Aboveground Biomass Density (Version 2.1)."
- [16] M. Santoro *et al.*, "Design and performance of the Climate Change Initiative Biomass global retrieval algorithm," *Sci. Remote Sens.*, vol. 10, p. 100169, Dec. 2024, doi: 10.1016/j.srs.2024.100169.
- [17] ESA-CCI, "ESA CCI Open Data Portal Dashboard." Accessed: Aug. 15, 2025. [Online]. Available: <https://climate.esa.int/en/data/#/dashboard>
- [18] GFOI, *Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative*, vol. 3.0. 2020. [Online]. Available: <https://www.reddcompass.org/mgd/en-3/>
- [19] GFOI, "Criteria for Consistently Assessing Levels of Maturity (CALM) of REDD+ Concepts." 2020. Accessed: Aug. 15, 2025. [Online]. Available: https://gfoi-rd.gfz.de/fileadmin/gfoird/documents/GFOI/4_GFOI_CALM_Criteria_1.0.pdf
- [20] IPCC, "Chapter 1: Introduction. In: 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 1: General Guidance and Reporting," in *2006 IPCC guidelines for national greenhouse gas inventories*, vol. Volume 1 of 2006 IPCC Guidelines for National Greenhouse Gas Inventories, H. S. Eggleston, L. Buendia, K. Miwa, T. Ngara, and K. Tanabe, Eds., Japan: IGES, 2006.
- [21] SERFOR, "Lineamientos para el otorgamiento de la autorización de desbosque," Ministerio de Agricultura y Riego, Perú, 2025. Accessed: Aug. 13, 2025. [Online]. Available: https://cdn.www.gob.pe/uploads/document/file/7708569/6523622-a-serforjjneamiento-desbosque_para-vistosff.pdf?v=1740777566
- [22] FAN, "SATRIFO: Sistema de Monitoreo y Alerta Temprana de Riesgos de Incendios Forestales." Accessed: Aug. 13, 2025. [Online]. Available: <https://incendios.fan-bo.org/Satrifo/plataforma/>
- [23] D. Villarroel *et al.*, "Estimacion y modelamiento de la distribucion espacial de la biomasa vegetal aerea para Bolivia," *Ecol. En Boliv.*, vol. 57, no. 1, pp. 5–18, Apr. 2022.
- [24] A. C. Shapiro *et al.*, "Forest condition in the Congo Basin for the assessment of ecosystem conservation status," *Ecol. Indic.*, vol. 122, p. 107268, Mar. 2021, doi: 10.1016/j.ecolind.2020.107268.
- [25] L. Xu *et al.*, "Spatial Distribution of Carbon Stored in Forests of the Democratic Republic of Congo," *Sci. Rep.*, vol. 7, no. 1, p. 15030, Nov. 2017, doi: 10.1038/s41598-017-15050-z.
- [26] IPCC, *2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 1: General Guidance and Reporting*. Japan: IGES, 2006.
- [27] FCPF/WB, "Carbon Fund Methodological Framework, Version 3.0," World Bank, on behalf of the Forest Carbon Partnership Facility, 2020. [Online]. Available: https://www.forestcarbonpartnership.org/system/files/documents/fcpf_carbon_fund_methodological_framework_revised_2020_final_posted.pdf
- [28] Architecture for REDD+ Transactions (ART), "The REDD+ Environmental Excellence Standard (TREES), Version 2.0," Winrock International, 2021. Accessed: Aug. 13,



2025. [Online]. Available: <https://www.artredd.org/wp-content/uploads/2021/12/TREES-2.0-August-2021-Clean.pdf>
- [29] N. Málaga *et al.*, "Precision of subnational forest AGB estimates within the Peruvian Amazonia using a global biomass map," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 115, p. 103102, Dec. 2022, doi: 10.1016/j.jag.2022.103102.
