EVALUATION OF AIRBORNE LIDAR TO ESTIMATE TREE HEIGHT IN A DENSE FOREST CANOPY

by

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ABSTRACT

EVALUATION OF AIRBORNE LIDAR TO ESTIMATE TREE HEIGHT IN A DENSE FOREST CANOPY

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George Mason University, Spring 2018

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The focus of this research will consider the application of Light detection and ranging (Lidar) to forestry and military terrain analysis. Lidar is a remote sensing technology that uses light in the form of a pulsed laser to measure ranges; it can provide a three dimensional image into structures, providing information extraction opportunities for use in civilian and military settings. Previous forestry Lidar research reports strong correlation and acceptable root mean squared error (RMSE) observations. Much of this research was conducted in simple forest conditions and have not been rigorously assessed in areas of more complex plant morphology. The primary objective of this thesis was to explore the suitability of an airborne, discrete return Lidar dataset to estimate tree heights in a dense, forested environment in Beltsville, MD using commercial software. Linear regression was used to relate field to Lidar tree height data with an R^2 correlation of 0.0008. Results comparing the Lidar canopy height model to field data by human interpretation had an R^2 correlation of 0.33 and an RMSE of 6.54 meters. The Lidar canopy height models explained little to none of the field-observed tree height

variation. These results were unexpected considering previous research, but fall in line with recent discussions and efforts to address the complexities and sources of error associated with relating field data to airborne Lidar in dense forest canopies. Future research should include exploration of different software, recently published standards of government agencies and professional societies, and altering data collection parameters.

CHAPTER ONE: INTRODUCTION

Remote sensing has drastically changed the way humans observe and understand the environment. Aerial and satellite imagery have assisted with many advances in modeling, mapping, and understanding natural processes on the earth's surface. While this technology has greatly assisted in areas such as military reconnaissance and interpretation of the environment, this information is only represented in a two dimensional or horizontal space. With the advent and incorporation of Light Detection and Ranging (Lidar) sensors on aerial or satellite platforms, this technology has shown promise in providing a three dimensional look into natural phenomena for many application areas.

The past few decades have seen an increase in developments of Lidar sensors, along with a variety of commercial software and algorithms to better manipulate the Lidar point cloud data and produce Digital Elevation Models (DEMs). This technology has opened new opportunities for information extraction for use in civilian and military settings. Today, airborne Lidar can be obtained from a number of providers with different system options depending on the application area for the data (E. P. Baltsavias, 1999b; Evans, Hudak, Faux, & Smith, 2009; Vauhkonen, Maltamo, McRoberts, & Næsset, 2014). Lidar can offer a cost-effective alternative to the traditional field based or two dimensional remote sensing methods (Jakubowski, Guo, & Kelly, 2013; Vauhkonen et al., 2014). Coupling this remote sensing technology with the growing number of options for analysis with different computer software, it is easy to see how Lidar can assist greatly in understanding the environment. Application areas include topographic mapping, military terrain analysis, hydrology, archeology, forestry, and bathymetric and coastal mapping (Lim, Treitz, Wulder, St-Onge, & Flood, 2003; Meng, Currit, & Zhao, 2010). The focus of this research will consider the application to forestry and military terrain analysis.

The primary objective of this thesis is to explore the suitability of an airborne, discrete return Lidar test dataset to estimate individual tree heights in a dense, forested environment. This will be accomplished by utilizing tools for processing Lidar and review the limitations of these software tools, algorithms, and the data. The tree height extracted from Lidar data using ENVI Lidar 5.4 (Harris Geospatial Solutions, Inc, 2018a) will be compared to field collected data using regression analysis to evaluate the accuracy of the two data sets in deriving accurate tree characteristics.

Chapter two will provide a description of the brief history and technical characteristics of a Lidar system. It will also include an overview of Lidar application areas by foresters and the military and how some of the current and emerging technology is being used in these sectors.

Chapter three will introduce in detail the study area and data sets to be analyzed. In Chapter four, the data analysis and descriptions of inputs, software tools, and evaluation techniques are discussed.

After discussing the results, Chapter five will provide an overall summary and commentary on the software, algorithms, and data used and provide suggestions for future work.

CHAPTER TWO: BACKGROUND

Section 2.1: Basic Principles of Lidar

Similar to radar, Light Detection and Ranging (Lidar) is an active remote sensing technology that is designed to transmit and receive backscattered energy to create an image of the earth's surface (Campbell, 2011; National Oceanic and Atmospheric Administration (NOAA), 2012). Unlike most optical sensors that only represent the horizontal distribution, Lidar can also directly measure the vertical (3-dimensional) distribution of surface features such as vegetation and/or buildings. Lidar uses a pulse of laser light to measure the roundtrip time between the sensor and an object. This elapsed time from the initial laser pulse to the return is converted into distance (Bachman, 1979; Baltsavias, 1999a). The use of airborne Lidar can be traced back to the 1990s with the integration of GPS and INS used to accurately position and record data (Shan & Toth, 2009; Vauhkonen et al., 2014).

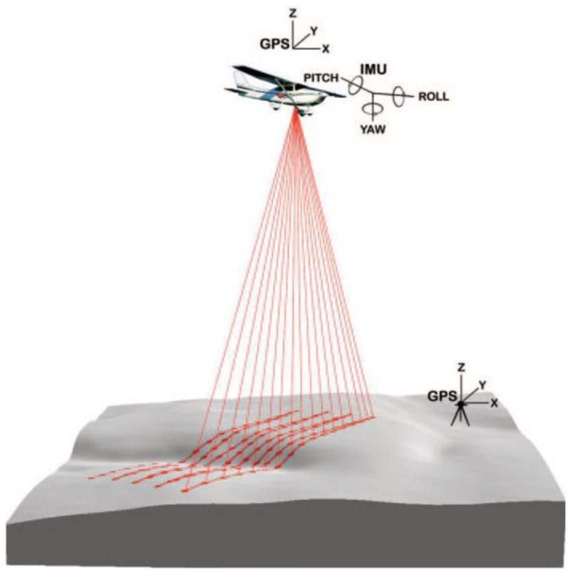


Figure 1. A representation of airborne Lidar data collection on bare earth (Reutebuch, Andersen, & McGaughey, 2005).

Section 2.2: Technical components of Lidar systems

Lidar systems can be either terrestrial, space borne, bathymetric, or airborne, but for the purposes of this paper, only airborne systems will be discussed in greater detail (Leeuwen & Nieuwenhuis, 2010). The airborne platform is either a helicopter or fixed-wing aircraft. While there can be design variations in Lidar sensors, there is still a set of typical system components onboard the airborne platform. This system typically consists of an inertial measurement unit (IMU) to record the orientation, a global positioning system (GPS), computer interface for data storage, and a laser scanner to measure distance to target (Reutebuch, Andersen, & McGaughey, 2005; Weng, 2011; Wulder et al., 2012). Also required is a GPS base station on the ground nearby (within 50 km). The laser beam is directed to its target by either rotating and/or oscillating mirrors or by a series of fiber optics (Leeuwen & Nieuwenhuis, 2010; Reutebuch et al., 2005; Shan &

Toth, 2009; Wehr & Lohr, 1999). This creates a band or swath of sampled points that can be gridded into an image (Lefsky, Cohen, Parker, & Harding, 2002). The following commercial scanners commonly used for Lidar systems are the Optech ALTM-series, Leica ALS-series, RIEGL LMSseries and the TopoSys Falcon series (Leeuwen & Nieuwenhuis, 2010; Wulder et al., 2012). Figure 2 represents a typical airborne Lidar system, taken from Weng (2011).

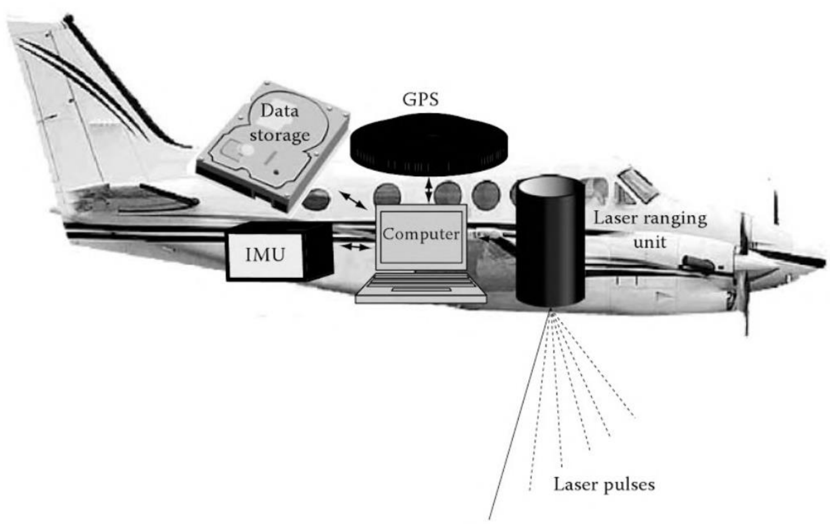


Figure 2. Airborne Lidar unit, taken from Weng (2011).

Airborne Lidar systems can be categorized as either discrete return or full waveform, each unique in how data is sampled. While a brief description will be given concerning full waveform systems, discrete return systems are the focus of this thesis.

The full waveform system collects all the reflected energy from a return, so it includes the entire record of all the vertical distribution information, including height (Hollaus, Mücke, Roncat, Pfeifer, & Briese, 2014; Mallet & Bretar, 2009). Waveform systems tend to be less common and did not gain much recognition in the literature until about a decade ago, and were not available for small-scale operational data acquisition until 2004 (Hollaus et al., 2014). According to Anderson, Hancock, Disney, & Gaston, (2016) and Evans et al. (2009)**,** this could be attributed to the lack of computer software and storage for the high data volumes associated with the higher number of returns and more dense point cloud. According to Cao et al. (2014) and Lefsky et al. (2002), there are negligible differences in estimating heights of features and deriving elevation models from waveform versus discrete systems. As mentioned by Chen, Gao, & Devereux (2017), this could likely be attributed to the fact that most researchers decompose the full-waveform into dense point clouds. Both systems can associate the last returns with the ground, when it may in fact be the height of dense understory growth (Lefsky et al., 2002). Additionally, waveform data requires that the end user has a good understanding of the complex signal interactions the sensor pulse can have in different environments. Despite these inherent complexities, waveform data are likely to continue to gain more recognition as a research tool as more signal processing approaches are discovered and other application areas are identified (Anderson et al., 2016; Mallet, Bretar, Roux, Soergel, & Heipke, 2011).

In contrast, discrete return systems allow for single/last returns or multiple returns to be recorded for each pulse (Evans et al., 2009; Lefsky et al., 2002). The term “pulse” refers to the laser signal sent out from the Lidar system (Jakubowski, Guo, et al., 2013). As mentioned by Gatziolis & Andersen (2008), frequently used alternatives to the term “return”, are “point” and “echo”. Each time the laser signal is reflected back to the sensor, that return is considered to represent an object and recorded as a point in the system. Evans et al. (2009) and National Oceanic and Atmospheric Administration (NOAA) (2012), provide a list of Lidar related terminology. Figure 3 presents the differences between full waveform and discrete return Lidar collection.

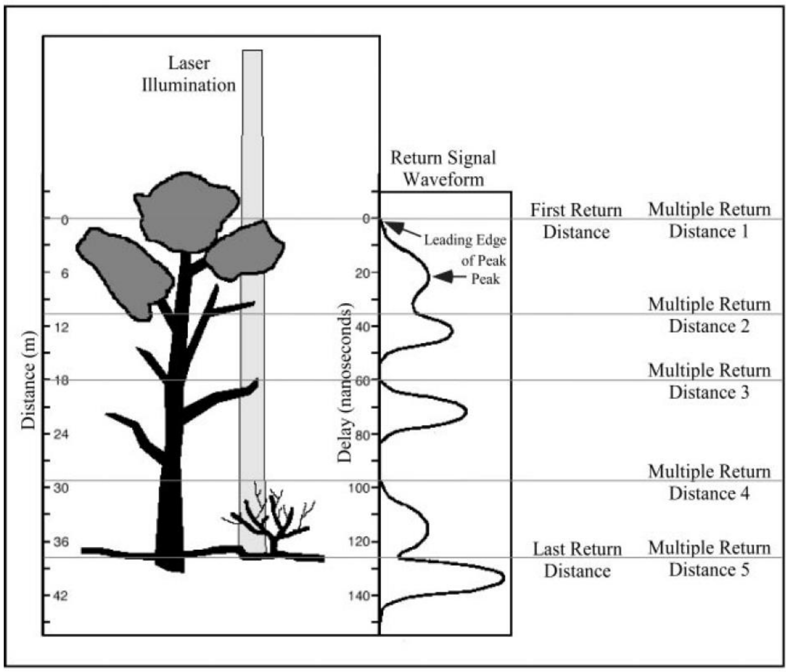


Figure 3. Representation of discrete return and full-waveform Lidar systems (Lefsky et al., 2002).

Generally, each pulse from the discrete system allows up to four to five bright returns to be recorded (Campbell, 2011; Wulder et al., 2012). These returns generate the final product: point clouds that represent different levels of intercepted features, such as the vegetation canopy, buildings, other intermediate surfaces, and the ground. This point cloud data is representative of these reflected features in georeferenced x, y, and z coordinates (Hyyppä et al., 2008). The data from the first return is representative of the first morphologically complex surface (i.e., a tree canopy), while the last return is most likely to represent the ground surface, given that the vegetation is not overwhelmingly dense (Akay, Oğuz, Karas, & Aruga, 2009; Blundell, Guthrie, & Simental, 2004; Lefsky et al., 2002). These point clouds can be of varying densities, as high as 50 points per meter squared or as low as 0.1 points per meter squared, which can total to several million points per kilometer at the higher densities (Jakubowski, Guo, et al., 2013; Lim et al., 2003; Reutebuch et al., 2005). The complexity of the surface can also have an influence on the number of points in a point cloud dataset, with 200,000 points per square mile in sub-urban area, and 350,000 points per square mile in forestland (Campbell, 2011; Reutebuch et al., 2005; Unger, Hung, Brooks, & Williams, 2014). According to Lim et al. (2003), it is recommended that computer workstations have a minimum of one GB RAM, but preferably two GB, to further process the point cloud data, in addition to what is already required for the operating system.

In using the point cloud data, researchers can create a number of widely recognized derived products, especially Digital Elevation Models (DEMs) (Reutebuch et al., 2005). It is important to note that DEM is a more generic term for models that are the best estimate of either the bare ground or surface features, or any elevation model (Chen et al., 2017). If the data collection was able to yield good last return data, then either automated or manual processing can be done to produce a Digital Terrain Model (DTM) that represents the earth surface and provides information on the terrain. Creating an estimated representation of the surface features can be created by using the first return data, referred to as Digital Surface Model (DSM) (Chen et al., 2017).

Further manipulation of these two digital models can produce a Canopy Height Model (CHM), or normalized DSM, which represents the heights of surface vegetation. The CHM can be produced in two ways, one is by subtracting the DSM from the DTM and the difference of the two rasters is the CHM (Lim et al., 2003). The second approach, accomplished by using the height above the DTM as the elevation (or z coordinate) subtract from the DTM (Khosravipour, Skidmore, Wang, Isenburg, & Khoshelham, 2015). Although both methods for calculating the CHM are conceptually simple, the accuracy of the CHM product is influenced by the acquired Lidar data, processing methods, and the conditions of the sampled area (Zhang, Zhou, & Qiu, 2015). Many studies over the past decade demonstrate that forest conditions such as site type, slope, density, species, and ages can influence the Lidar end products and performance of tree detection algorithms (Falkowski et al., 2008; Khosravipour et al., 2015; Vauhkonen et al., 2012; Yu, Hyyppä, Vastaranta, Holopainen, & Viitala, 2011). A good review of these challenges and attempts to address them can be found in Næsset, (2014).

