Quantifying and Restoring Stand-Level Spatial Pattern in Dry Forests of the Eastern Washington Cascades

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Abstract

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There is increasing evidence that spatial heterogeneity at multiple scales is a critical component of ecosystem resilience and adaptive capacity. In frequent-fire pine and mixed conifer forests in the western US, pre-settlement era forests were complex mosaics of individual trees, tree clumps, and openings. There is a broad scientific consensus that restoration treatments should seek to restore these mosaic patterns as these reference forests were adapted to frequent-fire and shifting climatic conditions. Yet, methods to quantify and incorporate spatial reference information into restoration treatments are not widely used. In addition, targets from reference conditions must be critically evaluated in light of climate change. In this dissertation, I develop a new set of spatial metrics to quantify within-stand pattern in terms of widely spaced individual trees, tree clumps, and openings (ICO). Within 0.5 ha tree neighborhoods, I found evidence that a definable range and distribution, or envelope, of pattern and structure was present. This envelope ranged from

low density patterns with few clumps and high opening levels, to patterns with a mid-range of density and varying levels of clumping, to high density, highly clumped patterns. The envelope was constrained by an upper limit of clump size, maximum density levels well below site potential, and the presence of at least some clumping in all plots. Across 3 x 6ha plots, tree neighborhood patterns of clumps and openings were spatially dependent. Aggregations of large clumps formed sub-patches that occupied 7-16% of plot area. A gradient of low to moderate density with low levels of clumping was found on the remainder. A silvicultural approach to translating reference patterns into restoration prescriptions and monitoring protocols was also developed and applied in a case study. Treatments using this ICO approach resulted in a distribution of tree clumps and openings within the range of reference envelopes. I also developed a method based on climatic water balance parameters, downscaled climate projections, and plant associations to assess historical reference sites in the context of projected future climate and identify climate analogue reference conditions.

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Table of Contents

List of Tables

List of Figures

List of Appendices

Introductory Chapter

Ongoing restoration of fire-frequent pine and mixed conifer forests throughout the western United States (hereinafter, *dry forests*) is one of the most extensive forest restoration programs ever undertaken (HFRA 2003, CFLRP 2012). Hundreds of thousands of hectares of public lands are being treated with prescribed fire and mechanical thinning each year (Schoennagel and Nelson 2010). These restoration efforts are being undertaken to address the effects of 100+ years of timber harvest, livestock grazing, fire suppression, and invasion by non-native species (Hessburg and Agee 2003). These activities have altered forest structure, composition, and disturbance regimes at multiple scales, leading to altered ecosystem function and increased risk of high severity wildfire (Covington and Moore 1994, Hessburg et al. 2005, Miller et al. 2009). Climate change projections indicate that warmer temperatures and more extreme variation in temperature and precipitation patterns will lead to increased drought stress, higher severity and area burned, and shifts in insect lifecycles and related outbreaks (Spracklen et al. 2009, Waring et al. 2009, Littell et al. 2010).

The primary goal of restoration in dry forests is to restore resilience and adaptive capacity to degraded ecosystems (Joyce et al. 2009, CFLRP 2012), not to recreate historic conditions per se. Ecological resilience is the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks (Holling 1996). Adaptive capacity is the ability of an ecosystem to adapt to changing environmental conditions through shifts in structure, composition, and genetic makeup, with minimal loss of function. Adaptive systems are less likely to undergo threshold responses in which rapid transitions to alternative systems states occur, typically involving a loss of diversity, complexity, and value to humans (Paine et al. 1998, Walker et al. 2004).

There is increasing evidence that spatial heterogeneity at multiple scales, in addition to forest structure and composition, is a critical component of ecosystem resilience, adaptive capacity, and biodiversity (Levin 1998, Moritz et al. 2011, Messier and Puettmann 2011, Lindenmeyer and Franklin 2002, Schoennagel et al. 2009, Gunderson and Holling 2002, van Nes and Scheffer 2005). Identifying spatial pattern targets for specific ecosystems that are empirically linked to resilience and other desired ecological functions is a major challenge, however (Puettmann et al. 2009). A related challenge is translating such targets into operationally-efficient prescriptions and monitoring protocols (North and Sherlock 2012, O'Hara et al. 2012).

In dry forests, pre-settlement era forests are commonly used as reference systems to provide targets for spatial heterogeneity (Hessburg et al. 1999b, 2013, Moore et al. 1999, Allen et al. 2002). These forests developed from pattern-process linkages that persisted through centuries of frequent disturbances and climatic fluctuation while sustaining a wide range of ecological functions (Agee 1993, Allen et al. 2002). Frequent fire maintained these forests well below their maximum carrying capacity for biomass and favored fire and drought tolerant species; thereby maintaining significant adaptive capacity to shifts in climate (Fule 2008). Contemporary, unlogged forests with minimally altered or restored fire regimes also exhibit resilience to modern fires (Taylor 2010, Lydersen and North 2012), even in the face of severe drought (Stephens et al. 2008). The rationale for using these reference systems as targets for restoration is based on the fact that these forests were adapted to frequent fire and shifting climatic conditions (Landres et al. 1999, Jackson and Hobbs 2009, Keane et al. 2009). Restoring historical spatial pattern, composition, and density for a specific site, however, is not a guarantee of resilience. Targets derived from reference conditions must be critically evaluated, and potentially modified, based on projected future climates and ecological knowledge to provide operative targets for restoration (Keane et al. 2009, Spies et al. 2010, Stephens et al. 2010).

The effective use of pre-settlement era and contemporary reference conditions as a template for restoring heterogeneity requires (1) quantifying their structure and pattern at multiple scales; and (2) a robust understanding of how structure and pattern are shaped by disturbance processes and biophysical conditions. Hierarchy theory and the hierarchical patch dynamic paradigm (HPDP) offer a powerful framework to quantify and understand these complex systems (Urban et al. 1987, Wu and Loucks 1995). HPDP holds that forest ecosystems can be understood and quantified as a multi-level hierarchy of vegetation patch mosaics (Wu and Loucks 1995). Each level of the hierarchy is a mosaic of patches and each patch is a mosaic of lower-level patches (Kotliar and Wiens 1990). The structure of a patch hierarchy for a specific ecosystem is dependent on the perspective of the organism or process of interest (Levin 1992). There is no single patch classification scheme that works for all organisms, processes, and management objectives (Wu, 1999). Yet in multi-scale management of landscapes, a central patch hierarchy and classification scheme is necessary for landscape analysis and management.

I define a landscape patch hierarchy for dry forest landscapes with four levels. At the highest level are regional landscapes or ecological sub-regions that are differentiated by differences in climate, geomorphology, and vegetation types (Hessburg et al. 2000). The patterns and variability within regions come from local landscapes, typically 5th or 6th field watersheds (Seaber et al. 1987), no two of which are the same. Watersheds in turn are mosaics of successional patches or stands (O'Hara et al. 1996). Stands are defined as patches of vegetation with similar composition, structure, and topo-edaphic conditions that contain variable patterns of tree neighborhoods. Tree neighborhoods are the lowest level of the hierarchy and consist of sub-patches within stands that have similar arrangements of tree clumps and openings and thus tree growing environments (Frelich and Reich 1999b).

The pattern and structure of patch mosaics at each level of the hierarchy in dry forests are shaped by top down and bottom up factors (Urban et al. 1987, Lertzman and Fall 1998). In tree neighborhoods and stands, fine-scale interactions between vegetation dynamics (e.g. clumped regeneration, competition, and fuel accumulation) and frequent, low-severity disturbances are major drivers (Cooper 1960, Agee 2003). However, meso-scale variation in topography, soil productivity, and species composition also play an important role directly and indirectly by creating greater variability in fire behavior (Schoennagel et al. 2004, Hessburg et al. 2007, Perry et al. 2011). Broad scale patterns of biota, geology, geomorphic processes, and climate provide top-down constraints at all levels, occasionally overriding bottom up controls and resetting stand-level patterns (Shinneman and Baker 1997, Turner 2010). At all levels of the hierarchy, patch configurations shift through time and exhibit non-equilibrium behavior (Moritz et al. 2011). This is due to the presence of both stationary and non-stationary properties of disturbance regimes, soils, biotic interactions, and climate.

HPDP, resilience theory, and empirical evidence indicate that underlying interactions among the vegetation, disturbance regime, and biophysical conditions constrain variation in pattern and structure to a realized subset of possible variation at each level of the hierarchy (Wu and Levin 1997, Levin 1998, Peterson et al. 1998, Falk et al. 2007, Scholl and Taylor 2010, McKenzie and Kennedy 2011, Moritz et al. 2011). This emergent subset of variation has both a range and a distribution of pattern and structure (Keane et al. 2009), and is hereinafter defined as an “envelope”. Furthermore, emergent patterns and structure at the base of the landscape hierarchy (i.e. tree neighborhoods) provide the basic organizing elements for higher levels

(Urban et al. 1987, Wu and Loucks 1995). Emergent patterns at larger scales can be thus quantified in terms of different configurations of lower level patch types (Wu 1999).

The emergent structure of historical dry forests at stand and tree neighborhood levels consisted of old fire-resistant trees, multiple-age cohorts, low to moderate canopy cover, snags and downed logs (Kaufmann et al. 2007). The emergent spatial pattern of dry forests was a fine-grained mosaic of openings, tree clumps, and individual trees, and there is clear evidence that this envelope was constrained to a quantifiable range (Larson and Churchill 2012). However, this emergent pattern has not been quantified in terms of the size distributions of openings, tree clumps, and individual trees. Likewise, the arrangement and assembly of these basic elements into larger patches are not well understood. It is not fully known what kinds of patterns were clearly outside of the pattern envelope. Attempting to restore these ecosystems and increase their resilience without knowing the envelope of pattern reference systems occupied is likely to result in unintended consequences (North et al. 2009).

The fine-scale, “clumpy gappy” pattern of historic dry forests is the emergent pattern that evolved from adaptation to a frequent and variable wildfire regime; a range of insect, pathogenic and abiotic disturbances; and shifting climatic conditions at decadal to century time scales (Allen et al. 2002, Kaufmann et al. 2007). On a mechanistic level, irregular tree patterns, large openings, and resulting variation in surface fuels inhibit the spread of crown fire and perpetuate variable post-fire patterns (Beaty and Taylor 2007, Pimont et al. 2011, Stephens et al. 2008), analogous to strategic placement of fuel treatments at larger spatial scales (Finney et al. 2007). Heterogeneous stand structures appear to reduce the buildup of epidemic insect outbreaks by disrupting pheromone plumes and breaking up the continuity of susceptible species and size classes (Fettig et al. 2007). Similarly, openings impede the spread of dwarf mistletoes and fungal pathogens (Goheen and Hansen 1993, Hawksworth et al. 1996, Shaw et al. 2005). Likewise, openings and frequent disturbances facilitate periodic tree regeneration (Boyden et al. 2005, Sánchez Meador et al. 2009), which is thought to be partly responsible for high levels of local genetic diversity of trees in dry forests (Linhart et al. 1981, Hamrick et al. 1989).

