



Plan Vivo Approved Approach:

Automating forest carbon quantification

March 11th, 2021



Overview

Title	Plan Vivo Approved Approach: Automating Forest Carbon Quantification
Developer	Taking Root
Approved Approach Type	Quantifying carbon stocks in live forest biomass for baseline and project intervention scenarios using a combination of field and remote sensing data.
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Applicable Project Types	Afforestation; Reforestation; Agroforestry
Applicable geographical area	Tropical/subtropical forests
Carbon pool/emission source included	Above-ground woody biomass; Below-ground woody biomass
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1 Summary

Smallholder reforestation is indispensable in the fight against climate change. Yet, the funding necessary to make reforestation projects possible depends on the ability to demonstrate successful project outcomes, and herein lies the challenge. Quantifying the carbon stocks in trees using robust scientific methods on thousands of farms—typical of smallholder reforestation projects—is traditionally expensive, time-consuming and requires a high-level of expertise. As a result, smallholder reforestation projects struggle to scale due to difficulties in providing robust evidence of successful outcomes.

This document describes Taking Root's Plan Vivo Approved Approach (hereinafter "The Approach") that makes it simple to quantify and report the carbon in live forest biomass (hereinafter "carbon estimates") for baseline and project intervention scenarios using a combination of field and remote sensing data. The Approach uses robust scientific methods while making it simple for non-technical experts to generate carbon estimates across thousands of farms using only a mobile phone, a web browser, and a measuring tape. This document was approved by the Plan Vivo Foundation in November 2022, while the technology review is still underway.

The Approach holds significant potential for advancing the aims of the Plan Vivo Standard and its certified projects. First, it provides a solution for existing Plan Vivo projects to scale their impact cost-effectively by reducing internal costs while creating carbon credits with greater transparency and traceability for the market. Second, it will help attract new Plan Vivo projects by providing an off-the-shelf solution which makes it simple for them to adhere to many of Plan Vivo's carbon certification requirements. Third, by enabling existing projects to scale and attracting new projects, this Approach will unlock access to the carbon market for large numbers of smallholder farmers, helping establish Plan Vivo's leadership in the market for smallholder carbon certification.

Once fully implemented, The Approach makes creating carbon estimates as simple as walking the perimeter of a farmer's land (hereby known as a parcel) using the mobile application and syncing the data. Moments later, certifiable carbon estimates are available on the web application. The Approach does not allow for the calculation of leakage, additionality and the risk buffer which are the other values needed for generating a carbon credit.

The Approach consists of:

- Four Workflows which describe how The Approach generates carbon estimates using a combination of human input and Tools,
- A series of Tools for how to unambiguously implement the specific components of The Approach by following a step-by-step process,
- A technology Platform that automates the Tools and workflows while making gathering the right inputs to generate carbon estimates simple for users in the field. The Platform consists of a mobile application, a web application and a cloud processing and data storage engine.



The first Workflow creates carbon estimates using field data. The user maps a farmer's area of land (hereinafter "a parcel") simply by walking its perimeter using the mobile app, which will automatically create a series of sampling plots within the parcel. The user then records all the trees within the sampling plot by noting their species and measuring their size. When an internet connection is available, the mobile phone is synced and all the calculations to create carbon estimates are automated.

The second Workflow automates the acquisition, pre-processing, and labelling of remote sensing and auxiliary data. Historical, contemporary, and continuous multi-spectral and radar data over the mapped parcels are acquired, cleaned, and composited so that only the best data is available. It is then matched with the field data from the first Workflow. Localized auxiliary data such as topographic, climactic, and other data are then added to the dataset.

The third Workflow automatically calibrates a machine learning algorithm using the data from the second Workflow to build a carbon prediction model using only remote sensing and auxiliary data. It then applies the algorithm to the remote sensing data to make a carbon prediction.

The fourth Workflow combines the remote sensing estimates from Workflow 3 and the field data estimates from Workflow 1 and creates localized carbon estimates and associated statistical precision (hereinafter 'precision') estimates for all parcels in a project, including those that have never been visited before.

Taking Root hopes its Approach will help accelerate the restoration of the world's forests by unlocking access to carbon markets for millions of farmers across the tropics.



2 Introduction

Reforestation is the only proven human activity capable of removing carbon dioxide from the atmosphere at the scale required to limit global warming to 1.5° C (IPCCC, 2018). And reforesting within agricultural landscapes in the tropics offers some of the greatest potential to mitigate climate change (Bastin et al., 2019) due to the amount of land available and the growth rate of the trees (Zomer et al. 2008; Griscom et al. 2017). Much of this agricultural land is owned and managed by smallholder¹ farmers (Graub et al. 2016). Smallholders are often more successful at reforesting more land and planting a greater variety of species than the corporate sector (Del Lungo, Ball, and Carle, 2006).

At the same time, there is large demand for forest restoration. It is forecast that by 2030 the carbon market for natural climate solutions will be worth \$100 billion USD per year (Aminetzah, D, 2021), which represents an amazing opportunity for smallholder farmers. Brands with climate commitments are seeking investible opportunities to remove carbon through natural climate solutions like agroforestry and reforestation. However, this market has historically been out of reach for smallholder farmers resulting in a lost opportunity to improve livelihoods, restore forests and reverse climate change.

One of the major barriers preventing smallholders from reforesting more land is accessing the necessary funding. This funding could be achieved through the creation and sale of forest carbon removals, but the complexity of quantifying and reporting the carbon stocks and fluxes in a way that is certifiable make this challenging. This complexity comes from the requirement of expert-level knowledge and tools (e.g., remote sensing, programming, field data collection and design, statistical analysis, machine learning modelling, etc.), which are rarely available to smallholder groups. Even when these resources are available, the cost of sending monitoring crews to 1) collect field measurements across hundreds or thousands of farms across large swaths of land and 2) process that information afterwards often consumes scarce project resources.

The recent proliferation of global satellite imagery and advancements in machine learning offers new possibilities for measuring the impact of reforestation efforts more cost-effectively with fewer boots on the ground. However, technological advancements are not a panacea. Localized field information is indispensable to calibrate machine learning models to interpret remote sensing data. (Consider the difference between what a boreal forest and a tropical forest look like from space or even the same tropical forest in the dry season versus the wet season.) Beyond just identifying forests and their characteristics, the carbon content within trees varies significantly between different types of forests and other vegetation cover types. For these reasons, a global one-size-fits-all solution to interpreting satellite imagery without field data collection is grossly inadequate for creating credible impact assessments at the smallholder scale. Furthermore, field information captures information critical to the successful management of smallholder carbon projects which is either impossible or hard to obtain from remote sensing in smallholder contexts. For example, obtaining seedling counts on parcels, tracking forest

¹ A smallholder is a small farm operating under a small-scale agriculture model.



management practices and managing farmer visits can only be readily done with robust ground information.

These challenges are why Taking Root created its Approach, a series of Tools automated by a turn-key technology platform that enables smallholder carbon forestry projects to quantify carbon accurately and cost-effectively. The Approach uses the latest scientific methods, advanced machine learning models, and satellite and localized data to create the most accurate carbon estimates. Despite this complexity, the only hardware required to harness the Approach is a mobile phone, a measurement tape, and a rope.



3 Relationship to Other Approved Approaches

As outlined in Table 1 below, the Taking Root Approach complements existing Plan Vivo Approved Approaches with minimal overlap. The "Small-Holder Agriculture Monitoring and Baseline Assessment" (SHAMBA) tool facilitates the creation of office-based projections to calculate the amount of carbon stored in individual trees, whereas the Taking Root Approach estimates the amount of carbon on a Parcel or Project at a given moment in time. The "Plan Vivo Approved Approach for Estimating Reference Emission Levels" (EREL) and the "Estimation of Climate benefits from REDD in community-managed Forests" (ECB REDD) provide a flexible methodology for estimating carbon stocks using remote sensing data. Similarly, the Taking Root Approach implements specific tools to come to a similar result.