There are a number of advantages to discrete return systems. They are preferable for the detailed mapping of the ground and canopy surfaces due to their high repetition rates (Vauhkonen et al., 2014). The result is high resolution data with dense distributions of sampled points, which is helpful when trying to amass data from different scales and areas, and in trying to pinpoint locations or features on the ground (Lefsky et al., 2002). Additionally, these discrete return systems tend to be more cost effective when the operation is over larger areas (Leeuwen & Nieuwenhuis, 2010). Small footprint discrete return systems are between 0.2 to 1 meter, and large footprint are 10 meters or greater

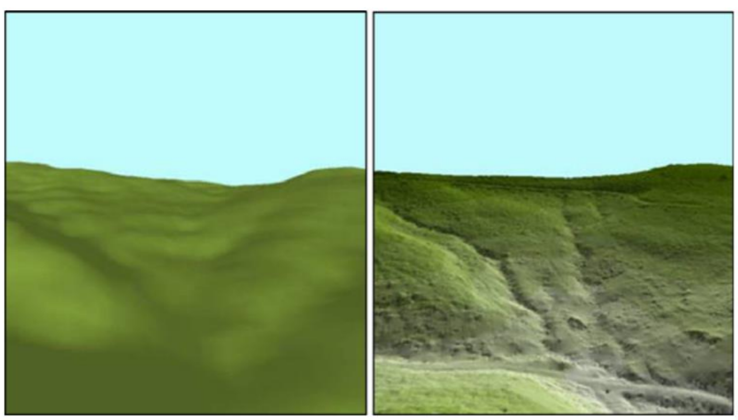
(Duncanson, Cook, Hurtt, & Dubayah, 2014; Evans et al., 2009; Lim et al., 2003; Thenkabail, 2015; Wulder et al., 2012).

Section 2.3: Selected applications--Military

For military applications, there is a need to understand the terrain conditions and the spatial arrangement of features as they can affect military operations and decision making. Historically, remotely sensed data has provided rapid assessment of the environment at high resolutions and still is an integral part of reconnaissance (Campbell, 2011). Many of the methods of terrain evaluation arose from mostly military needs, which can be further reviewed in Falls (1948), Whitmore (1960), Broughton & Addor (1968), Parry (1984), Rose & Nathanail (2000), and Harmon & McDonald (2014).

It should come as no surprise that the impact of imperfect intelligence can be potentially disastrous and cost lives and resources. The battlefield has demands for adaptive and predictive information flows, where time is the limiting factor (Hardaway, 2011; Whitmore, 1960). Information such as surface and terrain features can change dramatically between the time of data collection and data delivery. For example, an artillery strike can create an impasse from what was once a bridge or road, or buildings can be leveled and obstruct movement of mounted/dismounted troops. According to U.S. Army (2008), commanders and their staff must conduct continuous assessment of the factors of terrain, troops and mission objectives. At the battalion and company level, being able to disseminate information directly to commanders can greatly improve situational awareness and tactical maneuvers (Blundell et al., 2004). Evaluation of various biophysical and geophysical surface characteristics are a part of classical military terrain analysis (Krause, Puffenberger, Graff, & Gard, 2003). These characteristics include surface materials and configuration, water resources, soil type, and details about distinctive vegetation cover types. Databases for terrain analysis have specifications for vegetation structural variables, such as tree height, canopy closure, stem spacing and diameter, to name a few (Krause et al., 2003). This terrain and surface feature data are considered critical terrain elements and are provided to commanders to assist with mission planning details and generating analysis for line-of-sight, potential threats along supply routes, bivouac sites, and helicopter landing zone suitability (Blundell et al., 2004; Hardaway, 2011). For example, if commanders are looking at areas for vertical or helicopter takeoff, knowledge of low-level areas protected by valleys, ridges and forests are especially helpful in producing products such as ‘air movement maps’ (Whitmore, 1960).

While traditional nadir remote sensing imagery has shown itself to be a useful aid for intelligence collection and mobility work over urban and/or complex terrain, there are still a number of biophysical parameters that are under taller/wider dominant features that cannot be measured directly with this technology (Krause et al., 2003). High resolution Lidar data can assist with modeling terrain with vegetation to provide assessment of mobility and obstacle determination in a timely manner. These terrain obstacles are considered to be ‘gaps’ in a commander’s knowledge and ability to accomplish tactical maneuvers over land. Many of these ‘gaps’ fall within the error limits of standard elevation datasets such as the U.S. Geological Survey (USGS) Digital Elevation Models (Blundell et al., 2004). In an attempt to fill these ‘gaps’, airborne Lidar has been used more frequently to model complex terrains with a diversity of features (Lee et al., 2016). An example of complex terrain includes forested environments, which can have many effects on cross-country mobility, concealment for troops, airdrops, and construction materials (U.S. Army, 1990). Along with providing camouflage, dense vegetation also creates problems for movement of wheeled vehicles, along with slowing down dismounted troops. Understanding the spacing of trees is also advantageous, as some armor and wheeled vehicles can move between them if the understory is not impeding mobility (U.S. Army, 1972, 1990). Figure 4 provides an example of a Lidar-based DEM compared to a USGS DEM created from the same forested area, as mentioned in Akay et al. (2009).



a b

Figure 4. USGS DEM in (a) and Lidar based DEM in (b) (Akay, et al. 2009).

While airborne Lidar has shown to be more accurate in estimating terrain and vegetation surface features than optical remote sensing alone, it is important to note that it can be less effective in terrain modeling in dense, interlocking forest canopies and/or topographically complex areas (Leitold, Keller, Morton, Cook, & Shimabukuro, 2015). Because of Lidar's pointwise sampling nature, the laser data must be interpolated, which can introduce error into the DTM depending on the interpolation methods and the grid spacing chosen (Chen et al., 2017; Hyyppä et al., 2004; Suárez, Ontiveros, Smith, & Snape, 2005). As stated by Andersen, Reutebuch, & McGaughey (2006), the local area directly below the tree crown can cause a reduction in the DTM quality, attributed to the lower number of pulses reaching the ground. The authors also mention that ground vegetation and terrain relief can introduce variability of up to 0.5 meters in any measurements of height, especially in trees. Any inaccuracies in the DTM will propagate into the CHM (Leitold et al., 2015; Vauhkonen et al., 2014). Some researchers have attempted to improve the DTM accuracy by collecting during leaf-off conditions so pulses can better reach the ground and be intercepted only by tree branches (Gatziolis, Fried, & Monleon, 2010; Hawbaker et al., 2010) . Research efforts have focused on addressing known issues with canopy penetration capability, where the resulting point cloud under samples the understory and DTM (Lee et al., 2016; Leitold et al., 2015). For a more detailed comparison of DTM extraction methods from point clouds, the reader is pointed to Sithole & Vosselman (2004), Liu (2008), Meng et al. (2010), and more recent work by Chen et al. (2017).

While these research efforts on improving accuracy of the DTM are promising, the commercial/business environments tend to favor interpolating the point cloud into rasters because of relatively faster processing speed and easier access to software well suited to use rasters (Zhang et al., 2015). Some drawbacks to using these licensed software suites in business environments include the use of proprietary methods to process the point cloud data into the various derived products (Lefsky et al., 2002; Lim et al., 2003; Sithole & Vosselman, 2003). Additionally, many researchers develop and provide recommendations for DTM generation methods, but sometimes do not provide detailed explanation or feasible way to carry out these recommended algorithms or methods (Chen et al., 2017; Sithole & Vosselman, 2003; Unger et al., 2014).

Section 2.4: Selected applications--Forestry

Along with terrain visualization, it is possible for Lidar to produce point cloud data consisting of multiple returns that allow researchers to collect detailed information about the surface vegetation, especially in forests. Lidar data collection, compared to traditional field survey methods, can be performed more rapidly and in a cost effective manner (Andersen et al., 2006; Kangas, Eid, & Gobakken, 2014; Sibona et al., 2016; Vauhkonen et al., 2014). Typically, the systems used for forest inventory are airborne, discrete return systems and the common wavelength used is 1.064 μm (Evans et al., 2009; Leeuwen & Nieuwenhuis, 2010). This wavelength is used due to its ability to penetrate the atmosphere and that vegetation reflects strongly in these wavelengths (Evans et al., 2009; Kumar, Schmidt, Dury, & Skidmore, 2002; Lefsky et al., 2002; Wehr & Lohr, 1999). For reference, Figure 5 presents a detailed look at the vegetation spectrum, taken from Harris Geospatial Solutions, Inc. (2018b).

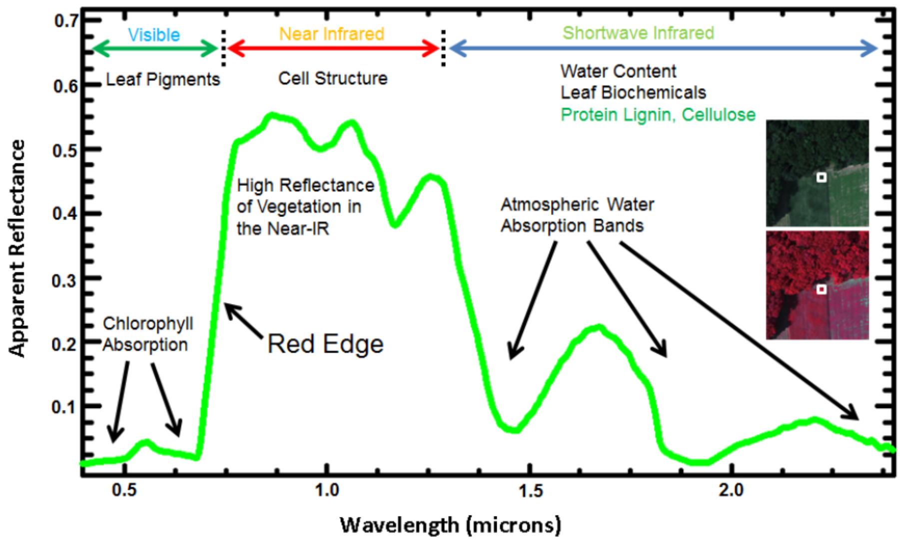


Figure 5. Vegetation spectrum (Harris Geospatial Inc., 2018b).

Traditionally, field surveys, along with aerial photos and photogrammetric techniques, were the primary method for collecting information related to forest characteristics. While these methods can produce reliable information about the forest, they do have a few drawbacks (Næsset, 2014). The primary disadvantage of these techniques is that they can be time and labor intensive, highly subjective, and difficult to carry out over a very large area (Falkowski et al., 2008; Sexton, Bax, Siqueira, Swenson, & Hensley, 2009), especially in areas where the forest canopy is dense and the bare ground cannot be viewed from aerial or satellite imagery (Lefsky et al., 2002). Writing by Ackermann (1999) and Baltsavias (1999) provide a more detailed comparison of photogrammetry and airborne laser scanning.

The early 1980s saw the first application of airborne Lidar for forest inventory, and by the early 2000s many foresters had adopted the use of airborne Lidar point cloud data and geographic information systems (GIS) to supplement information from field sample surveys (Hyyppä et al., 2008; Leeuwen & Nieuwenhuis, 2010; Næsset, 2014). In order to compare the ground truth data to the Lidar data, these studies use inventory techniques referred to as an area-based approach, an individual tree approach, or some combination (Kaartinen et al., 2012; Sačkov, Santopuoli, Bucha, Lasserre, & Marchetti, 2016; Vauhkonen et al., 2014). A few studies that used individual tree approach can be found in Persson, Holmgren, & Soderman (2002), Koch, Heyder, & Weinacker (2006), Jakubowski, Li, Guo, & Kelly (2013) and Hamraz, Contreras, & Zhang (2017). Research by Næsset (2002), Hansen, Gobakken, Bollandsås, Zahabu, & Næsset (2015), Sibona et al. (2016), and Lindberg, Holmgren, Olofsson, Wallerman, & Olsson (2010) provide examples of area-based techniques. An extensive discussion of these inventory techniques can be viewed in Næsset (2014) and Vauhkonen et al. (2014).

In the typical Lidar point cloud for forested environments, the returns represent different levels of the canopy, intermediate growth, and ideally the ground surface (Akay et al., 2009; Dong & Chen, 2017). Figure 6 represents an ideal situation in which Lidar scans a forested environment.

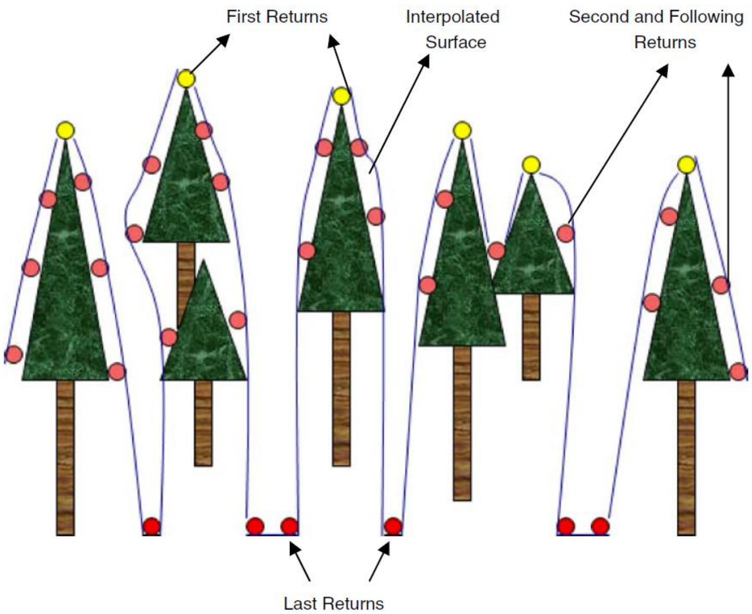


Figure 6. Lidar returns in a forested area (Akay, et al., 2009).

Since forests are three-dimensional systems, Lidar point cloud data can capture information such as location of individual tree tops and individual tree height (Dong & Chen, 2017; Unger et al., 2014). Segmenting the individual tree top and estimating height is useful to identify other information such as crown diameter, which in turn is helpful as input for growth estimation or allometric models, forest biomass, and carbon stocks (Andersen et al., 2006; Hansen et al., 2015; Lefsky et al., 2002; Mauya et al., 2015; Vauhkonen et al., 2014). Figure 7 presents a few fundamental tree parameters that can be estimated with Lidar, taken from Zhang et al. (2015).

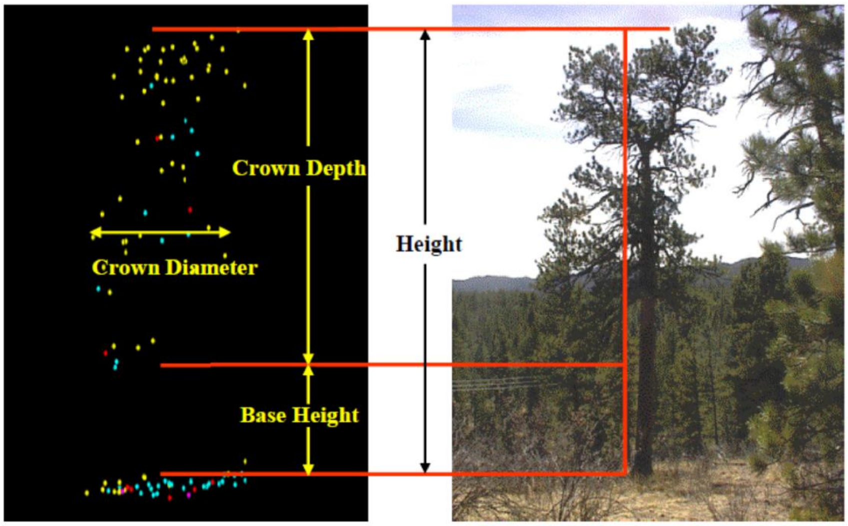


Figure 7. Tree metrics that can be captured with Lidar point clouds (Zhang et al., 2015).

All of the above are tied to understanding and monitoring forest health, photosynthetic activity, and carbon cycle processes (Hyyppä et al., 2012; Khosravipour et al., 2015). Other information such as canopy disturbances, plant growth, leaf area index (LAI), and percent canopy cover can be well characterized at both the plot and individual-tree level (Cao et al., 2014; Dubayah & Drake, 2000; Trochta, Krůček, Vrška, & Král, 2017). In some cases, Lidar can also measure sub-canopy topography and can increase the accuracy for topographic maps (Lee et al., 2016; Lefsky et al., 2002). Lidar can also improve fire and fuel management plans, scheduling harvesting, and designing roads (Akay et al., 2009; Reutebuch et al., 2005). Figure 8 provides a visual representation of the general categories of Lidar in forestry, as mentioned by Dong & Chen (2017).

