A Comparison of Methods for Obtaining Aboveground Biomass Estimates Using Terrestrial LiDAR

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ABSTRACT

The terrestrial biosphere acts a critical sink for atmospheric carbon, but little is understood about the dynamics of this sink. In order to better understand how the terrestrial biosphere acts as a carbon sink, the biomass of ecosystems must be accurately measured over time. Allometric equations are currently used to make these estimations, but are prone to large inaccuracies. Terrestrial laser scanning provides a way of making much more accurate biomass estimates by calculating the volume of trees, but is very expensive. This study examines the difference in biomass estimates in a stand of *Eucalyptus globulus* trees from allometric and volumetric approaches and assesses the feasibility of making biomass estimates from terrestrial laser scanners using only free and open-source software. The difference between volumetric and allometric equations increased exponentially as a function of diameter at breast height. The two estimation methods produced a concordance correlation coefficient of 0.95 for the 4 smaller trees studied and 0.48 for the four larger trees studied. This study establishes that the production of biomass estimates from terrestrial laser scanners is possible using only free and open-source software, but methods must be streamlined to make this process more efficient.

KEYWORDS

Laser scanning, Allometric equations, free and open source software, forest inventory, *Eucalytptus globulus*

INTRODUCTION

The mitigation of anthropogenically produced carbon dioxide is one of the most prominent and critical environmental issues of our time. Since the industrial revolution, global emissions of carbon are estimated at 270±30 Pg resulting from fossil fuel combustion and 136±55 Pg from land use change and soil cultivation (Lal 2004). The documented effects of increased carbon in the atmosphere include many global environmental problems such as sea level rise, drought, and ocean acidification (Orr et al. 2005, Church and White 2006, Carnicer et al. 2011). Because of this, a substantial amount of research is focused on how carbon levels in the atmosphere can be decreased. The terrestrial biosphere is one of the most critical carbon sinks, sequestering more carbon than the ocean since 1870 (Le Quéré et al. 2018). However, it is still not fully understood which ecosystems are responsible for carbon sequestration and what factors control the dynamics of this sink (Fung 2000, Houghton et al. 2009). Understanding the role of the terrestrial biosphere in the carbon cycle and assessing its potential as an increased carbon sink requires research efforts that accurately quantify the stocks and fluxes of carbon in different ecosystems (Pan et al. 2011).

The only way to directly measure the aboveground biomass (AGB) in an ecosystems is to destructively sample the vegetation. This process is incredibly labor intensive, expensive, error prone, and destroys the natural ecosystem being studied (Catchpole and Wheeler 1992). Because of this destructive approach, many ecologists have focused their research on developing methods of indirectly estimating the ABG of an ecosystem. The most common indirect method is allometry, which involves the estimation of AGB from basic ground measurements, most commonly diameter at breast (DBH) and tree height (*Forest Inventory and Analysis National Core Field Guide* 2016). Countless studies have produced allometric equations for vegetation in various ecosystems and most studies that estimate biomass rely on allometric equations. However, the accuracy of allometric models still relies on the availability of destructively sampled data (Chave et al. 2014). As a result, allometric models often produce inaccurate results, or results whose uncertainty is impossible to quantify (Chave et al. 2014, Calders et al. 2015).

In recent years, light detection and ranging (LiDAR) has emerged as a promising tool for producing more accurate AGB estimates. This approach involves the use of laser scanners to make point clouds that serve as accurate three dimensional models of trees. These laser scanners are typically mounted in aircrafts and flown over ecosystems, providing landscape scale three dimensional models. However, in ecosystems with dense canopy cover, airborne

LiDAR is not particularly useful making biomass estimates because few light pulses penetrate the canopy and little information is provided on the stems of trees (Jaboyedoff et al. 2012, Murgoitio et al. 2013). As a result, studies on biomass in forest ecosystems with a dense canopy often use terrestrial laser scanners (TLS) (Disney et al. 2018). This involves the use of a laser scanner that is operated by a person on the ground and is therefore not obstructed by the canopy. TLS data has the ability to calculate the volume of trees with high accuracy and this data can then be used to make highly accurate estimations of tree biomass (Raumonen et al. 2013, Hackenberg et al. 2014, Calders et al. 2015). However, the adoption of TLS in forestry has been slow because it is very expensive, labor intensive, and requires expensive software (Wulder et al. 2012). It is clear that TLS has the potential to revolutionize the measurement of AGB, but it is unclear what the best methods for utilizing this technology are.

