DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Robotics, Cognition, Intelligence

End-to-End Aboveground Biomass Estimation with Deep Learning and RGB Drone Imagery

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End-to-End-Schätzung der oberirdischen Biomasse mit Deep Learning und RGB-Drohnenbildern

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I confirm that this master's thesis in robotics, cognition, intelligence is my own work and I have documented all sources and material used.

Munich, 15.01.2022 Gyri Reiersen

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Abstract

While writing this thesis, the United Nations General Secretary declared "Code Red for Humanity" as a response to the published Intergovernmental Panel on Climate Change (IPCC) report [IPC21]. The deterioration of the natural world is unparalleled in human history and a key driver of the climate crisis and the sixth extinction[CE18]. The last 20 years, we have lost a the size of Europe of forest area accounting for 18% of global anthropogenic emissions [Han+13; IPC19]. Reducing deforestation, restoring ecosystems, and natural sequestrating of carbon is, therefore, utterly urgent.

To finance the restoration of forest ecosystems, many turn to carbon offsets. While demand is increasing, supply of carbon offsetting projects is low [Bla+21; KH21; Mar21]. The certification process for carbon offsetting projects is time and labor intensive, especially for Monitoring, Reporting, and Verification (MRV) of the forest carbon stock. In addition to the high upfront capital required, this is preventing small-scale foresters and farmers to access to the market [LLK19].

As recent research has shown, current manual practices allow for a systematical overestimation of forestry carbon credits [Bad+21; Wes+20]. There is thus a need for higher quality carbon offsetting protocols and more transparency and accountability in the MRV of the forest carbon stock [Hay+20]. In the last years, remote sensing and Machine Learning (ML) has been used to estimate biomass [NPM20; Dao+19]. However, these algorithms risk additionally contributing to the systematic overestimation of carbon stocks, unless they are transparently validated [Dun+19].

Combining remote sensing and ML has great potential to increase the quality of MRV of forestry carbon offsets and can play a key role in scaling natural carbon sequestration at the speed necessary to mitigate climate change. While satellite data is abundant, high-quality field data is rare and necessary for the training of these models. Until satellite imagery achieves a higher resolution, drone imagery offers more accurate features, especially in the spatial domain of fine-grained classification.

In this thesis we present 1) a methodology to build ML ready benchmark datasets from field data and drone imagery, 2) a benchmark of the quantified overestimation of current satellite-based maps highlighting the need to audit the algorithms and data to avoid systematic wrong estimations, and 3) a baseline biomass estimation Convolutional Neural Network (CNN) model that performs better than the alternative Low-Resolution (LR) satellite maps by leveraging High-Resolution (HR) drone imagery.

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1. Introduction

1.1. Scope

The thesis focuses on the following scope:

- **end-to-end estimation**
  - avoid the information bottle neck of indirect estimations through tree metrics such as Diameter at Breast Height (DBH) and species
- **of Aboveground Biomass (AGB)**
  - "ground truth" available through manual forest inventory and citizen science
  - preferred over carbon due to ambiguity in conversion and no increase in accuracy
- **of individual trees**
  - tree-based approaches show potential for increased accuracy compared to plot-based biomass estimations [Gra+18]
  - requires tree instance detection and mapping with field data, and therefore limited to open canopy forests
- **in tropical**
  - largest forest cover in the world [FAO20]
  - lack of available data and research due to geographic inaccessibility and structural challenges
- **Agriculture, Forestry and Other Land Use (AFOLU) projects**
  - one of the standard types of carbon offsetting and with high potential for scalability
  - need for accountability of MRV
  - agroforestry is a simple starting point for individual tree estimations due to open canopy and limited species diversity as all trees are planted

  - financial incentives, to certification upfront cost for farmers

- **through drone**
  - trade-off for low cost and HR
  - reduces time and cost for forest inventory compared to manual labor
  - HR (1cm/px) compared to current LR satellite imagery (>1m/px), as a first step to a global monitoring scheme

- **Red, Green, and Blue (RGB) imagery**
  - high availability and low cost compared to hyperspectral imagery and LiDAR alternatives
  - proof of concept, if high accuracy is achieved with the RGB-only solution, then additional data sources can only improve it

1.2. Thesis Structure

This thesis starts off with chapter 2 to give the context of the climate crisis, the role of forestry and biomass as climate mitigation strategy and biodiversity. Chapter 3 describes the current manual forest inventory methodology and the different remote sensing approaches to it, and relevant forestry tasks. In Chapter 4, we present the **ReforesTree** dataset and how we pre-processed it to become a ground-truth for individual tree AGB and carbon. The main contributions of this thesis are described in chapter 5 together with the results. The conclusions of the thesis are outlined in chapter 6 and in chapter 7 we discuss future work and improvements on the methods and models.

2. Background

In this chapter we provide the broader context of forest biomass and its role in the climate crisis and for biodiversity. Additionally, we outline the financial and verification schemes for reforestation and its relevance to remote sensing. This is important to understand the scope and focus of this thesis.

2.1. Forestry's Role in Climate Change and Biodiversity

The degradation of the natural world is unprecedented in human history and a key driver of the climate crisis and the Holocene extinction [CE18]. Forests play a significant role in the planet's carbon cycle, directly impacting local and global climate through their biogeophysical effects and, as carbon sinks, sequestering and storing carbon through photosynthesis [Gri+17].

2.1.1. Tropical Forests as Ecosystems

Tropical forests make up 45% of the world's forests and have the highest carbon uptake [FAO20]. They additionally account for around 70% of global gross forest sink[Pan+11]. However, since the year 2000, we have lost 361 million ha of forest cover, equivalent to the size of Europe, mainly in tropical areas [Han+13]. This accounts for 18% of global anthropogenic emissions and contributes to driving up atmospherical carbon levels [IPC19].

Forests, especially tropical forests, also provide habitats for 80% of land-based biodiversity and with the increasing risk and frequency of wildfires, droughts, and extreme weather, forest ecosystems are under severe pressure [Shi+21].

2.1.2. Climate Mitigation Strategy

To avoid planetary health tipping points [Roc+09] and maintain a stable and livable climate, mankind urgently need to reduce carbon emissions until 2050 and restore essential ecosystems [IPC21]. Forests and natural carbon sequestration are important climate change mitigation strategies [CR08] with a biophysical mitigation potential of 5,380 MtCO2 per year on average until 2050 [IPC19]. Most forest carbon is found in the living biomass (44 percent) and soil organic matter (45 percent), with the remainder in dead wood and litter [FAO20]. Restoration of forests and increasing the living biomass have the potential to sequester 100-200Gton of carbon, equivalent to 2-4 times the world's yearly green house gas emissions [Bas+19].

2.2. Carbon Offsets and Financing Schemes

Forestry is a large industry and the causes of deforestation are mostly economically driven[GL01]. For the last 20 years, major conservation efforts have been underway to mitigate and safeguard against these losses, initially through international and governmental funding schemes, such as REDD+. These have, however, lacked trust and little of the money go to indigenous people and forest owners [CR08]. A newer, more decentralised financing strategy is carbon credits.

The Clean Development Mechanism (CDM) was first introduced under the Kyoto Protocol in 1997, allowing governments and business organizations from industrialized countries to invest in forestry in developing countries by buying carbon credits to offset industrialized emissions. Several other independent bodies have later developed official standards for verifying and certifying carbon offsetting projects, such as the Gold Standard (GS) and the Verified Carbon Standard (VERRA). The certification process for forest carbon offsetting projects is capital and labour intensive, especially due to the high cost of manual monitoring, verification and reporting (MVR) of the forest carbon stock, as seen with references in Annex A.

The carbon offsetting market is rapidly increasing and expected to grow by a factor of 100 until 2050 due to high demand and available capital [Bla+21]. In 2021, the voluntary carbon market already exceeded $1 billion in transactions with increasing prices [Mar21]. However, the main obstacle is limited supply of offsetting projects as forest owners lack upfront capital and market access [KH21].

Recent research investigations [Bad+21; Wes+20] have shown that the current manual forest carbon stock practices systematically overestimate forestry carbon offsetting projects with up to 29% of the offsets analyzed, totaling up to 30 million tCO2e (CO_2 equivalents) and worth approximately $410 million. The overestimation was identified to come from subjective estimations and modeling in both the initial baseline carbon stock and of the project's additionally and leakage. There is thus a need for higher quality carbon offsetting protocols and higher transparency and accountability of the MVR of these projects [Hay+20].

2.3. Monitoring, Verification, and Reporting of Forest Carbon

There are three key aspects that are important for the use of remote sensing in MVR of forest carbon stock. One aspect is financial; using available and accessible technology and sensors to lower the cost and upfront capital requirements for forest owners to get certified, especially in low and middle-income countries. The second aspect is reducing subjectivity in estimating carbon stock and increasing trustworthiness and transparency in the carbon offsetting certification protocols. And lastly, the solutions need to be scalable due to the urgency of financing forest restoration, especially in tropical regions.

Various verification bodies, new ventures, and academia are currently developing remote sensing technologies to automate parts of the certification process of forestry carbon offsetting projects [NPM20; Dao+19; Kel+19]. Satellite imagery is increasing in quality and availability and, combined with state-of-the-art deep learning and lidar, promises to soon map every tree on earth [HA20] and to enable forest aboveground biomass and carbon to be estimated at scale [Saa+11; San+21]. Compared to current manual estimates, these advancements reduce time and cost and increase transparency and accountability, thus lowering the threshold for forest owners and buyers to enter the market [LLK19]. Nevertheless, these algorithms risk additionally contributing to the systematic overestimation of carbon stocks, not reducing it, and are not applicable for small-scale forests, below 10,000 ha [Whi+18], [Glo19], [Dun+19].