There is a growing scientific consensus that to increase resilience, mechanical and prescribed-fire treatments should seek to restore the range of mosaic patterns found in reference stands (Allen et al. 2002, Franklin and Johnson 2012, Hessburg et al. 2005, Moore et al. 1999, North et al. 2009, Perry et al. 2011), in addition to retaining large and old fire-tolerant trees and following other resilience principles. Widespread adoption of prescription approaches based on spatial reference information has been slow, however, despite numerous operational-level research studies (e.g. Graham et al. 2007, Knapp et al. 2012, Lynch et al. 2000, USFS 2008, Waltz et al. 2003).

The fundamental challenge facing managers is the mismatch between the grain and variation of pattern found in dry forests and the tools commonly used to quantify and manage them. Most silvicultural methods are based on stand-average density metrics originally designed to create homogenous stands (Puettmann et al. 2009). Modifying these approaches to manage for within-stand spatial variability requires re-conceptualizing stands as mosaics of lower level patches (Puettmann et al. 2009). This shift—and the associated changes in mensuration tools, operational methods, and contractual mechanisms—can be complex and time consuming (Knapp et al. 2012, North and Sherlock 2012). Thus, many managers continue to employ stand-average basal area or spacing-based approaches (e.g. Powell 2010). Projected changes in climate and related shifts in disturbance behavior present an additional challenge to the use of spatial pattern targets from historical reference conditions (Franklin et al. 1991, McKenzie et al. 2011, Williams et al. 2007). Methods are needed to better understand how stand-level pattern envelopes varied across biophysical gradients in order to use reference conditions in a climate change context.

In this dissertation, I address a number of aspects of stand level spatial pattern in dry forests of the Eastern Cascades of Washington. In chapter 1, I characterize and quantify a reference envelope of pattern at the tree neighborhood level. I analyze pattern on 32 x 0.5 ha reconstructed, pre-settlement era plots from Harrod et al. (1999) as well as 30 sub-plots from 3 contiguous 6ha plots. I develop and test a set of spatial metrics that quantify tree neighborhood patterns in term of individual trees, clumps, and openings. I then use hierarchical cluster analysis to group these patterns and quantify the boundaries and distribution of the reference envelope. In chapter 2, I examine whether tree neighborhoods form patterns of spatially aggregated sub-patches within stands, or whether they are randomly arranged. Prior stem map reconstructions in frequent-fire forests have found stationary point patterns that showed no spatial dependence of tree clumps and openings, suggesting that vegetation processes and mortality from low severity disturbance operating at fine scale (<0.4 ha) were the dominant factors influencing pattern. These studies generally used small plot sizes (<1ha), however. I tested whether stationarity was present at a 6ha spatial extent to detect influence of meso-scale topography, edaphic factors, or larger patch sizes of mortality (>1ha) from disturbances. Then in chapter 3, I develop and test an approach to translate the observed reference patterns into management guidelines. I compare this approach with crown spacing and basal area prescription approaches in terms of alignment with reference conditions and several aspects of resilience. Also in chapter 3, I introduce a method to use climate analogue reference sites to provide an empirical basis for integrating restoration with climate adaptation.

Chapter 1: Quantifying tree spatial patterns in dry forests of the Eastern Cascades of Washington

Abstract

Reference targets for tree spatial patterns are needed to guide restoration of resilience in fire-prone forests in the western U.S. We developed and tested a set of spatial metrics to quantify within-stand patterns in terms of widely spaced individual trees, variably sized tree clumps, and openings. We quantified a reference range of pattern on 32 x 0.5 ha plots dispersed over a wide range of biophysical settings, as well as 30 x 0.5 ha sub-plots from 3 contiguous 6 ha plots. We found a strong relationship between density, clumping levels, and openings and clear evidence that a definable envelope of pattern and structure was present. This envelope ranged from low density patterns with few clumps and high opening levels, to patterns with a mid-range of density and varying levels of clumping, to high density, highly clumped patterns with few openings. Low to moderate density patterns were the most prevalent. The envelope was constrained by an upper limit of clump size, maximum density levels well below site potential, and the presence of at least some clumping in all plots. No uniform patterns were found. Stand-level patterns representing different arrangements of these 0.5 ha pattern types likely represent highly adaptive structures in the context of a frequent and variable wildfire regime; a range of insect, pathogenic and abiotic disturbances; and shifting climatic conditions. Our results indicate that if restoration prescriptions approximate the clump size distribution associated with historic ranges for a specific density level, the desired amount of open space will result as a by-product, although additional effort may be necessary to create large openings (>0.4 ha).

1. Introduction

Significant efforts have been made to characterize stand-level reference conditions in frequent-fire ponderosa pine and dry-mixed conifer forests of the interior western US (hereinafter Dry Forests)in order to understand developmental processes and guide restoration and management (Larson and Churchill 2012, references within). The majority of this work has focused on pre-EuroAmerican settlement, open canopy, older forests as they embody structural and compositional conditions that persisted through multiple centuries of frequent fires and climatic fluctuation while sustaining a wide range of ecological functions (Allen et al. 2002, Agee 2003, North et al. 2009, Stephens et al. 2010, Franklin and Johnson 2012). Frequent fire maintained these forests well below their maximum carrying capacity for biomass and favored fire and drought tolerant species; thereby maintaining significant adaptive capacity to shifts in climate over decadal to century time scales (Fule 2008). Contemporary, unlogged forests with minimally altered or restored fire regimes also exhibit resilience to modern fires (Taylor 2010, Lydersen and North 2012), even in the face of severe drought (Stephens et al. 2008).

Climate change projections indicate that hotter and drier conditions and more extreme variation in climate will lead to increased drought stress, higher fire frequency and severity, and fluctuations in insect behavior (Spracklen et al. 2009, Waring et al. 2009, Littell et al. 2010). The rationale for using pre-settlement conditions as targets for restoration is based on the fact that the structure and pattern of historic dry forests emerged from adaptation to similar conditions (Swetnam et al. 1999, Allen et al. 2002, Falk 2006, Fule 2008, Keane et al. 2009). Site specific future conditions will undoubtedly be different than the past. Reference targets will likely need to be adjusted to match projected future climates for specific sites (Gärnter et al. 2008). Using historic conditions to guide restoration reduces short-term risk of loss to uncharacteristic wildfire while simultaneously preserving options for future generations. This strategy provides a foundation on which to implement climate adaptation strategies as new understanding accumulates (Diggins et al. 2010 p. 2, Spies et al. 2010).

Resilience theory and empirical evidence indicate that underlying interactions among the vegetation, disturbance regime, and biophysical conditions constrain variation in pattern and structure to an emergent, “realized” subset of possible variation (Levin 1998, Gunderson and Holling 2002, Scholl and Taylor 2010, McKenzie and Kennedy 2011, Messier and Puettmann 2011, Moritz et al. 2011). This realized subset has both a range and a distribution of pattern and structure (Keane et al. 2009), which is hereafter defined as an “envelope”. Furthermore, emergent patterns and structure at the base of the landscape hierarchy (e.g. tree neighborhoods and stands) provide the basic organizing elements for higher levels (Urban et al. 1987, Wu and Loucks 1995). Emergent patterns at larger scales (e.g. stands or watersheds) can be thus quantified in terms of different configurations of lower-level patch types (Wu 1999).

The emergent structure of historical dry forests at the stand level consisted of old fire-resistant trees, multiple-age cohorts, low to moderate canopy cover, snags and downed logs (Kaufmann et al. 2007). The emergent spatial pattern of dry forests was a fine-grained mosaic of openings, tree clumps, and individual trees and there is evidence that this envelope was constrained to a quantifiable range (Larson and Churchill 2012). Most tree-level patterns were statistically clustered, primarily at short distances (<6m,), while some patterns were random. However, this emergent pattern has not been quantified in terms of the size distributions of openings, tree clumps, and individual trees. In addition, the arrangement of these basic elements in larger patches is not well understood. Furthermore, it is not fully known what kinds of patterns were clearly outside of the pattern envelope. Attempting to restore these ecosystems and increase their resilience without knowing the emergent or envelope of possible pattern they occupied is likely to result in unintended consequences (North et al. 2009).

Capturing the range and distributions of pattern in historic dry forests requires sampling across a range of biophysical settings as well as over large spatial extents. Harrod et al. (1999) reconstructed and mapped 32 x 0.5 ha plots dispersed across a large area of dry forest (~6,500 ha) with complex topography. Comparing these plots with additional reconstruction plots from biophysically similar but geographically separated areas offers the opportunity to assess whether a definable historical envelope indeed existed. The small size of the Harrod plots (100 x 50 m) provides an appropriate spatial extent to characterize pattern at the tree neighborhood scale (Frelich et al. 2002, Boyden et al. 2012), but larger, contiguous plots are necessary to evaluate how these small scale patterns vary across stands.

The lack of pattern metrics that quantify within-stand heterogeneity has been a primary barrier to quantifying the pattern envelope of these forests. Existing studies of spatial pattern in dry forests have almost exclusively used global methods that provide average results for plots and quantify the inter-tree distances at which patterns are clumped, random, or inhibited (Larson and Churchill 2012). Global metrics are important tools in spatial analysis (Diggle 2003), but quantifying within-stand variability in terms of the distribution and spatial arrangement of lower level elements is also necessary to understand how trees form ecologically meaningful patterns (Fortin and Dale 2005, Perry et al. 2006).

Plotkin et al. (2002) developed an alternative method of characterizing spatial patterns that has been used in dry forests to quantify patterns of individual trees and tree clumps (Abella and Denton 2009, Churchill et al. 2013, Larson et al. 2012, Sánchez Meador et al. 2011). Clumps are defined as groups of trees with interlocking crowns (sensu White 1985), and identified using a single inter-tree distance. These studies have used the distribution of clump sizes, expressed in number of trees, as the primary spatial metric. This method has some limitations, however. It is not sensitive to the spatial arrange of individuals and clumps. Also, use of a single distance to define clumps does not capture the variation in crown size. Most importantly, the Plotkin et al. (2002) method does not explicitly quantify openings, which are a critical component of the structure and function of dry forests (Kaufmann et al. 2007). Quantifying openings in dry forests is challenging since they are often not well defined gaps due to the open nature of the canopy. Analysis methods are needed that capture variation in three ecologically important elements of spatial pattern: (1) tree density, (2) the extent to which tree crowns interlock and form clumps (the clump size distribution), and (3) the size distribution of openings.

In this paper, we expand on our previous work in Larson and Churchill (2012) and Churchill et al. (2013) to develop and evaluate a set of metrics that quantify tree patterns in terms of individuals, tree clumps, *and* openings. We then use these metrics with common multivariate statistical techniques to characterize the range and distribution of the observed envelope of pattern and structure on the 32 dispersed Harrod et al. (1999) plots and 3 x ~6ha contiguous plots. Finally, we also explore and quantify patterns that lie outside of the envelope in order to develop hypotheses about constraining factors and to provide guidance to forest managers regarding which patterns are most likely to be resilient.

