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

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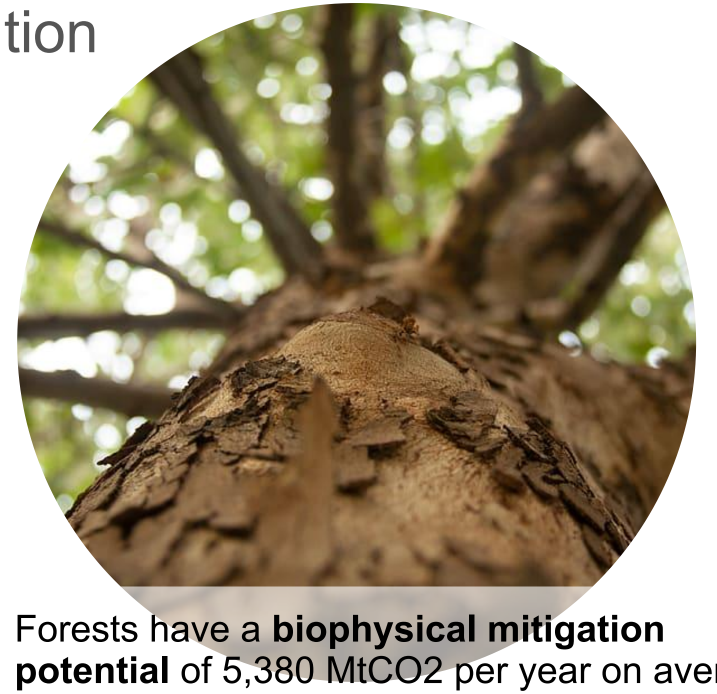
Forests are a key factor in limiting and mitigating climate change

Problem

- Deforestation and forest degradation account for **18% of anthropogenic greenhouse gas emissions** [1]
- We have **lost 361 million ha of forest cover** (the size of Europe) since 2000 [2]

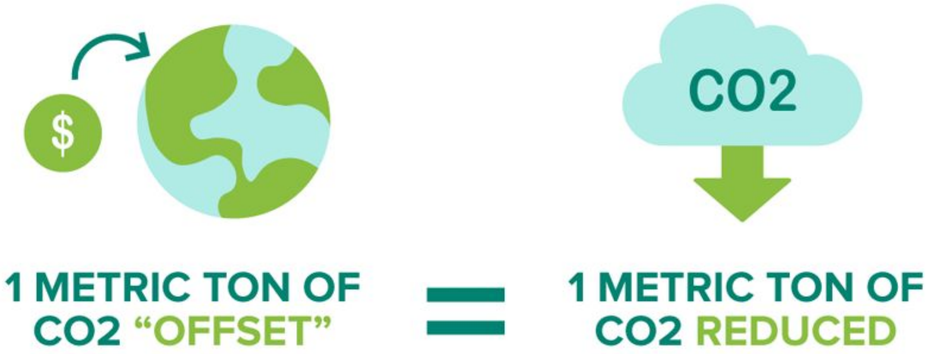
Solution



- Forests have a **biophysical mitigation potential** of 5,380 $MtCO_2$ per year on average until 2050 [1]

Carbon offsets can finance forests but certification is expensive and not transparent

- Carbon offsets are a way of financing restoration and protection of forests
- Certification processes long and have an avg. cost $10.000-15.000 annually[3]
- Accessible only for forests of +10.000ha
- Researchers have identified a systematic overestimation of forest carbon stock and are calling for more transparency and higher quality estimates [4,5]



Forest monitoring, verification and reporting is labor-intensive, biased, and hard to scale

Tree metrics
e.g. DBH,
species, etc

Allometric equations

Aboveground
biomass (AGB)
kg

Biomass = 2x Carbon

Carbon stock
kg of CO2e)

The current manual process is labor-intensive, biased, and hard to scale

Emergence of technical solutions leveraging advancements in remote sensing and machine learning models to automate estimation, decrease cost and improve time efficiency [6,7]

A benchmark dataset from six agro-forestry sites for forest carbon stock products

- AGB dataset from agro-forestry sites
- 4663 trees, 28 species and 3.17 ha
- Each tree registered with DBH, species, and GPS location