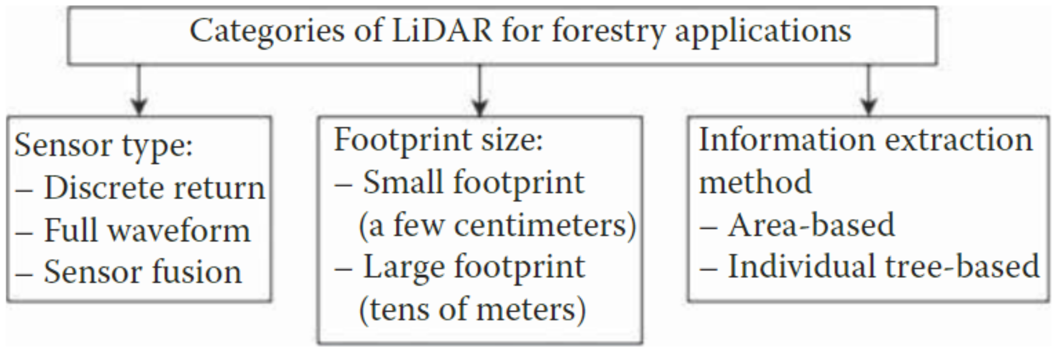


Figure 8. Representation of Lidar for forestry applications (Dong and Chen, 2017).

Much of the research conducted in the early 2000s demonstrated that incorporating Lidar technology greatly assisted forest researchers in measuring biophysical parameters such as mean height, basal area, and volume (Dong & Chen, 2017; Lim et al., 2003; Sibona et al., 2016; Vauhkonen et al., 2012). The regression models showed promising results with good r-squared and root mean squared error (RMSE) values areas where airborne Lidar was compared to plot level and/or individual tree biophysical characteristics (Næsset, 2014; Vauhkonen et al., 2014). A table of the results of several studies are outlined in Leeuwen & Nieuwenhuis (2010). A review and comparison on an international scale of Lidar-based tree detection methods can be found in Kaartinen et al. (2012). Similar research from Vauhkonen et al. (2012) compares fewer algorithms, but has greater variation in forest type. According to Falkowski et al. (2008), there are a handful of widely-used techniques used to automatically detect trees. These methods include: feature matching, local maximum filtering, object-based methods, variable window filters, and image segmentation. Over time, studies have shown an increased complexity in approaches to increasing the accuracy of the results. That is to say, there has been an increase in the use of just Lidar point cloud to extract individual trees instead of transforming the data into a raster (Jakubowski, Li, et al., 2013). A brief comparison of several automated segmentation methods can be found in Zhang et al. (2015).

The drive for segmenting trees from the point cloud is that pixel-based CHMs introduce errors and uncertainties due to both the interpolation methods used in the DTM and also the spacing of each grid cell (Zhang et al., 2015). According to Khosravipour et al. (2015) and Gatziolis et al. (2010) forest terrain/topography can also distort the CHM. Additionally, the scanning density and forest canopy structure can also mean that suppressed or intermediate growth trees are not usually detected (Hyyppä et al., 2012; Leeuwen & Nieuwenhuis, 2010; Lim et al., 2003; NOAA, 2012; Vauhkonen et al., 2012). Often, this is where the error comes from since tree delineation algorithms for Lidar data might not work on irregularly shaped and/or overlapping canopies (Unger et al., 2014). Many earlier studies (as early as 1995) using airborne Lidar were done in similar geographic regions (i.e., conifer-dominant forests), which facilitated easy comparison between studies (Hansen et al., 2015; Næsset, 2014). As mentioned by Gatziolis et al. (2010) and Sačkov et al. (2016), nearly all evaluations of Lidar suitability have been carried out in simple forest conditions. That is to say, areas of gentle topography, open canopy, homogenous species and/or age class, and/or little to no understory. While these studies were helpful in demonstrating the usefulness of airborne Lidar, in the early 2000s there were many researchers that began investigating the errors from the DTM and how such artifacts effect the CHM (Gatziolis et al., 2010; Leeuwen & Nieuwenhuis, 2010). A common issue is that the laser scanning samples the tree crown shoulder or various positions along the canopy surface, causing the CHM to represent underestimated tree heights (Dorigo, Hollaus, Wagner, & Schadauer, 2010; Gatziolis et al., 2010; Hyyppä et al., 2012; Lim et al., 2003; Popescu, Wynne, & Nelson, 2002). This has been an issue associated with, but not always limited to, Lidar systems that have footprints that are too small, presenting difficulties in detecting the true height of the tree canopy (Lefsky et al., 2002; Lim et al., 2003).

While algorithms for processing the point cloud data can perform well on a coniferous forest, it does not guarantee the same results in study areas with different plant morphology, such as a tropical mixed forest or broad-leaved deciduous forest (Maltamo et al., 2005; Unger et al., 2014). As mentioned by Sačkov et al. (2016), performances of processing techniques and algorithms have not been assessed at great lengths in these areas of more complex plant morphology. In more dense forests where the dominant or codominant trees clump together, the canopy can obscure the understory (shade-tolerant smaller trees) and ground (Dong & Chen, 2017; Hamraz et al., 2017; Lefsky et al., 2002). This is mostly attributed to the branches and leaves causing absorption or scattering of the laser pulse energy, which results in fewer, if any, backscatter returns from the actual ground (Dong & Chen, 2017; Shan & Toth, 2009).

Being able to retrieve an accurate tree height from Lidar data is essential since it is an input for growth models, forest biomass, and terrain analysis, but easy to see how complicated such a task can be in dense, forest types of different age classes and areas of varying topography. The necessary procedure of generating a reliable DTM can require extensive processing, somewhere between 60% to 80% of processing time (Chen et al., 2017; Evans et al., 2009; Sithole & Vosselman, 2003). Despite these complexities, exploring the options for either a semi-automated or automated process for generating a reliable DTM and CHM is a worthwhile endeavor.

CHAPTER THREE: MATERIALS AND METHODS

In reviewing the literature, it has been demonstrated that airborne discrete Lidar coupled with field data collection and different software packages can provide relatively good estimates in modeling terrain for the military or natural resource management. In trying to explore the suitability of BuckEye Lidar test data in a dense, forested environment, the following questions were asked:

1. Are ENVI and ENVI Lidar 5.4 viable options to produce DEMs and estimate individual tree heights in a forested environment when compared to field data processed in ArcGIS 10.5.1?
2. Can the Lidar point cloud density be reduced (decimated) and still achieve the same results?

A description of the study area, collection of the ground truth data, and software tools used are provided in the subsequent sections.

Section 3.1: Study Area Description

The study area falls within the Beltsville Agriculture Research Center (BARC) located in Beltsville, MD (Figure 9). The land is owned by the U.S Department of Agriculture-Agriculture Research Service (USDA-ARS), but the surrounding forested areas have experienced little anthropogenic influence and are considered to be a mature forest. The area experiences a mean annual precipitation of 40 to 50 inches. The physiographic province at this location is best described as the upland coastal plain and the topography is generally flat. The forest composition is best described as deciduous stands and mixed deciduous-coniferous stands of different age classes.

Figure 9. Study area in Beltsville, MD. Imagery from the BuckEye test data collection.

Section 3.2: Ground reference data

The ground truth data collection took place in the leaf-on season in late June 2017. The field data for the plots were collected in a 6.5 hectare area within the BARC. The location (x,y) of the plot center and each tree was determined by bearing and distance using a distance tape and a compass. This method was chosen for a few reasons.

Taking the bearing and distance expedited the data collection while in the field and also are in line with basic forest inventory techniques found in The University of Tennessee Agricultural Extension Service (2009) and chapter four of Avery & Burkhart (2015). Alternative options, such as using a differential GPS, would take time to assess positioning accuracy, which could still suffer (up to several meters) with the dense canopy in the study area (Dorigo et al., 2010). A discussion on GPS accuracy can be reviewed in Valbuena (2014). Additionally, the plot centers are all reasonably accurate, since the first plot center uses a property corner easily seen from imagery, and all subsequent plots can be traced back to this with a known distance and azimuth.

The first plot was established by walking 130 feet west of the northwest corner of the crop test field fence post. Subsequent plots were between 125 to 150 feet apart from each other and were established at random while in the field at either a north, south, east or west bearing. Each plot was assigned an identification number. A small wire flag was placed in the center in the ground to mark each plot, along with ribbon tape to mark the closest tree (Figure 10).

Figure 10. Example of marking field plots.

Within each 10 meter fixed-radius plot, trees were tagged by using chalk to draw a unique identification number. The following attributes were recorded for each tree using standard forestry measurement techniques shown in Avery & Burkhart (2015):

- species
- diameter at breast height (inches) [DBH]
- height (feet)
- canopy position
- distance and bearing from plot center

The estimated heights of all trees were measured using a Nikon Forestry PRO Laser Rangefinder/Hypsometer electronically measuring distance and angle (Nikon Corporation, 2011). Because line of sight was somewhat obstructed for certain trees, this height measurement was taken by two individuals pacing the forested area in an attempt to record a more accurate individual tree height.

Using tree diameter tape, DBH was recorded. Within the 10 meter plots, only trees with a DBH of 4 inches or larger were included. Within the 5 meter plots, only trees with a DBH of 3.9 inches or smaller were included. Stem distance at DBH from the center of the plot was recorded, along with species. The trees' canopy position (dominant, codominant, intermediate, and suppressed) was recorded according to definitions found in chapter seven of Avery & Burkhart (2015). Figure 11 presents different canopy positions in a forest, taken from Smidt & Blinn (1995).

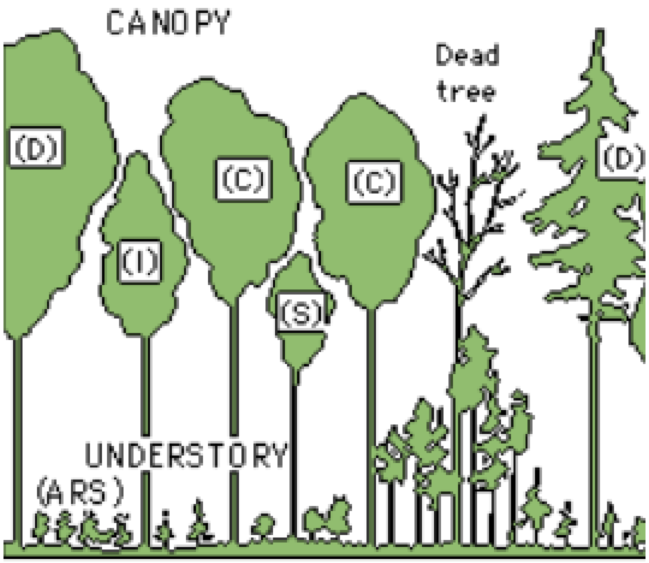


Figure 11. Representation of dominant (D), codominant (C) intermediate (I), supressed (S), and advance regeneration and shrubs (ARS) (Smidt & Blinn, 1995).

The following hardwood tree species were inventoried across the study area plots red maple (*Acer rubrum* L.), black oak (*Quercus velutina* L.), white oak (*Quercus alba* L.), red oak (*Quercus rubra* L.), and tulip poplar (*Liriodendron tulipifera* L.). Additionally, the following pine species were inventoried: Virginia pine (*Pinus virginiana* Mill.) and loblolly pine (*Pinus taeda* L.). In total, 25 plots were sampled with a total number of sampled trees equaling 410. The percentage of pine is 17.29% and the percentage of hardwood is 82.70%. There is a time difference Lidar acquisition in July 2012 and the field measurements in June 2017. However, our study area consists of mature forest and is not characterized by year-round high temperatures and rain, so we assume there is a relatively low tree growth rate (Johnson & Abrams, 2009; Waring & Running, 2007). Also, we assume that the difference in tree height due to natural growth between the time of the Lidar survey and the acquisition of ground data is negligible. This time difference in data collection is not unique to this study, and can be found in, Gould, Glenn, Sankey, & McNamara (2013), Unger et al. (2014), and Khosravipour et al. (2015).

Section 3.3: Data from BuckEye

The BuckEye Lidar test data collection is a 2 by 2 km area in July 2012 and consists of about 98 million points (Figure 12).

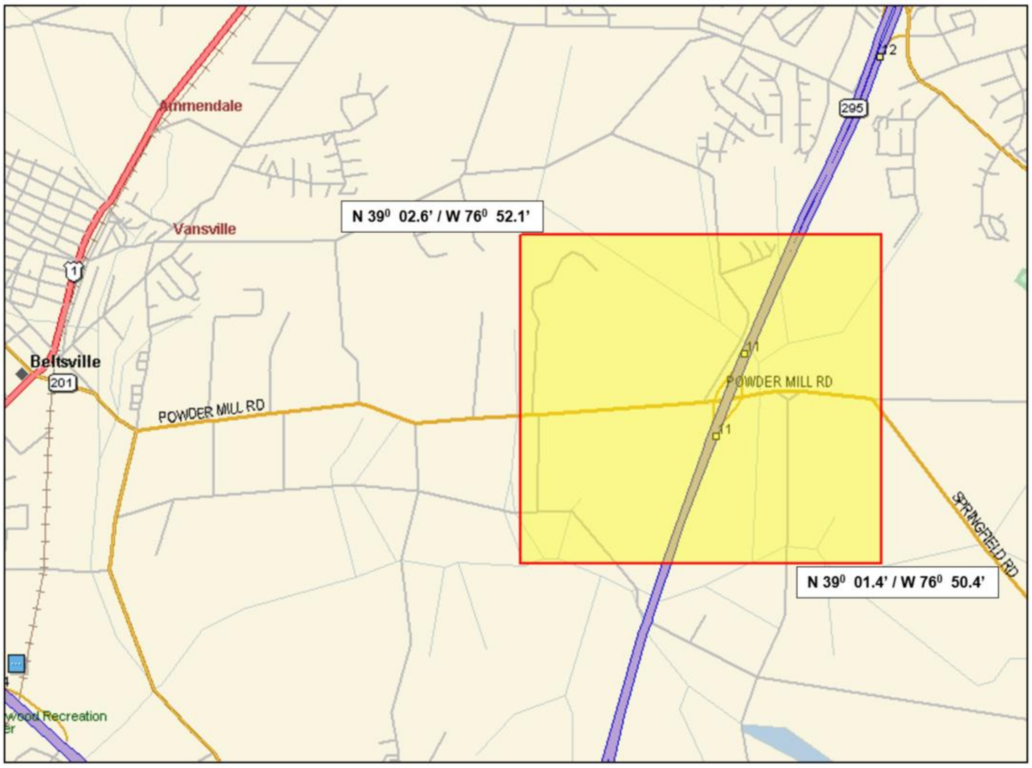


Figure 12. Lidar collection extent, as provided by the vendor.

The BuckEye system is intended for mapping/topographic data collection, so it has a relatively large footprint with a swath width of about 350 meters. The spot size is an estimated 24 to 30 inches. The aircraft was flying at 5500 feet AGL for this data collection. The point density was, on average, 10 to 15 points per m^2 with a distance between laser points (post-spacing) of 0.25 meters. According to Mitchell, Fisk, Clark, & Rounds (2018) and Heidemann (2018), this density is representative of a quality level 1 (Q1) dataset, suitable for forestry related acquisitions.

Accuracies are approximately 0.5 meter horizontal and 0.3 meter vertical. All data were delivered in the UTM 18N with respect to WGS84 G1674 ellipsoid, following the standard LAS format (American Society for Photogrammetry & Remote Sensing, 2015). BuckEye context imagery is 3-band color imagery taken with 39 megapixel color EO camera.

CHAPTER FOUR: DATA PROCESSING AND ANALYSIS

The field data discussed in Section 3.2: Ground reference data were visualized, processed, and analyzed primarily with ESRI's ArcMap 10.5.1 (ESRI, 2017). Statistics such as mean and standard deviation were calculated in Microsoft Excel.

