AN ASSESSMENT OF THE UTILITY OF AN UNMAMMNED AERIAL VEHICLE FOR MEASURING TREE HEIGHTS IN A JACK PINE PROVENANCE TRIAL

By

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ABSTRACT

Keywords: focal point seed zone, height, hypsometer, imagery, jack pine, northwestern, Ontario, point cloud, provenance trial, UAV

This independent study is an assessment of the utility of an unmanned aerial vehicle (UAV) for measuring the heights of jack pine (*Pinus banksiana*) trees in a provenance trial. An electronic hypsometer, the Haglöf Vertex IV, was used in the field to measure tree heights, and an UAV, the DJI Mavic Pro 1, was used to collect a point cloud of the provenance trial. Agisoft PhotoScan was the cloud-processing engine used for image processing and ArcMap was used for estimating tree heights. Tree height measurements were recorded for 256 jack pine in the study area. Measurements taken using the Haglöf Vertex IV displayed greater heights in comparison to the heights derived from the UAV imagery. The mean difference between the two datasets was 1.1 m with a standard deviation of 0.8 m. A correlation between the two datasets was observed when mean tree height per provenance was compared; a value of 0.9 was calculated using the Pearson Product-Moment Correlation Coefficient. This value of 0.9 indicated a positive association between the two datasets, however, ranking provenance means from highest to lowest indicated the two datasets differed. Although the UAV was capable of measuring tree heights, this study demonstrates that further understanding of measurement error is important for producing accurate results.

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ACKNOWLEDGEMENTS

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INTRODUCTION

Improving the methods used for collecting data in forestry is underway as numerous studies are assessing the use of unmanned aerial vehicles (UAVs) (Birdal et al. 2017; Mohan et al. 2017; Panagiotidis et al. 2016; Tang and Shao 2015; Ye Seul et al. 2015). UAVs are being used for forest mensuration; estimating tree height and crown diameter (Birdal et al. 2017; Mohan et al. 2017; Panagiotidis et al. 2016; Strigul et al. 2015). They are also being used for surveying and monitoring forests over time (Tang and Shao 2015). UAVs have been proven to be reliable, affordable, flexible, repeatable, and capable of capturing high spatial and resolution data (Araus et al. 2018; Anthony et al. 2014). In comparison to manual measurements, the use of an UAV is less time-consuming, labour-intensive, and expensive (Anthony et al. 2014; Birdal et al. 2017; Panagiotidis et al. 2016; Torres-Sánchez et al. 2015). Manual measurements are also subjective and prone to human error (Araus et al. 2018), therefore, more studies are assessing the use of UAVs for forest mensuration.

UAVs are a type of aircraft that can collect remotely sensed data. Remotely sensed data is the acquisition of information without physically interacting with the object of interest. UAVs are available in different sizes, shapes, and capabilities (Colomina 2014; Tang and Shao 2015), and the choice of platform most suitable for its application will depend on the intended work (Araus et al. 2018). UAVs are a unique invention that has evolved from conventional aerial photographic platforms. These platforms would collect aerial photographs, and they would be interpreted to identify, describe, and measure objects. UAVs pose as promising platforms that will assist in the acquisition of data; however, the utility of UAVs are still at an experimental stage (Tang and Shao 2015). Comparative research is important for determining the appropriate remote sensing technologies to employ for forest mensuration.

The objective of this independent study was to assess the utility of an UAV for measuring tree heights in a jack pine provenance trial and compare the UAV-derived height measurements with manual height measurements using an electronic hypsometer. If the results from both datasets are the same, then an UAV can be used instead of an electronic hypsometer to measure tree heights in provenance trials.

LITERATURE REVIEW

PROVENANCE TRIALS

Provenance trials are established for the purpose of assessing heritable traits of plants from different source populations. These populations are grown at a common site under the same climatic conditions and assessed over time to evaluate adaptive variation within each species (O'Brien et al. 2007). Provenance trials are used in forestry for detecting populations with superior heritable traits and used for forest restoration. Provenance trials are established by collecting source seeds of local provenances and planted individually, occupying their own plot. They are spaced apart and free-to-grow, and over time their growth can be assessed.

PHENOTYPING

Tree growth is commonly evaluated by physical traits such as canopy area, tree height and crown volume (Torres-Sánchez et al. 2015). These are also referred to as the phenotypic traits of a plant. Phenotypic traits can be easily observed and quick to measure (Aitken and Bemmels 2015) however, conducting these manual measurements can be time-consuming, labour intensive and expensive (Anthony et al. 2014; Birdal et al. 2017; Panagiotidis et al. 2016; Torres-Sánchez et al. 2015). Few studies have discussed alternative methods for assessing provenance trials in forestry, however, in crop breeding programs, remote sensing technologies are being used for high-throughput phenotyping (Araus et al. 2018).

A study conducted by Araus et al. (2018) discusses the effectiveness of remote sensing technologies used for high-throughput phenotyping in crop breeding programs. High-throughput phenotyping is a large-scale assessment of phenotypic traits. In crop breeding programs, it is especially important for quality phenotyping to be conducted because improvements in crop genetics rely on this information. Due to many different categories of phenotypic traits that exist in crop breeding programs, the remote sensing technologies to employ should not be generalized as the choice of platform most suitable for its application will depend on the intended work (Araus et al. 2018).

REMOTE SENSING TECHNOLGIES FOR FOREST RESEARCH

Remote sensing technologies encompass the use of aerial platforms used to collect remotely sensed data. Aerial platforms can be equipped with different remote sensing tools such as multispectral, hyperspectral, fluorescence or thermal sensors, imagers or digital red-green-blue (RGB) cameras to enhance phenotyping assessments. Remotely sensed aerial platforms have been proven to be an efficient means of collecting data in comparison to manual measurements as they are a flexible, affordable, reliable, repeatable, and can capture high spatial resolution data (Araus et al. 2018; Anthony et al. 2014).

Different aerial platforms such as those mentioned above are important in high-throughput phenotyping because they can detect different information about crops and their genetics (Araus et al. 2018; Torres-Sánchez et al. 2015). For example, RGB cameras are beneficial for plant phenotyping because abiotic and biotic stresses can be assessed from the imagery. Multispectral and hyperspectral sensors and imagers are useful for assessing vegetative indices like physiological and biochemical trait responses to environmental conditions (Araus et al. 2018; Yendrek et al. 2017). Collecting accurate data is important for crop breeding programs to improve crop genetics and "manual measurements are subjective, prone to human error, and lack robustness or repeatability" according to Araus et al. (2018).

Unmanned aerial vehicles (UAV) have been proven to be effective aerial platforms for collecting accurate data for crop breeding programs (Araus et al. 2018; Anthony et al. 2014; Malambo et al. 2018; Torres-Sánchez et al. 2015). Anthony et al. (2014) used a micro-UAV equipped with a laser scanner to assess and estimate corn crop height. The micro-UAV was a Firefly hexacopter, and it was flown close to the crops, within 1-2 m, to collect information on the foliage layers, and to detect ground level. Operating this close to the crops reduced atmospheric distortion in the data and enhanced the spatial resolution. Enhanced spatial resolution makes it easier to estimate crop height because the UAV was able to obtain stable height control. The results of this study were within 5 cm of the manual measurements obtained, and this study indicated the efficacy of an UAV being used to accurately assess and estimate corn crop heights.

Numerous studies reveal alternative methods to collecting, processing, and evaluating data. In the study described above, Anthony et al. (2014) used algorithms and Procedure *Process Scan* to estimate the corn crop heights. Indoor and outdoor testbeds were also used for evaluation. If the same features were present in both testbeds, then the same parameters could be used in both locations. This extensive study provided insight to alternative methods used to collect, process, and evaluate data for estimating corn crop heights.

Another study such as the one conducted by Malambo et al. (2018) also estimated crop heights using an UAV. The UAV was a DJI Phantom 3 Professional and the flying altitude was 20 m above the crops. Maize and sorghum were the two species used to evaluate height estimations. Height estimations were derived from three-dimensional (3D) point cloud and orthomosaics in Pix4Dmapper software unlike the previous study. Pix4Dmapper is a processing software used to generate structure-from-motion (SfM). The SfM generated was also compared to terrestrial lidar (TLS) to evaluate the accuracy of SfM to capture ground surfaces and crop canopies. Manual height measurements were also obtained to evaluate both methods. Overall, the results revealed a strong correlation between SfM, TLS, and the manual measurements for crop height estimation. The use of an UAV enhanced the data collection, and it demonstrated that an UAV based on SfM can be used for estimating crop heights.

From both studies, recommendations in respect to the methodologies, were provided to enhance future studies involving the use of remote sensing technologies for crop breeding programs (Anthony et al. 2014; Malambo et al. 2018). First, the use of multidimensional models was recommended by Anthony et al. (2014) to enhance the evaluation of crop development and health. Introducing new aerial platforms like sensors or cameras may enhance research; providing agronomists with more information about the crops. Additional aerial platforms may also increase the levels of the crop canopy, further enhancing the data collected. In contrast, Malambo et al. (2018), recommended more research should focus on environmental variables such as sunlight and wind, and the influence of these changing canopy structure over time. With SfM, it is unknown whether this may impact the accuracy of the data collected. Improved data quality is always aspired for, and these recommendations are helpful for other researchers conducting similar studies in crop breeding programs.

