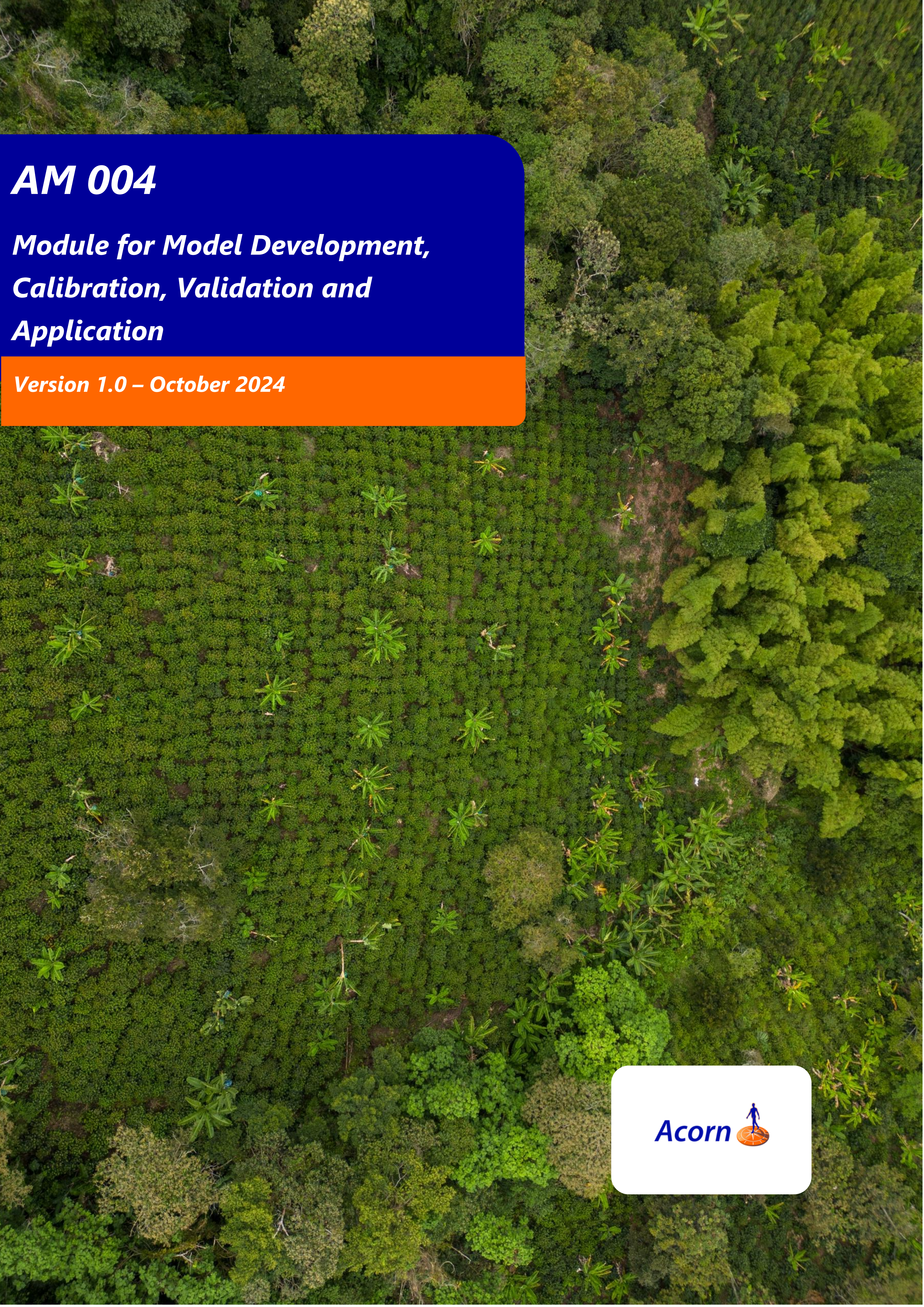

AM 004

Module for Model Development, Calibration, Validation and Application

Version 1.0 – October 2024

Acorn

Contents

1 Summary

This module provides a standard for model calibration using ground truth sampling, *biomass* modeling, model validation, and application. The model is calibrated using in-situ data collected following a stratified random sampling strategy. The strata for sampling are based on relevant environmental variables and satellite data to ensure that the *sample plots* used for model training are representative of the *project area*. The machine learning-based model is built to link *ground truth data* with satellite imagery. It is trained on features that are extracted from multiple satellite images to estimate *Aboveground Biomass* at a point in time. The model is then applied on a set of satellite imagery covering the *plot* of land belonging to a farmer. The change in *biomass* of a particular farm is then calculated by comparing *biomass* estimation from two time periods.

