

THESIS

POTENTIAL FOR UNMANNED AERIAL SYSTEMS TO INFORM PONDEROSA PINE RESTORATION: EVALUATION OF HORIZONTAL AND VERTICAL COMPLEXITY MONITORING

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ABSTRACT

POTENTIAL FOR UNMANNED AERIAL SYSTEMS TO INFORM PONDEROSA PINE RESTORATION: EVALUATION OF HORIZONTAL AND VERTICAL COMPLEXITY MONITORING

Over the last two decades, the restoration of dry conifer forests has increasingly prioritized the reintroduction of horizontal and vertical complexity. This emphasis has come from research showing that increased spatial complexity in forest structures is necessary to restore past ecological function and resilience to disturbance. However, most forest inventory and monitoring approaches lack the resolution, extent, or spatial explicitness required to describe within stand heterogeneity at a level adequate to inform forest management. Recently, Unmanned Aerial Systems (UAS) remote sensing has emerged with potential methods for bridging this gap. Specifically, photogrammetric Structure from Motion (SfM) algorithms have been shown as a cost-efficient way to characterize forest structure in 3-dimensions. Chapter 1 of this thesis reviews the relationship between forest heterogeneity and various ecological processes as well as methods and implications for restoring forest heterogeneity. Chapter 2 evaluates the accuracy of SfM-derived estimates of tree, clump, and stand horizontal and vertical heterogeneity metrics across 11 ponderosa pine-dominated stands treated with spatially-explicit silvicultural prescriptions. Specifically, we evaluated tree detection rates and extracted height and DBH error, analyzed stand-level density and canopy cover, and assessed UAS-derived derived distributions of individuals, clumps, and openings through metrics of the number of clump structures, percent of stand basal area, height CV, crown area, and distance

to the nearest tree. UAS-derived metrics were compared to 1-ha stem maps located in each of the 11 stands. We found that tree detection was relatively high in all stands (F-scores of 0.64 to 0.89), with average F-scores over 0.8 for all but the shortest size class (<5 m). Average height and DBH errors of 0.34 m and -0.04 cm were produced, although DBH RSME was greatest for the tallest trees. Stand estimates of TPH were over by 53, with the greatest errors in the shortest size class, and metrics of basal area, QMD, and canopy cover all had errors of less than 10% compared to the stem map. Finally, UAS could successfully characterize and describe individuals, clumps, openings, and inter-clump characteristics like the percent of stand basal area and height CV through all clump size classes. These results indicate that in ponderosa pine forests, UAS can describe both large- and small-scale forest structure metrics to effectively inform spatially explicit management objectives.

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CHAPTER 1: HISTORY AND IMPLICATIONS OF SHIFTING STRUCTURAL DYNAMICS IN PONDEROSA PINE-DOMINATED FORESTS: A REVIEW

1.1 Introduction

Historically, ponderosa-dominated forests were characterized by episodic regeneration and fire regimes with variable fire frequency and severity, typically resulting in patches of even-aged old growth forests with some uneven-aged patches across relatively open conditions (Figure 1.1; Veblen et al. 2000; Sanchez Meador et al. 2011; Larson and Churchill 2012; Addington et al. 2018). While fire regimes, species composition, and spatial patterns vary somewhat across regions and elevational gradients, ponderosa pine-dominated stands were often described as park-like mosaics and typically had a combination of individual trees, groups of trees with interlocking crowns, patches of regeneration, discrete openings, and grassy interspaces (Larson and Churchill 2012; Stevens et al. 2015; Rodman et al. 2016). Overall patterns could be aggregated or random (Abella and Denton 2009; Stevens et al. 2015), but integrated ample large gaps and openings that promoted a diverse herbaceous understory. One study estimates that grassy openings and mosaic meadows comprised an average of 55% of historical ponderosa pine (*Pinus ponderosa* var. *scopulorum* Dougl. Ex Laws.) forests, although the size and prevalence of these openings were highly variable and accounted for anywhere from 5% to 94% of historical ponderosa pine-dominated sites (Matonis et al. 2014; Brown et al. 2015; Matonis and Binkley 2017).



Figure 1.1. Historic conditions (ca. 1917) in a low-elevation ponderosa pine stand on the Sierra National Forest (Stephens et al. 2015).

Ponderosa pine-dominated stands around the southwestern United States and lower montane zones along the Colorado Front Range (<7800 feet on the northern Front Range, <8200 feet on the southern Front Range) were typically characterized by frequent (~10 to 20 years apart) low-severity surface fire (Sherriff et al. 2014; Brown et al. 2015; Battaglia et al. 2018). In contrast, evidence has shown that stands in the upper montane zones in the Colorado Front Range (7800-9100 feet on the northern Front Range, 8200-9300 feet on the southern Front Range) as well as those in the northern Rocky Mountains were often characterized by a lower fire frequency (~20 to 50+ years apart) and more variable fire severity, often resulting in larger openings and higher levels of heterogeneity at the landscape level (Sherriff et al. 2014; Veblen et al. 2014, Clyatt et al. 2016). Generally, studies have found that the proportion of low-

severity fire to mixed- or high-severity fire is inversely related to elevation and latitude in historically ponderosa pine-dominated systems (Addington et al. 2018).

Over the last century, forest management practices have shifted forest structure from pre-Euroamerican settlement conditions – particularly in frequent-fire forests such as those dominated by ponderosa pine. Early forest management approaches prioritized production and predictability, resulting in management practices often designed to limit natural disturbance at the cost of structural and biological complexity (Lundquist 1995; Fahey et al. 2018). Selective logging, grazing, and fire exclusion throughout the 20th century are believed to have caused changes in forest structure and are attributed with making forests both more susceptible to biotic and abiotic disturbances and leading these disturbances to be more severe (Veblen et al. 2000; Allen et al. 2002; Ager et al. 2016). In response, modern forest management has prioritized restoring historical structural and biologic diversity to promote and preserve ecosystem services beyond timber (Puettmann 2009).

Forest scientists generally agree that in ponderosa pine-dominated forests, structural dynamics such as forest density, species composition, and vertical and horizontal heterogeneity are closely intertwined with forest health and various ecosystem processes. These interactions are known to influence the understory environment (Meyer et al. 2001; Battaglia et al. 2002), herbaceous species richness and productivity (Moore et al. 2006; Korb et al. 2007), tree recruitment (Sánchez Meador et al. 2009; Sánchez Meador et al. 2011), pollinator biodiversity (Rhoades et al. 2018), and water availability (O'Hara and Nagel 2006). However, the full extent to which structural dynamics influence many of these processes has yet to be fully explored. In addition, successful restoration in ponderosa pine-dominated systems will likely require

silvicultural prescriptions that explicitly describe the desired horizontal and vertical forest structures, including clumps, openings, and variability within and between them (Churchill et al. 2013). This review aims to discuss how forest management has altered forest structure in ponderosa pine-dominated systems, the impact of local forest structure on ecological processes, and possible implications for future research and restoration efforts.

1.1.1 The Impact of Past Forest Management and Fire Exclusion

Fire exclusion and productivity-focused approaches to forest management led to significant increases in density within ponderosa pine-dominated stands across all regions (Stephens et al. 2015; Clyatt et al. 2016; Rodman et al. 2016; Battaglia et al. 2018). These increases in density closed many gaps and openings and resulted in denser stands with greater canopy cover, lower understory biodiversity, and higher fuel loadings (Figure 1.2; Rodman et al. 2016). Matonis and Binkley (2018) found that open space comprised an estimated average of 55% of forest area in ponderosa pine-dominated forests under pre-settlement conditions. However, these openings only comprised 3% to 14% of untreated stands by 2014.

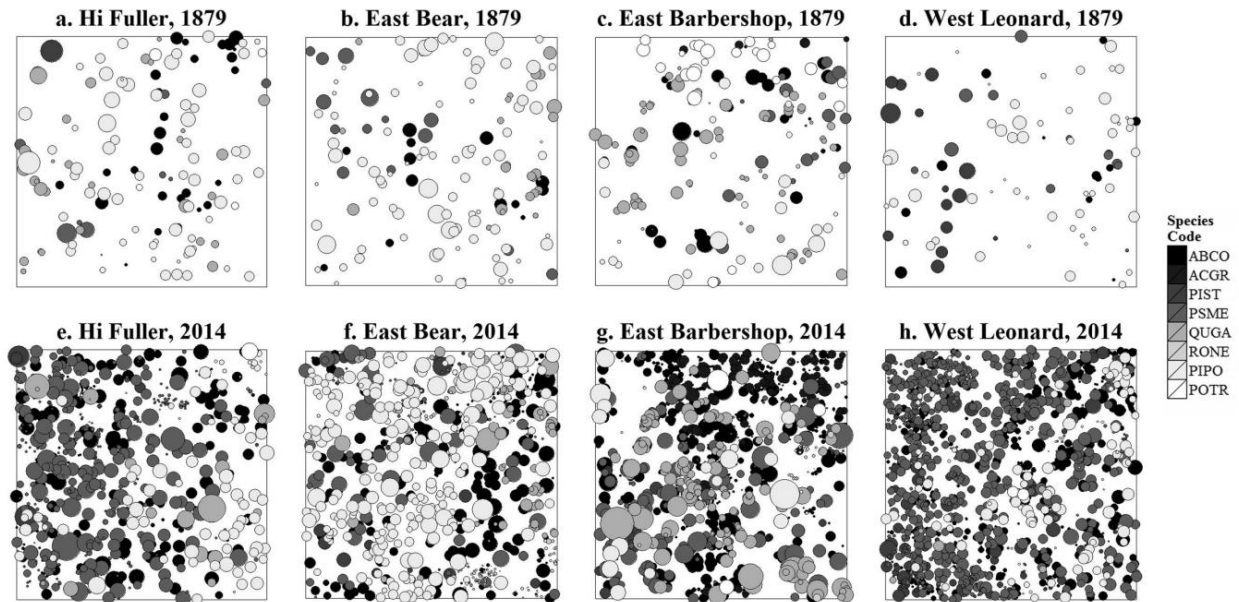


Figure 1.2. Historical (a–d) and contemporary (e–h) stem maps of plots from four different ponderosa-dominated stands in Arizona, where circles represent trees and sprouting hardwoods scaled by canopy area (Rodman et al. 2016).

The exclusion of fire also allowed for some encroachment by sprouting hardwoods like gambel oak (*Quercus gambelii* Nutt.) and shade tolerant conifers in southwestern ponderosa-dominated forests (Figure 1.2; Figure 1.3; Rodman et al. 2016). Similarly, studies throughout Colorado have found an increase in various shade tolerant species, including Douglas-fir and white fir (Brown et al. 2015; Battaglia et al. 2018; Korb; Fule). Inversely, one study in the eastern Cascade Mountains found that ponderosa pine densities increased at lower and drier elevations around the shrub steppe/forest ecotone (Haugo et al. 2010). But ponderosa pine still declined at higher elevations, where they saw increases in shade tolerant fir and Douglas-fir.

