Remote Estimation of Above Ground Forest Biomass Using LiDAR and Drone Imagery

Cade Parlato*, Neil Loftus‡, Sam McGrath§, Husnu S. Narman†, and Rick Gage¶

Email: *parlato@marshall.edu,‡loftus6@marshall.edu,§mcgrath11@marshall.edu,†narman@marshall.edu,¶gager@marshall.edu

Abstract—As concerns around climate change continue to rise, accurate and efficient monitoring of our planet's carbon stocks is becoming increasingly important. The carbon stocks of forests, one of the largest contributors to the Earth's carbon cycle, have historically been monitored through measurements of Above Ground Biomass (AGB). These measurements are traditionally done by hand over long periods of manual labor; however, the recent rise of remote sensing methodology has provided another avenue for AGB estimation. A large amount of research has been conducted in the past decade regarding a wide range of methods for remote AGB estimation. Many of these methods, however, require large amounts of data to be gathered in order to be conducted in areas not recently analyzed. This study aims to test the feasibility of remote AGB estimation in an environment with low access to existing ground-truth data in the Appalachian area and develop reliable methods for AGB estimation in smaller-scale plots. These estimations are built off of existing equations relating tree height, canopy diameter, and genus directly to biomass. Through the use of drone imagery and machine learning, we are currently building a dataset that would allow rapid identification of tree genus by canopy on an image-by-image basis. Combining this with existing methods of tree measurement using public satellite LiDAR data, our goal is to develop both a benchmark dataset and trained machine learning model that could estimate tree biomass without the need for specialized equipment.

Index Terms—Above Ground Biomass, Deep learning, Machine Learning, Classification

I. Introduction

While making up a small portion of our overall atmosphere, carbon dioxide is our planet's primary greenhouse gas; keeping consistent levels of CO_2 is vital for maintaining livable environments across the globe, as it directly relates to the amount of heat trapped within our atmosphere. The amount of greenhouse gas in the atmosphere is maintained by the Earth's natural carbon cycles, wherein plants take in CO_2 through photosynthesis and effectively release that carbon back into the atmosphere when they die. Forests are one of the primary contributors to this cycle, capable of taking in 2-4 Gt of carbon each year and acting as massive carbon sinks [1]. Consistent monitoring of forests allows us to keep track of the planet's carbon pool by looking at increases and decreases in observable biomass, and thus the amount of carbon being stored within that biomass.

The monitoring of carbon stocks continues to gain importance due to the increased production of carbon dioxide into the atmosphere by human activity. In recent decades, the rate at which carbon dioxide has been entering the atmosphere is higher than any point in the past 80,000 years and continues to rise in the present day [2]. This is primarily a result of the common burning of fossil fuels, which releases large amounts of CO_2 into the atmosphere as a primary byproduct. Additionally, increased deforestation has made it continually more difficult for this carbon to be captured. These factors combined have led to concerningly high levels of atmospheric carbon, which is a primary contributor towards our current global warming crisis. Biomass monitoring of forests, then, is an important way for us to keep tabs on the state of global warming as it becomes increasingly impactful on environments across the planet.

Forests are comprised of many types of biomasses. According to the Intergovernmental Panel on Climate Change (IPCC), there are five primary types of biomasses which act as significant carbon pools: above-ground, below-ground, litter, woody debris, and soil organic matter. Of these five, above-ground biomass (AGB) accounts for between 70% to 90% of the total biomass in forests [3]. Besides being the most common, AGB is also extremely volatile and most at risk from immediate environmental factors. To accurately monitor AGB, measurements must be taken frequently and repeatedly given that factors such as deforestation or forest fires can cause drastic changes in total biomass [4].

In recent years, the focus of AGB estimation research has begun shifting away from traditional methods and moving towards techniques that are more hands-off. Historically, AGB has been measured by-hand in plots through ground-based measurements. While effective, these methods are limited by both ground-coverage and speed of data collection. Remote-sensing approaches provide a massive increase in the amount of data that can be gathered at once, and the majority of this data can be processed very efficiently compared to hands-on methods [5]–[7]. Research on these approaches tends to rely on extensive existing data for the given study area, meaning research conducted in comparatively undocumented regions - or with low access to data - cannot easily approach these more efficient methods.

