

**Stem and canopy growth analysis in *Picea Engelmannii* with
UAVs and field measurements**

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ABSTRACT

Forests play a crucial role in mitigating climate change by sequestering large amounts of carbon dioxide from the atmosphere, so it is critical to evaluate their capacity to store carbon over time. Existing research on forest carbon sequestration relies on field methods that do not allow for sampling in rugged terrain and have limited coverage areas. This study utilizes field measurements of trees to calibrate UAS remote sensing estimations of forest carbon, allowing us to rigorously scale up data collection to large areas. Diameter at breast height (DBH) measurements and tree increment cores were obtained from 34 *Picea engelmannii* (Engelmann Spruce) trees in the vicinity of the Rocky Mountain Biological Laboratory in Colorado. A generalized linear model successfully relates field measurements of DBH to UAS estimates of canopy size and stand. Further, we find evidence of a “lagged” correlation between canopy and stem growth where canopy growth more strongly correlates to stem growth in the following year rather than the current year. Through a better understanding of canopy growth and stem growth correlations we can estimate forest carbon exclusively through UAV data, reducing the necessity for ground measurements and allowing effective scaling-up of data collection to the landscape level.

INTRODUCTION

Forests are invaluable terrestrial resources because of their capacity to sequester enormous amounts of carbon emissions from the atmosphere. Annually, they absorb approximately 7.6 billion metric tons of CO₂, acting as carbon sinks that help buffer the greenhouse effect (Harris et al., 2021). Because of their invaluable role in combating climate change, it is important to continuously evaluate forests' ability to store carbon over time through fluctuations in tree biomass.

Evaluating forest biomass growth has been a topic of heavy research in the past century. Tree growth models provide pertinent data for timber companies and conservation efforts. Additionally, given that trees are approximately 50% carbon by mass, total forest carbon can easily be calculated from biomass data and be used to estimate carbon storage dynamics (Smith et al., 2003). Historical studies have created generic allometric equations that use field measurements of DBH to calculate tree growth over time (Jenkins et al., 2003). However, the collection of field data measurements on trees is limited by time, expense, and safety concerns, so the ability to estimate carbon through remote sensing is desirable. Remote sensing estimates of above-ground carbon in trees could allow us to sample dangerous environments, minimize on-the-ground disturbances, and rigorously scale up measurements of individual trees to the landscape level.

In the past two decades, advances in remote sensing data from satellites, aircrafts, and unmanned aerial vehicles (UAVs) have allowed for detailed measurements of forest structure (Lines et al., 2022). Aircraft equipped with Light Ranging and Sensing (LiDAR) technology can create 3-dimensional point cloud models of forests which can be used to measure tree height and

crown volume (Ayrey et al., 2018). Another method is through structure from motion (SfM) photogrammetry, which uses a moving sensor (typically mounted to a UAV) to obtain overlapping images of a landscape from different perspectives to construct a 3D model of forests (Iglhaut et al., 2019). While existing literature is littered with studies using LiDAR and SfM photogrammetry to estimate forest structure (Dainelli et al., 2021), there has been far less research evaluating forest growth and carbon sequestration dynamics using these technologies. This is due to challenges in rigorously detecting small changes in individual tree crowns due to sparse point clouds, inaccurate GPS ground-truthing, and lack of high temporal resolution. Additionally, UAV-derived individual tree growth studies are limited to planted forest systems, small study sites, and have a ground resolution > 5cm (Guerra, 2017). Given that only 7% of the Earth's forests are planted systems, it is crucial to expand the research of UAV estimates of natural forest growth to scale up global tree carbon dynamic models (FAO, 2020).

However, the dynamic between tree stem growth and canopy growth in natural forests is understudied, a relationship that is critical for converting UAV canopy measurements into carbon storage estimates. Intuitively, we might assume that the phenology of canopy and stem growth are highly correlated. In reality, the two variables can be decoupled and vary drastically by tree species due to complex stand density distributions and competition for light interception (Arend et al., 2024). Additionally, environmental factors such as drought and temperature have shown to complicate the relationship (Pretzsch et al., 2021). One study found that *Pinus sylvestris* and *Picea abies* exhibited reduced stem growth for two years after a drought, while canopy growth recovered within one year. (Masek et al, 2024). This points to the potential of a physiological lag in tree biomass allocation between tree canopy and stem, although the concept is understudied.