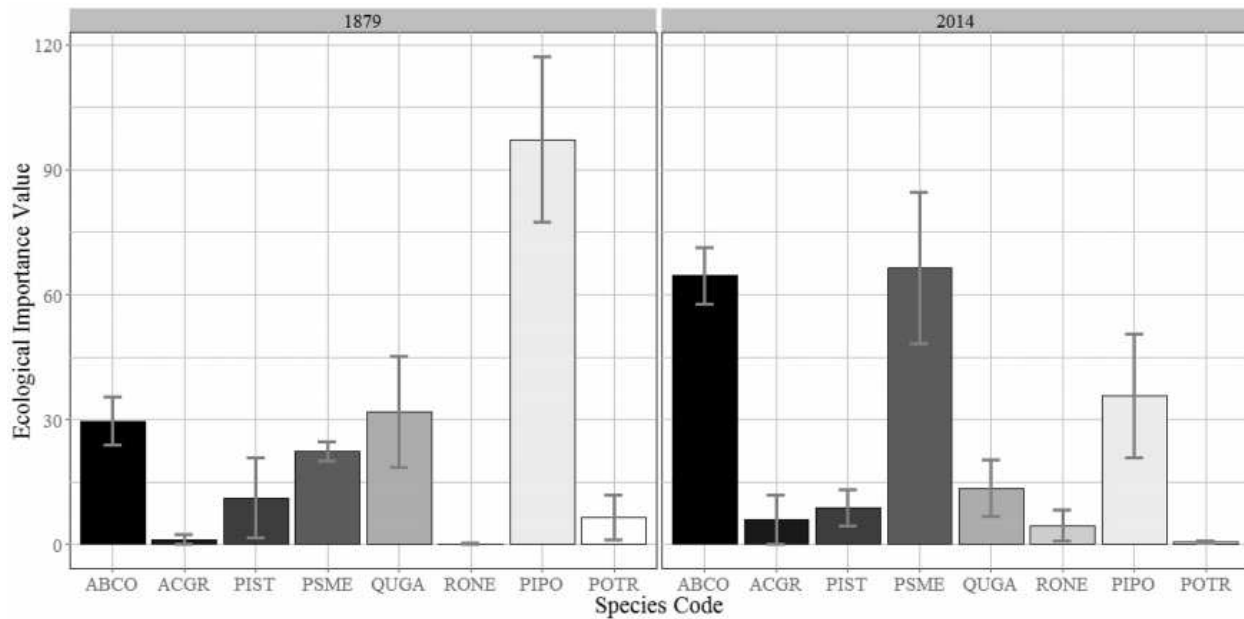


Figure 1.3. Changes in species composition between 1879 and 2014 within ponderosa pine-dominated stands in Arizona. Species composition is defined by ecological importance value ($EIV = (100 \times \# \text{ live trees of species } i / \# \text{ total live trees}) + (100 \times \text{live basal area of species } i / \text{total live basal area})$) (Rodman et al. 2016).

On the other hand, stands that were managed for timber generally maintained their ponderosa pine overstory species composition (Smith and Arno 1999). Additionally, thinning and fuels mitigation treatments resulted in fast-growing ponderosa pine stands with limited competition and disturbance (Smith et al. 1997). However, both timber and fuels management treatments transitioned stands from their characteristic gap-cluster spatial arrangement to a more uniformly spaced, single size class structure (Figure 1.4; Smith et al. 1997; Larson and Churchill 2012). While these treatments increased productivity for ponderosa pine, they also increased the overall canopy cover across the stand – decreasing light and resource availability for herbaceous understory vegetation (Larson and Churchill 2012).



Figure 1.4. A uniformly thinned, second-growth ponderosa pine forest (ca. 2007) on US Forest Service lands in northern California, USA (Larson and Churchill 2012).

In association with many of these structural changes, forests have seen shifts in tree growth, regeneration, and disturbance frequency and severity. While we are beginning to understand how stand structure changed during the 20th century, the full extent to which it has influenced ecological processes is yet to be understood. Realizing the relationship between stand horizontal and vertical structure and ecological processes is an essential step in managing for a healthier, more resilient ecosystem.

1.2 Quantifying Spatial Patterns

In addition to exploring and defining spatial interactions, forest scientists need to define standard methods to quantify and objectively describe forest structure (Larson and Churchill 2012). Such metrics are integral to our ability to further understand, replicate, and manage for spatial structures. Researchers have used a remarkably diverse array of techniques to analyze

and describe spatial patterns, but different methods often yield different results and interpretations – even when applied to the same dataset (Perry et al. 2006).

Larson and Churchill (2012) found that the vast majority (56 of 60 reviewed papers) of spatially-focused studies in fire-frequent forests employ global pattern analysis or generalized analyses that attempt to describe spatial patterns at the stand level. Given that groups and clusters are a defining characteristic in fire-frequent forests, like those dominated by ponderosa pine, most studies employed spatial aggregation analyses such as Ripley's K and Moran's I (Sánchez Meador et al. 2009). On the other hand, some studies focus on quantifying meadows and open space within the stand. Such approaches have ranged from simply describing the percent of the stand with open space (Matonis and Binkley 2018) to studies calculating the proportion of open space scaled by the Euclidean distance from trees (Churchill et al. 2013). Although these methods can give us a general idea of what spatial patterns exist over an entire study area, any attempt to address local patterns and interactions would be largely subjective. Such approaches have found limited success in being incorporated into management planning or restoration efforts.

Some studies have taken extra steps to identify and quantify local patterns to better describe stand structure in a way that may translate to how managers see trees within a stand. For instance, some studies describe tree clumps by describing intra-clump density and identifying tree size classes within clumps (Larson and Churchill 2012). Local-scale studies have also been more effective at identifying and describing the relative abundance of open-growing individuals and clumps of various sizes within a stand. Open-grown trees are often neglected in

global pattern analyses, even though they comprise an estimated 12%-50% of trees in southwestern ponderosa pine forests (Sanchez de Meador 2011, Larson and Churchill 2012).

Local pattern analyses can often be a valuable tool for informing silvicultural prescriptions when executed properly. One promising example of this is the ICO (individual/clump/opening) method developed by Churchill et al. (2013). For the ICO approach, researchers developed a clump algorithm to derive clump size distributions from historical reference plots. These distributions are summarized to describe the percent of trees arranged as individuals and in clumps of different sizes at a specified inter-tree distance (Figure 1.5). The method describes an inter-tree distance threshold to define tree clumps based on the observed distance at which most mature ponderosa pine trees display interlocking crowns and form patches of continuous canopy. In simulated silviculture prescriptions that contrasted ICO with traditional, non-spatial tree marking prescriptions (Figure 1.5), the ICO method was the most successful in recreating the distribution of reference forest structures. However, the ICO method still retained fewer large clumps than intended and did not create any large gaps. In response, Churchill et al. (2013) adapted their original marks to better achieve their 5+ tree clump targets and dubbed this their “adaptive management” scenario to illustrate the benefits of tallying clump size (Figure 1.5). Despite this, researchers found that even the adaptive management approach resulted in an insufficient number of larger clusters (8+ trees) and no large openings. After discussions with the field crew, researchers found that crews had difficulty deciding when to thin from below and when to leave smaller trees to form larger clumps. The marking crews also felt uncomfortable creating large gaps and openings, especially if it required removing large trees. This study further asserts the need to develop more explicit

quantitative descriptors and prescriptions to remove subjectivity and uncertainty from prescription implementation.

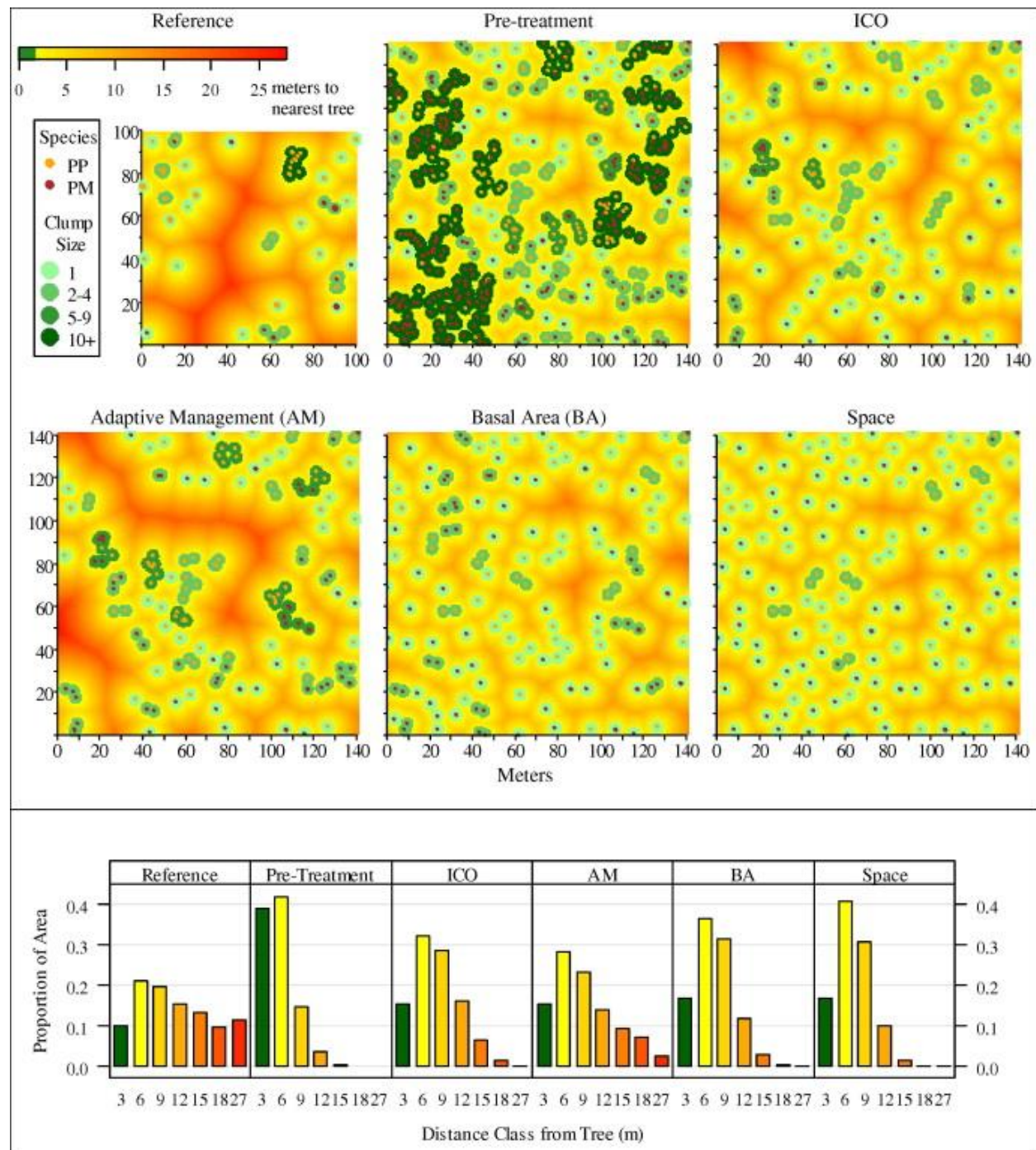


Figure 1.5. The results of conducting restoration projects in a spatially complex forest using different quantitative descriptors to inform prescriptions. Adaptive management methods were conducted after ICO to help integrate some qualitative characteristics (Churchill et al. 2013).

Since its conception, the approach for characterizing local structures outlined by Churchill et al. (2013) has commonly been integrated into restoration projects in spatially complex conifer forests. In particular, this has been a popular consideration in recent landscape-scale collaborative restoration projects. For example, the USDA Forest Service Collaborative Forest Landscape Restoration Program (CFLRP) has employed similar methods in restoring and evaluating treatments within ponderosa pine-dominated and other dry-mixed conifer forests along the Colorado Front Range. Post-treatment monitoring of these projects has consistently found that restoration efforts significantly lower basal area and TPH and increase QMD from pre-treatment conditions. However, they typically reduce horizontal heterogeneity and fail to reduce tree density to reference conditions despite significant reductions (Briggs et al. 2017; Cannon et al. 2018). These findings have been important in developing collaborative adaptive management and adaptive monitoring protocols. However, after assessing 24 projects within the Front Range CFLRP, Barrett et al. (2021) found that while these projects successfully contributed to meeting objectives related to forest density, they still failed to meet objectives relating to forest composition and horizontal complexity. The authors hypothesize that narrow basal area targets and a lack of explicit consideration for spatial patterns limited the ability of managers to meet horizontal heterogeneity objectives and led to an overall reduction in stand and landscape level horizontal variability (Barrett et al. 2021).

The evaluations of these CFLRP projects indicate the need for methods capable of quickly and efficiently characterizing tree-, group-, and stand-scale forest structures to better inform restoration efforts. Currently, most monitoring and data collection systems primarily use some combination of field measurements and/or aerial or satellite remote sensing (Larson et al.

