Ownership patterns drive multi-scale forest structure patterns across a large landscape in southern coastal Oregon, USA

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Abstract

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Globally, the physical structure of forests results from their environmental setting, disturbance history, and human management practices. Human management practices today arguably have the greatest impact on the types and patterns of forest structure through direct management and modification of disturbance regimes. Previous studies have found that land ownership affects forest cover, patch dynamics, structure, and ecosystem function and services. However, these assessments of forest structure across landscapes and ownerships have been limited by the availability of high-fidelity data across a large spatial extent. To expand upon prior research, I used airborne lidar to assess the multi-scalar patterns of forest structure across a large (471,000 hectare), multi-owner landscape of the Oregon Coast Range. I examined forest structure patterns by identifying six statistically distinct classes of forest structure and then examining their distribution across and within ownership types. I used these structure classes to examine their area within each ownership class, mean patch size, and intermixing at multiple scales. I found that the six different forest structure classes in the study area can be interpreted as two assemblages, production-style forests principally on private lands and structurally complex forests principally on public lands. I found that land ownership objectives manifested in the physical landscape pattern of forest structure as measured by mean patch size and intermixing of structures. Finally, I found that landscape pattern of forest structure varied across scales as well as between ownerships. These results can be used to aid in monitoring and implementation of conservation strategies, for instance, in the monitoring of structurally complex forest and Northern Spotted Owl habitat and implementation of the Oregon Forest Practices Act.

1.0 Introduction

Globally, the physical structure of forests results from their environmental setting, history of disturbances, and human management practices (Sanders 1984; Ryan 2002; Parotta et al. 2006; Wang et al. 2006; Kulakowski et al. 2011; Quesada et al. 2012). Forest structure—the horizontal and vertical arrangement of biomass (McElhinny et al. 2005) – plays a critical role in ecosystem services and functions such as net primary productivity, the accumulation, distribution, and melting of snowfall, water yield, microclimate, as well as providing important resources to forest-dependent communities (Tateno et al. 2004; Youn 2009; Teztlaff et al. 2013; Caldwell et al. 2016). Because forest structure is the arrangement of biomass, it dictates how much and where carbon can be stored in a tree and forest (Franklin et al. 2002). It also plays a critical role in habitat quality across functional groups, in terms of food availability as well as protection from predation and the elements (Schwab and Pitt 1991; Coops et al. 2016). Perhaps most importantly, forest structure is quantifiable and easy to manipulate, allowing it to be the focus of management actions (Franklin et al. 2002).

Human management today arguably has the greatest impact on the types and patterns of forest structure through direct management (e.g. harvest), modification of disturbance regimes (e.g. wildfire suppression), and increasingly, climate change (Nepstad et al. 1999; Bengtsson et al. 2000; Backer et al. 2004; Boisvenue and Running 2006; Allen et al. 2010; Brotons et al. 2013). In many societies, management goals and practices are organized by different classes of owners (Sorice et al. 2014). Their objectives vary and can include financial investment (Cubbage et al. 2007), sustainable community resources (Adhikari et al. 2007), wildlife conservation (Götmark 2013), lifestyle enhancement (Erickson et al. 2002), land investment (Kendra and Hull 2005), and more. The management practices that address these objectives vary by silvicultural treatment and intensity, rotation time, management of fire, and many other decisions. Both objectives and practices can be constrained and/or dictated by social goals, policy, and market forces (Lindhhem and Mitani 2012). The resulting combination of landowner objectives, management practices, and the constraints placed upon them creates a spatial pattern of forest structure dependent on anthropogenic decision-making and actions.

As a result, the effects of forest ownership on forest conditions have received more attention in recent years, in part due to emerging new forest owner types, ownership fragmentation and parcelization, and questions related to sustainable yield of forest products, as well as other topics (Weiss et al. 2019). The effects of forest ownership on ecological patterns have been explored using multiple approaches. For example, forest management, land cover, and land use are all critical components of ownership and have been used as lenses to examine ownership effects on forest cover, patch dynamics, structure, and ecosystem function and services (Mladenoff et al. 1993; Turner et al. 1997; Crow et al. 1999; Cohen et al. 2002; McComb et al. 2007; Nagendra et al. 2007; Ohmann et al. 2007; Schulte et al. 2007; Hudiburg et al. 2009; Kennedy et al. 2012; Pachavo and Murwira 2013; Hightower et al. 2014; Boucher et al. 2015; Rendenieks et al. 2015; Guo et al. 2017; Easterday et al. 2018). One of the main conclusions from this body of work is that forest structure, function, and services differ between private and public ownerships at broad scales both in the U.S. and internationally. This is typically because public lands have less intense land use regimes (Huntsinger et al., 1997; although this is not always the case, see Schaich and Plieninger 2014 and Vogeler et al. 2020) and were found to host more biodiversity (Schaich and Plieninger 2014).

In the western U.S., private landowner objectives and management reflect owners' individual goals, market forces, and reflect forest management policies implemented at the state and local levels. On federal lands, objectives and management often reflect policies set at the national level. This can result in a difference of forest processes and ecosystem services and their segmentation across the region. As an example, a substantial amount of research has been conducted in western Oregon on the effects of multi-ownership mosaics on forest structure and ecosystem services (Spies et al. 1994; Ohmann and Spies 1998; Cohen et al. 2002; Stanfield et al. 2002; Wimberley and Ohmann 2004; Ohmann et al. 2007; Kennedy et al. 2010). These studies added to the wider literature base with two key findings: segregation of structurally simplified younger and structurally more complex older forest based on private versus public lands (Nonaka and Spies 2005) and the expectation of landscape conditions across ownership boundaries to diverge over time due to the segregation of age classes and intensity of land use regimes (McAlpine et al. 2007).

The forests of southwest coastal region of Oregon, USA present an opportunity to further elucidate the relationship between structure and ownership of forests. This opportunity is available because here, forest structure is clearly connected to ecological and conservation goals due to the regional conservation plan's (the Northwest Forest Plan) focus on forest structure as a metric (Thomas et al. 2006). Secondly, ownership can act as a proxy for management and landowner objectives here because there has been little turnover between ownership types for several decades, so management practices at a given location have not changed substantially (Kennedy et al. 2008). Finally, the availability of spatially explicit data for management and landowner objectives allows us to relate conservation goals to management and landowner objectives. This is important, because while ownership itself is difficult to alter, management and objectives can be constrained by policy and market forces. A key limitation of most previous studies of ownerships and their effects on forests was the low fidelity of their data for forest structure (but see Dickinson et al. 2014). Most of these studies relied upon modeling or optical or spectral remote sensing that do not capture forest structure adequately at fine scales. Many of these studies' forest classes were broad and, while associated with ranges of actual forest structure, were not based on actual measurements of forest structure (e.g. Mladenoff et al. 1993; Turner et al. 1997; Crow et al. 1999; Cohen et al. 2002; Schulte et al. 2007; Kennedy et al. 2012; Pachavo and Murwira 2013; Rendenieks et al. 2015).

In this study, I leveraged a combination of datasets presented by our study area, a forested region along the coast of southern Oregon, USA: spatially explicit ownership data as a proxy for landowner objectives and management; high fidelity measurements of fine-scale forest structure; and forest structure directly linked to conservation values through the regional conservation plan. I expand upon prior research in this region by using a 471,000-hectare lidar acquisition and landscape metrics to quantify the landscape pattern of forest structure within ownerships at multiple scales (forest patches, ownership type, and subregion). To better understand the impact of ownership patterns, objectives, and management practices on patterns of forest structure across this region, I addressed these questions:

1. What distinct classes of forest structure exist across our study area?

2. How does the distribution and pattern of forest structure vary among types of owners at scales of patches, ownership types, and subregion?

3. What implications do the fine and sub-regional scale patterns have for managing this region for conservation values elucidated in the NWFP?

2.0 Methods

2.1 Study Area

The study area is a 471,116 hectare region in south-central Oregon, USA defined by the boundaries of a 2008-2009 lidar acquisition. The forests of the Oregon Coast Range are some of the most productive in the world (Smithwick et al. 2002) and as a result are both economically and ecologically important. A little less than half of the forested area is privately owned and managed for timber harvest. The forests are dominated by *Pseudotsuga menziesii* (Douglas fir), *Picea stichensis* (Sitka Spruce), and *Tsuga heterophylla* (Western Hemlock) (Franklin and Dyrness 1988). The climate is mesic temperate, receives approximately 500 mm of precipitation per year, and has a mean annual temperature of 11.4 Celsius (Franklin and Dyrness 1988). Elevations range from sea level to 600 meters.

This region has a high-severity, infrequent fire regime, with a mean fire return interval of approximately 200 years (Rollins 2009). The most recent fires in this area were in 1902 and burned approximately 31% of the study area (Figure 1), although it was preceded by another large fire in 1868(burn perimeter unknown)(Morris 1934; PNW-GTR-966 Vol. 1 2018). Other natural disturbance events, such as windthrow and pathogens, occur more frequently and at smaller scales (Cohen et al. 2002; Spies et al. 1994).

Previous studies of land cover patterns across the Oregon coastal region (including our study area) found that biophysical gradients had little influence on forest structure. They found that disturbance, predominantly timber harvest, had a strong influence on forest structure across the landscape (Wimberley and Spies 2001; Wimberley and Ohmann 2004; Ohmann et al. 2007). This relationship is likely due to the near-instantaneous structural changes that result from disturbance, compared to structural changes from the slow process of tree growth and densification driven by biophysical factors (Wimberley and Ohmann 2004). In exploratory random forest modeling (not reported), I found that biophysical predictors such as precipitation, mean January temperature, and vapor pressure deficit, had less predictive power compared to land ownership. This result was expected; the study area has high precipitation much of the year [approx. 1800mm; PRISM Climate Group], so typical drivers of topographic variation in forest structure that are precipitation-dependent, such as elevation, aspect, slope, and slope position, have limited influence. Additionally, the mean January temperature range [approx. 3-10 C; PRISM Climate Group] stays above freezing throughout the study area meaning that growth can continue throughout the year. For these reasons, I did not further consider biophysical factors in this study.

2.2 Identification of ownerships

Individual parcel land ownership data were aggregated into ownership types by The Nature Conservancy (TNC) of Oregon and were sourced from the 4th quarter 2017 CoreLogic ParcelPoint tax lot database, federal corporate datasets, and other datasets assembled by TNC. Before conducting statistical analyses, I removed ownerships that had less than 10,000 hectares of land in our study area, which left 13 ownership types for analysis (Table 1).

Timber production is the primary goal on private lands and the dominant harvest method is clearcutting (complete removal of overstory and understory trees; Keenan and Kimmins 1993) with replanting of commercially valuable tree species, commonly Douglas-fir. While timber production is the primary goal, there is a wide decision space of other goals that can include land investment, estate for children, habitat protection, and more (Table 1). On public lands, the regional conservation plan, the Northwest Forest Plan (NWFP), is a series of federal policies begun in 1994 that governs forests, endangered species, and timber production on federal lands in the range of the northern spotted owl, which includes most forests west of the Cascade Crest in the Pacific Northwest (PNW-GTR-966 Vol. 1 2018). Despite certain allowances for timber harvest in the area governed by the NWFP (e.g. railroad and matrix lands), harvest has almost entirely stopped on federal lands since the early 1990s (Franklin and Johnson 2014). The one state property here in our study area (Elliot State Forest) is managed both for ecological values as well as timber production, in contrast to other Oregon State Forests which are typically managed for intense timber production (Decker 2011). Both public and private forests are important to local communities for their income and employment opportunities and are important regionally because they store a disproportionately high amount of carbon (Smithwick et al. 2002) and provide critical habitat for the endangered Northern Spotted Owl and Marbled Murrelet (Hagar et al. 2020; PNW-GTR-966 Vol. 1 2018).