ENVI Lidar 5.4 was primarily used to manipulate the Lidar point cloud, especially when creating raster data and estimating the locations and height for individual trees to be imported into ArcMap for further analysis.

Regression analyses were carried out in Excel using the output tables from the vector data in ArcMap.

A subset of these processing techniques are carried out following suggestions by Mitchell, Jacokes-Mancini, Fisk, & Evans (2012) and chapter four of Dong & Chen (2017).

Section 4.1: Using ENVI and ENVI Lidar 5.4

ENVI 5.4 and ENVI Lidar 5.4 are well-known software tools for image processing and visualization and are the primary software used for manipulation of the LAS file. Figure 13 provides a representation of the point cloud in the study area:

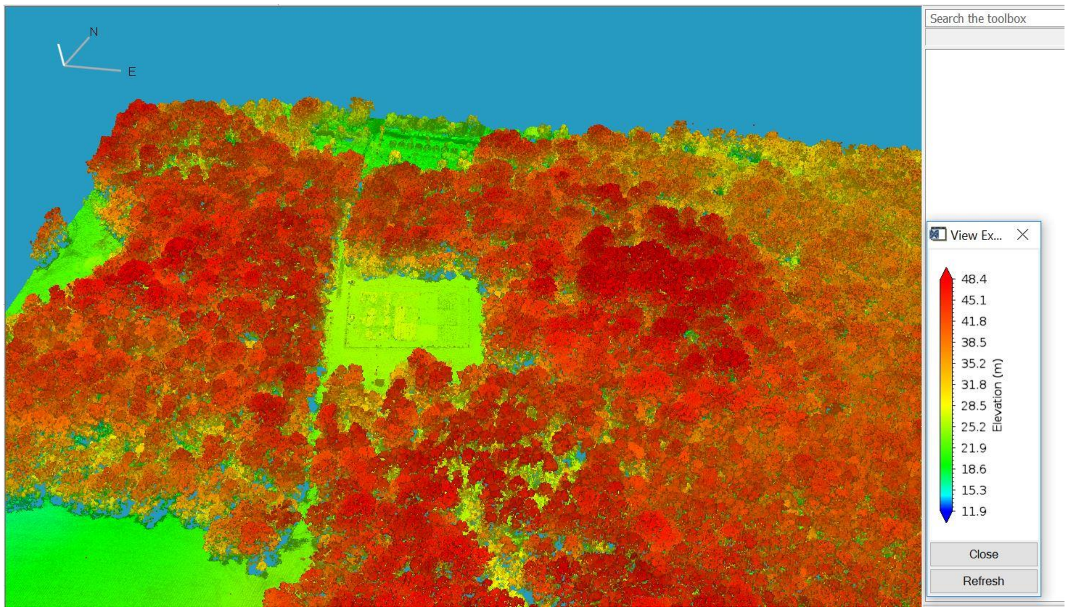


Figure 13. Study area point cloud as viewed in ENVI Lidar.

Section 4.1.1: Assessing the quality of the Lidar data

While quality assessment of Lidar data can vary case by case, methods used in this study were generally following suggestions by Dong & Chen (2017) and Mitchell et al. (2012), along with guidance from the BuckEye program's data providers. Once imported into ENVI Lidar, quality assessment of the point cloud was completed based on visual inspection within the study area. This consisted of looking for elevation outliers, any voids, gaps or artifacts with the QA tool and 3D Viewer in ENVI Lidar, as shown in Figure 14. No outliers were detected in the point cloud over the study area's sample plots, so it was deemed unnecessary to remove points before proceeding to create the DEMs and tree shapefile.

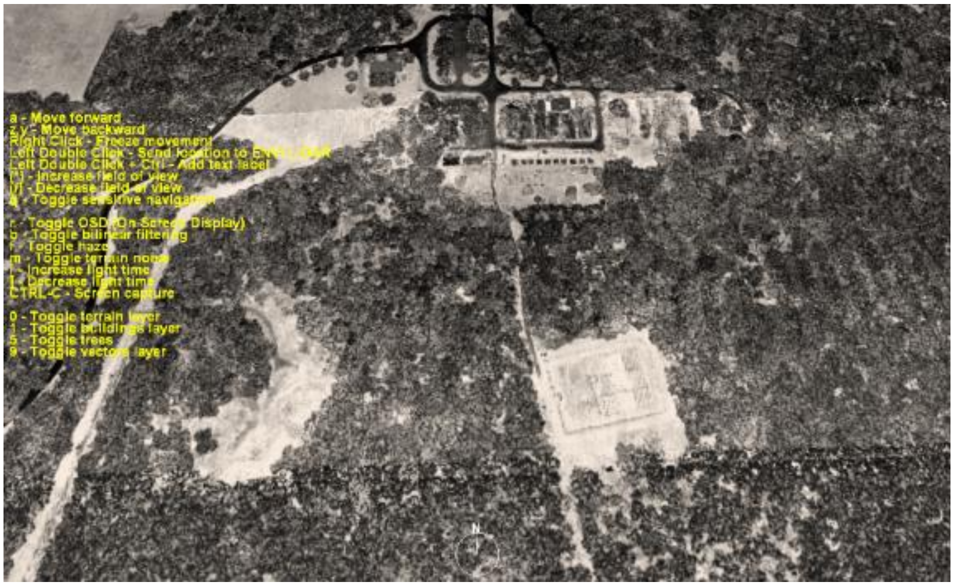


Figure 14. Using the 3D Viewer in ENVI Lidar.

Section 4.1.2: Creating DEMs and estimated trees

ENVI Lidar was used to create the DTM, DSM, and a point shapefile containing tree position (x, y location) and estimated height. ENVI Lidar determines the points that represent the last returns and create the DTM from these ground points. The methods in which the software calculates the DTM and DSM are not provided by the vendor, but is described as a combination of "crawling" and "sensitivity" algorithims according to online documentation (Harris Geospatial Solutions, Inc, 2018c). It is speculated that they use a patented method such as USOO6654690B2 (2003) or US 20070265781A1 (2007).

The grid size was set to one meter resolution. In creating the trees points, the software provides suggested default parameters for the height and DBH of the trees, and these defaults were used in this analysis. The minimum and maximum height were set to

130 centimeters and 5000 centimeters, respectively. The radius minimum for a tree was set to 200 cm and the maximum was 600 cm. The production of these can be seen in Figure 15, Figure 16, and Figure 17.

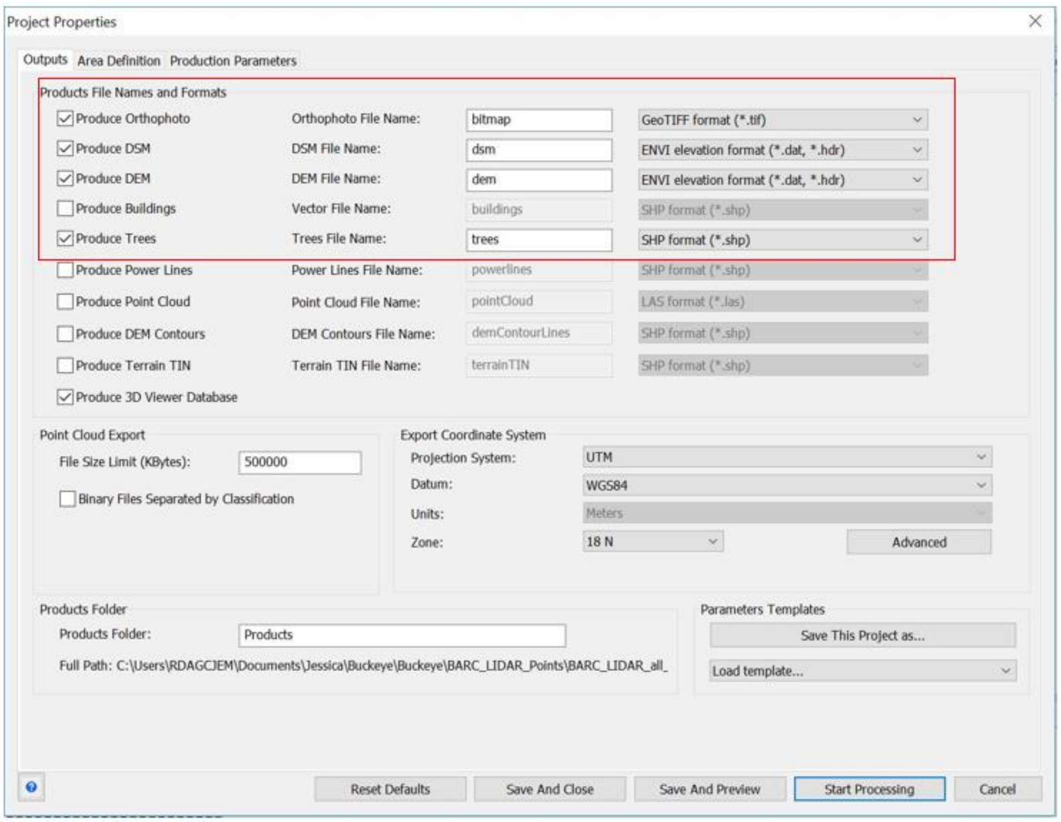


Figure 15. Project outputs, as viewed in ENVI Lidar.

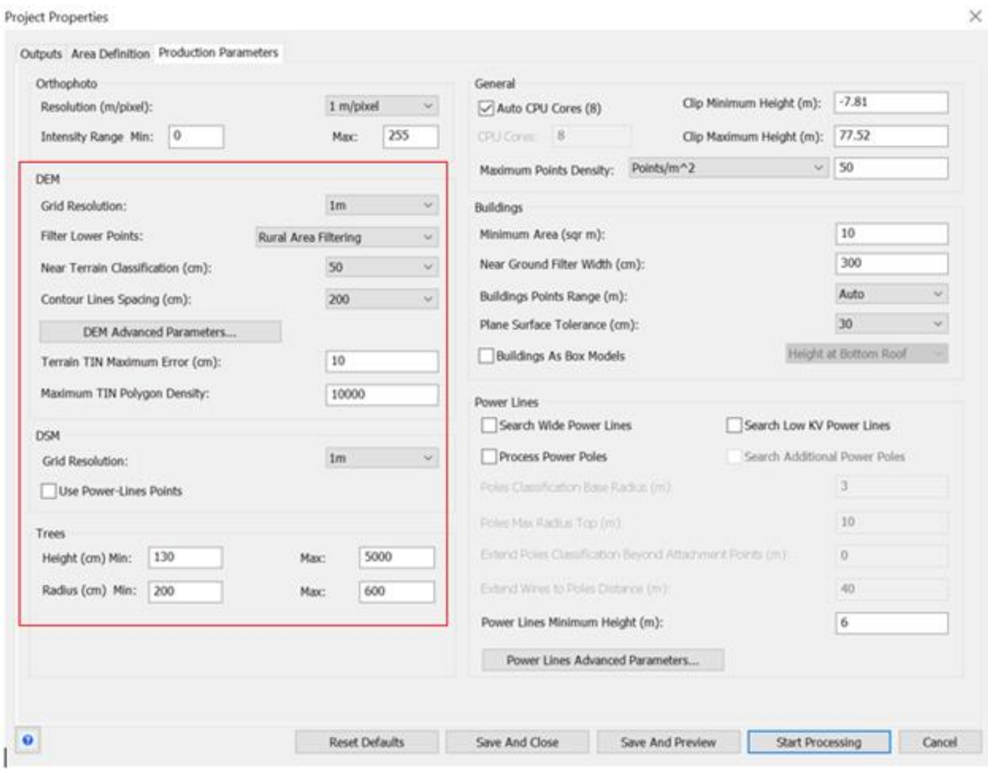


Figure 16. Parameters for the project outputs.

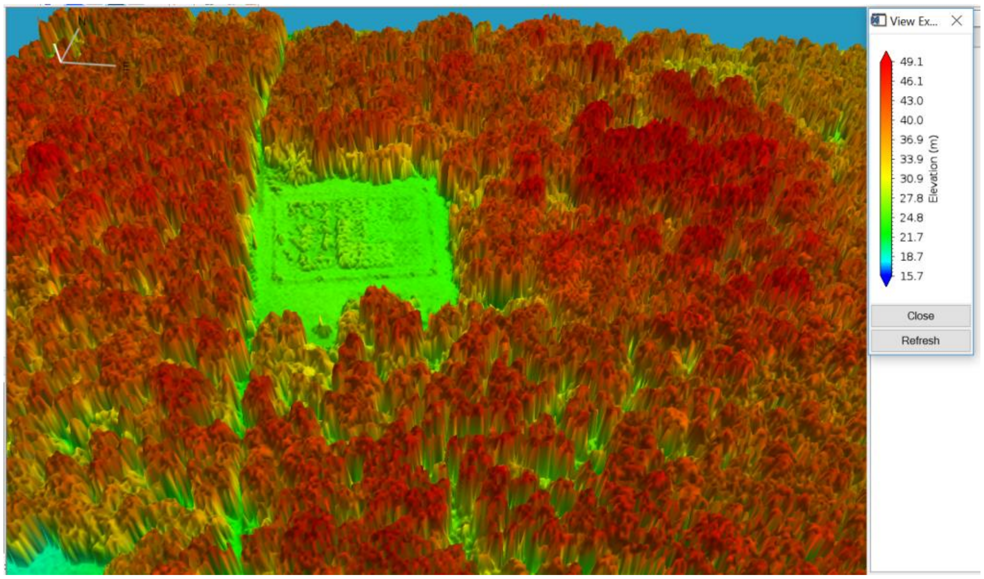


Figure 17. DSM, as viewed in ENVI Lidar.

Section 4.2: Manipulating ground truth data

The field data are digitized into ArcMap by using the Bearing Distance to Line tool. This tool was used to import the spreadsheet of field data containing the information on the bearing and distance to each tree from the plot center. From this, point shapefiles were created to represent the individual trees in each of the plots and the Add XY tool was used to append the latitude and longitude of each point. Once the plot centers and sampled trees were digitized into point shapefiles, a 10 meter buffer was drawn from the center of each of the 25 sample 10 m plots.

These 10 m buffers were used as an overlay to extract the tree point shapefile exported from ENVI Lidar. The trees that overlapped with the 25 sample 10 m plots were exported to Excel for analysis and averages per plot were calculated. The results indicate that the ENVI Lidar predicted tree height was consistently higher than the ground truth data by 3.79 meters, on average.   Figure 18 presents the field data in ArcMap.

Figure 18. The 25 sample plots. Background imagery provided by the accompanying air photo from BuckEye.

Section 4.3: Classifying height in ENVI

The CHM was calculated by taking the difference of the DSM and DTM created in ENVI Lidar. Tree points and buffers created in ArcMap were imported into ENVI to provide reference for assigning individual tree height.

Out of the 410 sampled trees (distributed in the 25 sample plots), 90 trees were selected at random. This selection was accomplished by using a random number generator within the Excel spreadsheet that contained the unique ID, heights, and location of each tree.

Heights of these 90 trees were assigned based on human interpretation. This was accomplished by using the digitized field data, the accompanying BuckEye air photo, and the CHM. Using the location of the tree as a guide, each of the 90 selected trees was assigned a height using the value of the CHM pixel at or nearby the location of the tree. This height was recorded in Excel for further analysis. Figure 19 presents an example of the field data and the CHM for assigning a height value.