Accurately estimating forest carbon stock, especially for small scale carbon offset projects, presents several interesting machine learning challenges, such as high variance of species and occlusion of individual tree crowns. There are many promising approaches, such as hyperspectral species classification [Sch+20], lidar-based height measurements [GKA19] and individual tree crown segmentation across sites [Wei+20a]. However, these applications have been developed mainly on datasets from temperate forests and, to the knowledge of the authors, there is no publicly available dataset of tropical forests with both aerial imagery and ground truth field measurements.

3. Related Work

In this chapter we first describe the manual forest inventory process which is the standard process to estimate forest carbon stock and therefore the benchmark to any remote sensing or technological substitute. Thereafter, we describe DL methods emerging in the field of remote sensing solving relevant tasks relevant for forestry such as tree detection and Land-Cover Land-Use (LULC).

3.1. Forest inventory

The standardized forest carbon stock inventory consists of manually measuring and registering sample trees on sample areas (called Model Units) of the project site. Tree metrics such as Diameter at Breast Height (DBH), height, and species are then put through scientifically developed regression models called allometric equations to calculate the AGB as seen in Figure 3.1. The total biomass of a forest is the total AGB added with the Belowground Biomass (BGB), calculated using a Root-Shoot Ratio (RSR) specific to the forest type and region [Ma+21].

According to the Gold Standard (GS) Methodology for forest inventory (see B) [PWB05], to calculate the carbon stock you include the carbon pools (total biomass, see 2.1.2) available. Two of these carbon pools are AGB and BGB. BGB is an important carbon pool for many vegetation types and land-use systems and accounts for about 20% [WS77] to 26% [Cai+97] of the total biomass. As one can choose to include different carbon pools into the total biomass for certification of carbon credits, there is some ambiguity to the measurement of carbon. We, therefore, operate mainly on AGB as ground-truth metric.

The procedure to calculate the amount of carbon credits, measured in Carbon Equivalents (CO_2e), to be certified for a project is standardized through [PWB05] as shown in Figure 3.1, and B. The CO_2e, also known as the baseline forest carbon stock, is equivalent to the total biomass divided by two. Despite being prone to error propagation [Pet+12; Mal+04] and shown to systematically overestimate carbon stock [Bad+21], this is currently the standardized forest inventory method for certification of forestry projects.

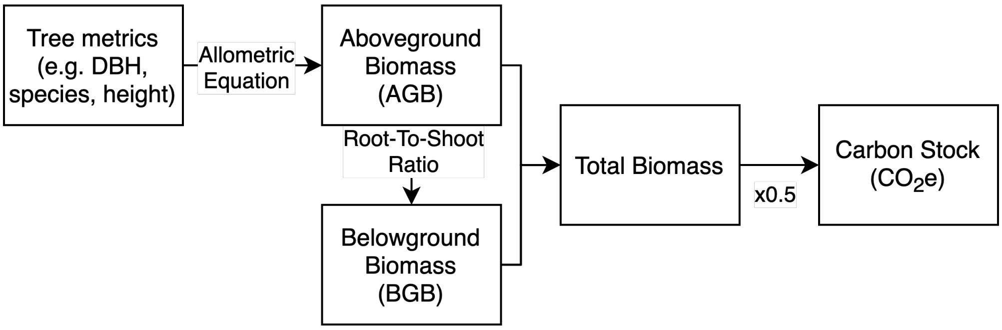


Figure 3.1.: The standard procedure for calculating the correct amount of carbon offsets to be certified for a reforestation project. The tree metrics are collected from manual forest inventory.

3.2. Remote Sensing + Deep Learning = True

In recent years, DL, and especially deep Convolutional Neural Network (CNN) are increasing in popularity for image analysis in the remote sensing community [Ma+19], [Zhu+17]. With the increase in computation power, larger datasets, transfer learning, and breakthroughs in network architecture, DL models have outperformed conventional image processing methods in several image tasks such as LULC classification, segmentation, and detection. Examples of deep supervised learning in remote sensing are the prediction of wildfires [YLM21] and the detection of invasive species [Bjo+21]. CNNs offer feature extraction capabilities in recognizing patterns in both spatial and temporal data, even with LR inputs. With recent advances in meta-and few-shot learning, these models can be trained and generalized on larger datasets and fine-tuned for local variance. This is of high relevance for estimating carbon stock in forests with regional ecosystem differences.

3.3. Carbon Stock Estimations

3.3.1. Plot-based

The following are three types of methods to estimate forest carbon stock remotely, adapted from [SL19]; 1) inventory-based models, based on national and regional forest inventories and regression models are known to overestimate due to overrepresentation of dense commercial forests in the data, [Glo19]. 2) Satellite-based models leveraging datasets from optical remote sensing, synthetic aperture radar satellites (SAR), and

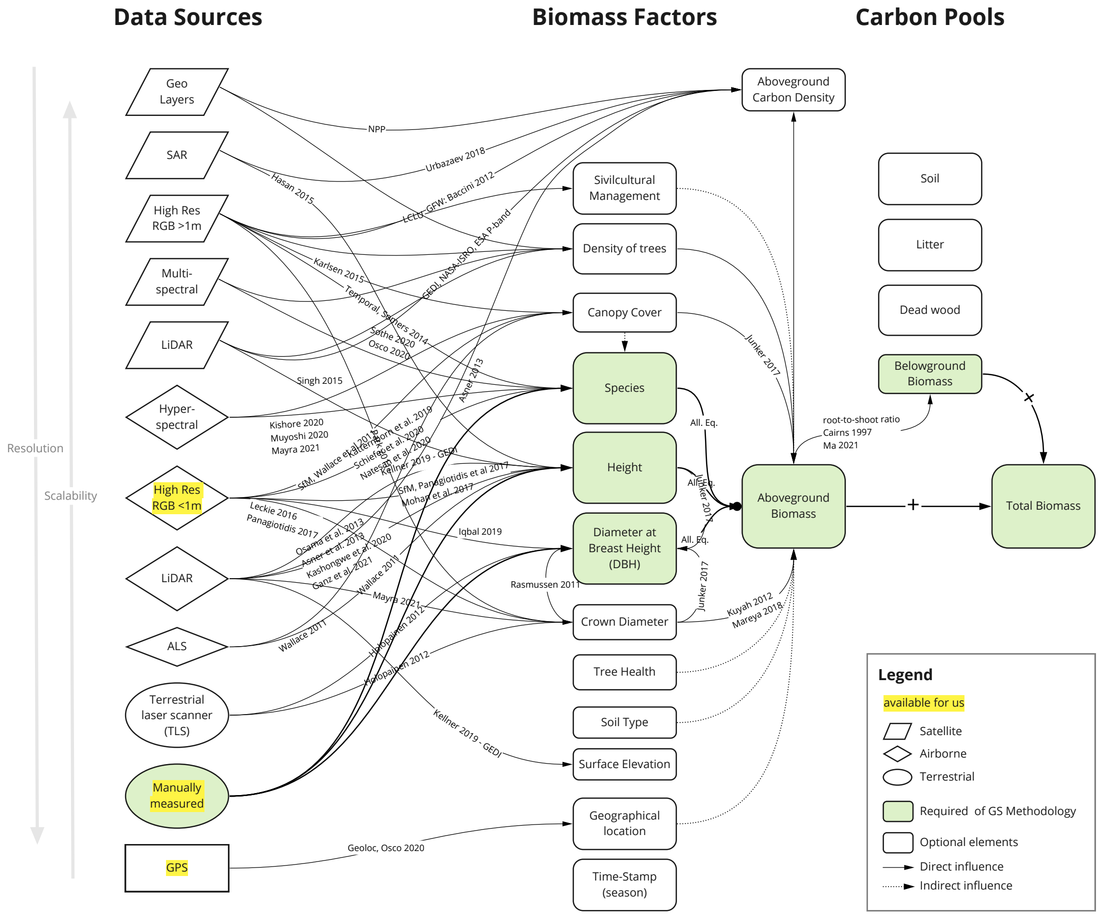


Figure 3.2.: An overview over the remote sensing potential for the forestry inventory process. The columns presents the remote sensing data sources available (left), the factors that influence the biomass stock in forests (middle), and the different carbon pools (right). The text on the edges refer to papers or research domains that prove the feasibility of estimating the biomass factor from the respective data source.

LiDAR to create global AGB and carbon maps [San+21; Saa+11]. 3) Ecosystem-based models using topography, elevation, slope, aspect, and other environmental factors to construct statistical models and quantitatively describe the process of forest carbon cycle to estimate forest carbon stock [Ma+21].

3.3.2. Individual Tree-based

The most scalable and affordable of these methods are evidently satellites-based models. Nevertheless, these models and global maps are yet to estimate carbon stock at local scale and provide accurate estimates of highly heterogeneous and dense forest areas due to their LR of 30-300m [BSE21]. An individual tree-based model that takes the individual overstory trees into account can provide this accuracy, especially if fused with geostatistical and satellite data.

In recent years, researchers have achieved high accuracy for standard forestry inventory tasks such as individual tree crown detection [Wei+19], LiDAR-based height estimation [GKA19], and species classification [Miy+20; Sch+20; Mäy+21], using DL models and aerial imagery. This shows high potential for combining HR imagery with DL models as a method for accurate carbon stock estimation for small-scale AFOLU projects [SL19].

As most tropical forests are situated in low to middle income countries, without access to hyperspectral, LiDAR, and other more advanced sensors, the models need to be developed using available technologies. A trade-off for accuracy and data availability is basic HR RGB drone imagery. Drone imagery (1-3cm/px resolution), combined with CNN, have previously been used to directly estimate biomass and carbon stock in individual mangrove trees [Jon+20] or indirectly by detecting species or tree metrics such as DBH or height [Nåf18; Oma+03], achieving an accuracy similar to manual field measurements. And by leveraging multi-fusion approaches [DZ20; Zha10], e.g. combining LR satellite, HR drone imagery, field measurements, and contextual ecological or topological data, and multi-task learning [Cra20], e.g. tree metrics and carbon storage factors as auxiliary tasks, these models can replace and scale the existing manual forest inventory. It is also worth mentioning that several research groups are calling for improved methods for direct biomass estimation, replacing the error-prone allometric equations with remote sensing also at the individual tree level [Jon+20; Gra+18].

