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# Using Unmanned Aerial Systems for Deriving Forest Stand Characteristics in Mixed Hardwoods of West Virginia

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## Abstract

Forest inventory information is a principle driver for forest management decisions. Information gathered through these inventories provides a summary of the condition of forested stands. The method by which remote sensing aids land managers is changing rapidly. Imagery produced from unmanned aerial systems (UAS) offer high temporal and spatial resolutions to small-scale forest management. UAS imagery is less expensive and easier to coordinate to meet project needs compared to traditional manned aerial imagery. This study focused on producing an efficient and approachable work flow for producing forest stand board volume estimates from UAS imagery in mixed hardwood stands of West Virginia. A supplementary aim of this project was to evaluate which season was best to collect imagery for forest inventory. True color imagery was collected with a DJI Phantom 3 Professional UAS and was processed in Agisoft Photoscan Professional. Automated tree crown segmentation was performed with Trimble eCognition Developer's multi-resolution segmentation function with manual optimization of parameters through an iterative process. Individual tree volume metrics were derived from field data relationships and volume estimates were processed in EZ CRUZ forest inventory software. The software, at best, correctly segmented 43% of the individual tree crowns. No correlation between season of imagery acquisition and quality of segmentation was shown. Volume and other stand characteristics were not accurately estimated and were faulted by poor segmentation. However, the imagery was able to capture gaps consistently and provide a visualization of forest health. Difficulties, successes and time required for these procedures were thoroughly noted.

**Keywords:** UAS, drones, forest inventory, forest stand management, automated tree crown segmentation

## Introduction

Forest inventory has often used aerial imagery as a compliment for the creation of stand level maps. These maps are often used in management to better understand stand layout and the spatial distribution of trees and landscape features from an aerial perspective. These maps are the backdrop for much of the geospatial analysis for these stands. Manned aerial vehicles are the most common method by which aerial imagery is collected in forestry though the manned flights can be expensive and cumbersome to coordinate. There are a number of reasons why UASs are desirable to forest managers and researchers. The primary advantages of utilizing UASs in assisting forest inventory

are the high spatial and temporal resolutions, low cost and ease of customization to project needs (Puliti et al., 2015). These advantages have the potential of cutting costs and time necessary for inventory as well as increasing accuracy.

This study provides a comprehensive evaluation of performing an automated forest inventory with an unmanned aerial system with a primary focus on the photogrammetric analysis of the imagery. The development of an applicable work flow and evaluation of the accuracy of the forest inventory metrics compared to field data were the primary aims of this study. Forest volume estimates are a primary driver of forest value in the central Appalachian Region and are a major concern of management in this location.

Forest inventories provide detailed information of a forest stand. These inventories measure the extent, quantity, and condition of trees within an area (Kangas et al., 2006). This information is utilized by forest managers and researchers to make management decisions on these lands. Ground work has been the primary way to implement these inventories due to the complexities of these ecosystems. Forests vary greatly not only by the species present but by topography, complex vertical structures of tree crowns and many more. The use of aerial imagery and other remote sensing techniques allows a different and supplementary glimpse into these highly variable forests. UAS use in forestry is still young and there are limited research articles published in this field (Puliti, et al., 2015). . Although it is difficult to compare prices directly due to the variation in markets and needs of projects, it is well cited in literature, that this method is cheaper than the conventional methods (Getzin et al., 2012; Wallace et al., 2012a; Puliti et al., 2015; Hernandez et al., 2016).

Generally, the use of a broad spectrum of photogrammetric analyses are the primary way drone imagery is utilized. With drone imagery, the resolution is often too fine to perform accurate remote rectification due to the coarseness of historic map scales, so manual installation of ground control points is necessary (Lillesand et al., 2014).

Alternatively, directly georeferencing UAS derived imagery without the use of intensive ground control points is possible. In Turner et al. (2014), data were collected by UAS with a simple navigation-grade GPS unit onboard for spatial referencing. The capture of each image was triggered by an automatic trigger and the onboard GPS unit assigned a spatial position to each image. This study was performed in a lettuce field in Australia and produced spatially accurate mosaics with an error of about 10.9 cm. The use of an inertial measurement unit (IMU), devices capable of measuring an object's force and rate of movement, shows promise in direct georeferencing in forest settings with an average RMSE of 25.9 cm (Wallace et al., 2012b). Emerging science has been shown that real-time kinematic (RTK) precise point position (PPP) systems can perform aerial triangulation of ground features to sub-centimeter accuracy for horizontal measurements and centimeter accuracy in vertical measurements (Shi et al., 2016).

Drone flights are performed with flight line overlap of around 80 percent to ensure sufficient coverage of the ground (Haala, 2013). UAS low flight altitude produces a much higher sensitivity to motion and can cause variability in single flight paths that is greater than that of the conventional method. The greater overlap is intended to reduce these errors. There are many different models of drones used in these applications but often the multi-copter varieties are used in small acreage applications which is typical for forestry applications (Puliti et al., 2015). The multirotor UAVs have slower flight speeds, but usually allow for more control over flight line overlap (Puliti et al,

2015). Fixed-wing drones have been used for large areas but these vehicles are far more expensive (Lisein et al., 2015).

For photogrammetric analysis, consumer grade, true-color digital cameras are the most common attachment on UAS. However, a wide array of sensor attachments are available. Multispectral sensors and thermal imaging sensors have been attached to UAS to gather information on vegetation (Berni et al., 2009).

The automation of flight paths is one of the principle luxuries with the utilization of UAS. Although a pilot is necessary to control the drone in some cases and respond to problems, much of the process is controlled by software once a flight path is programmed. This autonomous feature of drone flight paths and data collection makes UAS great for multi-temporal datasets due to the ability to capture the same area with great detail as many times as is necessary.

The preferred software package throughout UAS imagery literature is Agisoft Photoscan Professional (Agisoft LLC, St. Petersburg, Russia) image processing software. Photoscan has been compared to other software packages in performing georeferencing, mosaicking and orthorectification such as Pix4D (Pix4D, Lausanne, Switzerland) a cloud-based web imaging processing service. Photoscan produces very accurate results and has superior ability to accurately and efficiently process UAS captured imagery (Turner et al., 2014).

Structure from motion (SfM) models are created from UAV imagery via traditional photogrammetric methods. These images, when viewed stereoscopically, have the same point appear in multiple images. In the case of UAV imagery with 80% overlap, these points can occur in a great number of images which allows for a more accurate model of common points in 3-D space (Wallace et al., 2016). These SfM models can be a great asset in further image analysis, allowing users to manipulate the data much like they would LiDAR data. The difficulty then lies with segmenting out individual tree crowns from the imagery or point clouds to assign specific heights to the individual tree crowns. The tried-and-true method of performing segmentation is by heads-up digitizing individual tree crowns from the imagery and producing polygons across the area of interest. With the high resolution of UAS derived imagery, this can be done but would be time consuming. A number of methods have been developed using the point cloud, either SfM or LiDAR, for tree-scale segmentation. With point cloud returns, the user can visualize the structure of each individual tree and then segment these trees. A common method to segment crowns is to utilize a local maxima point from the point cloud canopy height model throughout the study area (Brandtberg et al., 2003; Tiede et al., 2005; Kwak et al., 2007; Jing et al., 2012; Zawawi et al., 2015).

Object-based image analysis (OBIA) is another technique used to improve the automation of the segmentation using imagery instead of using point clouds alone. This approach creates spectrally homogenous regions called objects and is very effective when applied to images with high spatial resolution (Husson et al., 2016). Segmentation using winter leaf-off images have been shown to produce the greatest contrast between ground and tree canopies when using a software package eCognition (Trimble Geospatial, Munich, Germany) (Kuzmin et al., 2017). Automated segmentation has been studied in umbrella pine (*Pinus pinea*) plantations in Portugal using eCognition software (Hernandez et al., 2016). The eCognition feature extraction software is becoming frequently cited as a method to automate the segmentation portion of photogrammetric analysis. The software allows for full automation or for

partial automation where the user has control over certain segmentation parameters. Remondino et al. (2014) showed the quality and time necessary for processing imagery can be affected by quality of images, noise in the imagery, low radiometric quality, shadows as well as shiny or textureless objects in both aerial imagery applications and 3-D building models. These differences can affect the quality of the point cloud generated or the feature extraction process entirely (Remondino et al., 2014).