2012; Cannon et al. 2018; Manfreda et al. 2018). However, these systems are limited by spatiotemporal constraints, and the drastic differences in extent, continuity, and resolution can often leave gaps in the data. Field measurements offer high-resolution data at specific points, but their extent or continuity is limited by time, personnel, and funding (Torresan et al. 2016). As such, field measurements are often confined to relatively small representative areas or samples, restricting their ability to adequately describe forest structure, its heterogeneity, and the ecological processes it informs across scales. Although satellites can collect data over large continuous areas, they offer very little flexibility in spatial and temporal resolution. Even with high resolution (3 m) satellite data, Cannon et al. (2018) were restricted to estimating the number of mature trees within each clump but were unable to characterize inter-clump density and structure. Both satellites and field surveys can leave gaps in our knowledge, and they currently lack the range and versatility to meet the increasing demand and complexity of natural resource monitoring (Manfreda et al. 2018). The integration of methods for collecting tree-scale data that can be summarized across tree groups and stands could greatly improve our ability to implement and evaluate management objectives related to forest heterogeneity.

1.3 Spatial Interactions

1.3.1 Competition

The tendency for ponderosa pine to form a mixture of groups and individuals in sites with intact disturbance regimes can result in spatial gradients of competition and facilitation between trees. At the stand level, it is known that increasing stand densities result in higher competition for sunlight and resources, often resulting in a reduction in growth or sometimes even self-thinning at the stand level (Forrester et al. 2016). In addition, spatial complexity

results in asymmetric competition, reinforcing both horizontal and vertical heterogeneity at a local level – even within even-aged stands (Figure 1.6; McGown et al. 2016). Vertical heterogeneity can influence light availability, while horizontal structure can influence light and belowground resource availability. Several studies have found that the “mode of competition” (i.e., influenced by either light availability and/or belowground resource availability) can significantly impact individual tree growth and exaggerate local structures over time (Pretzsch and Biber 2010; Riofrio et al. 2016).

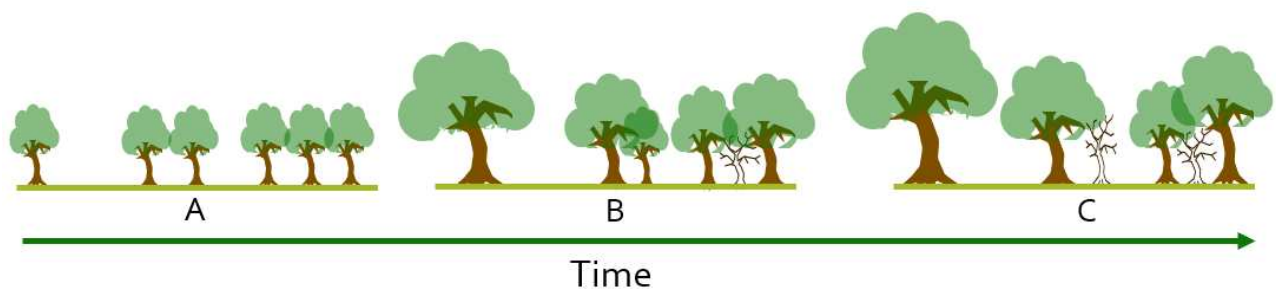


Figure 1.6. Asymmetric competition due to tree spacing: A) Little to no competition between individual trees. B) As trees grow and roots and crowns develop, competition for light and belowground resources begins. This impacts the rate of growth for some trees, and self-thinning begins to occur. C) Self-thinning increases horizontal heterogeneity as asymmetric competition and recruitment increase vertical heterogeneity.

While neighbors often compete for resources, neighboring trees may also facilitate regeneration recruitment or promote the growth of neighbors at lower local densities. Local structures have the potential to make water and nutrients more abundant via hydraulic redistribution and to lower transpiration levels by reducing wind speed (Forrester et al. 2016). However, the net effects of facilitation and competition may vary over time and across site conditions and ecological gradients. To better understand these interactions and their potential impacts on forest growth and structure, many researchers have conducted controlled local

density experiments such as the Nelder wheel plot (Uhl et al. 2015; Tinkham et al. 2021).

However, the results of such studies may be very site-specific and typically are not designed to understand how uneven-aged structures interact.

1.3.2 Recruitment

Despite the potential for some facilitation near groups and clusters, the role of spatial patterns in tree recruitment within ponderosa pine forests may be influenced by various factors. Many studies argue that recruitment patterns are largely random or are a product of abiotic factors such as site, climate, or topography (Rodman et al. 2016; Kemp et al. 2019). One study found that regeneration was driven by climate and water availability across the range of ponderosa pine. Areas at higher elevations, with low climactic stress generally saw higher regeneration levels (Korb et al. 2019). Another study found that in water-limited sites, regeneration was most prevalent under the shade of neighboring trees (Fajardo et al. 2006). Meanwhile, other studies have concluded that recruitment was largely promoted by existing gaps and openings within the stand (Sanchez Meador et al. 2009). However, further studies have found that different recruitment patterns were most strongly correlated to local tree density and the presence of seed-bearing trees (Iniguez et al. 2019; Korb et al. 2019). It is likely that recruitment patterns are attributed to a combination of site-related factors and spatial patterns.

1.3.3 Fire

Fire has always played an essential role in ponderosa pine spatial dynamics. Fire is popularly believed to be the primary driver for pre-Euroamerican settlement stand structure and the most important disturbance agent excluded from these forests over the past century

(Allen et al. 2002; Ehle et al. 2003; Rodman et al. 2016). As aforementioned, ponderosa pine fire regimes were variable and were often characterized by frequent low-severity fire at low elevations and less frequent mixed-severity fire at higher elevations – both of which resulted in various levels of complexity or heterogeneity within stands (Ehle and Baker 2003; Lentile et al. 2006; Sherriff and Veblen 2007).

Fire exclusion across the ponderosa pine range has shifted stand structure in various ways, including increased stand densities, encroachment by shade-tolerant species, slowed nutrient cycling, and decreased understory species diversity (Keeling et al. 2006; Brown et al. 2015). The prolonged suppression of fire in these systems is believed to have contributed to unprecedented fire severity (Hessburg et al. 2005; Hagmann et al. 2021) in recent years and has motivated forest managers to seek a greater understanding of the role of forest structure and spatial patterns in wildfire behavior (Ziegler et al. 2017, Hagmann et al. 2021). However, most available data has been retrieved from forests that have been logged at some point in the past (Naficy et al. 2010), and as a result, the effects of fire and logging can easily be conflated, making it difficult to determine the extent to which each factor has influenced stand density (Keeling et al. 2006; Naficy et al. 2010). However, research across logged and unlogged sites in the northern Rocky Mountains has found that logging resulted in fewer fire-tolerant old-growth ponderosa pine, a higher proportion of fire-intolerant species like Douglas-fir, and an increase in the density of small trees (Naficy et al. 2010). This makes logged sites more susceptible to severe fire as well as biotic disturbances (Naficy et al. 2010).

Studies exploring the relationship between forest structure and fire behavior have found that larger ponderosa pine trees are more fire resistant and that reducing small woody

understory growth substantially reduces torching within stands (Addington et al. 2018). Studies have also found that reintroducing gaps and openings through variable retention thinning moderated fire rate of spread, fireline intensity, and canopy consumption across a range of wind speeds (Ziegler et al. 2017). These factors indicate that a return to pre-settlement conditions would increase stand vitality and reduce severe fire behavior within these stands. However, it should also be noted that topography can significantly impact fire behavior. Steeper slopes tend to result in higher fire intensity and severity, and thus should be prioritized when considering restoration projects (Taylor et al. 2006).

1.3.4 Bark Beetles

At the individual-tree level, bark beetles (*Dendroctonus* spp.) have been found to prefer large, stressed ponderosa pine trees (Chubaty et al. 2009; Koontz et al. 2021). In addition, larger trees seem to be correlated with a higher likelihood of mortality (Koontz et al. 2021). At the stand level, forest density is positively correlated with mortality at the stand level due to biotic disturbances such as bark beetles – particularly following fire or drought (Negron et al. 2006). One study (Hood et al. 2016) found that thinning treatments resulted in significantly higher tree growth and axial resin duct production, likely contributing to higher resistance to bark beetle outbreaks than the control (~1% vs 50% mortality, respectively). While not quite as effective, researchers found that prescribed burns could increase resin flow. This potentially increased resilience, resulting in only 33% mortality during the same event (Hood et al. 2016). However, it is unclear whether increasing vertical heterogeneity (i.e., a range of size classes) impacts beetle behavior. One study concluded that “low-diversity” stands (only intermediate-sized trees) experienced significantly less bark beetle mortality than “high-diversity” stands (intermediate

and large trees) (Fettig and McKelvey 2010). However, low-diversity stands had an average of 282 trees ha⁻¹ with 10 m² ha⁻¹ of basal area, while high-diversity stands had 513 trees ha⁻¹ with 25 m² ha⁻¹ of basal area before the beetle outbreak. This discrepancy makes it impossible to discern whether the results were a product of vertical heterogeneity or stand density. Another study found that beetle infestations in uneven-aged ponderosa pine stands in the Black Hills were largely driven by the same factors as even-aged stands and were most strongly associated with stand density, or the density of medium- and large-diameter trees in particular (Negron et al. 2008).

1.3.5 Wildlife

We do not know the true extent to which wildlife populations have changed since Euro-American settlement. However, studies have attempted to characterize historical species ranges and habitat structure in ponderosa pine forests along the Colorado Front Range through responses to fire by wildlife, life history, habitat requirements, and trophic interactions of each species (Addington et al. 2018). Ponderosa pine-dominated forests are home to a wide range of fauna, so spatial complexity and patch dynamics play a significant role in providing wildlife forage and habitat as the presence of old growth ponderosa can provide roosting habitat, patches of closed canopy can provide nesting habitat and escape cover, and open spaces allow for greater understory diversity and forage (Reynolds et al. 2013; Addington et al. 2018).

A common species of particular interest to management in ponderosa pine-dominated forests is the northern goshawk (Reynolds et al. 2006; Addington et al. 2018; Latif et al. 2022). Although northern goshawks have been known to inhabit a wide range of forests and woodlands, forest structure is considered a primary limiting factor to goshawk habitat.

Northern goshawks preferentially select nesting sites in areas with dense patches of old growth and high canopy cover with an open understory (Reynolds et al. 2006). Their nests also tend to be centrally located within their hunting territory, overlapping with that of principal prey species habitat. Given the broad range of the northern goshawk, ideal forest structure can vary across regions and ecosystems (Reynolds et al. 1992; Reynolds et al. 2016). The management recommendations for the northern goshawk in the southwestern ponderosa-dominated ecosystems (Reynolds et al. 1992) prioritize a mosaic of tree clumps of varying maturities and large meadows and interspaces similar to that of pre-settlement ponderosa forests (Reynolds et al. 1992; Reynolds et al. 2012). As a result, spatially-explicit understanding of horizontal and vertical forest structure is pertinent to proper habitat management. Attempts to characterize northern goshawk habitat have included fixed radius forest plots and global pattern analyses (Sánchez Meador et al. 2011; Reynolds et al. 2012) which fail to characterize interspaces, clump size, crown connectivity, and the proportion of forest to meadow (Reynolds et al. 2012). Aerial imagery can fill in these gaps by characterizing the total area occupied by clumps and openings, but still fails to describe any inter-clump structure (Addington et al. 2018).

Studies have consistently found that ungulates prefer habitat in mosaic meadows where more forage is available (Germaine et al. 2004; Briggs et al. 2017). They specifically prefer habitat near patches of large-diameter ponderosa for easy access to both forage and escape cover (Lehman et al. 2015). Patches of large diameter ponderosa are also important to nesting species like the pygmy nuthatch and Abert's squirrel (Addington et al. 2018). Meanwhile, predators like mountain lions tend to have more success stalking prey in areas with thick patches of small-diameter trees for cover (Lehman et al. 2017). Along the Colorado Front

Range, the reintroduction of forest heterogeneity through fuels reduction and forest restoration are believed to improve the species richness of avian species and are especially expected to benefit specialists (Latif et al. 2022). They also found a positive relationship between ponderosa pine specialist species and open forest conditions.