2. Methods

2.1 Study Area

Within-stand tree patterns were analyzed on 32 x 0.5 ha stem mapped plots installed by Harrod et al. (1999) (hereinafter dispersed plots) and three large plots (5.9-6.7 ha) (hereinafter contiguous plots). Both sets of plots are located in the eastern Cascade Range of Washington, on sites that historically were dominated by ponderosa pine (*Pinus ponderosa*) and had frequent fire return intervals (6-10 years) (Everett et al. 2000, Kernan and Hessl 2010). Currently, ponderosa pine is the sole species on the drier sites, while interior Douglas-fir (*Pseudotsuga menziesii,* var. *glauca*) is co-dominant with ponderosa pine on the cooler, moister sites. Minor amounts of western larch (*Larix occidentalis*) and grand-fir (*Abies grandis)* are also present on some sites. The study area was extensively grazed between the turn of the century and ca.1930. Fire suppression became effective in the 1930s and has continued to the present (USFS 1995, 1997, 1998). All of the plots were selectively harvested during the late 1920's to the 1940's. A second round of selective harvests occurred on two of the contiguous plots in the early 1970's.

The dispersed plots are scattered over approximately 6,500 ha in the Mission Creek watershed of the Okanogan-Wenatchee National Forest, 17 km south of Cashmere, Washington. The plots are on sites characterized by forested plant associations from ponderosa pine and interior Douglas-fir series, ranging from *Pinus ponderosa/Purshia tridentata/Agropyron spicatum* on hotter drier sites to *P.menziesii/Spirea-betulifolia/ Calamagrostis rubescens* on colder and more mesic sites (Lillybridge et al. 1995, Harrod et al. 1999). The plots occupy a variety of slope positions, aspects, and elevations (650 m to 1150 m). Soils are well drained, sandy loams derived primarily from sandstone, with some loess and volcanic ash in the upper layers (NRCS 2010). Modeled precipitation for1971-2000 averages 675 mm annually, falling mostly as snow between November and April (ClimateWNA 2012). Modeled mean January and July temperatures are -2.8°C and 18.4°C.

The three contiguous plots are located south and east of the dispersed plots (Fig. 1). On all three plots, the dominant plant association is *P.menziesii/Spirea-betulifolia/ Calamagrostis rubescens,* although pockets of drier sites are present. Modeled annual precipitation averages between 650-950 mm and occurs mostly as snow between November and April with mean

January and July temperatures ranging from -1.9° to -3.0°C and 14.6°-16.6°C (ClimateWNA 2012). The Liberty plot is located in the Swauk Creek drainage of the upper Yakima River basin, approximately 50 km NE of the town of Cle Elum. The plot is at 1,050-1125 m in elevation, has a SW aspect, and slopes that range from 20-45%. Soils are deep, well drained and derived from siltstone, sandstone, and volcanic ash (NRCS 2010). The Nile plot is located 25 km NW of Naches in the Nile Creek drainage of the lower Yakima River basin. It has a NE aspect, slopes ranging from 40-60%, and elevation ranges from 950 – 1050 m. Soils are derived from conglomerate and tuffs with a mantle of volcanic ash (NRCS 2009). The Oak plot is 20 km W of Naches in the Oak Creek drainage and has slopes of 10-30% and an elevation range of 1275-1300 m. Soils are colluvium and residuum from basalt mixed with volcanic ash and loess (NRCS 2009).The Nile and Liberty sites were located within fire history study areas of Everett et al. (2000). Additional site selection criteria are discussed in chapter 2.

2.2 Reconstruction Methods

We followed the reconstruction protocols used by Harrod et al. (1999) for the contiguous plots. All live trees, stumps, snags, and logs that were estimated to have originated before 1865 were considered "historical" and mapped. Bark and crown characteristics were used to determine which live trees were historical (>145 years in age) using guidelines from Van Pelt (2008). All trees whose historical status was questionable were cored. Decay class, combined with dbh, were used to estimate whether snags and logs originated before 1865 using species specific equations from Everett et al. (2007). The year of harvest for stumps was estimated by first determining when harvest entries occurred using Forest Service records and evidence of release on tree cores taken from a selection of live trees adjacent to stumps. In the two stands that had multiple harvests, each stump was assigned to a harvest year (1930 or 1970) based on species and stage of decay. Trees harvested during early selection harvests (~1930) were generally large pine and had clearly established before 1865. For trees harvested in 1970, rings were counted on the stump to ensure establishment before 1865. All questionable stumps, logs, and snags were noted during mapping and then later revisited by a single person to ensure consistent calls regarding pre or post 1865 establishment. Age of questionable live trees was determined after drying, mounting, and sanding of tree cores. We could not reliably estimate densities of small trees (dbh < 30 cm) due to the limitations of reconstruction. Thus our methods reconstruct trees that were in the upper or mid canopy, similar to Youngblood (2004).

2.3 Primary Spatial Pattern Metrics

We employed three primary metrics to characterize within-stand tree patterns: density in TPH, the clump identification algorithm from Plotkin et al. (2002), and the empty space distribution (F-test) to quantify openings. The clump algorithm partitions a stem map of tree locations into clumps at a specified inter-tree distance (*t*), measured from tree center to tree center. Trees are members of the same clump if they are within distance *t* of at least one other tree in the clump. Trees with no neighbors within distance *t* are termed individuals. We elected not to use any edge correction method following Plotkin et al. (2002), and instead explore edge effects in a subsequent paper.

Tree clumps were identified using a single inter-tree distance threshold based on the observed distance at which most mature ponderosa pine trees (>120 years) in our study area display interlocking crowns and form patches of continuous canopy (White 1985, Graham et al. 2007). The number of clumps of different sizes, measured in numbers of trees, was then tabulated. As there is no single distance that defines tree clumps (Abella and Denton 2009, Sánchez Meador et al. 2011), distances of 4, 5, 6,and 7m were used. Mean clump size and the clump size distribution were then derived for each distance. This distribution summarized the percentage of trees arranged as individuals and in clumps of different sizes. Clump sizes were also reported in bins: individuals (1 tree), small clumps (2-4 trees), medium clumps (5-9 trees), and large clumps (10-20+ trees) based on functional differences (e.g. understory shading, number of "interior" trees) (Churchill et al. 2013).

The empty space function, *F(t,)* quantifies open space in terms of distance from the nearest tree (Diggle 2003). The *F(t)* function generates a grid of cells, set to 0.5 m in our case, and then derives the distance from the center of each grid cell to its nearest tree. These distances are pooled to create a cumulative distribution. We did not attempt to delineate and quantify individual gaps as this requires subjective decisions on what constitutes a gap and where it "closes", especially in low canopy cover forests such as ours. Gap size distributions also tend to have sharp breaks that can introduce complications when comparing them across plots, especially with small plots. Instead, *F(t)* has no subjective "settings" and is generally a smooth distribution. *F(t)* quantifies what percent of the plot is greater than a specified distance away from a tree. It thereby quantifies the total amount of "open" area in a plot and distinguishes whether the total amount of opening, the inverse of canopy cover, is distributed in many small openings or fewer, larger ones.

Many ecological processes such as regeneration and growth of shade-intolerant species (York et al. 2004), insect spread (Fettig et al. 2007), and crown fire spread can be related to distance from the nearest tree, or gap edge. A similar concept is used in variable retention harvesting to quantify the amount of area beyond the "tree influence zone", typically one tree height from a retention patch (Baker and Read 2011). To extract variables for multivariate analysis from the cumulative F(*t*) distribution, we converted the cumulative distribution into 3 m bins. This quantified the proportion of the total plot area in the different bin sizes. A graphical plot of this function was also created to visually assess the spatial distribution of cells in the 3 m bins across each plot.

In order to compare clump size and F(*t*) distributions on the contiguous plots with the dispersed plots over the same spatial extent, we partitioned the contiguous plots into 100 x 50 m sub-plots (0.5 ha). To do this, we superimposed a 250x 200m grid of ten 100 x 50m sub-plots over each big plot. The 10 sub-plots within each 250 x 200m grid were adjacent and remained fixed. We did not overlap the sub-plots to avoid partial repeat sampling of the patterns in the contiguous plots which did not occur with the dispersed plots. Each of the contiguous plots was larger than 250 x 200m, however, and so a portion of each plot had to be dropped. We ran 100 randomly located 250x 200m grids for each of the 3 contiguous plots and analyzed spatial pattern metrics for the 10 sub-plots within each 250 x 200m grid. As the primary objective of the study was to characterize the range of variation of pattern, we selected the 250 x 200m grid location that had the widest range of tree density for each contiguous plot. Initial analysis showed that tree density was strongly correlated with clumping and open space distribution.

2.4 Characterizing and Differentiating the Range of Pattern Types

Two commonly used multivariate statistical methods were used to characterize the range and distribution of patterns within the observed envelope. First, we used principal components analysis (PCA) (McCune and Grace 2002) to examine how our spatial metrics placed the plots in ordination space and explained variation in spatial pattern. Second, we used the distance matrix from the PCA to group plots using hierarchical cluster analysis (McCune and Grace 2002). While typically used with species to classify vegetation communities, PCA and hierarchical cluster analysis have been used to group variation in spatial pattern using the pair correlation function (Illian et al. 2006), and to classify structure types using diameter distributions and species composition (Taylor and Skinner 2003, Stephens and Gill 2005, Scholl and Taylor 2010). We explored different combinations of the F distribution bins and outputs from the cluster algorithm in the distance matrix. We examined the PCA loadings, correlation matrices, and amount of variance explained by each PCA axis to gain insight into the drivers of variation among the plots and relationships between variables.

Based on this exploratory analysis, we selected ten variables to create the final distance matrix: mean clump size at 4, 5, 6, and 7m; the proportion of the F distribution in 5 bins: <= 6m, 6.01 – 9 m, 9.01 – 12m, 12.01 – 15m, 15.01 + m; and trees per ha. These 10 variables captured key differences between pattern types by using multiple inter-tree distances to define clumps, and incorporating all open space distances. Using PCA axis scores to reduce the number of variables did not improve the groupings and resulted in less intuitive input variables. All variables were standardized by maxima. Euclidean distances and the “ward” method of evaluating hierarchical clusters were used.

To compare the range of pattern found in each dataset, ordinations and groupings were evaluated for three sets of plots: the dispersed plots alone, the sub-plots alone, and the combined plots. Inspection of dendrograms, scree plots, and group means of the input variables showed that 4 groups explained the variation among groups in a parsimonious manner. Hulls were generated to graphically illustrate the range of pattern types, in ordination space, occupied by each set and the amount of overlap. Once it was established that the dispersed and contiguous plots contained similar range and groups of pattern types, the groups from the combined set of plots were used for all subsequent analyses.

2.5 Evaluating the Pattern Groups

The 4 groups from the combined plots were evaluated in a number of ways to fully understand the portion of the envelope occupied by each group and where they overlapped. First, boxplots of trees per ha, basal area, and mean diameter of each group were generated. PERMANOVA (Anderson 2001) was used with the full set of ten variables to test whether the overall grouping was statistically significant. Contrast Tests and PERMANOVA were then used to test for differences between individual groups. A separate, non-parametric method to test for differences in replicated point pattern statistics from Diggle et al. (1991) was used to test for differences in the F(t) distribution among groups. This method is a permutation test similar to PERMANOVA, but uses the actual mean distributions of each group to calculate variance instead of a distance matrix. The pooled variance for the groups being tested is ranked against random permutations of the groups to generate a p-value (Diggle et al. 2000).

