VCS Tool

VT0005

Tool for measuring aboveground live forest biomass using remote sensing

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Sectoral Scope 14

This tool was developed by:

About Terra Global

Terra Global was founded in 2006 to facilitate market and results-based payment approaches for forest and agriculture emission reductions that provide community benefits. Terra Global is now the leader in forest and agriculture greenhouse gas emissions analytics, advice and finance, providing technical expertise and investment capital to their global client base in a collaborative and innovative manner. As a group, Terra Global has more global experience in climate change from the land-use sector than any other entity and is committed to working with its local partners to build capacity with rural communities and governments to sustainably manage their forest and agricultural lands. Terra Global has extensive developing country experience and is the leading developer of protocols and aggregation services for GHG emissions reductions from a full range of forest mitigation and climate smart agricultural activities in the internationally and in the United States.

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1 SOURCES

This tool uses the latest versions of the following tools and methodology:

- CDM tool *Calculation of the number of sample plots for measurements within A/R CDM project activities*
- CDM tool *Estimation of carbon stocks and change in carbon stocks of trees and shrubs in A/R CDM project activities*
- VCS methodology *VM0006 Carbon Accounting in Project Activities that Reduce Emissions from Mosaic Deforestation and Degradation*

2 SUMMARY DESCRIPTION OF THE TOOL

Precise estimation of carbon in aboveground live forest biomass (ALFB) is critical for the implementation of many agriculture, forestry and land use (AFOLU) projects. ALFB is the primary factor for determining baseline levels for forest carbon pools. The geographic area of AFOLU projects is often large (>40,000 ha) and encompasses a wide range of land use/land cover (LULC) types. Statistically valid sampling strategies for such large areas using traditional ground-based forest inventory plots are often infeasible due to cost and access constraints. Current VCS methodologies have no provision for the use of remote sensing (RS) methods to determine biomass and rely solely on traditional plot-based biomass measurements. This tool is intended to reduce the need for extensive ground-based sampling by leveraging remotely sensed data calibrated using a minimal number of ground-based sampling plots.

This tool provides a method for determining average ALFB density at the stratum or area of interest (AOI) through a combination of remote sensing data and field measurements to provide accurate and cost effective estimation of ALFB across varied LULC classification types and broad spatial extents. The use of RS (LiDAR, RADAR, hyperspectral/hyperspatial imagery) in combination with a relatively small number field plots and can be used to achieve a statistically valid sample applying this tool.

This tool is intended for use in estimating average ALFB density at a specific point in time. This tool does not present specific methods for detection of change in ALFB over time, or wall-to-wall carbon density mapping. This tool is intended for use with approved VCS methodologies within the scope of AFOLU involving estimation of ALFB. This tool is therefore limited to project categories within the AFOLU sectoral scope where forest is present and estimation of ALFB is required.

The main procedural steps in this tool are:

1. Field and remote sampling
2. Predictive model development
3. Assessment of error and uncertainty
4. Discounting estimates based upon step 3

3 DEFINITIONS

In addition to the definitions set out in VCS document *Program Definitions*, the following definitions apply to this methodology:

Aboveground Live Forest Biomass (ALFB)
Live forest biomass above the soil, including the stem, stump, branches, bark, seeds and foliage of vegetation. The ALFB includes live shrubs and trees biomass.

Area-normalized
The division of a metric derived in aggregate for a region, by a unit of area (eg, Mg ha^{-1}, t ac^{-1})

Area of Interest (AOI)
Geographic region within which carbon in aboveground biomass is to be estimated. It could be a reference region, project area, forest stratum, leakage belt or jurisdictional program area

Calibration Plot (CP)
A subset of SPs used to develop a predictive model relating RS metrics to ALFB

Land Use and Land Cover (LULC)
Definition used to stratify an AOI into regions with similar characteristics

Model Dependent Estimator (MDE)
A two-phase approach for estimating forest biomass that rests on the assumption that predictive models are correctly specified to estimate the biomass from remote sensing data for each forest type, land cover class, or forest stratum

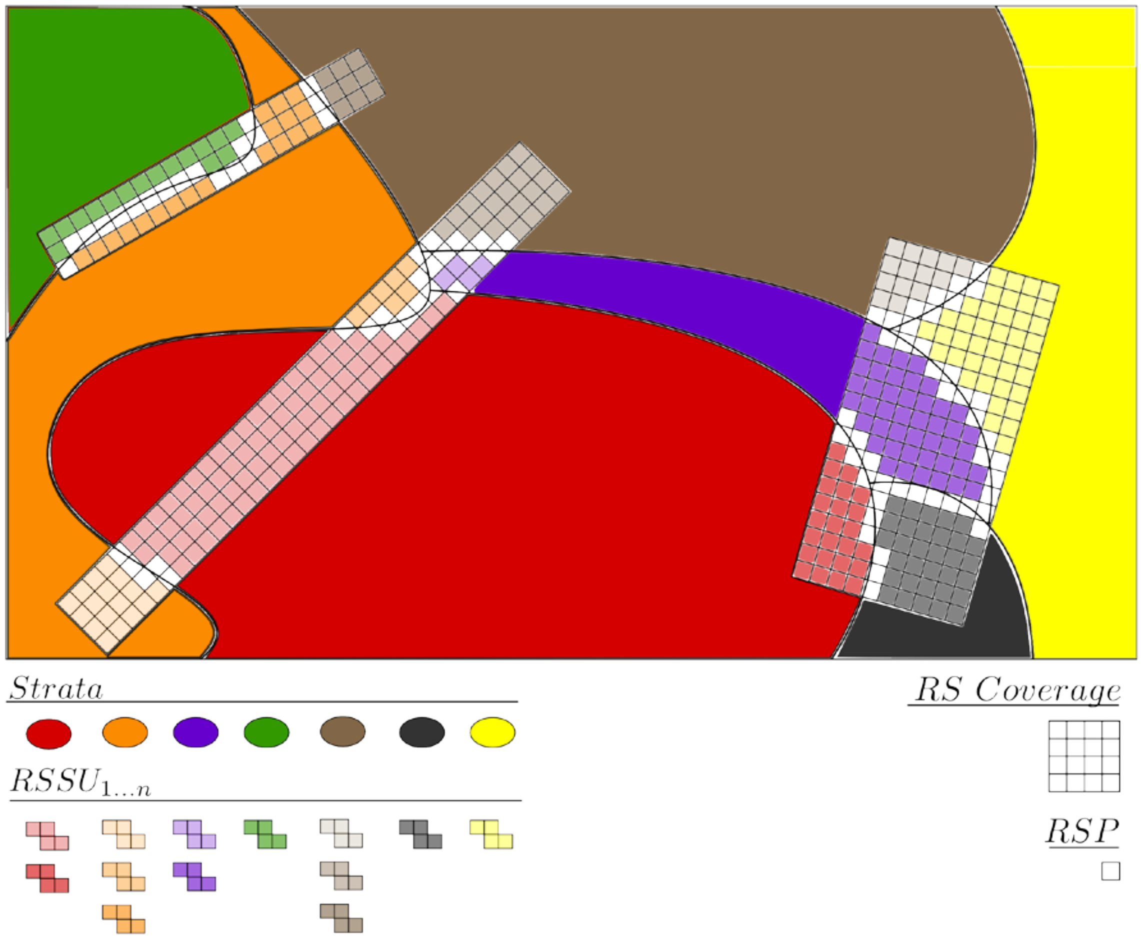
Predictive Model (PM)
Mathematical model relating predictor variables (independent) derived from RS data to ALFB (dependent)