1.4 Conclusion

Given the geographic scope of forest restoration operations and potential impacts on ecosystem functions, it is important for managers to incorporate tree spatial patterns and interactions in their restoration treatments in ponderosa pine-dominated systems. Restoring structural complexity appears to be a promising way to return fire-frequent forest ecosystems to a resilient condition and position them to adapt to shifting climates and disturbance regimes. However, restoration success will be dependent on our ability to understand spatial interactions. While there is a solid understanding of coarser stand-level interactions, researchers and managers need to invest in more research on the mechanisms of local spatial pattern formation and maintenance and the impact of spatial patterns on various ecosystem processes. In addition, restoration success depends on the ability to objectively define and quantify spatial attributes in research and management objectives. To incorporate spatial patterns in silvicultural prescriptions and restoration objectives, it is integral that researchers and managers adopt universal methods for describing and monitoring these patterns over time.

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CHAPTER 2: CHARACTERIZING HETEROGENEOUS FOREST STRUCTURES VIA UAS-DERIVED STRUCTURE FROM MOTION METHODS

2.1 Introduction

The proliferation of urban encroachment, shifting climates, and unprecedented disturbance in forested landscapes are accelerating changes to forest management approaches in dry conifer systems (Larson et al. 2012). Historically, forest management approaches prioritized production and predictability, resulting in management practices designed to limit natural disturbance as well as structural and biological complexity (Fahey et al. 2018). This type of management largely resulted in expanses of dense, homogenous forests, making them more susceptible to severe biotic and abiotic disturbances (Allen et al. 2002). As disturbances have increased in frequency and severity, societal and managerial priorities have shifted towards restoring historical structural and biologic diversity to promote ecosystem services beyond timber (Puettmann 2009). As a result, forest management plans and silvicultural prescriptions have begun to move towards reintroducing complexity to the horizontal and vertical arrangements of forest structures (Tinkham et al. 2017), while simultaneously calling for more frequent and widespread monitoring to facilitate adaptive management (Addington et al. 2018). However, informing these decisions requires an extensive understanding of the distribution and spatial arrangement of tree sizes (Cannon et al. 2018).

Numerous methods of describing tree spatial arrangement have been explored for their ability to inform management decision-making. Through a comprehensive review of spatial patterns in fire-frequent forests of the Western United States, Larson and Churchill (2012)

found that most (56 of 60 reviewed papers) studies employ global pattern analysis – or analyses strategies designed to describe spatial patterns at the stand level. Given that horizontal heterogeneity in tree density, or groups and clusters, are a defining characteristic in fire-frequent forests, many studies employ spatial aggregation analyses such as Ripley's K and Moran's I. These strategies have been able to connect ecological processes like the facilitation and repulsion of species-specific regeneration to established tree patterns (Ziegler et al. 2017a; Kuehne et al. 2015). Meanwhile, other studies focus on quantifying meadows and open space within the stand as a function of the percent of stand area in open space (Matonis and Binkley 2018) while others have described the area of open space scaled by the Euclidean distance from trees (Churchill et al. 2013) or as a distribution of opening sizes (Cannon et al. 2018). Although these methods can provide some general idea of spatial patterns within stands, they often neglect open-grown trees and fail to describe vertical heterogeneity entirely. Additionally, these stand-level approaches lack the detail and spatial explicitness required to inform management plan development or silvicultural marking prescriptions. Furthermore, traditional field sampling methods with networks of fixed and variable radius plots are limited in their ability to characterize these metrics.

To better inform management actions and describe stand structure, some studies have taken steps to identify and quantify local patterns of tree groups (Tinkham et al. 2017). For instance, some studies describe tree arrangement as the distribution of clump sizes and by characterizing tree size class variability within clumps (Larson and Churchill 2012). These local pattern analyses can often provide better insight into stand structure and are much easier to integrate with silvicultural prescriptions or translate for treatment marking plans. However, this

increased focus on the spatial arrangement of tree groups has led land managers to seek new methods of detecting, quantifying, and monitoring changes in individuals, clumps, and openings within complex forested landscapes.

Currently, monitoring and data collection systems for forest management primarily use some combination of field measurements and/or satellite data (Manfreda et al. 2018). However, these systems are limited by spatiotemporal constraints, and the drastic differences in coverage and resolution can often leave gaps in the data between field and satellite methods. Although satellites collect data over extraordinarily large areas, they typically fail to provide observations with sufficient resolution to inform stand-level management decisions (Smith et al. 2014). Additionally, as most satellites rely on the passive reflectance of energy from the Earth's surface, they are limited in their ability to describe vertical forest complexity. On the other hand, field measurements can offer high-resolution data at specific points, but their spatial extent is severely limited by time, personnel, and funding (Creasy et al. 2021). Both satellites and field surveys lack the range and versatility to meet the increasing demand for high resolution and frequent monitoring of forest structure (Manfreda et al. 2018).

In response, Unmanned Aerial Systems (UAS) have quickly risen as a versatile alternative monitoring platform with the potential to bridge these spatial and temporal divides (Manfreda et al. 2018). Specifically, individual tree detection methods have been able to capture greater than 90% of trees in ponderosa pine (*Pinus ponderosa* var. *scopulorum* Dougl. Ex Laws.) forests, facilitating high-resolution tree-to-tree spatial arrangement analysis (Creasy et al. 2021). Additionally, the integration of diameter at breast height (DBH) modeling strategies in UAS monitoring has made it possible to generate diameter distributions and stand basal area

estimates within 10% of stem map observations (Swayze et al. 2021). However, it is known that these results balance omission and commission errors and it is generally unknown how these tree-level errors will impact managers' ability to describe the local vertical and horizontal complexity that is now a common objective in forest restoration treatments (Addington et al. 2018; Stephens et al. 2021). The development of methods that can describe the spatial arrangement of all size classes of trees in a stand would fully enable the monitoring of restoration objectives.

This study evaluates the accuracy of UAS estimates of horizontal and vertical forest structural heterogeneity across a range of forest structures and restoration treatments in ponderosa pine-dominated forest systems. Specifically, we compare the spatial pattern of UAS single tree detection estimates against 11 structurally unique stem mapped 1-hectare sites exhibiting a gradient of horizontal and vertical heterogeneity. Metrics are summarized as tree-level DBH and height accuracy, distributions of clump sizes and vertical complexity, and stand-level density metrics.

2.2 Methods

2.2.1 Study Site Description

In 2018, eleven 1-ha (100 m x 100 m) ponderosa pine-dominated plots were inventoried within the Black Hills Experimental Forest, a part of the Black Hills National Forest in western South Dakota, United States (Figure 2.1). The plots were located in stands that had received one of four unique treatments designed to create variation in horizontal and vertical complexity of forest structure. Plots were stem mapped to include observations of tree location, species, DBH, height, and crown width along the major and minor axis of each tree greater than 1.37 m

tall. Stem mapping was completed by establishing a grid of survey locations in each stand with a Pentax PCS-515 (TI Asahi Co., Saitama, Japan) laser total station and then recording the northing and easting of each tree to a point in the survey grid with distance tapes. Further details of plot establishment can be found in Ritter et al. (2022). The crown width observations were used to determine crown area assuming the area of an ellipse.

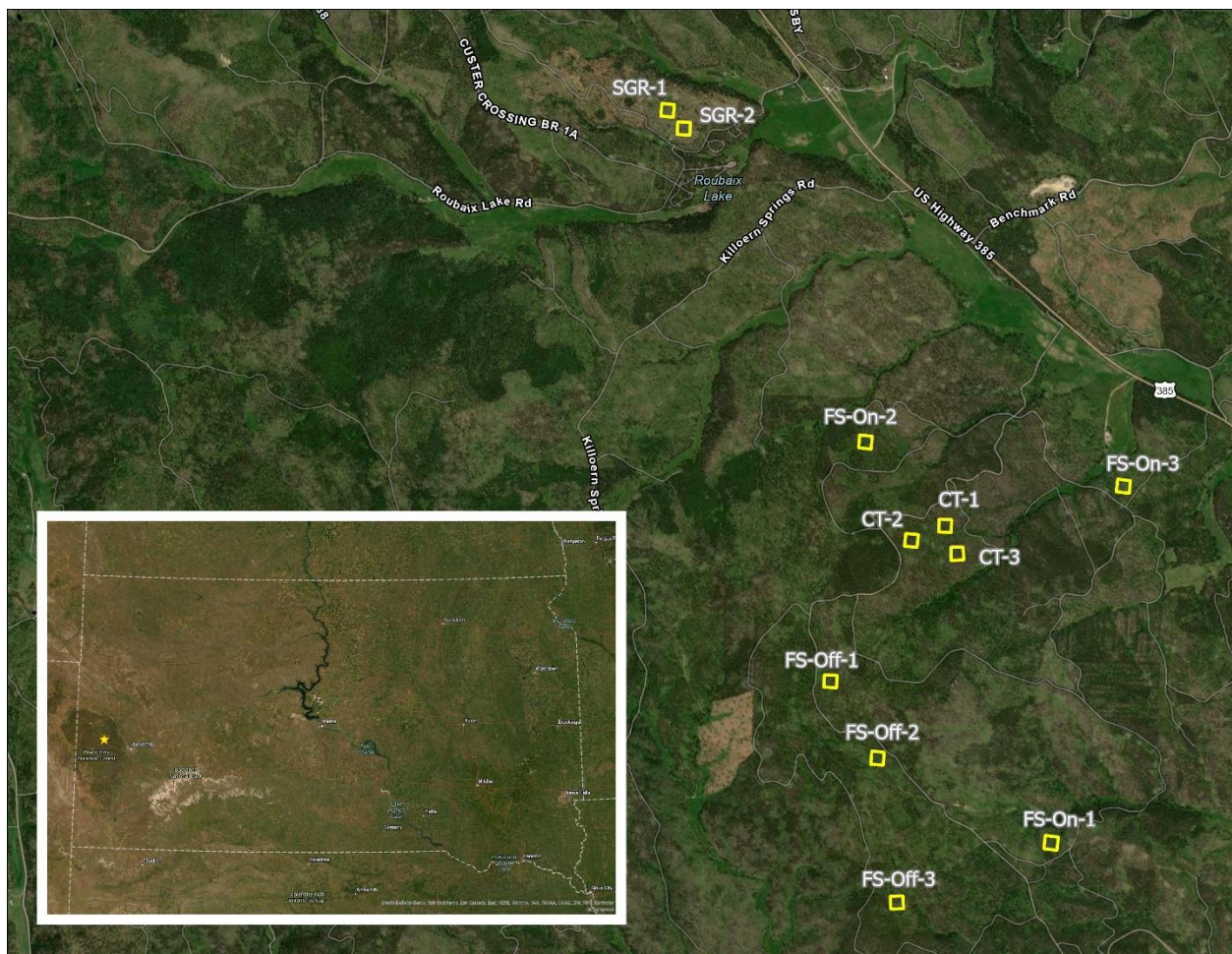


Figure 2.1. Study area showing the location of the eleven 1-ha study plots in western South Dakota, United States.

The plots were located in mechanical forest thinning treatments designed to capture a range of forest structure metrics (Figure 2.2). The thinning treatments occurred between 2012

to 2014. These methods consisted of small group retention (SGR), commercial-grade thinning (CT), free selection – ghost on (FS-On), and free selection – ghost off (FS-Off). The SGR treatments called for retention of $\sim 4.6 \text{ m}^2 \text{ ha}^{-1}$ ($20 \text{ ft}^2 \text{ ac}^{-1}$) of basal area (BA) with half of this in ~ 20 tree groups and half in scattered individuals. The retained groups emphasized large trees but also included trees of different sizes. In addition, precommercial ($< 22.9 \text{ cm DBH}$) understory trees were retained in large patches. The CT plots were thinned from below to 9.2 to $13.8 \text{ m}^2 \text{ ha}^{-1}$ (40 to $60 \text{ ft}^2 \text{ ac}^{-1}$) and trees were spaced a minimum of $\sim 4.9 \text{ m}$ (16 ft) apart. Both FS-On and FS-Off prescriptions called for thinning of commercial-sized trees ($> 22.9 \text{ cm DBH}$) to 9.2 to $13.8 \text{ m}^2 \text{ ha}^{-1}$ (40 to $60 \text{ ft}^2 \text{ ac}^{-1}$) where ponderosa pine was favored for retention. These two free selection prescriptions used a crown vigor selection criteria (Hornibrook 1939; Graham and Jain 2005) to select leave commercial-sized trees. However, they differed in their treatment of pre-commercial sized trees ($< 22.9 \text{ cm DBH}$) with the FS-On treatment ignoring the overstory and simply marking the pre-commercial stems to a fixed $\sim 4.3 \text{ m}$ (14 ft) spacing. In contrast, both the pre-commercial stems and commercial stems in the FS-Off treatment were retained at a 4.3 m spacing. On ghost-on sites, foresters were told to think of commercial stems as “ghosts”, or to imagine that they weren’t there when considering tree spacing whereas ghost-off sites included commercial stems in their tree spacing considerations. Overall, this resulted in greater vertical heterogeneity in the FS-On plots. Although each of the sites received one of these four treatments, they were all spatially unique and exhibited a gradient of structural complexity.