UNMANNED AERIAL VEHICLES

An UAV is a type of aircraft that can collect remotely sensed data. Remotely sensed data is the acquisition of information without physically interacting with the object of interest. UAVs are available in different sizes, shapes, and capabilities (Colomina 2014; Tang and Shao 2015), and the choice of platform most suitable for its application will depend on the intended work (Araus et al. 2018). UAVs are a unique invention that evolved from conventional aerial photographic platforms. Remote sensing technologies date back to as early as the 1860s, when aerial platforms would be suspended into the air by balloons to obtain aerial photographs. Then, during the times of World War, I and II, airplanes would be used to obtain aerial photographs (Tang and Shao 2015).

Major advances in remote sensing technologies continue into the twenty-first century, especially within the past few decades (Tang and Shao 2015). UAVs are being recognized more for their low-cost and efficiency in collecting data. In comparison to manual measurements, UAVs can collect the same data in less time, use fewer resources, cover larger areas, and obtain high spatial and temporal resolution data (Anthony et al. 2014; Bolton et al. 2018; Birdal et al. 2017; Strigul et al. 2015; Tang and Shao 2015; Malambo et al. 2018; Mikita et al. 2016; Panagiotidis et al. 2016). UAVs are being used in a plethora of fields like forestry, agriculture, natural disaster management, wildfire monitoring and detection, emergency search and rescue, etc. (Araus et al. 2018; Restas 2015; Strigul et al. 2015; Tang and Shao 2015; Ye Seul et al. 2015; Zeng et al. 2016).

Forestry practices often involve field work, which can be time-consuming, labour intensive, and expensive (Anthony et al. 2014; Birdal et al. 2017; Panagiotidis et al. 2016; Torres-Sánchez et al. 2015). Field work involves the collection of data in the form of notes, photos, coordinates, measurements, etc., and to collect some of this data, hand tools may be required. Training is important for data collections to minimize the chance of error because human error is common, and manual measurements are subjective (Araus et al. 2018). To minimize time-consuming, labour intensive, and expensive field work in forestry practices, UAVs are being implemented.

Many studies on forest mensuration are comparing manual measurements to UAVs (Birdal et al. 2017; Mikita et al. 2016; Mohan et al. 2017; Panagiotidis et al. 2016; Tang and Shao 2015). In most studies, the results demonstrate that an UAV can produce accurate results and is another method for conducting forest measurements (Birdal et al. 2017; Mikita et al. 2016; Mohan et al. 2017; Panagiotidis et al. 2016; Tang and Shao 2015). Estimating tree height is common in forestry, and a study by Birdal et al. (2017) uses imagery from an UAV to estimate tree height. This study took place in the Urban Forest of Eskisehir City, Turkey, and it contained two species of coniferous trees. The two species were black and scots pine, and they were planted in 1960. The UAV deployed was a lightweight platform, an eBee, and it was equipped with a consumer-grade camera. The UAV was programmed to obtain a high amount of overlap between each image during the flight; approximately 80% forward overlap and 70% side overlap. Within the Urban Forest, 53 trees were measured with a laser distance metre (± 1 mm) and each tree was georeferenced. Average tree height ranged between 1.20-7.10 m, and trees were identified as immature. Also, some areas within the Urban Forest were dense because the trees were growing too close together.

In total, 133 aerial images were obtained by the UAV, and used to generate point clouds, ortho-images and a digital surface model (DSM). The image processing software used was Terra 3D, powered by Pix4D (2014). Using the point cloud, a canopy height model was created to obtain above ground level heights of the trees. Since some areas within the Urban Forest were dense, the high amount of overlap helped to create a denser point cloud thereby increasing the amount of points in the point cloud over these areas. This increased the accuracy, although some points would be still be unable to reach the ground beneath the foliage. Nevertheless, tree heights were measured by using the highest peak in each point overtop of each tree. Measurements were validated by comparing the estimated and measured tree heights. The root-mean-square-error (RSME) was 28 cm, and this was acceptable for this study. The eBee equipped with the consumer-grade camera was able to obtain individual tree heights in the Urban Forest, and one recommendation from this study is for future work to focus on different species of trees and forest types that vary in density.

In a privately-owned, open canopy mixed conifer forest, in Jackson City, Wyoming, a study by Mohan et al. (2017) assessed individual tree detection from an UAV to derive a canopy height model (CHM). The UAV was a DJI Phantom 3 quadcopter equipped with an RGB digital camera. This UAV flew at an altitude of 115.29 m over a 32 ha forest comprised of Lodgepole pine (*Pinus contorta*), Engelmann spruce (*Picea engelmannii*), Subalpine fir (*Abies lasiocarpa*), and Douglas fir (*Pseudotsuga menziesii*). In total, 383 images were obtained by the UAV and used to generate a point cloud and CHM using the Agisoft PhotoScan Professional v1.0.0 software. This software program is used for image processing, and the reconstruction of 3D models by using SfM algorithms.

Individual tree detection was assessed by using a local maximum (LM) algorithm based on Light Detection and Ranging data processing for the CHM. By using this LM algorithm, other functions such as the FindTreesCHM can be used to enhance individual tree detection with automation. Individual tree detection was validated by conducting independent visual inspections using the images processed in Agisoft PhotoScan Professional v1.0.0 software. Results from this study revealed the UAV-SfM derived CHM combined with LM algorithm is effective for individual tree detection in open canopy mixed conifer forests. However, the LM algorithm only detected 81.4% of the trees in comparison to the independent visual inspections of which 93.2% of the trees were detected. Mohan et al. (2017) described this study as "a pioneering study for automatic individual tree detection" and suggested further research should focus on the processing parameters including filter sizes and conditions, and tree detection algorithms.

These two studies described above used an UAV to conduct a data collection for forest mensuration. Successful results were achieved from both studies, and Birdal et al. (2017) and Mohan et al. (2017) recommended UAV technology for forest mensuration. Recommendations for future research was also provided by both, and it differentiated in many ways because these two studies were very different. Finding two studies with the same objective and methodologies is very difficult thus far because, remote technologies and their uses for forest mensuration are still at an experimental stage (Tang and Shao 2015).

Panagiotidis et al. (2016) and Ye Seul et al. (2015) both used an UAV for assessing tree heights. Panagiotidis et al. (2016) used a DJI S800 equipped with a Sony NEX-5 R digital camera while Ye Seul et al. (2015) used a Phantom-3 Professional, Djibouti, equipped with a low cost camera (model not included in the study). One study took place in two research plots in Czech Republic and the tree species assessed were Norway spruce (*Picea abies*), European larch (*Larix decidua*), Scots pine (*Pinus Sylvestris*), and Silver birch (*Betula pendula*). In the other study, two test areas were established surrounding Sang-Huh Memorial Library at Konkuk University in Seoul, South Korea, and the trees assessed were Norway spruce (*Picea abies*) and Dawn Redwood (*Metasequoia glyptostroboides*). Panagiotidis et al. (2016) used the Agisoft PhotoScan software for image processing and ArcGIS for the calculation of tree heights while Ye Seul et al. (2015) used Pix4D software for the image processing and segmentation, and ESRI ArcGIS for assessing tree heights. Results from Panagiotidis et al. (2016) revealed mean tree height was 1.55 m in research plot one and -2.35 m in research plot two. Results from Ye Suel (2015) revealed mean tree height was 0.53 m in the one test area, and 2.07 m in the second test area. Both studies deemed their results as being close to the field measurements, which were used to validate the data collected by the UAV. Overall, measuring tree heights using images obtained by an UAV is possible, and further research should focus on the processing parameters including filter sizes, conditions, and segmentation (Mohan et al. 2017; Panagiotidis et al. 2016; Ye Suel 2015).