2 Sources

This module applies the following Acorn Module:

- **AM-003** Module for Ground Truth Sampling v1.0

3 Definitions

Definitions used in this module follow the latest version of the Acorn Glossary available on the Acorn website.

4 Applicability Conditions

For this module the applicability conditions of the Acorn Methodology **AM-001 v2.0** should be met.

5 Procedures

This module starts by describing the procedure of model development, followed by the strategy on how models should be calibrated, validated and applied.

5.1 Model Development

5.1.1 Sample Plots for Ground truth Data Collection

In-situ data from *sample plots* are used to calibrate models for estimating *biomass* from satellite imagery. *Sample plots* used for model calibration must meet the following requirements:

1. *Aboveground Biomass* 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 AM-003 . Plants below 1.3m should be counted, grouped per species, and averaged for height following the procedures in AM-003.
2. *Sample plots* must be within the same *ecoregion* of the *Acorn project* where the model will be applied.
3. The location of *sample plots* must be selected based on the model calibration strategy (**AM-003**).

5.1.2 Calculation of biomass from Ground Truth data

Biomass per tree is calculated with an appropriate allometric equation. The default equation is from Chave et al., (2014) . Th The Chave et al. (2014) equation uses three parameters, the DBH, height, and wood density. Wood density (in g/cm^3)) is a measurement of the amount of dry mass per volume of wood. Wood density differs per species. If two trees have the same dimensions (DBH and H), one tree can contain more *biomass*, since the mass per volume is higher, and vice versa. The data is then aggregated to estimate *biomass* per ha from all trees present in the one hectare *sample plot*. A description of the full method can be found in module **AM-003.**

5.1.3 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-2a, b and c offer the (currently) recommended resolution of 10 m or higher (Drusch et al., 2012). Optical remote sensing data with resolution coarser than 30 m (e.g. MODIS 250m products) 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 from Sentinel-1 sensor. S band and L band with a resolution of 5-10 m and multiple polarization modes across its two radar bands from NISAR. Upcoming ESA Biomass mission with P band and resolution of 250m is (currently) not recommended for smallholder farmer agroforestry monitoring but can be used as a feature in model calibration.

For all remote sensing data used, established approaches for pre-processing must be applied to ensure adequate data quality for estimating *Aboveground Biomass*. For example, remove cloudy pixels from the images or correct for terrain effects.. The desired temporal resolution is 1 or more cloud-free observations per 10-day period from optical or radar sensor. For modeling, at least 6 cloud-free images are required around the measuring date. Combine these images to create a composite (Fremout et al., 2022). If remote sensing data have a different resolution, a single value was extracted per sample for images with a resolution larger than 10 m. For Sentinel 2 data, take a median value of all pixels within the sample. We include the pixels only if their centers are within the polygon. This method allows you to combine data with different resolutions into a feature level.

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 which samples 13 spectral bands with a revisit time of 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 *biomass* by validating vegetation presence and vegetation change on the *plot*. 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 . The consistent temporal radar observations from Sentinel-1 are adding precious value to scientific efforts to track the state and dynamics of *biomass* 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 issues.
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. Ground-based 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 (GEDI) may be used to assist model building.
Weather data	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 to users within 5 days of real time.

Future satellite missions	The ESA's BIOMASS mission should be launched in 2024 and will be the first mission to use P-band SAR measurements to determine *biomass* amounts stored in forests. Once accuracy and quality of the data is fully tested, it has potential to enhance model performance as an additional data source. Another future mission, NISAR, is also set to launch in 2024. From NASA and the Indian Space Research Organisation (ISRO), this mission comprises L-band and S-band polarimetric SAR to monitor *biomass*, with a 6-day sampling time. As NISAR is designed for low-density vegetation , it could complement the BIOMASS mission once tested. Future hyperspectral sensors such as Enmap and PRISMA also have the potential for estimating *biomass*.

The two preferred satellite platforms are ESA and NASA satellites including Sentinel and Landsat constellations. These platforms have an operational lifetime between 12-20 years, as guaranteed by ESA and NASA. If and when they go offline, they will be followed by new and improved satellite missions, which will be compatible and transferable; such launches are planned by both space agencies.

LiDAR data are used as calibration/validation data. Discrete return LiDAR data are acquired to generate canopy height model. The point cloud data contain coordinates, intensity, return number, number of returns and GPS timestamps of the return. A digital elevation model (DEM) is produced based on the ground returns, which was then used to normalize all return heights. After normalization, the z value of each point indicated the height from the ground to that point (Butler et al., 2021). A canopy height model is then generated based on the normalized point cloud for the calibration/validation of ground truth height.

