DEEP LEARNING-BASED COARSE WOODY DEBRIS BIOMASS ESTIMATION FROM MOBILE LIDAR

By Merideth Reiser

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Approved:

Andrew Sánchez Meador, Ph.D., Chair

David Huffman, Ph.D.

Richard Hofstetter, Ph.D.

ABSTRACT

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MERIDETH REISER

Coarse woody debris is essential to the structure and function of forested ecosystems. It plays a role in carbon and nutrient cycling, soil health, and hydrological processes, and it provides a heterogeneous substrate for the development of forest soils, wildlife habitats, forest regeneration, and fire processes. Accurate coarse woody debris loading values are necessary to model fire behavior and calculate carbon budgets. Line-intercept methods, specifically Brown's transects, are the most commonly used methods for measuring coarse woody debris. While this method is fast, it is also labor intensive, especially in rough terrain and where access is limited. Brown's transects also cannot capture the variability of coarse woody debris biomass within a forest stand, which is the scale at which most fuel treatments occur. Advancements in remote sensing have opened new avenues for measuring forest biomass at larger scales and with finer resolutions. Mobile Lidar scanning (MLS) collects high-resolution 3D structural data of forest plots, which enables actual volumetric calculations instead of relying on geometric approximations. This technology can potentially conduct forest structural inventories that are competitive with fixed-area sampling methods in the time it takes to collect Brown's transects. However, this requires segmentation methods that distinguish vegetation from stems and coarse woody debris from the ground. The Forest Structure Complexity Tool (FSCT) is the first open-source program using deep learning to do just that. To assess this tool's performance on coarse woody debris segmentation, which is the most notable weakness of FSCT, we compared the original model and a model that we retrained for our study site to Brown’s transect and fixed-area plot measurements in the dry mixed-conifer and ponderosa pine forests on Mogollon Rim, AZ. Linear models fit to the original, untrained model predictions and field observed coarse woody debris loads produced R^2 values of 0.37 and 0.62 for ponderosa and dry mixed-conifer, respectively, and 0.38 and 0.45 for our retrained model, suggesting FSCT could be ready-to-use without the need for any user-defined parameters or tedious retraining steps. While Brown's transects overestimated mean coarse woody debris loads by 15.8% and 84.8% for ponderosa and dry mixed-conifer, respectively, FSCT underestimated these coarse woody debris biomass, with the original model underestimating by 19.5% and 10.7%, and the retrained model by 22.6% and 51.8%. We determined that for our study site, FSCT was able to provide estimates of coarse woody debris loading that aligned well with current field sampling methods. While FSCT needs to be tested and retained in more conditions, this tool may allow managers to utilize MLS technology for accurate coarse woody debris measurements.

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Dedication

To Florence Anita Weaver

Preface

The following thesis was written in the journal format described by the Northern Arizona University Graduate College. Chapter 3 has been written and formatted for submission to a peer-reviewed journal yet to be determined and is intended to stand on its own. For this reason, there is some redundancy between the following chapters.

Chapter 1

Introduction

Coarse woody debris plays a crucial role in the structure and function of forested ecosystems at various spatial scales. At the stand level, coarse woody debris provides a heterogeneous substrate for developing forest soils and contributes to forest regeneration processes (Brang *et al.*, 2003). At the landscape level, coarse woody debris influences hydrological and erosional processes, as well as nutrient cycling (Wohlgemuth *et al.* 2004, Stokland *et al.* 2012). Finally, on a global scale, coarse woody debris is a significant component of forest carbon storage, comprising 8-30% of forest carbon storage (Pan *et al.* 2011, Martin *et al.* 2021). Therefore, coarse woody debris loads should be heterogeneous across these scales in order to provide a mosaic of wildlife habitats, soils, and fire effects (Reynolds *et al.* 1992, Brown *et al.* 2003).

During fires, coarse woody debris serves as a source of fuel. These large fuels take a long time to ignite, but once they do, they can smolder for extended periods, impacting post-frontal fire behavior (Brown *et al.* 2003). These long-burning surface fuels can complicate fire suppression due to the increased chance of reburns, spot fires, and higher intensities associated with higher coarse woody debris biomass (Page *et al.* 2013). Accurate coarse woody debris loading is necessary to evaluate and implement strategies to reduce the risks associated with firefighter safety and to inform fuel treatment prioritization (Page *et al.* 2013).

To keep pace with management demands, we need to use fast survey methods to collect data across relevant scales: stand, landscape, and global. Line-intercept methods, such as those developed by Brown (1974) and now commonly referred to as Brown’s transects, are the most widely used inventory method for coarse fuels due to their speed, but this comes at the expense of accuracy. Fixed-area plots measure all fuels within a plot to make volumetric measurements or direct biomass calculations through destructive sampling. While these methods offer the highest accuracy data, they require considerable time and financial investments, so they are typically reserved for specific small-scale research questions. Brown's transects are less accurate but much faster, so this method is generally used for measuring coarse woody debris loads over management areas (Waddell, 2002, Woodall and Monleon, 2008, Woldendorp *et al.* 2004). However, methodological, human, and equipment biases can introduce errors to these biomass calculations which show up as inaccuracies in fuel load estimates (Araza *et al.* 2022). Therefore, we need a method with the speed of Brown's transects and the accuracy of fixed-area plots to meet management needs.

Innovations in remote sensing techniques, particularly Mobile Lidar scanning (MLS), have shown the potential to improve forest biometric measurements by increasing their spatial resolutions and extent. Ground-based Lidar techniques like MLS can collect high-resolution data, and due to their eye-level positioning, they are well-suited to measure sub-canopy objects like coarse woody debris. MLS offers greater mobility than fixed Terrestrial Lidar scanners and produces higher density point clouds than ALS (Bauwens *et al.* 2016, Del Perugia *et al.* 2019, Hyyppä *et al.* 2020). These point clouds allow researchers and Lidar practitioners to make direct volumetric calculations instead of using lidar geometric approximations for coarse woody debris loads. MLS has the combined benefits of Brown's transects and fixed-area plots, which could enable it to be the most effective solution for increasing forest inventories to meet the scales required by today's forest threats.

To realize the potential of this technology, we must also be able to delineate or segment forest structures in lidar data, structures like vegetation, tree stems, coarse woody debris and ground vegetation. Segmentation problems in forested point clouds have so far been solved with a combination of clustering, geometric fitting, and graph theory approaches. However, these are all inherently restrictive programming techniques because they assume predefined spatial arrangements of points. Specifically, these programming techniques were coded to explicitly define the expected distance and shape relationships between points of the same class. Then, objects are delineated or segmented based on how well they match the instructions. However, the natural world is rarely made of easy-to-determine patterns. In the hands of managers and lidar practitioners, the power of MLS is in exploring these patterns and relationships, not defining them, so why not leverage computers to find the patterns for us?

Deep learning is one method to achieve this goal. Deep learning is a subset of machine learning that uses artificial neural networks with multiple layers to learn and make predictions from complex data. These models do not require algorithms to write out which patterns to look for explicitly, instead, they are trained on large datasets to recognize patterns first-hand and construct models based on a series of weights and biases. The resulting models can be applied to make predictions on entirely new data as long as the conditions are similar enough to the conditions of the training data (see review by Mathew *et al.* 2021 for a comprehensive overview).

Forest Structure Complexity Tool (FSCT) uses deep learning to segment terrain, vegetation, coarse woody debris, and stem points from a variety of lidar sensors, including TLS, MLS, and UAV-LS. FSCT currently meets segmentation accuracies in the mid-90s for terrain (95.92%), vegetation (96.02%), and stems (96.09%), encountering more difficulties with coarse woody debris, reaching an accuracy of 54.98% in the original publication (Krisanski *et al.* 2021). For MLS to reach its potential in forest research and applications, we need segmentation algorithms that can be applied without finely-tuned datasets or specifically coded algorithms for them to work.

In this study, we compared the original FSCT model with a model that we retrained for our study site and evaluated the performance of FSCT with regard to coarse woody debris detection, which is currently FSCT's most significant limitation. We translated these segmentation results from both the original and retrained FSCT models. We then compared these coarse woody debris loads with those measured from Brown's transects and fixed-area plots. Our goals are to (1) test whether MLS-derived coarse woody debris biomass estimates are competitive with traditional field sampling protocols, (2) test the out-of-the-box functionality of FSCT and develop a workflow that translates segmentation results into coarse woody debris loading. To assess this tool's performance on coarse woody debris segmentation, which is the most notable weakness of FSCT, we compared the original model and a model that we retrained for our study site to Brown's transect and fixed-area plot measurements in the dry mixed-conifer and ponderosa pine forests on Mogollon Rim, AZ. This work shows how MLS can be used to improve traditional plot-based measurements to meet the needs of restoration treatments that are part of the Cragin Watershed Protection Project.

The chapters in the following thesis explore these research questions. Chapter two is a comprehensive literature review that covers: a) the role of coarse woody debris in forest health and ecosystem function, b) coarse woody debris and fire interactions, c) lidar applications and analysis methods in forestry, d) coarse woody debris detection and quantification with lidar, and e) deep learning in forestry and lidar application. Chapter three is an empirical study evaluating a deep learning approach to estimate coarse woody debris in ponderosa pine and dry mixed-conifer forests on the Mogollon Rim in northern Arizona. Finally, chapter four provides an overview of management implications.

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Chapter 2

Literature Review of Coarse Woody Debris and Lidar Analysis

Ecosystem dynamics, including tree physiology and mortality, have been altered from historic conditions across forests globally. In the southwestern U.S. these changes to historic conditions have been driven primarily by Euro-American fire suppression, grazing, and logging, resulting in less resilient forests with more smaller diameter trees (Moore *et al.* 2004, Lydersen *et al.* 2013). These changes in forest patterns and processes have led to a buildup of surface fuels (Covington and Moore 1994). Additionally, climate change, along with altered fire regimes and forest insect/disease cycles, are changing tree mortality rates and patterns from historic conditions, causing coarse woody debris inputs to diverge from pre-settlement conditions (Fien *et al.* 2019, McNellis *et al.* 2021).

Coarse woody debris is any bole, branch, or fragment of a dead tree with a largest diameter ≥10 cm and length ≥1 m (Harmon and Sexton 1996, Yan *et al.* 2006). Coarse woody debris can serve as an indicator of forest health due to its complex interactions with vegetation, fungi, wildlife, fire dynamics, soil and hydrology. Restoration practitioners concerned with any of these ecosystem components and processes need coarse woody debris inventories to measure how coarse woody debris loading has diverged from reference conditions, restore historic coarse woody debris loading, indirectly measure or make predictions about a related ecosystem component, or reevaluate current policies around forest operations. To do any of these, coarse woody debris inventories must be accurate, and taken at an appropriate spatiotemporal scale to address the problem. However, coarse woody debris loads have high spatial variability, which can easily be misrepresented by the sampling design and measurement method. Traditional field inventories for coarse woody debris employ the Brown transect method due to its speed and low personnel requirements (Waddell 2002, Woodall and Monleon 2008, Woldendorp *et al.* 2004). However, in practice this method often results in large uncertainties that can limit the effectiveness of restoration activities (Stokland *et al.* 2004).

Lidar has been proposed as a method to improve coarse woody debris inventories to match the spatiotemporal scales that are required for management (Brown 2002, White 2016). To understand how lidar can be applied to coarse woody debris inventories, I will discuss the role of coarse woody debris in forest health and fire dynamics, provide an overview of lidar in general and ways it has been applied to segmentation problems, and review methods that have been used to measure coarse woody debris with lidar.

Role of coarse woody debris in forest health and ecosystem function

One fifth of forest fauna, approximately a third of forest invertebrates, and over a quarter of bird species depend on coarse woody debris (Elton 1996, Speight 1989, McClelland *et al.* 1979, Hicks 1983). Wildlife use coarse woody debris for a variety of essential survival needs such as protection, nesting, and nutrition (Thomas 1979). In the Southwest, coarse woody debris is a key habitat requirement for many goshawk (*Accipiter gentilis*) prey species including chipmunks, northern flickers, red squirrels, Stellar's jays, tassel-eared squirrels, and Williamson's sapsuckers (Reynolds *et al.* 1992). These species are also key food sources for the threatened Mexican spotted owl (*Strix occidentalis lucida*) that is of management concern in the Southwest due to habitat degradation (Ganey and Balda 1994, Verner *et al.* 1992, Ward and Block 1995). Due to these associations, coarse woody debris loads can indirectly influence goshawk and Mexican spotted owl populations.

The goshawk and Mexican spotted owl are not the only predators that depend on coarse woody debris. Predator-prey dynamics are often mediated by coarse woody debris as a source of protection and these dynamics can be shifted due to a series of management or environmental factors. Small mammals hide in the peeling bark and into the softened cavities of coarse woody debris for protection from predation and environmental conditions (Fateaux *et al.* 2012). For larger mammals like caribou and deer, coarse woody debris serves as camouflage and makes the terrain more difficult for predators like wolves to navigate (Bentham and Coupal 2015, Keim *et al.* 2019)

Other animals, like woodpeckers, rely on coarse woody debris for food in more direct ways. Saproxylic food webs include all species that depend on dead wood, including wood feeders, fungus feeders, saprophages, scavengers, and predators, which all play an essential role in forest nutrient cycling (Stokland *et al.* 2012, Chen *et al.* 2016, Woelber-Kastner *et al.* 2021). At the lowest trophic level, fungi and bacteria metabolize the dead woody material and begin the nutrient cycling process. In addition to breaking down the lignin and cellulose from the wood, cord-forming saproxylic fungi also bring nitrogen into the system (Philpott *et al.* 2014). The microbial feeders that eat these decomposers turn the metabolized wood compounds into bioavailable nutrients for plants. They also change the decay rate of the coarse woody debris itself (Crowther *et al.* 2012). This process results in nutrient rich soils around the coarse woody debris that provide an excellent substrate for plant germination (Brang et at. 2003, Dumais and Prevost 2007), while the coarse woody debris itself physically protects the young seedling from grazing, trampling, and erosion (Ripple and Larsen 2001).

This decay process alters the physical properties of forest soils as well as their nutrient composition. As coarse woody debris decays it releases organic compounds that stimulate soil aggregation and increase soil porosity (Piaszczyk *et al.* 2019, Błońska *et al.* 2021). This improves the soil's water storage potential and makes it more resilient to compaction. Since different nutrients and compounds are released throughout the decay process, heterogeneous coarse woody debris results in heterogeneous soil properties across the landscape (Zalamea *et al.* 2016). The distribution of coarse woody debris also reduces soil erosion by damming sediment-carrying runoff (Williams *et al.* 2019). This damming effect is important in forests with steep slopes and after destructive fires, where erosion can deplete forest soils.