The main objective of this study is to compare biomass estimates generated by allometry and by volumetric models to assess the magnitude of the increased accuracy provided by volumetric models. In addition, this study will assess the ease, accuracy, and feasibility of free and open-source software for making biomass estimates using TLS. To do this, I used terrestrial laser scans of Eucalyptus trees and extracted DBH measurements from this data. These measurements were then used in allometric equations to make biomass estimates. I then used the same dataset to make volumetric estimates of the same trees and the biomass estimates were compared against each other. By using only free and open-source software, I provide methods for making accurate biomass estimates of trees using TLS data at a very low cost.

METHODS

Study site

The Eucalyptus Grove is a stand of *Eucalyptus globulus* trees (Tasmanian Blue Gum) on the western edge of the UC Berkeley campus situated near the confluence of the North and South Forks of Strawberry Creek (37.870765N, 122.263316W) (Figure 1). Like much of coastal California, this area has a Mediterranean climate with cool, wet winters and hot, dry summers (Purcell et al. 2007). The area of the Eucalyptus Grove is roughly 0.5ha and there are 52 *E. globulus* trees and very little other vegetation. The trees were planted in the 1880s and the tallest trees are now around 60m tall, making this one of the tallest even-aged stands of Eucalyptus in North America.

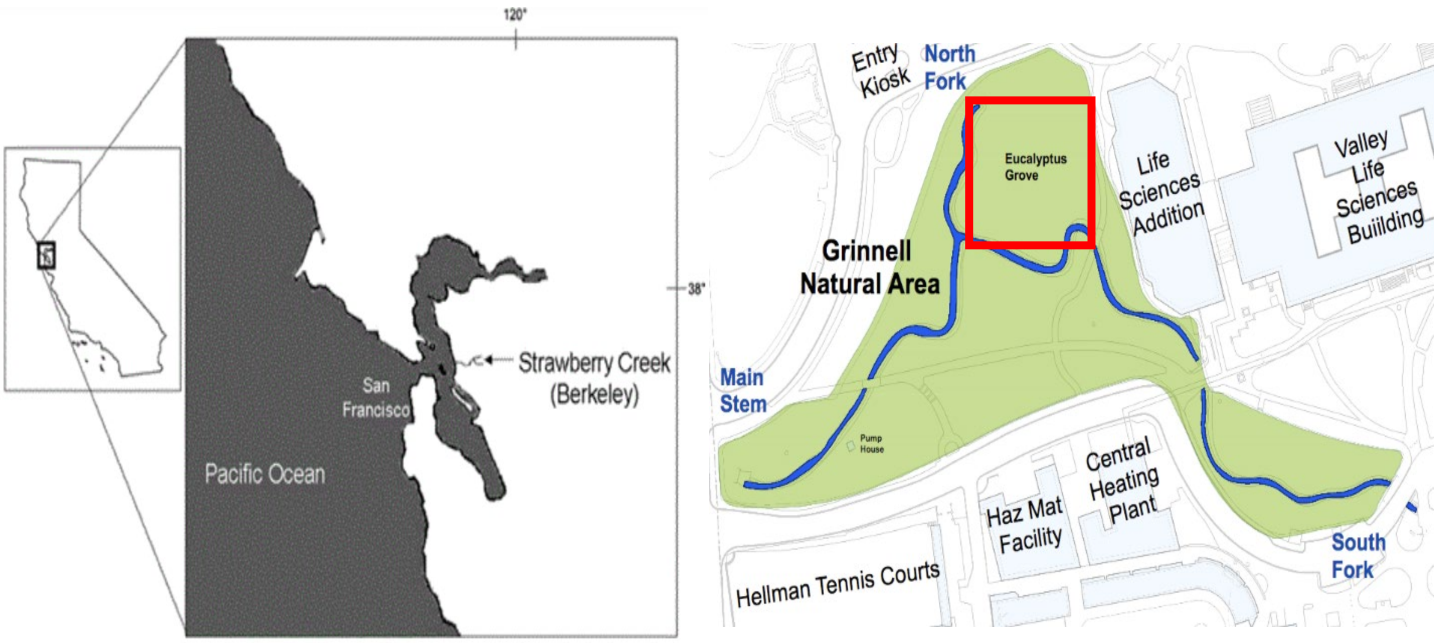

Figure 1. Study site location. The location of the study site in California (a) and the location of the study site on the campus of UC Berkeley (b). (a) is taken from Purcell et al. (2007).

