ForestBench: Equitable Benchmarks for Monitoring, Reporting, and Verification of Nature-Based Solutions with Machine Learning

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Abstract

Restoring ecosystems and reducing deforestation are necessary tools to mitigate the anthropogenic climate crisis. Current measurements of forest carbon stock can be inaccurate, in particular for underrepresented and small-scale forests in the Global South, hindering transparency and accountability in the Monitoring, Reporting, and Verification (MRV) of these ecosystems. There is thus need for high quality datasets to properly validate ML-based solutions. To this end, we present ForestBench, which aims to collect and curate geographically-balanced gold-standard datasets of small-scale forest plots in the Global South, by collecting ground-level measurements and visual drone imagery of individual trees. These equitable validation datasets for ML-based MRV of nature-based solutions shall enable assessing the progress of ML models for estimating above-ground biomass, ground cover, and tree species diversity.

1 Background

The deterioration of the natural world is unparalleled in human history and a key driver of the current climate crisis and global extinction [1–3]. In the past twenty years, we have lost forest area equivalent to the size of Europe, accounting for more than 7% of global anthropogenic emissions [4, 5]. Reducing deforestation, restoring ecosystems, and natural sequestrating of carbon are therefore of uttermost importance and urgency.

A current approach to finance the needed restoration of forest ecosystems are carbon offsets. The carbon offsetting market is expected to grow 100-fold until 2050 due to high demand and available capital [6, 7]. However, an obstacle is the limited supply of offsetting projects, as forest owners lack upfront capital and market access [8]. The standardized forest carbon stock inventory consists of manually measuring and registering sample trees on sample areas on 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 [9] to calculate the Aboveground Biomass (AGB). The total biomass of a forest is the sum of the total AGB and the total Belowground Biomass (BGB), calculated using a Root-Shoot Ratio (RSR) specific to the forest type and region [10].

Accurately estimating forest carbon stock, especially for small-scale carbon offset projects below 10,000 ha, presents several challenges, such as high variance of species and occlusion of individual tree

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crowns [11–13]. There are many promising approaches, such as hyper-spectral species classification [14], LiDAR-based height measurements [15] and individual tree crown segmentation across sites [16]. In recent years, remote sensing and Machine Learning (ML) have been used to estimate biomass [17, 18] based on drone and satellite data, to automate parts of the certification process of forestry carbon offsetting projects [19, 20]. We may soon have mapped every tree on earth [21], enabling forest AGB and carbon to be estimated at scale [22, 23, 18].

Recent research has however shown that the current manual forest carbon stock practices systematically overestimate forestry carbon offsetting projects [24–26], unless they are properly calibrated and transparently validated [13]. This even applies to the latest generation satellite programs such as GEDI [18, 27]. One reason is that these applications have been developed mainly on datasets from boreal and temperate forests, which are not suitable for other types of ecosystems. To the best of our knowledge, there is no publicly available dataset of tropical forests with both aerial imagery and ground truth field measurements, as reviewed in [28], and very little available data of that kind from the Global South in general, putting these regions at a disadvantage when competing in the global carbon emission market. There is thus need for higher-quality carbon offsetting data to achieve more transparency and accountability in the Monitoring, Reporting, and Verification (MRV) of the forest carbon stock [29].

2 Project description

In this position paper, we present ForestBench, which aims to collect and curate geographically-balanced gold-standard open datasets of small-scale forest plots, with a focus on currently under-represented forest ecosystems in the Global South. In particular, our aim is to collect field-based ground-level measurements of forest value, i. e., tree biomass, in order to develop equitable benchmarks for ML-based MRV, as well as drone aerial images that serve to calibrate the benchmarks.

Top-down monitoring with satellites is globally available, but less accurate. On the other hand, the bottom-up approach using drones and, e. g., wildlife cams and individual tree measurements, allows a more localized and accurate estimation of carbon content, in particular the below-ground carbon. We hence aim to provide data that allows for these two approaches to meet in the middle, allowing for a synthesis of comprehensive datasets. This is important to validate future ML models, and hence making sure that carbon credits are correctly evaluated and fair.

At the same time, we aim to provide economic opportunity for local and Indigenous communities by collaborating with them for the data collection. Our project builds on top of our previous work [26], and is integrated into the larger GainForest project [19]. We furthermore are currently developing ancillary work to quantify the amount of overestimation of carbon stock [manuscript in preparation], which will help evaluate the success of the project proposed here.

3 Community-centered data collection

With our approach, we want to establish a compromise between cost and scope. Using small RGB drones and smart phones for the data collection allows our approach to be employed cheaply, hence offering potential to be adapted for small-scale projects worldwide. However, this comes with certain limitations, such as more difficulty in measuring aspects such as tree height from the drone data, compared to, e. g., LiDAR-based technology.

For the ground-level field data, we will use the TreeMapper app (`https://www.plant-for-the-planet.org/treemapper/`), which estimates biomass based on species and diameter of each individual tree. Where logistically feasible, we will further collect aerial images using RGB drones, operated by experts in the local projects we are collaborating with. At the moment, we are enrolling data collection in four southern hemisphere countries, coverage a wide range of unique ecosystems, as follows.

Firstly, we conducted field tests of our technology in Paraguay, in collaboration with the Ministry of Environment of Paraguay (MADES). To this end, we collected drone and ground-level data in the Defensores del Chaco National Park, as shown in Figure 1. This is the largest national park of the country and consists of old-growth semi-arid closed-canopy shrub-land forests, for which

 

Figure 1: Field test data from the Defensores del Chaco National Park, Paraguay. Left: Orthomosaic of the ranger station at Fortin Madrejon, with surrounding dry forest. Right: Wildlife camera snapshot of a Capybara looking for water at a lake near the ranger station.

ML-models trained on Northern hemisphere forests with larger trees are not accurate. The first site for data collection[1] is currently in preparation. A second site is planned[2].

Second, we are setting up collaborations with mangrove forests sites in the Philippines, specifically, Lobo, Batangas, as well as Cagwait, Surigao del Sur[3]. Mangrove forests are particularly relevant, due to the high amount of carbon that is stored in the below-ground root system of these trees, which is hence inaccessible from just drone images. It is hence likely that current carbon estimation models severely underestimate the amount of carbon in mangroves, highlighting the importance of our data collection efforts in this under-sampled type of ecosystem.

Furthermore, we are establishing projects with the Kayapó indigenous people in central Brazil[4], one of the most inaccessible regions on the planet, yet becoming ever more threatened by ongoing deforestation. This unique dataset is a high-risk high-reward part of our project, and would yield ground-truth insights into the remote parts of the Amazonian forest.

Lastly, we are negotiating with project sites in Bhutan[5,6], to collect data on high elevation forests at almost 3000m altitude, contributing data from yet another under-represented ecosystem.

4 Making forest data fair and open

Recognizing the true costs of forest data origination is critical to empower an equitable benchmark [30]. Rewarding for data collection has the potential to provide an important additional funding source to frontline communities. For instance, the average monthly salary of forest rangers helping us to collect data in Paraguay's Chaco area is $400 per month. By contributing to ForestBench, many rangers have experienced an immediate financial improvement. Additionally, the benchmark incentivizes local upskilling through the frequent use of drone monitoring, a skill that empowers communities to monitor and protect larger forest areas.

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[3] https://beta.restor.eco/map/site/cagwait-mangrove-1
[4] https://beta.restor.eco/map/site/guard-post
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