RGB drone images per site

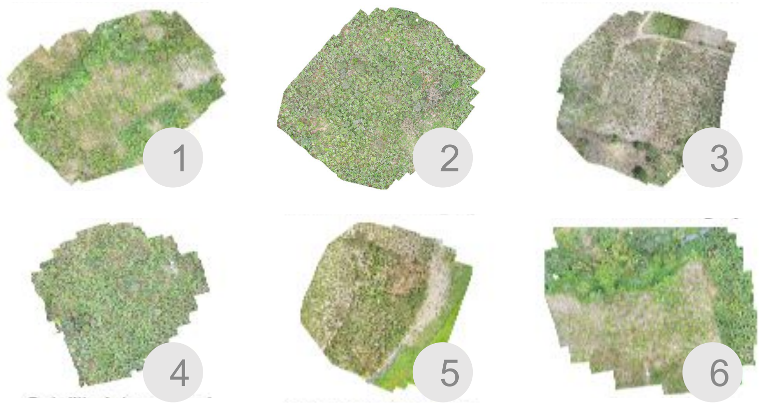


Fig. 1 Information about each site

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

Equations (1) and (2): Allometric equations from [8] and [9]

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

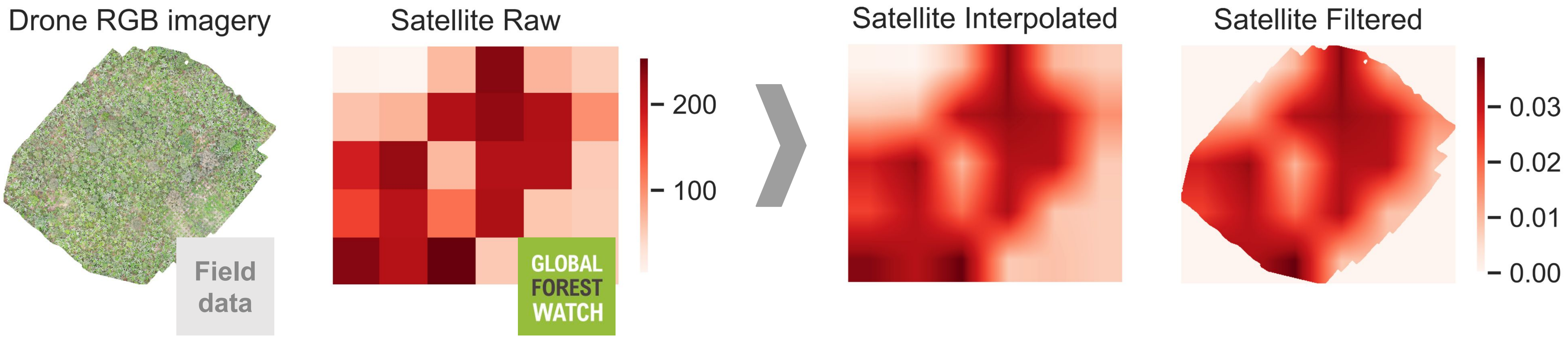
$$AGB_{musacea} = 0.030 * DBH^{2.13}$$

Benchmarking satellite-based AGB density estimation against field data

Global Forest Watch product: *Aboveground live woody biomass density*[10]

- 30mx30m resolution, 70k GLAS observations with deep learning model
- Lidar-derived canopy metrics and region-specific allometric equations

Map interpolated and filtered on the locations for all field data sites:



The satellite-based estimates significantly overestimates AGB density by a factor of 10

- The AGB density (kg/ha) per polygon was overestimated for **all of the 6 sites** with a factor ranging from 2 to 56 times the field data

Site No.	Ground Truth	Filtered	Over Estimation
1	19	240	$\times 13$
2	32	64	$\times 2$
3	26	970	$\times 37$
4	16	889	$\times 56$
5	24	597	$\times 25$
6	27	187	$\times 7$

Fig. 2 AGB density (kg/ha) of the field data (Ground truth) and of the satellite based estimations (Filtered).

A benchmark comparison of remote sensing forest carbon estimates is needed to ensure accuracy

- Forest carbon estimates from satellite imagery **can significantly overestimate aboveground biomass**
- **Aerial imagery products** seem more promising for automation of MVR of forest carbon offsetting projects
- Further work requires evaluating other available satellite and aerial forest carbon products and **increasing the variability of field datasets** to other forest project types
- Remote sensing-based forest carbon estimates have **high potential** but a global benchmark between options is important

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