CROWN SEGMENTATION USING HIGH RESOLUTION IMAGERY AND DEEP LEARNING IN VIRGINIA'S PINE PLANTATIONS

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Abstract

Pine plantations in the southeastern U.S. are some of the largest timber producing forests in the world. With 10% of the global production, forest managers need routine monitoring to measure health and mortality of their stands. High resolution imagery in combination with deep learning architectures have shown to be successful in this in other regions of the world. In this study, we used the U-Net convolutional neural network (CNN) architecture to delineate individual tree crowns over pine plantations in Virginia using three different types of training data. Success varied across age classes, but mid and late rotation pines (12 to 19 years old) performed the best with 95% of the crowns detected and 91% of the crown area calculated. However, visual interpretation of the CNN output shows cases of missed trees, combining of tree crowns, and trees counted more than once. Overall, there appears to be a general success of U-Net model application for individual tree crown mapping of certain ages in pine plantations.

*The paper is a partial report of the manuscript for this study which is currently in the process of submission.

1. Introduction

The southeastern United States is the dominant timber producing region in the world, representing 10% of the global wood product production through its pine plantations *(Johnston et al., 2023; Fagan et al., 2018)*. Loblolly pine *(Pinus taeda)* makes up over half of the standing pine volume, making it one of the most commercially important trees in the United States *(Baker and Langdon, 1990)*. Remote sensing, and more specifically high-resolution imagery, can help forest managers monitor their plantations and make informed management decisions about how to produce a profitable timber harvest. In this study we used high resolution imagery and machine learning techniques to segment individual loblolly pine tree crowns to:

1) Obtain stem counts for the plantations.
2) Calculate area measurements for each individual tree crown.
3) Compare the results across age classes.

2. Methods

2.1 Study Area

This study took place in south central Virginia, U.S. in the counties of Brunswick, Lunenburg, and Mecklenburg (Figure 1). These areas were chosen for their most common forest type being "Loblolly/Shortleaf", its large number of forested plots, and its availability of National Agricultural Imagery Program (NAIP) high resolution imagery *(FIA DataMart 2.0, 2023; USDA-FSA Aerial Photography Field Office, 2021)*. There were 17 NAIP images in the study areas. From these, we sampled 37 128x128 pixel cells as training and 25 as testing.

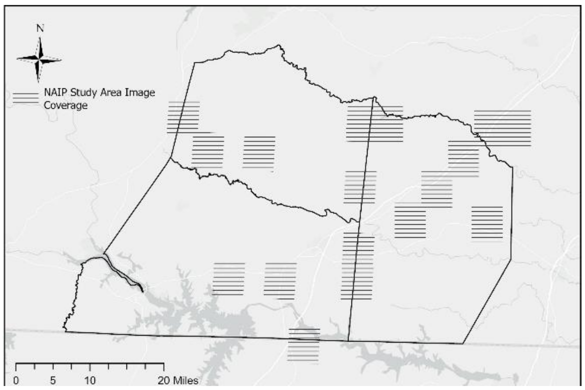

Figure 1: Study area. The hatched areas are where NAIP Imagery was used for training and testing loblolly pine plantations in Brunswick, Lunenburg, and Mecklenburg, Virginia.

2.2 Data

NAIP imagery for Virginia was collected in the agricultural growing season of 2021 *(Surdex Corporation, 2021)*. The collection was completed by the Surdex Corporation with twin-engine aircraft flying at 27,100 ft above the mean terrain. Cameras were calibrated by the manufacturer with a 27% side overlap and a 0.6 m (60 cm) spatial resolution. The red, green, blue, and near-infrared (RGBNIR) bands were collected and stored at an 8-bit pixel depth.

The Landscape Change Monitoring System (LCMS) was used in this study to calculate pine plantation age by subtracting the year of change from 2021 *(USDA Ag Data Commons, 2022)*. Ages were then verified by Google Earth Pro and then aggregated into age class bins to account for any other potential error in the age calculation. Table 1 includes a breakdown of the age classes.

Age Class	Ages	% Area Included
1	0-3	22
2	4-7	3
3	8-11	15
4	12-15	13
5	16-19	17
6	20+	30

Table 1: Pine plantation age distribution.

2.3 Neural Network Architecture

For this work, we used the deep learning U-Net instance segmentation model described by Ronnenberger et al. 2015. The U-Net architecture is a part of the convolutional neural network (CNN) supervised classification suite that has been previously used for tree crown mapping *(Freudenberg et al., 2022; Korznikov et al., 2021; Mugabowindekwe et al., 2022; Wagner et al., 2020)*. This model takes the input imagery and breaks the image down into smaller portions by pixel augmentation and finds similar patterns in the training data to segment out the individual tree crowns and their borders. The specific model architecture used comes from the code in Wagner et al. 2023. The work was completed in the R open-source platform using an interface to Keras with a TensorFlow backend *(Abadi et al., 2015; Allaire and Chollet, 2016; Chollet et al., 2015; R Core Team, 2016)*.

2.4 Tree Crown Segmentation

All 52 NAIP images were run through the model without any training data to get a baseline prediction of the tree crowns. Then a column of cells was randomly selected for each of the images and three different labels were applied to each cell in that column: (a) the model thought there were crowns when there were none, (b) the crowns were too dense to individually separate, or (c) the crowns were able to be hand drawn for training and testing. There were 10,680 trees that were labeled as correction type (c). Due to the layout of the images and 128x28 cells, 59% of the trees were used as training for the model and 41% were used for testing. The model was trained over 10,000 epochs with a batch size of 50 images. We selected the model with the lowest validation loss and applied it to the rest of the study area.

