Tropical Forest Carbon Accounting through Deep Learning-Based Species Mapping And Tree Crown Delineation

An Independent Research Project in Partial Fulfilment of the Requirements for the Degree MSc Environmental Data Science and Machine Learning

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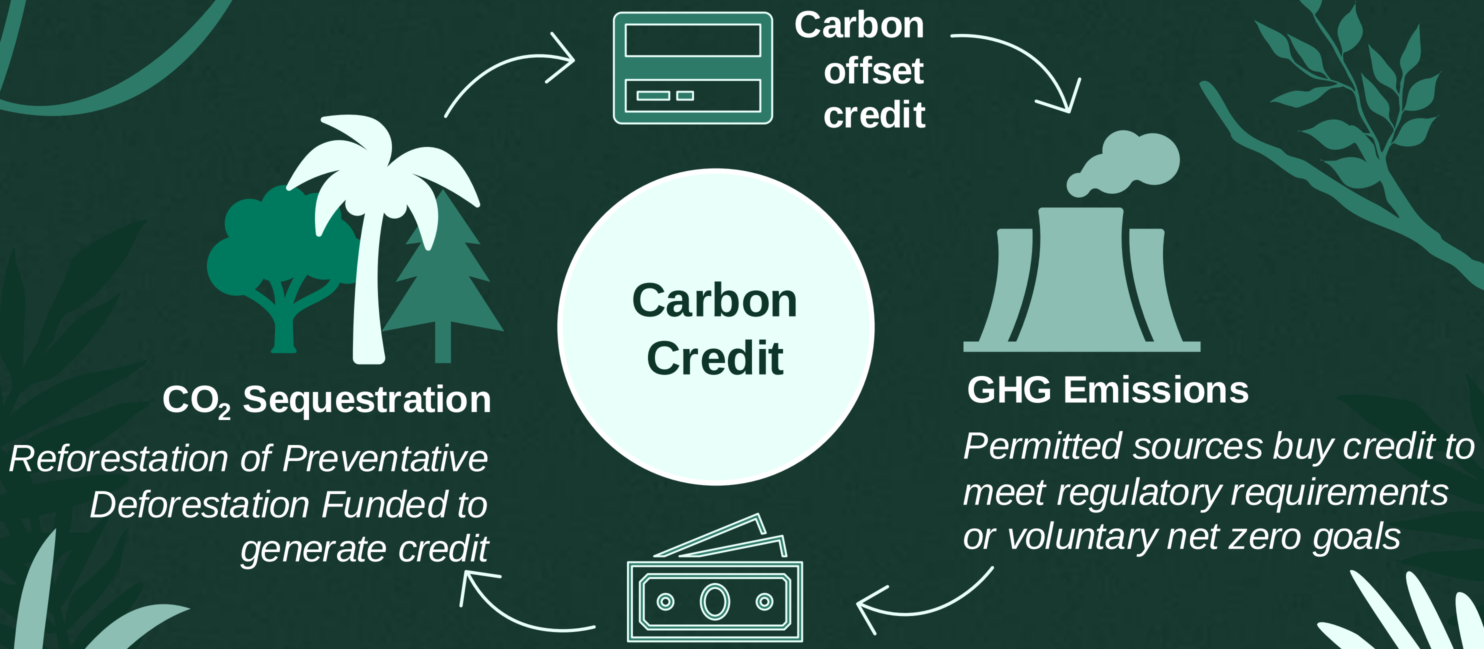

*Visualization inspired by similar chart from Blue Sky Analytics

Fast Facts

70%

Amount of global, vegetation-based
carbon storage attributed to forests

4.7 million ha

Forest land was lost per year; equating over the studied 10-year-period to approximately the whole of Kenya

$410 million

The cost of inaccurate carbon accounting of forests in California alone

78%

Recall achieved by a fine-tuned DeepForest model in Individual Tree Crown delineation (previous research)

89%

Species accuracy achieved by La Rosa et al. using a SEDD model

Study Area and Groundtruth

Used the ReforesTree Database provided by Reierson et al. for the purpose of developing Machine Learning solutions to the problem of carbon accounting:

- Six agroforestry carbon offsetting sites in the central coastal region of Ecuador
- Each site approximately 0.5 ha
- Dry tropical forest type
- Mavic 2 Pro drone with a resolution of 2cm per pixel
- Hand-gathered groundtruth measurements in Diameter at Breast Height (DBH), Aboveground Biomass (AGB), species type, and more

Species Name	Total ITCs	Percent ITCs
Cacao	2021	43.54%
Musacea	1504	32.41%
Guaba	597	12.87%
Other	428	9.22%
Mango	89%	1.92%

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SEDD and Deep Forest Models

A Note on Pre-Processing

- Started with 4000 x 4000 pixel orthomosaic image tiles.
- Applied image enhancements focusing on brightness, contrast, edge sharpening, and noise reduction.
- Techniques used: CLAHE, Gamma Correction, and Laplacian Sharpening.
- Excluded 8 tiles with over 80% whitespace from the dataset.