The two required metrics to estimate tree volume is a diameter at breast height (DBH) and a merchantable height. After the height and species data are collected for each of the segmented tree crowns, crown area can be calculated once these files have been converted to ESRI shapefiles. Tree crown areas and their relationship to tree stem diameter are a historically well studied allometric relationship in the field of forestry (Lockhart et al., 2005). These relationships are summarized for a number of species in Europe by Hemery et al. (2005). Crown radius and DBH relationships have been shown to be highly correlated for southern bottomland species such as *Carya illinoensis* ( $r^2=0.87$ ) and *Quercus texana* ( $r^2=0.84$ ) in Lockhart et al. (2005). For species in the Appalachian region of Tennessee, Gering and May (1995) found that yellow-poplar, *Quercus* and *Carya* had highly correlated relationships between crown radius and DBH ( $r^2=0.93$ ,  $0.85$ , and  $0.85$  respectively). Gering and May (1995) also compared relationships of DBH from aerially measured tree crown radii producing an  $r^2$  of  $0.67$  for *Quercus* and *Carya* and  $r^2$  of  $0.85$  for yellow-poplar. These relationships often need to be reassessed for very specific sites and species as the relationship can change based on relationships with surrounding species and growing conditions (Lockhart et al., 2005). Management practices influence the crown shape as well. For example, thinned and unthinned crowns will have different relationships (Medhurst & Beadle, 2001).

Merchantable height of a tree is important for estimating the overall board volume of the trees. The methods by which merchantable height is derived from remotely sensed data is not well defined. There are only a few reports explaining how to derive merchantable height from total height (e.g. Honer, 1964; Ek et al., 1984). Ek et al. (1984) showed a reasonable relationship (mean error difference in height of 2.21 m) between merchantable and total height across species of the Lakes States. Models have been created for specific species like Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) using diameter and total height (Puliti et al., 2015). Like total height, merchantable height is highly correlated with DBH, allowing one to estimate merchantable height values from diameter measurements for various species (Brooks & Wiant, 2006). The development of localized models to predict merchantable height from either total height or DBH appears to be the most appropriate fit at this time.

Past studies have addressed areas of interest that lacked complexity in species, variations in stand vertical structure, stand density and topographic variation. This lack of complexity of study areas is a distinct limitation of past research. The studies that have contributed to the collective knowledge of forest inventory performed by UAS have primarily been performed in areas with only marginally complex forest systems. These systems often lack complexity in species richness, topography, and vertical structure. Many of the studies have been performed in boreal forest conditions (Getzin et al., 2014; Puliti et al., 2015; Kuzmin et al., 2017). Other studies have focused on areas with very few forest tree species (e.g. pine plantations, forests with open canopies and sparse, dry forests) (Liesin et al., 2015; Mikita et al., 2016; Hernandez et al., 2016; Wallace et al., 2016). These study areas with only a few species have greatly differing crown shapes and sizes, often with little crown overlap, allowing for easier data extraction (Michez et al., 2016). It has also been addressed that research efforts have not been focused on deciduous

hardwood cover due to the complexities of the canopy (Ayrey et al., 2017). The interwoven crowns make segmentation and classification difficult in these deciduous hardwood forests (Ayrey et al., 2017).

## Method

### Study Area

This study was conducted on the West Virginia University (WVU) Research Forest, 22 km east of Morgantown, WV, USA. The Research Forest is primarily a continuous forested property of 3,097 ha. This forest is typical of mixed upland hardwoods within the Appalachian Plateau.

Five sites were targeted within the University Forest for their representation in species composition, vertical structure and topography of the forest. Access was also integral in dictating site selection (Figure 1). The average area of the five research sites was 11 ha with a total area sampled of 57 ha. The species composition of these research sites was generally consistent with the composition of the forest as a whole (Figure 2). Yellow-poplar (*Liriodendron tulipifera* L.), various oak species (*Quercus* spp.), and red maple (*Acer rubrum* L.) were the most frequently encountered species.

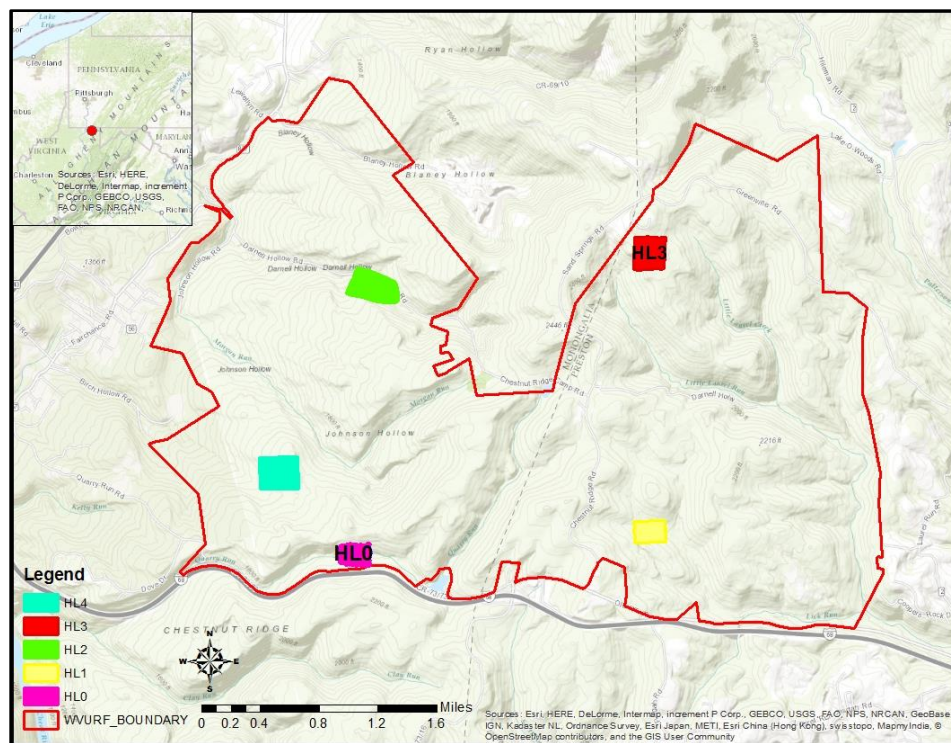


Figure 1. Site map of the WVU research forest. The five research sites are highlighted within the boundary of the forest. The location of the forest within the Mid-Atlantic region is displayed in the above data frame.

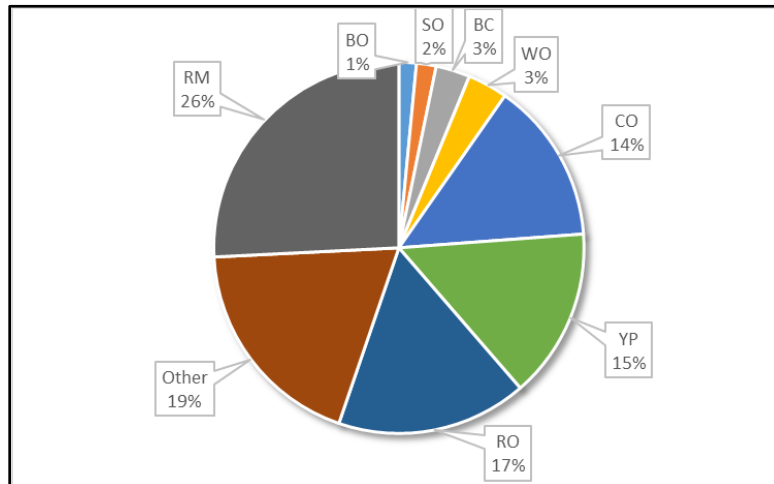


Figure 2. Species distribution by total number of stems greater than 10.16 cm DBH within the five research areas of the WVU research forest. RM= red maple; BO = black oak (*Quercus velutina* Lam.); SO = scarlet oak (*Quercus coccinea* Munchh.); BC = black cherry (*Prunus serotina* Ehrh.); WO = white oak (*Quercus alba* L.); CO = chestnut oak (*Quercus montana* Willd.); YP = yellow-poplar; RO = northern red oak (*Quercus rubra* L.).

Two of the sites were of primary interest. For these, a complete dataset of summer and fall imagery was collected. The HL0 site was about 7.6 ha and was located in the southwest side of the WVU Forest and is transected west to east by the perennial stream Quarry Run with the southern extent of this site being Monongalia County Route 73/73. The elevation of this site ranged from 535 m to 680 m. The southern plots have predominately a north facing aspect and the northern plots have predominately a southern facing aspect. This aspect change is due to the dissection of the site by Quarry Run.

The second site (HL3) was located in the northeast portion of the WVU Research Forest, east of Sand Springs Road. This site is transected, north to south, by a gas pipeline right of way and contains a .46 ha field near the center of the site. The total area of this site was about 11 ha and the elevation ranged from 676 m to 772 m. The aspect of this site was south to southwest and had very gentle terrain besides the southeast corner containing a small boulder field and a large slope change.