METHODS AND MATERIALS

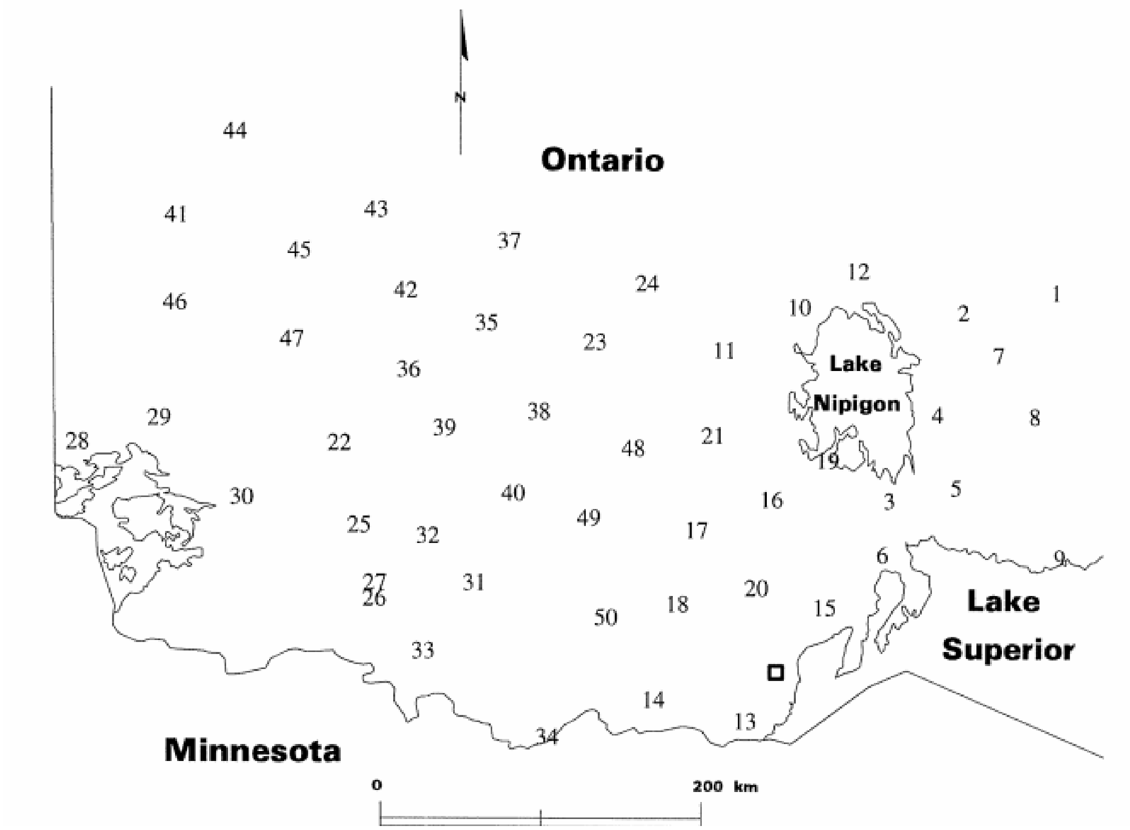
SITE DESCRIPTION

This independent study took place in a jack pine provenance trial located in the 25th Sideroad Tree Farm in Thunder Bay, Ontario. The provenance trial was established in 1994 by Dr. William Parker, a former Forest Genetics Professor at Lakehead University. Displayed below in Figure 1 is an aerial photograph of the jack pine provenance trial, and the yellow border defines the specific location of the study area.

(Google 2019)

Figure 1: The location of the study area in the 25th Sideroad Tree Farm.

The provenance trial is comprised of three separate blocks. Each block contains 50 different seed sources that were sourced from natural forest stands from across northwestern Ontario. Ten trees of each seed source were planted in each block and spaced 2 m apart; a total of 500 trees within each block. Displayed below in Figure 2 is a map of the jack pine seed sources from across northwestern Ontario (Parker 1994).



(Parker 1994)

Figure 2: A map of the jack pine seed sources from across northwestern Ontario.

FIELD MEASUREMENTS

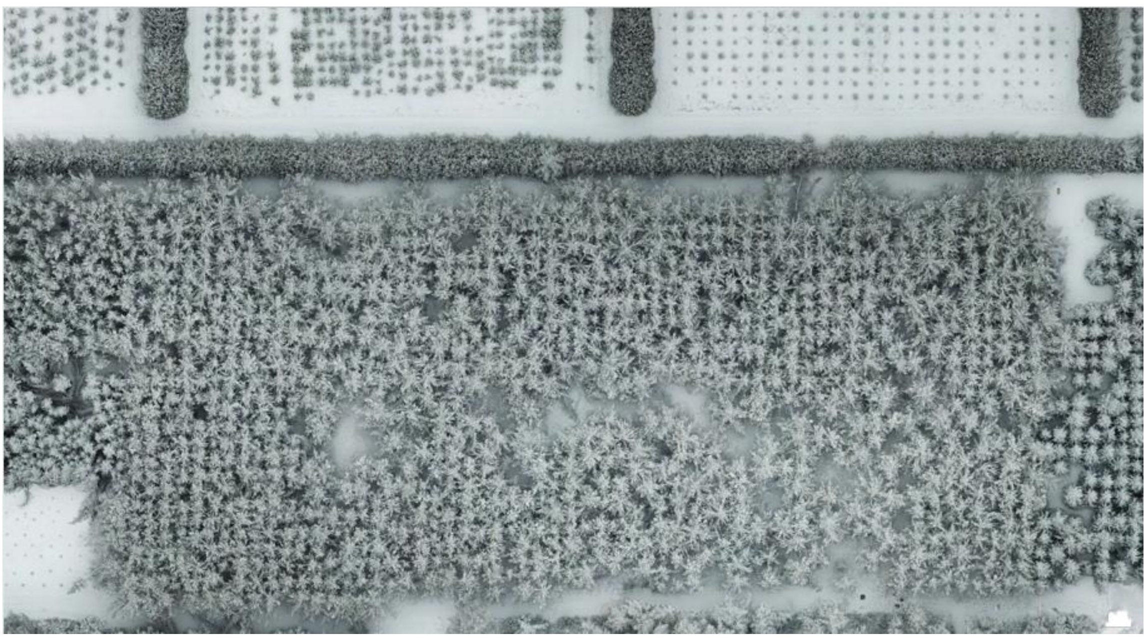
Field measurements were conducted early November 2018. The heights of 256 jack pine were manually measured using an electronic hypsometer, the Haglöf Vertex IV. This electronic hypsometer uses ultrasound technology to measure distances and heights. It is paired with a transponder T3 which is used for communication between these two instruments. The transponder T3 was positioned on each tree at 1.3 m and measured from a distance of 10 m away.

In late November 2018, an UAV, the DJI Mavic Pro 1, was flown over the jack pine provenance trial using a preprogrammed track of the study area (Figure 1). This UAV flew at an altitude of 52.2 m and it covered an area of 22700-metres-squared. The camera model was a FC220 (4.73 mm), with a resolution of 4000 x 3000, a focal length of 4.73 mm, and pixel size 1.57 x 1.57 µm. The ground resolution was 1.62 cm per pixel, and a total of 134 images were obtained in approximately eight minutes.

IMAGE PROCESSING

Postflight, the SD card stored inside the UAV was extracted, and the images saved on the card were downloaded onto a computer. The images were saved into a separate folder, and then uploaded and processed in Agisoft PhotoScan, a cloud-processing engine. Processing parameters in Agisoft PhotoScan were adjusted to achieve a low altitude error (cm) score. Both the alignment and reconstruction parameters were set to medium accuracies and depth filtering was disabled. The surface type was set to height field, source data was dense under the reconstruction parameters, mapping mode was set to adaptive mosaic, and blending mode was mosaic under the texturing parameters. All other processing parameters remained as the default setting in Agisoft PhotoScan.

A LAS dataset, digital elevation model (DEM) dataset and JPEG file was exported from Agisoft PhotoScan and imported into ArcMap, an application used to display geographic information system datasets. The LAS dataset contained a point cloud with coordinates (longitudinal, latitudinal and altitudinal) from the flight with the UAV. The DEM dataset was used to derive the longitudinal, latitudinal and altitudinal coordinates within the image, and the JPEG file was used as a photo reference of the jack pine provenance trial. Displayed below in Figure 3 is an image of the jack pine provenance trial, which was developed in Agisoft PhotoScan by using the images obtained by the UAV.

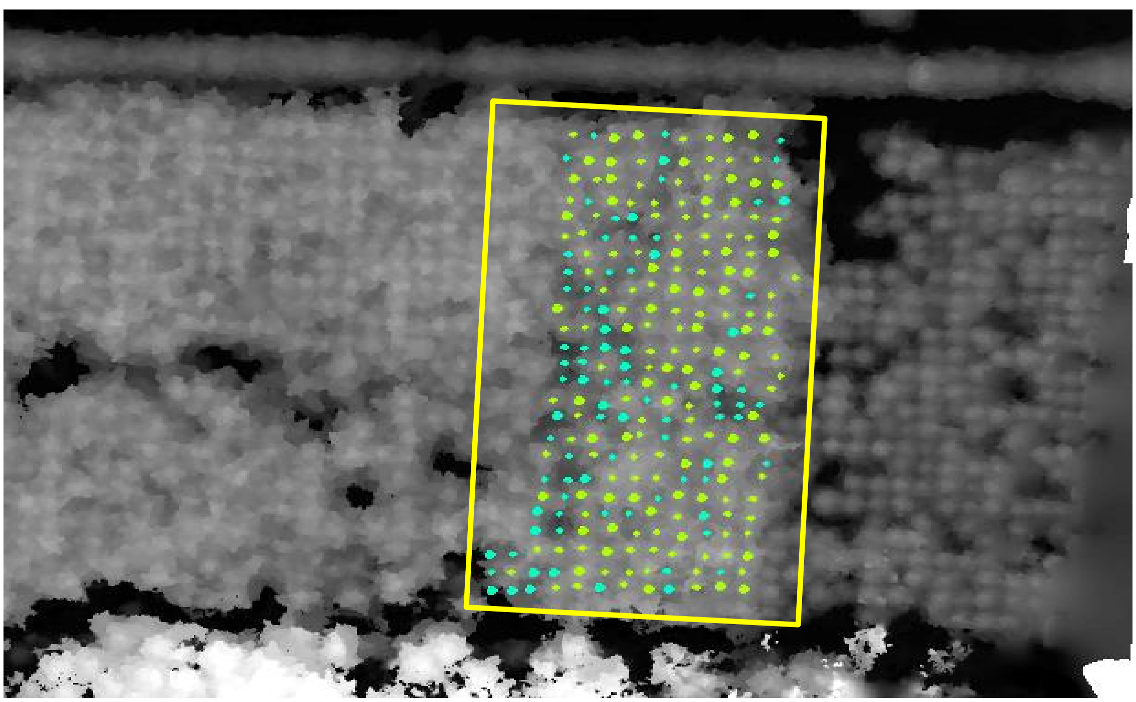


(Jackson 2019)

Figure 3: An image of the jack pine provenance trial after being processed in Agisoft PhotoScan.