Table 1 - Similar Approaches and Tool

Approach	Project Intervention	Purpose	Commonality with The Approach
Small-Holder Agriculture Monitoring and Baseline Assessment (SHAMBA)	afforestation, reforestation, agroforestry, agricultural land management	Estimation of emissions and removals for: 1) the baseline scenario; 2) project interventions	Tool for estimating carbon using field measurements
Plan Vivo Approved Approach for Estimating Reference Emission Levels (EREL)	Prevention of deforestation	Approach for estimates of: 1) the baseline deforestation rate; 2) the initial carbon stock	Methodology for estimating carbon and forest cover using remotely sensed data
Estimation of Climate benefits from REDD in community Managed Forests (ECB REDD).	REDD in community-managed forests	Estimates for: 1) baseline scenario emissions; 2) project scenario emissions; 3) leakage; 4) expected climate benefit	Methodology for estimating carbon and forest cover using remotely sensed data

The key defining feature of the Taking Root Approach is its technology platform that automates the execution of a series of Tools so that it is simple to create carbon estimates without the need for highly skilled carbon experts. Its users are field staff and managers that work for smallholder reforestation projects, not technical experts working in an office.

Furthermore, it should be noted that The Approach is not a carbon methodology, but rather a combination of Workflows, Tools, and a Technology Platform that fit within a carbon methodology. The Approach does not facilitate other key components necessary for calculating the number of sellable carbon removals, such as risk buffers, leakage and counterfactuals used as part of a baseline scenario, etc. Such values are often derived using behavioural, historical, and economic values that do not lend themselves as easily to automation.



4 Approach Focus and Applicability Conditions

The Approach provides a framework for quantifying the amount of carbon sequestered from tree restoration activities such as afforestation, reforestation, and agroforestry.

The Approach facilitates the following activities:

Conducting periodic field measured forest monitoring to estimate and report the carbon stocks in live forest biomass at the tree, sampling plot, parcel, planting design and project levels as part of a baseline scenario assessment or monitoring event.

Determining the carbon stock in live forest biomass both historically and into the present using remotely sensed data as part of a baseline scenario assessment or monitoring event.

Assessing the net change in forest carbon stock (i.e., carbon removals or emissions) between two time periods.

The temporal applicability conditions of the Approach are as follows. It provides historical estimates from remote sensing data starting in late 2016 and annually thereafter. This date is chosen because it uses satellite images from the European Space Agency's Sentinel-1 and 2 missions, which only started publishing images as of that date. Sentinel data is the best source of remote sensing data due to its global coverage, high-quality imagery (16 bands multi-spectral and radar), high revisit frequency (weekly but composited to create annual estimates), relatively high resolution (20 m), and low cost (i.e., free). The Taking Root team will continue to evaluate innovative remote sensing data sources as they become available to meet the requirements of The Approach.

The geographical applicability conditions of the Approach are global. However, its current emphasis is pan-tropical because the Approach is optimized for smallholder agricultural contexts, which are more prevalent in the tropics. In addition, the biomass models utilized for the tree allometry equations are almost exclusively from the tropics.

The Approach does not allow for the calculation of leakage and risk buffer - other values needed for generating a carbon credit.



5 The Taking Root Approach

Figure 1 below provides an overview of how The Approach uses four Workflows to produce carbon estimates using remote sensing and field data. Figure 1 provides a section reference to later in the document for more details on each task. The following is a high-level description of the four Workflows.

- Workflow 1 takes user-collected field data from specific parcels to produce carbon estimates using field data only.
- Workflow 2 retrieves remote sensing data, pre-processes them to create the Best Available Pixel (BAP), and labels them with the corresponding field data.
- Workflow 3 applies the remote sensing data and auxiliary data used for region-specific attributes to create remote sensing carbon estimates for every pixel that does not intersect with the field data estimates.
- Workflow 4 combines the remote sensing-based estimates with the field data estimates and creates parcel-level carbon values and precision estimates.

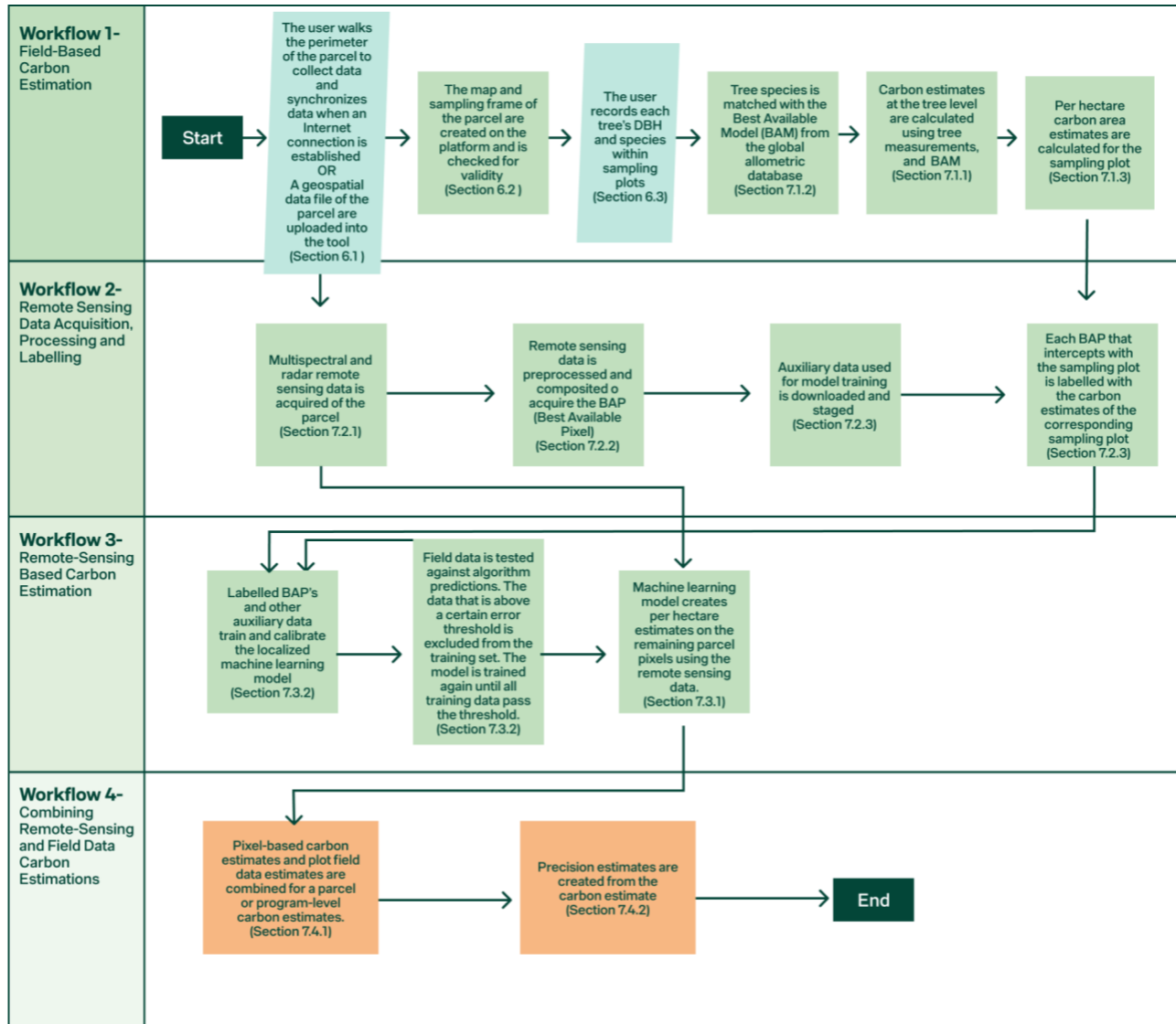


Figure 1 – The four Workflows of The Approach. Blue squares represent tools, whereas green parallelograms represent user inputs and orange parallelograms represent outputs.