#### *Aerial Imagery Acquisition*

Aerial imagery was acquired by University subcontractor Meteorlogik Aerial Resources from Morgantown, West Virginia in 2016. The five research sites were identified in collaboration between both WVU researchers and Meteorlogik Aerial Resources. These five areas were flown with a DJI Phantom 3 Professional Quadcopter UAV (Figure 3). This common, consumer grade, drone carried a 1/2.3" CMOS true-color sensor capable of 4K video recording and still images of 12.4 Megapixels. The sensor was stabilized by a three-axis gimbal (pitch, roll, yaw). Flight software used was the application Map Pilot for DJI (Drones Made Easy, San Diego, California). This application is downloadable onto a smartphone. The application controlled the area of interest, flight lines, flight speed, elevation above the terrain and many others (Figure 4). The application, in conjunction with the DJI drone products, creates a nearly fully automated aerial imagery data collection system. Each site was flown multiple times to collect summer and fall imagery.



Figure 3. 'Map Pilot' application on-screen display while UAV is in flight. Still images are shown in display in bottom center of screen. UAV location and flight direction represented by red triangle, orange circles represent corners of area of interest and grey circle represent locations of images that have already been acquired.



Figure 4. DJI Phantom 3 Professional on homemade landing pad.

Imagery datasets for both seasons were only completed for two sites. Some imagery and GCPs were installed for the other three sites but were not entirely completed due to difficulties with terrain and access. HL0 summer imagery was primarily collected on July 26<sup>th</sup> but some additional images from earlier test flights were used where there were missing data. The fall imagery for the HL0 was collected on both October 22 and 25 and were combined in the processing software. The summer imagery for HL3 was collected primarily on August 11 with a few images used from the flights on August 5. The HL3 early fall imagery was collected on October 19 and the late fall imagery was collected on November 1. It was the aim for the fall imagery to be collected at the height of fall color change to detect the greatest amount of difference in tree crown colors and extent which was believed to aid in the segmentation process. Two flights were taken for each batch of imagery. One flight was performed in an east-west

oriented grid over the area of interest the second was a north-south grid (Figure 5). This resulted in end and side lap of approximately 85%.

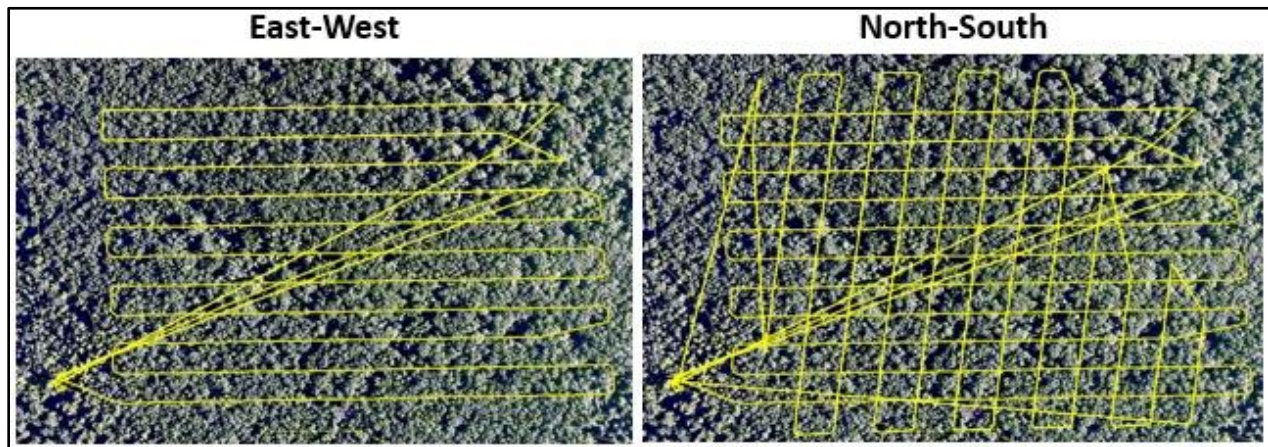


Figure 5. Orientation of UAV flight paths covering the area of interest. The diagonal lines result from when error in the flight occurred; likely exhausted battery. The UAV returns “home”, the batteries are replaced and the UAV returns to where it last collected data.

Target altitude for all flights was 76 m above ground level or lower. This was maintained by the feature ‘Terrain Aware’ in the Map Pilot application. Flights were conducted at the lowest flight altitude possible to get the clearest view of the tree crowns, but this had to be balanced with the risk of losing the drone in the canopy due to changes in topography and the added processing time of a greater number of images from a lower flying altitude. Overcast, but not rainy, days were targeted to produce the most consistency in image collection. Overcast situations have reduced shadows, and when flights took a greater amount of time due to wind or other factors, the lighting scheme would not change as drastically during the flight. Flight speed ranged from 8-16 KPH. This variability was primarily caused by changes in wind direction and speeds. Images were recorded every three seconds while the device was in flight. One day was typically necessary to cover each research area. The optimal light window for performing these flights was between 10:30 am and 2 pm to reduce shadows. This study was able to accomplish the collection of imagery in one directional (east-west or north-south) flight path for areas of interest no greater than 32 ha in typically one hour. Changeover time and the second direction flight path consume the rest of this important time frame. These flight times are greatly affected by wind speeds.

#### *Ground Control and Imagery Processing*

The limitations for installing GCPs were time, funds, and difficulty of landscape throughout the five research sites. The dense, nearly continuous canopy proved difficult to find gaps and usable sites for ground control in the interior of the forest. An open field to the southeast of HL0 was utilized for ground control, as well as County Route 73/73 and Goodspeed Road which bounded the site to the south and north, respectively. The HL0 site did not quite extend northward far enough to intersect Goodspeed Road, but a larger swath of land was flown to ensure proper coverage and capture of known landforms for easier ground control as well as to ensure proper coverage. The HL3 site contained distinct features like a gas pipeline right-of-way and a field, as well as a few large single-tree gaps to allow for proper dispersion of ground control throughout this site (Figure 6). The number of ground control points

that were withheld for analysis to be used as check points for error calculation within Agisoft was determined by the total number of ground control points collected.

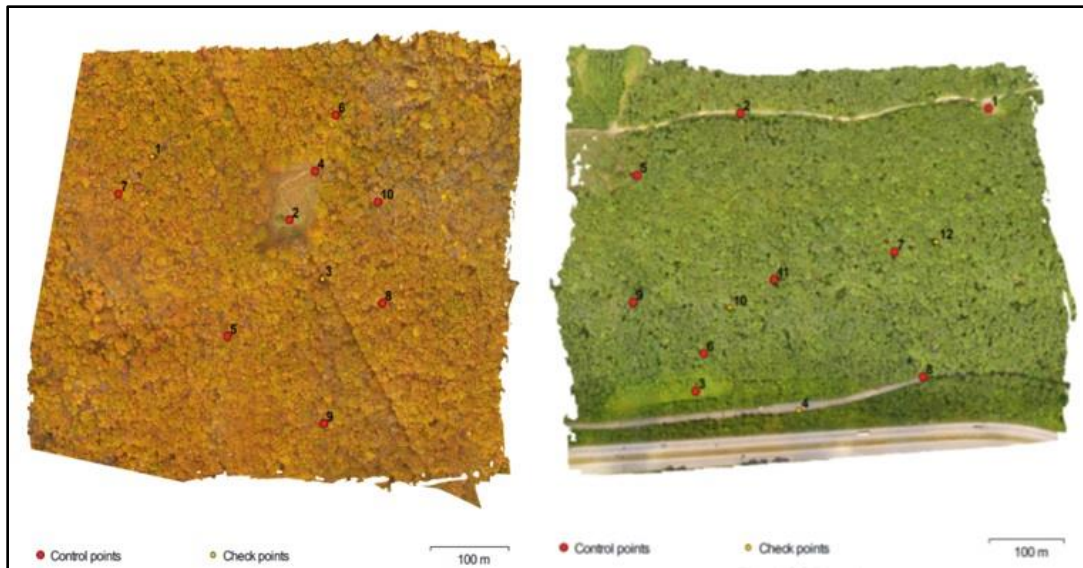


Figure 6. Distribution of ground control points throughout HL3 (left) and HL0 (right). These ground control points remained as permanent locations for use in all seasons of imagery collection.

Each ground control point consisted of a 1.2 m<sup>2</sup> plywood target. Each target was painted white and black for contrast. Targets were meant to be seen in the imagery when the drone flew over so contrast was essential. Larger targets would have been difficult to efficiently place in the interior of the forest. Once established, very accurate (average vertical and horizontal accuracy of two cm) GPS coordinates were taken using an iGage X900S-OPUS GNSS static receiver at a standardized height of two meters above ground level. At each GCP the GPS locations were recorded at each point for no less than 121 minutes to ensure proper readings.

Imagery was processed using Agisoft Photoscan Professional Version 1.2.6 (Agisoft LLC., St. Petersburg, Russia) using a Windows 64-bit device with Intel Xeon CPU E3-1271 v3 at 3.60 GHz and 32 GB of RAM. Images and ground control points were loaded into the software interface to create both the digital structure model (DSM) and the 3-D polygonal mesh (mesh). Both represent the surface of the object of interest based on the dense point cloud. The dense point cloud was processed on medium quality. The mesh was then used to create the orthomosaic. It is important to note that it was necessary for both the LiDAR and the SfM to be processed in the same height projection and for the height metric (ellipsoidal or orthometric) to be consistent to produce accurate and representative heights. In this study, both were processed using orthometric heights. The software identified features in these images and identified each of the images that these features exist in for better referencing. These features are called tie points.

