PV CLIMATE MODULE

PU006

Module for Development, Calibration, Validation and Application of Remote Sensing-based Models of Aboveground Biomass in Smallholder Agroforestry

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Contents

1 Summary

This *Module* provides a guidance for model calibration using *ground truth data* collection, remote sensing data, *Aboveground Biomass (AGB)* modeling, model validation, and implementation. It describes the minimum requirements and boundary conditions for *ground truth data* collection, the minimum requirement of spatial and temporal resolution of remote sensing data, and the minimum number of images and data sources necessary to achieve the desired model accuracy. The procedures involve model calibration using *ground truth data* collected following a stratified systematic sampling strategy. The strata for sampling should be based on relevant environmental variables and satellite data to ensure that the *sample plots* used for model training are representative of the *Project Areas*. The model should be built to link *ground truth data* with satellite imagery. It should be trained on features that are extracted from multiple satellite images to estimate *AGB* at a point in time. The model should then be applied to a set of satellite imagery covering the *Project Area* belonging to a *Smallholder*. The change in *AGB* of a particular *Project Area* should be then calculated by comparing *AGB* estimation from two time periods.

2 Sources

This *Module* applies the following *Tool*:

- **PT006** Tool for Ground Truth data Sampling v1.0

3 Definitions

All terms in this document follow the PV Climate Glossary and **PM002**.

4 Applicability Conditions

For this *Module* the applicability conditions of the *Methodology* **PM002** should be met.

5 Procedures

5.1 Model Development

This *Module* describes the minimum requirements and boundary conditions for *ground truth data* collection, the minimum requirement of spatial and temporal resolution, and the minimum number of images necessary to achieve the desired accuracy. An outline of the model development procedure is presented, followed by the procedure for model calibration, validation and implementation. These are not exhaustive and can be replaced by superior procedures when supported by scientific evidence. The *AGB* models developed under this *Module* must be accompanied by a peer-reviewed publication or a proof of independent model validation report outlining model soundness and accuracy. The models must be reproducible and representative of the full range of *AGB* in the *Project Areas*. The models have to demonstrate avoidance of overestimation of the *carbon benefit* through bias or conservative assumptions and parameters.

5.1.1 Minimum Model Soundness and Assurance Requirements

The model validation procedures and results must be described in the form of a third-party validation report or a peer-reviewed publication and must be available upon request by a reviewer or auditor. These should include:

- Information of the relevant *ecoregions* for which the model was calibrated at the time of validation;
- Number of *sample plots* used for model training, testing and verification;
- Model algorithm(s) for which the model was validated;
- Accuracy assessment based on the testing dataset represented in the form of R^2 and nRMSE.

In addition, description of the model validation procedures and results (accuracy in the form of R^2 and nRMSE) should include details of all relevant data sources and analysis if these are not described in publicly available, peer-reviewed literature.

An updated third party validation report with revision of model validation procedures and results has to be delivered in case of significant model change. Limited model changes are reported in the design document or process description document.

- Limited changes are those that meet one of the following four criteria:
  - The impact of the changes measured in R^2 is less than 0.2.
  - Change in nRMSE is less than 20% from the last version of the model before update.
  - There are no changes to the core model set-up or the purpose of the model.
  - Data is added as part of regular calibrations following the *Methodology* process

- If changes have a significant impact on model outcomes, i.e. greater than those outlined above, or include changes to model use or the core model set-up, new validation will be required.

5.1.2 Sample Plots for Ground truth Data Collection

Ground truth data from *sample plots* must be used to calibrate models for estimating *AGB* from satellite imagery. *Sample plots* used for model calibration must meet the following requirements:

1. *AGB* of plants with height > 1.3 meters should be measured. If species represent the same DBH and Height group, they can be counted and averaged as described in **PT006**.
2. *Sample plots* must be within the same *ecoregion(s)* as the *Project Areas* where the model will be applied.
3. The location of *sample plots* must be selected based on the model calibration strategy (see **PT006**).

5.1.3 Calculation of AGB from Ground Truth data

The parameter $AGB\ plot$ is used as an input for model development. A description of the full method of calculation on *ground truth data* can be found in *Tool* **PT006** (see **PT006** Section 5.2).