Remote Sensing (RS)
Imagery or other gridded data acquired from aerial or satellite platforms and ortho-rectified to a geometric coordinate system such that scale is uniform. Metrics derived from remote sensing platforms can include directly measured reflectance at a given frequency, or derivative metrics such as gridded raster of tree canopy height from LiDAR

Remote Sensing Plot (RSP)
Individual pixels t of RS data used to estimate ALFB, ≥0.25 ha in size with1 ha as optimum size (see diagram below).

Remote Sensing Sampling Unit (RSSU)
A distinct, contiguous area of a given stratum or AOI area covered by RS data as seen in the diagram below. There may be multiple RSSUs in a given stratum if there is non-contiguous overlap of RS data with a given stratum. RSSUs can be different sizes as long as the combined

area covered by RSSUs within a given stratum is equal or greater to the minimum specified in equation (2).



Root Mean Square Error (RMSE)

A measure of the differences between values predicted by a model and the values actually observed, represented as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\gamma'_i - \gamma_i)^2} \qquad (1)$$

Where:

RMSE = Root mean square error of the predictor (sample measurement units)

γ' , γ = Observed and predicted values (sample measurement units)

Sample Plots (SP)

A geographic subset of the AOI or strata within which ALFB is measured in-situ using field instrumentation and used as a basis for ALFB estimation at the strata or project scale

Validation Plot (VP)
A subset of SPs not used in developing predictive relationship between RS metrics and AFLB used to test predictive accuracy of the model developed using CPs

4 APPLICABILITY CONDITIONS

This tool is applicable to all forest types and age classes. The tool is applicable for use with methodologies or tools that require an estimate of area-normalized ALFB density. For such methodologies or tools, this tool can be used to produce estimates of ALFB density for initial inventory, or as a part of measurement, reporting, and validation. This tool is intended for the generation of ALFB density using a sampling approach. However, it can be used for wall-to-wall mapping of ALFB if remote sensing data covers the entire AOI. In addition the following are the conditions under which this tool may be used:

- The tool is applicable in conjunction with AFOLU methodologies in which estimation of ALFB is required.
- The remotely sensed data necessary to estimate ALFB is accessible for the time period desired.
- Predictive model (PM) relating RS metrics to ALFB is parametric (eg, $\mathrm{ALFB} = \mathrm{f}(\mathrm{x}, \alpha, \varepsilon)$)

This tool is not applicable under the following conditions:

- The overarching methodology requires specific method for determining change in biomass density over time. This tool does not provide methods for temporal change in ALFB density. However, the tool can be repeated at distinct points in time to determine an ALFB delta.

5 PROCEDURES

The product of this tool is an estimate of ALFB density using RS sampling at the stratum or AOI based. This method may employ a stratification of the AOI into like biophysical land cover or forest types. Stratification may be used to increase the accuracy of the ALFB density estimate or for the purposes of reporting AFLB density for a LULC class used in other methodologies. This tool does not present a method for stratification.

If this tool is being deployed in the context of an emissions reduction project in which a historical baseline of emissions is established for LULC classes within the AOI, the LULC classification map should be used as the basis for establishing a RS sampling design to ensure sufficient sampling density for each LULC type. Stratification may also be used to improve the accuracy of the RS → ALFB predictive relationship.

The procedures are outline here and are specified in greater detail in the following sections:

1. Consider stratification
2. Collect Remote Sensing (RS) samples

3. Collect *in-situ* samples
4. Develop and test predictive model (PM)
5. Use PM to estimate ALFB at the stratum or AOI
6. Discount estimate bade on uncertainty

5.1 Estimation Using RS Predictor

Remotely acquired data can capture an array of biophysical characteristics of the landscape at a range of scales. In many cases, data collected from RS platforms can be functionally *related* to ALFB such as $AFLB = f(x_1, x_2, \dots x_n)$ wherein x is one or many metrics derived directly from one or many sensors. The RS predictor method employed in this tool follows the model-dependent estimator (MDE) (Asner *et al.* 2013) and is based on a data collection design that insures correct and unbiased estimate of carbon density or total carbon. An RS predictor based on MDE accounts for sampling error and model error and allows for the user to partition the variance into these components for each stratum or AOI. The RS predictor accounts for the fact the RS data such as a LiDAR survey along a flight line is a cluster. The RS predictor also takes into account the model error, i.e. the variations due to the variability of model coefficients impacting estimates of carbon density.

