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

Project Plan

Georgia Ray[1]
[1] Imperial College London
GitHub: edsml-ger23
Email: georgia.ray23@imperial.ac.uk

Supervision by Minerva Singh and Adriana Paluszny

An Independent Research Project
Submitted to the Department of Earth Science and Engineering
Imperial College London
In Partial Fulfilment for the Requirements
For the Degree MSc Environmental Data Science and Machine Learning
June 14, 2024

Abstract

Tropical forests are essential ecosystems recognized for their carbon sequestration and biodiversity benefits. As the world undergoes a simultaneous data revolution and climate crisis, accurate data on the world's forests is increasingly important. The importance is particularly stark for burgeoning climate offset markets, reliant on accurate and verifiable estimates of carbon storage provided by afforestation or preventative deforestation. Traditional methods are often expensive and imprecise, relying on ground-based measurements and low-resolution satellite imagery, leading to an overestimation in accounted carbon.

Using the ReforesTree dataset (Reiersen et al., 2022), this project employs a single encoder, double decoder (SEDD) to generate a distance map used with a marker-controlled watershed segmentation for individual tree crown-delineation and pixel-based species identification. The SEDD architecture, featuring a shared ResNet-20 encoder and dual DeepLabv3+ based decoders, facilitates efficient processing of aerial RGB imagery. This solution is both scalable and cost-effective, allowing potential application to other global forests.

Introduction

Comprising the largest proportion of the world's forests, tropical forests play a crucial role as a carbon sink. Carbon is stored in forests via vegetation, soil, and litter (Sun and Liu, 2019), and over 70% of the global, vegetation-based carbon storage can be attributed to forests. 36% is attributed to tropical forests specifically (IPCC, 2022).

But deforestation, wildfires, and extreme weather threaten forests' future. Between 2010 and 2020, 4.7 million ha of forest land was lost per year, equating to a loss over the 10-year-period approximately equivalent to the whole of Kenya (FAO, 2020). This is particularly concerning because forests are essential not only for carbon storage but also for protecting against soil erosion, regulating the water cycle, and supporting local economic systems. Forests also provide a refuge 80% of the world's land-based biodiversity (Shi et al., 2021).

Accurate carbon storage metrics in forests are imperative to monitoring forest health and ensuring transparency in carbon offset markets. Carbon offset credits are often based on preventative deforestation, meaning a reliable carbon storage baseline helps calculate the number of credits issued. For most projects the minimum baseline is the regional average carbon stock density for the forest type (Haya 2023). Manual forest carbon stock practices systematically overestimate the amount of storage, up to a value of $410 million (Badgley et al., 2022, Sun and Liu, 2019).

Additionally, most afforestation and deforestation is happening in low and middle income countries, necessitating scalable and cost-efficient methods for calculating carbon storage. Mapping forests with remote sensing data has proven cheaper and faster than traditional methods (Fassnacht et al., 2016) and developing methods using free or easily accessible images and technologies is an emerging focus in the field (Korznikov et al., 2021, Reiersen et al., 2022). This research will focus specifically on the publicly available ReforesTree dataset, documenting six agro-forestry carbon offsetting sites in Ecuador. It is based on high resolution RGB drone imagery and contains groundtruth data on species type, tree crown size, and above-ground biomass (AGB) (Reiersen et al., 2022).

Accurate estimates of tree crown dimensions are indispensable in calculating biomass (Klein et al., 2021), but independent of this application, there is a strong body of research on Individual Tree Crown (ITC) delineation. Deep learning models, such as Faster R-CNN and Mask R-CNN, have shown promise in this delineation task. Braga et al. (2020) use an Instance Segmentation approach with Mask R-CNN in tropical forests while Wu et al. (2020) focuses on apple orchards using

Semantic Segmentation and convex boundary extraction. Weinstein et al. (2020) present DeepForest, a package specifically designed for ITC delineation on RGB images. Lassalle et al. (2022) show integrating deep learning models with advanced image processing techniques, such as watershed segmentation, can further enhance the accuracy of ITC.

Similarly, there is a significant body of research on tree species identification using deep learning. There has been research into 3D-CNNs for hyperspectral images (Zhang et al., 2020), a SVM classifier for a Mixed Ombrophilous Forest ecosystem (Sothe et al., 2019), and the integration of LiDAR data and multispectral imagery for enhanced species classification (Fassnacht et al., 2016). Korvnikov et al. (2021) demonstrated U-Net-like CNNs outperform traditional machine learning methods in pixel-based species segmentation using high-resolution RGB satellite images.

More recently, there has been a move towards a combined approach, training networks to identify species and perform ITC delineation simultaneously (Klein et al., 2021, La Rosa et al., 2021). In a tropical urban context, Martins et al. (2021) demonstrated CNNs can be trained to identify individual tree crowns and estimate their biomass using high-resolution RGB imagery, significantly improving the accuracy of carbon stock estimates. Ferreira et al. (2020) employed deep learning model to detect individual trees and classify their species in UAV-RGB images, applying these techniques to large-scale forest monitoring.