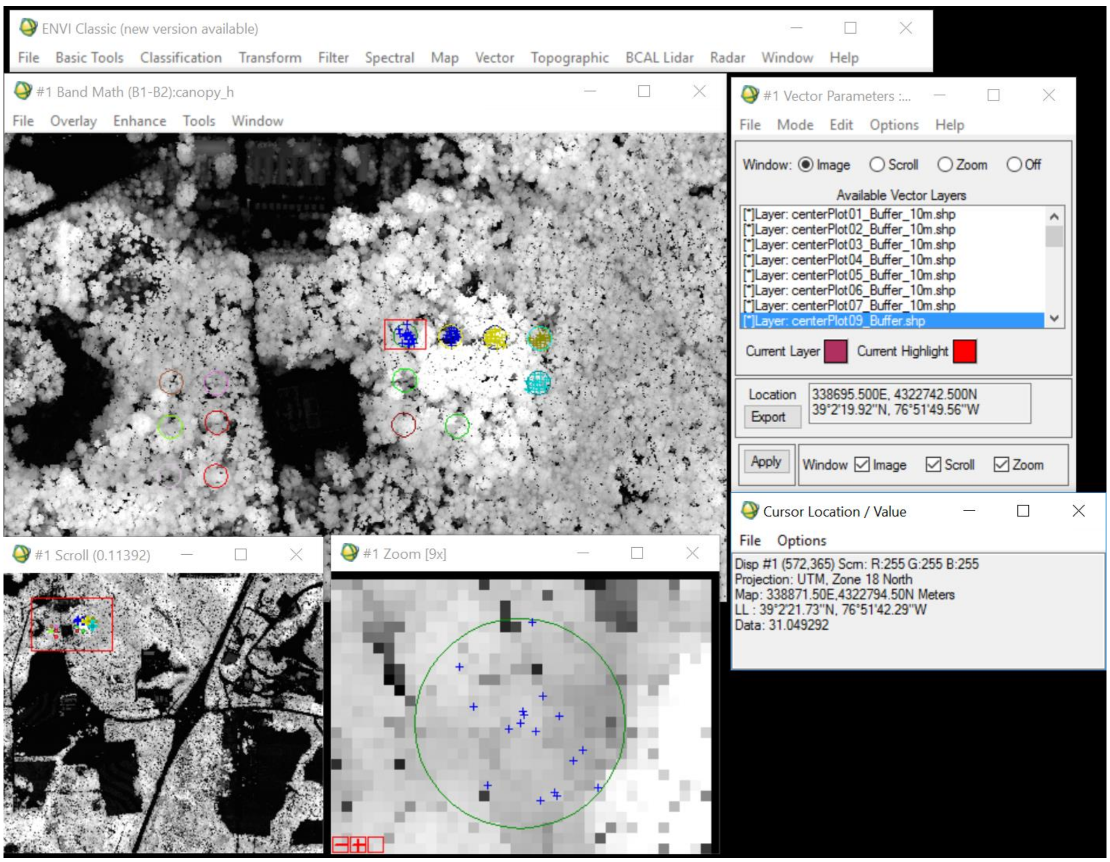


Figure 19. Zoom window displays the 10 meter sample plot with crosshairs representing trees. In the Cursor Location/Value window, 'Data' value represents the height at that cell in meters. This value changes as the cursor hovers to a different pixel.

Section 4.4: Regression using Excel

Linear regression was used to relate average tree height per plot for the 10 meter plots to the average ENVI Lidar prediction heights per plot. The field data were entered into MS Excel, and contained information about the tree biophysical characteristics mentioned in Section 3.2: Ground reference data. The average height per plot was calculated for the field data and Lidar data. These two data sets were compared using a scatter plot in Excel. Figure 20 is the result from the ground truth versus the ENVI Lidar prediction for the trees; Figure 21 shows the dominant and codominant measurements compared to the ENVI Lidar prediction. Figure 22 is the result from comparing the field height to the CHM height at the same location. The root mean square error (RMSE) for the CHM comparison was calculated in Excel and is 6.54 meters.

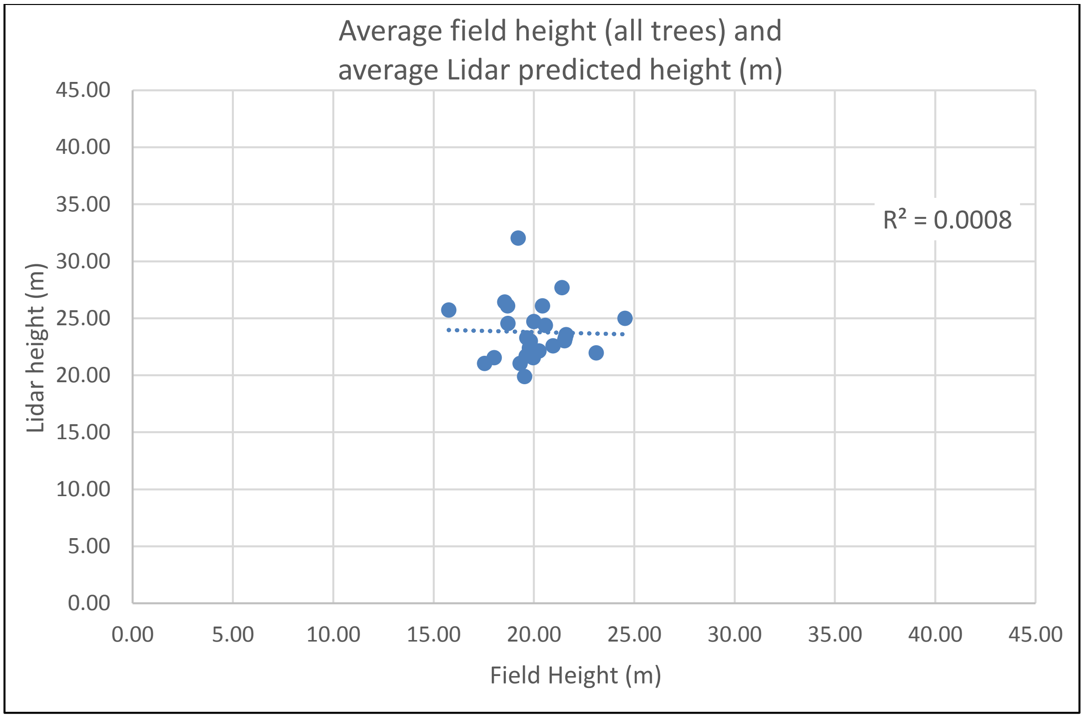


Figure 20. Comparing height of trees sampled in the field to heights estimated by the software.

As shown in Figure 20, R^2 is 0.0008 and the p-value is 0.89, at a confidence interval of 95%. With such a low R^2 and a high p-value, this means that little to none of the variation is explained by the field data compared to the Lidar predicted height.

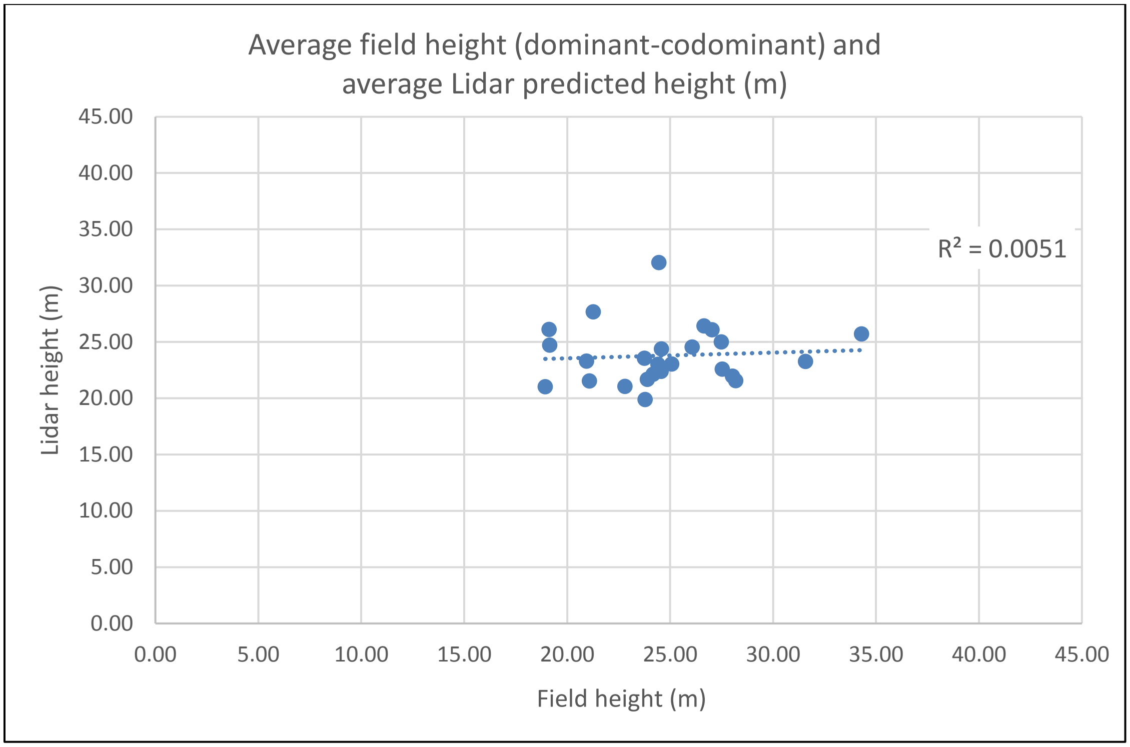


Figure 21. Comparing height of dominant and codominant trees sampled in the field to the software estimate.

Considering only the average field height per plot for dominant and codominant trees, the R^2 was 0.0051 with a p-value of 0.73 at a confidence interval of 95%. Compared to the results shown in Figure 21, the R^2 is only slightly larger and a p-value that is slightly smaller. This indicates that little to none of the variation is explained in the model.

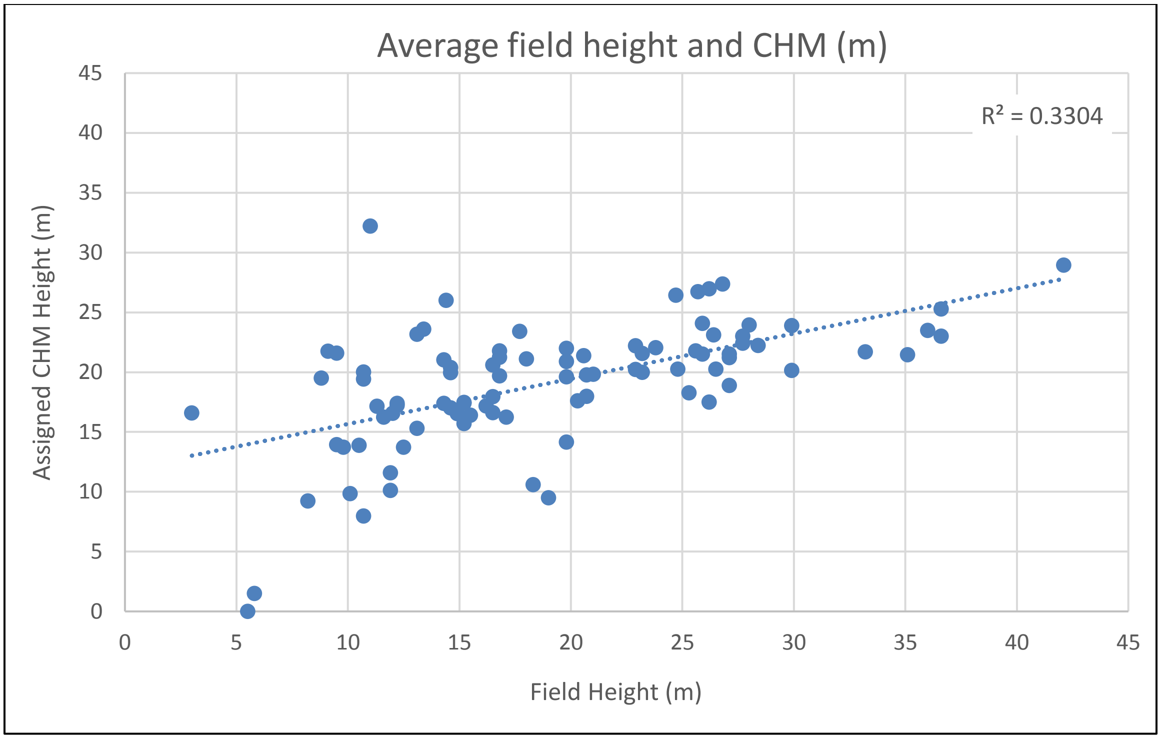


Figure 22. Randomly selected sample trees versus CHM, based on human interpretation.

As shown in Figure 22, R^2 was 0.33 and the p-value was 3.1289E-9 at a CI of 95%. While there is high variance around the mean, this statistically significant relationship indicates that using human interpretation to relate the field data measurement does help in finding a reliable height for the selected tree in the CHM.

Based on these results, it was determined that decimating the point cloud was not an option worth pursuing.

CHAPTER FIVE: DISCUSSION

Section 5.1: Discussion of results

In summarizing this research, the results indicate that relying on the parameters in ENVI Lidar and the Lidar data did not produce a strong correlation. The results from human visual interpretation produced a comparatively higher R^2, but still had an RMSE of 6.54 m. These results were unexpected, considering previous research mentioned in Section 2.3: Selected applications--Military and Section 2.4: Selected applications--Forestry, reported very strong correlations and low RMSEs. However, many previous researchers discuss issues with dense forest canopies influencing the DTM and biasing the CHM towards lower values. In a review of different effects of DTM quality, Hyyppä et al. (2004) states that accuracies vary as a function of site conditions such as slopes, undergrowth, and forest cover. Here, the USDA-ARS study area did include a deciduous forest with a dense canopy and different age classes. Further exploration of the data is warranted in an attempt to address these unexpected findings.

Section 5.1.1: Reviewing the point cloud data

As mentioned by Silva et al. (2018), Chen et al. (2017), Dong & Chen (2017), Falkowski et al. (2008), and Sithole & Vosselman (2004), classifying last returns to represent the actual bare earth surface is still challenging even though many algorithms have been proposed and implemented in various software packages. In chapter three of their book, Dong & Chen (2017) point out that the methods of filtering for ground returns are unsupervised classifiers which predict the elevation at unsampled locations, typically using a surface-based approach such as a raster or triangulated irregular network (TIN). Even though the methods in which ENVI Lidar creates the DTM are unknown, it could be reasonably assumed the software implements some interpolating technique to estimate the elevation of unsampled locations in order to create an elevation model. In reviewing a four meter cross section of the point cloud (Figure 23 and Figure 24), it can be seen that the last returns are between 5 to 10 meters apart. This is a relatively large gap to rely on an algorithm to create a reliable DTM, which could cause estimation errors.

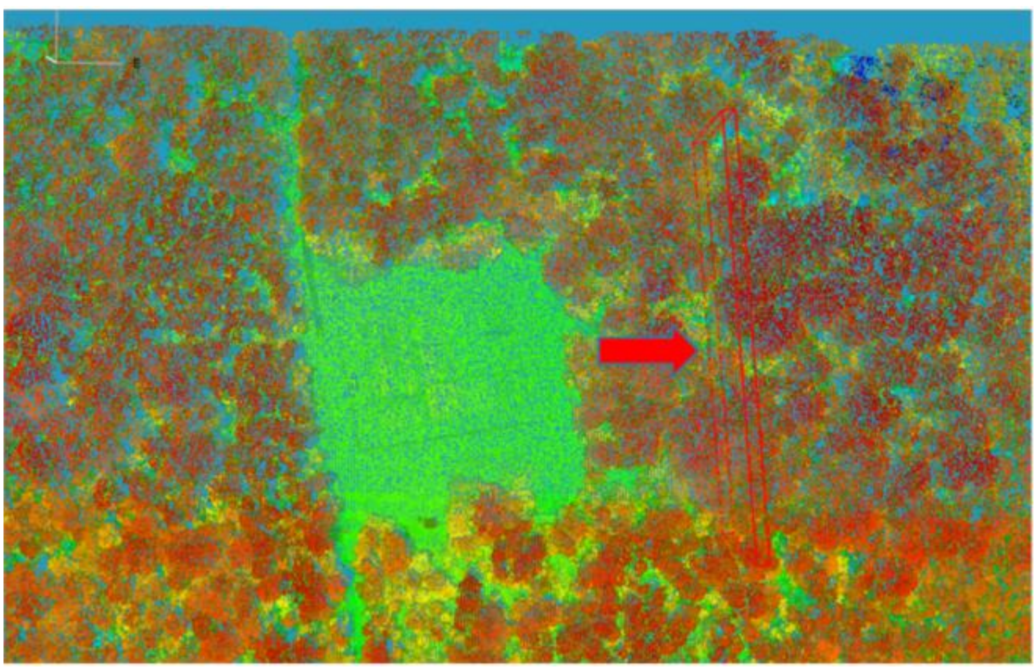


Figure 23. A screenshot of the cross section example, location indicated by the red box and arrow.