Table 1: Ownership types used in analysis. Landowner objectives are from Johnson et al. (1999) and personal communications (Derek Churchill, personal communication, December 3, 2019; Ryan Haugo, personal communication, January 15, 2020; Bryce Kellogg, personal communication, January 25, 2020). Ownership types are grouped by the simplified ownership groups identified through hierarchical classification (Sections 2.5 and 3.2). Rotation length is the average number of years between harvests.

Simplified Group	**Ownership Type**	**Description**	**Summary of Landowner Objectives**	**Rotation Length**

Private non-industrial	Private Private Very Small Private Small Private Medium	Land held by private owners less than 20.23 hectares (50 acres) 20.23-40.47 hectares (50-100 acres) 40.47-202.34 hectares (100-500 acres) 202.34-2023.43 hectares (500-5000 acres)	Harvest income; Land investment; part of residence; estate for children	35-70
Private-Industrial	Timber Investment Management Organization (TIMO) Real Estate Investment Trust (REIT) Integrated	Procure, manage, and sell timberland assets on behalf of institutions or investors Own cash producing real estate and distribute rents to investors, in addition to other requirements they must fulfill May own both timber land and milling infrastructure	Maximizing rate of return on investment; focus on net present value	35-60
	Family	Large forestland owners that are closely held or family owned	Diverse objectives, including but not limited to harvest income, wildlife habitat protection, land investment, and estate for children	35-60
Mixed Objective Government	State	Land owned by the state of Oregon. In this area, only Elliot State Forest	Stand diversity and heterogeneity; sustainable-yield timber production	80+

	Bureau of Land Management	Land managed by the Bureau of Land Management that was formerly not a part of railroad lands	Managed under the Northwest Forest Plan. Maintenance of late-successional and old growth species habitat and ecosystems, and native biological diversity; sustainable yield timber production on a small amount of designated lands.	80+
NWFP Objective Government	U.S. Forest Service Bureau of Land Management O&C Bureau of Land Management CBWR	Land managed by the U.S. Forest Service Land managed by the BLM that is part of the former Oregon and California railroad land grant Land managed by the BLM that is part of the former Coos Bay wagon road land grants	Managed under the Northwest Forest Plan. Maintenance of late-successional and old growth species habitat and ecosystems, and native biological diversity; sustainable-yield timber production on a small amount of designated lands.	80+

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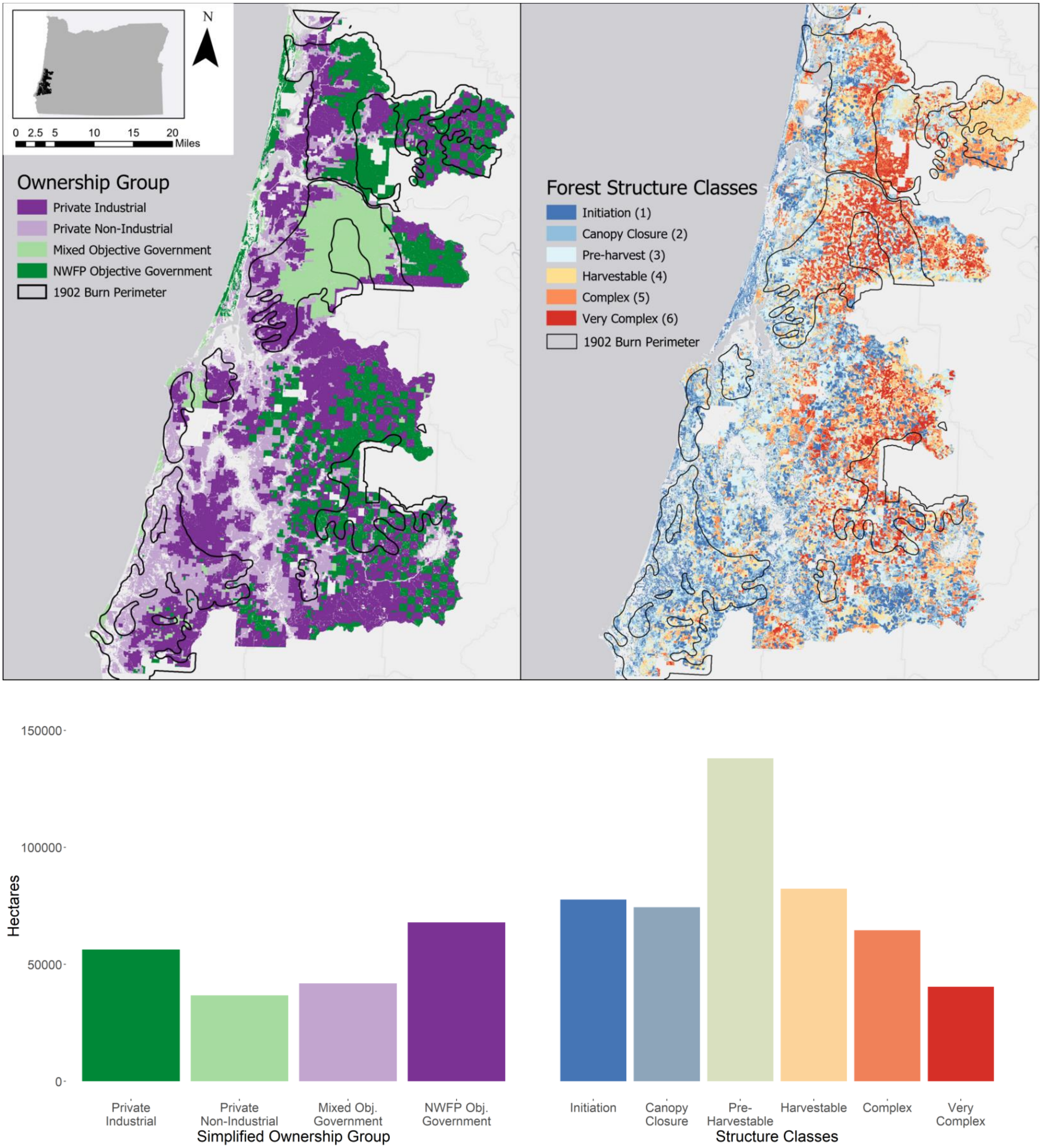

Figure 1: maps of simplified ownership groups (Left) and forest structure classes (Right) in the study area. Ownership types are grouped by the simplified ownership groups identified through hierarchical

classification (Sections 2.5 and 3.2). Burn perimeters from the 1902 Fires also appear on each map (PNW-GTR-966 Vol. 1 2018).

2.3 Airborne lidar data

The study area is a portion of the Oregon, USA, South Coast lidar acquisition, collected from April 2008 to April 2009 by Watershed Sciences, Inc. (now Quantum Spatial, Inc.) for the United States Bureau of Land Management. Our study omits a portion of the acquisition (15% of the original acquisition) that is of a substantially different forest type. The study area covers portions of Coos, Curry, and Douglas counties. Data were acquired with an average of 8 pulses/m^2 and up to four returns per pulse were recorded. I used the vendor-supplied, lidar-derived 1m digital terrain model. I processed the LiDAR data using the USDA Forest Service's Fusion software package (version 3.8, http://forsys.sefs.uw.edu/FUSION/fusion_overview.html).

2.4 Forest structure analysis and classification

I measured forest structure using four metrics derived from the lidar data at a 30 m resolution: 95th percentile of return height ≥2 m (P95, a surrogate for dominant tree height), 25th percentile of return height ≥2 m (P25, a surrogate for height to live crown), rumple (canopy surface rugosity, a measure of canopy complexity), and canopy cover (percent of points above 2m/all points). P95, P25, and canopy cover were calculated from all returns of the lidar data above 2 meters while rumple was calculated from the canopy surface model. Return heights were normalized to height above ground using the vendor-supplied ground models. I chose these metrics from a much larger set of candidate metrics produced by the FUSION software through a combination of Kolmogorov-Smirnov (K-S) tests, niche overlap tests (see North et al. 2017 for use in ecology), and previous literature (e.g. Kane et al. 2010a and 2013).

K-S and niche overlap tests were used to determine whether the distributions of a wider set of lidar metrics were distinct in different land ownerships. These tests demonstrated that measures of dominant tree height (e.g. P95, quadratic return mean height, P80) were the most distinct between ownerships, followed by measures of structural complexity (e.g. rumple, standard deviation of return height). Additionally, P95, rumple, and canopy cover have been previously identified to best represent forest structure in temperate Pacific northwest forests (Kane et al. 2010a, Kane et al. 2010b). I chose to include P25 because it represents height to live crown.

I identified forest structure classes, which use the combination of the four selected lidar metrics to rank forests by structural complexity. The classification process can identify forest structure stages from stand initiation to complex forests (Kane et al. 2010b; Smart et al. 2012; Simonson et al. 2014; Listopad et al. 2015; Moran et al. 2018). To remove correlation between lidar metrics, I centered and scaled our data and then performed a principle components analysis (PCA). To identify the structure classes, I then did a hierarchical clustering with the Ward.D2 method using the hclust function from the R statistical package (R Core Team 2020) on sampled point values using the PCA axis values. I used 30,000 random samples from across the study area and selected the most parsimonious grouping of structure classes that retained most of the original information (McCune and Grace 2002). This classification was then imputed across the landscape using random forest modeling (Breiman 2001; Cutler et al. 2007).

I used two ancillary datasets to aid in interpretation and analyses dependent on the structure classes. First, I used stand age estimates from the LEMMA GNN project (Landscape Ecology Modeling, Mapping and Analysis Gradient Nearest Neighbor project) post hoc as an interpretive aid for the structure classes (Ohmann and Gregory 2002). These data are derived from 2012 Landsat Thematic Mapper data and field plot data and are believed to be generally accurate at the scale of a small watershed (Ohmann et al. 2002). Stand age specifically has a reported r-squared value of 0.55 in the Coast Range (https://lemma.forestry.oregonstate.edu/data/structure-maps). Although there is a mismatch in fidelity between our lidar metrics and GNN estimated stand ages, because it is Landsat derived, GNN data have been used with lidar before (e.g., Zald et al. 2014; Bell et al. 2018; Kennedy et al. 2018; Kane et al. 2019). Second, in order to understand the relationship between our forest structure classes and endangered species habitat of conservation values, ranges of values from a lidar-derived habitat suitability index for the Northern Spotted Owl (*Strix occidentalis caurina)* were compared across the six forest structure classes (Hagar et al. 2020).

2.5 Quantifying landscape pattern and effect of ownership

To quantify landscape pattern of forest structure, I chose three landscape metrics, calculated in the R package *landscape metrics* (Hesselbarth et al. 2019): percent area of each structure class, area-weighted mean patch size (mean patch size), and interspersion and juxtaposition index (IJI; structural heterogeneity). I chose these metrics because they represent different aspects of structural pattern that a manager might manage for (abundance, size, and interspersion), particularly in light of size and interspersion as ecological goals in a 2018 synthesis of NWFP ecological goals. These three metrics were calculated on the six forest structure classes within the thirteen ownership types.

I chose to calculate area-weighted mean patch size (Equation 1) instead of arithmetic mean patch size because a weighted mean places more importance on larger patches. This is ecologically relevant because this metric represents, for example, the probability an individual organism would randomly occur in a patch of a given structure class (Turner and Gardner 2015; Harvey et al 2016).

$$AM = \sum_{n=1}^{m}\sum_{j=1}^{n}\left[x_{ij}\left(\frac{a_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n}a_{ij}}\right)\right]$$

Equation 1: Area-weighted mean patch size, where m is number of classes present in the landscape and a_{ij} and x_{ij} are equal to the area of patch ij.