We also elected to assess the four groups with the pair correlation function, g(t), which is the primary method recommended for spatial analysis of point patterns (Fortin and Dale 2005, Perry et al. 2006, Diggle et al. 2007, Illian et al. 2008). The g(t) function is a non-cumulative form of Ripley's $K(t)$ (Ripley 1988), and is calculated by taking the derivative of the kernel smoothed $K(t)$ distribution (Wiegand and Moloney 2004). The g(t) function avoids the problem of "cumulative effects" associated with $K(t)$ or $L(t)$, where patterns at short t values can lead to incorrect assessments of clumping, randomness, or inhibition at longer t values (Perry et al. 2006). In addition, the shape of the g(t) curve provides information on the size distribution and degree of clumping and open space (Wiegand et al. 2007b). We first tested for overall departure from complete spatial randomness at 0-12.5 m using the Cramer–von Mises goodness-of-fit test from Loosmore and Ford (2006) with *g(t)* for each pattern. We then tested for differences among the mean g(*t*) curves of the 4 groups using the same non-parametric permutation test discussed above. Finally, g(*t*) curves of each group were compared with 100 random patterns (CSR) to assess distances at which patterns where clumped, random, or inhibited. We also applied an isotropic (Ripley 1988) edge correction to all g(*t*) tests.

2.6 Quantifying the Realized vs. Potential Pattern Space

PCA ordinations of the combined set of plots framed the pattern envelopes in multivariate, ordination space. However, collapsing the 10 variables onto 2 PC axes did not display the 3 elements that define pattern space (openings, tree clumps, and density) in an intuitive manner that could be transferred to management. Thus, we selected a single variable for each of the three elements. For tree clumps, we averaged the mean clump size at 4,5,6, and 7m to represent the mean clump size across a wide range of maximum distances that define tree clumps. For openings, we selected the total plot area greater than 9m away from the nearest tree (F>9) based on where F(*t*) curves were maximally separated. Nine meters is approximately 1/3rd of the maximum tree height on these sites. Tree density was quantified in trees per hectare (tph).

We investigated how these three variables are related using scatter plots of the combined set of plots and linear regression models. We were able to combine all three variables on one scatter plot with tph on the x-axis and mean clump size on the y axis. Contour lines for F > 9m were added using a smoothed surface generated by a Gaussian smoothing function (Wood 2004).

Using this single figure, we plotted the hulls of the dispersed plots and each of the contiguous plots to illustrate the pattern envelope realized by each set of 0.5 ha plots.

To assess parts of the envelope not occupied by our data, we simulated random, inhibited, and clustered point patterns at density levels ranging from 5-270 tph on 0.5 ha plots to generate pattern types outside of the envelope realized by our plots. A Strauss inhibition point process model was used to generate inhibited patterns where trees were not allowed to have neighbors between 4.5-6m (Strauss 1975). These inhibited patterns could theoretically result from self-thinning as has been observed in other pine species (Kenkel 1988). Clustered patterns were generated with a Neyman Scott model (Neyman and Scott 1957).

We plotted these simulated plots with the observed plots on a simple plot of tph and mean clump size. We bounded the range of possible tph by setting a maximum tree density of 270 tph (110 tpa). This was based on estimates of full stocking for ponderosa pine on these sites, 75% of maximum SDI (864 metric, 350 english units) (Lillybridge et al. 1995, Harrod et al. 1999), and the lowest quadratic mean plot diameter observed (42.6 cm). In theory, the mean clump size of a 1 ha plot with 270 trees is 270 if all the trees are in one clump. However, we elected to bound mean clump size using data from contemporary unharvested, old growth ponderosa pine plots from Youngblood et al. (2004). These sites had experienced many decades of fire exclusion and so represented an upper biological bound of density and clumping in the absence of major disturbance. Both pre- and post-fire suppression trees were included, although we removed trees less than 20 cm to reflect the lower diameter limit of our plots. The maximum mean cluster size of these plots was 26. A mean clump size of 30 thus appeared to be a reasonable upper bound.

3. Results

3.1 Evaluating Pattern Metrics

The PCA axes loadings and resulting positions in ordination space were very similar between the 32 dispersed plots, 30 sub-plots from the 3x 6ha contiguous plots, and the combined 62 plots (Fig. 2, Table 1). The groups and structure of the PCA shifted somewhat when different randomized 250x200 m grids were used for the sub-plots. However, the basic positions of the explanatory variables and characteristics of the 4 groups remained the same (see Appendix). The dispersed groups shared a similar ordination space to the contiguous groups, but were shifted towards lower density patterns (Fig 2E). The sub-plots from the contiguous plots contained somewhat higher density and more clumped patterns, but also had some low density plots.

The two PCA axes shown on the ordination separated out major differences between patterns, as well as more subtle differences. PC 1 was weighted fairly evenly among all 10 variables and explained between 60 and 69 percent of the variance (Table 1). PC 1 separated higher density plots with more clumping and smaller openings on the right with low density, more open, and less clumped plots on the left. PC 2 explained an additional 15-21% of the variance. Plots with more open space and higher levels of clumping, relative to their density level, were located in lower half of the axis. Patterns with smaller clumps and small to medium F-distances, relative to their density level, are on the top half. Plots in the lower left corner have low density and high amounts of open space (e.g. plot H29 in Fig. 2E), while plots in the lower right corner (e.g. plot B18) have high density and high clumping levels. Plots in upper center have moderate density, low clumping levels, and small openings (e.g. plot B8). These are relatively evenly spaced plots with mostly individual trees and small clumps. In contrast, plots in the lower center have similar density levels but are much more closely clumped, which results in a higher amount of opening for that density level.

The simplified metrics, tph, mean clump size from 4-7m, and F > 9m (proportion of plot area > 9 m from the nearest tree), produced groups that were almost entirely driven by density, and did not capture the secondary differentiation between levels of clumping and open space. They were not sensitive to shifts in the F distribution at longer distances. In more open plots, individuals and clumps could be "packed" more closely together, but still far enough apart to be separate tree clumps. Such patterns have the same F > 9m as patterns where the clumps are well distributed, but have more area in large openings. This difference is captured by the F12-15 or F15m+ variables, as shown in the PCA ordination (Fig. 2). To capture these differences in the distribution of clumps across a plot we chose to use the full 10 metrics to create the groups.

The 3 simplified metrics worked well to model the underlying relationships. Our linear regression model predicting F > 9m from log transformed tph and mean clump size was remarkably strong ($r^2 = .92$), and the residuals were evenly distributed (Fig. 3). This model was the quantitative basis for plotting all three variables on one figure (Fig. 4), which provided a more intuitive and straightforward visualization of the pattern envelopes than the ordinations. Note that the F>9m values shown by the smoothed contour lines in Fig. 4 are not perfectly accurate. Mean clump size from 4-7m is strongly correlated with full clump size distributions (Fig. 4, Table 2). F > 9m is well correlated with most points along the F-distribution (Fig. 6, Table 2), although it does not perform as well at longer distances (F 15+ m).

3.2 Characteristics of the Pattern Groups

The 4 groups captured the major types of patterns observed. The overall grouping was statistically significant ($p < 0.001$), and each individual group was also significantly different from the other 3 ($p < 0.02$). The black group consisted of low density plots (20-50 tph) with mostly large (>50 cm), widely spaced trees and high amounts of opening (Figs. 5 and 6). At a six meter inter-tree distance, an average of half the trees were individuals in the black group, 46% were in small clumps (2-4 trees), and 5% were in medium clumps (Fig. 6, Table 2). However, density was low enough that they all had similar F distributions (Table 2). Ten of the 18 black patterns were not statistically different than complete spatial randomness (CSR) from 0.1- 12 m, based on the goodness-of-fit test from Loosmore and Ford (2006), while the other 8 were statistically clustered patterns ($p < 0.05$).

The green group was made up of moderate density plots (50-100 tph) with well distributed individual trees (41% of trees), small clumps (52% of trees), and a few medium clumps (7%). Clump size distributions were not statistically different from the black group (Fig. 6), but different from the pink and blue groups. The fact that trees were well distributed across the plot explains the relatively low amount of open space in larger openings. These plots were almost all random ($p<0.05$), except for 1 that was statistically clustered, and all had similar $g(t)$ curves (Fig. 7).

The pink group had somewhat higher density than the green group, but was much more clumped with only 29% as individuals, 42% in small clumps, 23% in medium clumps, and 6% in large clumps. Opening size distribution was not statistically different from the green group. Patterns in this group were mostly statistically clustered (13 out of 16) and had a wide range of configurations of individual, clumps, and openings (Figs. 4 and 7).

The blue group was at the other end of the spectrum and had statistically different clump size and F distributions. This group had high density (80-200 tph), high clumping, and low amounts of large openings. An average of 19% of trees were individuals, 34% were in small clumps, 18% in medium clumps, and 30% in large clumps. Mean diameter was also lower than the other groups. All patterns were statistically clustered (Fig 7). Similar to the pink group, a wide range of configurations of clumps and openings were present (Figs. 4 and 7).

3.3 Observed vs. Potential Pattern Envelops

The observed pattern envelope of the combined plots was relatively small compared with the total possible universe of patterns (Fig. 8). The envelope was constrained by density on the right. Plot B18 had the highest density at 196 tph and 30 m^2 /ha. This corresponded to 55% of maximum SDI. A number of other plots had higher basal area SDI levels due to larger mean diameters, but the maximum SDI observed was still only 60%. The bottom of the envelope was constrained by clump size. Low clumping levels associated with inhibited and most random patterns (< 2-4 mean clump size) were not observed at moderate and high density levels (50-200 tph). The highest mean clump size we observed was 12, much lower than what is theoretically possible. Highly clumped patterns where almost all trees are in large clumps were not observed in our pattern envelope. Finally, low density plots with moderate or low levels of clumping did not occur. Below 60 tph, patterns were dominated by individuals and small clumps and did not have any large clumps (< 2.5 mean clump size

4. Discussion

4.1 Underlying Structure of Observed Patterns

An underlying structure to the patterns we observed was evident in the PCA ordinations (Fig. 2), PC axis loadings (Table 1), and the strong relationship between density, clumping, and openings. Levels of clumping and opening size are strongly correlated at a given density level. Low density stands (< 50 tph) in this study have low levels of clumping with mostly individual trees, small clumps, and a high proportion of open space in larger openings (>35-70% F > 9m).

High density stands (> 125 tph) have higher levels of clumping with fewer individual trees, more trees in large clumps, and less space in larger openings (5-20% F > 9m).

We infer from the strength of our model predicting F>9 from tree density and mean clump size (Fig. 3) that knowing two of the three variables is sufficient to describe the pattern type (Fig. 4). The simple fact that as density increases in any point pattern the amount of opening decreases and the potential for clumping increases is partly responsible for this relationship (Fortin and Dale 2005). However, the same density and clump size distribution can result in different opening-size distributions depending on how the clumps are arranged across the plot or how tightly "packed" the clumps are. Tree clumps can be packed closely together, but still far enough apart to be separated from one another. Conversely, tree clumps can be more evenly distributed across the plot, resulting in a lower proportion of open space in larger openings. The pattern envelope we observed did not have extremely "packed" plots or extremely even plots in which the clumps are uniformly spaced (Fig. 8). While there were certainly some outliers and variation in our plots, the patterns we observed had a mid-range of packing. Within this range, the green group had more regularly distributed clumps, whereas the pink and blue groups were more tightly packed (Figs. 4 & 7).