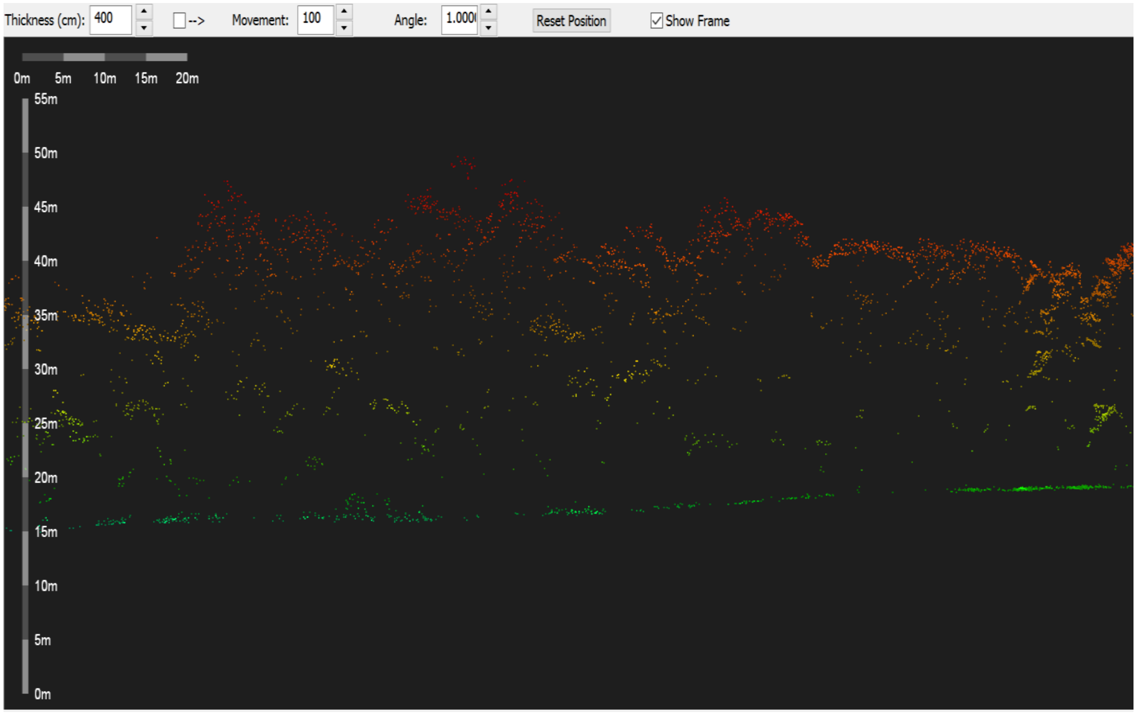


Figure 24. A view from the ground, looking into the four meter cross section.

Section 5.1.2: Reviewing the ENVI Lidar tree output

ENVI Lidar did not perform well in delineating individual trees in the sample plots, which had an influence on the average height per plot. This is similar to results in Unger et al. (2014), where the two software packages also struggled to delineate individual hardwood trees and produce tree count comparable to their field count. As mentioned by Falkowski et al. (2008), areas with overlapping or interlocking crowns can make it difficult to isolate an individual tree. In trying to examine the canopy surface, a horizontal profile was created in ENVI (Figure 25).

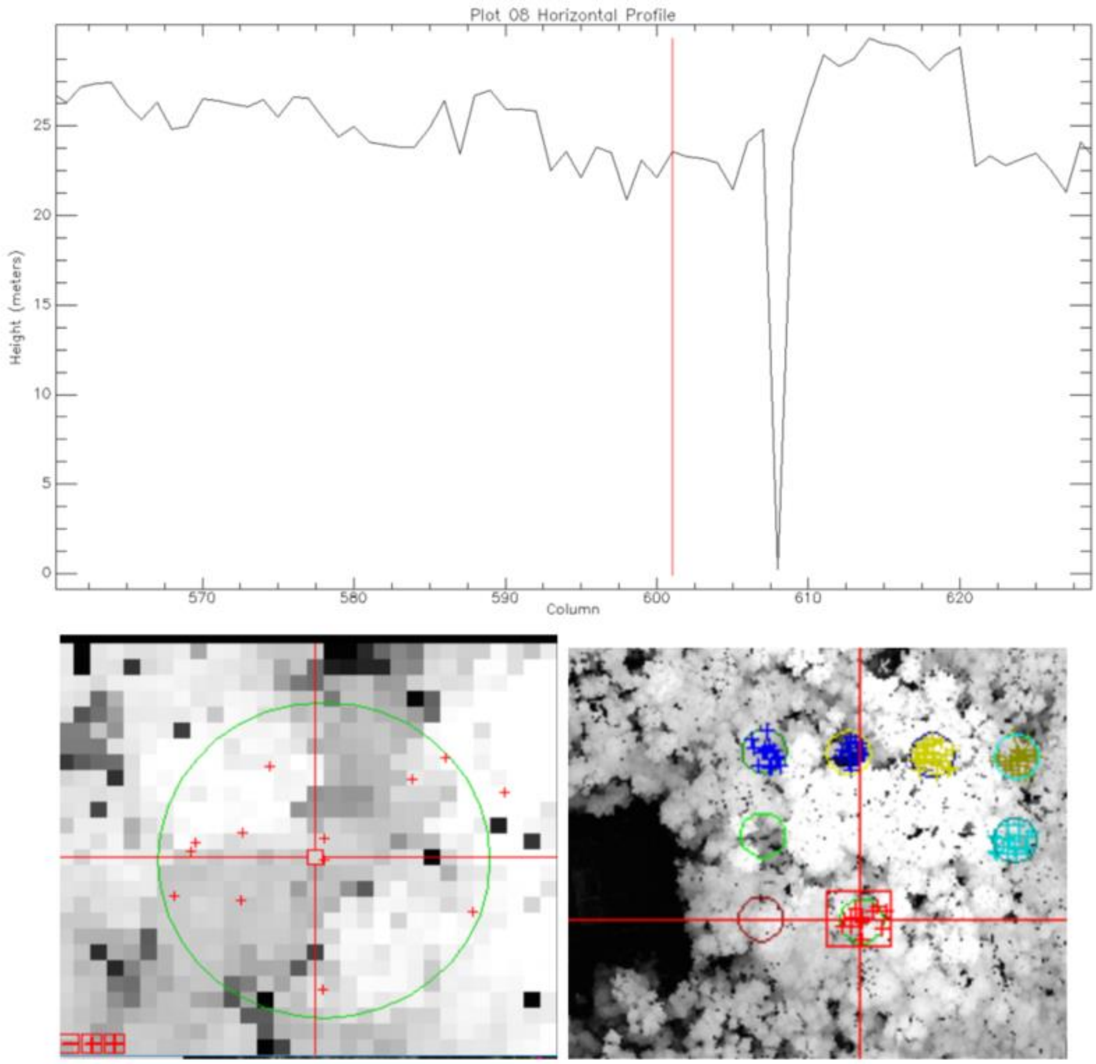


Figure 25. Horizontal profile across Plot 08 in ENVI, with the cross hairs at the center of the plot. Dark black pixel represents an elevation (height) of zero, and white represents a higher elevation (height). Grey represents elevations in between these values.

Inspecting the profile in ENVI and photos taken in the field, the canopy surface is fairly continuous and could be difficult to discern one tree from another while trying to detect an individual tree using an automated algorithim. This can also be seen by looking at the photos taken in the field, where very little light penetrates the canopy (Figure 26).

Figure 26. Left, center of plot facing east. Right, center looking directly above at the canopy.

Field plot 08 is shown in Figure 27, where the sample trees and the Lidar predicted trees are displayed within the plot. The tree detection algorithim does not match up well with the sample trees in this plot, but does seem to perform better on the edges of the forest, shown in Figure 28, near field plots 01 and 06. There are no field measurements of the trees outside of the plots to compare the heights, but based on visual interpretation, the algorithim appears to perform better in areas where the canopy is open.

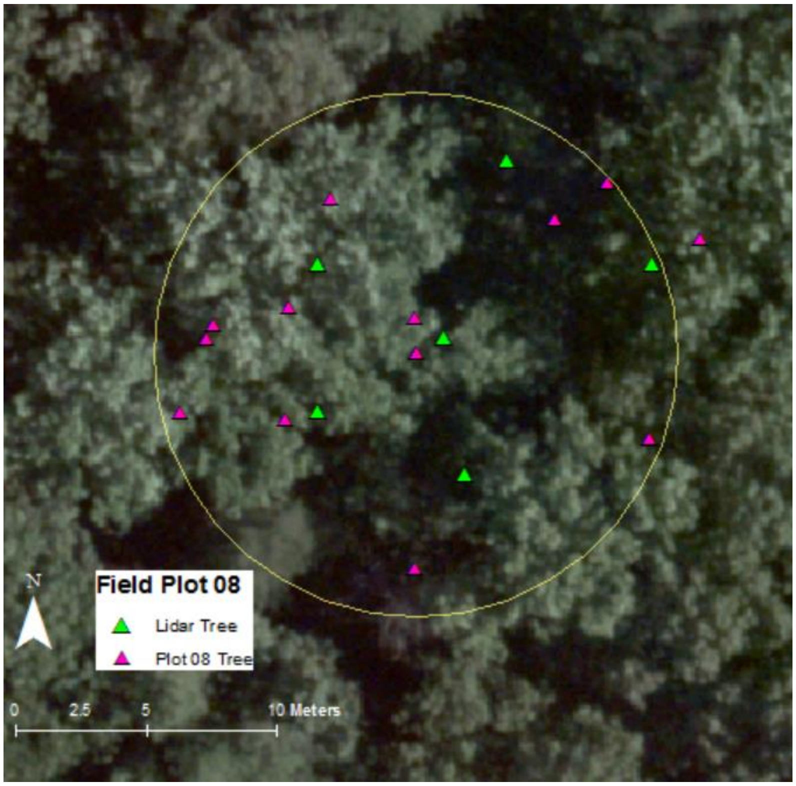


Figure 27. Plot 08 with trees sampled in the field and the trees output from ENVI Lidar.

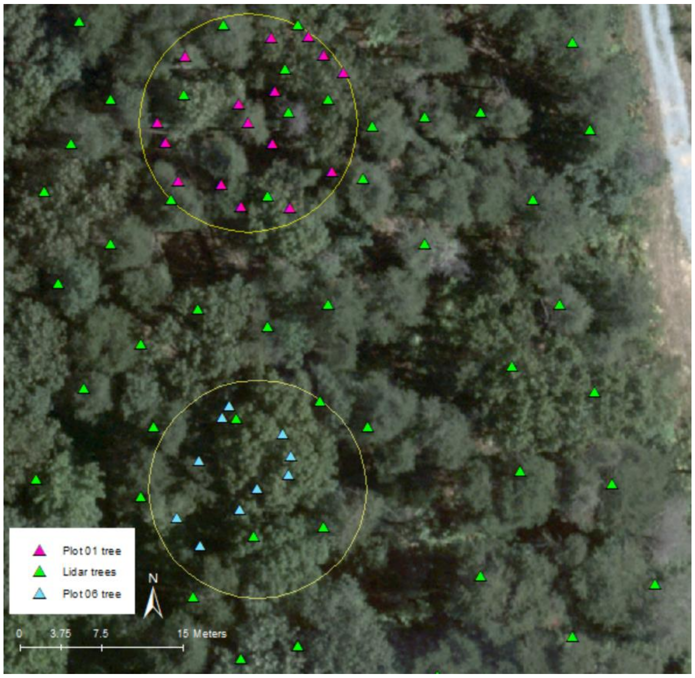


Figure 28. Plot 01 and 06 with trees sampled in the field and the trees output from ENVI Lidar.

Section 5.1.3: Evaluating field methods

In reviewing the height measurements from the field, the Lidar measurements consistently overestimate heights from ground truth. This result is inconsistent with what previous researchers mention that Lidar typically will underestimate height of trees (Dorigo et al., 2010; Gatziolis et al., 2010; Hyyppä et al., 2012; Lim et al., 2003; Popescu et al., 2002). According to Andersen et al. (2006), using a laser rangefinder is common practice for measuring tree heights, but is difficult to obtain a reliable height if treetops are not visible. Even though two individuals used a laser rangefinder using standard techniques to find tree heights, there is some level of error in field measurements due to the canopy cover and limited visibility of treetops. Markku & Muller-Landau (2013) discuss similar issues, stating that the performance of rangefinders have not been carried out in typical forest conditions with varying visibility and leaning trees. In the authors' quantitative comparison of field methods for measuring tree height, they concluded that laser rangefinders can result in systematic underestimation of heights by 20%. Williams, Bechtold, & LaBau (1994) compared instruments for measuring tree height, and found that for trees under 40 feet (12 meters), laser rangefinders were accurate within 2-5 feet. The study area trees were 19.8 m tall on average, so it is possible measurements were off by 5 feet (1.5 m) or higher, based on this information. Similar issues with field data underestimating height can be found in Sadadi (2016).

It is worth mentioning that there are differences in the definition of height measurements among different studies, which should be considered when comparing research results to one another. The term height can be defined as Lorey's mean height, predominant tree height, average tree height, or estimated tree height, which was used in this study (Leeuwen & Nieuwenhuis, 2010; Lovell, Jupp, Newnham, Coops, & Culvenor, 2005). As noted in Leeuwen & Nieuwenhuis (2010), some define average tree height to only include dominant and codominant trees, whereas other studies include intermediate and suppressed trees as well.

Section 5.2: Summary

This project evaluated how suitable certain software coupled with an airborne discrete return Lidar can estimate tree height compared to traditional field plot sampling. Airborne Lidar is a suitable technology in determining certain tree parameters, but for the purposes of modeling the canopy height and bare earth, there are many inherent complexities, as mentioned in Chapter Two. In line with many other research findings and discussions, the results have shown that creating a reliable CHM and DTM can be a complicated undertaking when relying on computer software or automated methods. Based on the data collected and results for this thesis, the combination of ENVI Lidar 5.4 and Lidar test data collected from the BuckEye sensor may not be the best combination in estimating individual tree height and creating a reliable bare-earth model (DTM) to use for terrain and feature analysis. While the methods used in this study are generally accepted and used in many of the studies discussed in Chapter Two, the little to no correlation between the ground data and Lidar data demonstrates the need for considerable additional research in order to further examine the suitability of ENVI Lidar 5.4 and BuckEye (or similar Lidar sensors) in dense, deciduous forests such as the one in the Beltsville, MD, study area.

Section 5.3: Future work

While the use of Lidar data has the potential to considerably increase information of forest structure, subsequent efforts should be aimed at exploring other software, adjusting Lidar data collection parameters, and altering methods in collecting field data.

Section 5.3.1: Software and algorithms recommendations

It is recommended to explore options within ENVI or alternative software tools and algorithms available for manipulating the Lidar point cloud and working with the derived products. The results of this study support what previous researchers have discussed that the DTM can be a source of error and the challenges associated with addressing this error, as discussed in Section 2.3: Selected applications--Military and Section 2.4: Selected applications--Forestry. Some of these suggestions are based on reviewing the methods used by research referenced in this writing, while also building off of tools used in this study.

Software that could be explored includes ArcMap's 3D Analyst extension (ESRI, 2017), as there are a handful of parameters that can be adjusted to select an interpolation technique that the end user finds appropriate. Additionally, LASTools could be explored as an option, as they offer extensions to work in concert with ArcMap (Isenburg, 2012). Also, ENVI could still be used in future work, but could explore the BCAL Lidar add-on (Boise State University, n.d.), as utilized in Gould et al. (2013), Yang et al. (2014), Leitold et al. (2015). Also, ENVI Lidar allows for varying the minimum or maximum cutoff for trees. The production parameters in Figure 16 demonstrate where these adjustments can be made. Varying the minimum tree height is similar in concept to research by Wiggins (2017), but using the FUSION software. FUSION is open-source and developed by the U.S. Department of Agriculture's (USDA) Forest Service (McGaughey, 2018).

