Tackling the Overestimation of Forest Carbon with Deep Learning on Aerial Imagery

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Abstract

Forest carbon offsets are increasingly popular and can play a significant role in financing climate mitigation, forest conservation, and reforestation. Measuring how much carbon is stored in forests is, however, still largely done via expensive, time-consuming, and sometimes unaccountable field measurements. To overcome these limitations, many verification bodies are leveraging machine learning (ML) algorithms to estimate forest carbon from satellite or aerial imagery. Aerial imagery allows for tree species or family classification, which improves on the satellite imagery-based forest type classification. However, aerial imagery is significantly more expensive to collect and it is unclear by how much the higher resolution improves the forest carbon estimation. In this proposal paper, we describe the first systematic comparison of forest carbon estimation from aerial imagery, satellite imagery, and "ground-truth" field measurements via deep learning-based algorithms for a tropical reforestation project. Our initial results show that forest carbon estimates from satellite imagery can overestimate above-ground biomass by more than 10-times for tropical reforestation projects. The significant difference between aerial and satellite-derived forest carbon measurements shows the potential for aerial imagery-based ML algorithms and raises the importance to extend this study to a global benchmark between options for carbon measurements.

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1. Introduction

The deterioration of the natural world is unparalleled in human history and a key driver of the climate crisis. Since 2000, we have lost 361 million ha of forest cover (the size of Europe) (Hansen et al., 2013) accounting for 18% of global anthropogenic emissions (IPCC, 2019). The causes of deforestation are mostly economically driven and major conservation efforts are underway to mitigate and safeguard against these losses.

Carbon offsets are a way of financing and trading on the capture of carbon for businesses and governments. The carbon offsetting market is expected to grow by a factor of 100 until 2050 and demand is rapidly increasing (Blaufelder et al.).

Recent investigations (Badgley et al., 2021) have shown that the current manual practices systematically overestimate forestry carbon offsetting projects with up to 29% of the offsets analyzed, totaling up to 30 million tCO2e and worth approximately $410 million. There is thus a need for higher quality carbon offsetting protocols and higher transparency and accountability in the monitoring, reporting, and verification (MRV) of these projects (Haya et al., 2020).

Several verification bodies and academic environments are currently developing remote sensing technologies to automate parts of the certification process of forestry carbon offsetting projects (Narine et al., 2020; Dao et al., 2019). Remote sensing through satellite or aerial imagery and lidar combined with ML models can be used to estimate carbon stock baselines and additionality, and for MRV of projects. 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 (Lütjens et al., 2019).

Satellite imagery is increasing in quality and availability and combined with state-of-the-art deep learning, promises to soon map every tree on earth (Hanan & Anchang, 2020). Nevertheless, these algorithms risk additionally contributing to the systematic overestimation of carbon stocks, not reducing it.

Table 1. Overview of the six project sites in Ecuador, as gathered in field measurements. Aboveground biomass density (AGB) is measured in metric tons per hectare and area in hectares.

SITE NO.	NO. OF TREES	NO. OF SPECIES	PLOT AREA	AGB DENSITY
1	743	17	0.53	19
2	929	19	0.47	32
3	789	21	0.51	26
4	484	13	0.56	16
5	872	15	0.62	24
6	846	16	0.48	27

2. Quantifying the difference in forest carbon stock estimations and field measurements

To quantify the difference between the estimated forest carbon stock taken from available remote sensing products, we propose a study of field measurements of six cacao agro-forestry sites in the central coastal region of Ecuador eligible for carbon offsetting certification. See Table 1 for information on each site. By mapping field measurements to trees instances from drone imagery, an end-to-end deep learning-based carbon stock estimations can be done for each individual tree as seen in Figure 2 in the Appendix. Calculating the carbon stock at an individual tree level increases the accuracy of the estimations as it allows both species (Schiefer et al., 2020) and metrics (Omasa et al., 2003) to be detected.

2.1. Data

Field measurements were taken manually for all live trees and bushes within the site polygon and include GPS location, species, and diameter at breast height (DBH). Drone imagery was captured by an RGB camera from a Mavic 2 Pro drone in 2020. Each site is around 0.5 ha, mainly containing banana trees (Musaceae) and cocoa plants (Cocoa). The aboveground biomass (AGB) is calculated using published allometric equations for tropical agro-forestry, as seen in equations 1 (Segura et al., 2006) and 2 (Van Noordwijk et al., 2002). These are commonly used in global certification standards.

$$log_{10}AGB_{standard} = -0.834 + 2.223(log_{10}DBH) \quad (1)$$

$$AGB_{musacea} = 0.030 * DBH^{2.13} \quad (2)$$

Table 2. Results from AGB density estimations derived from satellite-based data. Aboveground biomass (AGB) is measured in metric tonnes per hectare. The factor of overestimation is calculated from comparing the ground truth to the filtered estimation.