SEDD Model – A Combined Encoder and Two Decoders

Shared Encoder

- ResNet18 (He et al., 2015) with 7x7 convolutions, max pooling, and 3x3 convolutional layers for feature extraction.
- Pre-trained on ImageNet, fully connected layers were removed, deeper layers fine-tuned.

Semantic Decoder

- DeepLabv3 decoder (Chen et al., 2018) using Atrous Spatial Pyramid Pooling (ASPP).
- 3x3 and 1x1 convolutions, batch normalization, and softmax activation to produce probability map.
- Loss calculated using **Partial Weighted Categorical Focal Loss**.

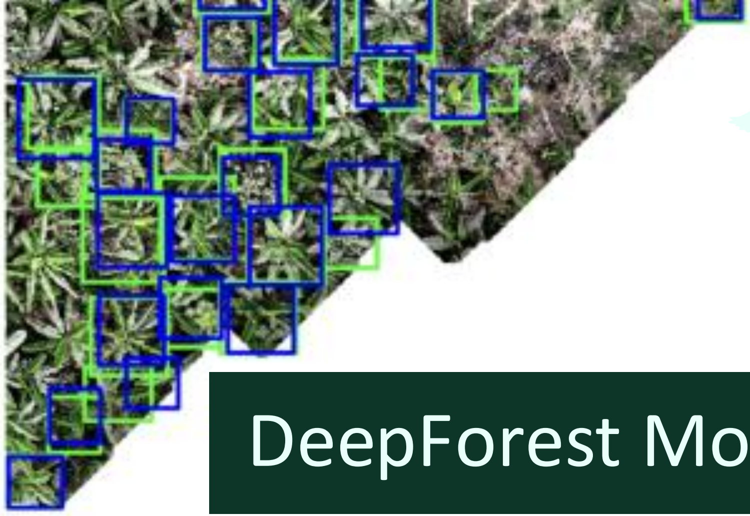
Distance Decoder

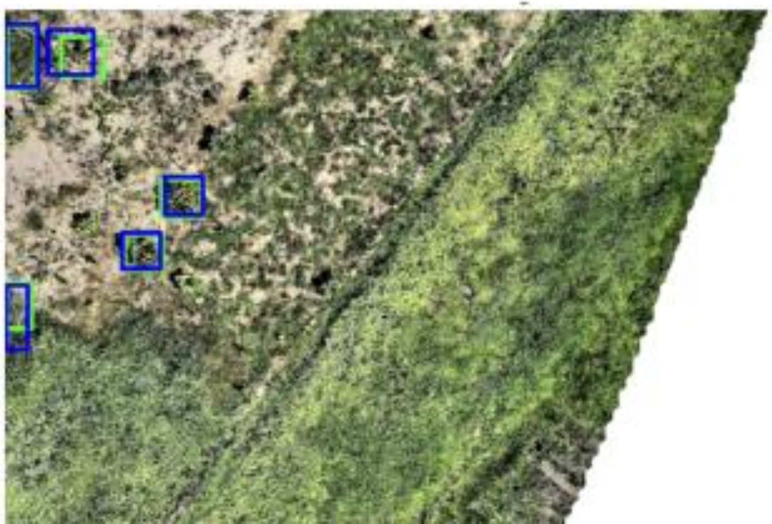
- 3x3 convolution, ReLU activation, and dropout (rate 0.65) to reduce overfitting.
- A 1x1 convolution refines the feature map, followed by a sigmoid activation to output normalized pixel distances (0-1).
- Loss calculated as MSE.

Final Loss

Combination of Semantic and Distance loss; either 1:1 or 2:1 favoring Semantic (termed S-SEDD model) ; S-SEDD model uses masking in semantic segmentation and DS-SEDD model does not.