5.2 Model Calibration

Machine learning models for estimating *Aboveground Biomass* from remote sensing imagery must be calibrated using *sample plot* data for each *ecoregion* they are applied to. A minimum of 30 *sample plots* must be used to calibrate the model for each *ecoregion*, and a further set of at least 20 *sample plots* not used for model calibration must be used for model validation to assess model accuracy. The number of *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 (**AM-003**). The number of *sample plots* is independent from the size of the *project area*. Model calibration must use at least 6 images. 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.

5.3 Model Validation

5.3.1 Validation Procedure

A validation dataset should be based on 20% stratified randomly selected *sample plots* per *ecoregion* not used for model calibration. The validation dataset must be representative of the sites to which the model will be applied. Alternatively, cross validation methods including bootstrap, leave-one-out, or similar can 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.

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \Big/ y^{95th}$$

Equation 1

Where:

$nRMSE$ = (Normalized) Root mean square error

y_i = Measured value of *biomass density* within *sample plot*

$\hat{y}_i$ = Value of *biomass* density within *sample plot* estimated from remote sensing imagery

y^{95th} = 95^{th} percentile of the in-situ *biomass* density value of *sample plots*

n = Total number of *sample plots*

Independent validation of each new model update must be performed before it is accepted for use in the production environment.

Model performance must be evaluated at least every 3 years in case of significant changes in data use or a significant amount of data is added during an *Acorn project's Crediting Period*. This evaluation is performed using R^2 and nRMSE as described above. Every new or optimized model, whether improved or with modified accuracy from the current model in place, must be evaluated following the same procedure.

5.3.2 Accuracy Criteria

The expected accuracy of the model has an R^2 value of 0.7 and nRMSE of 30%, calculated on the validation set. If the expected model accuracy is not met, the model cannot be applied to estimate *biomass*. We will reassess the model parameters and the *ground truth data* quality for potential re-collection. The program Acorn relies on models to ensure its scaling potential. If modeling is not possible, or a model is not available, the program will not operate in the area where this is true.

To complete VVB verification, the model validation procedures and results must be described in the form of a report and must be available upon request by a reviewer or validator. Description of the model validation procedures and results (accuracy in the form of R2 and nRMSE) should include details of all relevant data sources and analysis if these are not described in publicly available, peer-reviewed literature. If additional validation of the model is requested by the VVB, this can be performed following a standard auditing procedure at location.

5.4 Model Application

5.4.1 Estimating Biomass

Aboveground Biomass is estimated using a machine learning model (Shen et al., 2022). The model is applied to a composite of multiple images at the *Measurement Period*. A minimum of 6 cloud-free images must be available to estimate *biomass* per year. The same features are extracted from the remote sensing data for the *plots*. Then the machine learning models, once trained, are 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), it is also possible to estimate *biomass* using the *ground truth data* approach.

The measurement date is determined by the dry season (Liang et al., 2023) (precipitation data and *Local Partner's* expert knowledge). For each *Acorn project*, the average monthly precipitation data between multiple years from ERA5 is used to determine the dry season with low precipitation for each *ecoregion*. The measurement date for each *Acorn project* is fixed at the end of dry season when *ground truth measurements* take place. It is also the period when *biomass* growth is at its lowest.

The change in *biomass* within the *Measuring Period* is referred to as delta *biomass*.

6 Parameters

Data/Parameter	n
Units	No unit
Description	Total number of *sample plots*
Equations	Equation 1
Source	Acorn'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 *biomass* from satellite imagery
Comments	N/A

Data/Parameter	y_i
Units	Tonne/ha
Description	Ground truth value of *biomass* density within *sample plots*
Equations	Equation 1
Source	*Sample plots (see AM-003)*
Value	N/A
Justification of choice of data or description of measurement methods and procedures applied	*Biomass* that is measured via ground truthing used to evaluate model accuracy
Purpose of Data	Development and performance assessment of model for estimating *biomass* from satellite imagery
Comments	N/A

Data/Parameter	$\hat{y}_i$

Units	Tonne/ha
Description	predicted *Aboveground Biomass 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 *biomass* from satellite imagery
Comments	N/A

Data/Parameter	y^{95th}
Units	Tonne/ha
Description	95th percentile of value of *plot biomass density of sample plots*
Equations	Equation 1
Source	*Sample plots*
Value	N/A
Justification of choice of data or description of measurement methods and procedures applied	95th percentile indicates the ground truth *biomass* density range excluding outliers.
Purpose of Data	Development and performance assessment of model for estimating *biomass* from satellite imagery
Comments	N/A

7 References

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Shen, J. *et al.* (2022) 'Machine learning-based modeling approaches for estimating pyrolysis products of varied biomass and operating conditions,' *Bioresource Technology Reports*, 20, p. 101285. https://doi.org/10.1016/j.biteb.2022.101285.