The following section describes the user procedures for using the Platform.



6 Procedures For Using The Technology Platform

The sections below describe the steps required for users of Taking Root's technology platform to start producing carbon estimates. It is important to note that the mobile application was designed for rural smallholder farming contexts where cellular reception is often unavailable. As such, all the activities on the mobile application outlined below can be conducted offline and later synced to the web platform when service becomes available.

The following sections describe the three steps for using the technology platform: 1) mapping a parcel, 2) setting up the sampling plots, and 3) collecting tree measurements in the plots.

6.1 Mapping a Parcel

Parcels of land need to be mapped to create carbon estimates as mapping is used to identify the spatial area used in the analysis. The mapping can either be done by importing an existing geospatial file (e.g., a polygon) into the web platform or by walking the parcel's perimeter using the mobile application, which uses the phone's GPS and a series of algorithms to smooth positional errors caused by fluctuations in satellite signals.

The Approach requires that parcels are associated with a farmer that holds the rights to the carbon and responsibilities for managing the land. As such, a farmer first needs to be entered in the Platform before a Parcel can be mapped.

Instructions for adding a Farmer to the Platform are available here:

https://www.dropbox.com/s/o97s2hil5i6krzi/Printout_Eng_Adding_Farmers_In_FARM-TRACE.pdf?dl=0

Instructions for adding a Parcel using the mobile app are available here:

https://www.dropbox.com/s/fu8yaqrtb6n3fsg/Printout_Eng_Adding_Parcels_In_FARM-TRACE.pdf?dl=0

6.2 Setting the Sampling Frame

The Approach uses a sampling-based methodology to estimate the total carbon in a project. This methodology reduces the resources needed on the ground to generate forest carbon estimates compared to a census approach (i.e., having to count every single tree in a project). A sampling frame needs to contain an adequate number of sampling plots to ensure the estimates are within the precision targets of the project. To ensure that the Approach can reach the project target, a customized sampling frame is set up for each planting design entered into The Approach. Setting the sampling frame identifies the size, location and density within the parcels where trees are to be measured. When setting the sampling frame, a balance needs to be struck between the resources required to perform on the ground inventories vs the precision targets of the carbon estimates generated.



Taking Root's software platform automates the creation of a sampling frame using circular sampling plots for every new parcel mapped. The system administrator of each program can pre-configure the radius of the sampling plots and the target number of plots per hectare for each type of planting design (i.e. Technical Specification) used by that project. A planting design consists of a homogenous planting design, management objectives (e.g. low elevation shade-grown coffee, high elevation shade-grown coffee, etc.), and a carbon model

The Platform then uses an algorithm to overlay a grid of circular fixed radius sampling plots with a random start on the parcel and iteratively increases or decreases the spacing between plots until it converges to the desired user-defined density, as illustrated in Figure 2. If it cannot converge, it keeps the iteration that is as close as possible to the desired sampling density. The sampling frame is then added to the map of each parcel on the mobile application to facilitate field data collection.

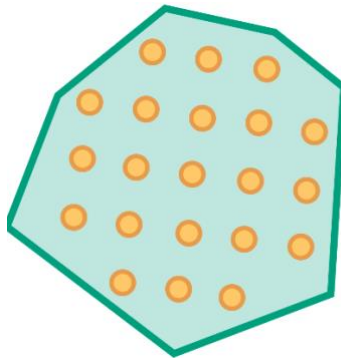


Figure 2 – Circular sampling plots arranged in a systematic grid with random start within a parcel

6.3 Collecting Tree Measurements

Collecting tree measurements to estimate biomass is the next step in creating carbon estimates. Taking Root's mobile application includes forms to enter tree measurements within individual sampling plots. To record trees' measurements, the mobile application user locates individual sampling plots within a parcel using the built-in web application map view to measure and record various tree attributes of all the trees within the plot. At a minimum, the user inputs the following data:

- Tree species
- Height for trees less than 1.3 meters in height
- DBH for trees above 1.3 meters

When recording the tree species, the user selects the correct species from a pre-set selection defined by the system by the system administrator. If the user cannot identify the tree species, there is an option to select "unknown species".



When users input tree measurements through the mobile application, the tree species they select will be cross-referenced against the Platform's database of hundreds of above-ground biomass (AGB) models to select the best available model (BAM) and calculate tree-level estimates as further described in Section 7.1,

The choices of tree species available to mobile users is set by the system administrator and are specific to the trees found within individual projects. The system administrator can pre-set tree species available for selection, based on the software platform's master list of tree species which includes tree species from around the world. Using the web application, the system administrator assigns tree species from the master list to be available within the project.

Instructions for how to collect tree measurements within the Platform are available here:

https://www.dropbox.com/s/9brg3p3zgd6y9/Printout_Eng_Conducting_field_monitoring_with_FARM-TRACE.pdf?dl=0

Instructions for best practices in recording a tree's DBH is available here:

https://www.dropbox.com/s/g4peo2dv1vao3op/Eng_Field_Monitoring_Best_Practices.pdf?dl=0

A guidance document for preparing to collect field measurements is available here:

https://www.dropbox.com/s/mz8vvchs6isk6eo/Printout_Eng_Preparation_guide_for_field_monitoring.pdf?dl=0



7 Quantification of Carbon Estimates

The Approach harnesses the full power of both field and remote sensing data to make it as simple as possible to create carbon removals from smallholder reforestation projects.

The use of remote sensing data alone to quantify carbon stored in live forest biomass offers numerous advantages in terms of cost, frequency, and coverage but also has several disadvantages which this Approach addresses using field data.

- First, remote sensing cannot accurately detect certain features essential to a project's overall success. For example, it cannot estimate metrics such as TPH and BAHA at an accuracy required in the first years after trees are planted. This is often essential for determining if a newly planted parcel is on track to achieve its carbon stock projections and as a basis of payment to farmers.
- Second, remote sensing data need to be trained using field data that is representative of the areas being assessed, which accounts for local ecology and the choice of tree species, which is expensive but automated through this Approach.
- Finally, carbon estimates using remote sensing estimates alone often lack the precision needed to make robust claims, especially over smaller areas typical of smallholder reforestation projects.

Using field data alone resolves the challenges outlined above but can be costly and requires all parcels to be monitored to create estimates. Therefore, by combining remote sensing and field data, the challenges of using either method alone are resolved while bringing about more precise carbon estimates.

The following five sections describe the tools within the Taking Root Approach for quantifying carbon estimates by combining remote sensing and field data:

- Section 7.1 describes the Workflow 1 for quantifying field-based carbon estimations in live forest biomass using field measurements at the individual tree and sampling plot level.
- Section 7.2 describes the Workflow 2 for acquiring, processing, and labelling remote sensing and auxiliary data using the field data so that it can be used to train a machine-learning algorithm (MLA).
- Section 7.3 describes Workflow 3 for using an MLA to create carbon estimates using remote sensing data.
- Section 7.4 describes Workflow 4 for combining the field data and remote sensing carbon estimates and creating a confidence interval from these estimates.