Coarse woody debris damming is crucial for the hydrology and microsite characteristics of riparian areas. In order to form pools, regulate organic matter, nutrient, and sediment transport, and create diverse habitat conditions for aquatic and semi-aquatic species, stream channels need coarse woody debris. (Beechie *et al*. 2000, Fetherston *et al.* 1995, Johnston *et al*. 2007, Welty *et al.* 2002).

Coarse woody debris and fire interactions

Globally, forests account for 45% of terrestrial carbon stocks (Bonan 2008), and coarse woody debris comprises about 8%-30% of forest carbon, depending on the forest type (Pan *et al.* 2011). Coarse woody debris can impact global carbon dynamics by both its input and decay rates and through its release of carbon during fires, so it is necessary to understand how fire and coarse woody debris interact in order to predict fire behavior, first- and second-order fire effects, and global carbon dynamics.

Managers must balance the amount of biomass stored in coarse woody debris to maintain wildlife habitat and forest heterogeneity while reducing the risk and danger of fire, as coarse woody debris is vital to valuable ecosystem processes. While fine woody debris contributes to the rate of spread and intensity of surface fires, coarse woody debris contributes to postfrontal fire behavior which adds complexity to fire behavior and heterogeneity to the post-fire landscape. Coarse woody debris can take seconds or minutes to ignite after the initial passage of the active flame front and remain smoldering for extended periods (Cheney 1990, Finney 1999). Smoldering is a type of combustion that happens on the surface of a compact fuel at low oxygen-to-fuel ratios. It's a slow, flameless process that occurs at low temperatures. Smoldering results in lower temperatures, fire spread rates, and heat released compared to flaming combustion, but since smoldering combusts over longer periods, it typically results in more heat release and energy output over the course of the fire (Byram 1959, Rothermel 1983).

Coarse woody debris smoldering can add complexity to fire behavior by reigniting flaming combustion after the initial flame front has already passed through (Brown *et al.* 2003). These long-burning surface fuels make fire suppression more challenging because of this reignition potential and high intensities (Page *et al.* 2013). The resulting spot fires and physical barriers from coarse woody debris make it more difficult to construct and hold firelines, which can pose a hazard to firefighter safety (Page *et al.* 2013).

Changes to tree mortality patterns alter the coarse woody debris biomass, spatial arrangement, and distribution of decay states, which all impact fire behavior and first-order fire effects. Coarse woody debris will burn for longer and more completely if it is surrounded by other pieces of coarse woody debris than if it were isolated (Anderson 1990, Albini and Reinhardt 1995). This is a problem in areas where bark beetles or other insect/pathogen outbreaks cause mortality pockets with jackstrawed dead and down (Page *et al.* 2012).

Decay can have mixed effects on coarse woody debris combustion, causing changes to ignition success, burn time, and flame temperatures. Decayed logs produce higher soil surface temperatures than their sound counterparts (Monsanto and Agee 2008). While the lower densities associated with advanced decay make coarse woody debris easier to ignite (Tolhurst *et al.* 2006, Hyde *et al.* 2011), increasing moisture content from 15% to 24% results in longer ignition times for ponderosa pine (*Pinus ponderosa*), Douglas-fir (*Pseudotsuga menziesii*) and subalpine fir (*Abies lasiocarpa*) (Stockstad, 1979). In addition to these longer ignition times, moisture content increases flame temperature (Babrauskas 2006), decreases rate of combustion (Dadkhah-Nikoo and Bushnell 1994), and increases air pollutants such as carbon monoxide (CO), methane, fine particulate matter (PM2.5), organic carbon, formaldehyde, acetaldehyde, benzene, toluene, ethylbenzene, and xylenes (van Zyl *et al.* 2019). The cracks and fissures that come from decay processes increase the surface-area-to-volume ratio which in turn increases the rate of burning (Byram 1959). Greater quantities of lignin result in higher temperature combustion (White 1987). Since brown rot fungi target cellulose, these fungi leave behind coarse woody debris with greater lignin quantities that burn hotter than sound or white rotted wood (Knoll *et al.* 1993). As management activities and forest structure changes alter the amount, size, and distribution of coarse woody debris on a landscape, fires respond accordingly.

Lidar applications and analysis methods in forestry

Remote sensing is frequently used to assess ecosystems and measure changes, but passive remote sensing devices are limited in forested settings because the canopy obstructs the underlying structure. Lidar, an active remote sensing technology, has opened new avenues for understanding ecology as it relates to forest structure. There are two modes of lidar data: discrete return and full waveform. Full waveform lidar is flown from high altitudes to measure vertical structure by determining the phase difference between emitted and received pulse. While this mode of lidar data has many applications to forestry, this literature review will focus on discrete return since that is the mode of lidar data used for this study. Discrete return lidar creates a three-dimensional point cloud by emitting a series of laser pulses that reflect off of vegetation and other structural elements and return high-precision position and intensity information for each returned point. Forest structure components in the point cloud may be observable with the human eye, but methods to quantify and measure these components require computational analysis. In the following sections I will cover how different discrete-return lidar collection methods vary, and general approaches for lidar analysis. Lidar can be used in ecology to improve forest inventories (Lefsky *et al.* 2002)

Detection method

LiDAR sensors can be mounted on a variety of platforms to capture information at different resolutions and spatial extents. Airborne laser scanning includes systems mounted on piloted and unpiloted aircrafts (Aerial Laser Scanning [ALS] and Unpiloted Aerial Vehicle Laser Scanning [UAV-LS]). Terrestrial laser scanning (TLS) includes systems mounted on a fixed stand, car, ATV, or on a handheld device or backpack (handheld Mobile LiDAR Scanning [MLS]).

ALS units are commonly mounted on a helicopter or fixed-wing plane and thus are able to cover spatial extents of hundreds to thousands of square kilometers. This method excels at capturing structure on the landscape scale, but it comes at the cost of point density especially for sub-canopy elements. UAV-LS have become competitive with ALS due to the decreasing cost of sensors and UAVs, making them a more viable remote sensing solution for many land managers who do not have the funds to fly ALS data. These units fly at lower altitudes, which allows them to capture a denser point cloud over a smaller extent. Since these units collect data from the top down, there is an attenuation of points as the laser pulse reaches the ground, resulting in point clouds with the highest point densities in the canopy and lowest for near-ground objects.

MLS units differ from ALS and UAV-LS units because they capture data from below the canopy, allowing for high-density point clouds of understory structure and lower densities at the top of the canopy. Overall, MLS units produce significantly higher point densities at the cost of spatial extent. Recent advances have provided MLS units that do not require Global Navigation Satellite Systems (GNSS) to establish the location, which can be highly inaccurate or altogether impossible depending on the topography, location, and canopy density (Chen *et al.* 2019). These systems are able to create a local coordinate system that can later be georeferenced with a separate GPS unit, improving their applicability to forest measurements.

Segmentation methods

Point cloud segmentation is the process by which points get sorted into discrete objects. The primary focus of point clouds segmentation in forestry has been on identifying ground and tree points. There are a variety of methods for each of these that depend on the characteristics of the terrain or tree/forest structure. With ALS and low point density UAV-LS data, tree segmentation typically relies on locating individual tree crowns to obtain heights and number of trees and then using allometric equations based on these heights to estimate other tree attributes like dbh or biomass (Hyyppä *et al.* 2001). This individual tree crown segmentation is a top-down approach and it can be used in combination with other methods like cluster analysis (Morsdorf *et al.* 2003, Lee *et al.* 2010) or distance thresholding (Dalponte and Coomes, 2016, Li *et al.* 2012) to assign the remaining points to each tree. With higher density point clouds – *i.e.* high density UAV-LS and scans taken below the canopy (TLS and MLS) – there are enough stem points to distinguish trees from the bottom-up. In this bottom-up approach, stems are often identified at breast height or root collar and the remaining stem points are "grown" from that point. The process of "growing" trees from the bottom-up can employ methods used in the top-down approach like cluster analysis or distance thresholding, but with improved stem resolution, cylinder fitting and eigenvalue decomposition techniques can also be used either independently or along with any of the other techniques (Hackenburg *et al.* 2014, Liang *et al.* 2014, Donager *et al.* 2021, Krisanski *et al.* 2021).

Coarse woody debris detection and quantification with Lidar

Since LiDAR can observe sub-canopy structures in forested settings, it has been considered as a potentially valuable tool for measuring coarse woody debris. Area-based approaches and individual piece segmentation have been used to measure coarse woody debris biomass. Much like ground and tree segmentation methods, the success of these algorithms depends on LiDAR detection method and forest structure.

The area-based approach is commonly used in lidar analysis for estimating forest structural attributes and their related effects on ecosystem processes. Typically, these approaches use metrics of vertical point distribution or the shape of the vertical profile with either point density values or intensity values, though other attributes could be summarized in this way as well. Pesonen *et al*. (2008) found that coarse woody debris biomass could be modeled using plot metrics of the standard deviation of the height distributions for first return pulses and the intensities in the 10th height percentile. Sherrill *et al.* (2008) also took the area-based approach but summarized the metrics with a PCA and found that the component associated with mid-canopy structure was also negatively correlated with coarse woody debris. Scaranello *et al.* (2019) used canopy gap metrics along with the traditional lidar metrics for percentiles of return distribution, return fraction in height intervals, canopy relief ratio, and ordered elevation returns to measure coarse woody debris loads in intact, logged, and burned forests. They measured RMSEs between 33-36% using only lidar-derived metrics, improving only slightly (~31%) when including historic land cover data derived from Landsat.

Individual piece detection requires high enough point densities to distinguish near-ground objects. The ALS pulse density has an estimated minimum detection threshold of 8-9 pulses/m^2 and an optimal density of 16 pulses/m^2 (Joyce *et al.* 2019), though this may differ by forest type. As ALS sensors have improved and UAV-LS and ground-based methods like TLS and MLS have become popularized, there is new potential to test out individual piece detection methods. Object-based image analysis can be applied to rasters that summarize different point statistics to detect coarse woody debris pieces, however it does not perform well with overlapping pieces or when there is nearby vegetation or rocks. (Blanchard *et al.* 2011, Mücke *et al.* 2013). Jarron *et al.* (2021) created a classification algorithm from ALS point data that took first returns below 1 m and applied a linearity filter to find logs. These were then vectorized and segments within 2 m of each other were connected to continuous pieces. Using this technique, they were able to detect 64% of logs and 79% of the biomass in logs with diameters ≥ 30 cm. Heinaro *et al.* (2021) used a similar method of line detection by applying iterative Hough transforms to their filtered point cloud data to classify linear points as coarse woody debris.

Machine learning is another useful tool in coarse woody debris segmentation. This requires manual segmentation of a subset of the data to train a model. Polewski *et al*. (2015) first applied shape classification methods to their filtered point cloud and then trained a classifier with the successfully segmented pieces of coarse woody debris to decrease the number of commission errors. Point cloud data can be combined with spectral indices obtained from multispectral or hyperspectral datasets, including multispectral lidar, to add information about vegetation productivity and reflectance to the structural lidar data (White *et al.* 2016). Lopes Quieroz *et al*. (2020) manually classified their point cloud into log, dirt, water, snag, or other and calculated multispectral lidar derived NDVI and NBR values, which were used to train a machine learning model, decreasing the RMSE by 12% from image-based analysis alone. Overall this method was able to detect coarse woody debris with 80% correctness and 75% completeness (Lopes Queiroz *et al.* 2019, Lopes Queiroz *et al.* 2020). The forest structure complexity tool (FSCT) is a deep learning method to segment terrain, coarse woody debris, tree stems, and vegetation (Krisanski *et* *al.* 2021). This tool shows great promise in its ability to differentiate different forest structural components, but the training data was limited to the study sites in Australian eucalyptus forests and has not been tested for its ability to measure coarse woody debris biomass in other forest types.

While many of these studies successfully delineate coarse woody debris or model its biomass, there has been little cross-validation of these studies in different forest types (Marchi *et al.* 2018). Many of these studies take place over small and relatively homogeneous study sites, which can skew their applicability to coarse woody debris segmentation over a landscape or in diverse terrain and forest conditions. This presents a problem for applying these algorithms to management concerns as they often require fine-tuning of parameters or manual oversite to check that coarse woody debris has been accurately segmented. While there has been great progress in coarse woody debris segmentation over the past few years, there is still a need for a method that can be applied at the scales required for forest management.

Deep Learning in Forestry and Lidar Application

Deep learning is a subset of machine learning that uses artificial neural networks with multiple layers to learn and make predictions from complex data (see review by Mathew et al. 2021 for comprehensive overview). It has emerged as a powerful tool for solving problems in a wide range of fields, including forestry. The ability of deep learning models to extract useful features from large, complex datasets has led to its use in applications such as forest inventory, tree species classification, and forest fire detection (Lui *et al.* 2018).

Deep learning models have been successfully applied to lidar data to accurately classify a range of attributes including tree species, aboveground biomass, and forest structure (Liu *et al.*

2021, Lang *et al.* 2022). For example, a study by Zhang et al. (2021) successfully used a deep learning model with lidar to estimate aboveground biomass in a forested areas of the Guangdong province in China and reporting high accuracies (R^2 of 0.935 and relative root mean squared error or $RMSE_r$ of 11.407%) compared to traditional, image-based methods. Another example of deep learning in forestry is found in its application in the detection of forest fires. Deep learning models can be trained on satellite imagery and other data to detect smoke, flames, and other signs of fire, thus enabling early detection and faster response times and potentially reducing the damage caused by wildfires. For instance, a study by Sathishkumar *et al.* (2023) used deep learning, specifically AI-powered computer vision techniques, for detecting fire and smoke from images. In this study, they used Convolutional Neural Networks (CNNs) - a type of AI method that excels at image classification and other computer vision tasks but takes a long time to train and often exhibits poor performance when using pre-trained models. To overcome these limitations, Sathishkumar *et al.* (2023) used transfer learning on pre-trained models to enable the network to learn a new task while preserving its pre-existing abilities.

Pointnet++ (Charles *et al.* 2017) is a deep learning model that has been used in forestry applications with lidar data. It is a neural network that can process point cloud data, such as those generated by lidar, and extract useful features for classification and segmentation tasks. Semantic segmentation is a type of image analysis that involves assigning each pixel in an image or point in a point cloud a label that corresponds to a specific class or object. Pointnet++ has been used for semantic segmentation of lidar data to classify individual trees and estimate their height and diameter at breast height (DBH) (Chen *et al.* 2021). Most recently, Krisanski *et al.* (2021) utilized Pointnet++ and deep learning to develop the Forest Structural Complexity Tool (FSCT). FCST is a tool that automates the extraction of plot-scale measurements from high-resolution point clouds obtained from various lidar sensors. It works on sensors such as TLS, MLS, and terrestrial photogrammetry, as well as above and below-canopy UAV-LS and UAV photogrammetry. However, it has been shown to be limited in predictive power when utilized with low resolution ALS datasets, situations where the segmentation model may incorrectly label stems as canopy vegetation points or CWD points as ground and surface vegetation points.