2.2.2 UAS Data Collection and Processing

In the summer of 2020, we planned and executed 11 flights over the 1-ha sites using a DJI Phantom 4 Pro to acquire very high-resolution imagery of each study site (Figure 2.3). The

Phantom 4 Pro is equipped with a 20-megapixel (5472 x 3648 pixels) metal oxide semiconductor (CMOS) red-green-blue sensor with a fixed 8.8 mm focal length. Altizure (version 4.6.8.193; Shenzhen, China) for Apple iOS was used to pre-program and conduct automated UAS crosshatch flight paths at an 80 m altitude, 90% forward and 85% side overlap at 4 m s⁻¹ flight speed using a nadir (perpendicular to the ground) camera orientation. To improve georectification and image alignment, ground control points were established using an Emlid Reach-2 real-time kinetic GPS at the center and four corners of each plot. The ground control points for two of the sites had large vertical errors that resulted in skewed height depth maps that overestimated tree heights by 5-7 m. These two sites were subsequently reprocessed without ground control points, but still maintained a horizontal accuracy of less than 2 m in comparison to the stem mapped sites. Corrected point locations had an average reported horizontal accuracy of 0.41 m.

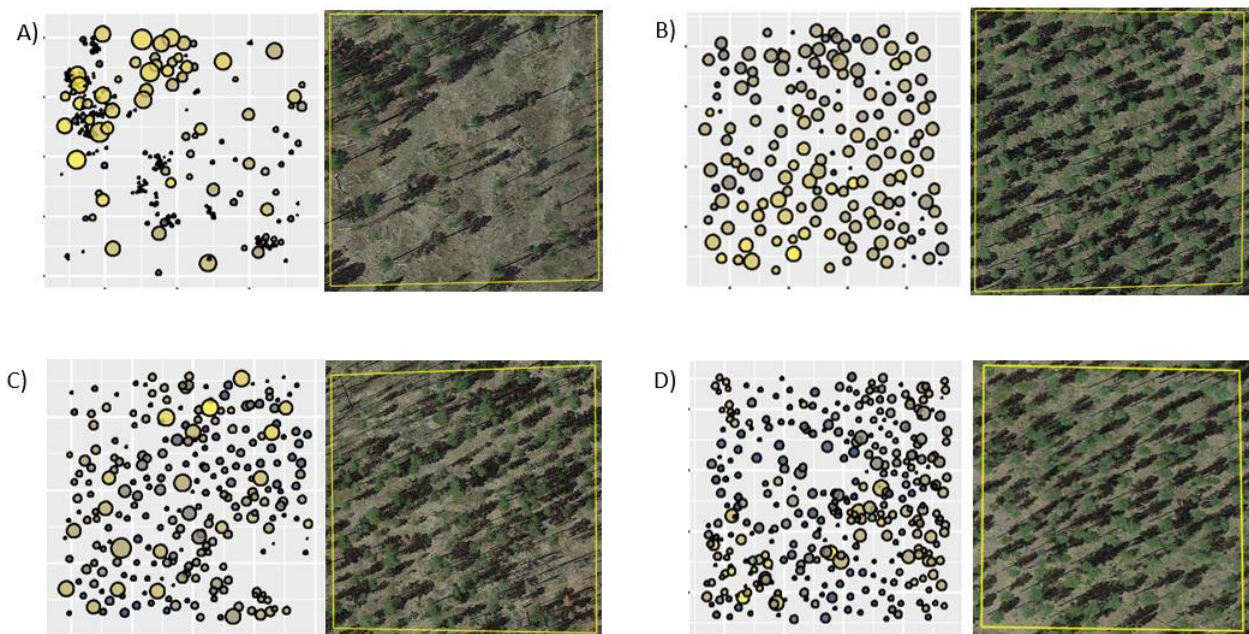


Figure 2.2. Stem Map and aerial photo of representative plots for each of the treatment types. A) Small group retention: SGR-1 B) Commercial Thinning: CT-1, C) Free Selection, Ghost Off: FS-

Off-1, D) Free Selection, Ghost On: FS-On-1. Where the stem map trees are scaled according to their crown diameter.

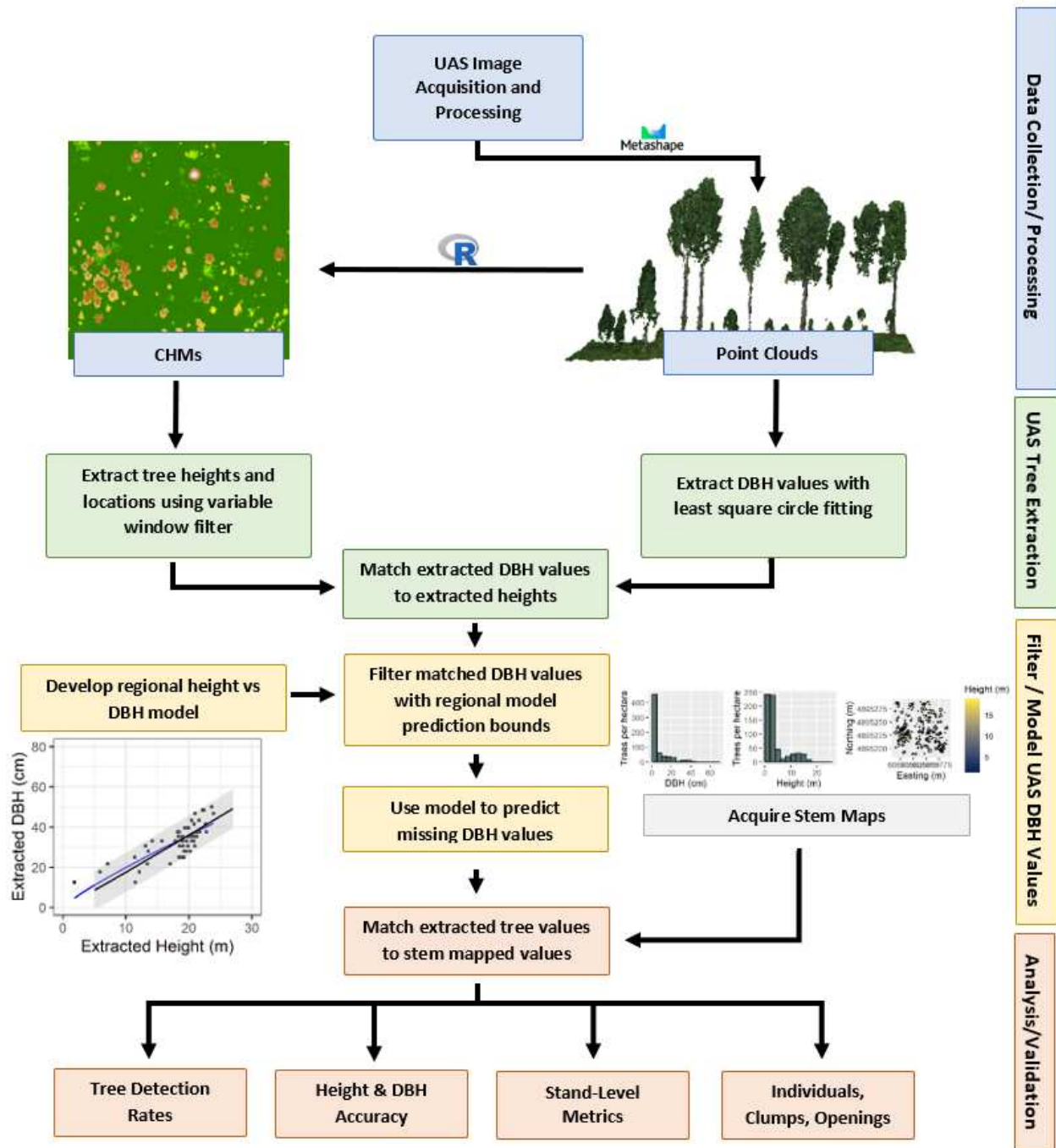


Figure 2.3. Workflow diagram showing the integration of UAS data collection, raw image processing through the structure from motion algorithm, extraction of individual tree height and DBH, filtering of DBH values with regional height to DBH model, prediction of missing DBH values from UAS modeled height to DBH relationship, matching of UAS and stem mapped trees for analysis of tree, stand, and clump level accuracy.

Images were processed using Agisoft Metashape Version 1.6.4 to generate Structure from Motion (SfM) point clouds following the methodology outlined by Tinkham and Swayze (2021). Study-specific processing parameters for Agisoft Metashape are reported in Supplemental Table 2.1. The resulting SfM point clouds underwent further processing in the lidR package (Roussel et al. 2020) for the R statistical program, including ground filtering, height normalizing, and canopy height model (CHM) generation at a resolution of 0.10 m. From the CHMs, individual trees were detected using a variable window function that reports tree location and height, following Creasy et al. (2021). The variable window function scaled the search radius around each focal cell of the CHM using Equation 1 to evaluate if the focal cell was the local maximum.

$$\text{Variable Window Radius} = \text{CHM Focal Cell Value} \times 0.2 \quad [\text{Equation 1}]$$

Additionally, the DBH for each tree was modeled by adapting the workflow of Swayze et al. (2021). The approach uses the TreeLS package (Conto 2019) to extract a slice of the height normalized point cloud at 1.32 m to 1.42 m, compress the points to a flat plane, and then iteratively fit an ordinary least squares circle algorithm to each tree location to estimate DBH. However, this process can mistakenly fit circles across branches and is only expected to extract 10-20% of DBH values in ponderosa pine forests (Swayze et al. 2021). To account for missing DBH values, regional United States Forest Service Forest Inventory and Analysis (FIA; Tinkham et al. 2018) data from the Black Hills National Forest were used to create a regional height vs DBH model. The successfully extracted UAS height and DBH pairs were filtered within the 90% prediction bounds of the regional model, and the remaining values were used to predict DBH values for all UAS extracted heights using a linear function to predict DBH from height. Finally,

individual tree crown areas were estimated from the UAS CHM using the marker-controlled watershed method of the ForestTools package (Plowright and Roussel 2021), providing a UAS dataset containing the location, DBH, height, and crown area of extracted trees.

2.2.3 Tree Matching and Error Assessment

Extracted and modeled UAS tree observations were evaluated in two ways: first, we spatially matched individual UAS-derived tree heights, diameters, and crown areas against stem mapped values following Silva et al. (2016) to provide an evaluation of True Positive, False Positive, and False Negative rates and to compare tree and stand-level structural attributes; then we evaluated the extent to which UAS can describe horizontal and vertical structural complexity by comparing the distribution of UAS-detected tree clusters and openings against distributions derived from the stem mapped trees.

Matching of UAS trees with field stem map trees was conducted by selecting a target UAS tree and identifying all candidate stem map trees within 4 m. If one or more candidate stem map tree was found to have less than a 2 m height error, the candidate with the smallest error was assigned as a True Positive match and removed from the process. If a match could not be found for the target tree, the target was considered a False Positive. The process considered each UAS tree iteratively until all UAS trees were classified as True Positive or False Positive. All remaining stem map trees that could not be matched were considered False Negatives. Based on the calculated True Positive, False Positive, and False Negative rates, F-score was calculated as an overall metric of tree extraction success. Our F-score, True Positive, False Positive, and False Negative rates were then summarized across understory (<5 m tall), intermediate (5-15 m) and overstory (>15 m) dominance classes.

