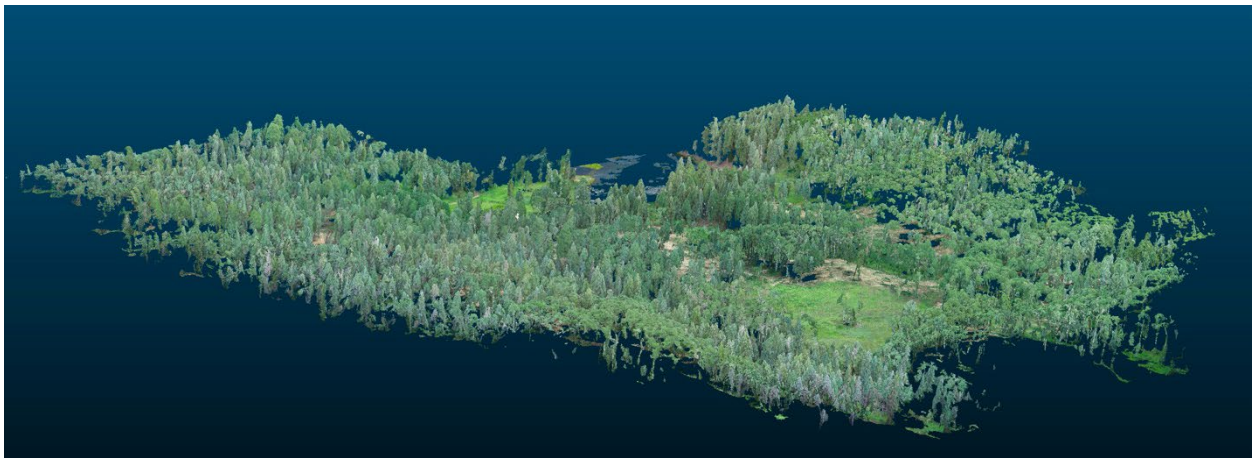


UAV Monitoring of Changes in Forest Structure Caused by Forest Restoration and Prescribed Fire Treatments

Edward MacKerrow, [Santa Fe Science, LLC](#)

Nick Dolecek, [Dolecek Enterprises, Inc.](#)

Caleb Stotts, [Chama Peak Land Alliance](#)



Point-cloud model of Thunderbird Ranch, Blanco Basin, Colorado during tree-thinning treatments.

Photogrammetric reconstruction based on 1,000 UAV RGB images collected on July 28, 2021.



Introduction

This project researches the feasibility and performance of using consumer grade UAVs (“drones”) using visible spectrum sensors (cameras) to measure and monitor forest structure and health.

Photogrammetric reconstruction of forest areas will be performed using the principles of [structure from motion](#) (SfM), where the spatial and geometric relationship of the target is determined by the motion of the camera and the perspective in the photographs it records. Our research aims to assess how well this technique can measure trees in the forest.

Photogrammetric forest analysis has the benefit of lower sensor platform costs as compared to UAV mounted lidar. Both photogrammetric and lidar based remote sensing of forests require complex data analysis and machine learning software to extract individual tree signatures from massive data sets.

Typical sizes for photogrammetric forest data are approximately 3 GB of raw image data, and up to 300 GB for lidar data. Fast multiprocessor computers with large memory (> 64 GB RAM) are required. Even with these computers our initial photogrammetric reconstructions of a 200-acre forest area requires 7-12 hours of processing time just to create orthomosaic photos and 3D point-clouds.



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Commercial software¹ to analyze photogrammetric and lidar data are tightly controlled and expensive. This research project is attempting to utilize open-source analysis software to avoid using expensive, opaque, and proprietary software. The trade-off is ease of use and time on the learning curve, versus turn-key commercial software.

We are evaluating how well forests can be monitored using visible low-altitude UAV aerial imagery, as opposed to lidar, multispectral, and hyperspectral remote sensing. If sections of forests can be effectively monitored using visible image photogrammetry from these consumer grade UAVs the cost and agility of forest monitoring will be improved.

By conducting this research on large private ranches in the Chama Peak Land Alliance (CPLA) network we can efficiently monitor forest treatments and prescribed burns. Successful forest analysis will utilize UAV sensor data to assess fire risk, forest health, wildlife habitat, and forest product inventory.

The data for this research were collected in 2020 and 2021 over private lands, with explicit permission from the landowners, in the Southern San Juan Mountains of Colorado and New Mexico.

¹ [Pix4D](#) and [DroneDeploy](#) are the most popular commercial software offerings.

The primary goal of this research is to assess the feasibility and performance of UAV RGB image sensors for measuring the metrics listed here. It is unclear at this point in our research how well our current data can identify tree species.

Target metrics for this research

Our research approach is to assess how well we can measure key metrics associated with forest monitoring solely from UAV based (visible spectrum) camera images.

Our target metrics are:

1. Tree detection and inventory parameters
 - a. Height of forest population
 - i. Distribution of tree heights independent of species
 - ii. Distribution of tree heights by species
 - b. Diameter at breast height (DBH) derived from established models relating tree height to DBH
 - i. Distribution of DBH independent of species
 - ii. Distribution of DBH by species
 - c. Crown area
 - i. Distribution of crown areas independent of species
 - ii. Distribution of crown areas by species
 - iii. Canopy coverage (percent)
 - iv. Canopy heights
 - d. Individual tree detection with crown delineation
 - i. 2D map showing bounding boxes around individual trees
 - ii. Individual tree delineation by species

- iii. Precision and recall measures of performance
 - e. Tree density
 - i. Trees per acre independent of species
 - ii. Trees per acre by species
- 2. Above ground biomass volume detection
 - a. Above ground biomass
 - b. Overall volume
 - c. Stock growing volume
 - d. Basal area
 - e. Woody debris and fallen logs
- 3. Using the above metrics to measure and monitor changes in forest structure before and after forest treatments (thinning, prescribed burns, planting)

Data Collection

Prescribed UAV flight paths were flown over large ranches in the Southern San Juan Mountains of Colorado. The primary forest type measured were mixed conifer. The UAV flight patterns were planned with the [DroneDeploy Desktop Planning tool](#). Flights were made when the sun elevation was high, and in cloudy weather, to avoid strong shadows degrading the imagery.