The objective of the existing research is to bring together current methods in ITC delineation and species identification, using allometric equations to provide a cost-effective and accurate method for forest carbon stock estimation. Results are compared to other satellite-based carbon stock estimates (Global Forest Watch, 2022, Spawn et al., 2020, Santoro et al., 2021) as well as a CNN approach trained on the same dataset (Reiersen et al., 2022).

Methodology

Pre-processing. Standard pre-processing will be applied including image cropping and data augmentation. Additionally, class weighting will be deployed to account for uneven species representation in the dataset (Martins et al., 2021).

SEDD with Instance Segmentation. The next step involves using a Single Encoder, Double Decoder (SEDD) for instance segmentation, enabling both distance map generation and pixel-based species identification. The architecture employs a shared backbone network learning common representations for both tasks and then uses two task-specific decoders: one for semantic segmentation and another for distance map regression (La Rosa et al., 2021).

For semantic segmentation, an output feature map from ResNet-20 is fed into a decoder based on the DeepLabv3+ architecture (Chen et al., 2018). This approach is based on Martins et al. (2021) architecture, itself an adaptation of La Rosa et al. (2021). Again following Martins et al., the species identification task will integrate partially weighted categorical focal loss. The SEDD model was selected for its computational efficiency, saving time and memory via shared encoding, without sacrificing accuracy.

Watershed Segmentation. Martins et al. (2021) uses a regression map to identify individual trees. Breaking with their approach, I will use apply a Laplacian of Gaussian (LoG) filter to the distance image, removing noise and enhancing crown borders (Lassalle et al., 2022, Marr et al., 1980). ITCs are then delineated using a marker-controlled watershed segmentation algorithm. This method treats the image like a topographic surface where high-intensity values represent peaks. Markers are used to identify the regions of interest, and the watershed algorithm delineates tree crowns based on these markers. This approach better handles overlapping or closely situated tree crowns.

Post-processing. Post-processing involves calculating tree height based on diameter at breast height (DBH) and applying carbon accounting formulas. Scientifically developed regression models called allometric equations are used to calculate AGB (Reiersen et al., 2022). Carbon stock is calculated through the standard forest inventory methodology using the dry tropical reforestation site root-to-shoot ratio of 22% (Qi et al., 2019).

Limitations. I have conceptualized this project using aerial RGB data. For the purposes of tree crown delineation, all data will require a resolution of 0.1–1 m/pixel (G. Braga et al., 2020). Current data has a resolution of 0.2 m/pixel (Reiersen et al., 2022). In the event that I were to transition to multispectral or LiDAR data, I could use more sophisticated techniques, but I would have to ensure consistent resolution.

For example, I could use pan-sharpening via the Nearest Neighbor Diffusion (NNDiffuse) algorithm available in ENVI as applied by Lassalle et al. (2022), a method they selected after comparing multiple pan-sharpening techniques. If I had LiDAR data, I could use the 3D point cloud to generate more accurate tree height estimations, allowing me to use allometric equations more accurately (relying on fewer estimations of tree dimensions) (Klein et al., 2021).

However, this trade-off for higher quality data would also mean the approach is less scalable and applicable to low and middle income countries, as well as historical data. In short, higher-quality data could provide sharper insights, but may also lessen the potential application of this research on a temporal scale or in specific geographic regions. The current design intends the scalability of solutions. Still, its effectiveness may vary across different forest types and geographical regions. Additional validation may be required to ensure the model's applicability in diverse forest ecosystems.

As I progress in the project, I will consider which approach has more merit, maybe even comparing the accuracy of RGB aerial data versus LiDAR.

Expected Outcomes/Deliverables

The anticipated outcome of this project is a deep learning-based framework for tropical forest carbon accounting. The key deliverables will be:

ITC Delineation. A methodology for accurately delineating individual tree crowns in high-resolution aerial RGB imagery using the SEDD architecture combined with marker-controlled watershed segmentation.

Species Identification and Mapping. A system for pixel-based species identification, leveraging the dual decoder approach of the SEDD model.

Carbon Stock Estimation. Estimation of forest carbon stocks validated against ground-truth data from the ReforesTree dataset and compared with other satellite-based and CNN-based carbon stock estimates.

These deliverables aim to address the problem of inaccurate and expensive forest carbon accounting methods. By developing a deep learning-based approach this research will use state-of-the-art approaches to ITC delineation and species identification, applying them on a critical dataset and concluding with an application for precise biomass and carbon stock estimations. Approaches like this have the ability to enhance the transparency and reliability of carbon offset markets.

Future Plan

See Table 1 for a timeline of deliverables.