To uncover patterns in tree canopy and stem dynamics this study explored *Picea engelmannii* (Engelmann Spruce) growth at the Rocky Mountain Biological Laboratory (RMBL) in Colorado. Engelmann Spruce is an ideal study organism because it is long-lived, highly valued for its timber, sequesters large amounts of carbon, and is the most common subalpine tree in the Southern Rockies. Additionally, E. Spruce is an ideal tree for detection by remote sensing. Since it is a conifer with evergreen needles and has a crown with a conical shape, its crowns are easily identified and segmented from drone imagery. It also typically grows in pure stands or alongside subalpine fir, so its canopies are relatively simple compared to the complex canopies of many broadleaf forests (Alexander et al., 1984).

In this study, increment cores and diameter at breast height (DBH) measurements were collected from 34 E. Spruce trees, varying in canopy volume and stand density in an area surrounding Gothic, CO. Through correlating DBH and tree ring widths with UAV estimates of canopy volume from 2021-2024, an allometric equation of E. Spruce growth can be formulated. The first hypothesis is canopy volume will be more steeply correlated with stem growth as stand density increases. Additionally, a second hypothesis is that this correlation will be lagged, wherein canopy growth strongly correlates to stem growth in the following year rather than the current year.

METHODS

Spatial Data:

This study makes use of extensive imagery and forest structure data from the Gothic townsite, an approximately 1 km x 1.2 km subalpine landscape with a mix of meadow, aspen, and conifer forest. Data was collected with an Uncrewed Aircraft System (UAS) in 2021-2024 and was used to inform both field site selection and tree growth analysis. RMBL's UAS (DJI m300 RTK) utilizes a DJI P1 mapping camera synchronized with the high-precision GPS on the aircraft. This allows for the generation of imagery orthomosaics and structure (vegetation height) data with high resolution (1-5 cm/pixel) and very high geospatial precision (3-5 cm). To collect images, the UAS flies at an altitude of 100m, and collects images every 0.7 seconds along flight lines with 20m spacing across the study area, producing ~4600 images of the townsite per flight. The horizontal and vertical overlap of the images is about 80% which yields an image dataset with approximately 1 cm ground resolution for 2D data, and approximately 2.5cm ground resolution for 3D data. Processing of the spatial data takes place in Agisoft Metashape, a structure-from-motion program.

To generate the initial map of conifer trees shown in Figure 1 we used the ITCSegment algorithm (Dalponte et al. 2016) to segment trees greater than 2m in height. The algorithm locates local maxima (tree tops) in a canopy height model (derived from 2021 data), and then grows segments from the local maxima according to the horizontal and vertical distance from the tree top. We excluded aspen canopies from the segmentation by computing the modal vegetation class in each putative tree crown based on a high-resolution vegetation classification. Each of these tree polygons has associated spatial measurements including tree crown diameter, tree height, and crown volume. The map of all the segmented conifer polygons in Gothic is available as the first entry in the appendix.

Site Selection:

60 conifer tree selections were made through stratified random sampling of trees by canopy volume and tree density. This was achieved by analyzing Gothic spatial data in QGIS Version 3.36.3 and R Studio Version 4.1.1 First, a 2023 Digital Elevation Model (DEM) and Digital Surface Model (DSM) of the Gothic townsite were imported into QGIS. Then, the DEM was subtracted from the DSM to form a Canopy Height Model (CHM) representing all of the conifer's heights above the surface of the Gothic townsite. I then calculated the sum of all heights within the tree polygons. Next, I multiplied the tree polygon height sums by $0.05\text{m} \times 0.05\text{m}$ to calculate the canopy volume in cubic meters for each tree polygon.

To quantify neighborhood forest density, I created a heatmap (kernel density smoother) of the tree polygons in Gothic, visualized in Map 2 in the appendix. First, I used the Centroids function in the processing toolbox of QGIS to generate a layer consisting of points in the center of each tree polygon. Then I used the Kernel Density Estimation function in the processing toolbox to create the heatmap. For the point layer, I used the centroid layer created in Step 1. Then I used a radius of 10 meters, and canopy volume as a weighting field. The resulting map provides estimates of the distance-weighted average crown volume of neighboring trees.