#### *Automated Crown Segmentation and Spatial Measurements*

Segmentation procedures were performed in Trimble eCognition Developer object based image analysis software. Three segmentations were performed for HL0 using combinations of the seasonal flights. All three were performed

by the multi-resolution segmentation tool in the software interface. The products of this process were ESRI shapefiles of the segmented tree crowns using the summer only imagery, fall only imagery and a combination of the two. Once segmented, the crown area ( $\text{m}^2$ ) was calculated in ArcMap.

A normalized digital structure model (nDSM) was produced for both HL0 and the HL3 sites. This was developed by subtracting LiDAR ground level from the SfM point cloud from the UAS imagery with the Raster Calculator function in ESRI ArcMap 10.3. The SfM point cloud was rasterized as a DSM which contained an average pixel size of 1.06 cm across all imagery acquisitions. The LiDAR data, filtered to display just the final ground return, was a 1m DEM produced by the West Virginia Department of Environmental Protection's Technical Applications and GIS Unit (TAGIS) in 2013 (Figure 7).

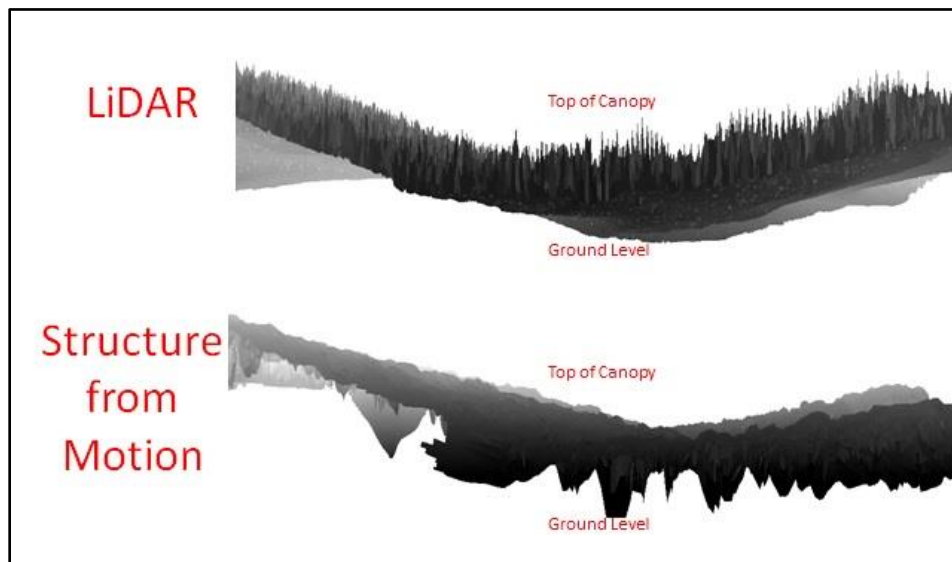


Figure 7. Data from West Virginia University HL0 site displaying the distribution of ground points from the LiDAR data collection while the SfM model lacks completeness in coverage of the ground. Structure from Motion point data that penetrated the forest canopy was seldom and very few reached ground level. This image depicts the importance of using LiDAR for ground level data.

The nDSM was then added as a fourth band, along with red, green and blue, to each the summer and fall imagery before the segmentation was performed for HL0. An nDSM was created for each of the three imagery sets (summer, early fall and late fall) for HL3 to examine whether it would be beneficial to utilize the height model from each imagery collection or to select one that is most representative of the area as was done with the HL0. These nDSMs, both for HL0 and HL3 sites, were added as additional bands to each of the associated images. Images were then stacked to produce composite images in Hexagon Geospatial's Erdas Imagine remote sensing application, creating a seven band image for HL0 and a 12 band image for HL3. HL0 and HL3 images were then inputted into eCognition and individually analyzed using parameters specific to the dataset (Table 1).

Table 1. Optimal settings and for each of the composite images for multi-resolution segmentation processing in HL0. The bands are as follows: red, green and blue from the summer mosaic are represented as bands 1, 2 and 3. Red, green and blue bands from the fall mosaic are represented as bands 4, 5 and 6. The 7<sup>th</sup> band is the nDSM.

<b>Band Weights</b>			
<b>Bands</b>	<b>Summer</b>	<b>Fall</b>	<b>Summer+Fall</b>
<b>1</b>	3	-	4
<b>2</b>	1	-	1
<b>3</b>	1	-	1
<b>4</b>	-	3	3
<b>5</b>	-	1	1
<b>6</b>	-	1	1
<b>7</b>	5	5	5
<b>Multi-Resolution Segmentation Parameters</b>			
<b>Scale</b>	210	250	260
<b>Shape</b>	0.4	0.4	0.4
<b>Compactness</b>	0.9	0.9	0.9

The values for the multi-resolution segmentation parameters and band weights were developed using an iterative process on a subset of each batch of imagery. The tested optimum settings were chosen for each dataset. This proved to be a difficult task for the full composite HL3 segmentation due to the great number of weights and parameter setting possibilities (Table 2). After these parameters were established, they were then applied to the entire image for the final segmentation of each image.

The scale parameter seemed to have the greatest effect on the segmentation results. The lower the scale parameter, the greater number of segmentation objects were created. Finding the balance that captured primarily individual tree crown objects was the focus of the evaluation of the optimum parameter settings. The scale parameter is an arbitrary parameter within eCognition that defines the size and number of objects created. There is no range for scale values. The shape parameter ranges from 0-0.9. The higher the value for this parameter, the more consideration the shape of objects is given when performing the segmentation. The compactness parameter defines the weight of the object compactness. This parameter is scaled from 0-0.9. The higher the number, the more compact the objects will be and the lower the number the more abstract and stringy the objects will appear.

Table 2. Optimal eCognition settings used for each of the multi-resolution segmentations produced for site HL3. The bands are as follows: 1-3 are red, green and blue bands from the summer mosaic; 5-7 are red, green and blue bands from the early fall mosaic; 9-11 are red, green and blue bands from the late fall mosaic and 4, 8 and 12 are bands containing the nDSM for summer, early fall and late fall respectively.

<b>Band Weights</b>				
<b>Bands</b>	<b>Summer</b>	<b>Early Fall</b>	<b>Late Fall</b>	<b>Summer+ Early Fall+ Late Fall</b>
<b>1</b>	2	0	0	1
<b>2</b>	1	0	0	1
<b>3</b>	1	0	0	1
<b>4</b>	10	0	0	1
<b>5</b>	0	2	0	1
<b>6</b>	0	1	0	1
<b>7</b>	0	1	0	1
<b>8</b>	0	10	0	1
<b>9</b>	0	0	2	1
<b>10</b>	0	0	1	1
<b>11</b>	0	0	1	1
<b>12</b>	0	0	10	10
<b>Multi-Resolution Segmentation Parameters</b>				
<b>Scale</b>	330	260	290	260
<b>Shape</b>	0.6	0.6	0.7	0.6
<b>Compactness</b>	0.9	0.9	0.9	0.9

Each of the segmentations were performed in roughly 30 minutes. The nDSM weight was treated as the greatest due to the practice of local maxima segmentation methods for tree crown segmentation (Zawawi et al., 2015). The high points would be established as the highest point of each of the individual tree crowns and the shadows surrounding each one of these tree crowns would be represented by consistently decreasing height values as pixels proceed to the edges of the crown. Also, the red bands of most of the images were weighted higher than the green and blue bands due to the observation that contrast in brightness values was greatest in these bands when viewed individually. It was believed that this contrast would give the segmentation the most information to predict tree crown boundaries. The red band in the summer image of HL0 provided more contrast than that of the red band of the fall image of HL0, thus was given a higher weight.

Gaps in the tree canopy for HL0 were removed from the object list before further processing by selecting all objects with a mean nDSM value less than 18.8 m. This threshold was chosen by being half of the maximum nDSM value of 37.7 m to target the removal of trees with a crown class of intermediate or suppressed. This resulted in the removal of 116 objects with a grand total of 2,305 objects for the fall and summer composite image. This method also removed 36 objects from the fall imagery and 68 from the summer, resulting in a grand total of 2,574 and 3,715

objects respectively. An attempt to remove gaps and the large field within HL3 was performed by removing all objects with a mean nDSM value less than 16.9 m. Although the mean nDSM value for this site was 39 m, when half of this maximum height was utilized many trees were selected within this site due to the stunted growth of a number of trees in a boulder field in the southwest corner of this site. Adjustments were made (to 16.9 m) until the selection excluded canopy trees and targeted gaps.