5.1.4 Remote Sensing Imagery

Possible sources of remote sensing data include, but are not limited to, those listed in Table 1 below. The minimum required spatial resolution for optical data is 30 m (as currently available with Landsat 8 and Landsat 9 products) (Irons et al., 2012). Sentinel-2 (Drusch et al., 2012) offer the (currently) recommended resolution of 10 m. Other missions with higher resolution (e.g. Planet Scope, 3 m or similar) can be used when meeting the requirements in this Section. Optical remote sensing data with resolution coarser than 30 m (e.g. MODIS 250 m products or similar) cannot be used independently.

The required specifications for radar remote sensing include C band, vv and vh polarizations with a spatial resolution of 5-20 m resampled to 10 m (or corresponding higher resolution of the multi-spectral optical sensor), i.e. from Sentinel-1 or similar. S band and L band with a resolution of 5-10 m and multiple polarization modes across its two radar bands can also be used (i.e. from The NASA-ISRO Synthetic Aperture Radar (NISAR) or similar). The upcoming ESA BIOMASS mission with P band and resolution of 250 m is (currently) not recommended for *Smallholder agroforestry monitoring* but can be used as a feature in model calibration. *AGB* products derived from remote sensing data, which meet the above criteria, can be used when accompanied by peer-reviewed publication and corresponding accuracy assessment per *ecoregion.*

For all remote sensing data used, established approaches for pre-processing must be applied to ensure adequate data quality for estimating *AGB* and supported by peer-reviewed literature. For example, remove cloudy pixels from the images or correct for terrain effects. For modelling, the required number and frequency of observations is 1 or more images per 12-day period from optical or radar sensors within the *Measurement Period* (Fremout et al., 2022). If remote sensing data of various resolutions is used, a single value must be extracted per sample for images with a resolution larger than 10 m. The median value of all pixels within the *Project Area* boundary is used to produce a single *AGB* value per *Project Area*. Include pixels only if their centroid is within the polygon (except if the resolution of the image is larger than the sample polygon). This method allows to combine data with different resolutions.

Table 1. Example sources of remote sensing data

Source	Application
Multispectral optical data	Sentinel-2 is a multispectral imaging mission from the European Space Agency (ESA) which samples 13 spectral bands with a revisit time of approximately 5 days at the equator. One of the mission objectives is the monitoring and detection of land change. Several parameters are derived from this data to increase the performance of the modeled *AGB* by validating vegetation presence and vegetation change on the *Project Area*. Sentinel-2 offers a higher revisit time and resolution data than NASA's Landsat mission. Landsat data would be used for calibration in case Sentinel data are not available.
Radar	Copernicus Sentinel-1 is a C-band synthetic aperture radar (SAR) sensor, providing continuous all-weather day-and-night imagery, mission from the European Space Agency. The consistent temporal radar observations from Sentinel-1 contribute to improved tracking of the state and dynamics of *AGB* globally. Several features are derived from this data to compliment Sentinel-2 data, especially where high quality Sentinel-2 images are not available due to cloud presence.

LIDAR	This technology uses laser light to create a 3D representation of the Earth's surface (or objects). Any type of LiDAR data (including terrestrial and space-born) can be considered, but due to feasibility and availability, the focus is currently on airborne LiDAR. Terrestrial LiDAR and imagery are an efficient way of deriving ground measurements. Using airborne LiDAR will be complimentary for ground measurements in model building and validation. Satellite-based LiDAR Global Ecosystem Dynamics Investigation (GEDI) may be used to assist model building.
Weather data	European Centre for Medium-Range Weather Forecasts (ERA5) provides hourly estimates of many atmospheric, land and oceanic climate variables. The data covers the Earth on a 30 km grid and resolves the atmosphere using 137 levels from the surface up to a height of 80 km. Quality-assured monthly updates of ERA5 (1940 to present) are published within 3 months of real time. Preliminary daily updates of the dataset are available within 5 days after the time of satellite overpass.
Future satellite missions*	The ESA's BIOMASS mission launched in 2025 will be the first mission to use P-band SAR measurements to determine *AGB* amounts stored in forests. Once the accuracy and quality of the data is fully tested, it has the potential to enhance model performance as an additional data source. Another future mission, NISAR, is set to launch in 2025. From NASA and the Indian Space Research Organisation (ISRO), this mission comprises L-band and S-band polarimetric SAR to monitor *AGB*, with a 6-day sampling time. As NISAR is designed for low-density vegetation, it could complement the BIOMASS mission once tested. NISAR and BIOMASS are distinct missions. NISAR will provide temporally dense, high-resolution radar data, similar to Sentinel-1, making it a more appropriate sensor for mapping. BIOMASS on the other hand, is an Earth Explorer mission that will offer limited coverage and is not intended for long-term operational monitoring. Hyperspectral sensors such as EnMAP, a German hyperspectral satellite mission, and the Italian Space Agency funded satellite PRISMA, also have the potential for contributing to enhanced estimation of *AGB*. **At the time of the publication, NISAR has not been launched or available for commercial use.*