There are three important qualifications to our observed relationship between density, clumping, and openings. First, we observed this relationship between density, clumping, and openings within a specific pattern envelope. It does not appear that the same relationship holds outside of this envelope. While we did not analyze this in depth, our regression model became significantly weaker when we included patterns outside of the envelope. The second qualification is that F>9m does not capture all of the variation in openings. In more open stands, "packed" patterns may have the same F > 9m as patterns where the clumps are better distributed.

Finally, the third qualification is that the relationships we observed are based on 0.5 ha plots. The way in which these relationships scale up to stands (> 4 ha) and implications for restoration prescriptions are explored in a subsequent chapter.

4.2 The Observed Pattern Envelope

The similarity of the PC loadings and dendrograms between the dispersed plots and the sub-plots from the 6ha contiguous suggests that processes structuring these forests did produce emergent patterns. Furthermore, patterns were constrained to a relatively small portion of the total possible range of variation (Fig. 8) We infer from these results, as well as those from other regions, that there is indeed a quantifiable envelope of within-stand pattern and structure characteristic of frequent-fire forests (Larson and Churchill 2012). Our black group of low-density patterns with large, widely spaced individual and small clumps has been observed in many studies across the interior west (Taylor 2004, Youngblood et al. 2004, Stephens and Gill 2005, Abella and Denton 2009). Our pink and blue groups, which consist of moderate to high density patterns with high levels of clumping and commonly with smaller diameters, have also been observed in other studies (White 1985, Arno et al. 1997, Abella and Denton 2009, Fry and Stephens 2010, Scholl and Taylor 2010). Statistically random patterns with a mid-range of density and well distributed small clumps and individuals (our green group) are less common, but also have been reported (Youngblood et al. 2004, North et al. 2007b, Larson et al. 2012).

The pattern types that we did not find within the pattern envelope are equally informative (Fig. 8). No spatially uniform or inhibited patterns occurred at any density level. Some portion of the trees were always found in clumps. At low density, there were no patterns with moderate or high levels of clumping. The maximum clump size we observed at a 6m inter-tree distance was 22 trees, which is in the same range found in other studies (Larson and Churchill 2012). Clumps of 40+ overstory trees have were not observed in the dry Forests that we studied but have been found in sub-alpine parkland systems (Lingua et al. 2009), during meadow invasion (Halpern et al. 2010 p. 2), and in temperate and tropical forests (Parish et al. 1999, Plotkin et al. 2002). Finally, as has been well documented in frequent fire forests (Kaufmann et al. 2007), overall density across a stand is constrained well below maximum carrying capacity.

It is likely that patterns outside of the envelope we quantified did occur historically. Clearly, openings larger than a 100 x 50m rectangle with no or very few trees were present on parts of the landscape (Hessburg et al. 1999a). Likewise, historical reconstructions in similar forest types have found higher densities (Everett et al. 2007), especially when smaller trees are considered. Outlier plots can significantly change the shape of the envelope (Fig. 8). For example, large clumps exceeding 30 trees were likely present but relatively rare. They were most likely to occur after moderate to large scale stand replacement disturbances (Agee 1998). However, the range of density levels we found, both in tph and basal area, are broadly consistent with those found in dry forests across the interior west (Hagmann et al. In review, Munger 1917, Covington and Moore 1994, Everett et al. 2007). Also, we found a similar envelope in both the 6-ha plots and the 32 0.5-ha plots dispersed over 6,500 ha, which occurred on a range of topographic and edaphic settings (Fig. 2E). While the actual envelope is undoubtedly larger, our current understanding of structure and pattern in dry forests with frequent fire regimes suggest it is not dramatically larger.

The size and shape of the envelope we observed is highly dependent on the size of our plots. Our plot size is appropriate to capture pattern at the tree neighborhood scale, which was the focus of this study. As spatial extent increases, the range of the envelope should become smaller as high variation in clump and opening size distributions and density average out (Wu and Loucks 1995). Another effect of small plot size is increased edge effects (Perry et al. 2006). It is evident that in many of our plots, clumps and openings were severed along the plot edges. This is inevitable when patterns are carved into rectangular, square, or hexagonal boundaries. Although we found statistically distinct groups, it is clear that the envelope of pattern is really a continuum of pattern that is bounded. Our plots are imperfect snapshots of that continuum.

Despite these limitations, our results confirm that stands in dry forests are indeed comprised of different combinations of lower-level patch types. In our case, the 6-ha contiguous plots contain different spatial configurations of 0.5-ha pattern types (Table 3). The high variability within and among 0.5 ha patterns across the 6-ha plots makes clear that these forests were highly variable and discontinuous at fine scales. Openings of different shapes and sizes are interspersed through all pattern types. Although variably-sized patches of high stem density and large clumps occurred, they occupied a relatively small portion of the total area and were mostly embedded within lower density, less clumped, and more open patches.

Stephens and Gill (2005) found a similar combination of high variability in structure and discontinuous canopy in contemporary frequent-fire forests in Baja, Mexico. They termed this structural pattern “old forest, spatially distinct multi-strata”. They also showed that the variability across a stand was constrained to a defined set of lower-level patch types. Patterns created by contemporary fires burning in landscapes where fire regimes are being restored are also comprised of different combinations of lower-level patch types (Kane et al. 2013). These forests are highly variable at multiple scales but the variability has a definable envelope that can be explained by hierarchy theory (Urban et al. 1987, Wu 1999).

4.3 Ecological Implications of Pattern

The envelope of pattern that we observed evolved from adaptation to a frequent and variable wildfire regime; a range of insect, pathogenic and abiotic disturbances; and shifting climatic conditions at decadal to century time scales (Agee 1993). The combination of low density relative to carrying capacity, frequent canopy discontinuities, and variation in clump size creates a spatial structure that is resilient to a variety of disturbance types and severities, but also one that is not optimized for any single type of disturbance (Moritz et al. 2005). For example, the highest densities found in the 0.5 plots were right at the threshold of self-thinning and bark beetle mortality for ponderosa pine (Cochran 1994). Large clumps within these plots were likely susceptible to bark beetle mortality but whole stands were not.

Stand-scale patterns (>4 ha) representing different arrangements of these 0.5 ha pattern types are not likely to be fire or beetle proof but they are likely to be resistant to high severity events under most climate scenarios (Stephens et al. 2008) and maintain key structural elements through time (Donato et al. 2011). For example, while the number of old trees and area in openings will vary over time, they will likely remain within a theoretical envelope of upper and lower limits at stand scales. During periods of drought, large clumps are likely to suffer higher mortality and stands may shift towards a higher proportion of patches from the black and green groups. In more mesic periods, substantial growing space exists for density and clump size to increase while still remaining well below maximum carrying capacity.

A key element of the resilience of these patterns is the presence of a gradient of resistance. At one end of the spectrum are patches or corridors of high resistance (e.g. black and green group) that slow or stop the spread of disturbances. At the other end of the gradient are patches of instability (e.g. blue group) that are more susceptible to disturbance and subsequent regeneration of early-seral species (Frelich and Reich 1999a, Odion and Sarr 2007). These "fences and corridors" resist *and* facilitate the percolation of disturbances (sensu Moritz et al. 2011). This gradient and stochastic variation in disturbances leads to high variability in disturbance effects and post-disturbance development pathways, thus replenishing and maintaining a self-organizing mosaic pattern over time (Turner et al. 1999, Peterson 2002, Scholl and Taylor 2010). Results from stand-level simulation studies indicate that greater heterogeneity in pre-disturbance pattern leads to a finer grain size and higher patch type diversity in post-disturbance pattern (Kerby et al. 2007, Parisien et al. 2010, Pimont et al. 2011, Simeoni et al. 2011). However, local shifts in wind or weather patterns can cause disturbances to override these bottom-up constraints (Turner 2010).

The notion that resilient forests require some areas of instability to perpetuate mosaic patterns is relatively new (Moritz et al. 2011). The resistance capacity of widely spaced, large, fire tolerant trees has been heavily emphasized in dry forest restoration (Hessburg and Agee 2003, Agee and Skinner 2005, Peterson et al. 2005). Resistance is only one aspect of resilient and adaptive systems (Walker et al. 2004, Messier and Puettmann 2011). It is in areas of instability where reorganization and adaptation occurs (Gunderson and Holling 2002). These patches also support high levels of biodiversity (Swanson et al. 2011).

4.4 Management implications

Our results support the recommendation that managers charged with restoring conditions found in forests with intact frequent-fire regimes should considered spatial pattern in treatment design (Allen et al. 2002, North et al. 2009, Stephens et al. 2010, Franklin and Johnson 2012). Density, clumping, and openings are highly variable within relatively small areas (e.g. 6 ha).

Breaking the variability down into lower-level patch types, such as the four 0.5 ha pattern groups we found, can help quantify and conceptualize how this variability is arranged across a stand. For example, treatments can be designed to create areas with mostly individual trees and small clumps (black and green groups), but also areas of higher density and clumping (pink and blue groups). Finally, we conclude that patterns created by strict spacing-based treatments, which eliminate most or all the clumps, will be outside of the historical forest envelope (Fig. 8) (Churchill et al. 2013).

Desired levels of open space will be an assured byproduct of restoration if the prescription gets the clump-size distribution within the envelope for a specific density of stand, because of the strong relationship of openings to the parameters of density and clumping. This is important because tree density and clump size are much easier to measure and visualize on the ground than the F-distribution. Clumps can be identified and tallied as one moves through a stand during marking, monitoring, or when quantifying reference conditions (Churchill et al. 2013), whereas a full stem map is necessary to quantify the F-distribution. However, we recommend including guidelines for large openings ($F > 12$ or $F > 15$ m) to ensure variability in density and clump size distributions across a stand (i.e. variability in 0.5 ha pattern groups). This will prevent situations where large clumps are excessively packed into one area of a stand or where the clumps are uniformly distributed throughout the whole stand. Also, we have learned that working with and responding to the variability in pre-treatment conditions, in conjunction with the clump targets, will result in different types of 0.5 ha patterns across a stand (Churchill et al. 2013).

Tables

Table 1: Loadings for 10 explanatory variables for first 3 principal components axes. The proportion of variance explained by each axis is also shown. Clump sizes are the mean clump size for the specified intertree distance. F variables are binned proportions of the F distribution.