- [30] N. Málaga *et al.*, "Global biomass maps can increase the precision of (sub)national aboveground biomass estimates: A comparison across tropical countries," *Sci. Total Environ.*, vol. 947, p. 174653, Oct. 2024, doi: 10.1016/j.scitotenv.2024.174653.
- [31] W. G. Cochran, *Sampling techniques*, 3. ed. in Wiley series in probability and mathematical statistics. New York, NY: Wiley, 1977.
- [32] J. A. Westfall, P. L. Patterson, and J. W. Coulston, "Post-stratified estimation: within-strata and total sample size recommendations," *Can. J. For. Res.*, vol. 41, no. 5, pp. 1130–1139, May 2011, doi: 10.1139/x11-031.
- [33] E. Næsset *et al.*, "Model-assisted regional forest biomass estimation using LiDAR and InSAR as auxiliary data: A case study from a boreal forest area," *Remote Sens. Environ.*, vol. 115, no. 12, pp. 3599–3614, Dec. 2011, doi: 10.1016/j.rse.2011.08.021.
- [34] R. E. McRoberts *et al.*, "On the model-assisted regression estimators using remotely sensed auxiliary data," *Remote Sens. Environ.*, vol. 281, p. 113168, Nov. 2022, doi: 10.1016/j.rse.2022.113168.
- [35] G. Ståhl, S. Holm, T. G. Gregoire, T. Gobakken, E. Næsset, and R. Nelson, "Model-based inference for biomass estimation in a LiDAR sample survey in Hedmark County, Norway This article is one of a selection of papers from Extending Forest Inventory and Monitoring over Space and Time.," *Can. J. For. Res.*, vol. 41, no. 1, pp. 96–107, Jan. 2011, doi: 10.1139/X10-161.
- [36] D. J. Brus and J. J. De Gruijter, "Random sampling or geostatistical modelling? Choosing between design-based and model-based sampling strategies for soil (with discussion)," *Geoderma*, vol. 80, no. 1–2, pp. 1–44, Oct. 1997, doi: 10.1016/S0016-7061(97)00072-4.
- [37] C. Babcock, A. O. Finley, J. B. Bradford, R. Kolka, R. Birdsey, and M. G. Ryan, "LiDAR based prediction of forest biomass using hierarchical models with spatially varying coefficients," *Remote Sens. Environ.*, vol. 169, pp. 113–127, Nov. 2015, doi: 10.1016/j.rse.2015.07.028.
- [38] C. Babcock *et al.*, "Geostatistical estimation of forest biomass in interior Alaska combining Landsat-derived tree cover, sampled airborne lidar and field observations," *Remote Sens. Environ.*, vol. 212, pp. 212–230, Jun. 2018, doi: 10.1016/j.rse.2018.04.044.
- [39] R. E. McRoberts *et al.*, "Assessing components of the model-based mean square error estimator for remote sensing assisted forest applications," *Can. J. For. Res.*, vol. 48, no. 6, pp. 642–649, Jun. 2018, doi: 10.1139/cjfr-2017-0396.
- [40] R. E. McRoberts, E. Næsset, S. Saatchi, and S. Quegan, "Statistically rigorous, model-based inferences from maps," *Remote Sens. Environ.*, vol. 279, p. 113028, Sep. 2022, doi: 10.1016/j.rse.2022.113028.
- [41] E. Emick, C. Babcock, G. W. White, A. T. Hudak, G. M. Domke, and A. O. Finley, "An approach to estimating forest biomass while quantifying estimate uncertainty and correcting bias in machine learning maps," *Remote Sens. Environ.*, vol. 295, p. 113678, Sep. 2023, doi: 10.1016/j.rse.2023.113678.



- [42] P. May, K. S. McConville, G. G. Moisen, J. Bruening, and R. Dubayah, "A spatially varying model for small area estimates of biomass density across the contiguous United States," *Remote Sens. Environ.*, vol. 286, p. 113420, Mar. 2023, doi: 10.1016/j.rse.2022.113420.