Following the importation of the files into ArcMap, the next task involved identifying each individual jack pine within the study area. Then, it was to differentiate the present and absent jack pine. During this step, two different coloured polygons were used to differentiate the jack pine that were present and absent. A polygon was positioned overtop the jack pine near the central leader. For consistency purposes, each polygon was 0.025 m in size. A light green polygon was representative of a jack pine that was present, and a light blue polygon was representative of a jack pine that was absent.

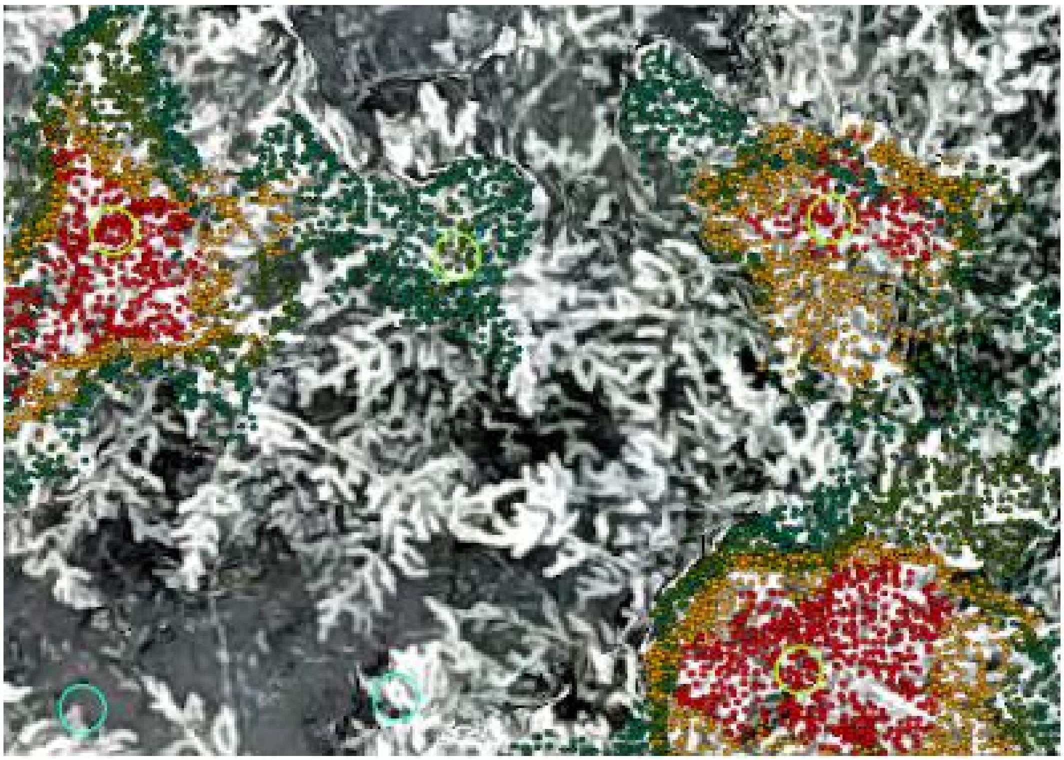
Employing this method was helpful for identifying the present and absent jack pine, and positioning the polygons overtop the jack pine near the central leader would help derive tree height. Presumably, the central leader would be the highest height and with the datasets, this information could be extracted using the point cloud with the longitudinal, latitudinal and altitudinal coordinate data. This was an important task, and it ensured the total number of jack pine could be accounted for within the image. Displayed below in Figure 4 is an image of what the study area looked like following the positioning of the 256 polygons overtop the central leader of each jack pine within the study area.



(Jackson 2019)

Figure 4: Polygons defining the central leaders overtop the jack pine within the study area.

After that, a LAS dataset layer feature was created in ArcMap. This layer feature projected the longitudinal, latitudinal and altitudinal coordinates within the point cloud into different elevation classes. This made identifying elevations in the imagery easier as different colours represented different elevations. An example of this is displayed below in Figure 5.



(ArcMap 2019)

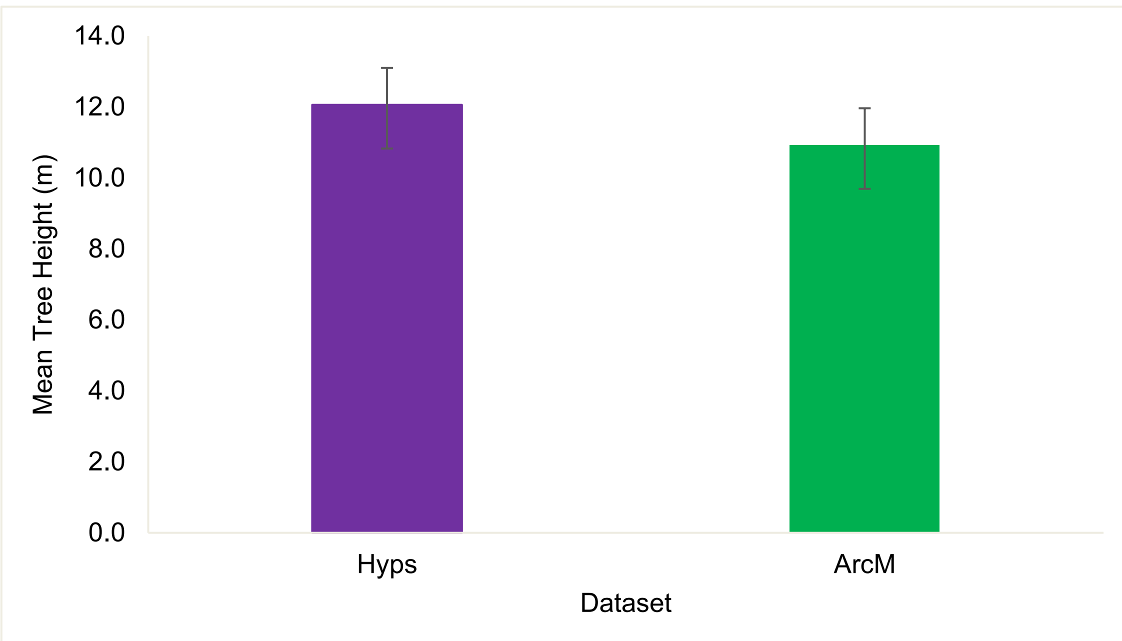
Figure 5: Different colours displaying elevation heights in the imagery.

Tree height was estimated by using the inquiry tool in ArcMap to project the elevation within the DEM dataset. Ten random points (within the point cloud) were selected within the polygon overtop the jack pine. Then the ten points were totaled together and divided by the total number of points to derive an average elevation overtop the jack pine. This method was employed for the rest of the jack pine within the study area.

Following the previous method, the heights for the jack pine could be estimated by subtracting ground elevation from the elevation overtop the jack pine. Ground elevation was obtained from an Ontario DEM, downloaded from Land Information Ontario (LIO) (2019). An average ground elevation was estimated by employing the same method that was previously used to estimate elevation overtop the jack pine. As mentioned, by subtracting the ground elevation from the elevation overtop the jack pine, tree height could be identified.

RESULTS

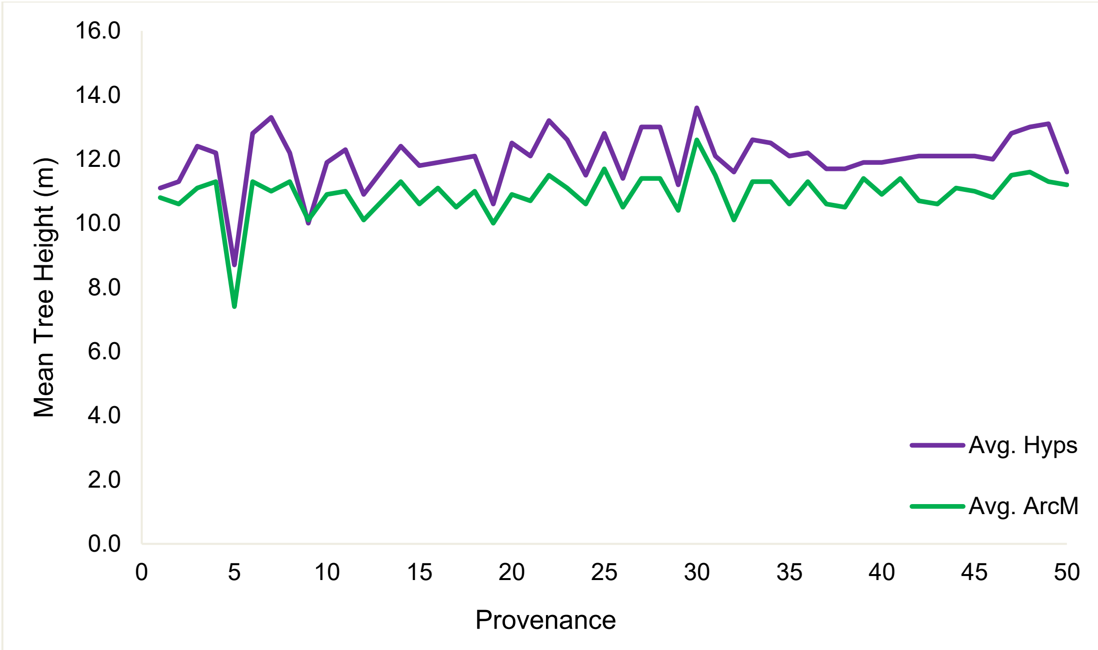
The mean difference between the two datasets was 1.1 m and the standard deviation was 0.8 m. The measurements obtained using the Haglöf Vertex IV display a greater mean height difference in comparison to the measurements obtained using ArcMap. Mean tree height for the jack pine using the Haglöf Vertex IV was 12.1 m and 10.9 m using ArcMap. Displayed below in Figure 6 are these results, displaying the differences between the two datasets.