3.4. Our contribution

There are several datasets for tree detection and classification from drone imagery, such as the species classification NEON dataset [Wei+20b], or the Swedish Forest Agency forest damage classification dataset[Lab21] mainly from temperate forests from the US or Europe. To our knowledge, there are no publicly available datasets including both field measurements and drone imagery of heterogeneous tropical forests. With the **ReforesTree** dataset and our methodology, we create the first open-source tropical machine learning ready bounding box dataset for forest carbon stock estimations.

Additionally, we use the **ReforesTree** dataset to benchmark available satellite-based global biomass estimation maps and highlight the need to audit the algorithms and data used in MRV of forests to avoid systematic wrong estimations.

Further, we provide the first proof of concept of an individual tree biomass estimation DL model, based on RGB-imagery only. We hope that this can serve as inspiration for the ML and remote sensing community to improve on accuracy, accountability, and transparency when scaling the remote sensing solutions of forest carbon.

4. The ReforesTree Dataset

In this chapter, we present the **ReforesTree** dataset and the processing steps to create a ground truth for individual tree AGB and carbon. Additionally, the total amounts of AGB and carbon are later used as a benchmark for plot-based biomass estimation models.

The **ReforesTree** dataset consists of six agro-forestry sites spread throughout the central coastal region of Ecuador. The sites are of dry tropical forest type and eligible for carbon offsetting certification with forest inventory collected and drone imagery captured in 2020. See Table 4.1 for information on each site.

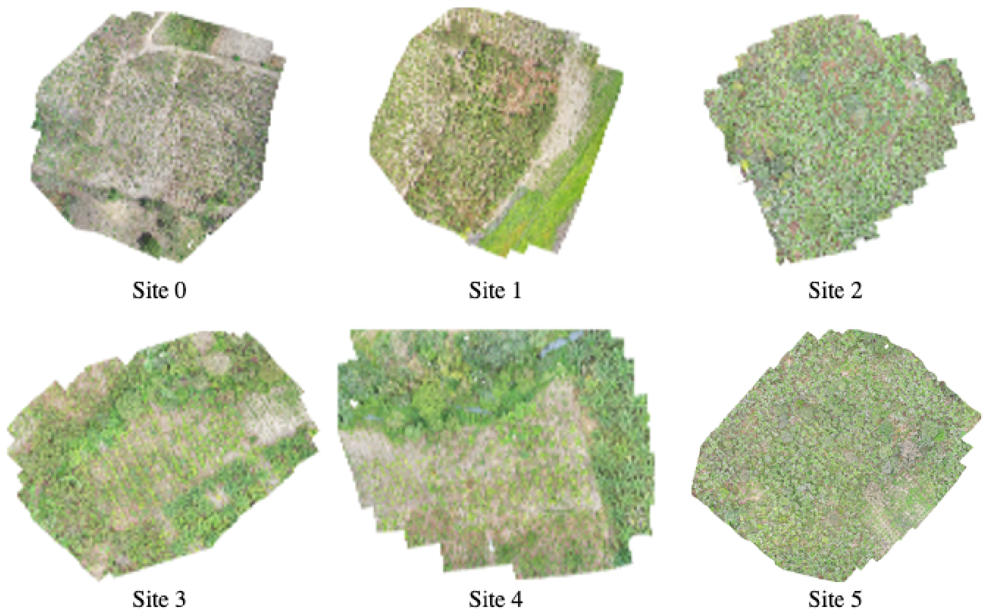


Figure 4.1.: High-Resolution drone imagery of each site of the **ReforesTree** dataset.

Table 4.1.: Overview of the field data from the six project sites in the **ReforesTree** dataset. AGB and CO_2e are measured in metric tons and area in hectares.

Site no.	No. of trees	No. of species	Site area	Total AGB	Total CO_2e
0	743	18	0.53	8	3
1	929	22	0.47	15	6
2	846	15	0.48	13	5
3	789	20	0.51	8	3
4	484	12	0.56	3	1
5	872	14	0.62	15	6
total	4463	27	3.17	62	24

4.1. Data Collection

The field data was collected in 2020. All live trees had Diameter at Breast Height (DBH) manually measured and noted down the species, year planted, and Global Positioning System (GPS) location. Height was also measured for 230 of the cacao plants with an average of 57cm, but we have excluded this metric in our dataset due to the limited number of trees. All trees were planted in the years 2016, 2017, 2018, or 2019. In total, there were 27 different species belonging to 6 different family groups. The drone imagery was collected by OpenForest in late October 2020 by an RGB camera from a Mavic 2 Pro drone with a resolution of 1cm per pixel.

4.2. Data Processing

4.2.1. Species Family Groups

The 27 species were divided into 6 species family groups: *banana*, *cacao*, *fruit*, *citrus*, *timber*, and *other*, as shown in Figure 4.2. *Banana* and *cacao* are over-represented and make up over 75% of the dataset.

4.2.2. Missing Values

As the field data was manually collected, we can assume that there were some human errors leading to missing values, noise, and outliers. It was important not to remove trees unnecessarily, to keep the total tree count and biomass as accurate as possible.

4465 trees were identified, of which two trees lacked information on both diameter and species. These were removed from the dataset, as no robust assumptions could be made. In total, 4663 trees are now part of the dataset.

2621 of the 4663 trees were missing DBH values. 1806 of these were cacao plants. According to the field data collectors, the cacao trees planted the same year were so similar that only a representative sample, in total 236 cacao trees, was measured. The missing DBH values were interpolated based on the median DBH of the same species for the year it was planted. For example, a cacao tree planted in 2016 without a DBH value was given the median DBH value of all cacao tree planted in 2016.

Of the 27 species, only three species (in total 25 trees) had no DBH values: 23 lemon (*citrus*), one balsa (*timber*), one bariable (*other*) tree. These were given DBH values interpolated from the other species in the same family group planted the same year. For example, the balsa tree was planted in 2018 and was given the DBH median of all timber trees planted in 2018.

4.2.3. Outliers

Additionally, eight banana trees that had DBH values larger than 50cm, which is unrealistically high. Assuming that there was a manual entry mistake, these values were exchanged with the maximum value of the banana trees for the year planted.

That left six trees with DBH values above 30cm: three *timber*, two *fruit*, and one *other*. All of these were below 50cm and, therefore, kept in the dataset as is.

4.3. Calculation of AGB and Carbon

4.3.1. Allometric equations

Aboveground Biomass (AGB) is calculated using published allometric equations for tropical agro-forestry, namely, (4.1) *banana* trees (musacea) [Van+02], (4.2) *cacao* [YWP09], (4.3) *fruit* trees, including *citrus* fruits [SKS06], and (4.4) *timber* [BI92] and (4.5) *other* trees [PWB05]. These are commonly used in global certification standards [PWB05].

It is worth mentioning that as seen in Figure 4.3, *cacao* and *banana* have less biomass density compared to the other tree family groups.

$$AGB_{musacea} = 0.030 * DBH^{2.13} \tag{4.1}$$

$$AGB_{cacao} = 0.1208 * DBH^{1.98} \tag{4.2}$$

$$AGB_{fruit} = 0.0776 * DBH^{2.64} \tag{4.3}$$

$$AGB_{timber} = 21.3 - 6.95 * DBH + 0.74 * DBH^2 \tag{4.4}$$

$$AGB_{other} = 0.1466 * DBH^{2.223} \tag{4.5}$$

4.3.2. Carbon Stock

Belowground Biomass (BGB) in our dataset is calculated through a Root-Shoot Ratio (RSR) of 22%, which is standard for dry tropical reforestation sites [Ma+19] as seen in (4.7). The carbon stock was calculated as a factor of 0.5 of the total biomass as described in Figure 3.1, and in (4.8).

$$Biomass = AGB + BGB \tag{4.6}$$

$$RSR = \frac{BGB}{Biomass} \tag{4.7}$$

$$Carbon = \frac{Biomass}{2} = \frac{AGB}{2 * (1 - RSR)} \tag{4.8}$$

4.4. Limitations

4.4.1. GPS noise

When collecting the field data the collectors recorded the GPS coordinates, latitude and longitude, of each tree on their phone. It turns out that the coordinates are very noisy as seen in Figure 4.4 and therefore makes the mapping of the drone imagery with individual trees challenging.

4.4.2. Unbalanced DBH and species

The dataset is unbalanced with regards to species, of which 43% is cacao and 32% is banana. Additionally, due to all of the trees being planted between 2016-2019, many of the trees have a similar size (e.g. DBH) and half of the trees have DBH between 7-10cm.