#### *Field Inventory*

Circular plots of 0.04 ha were distributed throughout the five research areas on a grid pattern with spacing appropriate to create roughly a 0.4: 1 plot ratio throughout each of the five areas. A total of 129 field plots were installed. Navigation to all field plots was done using a WAAS-enabled, handheld Garmin eTrex Legend H GPS receiver.

The metrics recorded at each of the field plots were: aspect, tree number, species of each tree, DBH, crown class, total height, merchantable height (to a 25.4 cm top or other form of stoppage), and azimuth and distance from plot center to each stem. All stems above 10.16 cm in DBH were recorded and the crown classes that were used were suppressed, intermediate, co-dominant and dominant. Total heights were recorded for all trees that were of co-dominant or dominant crown class or individuals who existed in gaps and would be visible in aerial imagery. Merchantable height was measured on individuals whose DBH was of 30.48 cm or greater and was recorded to the nearest quarter log. Standard log measurements of 4.8 m lengths were used in this study. Total height was recorded with Laser Technology TruPulse 200 Laser hypsometer and the upperstem limit of merchantable stems was identified using both the TruPulse laser and Laser Technology Criterion RD 1000 laser linked via cable. All trees were marked with unique number identifiers within each plot for revisiting.

#### *Field Crown Measurements*

A subset of plots was chosen to represent the crown verification measurement group. Five plots from each of the five research sites. These individuals from the five plots were used to verify the crown area measurements produced from the automated segmentation process as well as in the development of the allometric relationship of tree crown area and DBH. A total of 218 tree crowns were measured throughout this process.

The calculation of tree crown area was done by dissecting the tree crown, on the ground, into six irregular triangles. The sum of the area of all six triangles would result in the area of the entire tree crown. The first step in the calculation of tree crown area was creating vertices at the drip line every 45 degrees from the stem of the tree, totaling 8 vertices per crown (Figure 8). Field observers utilized a clinometer to ensure that measurements were taken directly below the dripline.

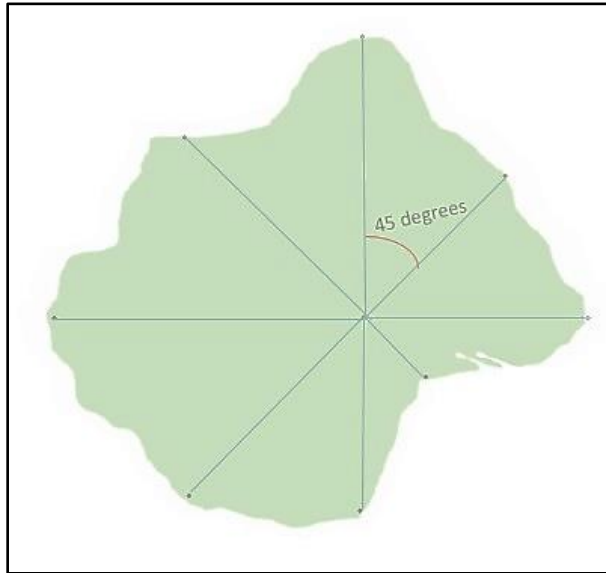


Figure 8. Vertices at the drip line of the tree crown every 45 degrees around the stem of the tree. North is in the direction of the top of the page.

Measurements were taken starting from the vertex at the drip line, 0 degrees north of the stem to each of the succeeding vertices. These measurements, recorded to the nearest 0.03 m, created two legs of the irregular triangles for each of the six triangles of interest. The final leg was created by measuring between each vertex beyond 0 degrees north. For example, measurements were taken from the 45 degree vertex and the 90 degree vertex, the 90 degree vertex and the 135 degree vertex and so on. These measurements resulted in six triangles (Figure 9).

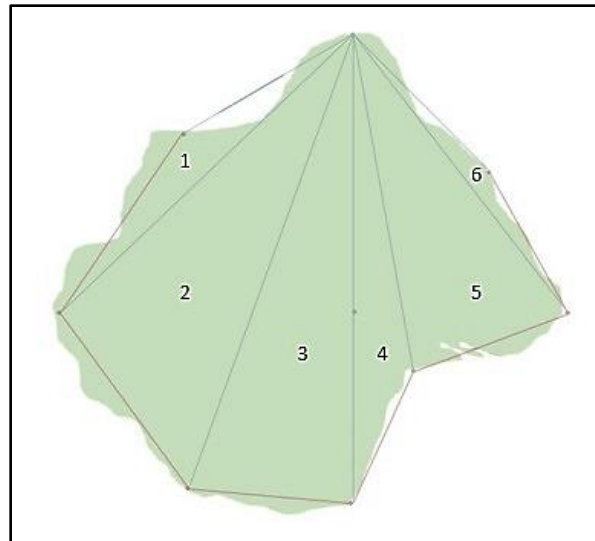


Figure 9. The six triangles produced from field measurements to calculate area of irregular octagon. Blue lines represent measurements to vertices from 0 degrees north and red lines represent measurements between vertices beyond 0 degrees north. Top of page represents north.

The field data was synthesized using Heron's formula (Stubberud & Kramer, 2009):

$$\text{Triangle Area} = \sqrt{s(s-a)(s-b)(s-c)}$$

where: a, b and c are all vertices of one of the six triangles and

$$s = \frac{1}{2}(a + b + c)$$

The above equation calculates the area of one of the six equations. The total tree crown area was calculated by taking the sum of all six triangle area calculations. The mean of the four radius measurements was calculated for each tree crown and the tree crown area using this method was calculated by using the equation for the area of a circle.

#### *Field Volume*

All inventory data, field and drone derived, was processed in EZ CRUZ Version AR 4.03 inventory software package. The inputs into this software include: individual identification number, plot number, species, DBH, product, merchantable height in logs, and Girard form class. The plot size was set to 0.04 ha for field data. The log rule used for both field and drone derived volumes was International  $\frac{1}{4}$ ".

Product numbers were either 1 for sawtimber or 2 for pulpwood. This distinction was created at the 30.48 cm DBH cut off. Above this cutoff, individuals were classified with a product of sawtimber and below this threshold they were classified as pulpwood. The merchantable height was rounded down to the nearest quarter log. Standard 4.87 m full logs were used for this inventory. The Girard form class that was set automatically by the software for the red oak species was 78. The data was processed and output into a Microsoft Excel format.

#### *UAS Derived Volume*

Without species classification data, volume numbers would need to assume a form class 78 for all observations. The species that was chosen to represent all observations was northern red oak. This is due to northern red oak's prevalence across the site and it is understood to be indicative of quality sites throughout the WVU Research Forest.

A nonlinear model was developed to predict stem DBH from field measured crown area. This model was developed using field DBH and ground measured tree crown areas throughout all five field sites for this study. The model developed and utilized through this process was:

$$\text{DBH} = \text{Exp}(1.20001 + (0.12968 * \ln(C)) + (0.00966 * \text{tht}))$$

Where C = crown area in m<sup>2</sup>, tht was total height measured in m and DBH was measured in cm.

The DBH derived from the above equation was then inputted into a model to predict merchantable height from DBH (Brook & Wiant, 2006). Such as for the field data, northern red oak was the assumed species and the equation that was utilized is as follows:

$$\text{MHT} = \text{Exp}\{4.0269 + -8.390\left(\frac{1}{\text{DBH}}\right)\}$$

Where MHT is represented in m and DBH in cm.

#### *Evaluation of Accuracy and Statistical Review*

For much of this study, qualitative analysis and evaluation were the primary measure of success. Visual evaluation of segmentation quality of fit was performed for all segmentation results. Each of the results were displayed on their associated orthomosaic. For the HL0 composite segmentation, summer imagery was used. For the HL3 composite segmentation, a combination of early fall and summer imagery was used. A random number generator was used to select 50 segmented objects. These 50 tree crowns would be turned on and evaluated for their goodness of fit to the targeted tree crown in the imagery using a chi-squared test of homogeneity. If the random number represented a gap polygon, a new number would be generated until a polygon did not obviously align with a gap. For each of these segmentations, the number of correctly delineated tree crowns was recorded. A correctly segmented tree crown was considered a polygon that reasonably defined the full extent of an individual tree crown with minimal under or over segmentation (Figure 10). The optical threshold for a correctly segmented tree crown was 80% of the tree crown area correctly segmented.



Figure 10. Counterclockwise from the upper left: (1) Correctly segmented tree crown that would be considered a success; (2) correctly segmented tree crown that would be considered a success; (3) Over segmented tree crown that would be considered a failure; (4) Under segmented tree crown that would be considered a failure.

Segmentation of gaps was evaluated in a similar fashion between seasonal imagery. Gaps that were removed before volume calculations were evaluated optically on goodness of fit and random objects were selected to represent a reference point for a further analysis. The gap nearest to the random object was considered either successfully segmented or not. An 80% optical threshold of fit was used to determine successful segmentation. If the random object selected was a gap and it was 80% segmented correctly, then it was considered successfully segmented.