(Excel 2019)

Figure 6: Mean tree heights between the two datasets.

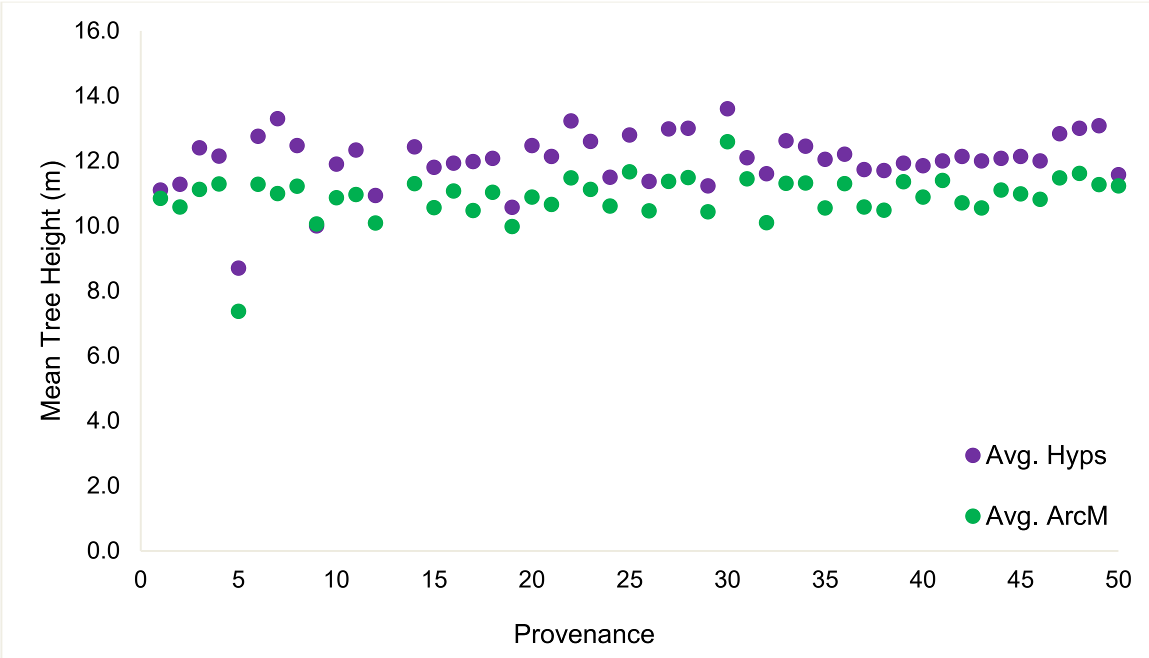
Mean tree height for each provenance was also compared and is displayed below in Figure 7. These results display a trend between the two datasets as they both follow a similar pattern once displayed on a line graph. Additionally, provenance number thirteen was removed from the analysis as only one jack pine from this provenance was recorded during the data collection, and it was recorded as absent from the study area.



(Excel 2019)

Figure 7: Mean tree height per provenance.

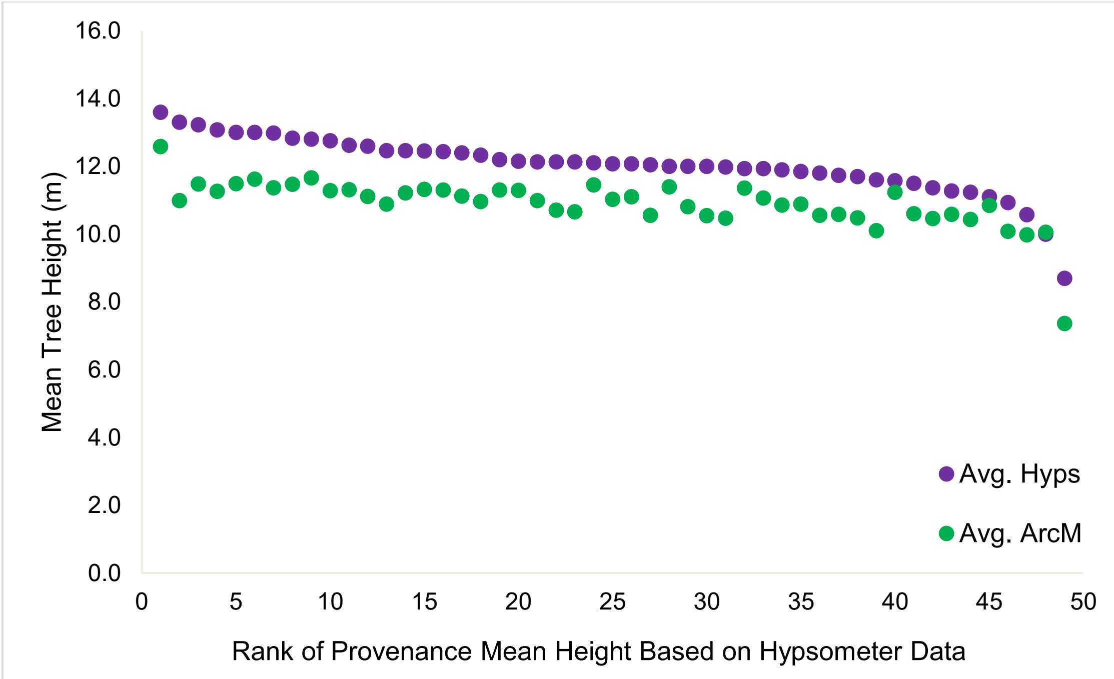
Using the Pearson Product-Moment Correlation Coefficient, a correlation of 0.9 was calculated. A correlation between both datasets indicates a positive association, and this is displayed below in Figure 8.



(Excel 2019)

Figure 8: Mean tree heights per provenance for the two measurement methods.

Provenance mean height based on the Haglöf Vertex IV data was ranked from highest to lowest mean and compared to the results from ArcMap. This comparison revealed that the two datasets no longer correlated, and both provenances mean tree height is different. Displayed below in Figure 9 and Table 1 are the results of this comparison.



(Excel 2019)

Figure 9: Provenance means ranked highest to lowest based on average hypsometer data.

Table 1: Provenance means ranked highest to lowest using the average hypsometer data and compared to the average ArcMap data.

Provenance	Avg. Hyps.	Avg. ArcM.	Difference
30	13.6	12.6	1.0
7	13.3	11.0	2.3
22	13.2	11.5	1.7
49	13.1	11.3	1.8
28	13.0	11.5	1.5
48	13.0	11.6	1.4
27	13.0	11.4	1.6
47	12.8	11.5	1.4
25	12.8	11.7	1.1
6	12.8	11.3	1.5
33	12.6	11.3	1.3
23	12.6	11.1	1.5
20	12.5	10.9	1.6
8	12.5	11.2	1.3
34	12.5	11.3	1.1
14	12.4	11.3	1.1
3	12.4	11.1	1.3
11	12.3	11.0	1.4
36	12.2	11.3	0.9
4	12.2	11.3	0.9
45	12.1	11.0	1.1
42	12.1	10.7	1.4
21	12.1	10.7	1.5
31	12.1	11.5	0.6
18	12.1	11.0	1.1
44	12.1	11.1	1.0
35	12.1	10.6	1.5
41	12.0	11.4	0.6
46	12.0	10.8	1.2
43	12.0	10.5	1.5
17	12.0	10.5	1.5
39	11.9	11.4	0.6
16	11.9	11.1	0.9
10	11.9	10.9	1.0
40	11.9	10.9	1.0
15	11.8	10.6	1.2
37	11.7	10.6	1.2
38	11.7	10.5	1.2
32	11.6	10.1	1.5
50	11.6	11.2	0.3
24	11.5	10.6	0.9
26	11.4	10.5	0.9
2	11.3	10.6	0.7
29	11.2	10.4	0.8
1	11.1	10.8	0.3
12	10.9	10.1	0.8
19	10.6	10.0	0.6
9	10.0	10.1	-0.1
5	8.7	7.4	1.3

(Excel 2019)

Within the study area, the number of trees absent from the stand was 86 or 34% of the jack pine. This was calculated using the field measurement data.