Overall, deep learning has the potential to revolutionize the way we manage and conserve forests. Its ability to extract useful features from large, complex datasets has made it a valuable tool for applications such as lidar analysis and forest fire detection. As deep learning models continue to improve, we can expect to see even more applications in the field of forestry and beyond.

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Chapter 3

Deep Learning-Based Coarse Woody Debris Fuel Load Estimation from Mobile Lidar

Abstract

Coarse woody debris is essential to the structure and function of forested ecosystems. It plays a role in carbon and nutrient cycling, soil health, and hydrological processes, and it provides a heterogeneous substrate for the development of forest soils, wildlife habitats, forest regeneration, and fire processes. Accurate coarse woody debris biomass values are necessary to model fire behavior and calculate carbon budgets. Line-intercept methods, specifically Brown's transects, are the most used technique to measure coarse woody debris. While this method is fast, it is also labor intensive, especially in rough terrain and where access is limited. Brown's transects also cannot capture the variability of coarse woody debris biomass within a forest stand, which is the scale at which most fuel treatments occur. Advancements in remote sensing have opened new avenues for measuring forest biomass at larger scales and with finer resolutions. Mobile Lidar scanning (MLS) collects high-resolution 3D structural data of forest plots, which enables actual volumetric calculations instead of relying on geometric approximations. This technology can potentially conduct forest structural inventories that are competitive with fixed-area sampling methods in the time it takes to collect Brown's transects. However, this requires segmentation methods that distinguish vegetation from stems and coarse woody debris from the ground. The Forest Structure Complexity Tool (FSCT) is the first open-source program using deep learning to do just that. To assess this tool's performance on coarse woody debris segmentation, which is the most notable weakness of FSCT, we compared the original model and a model that we retrained for our study site using Brown's transects and fixed-area plot measurements in the dry mixed-conifer and ponderosa pine forests on Mogollon Rim, AZ. Linear models fit to the original, untrained model

predictions and field observed coarse woody debris loads produced R^2 values of 0.37 and 0.62 for ponderosa and dry mixed-conifer, respectively, and 0.38 and 0.45 for our retrained model, suggesting FSCT could be ready-to-use without the need for any user-defined parameters or tedious retraining steps. While Brown's transects overestimated mean coarse woody debris loads by 15.8% and 84.8% for ponderosa and dry mixed-conifer, respectively, FSCT underestimated these loads, with the original model underestimating by 19.5% and 10.7%, and the retrained model by 22.6% and 51.8%. We determined that for our study site, FSCT was able to provide estimates of coarse woody debris biomass that aligned well with current field sampling methods. While FSCT needs to be tested and retained in more conditions, this tool may allow managers to utilize MLS technology for accurate coarse woody debris measurements.

Introduction

Coarse woody debris is a vital component of forest ecosystems, providing ecological services from seedling protection to carbon sequestration. Various wildlife species, including birds, mammals, and invertebrates, use coarse woody debris for shelter, nesting, foraging, and other essential activities. Maintaining healthy coarse woody debris loads is critical for conserving and restoring wildlife habitats for species such as the Mexican Spotted Owl and Northern Goshawk. Coarse woody debris also plays an essential role in hydrologic processes such as stream channel stability, erosion control, and water quality. Coarse woody debris can help to reduce erosion and sedimentation, stabilize stream channels, and provide essential nutrients to aquatic ecosystems. Accurate coarse woody debris biomass can be valuable in managing and protecting aquatic ecosystems and anticipating erosion and runoff events from water-repellent fire scars.

In wildfire and prescribed burns, coarse woody debris can spend long periods smoldering, increasing fire behavior and spreading across the landscape due to spotting and post-frontal reignition events. In addition, smoldering coarse woody debris releases high levels of heat over long periods that can have detrimental effects on soils and nearby vegetation, increasing the number of fire-killed trees, soil heating, and altering tree regeneration and erosional processes.

Accurate coarse woody debris loading is essential to predict fire behavior and intensity, enabling managers to develop effective strategies for preventing and controlling wildfires and planning prescribed burn operations. These loading estimates can help managers identify areas of high fire risk and prioritize fuel reduction efforts. Making accurate and reliable estimates of coarse woody debris biomass is crucial to prescribed and wildfire management and planning, as well as for conserving and restoring wildlife habitats and protecting hydrologic processes. In addition, these biomass estimates are vital to understanding forest dynamics and carbon cycling, especially in climate change, where mortality events are large, and margins of error for management are small.

Coarse woody debris biomass can be estimated with photographs, visual guides, transect, planar intercept, and fixed-area methods. The line transect method assumes that the probability of sampling a piece of woody debris is proportional to its size (Warren and Olsen, 1964, Van Wagner, 1968). Visual surveys and planar intercept (Brown’s transects) are used most frequently. In visual surveys, biomass is estimated by comparing an area to sites where this value has been calculated, which is subjective and requires a trained eye and a well-documented collection of different coarse woody debris conditions. Brown’s transects were explicitly developed for sampling fine and coarse woody debris in forests (Brown, 1974). This method is a variation of the line transect method but uses sampling planes instead of lines. Fixed-area, nested, or quadrat methods are based on frequency concepts where all fuels meeting specific criteria within the plot boundary are measured using various methods, ranging from destructive collection to volumetric measurements. These volumetric measurements approximate the shape of coarse woody debris into simplified geometric shapes like cylinders of frustums. While these geometric approximations are more accurate than other sampling methods, it is still an approximation and not the true biomass. The resulting biomass depends on which shape is chosen to represent coarse woody debris and the best available density data. Since wood densities change depending on the state and type of decay, species, and site climatic conditions, these variables cannot all be accounted for without destructive sampling, and thus are also an approximation of the truth. Due to the significant investments of time and money required, these methods are typically used for specific small-scale research questions. At the same time, Brown's transects are reliable and fast, so they are usually used for monitoring or inventorying management areas. While Brown's transects are faster than fixed-area methods, they can still be labor-intensive, especially in rough terrain with limited access. In addition, they do not capture the variability of coarse woody debris loads within a forest stand.

Advancements in remote sensing technologies have opened new avenues to measure forest biomass at larger scales, making managing forest ecosystems easier and more effective. One technology that could be applied to coarse woody debris inventories is light detection and ranging (Lidar). Lidar collects highly detailed 3D images (*i.e.*, point clouds) by emitting a series of laser pulses that map the locations of objects within the range of the sensor. Lidar is a promising tool for improving forest biomass inventories, as it can accurately estimate forest canopy height, volume, and aboveground biomass. While scan shadows and low point densities make it challenging to measure coarse woody debris biomass with airborne Lidar methods (ALS), ground-based Lidar methods, like TLS and MLS, have high subcanopy point densities due to their scan positioning. MLS technologies could benefit coarse woody debris surveys since these scanners are highly transportable and require smaller crews than traditional sampling methods (Chen *et al.* 2019).

Researchers are beginning to develop new ways to extract critical information from MLS data in forested ecosystems, still, most of this work has been in algorithm development without associated published code. This leaves Lidar practitioners and forest managers needing clarification on which tools have been successful and are ready for real-world forest management. Additionally, these tools can be locked behind paywalls, require translating into code, or require parameterization that needs to be more intuitive and well documented, which translates to processing and re-processing the same data to optimize an algorithm to the area of interest.

Point clouds must be attributed with identifiers such as a tree or coarse woody debris before other forest structure questions can be answered. So, having segmentation tools that work can streamline MLS workflows and allow Lidar practitioners to answer their ecological questions. Semantic segmentation is identifying and attributing points within a point cloud to objects. Segmentation methods typically use geometric fitting, clustering, and/or graph theory approaches to meet this end.

Geometric fitting finds geometric shapes in the point cloud data, such as cylinders or cones, to represent individual objects. However, coarse woody debris is often non-cylindrical, and neighboring points from trees, vegetation, or ground may obscure the shape of coarse woody debris in dense scenes. The user must finely tune parameters to attribute point cloud data accurately. This also presents a challenge for clustering methods, which are challenging to parametrize when coarse woody debris and surrounding ground objects are easy to visually identify but take a variety of odd shapes that can have different clustering coefficients optimized for different size and decay classes. Graph theory approaches have helped mend these difficulties by connecting similar but disjointed points first identified through clustering or geometric fitting. These approaches have been explored in the overstory and understory segmentation problems, but applying these methods to forest segmentation problems is complex. While researchers have found many successful methods to segment trees and even coarse woody debris, these methods only sometimes translate to different forest, terrain, or coarse woody debris conditions. Ultimately traditional programming methods require the tedious work of fine tune parameters to optimize for site conditions, and the assumptions made by these models cannot fully capture the structural complexity of natural systems.

Deep learning models employ a different framework, removing the need for tedious and inconsistent fine-tuning. Deep learning models differentiate objects from patterns learned through a subset of training data with manually labeled objects of different classes. They then construct models from the patterns learned in the training data, which can be applied to new data containing the same objects. For example, the Forest Structure Complexity Tool (FSCT) is a deep learning model which segments high density forested Lidar point clouds (MLS, TLS, high density UAV-LS, and ALS) into terrain, vegetation, coarse woody debris, and stems/branches (Krisanski *et al.* 2021a). FSCT is open-source, and users can decide whether to run the model as-is or retrain it for their particular area of interest. While running FSCT is simple, albeit computationally slow, retraining FSCT and similar deep-learning models can take weeks due to long processing times and the tedium of manual segmentation on high-density point clouds. Retraining FSCT should only be necessary when new data significantly differs from the training data, but what that means for different forest structures is still being determined.

Since deep learning models require little input from the user, Lidar practitioners can obtain detailed descriptions of forest structure and composition data without needing advanced computational knowledge. FSCT has shown high accuracies (~96%) for terrain, vegetation, and stems/branches, but it has struggled with segmenting coarse woody debris, reaching an accuracy of 54% (Krisanski *et al.* 2021b). While FSCT falls short at coarse woody debris segmentation, it is still competitive with other traditional segmentation methods (Jarron *et al.* 2021, Nyström *et al.* 2014, Joyce *et al.* 2019). FSCT also offers additional functionality that other coarse woody debris segmentation methods do not have.

MLS is a versatile tool providing valuable information on overstory structure and fuel characteristics. However, while MLS surveys can save time in the field, the subsequent data analysis requires specialized skills and can be time-consuming, which is one of the major reasons MLS has primarily been in the research and development phase without being applied to management scenarios. Land management agencies frequently acknowledge the potential of MLS and other Lidar datasets to advance forest management objectives. However, such agencies often need more personnel with the necessary expertise to analyze and interpret this data. Thus, proficient lidar practitioners must develop lidar and test open-source tools, such as FSCT, to alleviate the computational skills gap and enhance the usability and accessibility of Lidar data. These tools can make a significant difference in the decision-making process by reducing analysis time and costs associated with data collection. In addition, deep learning models like FSCT can streamline MLS workflows by reducing the need for user inputs. While retraining these models adds significantly to analysis time, this may only be necessary for some cases. Without the need to retrain FSCT, lidar practitioners only have to pre-process MLS data and run FSCT to obtain detailed forest structure and composition data without extensive programming knowledge, making it an accessible tool for forest management decisions.

In this study, we compared the original FSCT model with a model that we retrained for our study site and evaluated the performance of FSCT with regards to coarse woody debris detection, which is currently FSCT's biggest limitation. We translate these segmentation results from both the original and retrained FSCT model. We then compared these coarse woody debris loads to those measured from Brown's transects and fixed-area plots. Our goals were to (1) test if MLS-derived coarse woody debris biomass estimates are competitive with traditional field sampling protocols, and (2) test the out-of-the-box functionality of FSCT and develop a workflow that translates segmentation results into coarse woody debris loads.

Methods

Study design

To capture the range of forest conditions on the Mogollon Rim Ranger District of the Coconino National Forest, we established two study sites ranging in elevations from 6950 to 7600 meters. The Mogollon Rim experiences mean annual temperatures of 9.3°C, varying between 16.3°C, generally observed in July, to 2.25 °C in January, and a mean annual precipitation of 89 cm (Jaquette *et* al. 2021). Soils at the site originated from Kaibab limestone residuum (Ramcharan et al., 2018). Due to the a combination of seasonal monsoons and the strong orthographic lift effect of the rim, this area experiences high lightning, which resulted in frequent, low-severity fires burning with a mean fire interval of 2 to 8.5 years before Euro-American settlement (Huffman *et al.* 2015).

The forests on the Mogollon Rim vary from ponderosa pine (*Pinus ponderosa*) into dry mixed conifer. At lower elevations further from the rim, these ponderosa forests historically had open conditions and bunchgrass understories, though much of the understory diversity has been reduced due to the impacts of grazing and increased tree densities from fire exclusion. Gambel oak (*Quercus gambelii*) and juniper (*Juniperus scopulorum, J. deppeana, J. monosperma*) trees can be found intermixed throughout these ponderosa pine forests. At higher elevations and more mesic conditions, the forest becomes dry mixed-conifer forests, where ponderosa pine, Douglas-fir (*Pseudotsuga menziesii*), and white fir (*Abies concolor*) dominate the landscape, alongside Southwestern white pine (*Pinus strobiformis*) in more northern aspects, aspen (*Populus tremuloides)* in pockets, and bigtooth maple (*Acer grandidentatum*) and New Mexico locust (*Robinia neomexicana)* found in the lowest drainages. In this study we collected data across the two study sites, Kinder and Kehl, that are in high-priority treatment areas within the Cragin Watershed Protection Project boundaries. Kinder captured the lower-elevation ponderosa forests, and Kehl captured the higher-elevation dry mixed-conifer forests closer to the escarpment.

We collected field data during the summers of 2020 and 2021 under the supervision of the Ecological Restoration Institute with Northern Arizona University. This project was funded by the Salt River Project to monitor coarse woody debris and test ALS, UAV-LS, and MLS methodology. ALS and UAV-LS data were collected for both treatment areas in the fall of 2020 through a subcontract, awarded after a competitive bid, from Quantum Spatial (now NV5 Geospatial, https://www.nv5.com/geospatial). The plot design is part of a bigger test that uses multi-platform Lidar methodology. However, the sites used to test the MLS methodology are only a part of the plots used for UAV-LS acquisition areas. The field data were collected across all sites. Therefore, in this thesis, Brown's transect method analysis, independent of MLS data, uses plots from both UAV-LS and ALS sampling areas. On the other hand, the MLS portion of this thesis only uses a subset of the plots from the UAV-LS sampling areas. Lidar field crews sampled data at 171 plots nearly evenly distributed between the two study areas, 88 in Kinder and 83 in Kehl. Each ALS acquisition area contains four nested UAV-LS acquisition sites with 35 and 39 plots, respectively. Plots are sampled on a grid with 470 m spacing in the ALS and 200 m in the UAV-LS acquisitions. Field crews collected MLS scans and coarse woody debris loading on each plot using Brown's transect and fixed-area plot methodologies.