To employ this predictive approach, a two-phase sampling design is required, as follows:

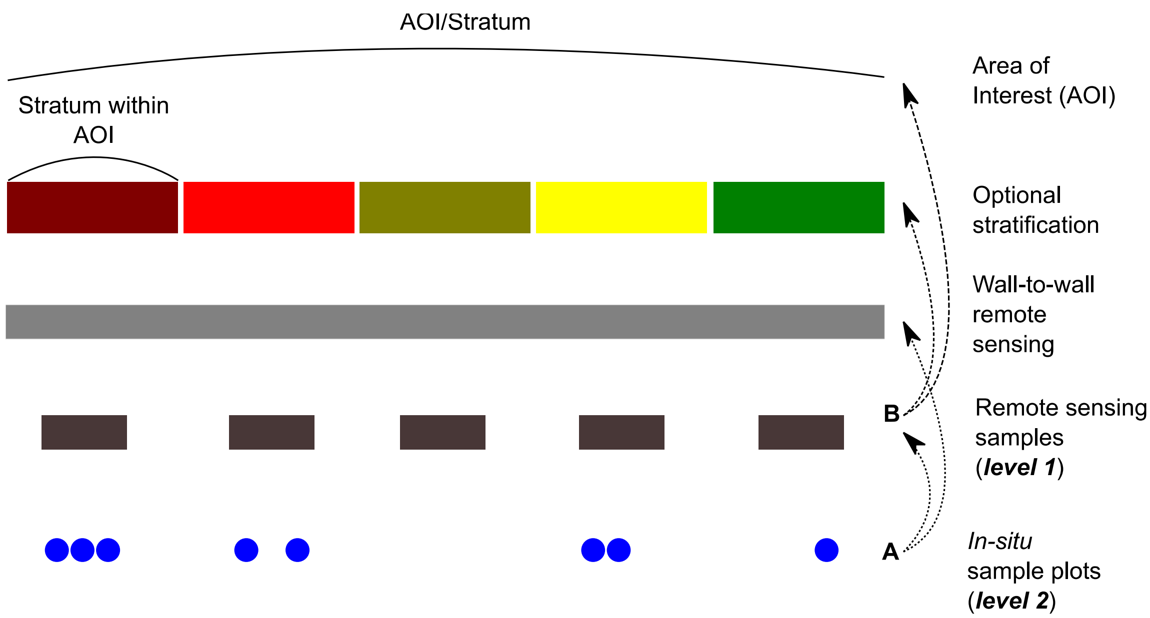
1. **Remote sensing sampling:** RS surveys from airborne flights or satellite orbits are referred to as remote sensing sampling unit (RSSU, or level 1 sampling (Saatchi *et al.* 2011). The RS surveys are random samples. Systematic sampling may be employed and treated as if random. For cases in which there are trends in the biomass density (such a north-south or east-west trend), an unaligned systematic sampling design can be treated as random without inflating the estimator errors (Nelson *et al.* 2012).
2. ***In-situ* sampling:** Sampling plots (SP), or level 2 sampling, coincident with RS sampling (level 1 sampling) is needed to calibrate and validate the predictive model. Sampling plots must be located within an RSSU. The level 2 samples must be selected randomly with replacement or systematically in order to represent to the greatest extent possible the full range and variability of ALFP within stratum or AOI and to reduce the bias. The objective of SPs is to facilitate PM development. SP's as defined in this tool cannot be used as an unbiased estimation tool such as in forest inventory sampling. For other sampling references aligned with this approach see Maltamo *et al*. (2010) and Juntilla *et al*. (2013).

RS survey must not be designed to use existing plots. RS data collection must be planned to cover sufficient area within each stratum (or AOI) to achieve the project proponent's uncertainty threshold for the estimate. Predictive model relationships between level 1 and level 2 data are established using a subset (calibration plots) of the sampled area (SPs) and tested using the remainder of the sampled area (validation plots) using a cross validation (Picard & Cook 1984) procedure to provide both accuracy and precision, which must be clearly documented. The use of SPs is limited to calibration and validation of predictive model only and is not used to independently estimate ALFB at the stratum or AOI scale.

This tool can be used for developing a tessellated (wall-to-wall) carbon map from RS data only if RS data covers the entire AOI. In this case, the PM can be directly used to estimate the mean and variance of ALFB of AOI based on predicted ALFB density for all RSP's without the need for stratification or statistical sampling approach (Saatchi *et al.* 2011).

The result of the use of this tool will be an area-normalized (eg, t C/ha) estimate of average AFLB density within the AOI or for each stratum within the AOI. Figure 1 below presents a high-level schematic representing the process described in this tool for estimating ALFB density at the stratum or AOI level.

Figure 1: Schematic Diagram of Procedure Specified in this Tool to Estimate ALFB Density for Strata or AOI from Systematic and Random RSSUs and CP and VP plots



A uses ALFB density in measured in-situ plots to calibrate RS data.
B estimates ALFB density at the stratum or AOI level based on RS sampling

5.1.1 Step 1: AOI Stratification

Stratification of the AOI may improve prediction of AFLB densities from RS data within like land cover types. Deployment of this tool without stratification may require the project proponent to: a) accept increased uncertainty in the estimate, or b) obtain RS metrics that that can achieve sufficient accuracy without the use of stratification.

If this tool is being used in the context of emissions reductions projects that require demonstration of a historical baseline the project proponent should consider use of those LULC classes as the basis for stratification.

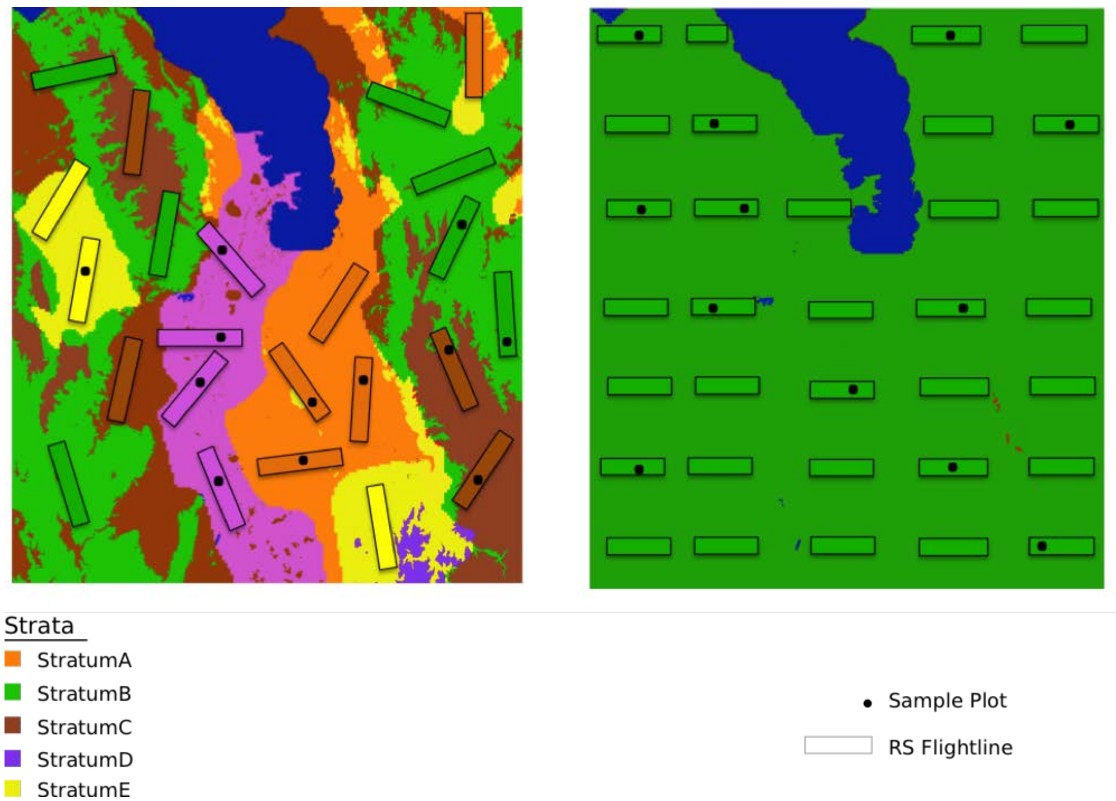
The project proponent should consider two stratification options: 1) LULC classes may be used as strata if ALFB densities within each LULC class are relatively constant; or 2) LULC classes may be further subdivided into multiple strata if sufficient biophysical variance exists within the LULC class. Reduction in uncertainty of ALFB estimation may be achieved through establishing strata with homogeneous biophysical (ie, biomass density) characteristics. Stratification if employed, must result in a wall-to-wall (tessellation) map of like land cover types covering the AOI. A range of RS (or other) data sources can be used in this step. However, the functional relationship between the RS and ALFB must be described in detail and reference empirical relationships demonstrated in relevant scientific literature. The same RS data may be used in stratification and biomass estimation, however *in-situ* sampling data used for stratification and *in-situ* sampling data (SP) used in biomass estimation must be independent and distinct.