DISCUSSION

This independent study was an assessment of the utility of UAVs for measuring tree heights in provenance trials. Although the datasets revealed different results, the UAV was capable of measuring the heights of the jack pine. With a mean difference of 1.1 m and a standard deviation of 0.8 m, these results are acceptable, and they are similar to the results of other studies that also involve the use of an UAV for forest mensuration (Birdal et al. 2017; Mohan et al. 2017; Panagiotidis et al. 2016; Ye Seul et al. 2015). However, to compare this independent study to other studies is difficult because every UAV study is unique.

Many studies are assessing the use of an UAV for forest mensuration because manual measurements are time-consuming, labour-intensive, and expensive (Anthony et al. 2014; Birdal et al. 2017; Panagiotidis et al. 2016; Torres-Sánchez et al. 2015). They are also subjective and prone to human-error (Araus et al. 2018), therefore, if an UAV can collect the same data and produce accurate results then UAVs will be used more frequently for forest mensuration (Anthony et al. 2014; Bolton et al. 2018; Birdal et al. 2017; Strigul et al. 2015; Tang and Shao 2015; Malambo et al. 2018; Mikita et al. 2016; Panagiotidis et al. 2016). Currently, the use of UAVs are still at an experimental stage, and there is not enough comparative research that has been conducted to determine the appropriate remote sensing technologies to employ for forest mensuration (Tang and Shao 2015).

What is useful from studies that involve the use of an UAV for forest mensuration are the recommendations. For example, the study by Birdal et al.

(2017) involved the use an UAV to estimate tree heights for two coniferous species within an Urban Forest. Birdal et al. (2017) provided some insight into some of the problems that could occur if an UAV is used in a dense forest area. Something that was suggested was to increase the number of overlap images which would increase the number of points collected for the point cloud. Increasing the number of points collected would create a denser point cloud and help produce more accurate results.

Unfortunately, density was a factor in obtaining accurate results for this independent study. Most of the jack pine within the study area had very large branches and the branches would overlap. These large-overlapping branches were not easy to discern during the field measurements and they were not considered an issue prior to flying the UAV over the jack pine provenance trial. It was only until the image processing that the density within the study area became an obvious issue with differentiating each jack pine. Additionally, the ground beneath the canopy could not be seen due to the large-overlapping branches, and because of this, a DEM could not be generated. The DEM is essential for deriving tree heights of the jack pine from the UAV imagery, and the DEM from LIO (2019) was used instead, as a reference to the UAV imagery.

Another suggestion for working in a dense forest area is to adjust the flying altitude to fly closer to the object(s) of interest. This has been used for crop breeding programs to assess and estimate crop heights. Anthony et al. (2014) adjusted the flying altitude for the UAV when collecting data on the foliage layers of the crops and to detect ground level. The UAV was flown at a flying altitude of 1-2 m above the crops which reduced atmospheric distortion and enhanced the spatial resolution in the data. Therefore, if this independent study was to be completed again, the flying altitude would be adjusted to fly closer to the jack pine within the study area to collect more data on the foliage layers and to detect ground level like Anthony et al. (2014) did for assessing and estimating crop heights. The number of overlap images would also be adjusted to enhance the number of points collected for the point cloud (Birdal et al. 2017).

Overall, the UAV used for this independent study could collect data like the manual measurements, but the UAV took far less time to collect the data in comparison to the manual measurements. The UAV flew over the study area in eight minutes and collected all the data that was required for the analysis. In comparison, the manual measurements took a few days to measure the 256 jack pine provenances, and it involved labour-intensive and time-consuming work. However, after the field measurements were completed, it took far more time to process the UAV images, and it involved the use of two different software programs to be used. This was a predicament for Mikita et al. (2016) when comparing field measurements to UAV usage because the image processing can be expensive especially for the software and hardware equipment. Although the UAV can collect data faster, it may be the time and cost of the image processing that may hinder this alternative for data collections.

Data collections are important for the development of new information, and for this independent study, the objective was to assess the utility of UAVs for measuring tree heights in provenance trials. UAVs are an alternative to manual measurements but, there are still some glitches with using remote sensing technologies as they are still at an experimental stage (Tang and Shao

2015). Manual measurements have been used for as long as they have been because the data that is collected can be used immediately and it often involves a lot of details which can be very important for unforeseen reasons. In this independent study, if it was not for the manual measurements, the number of absent trees from the stand would not have been quantified because of the density of the jack pine provenance trial. As mentioned above, it was the density within the study area that made it difficult to differentiate each jack pine, and although it was possible, the manual measurements were used as a reference.

Until more studies have assessed the utility of UAVs for measuring tree heights in provenance trials, the consensus of this independent study is that an UAV can measure tree heights in provenance trials. Although the datasets revealed different results, tree heights were still derived, and future research should focus on the recommendations that have been provided.

CONCLUSION

An UAV can be used for forest mensuration. In this independent study, the UAV used was the DJI Mavic Pro 1, and it was capable of collecting data for measuring the heights of 256 jack pine trees in the provenance trial located at the 25th Sideroad Tree Farm in Thunder Bay, Ontario. Despite the differences in mean tree heights for both datasets, the results from this independent study are sufficient for this assessment. It should be noted that these results do not reflect anything more than mean tree height for the jack pine in the provenance trial, and further research is required to assess the provenance trial for its purpose of establishment.

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APPENDICIES

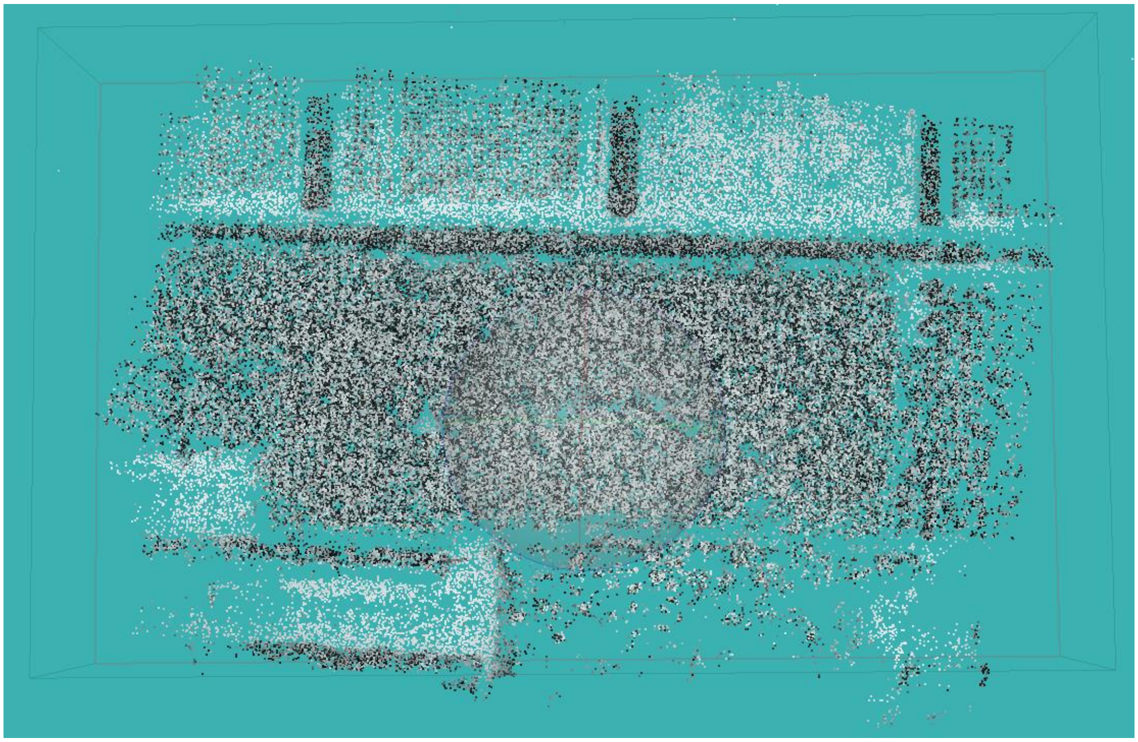
APPENDIX I: AGISOFT PHOTOSCAN IMAGE PROCESSING

AGISOFT PHOTOSCAN IMAGE PROCESSING

The steps involved in the Agisoft PhotoScan image processing are described in detail below. The settings that were chosen to complete my image processing are unique to my study, and I recommend researching more information about Agisoft PhotoScan to enhance the end results.

First, the SD card was extracted from the UAV. Second, the images on the SD card were downloaded and saved onto a computer. Third, the images were saved into a separate folder. Then in Agisoft PhotoScan, under the ‘Workflow’ tab, the ‘Add Folder’ was selected and the folder that contained the images from the flight was chosen. In my thesis, 134 photos were captured using the UAV.

