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

Cade Parlato, Neil Loftus, Sam McGrath, Husnu S. Narman, Rick Gage

Background

Forests are one of the world's largest carbon sinks; monitoring their biomass can help track factors impacting global warming

Remote biomass estimation can drastically speed up the rate at which this data can be analyzed

These estimations historically require large amounts of existing data

Goals

Investigating the feasibility of remote AGB estimation with low access to ground-truth data through:

1. Review and analysis of existing methodology
2. Creation of a dataset for use in machine learning
3. Evaluation of multiple machine learning models for prediction in the Appalachian area

Previous Works

Biomass Calculation

Allometric models allow estimation of Above Ground Biomass (AGB) through parameters like Diameter at Breast Height (dbh), Tree Height (H), and Density (ρ)

Biomass density is directly correlated to tree genus

Our estimation uses the following formula from Aabeyir et al.:

$$AGB = 0.0580\rho((dbh)^2 H)^{0.999}$$

Aabeyir, R. *et al.* (2020) 'Allometric Models for Estimating Above Ground Biomass in the Tropical Woodlands of Ghana, West Africa', *Forest Ecosystems*, *7* (1). doi:10.1186/s40663-020-00250-3.

Diameter at Breast Height Estimation

A linear regression model has been created correlating canopy diameter to DBH: DBH=13.866+0.509*canopy area

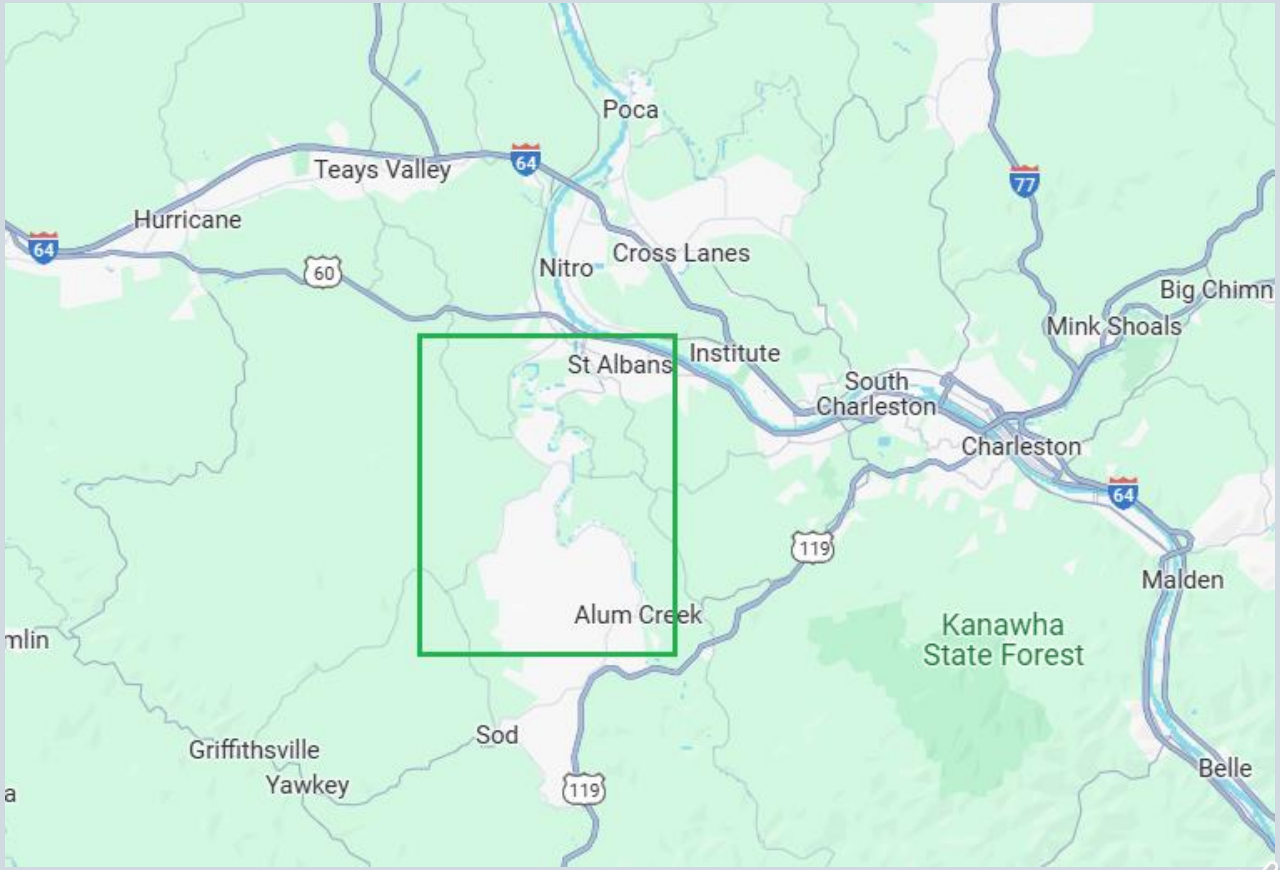
This model allows for DBH estimations from an aerial view

When compared to the DBH measurements, the estimation model had an accuracy ranging from 41-87%

Model and Dataset

Study Area

All hand-gathered data was within the following region south of St. Albans, WV



xCeption Architecture

Developed by François Chollet

Light-weight Convolutional Neural Network for classification

Smaller version designed for Keras by the original author utilized

Performed both binary and categorical classification

Training Parameters

Epochs: 250

Training Images: 104 (Binary), 120 (3 Classes)

Test Images: 15 (Binary), 18 (3 Classes)