	Dispersed Plots			Sub-Plots from 3 Contiguous Plots			Combined Plots		
Variable	PC1	PC2	PC	PC1	PC2	PC3	PC1	PC2	PC3
Clump Size: 4m	0.32	-0.13	-0.10	0.32	-0.26	-0.35	0.32	-0.19	-0.30
Clump Size: 5m	0.35	-0.21	-0.18	0.31	-0.32	-0.26	0.32	-0.27	-0.34
Clump Size: 6m	0.33	-0.27	-0.31	0.32	-0.33	-0.25	0.34	-0.28	-0.26
Clump Size: 7m	0.33	-0.27	-0.28	0.33	-0.22	-0.02	0.33	-0.28	-0.05
F <6m	0.37	0.14	0.17	0.36	0.30	0.16	0.37	0.24	0.19
F 6-9m	0.16	0.71	-0.06	-0.24	0.31	-0.62	-0.02	0.60	-0.45
F 9-12m	-0.23	0.24	-0.75	-0.34	-0.23	-0.36	-0.31	-0.06	-0.60
F 12-15m	-0.33	-0.20	-0.38	-0.27	-0.48	0.01	-0.32	-0.36	-0.19
F 15+ m	-0.31	-0.41	0.22	-0.22	-0.45	0.44	-0.28	-0.43	0.26
Trees per ha	0.37	-0.04	0.02	0.40	0.05	0.12	0.39	0.01	0.15
Prop Variance	0.69	0.15	0.09	0.60	0.23	0.10	0.62	0.21	0.09
Cumul. Prop.	0.69	0.84	0.93	0.60	0.83	0.93	0.62	0.83	0.92

Table 2: Key metrics for 4 pattern groups. Open space metrics are binned proportions of the F distribution. A value of 0.29 for F < 6 means that 29% of the plot area is less than 6m away from the nearest tree. The clump size distribution is based on an inter-tree distance of 6m and is binned into 4 clump sizes: individual trees, small clumps (2-4 trees), medium clumps (5-9 trees), and large clumps (10-20+ trees). Summary metrics include trees per hectare, the mean clump size from 4,5,6, and 7 m inter tree distances, and F > 9m (the proportion of plot area greater than 9m from the nearest tree).

	Open Space Distribution					Clump Size Distribution @ 6m				Summary Metrics		
Group	F <6	F 6-9	F 9-12	F 12-15	F > 15	Indivi-duals	Small Clumps	Med. Clumps	Large Clumps	Mean Clmp Sz	F > 9	TPH
Black	0.29	0.22	0.18	0.13	0.18	0.49	0.46	0.05	0.00	1.88	0.49	40
Green	0.49	0.26	0.14	0.06	0.04	0.41	0.52	0.07	0.00	2.05	0.24	73
Pink	0.50	0.24	0.14	0.06	0.05	0.29	0.42	0.23	0.06	3.46	0.25	88
Blue	0.55	0.22	0.12	0.06	0.05	0.19	0.34	0.18	0.30	6.66	0.23	119

Table 3: Numbers of 0.5 ha plots by pattern group for 3 x 6ha contiguous plots and plant association groups from dispersed plots. Colors correspond to pattern groups in later analyses.

	Pattern Group			
	Black	Green	Pink	Blue
Contiguous Plots All	3	11	5	11
Liberty	0	5	3	2
Nile	1	3	1	5
Oak	2	3	1	4
Dispersed Plots All	15	1	11	5
PIPO High	7	0	2	1
PSME High	1	1	1	1
PSME Moderate	4	0	4	1
PSME Low	3	2	4	3
Combined Plots	18	12	16	16

Figures

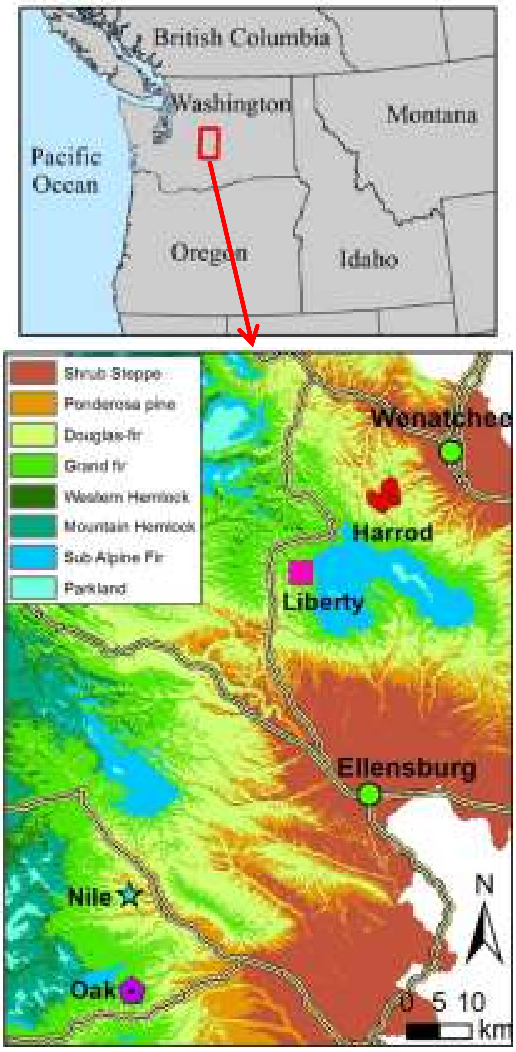


Fig. 1: Map showing locations of study sites and plant association groups from Okanagon Wenatchee National Forest plant association data. White space is area not covered by the data source. The 32 Harrod plots are dispersed over 6,500 acres. The Liberty, Nile, and Oak sites are 6ha contiguous plots. The size of the symbols are not proportionate to actual size.

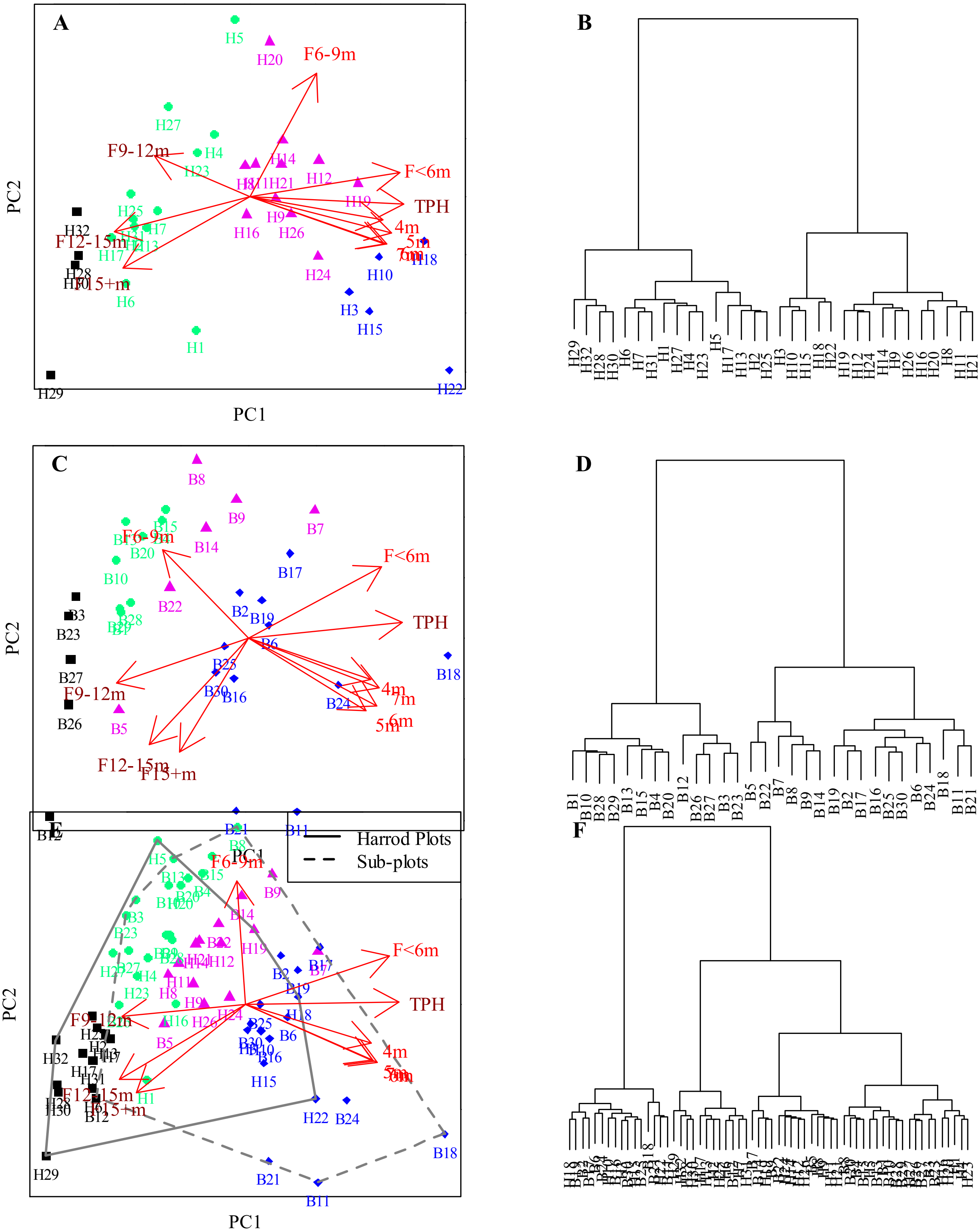

A
B
C
D
E
F
PC1
PC2
F6-9m
F<6m
TPH
F9-12m
F12-15m
F15+m
4m
5m
6m
7m
Harrod Plots
Sub-plots

Fig. 2: PCA ordinations and hierarchical cluster dendrograms of 32 x 0.5 ha dispersed plots (A & B), 30 x 0.5 ha sub-plots from 3 contiguous plots (C & D), and 62 combined plots (E & F). Y axes on dendrograms (B, D, & F) are total height, which corresponds to the amount of variance between plots explained by the clustering. Variables used in the PCA include mean clump size at 4,5,6, and 7 m; the proportion of the plot area <6m, 6-9m, 9-12m, 12-15m, and 15+m from the nearest tree (F distribution); and trees per hectare (TPH). Colored groups were created using hierarchical cluster analysis with the same input data. Overall groupings in all three sets of plots were significant ($p<0.001$). In the combined set (E & F), all groups were different from every other group ($p<0.001$). PC 1 separated higher density plots with more clumping and smaller openings on the right with low density, more open, and less clumped plots on the left. PC 2 explained an additional 15-21% of the variance. Plots with more open space and higher levels of clumping, relative to their density level, were located in lower half of the axis. Patterns with smaller clumps and small to medium F-distances, relative to their density level, are on the top half.

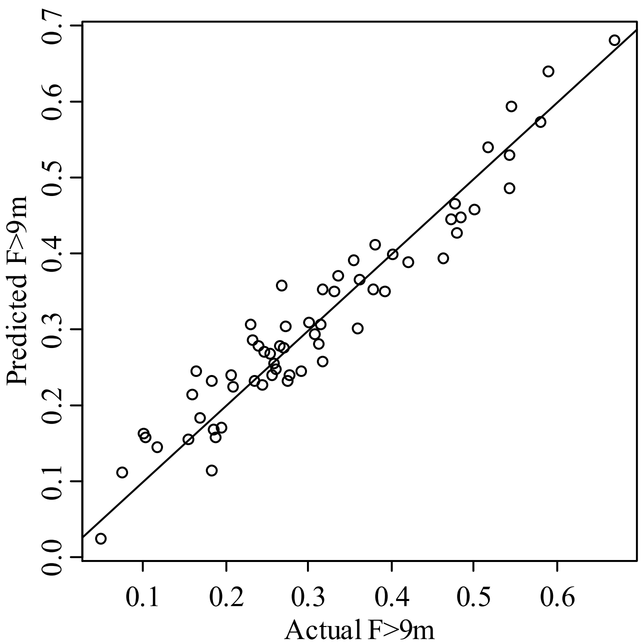


Figure 3. Scatter plot of predicted F > 9m values vs. actual values. Values were predicted from tph and mean clump size using the following model: *y = 1.841 + 0.144 x log(Mean Cl Sz) - 0.396 x log(TPH);* $r^2 = .92$. The line represents a perfect fit where residuals equal 0.