Data description

The raw data consists of LiDAR scans that were made over four consecutive days beginning on March 17, 2018 using a Trimble TX6 Scanner by Liam Maier, Weijie Dong and Patina Mendez (Dong 2018). This device has a scanning speed of 500,000 points per second and can scan 360 degrees horizontally and 317 degrees vertically. The scans were taken of the entire Grinell and Wickson nature areas on the UC Berkeley campus but I only included the scans in the Grinell Nature Area containing the Eucalyptus grove. This subset of the data includes seven scans totaling about 1.5 billion points.

Data processing

To visualize and edit the point clouds, I used CloudCompare version 2.10.2. This free and open-source software is designed for point cloud processing and meshing ("CloudCompare" 2019). I loaded in all the scans that contained point returns for the Eucalyptus Grove and combined them into one large point cloud using the "Merge" tool. This step was necessary because scans from multiple angles are needed to obtain points from enough of the tree exterior to produce an accurate three dimensional model. I then used the "Segment" tool to clip individual trees from the larger point cloud (Figure 2). The clipped point cloud of a single tree was saved as a single file for export to other softwares. Because the raw data was so dense and because the canopies of the trees have substantial overlap, I was only able to isolate the points for eight trees.

Because the original scans were saved in the file format .las version 1.4 and the software used for the data analysis can only accept .las version 1.2, the files of individual trees produced in CloudCompare had to be converted. This step was performed using a software called LAStools. This free and open-source software is made by rapidlasso and is made for processing point cloud data ("LAStools" 2019). This software has no user interface so this step had to be performed using command line scripts. I used the LAStools command las2las to downgrade the files from version 1.4 to 1.2.