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We used a [DJI Phantom 4 Pro v2](#) drone as the sensor platform. We recorded images from the 20 megapixel camera on the drone in JPEG format. These JPEG files, like any JPEG file, are stored with 8-bit color depth (256 levels). The individual tree detection algorithms in the software we analyzed these data sometimes gave us warnings (but not errors) that they expected 16-bit color depth (65,536 levels). Any JPEG image file is [limited to 8-bit color depth](#).

More [experimentation](#) on our part is needed here to compare 8-bit to 16-bit color depth images in the workflow. The open-source software, [Open Drone Map](#) (ODM), we used to generate photogrammetric reconstructions recently added the ability to input 16-bit TIFF files.

The DJI Phantom 4 Pro v2 can store images in the DNG raw format (we need to verify this as [DJI claims 16-bits per pixel](#)). Future flights should ensure we record in DNG to utilize 16-bit color if it is found to improve the performance of the image analysis software we use. These will need to be converted from DNG → 16 bit TIFF for input for photogrammetric reconstruction of the forest scenes.

Ideal flight patterns for photogrammetric data collection

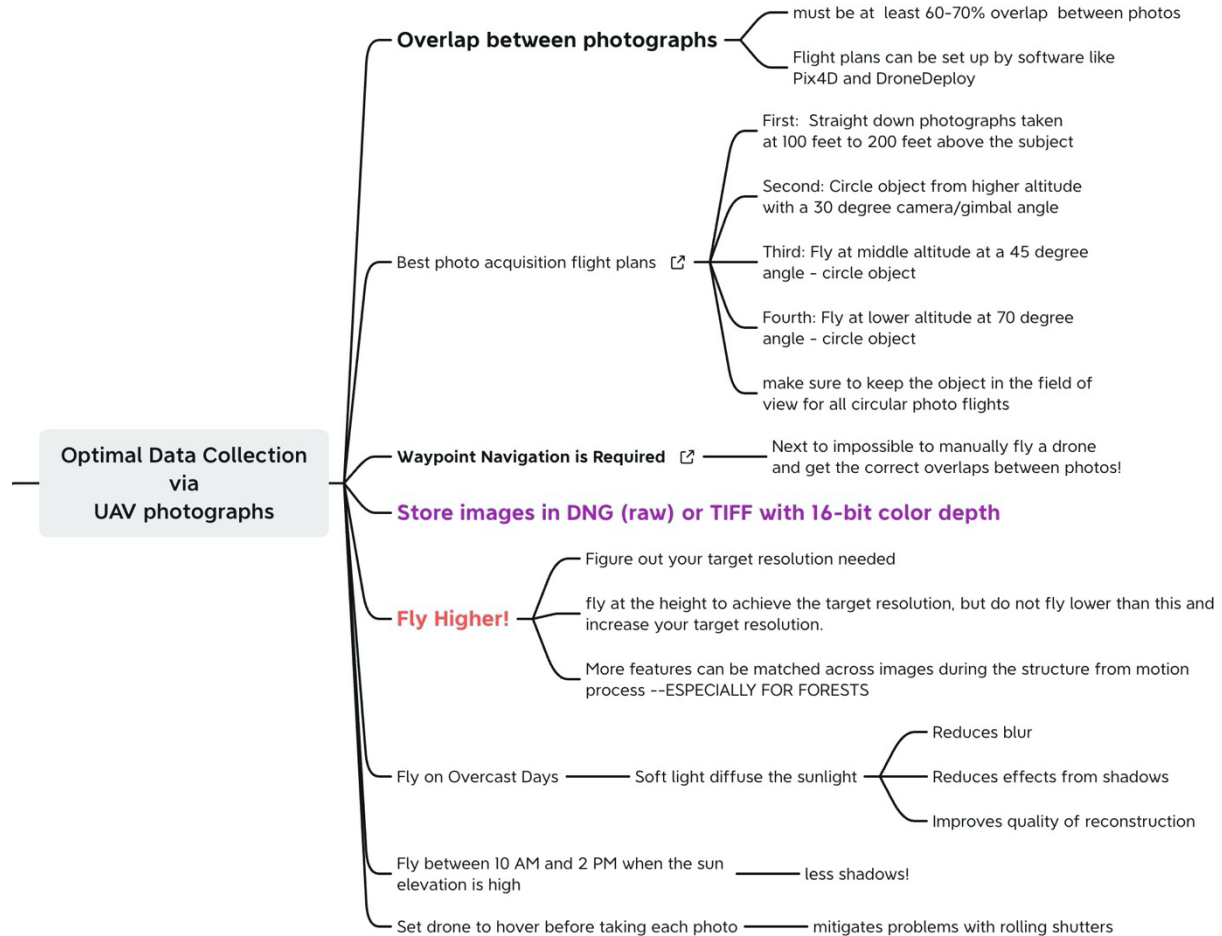


Figure 1. Optimal data collection requires waypoint navigation (flight plans) at different altitudes and angles, and storing images in a file format with 16-bit color depth (TIFF or DNG (raw)).