2.5 Accuracy Assessment

Accuracy was tested using validation and model crowns with an intersection over union (IoU), which detects the overlap between the predicted crown and the validation crown, greater than 0.25 (or 25% overlap). Those crowns that meet the IoU threshold were then put into the *Compute Accuracy for Object Detection* tool in ArcGIS Pro *(ArcGIS Pro: Deep Learning toolset)*. This calculated a Precision, Recall, and F1 score for each crown. We first applied this tool to the entire model as one section and then applied the tool to each age class of crowns.

3. Results

The model had an accuracy of 78% for individual stem count but an accuracy of only 47% for crown area. Its Precision, Recall, and F1 scores were 0.45, 0.36, and 0.40, respectively. Individual stem count and crown area (measured in square meters) measurements for the model by pine plantation age class can be found in Table 2. Precision, recall, and F1 scores for the model can be found in Table 3.

Age Class	Measurement	Model	Validation Crowns	Model Percentage
1	Count	344	682	50
	Crown Area	1,489	3,174	47
2	Count	74	962	8
	Crown Area	290	3,222	9
3	Count	1,123	2,643	42
	Crown Area	9,303	15,617	60
4	Count	1,730	1,822	95
	Crown Area	14,360	15,834	91
5	Count	2,074	1,999	104
	Crown Area	18,846	26,847	70
6	Count	2,934	2,572	114
	Crown Area	28,043	55,275	51

Table 2: Stem Counts and Crown Area results for the model based on pine plantation age class.

Age Class	Measurement	Model
1	Precision	0.45
	Recall	0.22
	F1 Score	0.30
2	Precision	0.46
	Recall	0.04
	F1 Score	0.07
3	Precision	0.79
	Recall	0.28
	F1 Score	0.42

4	Precision	0.75
	Recall	0.74
	F1 Score	0.74
5	Precision	0.81
	Recall	0.73
	F1 Score	0.77
6	Precision	0.49
	Recall	0.39
	F1 Score	0.43

Table 3: Precision, Recall, and F1 scores for the CNN model based on pine plantation age class.

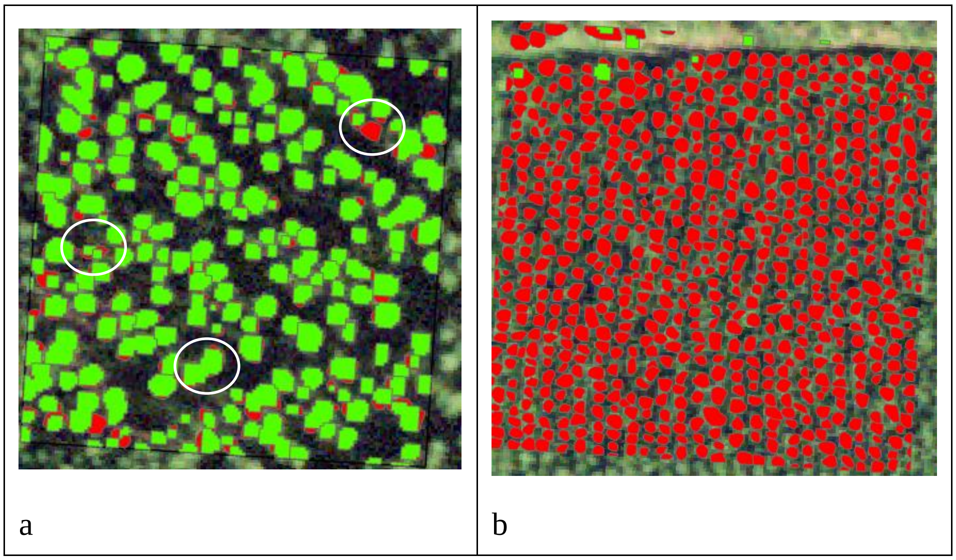

Figure 2: Examples of the model's performance at different locations of the study area. a) a 12-15-year-old pine plantation; b) a 4-7-year-old pine plantation. The green polygons are the model output, and the red are the hand-drawn polygons. The white circles show examples of where the model missed a tree, counted a tree more than once, and merged two tree crowns together.

4. Discussion

At first glance, the model appears to do very well in the older pines compared to the younger ones (Figure 2). However, with the included statistics and further investigation of the imagery, there appears to be some larger problems at play. The first thing to note is that in Table 2, the stem count is over predicted by both the 16–19 and 20+ year old stands and vastly under predicted by the 4-7- and 8–11-year-old stands. This would not be helpful to a plantation manager who may be trying to get trees per acre (TPA) for his stand. What may be attributed to the missing trees, merging of trees, and double counting of trees by the model. Examples of these can be found in Figure 2a, circled in white.

Younger stands, such as in Figure 2b, show where the model is doing very poorly and capturing almost none of the trees. This is reflected in the poor crown count and crown area percentages (Table 2) as well as in the very low F1 score (Table 3).

5. Conclusions

Overall, there is the potential for the model to increase its accuracy by collecting more training data, especially in the 4-7-year-old age class, which had a very low percentage as they were harder to locate in the study area.

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