IJI (Equation 2) is a unitless index that measures the distribution in terms of interspersion and juxtaposition of patch types across a landscape (Turner and Gardner 2015). IJI measures patch adjacencies and therefore the intermixing of patch types. I use IJI as a measure of structural heterogeneity across ownership types, where lower percentages are more homogeneous (less complex interspersion) and higher percentages are more heterogeneous (more complex interspersion).

$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right) * \ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln(0.5[m(m-1)])}(100)$$

Equation 2: Interspersion and Juxtaposition Index (IJI), where m is number of classes present in the landscape, e_{ik} is equal to total length of edge between classes i and k, and E is equal to the total length of edge in landscape.

I conducted a hierarchical clustering analysis using percent area of each forest structure class in an ownership to determine simplified groups of ownerships that had similar structural composition. I then used principal component analysis (PCA) and its resulting ordination to visualize the relationship between ownership types, their simplified groups, and forest structure classes.

To test for the relative influence of ownership types, property size, and structure class proportion on mean patch size and structural heterogeneity, I conducted twelve linear regressions, where mean patch size or IJI for each structure class was the response variable (1 model per mean patch size and IJI multiplied by 6 structure classes equals 12 models). I used a simple linear regression formula, $y \sim x + a + b + c$, where y is either mean patch size or IJI. I used the thirteen ownership types as the predictor, categorical variable of interest, a. To control for the effects on the response variable of property size and structure class proportion, I included numeric terms for property size, b, and proportion of ownership, c, in the modeled structure class. All statistical analyses were performed in the R statistical package (R Core Team 2020).

3.0 Results

3.1 Forest structure classes

I identified six classes of forest structure from the classification method (Figure 2) that span a conceptual spectrum from structurally simple to structurally complex. Median values and interquartile ranges for three of the four input lidar metrics-- P95, P25, and rumple-- increased approximately linearly from the structurally simple to structurally complex classes, while canopy cover reached its maximum in the Pre-Harvest structure class (3). Based on the PCA values used in the classification, dominant tree height (P95) and height to live crown (P25) were most correlated with PCA axis 1, which drove 71.65% of the variation in the classification, while rumple and canopy cover were most correlated with PCA axis 2, which drove 17.15% of the variation in the classification.

I assigned names to the forest structure classes based on their structural similarities to *a priori* forest developmental stages. For forest structure classes 1 through 4, names were based on probabilistic stand development stages because these classes exhibit structural development expected in managed plantations (Oliver and Larson 1996). The Initiation and Canopy Closure forest structure classes (1 and 2) grouped closely together in the PCA (Figure 5); the main difference between these two classes is the fourfold increase in canopy cover between them, hence the name Canopy Closure for class 2. The other four classes are all post-canopy closure and all exhibit increasing dominant tree height (P95), structural complexity (rumple), and height to live crown (P25). Using Landsat-derived maps of stand clearing disturbances (Hansen et al. 2013) to examine stand clearing disturbances in the years before and after the lidar data were collected, I determined that harvest typically occurs in the Harvestable class (4), hence the names Harvestable and for class 3, Pre-Harvest. For forest structure Classes 5 and 6, names were based on ranges of structural complexity that arise from structural development post-natural regeneration (Franklin et al. 2002).

GNN stand age estimates also corroborate these names, as they align with known rotation times of this area (Figure 3). Initiation through Harvestable classes (1-4) had an estimated mean age of ≤ 41 years while the Complex and Very Complex classes had an estimated mean age of 104 years. The Complex and Very Complex classes also had the highest ranges of values of the Northern Spotted Owl habitat suitability index from Hagar et al. 2020 (Figure 3).

The Pre-Harvest class was closer to the Initiation and Canopy Closure classes on the PCA ordination while the Harvestable class was closer to the Complex class (Class 5). However, both were fairly isolated from the other classes and each other in the PCA. The Complex and Very Complex classes (Classes 5 and 6) also grouped together in the PCA on the opposite side of the ordination from the other structure classes.

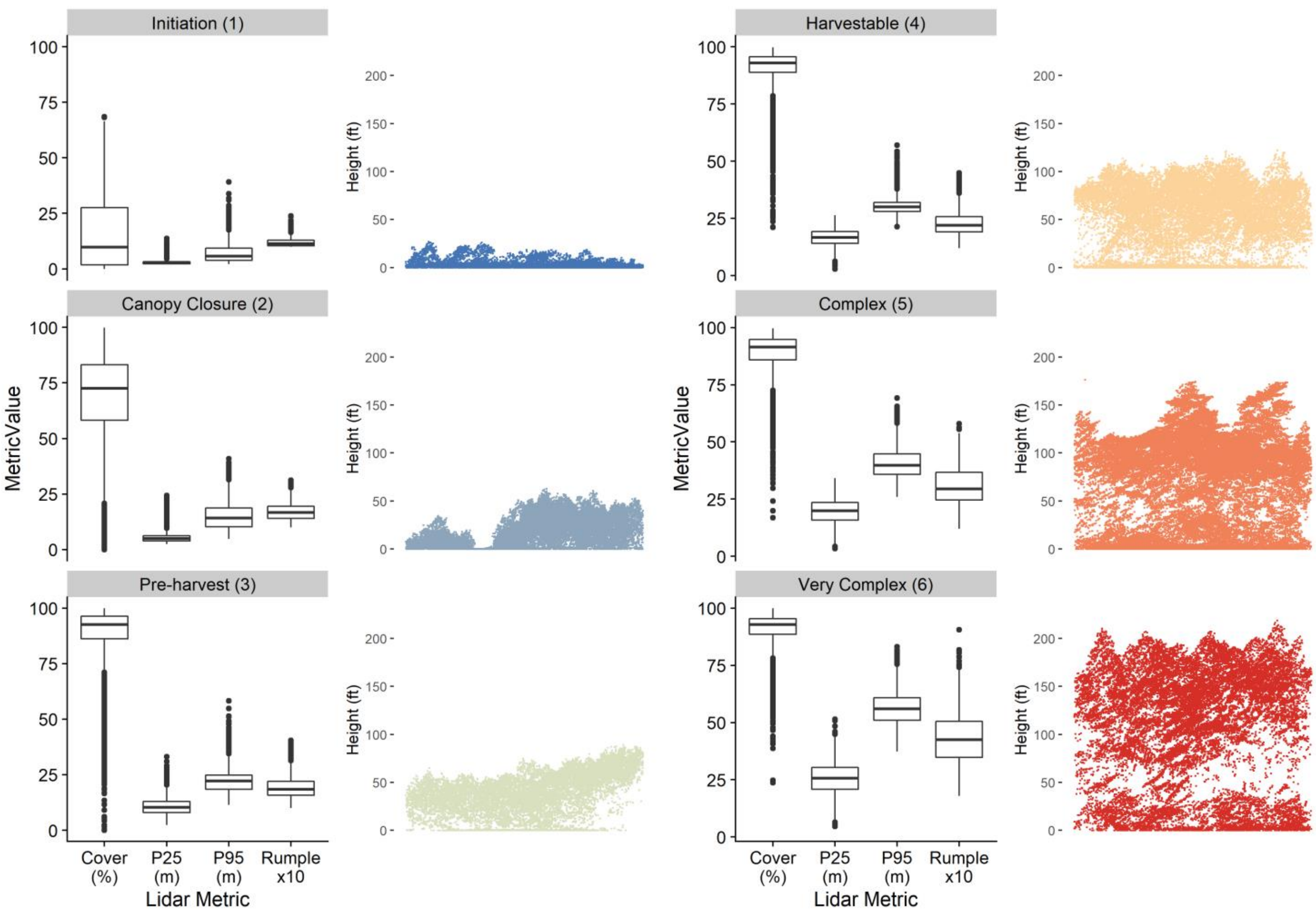

Figure 2: Distribution of lidar metric values within each forest structure class identified in the study and transects of lidar point clouds representative of each forest structure class. These classes lie on a spectrum of structurally simple to structurally complex, evidenced by the linear increase in P95, P25, and rumple from the Initiation to Very Complex classes.

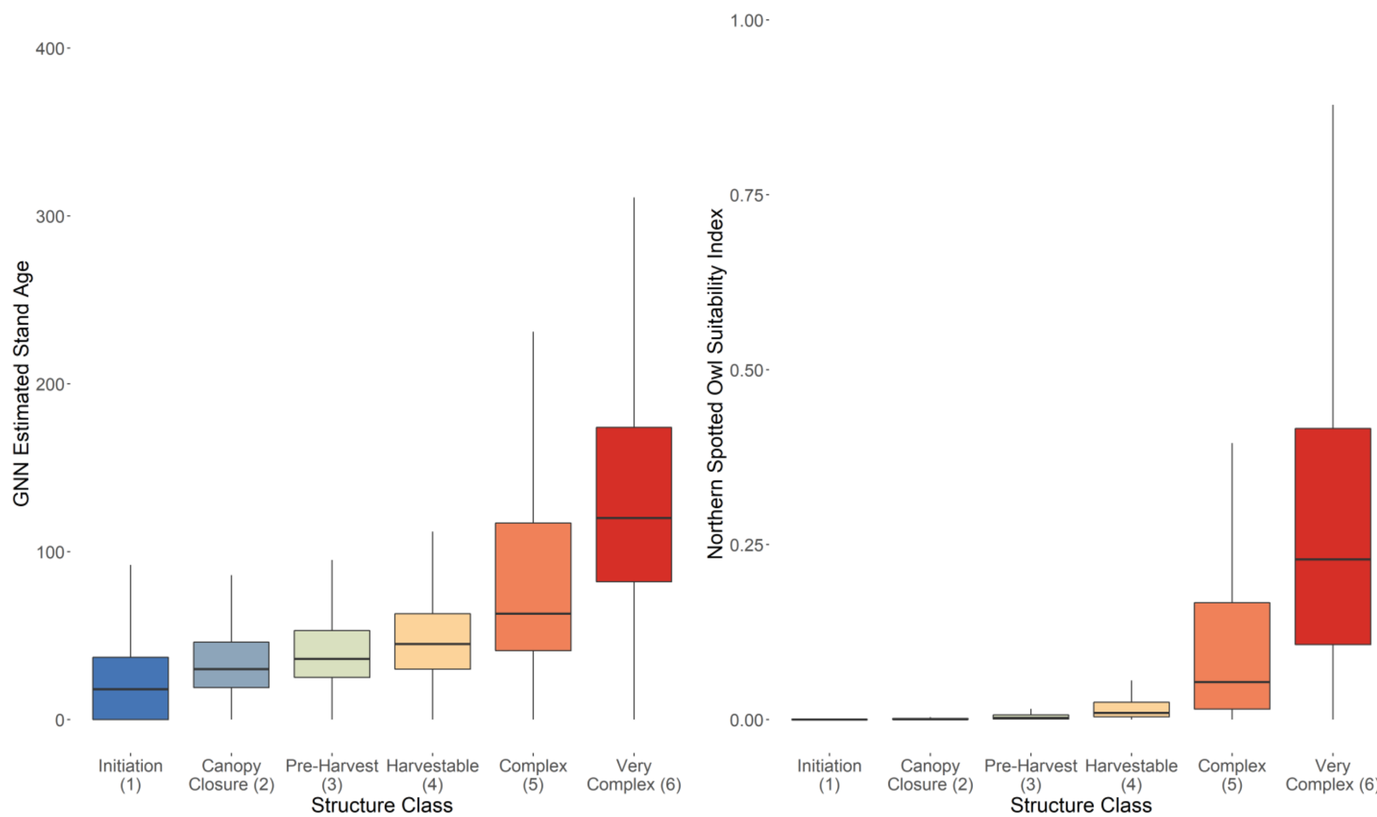

Figure 3: Boxplots of GNN stand age estimates (Left) and Northern Spotted Owl Suitability Index values (Right) across the six forest structure classes (Ohmann and Gregory 2002; Hagar et al. 2020). Stand age estimates generally increase as structural complexity increases from Initiation to Very Complex (Classes 1 through 6) classes. Northern Spotted Owl Suitability Index values are generally below 0.5 but are highest in the Complex and Very Complex (Classes 5 and 6) classes relative to other classes.