Augmentations: Random flip, translation, rotation, and brightness

Custom Dataset

Trees are identified on-site, hand annotated, then passed to the ML model

Most classes do not have enough data

Image augmentation is used to increase label counts

Genus	Label Count
Hickory	11
Linden	3
Locust	1
Maple *	39
Oak *	80
Poplar	8
Walnut	2

LiDAR Processing

10m resolution Digital Surface Models (DSM) sourced from OpenTopography

Canopy Height Models were generated in R by subtracting the bare-earth elevation model from the DSM

The ForestTools library was tuned for our area to locate treetops and estimate individual canopy shape

Results

LiDAR

Results appear erratic

Canopy shapes are not reliable, but canopy detection is promising

Needed level of detail must be examined

xCeption Results

2 Classes

Oaks: 10/11 Identified

Maple: 6/6 Identified

Average Accuracy: 94%

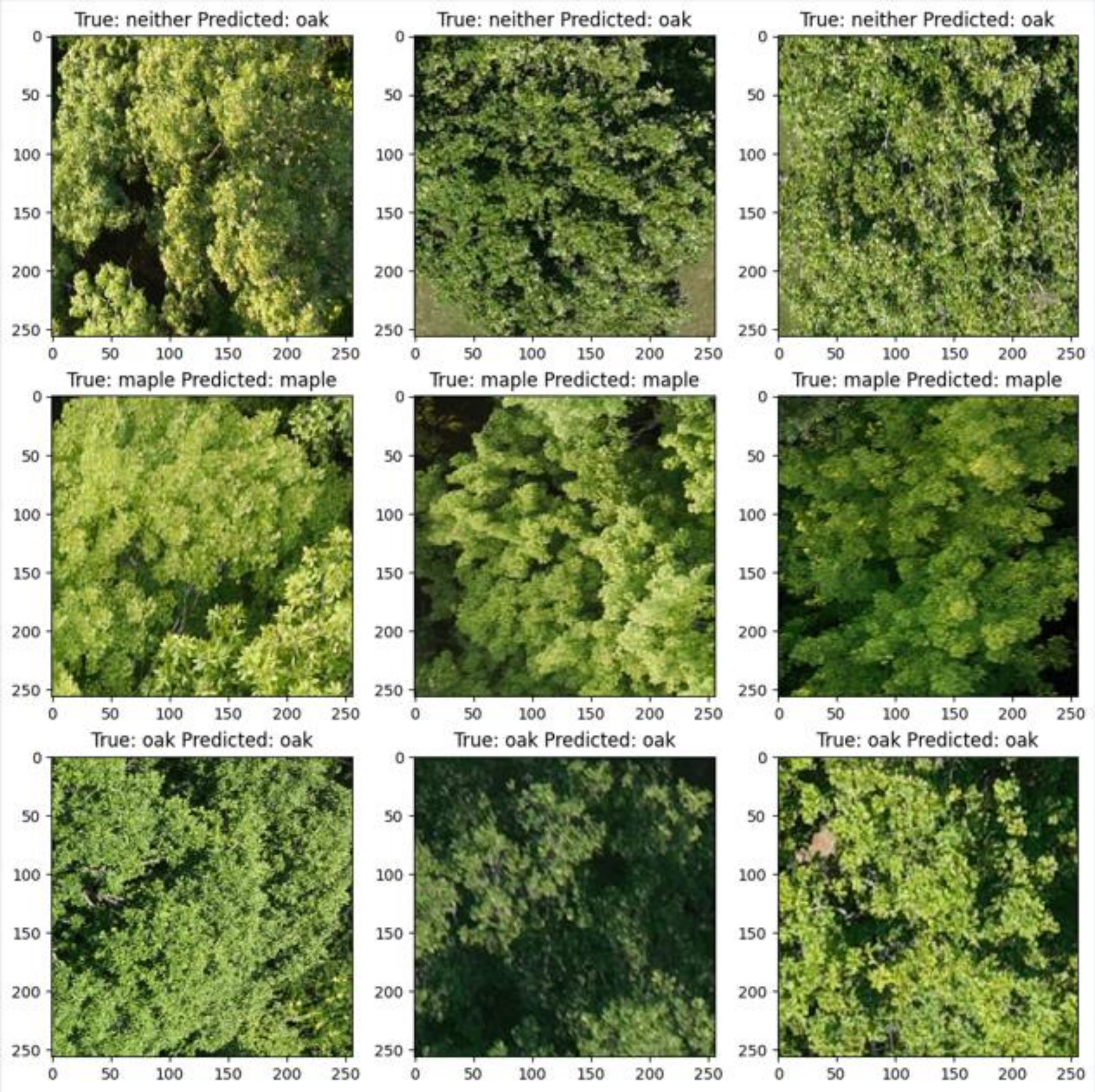
3 Classes

Oaks: 10/11 Identified

Maple: 5/6 Identified

Neither: 0/3

Average Accuracy: 80%


True: neither Predicted: oak
True: neither Predicted: oak
True: neither Predicted: oak
True: maple Predicted: maple
True: maple Predicted: maple
True: maple Predicted: maple
True: oak Predicted: oak
True: oak Predicted: oak
True: oak Predicted: oak

Conclusion

Genus identification with deep learning is effective, but requires sufficient samples

For best results, different genera should not be grouped together into one class for classification.

Satellite LiDAR data has not been reliable for segmentation, but shows promise in canopy identification

Future Works

Additional neural network architectures will be tested and compared to current results

Hyperspectral and multispectral imagery will be tested for deep learning

Truthed LiDAR data will be sourced to perform more accurate and testable canopy measurements

Thank you!