Static GPS coordinates were collected for the plot centers of three of the field plots in HL0 at which field crown measurements were also collected. These GPS measurements provided a highly accurate measure of these locations in space. The distance from plot center as well as the azimuth recorded through the field inventory were used to create a stem map of each of the three plots. These stem maps were used to visually understand where the location of each stem in these plots should exist in space and to allow the user a measure of how well each tree crown within these plots was segmented. Centered on each plot, a 0.04 ha circular plot was placed in ArcMap. Within each plot, crowns were heads-up digitized. Field crown measurements were used to verify delineated tree crown area measurements.

The goodness of fit measures for each of the tree crown segmentations and gap fit were statistically analyzed through a chi-squared test of homogeneity in RStudio, open-source integrated development environment. Evaluation of field and heads-up digitized tree crown areas for the three 0.04 ha plots was also done in RStudio by way of Welch's two-sample t-test. A statistical evaluation of field measured merchantable heights and Brooks & Wiant (2006) derived merchantable heights was performed using a Welch's two-sample t-test. This comparison was done on field measured merchantable heights for trees in HL0 and HL3 and merchantable heights were also estimated for these same individuals using the measured DBH from field data collection. The alpha value for all statistical analyses was 0.05.

## Results

The initial results of this project revolve heavily around the evaluation of the quality of the UAS imagery (Table 3). The RMSE was calculated by the Agisoft software and is an estimate of error utilizing the inputted GCP check points. This error value is the difference between measured GPS location and software estimated GPS location for the check points. Flight time resulted in an approximate four hours per site per day which constitutes a full day for purposes of aerial imagery acquisition.

Table 3. Evaluation of imagery from all sites and seasons available. The processing time is the sum of all processing times necessary for all stages of the image processing.

<b>Site</b>	<b>HL0</b>		<b>HL3</b>		
<b>Season</b>	Summer	Fall	Summer	Early Fall	Late Fall
<b>Area Flown (ha)</b>	31	30	26	27	28
<b>Processing Time (hrs/ha)</b>	0.33	0.17	0.46	2.07	0.62
<b>Total Processing Time (hrs)</b>	29	51	17	4.0	14
<b>Number of images</b>	1673	2046	1496	778	1571
<b>RMSE (m)</b>	5.15	4.52	11.27	9.47	0.49
<b>Number of points (millions)</b>	57.9	49.0	56.7	49.5	56.0
<b>Number of GCPs</b>	12	12	9	8	10
<b>Hectares per GCP</b>	2.6	2.54	2.87	3.39	2.91
<b>Resolution (cm)</b>	3	2.9	2.38	2.48	2.48
<b>Flying Altitude (m)</b>	81	77	61	67	69
<b>Tie points (millions)</b>	3.75	2.27	2.24	0.95	0.84

The area flown is greater than the site area due to the significant amount of overlap needed to ensure proper coverage. It is important to note that the early fall imagery only used half of the images (north and south flight lines) due to the lighting change throughout the day of acquisition. The HL3 early fall dataset had the fewest number of images and the shortest processing time. The late fall imagery had shorter processing time (82%) than summer HL3 imagery but greater number of images. The RMSE was the lowest for the late fall imagery. The resolution was the highest for the summer HL3 imagery and also had the lowest flying altitude. The processing time for both of the sets of HL0 imagery was far greater than those of the HL3 imagery. Fall imagery datasets had 13% lower ground control RMSE than summer imagery for HL0 and 18% lower error for early fall compared to summer imagery in HL3. Late Fall RMSE was 23 times lower than summer imagery RMSE for HL3.

The quality of segmentations when evaluated visually was unsatisfactory compared to past research. The least successful segmentations were the summer, early fall and composite images for HL3 with only a 17 % success rate. Although the fall and summer composite image for HL0 produced the greatest number of successes at 43%, there is no statistical difference between any of the segmentation goodness of fit evaluations. Similarly, there were no statistical differences among temporal UAS aerial imagery for correctly segmenting tree crowns (Table 4).

Table 4. Segmentation results for all imagery and combinations. Chi-squared tests of homogeneity were performed on successes between segmentations of each site as well as between both sites.

Site	Segmentation	Successes	Failures	Success Rate	chi-squared p-value	chi-squared p-value
HL0	Summer	13	37	26%	0.19	0.34
	Fall	9	41	18%		
	Stacked Image	17	33	34%		
HL3	Summer	9	41	18%	0.14	
	Early Fall	6	44	12%		
	Late Fall	15	35	30%		
	Stacked Image	9	41	18%		

Average crown area from field data was 35 m<sup>2</sup> and the average crown area for heads-up digitized crowns was 32 m<sup>2</sup> in three plots in HL0, which was not a significant difference ( $p=0.62$ ). This verified the field crown measurements that were used in the DBH relationship equation. The relationship between DBH and crown area derived from field data had an  $R^2$  value of 0.51.

There was a significant difference between field measured and predicted merchantable height values, using Brooks and Wiant (2006), in both HL0 and HL3 ( $p=0.003$ ). The volume numbers were inconsistent with large variation between segmentations and field data (Table 5).

Due to the crown area diameter relationship, the segmented datasets primarily estimated individual trees with DBH 10.16 cm or greater. The maximum number of trees per hectare for any segmented dataset was 2.9 trees/ha for summer HL0. The segmented datasets underestimate trees/ha when stems under 30.48 cm are included (with the exception of HL0 summer segmentation) but overestimate when stems below 30.48 cm are removed. Basal area was overestimated in the segmentation datasets regardless of stems less than 30.48 cm DBH are included. Average diameter was within 6% of the field calculated average diameter for HL0 segmentations except for the summer segmentation and within 9% for all HL3 segmentations. HL0 average MHT had a greater range of data than that of HL3 (1.15 m and 0.3 m respectively).

HL3 early fall segmentation produced the closest results to field estimates which were 14% greater than the mean field estimate. The greatest difference in HL0 volume estimates was from the summer only segmentation derived volume estimates. These estimates were more than 200% greater than the field estimates. This estimate was the poorest out of all segmentation results. The highest volume estimate for HL3 was the composite stack segmentation with volumes 161% greater than the field data estimates.

Table 5. The EZ CRUZ derived volume and other forest metrics for all of the segmentations compared with the field data for each of these sites. Field estimates are shown with a 95% confidence interval.

	Season	m <sup>3</sup> /ha	trees/ha	BA (m <sup>2</sup> /ha)	AVG DBH (cm)	AVG MHT (m)
<b>HL0</b>	Field (10.16 cm DBH and above)	104.9 ± 17.5	416.6 ± 19.5	35.8 ± 3.5	30.0	11.2
	Field (30.48 cm DBH and above)	104.9 ± 17.5	201.1 ± 19.5	29.4 ± 3.5	42.7	11.2
	Fall/Summer	171.4	312.6	50.2	45.2	10.5
	Fall	181.3	337.0	53.4	45.0	10.5
	Summer	219.2	488.5	67.5	41.9	10.1
<b>HL3</b>	Field (10.16 cm DBH and above)	79.3 ± 15.7	470.7 ± 21.7	35.6 ± 4.5	27.7	10.0
	Field (30.48 cm DBH and above)	79.3 ± 15.7	198.9 ± 21.7	27.8 ± 4.5	40.4	10.0
	eFall/lFall/Summer	127.7	366.0	41.9	39.4	9.6
	early Fall	91.5	446.5	39.6	37.3	8.7
	late Fall	114.9	313.3	37.8	40.4	9.6
	Summer	114.9	326.7	38.4	39.6	9.7
		assumes 1mbf/ac=5.83 m <sup>3</sup> /ha				

Gaps were identified with higher success than tree crowns regardless of imagery season for both sites. The gaps that were removed before volumetric analysis were evaluated to produce how well each season of imagery uniformly identified gaps as gaps when these objects were queried for removal (Table 6). Each set of imagery was also evaluated on the ease of gap segmentation in general (Table 7).

Table 6. Quality of gap identification within each set of imagery.

Site	Segmentation	Successes	Failures	Success Rate	chi-squared p-value
<b>HL0</b>	Summer	23	7	77%	0.09
	Fall	15	15	50%	
	Summer and Fall	20	10	67%	
<b>HL3</b>	Summer	10	20	33%	0.19
	Early Fall	4	26	13%	
	Late Fall	6	24	20%	
	Sum + EFall + LFall	10	20	33%	

Table 7. Quality of gap identification across all sets of imagery. The values below were not queried for removal but were identified from all objects in segmentation results.