SITE NO.	GROUND TRUTH	ROUGH	FILTERED	OVER ESTIMATION
1	19	388	240	×13
2	32	111	64	×2
3	26	1383	970	×37
4	16	1025	889	×56
5	24	783	597	×25
6	27	282	187	×7

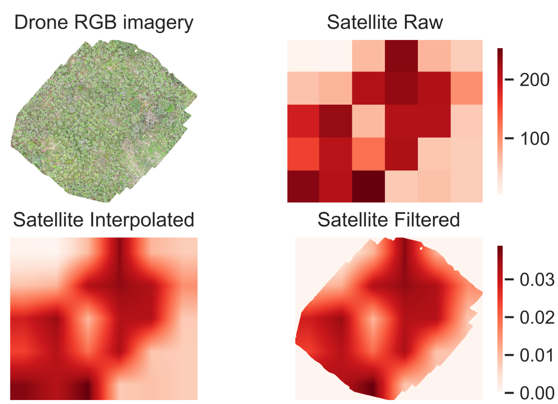

Figure 1. The drone imagery of project site 6 with the respective AGB density map from Global Forest Watch.

We used the Global Forest Watch (GFW)'s aboveground live woody biomass density dataset as a comparison (Global Forest Watch, 2019). It is a global map of AGB and carbon density at 30m x 30m resolution based on more than 700.000 quality-filtered Geoscience Laser Altimeter System (GLAS) lidar observations and allometric equations for the different regions.

2.2. Approach

For each site, we computed the total AGB from the field measurements and the allometric equations. We compare this ground truth with two estimates obtained from GFW for the same location.

- Ground Truth: Total AGB values from field measurements divided by the area of the site.
- Rough Estimation: The total AGB density from satellite for the rectangular area divided by the share of cover by the polygon.
- Filtered: The AGB density cubically interpolated to the resolution of the drone imagery and filtered on its polygon.

Comparing the three AGB density estimations in tonnes AGB per hectare for each site in Table 2 we see that for all plots the satellite-based estimations significantly overestimate the AGB in the plots, despite their relatively high resolution of 30m x 30m. Drone imagery (1cm/px) combined with convolutional neural networks (CNN) have previously been used to directly estimate biomass and carbon stock in individual trees (Jones et al., 2020) or indirectly by detecting species or tree metrics such as DBH or H (Nåfält, 2018) (Schiefer et al., 2020), achieving an accuracy similar to manual field measurements. We propose an end-to-end carbon stock estimation at the individual tree level by leveraging multi-fusion approaches (Du & Zare, 2020) (Zhang, 2010) (e.g. combining low-resolution satellite, high-resolution drone imagery, and field measurements or contextual data) and multi-task learning (Crawshaw, 2020) (e.g. tree metrics and carbon storage factors as auxiliary tasks).

3. Conclusion

There is great potential in combining remote sensing and ML to increase the quality of forestry carbon offsets and to play a key role in is scaling natural carbon sequestration at the speed that is required to mitigate climate change. However, in this proposal, we identify and highlight the need to audit the algorithms and data used to avoid systematic wrong estimations by quantifying its current gap. We propose to leverage current advancements in remote sensing and ML when creating new automated carbon offset certification protocols, starting with high-resolution data combined with field measurements as benchmarks.

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A. Appendix

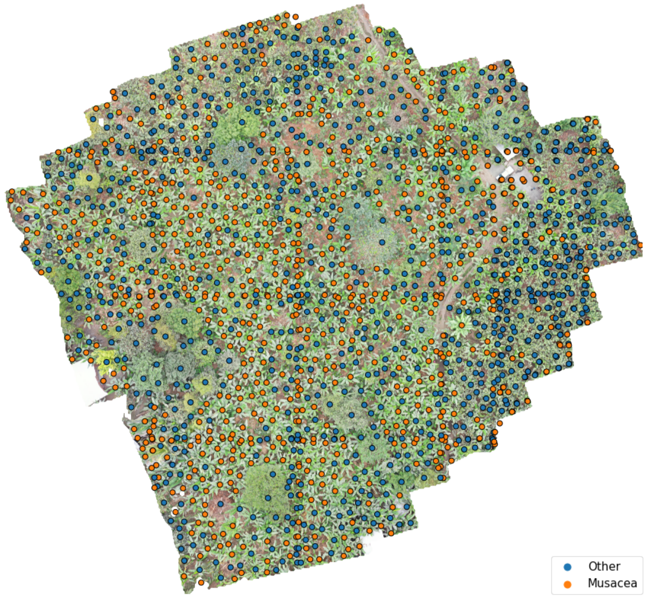

Figure 2. High-resolution aerial mapping and field measurements of a project site. First, we manually collected tree diameter, GPS information and species data for all trees within each of the six project size areas. Afterwards, we ran DeepForest (Weinstein et al., 2019) to detect individual trees and map each field measurement to its corresponding tree. This allows us to apply species-specific allometric equations on a fine-grained resolution and create our ground truth data.