Photogrammetry, Creating Orthomosaic and Point Clouds from UAV Images

Initially in the project we experimented using trial licenses with commercial software vendors ([Pix4D](#) and [DroneDeploy](#)) to generate photogrammetric reconstructions of the forest areas we collected UAV images over. Both of these commercial solutions proved to be expensive and very limited in the number of photos you could submit for processing per unit time, or trial (e.g. 1000 images total for your trial). Their pricing tiers ramped up quickly for large image sets (1000 images or more). For our experiments we are collecting approximately 1,000 images per 200 acres.

Fortunately, the open-source software community is very active in photogrammetry. We found success using Open Drone Map (ODM) (free) and its cloud-based variant, Web ODM Lightning (\$30 per month). ODM requires a multiprocessor computer (more than 4 processors) and significant RAM (at least 64 GB) to run efficiently.

On a 4.4 GHz quad-core Mac with 64 GB of RAM it can take anywhere from 4-18 hours to perform the photogrammetric reconstruction, depending on the many different input parameters and settings ODM needs.

One of our initial hurdles we faced in the data analysis of our UAV imagery is tweaking the input parameters to ODM and fine-tuning things in order to generate high-quality point-clouds, orthomosaic images, digital terrain models (DTMs) of the ground, and digital surface models (DSMs) of the tops of the objects on the ground (trees).



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Since each ODM photogrammetric generation takes approximately 6 hours or more, this exploratory phase of finding the best input settings to ODM has been challenging. We are investigating how to find the ideal photogrammetric settings on a smaller set of UAV data. Our current data sets were collected using striped UAV flight patterns, making it difficult to generate photogrammetric reconstructions for a small fraction of the forest area we surveyed. We may have to collect test data by aerial survey of a small area (5 acres) of forest and use these data to determine the optimal input parameters to ODM, before scaling up to a larger survey area.

Ground Control Points

Ground control points (GCP) increase the georeferencing accuracy of a photogrammetric reconstruction. Highly visible targets are secured to the ground and measured with high-precision GPS. UAV images that contain a ground control point are then labeled with the prefix "GCPXXXX_" in the image filename for each numbered "XXXX" GCP. Each image that contains a GCP is then manually tagged with the pixel location of the center of GCP.



Figure 2. An example UAV image containing a view of a (red) ground control point (GCP), seen just above the dirt road near the center of this photo. Ground control points should be spaced evenly around the survey area, and ideally placed in the middle of open areas so that they are recorded in many images, and not blocked by trees.

A file containing the image names of all images that contain a given GCP, the pixel locations of the GCP in each of these images, and the ground truth GPS coordinates of the GCP locations is used as input to ODM which relates GPS location, pixel location, and image.

Ideally, 5-8 ground control points are spaced evenly across the survey area. If the same GCP marker is visible from multiple images, it should be tagged multiple times for each image.

Ideally each GCP marker should be tagged in at least three images – to allow for triangulation of the GCP position.

```

gcp_list_utm.txt
1 WGS84 UTM 11N
2 490350.812050421 7624268.107392277 2519.236652 2549.1218130311618 1822.9666142882438 GCP1010_DJI_0001.JPG
3 490350.812050421 7624268.107392277 2519.236652 2576.6798866855524 2245.9830028328615 GCP1010_DJI_0002.JPG
4 490350.812050421 7624268.107392277 2519.236652 2576.6798866855524 2714.470254957507 GCP1010_DJI_0003.JPG
5 490350.812050421 7624268.107392277 2519.236652 2218.4249291784704 1356.546343838527 GCP1010_DJI_0201.JPG
6 490350.812050421 7624268.107392277 2519.236652 1212.5552407932012 2872.2403948300284 GCP1010_DJI_0992.JPG
7 490350.812050421 7624268.107392277 2519.236652 1116.1019830028329 3395.8437942634564 GCP1010_DJI_0993.JPG
8 490350.812050421 7624268.107392277 2519.236652 2411.331444759207 1471.600964943343 GCP1010_DJI_0999.JPG
9 490418.0526864813 7624123.215428131 2533.824632 1253.8923512747876 2810.9235127478755 GCP1020_DJI_0224.JPG
10 490418.0526864813 7624123.215428131 2533.824632 2397.5524079320116 2494.00566572238 GCP1020_DJI_0273.JPG
11 490418.0526864813 7624123.215428131 2533.824632 220.4645892351275 1832.6118980169972 GCP1020_DJI_0856.JPG
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23 490511.20627800375 7624078.345396605 2538.163557 1788.37765746894 2344.0594094708013 GCP1030_DJI_0019.JPG
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25 490511.20627800375 7624078.345396605 2538.163557 1809.8015057299833 1131.5120341522725 GCP1030_DJI_0173.JPG
26 490511.20627800375 7624078.345396605 2538.163557 1548.6290976691637 1924.850329421321 GCP1030_DJI_0174.JPG
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28 490511.20627800375 7624078.345396605 2538.163557 2580.955984629372 2904.3953418495134 GCP1030_DJI_0176.JPG
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30 490511.20627800375 7624078.345396605 2538.163557 3766.426817945578 663.8382985827265 GCP1030_DJI_0333.JPG
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34 490511.20627800375 7624078.345396605 2538.163557 4052.930565853788 2606.824564115345 GCP1030_DJI_0337.JPG

```

Figure 3. A ground control point (GCP) input file for Open Drone Map photogrammetric reconstruction. The columns contain {UTM x, y, z, measurements from the precision GPS, the x and y pixel location of the GCP marker in the image, and the filename of the image containing the GCP}.