7.1 Quantification of Carbon Estimates Using Field Data

7.1.1 Tree-level Carbon estimates

Carbon estimates for individual trees (C_t) is determined by Equation 1 and expressed in terms of kilograms of CO_2 such that:

$$C_t = (AGB + BGB) \times F_c \times M \quad (1)$$

Where:

AGB = Above-ground biomass (kg)

BGB = Below-ground biomass (kg)

F_c = Fraction of carbon within the biomass set to a constant value 0.47 (IPCC, 2006)

M = Ratio of the molecular weight of carbon dioxide (CO_2) to carbon (C) set at a constant of 44/12 (USDA, 2014)

The following sections describe the tools for quantifying the carbon estimates

7.1.2 Tool for Selecting the Best Available Model (BAM) for above-ground biomass (AGB)

This Tool determines the best available model (BAM) for calculating the above-ground biomass (AGB) of individual trees based on Taking Root's extensive database of models and the field measurements available. The field measurements are obtained when users of the mobile application measure trees in the field. At a minimum, users need to measure the tree's diameter at breast height (DBH) but preferably enter the species, if known. Height measurements are optional. If the height is not measured, it is estimated using a global height prediction model using DBH as the independent variable (Feldpausch, 2012). Taking Root's database of AGB models is an extensive and curated collection of published species-specific, genus-specific and globally applicable tropical tree models. The database is continuously updated as new research becomes available and curated to only include high-quality models using the following set of rules:

- Inputs are constrained to their model's minimum and maximum values when the selected model is exponential to avoid runaway estimates at the extremes. Sigmoidal and linear models are not similarly constrained.
- Models are rejected if their average value diverges from the Chave global model (Chave et al., 2014) by more than 1000% or less than -90% for DBH values of 5, 25 and 50 cm.
- A minimum allometric model sample size of 40 is needed for any allometric model to be selected from the database. Recent literature suggests that 40 is the minimum needed for viable allometric models (Roxburg, 2015).

Each model includes the following additional information to determine the appropriateness of the model for any individual measured tree:



- The sample size used to build the models,
- The DBH range used to build the model,
- The height range used to build the model,
- The country(ies) the data was collected from
- The Koppen-Geiger climate type where the data was collected
- The model's functional form

Figure 3 provides the decision tree used to select the BAM. Species-specific models are selected if the tree specie is known and available. A genus-specific model is selected if a species-specific model isn't available. As a catch-all, the global tropical tree model from Chave et al. (2014) is used for unknown species or when no species-specific or genus-specific model is available.

There are a few other high-level rules for the model selection:

- If there are multiple models for the species or genus, the algorithm will match the model in the following priority: 1) Koppen class (i.e. climate zone), 2) the country, and 3) the sample size of the model, where the minimum sample size is 40.
- The algorithm will only select a model if the tree's dbh and height values fall within the dbh and height range of the selected AGB model.

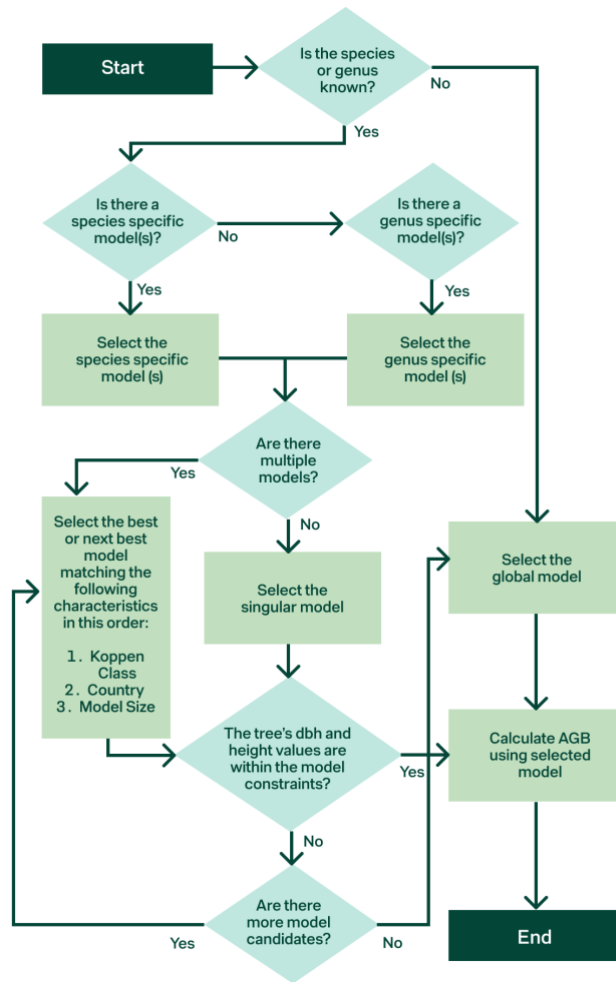


Figure 3 – Decision tree for which biomass models to use.

The below-ground biomass (BGB) for individual trees is calculated using the BAM. Given the lack of BGB models in the literature, only three models are currently being used for tropical dry, moist, and wet forests (IPCC, 2006). The appropriate mode is automatically selected based on cross-referring the GPS coordinates of where the tree measurement was collected with the global 1 km resolution precipitation database, WorldClim 2 (Fick, 2017).

7.1.3 Sampling Plot Level Carbon Estimates using Field Measurements

Carbon estimates for individual sampling plots (C_{sp}) are determined by Equation 2 and expressed in terms of tCO_2/ha . In simple terms, it is the sum of carbon in all the individual trees within the sampling plot.

$$C_{sp} = \left(\sum_{j=1}^n \frac{Ct_j}{1000} \right) \times \frac{10,000}{A_{sp}} \quad (2)$$



Where:

C_{t_j} = the amount of carbon in j^{th} tree (KG)

n = the number of trees within a sampling plot

10000 = the area of a hectare (m^2)

1000 = the ratio of the weight units kilograms to tonnes

A_{sp} = the area of the sampling plot (m^2)

Plot-level carbon estimates also train the machine learning algorithm (MLA) to interpret remote sensing data, as described in the sections below.

7.2 Acquiring, Pre-Processing, and Labelling Remote Sensing Data

The Platform completely automates the process of acquiring and processing historical, contemporary, and ongoing remote sensing and auxiliary data over time as it becomes available for every parcel within a project.

The acquired and processed data is used for two purposes. The first is for labelling data so that it can be used to train the machine learning algorithm to create carbon estimates using remote sensing data by matching it with the field carbon estimates at the plot-level described in Section 7.1. The second is to provide the input used to create carbon estimates using remote sensing data using the model built by the machine learning algorithm.

The processes for acquiring remote sensing and auxiliary data, for pre-processing remote sensing data and for labelling the data are described using the four tools described below.

7.2.1 Tool for Acquiring Remote Sensing Data

This Tool determines the types, location and frequency of remote sensing data acquired.

Types of remote sensing data: Two types of remote sensing data are acquired. The first is synthetic aperture radar (SAR) acquired from the European Space Agency's Sentinel-1 mission. Sentinel-1 operates in C-band (5.6 cm) wavelength, which provides a metric of forest structure, especially sparse and low biomass vegetation. While Sentinel-1 operates with different acquisition modes, this Tool works with the strip-map mode that provides coverage with a 5 m by 5 m resolution. The second is multi-spectral optical imagery acquired from the European Space Agency's Sentinel-2 mission. Sentinel-2 provides multi-spectral data with 13 bands in the visible, near-infrared and shortwave infrared parts of the electromagnetic spectrum.

Location of data acquisition: All pixels are acquired that have any overlap with the geometry of every parcel within the project.



Frequency of data acquisition: All available data is acquired. For Sentinel-1, the repeat cycle is every 6 days. For Sentinel-2, the repeat cycle is every 5 days

7.2.2 Tool for Pre-Processing Remote Sensing Data

This Tools describes the two pre-processing phases of the remote sensing data (i.e. Sentinel 1 and 2) so that quality data is available for analysis, even in **very cloudy regions of the world**. In the first phase for the Sentinel-2 data, a standard algorithm is used on each image to mask and remove clouds covering individual pixels. Anything above 5% cloud cover or other forms of atmospheric contamination is removed. No additional processing is performed for Sentinel-1 data.

In the second phase of pre-processing remote sensing data, composites are created, and only the best available pixels (BAP) are selected for analysis, as illustrated in Figure 4. To do so, all scenes from Sentinel 1 and 2 within the selected date range are stacked and the median value from each band from across the entire stack is selected. This median compositing Approach further removes the remainder of clouds, their shadows, and other types of "noise" that were not detected in the cloud mask.