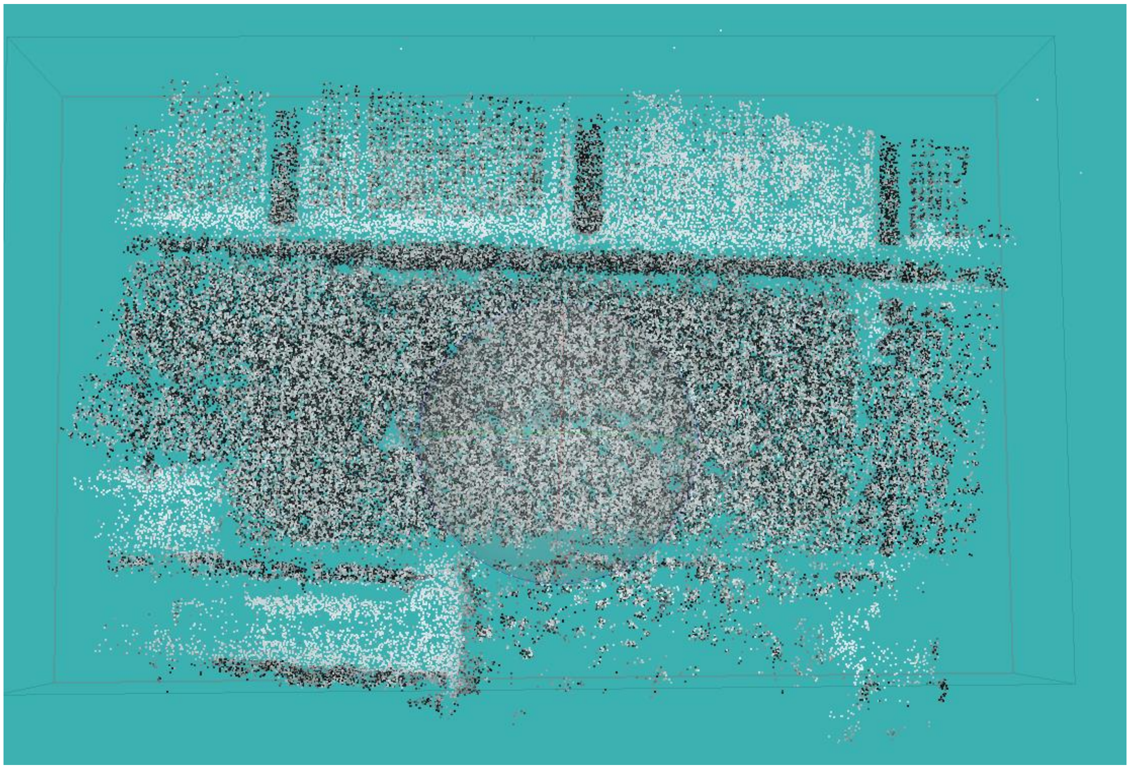
Following this step, still under the ‘Workflow’ tab, another option became available which prompted to ‘Align Photos’. For my image processing, the only option that I altered from the default settings was accuracy, and I selected medium. Displayed below in Figure 12 is the outcome of the ‘Align Photos’ step in Agisoft PhotoScan. This image displays the study area from an aerial perspective, and it features a point cloud that was obtained with the UAV. Each point in the cloud has a specific longitudinal, latitudinal and altitudinal coordinate and a collection of these points represents a three-dimensional (3D) point cloud.



(Agisoft PhotoSCan 2019)

Figure 10: Outcome of the 'Align Photos' process.

Again, under the ‘Workflow’ tab, the ‘Build Dense Cloud’ option was selected, and the quality was set to medium, and depth filtering was set to disabled. This step in image processing creates an image that appears more in depth by increasing the number of points in the cloud. Displayed in Figure 13 is the outcome of the ‘Build Dense Cloud’ option in Agisoft PhotoScan.

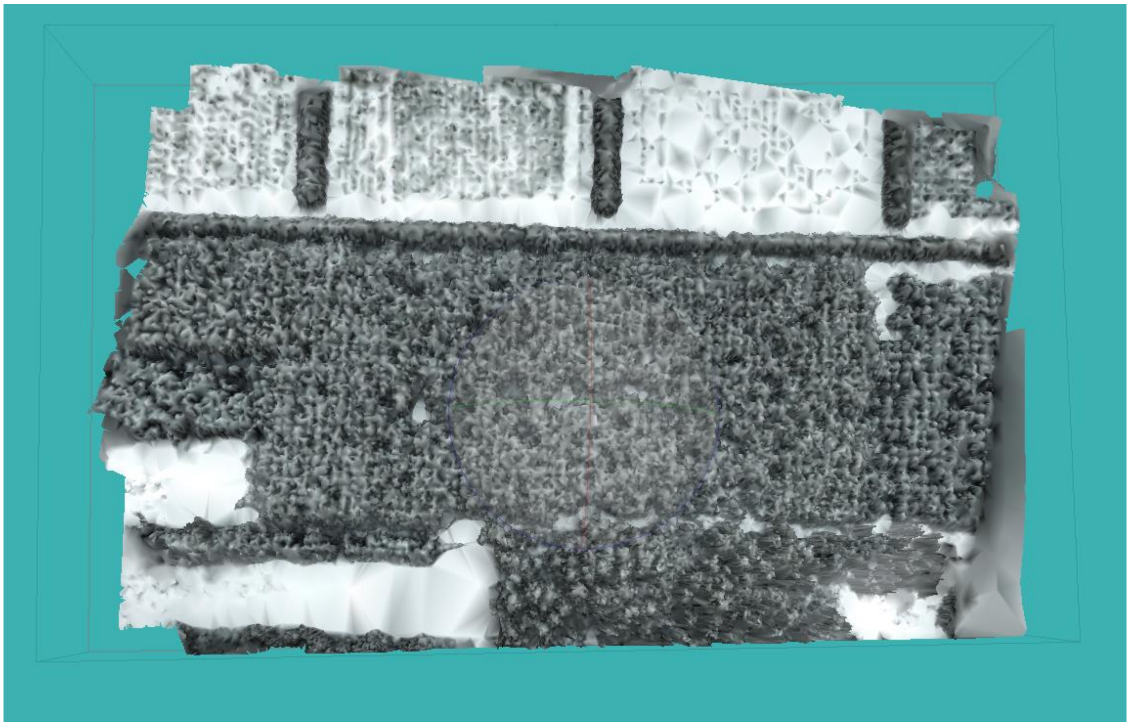


(Agisoft PhotoSCan 2019)

Figure 11: Outcome of the 'Build Dense Cloud' process.

Next in the image processing under the ‘Workflow’ tab is an option to ‘Build Mesh’. Under this option, the surface type selected is height field and the source data is dense cloud. All other options remained as the default settings. The outcome of the ‘Build Mesh’ feature is displayed below in Figure 14. Now the image is beginning to appear more 3D with the depth continuing to increase.

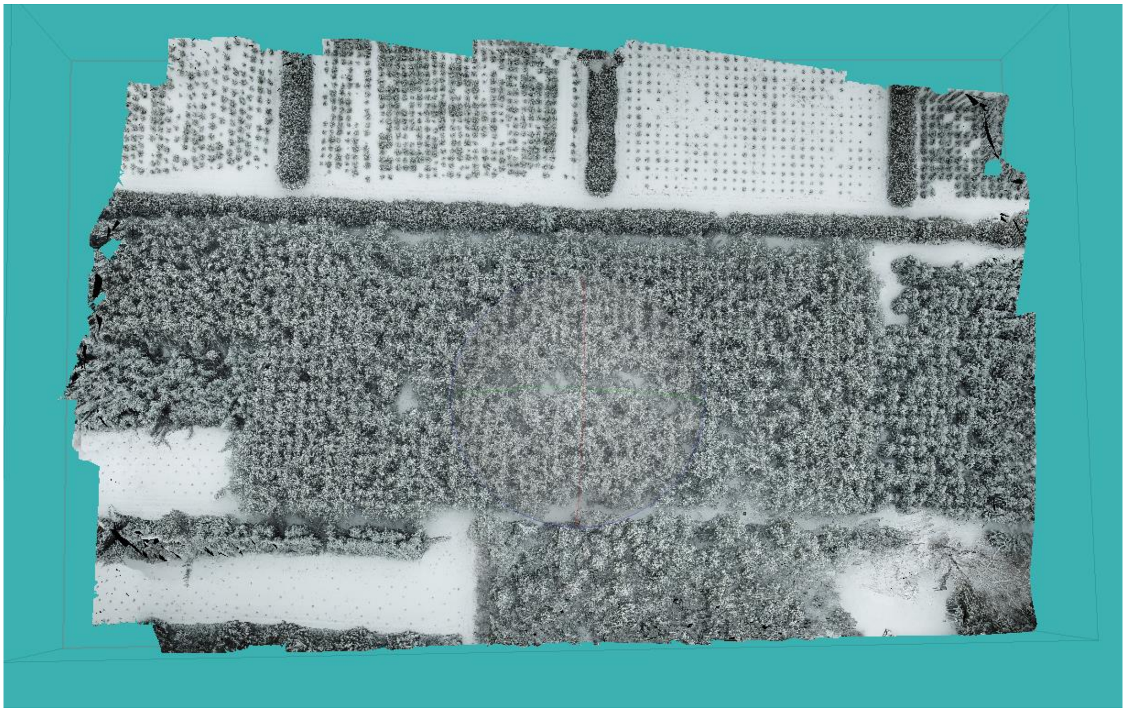
The purpose of this image processing in Agisoft PhotoScan is to create a 3D image using the point clouds recorded by the UAV. An in-depth photo is important for obtaining details about the photo and delineating the individual jack pine trees from my images.