Open Drone Map does not require GCP's to do a reconstruction of the image.

Georeferencing of the generated orthomosaic and point clouds can still be made by ODM, although the accuracy will not be as good.

Initial Photogrammetric Reconstructions from Thunderbird Ranch, Colorado

Drone flights were made over the Thunderbird Ranch, located in the Blanco Basin area of the Southern San Juan Mountains, Colorado. Drone flights were also made over Banded Peak Ranch, and other ranches in the CPLA region. Our initial research focuses on the Thunderbird Ranch flights over an area of approximately 200 acres of mixed-conifer forests, before, during, and after thinning operations.

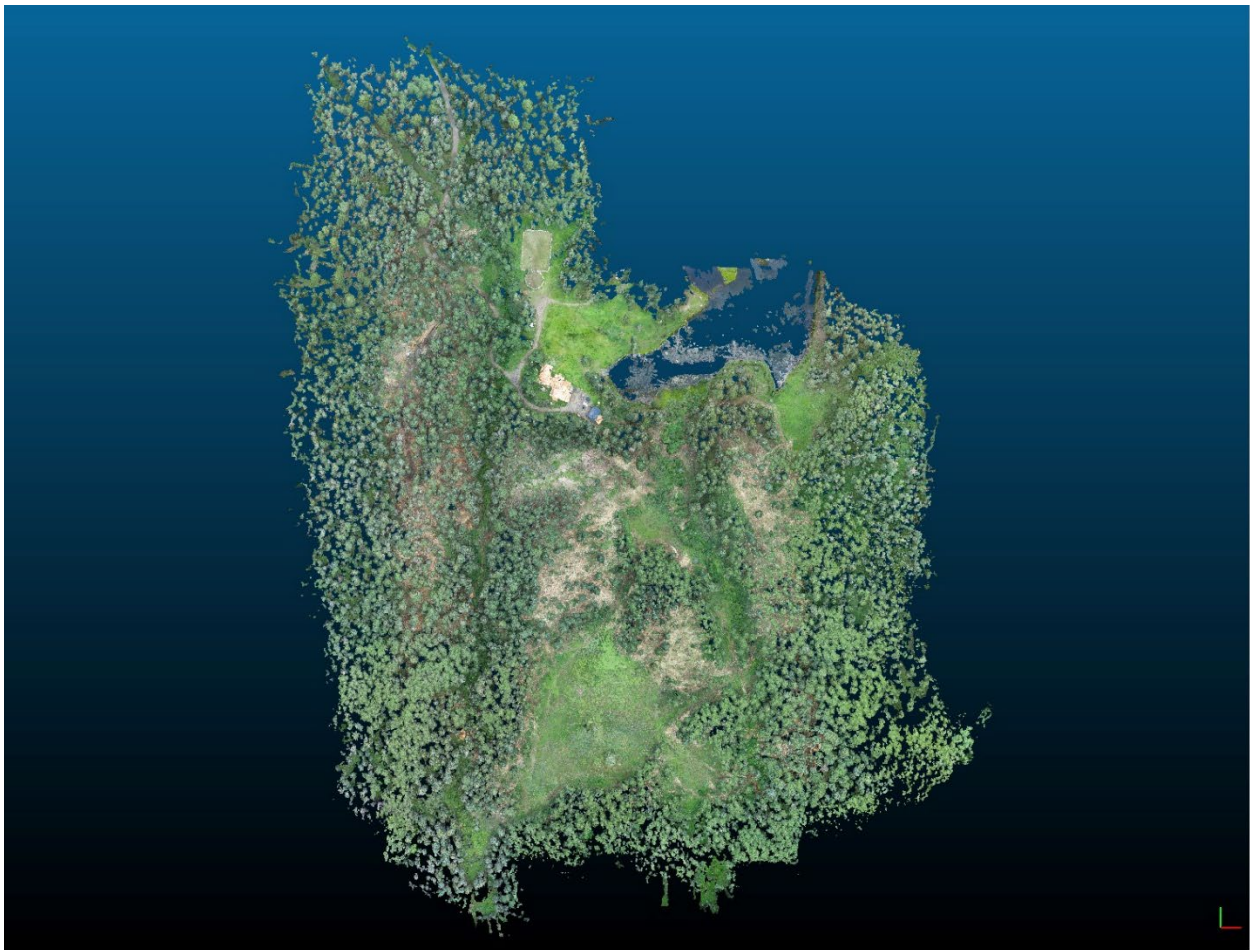


Figure 4. Point-cloud output for the July 28, 2021, Thunderbird Ranch survey. Viewed in [CloudCompare](#).

To better discriminate trees from the ground a cloth simulation filter was used in the open-source CloudCompare software. Cloth simulation filtering (CSF) is based on [Zhang et al 2016](#) and consists of simulating a piece of cloth draped over a reversed point cloud. In this method the point cloud is turned upside down and then a cloth is dropped on the inverted surface. Ground points are determined by analyzing the interactions between the nodes of the cloth and the inverted surface.