Ground Truthing

We used a fixed-area plot design to calculate each plot's coarse woody debris biomass and ground truth of our MLS-derived and Brown's transect results. These fixed-area plots comprise three concentric circles with radii of 16.05 m, 11.35 m, and 6.55 m (Figure 2). First, we sampled coarse woody debris within certain diameter ranges in each fixed-area plot: all pieces at least a meter long with diameters greater than or equal to 30 cm, 20 cm, and 7.62 cm for each fixed-area plot, respectively. Since larger pieces are rarer than smaller pieces, this method allows us to capture coarse woody debris across all size classes without over-sampling small pieces. Next, we calculated the biomass per area for each of these three subplots and summed these to find the total tons per acre of coarse woody debris on each plot.

To calculate coarse woody debris biomass, we measured the length, diameter at both ends and middle, the species, and decay class and mapped the position from the plot center for each piece using a TruePulse 360 rangefinder. Decay classes were chosen based on the criteria shown in Figure 1 and outlined further by Masser *et al.* (1979). We also measured each stump and snag that met the diameter requirements listed above, but this was not used for further analysis. Finally, we measured each stump and snag's height, diameter (at root collar or breast height, respectively), species, decay class, and map position from the plot center.

We calculated the biomass of each piece of coarse woody debris by approximating its shape as a double frustum (two truncated cones) to account for the tapering at each end that occurs as logs decay from the ends.

$$V = \frac{1}{3}\pi l[d_1^2 + d_2^2 + d_{mid}(d_1 + d_2) + 2d_{mid}^2\ ] \qquad \textbf{Eq 1}$$

Where l is the log length, d_1 and d_2 are the end diameters, and d_{mid} is the midpoint diameter. We then converted these volumes into biomass estimates by multiplying the specific gravity of the piece determined by its species and decay state, listed in table 1.

Brown's Transects

We collected Brown's transects on each plot along three lines at 0°, 120°, and 240° (Figure 2). On each 15.24 m (50ft) long transect, we measured all coarse woody debris with a diameter greater than 7.62 cm at the intersection point and a length of 1 m. For each piece of coarse woody debris intercepted along the line, we measured the diameter at the intersection point, the species, decay class, and distance from the plot center following standard sampling protocols (Brown, 1974). We calculated the biomass using the following equation:

$$W = \sum d^2 * \left(\frac{k*SLP}{l}\right) * \sum_{spp}\left(SEC_{spp}\right) * \sum_{spp}\left(SG_{spp}\right) \qquad \textbf{Eq 2}$$

Where W is the total plot loading, d is the diameter of the piece, k is a unit correction factor, SLP is the slope correction factor, SEC_{spp} is the angular correction for each species, SG_{spp} is the specific gravity for each species (which we further separate into sound and rotten summations), and length is the transect length. These coefficients were calculated from data from the mixed-conifer forests of Sierra Nevada and are listed in Table 1 (Van Wagtendonk *et al.* 1996). We also evaluated the impact of using one and two Brown's transects on the coarse woody debris biomass.

MLS Collection and Analysis

On each plot we collected MLS scans with a GeoSLAM Zeb Horizon scanner. First, we placed reflective balls at the plot center, at 0°, 120°, and 240° at a distance of 16.06 m from the plot center. Next, we scanned the plots using the lotus scanning method, where the scanner was walked from the plot center in loops around each reflective ball and then in a circle enclosing the plot's perimeter, as shown in Figure 3**.** These scans were moved onto a USB drive in the field and then transferred into GeoSlam Hub 6.1.0 for pre-processing. In GeoSlam Hub, we set the local parameters as follows: convergence thresholds to 3, window size to 3, voxel density to 1, rigidity to 0, and maximum range to 100 m. For global parameters, we set the convergence threshold to 3 and the rigidity to 0. In addition, we selected to optimize laser position and the closed loop processing options. Finally, we visually inspected each scan for ghosting or registration errors and reprocessed point clouds that were not up to standard, for some, this was solved by increasing the convergence threshold, but a handful of scans could not be fixed in post-processing were removed from the analysis.

To retrain FSCT, we visually assessed our plots and selected 12 that represented the overstory conditions, understory vegetation, topography, and coarse woody debris loading found across the area. For these 12 plots – 6 in each study site – we corrected the segmentation from the original FSCT model output. First, we manually corrected the segmentation using CloudCompare v2.12, primarily correcting the segmentation for coarse woody debris points. Next, we normalized the point clouds and separated each label into its point cloud using R 4.2.0 (R Core Team, 2022) and the lidR package (v4.0.1, Roussel *et al.* 2021). We then imported the set of point clouds into CloudCompare, and for each layer, we colorized the point by Z values and combed through near-ground points to detect mislabeled coarse woody debris points. Next, we used the segmentation tool to clip out coarse woody debris points, and the merging tool to combine clipped-out coarse woody debris points into a single source. We also relabeled non-coarse woody debris points labeled as coarse woody debris. Finally, we imported the newly labeled layers into R to update the label values.

From each of these 12 manually segmented plots, we clipped out 1-3 subsections that had three or more trees with at least one piece of coarse woody debris. However, some subsections contained significantly more trees or coarse woody debris depending on how interconnected the crowns were or the dimensions of the coarse woody debris. We divided these into 18 training and six validation subplots so that the size of the validation data was roughly a third of the training data to account for the variability in the sizes in these datasets. The training set is what the model trains and learns from, while the validation set evaluates the model's performance on unseen data. During the training process, the model tries to minimize the loss function, which measures how different the predicted segmentation is from the manual segmentation. We monitored the accuracy of the predictions on the training set and the validation set while the model was training. The accuracy metric shows how well the model correctly predicts the class label for each point. We trained and validated for 100 epochs on a desktop computer with an Intel Xeon(R) Silver CPU, 128 GB of RAM**,** and an Nvidia RTX A4000 GPU with 24 GB of VRAM. Our retrained model is from epoch 56, where accuracy and loss were high.

Estimating coarse woody debris biomass from MLS

FSCT labels each point in the point cloud with a class label between 1-4 (1 = terrain, 2 = vegetation, 3 = coarse woody debris, and 4 = stems/branches). We developed a linear regression model to predict the coarse woody debris loading based on the number of coarse woody debris points and the total number of points, shown in equation 3. The total points variable was included to compensate for the fact that plots had different point densities depending on how long we ran the scanner. We tested the combined and separate models for the two forest types and decided to model all the data by forest type since it unanimously improved fitting parameters.

$$lm = a * pts_{cwd} + b * pts_{total} + c * pts_{cwd} * pts_{total} \qquad \textbf{Eq 3}$$

We estimated the expected coarse woody debris loads from the original and retrained FSCT by applying the coefficients from our linear model in Eq 3 to calculate the predicted coarse woody debris load for each plot. Then, we repeated the model fitting and biomass estimation for the original and retrained models.

Results

Coarse woody debris loading

As expected, we found higher coarse woody debris loads across the dry mixed-conifer sites than the ponderosa pine sites, though overall the coarse woody debris loads were low. The mean biomass was 1.90 tons per acre (0.98 sound, 0.92 rotten) in Kinder and 3.85 tons per acre (2.49 sound, 1.36 rotten) in Kehl (Table 2). These coarse woody debris loads are lower than expected, 3-7 tons per acre in ponderosa pine forest types and 10-15 tons per acre in mixed conifer.

This biomass was primarily stored in large logs (diameter ≥ 30 cm) in both sites (Figure 5). There was a shift in decay classes between the two sites. While the most common decay class in both sites was a 4 – where logs have lost all bark and show obvious signs of deformation due to decay – Kehl has an almost equal amount of biomass stored in logs with a decay class of 3, which matches with this site having a lower proportion of rotten to sound pieces. In these dry mixed-conifer sites, more logs have remaining bark and show fewer signs of deformation (Figure 6). There was greater variability in the coarse woody debris biomass in the mixed-conifer site compared to the ponderosa site, with the largest accumulation of coarse woody debris found on plots closest to the escarpment (Figure 4).

FSCT Training Results

We plotted the accuracy and loss (Figures 8 and 9) of the training and validation results as we retrained the model over 100 epochs. These accuracy and loss plots level off around epochs 25-75 but may show signs of overfitting at the tail end, but we will have to run this beyond 100 epochs to explore this behavior fully. The model we used was from epoch 56, where accuracies were high while losses were low, with both being stable. This method of selecting a model from an epoch before signs of overfitting appear is considered early stopping and is a common approach to handle overfit data in deep learning models.

Retraining the model slightly increased precision and recall for coarse woody debris across both sites (Table 4). The confusion matrices show how our manual classifications compared to the FSCT classifications, where perfect segmentation would result in 25% along the diagonal and 0% in all other classification boxes. In both forest types we found an incremental increase in coarse woody debris detection with retraining (Figures 10 and 11). Still, it is clear that the model is too selective for coarse woody debris points, resulting in 1.1-1.4% of manually segmented coarse woody debris points being identified, while most points were misclassified as terrain or vegetation. The overall accuracy of the original model was 0.608 for Kinder and 0.594 for Kehl. Retraining the model resulted in a slight increase in accuracy in Kinder to 0.605 and a slight decrease in accuracy in Kehl to 0.593. From the confusion matrix for Kehl, the drop in accuracy appears to be driven by the misclassification of the ground as vegetation rather than any changes to coarse woody debris segmentation. Similarly, the retrained model resulted in a slight increase in kappa in Kinder and a slight decrease in Kehl. These changes in kappa scores – a measure of the agreement between manually and the predicted segmentation – mean that the agreement across all segmentation improved for Kinder but not for Kehl. Ultimately, these changes to model performance by retraining are minor.

Comparison of Coarse Woody Debris Biomass

Brown's transects overestimated the mean coarse woody debris biomass across both sites, with a mean loading of 3.33 tons per acre for Kinder and 6.39 tons per acre for Kehl. To test if this difference was significant, we conducted a pairwise Wilcox signed rank test of the coarse woody debris loading derived from Brown's transects and fixed-area plots (Figure 7), which resulted in a p-value of 0.116 in Kinder and 0.00043 in Kehl. Biomass measurements with fewer (two and one) Brown's transects reduced the mean while still overestimating on high load sites (Figure 12).

We found that the original training model did not perform as well in ponderosa pine stands as in dry mixed conifer conditions. Retraining the model improved these ponderosa sites but resulted in a reduced R^2 for the dry mixed conifer sites. Despite the low performance on segmenting all coarse woody debris points, there is still a clear relationship between the points captured and the total coarse woody debris loading. Therefore, we used the coefficients from our linear model to calculate the expected coarse woody debris load from the number of coarse woody debris and total points (Eq 3, Table 5).

Boxplots of the coarse woody debris loads measured with Brown's transects (Figure 13) showed the original and retrained FSCT models, and the ground truth had a similar estimate of central tendency but varied greatly. Summary statistics for each method are listed in Table 3. The biomass estimates from Brown's transects were consistently higher than those obtained through nested sampling, with mean values of 1.54 tons per acre and 7.06 tons per acre for Kinder and Kehl, respectively. In contrast, the FSCT models produced lower mean biomass estimates, with the original FSCT model yielding means of 1.07 and 3.41 tons per acre for Kinder and Kehl, respectively. Our retrained FSCT model further reduced the mean coarse woody debris load estimates, with values of 1.03 and 1.84 tons per acre for Kinder and Kehl, respectively.

Brown's transects overestimated mean coarse woody debris loads by 15.8% and 84.8% for Kinder and Kehl, respectively. In contrast, the original FSCT model underestimated the coarse woody debris loads by 19.5% and 10.7% for Kinder and Kehl, respectively. In contrast, our retrained FSCT model led to coarse woody debris load underestimates, with percentage differences of 22.6% and 51.8% for Kinder and Kehl, respectively. Retraining FSCT did not improve coarse woody debris biomass estimates in the model for dry mixed-conifer or ponderosa pine forests. While FSCT Brown's transects overestimated coarse woody debris loading, the original and retrained FSCT model underestimated the loading. However, the only method that failed to capture the mean was the retrained FSCT model in Kinder.

Discussion

Coarse Woody Debris Loading

The structure of ponderosa pine and dry mixed-conifer forests in the Southwest were historically driven by low intensity, frequent fires with more localized disturbances from windthrow, insects, and pathogens that created an open and heterogeneous landscape dominated by larger trees (Reynolds *et al*. 2013, Rodman *et al.* 2016, and Jaquette *et al*. 2021). With larger and sparser trees than current conditions, coarse woody debris was primarily stored in larger pieces a distributed infrequently across the landscape. With fire exclusion and changing land use since the late 1800s, forests have increased in density and shifted to smaller diameter trees and less fire-resistant species, such as white fir. Since coarse woody debris loading is a balance between input rates from mortality patterns and loss rates from decay and combustion, live and dead wood patterns have been dramatically altered as forest patterns and processes have changed (Shorohova and Kapitsa 2015).

Coarse woody debris loads were lower than expected in both forest types sampled on the Mogollon Rim, but surveys done with Brown’s transects inflated these values. Brown’s transects are the most common method to measure coarse woody debris, but the resulting biomass estimates are highly dependent on the length and number of transects (Waddell 2002, Woodall and Monleon 2008, Woldendorp *et al.* 2004). We tested the accuracy of Brown’s transects using the average of three transects per plot, however it is common practice to use a single transect, with increases the likelihood of missing the coarse woody debris. While using fewer transects still overestimates high coarse woody debris loads, the mean decreases as the number of transects decreases. This is because fewer transects are more likely to miss the coarse woody debris and return false null values, which gets further from a true representation of the coarse woody debris on the landscape.

Overestimating coarse woody debris loads can lead to unnecessary and expensive mitigation efforts that degrade wildlife habitat and underestimating these loads can cause unexpected fire effects (Harmon and Sexton 1996). Since Brown's transects depend on site characteristics and sampling design (Waddell 2002), our findings may not apply to other areas with different fuel characteristics, even within the same forest type. Therefore, Brown's transects should be tested across different forest conditions to appraise when this method is unsuitable for measuring coarse woody debris.

Ground-based lidar methods – TLS and MLS – are a remote sensing alternative to traditional field surveys. MLS is a plot-based survey method, so the data it collects represents forests with greater detail than other lidar methods, like ALS or UAV-LS. MLS point clouds have high sub-canopy point densities (Chen *et al.* 2019). While this creates visually stunning imagery, not many tools are available for streamlined MLS analysis since ALS tools and methods often do not translate across technologies. Lidar practitioners trying to derive first- and second-order products like DEMs, canopy cover maps, and tree density estimates need to be able to develop or translate segmentation algorithms into functioning code. Until there are easy-to-use tools to alleviate this need, MLS will be confined to the research and development stage.