The full stack encompasses all the pixels within a year of retrieval. This stack ensures a large dataset of scenes from which we can extract the BAP. For example, a mapped parcel reanalyzed on January 15th will have data from January 16th of the previous year. Therefore, the Platform will likely have 12 images acquired in this timeframe. See Figure 4 for a visualization of image stacking to create BAPs.

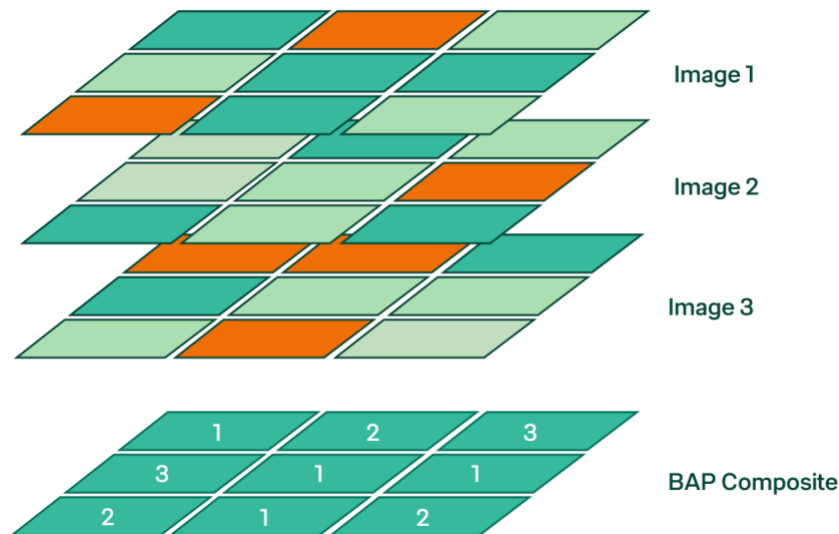


Figure 4 – Example creation of a composite. Teale polygons represent the best available pixel (BAP) from the stack of three images. The white numbers within the composite represent from which image the BAP is composed. All other pixels are discarded.



7.2.3 Tool for Acquiring Auxiliary data

This Tool is used to acquire localized information from global datasets beyond what is observed from space to account for some of the diversity in forest ecologies across the tropics that could be correlated with the carbon stocks in live forest biomass. This information is obtained from the datasets listed in the table below by cross-referencing the spatial data coordinates with the spatial coordinates of each parcel.

Table 2 - Example variables harnessed in the MLA

Data type	Source	Resolution	Justification
Mean annual precipitation	WorldClim (accessed through Google Earth Engine)	5 km	Precipitation plays a foundational role in growth potential and species distribution
Elevation	NASADEM (accessed through Google Earth Engine)	30 m	Elevation profoundly shapes the distribution and growth form of plants. Elevation is also correlated with several other important variables such as temperature.
WWF's Terrestrial Ecoregions of the World	Olson et al (2001)	Variable	To account for the various forest ecologies of the world
Slope	Global ALOS Landforms accessed through GEE (Theobald, 2015)	30m	Determine slope position, ridge vs upper slope e.g., which can affect plant growth and stress.
Drought	TerraClimate accessed through GEE (Abatzoglou, 2018)	5km	Drought can reduce plant growth.

7.2.4 Tool for Labelling Data

This Tool describes the process used to label the remote sensing data with carbon values obtained from the field data. This labelling is needed to train a machine-learning algorithm to create carbon estimates in areas or time periods where field data is not available.

The first step is to match the circular sampling plots of various sizes with the pixels from the remote sensing data, as illustrated in Figure 5. To do so, rectangular plot windows are created by selecting all the BAPs that have any spatial overlap with the sampling plots. It is common for a sampling plot to overlap more than one BAP. See Figure 5 for examples of this intersection.

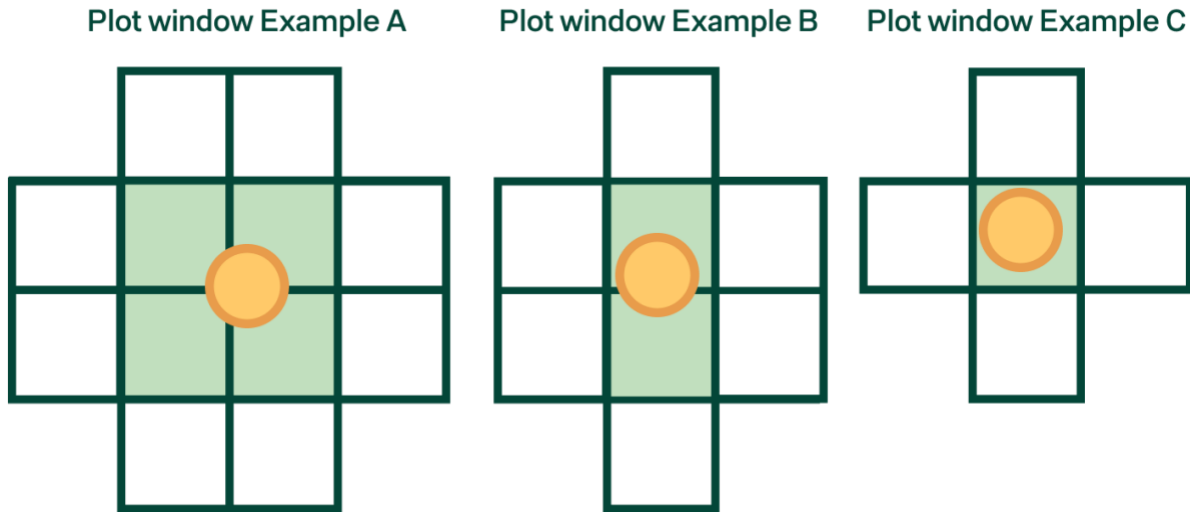


Figure 5 - Plot Window Examples - Green Squares are the BAPs that are part of the plot window. White squares are non-plot window BAPs. The yellow circle is the sampling plot.

The second step is to assign the sampling plot's carbon value (C_{sp}) to its corresponding plot window (C_{pw}) such that:

$$C_{pw} = C_{sp} \quad (3)$$

The plot windows will serve as the dependent variable when creating the carbon model and are a crucial step in training the MLA.

7.3 Remote Sensing Based Carbon Estimates

7.3.1 Creating the carbon estimates

Remote sensing-based carbon estimates (C_{rs}) are created based on a machine learning algorithm (MLA) that is trained on high-quality data using a combination of field data as the observed dependent variable as a function (f) of remote sensing data (rs), auxiliary data (aux), and project-specific variables ($PROJECT$) such that:

$$C_{rs} f(rs, aux, PROJECT). \quad (4)$$

Once trained, the MLA is applied and produces remote sensing-based carbon estimates (C_{rs}) for individual pixels for all historical and contemporary BAPs that intersect with any proportion of any parcel's geometry within the project that do not already have a remote sensing-based carbon estimate (C_{BAP}) such that:

$$C_{rs} = C_{BAP} \times \frac{A_{BAP_overlap}}{A_{BAP}} \quad (5)$$



Where:

$A_{BAP_overlap}$ = Area of the BAP that intersects with the parcel (m²)

A_{BAP} = Area of the BAP (m²)

The overlap between BAPs and the parcel's geometry is illustrated in Figure 6 below. The blue polygon represents the parcel's geometry, the turquoise square represents the area of the BAP, and the darker shaded area of the BAP represents the area that overlaps with the parcel.