If stratification is employed, overarching methodologies should be consulted for guidance. This tool does not present a method for stratification. If this tool is being deployed outside of the context of another overarching (VCS or otherwise) methodology, see Johnson (Johnson 2000) for a useful general reference on the subject.

5.1.2 Step 2: Sampling

Sampling is a means of collecting representative data from a geographic subset of the AOI used in predicting and validating ALFB density for the AOI. This tool presents a method for combining *in-situ* plots (SPs) with sampling via a RS platform. The combination of *in-situ* plots and RS can substantially reduce the cost of collecting necessary sample data to achieve a level of uncertainty within the desired threshold. Figure 2 below provides an example sampling schematic.

Figure 2: Schematic representation of sampling strategy for using SP and RS metrics to estimate ALFB density for strata/AOI.



The sampling frame, or area within which sampling should be conducted is specified by the project area for which an estimate of ALFB is required in any overarching methodology. Unless a buffer for the AOI is specified in an overarching methodology, a spatial buffer of 1000m around the perimeter of the AOI must be included in the sampling frame to ensure that results accurately reflect the ALFB gradients at the perimeter of the AOI.

5.1.2.1 Step 2a: Sampling with RS Data

The volume of emission reductions generated by a project must be discounted based on the uncertainty of the estimation methods. Statistically, reduced uncertainty is achieved with greater sampling intensity. Increased sampling intensity may, however substantially increase cost. Thus, the project developer must establish a threshold of uncertainty balancing cost and emission reduction volume. No objective standard can be used to arrive at such a threshold as project development costs vary greatly, as do expectations of emission reduction return.

Sampling sufficient area to achieve the uncertainty threshold over large areas based solely upon in-situ measurement plots may be infeasible due to cost and logistics. Aerial RS data such as Light Detection And Ranging (LiDAR), RAdio Detection And Ranging (RADAR), or multispectral imagery can substantially reduce the overall cost of field data collection as large areas can be covered in much less time and with less expense than field crews. However, the use of RS data introduces an additional source of error resulting from converting the RS metrics to ALFB (ie, model error). Thus, selection of an RS platform such as LiDAR that can directly obtain metrics strongly related to AFLB is critical. In the case where such data can be obtained, additional error can be readily reduced when averaged over larger area (Asner *et al.* 2013; Vincent *et al.* 2014). The accuracy of the predictive relationship between RS and ALFB must be clearly presented and the uncertainty in the estimate must be used in discounting ALFB (see Section 5.1.3)

In this tool the term remote sensing sampling unit (RSSU) is used to refer a spatially contiguous area within a stratum for which RS data has been collected (see figure in definition section for a schematic representation of the RSSU). Simple random sampling, systematic sampling, or stratified random sampling can be employed in designing RSSUs. In general, ALFB estimation based solely on RSSU is assumed to have larger errors than estimation based only on SPs. The use of larger RS sampling sample units reduces the estimator error.

Remote sensing plots (RSPs) are distinct and equally sized regions within an RSSU. In remote sensing terminology, the RSP is equivalent to the pixel. For this tool, the RSP must be 1 ha in area. RSPs are inherently clustered due to the swathing or field-of-view configuration of airborne or space-borne sensors. See figure in definition section for a schematic representation of the RSP. ALFB estimation using the RSSU must include the spatial correlation among RSPs. The combined size of RSSUs within a stratum must be larger than the spatial correlation length (range of the semivariogram) of RSSU estimator error (see equation (2)). The number of RSSUs and the size of RSSUs necessary to achieve the required precision are inversely related: the smaller the sample size, the larger the number of samples.

The combined area samples with an RS platform within each stratum or for the AOI must be of a minimum size to allow unbiased estimation of mean ALFB. Determination of the extent of RS data collection is dependent on the desired confidence in the estimate produced by this tool and on the use of ALFB density estimates known *a-priori* either from a pilot study, from appropriate literature, or using default values provided herein. The number of RSSUs for each stratum or of the AOI can be calculated from the following:

$$n = \left(\frac{t\infty_{val}}{E}\right)^2 \sigma_L^2 \qquad (2)$$

$$\sigma_L^2 = \sum_{i=1}^{m}\sum_{j=1}^{m} cov(\sigma_{ui}, \sigma_{uj}) = \sum_{i=1}^{m} var(\sigma_{ui}) + 2\sum_{i=1}^{m}\sum_{j<i}^{m} cov(\sigma_{ui}, \sigma_{uj})$$

or (3[1][2])

$$\sigma_L^2 = \frac{1}{m}\left(\sum_{i=1}^{m} \sigma_{ui}^2 + 2\sum_{i=1}^{m}\sum_{j<i}^{m} \rho(d)\sigma_{ui}\,\sigma_{uj}\right)$$

$$\rho(d) = \exp(-\frac{d}{cr}) \qquad (4^3)$$

Where:

i, j = Generic indices representing pixels in the RSSUs (unitless)