While lidar practitioners have relied on traditional programming techniques, the effectiveness of these methods is highly dependent on the site conditions. In open forested conditions, these techniques have been effective (Donager *et al.* 2021), but they have been much less effective in more complex forest structures such as the mixed-conifer forests of the Mogollon Rim (Pelak 2022). These methods struggle to capture small diameter trees while overestimating the diameters of large trees (Pelak 2022). More robust computational methods are therefore needed not only for coarse woody debris mensuration, but also to improve the functionality of MLS across forest types.

Tools like FSCT are helping to bridge this gap for Lidar practitioners by providing an open-source tool that can obtain tree heights, diameter distributions, and canopy metrics and return a labeled point cloud that can be used for further analysis. Since FSCT uses deep learning techniques, this method does not require site parameterization. There likely are cases where FSCT will need to be retrained, but we found that retraining FSCT did not improve the model, instead resulting in a reduction in model performance in Kehl, the only sampling method that did not capture the mean coarse woody debris load. This was due to the subjective nature of manually segmenting data.

When we retrained FSCT, we focused on capturing all coarse woody debris on each plot, but because of fragmentation, deformation, and decay, some pieces look identical to the ground or near-ground features without the larger context of the site. This meant we captured highly rotten sections of logs between more sound fragments and pieces that were noticeable through their point densities and proximity to other fragments, not by Z values alone. Training the model with these data could have altered the results, as the model detects patterns from spatial coordinates alone, and with minor differences in Z values, the ground can be indistinguishable from coarse woody debris.

Manually segmenting point clouds is a slow and tedious process, and care needs to exercised if practitioners plan to retrain FSCT. While it is essential for the manually segmented training data to be accurate, point clouds do not always have clear delineations between different objects. There are not clear boundaries between coarse woody debris and the ground, which means that subjective decisions must be made about how to classify each point, especially in MLS point clouds where there is more noise compared to their TLS counterparts. Since the original FSCT was trained with manually segmented TLS point cloud data, the reduced noise decreases some of this challenge, but cannot get around this subjectivity. The addition of color data would help users more easily differentiate objects, but this data is not collected by most lidar scanners.

However, FSCT performed well without the need to retrain. While Brown's transects overestimated coarse woody debris loads by 15.8% and 84.8% for Kehl and Kinder, respectively, the original FSCT underestimated these loads by 19.5% and 10.7%, meaning that FSCT was at least as effective as Brown's transects for measuring coarse woody debris loads.

Deep learning vs. traditional segmentation approaches to MLS.

Since ALS data are commonly used for forest operations and management, researchers have been developing methods to detect coarse woody debris from these datasets. These approaches for ALS have to compensate for scan shadows and low point densities. So far, detection rates have hovered around 30-40%, reaching as high as 64% (Nyström *et al.* 2014, Joyce *et al.* 2019, Jarron *et al.* 2021). The most effective approach so far, detected lines and connected neighboring line fragments to form continuous logs, combining geometric fitting and graph theory approaches (Jarron *et al.* 2021). However, as stated previously, these algorithms are not always transferrable between ALS and MLS point clouds.

MLS approaches for coarse woody debris detection have only recently become an area of research and development, so the literature is limited. One study collected TLS and TLS/UAV-LS fusion data and applied a series of masks created by random forest modeling to remove points surrounding coarse woody debris. This resulted in a coarse woody debris completeness score of 20% and a correctness score of 86% (Shokirov *et al.* 2021). While using a completely different modeling framework based on traditional programming techniques, this result still mirrors the high selectivity of coarse woody debris points detecting with FSCT. FSCT achieved precision values of 0.97 and 0.99 and recall scores of 0.044 and 0.048 for Kinder and Kehl, respectively. Coarse woody debris segmentation is challenging in these high-density point clouds where vegetation, ground, and other near-ground objects can obscure logs and make underlying geometric patterns indistinguishable. While these values highlight the potential of MLS methods to detect coarse woody debris correctly, they also underscore the challenges of working with high-density point clouds. As MLS technology advances, new techniques, and tools will be needed to extract valuable information from these complex datasets. Low recall or completeness scores mean that these models fail to identify a significant number of coarse woody debris points.

However, even if these points are a subset of the coarse woody debris points, they can still model the biomass as long as the selected points are representative of the coarse woody debris across the plot. This is a similar modeling framework to Brown's transects – sampling a subset of coarse woody debris can model the entire plot's loading based on a known sample. As opposed to Brown's transects, MLS is continuing to improve the size of that subsample with the potential for whole piece mensuration. As it stands, MLS is already producing coarse woody debris loading accuracies that are competitive with Brown's transects. For example, in Kehl, the original FSCT captured the mean and standard deviation better than any other method, implying that while the model could not capture all the coarse woody debris points, the points adequately captured the total biomass. This may vary depending on the range of decay and size classes in the sampling area. The original FSCT did not perform as well in Kinder as in Kehl, possibly due to lower coarse woody debris loads or a greater proportion of rotten/decayed pieces. More forest types and fuel conditions must be measured to uncover these underlying dynamics.

While FSCT has room for improvement, it can still identify coarse woody debris with enough precision to make reasonable biomass estimates across the landscape. Other deep learning-based approaches have been used to distinguish tree and vegetation points, but FSCT is the only method that includes coarse woody debris segmentation. However, these other deep learning approaches have reached similar accuracies for their tree segmentation results. In its original publication, FSCT reported an accuracy of 0.954 across all classes and 0.961 for stem and vegetation only. While applying this model to our study sites resulted in an accuracy of around 0.6 with minor changes to this value from retraining the model, these accuracies could differ from these other reported accuracies as we did not aim to improve tree segmentation results. Studies that do seek to segment trees with deep learning have resulted in accuracies competitive with FSCT. For example, another model using a different implementation of PointNet++ produced tree segmentation accuracies of 0.90 (Morel *et al.* 2020), while another model using a PointCNN backend produced tree segmentation accuracies of 0.93 (Shen *et al.* 2022). Deep learning is well suited for segmentation problems in natural systems as they do not require estimations about the geometries or point distributions within these scenes. However, while there are promising results for tree segmentation, we need more research to explore how well these models work for coarse woody debris, which has the additional challenge of high structural variability and the presence of a background, which especially obscures small and highly decayed pieces.

Future Research Directions

This study shows that MLS-based coarse woody debris surveys may be a competitive alternative to Brown's transects. However, more research is needed to explore this method across other forest types and use different segmentation methods. In addition, while FSCT successfully estimated fuel loads, the low recall scores for coarse woody debris show room for improvement.

One area FSCT could see improvement is the way it handles ground segmentation. While deep learning has effectively segmented the ground in FSCT and other deep-learning models (Krisanski *et al.* 2021b, Fareed *et al.* 2023), the cloth simulation filter (CSF) can outcompete different ground segmentation algorithms and obtain similar results to deep-learning methods (Fareed *et al.* 2023). The choice of ground segmentation algorithm impacts coarse woody debris detection as coarse woody debris can easily be misclassified as ground, especially in rough terrain. The option to define and remove the ground using CSF can allow users to optimize for different terrain conditions. While these optimization problems can be problematic, CSF offers only a few easily interpretable parameters. These parameters are to adjust the resolution of the simulated cloth (the gridded distance between cloth nodes), the distance from the cloth for points to be classified as ground, the rigidity of the cloth (which has three options that are chosen based on the ruggedness of the terrain), and a true/false toggle to adjust for steep slopes. These parameters are easy to interpret, which has led to the widescale use of this ground segmentation method. Replacing the ground segmentation method with a manual approach could lead to faster run times and improved coarse woody debris segmentation since these points stand out more against a null background.

Including intensity values has improved deep learning-based tree segmentation models, increasing the overall precision of a 3D CNN model from 0.79 to 0.82 and a PointNet-based model from 0.75 to 0.77 (Windrim and Bryson, 2020). These methods currently outcompete FSCT in vegetation segmentation, but the impact of intensity values for coarse woody debris segmentation has yet to be explored. Nevertheless, including intensity values could make a large difference for coarse woody debris since positional information alone is easy to confuse for neighboring vegetation and ground points.

With increasing interest in machine learning and deep learning models, FSCT is a valuable tool for those interested in applying such methods to MLS segmentation. While deep learning models show great promise, coarse woody debris has additional complexity due to the presence of the ground, and it is, therefore, important to explore further which specific methods and architectures work best for segmenting objects on forest floors. Since FSCT is an open-source tool, researchers can easily collaborate and adapt the existing framework to their specific research questions rather than build a new model from scratch. This flexibility allows for continued innovation and advancement in MLS segmentation methods that practitioners can directly apply to forest management applications.

Conclusions

Climate change profoundly impacts mortality patterns in forests globally, making it more important than ever to ensure that coarse woody debris inventories are accurate and up to date. These inventories are essential for effective forest management decisions, such as planning prescribed burns, modeling fire behavior, and monitoring wildlife, soils, and hydrology. As wildfires increase in scale, it is more important to understand the role of coarse woody debris loading, arrangement, and decay state on fire behavior and first- and second-order fire effects. Since Brown’s transects provide inflated coarse woody debris biomass estimates with high variability, alternative methods may be required to keep pace with inventory needs.

Aerial Lidar has already found a place in strategic management with high-resolution DEMs, tree overstory inventories, and other valuable geospatial layers like roads or streams. Mobile Lidar, however, has been mainly in the research and development phase. This work shows that while MLS coarse woody debris segmentation methods have room for improvement, they may already be competitive with current plot-based coarse woody debris sampling methods. A single MLS scan can be used to estimate multiple forest attributes, and sites be re-scanned to track changes in detail through time. Collecting MLS scans is also faster than traditional field surveys, which means that more area can be covered by a crew with a scanner than a crew with tapes, though this type of sampling will still require ground truthing on at least a portion of the plots.

However, while MLS takes less time and field personnel, it currently has longer analysis time than traditional field methods. In addition, that analysis requires specialized computational skills that not all Lidar practitioners have. Open-source tools like FSCT help bridge this skills gap and allow MLS to find practical management applications. Although FSCT currently only segments a small percentage of coarse woody debris points, it can still estimate biomass even with incomplete segmentation. This indicates that even though FSCT has room for improvement, this technology already has the potential to measure coarse woody debris from MLS.

Deep learning models are straightforward since they do not require the same fine-tuning of parameters as traditional programming methods. Instead, deep learning methods build their models from patterns learned from a set of training data. When these models are presented with conditions that significantly differ from that training data, they need new training data to adapt their models to suit these different conditions. Retraining a model like FSCT is labor intensive and introduces subjectivity that can negatively impact the results. Thankfully, we found that this effort is unnecessary for all applications of FSCT. However, since retraining FSCT in this study resulted in less accurate coarse woody debris biomass estimates, we advise those wishing to retrain FSCT to take caution while manually segmenting their point clouds.

Since MLS is a plot-based method, it is unable to make continuous predictions across a landscape, which is essential for effective forest management, wildfire prevention, and response planning. However, random forest classification models are commonly used in forestry to extrapolate point data into continuous maps. MLS can be used with other spatially continuous remote sensing methods, like ALS, to create these continuous maps of coarse woody debris and other MLS-derived forest metrics. The use of MLS in conjunction with ALS and other remote sensing methods can revolutionize the way forest inventory and management are carried out, enabling more efficient, data-driven decision-making.

Moving forward, it will be critical to developing more tools for analyzing MLS data so that this technology can meet management demands. Open-source, easy-to-use tools are necessary for MLS to answer questions about wildlife habitat, fire behavior, hydrology, and forest regeneration. FSCT is the first tool to offer automated segmentation for high-density forested point clouds. These results suggest that FSCT can segment coarse woody debris with enough accuracy to measure biomass, even with low recall scores. However, these low recall scores are not likely due to a deficit in deep learning models but instead due to the complications of separating highly geometrically diverse objects with positional information often indistinguishable from the background. While FSCT has low accuracies for coarse woody debris segmentation, researchers can expand and improve upon this model to include additional variables, such as intensity, and explore different ground segmentation and removal methods.

MLS-based coarse woody debris mensuration methods are still in their infancy and require further validation and refinement. However, results here indicate that MLS can accurately estimate coarse woody debris loading with the help of FSCT.

Tables

Table 1: Coefficients for biomass calculation (Eq 2), where SEC is the angular correction, and SG is the specific gravity.

Species	**AbCo**	**PiPo**	**PsMe**	**PiSt**	**QuGa**	**PoTr**
SEC	1.01	1.01	1.02	1.01	1.02	1.02
SG_{sound}	0.32	0.4	0.35	0.4	0.47	0.4
SG_{rotten}	0.36	0.36	0.36	0.36	0.36	0.36

Table 2: Mean coarse woody debris load from fixed-area plots across the Lidar acquisition areas measured in tons per acre and divided into sound/rotten classes.

	Sound	**Rotten**	**Total**
Kinder	0.92	0.98	1.90
Kehl	2.49	1.36	3.85

Table 3: Evaluations of FSCT's performance for the original and retrained model. FSCT made minimal adjustments to evaluation metrics. Kappa and accuracy are measures across all labeled classes, while precision and recall are for coarse woody debris. The model performed slightly better at the Kinder site, but performed better at the Kehl site for coarse woody debris alone. These precision and recall scores indicate that FSCT accurately but incompletely segmented coarse woody debris.

	Kinder		**Kehl**	
	Original	Retrained	Original	Retrained
Kappa	0.471	0.474	0.459	0.458
Accuracy	0.604	0.605	0.594	0.593
Precision	0.973	0.977	0.991	0.993
Recall	0.044	0.050	0.048	0.055

Table 4: Evaluation of the linear fits for the original and retrained FSCT. The p-values indicate that there is a relationship between the number of coarse woody debris points and the plot fuel loading. The R2 shows this relationship is more robust in Kehl than in Kinder. While retraining the model resulted in a slightly stronger fit for Kinder, this resulted in a much weaker fit for Kehl.

	Original FSCT		**Retrained FSCT**	
	Kinder	**Kehl**	**Kinder**	**Kehl**
R^2	0.367	0.625	0.381	0.452
RSE	1.478	3.584	1.462	2.173
CI_{95}	0.529 - 1.61	2.21 – 4.61	0.487 – 1.57	1.30 – 2.38
p-value	0.00118	$5.31x10^{-8}$	$8.78\ x10^{-4}$	$3.01\ x10^{-4}$
$coef_{cwd}$	$1.71\ x10^{-6}$	$4.94x10^{-6}$	$4.48\ x10^{-6}$	$6.08x\ x10^{-6}$
$coef_{total}$	$2.61\ x10^{-8}$	$3.09x10^{-8}$	$2.70\ x10^{-8}$	$3.14x\ x10^{-8}$
$coef_{combined}$	$-2.86\ x10^{-14}$	$1.54x10^{-14}$	$-7.12\ x10^{-14}$	$9.59\ x10^{-14}$

Table 5: Mean coarse woody debris loads (tons per acre) for the subset of plot that we segmented MLS point clouds with FSCT.