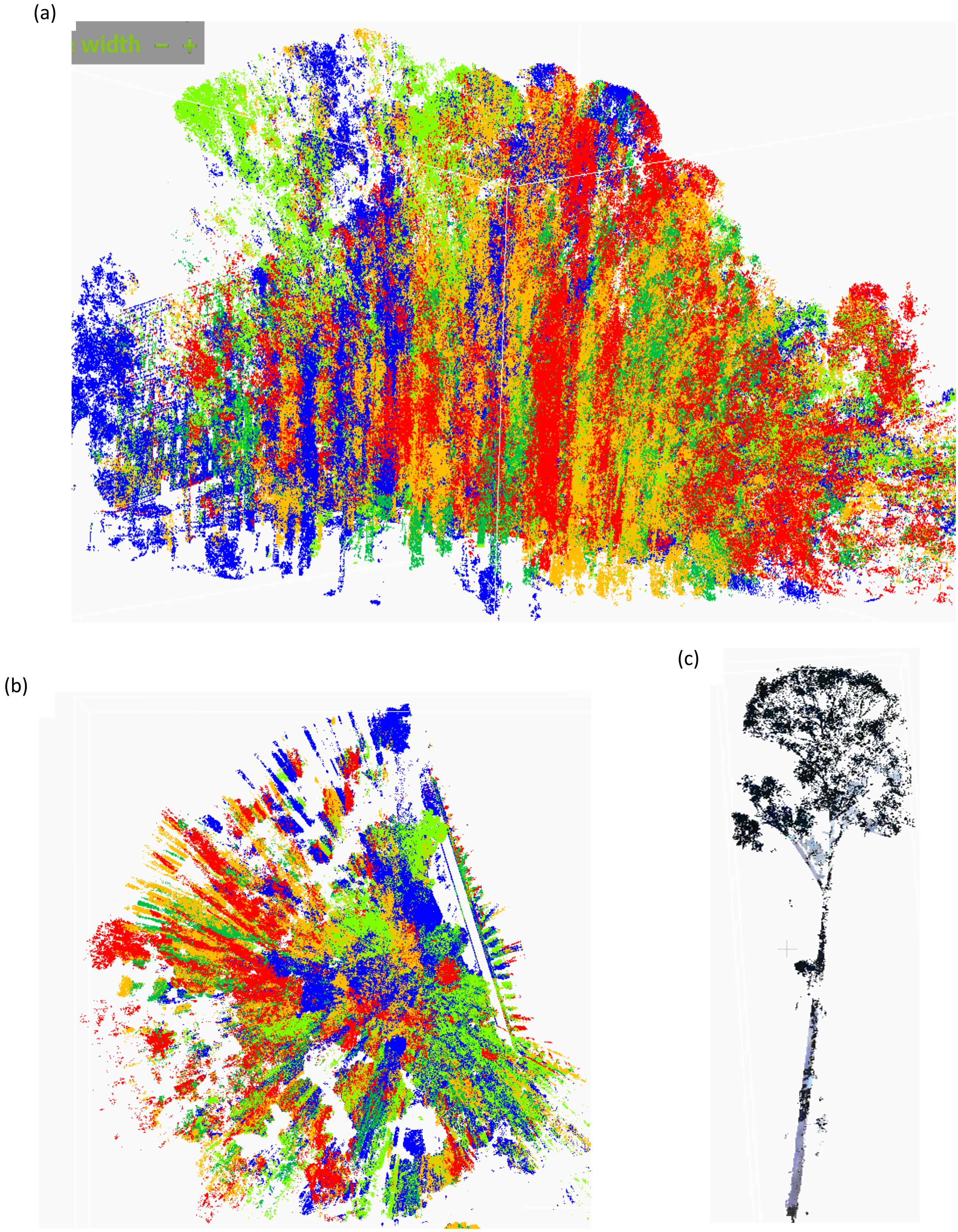

Figure 2. Examples of point cloud data. Combined point cloud of five scans looking laterally at the Eucalyptus Grove from the North (a). The same point cloud viewed from above (b). A single *E. globulus* tree that was extracted manually from the larger point cloud (c). With an estimated height of about 60m the tree in (c) is possibly the tallest Eucalyptus tree in North America. All three figures were generated in CloudCompare.

Allometric equations

All of the data analysis was completed in a free and open-source software called 3D Forest. This software is specifically designed for forestry applications of TLS (Trochta et al. 2017). After converting point clouds to las version 1.2, I loaded the clouds of individual trees into 3D Forest. Within 3D Forest, I used the “terrain from octree” tool to establish where the ground is in the point cloud. Then I used the “DBH RHT” tool to calculate the diameter at breast height of the tree. In order to test the accuracy of dbh measurements produced by TLS, field measurements were taken of the eight trees. I did not have access to a diameter tape, so DBH in the field was calculated by wrapping a string 4.5 feet above the base of the tree. The length of the string was then measured and this value was divided by pi. Because the tape measurer used had millimeter accuracy, this method also produced DBH values with millimeter accuracy.

To obtain biomass estimates, the DBH values calculated in 3D Forest were plugged into an allometric equation. The allometric equation used is from Antonio et al. 2007 and has the form:

$$w = 0.11(D)^{2.3} \qquad \text{Eqn.1}$$

where D is the diameter at breast height in centimeters and w is the estimated mass of the tree in kilograms. Though this equation was generated from trees in Portugal, it is the most complete study of allometry in *E. globulus.*

Volumetric estimates

To generate volumetric estimates, I calculated the volume of each tree in 3D Forest sing the “Stem Curve” tool which uses Randomized Hugh transformations to fit diameters around the stem of the tree at various heights. The algorithm starts with computing first the stem diameter at 0.65 m above the ground, then at 1.3m and 2m above the ground and then continues computing diameters with 1 m spacing until the new diameter is two times wider than both previous two diameters (Trochta et al. 2017). I then used the “Export stem curve” tool which creates a text file with the diameters of each fitted circle. To estimate the volume of each tree, I wrote an R script that calculates the volume of each segment using the distance between the fitted rings and the diameters exported in the text file (R Development Core Team 2016). I added these values together for a whole tree to estimate the volume of the tree. To calculate the mass of the tree, I multiplied by 539kgm^{-2}, the average density of *E. globulus* wood (Stackpole et al. 2010).

Comparison between estimation methods

The difference in estimation methods was computed by subtracting the volumetric estimate for a single tree from the allometric estimate for the same tree. Volumetric estimates generated from TLS scans are highly accurate so these numbers represent the underestimation of allometric estimates. To compare the two estimation methods, I used Lin's Concordance Correlation Coefficient which is a statistic designed to quantify the agreement between two measures of the same variable. This statistic varies between 1 and -1 with 1 meaning perfect agreement and -1 being perfect discordance (Lin 1989).

RESULTS

Allometric Equations

The LiDAR derived DBH measurements tended to produce small underestimations when compared to field derived measurements (Figure 3). The linear regression shows a RMSE of 1.70 cm and a slope of 0.9252. Overall, the LiDAR DBH estimates were highly accurate, with some small underestimations in large trees. The aboveground biomass estimates generated from the allometric equation are shown in Figure 4.