E = Accepted margin of error (ie, one-half of the confidence interval) in estimation of carbon density or ALFB at each stratum or AOI (t ha^{-1})

n = Number of RSSUs within each stratum or AOI (unitless)

$t\infty_{val}$ = Two-sided Student's t-value at infinite degrees of freedom for the required confidence level (unitless)

r = Range from semivariogram estimating the spatial correlation of errors associated within cluster samples in RSSU (distance measurement units in units of pixels)

c = Fit for exponential spatial correlation function derived from semivariogram analysis (unitless)

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[1] Weisbin et. al (2014), equation 13. Note that equation 13 in Weisbin et al. (2014) is for a specific case where $\sigma_{ui,j}^2$ is expressed in terms remote sensing variables. The second term in the equation represents the spatial correlation effect through covariance matrix of i,j pixels. See other sources for similar formulations (Wagner 2003; Chilès & Delfiner 2012).

[2] $cov()$ is the covariance function -- $\rho(d)$ in the alternate form -- associated with ALFB variance for each RSP

[3] Weisbin et. al (2014), equation 13.

d = Distance between pixels *i* and *j* within m (pixels)

$\rho(d)$ = Spatial correlation function in terms of distance d based on exponential semivariogram model (unitless)

σ_L^2 = Variance derived from *a-priori* RS data, a pilot study, or default values of ALFB density for the stratum or AOI[4] $(t\ ha^{-1})^2$

m = A dummy large number representing pixels in RSSU (pixels)

$\sigma_{ui,j}^2$ = Estimated variance associated with ALFB values for each 1-ha pixel $(t\ ha^{-1})^2$

In above equations, n is the number of RSSUs for stratum *j*. The value of n will depend on the desired E and the estimated standard deviation of biomass stock for each RSSU as defined by σ_L^2. When the value of m is large, the standard deviation σ_L^2 will be small and hence the number of RSSUs will be small. The target number of pixels in each RSSU (m) is selected to allow efficient and cost-effective sampling design, while ensuring sufficient sampling density. In most applications a larger m, meaning a larger area coverage for each RSSU and resulting in a smaller n, is a cost effective. In most applications, m is larger than required because of flight plans, causing a much smaller error of ALFB at the stratum or AOI scale, providing oversampling for conservativeness of estimation uncertainty.

The semivariogram analysis defining the correlation coefficient (Chilès & Delfiner 2012) quantifies spatial correlation of pixel level estimates of ALFB within the RSSU due to variations of forest structure, environmental conditions (moisture or temperature), and edaphic conditions (topography and soil types). In RS sampling, the spatial correlation can be described by the covariance function of observations at a distance *d* apart from each other indicating that pixels at smaller distances tend to be more similar (higher correlation) than pixels at larger distances. The correlation among pixels suggests that each pixel cannot be assumed independent (Weisbin *et al.* 2014).

The method to estimate the variance in ALFB to determine RS sampling intensity using correlation length from semi-variogram analysis requires a priori knowledge of variation in ALFB, access to existing RS data over the region of interest (eg, stratum) or the use of default conservative values. One of the following three options can be used to determine the spatial correlation function:

1. Use a priori RS data (eg, LiDAR scanning) for the area to establish a range of correlation lengths (range of semi-variograms) for the region to upper and lower bounds for the

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[4] If a previous study is available estimating average ALFB within the AOI or stratum with no spatial variability, a default value of 15% of the estimate can be used. If a spatially variable estimate is available this function should be used to account for spatial covariance. The equation is represented in terms of a covariance matrix of errors associated with the pixels as in Wagner (2003) eq. 3 and written in terms of variogram function as in Chilès and Delfiner (2012) chapter 2.

number of RSSUs for each strata. Chilès & Delfiner (2012) provide guidance on semivariogram analysis. A reference for the method used to develop the *a priori* dataset must accompany documentation of the application of this tool (eg, project description, etc.) if this option is chosen.

2. Perform a pilot study by first collecting sample RS data over the region to establish the bounds for the number of RSSUs. Chilès & Delfiner (2012) provide guidance on semivariogram analysis. A detailed description of the methods used in the pilot study must accompany documentation of the application of this tool (eg, project description, etc.).
3. Use the default values from literature (Weisbin *et al.* 2014; Zolkos *et al.* 2013; Asner & Mascaro 2014) specified below. If an estimate of ALFB from a previous study that does not vary across the AOI or stratum is used, reference to the method used to estimate ALFB must accompany documentation of the application of this tool (eg, project description, etc.).

$$c = \frac{1}{3} \tag{5}$$

$$r = 10 \text{ (1 ha pixels)} \tag{6}$$

$$\sigma^2_{ui,j} = \left(0.15\widehat{ALFB}_p\right)^2 \tag{7}$$

Where:

$\widehat{ALFB}_p$ = Average ALFB density for the AOI or stratum from previous study or relevant literature.[5]

RSSU layout must take into consideration the following:

1. RSSU must be located randomly or systematically within the AOI. In the case of random selection with airborne RS data, the center location and the heading of airborne flight must be randomized.
2. Unless a buffer for the AOI is specified in an overarching methodology, a spatial buffer of 1000m around the perimeter of the AOI must be included in the sampling frame to ensure that results accurately reflect the ALFB gradients at the perimeter of the AOI.

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[5] A conservative estimate of 15% of the mean ALFB from LiDAR measurements over the tropical forests can be used as an estimate of the variance to determine sample size and intensity (Asner & Mascaro 2014; Meyer, Saatchi, Jerome Chave, *et al.* 2013)

3. RSSU may be a contiguous transect of size m covering the variability of ALFB within each stratum for cost and operational considerations.
4. RSSU may also be divided into segments to cover the variability of ALFB within each stratum by keeping the total area of RSSU as required.
5. The pixel resolution of the data derived from the RS platform must not exceed the size of the SP when applying the RS predictor to avoid any potential estimation bias. After ALFB prediction, the RS product can be aggregated to any pixel resolution (e.g. 1-ha or greater) for ALFB estimate for stratum/AOI (see section 5.1.3.3). For SP plot size and design, see Section 5.1.2.2.