	Kinder		**Kehl**	
(tons per acre)	**Mean**	**SD**	**Mean**	**SD**
Nested	1.33	1.32	3.82	4.50
Brown's	1.54	2.32	7.06	10.4
FSCT Original	1.07	0.59	3.41	3.33
FSCT retrained	1.03	0.68	1.84	1.02

Figures

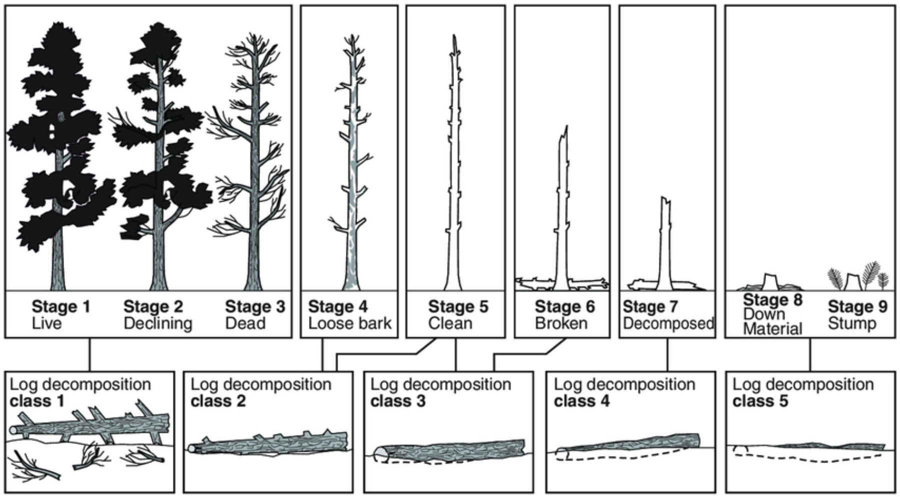

Figure 1: Decay classification for snags, stumps, and coarse woody debris. Bark and branch characteristics as the tree moves through the snag stages and log decay classes are described in more detail in the original publication (Maser et al. 1979).

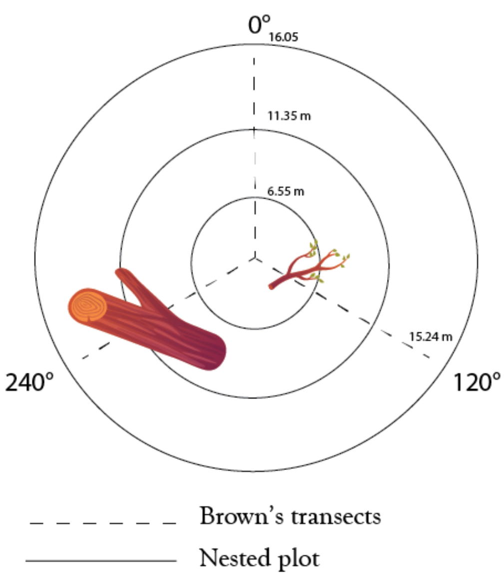

Figure 2: Plot design for coarse woody debris ground measurements. Fixed-area plots have diameter thresholds of 30 cm, 20 cm, and 7.62 cm in each plot diameter, while the diameter threshold for Brown's transect is 7.62 cm for the entire 15.24 m transect at all three angles.

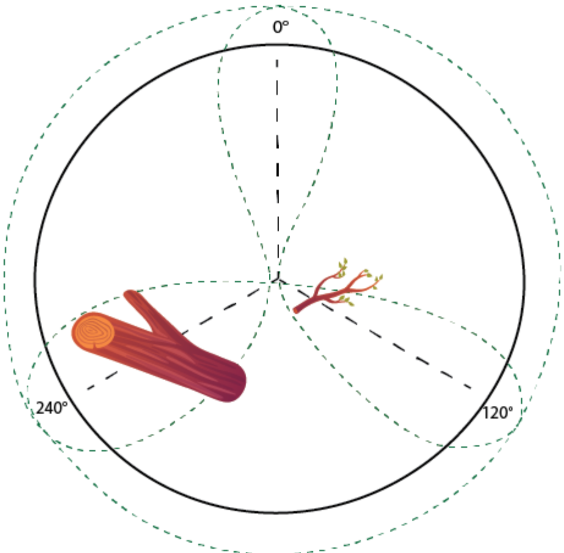

Figure 3: Three lotus method scan pattern for plot measurements with MLS. Width of "petals" varied on the plots due to trees or other obstructions.

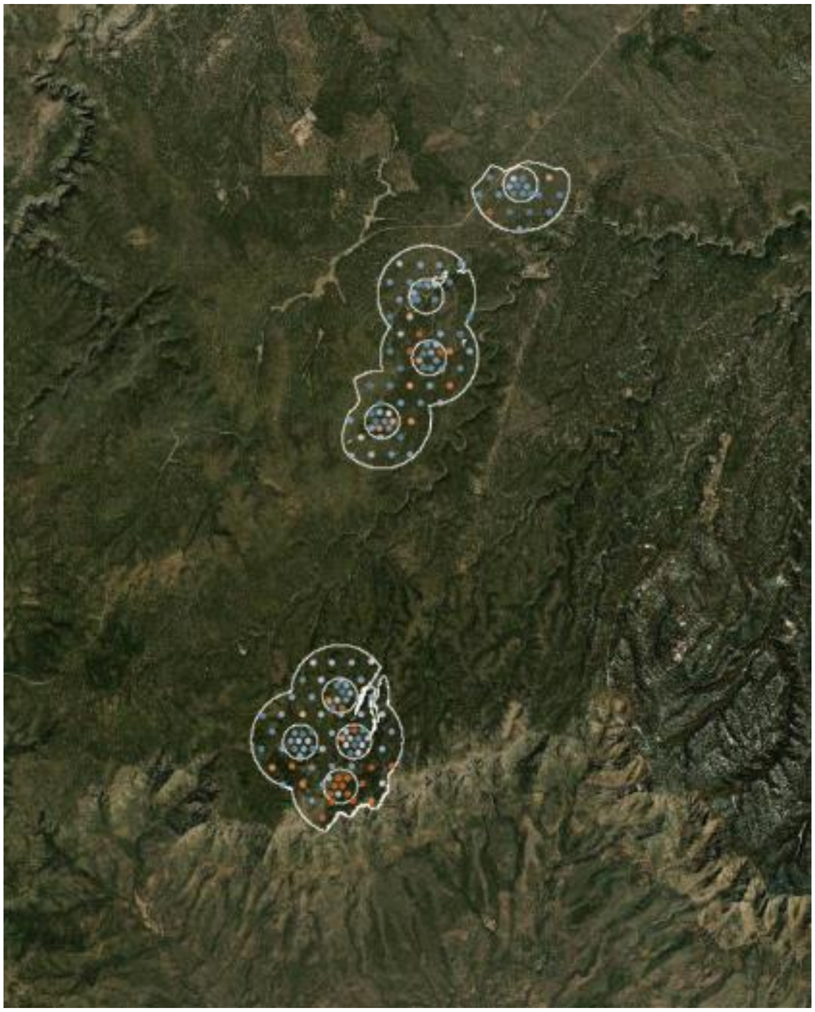

Figure 4: Coarse woody debris loading across all study sites. Blue indicates low coarse woody debris loads, and orange indicates high coarse woody debris loads. Most of the sites have low biomass, with occasional high biomass along the rim and interspersed throughout

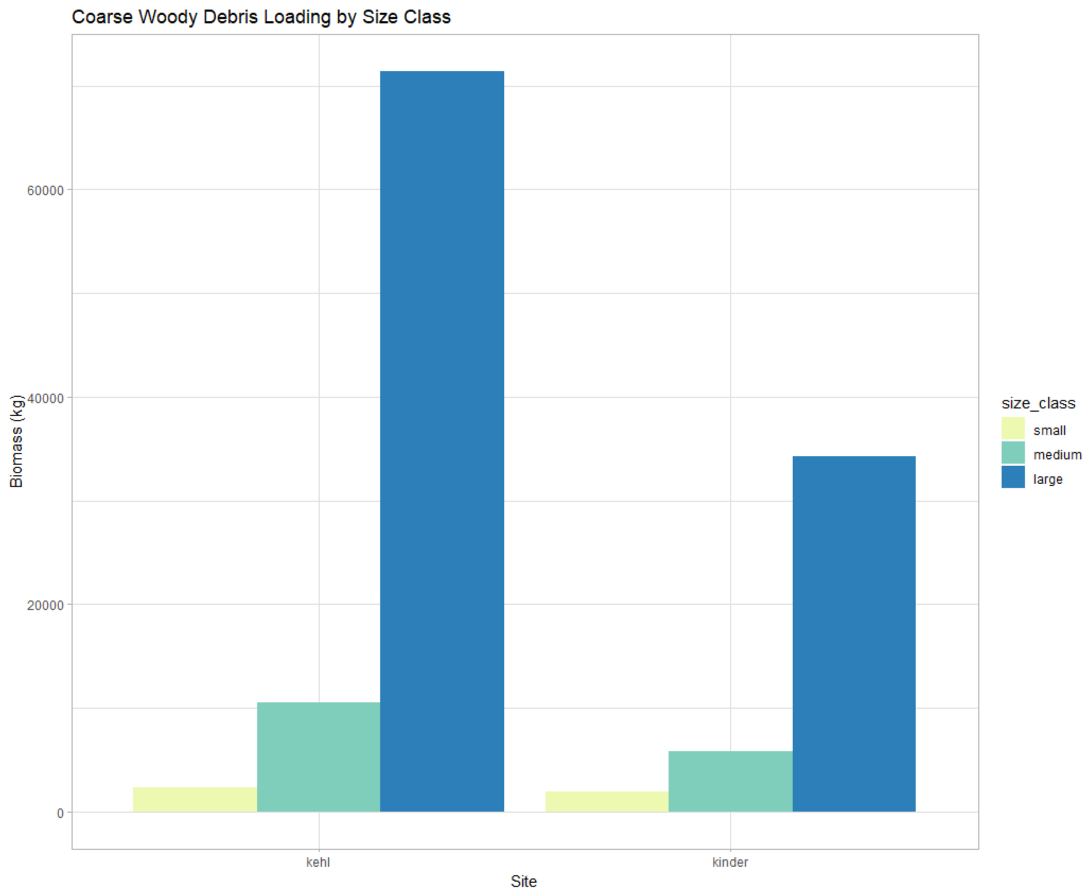

Figure 5: Coarse woody debris biomass stored in different size classes in the two forest types. Both forest types have more biomass stored in larger pieces than small ones. Dry mixed-conifer forests are expected to have higher coarse woody debris loads than ponderosa pine forests, which is valid here. The difference is primarily due to an increase in the large size class rather than an increase in all size classes

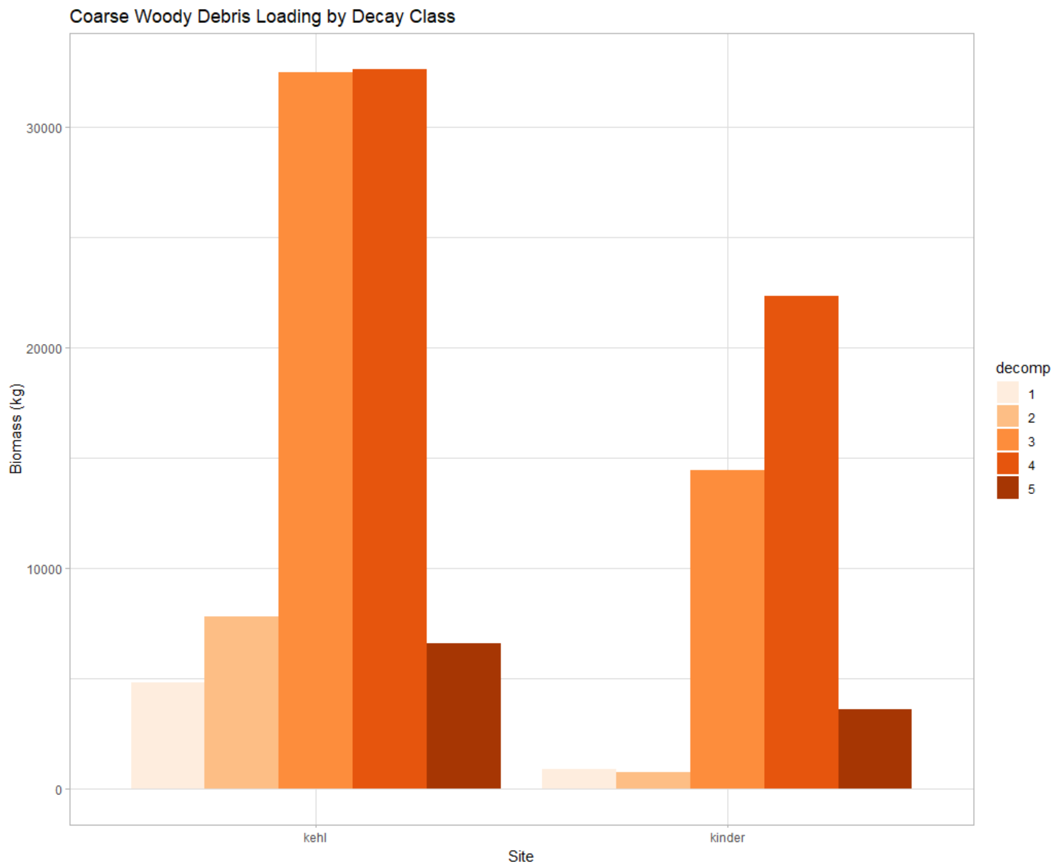

Figure 6: Coarse woody debris biomass broken down by decomposition class. The dry mixed-conifer site (Kehl) has more biomass stored in less decayed material. As pieces decay, this may impact their ability to be identified in MLS data due to fragmentation and deformation.