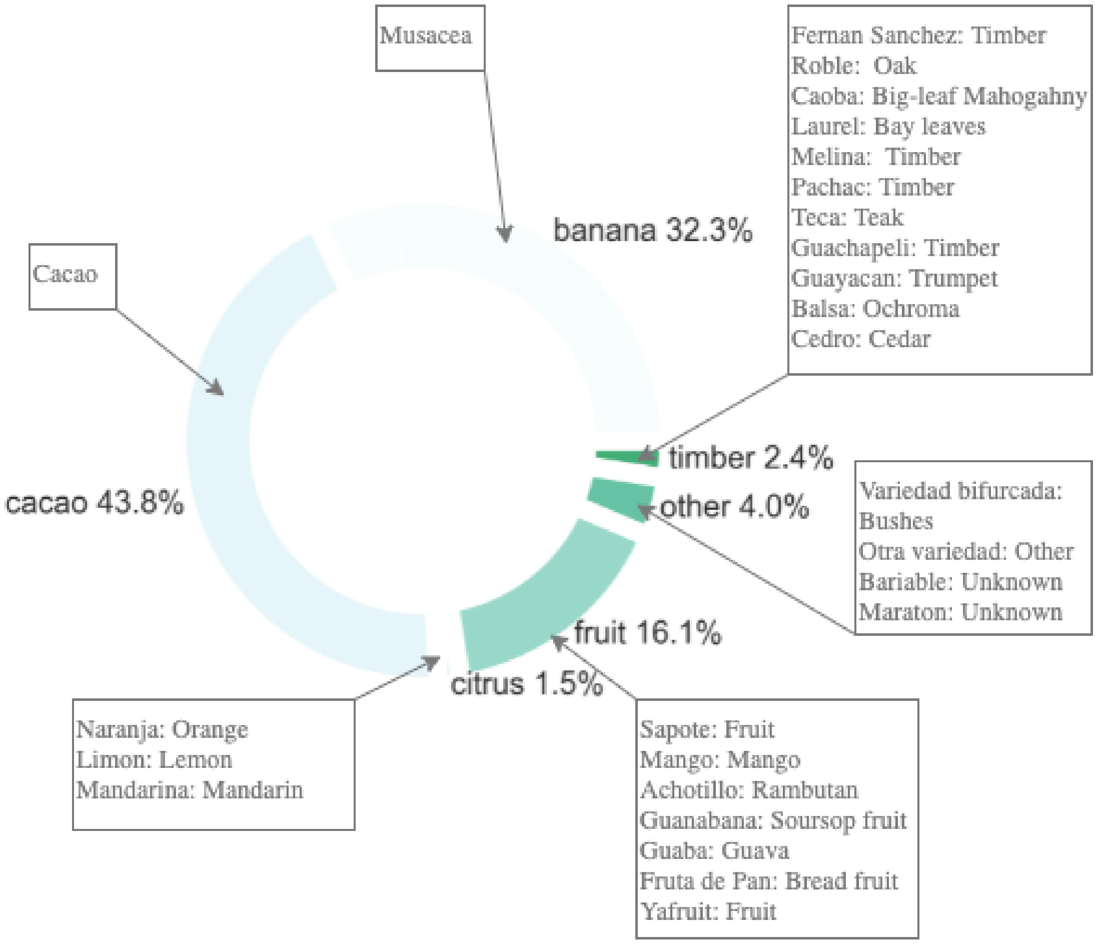


Figure 4.2.: An overview of the tree families and species in the dataset. The circle shows the percentage of the total number of trees in the different tree family groups. The boxes contain all the species belonging to the group with the original Spanish name and English description. As we can see, *banana* and *cacao* make up over 75% of the trees in the dataset.

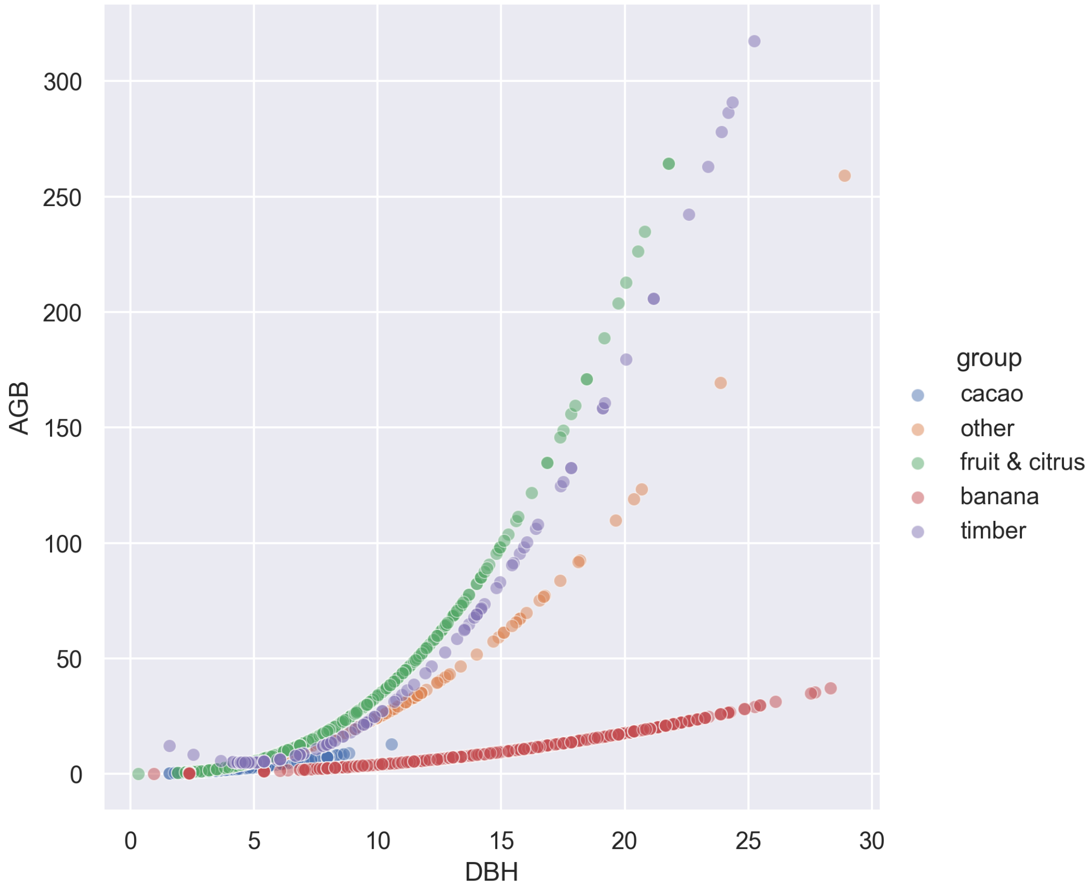


Figure 4.3.: Plot of the allometric equations used for the different family groups, for all trees excluding outliers. As we can see, the *bananas* and *cacao* have less biomass density per diameter at breast height compared to the other trees.

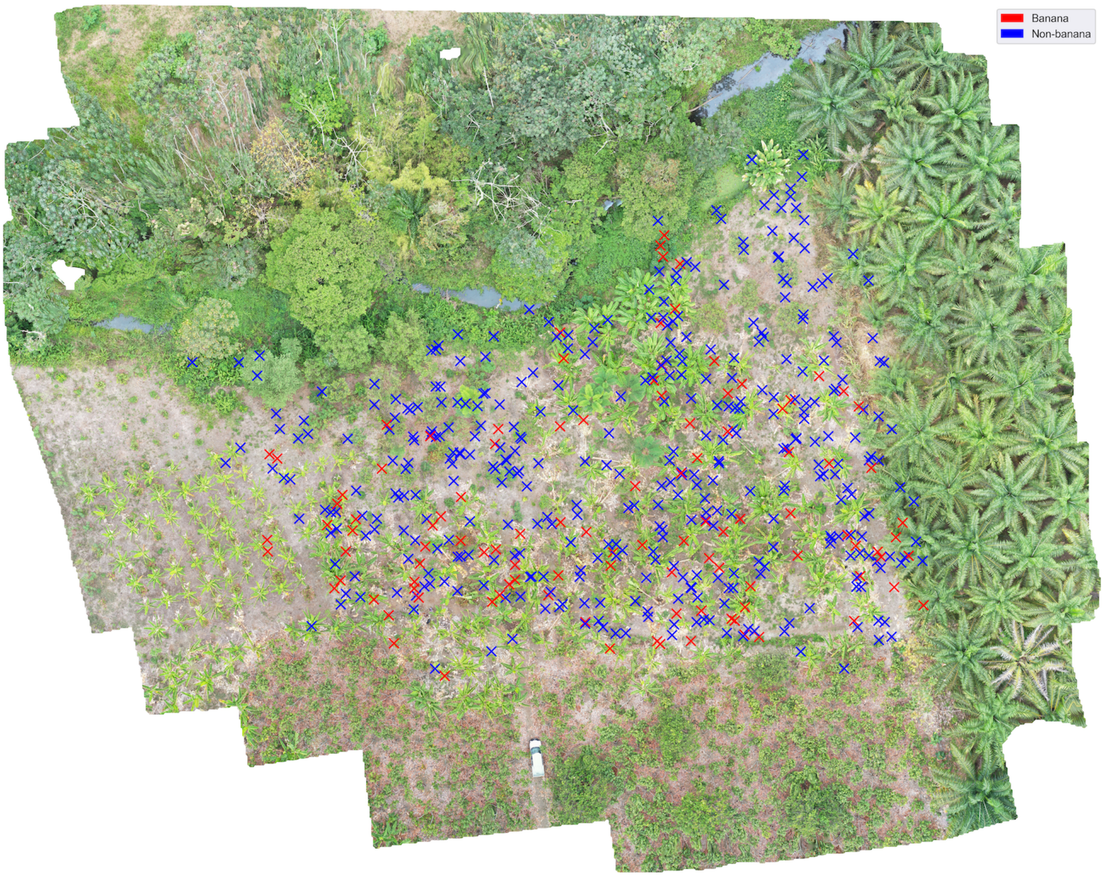


Figure 4.4.: A plot of site no. 4 and the raw GPS coordinates (latitudes and longitudes) of the field data collected. Blue crosses represent *non-banana* and red crosses represents *banana*. As we can see the noise of the GPS data is significant, and it is difficult to recognize any pattern of trees which they belong to.