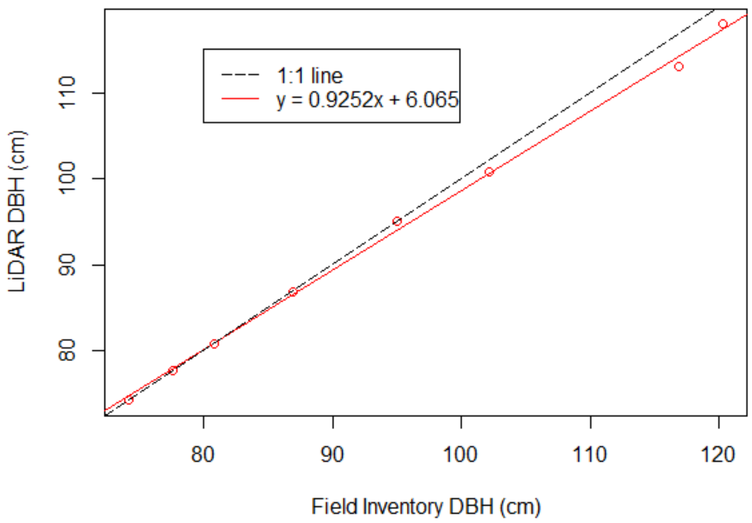

Figure 3. A comparison of field measured dbh values and LiDAR derived dbh values. The 1:1 dotted line represents where the points should fall if LiDAR measurements perfectly match the ground measurements. The red line is the least squares regression generated from the DBH values generated from the TLS scans.

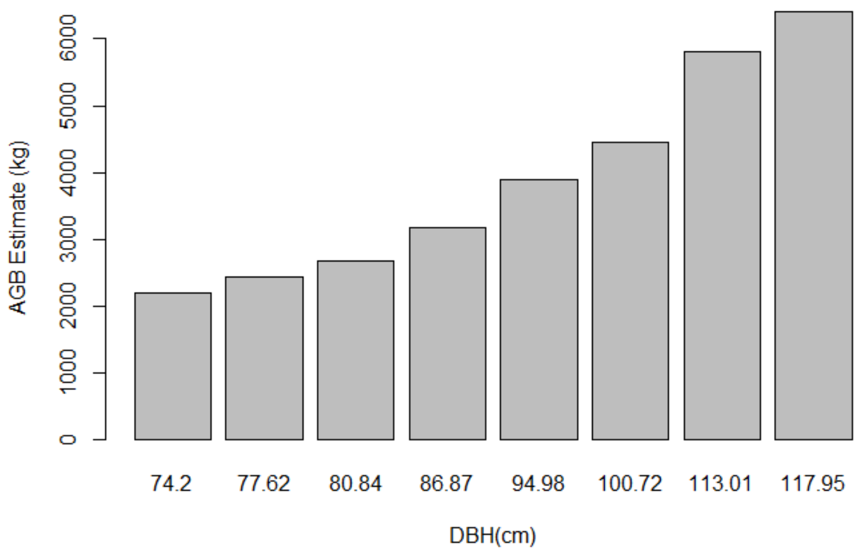

Figure 4. Biomass estimates produced by DBH allometry. The allometric equation used is from Antonio et al. (2007) and is specifically for *E. globulus.*

Volumetric Models

Tree volume is directly inferred from the TLS data by constructing three dimensional models of each tree and AGB is calculated by multiplying these volumes by the wood density. The estimates generated by this method increased with increasing dbh (Figure 5). Unlike the allometric estimates, these estimates do not follow an exact exponential equation, but are the result of direct estimates of biomass based on the point cloud data. The actual dbh of each tree does not directly factor into how the volume was estimated.

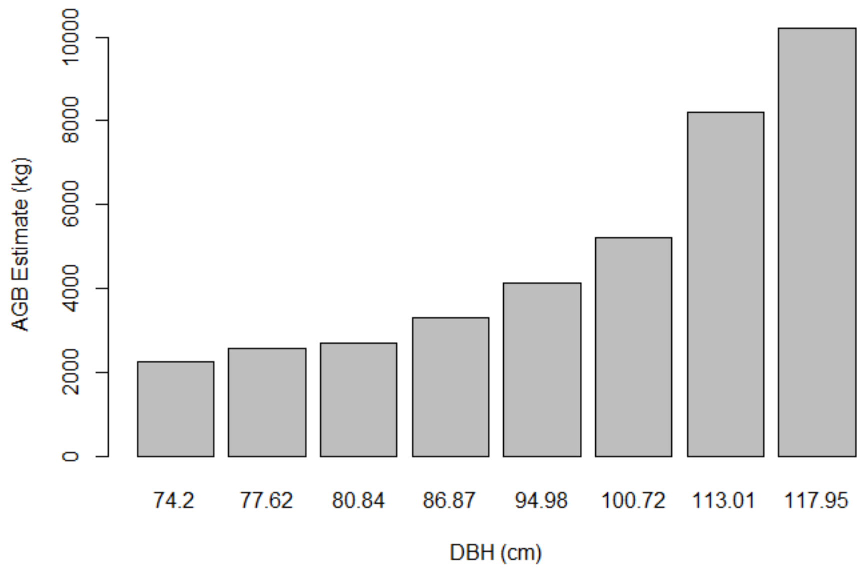

Figure 5. Bar chart showing biomass estimates from volumetric models. These estimates are for the same eight trees but were created by making three dimensional models for each tree TLS scans