3.2 Ownership clustering created four structurally similar groups of ownerships

The hierarchical classification of the 13 ownership types resulted in four groups of ownerships and was based on the percentage of area in each structure class. The private non-industrial group consisted of properties classified as Private, Very Small, Small, and Medium and was distinguished by a larger proportion of area in the Stand Initiation (Class 1) and Canopy Closure (Class 1) structure classes (Figure 4). The private industrial group consisted of properties classified as Family, TIMO, REIT, and Integrated and was distinguished by more area in the Pre-Harvest (Class 3) and Harvestable structure classes (Class 4) (Figure 4). The two private groups were distinguished from all public ownership types by the small proportion of their properties in the Complex and Very Complex (Classes 5 and 6) structure classes.

Among the public ownership types, the mixed objective government group consisted of Bureau of Land Management and Oregon State properties and was distinguished from other public ownership types because it has a higher proportion of Initiation, Canopy Closure, Pre-Harvest, and Harvestable classes (Classes 1 through 4). The NWFP objective government group consisted of the remaining other government ownership types, USFS, O&C and CBWR, and had a higher proportion of Complex and Very Complex classes (5-6) than the mixed objective group (Figure 4). I interpret PC axis 1 as a spectrum of structural complexity which represents the dominant split (91.46% of variance) between ownership types based on the relative amounts Stand Initiation through Harvestable (Classes 1 through 4) and Complex and Very Complex (Classes 5 and 6) structure classes (Figure 5). The second axis (4.08% of variance) separates ownerships based on their differences in the proportion of Stand Initiation through Harvestable structure classes (Classes 1 through 4) (Figure 5).

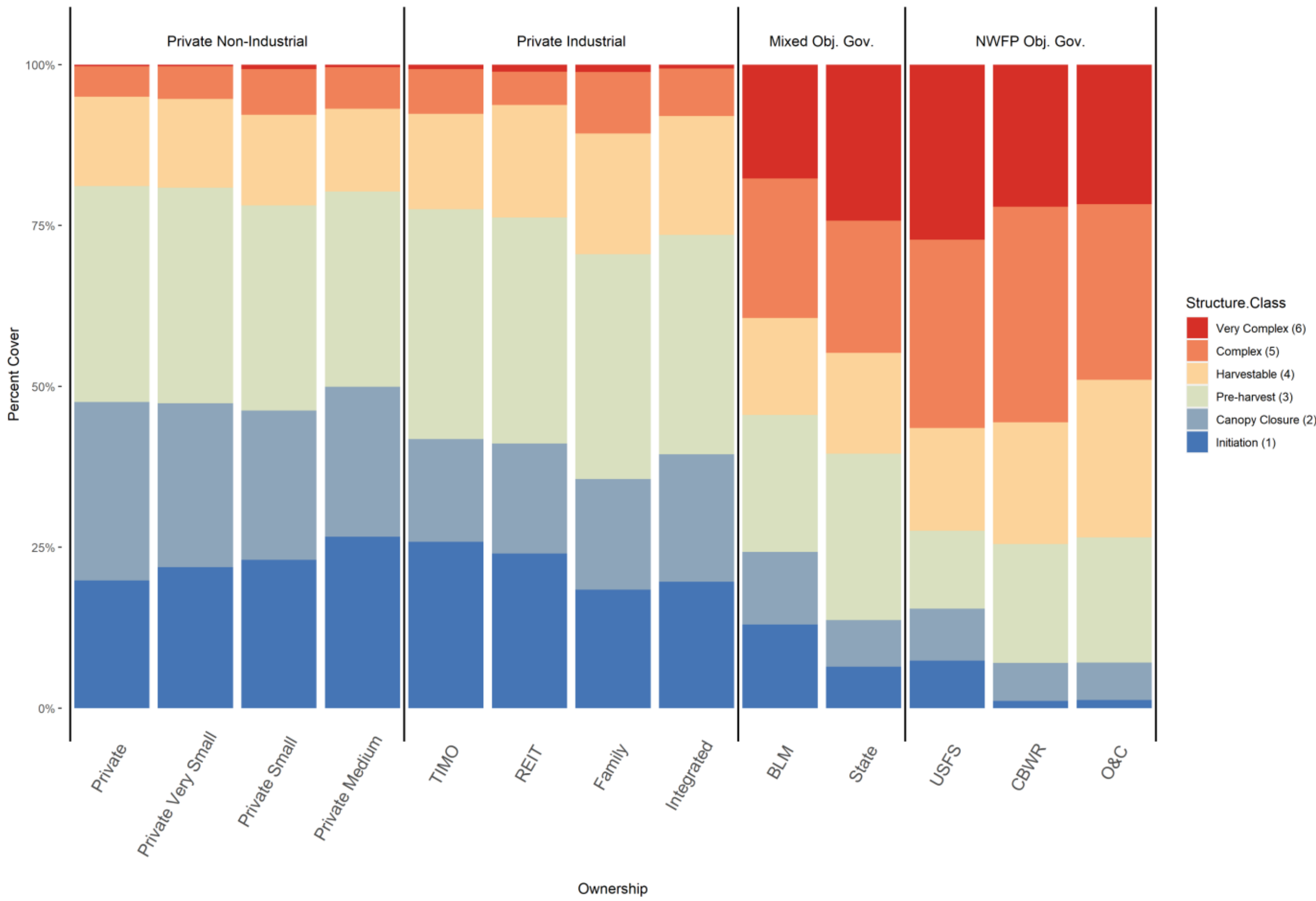

Figure 4: The percentage of area in each structure class per ownership. The thirteen ownership types are grouped according to the results of the hierarchical clustering of ownership types by percentage of area in each structure class.

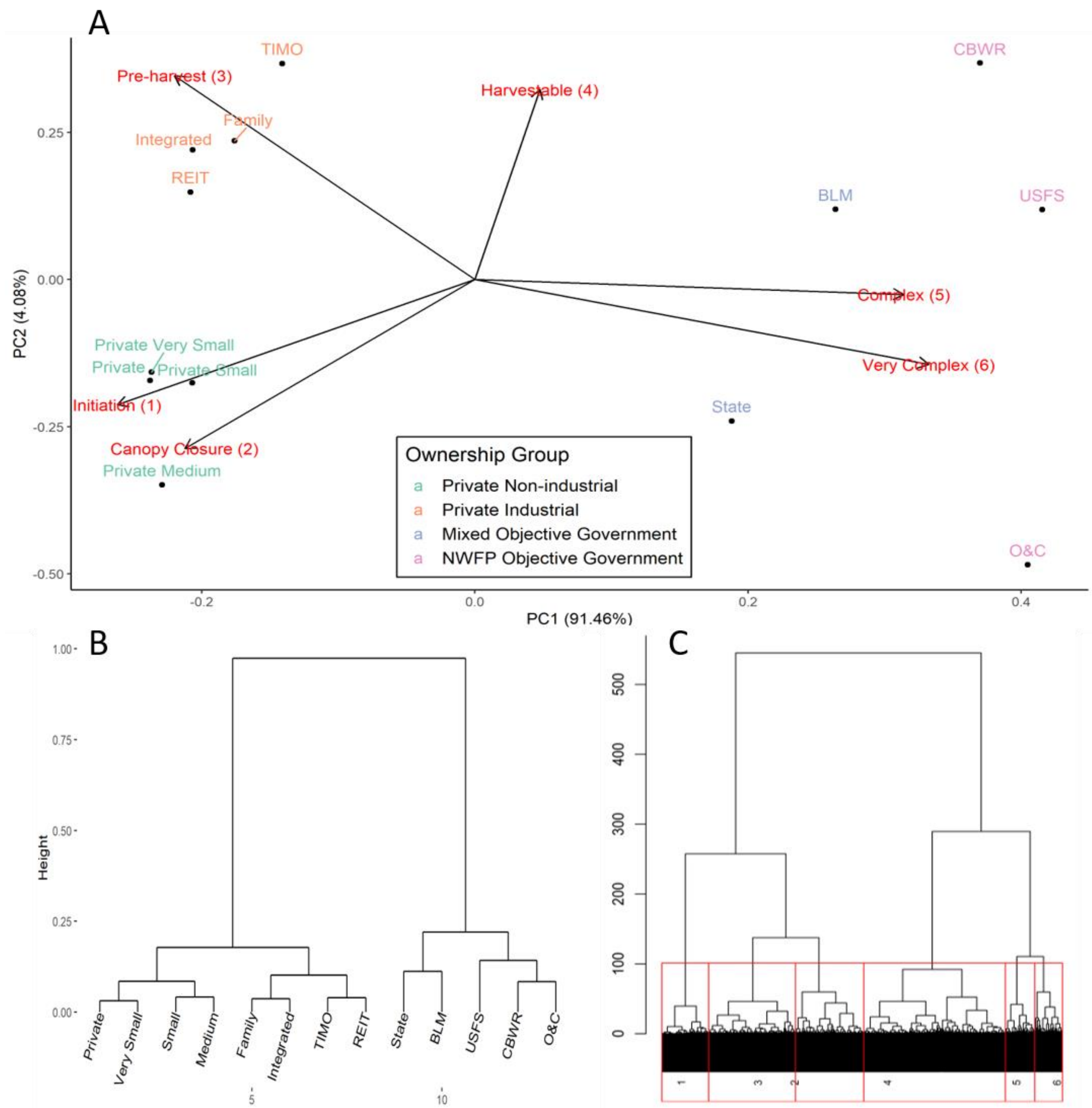

Figure 5: A. Ordination of Principal Component Analysis of forest structure classes. Ownership types are overlaid on the ordination to show their relationships with each of the forest structure classes. Ownership types are colored based on their assigned hierarchical clustering group. B. Dendrogram of ownership types from hierarchical clustering by percent area of structure class. C. Dendrogram of structure classes from hierarchical clustering of lidar metrics (P95, P25, canopy cover, rumple)

3.3 Landscape structure metrics significantly differ among ownerships

Our assessment of the effects of ownership type on mean patch size and structural heterogeneity (Interspersion and Juxtaposition Index (IJI)) showed that ownership types had a significant effect on these two metrics, independent of property size or structure class proportion. I would expect based on landscape ecology theory (Turner and Gardner 2015) that the size of each property and the proportion of that property in each structure class could affect values of mean patch size and IJI. Our modeling tested whether values of mean patch size and IJI were higher or lower when ownership type was considered in association with size and proportion. When I state that values for mean patch size and IJI are higher or lower than expected, I mean higher or lower than expected given the property size. Similarly, a significant effect on mean patch size and structural heterogeneity means that the term in the model (ownership type, property size, or structure class proportion) influenced the response variable with a confidence of $p < 0.05$. P- and r-squared values of the entire models themselves are not relevant to this analysis since I are interested in the relative influence of each predictor variable.

Of the significant models of ownership types for the Initiation (1), Canopy Closure (2), and Pre-Harvest (3) structure classes, the private industrial ownership group had larger than expected mean patch sizes while the NWFP Objective Government ownership group had smaller than expected mean patch sizes (Figure 6). Of the significant models of ownership types for the Complex and Very Complex (Classes 5 and 6), private industrial ownership types had smaller than expected mean patch sizes while the NWFP objective government ownership group had larger than expected mean patch sizes (Figure 6). The mixed objective government ownership group and private non-industrial ownership group did not show a strong relationship with mean patch size (Figure 6).