Our aim in this paper is to investigate the feasibility of remote AGB estimation in an environment with low access to existing ground-truth data and develop reliable machine learning methods for AGB estimation in smaller-scale plots. The key contribution of this paper is (i) reviewing the existing works for the AGB estimation, (ii) creating dataset

to train the machine learning models, and (iii) evaluating the performance of the machine learning models on the case area in Appalachian area. The initial results show that machine learning algorithms can be used to identify the tree types by using drone and satellite images.

The rest of the paper is organized as follows: Section II summarizes the exiting works. The system model and dataset creation are explained in Section III. The results and our discussion are included in Section IV, and finally Section V has the concluding remarks and the future works.

II. DEEP LEARNING

Image processing through deep learning is a highly effective method for achieving impressive accuracy in object detection tasks, provided that a well-constructed training dataset is available. The depth and specifics of the neural networks depend on the specific goal of the network, with networks that classify single trees being significantly smaller than networks which both classify and disseminate trees.

The simplest deep learning approach would be to develop a network which takes a tree that has already been disseminated, such as by LiDAR, and classifying its species. This approach has been proven effective in other domains of image processing, with one of the most famous examples being the MNIST numerical digit dataset [8]. One of the most effective network architectures for this approach are convolutional neural networks, and more specifically a sub-category known as a residual network [9]. The architecture, also known as a "resnet" stacks several convolutional layers on top each other, like other convolutional networks do, while also implementing shortcut pathways that skip over layers, to prevent errors that can be caused by too deep of networks. This approach has been applied to tree species classification with an accuracy of 80% by authors Natesan et al [10].

The networks utilized for models that delineate tree canopies are far more complex in their construction. These networks are very desirable, due to their ability to identify and classify trees quickly once properly developed. However, the development of these networks, along with just classification networks, can be a difficult process. In some cases, an effective deep learning model can require thousands of images, if not tens of thousands of images. This is especially difficult in a supervised learning approach, as it necessitates that the images used to train these networks are labeled in some manner, such as through manual review. These networks have been proven effective for tree delineation by several authors, with a notable example being "DeepForest" by Weinstein et al. [11]. This network was developed as a python library, allowing other researchers to build upon their work and specialize the network for other trees by providing more training data, through a process known as transfer learning [12].

DeepForest represents its tree detections through rectangular bounding boxes, which can be slightly inaccurate for more irregular canopy shapes. This is corrected by networks which produce multipoint polygons. Tree segmentation approaches are common among point cloud-based delineation approaches, but it is a more uncommon approach for image-based networks, due to the added complexity. One of the most generically popular bounding box deep learning networks is that of YOLO, which has been extended to produce polygons instead [13].

III. SYSTEM MODEL AND DATASET

The previous works [14] shows that AGB and DBH can be estimated based on tree properties such as tree height, canopy area, and genus. The following equations are examples of estimation of AGB and DBH:

$$AGB = 0.058P * ((DBH)^2 * H)^{0.999} \text{ [15]}$$

$$DBH = 13.866 + 0.509C$$

where P is density of genus, DBH is trunk diameter at breast height, H is tree height, and C is canopy area.

While these equations were created for the purpose of expediting by-hand AGB estimation, they lay a groundwork for easier approaches in remote sensing scenarios. In the case of our remote sensing-based research, the three required pieces of data can be split into two categories: spatial (height and canopy area) and visual (genus). While genus itself is not a visual attribute, multiple approaches for estimation utilize optical drone data to train machine learning models to identify genus based solely on visuals [6], [7], [16]. These approaches often make use of non-visible wavelengths of light from multispectral sensors; due to the lower availability of such sensors compared to standard red-green-blue (RGB) sensors, we aim to test the validity of standard RGB imagery as a means of estimation instead. For similar reasons, this study will also not be making use of our own remote spatial data, such as LiDAR, for tree measurements; we will instead be sourcing LiDAR data from public databases as a means for remote measurements. As both our LiDAR data and images will store geographic information, the two sources of data can be combined to produce a testable final result. The ground-truth data is still in the process of being collected to test both forms of data. The reliability of these methods separately and combined will be tested as data continues to be gathered.