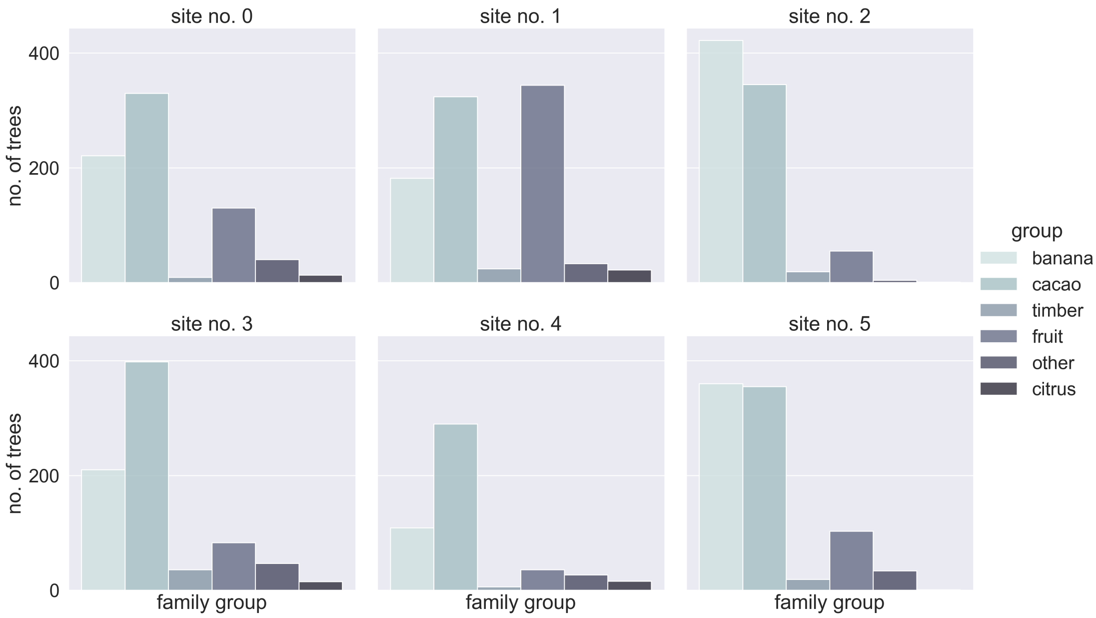


Figure 4.5.: This figure represents the count of species family groups for each of the sites. All sites have trees of each family group, with an over-representation of *cacao* and *banana*.

5. Methodology and Results

In this chapter, we describe in detail the three contributions of this thesis, the methodology, and our results. Firstly, we outline the end-to-end data processing pipeline for creating a training dataset for tree-based biomass models. Secondly, we present a CNN baseline model for estimating AGB trained on the above-mentioned dataset. Lastly, we benchmark our model with available LR satellite-based maps.

5.1. End-To-End Data Pipeline

The raw data is processed in several steps as seen in Figure 5.1. The goal of this process is to have a ML ready dataset that consists of matched drone images of individual trees with the trees labels, such as AGB values.

5.1.1. DeepForest: Tree Crown Detection

DeepForest is a Python package and an open source implementation of a CNN model for individual tree crown detection from RGB imagery [Wei+19] using TensorFlow. DeepForest has been developed for north-American stand-alone trees. We, therefore, fine-tuned the model on 324 manually labelled bounding boxes to better detect the site specific tropical trees achieving an improvement in recall from 0.27 to 0.61.

Initially, the RGB orthomosaics were cut into 4000×4000 tiles with an overlap padding of 200 to detect all tree crowns. These tiles were individually sent through the DeepForest fine-tuned model to generate bounding boxes.

5.1.2. White Filter and Manual Labeling

By visual inspection, several of the bounding boxes were of poor quality such as not being of a tree, too small (zoomed in on a leaf) or large (several trees), or being on the edge of the drone imagery and therefore largely consist of white pixels.

All bounding boxes with more than 80% white pixels were automatically filtered out. The rest, was manually labeled in two steps 1) reject or accept, and 2) banana or non-banana as seen in Table 5.1. Banana has recognizable characteristics (looks like a palm tree) and could therefore be labeled easily for a better ground truth dataset.

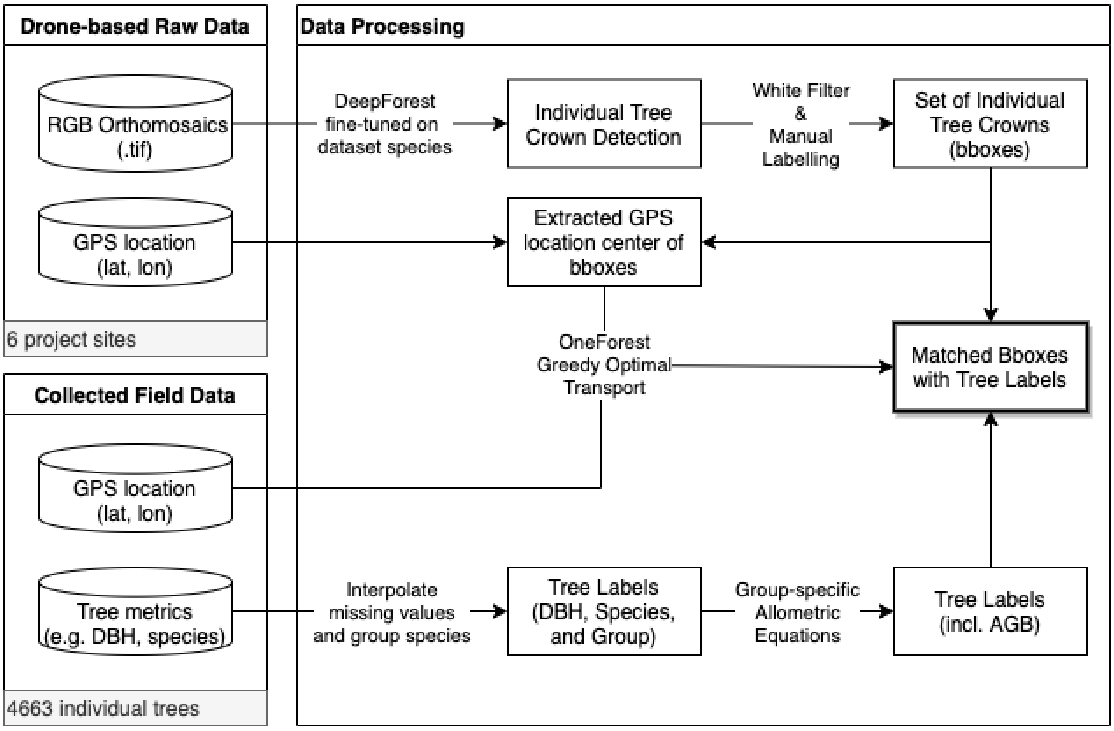


Figure 5.1.: The raw data and data processing pipeline for the **ReforesTree** dataset, resulting in labels matched to bounding boxes per tree.

After manual labeling, some sites (3 sites in total) had less bounding boxes than the actual number of trees. To augment the number of bounding boxes, the existing boxes were copied, shifted, and made larger by 5 pixels. There is, therefore, improvement potential by manually adding the missing bounding boxes. However, due to the low amount of missing bounding boxes, the high density, and similarity of the trees per site, the set was considered as good enough, as seen in Figure 5.2.

5.1.3. OneForest: GPS Matching Algorithm

To fuse the tree information extracted from the field data with the bounding boxes, we used OneForest, a recent machine learning approach for fusing citizen data with drone imagery. OneForest uses a greedy optimal transport algorithm to remove noise from the GPS signals. This is a known coupling method to map between two GPS positions (the center of the bounding box from drone imagery and GPS location of tree from field data). Developed by Villani [Vil03], the method finds the minimal distance between two

Site no.	Original no. of bboxes	>80% white pixels	Rejected	Accepted Banana	Accepted Non-banana	Total Accepted
0	978	0	417	179	382	561
1	1299	0	386	226	687	913
2	2026	1	371	1076	579	1655
3	1389	2	406	382	601	983
4	1158	2	430	349	379	728
5	1670	3	225	1045	400	1445
total	8520	8	2235	3257	3028	6285
%	100%	-	26.2%	-	-	73.8%

Table 5.1.: Overview over the cleaning of the DeepForest bounding boxes per site. The cleaning consisted of automatic filtering of images with more than 80% white pixels and manual labeling.

distributions via a convex linear program optimizing for a matching that moves the mass from one distribution to the other with minimal cost. The cost is usually defined as the euclidean distance or the Kulback-Leibler divergence between the distributions. The optimum, i.e., the minimal distance between the two distributions, is called the Wasserstein metric.

5.1.4. Evaluation of the Dataset

OneForest is developed to remove GPS noise in the mapping. However, the high amount of noise in the field data did introduce some challenges. To evaluate the quality of the matched bounding box and tree label pairs, we did a correlation analysis between the DBH from the field data and the estimated crown size of the tree calculated from the bounding box size. The very low negative correlation, as seen in Table 5.2, can come from two reasons. One reason can be that the GPS noise is significant and that OneForest is not able to remove the noise to robustly do the matching. Secondly, it can also come from poorly fitting bounding boxes around the tree crown.

Additionally, by visual inspection of images matched with the different family groups, one can see that similar looking trees are spread randomly. In other words, the trees matched from the same group does not look more similar than trees from other groups. This signify that the current matching can not be used for robust family group prediction. The only exception is in the species classification of banana/non-banana as this has a ground truth.