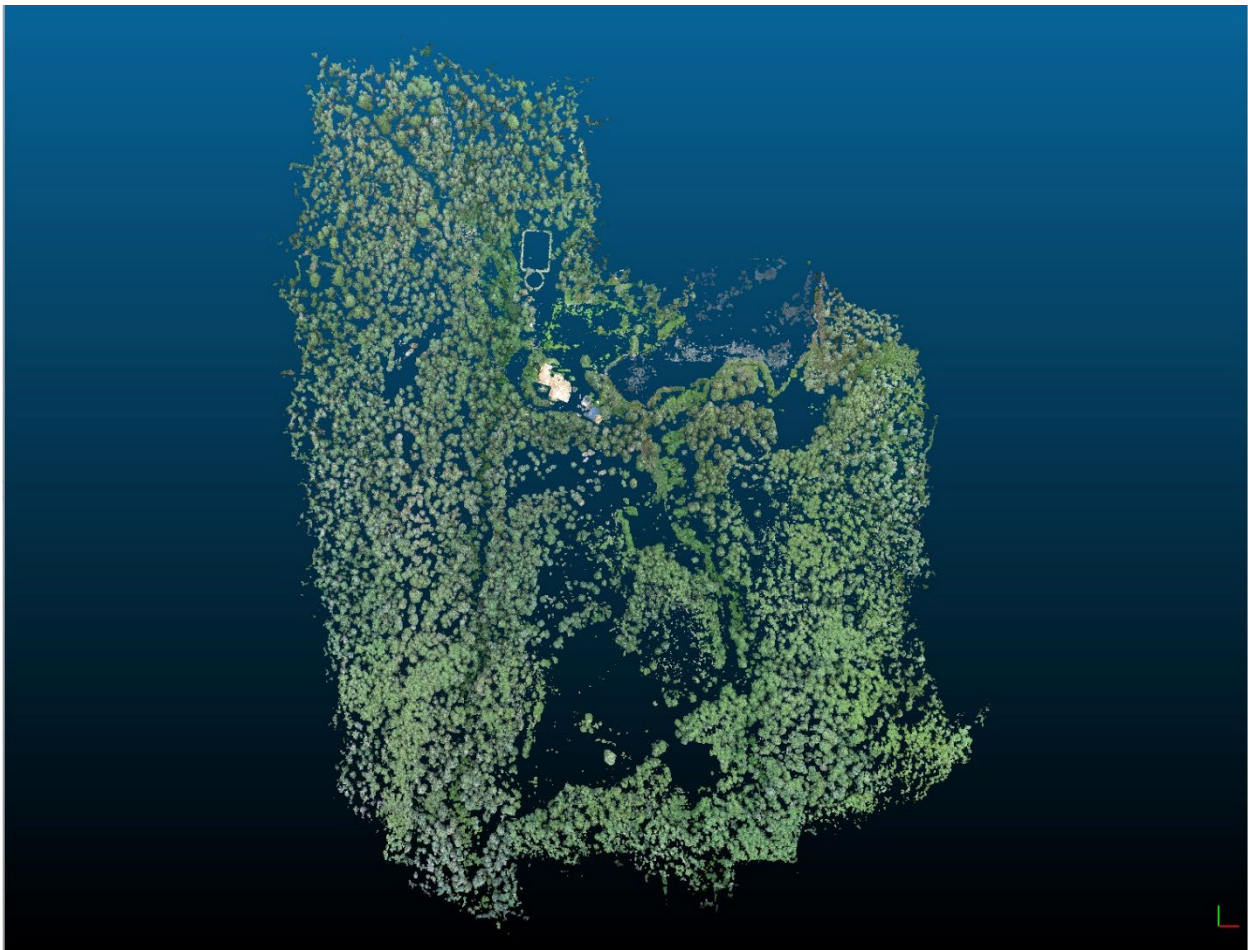


Figure 5. Point-cloud data (.las file) from photogrammetric reconstruction of July 28, 2021 drone flights over Thunderbird Ranch, Colorado. These point-cloud data have been filtered using the [Cloth Simulation Filter](#) (CSF), as a plugin to CloudCompare, to extract the ground surface.