(Agisoft PhotoSCan 2019)

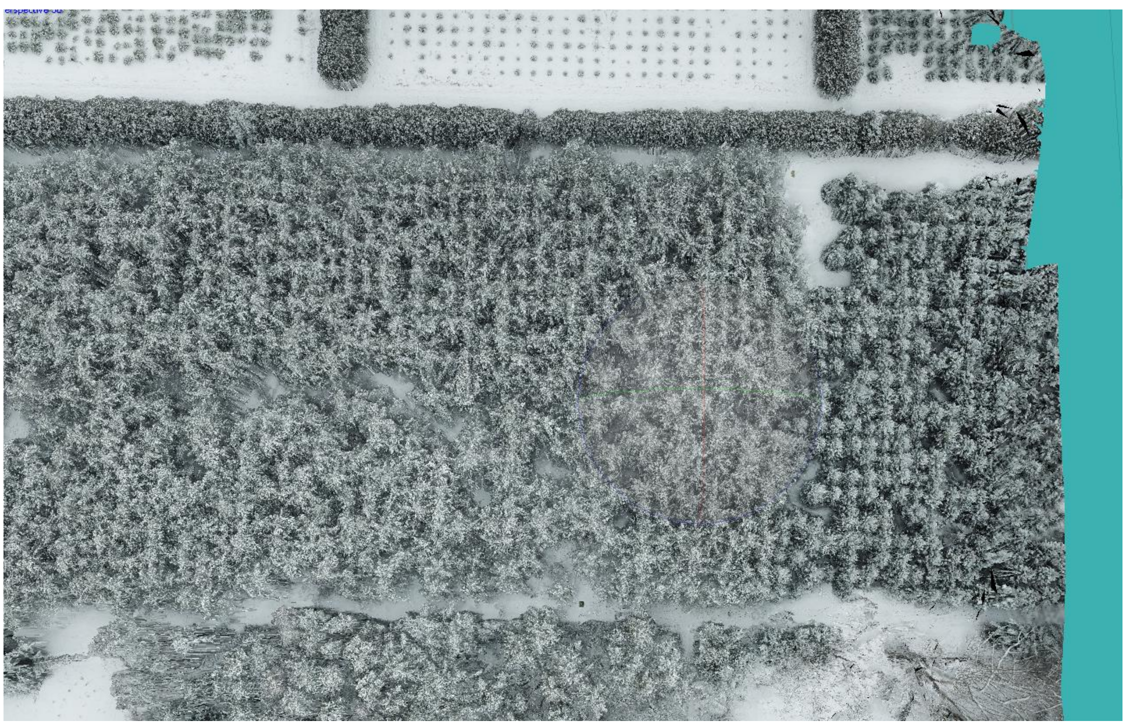
Figure 12: Outcome of the 'Build Mesh' process.

The next step in the image processing is to select ‘Build Texture’ also under the ‘Workflow’ tab. No changes were made as the default settings were used. However, the mapping mode was set to orthophoto and the blending mode was mosaic (default). The outcome of this image processing always results in an image clearer than the last. Now in the image, the jack pine trees are becoming clearer and more defined. Figure 15 is a screenshot of the stand and Figure 16 is a close-up of the study area.



(Agisoft PhotoSCan 2019)

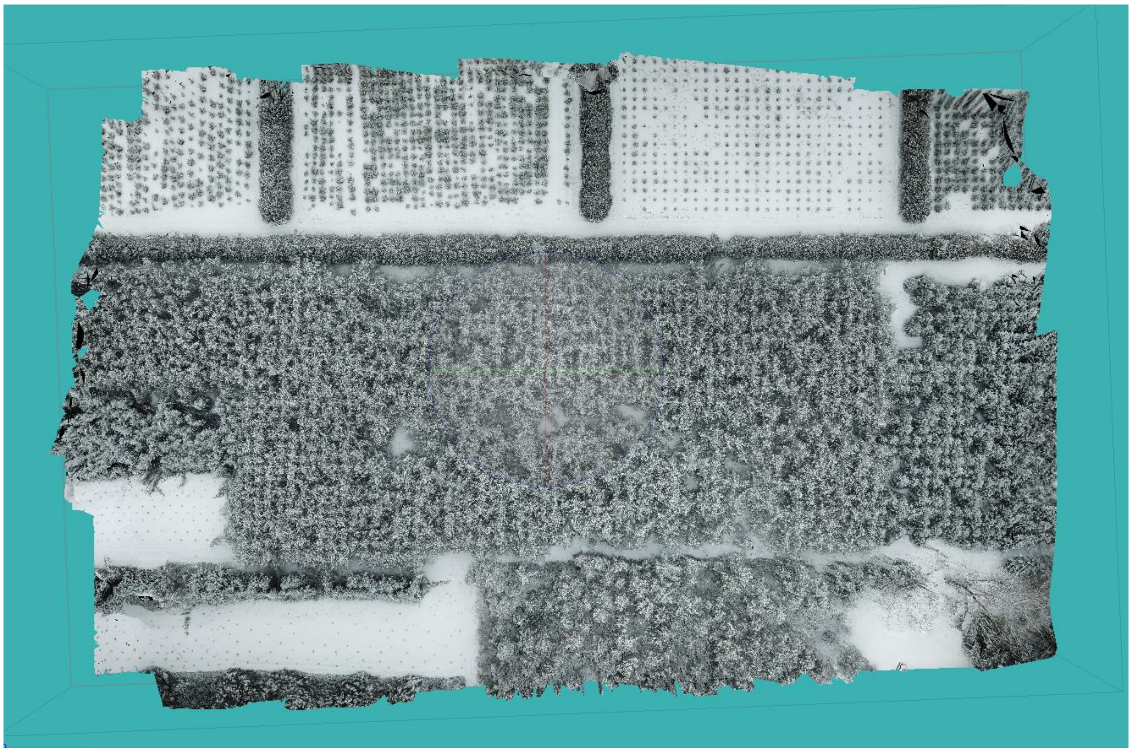
Figure 13: Outcome of the 'Build Texture' process.



(Agisoft PhotoSCan 2019)

Figure 14: Close-up of the image after the ‘Build Texture’ process.

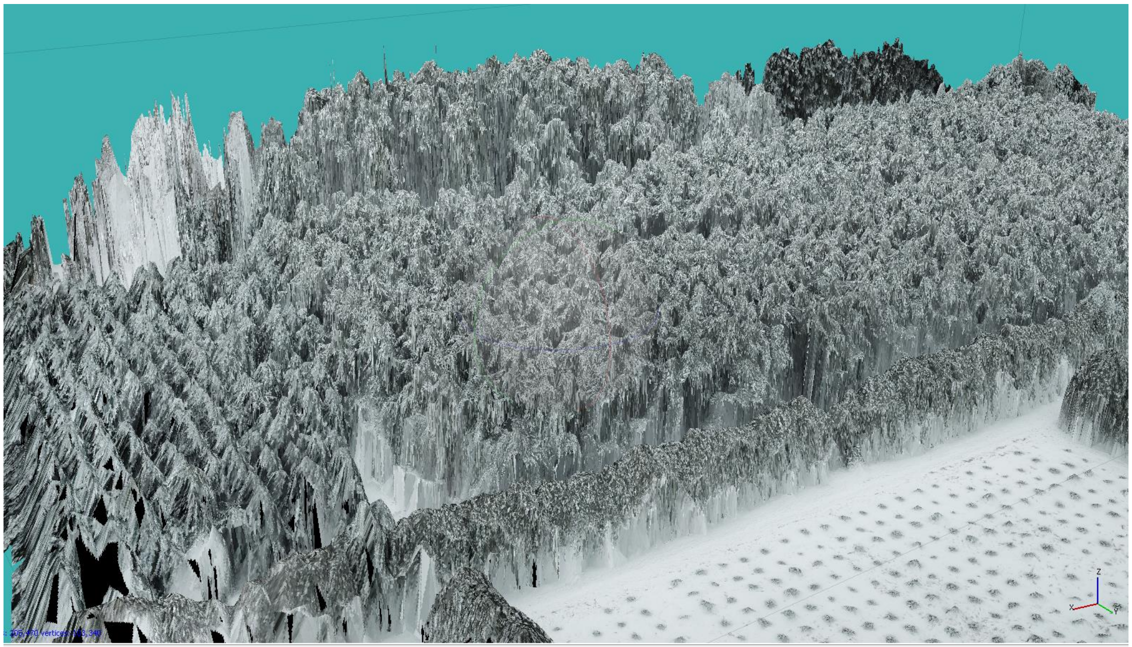
Next was to build a ‘Tiled Model ‘, which was now an option under the ‘Workflow‘ tab. The source data was programmed to dense cloud. The results from this option do not show any significant changes to the image. The image is displayed below in Figure 17.



(Agisoft PhotoSCan 2019)

Figure 15: Outcome of the 'Titled Model' process.

The final step in the image processing in Agisoft PhotoScan is to build a ‘DEM‘. DEM stands for digital elevation model and this option will depict the longitudinal, latitudinal and altitudinal coordinates recorded by the UAV. All the parameters in this option remained as the default settings. The final image in the image processing is displayed below in Figure 18. This figure displays the stand from a lower perspective rather than an aerial view of the study area. Now the trees are more noticeable and defined. This image was exported as a DEM and saved as a TIFF file. The DEM file contains longitudinal, latitudinal and altitudinal coordinates from the UAV, and this is used to determine the heights of the jack pine.



(Agisoft PhotoSCan 2019)

Figure 16: The final processed image of the jack pine provenance trial.