For the baseline model we created a dataset by matching for bananas and non-bananas independently. With this dataset we have ground truth value for the group

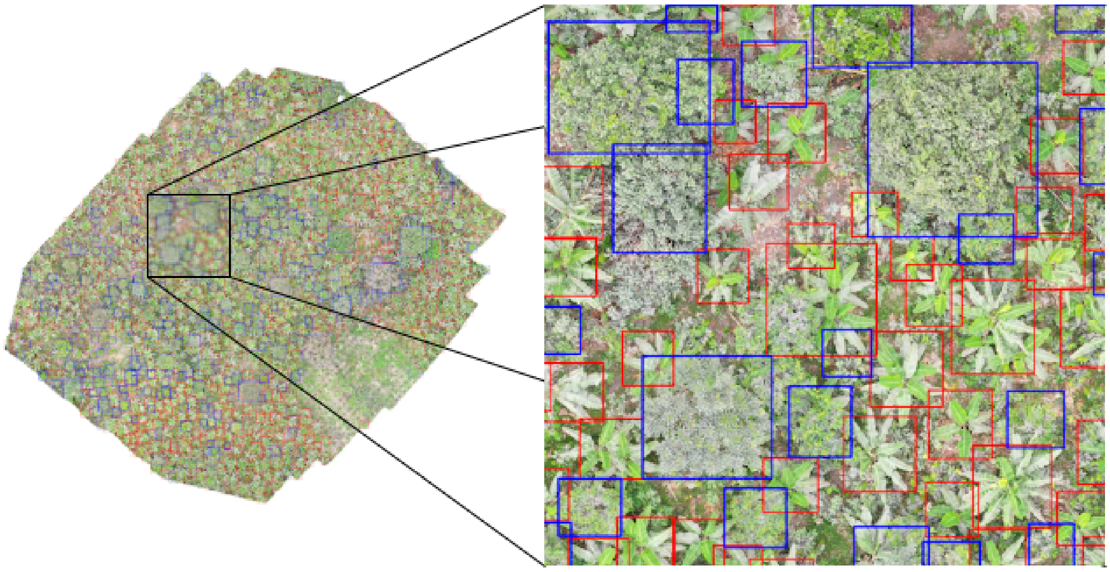


Figure 5.2.: Bounding box annotations per tree, as a result of fine-tuned DeepForest tree crown detection and manual cleaning. Red boxes represent banana trees and blue boxes represent other species.

(banana/non-banana) and optimal transport matching of the GPS locations. As the allometric equation for banana is significantly different from the other groups (see Figure 4.3), we decided not to change the use of allometric equations for the AGB values in this dataset.

5.2. Baseline CNN Model

The two main hypotheses in this thesis are 1) AGB estimation from RGB images of individual trees is feasible and 2) perform on par or better than existing satellite-based solutions. In this section, we describe the training of a CNN model for direct estimations of AGB and its performance.

With a dataset of matched bounding boxes and AGB values, we trained convolutional neural network (CNN) to estimate the AGB directly. We used the architecture ResNet18 [He+15] pre-trained on the ImageNet dataset. This a standard residual network model with 18 layers used for visual classification and regression tasks. The last fully connected layer was changed to output only one value. Mean-square error (MSE, eq. 5.1) was used as a loss function, root-mean-square error (RMSE, eq. 5.2) and R-squared (R2,

Corr. of all	Corr. of banana	Corr. of non-banana
-0.104	0.057	-0.101

Table 5.2.: The results from the correlation analysis between the crown diameter and the DBH of the matched trees. This might show that the matching algorithm is not able to remove the GPS noise and that the matching therefore is not done correctly.

eq. 5.3) as accuracy metrics and ADAM as optimizer. The learning rate used was 1e^{-3}, batch size of 64 for 30 epochs and was run on a single GPU of the type GeForce RTX 3090.

$$MSE = \frac{1}{N}\Sigma_{i=1}^{N}|y_i - \hat{y}| \tag{5.1}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}|y_i - \hat{y}|} \tag{5.2}$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{N}(y_i - \hat{y})^2}{\Sigma_{i=1}^{N}(y_i - y_*)^2} \tag{5.3}$$

5.2.1. Image Pre-Processing

Fourteen images were identified as being larger than the expected crown size of a large tree, and they were center cropped at 800×800. To preserve the crown size information in the dataset, the smaller images were zero-padded up to 800×800, before all images were resized to fit the network architecture of 224×224. All images and AGB values were normalized.

5.2.2. Train-Test Split

To balance the dataset, 100 data pairs were sampled from each site and per group (banana/non-banana). In total 1200 data samples. The reduced number of data samples allowed for faster training and more robust testing of images unknown to the model. The sampled dataset was split into 30% test and 70% training.

5.2.3. Results

As we can see from Figure 5.3 and Figure 5.4, the model is able to estimate both the AGB for the group- and site specific distributions, despite having been trained on only a subset of the entire dataset. The results are not accurate on the individual tree level, but gives a good plot estimation. This simple baseline model, therefore, shows that tree-based AGB estimation from RGB drone imagery has potential, despite not being robust enough for individual tree estimation.

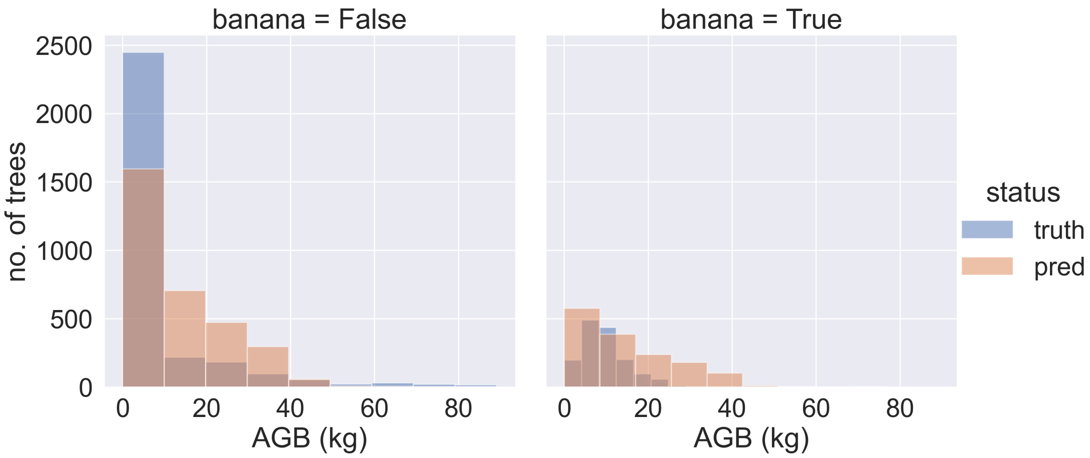


Figure 5.3.: Comparison of the ground truth and the prediction of AGB through our baseline model.

5.3. Benchmark of Other Models

To benchmark the Low-Resolution (LR) satellite-based maps, we fitted it to the High-Resolution (HR) drone imagery overlapping the GPS coordinates.

The calculation of the total AGB was done in five steps, illustrated in Figure 5.5:

1. cropping the LR satellite map with a padding around the polygon of the site to reduce computation intensity (Satellite Raw)
2. linearly interpolating the values for this map and resize the map with the same HR pixel resolution as the drone imagery (Satellite Interpolated)
3. cropping the map further fitting with the GPS locations (max/min) of the drone imagery
4. filtering out the site area by removing all pixels in the satellite-based map, that are outside of the drone imagery, coloured white (Satellite Filtered)

5. lastly, multiplying the AGB mean density of the filtered map with the project site area to get the total AGB

We analysed the following three maps:

- [Glo19]: The Global Forest Watch's Above-Ground Woody Biomass dataset is a global map of AGB and carbon density at 30m×30m resolution for the year 2000. It is based on more than 700,000 quality-filtered Geoscience Laser Altimeter System (GLAS) LiDAR observations using ML models based on allometric equations for the different regions and vegetation types.

- [SSL20]: Global Aboveground and Belowground Biomass Carbon Density Maps, a 300m×300m harmonized map based on overlayed input maps for the year of 2010. The input maps were allocated in proportion to the relative spatial extent of each vegetation type using ancillary maps of tree cover and landcover, and a rule-based decision schema.

- [San18]: GlobBiomass - Global Datasets of Forest Biomass with 100x100m resolution for the year 2010. The last, and most recent 100m×100m dataset from [San+21] is obtained by spaceborne SAR (ALOS PALSAR, Envisat ASAR), optical (Landsat-7), LiDAR (ICESAT). In addition to auxiliary datasets with multiple estimation procedures with a set of biomass expansion and conversion factors, following approaches to extend ground estimates of wood density and stem-to-total biomass expansion factors.

5.4. Interpreting the Results

We used **ReforesTree** dataset to benchmark available satellite-based maps and compare with our baseline CNN model for AGB estimation. As seen in Table 5.3, all of the available global AGB maps have a tendency to overestimate the ground truth measurements up to a factor of 25. These are not encouraging results showing that these maps are far from being accurate enough to be used in remote sensing of forest carbon stock at a small scale, as is the case for the **ReforesTree** dataset. The exception is the most recent map from [San+21], which overestimates only slightly on all sites except for one.

Our baseline model, on the other hand, has a slight tendency of underestimating the biomass. The model has an evident advantage, to be trained on the dataset, but these initial results show promise for the tree-based estimation approach using drone imagery for forest carbon inventory, as this simple model is able to predict the total AGB of each site accurately on RGB image only.

Site no.	Field data	GFW 2019		Spawn 2020		Santoro 2021		Baseline	
0	8	90	**x11.5**	84	**x10.7**	14	**x1.9**	7	**x1.0**
1	15	99	**x6.6**	102	**x6.8**	12	**x0.8**	8	**x0.5**
2	13	25	**x1.9**	33	**x2.6**	19	**x1.5**	15	**x1.2**
3	8	9	**x1.1**	82	**x10.1**	12	**x1.4**	9	**x1.1**
4	3	78	**x25.0**	76	**x24.2**	15	**x4.8**	11	**x3.7**
5	15	30	**x2.0**	35	**x2.4**	16	**x1.1**	15	**x1.0**
total	62	331	-	413	-	89	-	65	-

Table 5.3.: The benchmark results from comparing different models for estimating AGB with the forest inventory of the **ReforesTree** sites. All numbers are given as AGB in metric tonnes. GFW is [Glo19], Spawn is [SSL20], Santoro is [San+21]. Lastly, the baseline CNN is our drone-based model.