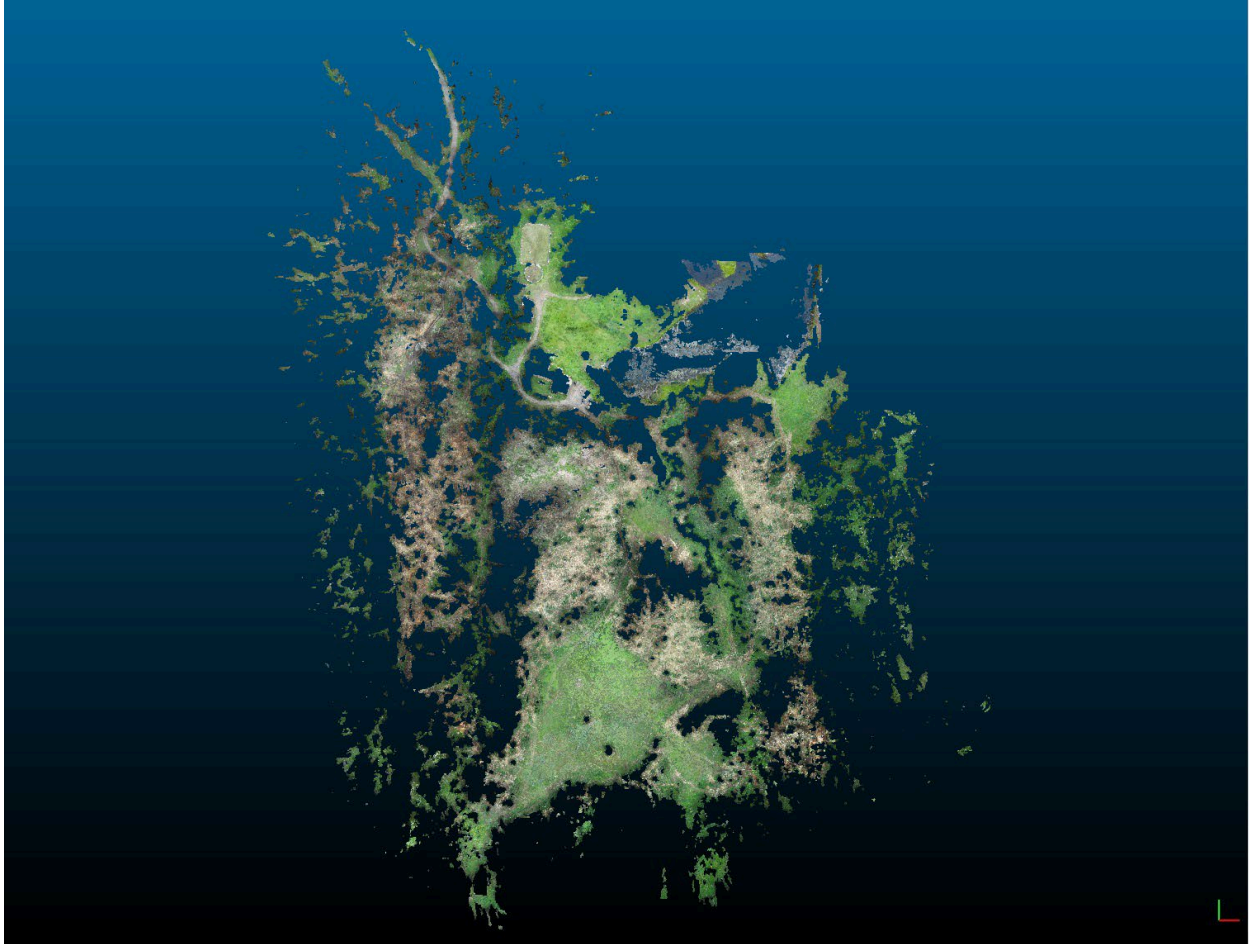


Figure 6. Extraction of the ground surface from photogrammetric point cloud data, using the CSF plugin in CloudCompare, is shown here.

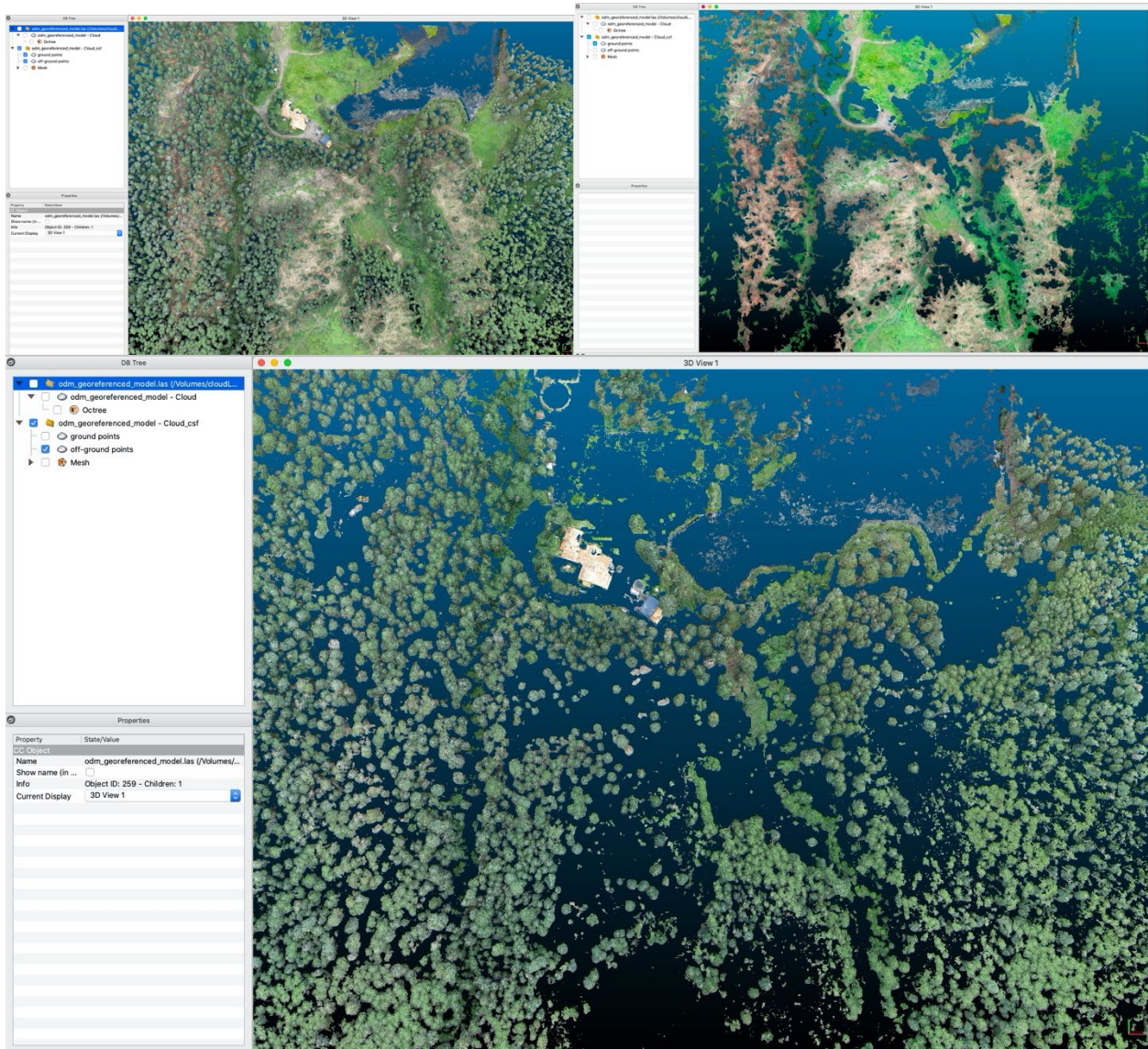


Figure 7. A zoomed in region of the Thunderbird Ranch is shown here. The top left image is the unfiltered point-cloud image, the upper right is the ground as extracted by the CSF filter in CloudCompare, and the bottom image are the trees (above ground objects) extracted by the CSF filter on the point-cloud data analyzed in CloudCompare. The CSF filter was set to 0.5 meters vertical threshold height – so objects less than this height would be classified as ground.