Comparison between Estimation Methods

The biomass estimates generated by allometric equations and volumetric models are very similar for small trees but are drastically different for large trees (Figure 6). The difference between the two estimation methods follows an exponential curve when graphed against dbh (Figure 7). The two estimation methods have a CCC of 0.75. However, if the four trees with the smallest and largest DBH values are treated as two separated data sets, the CCCs are 0.95 and 0.48, respectively.

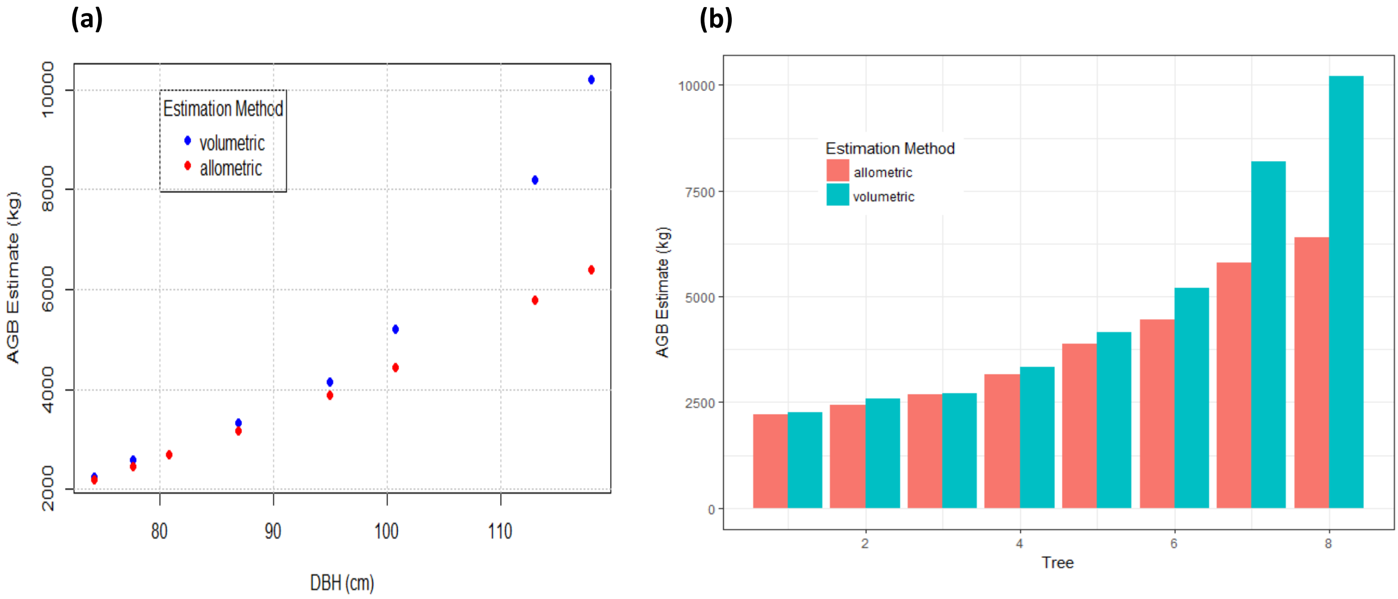

Figure 6. Comparison of AGB estimates from allometry and volumetric estimates. The graphed against each other in a scatter plot (a) and a grouped bar plot (b). In the bar chart, the trees are listed in order of increasing DBH.