- [43] A. Araza *et al.*, "A comprehensive framework for assessing the accuracy and uncertainty of global above-ground biomass maps," *Remote Sens. Environ.*, vol. 272, p. 112917, Apr. 2022, doi: 10.1016/j.rse.2022.112917.
- [44] N. Hunka *et al.*, "A geostatistical approach to enhancing national forest biomass assessments with Earth Observation to aid climate policy needs," *Remote Sens. Environ.*, vol. 318, p. 114557, Mar. 2025, doi: 10.1016/j.rse.2024.114557.
- [45] D. B. Rubin, *Multiple imputation for nonresponse in surveys*. in Wiley series in probability and mathematical statistics Applied probability and statistics. New York: Wiley, 1987. doi: 10.1002/9780470316696.
- [46] B. N. I. Eskelson, H. Temesgen, V. Lemay, T. M. Barrett, N. L. Crookston, and A. T. Hudak, "The roles of nearest neighbor methods in imputing missing data in forest inventory and monitoring databases," *Scand. J. For. Res.*, vol. 24, no. 3, pp. 235–246, Jun. 2009, doi: 10.1080/02827580902870490.
- [47] R. E. McRoberts, "Imputation and Model-Based Updating Techniques for Annual Forest Inventories," *For. Sci.*, vol. 47, no. 3, pp. 322–330, Aug. 2001, doi: 10.1093/forestscience/47.3.322.
- [48] R. J. A. Little and D. B. Rubin, *Statistical analysis with missing data*, 3rd edition. in Wiley series in probability and statistics. Hoboken, NJ: Wiley, 2020. doi: 10.1002/9781119482260.
- [49] C.-E. Särndal, B. Swensson, and J. H. Wretman, *Model assisted survey sampling*. in Springer series in statistics. New York Berlin Heidelberg: Springer, 1992.
- [50] R. E. McRoberts, E. Næsset, J. Heikkinen, and V. Strimbu, "Two-stage, model-assisted estimation using remotely sensed auxiliary data," *Remote Sens. Environ.*, vol. 307, p. 114125, Jun. 2024, doi: 10.1016/j.rse.2024.114125.
- [51] E. L. Bullock *et al.*, "Estimating aboveground biomass density using hybrid statistical inference with GEDI lidar data and Paraguay's national forest inventory," *Environ. Res. Lett.*, vol. 18, no. 8, p. 085001, Aug. 2023, doi: 10.1088/1748-9326/acdf03.
- [52] R. Dubayah *et al.*, "GEDI launches a new era of biomass inference from space," *Environ. Res. Lett.*, vol. 17, no. 9, p. 095001, Sep. 2022, doi: 10.1088/1748-9326/ac8694.
- [53] Republic of Zambia, *Zambia's Forest Reference Emissions Level Submission to the UNFCCC*. Bonn, Germany, 2016.
- [54] FCPF and Government of Nepal, "Emission Reductions Program Document (ERPD): People and Forests - A Sustainable Forest Management-Based Emission Reduction Program in the Terai Arc Landscape," Forest Carbon Partnership Facility; Government of Nepal (Ministry of Forests and Environment / REDD Implementation Centre), 2018. [Online]. Available: https://www.forestcarbonpartnership.org/system/files/documents/Nepal%20ERPD%2024May2018final_CLEAN_0.pdf
- [55] L. Birigazzi, J. G. P. Gamarra, and T. G. Gregoire, "Unbiased emission factor estimators for large-area forest inventories: domain assessment techniques,"



Environ. Ecol. Stat., vol. 25, no. 2, pp. 199–219, Jun. 2018, doi: 10.1007/s10651-018-0397-3.

- [56] T. Kauranne *et al.*, “LiDAR-Assisted Multi-Source Program (LAMP) for Measuring Above Ground Biomass and Forest Carbon,” *Remote Sens.*, vol. 9, no. 2, p. 154, Feb. 2017, doi: 10.3390/rs9020154.