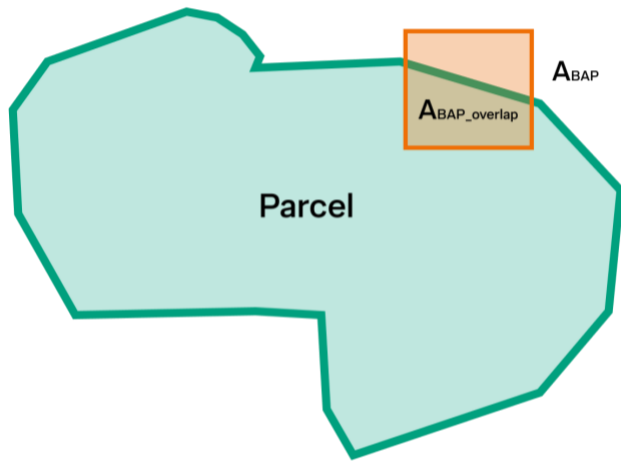


Figure 6 - Overlap between a parcel's geometry and a BAP

The MLA results are constrained by upper and lower bounds to avoid the model creating impossible results. At the lower bound, the model is constrained to zero such that it can't create negative carbon values. At the upper bound, the maximum carbon prediction is at 3 times the largest carbon estimate from the field data (Halperin et al., 2016). These bounds temper any effects that an erroneous input may have on plot estimations.

Newly trained MLA are released on a regular basis based on the latest dataset available as users across the Platform add new field data and applied to the newly available scenes such that new results are always produced using the latest MLA.

How the MLA is built and how high-quality data is obtained to train it is explained in the sections below.

7.3.2 Calibrating the Machine Learning Algorithm (MLA)

The machine learning algorithm (MLA) is designed to create the best possible carbon estimates. Its objective function is to minimize the mean percentage error and mean absolute error between the carbon values measured in the field and those predicted by the algorithm while minimizing large under and over predictions (e.g. less than 30% mean percent error). To measure error the full dataset is randomly divided into two groups: one for training the model and the other to compare how well the model performs outside of the dataset used to train it.



The MLA is trained using three categories of independent variables: remote sensing data, auxiliary data, and project-specific data. These project-specific variables allow a pan-tropical model to account for the unique characteristics of individual projects and the incredible diversity that exists in forest ecologies around the world.

The type of MLA is dynamic and updated periodically based on reducing the mean percentage error (i.e. the model fit) as new data becomes available across different projects. Examples of MLAs include LASSO and Random Forest.

7.3.3 Ensuring high-quality data is used to train the machine learning algorithm

To avoid low-quality data from being used as inputs to train the MLA, an exclusion algorithm prevents certain data from being used as inputs. The exclusion algorithm is important given that the data labelling is not done purposefully by experts but rather by opportunistically repurposing data collected by numerous mobile app users based on a random sampling design.

The exclusion algorithm excludes two types of low-quality data from being used as inputs. The first is non-representative data due to high heterogeneity. This data type occurs when the sampling plots are located at the intersection of irregular vegetation covers, which can confuse the training of the MLA. For example, if a sampling plot falls on the boundary of a forest and a field or if a user is in a forest, but the GPS error of their phone places them in a field right beside the forest. The second is falsified data. This occurs when a user enters tree data from a sampling plot without visiting the sampling plot or by entering tree data when there are no trees.

Two conceptual methods are used to detect low-quality data from being used as inputs: data triangulation and statistics. Data triangulation detects inconsistencies between the various types of field data collected. For example, if the distance between the location of the sampling plot and the GPS coordinates of the mobile phone is greater than the positional error reported by the phone, the field data is likely non-representative. Statistics detect large divergences between what is reported in the field and what is predicted in the model, primarily informed from what is observed from the remote sensing data. For example, if a user reports that they are in a forest, the remote sensing data implies that the data was collected in an open field. The exclusion algorithms continually develop over time as the Platform gathers more reference data and empirical evidence.

7.4 Combined Remote Sensing & Field-Based Carbon And Precision Estimates

7.4.1 Parcel-Level and Project-Level Combines Carbon Estimates

Combined remote sensing and field-based carbon estimates at the parcel level (CCp) are simply the sum of the field-based carbon values on plot windows (Cpw) measured within the last 12 months and the remote sensing values at the pixel-level (Crs) such that:



$$CCp = \sum_{w=1}^{n_{pw}} C_{pw_w} + \sum_{s=1}^{n_{rs}} C_{rs_s} \quad (6)$$

Where:

n_{pw} = the number of plot windows within the parcel

n_{rs} = the number of remote sensing pixels within the parcel without overlap with the plot windows

Figure 7 illustrates how remote sensing and field-based carbon estimates are combined. The green boxes represent the carbon values from the plot windows, and the blue areas of the turquoise boxes represent the carbon values from the remote sensing data. For parcels that have no field data collected within the last 12 months, the carbon values are entirely based on remote sensing data. The more field data collected, the greater the ratio of field data used to create the total carbon estimate.

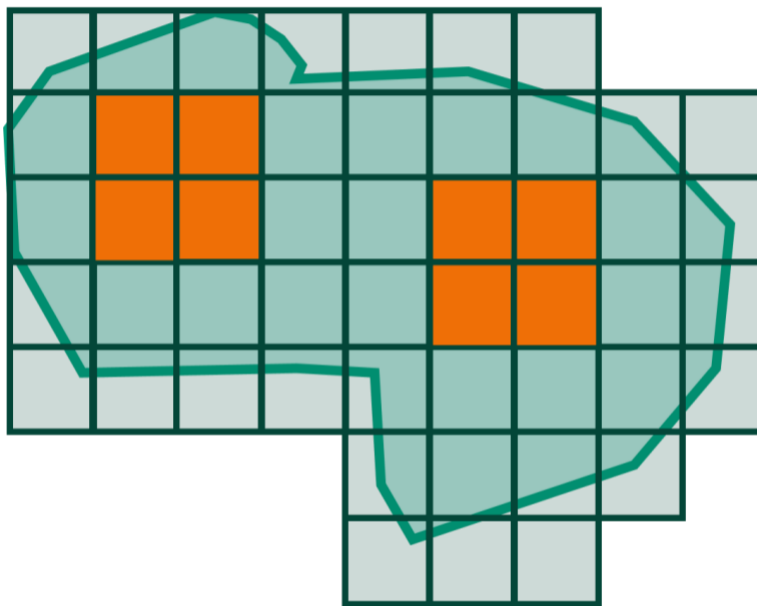


Figure 7 - Combining remote sensing and field estimates

Carbon estimates are also created for groups of parcels so that estimates can be reported at the parcel-level, farmer-level, project-level, or any other combination of parcels simply by summing the carbon values across parcels.

7.4.2 Confidence Intervals

The Approach creates confidence intervals around the carbon estimates based on the errors observed between the values obtained in the field data and the values predicted by the MLA. The confidence intervals define a range of values within which the user can be 90% confident that the actual estimate lies.



Challenges to applying a classical Approach

Often, confidence intervals are created using classical parametric statistics, which assume a certain distribution of values. Considering the field data collected, there are a few challenges in creating confidence intervals using this method.

Empirically, there are a few challenges:

- 1) Data from field monitoring typically has a skewed (power-law) distribution, with some plots having a bunch of trees but a significant number having zero recorded trees (e.g., if they're in the middle of a field or unplanted area).
- 2) There is likely spatial autocorrelation in measurement within a parcel that will erroneously deflate the confidence intervals.
- 3) Trees and carbon estimates are truncated at zero (i.e. one can't have negative carbon or trees). A parametric approach assumes continuous values that can fall below zero.
- 4) To calculate project level precision, heterogeneous groups - such as different planting designs - need to be sampled. Creating confidence intervals from heterogeneous sampled groups can create biased estimates.

Addressing these challenges through bootstrapping

Nonparametric bootstrapping uses sampling with replacement of an original dataset which is used to generate repeated samples resulting in an approximate distribution of the population of interest. The Approach follows a bootstrapping technique, which helps address these issues because bootstrapping:

- 1) is very robust to skewed data (Efron et al., 1994);
- 2) can easily be adapted to account for "clustering" and spatial autocorrelation (Harden, 2011);
- 3) handles upper and lower bounds by design, as a bootstrapping technique resamples from the empirical data;
- 4) is non-biased when sampling from heterogeneous groups.