From QGIS, I exported a dataset containing the canopy volume data for each conifer in Gothic and their associated kernel density values. I then imported this dataset into R to execute stratified random sampling. An R script was used to separate canopy volume into three categorical variables: young ($3.33\text{--}43.52\text{ m}^3$), semi-mature ($43.52\text{--}151.98\text{ m}^3$), and mature ($151.98\text{--}1398.72\text{ m}^3$). Kernel density was separated into two categorical variables: sparse ($0\text{--}555.49$) and dense ($555.49\text{--}2012.622$). Each of these separations were based on equal quantiles. I then executed an R script that randomly sampled 60 trees from my dataset with 10 young, 10 semi-mature, and 10 mature trees in dense stands, and 10 young, 10 semi-mature, and 10 mature trees in sparse stands. While only 34 trees were ultimately sampled in the field, 60 were generated in anticipation that many trees would be excluded because they were the incorrect species or did not pass a rapid health assessment described in the next section.

Field Data

Once selections were made, field data was collected within the month of July 2024. I first used a 2cm accuracy Trimble GPS unit and ArcGIS Field Maps mobile app to geolocate the trees in the field from a point layer. Once located, I identified trees as E. Spruce by their purplish/reddish bark and their sharp, square, blue-green needles (Alexander et al., 1984). Then, I performed a rapid health inspection to ensure the tree was a viable sample for my experiment. E. Spruce trees in the study site are subject to infestations by *Choristoneura occidentalis* (Western spruce budworms) and *Dendroctonus rufipennis* (Spruce bark beetles) which negatively impact growth and can ultimately kill the trees. Trees infested with budworms can be identified by missing, damaged, or dead needles and webs between needles. Also, canopy top kill is another common sign of infestation (Garrison et al., 2016).



Figure 3: (left, right, bottom) Examples of dead and damaged needles, webbed needles, and an image of a western spruce budworm (Garrison et al., 2016)

Trees infested with spruce beetles can be identified by pitch streamers, which are strings of resin visible 8 feet or higher on the tree trunk. Infestations also result in a faded yellow-green needle color before dropping off the tree completely. (Grant, 2014).



Figure 4: (left to right) Pitch streamers and a spruce bark beetle (Grant et al., 2014)

Acceptable trees for my study needed to have full canopies of green needles and have less than half of new needle growth defoliated by budworms. I further eliminated trees that were dead, were leaning on their neighbors, had canopy top kills, and had yellowish-green needles due to bark beetle infestation.

If a selected tree was identified as a species other than E. Spruce (typically Subalpine fir or Douglas fir) or if the tree failed to pass the health test, then a substitute tree was chosen from the surrounding area. This substitute tree needed to be in the same strata classification and same general geographic area as the tree it was replacing (i.e. sparse mature). If a substitute tree could not be found under these requirements, then a new tree would be chosen from the 60 initially generated conifers. Using this methodology, the trees ultimately sampled in the study are often different from the specific trees generated by stratified random sampling. In this sense, samples generated using my R Script established general randomized locations for trees rather than specific trees themselves.