All hand-gathered data for this study was taken from the region seen in Fig. 1 slightly south of Saint Albans, WV (38.327417N,-81.832858E). The area is primarily covered in dense forests but is bisected by a road with multiple branching residential areas. With a mostly flat elevation and even split between residential and forested areas, this region is ideal for testing reliability in multiple types of environments. The ground-truth data was gathered near the edges of these residential areas due to ease of access, and environments were made sure to include non-tree objects for the sake of analyzing potential false positives such as buildings or grass which may interfere with the predictive models.
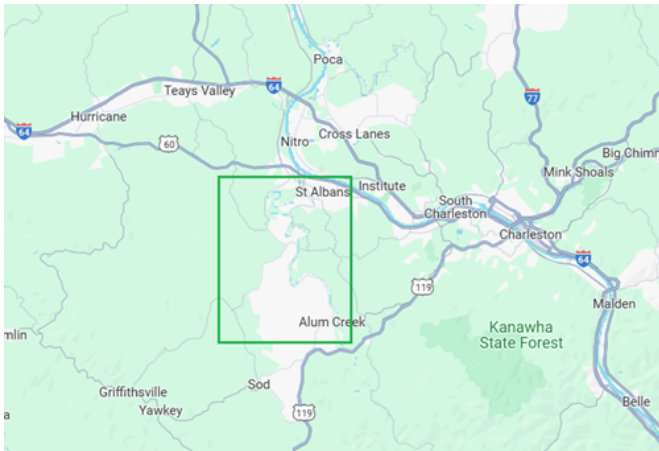
Fig. 1: Visualization of study area.

Genus	Label Color	Total Labels
Hickory	Blue	11
Linden	Purple	3
Locust	Black	1
Maple	Red	39
Oak	Yellow	80
Poplar	Gray	8
Walnut	White	2

TABLE I: Label information across all plots, including label colors and total number of labeled canopies per genus.

A. LiDAR

As part of our investigation, we also investigated LiDAR based methodologies for canopy isolation. Both a digital surface model and elevation model of the study area were sourced from the USGS 3D Elevation Program datasets through OpenTopography at 10m resolution. Both rasters were cropped to fit our study area as well as warped to match their Coordinate Reference System (CRS) using QGIS 3.36.3. A Canopy Height Model (CHM) was generated from both rasters by subtracting the bare-earth elevation model from the digital surface model using a script written in R. The resulting raster represented only the heights of objects from where they stood on the surface. 10m resolution Sentinel-2 satellite imagery was also sourced through OpenTopography of the same area so that results could be overlaid onto a corresponding visual map for analysis [17], [18].

ForestTools, an R library designed to analyze remote forest data, was used for canopy detection and processing. We first generated treetop estimations using the 'locate trees' Method provided in ForestTools with our CHM as input data. This point data was then used in the 'mcws' (Marker-Controlled Watershed Segmentation) method to create polygons representing estimations of entire crowns on a tree-by-tree basis. These polygons were exported as a singular shape file and transferred into QGIS to overlay onto a satellite image representing our study area. Analysis of this data has currently only been conducted visually in sparse areas to ensure that only trees were being segmented in areas dense with clear false positives. Due to the limited ground-truth data, we have not yet been able to test the reliability or accuracy of these results in anyway regarding measurements of the trees themselves. To measure the accuracy of these results in the future, the estimations generated by ForestTools will be compared directly to the real-world measurements in their respective plots, both in terms of canopy radius and the accuracy of their heights based on the generated CHM [19], [20].

B. Deep Image Processing

With the subset of our image dataset we have collected so far, we have been investigating two different deep learning techniques, a small residual network for individual classification and transfer learning on top of DeepForest for canopy isolation, with the possibility of classification. Our current tests have shown that approximately 50 labeled tree samples per class is not sufficient to perform consistent classification, even when performing binary classification with trees only being considered oak or not oak for this test. Our dataset currently comprises 144 labeled drone images from 6 sites with the genus for each tree identified in person at each site. The number of trees as well as classes can be viewed in Table I. Once having enough samples, we can use image augmentation techniques to increase the size of the training dataset.

We will also evaluate the effectiveness of transfer learning on DeepForest once we have accumulated a sufficient number of image frames. For the residual network, we utilized small, isolated tree images. However, DeepForest necessitates larger images with bounding box annotations, with each image containing multiple trees. This approach will allow us to leverage the full potential of DeepForest's capabilities in detecting and classifying trees within a more complex and realistic context [11].

By comparing the performance of our residual network with DeepForest, we aim to determine the most effective method for tree identification and classification. This comparison will provide valuable insights into the strengths and limitations of each approach, guiding us in refining our models for better accuracy and reliability.

One challenge in training isolation models with our dataset is that not every tree in a given frame is accessible by foot for manual verification. If these trees are left unlabeled during training, the results may be negatively impacted. There are several strategies to address this issue. One approach is to crop images to exclude unlabeled trees. Another method is to remove these trees using image editing software, though this carries the risk of introducing visual errors. Finally, these trees could be identified in the image by human observation, although this is less accurate than the manual ground truth method we have utilized.

