

ASSESSING RED PINE SEEDLINGS USING UAV POINT CLOUDS AND FIELD-VERIFIED DATA

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ABSTRACT:

Accurate, reliable, and cost-efficient approaches to forest monitoring are critical for sustainable forest management. The use of digital photogrammetry for tree height estimation is well-known among forest managers and remote sensing researchers. Satellite remote sensing has not been very successful in providing detailed and reliable estimates of tree height. Unmanned Aerial Vehicles (UAVs) are one of the latest remote sensing platforms to get forest attributes information at very high temporal and spatial resolution. This study assessed the potential of using digital aerial photogrammetry point clouds and UAV acquired high-resolution imagery to estimate red pine seedlings' height in Adirondacks, New York. Seedling's location, height, crown width, and diameter were measured from 16 fixed area sample plots, and multispectral imagery was acquired with DJI Matrice 100- UAV fitted with Micasense RedEdge-M camera. UAV was flown under clear sky conditions at 93-meter height in a single grid pattern with 80% front and side overlap. PIX4D software was used to process UAV multispectral imagery and generate Digital Surface Model (DSM) and Orthomosaic at 6.08 cm/pixel resolution along with 3D Digital Terrain Model (DTM). 3D densified point cloud layers of regeneration canopy were generated at an average density of 1.54 per m³. Seedlings were differentiated from bare ground cover through supervised image classification methods. Preliminary results of this study highlight that multispectral imagery acquired from UAVs has the potential to characterize and provide detailed structural information to estimate red pine seedlings' height.

1. INTRODUCTION

Forest monitoring activities such as field inventory are critical to sustainable forest management. One crucial element of this monitoring program is assessing regeneration or restoration success as the entire life cycle of a forest/timber stand is influenced by the extent of the stand's establishment. Also, the financial and ecological investment in plantations relies on monitoring and assessing these young regenerating stands. The primary purpose of a forest regeneration survey is to determine current stocking levels, potential future stand density, and spatial arrangement of the desired forest stand (Brand, 1988; Brand, Leckie, & Cloney, 1991; Gougeon & Leckie, 1998;). However, additional information on species, competition, and forest productivity can also be collected as part of a regeneration survey (Brand et al., 1991). Farmers, forest land planners and managers, woodlot industry, and natural resources management groups are some users of forest and natural resources inventory data. Timely and accurate assessment of regeneration is critical for landowners and foresters to make future stand management decisions (Matney & Hodges, 1991). Furthermore, effective silvicultural treatments such as pre-commercial thinning and replanting choices are dependent on stand stocking levels, health, and competing species abundance (Pouliot, King, Bell, & Pitt, 2002).

The monitoring frequency of these young stands is dependent on the cost of field-based regeneration assessment methods and can result in poor stands with limited assessment frequency (Pouliot et al., 2002). Even though field-based measurements produce unbiased estimates of plant density over repeated sampling, spatial patterns characteristics such as site productivity, competing vegetation, and survival are not completely acquired during field-based measurements. Traditional regeneration assessment activities based on field sampling can be cost and time-prohibitive, prompting managers to seek alternatives such as reducing sample plots to accommodate cost and labor requirements (Green & Burkhart, 2020). Evaluating new

methodologies to improve monitoring efficiency is an important and valued research activity. UAV are among the latest cutting-edge geo-spatial technologies used to monitor and acquire information on forest attributes at the high spatial and temporal resolution to support decision making, increase timber farming efficiency and enhance profitability. Ease of flight mission planning, accessibility to remote areas, low operating costs, and time effectiveness of UAV applications allow users to conduct research periodically and frequently. The high-resolution imagery maximizes individual tree detection and measurements of canopy gaps and improves understory plant identification.

Additionally, farmers and foresters can utilize UAV-derived imagery to perform stem counts early in the season and detect nutrient deficiency. Photogrammetric point clouds and plant height models will help determine plant height and estimate plant biomass. Multispectral bands can be used to detect a plant's chlorophyll content and assess the plant's health status.

The goal of the study is to employ an unmanned aerial vehicle (UAV) to capture forest structure information in a young red pine plantation stand and support farmers and foresters in the decision-making by estimating the seedling heights. Specifically, young plants will be detected and mapped based on the imagery products derived from UAV, which will visualize plants and help understand the stands' current stocking level. Study sites include recently cut areas with red pine plantations in Adirondack, New York.