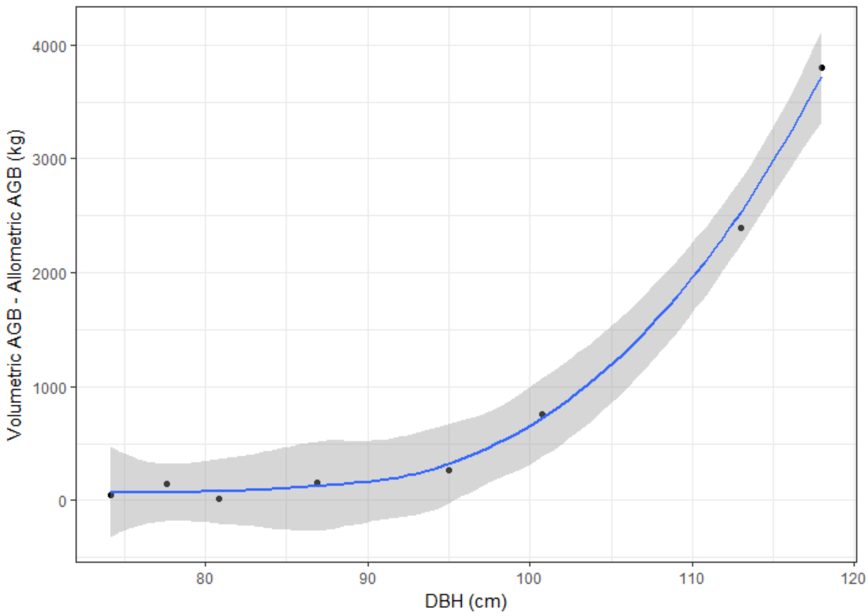

Figure 7. The difference in AGB estimates between volumetric and allometric estimation methods.

DISCUSSION

This study found that biomass estimates of *E. globulus* produced by allometric equations and by volumetric methods showed increasing disagreement with increasing DBH. Though it is impossible to know what the true biomass values are without destructively sampling, allometric estimates of biomass in Eucalyptus trees tend to underestimate the true value, especially in large trees (Calders et al. 2015). This leads me to conclude that volumetric estimates produce more accurate biomass results, especially in trees with large diameters. These results illustrate the value of TLS in biomass studies because they use novel methods to produce more accurate estimates than allometry. In addition, this study demonstrates the feasibility of producing biomass estimates from TLS using only free and open source software. The further development of free and open source software is critical for bringing this technology to a wider audience because licensed LiDAR processing software is very expensive.

Data Interpretation

The ground measurements demonstrate that the dbh measurements are accurate to an extent. Millimeter level accuracy is common in assessments of LiDAR derived dbh measurements compared to ground truth measurements (Hopkinson et al. 2004, Roberts et al. 2010, Calders et al. 2015). Problems in dbh estimation arise not from inherent inaccuracy in LiDAR scans but from problems with the dbh metric itself. The definition of a "diameter" assumes that the object being measured is a circle, which is often not true for trees. This problem has been particularly well documented in tropical forestry where most trees form a buttress near their base that causes trees to have highly variable morphologies at breast height (Clark and Clark 2000, Cushman et al. 2014). Similarly, many of the trees in the UC Berkeley Eucalyptus Grove are not circular at breast height, which causes problems for the algorithm in 3D Forest that calculates dbh. This algorithm attempts to fit circle around the points 130cm off the ground and is prone to error if the points do not form a clear circle (Trochta et al. 2017). Nevertheless, this was only a problem with three trees and the LiDAR dbh estimates from these trees were still within 95% of the field-measured value.

The two biomass estimation methods produced similar results for trees with smaller dbh values but very different results for large trees. The CCC of 0.95 confirms a very strong agreement between estimation methods for the four smallest trees and the CCC of 0.48 reveals a very strong disagreement between estimation methods for the four largest trees. These results closely match a similar study on Eucalyptus trees in Australia where tree biomass was estimated using allometry and volumetric models (Calders et al. 2015). In this case, allometric and volumetric estimates are very similar in smaller trees but very different in larger trees. Furthermore, the true biomass taken from destructive sampling demonstrated that volumetric estimates are highly accurate, even in large trees (Calders et al. 2015). This coincides with a larger body of work showing how allometric equations tend to produce inaccurate estimates with increasing dbh (Muukkonen 2007, Chave et al. 2014). This is not surprising given that large trees have rarely been harvested and measured for the calibration data of allometric equations (Stephenson et al. 2014). The results of this study further demonstrate that current allometric equations are useful for estimating biomass in small trees, but are grossly inaccurate for large trees. Given how the error in allometric estimates increases exponentially with dbh (Figure 5), allometric equations are discouraged for *E. globulus* trees with a dbh above 90cm.

Advantages and Disadvantages of TLS

Unlike other remote sensing technologies, the usefulness of TLS is often questioned because it requires a tremendous amount of field work. To scan a 1 hectare plot takes three people between three and eight days (Wilkes et al. 2017). The question of the usefulness of TLS is particularly pertinent when it is being used to calculate metrics that could be done in the field like dbh or tree height. However, TLS is extremely useful for biomass studies because it provides significantly more accurate estimates than any other non-destructive method (Calders et al. 2015). Though it does require people to be physically in the field and can take a tremendous amount of field work, the biomass estimates made by TLS scans cannot be made by taking ground measurements, so remote sensing is necessary to produce these estimates. Furthermore, airborne LiDAR cannot provide accurate scans of the stems of trees in forests with dense canopy cover (Dassot et al. 2011).