DeepForest Model





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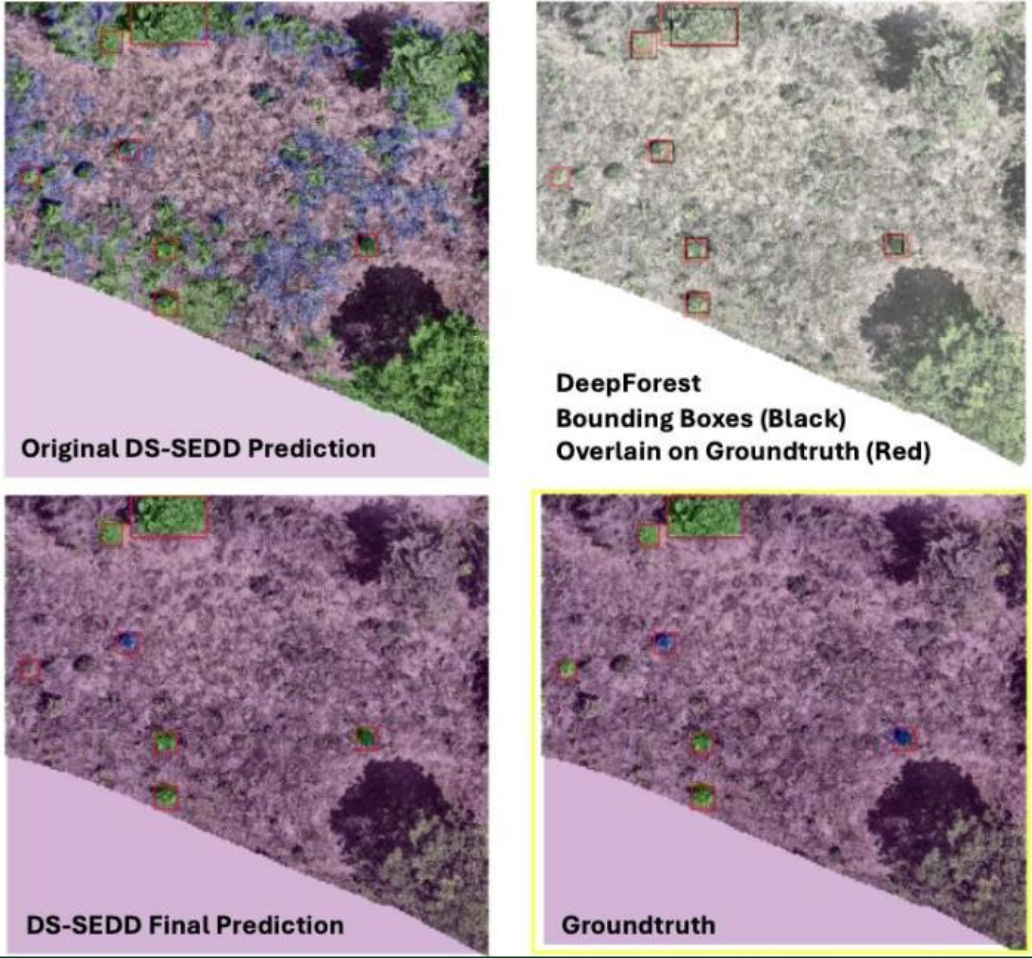
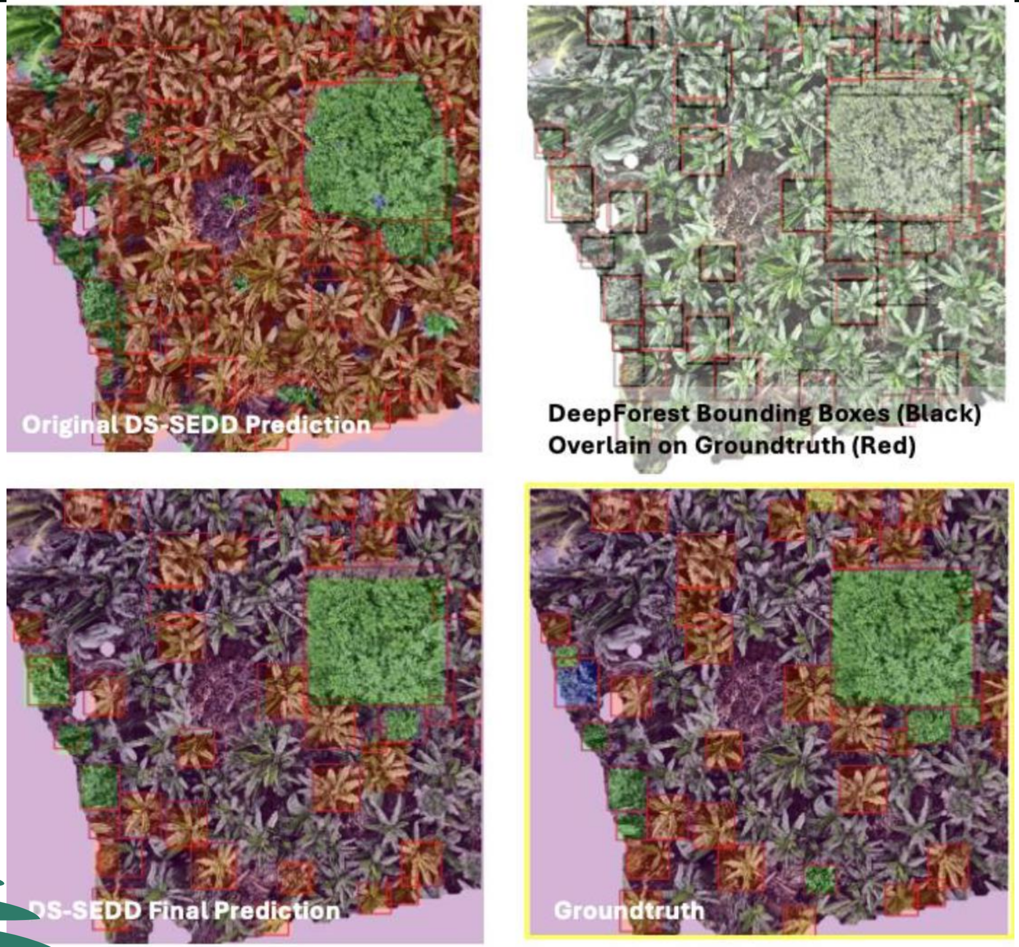
Post-Processing & Results