For structural heterogeneity (IJI) in Canopy Closure and Pre-Harvest structure classes (Classes 2 and 3), only private non-industrial ownerships were significant ownership terms (Figure 7). In the Harvestable, Complex and Very Complex structure classes (Classes 4 through 6), patch-scale structural heterogeneity was significantly influenced by private industrial and both government ownership simplified groups. Structural heterogeneity was greater than expected (given the proportion of the ownership within the modeled structure class) for all the aforementioned ownerships. Family ownership had a significant effect on patch-scale structural heterogeneity and was higher than expected in all structure classes.

For models of mean patch size, property size was statistically significant in all six structure classes while structure class proportion was significant in five structure classes. Property size had a strong linear relationship with mean patch size by structure class (Figures 8) while structure class proportion did not. For models of structural heterogeneity, structure class proportion was statistically significant in all six structure classes while property size was significant only in the Initiation class (1). Neither property size nor structure class proportion had strong linear relationships with structural heterogeneity.

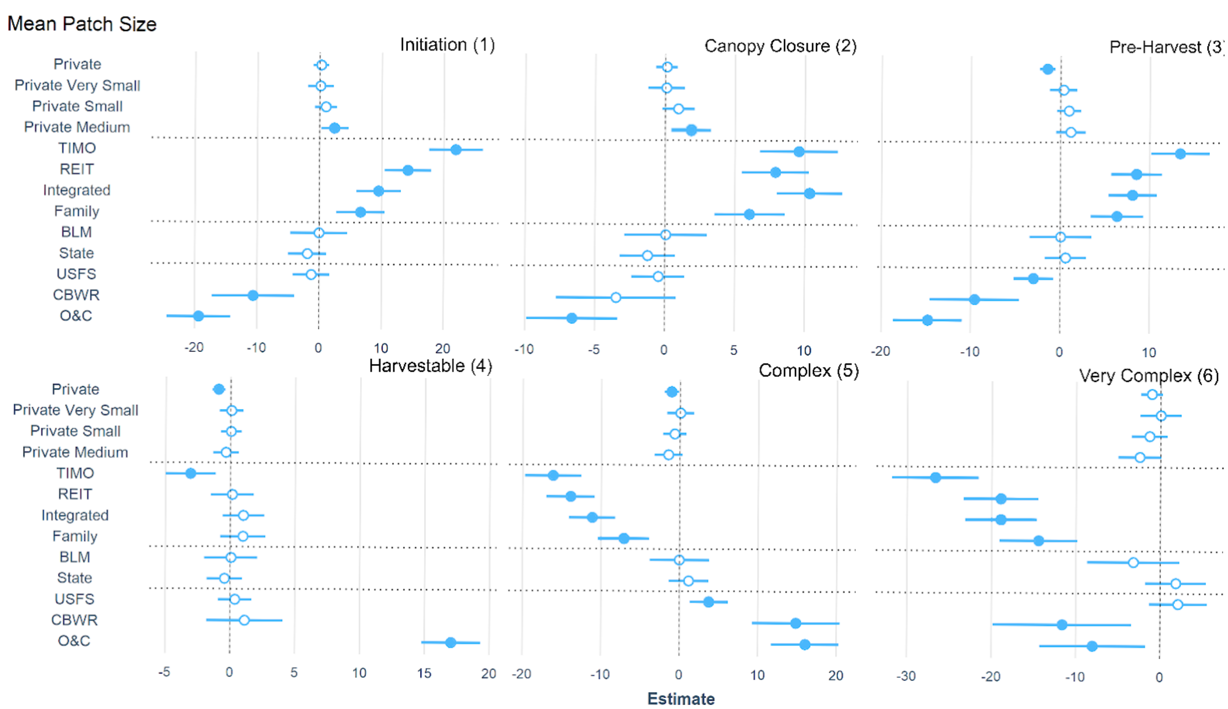

Figure 6: Values and influence (coefficient term) of the ownership type variable to model mean patch size for each structure class given each property size and the proportion of that structure class within each

property. Filled circles indicate mean significance for the ownership terms at $p < 0.05$; open circles indicate mean significance for the ownership terms at $p > 0.05$. Lines show range of values for the coefficient term. More negative coefficient terms indicate that mean patch size was smaller given property size and structure class proportion while more positive coefficient terms indicate that mean patch size was larger given property size and structure class proportion.

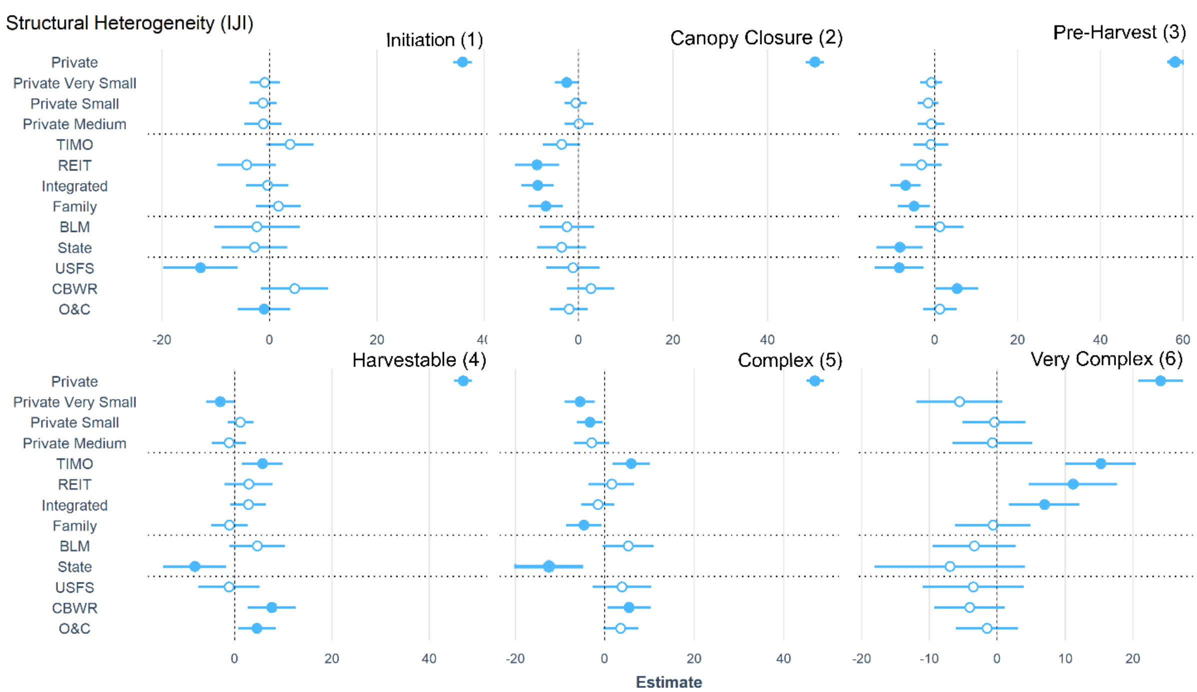

Figure 7: Values and influence (coefficient term) of the ownership type variable to model structural heterogeneity for each structure class given each property size and the proportion of that structure class within each property. Filled circles indicate mean significance for the ownership terms at $p < 0.05$; open circles indicate mean significance for the ownership terms at $p > 0.05$. Lines show range of values for the coefficient term. More negative coefficient terms indicate that structural heterogeneity was smaller given property size and structure class proportion while more positive coefficient terms indicate that structural heterogeneity was larger given property size and structure class proportion.

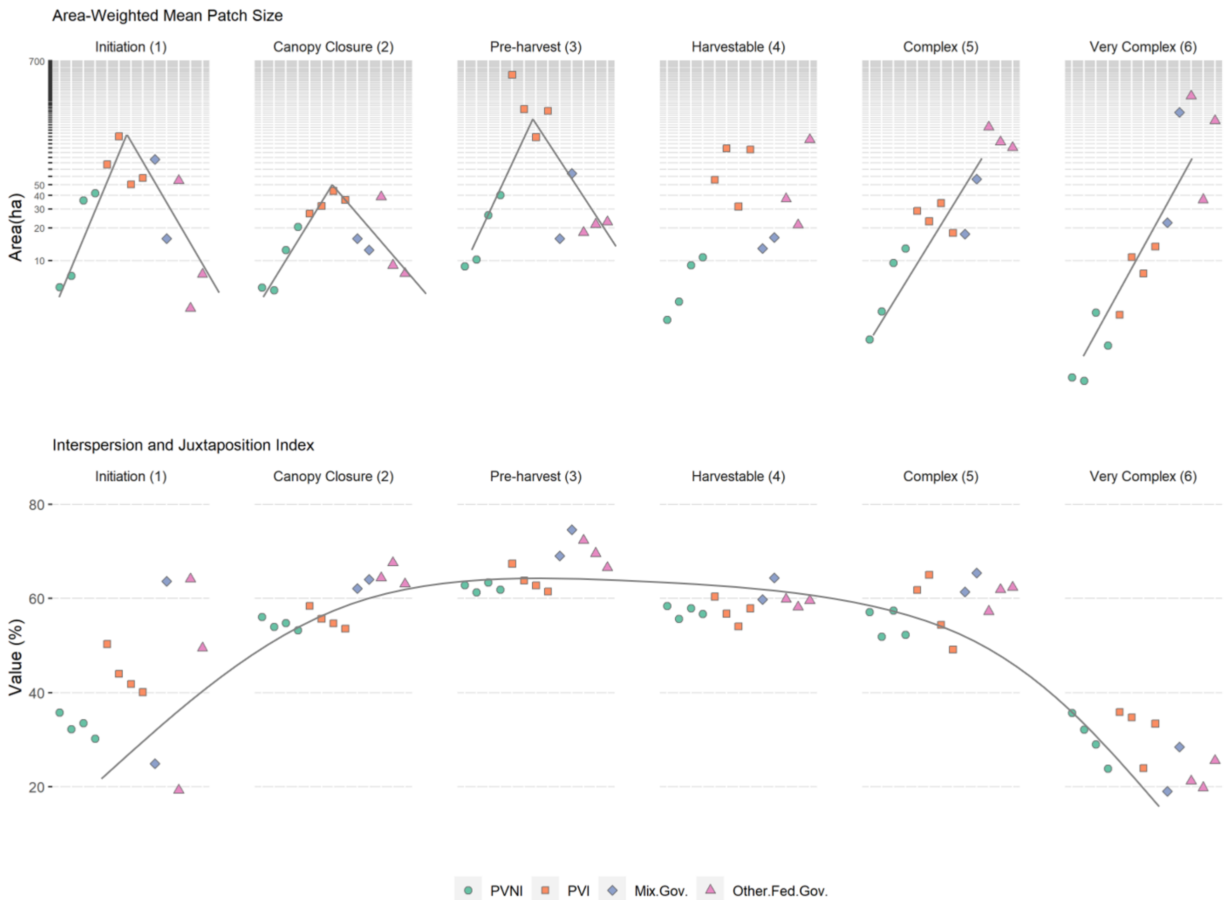

Figure 8: values of mean patch size and structural heterogeneity for the 13 ownership types. Each point represents the value of one of the thirteen ownership types, but for ease of visualization, symbols and colors are used to denote the ownership group to which the ownership belongs. Mean patch size is on a log scale but to aid in interpretation the y-axis is not transformed. Lines are drawn on top of data to demonstrate patterns.