Application of the bootstrap to various groups

Carbon estimates are aggregated into various groups for bootstrapping. Some examples of these groups are:

- Parcel-level
- Planting Design-Level
- Vintage
- Project-Level
- Remote-sensing data only (from pixel data)
- Field Data only (from plot data)
- Combined Remote Sensing and Field Data

Conditions for bootstrapping



Bootstrapped precision is estimated for any planting design where at least 50 plots have been monitored. It is important to note that parcel-level bootstrapping resamples from its group cohort.

Steps in bootstrapping

Bootstrapping is created using the following algorithm:

1. Draw a resample of size n (where n = number of plots within a group) with replacement from the sample of carbon per hectare (tCO₂/ha) from plots within the same group ($\{X_1, \dots, X_n\}$).
2. Set number of realizations(m) to be performed, minimum m of 100.
3. Run realizations m times to get a distribution for each group, $\theta^*1, \dots, \theta^*n$.
4. Compute the average of carbon per hectare of each group across realizations:
 $sum(carbon\ per\ hectare)/m$
5. Compute percentiles parcel carbon average from step 4 for each group. For a 90% confidence interval, the percentiles are 5th and 95th.

Where:

- For monitored plots, carbon per hectare plot field data (tCO₂/ha) is used
- For non-monitored plots, carbon per hectare (tCO₂/ha) remote sensing predictions of the plot window is used



8 User Input required

The software platform automates the selection of all necessary parameter types a project would need—including geographic location, tree model allometries, and environmental and geographic data—when creating carbon estimates, with only one exception: the sampling frame parameters. The sampling frame parameters need to be reported in Plan Vivo project design documents when using the Approach.

The parameters include includes:

- The size and shape of the monitoring plot (e.g., circular with a 10-metre radius)
- What will be measured in the monitoring plots (e.g., trees with DBH > 5 cm, etc.)
- The density of monitoring plots per hectare (e.g., 5 per hectare)
- The planned frequency of field monitoring (e.g., every five years).



9 Conservativeness

The Approach was designed to create unbiased estimates; they are neither optimistic nor conservative. However, Section 5.11 of the Plan Vivo Standard (2013 version) states that "... the level of uncertainty must be factored into the level of conservativeness applied in the accounting method for quantifying ecosystem services." To ensure that projects under The Approach are adequately conservative, uncertainty adjustments² are applied at the level stated by the latest version of the Plan Vivo Standard.

² An example adjustment: In a project where the lower bound confidence interval was 70% of the estimated value, $U = 0.7$. Therefore, the adjustment would be $0.25 * (0.7 - 0.5) = 0.05$, so the estimates the project could claim would be reduced by 5%.



10 Associated Projects and Carbon Removals Potential

There is an opportunity for 200 million hectares of forest to be restored across the globe (Bastin, 2019). One of the largest pieces of this opportunity lies with smallholder farmers in the tropics, who can grow trees alongside their existing crops. Forest restoration could be one of the most effective solutions to the climate crisis, while also providing innumerable benefits to people and local ecosystems.

However, forests will only be restored if farmers can improve their livelihoods by growing trees. Selling the carbon that trees remove from the atmosphere could unlock new and diversified revenue streams for farmers. However, historically they have not been able to access the carbon market due to the small and fragmented nature of their farms and the complexity of developing the rigorous carbon baseline scenarios and reporting needed to achieve carbon certification.

The Approach outlined in this document has been specifically designed to remove many of the historic barriers facing smallholder farmers wanting to create certified carbon credits, advancing the aims of the Plan Vivo in three ways: First, it provides a solution for existing Plan Vivo projects to scale their impact cost-effectively by reducing internal costs while creating carbon credits with greater transparency and traceability for the market. Second, it will help attract new Plan Vivo projects by providing an off-the-shelf solution which makes it simple for them to adhere to many of Plan Vivo's carbon certification requirements. Third, by enabling existing projects to scale and attracting new projects, this Approach will unlock access to the carbon market for large numbers of smallholder farmers, further establishing Plan Vivo's leadership in the market for smallholder carbon certification.

The potential that carbon removals generated by The Approach could enable is substantial and could benefit four main Plan Vivo stakeholders: program developers, buyers, auditors and farmers. For program developers, this Approach could conceivably be used across all applicable Plan Vivo programs. As of January 2021, The Approach is being used by Taking Root's CommuniTree Carbon Program in Nicaragua and piloted by Ecotrust's Trees for Global Benefit Program in Uganda. These are the two largest Plan Vivo programs and demonstrate The Approach's usefulness at scale. Other existing and prospective Plan Vivo programs have expressed interest in adopting The Approach.

For buyers, The Approach provides greater levels of transparency and rigour being demanded by the market. This will unlock greater market access and higher prices for Plan Vivo carbon credits. Major buyers have already expressed their desire that other projects adopt The Approach so they can create carbon credits which meet their purchasing requirements.

For auditors, The Approach offers the potential to facilitate independent audits of carbon projects remotely, which is particularly valuable during pandemics, violence, and areas of political instability. This is because many of the Platform's estimates are created independently,



which are partially calculated from remote sensing data that does not require human field visits once a project-specific machine learning model is generated. Furthermore, all data and reporting are centralized in our web application which is accessible to anyone anywhere in the world with login credentials.

Finally, and most importantly, The Approach will benefit smallholder farmers. By making it easier to create Plan Vivo carbon credits, it will unlock new and diversified revenue streams for farmers restoring forests. It is our hope that The Approach will enable millions of farmers to improve their livelihoods from growing trees, resulting in enormous climate impacts and revitalizing local ecosystems around the world.



11 Development Team

The Platform is developed and continuously maintained by a full-time and growing team of professional software engineers.

The scientific methods in The Approach were developed by a team of academics described below with expertise in smallholder forestry, forest statistics, GIS, and remote sensing.

Kahlil Baker, Ph.D. | Executive and Lead Forest Scientist at Taking Root

Kahlil Baker is a founder, Executive Director and lead forest scientist at Taking Root with 20 years of experience developing solutions for tropical deforestation. He is also the co-founder of Taking Root, The Tool's parent organization, an award-winning multimillion-dollar impact-driven enterprise connecting thousands of smallholder farmers to international carbon markets. He created the Tools to replicate the same impacts at scale by automating scientifically robust monitoring and reporting across smallholder farms and connecting them to markets in a simple and easy way. He was selected and featured on the CBC as part of Canada's next generation of changemakers. For his work at Taking Root, he also received the Meritorious Service Cross, one of the highest honours from the Governor-General of Canada. Kahlil's Ph.D. work at the University of British Columbia was on the economics of smallholders' forestland-use choices. Kahlil also holds an MSc in forestry statistics from the same university, a BA in economics from Concordia University, and a permaculture design certificate.

Ignacio San-Miguel, Ph.D. | Remote Sensing Specialist at Hatfield Consultants

Dr. Ignacio San-Miguel is a remote sensing scientist with strong skills in machine learning and big-data analytics and more than seven years of experience in international consulting and academic settings. Ignacio holds a Ph.D. in remote sensing at the University of British Columbia, a Master of Science in forestry engineering from the University of Valladolid, and a B.Sc. in the same field from the Polytechnic University of Madrid, where he gained a strong foundation in ecosystem dynamics, modelling and landscape ecology/connectivity analyses.

Ignacio is an expert using Python and Docker to automate workflows involving processing/fusing large datasets from LiDAR, optical and radar sensors, time-series analysis, cloud computing, and testing and validating machine and deep learning algorithms. Ignacio's application experience includes disturbance mapping, forest recovery, land cover classification and change detection analyses. Before completing his Ph.D., Ignacio spent nearly two years at the Joint Research Centre (JRC) of the European Commission, working on remote sensing applications as an analyst programmer. His tasks included coordinating the acquisition, analysis, and processing of images from different very high-resolution satellite sensors supporting the implementation of the European Union Community Agricultural Policy.