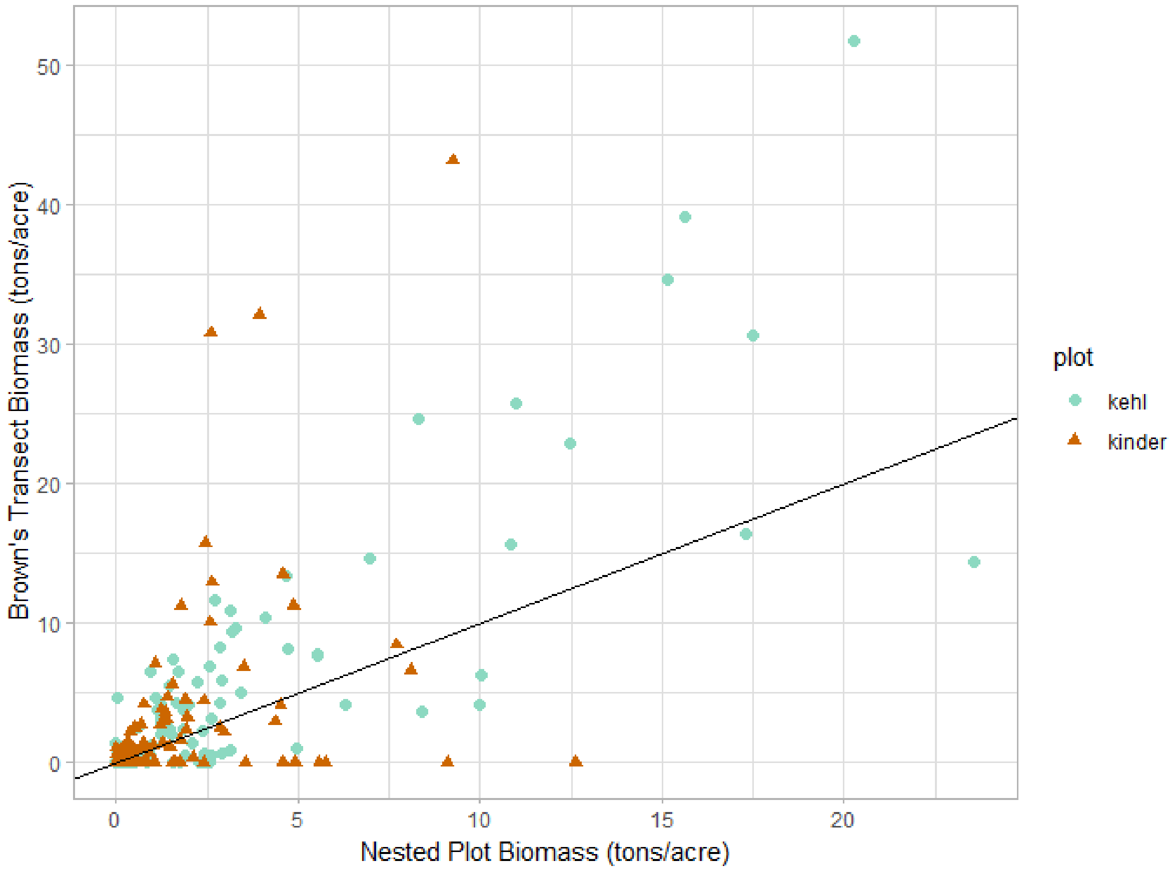

Figure 7: Brown's transects compared to ground truthed biomass from fixed-area plots. A one-to-one line is shown in black to emphasize the difference between each method. Brown's transects overestimate to a greater degree as coarse woody debris biomass increases. This effect impacts the measurements in dry mixed-conifer forests more than in ponderosa forests because of their higher fuel loads. However, Brown's transects have high variability even at coarse woody debris loads

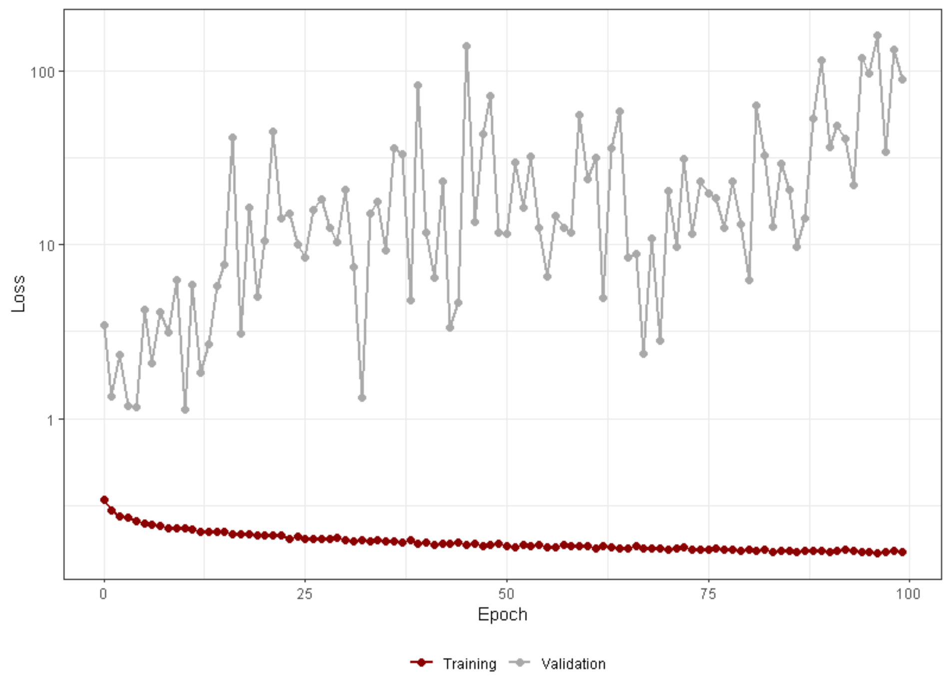

Figure 8: Training and validation loss over the 100 epochs we retrained FSCT over. Training loss decreases and plateaus as expected, while validation loss increases, indicating overfitting. Our retrained model was the output from epoch 56, while there is a plateau in validation loss.

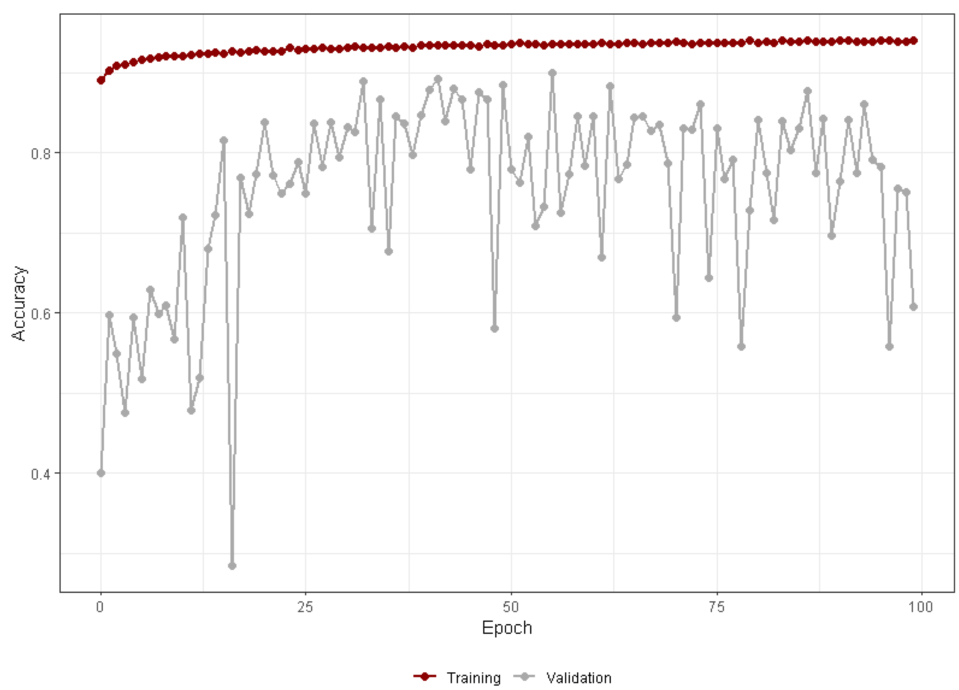

Figure 9: Training and validation accuracy over the 100 epochs we retrained FSCT over. Accuracy increases and plateaus as expected, with a slight dip around epoch 90. Our retrained model was the output from epoch 56.

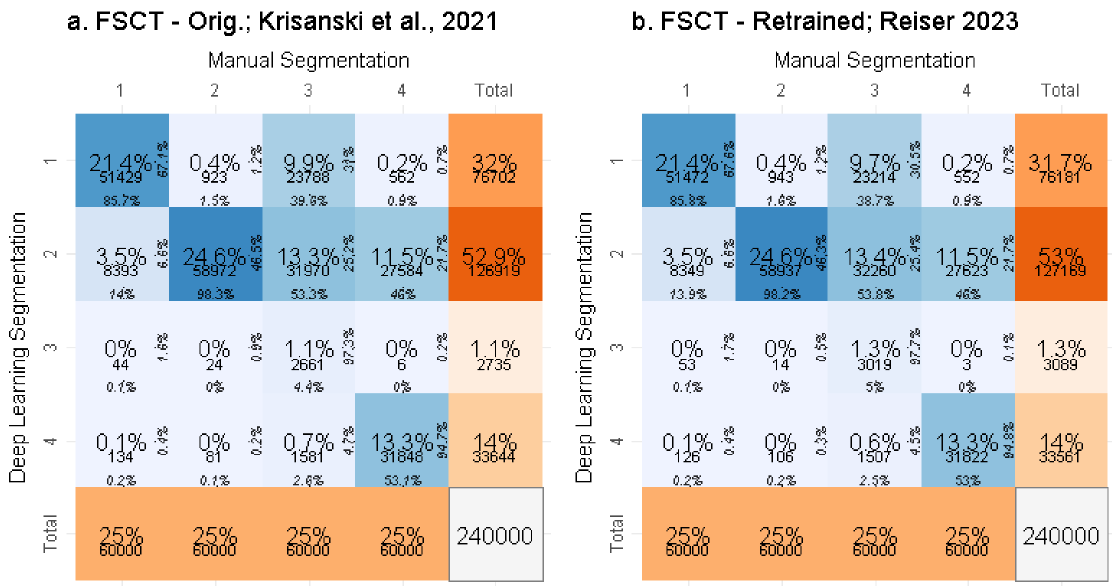

Figure 10: Confusion matrices for (a) the original FSCT and (b) our retained model in the ponderosa site, Kinder. This was calculated from each model's performance on our subset of 12 manually segmented plots. (1 = terrain, 2 = stems, 3 = coarse woody debris, 4 = vegetation)

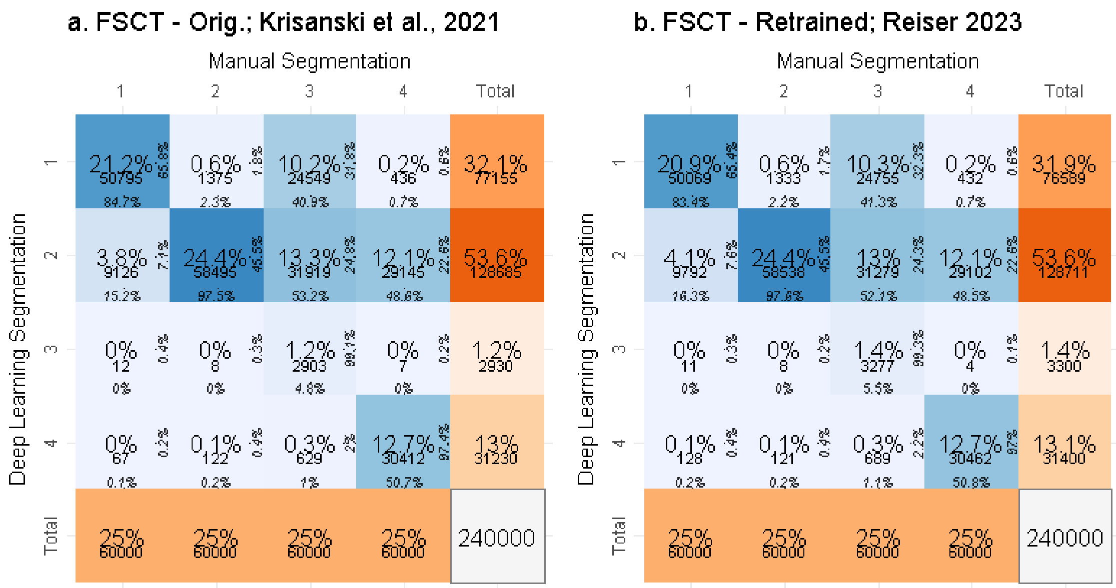

Figure 11: Confusion matrices for (a) the original FSCT and (b) our retained model in the dry mixed-conifer site, Kehl. This was calculated from each model's performance on our subset of 12 manually segmented plots. (1 = terrain, 2 = stems, 3 = coarse woody debris, 4 = vegetation)

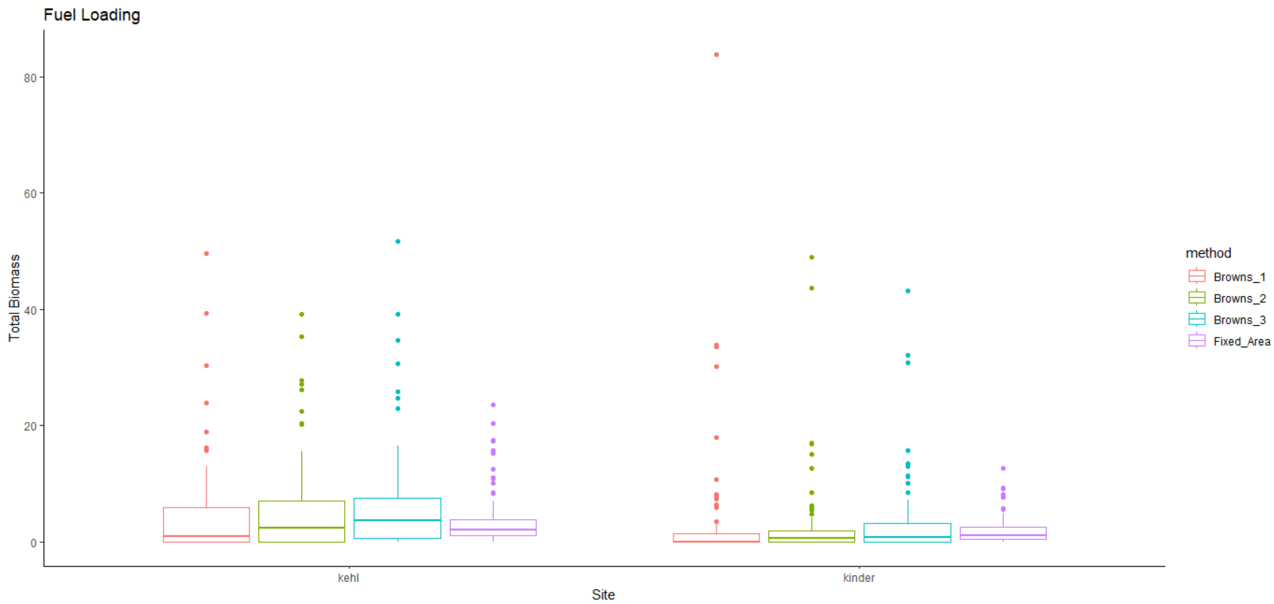

Figure 12: Summary of fuel loads for one, two, and three Brown's transects compared to the fixed-area true fuel loading. While decreasing the number of transects decreases the mean, this is due to more plots where coarse woody debris was missed (fuel load of 0). Regardless of the number of Brown's transects this method overestimates fuel loads when it does detect coarse woody debris.