The preferred satellite platforms include Sentinel-1 and Sentinel-2 (ESA) and Landsat (NASA) due to their global coverage and data continuity. These platforms have an operational lifetime of 12–20 years, and follow-up missions guarantee the long-term data continuity.

Airborne and spaceborne LiDAR data must be used as calibration/validation data. Discrete return LiDAR data must be acquired to generate a canopy height model. A digital elevation model (DEM) must be produced based on the ground returns, which must then be used to normalize all return heights. After normalization, the z value of each point will indicate the height from the ground to that point (Butler et al., 2021). A canopy height model must then be generated based on the normalized point cloud for the calibration/validation of ground truth height.

When airborne LiDAR is not available, alternative height data should be used. Such data can be acquired via in-field terrestrial LiDAR instruments (i.e. cameras or mobile devices), photogrammetric techniques from high-resolution stereographic imagery, and height values derived from peer-reviewed height maps, all accompanied by accuracy assessment and developed at the time of data collection (Tolan et al., 2023; Lang et al., 2023; Schwartz et al., 2024). Digitally derived height data can be used to verify and improve the quality of height derived from *ground truth data.*

5.2 Model Calibration

Models for estimating *AGB* from remote sensing imagery, typically following a machine learning approach, must be calibrated using *sample plot* data for each *ecoregion* they are applied to. A minimum of 30 *sample plots* must be used to train and calibrate the model for each *ecoregion*, The number of *sample plots* used for model calibration and accuracy assessment should be determined based on variability in the landscape and the desired level of precision, following a designed sampling strategy (**PT006**). The number of *sample plots* is independent from the extent of the *Project Areas*. Model calibration must use at least 1 optical and 1 radar image (David et al., 2022). At least one pixel must be fully contained within each *sample plot* used for model calibration. Pixels that have centroid outside the *sample plot* boundaries are excluded. Data combination is recommended where multiple sources of data are used as input to the model.

5.3 Model Validation

5.3.1 Validation Procedure

A validation dataset should be based on 20% or 30 of the *sample plots* per *ecoregion* (whichever number is higher) not used for model calibration, which are selected following a stratified systematic approach. The validation dataset must be representative of the sites and the *AGB* range to which the model will be applied.

This has to be demonstrated through the means of statistical tests. At *ecoregions* where 20% contributes to less than 30 *sample plots*, or representativeness cannot be demonstrated, cross validation methods including bootstrap, leave-one-out, or similar must be used.

Model performance must be assessed by calculating the coefficient of determination (R^2), and model error (nRMSE) based on the validation dataset. The normalized root mean square error is calculated as shown in Equation 1. The coefficient of determination is calculated following the equation in Steel et al., (1960).

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{n}(AGBplot_i - \hat{y}_i)^2}{n}} \Big/ y^{range}$$

Equation 1

Where:

$nRMSE$ = (Normalized) Root mean square error

$AGBplot_i$	= *Aboveground Biomass* density *Project Area i* (tonne/ha; see **PT006**)
$\hat{y}_i$	= Value of *AGB* density within *sample plot* estimated from remote sensing imagery
y^{range}	= Range of the ground truth *AGB* density value of *sample plots*
n	= Total number of *sample plots* used for model validation

The models developed must be accompanied by a peer-reviewed publication or a proof of independent model validation report outlining model soundness and accuracy (see Section 5.1.1). The models must be reproducible and reviewed and tested across the full range of *AGB*.

Accuracy Criteria

The minimum accuracy threshold of the model has an R^2 value of 0.7 and nRMSE of 30%, calculated on the validation set. If the minimum model accuracy is not met, the model cannot be applied to estimate *AGB,* and the model parameters and the *ground truth data* quality should be reassessed for potential re-collection.