Trevor Jones, Ph.D. | Geospatial Scientist & Advisor at Ostrom Climate

Trevor is a senior geospatial consultant with 15+ years of experience using remotely sensed data and field measurements to map, measure and monitor forested ecosystems around the world and in the tropics. He oversees all geospatial requirements and forest carbon components of international projects for NatureBank, including feasibility studies in the Philippines and Costa



Rica. In Madagascar, while working with the marine conservation NGO Blue Ventures, Trevor helped establish the Blue Forests Project leading to their flagship Plan Vivo conservation project in Velondriake (Tahiry Honko). Trevor also helped establish and currently advises the University of British Columbia's Professional course-based Master of Geomatics for Environmental Management (MGEM) Program. Trevor holds a BA in Geography and an MA in GIS from Clark University and a Ph.D. in Forest Resources Management from the Integrated Remote Sensing Studio in the Faculty of Forestry at the University of British Columbia (UBC).

David Baumann, MPA | Director of Methodology and Standards at Taking Root

David leads a team of data analysts and forest researchers to create science-based methodologies, metrics, and tools for projects on the Taking Root platform. His team also ensures that our Approach aligns with industry standards. David has extensive experience of working with carbon and environmental data, having spent six years developing forest carbon projects with smallholder farmers at Taking Root and working as a Senior Analyst at Dunsy Energy and Climate Advisors. He holds a Master's in Public Affairs from the University of Texas at Austin.

Jason Barker, Ph.D. | Forest Researcher at Taking Root

Jason maintains and improves the accuracy of Taking Root's carbon modelling capabilities using a fusion of field and remote sensing data. He previously worked as a Research Forester at the US Forest Service Forest Inventory and founded AltaLarix Consulting. Jason has a Ph.D. in Forestry at the University of British Columbia.

Jacob Model Ph.D. | Director of Product and Engineering at Taking Root

Jacob helps prioritize and build new products and features on Taking Root's technology platform. Previously, he worked as the Vice President of Product and Data at Community Connect labs, where he helped governments and non-profits revolutionize service delivery through mobile messaging. Jacob holds a Ph.D. in Organizational Behaviour Studies at the Stanford Graduate School of Business.



12 Funding

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13 Signature

Signed for and on behalf of:

Name of entity: Taking Root

Signature: _____

Name of signatory: Kahlil Baker, PhD

Date: _____

14 Glossary

This document was written using a balance of technical terms necessary for scientific experts with terms accessible and relevant to everyday practitioners. For this reason, the authors have attempted to limit the use of acronyms and minimize technical jargon.



15 Abbreviations

The following acronyms are used throughout and are defined as follows:

- **AGB:** Above ground biomass, a measure of the dry weight of all components of a tree that are above ground (i.e. everything other than a tree's roots);
- **BAHA:** Basal area per hectare, a commonly used measurement for biomass density in an area of land. Expressed in squared meters;
- **BAM:** Best available model, the best equation available within Workflow 1 to quantify AGB and BGB given the amount of data available;
- **BAP:** Best available pixel, the best available pixel obtained from the remotely sensed data that Workflow 2 uses to create assessments;
- **BGB:** Below ground biomass, a measure of the dry weight of all components of a tree that are below ground (i.e. all the tree's roots);
- **DBH:** Diameter at breast height, a standard measurement where the diameter of a tree is measured at 1.3 metres from the ground;
- **MLA:** Machine learning algorithm, a procedure used to estimate carbon values of remotely sensed data.
- **MRV:** Monitoring, Reporting and Verification
- **PDD:** Project Design Document, used by the Plan Vivo Standard.
- **REDD:** Reduced Emissions from Deforestation and Degradation
- **TPH:** Trees per hectare, a measure of the count of trees in a hectare of land.



16 Definitions

The following terms are used throughout and are defined as follows:

- **Above-ground Biomass:** Living biomass above the soil, including the tree's stem, stump, branches, bark, seeds and foliage, expressed as dry weight
- **Additionality:** The benefits from a project intervention are additional if they would not be achieved in the absence of the Project.
- **Afforestation:** The direct human-induced conversion of land that has not been forested for a period of at least 50 years to forested land through planting, seeding and/or the human-induced promotion of natural seed sources
- **Agroforestry:** An ecologically based natural resource management system in which trees are integrated in farmland and rangeland
- **Baseline Scenario:** The most likely future scenario for land use and land management in a project area in the absence of project intervention(s).
- **Below-ground Biomass:** Living biomass of live tree roots, sometimes excluding fine roots of less than 2 mm diameter because these often cannot be distinguished empirically from soil organic matter or litter
- **Bootstrapping:** Bootstrapping is a statistical procedure that resamples a single dataset to create many simulated samples. This process allows for the calculation of standard errors, confidence intervals, and hypothesis testing
- **Carbon Credit:** A credit for emissions reductions given to one party that can be sold to another party to compensate for its emissions
- **Carbon Estimate:** Shorthand for the more accurate but longer "estimates of carbon stocks in live forest biomass." The two terms should be understood inter-changeably
- **Carbon Model:** A statistical or mathematical model that estimates the carbon sequestered in forest biomass.
- **Carbon Removals:** A carbon credit that represents the creation of carbon pools/sinks that sequesters carbon dioxide from the atmosphere
- **Carbon Pool:** A system that can store or release carbon, including above-ground biomass, below-ground biomass, litter, dead wood, soil organic carbon and harvested wood products.
- **Carbon Stock:** The quantity of carbon held within a pool, measured in tonnes of CO₂
- **Confidence Interval:** a range of values so defined that there is a specified probability that the value of a parameter lies within it.
- **Forest Monitoring:** Forest monitoring or inventory is the systematic collection of data and forest information for assessment or analysis
- **Forest Restoration:** the process of improving the health, productivity, and array of life of a forest



- **Leakage:** Net changes of anthropogenic emissions by GHG sources that occur outside the project or program boundary, but are attributable to the project or program
- **Live Forest Biomass:** The aggregation of above-ground and below-ground tree biomass in a forest
- **Machine Learning Algorithm:** The method by which an artificial intelligence system conducts its task, generally predicting output values from given input data
- **Permanence:** Maintenance of the project benefits beyond the crediting period. The period for assessment of non-permanence of Carbon Benefits is dependent on the standard.
- **Planting Design:** The species, density and rotation details of a planting intervention.
- **Platform:** The Platform consists of a mobile application, a web application and a cloud processing and data storage engine
- **Plot Window:** The remote sensing geospatial data that intersect with the sampling plot in a project
- **Precision:** Precision refers to how closely individual measurements agree to each other, the lower the CV, the more precise the values.
- **Project:** A smallholder land-use project using the Approach
- **Project Intervention:** a human-based activity that directly results in the growing of trees and restoration of forests
- **Smallholder:** A small farm or farmer operating under a small-scale agriculture model.
- **Reforestation:** The direct human-induced conversion of non-forested land to forested land through planting, seeding and/or the human-induced promotion of natural seed sources on land that was once forested but has been converted to non-forested land
- **Remote Sensing:** Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft).
- **Risk Buffer:** A reserve of climate services generated by Plan Vivo projects but not eligible to be sold as Plan Vivo Certificates, to protect against unexpected losses of carbon stocks or increases of emissions
- **Sampling frame:** The source from which a sample is drawn. For projects using The Approach, the source is the trees located in the generated sampling plots.
- **Sampling Plot:** A subset of an area of land in a smallholder farm used to represent the land as a whole for statistical sampling.
- **Tools:** A tool unambiguously implements the specific components of The Approach by following a step-by-step process
- **Vintage:** The set of GHG emission reductions or removals generated by a project or program during a single vintage period



- **Vintage Period:** The period for which a particular set of GHG emission reductions or removals generated by the project or program are verified
- **Workflow:** A description of how The Approach generates carbon estimates using a combination of human input and Tools



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