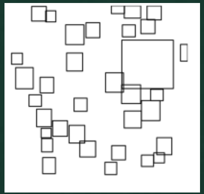
Carlos Vera Arteaga RGB_7



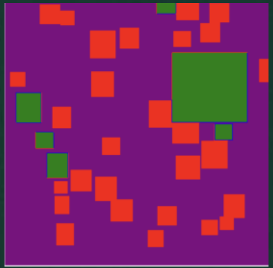
Flora Pluas RGB_9

Post-Processing Pipeline

SEDD Results – **Species Identification**



DeepForest Results – **ITC Delineation**

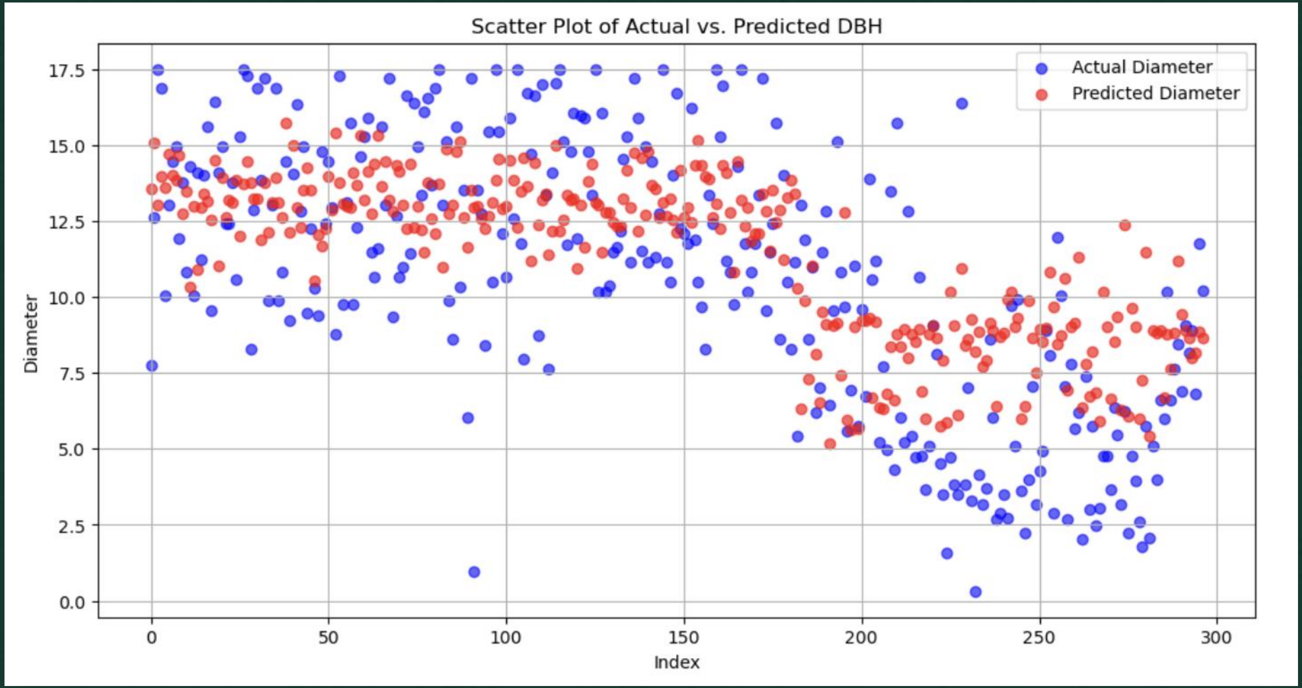


Combined ITC and Species Prediction map

Diameter Model uses species and bounding box information to predict DBH

Five Custom Allometric Statistical Models Predict AGB from DBH and Species Classification

Diameter Model



Custom Allometric Models

	Log Log	Linear	Exponential	Logarithmic	Polynomial	GAM
Musacea	1.0	0.99	0.99	0.97	1.0	1.0
Cacao	1.0	0.99	0.98	0.95	1.0	1.0
Guaba	1.0	0.97	0.98	0.93	1.0	1.0
Mango	1.0	1.0	1.0	0.99	1.0	1.0
Other	0.87	0.86	0.92	0.71	0.93	0.98

Species Matching Results (DS-SEDD Model)

	Actual Carbon	Predicted Carbon	Absolute Difference	Relative Difference
Test Tile 1	46.16	36.73	9.43	**0.2**
Test Tile 2	16.6	15.84	0.77	**0.05**
Test Tile 3	6.64	6.74	0.09	**0.01**
Test Tile 4	104.34	94.44	9.91	**0.09**
Test Tile 5	88.1	68.13	19.97	**0.23**
Test Tile 6	157.86	131.07	26.79	**0.17**
Test Tile 7	93.55	71.39	22.16	**0.24**
Test Tile 8	16.69	20.84	4.16	**0.25**
Test Tile 9	87.63	113.82	26.19	**0.3**
Test Tile 10	134.21	147.01	12.8	**0.1**
Test Tile 11	168.7	171.92	3.23	**0.02**
Test Tile 12	17.85	18.28	0.42	**0.02**
Test Tile 13	16.29	24.13	7.84	**0.48**
Test Tile 14	0.53	2.95	2.42	**4.6**
Test Tile 15	106.47	99.9	6.57	**0.06**
Test Tile 16	160.42	166.26	5.84	**0.04**
Total	**1222.04**	**1189.45**	**32.59**	0.02

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Discussion

Discussion & Comparison of Results