Fig. 2: Examples of labeled drone images taken within study area.

IV. RESULTS AND DISCUSSION

A. LiDAR

With our current methodology and data sourcing, the results appear to be quite inconsistent. When focusing solely on treetop estimations, false positives are prevalent, and single trees are often mistaken for multiple smaller canopies. While the process of crown segmentation helps mitigate these issues, it introduces very noticeable gaps where significant portions of the forested areas are not accounted for by the predictions. While our current results are based solely on visual analysis due to insufficient testing data, the existing methods do not yet appear reliable for precise canopy measurement.

While the shapes of the canopy polygons are not necessarily critical for estimations, we were pleasantly surprised by the model's accuracy in pinpointing canopy locations in open regions. The points corresponding to the generated polygons almost always lie within a unique canopy and rarely appear on non-tree objects. While the current results do not yet meet the accuracy required for AGB estimation, they do demonstrate the potential of LiDAR as a viable measurement tool. Future testing, once equipped with the appropriate data, will primarily focus on determining the level of detail required to meet the specifications of our AGB equation. For instance, if only the rough radius of a canopy is needed, we could derive this value from the size of the polygons for each tree. However, if no level of simplicity proves accurate with our current data sources, we may need to seek alternative LiDAR data sources to achieve the desired level of accuracy.

B. Image Processing

For an initial test of our dataset, we conducted a binary classification task using a smaller version of the Xception network, as described by François Chollet [21]. This model uses the keras framework for operation, with the language being python 3 [12], [22]. We trained the model for 250 epochs on image patches from among our dataset, with 104 images being used for training and 15 images being used for testing. Additionally, a stock image of an oak and a maple were added to best test sets. To improve results, we duplicated every image in the dataset and then applied the following augmentations to the duplicated half: Random Flip (Horizontal), Random Translation (plus or minus 20%), Random Brightness (plus or minus 30%), and Random Rotation (maximum 10%). For this test, due to the large amount of oak and maple, only images of those two classes were used to test or train the model. Three different model epochs were tested, and for each of them 10/11 oaks and 6/6 were correctly identified for an average accuracy of 94%. Notably, the only image that was falsely identified was the oak stock image. It is very likely that this stock image was not the exact type of oak native to this area, therefore it was not properly detected. While these results are very positive, it is important to note that the test images were taken in the

Fig. 3: Sample of LiDAR treetop estimations (white points) and canopy segmentation (purple masks) over residential area.

same geographic locations and under similar conditions as the training images. Consequently, the accuracy is likely to decrease when more challenging samples are introduced. This training was repeated with poplar and hickory combined into a third class, "neither," which increased the training set by 16 images and the test set by 3 images. This test correctly identifies 11/11 oak, 5/6 maple, and 0/3 neither, for an average accuracy of 80%. These results showed that 10-20 images of each class is not nearly enough for recognition, and that two classes cannot be combined well unless they are notably similar. However, the addition of a third class did not heavily reduce the performance of the other two classes, though this may change if the third class performs better.

V. CONCLUSION AND FUTURE WORKS

A. Conclusion

Although we have not yet completed the development of methods for remote Above-Ground Biomass (AGB) estimation, the approaches tested thus far have demonstrated both potential advantages and limitations in data-rich environments. Our machine learning techniques for genus identification have shown promising results with the limited data available. However, as additional classes are introduced, the reliability of these results remains uncertain. It may become necessary to incorporate more variables into our predictions to achieve high accuracy across diverse environments as the study progresses.

Conversely, satellite LiDAR data has yielded more promising outcomes than anticipated, even with relatively sparse data. While canopy segmentation has not proven reliable using only publicly available data, canopy locations in open areas have been identified with a seemingly high degree of accuracy. As we continue to gather more data, we anticipate that the accuracy and reliability of both methods will improve.

B. Future Works

Moving forward, our long-term objective is to continuously gather and annotate data to enhance the accuracy of our deep learning processes. We will persist in testing classification and canopy isolation models in parallel, with plans to compare the performance of various model architectures on the same dataset. This comparison will help us determine whether an all-in-one detection and classification model is more effective, or if separate models for isolation and classification yield better results.

Throughout the year, the color of the leaves will change significantly, with different trees changing colors at various times. To account for this, we aim to collect data at multiple intervals over the coming months, incorporating the time of year as a feature in our classification model. We will consider our efforts successful if we achieve at least 90% class accuracy on a test sample of at least 100 images and five classes.