2. METHODS

2.1 Study area

The study area is in Adirondack Park, New York (Figure 1). It is a 1.5-hectare red pine plantation area managed by the State University of New York (SUNY), College of Environmental Science and Forestry (ESF). The study site was harvested in

2009-10, and red pine plantation was done in 2020 with a seed tree treatment method where healthy and mature red pine trees were left to provide seed for regenerating new stand.

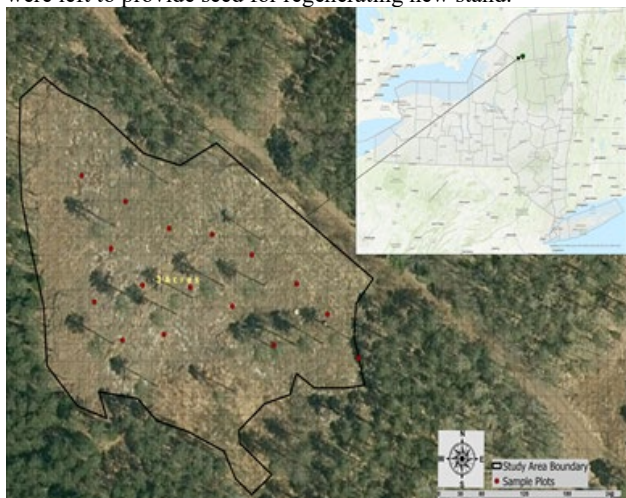


Figure 1: Location of the study area



Figure 2: Plot centered plant with a tag

2.2 Sampling design

Field-based data collection involved remeasuring or creating a systematic grid of a minimum of sixteen 1/200th-acre fixed area plots. We adopted a random/systemic design where starting location was flagged with a line number and walked one chain in from the starting point. The closest tree within one chain was identified at the plot center so that we can avoid having gaps with no plantation in sample plots. We traveled along the same transect with assigned bearing and used tape as a guide for the centerline of the transect. The distance between each plot and transect line was set up to be one chain. We acquired data from 16 sample plots.

2.3 Field data collection

The plot-centered plant is tagged with a line and plot number (Figure 2). The precise location of the plot center was recorded using the Trimble Geo XH 3000 global positioning system (GPS) unit (Figure 3). Every seedling/tree within each plot meeting minimum size criteria was tallied by species, diameter-at-breast (dbh), top height, and average crown width. The distance and azimuth of plants within the plot were measured from plot-centered species to determine the spatial location of those plants. The diameter was measured at the plant Crown cover photo was captured at Jake's staff's height with a fisheye lens mounted on the cell phone (Figure 4). The foliage was categorized into ferns, shrubs, and herbaceous, and coverage was estimated through visual inspection.



Figure 3: Trimble Geo XH 3000 global positioning system (GPS) unit



Figure 4: Crown cover photo taken with the fisheye lens mounted on a cell phone

2.4 UAV imagery acquisition

DJI Matrice 100-UAV (Figure 5) equipped with Micasense RedEdge-M camera (mounted under the batteries), and Zenmuse X3 camera (mounted to front through 3-axis gimbal) was used for image collection. Pix4D mapper was used for planning UAV mission parameters such as flight speed, angle, and altitude. It was flown under clear sky conditions at a 93-meter height in a single grid pattern (Figure 6) with 80% front and side overlap. The acquired images were checked and transferred to the memory card in the field.

The RedEdge camera consist of a five-sensor collection and measures Blue (center wavelength = 475 nm, bandwidth = 20 nm), Green (center wavelength = 560 nm, bandwidth = 20 nm), Red (center wavelength = 668 nm, bandwidth = 10 nm), Near Infrared (NIR) (center wavelength = 840 nm, bandwidth = 40 nm), and Red Edge (center wavelength = 717 nm, bandwidth = 10 nm) respectively. Two ground control points were implemented in the study site.



Figure 5: DJI matrice 100



Figure 6: UAV flight path.

2.5 UAV image processing

Images acquired from the RedEdge camera were radiometrically utilizing the workflow developed by Micasense. We used PIX4DMapper to generate a point cloud, Digital Surface Model (DSM), and five separate reflectance orthomosaic.

The image processing workflow started with initial processing in PIX4DMapper, where the software first computes key points on the images and utilizes these images to find matches between the images. 335 out of 375 images were calibrated with a median of 10224.5 matches per calibrated image with a Ground Sampling Distance (GSD) of 6.08 cm. The total time required for initial processing was 3 minutes and 13 seconds. After initial processing, a text file with the spatial location of Ground Control Points (GCPs) was loaded in PIX4DMapper to geo-tagged the images. 2 GCPs were used for georeferencing, which were distributed inside the study area. The resulting Root Mean Square Error (RMSE) of the collected points was 0.04 meters.