Using the matched field stem map and UAS extracted trees, the mean error (ME) and root-mean-squared error (RMSE) of tree height and DBH were calculated for each study site. To determine how tree size influences detection rate and tree height and DBH error, the tree extraction and size metrics were summarized across 5-meter tree height size classes. Finally, to evaluate the efficacy of UAS measurements for stand-wide data collection and analysis, we compared estimates of stand basal area, trees per hectare, quadratic mean diameter (QMD), and percent canopy cover between the stem mapped and UAS extracted trees for each site. Canopy cover was defined as the proportion of CHM pixels identified as crown within each site.

To understand the ability of UAS extracted trees to characterize horizontal and vertical heterogeneity within tree arrangement, clusters of trees were identified within the stem mapped and UAS trees. A cluster of trees was defined as two or more trees with the potential for interlocking crowns. Overstory trees on the stem maps generally had a crown radius of ~3 meters, so stems within 6 meters of one another were considered to have the potential for developing interlocking crowns. Density-based spatial clustering of applications with noise (DBSCAN) from the *fpr* package in R was used to identify clusters within the UAS and stem map datasets for each plot (Hahsler et al. 2019). Additionally, individuals were defined as trees without the potential to develop interlocking crowns (> 6 m from other trees).

To analyze the effect of aggregation on data collection, the identified trees and clusters were designated as an “individual” or as a cluster consisting of 2-4, 5-9, 10-15, and >15 trees. We then calculated the number of structures, the percent of stand basal area, height coefficient of variation, and canopy area within the cluster size classes for each site. The

distribution of these metrics was compared through a series of one-way analyses of variance (ANOVA) between the UAS and stem map datasets.

Finally, to assess the efficacy of UAS for identifying and describing openings within each plot, distributions of inter-tree distances to every location in a 1 m grid were determined for each dataset. Distance distributions were used to calculate the proportion of total plot area within 3 m intervals of distance away from a tree. The total plot area detected within each distance interval was compared between the UAS and stem map datasets using a series of one-way ANOVAs.

2.3 Results

2.3.1 Tree and Stand Summarization

Overall, UAS tree detection resulted in F-scores ranging from 0.64 to 0.89 across the 11 sites, with F-score tending to decrease from the tallest to shortest height dominance classes. For all but the shortest class, the average F-score exceeded 0.80 and the maximum exceeded 0.95. Within the shortest height class, F-score ranged from 0.31 to 0.80. Similar trends occurred for the True Positive rate, with performance being the greatest for taller classes and decreasing to the smallest class (Figure 2.4). At the stand level, False Positive and False Negative detection rates partially balanced and resulted in average values of 29.5 and 16.8%, respectively (Figure 2.4). However, the smallest size class had exceptionally high False Positive rates with an average of 61.4%.

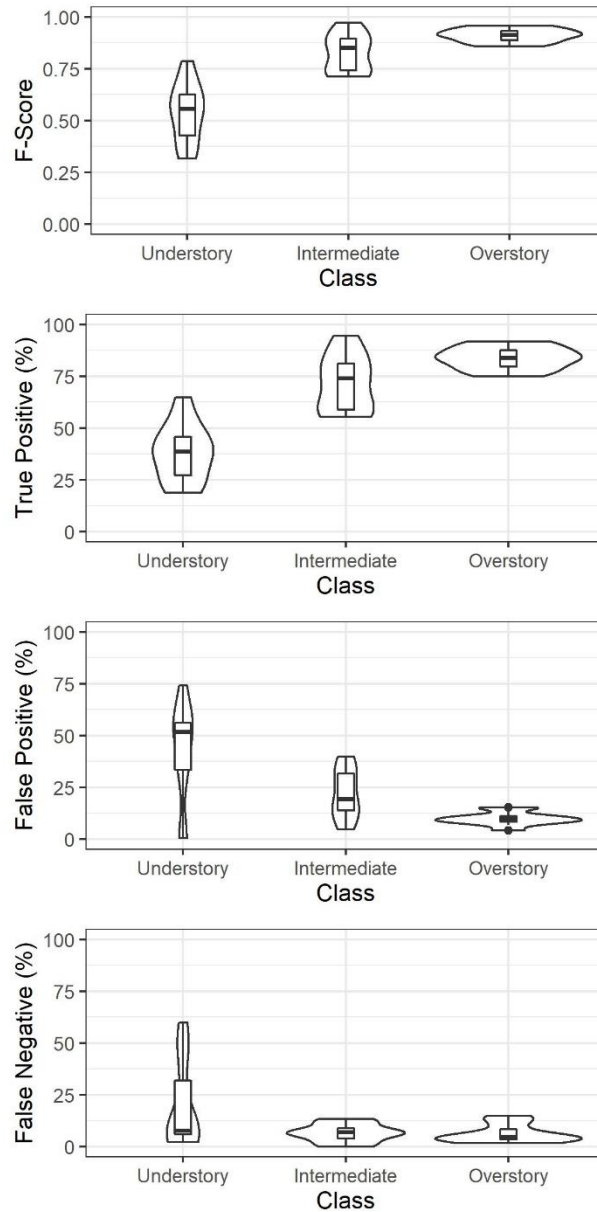


Figure 2.4. Summary of UAS tree extraction across understory (<5 m), intermediate (5-15 m), and overstory (>15 m) tree dominance classes. Each violin and nested boxplot represent the 11 observations from the different study sites, where each violin represents the complete distribution and the nested boxplot shows the median and interquartile range.

Stand level UAS tree height estimates tended to be slightly taller than the stem mapped values with an average mean error of 0.36 m and average RMSE of 1.32 m across the 11 sites (Figure 2.5). However, mean error tended to increase as tree height increased, while RMSE was similar across the tree size classes. The overall tree-level DBH mean error across the stand

averaged -0.04 cm with the UAS DBHs tending to be overestimated for the smaller tree size classes and underestimated for the largest size classes (Figure 2.5). UAS DBH predictions resulted in an average RMSE of 4.8 cm. When summarized across the 11 sites, the UAS estimated QMD was on average underestimated by 2.5 cm (Table 2.1).

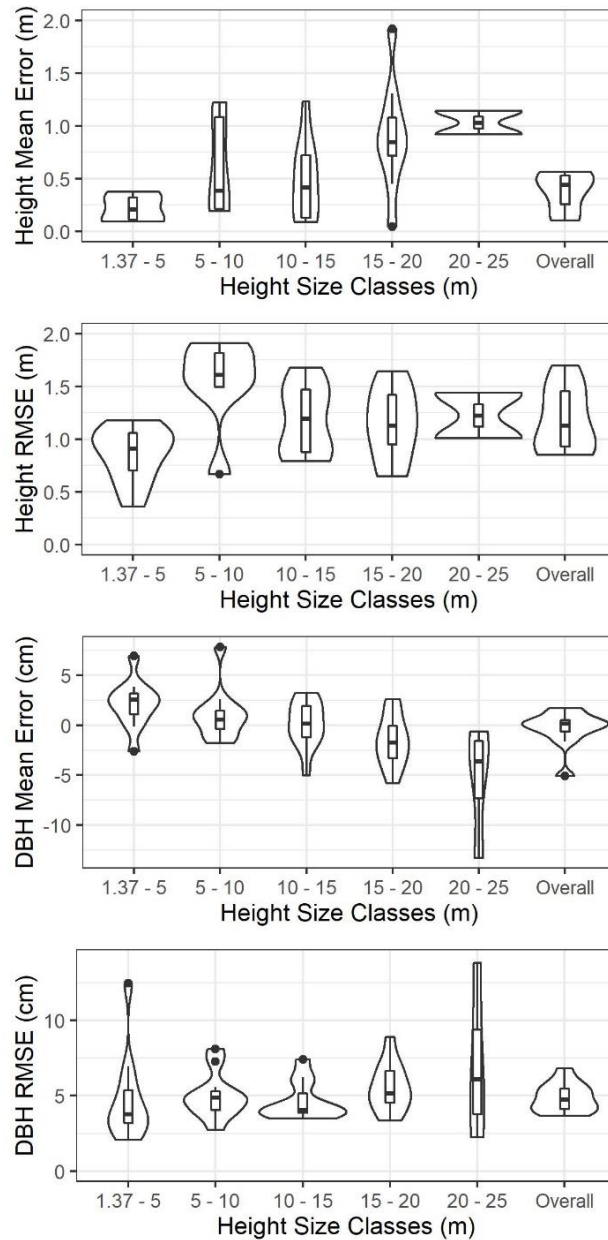


Figure 2.5. Summary of UAS extracted tree height and DBH. Each violin and nested boxplot represent the 11 observations from the different study sites, where each violin represents the complete distribution and the boxplot shows the median and interquartile range.

Sites had an average TPH of 332, with values ranging from 159 to 658 TPH. The UAS strategy generally overestimated TPH compared to the stem maps by an average of 53 TPH, but this varied across the sites and treatments (Table 2.1). The largest overestimations in TPH came from free-selection treatments at 187 and 121 TPH on average for the FS-On and FS-Off, respectively. Conversely, the small-group retention treatments underestimated TPH on average by 204, while the commercial thinning treatments were only over by 22 TPH. The sites where TPH was overestimated had the greatest False Positive rates in the shorter height size classes, while the underestimated sites had the largest False Negative rates in the same size classes (Figure 2.4). When only evaluating TPH of trees greater than 5 m in height, the UAS was far more successful with an average error of -10 TPH and RSME of 17 TPH. Stand basal area estimates across all trees were relatively similar between the UAS and stem maps with a mean underprediction error of $0.1 \text{ m}^2 \text{ ha}^{-1}$ or -1.7% (Table 2.1). There were no consistent trends in the UAS errors for basal area, potentially pointing to site-specific drivers like site index, or pre-treatment densities impacting the UAS modeling of tree DBH. Stand level canopy cover estimates from the UAS ranged between underestimating by 5.1% and overestimating by 8.4% with a mean absolute error of 2.6% (Table 2.1).

Table 2.1. Summary of stand estimates of tree density, size, and canopy cover for the field stem mapped and UAS extracted trees.

Plot Name	Basal Area (m ² ha ⁻¹)		Trees ha ⁻¹		Trees ha ⁻¹ (>5 m)		QMD (cm)		Canopy Cover (%)	
	Stem Map	UAS	Stem Map	UAS	Stem Map	UAS	Stem Map	UAS	Stem Map	UAS
SGR-1	6.4	4.5	307	195	84	78	16.2	17.2	12.8	10.4
SGR-2	6.5	6.9	658	362	151	146	11.2	15.5	12.6	12.9
FS-Off-1	11.1	10.1	251	387	206	221	23.7	18.2	17.8	21.7
FS-Off-2	11.5	12.5	254	420	168	196	24.0	19.4	22.8	21.5
FS-Off-3	10.3	11.0	263	323	225	239	22.4	20.9	15.7	19.2
FS-On-1	10.8	12.6	244	516	158	193	23.8	17.6	22.0	23.1
FS-On-2	11.3	12.3	348	540	288	284	20.3	17.1	20.3	28.7
FS-On-3	6.3	6.7	225	321	70	71	18.9	16.3	12.2	13.5
CT-1	10.9	10.4	171	196	158	163	28.4	26.0	24.1	19.0
CT-2	13.9	13.9	159	167	149	156	33.4	32.5	26.8	27.5
CT-3	11.8	8.4	189	222	179	202	28.2	22.0	24.7	24.6

2.3.2 Characterization of Horizontal and Vertical Heterogeneity

When evaluating the horizontal arrangement of trees, no significant differences were found between the stem maps and UAS data for the number of clumps within each of the size classes (Figure 2.6, Table 2.2), although we saw error in TPH estimates. Additionally, there were no significant differences in the coefficient of variation of tree heights within the different clump sizes (Figure 2.6). However, the differences within the 10 – 15 tree clump size did provide the largest marginal differences between the two datasets. The increased coefficient of variation of tree heights for the UAS dataset in the 10 – 15 tree clumps could correlate with the slightly higher False Negative (Figure 2.4) and height mean error (Figure 2.5) seen in these structures for some sites.