Site	Segmentation	Successes	Failures	Success Rate	chi-squared
					p-value
<b>HL0</b>	Summer	38	12	76%	<b>0.003</b>
	Fall	27	23	54%	
	Summer and Fall	32	18	64%	
<b>HL3</b>	Summer	21	29	42%	0.063
	Early Fall	23	27	46%	
	Late Fall	33	17	66%	
	Sum + EFall				
	+LFall	29	21	58%	

Although HL0 summer imagery had the greatest success rate for gap identification (76%) in both HL0 and for all sites as a whole and HL3 early fall had the worst (42%). There was a significant difference between summer and fall gap detection ( $p=0.0051$ ). Overall gap identification was on average 36% greater than tree crown identification for all sites, 49% better for HL0, and 34% better for HL3. There was only a 7% average difference between success rates in HL0 for gaps queried for removal, while there was 30% average difference for HL3 gaps queried for removal. This shows a distinct deficiency of the query at representing the gap identification quality of the segmentations for HL3.

## Discussion

This development of a work flow for UAS forest imagery is not an entirely new process (Puliti et al., 2015; Lisein et al., 2015) but the application of these methods to a complex mixed hardwood forest ecosystem is a challenging and rewarding beginning. The discovery of the difficulties in the acquisition of the imagery were of great importance for these settings. Ground control was a laborious task. It was believed that GCPs could be viewed easily throughout each stand. However, in very few instances was a single tree canopy gap sufficient for ground control as these gaps were not large enough for the visual identification of the targets when imagery was collected due to the presence of the midstory. It was soon realized that large openings, typically greater than a single tree gap, and visible structures such as rock outcroppings, roads or fields would need to be used for this practice. Through observation, it was essential to utilize at least 121 minutes for the occupation using the iGage X900S-OPUS GNSS static GPS receiver or the risk of GPS coordinates failing to be returned was great.

The collection of imagery in one day was limited to no more than one 32 hectare site with proper overlap and coverage. The amount of area that can be flown is greatly limited by the lighting of the day and battery life but the battery capacity for the DJI Phantom 3 Professional is adequate for this application. The type of drone used is also a limitation to the area of coverage. An increase in extent would require the UAV to be flown at a higher altitude which would reduce the resolution of the final imagery product. The use of a professional grade UAV, more suitable for larger extents, could also increase the speed at which data could be collected without suffering a decrease in quality. There is an inverse relationship between flight altitude and spatial resolution; the greater the flight altitude

the lower the resolution.

At the HL3 site, it was possible to develop imagery with high spatial resolution with only one direction of flight lines (e.g. east-west flight lines) for the early fall. However, this set of imagery produced one of the worst segmentation results as a result of unreliable data from the lack of images. This point cloud had the second fewest number of points, the second fewest number of tie points and the least amount of ground control points which produced a less reliable product for measurements. The overlap of 85% is supported in literature as a means to avoid gaps in data and to ensure that the best coverage of all sides of tree crowns is established (Haala, 2013).

In many cases the imagery processing with Agisoft was the most time consuming step in the procedure. Dense point cloud construction, which all later processes within Agisoft require, was performed with medium quality. The difference between products produced on medium and high quality was negligible but was actually better on medium accuracy with a ground resolution and ground control RMSE of 3.02 cm and 5.15 m on medium accuracy and 3.14 cm and 5.16 m on high accuracy respectively. But, the medium processing time was far less (29 hours) than that of the high quality (164 hours). Processing was initially performed on high accuracy but negligible differences in accuracy and high processing times determined that medium accuracy was a better fit. These same tradeoffs were also selected as the optimal settings through trial and error in Puliti et al. (2015). There are few methods beyond improving the hardware of the machine used for processing to reduce this time needed to produce fully rectified orthomosaics. Smaller areas of interest would produce fewer images that would lessen the time of processing if this is allowable within the scope of future projects (i.e. smaller forest stand management).

There were great differences between the processing times between many of the sets of imagery. This is believed to be the result of a combination of features including the number of images, the resolution of the image, the number of tie points produced and the accuracy of the ground control. It is a complicated process that cannot be easily defined by one causal factor. It was believed that the number of images, more specifically the number of pixels, has the greatest effect on processing time, while other features (tie points, ground control, etc.) have smaller individual effects (Remondino et al., 2014). There is also a difference between pixel sizes between datasets which affects the number of pixels per image, creating a more complicated algorithm to predict processing time.

The most novel approach in this process was the method by which the automated segmentation was performed. Object based image analysis (OBIA) has been used for a great number of applications in remote sensing but these procedures challenged these methods with a set of very complex features (Husson et al., 2016). The segmentation is the limiting factor by which volume estimates and other forest metrics can be derived. The results of the segmentations performed for this project were not as accurate as in less complex stands. Deng et al. (2016) showed a segmentation success rate of a predominately broadleaved stand at 71.8% using a combination of LiDAR data and true color imagery of coarser resolution (24.8 cm) than what was produced in this study. Hernandez et al. (2016) produced tree detection results of 100% in a stone pine (*Pinus pinea* L.) plantation with a spacing of 10 x 16 m. Stone pine is distinctive for its flat-topped, umbrella like crowns which are very unique in open canopy forests. The imagery in this study was collected with a professional fixed wing UAV. Kuzmin et al. (2017) produced segmentation and classification results of 81.9% in boreal forests with only 30-70% canopy cover dominated by Norway spruce and Scots pine. For the current study, the greatest accuracy of 43 percent in the fall and summer

composite image is promising. With consumer grade technology, 43 percent of tree crowns were able to be segmented properly in a very complex canopy for feature extraction. The increase in accuracy from the single fall and summer images to the composite image was as great as 20% for HL0, showing the importance of capturing as much data as. But, the issues with eCognition parameters not easily being transferred between images makes this process difficult to replicate on other sites.

An explanation for the difference in segmentation quality between sites could be influenced by sites themselves. HL0 was split between north and south facing aspects with the north facing aspects being dominated by red maple and yellow-poplar, while HL3 was predominately south and southwest facing aspects containing primarily mixed oak species (Table 8).

Table 8. Summary of species prevalence between HL0 and HL3. The top three most prevalent species in each site are displayed.

	HL0	HL3
<b>Total Number of Species</b>	15	11
<b>Top Species</b>	RM (38%)	RO (33%)
<b>Second Species</b>	YP (17%)	RM (32%)
<b>Third Species</b>	CO (11%)	CO (16%)
<b>Total % of Top 3</b>	66	81
<b>% Oak</b>	29	56

HL3 has fewer species and is more homogenous than HL0. More than on half of the species composition is comprised of the oak group. The more homogeneous a high density canopy is, the more difficult the segmentation becomes to an extent. Although there are only 11 total species and much of HL3 is dominated by three species, these species have variable crown shapes and the mixture of additional species makes it difficult to recognize for segmentation. Conifers have unique and easily identifiable crown shapes from an aerial view as compared to broadleaved trees (Deng et al, 2016). The dominance of HL3 by entirely broadleaved trees makes the complexity greater than most studies that have been published in this field but not as great as HL0. This difficulty to segment broadleaved trees due to their interwoven crowns is consistent with previous results (Ayrey et al., 2017).

The prevalence of oak species in HL3 is a glimpse into why this site was more poorly segmented due to the difficulty of segmenting individual oak tree crowns. Segmentation was made particularly difficult due to the fact that these oak crowns are not as homogenous in color as they would be without cicada damage. The hatching of brood five of the 17-year cicadas (*Magicicada septendecium*) throughout the north central portion of West Virginia during the data collection period caused an obvious amount of damage to many tree crowns. The damage was mostly observed in white oak species (chestnut oak and white oak). The brown color and discoloration in some pixels due to the cicadas are an added element of information that could potentially be disruptive to the segmentation process. Visual assessment of oak crown delineation showed poor segmentation quality on these individuals. Fall color did not have great effect for HL3 imagery, the lower species diversity made fall color discrimination less effective.

The statistical difference between fall and summer gap identification success rates in HL0 provide a suggestion that

one season of imagery may be the optimal time for gap analysis. Summer imagery was shown to be a better tool at identifying these gaps and more repetition among sites may yield similar results in the future.

It also appears that there may be too much information for the segmentation to be performed when three sets of images are stacked as was done in HL3, specifically the inclusion of the early fall imagery in the 12 band image stack. The variability of this dataset may be a cause for the distinct decline in success for HL3 segmentations. This could also be due to the fact that it is difficult for the software to group pixels into similar groups (objects) when each of the pixels is represented by so much information, some of it may even be contradictory as colors change in seasons. Although there are numerous bands available, these data differ from hyperspectral because they have different acquisition times while hyperspectral has one. There was not a single individual season that captured the segmentation best, but the most accurate spatial measurements after segmentation (i.e. tree height) can be taken from fall imagery as was shown by the fall seasonal imagery for both sites had the lowest RMSE (4.57 m for HL0 fall and 0.49 m for HL3 late fall). This is believed to be due to the greater visibility of the ground for development of tie points and referencing during the HL3 late fall acquisition.