5.1.2.2 Step 2b: *In-situ* Measurement Plots

In-situ measurement plots, or sample plots (SPs) are considered the level 2 sampling and are used to develop predictive models, validate, and quantify uncertainty in the relationship between RS metrics and ALFB. The relationship between RS data and ALFB density can be considered an allometric relationship. Level 1 and level 2 sampling must be independent; hence the location of SPs must be established at random or systematically within each stratum (or across the AOI). If a random approach is used, adherence to random selection without replacement[6] of SP locations is critical.

If the coefficients of allometric relationships for distinct species do not vary across the AOI (between strata), there is no requirement for SPs to be co-located with all RSSUs. If stratum-specific allometric relationships are used (ie, regression coefficients vary across strata), sampling to develop the relationship must be conducted within the overlapping area of the RS data extent and the each stratum. Otherwise, if allometric equation coefficients do not vary across the AOI, only one RS → ALFB allometric relationship can be used (Saatchi *et al.* 2011).

A minimum of 45 SPs must be established within the area covered by the RS data within the AOI. Of the 45 SPs 30 Calibration Plots (CP) must be used to develop the PM and 15 used as Validation Plots (VP) (Asner & Mascaro 2014). In the case of stratification within one forest type (ie, one allometric equation), the total number of plots required for the tool will remain at minimum of 45.

Sample plots must be large enough to avoid edge effects and provide unbiased relationship with RS metrics (eg, mean canopy height, top canopy height). Minimum size of 0.25 ha (rectangular: 50 m x 50 m) or 0.28 ha (circular: 30 m radius) (Meyer, Saatchi, J. Chave, *et al.* 2013; Asner *et al.* 2012; Asner *et al.* 2013) must be used for developing RS → biomass allometry. These plots are temporary plots used to calibrate the RS data. Standard quality control / quality assurance (QA/QC) procedures for field data collection and data management must be applied. Use or adaptation of QA/QCs already applied in national forest monitoring, or available from published

[6] In the event that subsequent randomly selected plot locations overlap, the later plot must be discarded and another random selection made.

handbooks, or form the chapter 5.5 of *Good Practice Guidance for Land Use, Land-Use Change and Forestry* (Intergovernmental Panel on Climate Change 2003), is recommended.

Positional accuracy of plots used in calibrating RS models is critical in contrast with traditional stratified random sampling. The error in positional accuracy of *in-situ* plot location reported by the GPS system used must be equal to or less than 10 meters and must accompany documentation of the application of this tool (eg, project description, etc.). The manufacturer and model of the global positioning system (GPS) used must accompany documentation of the application of this tool and the reported accuracy of the location by the instrument must be recorded at each plot.

5.1.2.2.1 Estimation of ALFB in Plots

Field data collection at SPs must include diameter and height for measured trees and specific identification for wood density estimation. If wood density for each species is not collected in field sampling, values must be taken from the Global Wood Density Database[7] (Zanne *et al.* 2009; Chave *et al.* 2009).

To estimate the ALFB of a specific tree species within a sample plot based on field measurements, relevant allometric equation must be applied. If this tool is used in conjugation with REDD/REDD+, ARR, WRC or IFM methodologies that specify allometric equations, selection and use of allometric equations must follow the guidelines therein. For cases in which there is no guidance from overarching AFOLU methodologies, allometric equations for forests similar to those found in the AOI found in GPG-LULUCF Annex 4A.2 Table 4.A.1 (Intergovernmental Panel on Climate Change 2003), or in Chave *et al.* (2014) may be used. See additional guidance on selection and use of allometric equations as well as development allometric equations from field data for ALFB in Picard *et al.* (2012) and Chave (2005). A useful reference for documenting the allometric equation used can be found in Cifuentes Jara (2014).

5.1.3 Step 3: Prediction

SPs must be extrapolated to the extent of the strata or AOI. This involves the following two steps:

1. Develop a PM and estimating its precision in predicting ALFB density within each RSSU; and,
2. Calculate ALFB for each stratum or AOI based upon the ALFB estimates obtained by the PM in step 1.

Estimation of ALFB density for each stratum or AOI involves development and validation of a PM relating RS metrics to ALFB measured in SPs. The PM is then used to estimate ALFB for all RSPs in the stratum.

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[7] http://datadryad.org/repo/handle/10255/dryad.235

5.1.3.1 Step 3a: Model Development

ALFB density prediction for each stratum or for the AOI (S_j) is accomplished using the SPs within S_j to develop and validate the PM relating RS data to field-measured ALFB. In this step, metrics contained in the RS data are mined for their predictive power *vis a vis* ALFB as measured in CPs. One or several predictors are selected and used to estimate ALFB for the VPs within S_j. This process is conducted iteratively (cross validation) preserving the ratio of CP to VP to improve the strength of the predictor. It is critical that, for each iteration, CPs are used only for developing the predictive model and VPs are used only for assessing the accuracy of the model. A minimum of 10 rounds ($K \geq 10$) of cross validation must be employed and results reported in any documentation of the application of this tool (eg, project description, etc.) to assess the precision of the PM.

5.1.3.2 Step 3b: Reporting PM Precision

The models RMSE, coefficient of variation and bias must accompany documentation of the application of the results of this tool (eg, project description, etc.). Assuming K cross validation rounds, RMSE must be calculated from all rounds comparing the observed versus predicted ALFB density values for the VPs as follows:

$$\varepsilon_{S_j} = \sqrt{\frac{1}{n \times K} \sum_{l=1}^{n} \sum_{k=1}^{K} (\gamma'_{kl} - \gamma_{kl})^2} \tag{8}$$

$$R^2_{\mathrm{S_j}} = 1 - \frac{SSR_{\mathrm{j}}}{SST_{\mathrm{j}}} \tag{9}$$

$$SSR_j = \sum_{l=1}^{n} \sum_{k=1}^{K} (\gamma'_{kl} - \gamma_{kl})^2 \tag{10}$$

$$SST_j = \sum_{l=1}^{n} \sum_{k=1}^{K} \left(\gamma_{kl} - \left(\frac{1}{n \times K} \sum_{l=1}^{n} \sum_{k=1}^{K} \gamma_{kl} \right) \right)^2 \tag{11}$$

$$B_{\mathrm{S_j}} = \frac{\sum_{l=1}^{n} \sum_{k=1}^{K} (\gamma_{kl} - \gamma'_{kl})}{n \times K} \tag{12}$$

Where:

ε_{S_j}	=	RMSE for stratum *j* (t ha^{-1}) derived from observed and predicted biomass density
$R^2_{\mathrm{S_j}}$	=	Coefficient of determination for stratum *j* (unitless)

SSR_j = Sum of squares of residuals, stratum *j* (t ha^{-1})

SST_j = Total sum of squares, stratum *j* (t ha^{-1})

B_{S_j} = Bias stratum *j* (t ha^{-1})

n = Number VPs in stratum *j* (plot)

K = Number rounds of cross validation stratum *j* (cross-validation round)

γ'_{kl}, γ_{kl} = Predicted and observed ALFB density at VP *l*, validation round *k* respectively (t ha^{-1})

The range of applicability of the PM must be described in terms of the range of biomass densities in measured SPs and the range of RS metrics used in the PM.