Progress to date has included data acquisition and visualization. Some feature extraction has been performed to better understand the applicability of pre-processing steps.

Resources

[1] 2022. Global Forest Watch Dataset. Global Forest Watch.

[2] BADGLEY, G., FREEMAN, J., HAMMAN, J. J., HAYA, B., TRUGMAN, A. T., ANDEREGG, W. R. L. & CULLENWARD, D. 2022. Systematic over-crediting in California's forest carbon offsets program. *Global Change Biology,* 28**,** 1433-1445.

[3] CHEN, L.-C., ZHU, Y., PAPANDREOU, G., SCHROFF, F. & ADAM, H. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. *In:* FERRARI, V., HEBERT, M., SMINCHISESCU, C. & WEISS, Y., eds. Computer Vision – ECCV 2018, 2018// 2018 Cham. Springer International Publishing, 833-851.

[4] FAO 2020. Global Forest Resources Assessment 2020.

[5] FASSNACHT, F. E., LATIFI, H., STEREńCZAK, K., MODZELEWSKA, A., LEFSKY, M., WASER, L. T., STRAUB, C. & GHOSH, A. 2016. Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment,* 186**,** 64-87.

[6] FERREIRA, M. P., ALMEIDA, D. R. A. D., PAPA, D. D. A., MINERVINO, J. B. S., VERAS, H. F. P., FORMIGHIERI, A., SANTOS, C. A. N., FERREIRA, M. A. D., FIGUEIREDO, E. O. & FERREIRA, E. J. L. 2020. Individual tree detection and species classification of Amazonian palms using UAV images and deep learning. *Forest Ecology and Management,* 475**,** 118397.

[7] G. BRAGA, J. R., PERIPATO, V., DALAGNOL, R., P. FERREIRA, M., TARABALKA, Y., O. C. ARAGãO, L. E., F. DE CAMPOS VELHO, H., SHIGUEMORI, E. H. & WAGNER, F. H. 2020. Tree Crown Delineation Algorithm Based on a Convolutional Neural Network. *Remote Sensing* [Online], 12.

[8] IPCC 2022. Land–climate interactions. *In:* INTERGOVERNMENTAL PANEL ON CLIMATE, C. (ed.) *Climate Change and Land: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems.* Cambridge: Cambridge University Press.

[9] KLEIN, L., ZHOU, W. & ALBRECHT, C. 2021. *Quantification of Carbon Sequestration in Urban Forests*.

[10] KORZNIKOV, K. A., KISLOV, D. E., ALTMAN, J., DOLEžAL, J., VOZMISHCHEVA, A. S. & KRESTOV, P. V. 2021. Using U-Net-Like Deep Convolutional Neural Networks for Precise Tree Recognition in Very High Resolution RGB (Red, Green, Blue) Satellite Images. *Forests* [Online], 12.

[11] LA ROSA, L. E. C., SOTHE, C., FEITOSA, R. Q., DE ALMEIDA, C. M., SCHIMALSKI, M. B. & OLIVEIRA, D. A. B. 2021. Multi-task fully convolutional network for tree species mapping in dense forests using small training hyperspectral data. *ISPRS Journal of Photogrammetry and Remote Sensing,* 179**,** 35-49.

[12] LASSALLE, G., FERREIRA, M. P., LA ROSA, L. E. C. & DE SOUZA FILHO, C. R. 2022. Deep learning-based individual tree crown delineation in mangrove forests using very-high-resolution satellite imagery. *ISPRS Journal of*

Photogrammetry and Remote Sensing, 189**,** 220-235.

[13] MARR, D., HILDRETH, E. & BRENNER, S. 1980. Theory of edge detection. *Proceedings of the Royal Society of London. Series B. Biological Sciences,* 207**,** 187-217.

[14] MARTINS, G. B., LA ROSA, L. E. C., HAPP, P. N., FILHO, L. C. T. C., SANTOS, C. J. F., FEITOSA, R. Q. & FERREIRA, M. P. 2021. Deep learning-based tree species mapping in a highly diverse tropical urban setting. *Urban Forestry & Urban Greening,* 64**,** 127241.

[15] QI, Y., WEI, W., CHEN, C. & CHEN, L. 2019. Plant root-shoot biomass allocation over diverse biomes: A global synthesis. *Global Ecology and Conservation,* 18**,** e00606.

[16] REIERSEN, G., DAO, D., LüTJENS, B., KLEMMER, K., AMARA, K., STEINEGGER, A., ZHANG, C. & ZHU, X. 2022. ReforesTree: A Dataset for Estimating Tropical Forest Carbon Stock with Deep Learning and Aerial Imagery. *Proceedings of the AAAI Conference on Artificial Intelligence,* 36**,** 12119-12125.