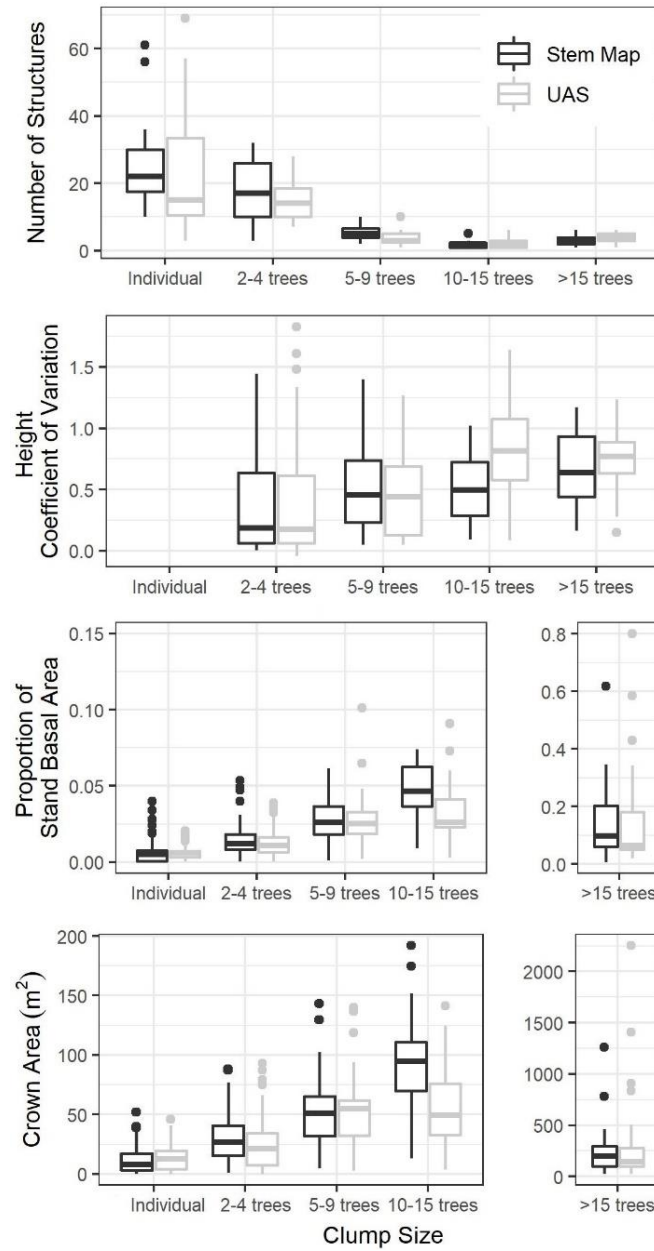


Figure 2.6. Evaluation of stem mapped and UAS extracted tree clusters, presented from top to bottom as boxplots showing the number of unique cluster structures, coefficient of variation for height within the clusters, and proportion of stand basal area within the clusters, and the crown area within clusters. The boxplots show the median and interquartile range.

Table 2.2. Summary of one-way ANOVAs comparing the distribution from the UAS and stem map datasets for the number of clumps by size, the proportion of stand basal area within clumps, height coefficient of variation within clumps, and the proportion of stand area at different distances from the nearest tree. Analysis used a Bonferroni correction to determine adjusted p-values, with significant differences ($\alpha = 0.05$) indicated in bold.

Metric & Class	Data Source		F	p
	Stem Map	UAS		
Number of Clumps				
Individual trees	28 (17)	25 (21)	0.126	1.000
2 – 4 trees	18 (10)	15 (7)	0.435	1.000
5 – 9 trees	5 (2)	4 (3)	1.248	1.000
10 – 15 trees	2 (1)	3 (2)	0.301	1.000
>15 trees	3 (2)	4 (2)	0.402	1.000
Height Coefficient of Variation (%)				
2 – 4 trees	38.3 (18.1)	34.3 (17.4)	0.077	1.000
5 – 9 trees	48.3 (24.3)	52.0 (26.9)	0.735	1.000
10 – 15 trees	50.4 (28.5)	88.3 (40.1)	5.832	0.084
>15 trees	63.2 (26.3)	73.4 (22.7)	0.896	1.000
Proportion of Stand Basal Area (%)				
Individual	0.5 (0.2)	0.5 (0.1)	0.215	1.000
2 – 4 trees	1.3 (0.3)	1.1 (0.3)	0.111	0.555
5 – 9 trees	2.8 (0.7)	2.4 (1.1)	0.779	1.000
10 – 15 trees	4.4 (2.0)	3.2 (0.7)	0.053	0.265
>15 trees	15.5 (7.2)	14.3 (6.9)	0.941	1.000
Crown Area (m ²)				
Individual	9.8 (4.0)	12.5 (4.4)	5.721	0.085
2 – 4 trees	24.2 (10.7)	21.0 (9.5)	7.755	0.030
5 – 9 trees	51.2 (20.7)	44.5 (19.3)	0.025	1.000
10 – 15 trees	105.9 (44.9)	54.7 (19.2)	10.955	0.010
>15 trees	280.8 (165.2)	299.6 (222.5)	0.250	1.000
Proportion of Stand at Distance to a Tree (%)				
< 3 m	1.3 (1.6)	1.3 (2.1)	0.471	1.000
3 – 6 m	40.9 (6.4)	38.3 (8.3)	0.679	1.000
6 – 9 m	7.3 (5.6)	6.8 (6.5)	0.029	1.000
9 – 12 m	0.2 (0.4)	0.2 (0.5)	0.000	1.000
> 12 m	50.3 (9.7)	53.5 (12.3)	0.037	1.000

In describing each clump size class using the proportion of stand basal area within each clump size class, there were no significant differences between the UAS and stem map datasets (Figure 2.6, Table 2.2). However, the comparison of the crown area in each clump size class

between the datasets showed that the UAS method significantly underestimated the crown area within the 2 – 4 trees and 10 – 15 trees clump sizes (Table 2.2). Assessment of the openings within the stands revealed no significant differences in the proportion of stands at different distance intervals from the nearest tree between the stem map and UAS datasets (Figure 2.7, Table 2.2).

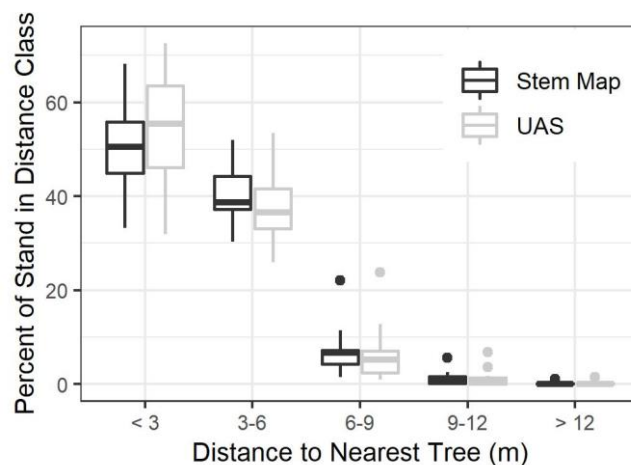


Figure 2.7. Boxplots showing the distribution of distance to the nearest tree within the stem mapped and UAS extracted tree datasets. The boxplots were developed from the 11 study sites and show the median and interquartile range of distance to the nearest tree within consecutive 3 m wide bands.

2.4 Discussion

This study evaluated the accuracy of UAS estimates of horizontal and vertical forest structural heterogeneity across various levels of spatial complexity in ponderosa pine-dominated forest systems. Specifically, we first evaluated tree detection rates and extracted height and DBH error across tree height classes. Then we compared the accuracy of stand-level basal area, TPH, QMD, and canopy cover across 11 sites. Finally, we assessed UAS-derived derived distributions of individuals, clumps, and openings against stem mapped data through metrics of the number of clump structures, percent of stand basal area, height CV, crown area,

and distance to the nearest tree. Our results indicated that tree detection was relatively successful for all size classes but improves as height increases and in treatments where small trees were thinned away from large trees. Individual tree height and DBH estimates were also very accurate, although DBH RSME was the greatest for the tallest trees. Stand-level metrics were generally very accurate with the exception of TPH, with smaller trees being disproportionally misevaluated by the UAS methods. UAS could successfully characterize and describe individuals, clumps, and openings as well as inter-clump characteristics like the percent of stand basal area and height CV through all clump size classes.

2.4.1 Tree Detection Performance

Overall, we found strong tree extraction metrics across our 11 sites, producing F-scores ranging from 0.64 to 0.89, which is comparable to findings from recent studies extracting individual trees from point clouds that have produced F-scores ranging from 0.71 to 0.94 (Creasy et al. 2021; Mohan et al. 2017; Silva et al. 2016). However, the slight differences in these tree detection results could be attributed to study differences in the trees that were targeted, tree extraction algorithm, treatment status, and ecosystem. This study differed from past studies, in that it was designed to assess a wide range of forest horizontal and vertical heterogeneity produced through restoration treatments. We assessed the accuracy of data collection for trees of all size classes within both even and uneven-aged stand structures with densities ranging from 159 to 658 TPH. In our study, only trees detected within 2 m of height and 4 m of horizontal distance to a stem mapped tree were considered True Positive matches. Mohan et al. (2017) achieved an overall F-score of 0.86 through a visual assessment of UAS-detected trees versus UAS-derived orthomosaics, point clouds, and crown height models. This

approach may have had a higher likelihood of introducing human error as only trees that were visible in the orthomosaic were assessed. Creasy et al. (2021) and Silva et al. (2016) both took similar approaches to this study's tree matching methodology and achieved F-scores of 0.69-0.79 and 0.83 respectively. Some differences in results can be attributed to the fact that Silva et al. (2016) allowed for a wider margin of horizontal error (10 m) and only tested forest densities up to 200 TPH. The relatively lower F-scores of these studies might be attributed to them being conducted in untreated stands of varying complexity and the fact that Silva et al. (2016) used a fixed radius tree detection window. Similarly, although Creasy et al. (2021) used tree detection and matching methods comparable to our study, their F-scores were lower likely due to characterizing untreated dense forest stands in similar forest types with a coarser resolution CHM (0.25 m) compared to our treated stands and finer resolution CHM (0.10 m). Finer resolution CHMs reduce the likelihood of multiple stems being generalized into the same pixel.

2.4.2 UAS Extracted Height and DBH

Extracted tree heights saw similar success as other UAS studies, with an overall RMSE of 1.32 m for extracting tree heights. This is in line with results from other recent studies producing RSME ranging from 1.30 m to 3.94 m (Panagiotidis et al. 2017; Wallace et al. 2016; Belmonte et al. 2020). However, our study had an overestimation bias of 0.36 m which is double the 0.15 m seen by Swayze et al. (2021) and 0.13 m by Krause et al. (2019). Both of these studies acquired their UAS data within one year of their field data whereas our increased overestimation bias is attributed to the two years between field stem mapping and UAS acquisitions, with a recent study in adjacent stands finding that regeneration height growth averages 0.4 m every two years (Tinkham et al. 2021). Along with this, during plot stem

mapping it was noted that some sites had many trees between 1.0 and 1.3 m tall, but shorter than the 1.37 m threshold for inventorying at the time. As a result, many trees that were too short to be inventoried initially could have grown to be over 1.38 m by the time the UAS inventory occurred. Such a discrepancy would contribute to the smallest tree size classes having the greatest False Positive rate (Figure 2.4). In addition, any amount of growth over this two-year period would have been a consistent source of error across all size classes.