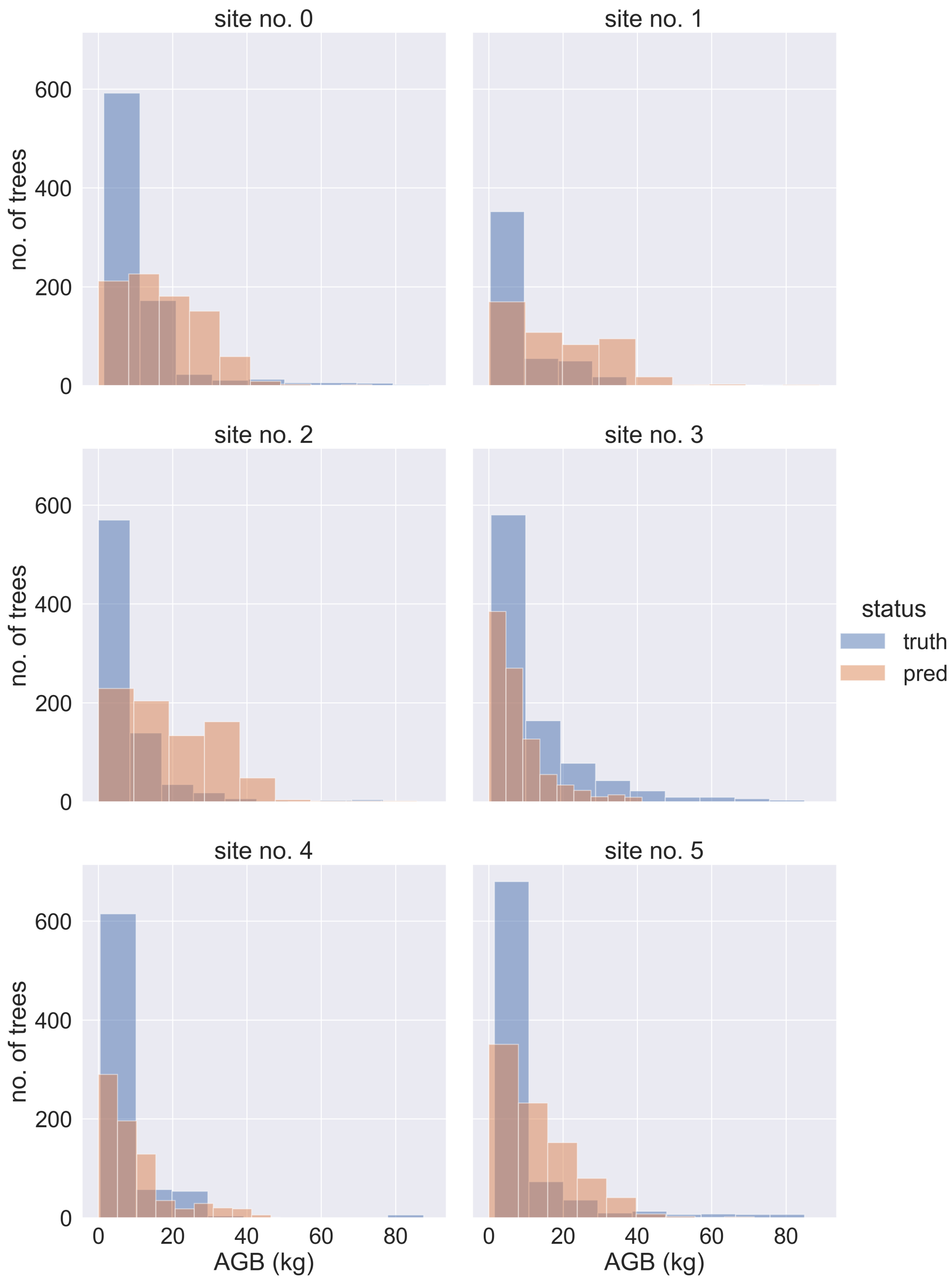


Figure 5.4.: Comparison of the ground truth and the prediction of AGB through our baseline model for each of the **ReforesTree** project sites. As we can see, the model approximate the AGB values.

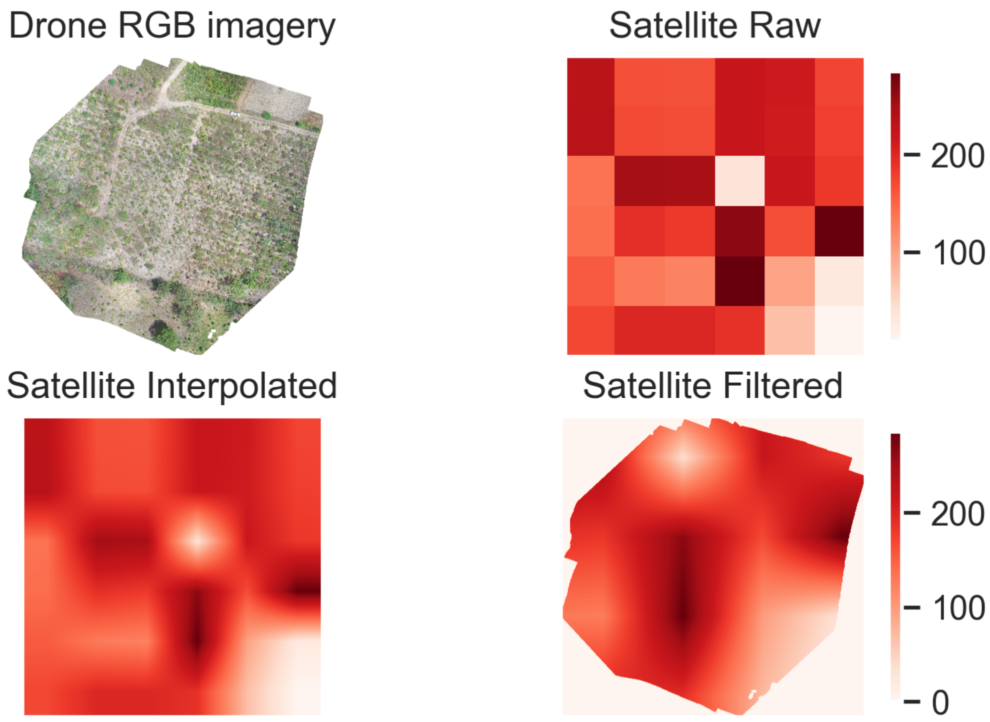


Figure 5.5.: This figure represents the different steps in the benchmark analysis and how we calculated the total AGB amount from the satellite-based maps for the **ReforesTree** sites. This is taken from site no. 0. The values represented in the image is AGB density (tons/ha).

6. Conclusion

There is great potential in combining remote sensing and ML to increase the quality of MRV of forestry carbon offsets and to play a key role in is scaling natural carbon sequestration at the speed necessary to mitigate climate change. As our results show, RGB drone imagery can offer a low-cost and medium scalable solution for accurate biomass estimations. However, we also identify and highlight the need to audit the algorithms and data used to avoid systematic wrong estimations by quantifying the current gap in available maps.

While working on this thesis, we published the **ReforesTree** dataset in hopes of encouraging the fellow ML and remote sensing community to take on the challenge of developing low-cost, scalable, trustworthy, and accurate solutions for MRV of tropical reforestation inventory. We also present the outlined methodology for creating an annotated ML dataset from field data and drone imagery, to facilitate the generation of high-quality data used for this purpose. This methodology includes a data processing pipeline leveraging, a fine-tuned tree crown detection algorithm and an optimal transport matching algorithm for the reduction of GPS noise.

The **ReforesTree** dataset of field measurements and low-cost, high-resolution RGB drone imagery represents the trade-off for accuracy and data availability of remote sensing of forest carbon stock in tropical regions. It can be used to train new or benchmark existing models for MRV of carbon offsetting reforestation protocols. Remote inventory of small-scale tropical reforestation projects comes with several ecological challenges, such high biodiversity, level of canopy closure, and topology. This dataset is a start to develop a generalized model that can be fine-tuned on a local scale. In 7 we will investigate ways to improve the methodology and reduce error in the ML ready dataset, and increase the explainability to have a trustworthy and transparent model. We propose to leverage current advancements in remote sensing and ML when creating new automated carbon offset certification protocols, starting with HR data combined with field measurements as benchmarks. Explicitly, we see further potential in fusing satellite and other available geoecological data layers as well as leveraging the multiple labels available (e.g. DBH, species) as auxiliary tasks in a multitask learning problem.

As the world is rapidly approaching planetary doom, we need to collaborate across disciplines to implement and scale the climate mitigation strategies available. Restoration of forests is one of our most important climate mitigation strategies. And by reducing the overestimation of carbon offsets, we can allow every man on earth who owns a tree to participate in climate action. Biodiverse and sustainable forestry can provide hope not only for the machine learning community, but also beyond.

7. Future Work

7.1. The Future of Remote Monitoring, Verification, and Reporting of Forests

Remote sensing and ML models have great potential to automate and increase the quality, transparency, and accountability of MRV of forestry. There are some challenges that still have to be solved. One key aspect is availability of high-quality data with mapped field data with other sensors.

7.2. Multi-Fusion Data Sources

Satellite sensors are getting better and the number of satellite products are increasing. With new satellites such as the ICESat-2 or GEDI, data sources such as HR imagery and LiDAR can soon be available for the entire globe. As we have seen in our benchmark, the map from [San+21] which is fusing sensors and data sources, may positively improve the estimations. However, it still overestimates on this type of small-scale agroforestry sites. Before satellite imagery reaches a higher resolution, drone imagery offers more accurate features, especially in the spacial domain.