[17] SANTORO, M., CARTUS, O., CARVALHAIS, N., ROZENDAAL, D. M. A., AVITABILE, V., ARAZA, A., DE BRUIN, S., HEROLD, M., QUEGAN, S., RODRíGUEZ-VEIGA, P., BALZTER, H., CARREIRAS, J., SCHEPASCHENKO, D., KORETS, M., SHIMADA, M., ITOH, T., MORENO MARTíNEZ, Á., CAVLOVIC, J., CAZZOLLA GATTI, R., DA CONCEIçãO BISPO, P., DEWNATH, N., LABRIèRE, N., LIANG, J., LINDSELL, J., MITCHARD, E. T. A., MOREL, A., PACHECO PASCAGAZA, A. M., RYAN, C. M., SLIK, F., VAGLIO LAURIN, G., VERBEECK, H., WIJAYA, A. & WILLCOCK, S. 2021. The global forest above-ground biomass pool for 2010 estimated from high-resolution satellite observations. *Earth Syst. Sci. Data,* 13**,** 3927-3950.

[18] SHI, H., TIAN, H., LANGE, S., YANG, J., PAN, S., FU, B. & REYER, C. P. O. 2021. Terrestrial biodiversity threatened by increasing global aridity velocity under high-level warming. *Proceedings of the National Academy of Sciences,* 118**,** e2015552118.

[19] SOTHE, C., DALPONTE, M., ALMEIDA, C. M., SCHIMALSKI, M. B., LIMA, C. L., LIESENBERG, V., MIYOSHI, G. T. & TOMMASELLI, A. M. 2019. Tree Species Classification in a Highly Diverse Subtropical Forest Integrating UAV-Based Photogrammetric Point Cloud and Hyperspectral Data. *Remote Sensing* [Online], 11.

[20] SPAWN, S. A., SULLIVAN, C. C., LARK, T. J. & GIBBS, H. K. 2020. Harmonized global maps of above and belowground biomass carbon density in the year 2010. *Scientific Data,* 7**,** 112.

[21] SUN, W. & LIU, X. 2019. Review on carbon storage estimation of forest ecosystem and applications in China. *Forest Ecosystems,* 7**,** 4.

[22] WEINSTEIN, B. G., MARCONI, S., AUBRY-KIENTZ, M., VINCENT, G., SENYONDO, H. & WHITE, E. P. 2020. DeepForest: A Python package for RGB deep learning tree crown delineation. *Methods in Ecology and Evolution,* 11**,** 1743-1751.

[23] WU, J., YANG, G., YANG, H., ZHU, Y., LI, Z., LEI, L. & ZHAO, C. 2020. Extracting apple tree crown information from remote imagery

using deep learning. *Computers and Electronics in Agriculture,* 174**,** 105504.

[24] ZHANG, B., ZHAO, L. & ZHANG, X. 2020. Three-dimensional convolutional neural network model for tree species classification using airborne hyperspectral images. *Remote Sensing of Environment,* 247**,** 111938.

Table 1. Project Timelines

Task	Description	Start Date	Completion Date
Project Start	Begin Independent Research Project (IRP)	27th May 2024	27th May 2024
Writing Course	Participate in Writing Course	10th June 2024	10th June 2024
Data Acquisition and Visualization	Acquire and visualize data, perform initial feature extraction	27th May 2024	14th June 2024
Project Plan Submission	Submit detailed project plan		14th June 2024, 12:00 BST
Pre-processing and Augmentation	Apply standard pre-processing and data augmentation	15th June 2024	21st June 2024
SEDD Model Development	Develop and Test Single Encoder, Double Decoder architecture	22nd June 2024	28th June 2024
Model Training and Validation	Train and validate SEDD model using ReforesTree dataset	29th June 2024	5th July 2024
Watershed Segmentation Development and Whole Pipeline	Develop marker-controlled watershed segmentation algorithm and apply allometric algorithms, having first attempt at completed model and results	6th July 2024	12th July 2024
Results Comparison, Analysis, and Improvements	Compare results with other methods and make changes to base models to improve outputs	13th July 2024	31st July 2024
Plan for First Draft of Entire Report	Use outputs to create outline for entire report	1st August 2024	4th August 2024
Presentation Workshop	Attend presentation workshop	N/A	6th August 2024, 10:00-11:30 BST
First Entire Report Draft	First draft of the compiled report, including outputs and analysis	6th August 2024	9th August 2024
Refine and Complete Report Draft	Finalize Report Draft, making any necessary changes to code and models as required	13th August 2024	30th August 2024
First Draft of Presentation	Prepare Initial Slides and Script for Final Presentation	13th August 2024	30th August 2024

Final Report Submission	Submit final report	N/A	30th August 2024, 12:00 BST
Presentation Preparation	Finalize preparations for project presentation	1st September 2024	8th September 2024
Project Presentations	Present project findings	N/A	9-13th September 2024, 09:00-18:00 BST