Remotely sensed forest volume estimates only seldom have been addressed in literature let alone attempts to estimate board volumes so there are a few studies to compare these methods (Puliti et al., 2015). Messinger et al. (2016) were able to produce above ground carbon estimates of Amazon forests with error values as low as 0.05%. These numbers are comparable to other studies that have studied biomass estimation in eastern forests (Wu et al., 2016) and this is not a surprise that the accuracy of these estimates is greater than that of merchantable tree volumes. This measure was coarser than what was performed in this study and does not take into account a great number of details necessary to evaluate useable board volumes. The allometric relationships studied for above ground carbon biomass are better understood than the relationships necessary for merchantable volumes (Radtke et al., 2017). Although there is error involved in the volume estimates produced from this study, an essential framework has been laid for future work.

Evaluation of image segmentations was a challenge without a fully defined reference dataset. The area of coverage was far too great to develop a full reference dataset. The lack of reference data in this study required the development of an objective as possible system of steps in order to compare the different seasonal segmentations. The method of visually evaluating segmentation fit contains subjectivity as compared to measuring the amount of overlap between segments which is common when reference data is available (Clinton et al., 2010). This method could be improved by increasing the number of test segmentations and filtering out segmentations of negligible size. It may also be prudent in the future to classify the error associated with the segmentation by defining whether the individual tree was over segmented, under segmented or misinterpreted. This provides the user more information for future segmentations.

Aerial imagery data collected in this study are viewed as a success for many of this study's objectives. The high resolution imagery supplied a visualization of forest health and sudden changes such as with the recent damage caused by the large 17-year cicada outbreak (Figure 11).



Figure 11. Example of crown damage caused by 17-year cicada outbreak of the summer of 2016. The brown blemishes on the summer leaf on-images were caused during this season and it was a goal of the team to capture the height of this damage.

The successful gap detection was promising as well, these gaps allow managers a glimpse at the structure of the forest underneath the canopy and the succession of the forest. An increase in forest gaps, that are continually filled, allude to the transition between forest successive stages and the creation of a method to monitor this change from above would be highly valuable to managers. In particular, the number of canopy gaps is especially important habitat for forest songbirds such as the cerulean warbler (*Setophaga cerulea*), a federal species of concern (Perkins & Wood, 2014). There was no significant statistical evidence that an individual season was greater than another at detecting gaps but summer imagery in HL0 did have the greatest success rate at 76%. The average difference between overall gap identification and queried gaps in HL3, the failure to identify gaps in the query, may be a small reason why volume numbers were inflated for this site.

The most distinct limitation to this process was the high cost of necessary software. An Agisoft Photoscan Professional license costs \$3,499 and an eCognition Developer commercial license costs \$20,880. Other limitations include the intensive ground control requirement necessitates expensive GPS equipment and labor and difficulties navigating the UAS policies of the Federal Aviation Administration. It is important to note that although UAS imagery acquisition is highly flexible, this also produces issues with transferable data between studies. The time at which imagery should be captured is highly specific to areas due to local weather patterns and lighting schemes as well as extreme differences in topography. Some canopies demand higher resolution at a lower flight altitude than others, and some topography is very complex and needs greater overlap to capture the complexities. It was also difficult to capture exact phenological changes. Elevation and variable levels of moisture from season to season make the peak season changes difficult to capture. If phenological events are of interest for future studies, multi-temporal data is essential. Segmentation accuracy is also a primary limit to the advancement of these methods. Creating segmentations of greater quality will need to be the emphasis moving forward for this type of work to be

viable.

Future work for this study site will target the use of new sensors compatible with UAS to create a dataset that promotes greater ease of segmentation. The use of a hyperspectral sensor would promote the identification of individual crowns using unique spectral signatures and this work would also aid in the classification of species which would provide an essential piece to completing an entire UAS derived forest inventory. The combination of spectral and UAS derived point cloud data was used to segment and classify individual trees in Finland to accuracies of 95% (Nevalainen et al., 2017). Nevalainen et al. (2017) states that at time of submission their study was the only investigation into boreal forest species classification using the combination of hyperspectral data and UAS point clouds.

## Conclusions

Difficulties and time constraints prevented researchers from completing the processing of all five sites intended for this study but the findings presented from the two sites are valuable for future studies. It is important to capture phenology as close to the peak as possible to give a multi-temporal dataset the most information for differentiating for segmentation technology. It is essential to complete data collection with an 85% overlap in multiple directions to allow for the greatest number of tie points and most reliability in measurements from these data. The target areas should not exceed 30 hectares for the use with a consumer grade multicopter UAS and preferably fewer hectares should be targeted as data collection with this device is not fast enough to capture these data easily without lighting schemes changing even within the optimal lighting window. Time necessary for ground control could be reduced by the use of remote referencing techniques that need to be tested for these conditions. Inertial measurement unit remote referencing techniques could remove the only task that requires entering the stand physically (Wallace et al., 2012b) or the use of RTK PPP technology that is newly being used for aerial triangulation could be used in this same approach (Shi et al., 2016). Winter and spring seasons need to also be collected for each site to gain insight on whether seasonality truly has an effect on segmentation quality. But from the findings in this study there is no significant difference between fall or summer seasonal imagery or a composite image for segmentation quality.

Volume estimates derived from segmentation results are currently unreliable due to the poor quality of segmentation and deficiencies in estimates of trees per acre, merchantable height and diameter. Improvements in segmentation quality need to be the primary focus in future work either through introduction of more advanced sensors or through the development of a more objective method for optimizing eCognition segmentation parameters. Segmentation results can vary by site conditions (e.g. slope, aspect, terrain, etc.). It is important to note that an increased ability of these methods to segment tree crowns may be a sign of species diversity. Complex canopies with interlacing crowns that have more homogenous species are more difficult to segment such was the case on HL3. It is important to design stands that are consistent throughout, whether there are high levels of variation or not, to ensure issues with segmentation do not occur.

These methods are not currently sound enough to replace forest managers or forest inventory crews but are in a position to compliment the process. Quick mobilization of these tools to capture post-harvest stand density or effect of deer browse on regenerating stands is a valuable information for managers. Entering stands post-harvest is a difficult and tedious process and is sometimes abandoned all together due to the tangle of tops and sometimes few

residual stems to be inventoried. These methods could be tailored heavily to removing the need for post-harvest cruises or aiding in the decision when these cruises are entirely necessary. Forest volume evaluation of stands such as the ones that were evaluated today could potentially be performed if segmentation quality was improved. If this is the case, the identification of individual crowns and their spatial location could allow a glimpse at the stand density and stocking levels, another very important management tool. It is likely that improvements in these methods will come with improvements in technology and optimization of software parameters.

There are a number of improvements that could be addressed in future work for this study area that could greatly improve the segmentation quality and the estimation of forest stand characteristics. The segmentation error is the most distinct issue in this project and addressing ways to improve this should be the primary emphasis of future work. Without accurate estimates of the number of tree crowns that exist in a forest stand, the number of stems cannot be accurately assessed. The number of trees in a stand is a pivotal piece of information in conducting forest inventory. The use of hyperspectral data flown on UAS would be an addition to the dataset that would provide researchers a new perspective on the question of how much data and what kinds of data are really the best for performing a tree crown segmentation in mixed hardwoods. The use of stands of varying stem densities would also be of use to evaluate the threshold of stand density that these methods are suitable. These stands could be open plantations, thinned stands or stands that had undergone intermediate treatments like timber stand improvement or shelterwood harvest techniques. The question of how high of spatial resolution is necessary for quality segmentation has yet to be answered and should be addressed in future studies.

Another approach to improve segmentation could be to set eCognition parameters to intentionally oversegment the tree crowns and then manually merge some polygons that represent a single tree crown. This would be a less autonomous process but may yield better results.

Addressing the lack of species level data for this study would also be a need for future improvements. Without this data, the inventory cannot be completed with each species having different form characteristics affecting the volume of the trees as well as monetary values for individual trees. Improvements to the relationships of crown area to DBH as well as how merchantable height is derived need to be improved. The crown area and DBH relationship may be improved by separating out site specific crown and DBH data to produce a dataset that is specific to each site. Introducing total height into that equation may also improve this relationship. The use of SfM and LiDAR derived total height measurements and their relationships to merchantable height, using field total height and merchantable height ratios for each specific site, may be an approach that would yield better results than utilizing species specific coefficients and an estimated DBH to predict merchantable height.

The creation of a reference dataset for even small areas throughout the five research sites should be another focus for future studies. A reference dataset would allow researchers to more objectively evaluate segmentation quality. This could be done through accurate field GPS measurements of tree crown locations or using stands of lesser density and apply another segmentation method such as the local maxima watershed segmentation method. A comparison between these two common segmentation methods should also be assessed to understand if the use of photogrammetric methods or the use of primarily the SfM would be the best approach for segmentation. The collection of winter and spring imagery should also be performed to complete the seasonal dataset and perform a

more robust test on which time is best to implement these methods for a forest inventory.

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