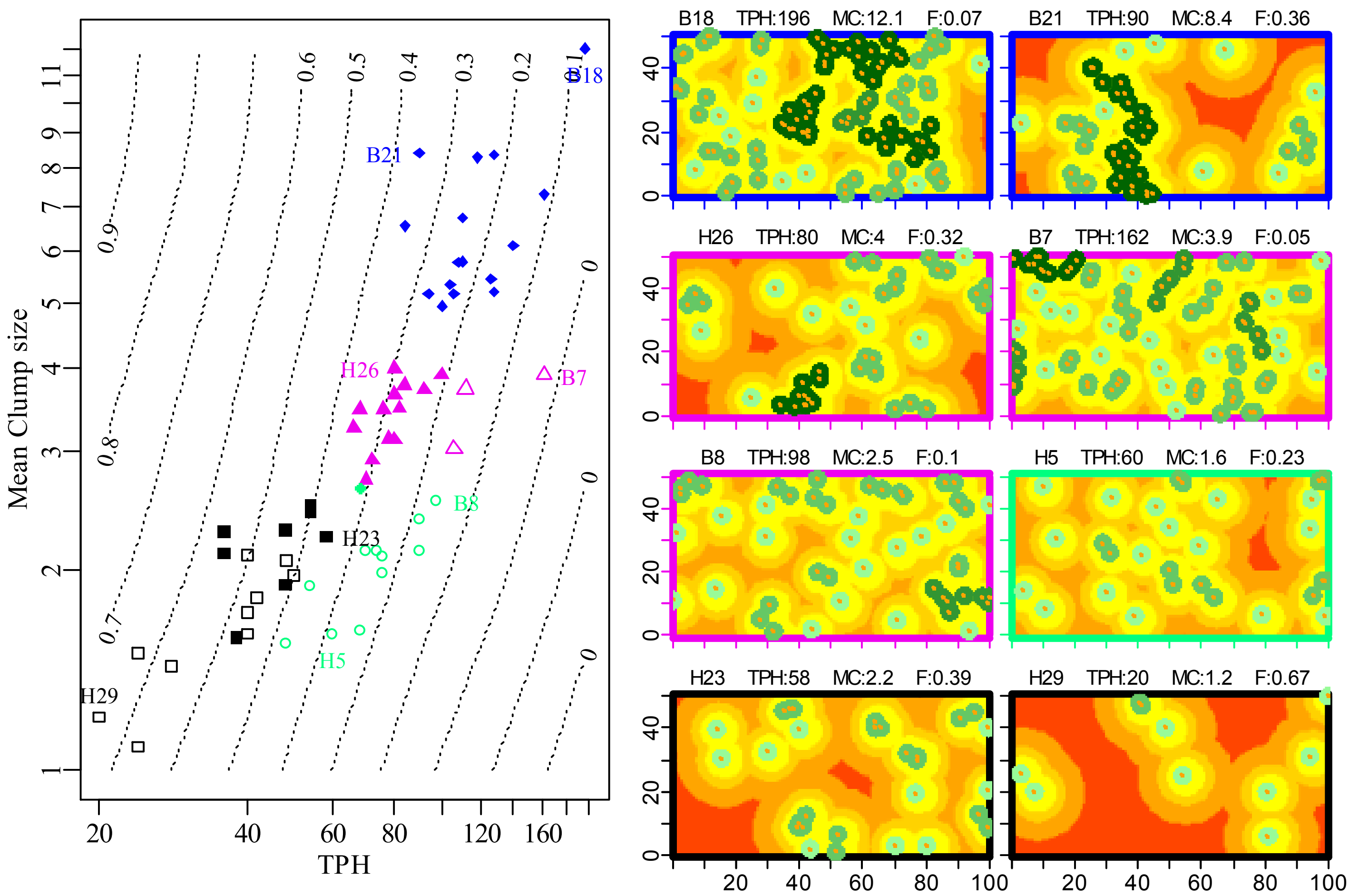


Fig. 4. Scatter plot of 62 x 0.5 ha plots from dispersed and contiguous sets with logarithmic axes. Contour lines are F > 9m values (the proportion of plot area greater than 9m away from a tree). Lines come from a smoothed surface created from the model in Fig 3. Colors of plots indicate pattern group. Closed symbols are statistically clustered patterns from 1-12m (p<0.05), and open symbols are statistically random patterns. Statistical clustering was determine using a GoF test with the pair correlation function (Loosmore and Ford 2006). Numbered plots show edges of the pattern envelope. The corresponding stem maps include values for TPH, mean clump size, and F > 9. Green colors around points indicate tree crowns. Darker green colors show progressively larger clumps. Background surface shows distances to the nearest tree (F distance): yellow (<9m), light orange (9-12m), dark orange (12-15m), and red (15m+).

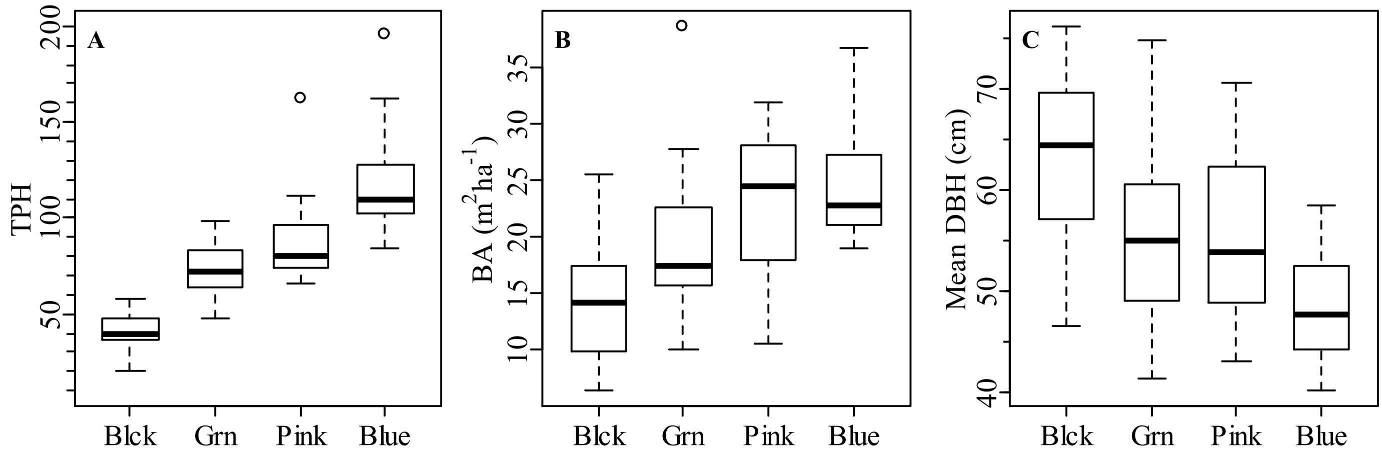


Fig. 5: Boxplots of trees per ha, basal area per ha, and mean dbh of the 4 pattern groups. Black lines are median values, boxes represent 50% of distribution, and whiskers capture 95% of the distribution.

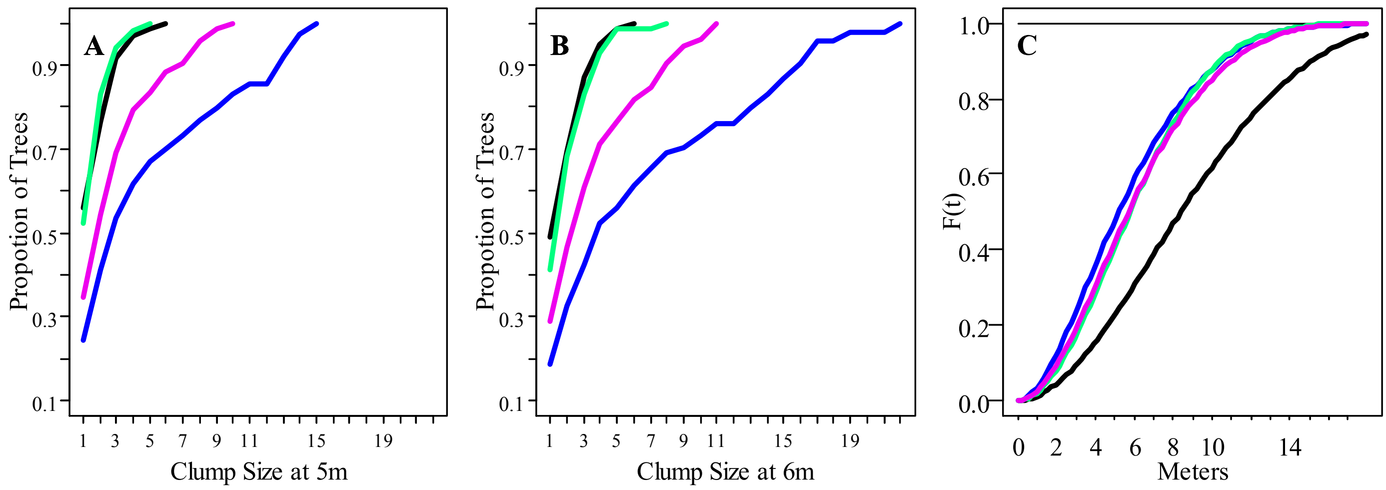


Fig. 6. Panels A and B display average clump size distributions of 4 pattern groups at 5 and 6m inter-tree distances. Clump size is in number of trees. At 5 and 6m, the green and black groups are not different (p >0.05), while the pink and blue lines are different from all other groups (p <0.05). Panel C displays the average F distribution (Empty Space Distribution) of the 4 pattern groups. The Black group is different from the other 3 (p <0.05). A non-parametric permutation test for replicated point patterns (Dale et al. 1991) was used to test for differences in distributions.

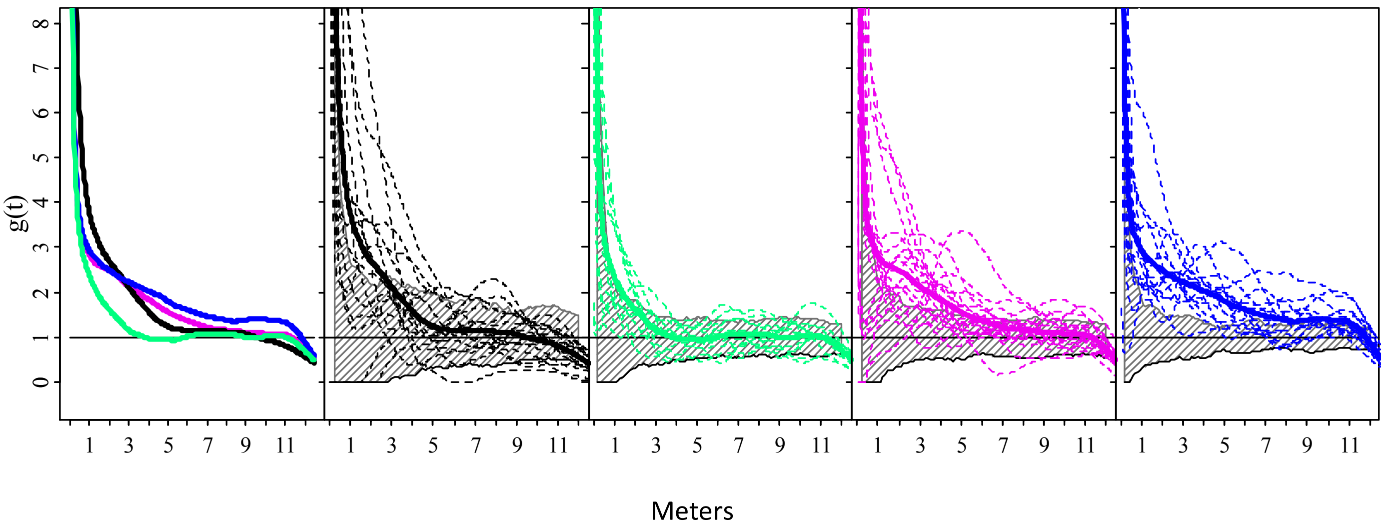


Fig. 7: Pair correlation function for the four pattern groups. Bold lines area means of each group and dashed lines are individual plots. Hashed areas are 95th percentile envelopes generated from 100 simulated completely spatially random (CSR) patterns using the median density of the pattern group. Portions of lines that are above CSR envelopes indicate distances at which patterns are clustered, while portion below envelopes indicate inhibition or uniform patterns.