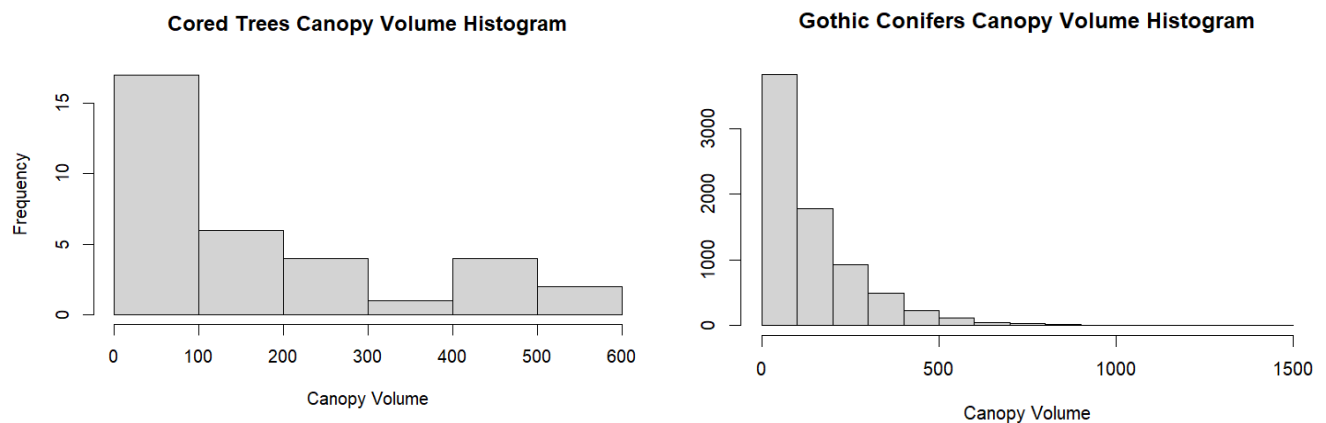
Once a tree was determined to be a healthy E. Spruce, I then proceeded to take field measurements. First, I measured the diameter at breast height (DBH) of the selected tree and then took 2 tree cores using a Hagl f 2-Thread Increment Borer with a core diameter of 5.15mm. Lastly, I used a 2cm accuracy Trimble GPS unit to map a polygon of the selected tree by walking around the projected canopy and taking 8-12 GPS points of the perimeter.

Increment cores were stored in labeled plastic straws and dried in a drying oven at 60°C until their dry masses stabilized (~48 hours). Once dried, cores were analyzed under a microscope. First, a Kim Tech wipe sprayed with 70% alcohol was carefully dabbed against the core surface to clean it and enhance the contrast between the earlywood and latewood. The 2018-2023 ring widths were each measured under the microscope using precision digital calipers accurate to 0.01mm. Since two increment cores were obtained per tree, a final width was calculated by averaging the two tree ring measurements. If one of the cores was deformed through sample collection in a manner that prevented accurate measuring, the other core was used solely for statistical analysis. Ring width measurements were then paired with DBH to calculate basal area increment for each tree in the growing periods 2021-2022 and 2022-2023. The microscope methodology was used instead of traditional sanding, mounting, and imaging of cores because only six years of ring growth measurements were needed, instead of the hundreds required for a typical dendrochronological analysis.

Ultimately, DBH measurements and two increment cores each were obtained from 34 E. Spruce trees in the Gothic study area, stratified by canopy volume, location, and stand density. Map 3 details the locations and corresponding stand densities/ages of all the sampled trees in the Gothic townsite.

RESULTS

Figure 5:



First, we compared histograms of canopy volume for all of the conifer trees in the study area and the trees sampled to offer insight into whether a representative sample was gathered. As seen in Figure 6, both histograms show a right-skewed distribution of canopy volume, best characterized as a Gamma distribution for statistical analyses. The E. spruce trees sampled in this study show a similar canopy volume distribution to the total conifer population in the study site. Combined with stratification by stand density and geographical location, this means that the trees in this study were a fairly representative sample of the population as a whole.

Figure 6: Generalized Linear Model relating 2024 E. Spruce DBH with Canopy Volume with two lines of predicted values in the 1st and 99th quantile of stand density.