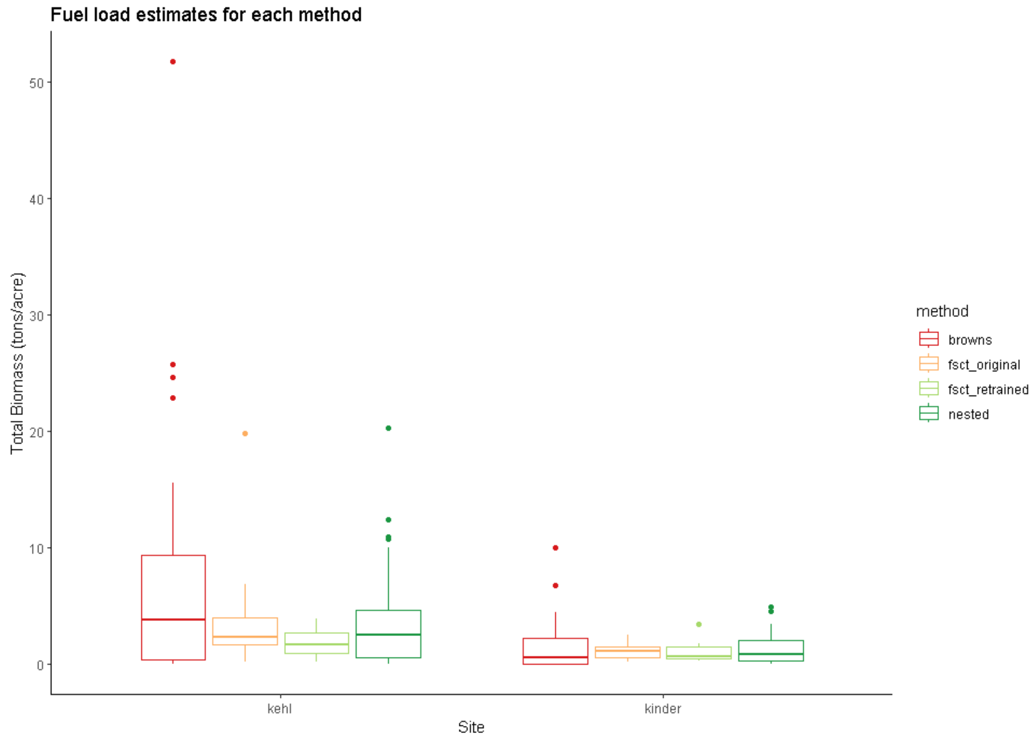

Figure 13: Summary of fuel loads for the dry mixed-conifer (Kehl) and ponderosa (Kinder) sites using each inventory method: Brown's transects, the original FSCT, our retrained FSCT, and fixed-area. Brown's transects overestimate fuel loading while FSCT underestimates fuel loading.

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Chapter 4

Management Implications

Introduction

In 2018, the Tinder Fire burned 16,309 acres encompassing East Clear Creek on the Mogollon Rim (U.S. Forest Service, 2018a). The Tinder Fire burned for weeks and around 30% of the area burned with moderate to high fire severity (U.S. Forest Service, 2018b). This impacts erosional and hydrological processes not just for East Clear Creek, but also for C.C. Cragin Reservoir, which is only 1.5 miles west of the Tinder Fire scar.

Areas that had received prescribed thinning and/or burning treatments from the 2006 East Clear Creek Improvement Project, 2001 Blue Ridge Urban Interface Project, and Blue Ridge Community Fire Risk Reduction Project experienced low burn intensities, and one area that received a prescribed burn treatment in 2017 experienced low intensity to "no burn" classification (U.S. Forest Service, 2018b).

Considering the threats to valuable water resources and the impacts of past restoration treatments, the Cragin Watershed Protection Project (CWPP) was created to reduce the risk of uncharacteristic fire, post-fire erosion, and flooding, and restore forest structure, composition, and function (U.S. Forest Service, 2018b). This project is targeted at three sub-watersheds to C.C. Cragin on the Mogollon rim – East Clear Creek-Blue Ridge Reservoir, Bear Canyon, and Miller Canyon – that makeup nearly 70% of the project area (U.S. Forest Service 2018c). CWPP is a collaborative effort between the Forest Service, the Salt River Project, the Bureau of Reclamation, the National Forest Foundation, and the Town of Payson whom all have a vested interest in the health and safety of these forests and watersheds.

From the beginning, CWPP has embraced the principles of ecological restoration as defined by the Society of Ecological Restoration. These principles are to 1) engage stakeholders, 2) draw on many types of knowledge, 3) be informed by native reference ecosystems, 4) support ecosystem recovery processes, while considering environmental change, 5) be assessed against clear goals and objectives, using measurable indicators, 6) seek the highest level of ecosystem recovery possible, 7) gain cumulative value when applied at large scales, and 8) be part of a continuum of restorative activities (Gann *et al.* 2019). In the following sections, we will discuss how the findings of this study fit into the larger picture of CWPP and how MLS contributes to the fourth and fifth principles of ecological restoration, which through its application can help CWPP meet its restoration goals.

Historic and Present Conditions

The historic (or natural) range of variability (HRV/NRV) is one commonly used tool to guide forest restoration targets. HRV is any value that describes past historic conditions of an ecosystem that can be applied to assess the current conditions and to restore them to natural state (Swetnam *et al.* 1999, Fulé 2008). HRV can be quantified from areas with relict reference conditions (Fulé *et al.* 2003a, Stephens and Fulé 2005), historical plot data (Moore *et al.* 2004), and reconstructions (Fulé *et al.* 1997).

The ponderosa and dry mixed-conifer forests on the Mogollon Rim experienced frequent, low-severity fires (Covington and Moore, 1994, Huffman *et al.* 2015). The fire return interval was every 2 to 8.5 years between 1670 to 1879, with the average tree experiencing fire every 11.8 years (Huffman *et al.* 2015). Fire suppression along with logging and grazing have changed the forest structure and composition. In the mixed conifer forests tree densities increased from 129.5 to 744.3 live trees ha^{-1}, basal area increased from 10.1 to 41.9 m^2 ha^{-1}, and mean canopy cover increased from 14.8% to 54.7% (Rodman 2016). Trees have also shifted to less fire-resistant species and grouping structures. *Abies concolor* and *Pseudotsuga menziesii* are more common today than they were pre-fire exclusion and *Pinus ponderosa* and *Quercus gambelii* are less common, and overall forests have become more aggregated and less open (Rodman 2016).

While the changes to overstory structure are the most obvious change to these forests, the same processes that shape overstory conditions shape fuel beds as well. These heterogeneous, frequent fire forests also had heterogeneous fuel conditions (Skinner 2002). Fuel loads were low in the ponderosa and mixed conifer forests on the Mogollon Rim, averaging 1.33 tons/acre in the ponderosa forest and 3.82 tons/meter in the dry mixed-conifer forest, while the optimal loads are and 3-7 tons per acre in ponderosa and 10-15 tons per acre in mixed conifer (Gainey and Vojta, 2010). We did not assess the heterogeneity of these fuels, but we observed that they are not evenly distributed throughout the landscape, with the largest accumulation of fuels in the mixed conifer forest along the Mogollon rim, and other large accumulations in pockets, but this heterogeneity is likely less than historic conditions due to increased tree aggregation from historic levels.

Mortality patterns

Without fire, environmental factors and other disturbances, like insects and diseases are driving forest structure and mortality patterns, which changes coarse woody debris loading and distribution. In arid environments coarse woody decomposes slowly (Busse 1994, McColl and Powers 2003), but fires would have consumed coarse woody debris far faster than it takes to decompose (Busse 1994). Under fire suppression, the decay becomes the primary driver by which coarse woody debris is broken down, so pieces are able to last longer on the landscape, and areas accumulate more fuel (Ffolliott and others 1977).

Across the southwest, bark beetle outbreaks are causing an increase in *P. ponderosa* mortality, with a total of 165,660 acres affected on the Coconino National Forest, an 80% increase between 2020 and 2021 (Forest Service 2021). However, this has a delayed impact on coarse woody debris loading due to the delay of snag fall, which can vary by species and diameter but for bark beetle-killed trees this can be anywhere from 3-17 years (Cluck and Smith 2007). With the low coarse woody debris loads we found in the ponderosa forests, this is likely because the primary mortality agents in these forests are fire and bark beetles, both of which leave trees as standing dead. While fuel loads were low, this does not indicate there are not major mortality events happening, but that these snags have not yet fallen. Treatments should not be concerned with these low coarse woody debris values and the snag dynamics in this area should be further explored.

In dry mixed-conifer forests, more trees are the hosts of fungal pathogens that cause trees to rot while standing, resulting in much faster snag fall rates. *Armillaria* is the most common root rot, accounting for 80% of root disease mortality in the southwest, and it targets many species found on the Mogollon rim including *Abies concolor*, *Pseudotsuga menziesii*, *Quercus gambelii, and Populus tremuloides.* Root diseases like *Armillaria* form pockets of jackstrawed coarse woody debris (Fields 2003). While *Armillaria* and other root diseases are a natural part of these forests, these jackstrawed pockets require special consideration in fuels planning as they increase fire risk due to the higher chance of spotting, torching, and reburn. If these pockets catch fire the effects of smoldering can cause detrimental effects to soils that can impact regeneration and erosion. The *Armillaria* Response Tool (ART) is a web-based tool that helps managers identify potential disease pockets and plan treatments accordingly, but this tool is not available across the entire range of this pathogen and does not cover any forest in Arizona.

Thus, managers must determine areas of risk within the CWPP treatment areas from local measurements using ground-based and/or remote sensing methods. We need continuous coverage maps or a sampling design meant to capture the variable extents of these root disease pockets. Without these, managers must adapt fuel treatment plans based on their on-the-ground observations using adaptive management.

The Role of Adaptive Management

Adaptive management is a cyclical approach to ecosystem management where treatments are applied and learned from so future treatments can be adapted based on how ecosystems responded and conditions have changed (Nyberg, 1999, Murray and Marmorek, 2003). This approach allows managers to adjust their strategies based on ecosystem responses. The goal of adaptive management is to improve the effectiveness and efficiency of management actions over the long term where conditions are complex and uncertain, like over highly biodiverse areas or in times of change.

This method requires continuous monitoring, evaluation, and adjustment of management strategies to ensure that management practices are meeting restoration targets. CWPP includes adaptive management methods as part of their fuels treatment plans. CWPP determined treatments and acreages using vegetation cover and habitat type maps, supplemented with on-the-ground visits to verify their model predictions reflected ground conditions so they could write effective silvicultural prescriptions (Camp 2018). Overall, these ground visits changed prescriptions on 0.1% of the entire project area (Camp 2028). CWPP also specifies applying adaptive management to handle slash since it can harbor bark beetles and mechanical treatments are known to increase slash (U.S. Forest Service, 2018c).

Projects like CWPP that aim to restore ecosystem processes, not just restore numerical targets need adaptive management to meet their restoration targets. CWPP's restoration targets will increase the frequency and total expected number of wildfires but decrease the scales and intensities of these fires. Through this transition, managers should expect changes they could not account for with information they had during the planning process. During this transition period monitoring will be especially important. For adaptive management to work monitoring must keep pace with the spatiotemporal changes at hand so managers can understand trends and adjust restoration treatments and objectives.

Integrated Approach with MLS

In Chapter 3, we showed that Brown's transects can misrepresent the true coarse woody debris loading. Even in cases where this method is representative of the true loading, it can only be used as a synoptic tool without offering insights on the stand level. MLS measures forests more accurately but our ability to extract this information has been limited by the computational complexity of modeling different forest structures. Deep learning segmentation algorithms extract this information without the drawbacks of traditional programming methods. Geometric deep learning in particular is improving the way we can extract data from complex geometric datasets like MLS, but these are new concepts in the field of computer science (Bronstein *et al.* 2021) and we still need more efficient ways to handle extremely large datasets like those found in an MLS point cloud. Despite these challenges, tools like FSCT are already becoming publicly available. Deep learning is gaining popularity and with it we should expect our tools to extract information from MLS to improve.

CWPP and even larger landscape restoration projects like 4FRI need to be able to scale up plot-based monitoring to match their landscape-scale needs without sacrificing data quality. Monitoring is a sustained effort and inaccuracies aside, plot-based sampling methods are too slow and expensive to meet these needs. The cost of collecting Brown's transects for this study came out to $81.25 per acre while MLS was only $13.00 per acre. Monitoring is a constant expense and adaptive management decisions cannot be made without up-to-date measurements. Remeasuring plots introduces new sources of error due to personal bias (Omule 198) and the practical challenge of relocating trees (Castelo *et al.* 2018). MLS can be geolocated back to past measurements to make direct comparisons.

Lidar excels at change detection, and it has been one of the main applications of ALS since its inception (see Okyay *et al.* 2019 for a review). Time-series measurements using TLS have been able to quantify biomass changes in individual trees (Kaasalainen *et al.* 2014), changes in DBH down to centimeter accuracies, and changes in canopy density due to seasonal growth (Liang *et al.* 2012). In adaptive management, monitoring seeks to quantify forest changes from different treatment activities. MLS offers the chance to measure these changes at finer scales than we can with traditional plot-based methods.

These finer scale measurements can also improve our understanding of landscape-scale patterns. Plot-based sampling methods provide different forest attribute measurements that can be used to create wall-to-wall coverage using interpolation (Miller *et al.* 2004). MLS is a plot-based sampling method that lends particularly well to integrating with other remote sensing methods. ALS lends especially well to this, as integrating ALS and MLS increases the spatial extent of MLS and improves the vertical coverage of both (Zhang *et al.* 2022). With the fusion of remote sensing technologies, especially ALS and MLS, we have unprecedented opportunities to measure forest fuels at greater spatiotemporal scales and higher resolutions compared to traditional plot-based techniques.

Conclusion

In conclusion, the accurate measurement of coarse woody debris is essential for managers to make informed decisions regarding forest restoration and conservation efforts. The Cragin Watershed Protection Project is a collaborative effort that embraces ecological restoration principles to reduce the risks of uncharacteristic fire, erosion, and flooding, and restore forest structure, composition, and function. The historic range of variability is a useful tool to guide forest restoration targets, and MLS is an important tool for measuring coarse woody debris and assessing forest conditions. Adaptive management is necessary to account for changes in forest conditions, and the findings of this study can help CWPP meet its restoration goals. By following ecological restoration principles, engaging stakeholders, using many types of knowledge, supporting ecosystem recovery processes, and assessing against clear goals and objectives, the highest level of ecosystem recovery possible can be achieved. Overall, accurate measurement of coarse woody debris and the use of MLS are crucial components of successful forest restoration and conservation efforts, and these efforts must be adaptive to account for changing environmental conditions.

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