- Comparing this research to others is challenging because most methods are not based on individual tree crowns (ITCs) and apply to the entire area.
- Relative error comparisons are used to avoid data leakage, as most similar studies focus on non-ITC methods.
- This study achieved a 2% relative error in predicting carbon sequestration, outperforming previous methods, including those requiring more data (e.g., manually collected DBH and species metrics).
- The approach is lightweight, relying only on RGB imagery, showing that deep learning and statistical models can accurately estimate individual tree-level carbon sequestration from aerial images.

Site Number	GFW 2019	Spawn 2020	Santoro 2021	Reierson 2022
1	10.3	9.5	0.75	0.13
2	5.6	5.8	0.2	0.46
3	1.5	2.3	0.9	0.5
4	0.8	15.4	1.4	0.27
5	4.2	4.1	0.0	0.27
6	1.5	1.91	0.33	0.25
Total	**4.0**	**5.25**	**0.34**	**0.02**

Limitations & Future Work

Data Accessibility

RGB aerial data was chosen for its availability in lower-income areas, though using multispectral or LiDAR data could improve DBH approximation.

Sparse and Unbalanced Data

Future Efforts could explore more techniques to remedy this.

Scalability Challenge

High-performance computing (HPC) requirements for model evaluation limit scalability; future work may focus on a more efficient model for less powerful infrastructure.

Commercial Application

Future development could focus on creating a user-friendly software product where users upload images and receive tree-level carbon metrics, advancing this technology toward commercial use in the global carbon market.

Resources

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Thanks!