4. Discussion

Previously, assessments of forest structure across landscapes and ownerships have not had or otherwise not made use of spatially explicit datasets of management practices and landowner objectives in addition to high-fidelity forest structure data across a large spatial extent. I expand upon previous work by using such datasets. Our results produced two key insights: first, our study reveals the effects of different land ownerships, their management practices, and their objectives on forest structure pattern. Through three different metrics of forest structure landscape pattern-- percent area, mean patch size, and patch-scale structural heterogeneity-- our results show that landowner objective affects the size and regularity of forest structure pattern, usually independent of property size and forest structure class proportion. Second, I found that ownership has different effects on forest structure pattern at multiple scales, due to different management practices within properties and the additive effect of differing landowners and practices at a sub-regional scale.

4.1 Two distinct assemblages of forest structure classes

I identified six different forest structure classes in the study area which I interpreted as two assemblages: production-style forests and structurally complex forests. The production-style forests consist of the first four structure classes, which are predominantly found on private lands and likely represent a sequence of stand development from planting after harvest (Initiation, class 1) to stands commercially viable for harvest (Harvestable, Class 4). The structurally complex forests consist of the final two structure classes (Complex and Very Complex, Classes 5 and 6) and have structures typically found in older stands (Kane et al. 2010 a, b). I view these as two distinct assemblages because their proportion of area is based on ownership and physical location (Figure 4). These two assemblages differ particularly in their dominant tree heights (P95 of lidar return heights) and the structural complexity of their canopies (rumple). Except for the Initiation and Canopy Closure structure classes (Classes 1 and 2), the structure classes have similar ranges of values for canopy cover.

I found strong statistical association between the production-style forests and private ownership groups and between the structurally complex classes and government ownership groups. Based on the proportion of structure classes in different ownerships, public and private ownerships fall into two distinct groups (Figure 5). Within each public and private sub-grouping came a further split, into the four simplified ownership groups. The simplified ownership groups separate by their relative proportions of forest structure classes predominately representing production forests (Classes 1 through 4) and complex forests (Classes 5 and 6), respectively (PCA axis 1), which represents 94% of the variation in the data (Figure 5). Similarly, the production-style and structurally complex forest structure classes separated along this axis. These results are supported by past work that found similar differences in forest patterns between public and private ownership types (see Huntsinger et al. 1997).

I found that estimated forest ages from the GNN stand age estimates are consistent with our interpretation of the structure classes I identified. Our structure classes are not inherently associated with stand age, as forest structures can be only loosely associated with age (e.g. Larson and Franklin 2006; Kane et al. 2010b; Kane et al. 2011; Donato et al. 2012). However, in our study area, estimated stand age did increase with our ordinal ranking of structure classes. This helped to place production forests in the study area in our proposed Initiation through Harvestable classes (Classes 1 through 4), all within an estimated mean age of $\leq$ 41 years.

The Very Complex class only had an estimated mean age of 134 years. If accurate, this could imply that forests in our study area can develop high structural complexity in a relatively short period of time. While I do not have field stand age data in the Coast Range, the high structural complexity values in 134 years are comparable to structural complexity values in 250-300 year old forests in the Washington Cascades where field stand age data was available (Kane et al. 2010b). That study also showed that stands greater than 80 years old can have considerable structural complexity and have greater structural complexity than stands 200 to 300 years old. These stands may have been initiated after the high-severity fires of 1902 or the earlier 1868 fire which, in combination with high productivity found in this region, has been shown to accelerate structural complexity (Larson et al. 2008). If the younger mean age for these more complex stands in our study area are confirmed by future research, then this suggests that a strategy to leave stands on private lands to develop complexity naturally could add to habitat connectivity in a matter of decades to a century.

4.2 Land ownership objectives manifested in landscape pattern of forest structure

Land ownership objectives in our study area can be condensed into three broad categories: objectives for federal lands as outlined under the Northwest Forest Plan, maximizing net present value of timber stock for private industrial lands, and a combination of timber harvest and land investment for private non-industrial lands (Table 1). I expected the proportion of complex forest structure (Classes 5 and 6), mean patch size, and intermixing to increase from low values on private industrial lands, medium values on private non-industrial lands, and high values on public lands. I expected these results because these ownerships are also on a spectrum of objectives from intense timber production to ecological forest management. Our results support these expectations for private industrial and public lands, but not for private non-industrial lands.

On both simplified groups of government lands (i.e. Mixed Objective Government ownership types and NWFP Objective Government ownership types), large blocks of potentially connected habitat have been created consisting of large patches of Complex and Very Complex structure classes, but these blocks are not well intermixed with other forest structures. The NWFP identifies contiguous high quality habitat (best represented by our Complex and Very Complex structure classes, 5 and 6) as a goal, but also recognizes landscape diversity as a goal (PNW-GTR-966 Vol. 1 2018). I found that the Very Complex structure class (Class 6) had the least intermixing, and an examination of adjacency tables (data not shown) shows that this class was most commonly adjacent to the Complex structure class (Class 5). Except for the initiation structure class (Class 1) which had lower intermixing, the other classes (Classes 2 through 5) are moderately intermixed, creating moderate (IJI values in the range of 60 to 80) landscape heterogeneity.

I found that these intermixing patterns held across ownership groups, with different implications by ownership type based on the types of structures most commonly found on that type. For government ownership types, the effect of these intermixing patterns are connected larger blocks of structurally more complex forest (the adjacent Complex and Very Complex structure classes, Classes 5 and 6) and larger blocks of intermixed less structurally complex forest (Classes 1 through 4, that together constitute half or more of these properties). Privately owned properties also have high intermixing of structure classes that creates landscape heterogeneity, but with structurally simple forests of lower habitat quality.

The effects of management objectives for private lands were represented by their high proportion of and higher mean patch sizes of structurally simple forests. Both private industrial and non-industrial lands had a higher proportion of structurally simple (production-style) forests (Classes 1 and 4) than structurally complex forests (Classes 5 and 6). Private industrial ownership types, though not private non-industrial, had higher mean patch sizes in structurally simple forests, because of their owner’s focus on maximizing timber production. Because private land objectives are primarily timber-oriented, it is possible that structurally complex forest (Classes 5 and 6) only occurs where there are timber harvest restrictions (such as stream buffers (Cloughesy and Woodward 2018)) to improve ecological health or where there are barriers to harvest such as excessively steep slopes

I expected private non-industrial ownership types to have proportions of structure classes in between private industrial and government ownership types, because private non-industrial owners have a wider range of land objectives. Mean patch sizes for private non-industrial ownership types did fall between private industrial and government ownership types; however, the non-industrial private ownership types had a similar proportion of structure classes as private industrial ownership types. The structural similarity between private industrial and non-industrial ownership types could indicate that timber harvest is more important to non-industrial owners than previously thought or that use of ecological forest management techniques is limited.

4.3 Land ownership creates different scales of forest structure pattern through differing objectives and management practices

Examining homogeneity and heterogeneity of forest structure across landscapes is important for examining broad scale effects of varying management practices and the effects of regional conservation planning. Differing patterns of homogeneity and heterogeneity at multiple scales have been found in the boreal forests of Canada (Boucher et al. 2015) and in the American Upper Midwest (Mladenoff et al. 1993; Schulte et al. 2007) due to variability in harvest practices. If our structure classes are linked to stand age and therefore rotation length, as suggested by GNN stand age estimates, then our study area may also display patterns of homogeneity and heterogeneity at different scales due to harvest practices and historical land practices. In our study I examined forest structure at the scales of individual patches, patches within individual properties analyzed across all properties of the same ownership type, and patterns of forest structure across ownership types.

As a result of clearcutting and resulting differently aged stands, private owners primarily have a range of structures from Initiation (Class 1) to Harvestable (Class 4) that are moderately intermixed. Since these ownership types are aggregated (Figure 1), a homogeneity of similar repeating patterns of forest structure across a large proportion of the landscape is created. Due to a lack of active spatial planning of harvests, across and even within ownerships, these fine scale management choices result in a sub-regional mosaic of structurally similar forest patches that differ only in time since harvest (i.e. different age cohorts of even aged stands). There is little structurally complex forest in lower elevation private lands and a visual inspection of their patterns suggest they often may be riparian buffers excluded from harvests.

Forest structure classes are spatially aggregated between ownership groups due to the lasting effects of historical land practices. Forest structure in this landscape is bifurcated by private versus public ownership that also divides by elevation. This bifurcation is the result of the federal government ceding productive lands to private interests and retaining the leftover land that was more difficult to utilize (because of its higher elevation and topographic complexity) in the early 1900s (Maestas et al. 2001).

4.4 Conservation Implications

Because forest structure is tightly linked to conservation values, such as carbon storage and habitat emphasized in the Northwest Forest Plan, the results of this study can be used to suggest considerations in conservation strategies for policymakers and managers. Here, I highlight multiple cases where this study could help monitor and implement conservation strategies, one through policy compliance and one through voluntary participation.

This analysis shows that federal lands governed under the NWFP are successfully creating and/or conserving large patches of contiguous structurally complex forest. As discussed earlier, these patches could even be structurally complex forest that developed relatively quickly (Larson et al. 2008). Regardless of their age though, these forests are likely to continue to develop greater structural complexity in the years to come. These results support trends found approximately ten years after the implementation of the NWFP, which stated that the rate of old growth decline had slowed and development of structurally more complex forests had increased (Mouer et al. 2005). However, structural complexity is only one of multiple components of old growth and late successional forest. Other components that characterize old-growth forest, for instance snags with natural cavities and tree crowns with broken tops (Spies and Franklin 1991), are not readily measurable by lidar, so I are unable to make statements about the presence of these other key structural attributes in our study area. Based on observations of structural complexity for the wider region (Franklin et al. 2002), these other characteristics often develop at forest ages greater than those estimated for our study area

Our analysis of Northern Spotted Owl habitat suitability and structure classes showed that habitat suitability is associated with our structurally complex classes, but even our most structurally complex classes do not have a high mean habitat suitability index (~0.5) (Hagar et al. 2020). This is likely because the habitat suitability model emphasizes slightly different elements of forest structure than our classification. However, the lower than expected habitat suitability values illustrate that when managing for the northern spotted owl, I should not simply rely on structural complexity and old growth classification as surrogates for suitable habitat.

At their simplest, conservation easements are agreements between a landowner and a land trust or government agency where the landowner retains ownership of the land but transfers developmental rights over the land to the grantee, typically for tax relief (Kamal et al. 2015). In our study area, I found that there was a substantial geographic bifurcation of public and private lands, with the vast majority of quality habitat on government land. This bifurcation increases the need for focus on private lands interspersed with government lands, given the lack of feasibility in accomplishing conservation goals only on public land (Woodley et al. 2012). One part of our study area this could be implemented in is the checkerboard pattern of public and private lands found on the eastern boundary of the study area. Targeting private lands of higher habitat value that widen the connecting corners of private and public lands in the checkerboard would increase landscape connectivity. Not only is landscape connectivity recognized in ecological literature as a basis for biological diversity because it increases species movement (Shafer 2015) and is important to consider as species ranges may shift due to climate change (Heller and Zavaleta 2009).

Finally, the Oregon Forest Practices Act is a series of state-level policies implemented by the Oregon Board of Forestry that manages forest practices on private land (Cloughesy and Woodward 2018). Two harvest limitations under this act are a harvest limit of approximately 49 hectares (120 acres) and of “adjacent areas in the same ownership until new trees on the original harvest site are at least four feet tall or are four years-old” (Cloughesy and Woodward 2018). These rules are designed to limit landscape level aggregation of harvested areas. However, our results show that mean patch size created by private industrial lands in the Pre-Harvest structure class (3) had a substantially larger mean patch size~~,~~ (138 hectares)~~,~~ than the desired 49-hectare patch size. This illustrates that current harvest patterns still result in aggregation of similar structures larger than desired under the Practices Act, likely because only waiting four years until an adjacent harvest takes place is not long enough for patches to develop into different structure or class cohorts. If policymakers and managers wish to achieve a greater diversity of landscape patterns following harvest, they may wish to consider limiting harvest size or increase the number of years waited before a neighboring patch can be harvested. Considering these changes is especially important as more than 75% of future timber harvest in our study area is expected to come from private industrial lands for whom the Oregon Forest Practice Act is designed to manage (Spies et al. 2007).