Tree height distribution estimated by normalizing above ground object heights to calculated ground-levels

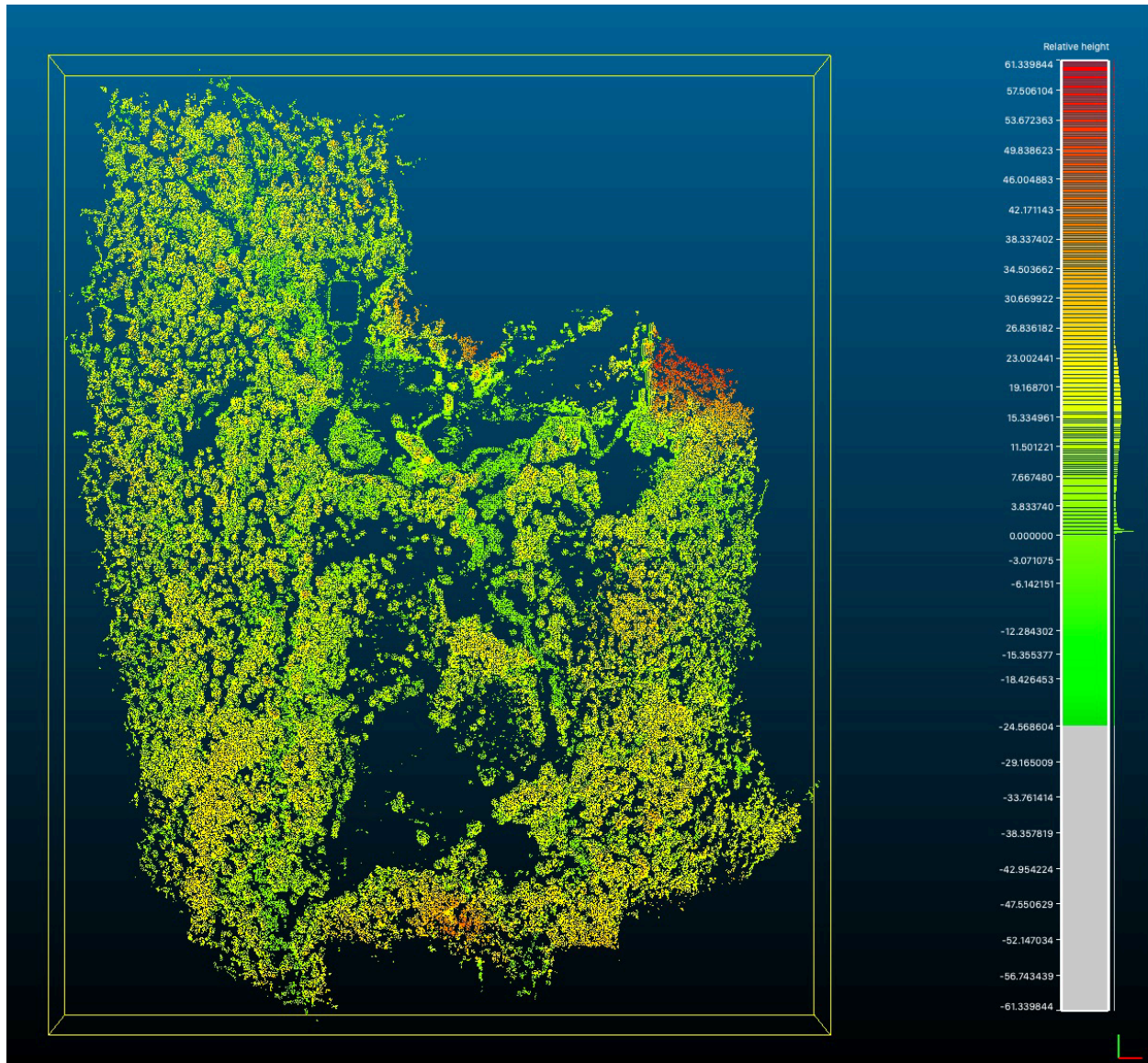


Figure 8. Estimate of tree height distribution is shown here. The tree heights (meters) were estimated by using a cloth simulation filter (CSF) on the point-cloud data. The cluster of estimated tall trees in the upper right corner is suspect and needs to field verified – the calculated mesh for the ground surface most likely has errors on the perimeter of the survey area. The center of the distribution at 15 m height is reasonable for this forest.



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Analysis of point cloud data for our key forest metrics

We are currently analyzing the point-cloud data from the photogrammetric reconstructions of the Thunderbird Ranch forest drone imagery.

Python DeepForest package

We have tried using the open-source Python analysis package, [DeepForest](#), for individual tree detection and segmentation. This Python package has been successful in individual tree detection and segmentation for other researchers. DeepForest contains a prebuilt model from semi-supervised learning trained on extensive tree data from around the world, included in the National Ecological Observatory Network (NEON).

We are in the process of annotating and training mixed-conifer forests in sections of the Southern San Juan Mountains to improve its precision and recall.