Other areas that could be explored is investigating just point cloud itself for individual segmentation of trees as a way to improve the height of the trees. This individual tree detection approach uses the raw Lidar point cloud and is gaining more attention in the literature over the past few years. Methods such as this have been used in research by Li, Guo, K Jakubowski, & Kelly (2012), Zhang et al. (2015), and Khosravipour, Skidmore, & Isenburg (2016).

Efforts could be made to improve the accuracy of the DTM (and consequently the CHM) using different interpolation techniques and/or ground filtering algorithms (Liu, 2008; Meng et al., 2010). Choosing such from the different ground filtering algorithms depends on the study site's terrain and surface features, but in a review of DTM generation, Chen et al. (2017) and Dong & Chen (2017) recommend surface-based approaches for forested areas, based on using a raster or TIN. The iterative process is best described as filtering out ground points that do not meet an error threshold established by the initial control ground points until a DTM with acceptable accuracy is achieved. Silva et al. (2018) used four ground filtering algorithms available in FUSION (McGaughey, 2018). The results showed that the algorithms performed well and produced accurate DTMs in closed and intermediate canopy forest, so similar methods could be followed. Benefits of using FUSION include having open-source code for the end user to better understand the algorithms being used (Pacific Northwest Research Station, 2018; Remote Sensing Applications Center, 2018).

Section 5.3.2: Lidar data acquisition

It could be helpful to change some of the collection parameters for the Lidar data collection. Some of these suggested parameters could come from reports by Federal Emergency Management Agency (2003) and USDA (Mitchell et al., 2018). The option of a leaf-off Lidar and ground truth data collection could be explored, but should take into consideration research by DeWitt, Warner, Chirico, & Bergstresser (2017) and Gatziolis et al. (2010), where a leaf-off collection did not provide large improvements to the DTM errors. However, taking measurements on the ground of tree heights during leaf-off could address the potential errors of measuring height in the field discussed in Section 5.1.3: Evaluating field methods as treetops are likely to be more visible. Another change in Lidar data acquisition could include an increase in point density. A number of studies explore varying the densities of the point cloud; Jakubowski, Guo, et al. (2013) discuss the tradeoffs of cost and point density. Other changes to data collection include trying to determine an optimal plot size for sampling. Since field work is time consuming, this would require assessing travel costs for people and equipment, along with complications associated with making measurements of larger plots (Mauya et al., 2015).

Future research should consider the recently published standards of government agencies and professional societies. Examples include reports from Heidemann (2018) and Mitchell et al. (2018, 2012). The American Society for Photogrammetry and Remote Sensing (2017) acknowledges that although the technology and quality of Lidar data have improved in a short time frame, there is a lack of standardization for the QA/QC of the data, semantics, procedures for measurements, and metadata. Publications and outreach campaigns from the Society's working group with the U.S. Geological Survey are expected to continue, with the most recent guide published in March 2017 (American Society for Photogrammetry and Remote Sensing, 2017).

Section 5.4: Conclusion

This research emphasizes the need for continued work in understanding the uncertainties and biases associated with estimating tree height using airborne Lidar collection in dense forests such as the one in this study. Any information extraction would be difficult in areas with features similar to the USDA-ARS study site when relying solely on automated methods. These algorithms could perform better in more open canopies. Human interpretation can provide slightly better results, but is more time consuming and not necessarily repeatable. While the results of this study were not entirely expected, there is room for continued work in producing more meaningful results for terrain analysis and forestry applications. Lidar has progressed from the research realm to operational use, demonstrating its utility to many communities (Evans et al., 2009; Hardaway, 2011; Lim et al., 2003). This remote sensing technology is still expanding and maturing in practice and will continue to play an important role in understanding and observing the environment.

REFERENCES

Ackermann, F. (1999). Airborne laser scanning—present status and future expectations. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2), 64–67. https://doi.org/10.1016/S0924-2716(99)00009-X

Akay, A. E., Oğuz, H., Karas, I. R., & Aruga, K. (2009). Using LiDAR technology in forestry activities. *Environmental Monitoring and Assessment*, *151*(1–4), 117–125. https://doi.org/10.1007/s10661-008-0254-1

American Society for Photogrammetry & Remote Sensing. (2015, January 14). LAS (LASer) File Format, Version 1.4 [web page]. Retrieved April 14, 2018, from https://www.loc.gov/preservation/digital/formats/fdd/fdd000418.shtml

American Society for Photogrammetry and Remote Sensing. (2017, September). LIDAR Standards And Guidelines Public Review Process – ASPRS. Retrieved from https://www.asprs.org/news/general/lidar-standards-and-guidelines-public-review-process.html

Andersen, H.-E., Reutebuch, S. E., & McGaughey, R. J. (2006). A rigorous assessment of tree height measurements obtained using airborne LIDAR and conventional field methods. *Canadian Journal of Remote Sensing. 32(5): 355-366*. Retrieved from https://www.fs.usda.gov/treesearch/pubs/25922

Anderson, K., Hancock, S., Disney, M., & Gaston, K. J. (2016). Is waveform worth it? A comparison of LiDAR approaches for vegetation and landscape characterization. *Remote Sensing in Ecology and Conservation*, *2*(1), 5–15. https://doi.org/10.1002/rse2.8

Avery, T. E., & Burkhart, H. E. (2015). *Forest Measurements: Fifth Edition*. Waveland Press.

Bachman, C. G. (1979). *Laser Radar Systems and Techniques*. Dedham, Mass: Artech House Publishers.

Baltsavias, E. (1999). A comparison between photogrammetry and laser scanning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2), 83–94. https://doi.org/10.1016/S0924-2716(99)00014-3

Baltsavias, E. P. (1999a). Airborne laser scanning: basic relations and formulas. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2), 199–214. https://doi.org/10.1016/S0924-2716(99)00015-5

Baltsavias, E. P. (1999b). Airborne laser scanning: existing systems and firms and other resources. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2), 164–198. https://doi.org/10.1016/S0924-2716(99)00016-7

Blundell, S. B., Guthrie, V., & Simental, E. (2004). *6.2 Terrain Gap Identification and Analysis for Assured Mobility*. Alexandria, VA: Army Topographic Engineering Center. Retrieved from http://www.dtic.mil/docs/citations/ADA430982

Boise State University. (n.d.). BCAL Lidar Tools (Version X.X.X.). 1910 University Drive, Boise, Idaho: Boise State University, Department of Geosciences. Retrieved from https://bcal.boisestate.edu/tools/lidar

Broughton, J. D., & Addor, E. E. (1968). *Mobility environmental research study: a quantitative method for describing terrain for ground mobility : volume IV : vegetation*. Vicksburg, Miss.: Waterways Experiment Station.

Campbell, J. B. (2011). *Introduction to Remote Sensing, Fifth Edition* (5th ed.). The Guilford Press.

Cao, L., Coops, N. C., Hermosilla, T., Innes, J., Dai, J., & She, G. (2014). Using Small-Footprint Discrete and Full-Waveform Airborne LiDAR Metrics to Estimate Total Biomass and Biomass Components in Subtropical Forests. *Remote Sensing*, *6*(8), 7110–7135. https://doi.org/10.3390/rs6087110

Chen, Z., Gao, B., & Devereux, B. (2017). State-of-the-Art: DTM Generation Using Airborne LIDAR Data. *Sensors (Basel, Switzerland)*, *17*(1). https://doi.org/10.3390/s17010150

DeWitt, J. D., Warner, T. A., Chirico, P. G., & Bergstresser, S. E. (2017). Creating high-resolution bare-earth digital elevation models (DEMs) from stereo imagery in an area of densely vegetated deciduous forest using combinations of procedures designed for lidar point cloud filtering. *GIScience & Remote Sensing*, *54*(4), 552–572. https://doi.org/10.1080/15481603.2017.1295514

Dong, P., & Chen, Q. (2017). *LiDAR Remote Sensing and Applications*. Boca Raton, FL: CRC Press. Retrieved from https://books.google.com/books?id=jXFQDwAAQBAJ&printsec=frontcover#v=onepage&q&f=false

Dorigo, W., Hollaus, M., Wagner, W., & Schadauer, K. (2010). An application-oriented automated approach for co-registration of forest inventory and airborne laser scanning data. *International Journal of Remote Sensing*, *31*(5), 1133–1153. https://doi.org/10.1080/01431160903380581

Dubayah, R. O., & Drake, J. B. (2000). Lidar Remote Sensing for Forestry. *Journal of Forestry*, *98*(6), 44–46. https://doi.org/10.1093/jof/98.6.44

Duncanson, L. I., Cook, B. D., Hurtt, G. C., & Dubayah, R. O. (2014). An efficient, multi-layered crown delineation algorithm for mapping individual tree structure across multiple ecosystems. *Remote Sensing of Environment*, *154*, 378–386. https://doi.org/10.1016/j.rse.2013.07.044

ESRI. (2017). ArcGIS Desktop Release 10.5.1 (Version 10.5.1). Redlands, CA: Environmental Systems Research Institute, Incorporated. Retrieved from http://desktop.arcgis.com/en/arcmap/

Evans, J. S., Hudak, A. T., Faux, R., & Smith, A. M. S. (2009). Discrete Return Lidar in Natural Resources: Recommendations for Project Planning, Data Processing, and Deliverables. *Remote Sensing*, *1*(4), 776–794. https://doi.org/10.3390/rs1040776

Falkowski, M. J., Smith, A. M. S., Gessler, P. E., Hudak, A. T., Vierling, L. A., & Evans, J. S. (2008). The influence of conifer forest canopy cover on the accuracy of two individual tree measurement algorithms using lidar data. *Canadian Journal of Remote Sensing. 34(2): S338-S350.*, S338–S350.

Falls, C. (1948). Geography and War Strategy. *The Geographical Journal*, *112*(1/3), 4–15. https://doi.org/10.2307/1789151

Federal Emergency Management Agenc. (2003). *Appendix A: Guidance for aerial mapping and surveying P. A39–A57 in Guidelines and specifications for flood hazard mapping partners.* Retrieved from https://www.fema.gov/media-library-data/1387814416677-caa613eeca53246cb7a7dcbf342a7197/Guidelines+and+Specifications+for+Flood+Hazard+Mapping+Partners+Appendix+A-Guidance+for+Aerial+Mapping+and+Surveying+(Apr+2003).pdf

Gatziolis, D., & Andersen, H.-E. (2008). *A guide to LIDAR data acquisition and processing for the forests of the Pacific Northwest.* (No. PNW-GTR-768). Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-GTR-768

Gatziolis, D., Fried, J. S., & Monleon, V. S. (2010). Challenges to estimating tree height via LiDAR in closed-canopy forest: a parable from western Oregon. *Forest Science. 56(2): 139-155*, 139–155.

Gould, S. B., Glenn, N. F., Sankey, T. T., & McNamara, J. P. (2013). Influence of a Dense, Low-height Shrub Species on the Accuracy of a Lidar-derived DEM. *Photogrammetric Engineering & Remote Sensing*, *79*(5), 421–431. https://doi.org/10.14358/PERS.79.5.421

Hamraz, H., Contreras, M. A., & Zhang, J. (2017). Forest understory trees can be segmented accurately within sufficiently dense airborne laser scanning point clouds. *Scientific Reports*, *7*(1), 6770. https://doi.org/10.1038/s41598-017-07200-0

Hansen, E. H., Gobakken, T., Bollandsås, O. M., Zahabu, E., & Næsset, E. (2015). Modeling Aboveground Biomass in Dense Tropical Submontane Rainforest Using Airborne Laser Scanner Data. *Remote Sensing*, *7*(1), 788–807. https://doi.org/10.3390/rs70100788

Hardaway, M. (2011, October 17). LiDAR Magazine - BuckEye in 2011 and Beyond: Delivering High-Resolution Terrain Data to the Warfighter. Retrieved from http://www.lidarmag.com/content/view/8646/

Harmon, R. S., & McDonald, E. V. (2014). Military geoscience in the twenty-first century—A historical perspective and overview. In *Reviews in Engineering Geology* (Vol. 22, pp. 1–10). Geological Society of America. https://doi.org/10.1130/2014.4122(01)

Harris Geospatial Solutions, Inc. (2018a). ENVI - The Leading Geospatial Analytics Software | Harris Geospatial (Version 5.4). Harris Geospatial Solutions, Inc. Retrieved from http://www.harrisgeospatial.com/SoftwareTechnology/ENVI.aspx

Harris Geospatial Solutions, Inc. (2018b). Vegetation Analysis: Using Vegetation Indices in ENVI [Help article]. Retrieved April 13, 2018, from http://www.harrisgeospatial.com/Support/SelfHelpTools/HelpArticles/HelpArticles-Detail/TabId/2718/ArtMID/10220/ArticleID/16162/Vegetation-Analysis-Using-Vegetation-Indices-in-ENVI.aspx

Harris Geospatial Solutions, Inc. (2018c). Make Manual Changes, Documentation Center [Help article]. Retrieved April 15, 2018, from http://www.harrisgeospatial.com/docs/MakeManualChanges.html

Hawbaker, T. J., Gobakken, T., Lesak, A., Trømborg, E., Contrucci, K., & Radeloff, V. (2010). Light Detection and Ranging-Based Measures of Mixed Hardwood Forest Structure. *Forest Science*, *56*(3), 313–326. https://doi.org/10.1093/forestscience/56.3.313

Heidemann, H. K. (2018). Lidar Base Specification. *U.S. Geological Survey Techniques and Methods*, 101. https://doi.org/10.3133/tm11b4

Hollaus, M., Mücke, W., Roncat, A., Pfeifer, N., & Briese, C. (2014). Full-Waveform Airborne Laser Scanning Systems and Their Possibilities in Forest Applications. In *Forestry Applications of Airborne Laser Scanning* (pp. 43–61). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8_3

Hyyppä, Hyyppä, Leckie, Gougeon, Yu, X., & Maltamo, M. (2008). Review of methods of small- footprint airborne laser scanning for extracting forest inventory data in boreal forests. *International Journal of Remote Sensing*, *29*(5), 1339–1366. https://doi.org/10.1080/01431160701736489

Hyyppä, J., Yu, X., Hyyppä, H., Vastaranta, M., Holopainen, M., Kukko, A., … Alho, P. (2012). Advances in Forest Inventory Using Airborne Laser Scanning. *Remote Sensing*, *4*(5), 1190–1207. https://doi.org/10.3390/rs4051190

Hyyppä, Yu, X., Hyyppä, J., Kaartinen, H., Kaasalainen, S., Honkavaara, E., & Rönnholm, P. (2004). Factors Affecting the Quality of DTM Generation in Forested Areas. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci*, *36*.