Final processing in PIX4DMapper included radiometric processing and calibration. The reflectance index for each five bands was verified and calibrated. Digital Surface Model (DSM) and Orthomosaic (Figure 7) were generated at 6.08 cm/pixel resolution along with the 3D Digital Terrain Model (DTM). 3D densified point cloud layers of regeneration canopy were generated at an average density of 1.54 per m³. The resulted point clouds were exported in LAS format.

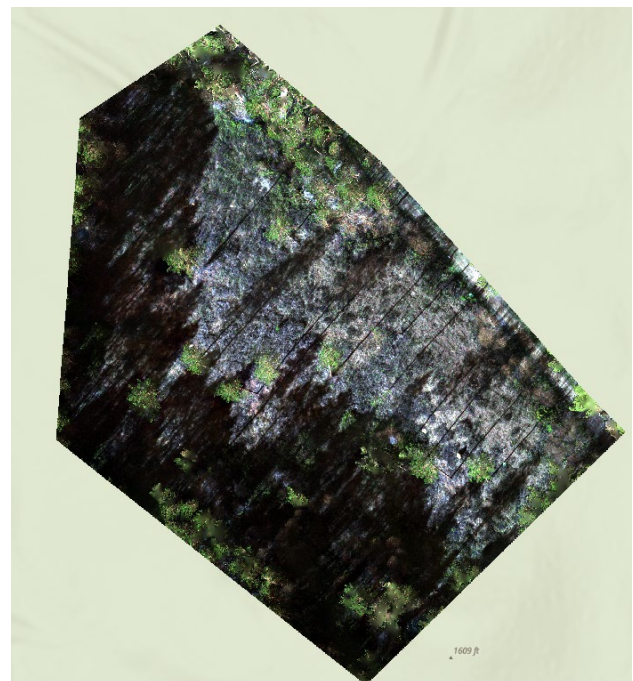


Figure 7: Orthomosaic generated at 6.08 cm/pixel resolution.

3. RESULTS AND DISCUSSION

3.1 Point clouds processing height estimation

The resulted point clouds were processed using LAStools (Isenburg, 2019). The datasets were first classified into ground and non-ground and denoised using 'lasnoise.' The 'lasground_new' tool was used to classify dense point clouds into ground points with a step size of 10 m. Then, 'lasheight' tool was used to derive the normalized heights for each point. The normalized height point cloud was then processed in ArcGIS Pro software and converted into TIN format (Figure 8). The point cloud height ranged from 0.1 meters to 6.5 meters. Plants' heights were then derived by iterating through TIN and orthomosaic and converted into a point shapefile. These points were validated with field data.

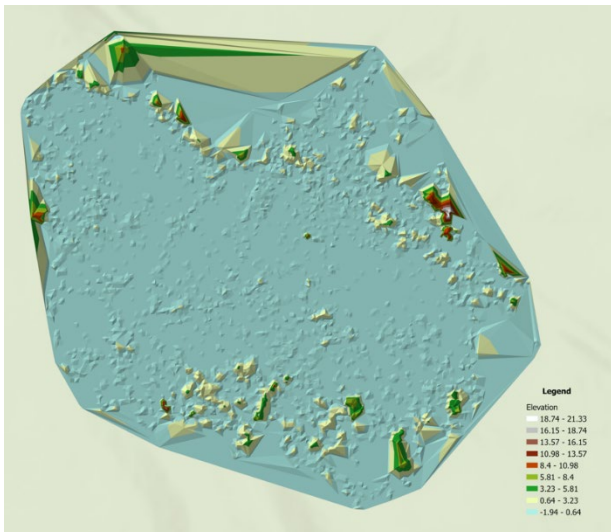


Figure 8: Normalized point cloud converted to TIN.

4. CONCLUSION AND FUTURE WORK

This study utilized the field-based measurements and UAV-derived point cloud to estimate red pine seedling's height in Adirondack, New York. Initial results look promising as we were able to classify point clouds into ground and non-ground and derived normalized point clouds for plants' height. Initial results show promise but require further investigation potential to serve as reference data for mapping, detecting, and estimating individual seedlings' height. Additionally, further investigation is needed to explore the possibility of machine learning and deep learning approaches in individual plant detection and height estimation. The author plans to continue with this study in the near future with advancements in point cloud processing, classification, and young plant height estimation. The point cloud data will be further analyzed through deep learning and machine learning algorithms.

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