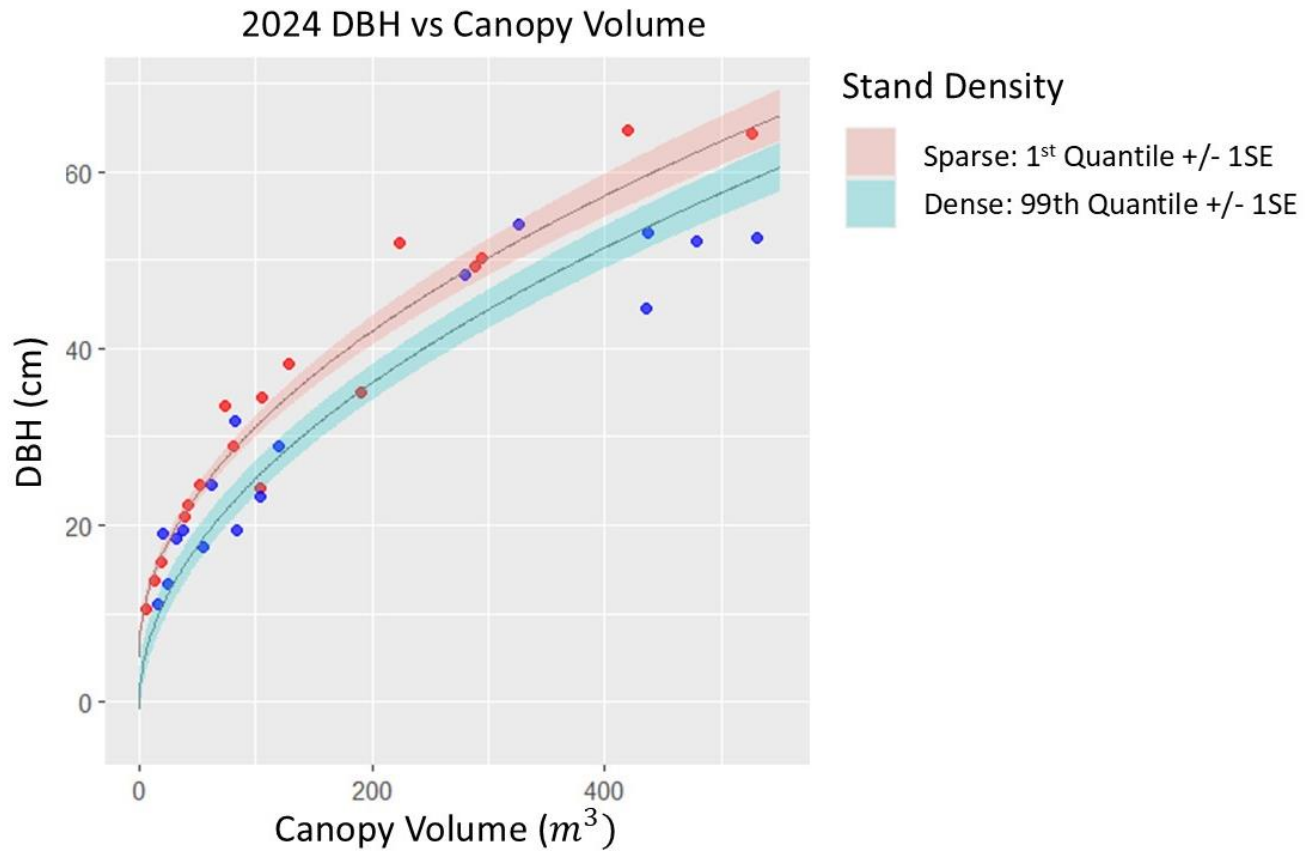


Table 1: Summary of Generalized Linear Model relating 2024 Canopy Volume to DBH

Coefficients	Mean Estimates	Standard Errors	p-value
Intercept	4.939769	1.218563	0.000315
$\sqrt{\text{Canopy Volume}}$	2.620095	0.151715	< 2e-16
Kernel Density	-0.004248	0.001941	0.036269

AIC = 200.73

A generalized linear model was created relating 2024 DBH vs Canopy volume with stand density as an additional covariate. Shown in Figure 5, the model demonstrates a non-linear relationship between 2024 DBH and canopy volume of the sampled trees. It plots two square root lines, with the red line corresponding to a fitted relationship for the 1st quartile of stand density, and the blue line corresponding to a fitted relationship for the 99th quartile of stand density. Each line has a corresponding, colored ribbon showing +/- 1 standard error. It is evident that the model is better at estimating canopy volume at lower values of DBH with standard error increasing with larger values of DBH. Table 1 demonstrates that all of the models' coefficients have significant p-values.

Figure 7:

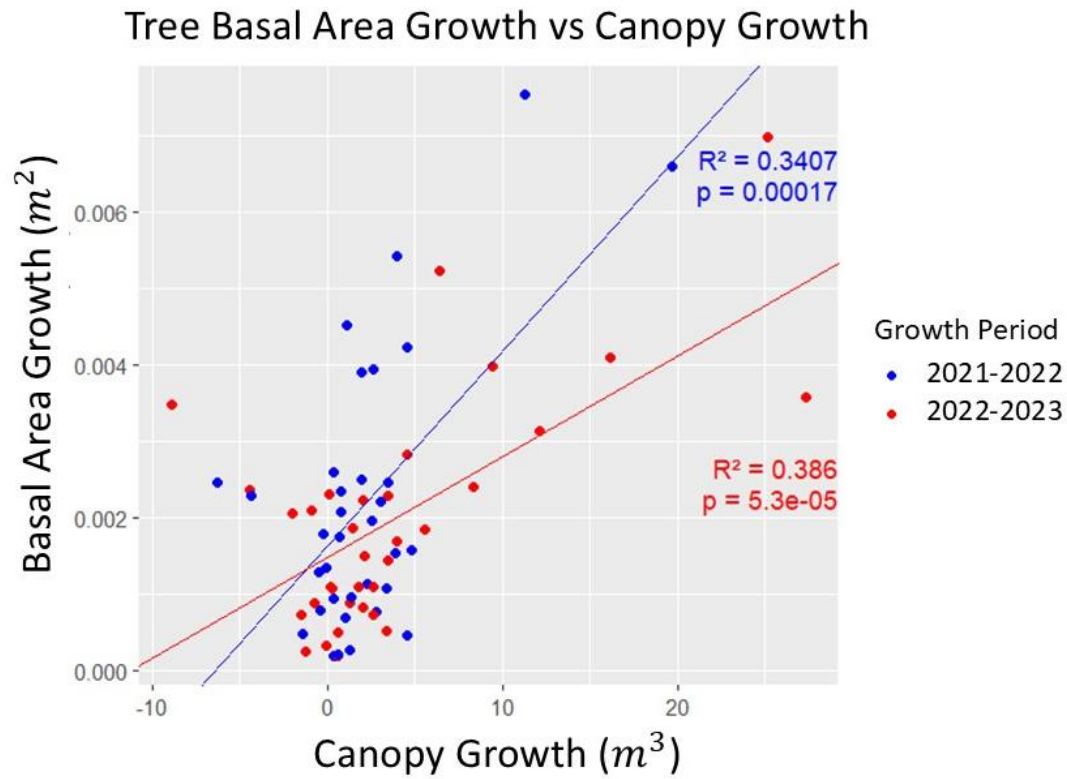


Figure 7 plots Basal Area Growth vs Canopy Growth in two different growth periods. Canopy growth shows moderate, positive correlations with basal area growth in both 2021-2022 and 2022-2023, with R -squared = 0.3407 and R -squared = 0.3860 respectively. The p -values are highly significant for these correlations.

Figure 8:

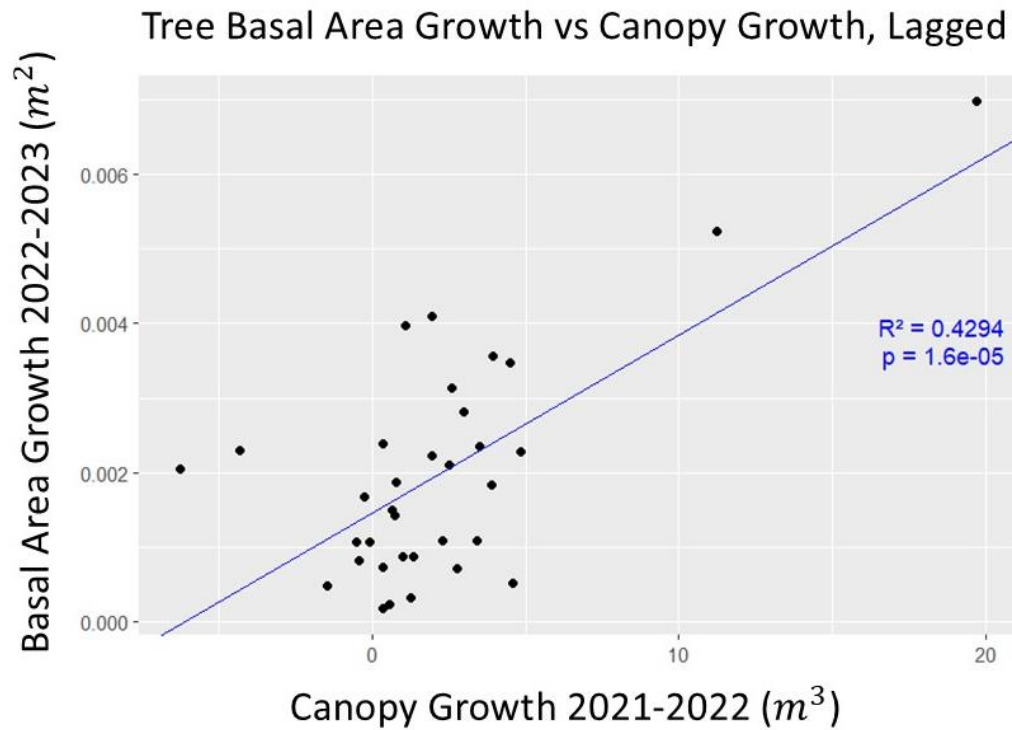


Figure 8 shows a linear regression to test the hypothesis of a lagged correlation between stem growth and canopy volume. It plots tree basal area growth from 2022-2023 with canopy growth from the previous year: 2021-2022. The regression has an R -squared = 0.4294, with a highly significant p -value = $1.6e-05$. Plotting current year canopy growth with the following year's stem growth provides a more strongly correlated and significant regression (R -squared = 0.4294 vs R -squared = 0.3407).

DISCUSSION

Results from this study first model the relationship between canopy volume and stem growth in Engelmann Spruce in the Gothic study site. It was hypothesized that canopy volume and stem growth would be more steeply correlated in dense stands than in sparse stands. This hypothesis is strongly supported by the model shown in Figure 6, wherein plotting the 99th quartile of the kernel density random effect yields a steeper quadratic relationship than the 1st quartile. These findings support that Engelmann Spruce trees tend to adjust biomass allocation to prioritize canopy growth and limit stem growth when under density stress. A global meta-analysis of trees across functional groups conversely found that stand density did not change the ratio of canopy biomass to above-ground biomass (Qichang, 2022). This divergence could underly the importance of conducting species-specific allometric studies to detect unique tree biomass allocation strategies, as opposed to researching broad tree functional groups and mixed forests.

The second hypothesis of this study postulated a lag in correlation between canopy volume and basal area growth. We tested for current-year canopy growth being more strongly

correlated with stem growth in the following year, and found strong support for that hypothesis. When comparing Figure 7 and Figure 8, it is evident that a regression accounting for a one-year lag in basal area growth results in a stronger and more significant correlation. However, it is important to acknowledge that all the regressions rely heavily on two outliers with large stem and canopy growth. When these outliers are removed, the lagged correlation is still the strongest, but its R-squared value decreases to ~ 0.14 . It is desirable that future research and analysis sample a larger number of trees with substantial canopy growth to reinforce the relationships established in our preliminary models. Ultimately, these results provide insight into plant physiology growth and resource allocation between the stem and the canopy. Through further research, I plan to sand and mount the increment core samples to construct a master chronology of the study trees. This will help elucidate the mechanism of our observed growth correlation lag through rigorous analysis of environmental stresses and climatic data.

The models from this study will ultimately be used to estimate the above-ground biomass and forest carbon stocks of all the conifers in the Gothic study site. This can be achieved by first calculating DBH measurements for all of the trees in the Gothic townsite using the model in Figure 4, and then utilizing existing allometric equations that relate DBH to tree biomass (Means et al., 1994; Duursma, 2007), to estimate the total carbon stored by forests in Gothic. Furthermore, given access to Canopy Height Models from 2021-2024, we could calculate the flux in carbon storage of Gothic conifer forests from year to year. Given increased infestations of spruce budworm and bark beetle due to climate change, tree canopy volumes may actually decrease from year to year, so it is possible to detect a decrease in carbon storage in Gothic forests over time.

Research from this study provides strong empirical models for utilizing UAV remote sensing to relate canopy measurements to estimates of forest carbon dynamics. These models can scale up data collection and allow for the analysis of tree growth in rugged terrain where field studies are dangerous and impractical. This research bolsters existing forestry remote sensing literature, which understudies forest growth in natural systems and lacks the high spatial and temporal resolution available at RMBL. Continued analysis of the Gothic tree growth spatial data as it becomes available is crucial to reinforce preliminary findings from this study and continue to evaluate changing forest dynamics in the study site.