5.0 Conclusion

I found that land ownership, objectives, and management create multiple assemblages of forest structure and that these assemblages vary in their homogeneity at different scales. Private lands create their own homogenous forest structure a fine scale and create heterogeneity at a sub-regional scale, but only through the difference in age cohorts of the homogenous fine scale forest structure. Public lands create their own, more complex forest structure compared to private lands, but the patterns of this structure vary across specific public ownership types. Our results suggest the opportunity for spatial planning of harvests across private ownership boundaries and emphasize the need for high fidelity data to examine complex multi-ownership landscapes. Our work in the Coast Range provides an update to previous research in western Oregon that focused on the relationship between land ownership and forest conditions. While our work has direct implications for pacific northwest forests, this work also provides a framework of analysis across a range of ownership categories and ecosystems.

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6.0 Citations

Adhikari, B., F. Williams, and J. C. Lovett. 2007. Local benefits from community forests in the middle hills of Nepal. Forest Policy and Economics 9:464–478.

Allen, C. D., A. K. Macalady, H. Chenchouni, D. Bachelet, N. McDowell, M. Vennetier, T. Kitzberger, A. Rigling, D. D. Breshears, E. H. (Ted) Hogg, P. Gonzalez, R. Fensham, Z. Zhang, J. Castro, N. Demidova, J.-H. Lim, G. Allard, S. W. Running, A. Semerci, and N. Cobb. 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. Forest Ecology and Management 259:660–684.

Backer, D. M., S. E. Jensen, and G. R. McPherson. 2004. Impacts of fire-suppression activities on natural communities. Conservation Biology 18:937–946.

Bell, D. M., M. J. Gregory, V. Kane, J. Kane, R. E. Kennedy, H. M. Roberts, and Z. Yang. 2018. Multiscale divergence between Landsat- and lidar-based biomass mapping is related to regional variation in canopy cover and composition. Carbon Balance and Management 13.

Bengtsson, J., S. G. Nilsson, A. Franc, and P. Menozzi. 2000. Biodiversity, disturbances, ecosystem function and management of European forests. Forest Ecology and Management 132:39–50.

Boisvenue, C., and S. W. Running. 2006. Impacts of climate change on natural forest productivity - Evidence since the middle of the 20th century. Global Change Biology 12:862–882.

Boucher, D., L. De Grandpré, D. Kneeshaw, B. St-Onge, J.-C. Ruel, K. Waldron, and J.-M. Lussier. 2015. Effects of 80 years of forest management on landscape structure and pattern in the eastern Canadian boreal forest. Landscape Ecology 30:1913–1929.

Breiman, L. 2001. Random forests. Machine Learning 45:5–32.

Brotons, L., N. Aquilué, M. de Cáceres, M. J. Fortin, and A. Fall. 2013. How Fire History, Fire Suppression Practices and Climate Change Affect Wildfire Regimes in Mediterranean Landscapes. PLoS ONE 8.

Caldwell, P. V., C. F. Miniat, K. J. Elliott, W. T. Swank, S. T. Brantley, and S. H. Laseter. 2016. Declining water yield from forested mountain watersheds in response to climate change and forest mesophication. Global change biology 22:2997–3012.

Chen, X., and R. Fraser. 2009. Quantifying impacts of land ownership on regional forest NDVI dynamics: A case study at bankhead national forest in Alabama, USA. Photogrammetric Engineering and Remote Sensing 75:997–1003.

Cloughesy, M., and J. Woodward. 2018. Oregon Forest Practice Act Rules Manual. Oregon Forest Resources Institute, Portland, Oregon.

Cohen, W. B., T. A. Spies, R. J. Alig, D. R. Oetter, T. K. Maiersperger, and M. Fiorella. 2002. Characterizing 23 years (1972-95) of stand replacement disturbance in western Oregon forests with landsat imagery. Ecosystems 5:122–137.

Coops, N. C., P. Tompaski, W. Nijland, G. J. M. Rickbeil, S. E. Nielsen, C. W. Bater, and J. J. Stadt. 2016. A forest structure habitat index based on airborne laser scanning data. Ecological Indicators 67:346–357.

Crow, T. R., G. E. Host, and D. J. Mladenoff. 1999. Ownership and ecosystem as sources of spatial heterogeneity in a forested landscape, Wisconsin, USA

Cubbage, F., P. Mac Donagh, J. Sawinski, R. Rubilar, P. Donoso, A. Ferreira, V. Hoeflich, V. M. Olmos, G. Ferreira, G. Balmelli, J. Siry, M. N. Báez, and J. Alvarez. 2007. Timber investment returns for selected plantations and native forests in South America and the southern United States. New Forests 33:237–255.

Cutler, D. R., T. C. Edwards, K. H. Beard, A. Cutler, K. T. Hess, J. Gibson, and J. J. Lawler. 2007. Random Forests for Classification in Ecology. Ecology 88:2783–2792.

Decker, D. 2011. Elliot State Forest Management Plan. Oregon State Department of Forestry. http://www.orww.org/Elliott_Forest/References/Agency/ODF/Decker_et_al_20111100.pdf

Dickinson, Y., E. K. Zenner, and D. Miller. 2014. Examining the effect of diverse management strategies on landscape scale patterns of forest structure in Pennsylvania using novel remote sensing techniques. Canadian Journal of Forest Research 44:301–312.

Donato, D. C., J. L. Campbell, and J. F. Franklin. 2012. Multiple successional pathways and precocity in forest development: can some forests be born complex? Journal of Vegetation Science 23:576–584.

Easterday, K., P. McIntyre, and M. Kelly. 2018. Land ownership and 20th century changes to forest structure in California. Forest Ecology and Management 422:137–146.

Franklin, J. F., T. A. Spies, R. Van Pelt, A. B. Carey, D. A. Thornburgh, D. R. Berg, D. B. Lindenmayer, M. E. Harmon, W. S. Keeton, D. C. Shaw, K. Bible, and J. Chen. 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. Forest Ecology and Management 155:399–423.

Franklin, J. F., and C. T. Dyrness. 1988. Natural vegetation of Oregon and Washington. 452.

Franklin, J. F., and K. Norman Johnson. 2014. Lessons in policy implementation from experiences with the Northwest Forest Plan, USA. Biodiversity and Conservation 23:3607–3613.

Götmark, F. 2013. Habitat management alternatives for conservation forests in the temperate zone: Review, synthesis, and implications. Forest Ecology and Management 306:292–307.

Guo, X., N. C. Coops, P. Tompalski, S. E. Nielsen, C. W. Bater, and J. John Stadt. 2017. Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. Ecological Informatics 38:50–61.

Hagar, J. C., A. Yost, and P. K. Haggerty. 2020. Incorporating LiDAR metrics into a structure-based habitat model for a canopy-dwelling species. Remote Sensing of Environment 236:111499.

Hansen, M. C., P. V Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342:850 LP – 853.

Harvey, B. J., D. C. Donato, and M. G. Turner. 2016. Drivers and trends in landscape patterns of stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). Landscape Ecology 31:2367–2383.

Heller, N. E., and E. S. Zavaleta. 2009. Biodiversity management in the face of climate change: A review of 22 years of recommendations. Biological Conservation 142:14–32.

Hesselbarth, M.H.K., Sciaini, M., With, K.A., Wiegand, K., and J. Nowosad. 2019. landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography 42:1648-1657 (ver. 1.4.2)

Hightower, J. N., A. C. Butterfield, and J. F. Weishampel. 2014. Quantifying ancient maya land use legacy effects on contemporary rainforest canopy structure. Remote Sensing 6:10716–10732.

Hudiburg, T., B. Law, D. P. Turner, J. Campbell, D. Donato, and M. Duane. 2009. Carbon dynamics of Oregon and Northern California forests and potential land-based carbon storage. Ecological Applications 19:163–180.

Huntsinger, L., L. Buttolph, and P. Hopkinson. 1997. Ownership and management changes on California hardwood rangelands: 1985 to 1992. Journal of Range Management 50:423–430.

Johnson, R., R. Alig, J. Kline, R. Moulton, and M. Rickenbach. 1999. Management of Non -Industrial Private Forest Lands: Survey Results From Western Oregon and Washington Owners. Forest Research Laboratory, Oregon State University, Corvallis: Research Contribution 28, p. 43.

Kamal, S., M. Grodzińska-Jurczak, and G. Brown. 2015. Conservation on private land: a review of global strategies with a proposed classification system. Journal of Environmental Planning and Management 58:576–597.

Kane, V. R., R. J. McGaughey, J. D. Bakker, R. F. Gersonde, J. A. Lutz, and J. F. Franklin. 2010a. Comparisons between field- and LiDAR-based measures of stand structural complexity. Canadian Journal of Forest Research 40:761–773.

Kane, V. R., J. D. Bakker, R. J. McGaughey, J. A. Lutz, R. F. Gersonde, and J. F. Franklin. 2010b. Examining conifer canopy structural complexity across forest ages and elevations with LiDAR data. Canadian Journal of Forest Research 40:774–787.

Kane, V. R., R. F. Gersonde, J. A. Lutz, R. J. McGaughey, J. D. Bakker, and J. F. Franklin. 2011. Patch dynamics and the development of structural and spatial heterogeneity in Pacific Northwest forests. Canadian Journal of Forest Research 41:2276–2291.

Kane, V. R., J. A. Lutz, S. L. Roberts, D. F. Smith, R. J. McGaughey, N. A. Povak, and M. L. Brooks. 2013. Landscape-scale effects of fire severity on mixed-conifer and red fir forest structure in Yosemite National Park. Forest Ecology and Management 287:17–31.

Keenan, R. J., and J. P. Kimmins. 1993. The ecological effects of clear-cutting. Environ.Rev. 1:121–144.

Kendra, A., and R. B. Hull. 2005. Motivations and behaviors of new forest owners in Virginia. Forest Science 51:142–154.

Kennedy, R. S. H., T. A. Spies, and M. J. Gregory. 2008. Relationships of dead wood patterns with biophysical characteristics and ownership according to scale in Coastal Oregon, USA. Landscape Ecology 23:55–68.

Kennedy, R. E., Z. Yang, W. B. Cohen, E. Pfaff, J. Braaten, and P. Nelson. 2012. Spatial and temporal patterns of forest disturbance and regrowth within the area of the Northwest Forest Plan. Remote Sensing of Environment 122:117–133.

Kennedy, R. E., J. Ohmann, M. Gregory, H. Roberts, Z. Yang, D. M. Bell, V. Kane, M. J. Hughes, W. B. Cohen, S. Powell, N. Neeti, T. Larrue, S. Hooper, J. Kane, D. L. Miller, J. Perkins, J. Braaten, and R. Seidl. 2018. An empirical, integrated forest biomass monitoring system. Environmental Research Letters 13.

Kulakowski, D., P. Bebi, and C. Rixen. 2011. The interacting effects of land use change, climate change and suppression of natural disturbances on landscape forest structure in the Swiss Alps. Oikos 120:216–225.

Larson, A. J., and J. F. Franklin. 2005. Patterns of conifer tree regeneration following an autumn wildfire event in the western Oregon Cascade Range, USA. Forest Ecology and Management 218:25–36.

Larson, A. J., J. A. Lutz, R. F. Gersonde, J. F. Franklin, and F. F. Hietpas. 2008. Potential site productivity influences the rate of forest structural development. Ecological Applications 18:899–910.