5.1.3.3 Step 3c: Estimation of ALFB at the Stratum/AOI

In a general case with forest stratification and different RS-ALFB allometric relations for each stratum, the estimator specified below must be used to estimate the mean and variance for each stratum and project area (Asner *et al.* 2013; Nelson *et al.* 2012; Næsset *et al.* 2013). Assuming n strata, and n_j remote sensing sampling units (RSSU) within each stratum *j*, the estimator for the mean value of ALFB and the variance for stratum *j* are:

$$ALFB_j = \frac{\frac{1}{n_j}\sum_{i=1}^{n_j} F_{ij}(\alpha_j)}{\frac{1}{n_j}\sum_{i=1}^{n_j}\eta_{ij}} \qquad (13)^{8}$$

$$\widehat{ALFB} = \sum_{j=1}^{N} w_j\, ALFB_j \qquad (14)^{9}$$

$$\sigma_j^2 = \frac{1}{\overline{\overline{\eta_j^2}}}\frac{\sum_{i=1}^{n_j}\left(F_{ij}(\alpha_j) - ALFB_j\eta_{ij}\right)^2}{n_j(n_j-1)} + \frac{1}{\overline{\overline{\eta_j^2}}}\sum_{k_1}^{P_j}\sum_{k_2}^{P_j} Cov(\alpha_{k_1 j}, \alpha_{k_2 j})\overline{F'_{k_1 J}}\,\overline{F'_{k_2 J}} \qquad (15)^{10}$$

$$\overline{\eta_j} = \frac{1}{n_j}\sum_{i=1}^{n_j}\eta_{ij} \qquad (16)^{11}$$

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[8] Ståhl (2011), equation 11.
[9] Ståhl (2011), equation 12; Nelson *et al.* (2012).
[10] Ståhl (2011), equation 15
[11] Ståhl (2011), equation 15

$$\overline{F'_{k_1 J}} = \sum_{i=1}^{n_j} \sum_{t=1}^{T} \frac{\partial f(x_{i_t}, \alpha_{k_1})}{\partial \alpha_{k_1}} \quad (17)$$ [12]

$$u_j = \frac{t_{val} \sqrt{w_j^2 \times \frac{\sigma_j^2}{n_j}}}{ALFB_j} \quad (18)$$ [13]

$$w_j = \frac{A_j}{A} \quad (19)$$

Where:

$ALFB_j$	=	Mean ALFB density of stratum *j* (t ha^{-1})
$\widehat{ALFB}$	=	Mean ALFB across all strata, which can be multiplied by the total area to obtain the overall total carbon in AOI (t ha^{-1})
F_{ij}	=	Sum of all of RSP ALFB estimates derived from the PM in each RSSU *i* and stratum *j* (t/ha)
n_j	=	Number of RSSUs intersecting stratum *j* (RSSU)
α_j	=	Vector of parameters used in the PM, eg, *a* and *b* in above ALFB equation (unitless)
P_j	=	Number of parameters, ie, the number of independent variables (eg, height metrics in ALFB equation) (unitless)
T	=	Total number of RSPs within each RSSU[14] (RSP)
η_{ij}	=	Number of RSPs within RSSU *i*, stratum *j* (RSP)
$\frac{\partial f}{\partial \alpha}$	=	First derivative of the function *f* with respect to the coefficients of the model and evaluated for t^{th} RSP within the i^{th} RSSU in stratum *j*[15] (t)
t_{val}	=	Two-sided Student's t-value for the desired confidence level and degrees of freedom equal to *n* – M, where *n* is total number of sample plots within the tree biomass estimation strata and M is the total number of tree biomass estimation strata (unitless)
w_j	=	Ratio of the area of stratum *j* to the sum of areas of all strata (unitless)
σ_j^2	=	Variance of ALFB per hectare in stratum j (t ha^{-1})^2

12 Ståhl (2011), equation 15
13 Kangas and Maltamo (2006)
14 As RS ALFB estimates are at 1-ha units, T represents the size of RSSU in ha.
15 See Ståhl et al. (2011), Appendix A.

A_j = Area of stratum *j* or AOI (ha)

A = Total area of AOI consisting of j strata

N = Number of stratum in AOI

u_j = Uncertainty of mean value of ALFB for stratum j (t ha^{-1})

In the variance equation (15), $Cov(\alpha_{k_1 j}, \alpha_{k_2 j})$ is the covariance of k_1 and k_2 coefficients of the RS-ALFB PM, represented by function *f* for stratum *j*. The first term in equation in variance estimate represents the sampling error and the second term describes the model error for each stratum. The above relations will be simplified if only one model is used for all strata.

The uncertainty in the estimate of the mean ALFB for stratum *j* is defined as the standard error of the mean expanded by the desired percent confidence interval, divided by the mean value, and expressed as percentage. The uncertainty is given by CDM tool *Estimation of carbon stocks and change in carbon stocks of trees and shrubs in A/R CDM project activities*, and calculated for this tool using equation (15).

In the case where uncertainty exceeds the desired threshold, the estimate must be discounted per Section 5.1.4. To reduce uncertainty in the estimate, the parameter E in Section 5.1.2.1 can be decreased which will result in increased RSSU area.

5.1.4 Step 4: Discounting

If this tool is being deployed in the context of an overarching methodology (eg, VCS, CDM, etc.), estimates of carbon in ALFB may be required to be discounted based upon the accuracy of the estimate. In this case, guidance on discounting carbon volume should be sought from the overarching methodology for the following aspects of this tool:

- **Allometric equations.** Allometric equations used in estimating ALFB at the SP may be required to be assessed according to the standards of the overarching methodology being used.
- **Stratum mean ALFB.** Discounting of the estimated ALFB density may be required to be performed based upon standard of the overarching methodology.