Though it is the best way to make accurate biomass estimates TLS is still rare in ecological studies because of the inherent difficulty in working with this volume and resolution of data. The scanners and proprietary software necessary are very expensive (Tilley et al. 2004, Wulder et al. 2012, Jakubowski et al. 2013). Furthermore, most softwares do not have many of the tools necessary to process point clouds and perform the analysis necessary for forestry applications. In addition, the files that contain point clouds are extremely large and often require computers with a large amount of RAM and GPUs to be viewed and processed. This study demonstrated that it is possible to produce biomass estimates of trees using only free and open source software, but these softwares are very slow on consumer grade laptops and were not equipped for processing large data sets. For example the tool in 3DForest that automatically separates trees took around ten hours to run per tree and often experienced various crashes and failures.

Challenges of TLS Approaches

The most prominent limitation in this study was that the scans were not made for the purpose of doing a biomass analysis. These scans were extremely high resolution which made the processing of point clouds very slow. Furthermore, the immense density of the point clouds made it very hard to isolate individual trees in the point clouds. Because of this, I could only render three dimensional models of eight out of forty trees in the eucalyptus grove. This is a very poor success rate given that the UC Berkeley Eucalyptus Grove is very good for a TLS biomass study because there stand is not very dense and *E. globulus* trees have very clear stems.

In addition, the method I used to generate the biomass estimates from volumetric models has many limitations. This approach requires trees to have one clear and distinct stem. This would not work, for example, in oak trees because it starts branching very low. Furthermore, this method only estimates the volume of the stem and some large branches, but is not able to include the volume in small branches or leaves. Though most of the mass in trees in the stem, Eucalyptus trees can have over 100 kg of mass in their crowns (Attiwill 1966). There is also an inherent small overestimation in the volume of the stem because it treats each segment as a cylinder when in reality the stem decreases in diameter with height. This adds a variable amount to the volume of each segment, depending on how fast the stem tapers in that segment. Researchers are working on methods for estimating the volume of trees from point clouds that do not include these biases. These methods are usually referred to as quantitative structure models and currently require very complicated mathematical algorithms but are proving to produce very accurate biomass estimates when tested against destructively sampled values (Raumonen et al. 2013, Calders et al. 2015).

Conclusions

LiDAR is potentially a very useful tool for biomass studies yet its widespread adoption is constrained by the difficulty involved in working with this type of data. In order to make TLS more widespread, it must become more accessible. There is not one defining software, processing algorithm, or even file type for TLS data. These barriers make it incredibly difficult to perform a TLS analysis. We do not know many fundamental characteristics of TLS data like the density of points required to make accurate measurements, how many angles a tree needs to be scanned from to make accurate measurements, what the best algorithms are for separating trees, and what the best algorithms are for calculating volume. This study provides methods for making biomass estimates using only free and open source software, but this process is extremely inefficient and only works on trees with a specific morphology. If algorithms like quantitative structure models are made publicly available in common point cloud processing software and the optimal scanning resolution is established, it would greatly abet the widespread adoption of TLS for biomass studies.

ACKNOWLEDGEMENTS

This project relied on the hard work, dedication, patience, and creativity of Patina Mendez. Without her, this project would not have been possible. Patina, along with Liam Meyer, Weijie Dong, and Michelle Yang took the LiDAR scans and I am very grateful for the hard work they put in to create this data set. Professor Greg Biging was very generous to let me use his computer. I am also very grateful to the ESPM 100ES staff, namely John Battles and Jacob Bukoski, who helped me formulate my ideas and got me excited about research. The staff of both ESPM 175 and 100ES are truly passionate about undergraduate research and for that I am very grateful. I would also like to extend my appreciation to the creators of CloudCompare, 3DForest, and LAStools for making their valuable software free and open source. All of these softwares took an incredible amount of work to create and could have easily been copyrighted and sold for profit but the decision to make them free and open source has greatly made research involving laser scans much more accessible for me and countless others. Katelyn Yu provided valuable peer review comments throughout the writing of this thesis. I would also like to thank my friends Hannah Marsh and Sophia Bagshaw for their support and inspiration. Lastly, I am forever grateful to my friends and family for the incredibly selfless support they have given me throughout my life.

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