Isenburg, M. (2012). *LAStools*. Germany: rapidlasso GmbH. Retrieved from https://rapidlasso.com/lastools/

Jakubowski, M. K., Guo, Q., & Kelly, M. (2013). Tradeoffs between lidar pulse density and forest measurement accuracy. *Remote Sensing of Environment*, *130*, 245–253. https://doi.org/10.1016/j.rse.2012.11.024

Jakubowski, M. K., Li, W., Guo, Q., & Kelly, M. (2013). Delineating Individual Trees from Lidar Data: A Comparison of Vector- and Raster-based Segmentation Approaches. *Remote Sensing*, *5*(9), 4163–4186. https://doi.org/10.3390/rs5094163

Johnson, S. E., & Abrams, M. D. (2009). Age class, longevity and growth rate relationships: protracted growth increases in old trees in the eastern United States. *Tree Physiology*, *29*(11), 1317–1328. https://doi.org/10.1093/treephys/tpp068

Kaartinen, H., Hyyppä, J., Yu, X., Vastaranta, M., Hyyppä, H., Kukko, A., … Wu, J.-C. (2012). An International Comparison of Individual Tree Detection and Extraction Using Airborne Laser Scanning. *Remote Sensing*, *4*(4), 950–974. https://doi.org/10.3390/rs4040950

Kangas, A., Eid, T., & Gobakken, T. (2014). Valuation of Airborne Laser Scanning Based Forest Information. In *Forestry Applications of Airborne Laser Scanning* (pp. 315–331). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8_16

Khosravipour, A., Skidmore, A. K., & Isenburg, M. (2016). Generating spike-free digital surface models using LiDAR raw point clouds: A new approach for forestry applications. *International Journal of Applied Earth Observation and Geoinformation*, *52*, 104–114. https://doi.org/10.1016/j.jag.2016.06.005

Khosravipour, A., Skidmore, A. K., Wang, T., Isenburg, M., & Khoshelham, K. (2015). Effect of slope on treetop detection using a LiDAR Canopy Height Model. *ISPRS Journal of Photogrammetry and Remote Sensing*, *104*, 44–52. https://doi.org/10.1016/j.isprsjprs.2015.02.013

Koch, B., Heyder, U., & Weinacker, H. (2006). Detection of Individual Tree Crowns in Airborne Lidar Data. *Photogrammetric Engineering & Remote Sensing*, *72*(4), 357–363. https://doi.org/10.14358/PERS.72.4.357

Krause, P. F., Puffenberger, H. B., Graff, B. J., & Gard, C. D. (2003). *Understory Density Characteristics in Several Midlatitude Temperature Forests* (No. ERDC/TEC-TR-03-1). Alexandria, VA: Engineer Research And Development Center Topographic Engineering Center (ERDC-TEC). Retrieved from http://www.dtic.mil/docs/citations/ADA413189

Kumar, L., Schmidt, K., Dury, S., & Skidmore, A. (2002). Imaging Spectrometry and Vegetation Science. In *Imaging Spectrometry* (pp. 111–155). Springer, Dordrecht. https://doi.org/10.1007/978-0-306-47578-8_5

Lee, H., Starek, M. J., Blundell, S. B., Schwind, M., Gard, C., & Puffenberger, H. (2016). Estimation of 2-D Clutter Maps in Complex Under-Canopy Environments From Airborne Discrete-Return Lidar. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(12), 5819–5829. https://doi.org/10.1109/JSTARS.2016.2546251

Leeuwen, M. van, & Nieuwenhuis, M. (2010). Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*, *129*(4), 749–770. https://doi.org/10.1007/s10342-010-0381-4

Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. *BioScience*, *52*(1), 19–30. https://doi.org/10.1641/0006-3568(2002)052[0019:LRSFES]2.0.CO;2

Leitold, V., Keller, M., Morton, D. C., Cook, B. D., & Shimabukuro, Y. E. (2015). Airborne lidar-based estimates of tropical forest structure in complex terrain: opportunities and trade-offs for REDD+. *Carbon Balance and Management*, *10*(1), 3. https://doi.org/10.1186/s13021-015-0013-x

Li, W., Guo, Q., K Jakubowski, M., & Kelly, M. (2012). A New Method for Segmenting Individual Trees from the Lidar Point Cloud. *Photogrammetric Engineering and Remote Sensing*, *78*, 75–84. https://doi.org/10.14358/PERS.78.1.75

Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography: Earth and Environment*, *27*(1), 88–106. https://doi.org/10.1191/0309133303pp360ra

Lindberg, E., Holmgren, J., Olofsson, K., Wallerman, J., & Olsson, H. (2010). Estimation of tree lists from airborne laser scanning by combining single-tree and area-based methods. *International Journal of Remote Sensing*, *31*(5), 1175–1192. https://doi.org/10.1080/01431160903380649

Liu, X. (2008). Airborne LiDAR for DEM generation: some critical issues. *Progress in Physical Geography: Earth and Environment*, *32*(1), 31–49. https://doi.org/10.1177/0309133308089496

Lovell, J. L., Jupp, D. L. B., Newnham, G. J., Coops, N. C., & Culvenor, D. S. (2005). Simulation study for finding optimal lidar acquisition parameters for forest height retrieval. *Forest Ecology and Management*, *214*(1), 398–412. https://doi.org/10.1016/j.foreco.2004.07.077

Mallet, C., & Bretar, F. (2009). Full-waveform topographic lidar: State-of-the-art. *ISPRS Journal of Photogrammetry and Remote Sensing*, *64*(1), 1–16. https://doi.org/10.1016/j.isprsjprs.2008.09.007

Mallet, C., Bretar, F., Roux, M., Soergel, U., & Heipke, C. (2011). Relevance assessment of full-waveform lidar data for urban area classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(6, Supplement), S71–S84. https://doi.org/10.1016/j.isprsjprs.2011.09.008

Maltamo, M., Packalén, P., Yu, X., Eerikäinen, K., Hyyppä, J., & Pitkänen, J. (2005). Identifying and quantifying structural characteristics of heterogeneous boreal forests using laser scanner data. *Forest Ecology and Management*, *216*(1), 41–50. https://doi.org/10.1016/j.foreco.2005.05.034

Markku, & Muller- Landau. (2013). Measuring tree height: a quantitative comparison of two common field methods in a moist tropical forest. *Methods in Ecology and Evolution*, *4*(9), 793–801. https://doi.org/10.1111/2041-210X.12071

Mauya, E. W., Hansen, E. H., Gobakken, T., Bollandsås, O. M., Malimbwi, R. E., & Næsset, E. (2015). Effects of field plot size on prediction accuracy of aboveground biomass in airborne laser scanning-assisted inventories in tropical rain forests of Tanzania. *Carbon Balance and Management*, *10*. https://doi.org/10.1186/s13021-015-0021-x

McGaughey, R. J. (2018). *FUSION/LDV: Software for LIDAR Data Analysis and Visualization, January 2018 – FUSION Version 3.70* (p. 212). United States Department of Agriculture Forest Service Pacific Northwest Research Station. Retrieved from http://forsys.cfr.washington.edu/fusion/FUSION_manual.pdf

Meng, X., Currit, N., & Zhao, K. (2010). Ground Filtering Algorithms for Airborne LiDAR Data: A Review of Critical Issues. *Remote Sensing*, *2*(3), 833–860. https://doi.org/10.3390/rs2030833

Mitchell, B., Fisk, H., Clark, J., & Rounds, E. (2018). *Lidar Acquisition Specifications for Forestry Applications* (p. 27). Salt Lake City, Utah: U.S. Forest Service, Geospatial Technology & Applications Center. Retrieved from

https://www.fs.fed.us/eng/rsac/lidar_training/pdf/Lidar_Acquisition_Specifications.pdf
Mitchell, B., Jacokes-Mancini, R., Fisk, H., & Evans, D. (2012). *Considerations for using lidar data—a project implementation guide* (No. RSAC-10032-MAN1) (p. 13). Salt Lake City, UT: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. Retrieved from https://www.fs.fed.us/eng/rsac/lidar_training/pdf/10032-MAN1.pdf
Næsset, E. (2002). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, *80*(1), 88–99. https://doi.org/10.1016/S0034-4257(01)00290-5
Næsset, E. (2014). Area-Based Inventory in Norway – From Innovation to an Operational Reality. In *Forestry Applications of Airborne Laser Scanning* (pp. 215–240). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8_11
National Oceanic and Atmospheric Administration (NOAA). (2012). *Lidar 101: An Introduction to Lidar Technology, Data, and Applications*. Charleston, SC: National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. Retrieved from https://coast.noaa.gov/digitalcoast/training/lidar-101.html
Nemethy, Workum, Sarkar, Karp, Dubois, Bell, … Venezia. (2007, November 15). *US 20070265781A1*. Melbourne, FL. Retrieved from https://patents.google.com/patent/US20070265781A1/en
Nikon Corporation. (2011, September 9). Nikon | News | Nikon Introduces New Laser Rangefinder “Forestry Pro.” Retrieved April 22, 2018, from https://www.nikon.com/news/2011/0909_foresty-pro_01.htm
Pacific Northwest Research Station, F. S., US Department of Agriculture. (2018). Getting Started with FUSION. Retrieved April 12, 2018, from http://forsys.sefs.uw.edu/fusion.html
Parry, J. T. (1984). Terrain evaluation, military purposes. In *Applied Geology* (pp. 570–581). Springer, Boston, MA. https://doi.org/10.1007/0-387-30842-3_69
Persson, A., Holmgren, J., & Soderman, U. (2002). Detecting and measuring individual trees using an airborne laser scanner. *Photogrammetric Engineering and Remote Sensing*, *68*(9), 925–932.
Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2002). Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture*, *37*(1), 71–95. https://doi.org/10.1016/S0168-1699(02)00121-7
Rahmes, M., & Karp, J. (2003, November 25). *USOO6654690B2*. Melbourne, FL. Retrieved from https://patents.google.com/patent/US6654690B2/en
Remote Sensing Applications Center. (2018). Remote Sensing Applications Center - USDA Forest Service - About Us. Retrieved April 12, 2018, from https://www.fs.fed.us/eng/rsac/lidar_training/
Reutebuch, S. E., Andersen, H.-E., & McGaughey, R. J. (2005). Light Detection and Ranging (LIDAR): An Emerging Tool for Multiple Resource Inventory. *Journal of Forestry*, *103*(6), 286–292. https://doi.org/10.1093/jof/103.6.286

Rose, E. P. F., & Nathanail, C. P. (2000). *Geology and Warfare: Examples of the Influence of Terrain and Geologists on Military Operations*. Geological Society of London.

Sačkov, I., Santopuoli, G., Bucha, T., Lasserre, B., & Marchetti, M. (2016). Forest Inventory Attribute Prediction Using Lightweight Aerial Scanner Data in a Selected Type of Multilayered Deciduous Forest. *Forests, 7*(12), 307. https://doi.org/10.3390/f7120307

Sadadi, O. (2016, February). *Accuracy of measuring tree height using airborne Lidar and terrestrial laser scanner and its effect on estimating Forest Biomass and Carbon stock*. University of Twente. Retrieved from https://webapps.itc.utwente.nl/librarywww/papers_2016/msc/nrm/ojoatre.pdf

Sexton, J. O., Bax, T., Siqueira, P., Swenson, J. J., & Hensley, S. (2009). A comparison of lidar, radar, and field measurements of canopy height in pine and hardwood forests of southeastern North America. *Forest Ecology and Management*, *257*(3), 1136–1147. https://doi.org/10.1016/j.foreco.2008.11.022

Shan, J., & Toth, C. K. (2009). *Topographic Laser Ranging and Scanning: Principles and Processing*. CRC Press.

Sibona, E., Vitali, A., Meloni, F., Caffo, L., Dotta, A., Lingua, E., … Garbarino, M. (2016). Direct Measurement of Tree Height Provides Different Results on the Assessment of LiDAR Accuracy. *Forests, 8*(1), 7. https://doi.org/10.3390/f8010007

Silva, C. A., Klauberg, C., Hentz, Â. M. K., Corte, A. P. D., Ribeiro, U., Liesenberg, V., … Liesenberg, V. (2018). Comparing the Performance of Ground Filtering Algorithms for Terrain Modeling in a Forest Environment Using Airborne LiDAR Data. *Floresta e Ambiente*, *25*(2). https://doi.org/10.1590/2179-8087.015016

Sithole, G., & Vosselman, G. (2003). Comparison of filtering algorithms. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *34*.

Sithole, G., & Vosselman, G. (2004). Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, *59*(1), 85–101. https://doi.org/10.1016/j.isprsjprs.2004.05.004

Smidt, M., & Blinn, C. R. (1995). *Logging for the 21st Century: Forest Ecology and Regeneration*. Minnesota Extension Service, University of Minnesota, College of Natural Resources. Retrieved from http://www.extension.umn.edu/environment/trees-woodlands/logging-for-the-21st-century-forest-ecology-and-regeneration/

Suárez, J. C., Ontiveros, C., Smith, S., & Snape, S. (2005). Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. *Computers & Geosciences*, *31*(2), 253–262. https://doi.org/10.1016/j.cageo.2004.09.015

The University of Tennessee Agricultural Extension Service. (2009). PB1780 Conducting a Simple Timber Inventory. *Forestry, Trees, and Timber*. Retrieved from http://trace.tennessee.edu/utk_agexfores/39

Thenkabail, P. S. (2015). *Remote sensing of land resources: Monitoring, modeling, and mapping advances over the last 50 years and a vision for the future*. CRC Press. Retrieved from https://pubs.er.usgs.gov/publication/70134264

Trochta, J., Krůček, M., Vrška, T., & Král, K. (2017). 3D Forest: An application for descriptions of three-dimensional forest structures using terrestrial LiDAR. *PLOS ONE*, *12*(5), e0176871. https://doi.org/10.1371/journal.pone.0176871

Unger, D. R., Hung, I.-K., Brooks, R., & Williams, H. (2014). Estimating number of trees, tree height and crown width using Lidar data. *GIScience & Remote Sensing*, *51*(3), 227–238. https://doi.org/10.1080/15481603.2014.909107

U.S. Army. (1972). *Field Manual FM 30-10, Military Geographic Intelligence (Terrain)*. Retrieved from https://digitalcommons.unl.edu/dodmilintel/85

U.S. Army. (1990). *Field Manual 5-33 Terrain Analysis*. Washington, D.C.: U.S. Army. Retrieved from http://www.bits.de/NRANEU/others/amd-us-archive/fm5-33(90).pdf

U.S. Army. (2008). *Military Operations- Force Operating Capabilities* (TRADOC Pamphlet 525-66 No. 525–66). Fort Monroe, Virginia 23651-1047: Department of the Army Headquarters, United States Army Training and Doctrine Command. Retrieved from http://adminpubs.tradoc.army.mil/pamphlets.html

Valbuena, R. (2014). Integrating Airborne Laser Scanning with Data from Global Navigation Satellite Systems and Optical Sensors. In *Forestry Applications of Airborne Laser Scanning* (pp. 63–88). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8_4

Vauhkonen, J., Ene, L., Gupta, S., Heinzel, J., Holmgren, J., Pitkänen, J., … Maltamo, M. (2012). Comparative testing of single-tree detection algorithms under different types of forest. *Forestry: An International Journal of Forest Research*, *85*(1), 27–40. https://doi.org/10.1093/forestry/cpr051

Vauhkonen, J., Maltamo, M., McRoberts, R. E., & Næsset, E. (2014). Introduction to Forestry Applications of Airborne Laser Scanning. In *Forestry Applications of Airborne Laser Scanning* (pp. 1–16). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8_1

Waring, R. H., & Running, S. W. (2007). CHAPTER 5 - Temporal Changes in Forest Structure and Function. In *Forest Ecosystems (Third Edition)* (pp. 149–182). San Diego: Academic Press. https://doi.org/10.1016/B978-012370605-8.50011-6

Wehr, A., & Lohr, U. (1999). Airborne laser scanning—an introduction and overview. *ISPRS Journal of Photogrammetry and Remote Sensing*, *54*(2), 68–82. https://doi.org/10.1016/S0924-2716(99)00011-8

Weng, Q. (2011). *Advances in Environmental Remote Sensing: Sensors, Algorithms, and Applications*. CRC Press.

Whitmore, F. (1960). Terrain intelligence and current military concepts. *American Journal of Science*, *258-A*, 375–387.

Wiggins, H. (2017, January 1). *The Influence of Tree Height on Lidar's Ability to Accurately Characterize Forest Structure and Spatial Pattern Across Reference Landscapes*. University of Montana. Retrieved from https://scholarworks.umt.edu/etd/11025

Williams, M. S., Bechtold, W. A., & LaBau, V. J. (1994). Five Instruments for Measuring Tree Height: An Evaluation. *Southern Journal of Applied Forestry*, *18*(2), 76–82. https://doi.org/10.1093/sjaf/18.2.76

Wulder, M. A., White, J. C., Nelson, R. F., Næsset, E., Ørka, H. O., Coops, N. C., … Gobakken, T. (2012). Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment*, *121*, 196–209. https://doi.org/10.1016/j.rse.2012.02.001

Yang, P., Ames, D. P., Fonseca, A., Anderson, D., Shrestha, R., Glenn, N. F., & Cao, Y. (2014). What is the effect of LiDAR-derived DEM resolution on large-scale watershed model results? *Environmental Modelling & Software*, *58*, 48–57. https://doi.org/10.1016/j.envsoft.2014.04.005

Yu, X., Hyyppä, J., Vastaranta, M., Holopainen, M., & Viitala, R. (2011). Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(1), 28–37. https://doi.org/10.1016/j.isprsjprs.2010.08.003

Zhang, C., Zhou, Y., & Qiu, F. (2015). Individual Tree Segmentation from LiDAR Point Clouds for Urban Forest Inventory. *Remote Sensing*, *7*(6), 7892–7913. https://doi.org/10.3390/rs70607892

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