REFERENCES

[1] O. Mutanga, C. Shoko, S. Adelabu, and T. Bangira, "Remote sensing of aboveground forest biomass: A review," *Tropical Ecology*, vol. 57, pp. 125–132, 05 2016.

[2] K. Vashum, "Methods to estimate above-ground biomass and carbon stock in natural forests - a review," *Journal of Ecosystem & Ecography*, vol. 02, 01 2012.

[3] L. Kumar and O. Mutanga, "Remote sensing of above-ground biomass," *Remote Sensing*, vol. 9, no. 9, 2017. [Online]. Available: https://www.mdpi.com/2072-4292/9/9/935

[4] M. Singh, D. Evans, D. A. Friess, B. S. Tan, and C. S. Nin, "Mapping above-ground biomass in a tropical forest in cambodia using canopy textures derived from google earth," *Remote Sensing*, vol. 7, no. 5, pp. 5057–5076, 2015. [Online]. Available: https://www.mdpi.com/2072-4292/7/5/5057

[5] S. Björk, S. N. Anfinsen, M. Kampffmeyer, E. Næsset, T. Gobakken, and L. Noordermeer, "Forest parameter prediction by multiobjective deep learning of regression models trained with pseudo-target imputation," 2023. [Online]. Available: https://arxiv.org/abs/2306.11103

[6] J. Liu and Y. Zhang, "A multi-scale forest above-ground biomass mapping approach: Employing a step-by-step spatial downscaling method with bias-corrected ensemble machine learning," *Remote Sensing*, vol. 16, no. 7, 2024. [Online]. Available: https://www.mdpi.com/2072-4292/16/7/1228

[7] T. D. Pham, N. Yokoya, J. Xia, N. T. Ha, N. N. Le, T. T. T. Nguyen, T. H. Dao, T. T. P. Vu, T. D. Pham, and W. Takeuchi, "Comparison of machine learning methods for estimating mangrove above-ground biomass using multiple source remote sensing data in the red river delta biosphere reserve, vietnam," *Remote Sensing*, vol. 12, no. 8, 2020. [Online]. Available: https://www.mdpi.com/2072-4292/12/8/1334

[8] L. Deng, "The mnist database of handwritten digit images for machine learning research [best of the web]," *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 141–142, 2012.

[9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2015. [Online]. Available: https://arxiv.org/abs/1512.03385

[10] S. Natesan, C. Armenakis, and U. Vepakomma, "Resnet-based tree species classification using uav images," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLII-2/W13, pp. 475–481, 2019. [Online]. Available: https://isprs-archives.copernicus.org/articles/XLII-2-W13/475/2019/

[11] Z.-H. Zhou and J. Feng, "Deep forest," 2020. [Online]. Available: https://arxiv.org/abs/1702.08835

[12] G. Van Rossum and F. L. Drake, *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace, 2009.

[13] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," 2016. [Online]. Available: https://arxiv.org/abs/1506.02640

[14] J. C. Jenkins, D. C. Chojnacky, L. S. Heath, and R. A. Birdsey, "National-scale biomass estimators for united states tree species," *Forest science*, vol. 49, no. 1, pp. 12–35, 2003.

[15] R. Aabeyir, S. Adu-Bredu, W. A. Agyare, and M. J. Weir, "Allometric models for estimating aboveground biomass in the tropical woodlands of ghana, west africa," *Forest Ecosystems*, vol. 7, pp. 1–23, 2020.

[16] T. Chan, C. A. Gomez, A. Kothikar, and P. Baiz, "Joint study of above ground biomass and soil organic carbon for total carbon estimation using satellite imagery in scotland," 2022. [Online]. Available: https://arxiv.org/abs/2205.04870

[17] "Qgis geographic information system," Open Source Geospatial Foundation Project, 2024. [Online]. Available: http://qgis.org/

[18] USGS, "Wv femar3 southcentral b3 2018," Provided by OpenTopography, 2018.

[19] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2023. [Online]. Available: https://www.R-project.org/

[20] A. Plowright, "Foresttools: Tools for analyzing remote sensing forest data. r package version 1.0.2," 2023. [Online]. Available: https://github.com/andrew-plowright/ForestTools.

[21] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," 2017. [Online]. Available: https://arxiv.org/abs/1610.02357

[22] ——, "keras," https://github.com/fchollet/keras, 2015.