Our initial results in using DeepForest on the Thunderbird Ranch data, trained only on the NEON tree databases, require refinement.

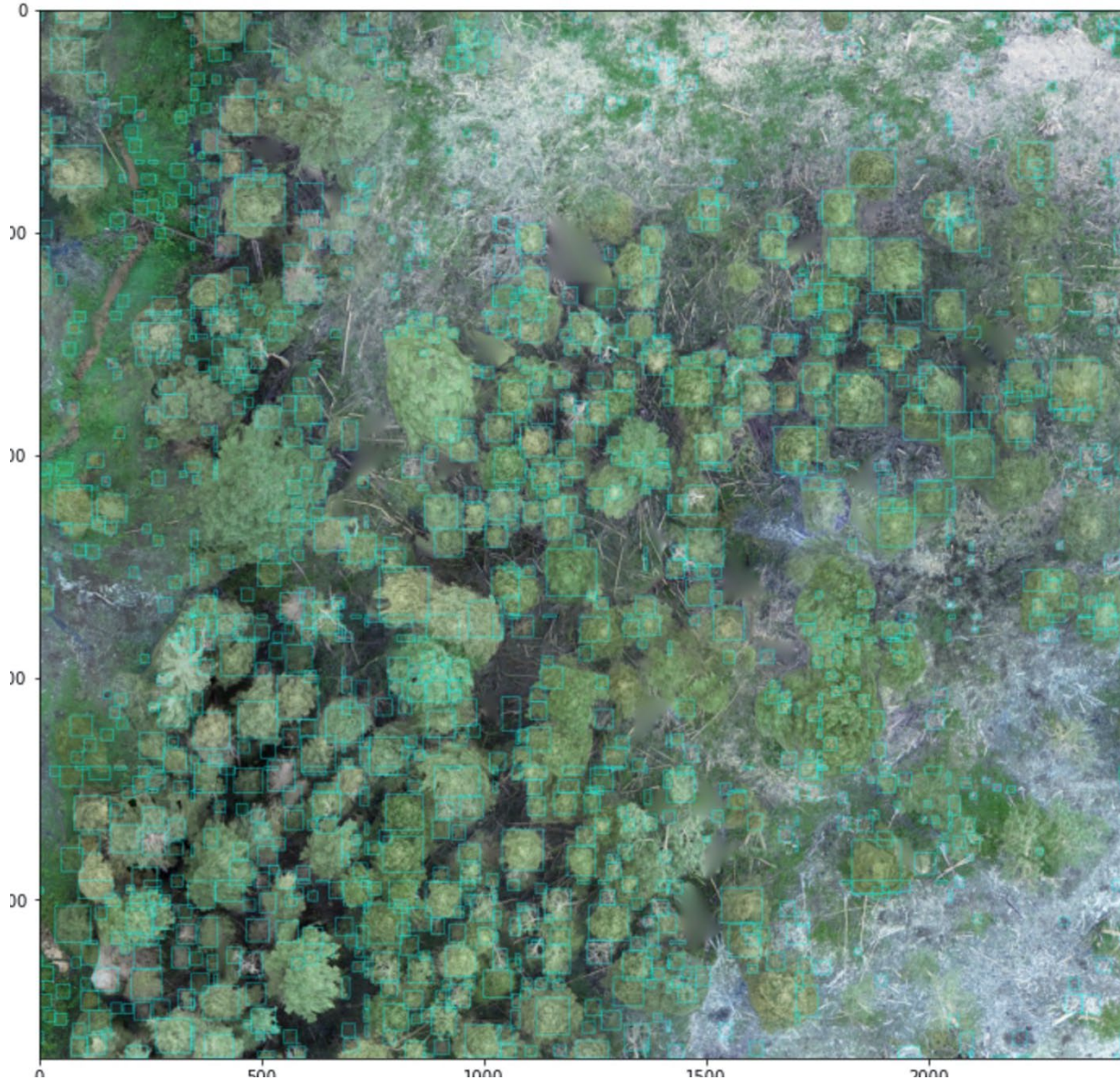


Figure 9. Initial results of individual tree detection using the Python based DeepForest package. The identified trees are shown by the green (poor color choice...) square bounding boxes. The results shown here are entirely based on the pre-built models built from the NEON data, with no learning from manual annotations of trees by us. We are currently researching how well the DeepForest tree detection algorithms work with supervised learning based on our ground truth tree location, species, and DBH field measurements.

Forest metrics using the R lidR module

Researchers using *lidar* data have found success in using the R module, lidR.

We are currently assessing how well the lidR software can help us analyze our photogrammetric point cloud data. So far we have run into problems using the lidR module in R Studio. The intensity data column in our .las point cloud files contain all zeroes – as expected since we are not integrating laser pulse returns. The classification data columns in our point cloud files are also suspect at this point. We are investigating what features (ground, water, vegetation, etc.) the Open Drone Map photogrammetric reconstruction software calculates.

Current analysis focus

Our focus continues in applying machine learning tools (lidR and DeepForest) to the photogrammetric reconstruction point cloud data.

1. We are redoing previous analyses on the full survey area, on smaller portions, to avoid running into memory limitations (we are working with 64 GB RAM).
2. We are refining the point cloud data before applying machine learning software to detect individual trees in it. The most important refinement we are working on is



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normalizing the elevation data (height) before applying tree detection routines.

3. After height normalization we plan on manually annotating approximately 50 individual trees in which we measured their DBH, GPS coordinates, and species (Douglas Fir, White Fir, Ponderosa Pine, Engelman Spruce, Blue Spruce, Aspen). These data will be used for supervised learning.