6 DATA AND PARAMETERS

6.1 Data and Parameters Available at Validation

Data / Parameter	E
Data unit	t ha^{-1}
Description	Accepted margin of error (i.e. one-half of the confidence interval) in estimation of carbon density or ALFB at each stratum or AOI.
Equations	(2)

Source of data	Arbitrary dependent upon project requirements
Value applied:	10% of the mean ALFB at the stratum or AOI.
Justification of choice of data or description of measurement methods and procedures applied	The default value of E is 10% of the mean stratum or AOI biomass stock (t ha^{-1}).
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	$t\infty_{val}$
Data unit	Unitless
Description	Two-sided Student's t-value at infinite degrees of freedom for the required confidence level.
Equations	(2)
Source of data	At infinite degrees of freedom the Student's T is equivalent to a normal distribution
Value applied:	Dependent on the desired confidence level.
Justification of choice of data or description of measurement methods and procedures applied	Enables the calculation of the RSSU sample size such that the desired confidence interval in the estimate of ALFB can be achieved
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	r
Data unit	Pixels
Description	Range from semivariogram estimating the spatial correlation of errors associated within cluster samples in RSSU. See below (this section) for a discussion of semivariogram analysis
Equations	(4
Source of data	Default value may be used. See section 5.1.2.1 for alternatives to the default value.
Value applied:	10
Justification of choice of data or description of	Conservative estimate of the correlation length. Ten 1-ha pixels.

measurement methods and procedures applied	
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	d
Data unit	Pixels
Description	Distance between pixels within the stratum and all other pixels within the stratum
Equations	(4
Source of data	Calculated based on the size of m.
Value applied:	N/A.
Justification of choice of data or description of measurement methods and procedures applied	Canonically used in determining spatial covariance.
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	c
Data unit	unitless
Description	Parameter of fit for exponential spatial correlation function derived from semivariogram analysis
Equations	(4
Source of data	Weisbin, Zolkos et al. and Asner and Mascaro (2014; 2013; 2014).
Value applied:	$\frac{1}{3}$
Justification of choice of data or description of measurement methods and procedures applied	Demonstrated in Weisbin, Zolkos et al. and Asner and Mascaro (2014; 2013; 2014).
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	m
Data unit	pixels
Description	A dummy large number representing pixels in RSSU. The number can be arbitrarily large or at least twice the default value of range (*r*).
Equations	(3)
Source of data	Calculated based on stratum size.
Value applied:	Minimum (default) value is 2*r* = 20 pixels, can be larger.
Justification of choice of data or description of measurement methods and procedures applied	This parameter establishes the minimum size of the RSSU based upon the estimated covariance of an a-priori, spatially variable ALFB estimate.
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	$\widehat{ALFB}_p$
Data unit	Tonnes (metric) ha^{-1}
Description	Average ALFB density for the AOI or stratum from previous study or relevant literature.
Equations	(7)
Source of data	Previous study.
Value applied:	N/A.
Justification of choice of data or description of measurement methods and procedures applied	Estimates of ALFB density from a previous study can be used to estimate RS sampling intensity.
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	K
Data unit	Integer
Description	Number of validation rounds used in cross validation of predictive RS model.
Equations	(8)(10), (11) and (12)

Source of data	Define based upon the number of iterations that result in reduction of RMSE relative to previous round, must be 10 or greater.
Value applied:	≥10
Justification of choice of data or description of measurement methods and procedures applied	Greater than 10 rounds of cross validation will provide sufficient training and validation to robustly assess the accuracy of the PM
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	γ'
Data unit	Tons (metric) ha^{-1}
Description	Predicted ALFB density
Equations	(8)(10), (11) and (12)
Source of data	Predictive Model, RS Metrics
Value applied:	N/A
Justification of choice of data or description of measurement methods and procedures applied	RS metrics are correlated with ALFB from SPs to derive a parametric model relating RS Metrics to ALFB
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	γ
Data unit	Tonnes (metric) ha^{-1}
Description	Observed ALFB density in SPs
Equations	(8)(10), (11) and (12)
Source of data	In-situ sampling
Value applied:	N/A
Justification of choice of data or description of measurement methods and procedures applied	Observed ALFB density is measured in the field at *in-situ* sample plots.

Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	n
Data unit	plot
Description	Number of VPs used validating the PM.
Equations	(8)(10), (11) and (12)
Source of data	N/A
Value applied:	15
Justification of choice of data or description of measurement methods and procedures applied	Ratio of CP to VP is based on Asner and Mascaro (2014)
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	t_{val}
Data unit	Unitless
Description	Two-sided Student's t-value for a confidence level of 90 or 95 per cent as required by the overarching methodology and degrees of freedom equal to the total number of sample plots within the ALFB estimation strata minus the total number of ALFB estimation strata
Equations	(18)
Source of data	N/A
Value applied:	N/A
Justification of choice of data or description of measurement methods and procedures applied	N/A
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	A_j

Data unit	Hectare
Description	Area of stratum *j* or the area of the entire AOI if stratification is not employed.
Equations	(19)
Source of data	Land use or land cover stratification or project boundary.
Value applied:	
Justification of choice of data or description of measurement methods and procedures applied	The size of the area to be sampled is critical to determining sampling intensity. Area should be measured using appropriate survey methods or, in the case where a linear boundary around the AOI or stratum area has been established, the use of standard mathematical methods for calculating the area of a polygon (stratum or AOI) should be used. This may be accomplished using Geographic Information Systems software.
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	A
Data unit	Hectare
Description	Total area of AOI consisting of j strata
Equations	(19)
Source of data	Land use or land cover stratification or project boundary.
Value applied:	
Justification of choice of data or description of measurement methods and procedures applied	The size of the area to be sampled is critical to determining sampling intensity. Area should be measured using appropriate survey methods or, in the case where a linear boundary around the AOI or stratum area has been established, the use of standard mathematical methods for calculating the area of a polygon (stratum or AOI) should be used. This may be accomplished using Geographic Information Systems software.
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

Data / Parameter	N

Data unit	unitless
Description	The number of strata *j* in AOI
Equations	(19)
Source of data	Land use or land cover stratification or project boundary.
Value applied:	
Justification of choice of data or description of measurement methods and procedures applied	The number of strata is necessary to calculate ALFB for the AOI
Purpose of Data	Determination of baseline scenario (for AFOLU methodologies, where relevant)
Comments	N/A

6.2 Data and Parameters Monitored

None.

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DOCUMENT HISTORY

Version	Date	Comment
v1.0	6 March 2015	Initial version