To continue the work on individual tree-based estimations, one can explore multifusion approaches [DZ20] [Zha10](e.g. combining LR satellite, HR drone imagery, and field measurements or contextual data).

7.3. Improvements to Data Pipeline

7.3.1. GPS Noise

As seen in Chapter 4, the **ReforesTree** dataset has high level of noise in the GPS location of the field data. This is a common problem for localisation with phones in remote areas. However, there might be ways to remove part of the noise by scaling it to better fit the drone imagery before matching.

7.3.2. Species Classification

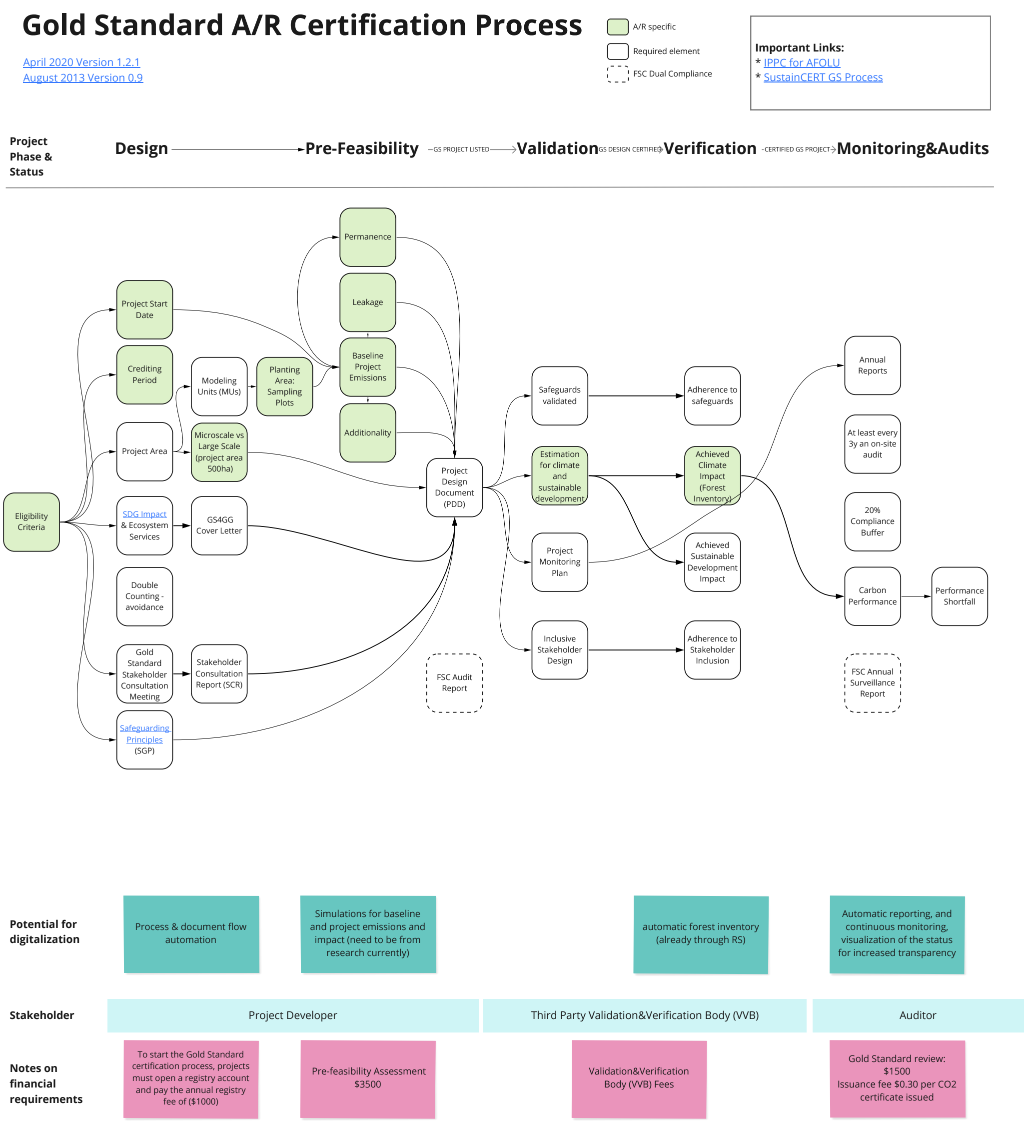
As species classification cannot be done through GPS mapping alone, it should be handled as a separate machine learning task. To improve the bounding boxes before matching, future work can explore clustering algorithms or unsupervised methods for labeling species based on spacial features. The clusters can then be matched with the correct label through domain expertise or through numerical models.

7.4. Beyond the Baseline - Multi-Task Learning

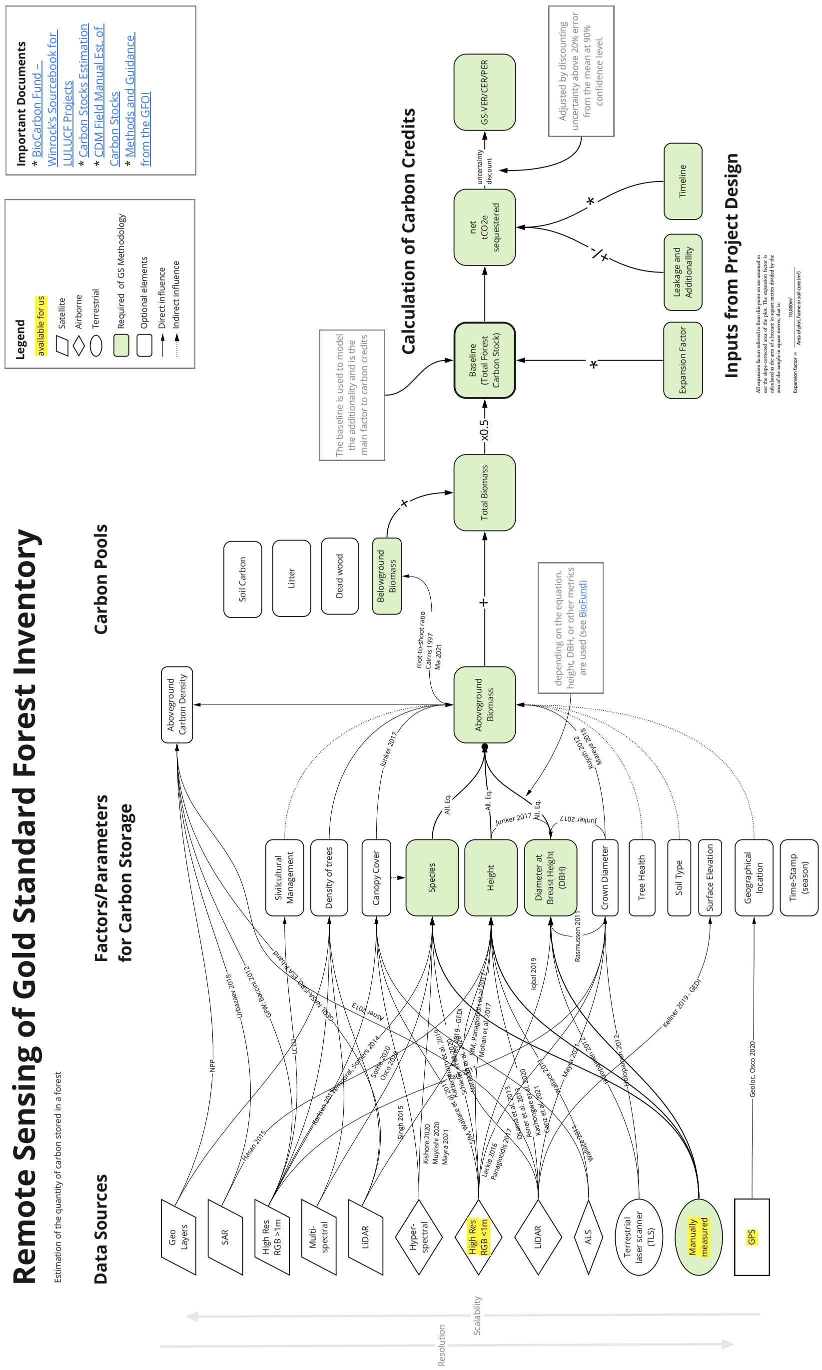
The baseline model, is in it's current form a simple model with high potential for improvements. and multi-task learning [Cra20] (e.g. tree metrics and carbon storage factors as auxiliary tasks).

Appendices

A. Gold Standard Certification Process



B. Remote Sensing of Forest Inventory



Acronyms

AFOLU Agriculture, Forestry and Other Land Use. 1, 9

AGB Aboveground Biomass. v, 1, 2, 6, 9, 11–14, 19, 22–28, 40, 41

BGB Belowground Biomass. 6, 14

CNN Convolutional Neural Network. iv, 7, 9, 19, 25, 26, 41

CO_2e Carbon Equivalents. 6, 12, 41

DBH Diameter at Breast Height. vi, 1, 6, 9, 12–14, 21, 23, 29, 41

DL Deep Learning. 6, 7, 9, 10

GPS Global Positioning System. vi, 12, 14, 17, 24, 29, 39

GS Gold Standard. 6

HR High-Resolution. iv, 2, 9, 11, 24, 29, 31, 39

IPCC Intergovernmental Panel on Climate Change. iv

LiDAR Light Detection and Ranging. 2, 9, 25, 31

LR Low-Resolution. iv, 2, 7, 9, 19, 24, 31

LULC Land-Cover Land-Use. 6, 7

ML Machine Learning. iv, 10, 19, 25, 29, 31

MRV Monitoring, Reporting, and Verification. iv, 1, 10, 29, 31

RGB Red, Green, and Blue. 2, 9, 10, 12, 19, 22, 24, 25, 29

RSR Root-Shoot Ratio. 6, 14

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