Following flight, processing, and DBH filtering suggestions of Swayze et al. (2021) for extracting DBH values from UAS point clouds, an average of 26.3% of all tree DBHs were successfully extracted across the 11 sites. This extraction rate is more than three times greater than that achieved by Swayze et al. (2021) in untreated ponderosa pine forests. With a RMSE of 4.8 cm, our DBH estimates were on-par with past UAS studies conducted in coniferous systems with RMSE ranging from 3.46 to 4.24 cm (Brede et al. 2017; Dalla Corte et al. 2020). Similar trials have been conducted in broadleaf systems to varying results with RMSE ranging from 15 to 42 cm depending on scan angle and leaf presence (Neuville et al. 2021). All of the referenced studies, except Swayze et al. (2021), employed LiDAR sensors, indicating that SfM point clouds are a comparably effective approach for DBH measurements. However, since our DBH errors tended to increase with tree height, it would suggest that moving beyond the simple linear model of height predicting DBH by including covariates of local stem density or crown area might improve the overall accuracy of DBH estimates. Unfortunately, the current study only looked at post-treatment environments and was not able to explore if the inclusion of past local density metrics could improve DBH modeling, but future studies could track this through pre- and post-treatment monitoring to potentially enhance DBH modeling.

Other options potentially exist for improved modeling of missing DBH values within UAS datasets, including hybrid terrestrial SfM remote sensing or targeted field sampling of DBH values. Both of these strategies aim to reduce any error propagating through the modeling by extracting DBH values from UAS SfM point clouds. While UAS SfM is capable of detecting and accurately assessing most tree heights, terrestrial SfM or targeted field sampling have the potential to better describe the DBH of small trees or trees in dense areas. Hybrid SfM photogrammetry has been shown to provide RMSE of less than 1 cm and 1 m for tree DBH and height, respectively (Mikita et al. 2016). Despite the precision of this approach, terrestrial image collection is still limited by its extent and will likely only function as a sampling tool. Nonetheless, there is potential for hybrid approaches to collect training data from within a project area to improve DBH modeling.

2.4.3 UAS Estimated Stand Metrics

Overall, UAS were successful in describing stand-wide metrics of forest density, tree size, and cover (Table 2.1). However, UAS did see fluctuating error levels in estimating TPH. UAS overestimated TPH in every plot except for the SGR treatments where UAS underestimated TPH by a wide margin. After excluding all trees <5 m in height from TPH estimates, UAS saw very little error – indicating that small stems had been the primary source of error. The authors attribute these discrepancies in small stem TPH to two primary sources of error: 1) underestimation of TPH is likely due to limitation in identifying small stems in CHMs due to issues with their interlocking crowns (Creasy et al. 2021), and 2) the overestimation is attributed to the ingrowth that happened during the two-year separation between stem mapping and UAS acquisitions. Underestimation was especially prominent in the SGR sites,

where small stems were intentionally grouped together, and overestimation was more common in sites where regeneration was allowed to grow by itself – contributing to ingrowth. Despite errors concerning small stem TPH, it did not appear to have any discernable impacts on our ability to describe other stand-level metrics. Average absolute error in basal area estimates for the different treatments fell between 6.9% and 17.3%, with a mean underprediction error of $0.1 \text{ m}^2 \text{ ha}^{-1}$ or -1.7%. This is in line with results reported within other ponderosa pine forests where stand-level basal area estimates were within 4.1% to 24.7% of field observed values (Swayze et al. 2021), and exceeds results reported in complex mixed species forests where basal area was overestimated by 14.6% to 42.1% (Fraser and Congalton 2021). Although error for stand basal area estimates varied between the study sites, we were unable to find any trends in the UAS errors to indicate that site-specific drivers that could have impacted our DBH modeling and therefore basal area. More research should be conducted to identify and adjust for how pre-treatment conditions may have propagated to impact this process.

Stand level canopy cover estimates were in line with field observations providing a mean absolute error of 2.6%. This follows other UAS-based approaches that have found LiDAR estimates of crown cover to fall within 5% of field observations (Ahmed et al. 2015). Overall, remote sensing strategies have consistently been shown to effectively assess crown cover, as studies employing a variety of methods have found strong correlations to field observations with r^2 values ranging from 0.78 to 0.91 however it is worth noting that different studies can have drastically different approaches to extracting and describing crown cover (Dickinson et al. 2016; Gülci 2019; Tang et al. 2019). Although these results were described at a stand level, they were achieved with high resolution on relatively small plots of land – indicating that crown

cover can still be accurately assessed at small extents. In addition, SfM is not limited by temporal resolution, making it ideal for assessing post-treatment or post-disturbance canopy cover compared to other remote sensing methods.

2.4.4 Implications for Management

This study demonstrated a UAS method for extracting spatially-explicit tree lists across a range of treatments designed to create variation in horizontal and vertical heterogeneity. Such tree lists would be a valuable resource for land managers in planning, implementing, and evaluating spatially explicit silvicultural prescriptions (Addington et al. 2018). This level of data would enable managers to map explicit locations for tree retention and planned openings for use by marking crews. While not all trees were successfully extracted from the UAS data, the presented methods captured the relative local trends and stand-level averages that are necessary for informing a broad range of thinning and restoration (Almeida et al. 2019) actions in low to moderate canopy cover (e.g., <60%) pine-dominated or mixed conifer systems. This could facilitate prescription development and marking of a heterogeneous matrix of openings and tree groups. Such matrices of variable tree densities have been proven to limit crown fire spread (Ziegler et al. 2017b; Tinkham et al. 2016; Ritter et al. 2022) and reduce beetle mortality intensity in dry conifer forests by fragmenting continuity between susceptible hosts (Fettig et al. 2007). Such management strategies often target the removal of understory and suppressed trees, and while UAS understory stem density precision is limited by the density of small trees, the methods tested in this study accurately reflect relative understory densities across the stand. Characterization of relative understory density across a stand has been proposed as sufficient to guide thinning objectives that target understory trees (Allen et al. 2002), especially

as traditional field plot sampling only provides estimates of stem density but not the stem locations.

The increased focus on spatial heterogeneity in management objectives within dry conifer forests has elevated the need for monitoring strategies capable of quantitatively describing the matrix of trees, clumps, and openings that comprise a stand (Tinkham et al. 2017). One approach to describing and reintroducing mosaic patterns in pine and mixed conifer forests is the ICO (individuals, clumps, and openings) method initially developed by Larson and Churchill (2013). Such approaches draw on intensive stem map datasets, similar to the validation data used in this study, to develop historical guidelines of clump size distributions for silviculture prescription development. However, such comprehensive data are rarely available or attainable to forest managers and have made implementation and monitoring of such strategies harder. This distribution summarizes the percent of trees arranged as individuals and in clumps of different sizes at a specified inter-tree distance. They selected a single inter-tree distance threshold to define tree clumps based on the observed distance at which most mature ponderosa pine trees display interlocking crowns and form patches of continuous canopy. These metrics were applied to a model of a case-study stand in contrast with more common quantitative metrics like tree spacing and stand basal area (Figure 2.6 and Figure 2.7). Of the purely quantitative methods, ICO was the most successful in recreating reference conditions (Larson and Churchill 2012). Additionally, this method could then be further improved upon by tallying clumps and adapting marking protocol on the fly. One of the biggest barriers to the implementation and monitoring of approaches like the ICO method is their reliance on spatially-explicit data. The ICO implementation guide provides a relatively straightforward protocol for

field-based implementation, but also addresses the benefits of incorporating a LiDAR-based canopy surface model to quantify spatial patterns over large areas quickly and efficiently. However, the methodology outlined in this study could prove to be a cheaper alternative for quantifying these spatial patterns.

Some studies have also addressed the potential for remote sensing techniques to describe and monitor habitat distributions for species of conservation interest (Vogeler et al. 2016). In the Black Hills specifically, species like the northern goshawk and black-backed woodpecker have been of particular concern in forest management and forest structure is considered to be a primary limiting factor for both species. Black-backed woodpeckers depend on a patchwork of recently burned, beetle-killed, and undisturbed forest for successful nesting and forage (Matseur et al. 2018). Northern goshawks preferentially select centrally-located nesting sites in areas with dense patches of old growth and high canopy cover with lifted crowns for sub-canopy flight within range of principal prey habitat (Reynolds et al. 2006, Reynolds et al. 2012). In ponderosa-dominated ecosystems, principal prey habitat occurs in mosaics of tree clumps of varying maturities and large grass/forb-dominated meadows and interspaces – much like that of pre-settlement ponderosa structure (Reynolds et al. 1992; Reynolds et al. 2012). As a result, habitat management recommendations for the northern goshawk (Reynolds et al. 1992) promote a shifting mosaic of interspersed tree groups in different vegetative structural stages (Reynolds et al. 1992; Reynolds et al. 2012). However, adequate implementation of these recommendations require some spatially-explicit understanding of horizontal and vertical forest structure is pertinent to proper habitat management.

Current methods for assessing northern goshawk habitat include implementing transects and fixed radius plots to describe local structure and individual tree metrics, global point pattern analyses to describe aggregation, and aerial imagery to describe patch/opening size and proportions (Addington et al. 2018; Reynolds et al. 2012). However, the methods outlined in this study would likely provide a more robust understanding of current and recommended conditions. UAS are capable of describing local patterns and individual tree metrics similar to those collected in forest plots and transects as well as canopy cover and patch size like other remote sensing methods. But in addition to these metrics, UAS were also capable of describing inter-clump metrics like density and height variability. UAS could be a valuable tool in efficiently assessing northern goshawk habitat and implementing treatments across landscapes.

Structure is also a significant factor for other wildlife. Ungulates and game birds have been shown to preferentially select habitat in mosaic meadows near clumps of large-diameter ponderosa for easy access to both forage and escape cover (Lehman et al. 2011; Lehman et al. 2015) and predators like mountain lions tend to have more success stalking prey in areas with thick patches of small-diameter trees for cover (Lehman et al. 2017). Results from this study demonstrate the potential for UAS techniques to successfully describe the size, density, and proximity of these types of spatial structures. Being able to identify these forest structures in pre- and post-treatment monitoring could better inform and promote wildlife-based management objectives.

2.4.5 Limitations/Potential Sources of Error

As with all validated research, the accuracy of our results needs to be interpreted within the context of their application and the dataset used to validate them. Our use of 1-ha stem maps located within treated stands likely increased the False Positive rate within larger tree sizes as the crowns of these trees were observed to overlap into the study area and were extracted as actual trees. However, scaling these methods to full management units and utilizing common stand boundaries like roads should reduce this effect during operational monitoring. Additionally, there is potential for discrepancies between UAS and stem mapped tree locations. The stem mapped trees were described by the location of the stems whereas the UAS approach determined tree locations by the highest point in the crown. While this may seem like a small difference, this likely resulted in a shift in many of our tree locations – especially in larger, leaning trees. This likely had some impact on our ability to adequately assess and validate some of our metrics for horizontal heterogeneity and contributes to why our False Positive and False Negative rates balance each other.

Studies have also found that field observations tend to underestimate tree heights by about 5%, and can vary in precision by 10% (Vastaranta et al. 2009). Similarly, Krause et al. (2019) found that field measurements generally misestimated tree heights with a RMSE of 0.30 m and a systematic error of 0.14 m. Such a bias could be a consistent source of error in accuracy assessments and potentially lead to the misinterpretation of results. These types of errors are likely compounded by the two years separating the stem map and UAS data acquisitions. In addition to height error, field measurements may have an impact on canopy cover assessments as well. The stem maps provided for this study approximated a single crown

width for each tree. While this provided some insight on forest canopy cover, it may not have been a robust enough measurement to account for irregularities in crown shape.

2.5 Conclusion

As management objectives in dry conifer forests shift toward promoting horizontal and vertical complexity, there is a growing need for forest inventory techniques capable of capturing the resolution, extent, and spatial explicitness required to inform management decisions. This study found that UAS SfM could successfully detect individual trees from most size classes and estimate tree-level height and DBH across all size classes. This data could be reliably summarized to describe estimate stand-level density and cover, with slightly larger errors for TPH estimates stemming from detection issues with smaller trees. Additionally, the data could be summarized to characterize and describe individuals, clumps, and openings as well as inter-clump characteristics like the percent of stand basal area and height CV through all clump size classes. These findings indicate that aerial SfM photogrammetry can effectively characterize large- and small-scale forest structure metrics within ponderosa pine-dominated stands to a level likely adequate for monitoring and implementing spatially explicit management objectives. This approach could also be easily integrated into management process to inform approaches like the ICO method of stand prescription development. However, future work is needed to evaluate if incorporation of site-specific drivers of height to DBH relationships can improve DBH modeling and how these techniques will transfer to sites with more complex species compositions.

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