Lindhjem, H., and Y. Mitani. 2012. Forest owners' willingness to accept compensation for voluntary conservation: A contingent valuation approach. Journal of Forest Economics 18:290–302.

Listopad, C. M. C. S., R. E. Masters, J. Drake, J. Weishampel, and C. Branquinho. 2015. Structural diversity indices based on airborne LiDAR as ecological indicators for managing highly dynamic landscapes. Ecological Indicators 57:268–279.

Maestas, J. D., R. L. Knight, and W. C. Gilgert. 2001. Biodiversity and Land-Use Change in the American Mountain West. Geographical Review 91:509–524.

McAlpine, C. A., T. A. Spies, P. Norman, and A. Peterson. 2007. Conserving forest biodiversity across multiple land ownerships: Lessons from the Northwest Forest Plan and the Southeast Queensland regional forests agreement (Australia). Biological Conservation 134:580–592.

McComb, B. C., T. A. Spies, and K. A. Olsen. 2007. Sustaining biodiversity in the Oregon Coast Range: Potential effects of forest policies in a multi-ownership province. Ecology and Society 12.

McCune, B., and J. B. Grace. 2002. Analysis of Ecological Communities. MjM Software Design, Oregon, USA.

McElhinny, C., P. Gibbons, C. Brack, and J. Bauhus. 2005. Forest and woodland stand structural complexity: Its definition and measurement. Forest Ecology and Management 218:1–24.

Mladenoff, D. J., M. A. White, J. Pastor, and T. R. Crow. 1993. Comparing spatial pattern in unaltered old-growth and disturbed forest landscapes. Ecological Indicators 3:294–306.

Moeur, M., Spies, T. A., Hemstrom, M., Martin, J. R., Alegria, J., Browning, J., Cissel, J., Cohen, W. B., Demeo, T. E., Healey, S., and R. Warbington. 2005. Northwest Forest Plan—the first 10 years (1994-2003): status and trend of late-successional and old-growth forest. Gen. Tech. Rep. PNW-GTR-646. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 142 p

Moran, C. J., E. M. Rowell, and C. A. Seielstad. 2018. A data-driven framework to identify and compare forest structure classes using LiDAR. Remote Sensing of Environment 211:154–166.

Morris, W. G. 1934. Forest Fires in Western Oregon and Western Washington Published by : Oregon Historical Society FOREST FIRES IN WESTERN OREGON AND WESTERN WASHINGTON ' 35:313–339.

Nagendra, H., S. Pareeth, B. Sharma, C. M. Schweik, and K. R. Adhikari. 2008. Forest fragmentation and regrowth in an institutional mosaic of community, government and private ownership in Nepal. Landscape Ecology 23:41–54.

Nepstad, D. C., A. Veríssimo, A. Alencar, C. Nobre, E. Lima, P. Lefebvre, P. Schlesinger, C. Potter, P. Moutinho, E. Mendoza, M. Cochrane, and V. Brooks. 1999. Large-scale impoverishment of amazonian forests by logging and fire. Nature 398:505–508.

Nonaka, E., and T. A. Spies. 2005. HISTORICAL RANGE OF VARIABILITY IN LANDSCAPE STRUCTURE: A SIMULATION STUDY IN OREGON, USA. Ecological Applications 15:1727–1746.

North, M. P., J. T. Kane, V. R. Kane, G. P. Asner, W. Berigan, D. J. Churchill, S. Conway, R. J. Gutiérrez, S. Jeronimo, J. Keane, A. Koltunov, T. Mark, M. Moskal, T. Munton, Z. Peery, C. Ramirez, R. Sollmann, A. M. White, and S. Whitmore. 2017. Cover of tall trees best predicts California spotted owl habitat. Forest Ecology and Management 405:166–178.

Ohmann, J. L., and M. J. Gregory. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest- neighbor imputation in coastal Oregon, U.S.A. Canadian Journal of Forest Research 32:725–741.

Ohmann, J. L., M. J. Gregory, and T. A. Spies. 2007. INFLUENCE OF ENVIRONMENT, DISTURBANCE, AND OWNERSHIP ON FOREST VEGETATION OF COASTAL OREGON. Ecological Applications 17:18–33.

Ohmann, J., and T. Spies. 1998. Regional gradient analysis and spatial pattern of woody plant communities of Oregon forests. Ecological Monographs 68:151–182.

Oliver, C. D., and B. C. Larson. 1996. Forest stand dynamics: updated edition. Forest stand dynamics: 520.

Pachavo, G., and A. Murwira. 2014. Land-use and land tenure explain spatial and temporal patterns in terrestrial net primary productivity (NPP) in Southern Africa. Geocarto International 29:671–687.

Parrotta, J. A., J. K. Francis, and O. H. Knowles. 2002. Harvesting intensity affects forest structure and composition in an upland Amazonian forest. Forest Ecology and Management 169:243–255.

Quesada, C. A., Phillips, O. L., Schwarz, M., Czimczik, C. I., Baker, T. R., Patino, S., et al. 2012. Basin-wide variations in Amazon forest structure and function are mediated by both soils and climate. Biogeosciences, 9(6): 2203-2246.

R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Rendenieks, Z., O. Nikodemus, and G. Brumelis. 2015. The implications of stand composition, age and spatial patterns of forest regions with different ownership type for management optimisation in northern Latvia. Forest Ecology and Management 335:216–224.

Rollins, M. G. 2009. LANDFIRE: A nationally consistent vegetation, wildland fire, and fuel assessment. International Journal of Wildland Fire 18:235–249.

Ryan, K. C. 2002. Dynamic Interactions between Forest Structure and Fire Behavior in Boreal Ecosystems. Silva Fennica 36:13–39.

Schaich, H., and T. Plieninger. 2013. Land ownership drives stand structure and carbon storage of deciduous temperate forests. Forest Ecology and Management 305:146–157.

Schulte, L. A., D. J. Mladenoff, T. R. Crow, L. C. Merrick, and D. T. Cleland. 2007. Homogenization of northern U.S. Great Lakes forests due to land use. Landscape Ecology 22:1089–1103.

Schwab, F. E., and M. D. Pitt. 1991. Moose selection of canopy cover types related to operative temperature, forage, and snow depth. Canadian Journal of Zoology 69:3071–3077.

Shafer, C. L. 2015. Land use planning: A potential force for retaining habitat connectivity in the Greater Yellowstone Ecosystem and Beyond. Global Ecology and Conservation 3:256–278.

Simonson, W. D., H. D. Allen, and D. A. Coomes. 2014. Applications of airborne lidar for the assessment of animal species diversity. Methods in Ecology and Evolution 5:719–729.

Smart, L. S., J. J. Swenson, N. L. Christensen, and J. O. Sexton. 2012. Three-dimensional characterization of pine forest type and red-cockaded woodpecker habitat by small-footprint, discrete-return lidar. Forest Ecology and Management 281:100–110.

Smithwick, E. A. H., M. E. Harmon, S. M. Remillard, S. A. Acker, and J. F. Franklin. 2002. Potential upper bounds of carbon stores in forests of the Pacific Northwest. Ecological Applications 12:1303–1317.

Sorice, M. G., U. P. Kreuter, B. P. Wilcox, and W. E. Fox. 2014. Changing landowners, changing ecosystem? Land-ownership motivations as drivers of land management practices. Journal of Environmental Management 133:144–152.

Spies T.A. and J. F. Franklin. 1991. The structure of natural young, mature, and old-growth Douglas-fir forests in Oregon and Washington. Wildlife and vegetation of unmanaged Douglas-fir forests: 91-109.

Spies, T. A., W. J. Ripple, and G. A. Bradshaw. 1994. Dynamics and patterns of a managed coniferous forest landscape in Oregon. Ecological Applications 4:555–568.

Spies, T. A., K. N. Johnson, K. M. Burnett, J. L. Ohmann, B. C. McComb, G. H. Reeves, P. Bettinger, J. D. Kline, and B. Garber-Yonts. 2007. Cumulative ecological and socioeconomic effects of forests policies in coastal Oregon. Ecological Applications 17:5–17.

Spies, T.A.; Stine, P.A.; Gravenmier, R.; Long, J.W.; Reilly, M.J., tech. coords. 2018. Synthesis of science to inform land management within the Northwest Forest Plan area. Gen. Tech. Rep. PNW-

GTR-966. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 1020 p. 3 vol.

Stanfield, B. J., J. C. Bliss, and T. A. Spies. 2002. Land ownership and landscape structure: a spatial analysis of sixty-six Oregon (USA) Coast Range watersheds. Landscape Ecology 17:685–697.

Tateno, R., T. Hishi, and H. Takeda. 2004. Above- and belowground biomass and net primary production in a cool-temperate deciduous forest in relation to topographical changes in soil nitrogen. Forest Ecology and Management 193:297–306.

Tetzlaff, D., C. Soulsby, J. Buttle, R. Capell, S. K. Carey, H. Laudon, J. Mcdonnell, K. Mcguire, J. Seibert, and J. Shanley. 2013. Catchments on the cusp? Structural and functional change in northern ecohydrology. Hydrological Processes 27:766–774.

Thomas, J. W., J. F. Franklin, J. Gordon, and K. N. Johnson. 2006. The Northwest Forest Plan: Origins, components, implementation experience, and suggestions for change. Conservation Biology 20:277–287.

Turner, M. G., D. N. Wear, and R. O. Flamm. 1996. Land ownership and land-cover change in the southern appalachian highlands and the Olympic Peninsula. Ecological Applications 6:1150–1172.

Turner, M., and R. H. Gardner. 2015. Landscape Ecology in Theory and Practice. Second edition. Springer-Verlag New York.

Vogeler, J. C., R. A. Slesak, P. A. Fekety, and M. J. Falkowski. 2020. Characterizing over Four Decades of Forest Disturbance in Minnesota, USA. Forests 11:362.

Wang, X., J. Fang, Z. Tang, and B. Zhu. 2006. Climatic control of primary forest structure and DBH–height allometry in Northeast China. Forest Ecology and Management 234:264–274.

Watershed Sciences, I. 2008. LiDAR Remote Sensing Data Colletion: DOGAMI, South Coast Study area.

Weiss, G., A. Lawrence, G. Lidestav, D. Feliciano, T. Hujala, Z. Sarvašová, Z. Dobšinská, and I. Živojinović. 2019. Research trends: Forest ownership in multiple perspectives. Forest Policy and Economics 99:1–8.

Wimberly, M. C., and J. L. Ohmann. 2004. A multi-scale assessment of human and environmental constraints on forest land cover change on the Oregon (USA) coast range. Landscape Ecology 19:631–646.

Wimberly, M. C., and T. A. Spies. 2001. Influences of environment and disturbance on forest patterns in Coastal Oregon Watersheds. Ecology 82:1443–1459.

Woodley, S., B. Bertzky, N. Crawhall, N. Dudley, J. M. Londono, K. MacKinnon, K. Redford, and T. Sandwith. 2012. Meeting Aichi Target 11: what does success look like for protected area systems? Parks 18:1–13.

Youn, Y.-C. 2009. Use of forest resources, traditional forest-related knowledge and livelihood of forest dependent communities: Cases in South Korea. Forest Ecology and Management 257:2027–2034.

Zald, H. S. J., J. L. Ohmann, H. M. Roberts, M. J. Gregory, E. B. Henderson, R. J. McGaughey, and J. Braaten. 2014. Influence of lidar, Landsat imagery, disturbance history, plot location accuracy, and plot size on accuracy of imputation maps of forest composition and structure. Remote Sensing of Environment 143:26–38.

Zald, H. S. J., and C. J. Dunn. 2018. Severe fire weather and intensive forest management increase fire severity in a multi-ownership landscape. Ecological Applications 28:1068–1080.