5.4 Model Implementation

5.4.1 Estimating AGB

The required number and frequency of observations is 1 or more images per 12-day period from optical or radar sensors within the *Measurement Period*. The same features as the ones used for model calibration must be extracted from the remote sensing data for the *Project Areas*. Then the models, once calibrated, will be applied to these features to estimate *AGB*.

If models are unavailable (e.g. for a particular region images are not available, model does not meet accuracy), no value will be generated for the year of measurement.

The *Measurement Period* is determined by the dry season (Liang et al., 2023) (determined from precipitation data and *Project Coordinators* expert knowledge). For each *Project*, the average monthly precipitation data between multiple years from ERA5 must be used to determine the dry season with low precipitation for each *ecoregion*. The *Measurement Period* for each *Project* must be fixed at the end of the dry season when *ground truth data* collection takes place. It is also the period when *AGB* growth is at its lowest. This allows for a multi-year measurement if *Project Area uncertainty* does not meet threshold of 50%.

The change in *AGB* within the *Measurement Period* is referred to as $AGB_{\Delta,p}$ and estimated following Equation 2.

$$AGB_{\Delta,p} = AGB_t - AGB_{t-p}$$

Equation 2

Where:

$AGB_{\Delta,p}$	= Change in *Aboveground Biomass* within *Measurement Period p* (tonne)

AGB_t = *Aboveground Biomass* per *Project Area* at the most recent measurement point in time *t* (tonne)

AGB_{t-p} = *Aboveground Biomass* per *Project Area* at the most recent measurement point in time *t* minus *Measurement Period p* (tonne)

6 Parameters

Data/Parameter	$AGBplot_i$
Units	Tonne/ha
Description	*Aboveground Biomass* density *Project Area i*
Equations	Equation 1
Source	*Sample plots* (see **PT006**)
Value	N/A
Justification of choice of data or description of measurement methods and procedures applied	*AGB* that is measured via ground truthing used to evaluate model accuracy
Purpose of Data	Development and performance assessment of model for estimating *AGB* from satellite imagery
Comments	N/A

Data/Parameter	$AGB_{t,t-p}$
Units	Tonne
Description	Predicted *Aboveground Biomass* of a *Project Area* at the most recent measurement point in time *t*; Predicted *Aboveground Biomass* of a *Project Area* at the most recent measurement point in time *t* minus *Measurement Period p*, allowing for a multi year measurement if *Project Area uncertainty* does not meet the threshold of 50%.
Equations	Equation 2
Source	Remote sensing model
Value	Number
Justification of choice of data or description of measurement methods and procedures applied	The change in *biomass* needs to be adjusted for the *uncertainty* of the predicted *biomass* during the *Measurement Period*. Both these predictions have an *uncertainty* based on the model and *Project*.
Purpose of Data	Calculating *uncertainty* of the change in *biomass* per *Project Area*
Comments	-

Data/Parameter	n

Units	No unit
Description	Total number of *sample plots* used for model validation
Equations	Equation 1
Source	Project's calibration strategy
Value	N/A
Justification of choice of data or description of measurement methods and procedures applied	*Sample plots*
Purpose of Data	Development and performance assessment of model for estimating *AGB* from satellite imagery
Comments	N/A

Data/Parameter	$\hat{y}_i$
Units	Tonne/ha
Description	Predicted *AGB* density from the model within the *sample plot*
Equations	Equation 1
Source	Analysis of remote sensing imagery
Value	N/A
Justification of choice of data or description of measurement methods and procedures applied	It is used to compare with *ground truth data* for accuracy assessment
Purpose of Data	Development and performance assessment of model for estimating *AGB* from satellite imagery
Comments	N/A

Data/Parameter	y^{range}
Units	Tonne/ha
Description	Range of the ground truth *AGB* density value of *sample plots*
Equations	Equation 1
Source	The predicted *biomass* of the *sample plots*
Value	N/A

Justification of choice of data or description of measurement methods and procedures applied	It indicates the ground truth *AGB* density range. (Bayat, B., et al., 2016). y^{range} is used as a normalization factor. It describes the range of predicted *AGB* from the dataset (*AGB* minimum to *AGB* maximum). The normalization process ensures that the $NRMSE$ value is relative to the variability present in the dataset, making it more interpretable and facilitating meaningful comparisons between models or datasets with varying scales.
Purpose of Data	Development and performance assessment of model for estimating *AGB* from satellite imagery
Comments	N/A

7 References

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