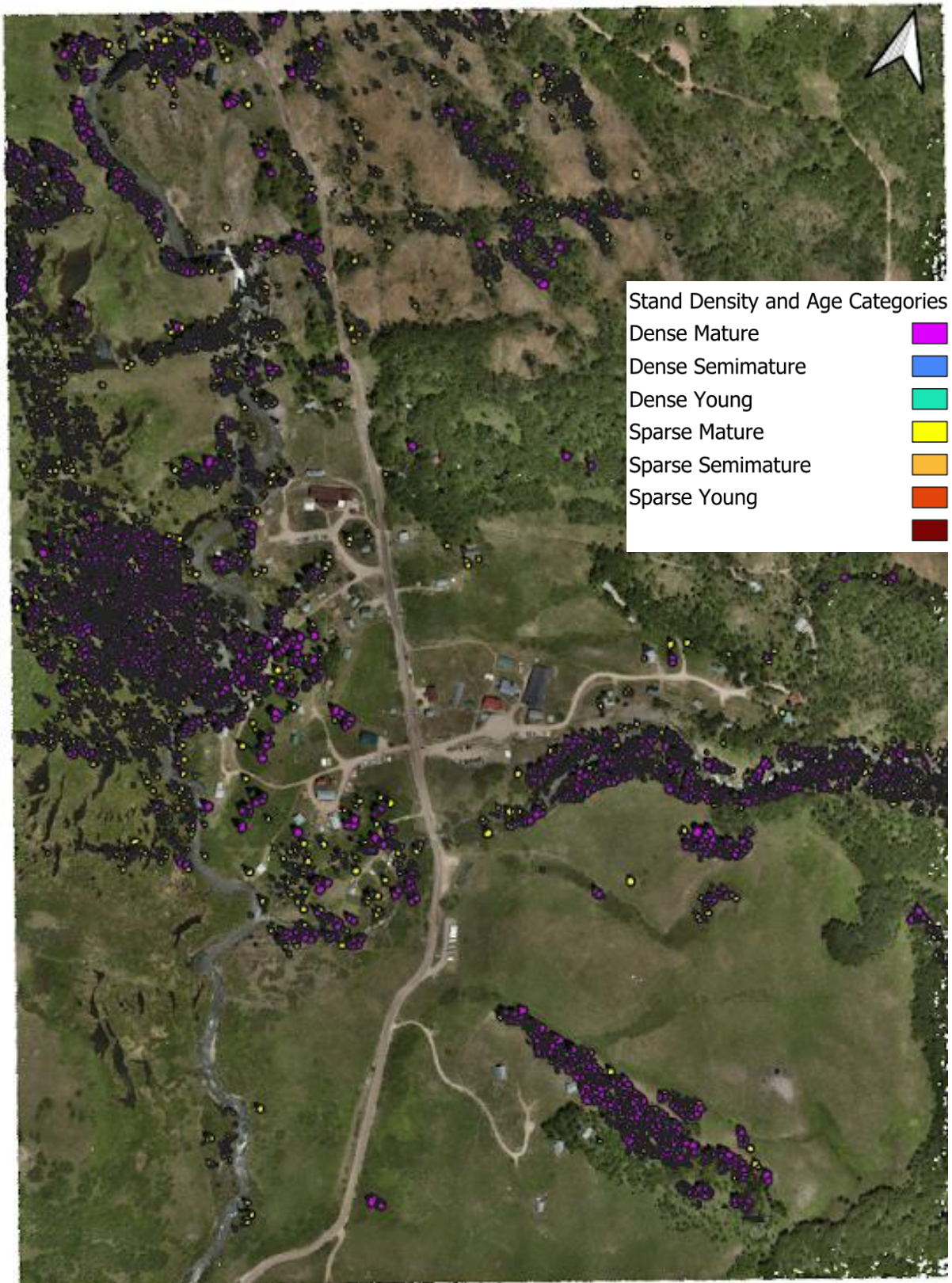
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Appendix

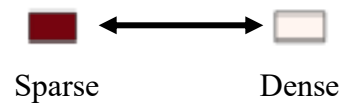
Map 1: Orthomosaic of the Gothic Townsite with overlaid Conifer Polygons



Map 2: Kernel density heatmap visualization of conifer polygons located in a forest West of the East River. White represents high density with a gradient towards dark purple showing low density.



Stand Density



Map 3: Map of 34 E. Spruce sampled in the study,