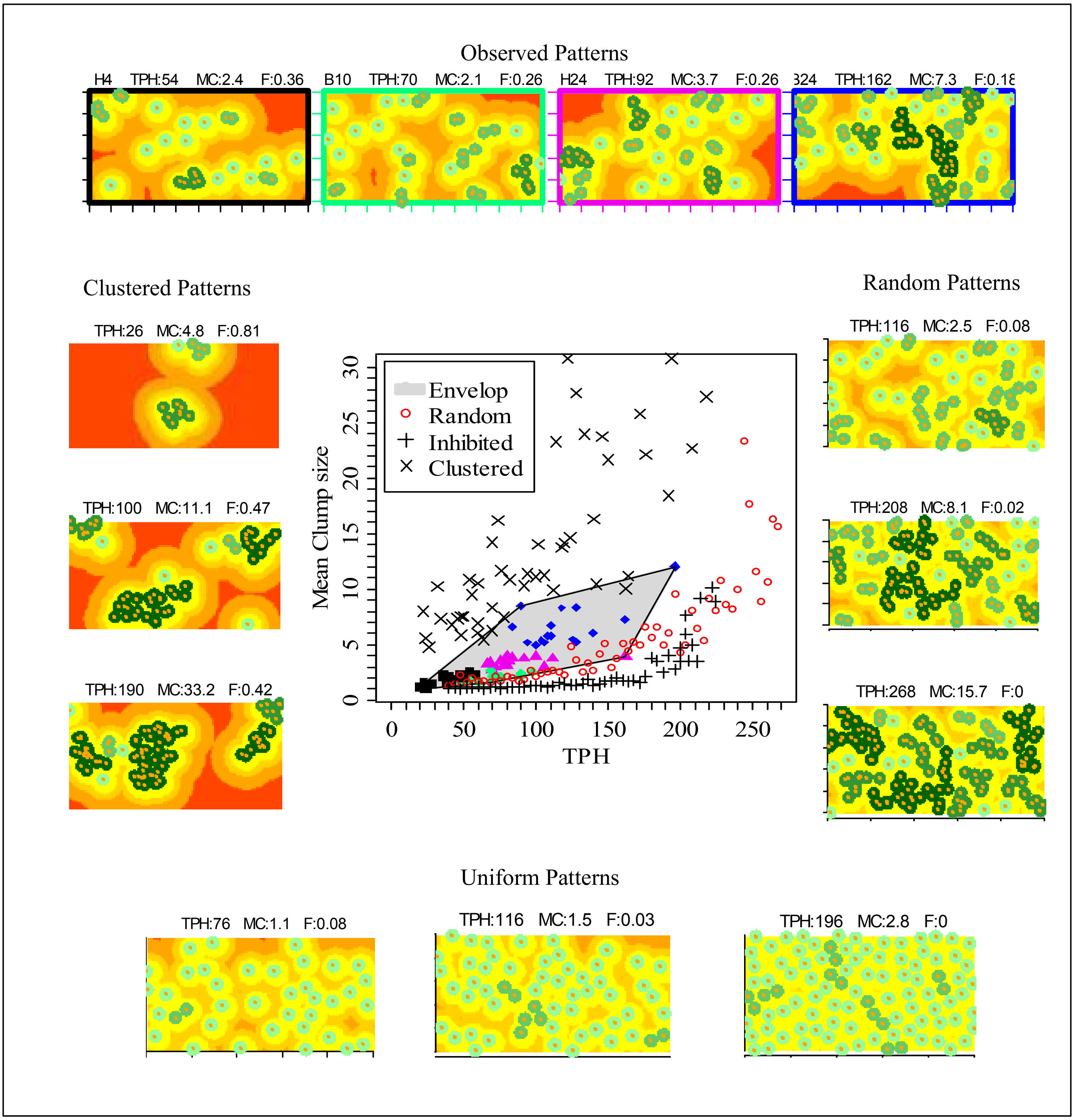
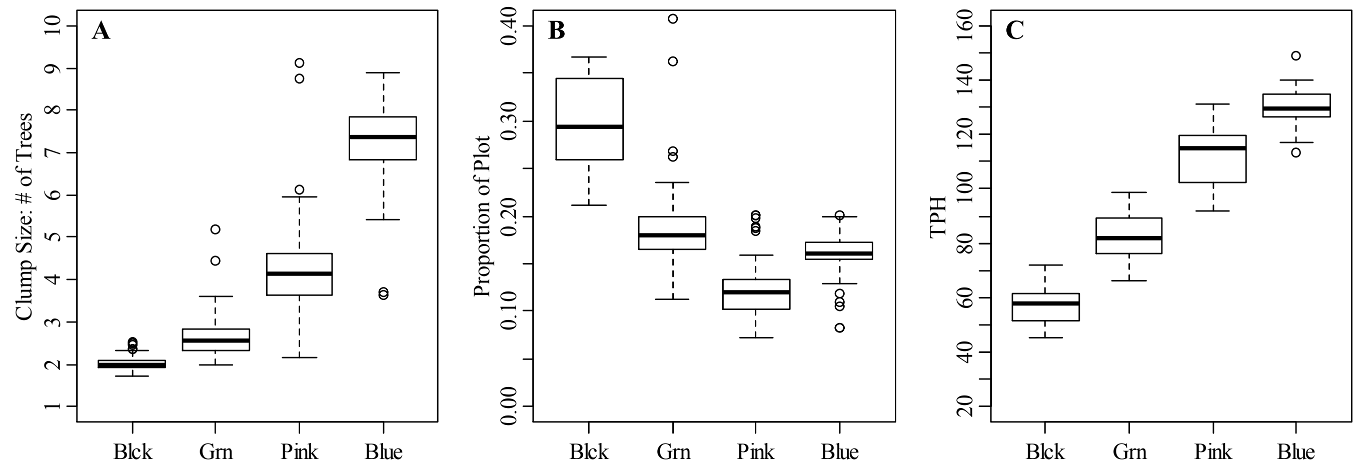
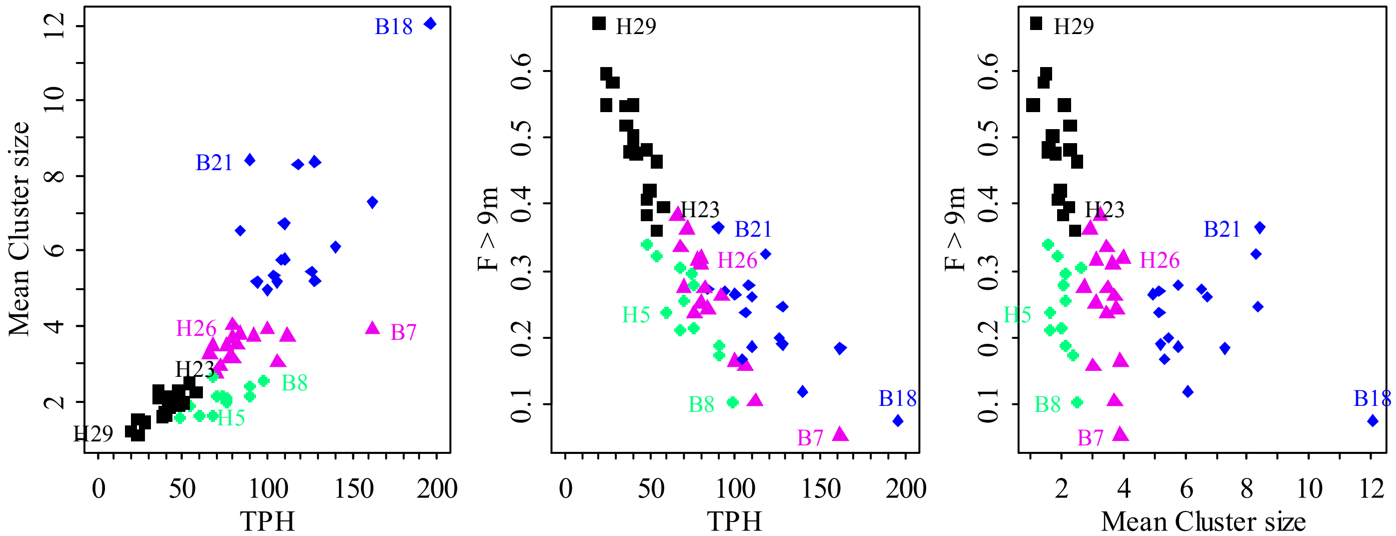


Fig. 8: Potential vs. observed pattern envelopes for 0.5 ha plots from both dispersed and contiguous datasets. Random, inhibited, and clustered points are simulated patterns intended to demonstrate patterns outside of the observed envelope. Colors for solid symbols in gray shaded hull correspond to 4 pattern groups.

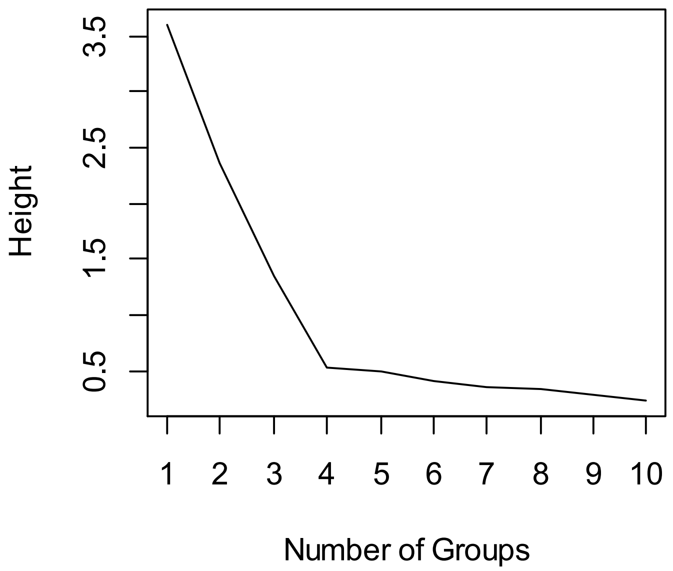
Appendices



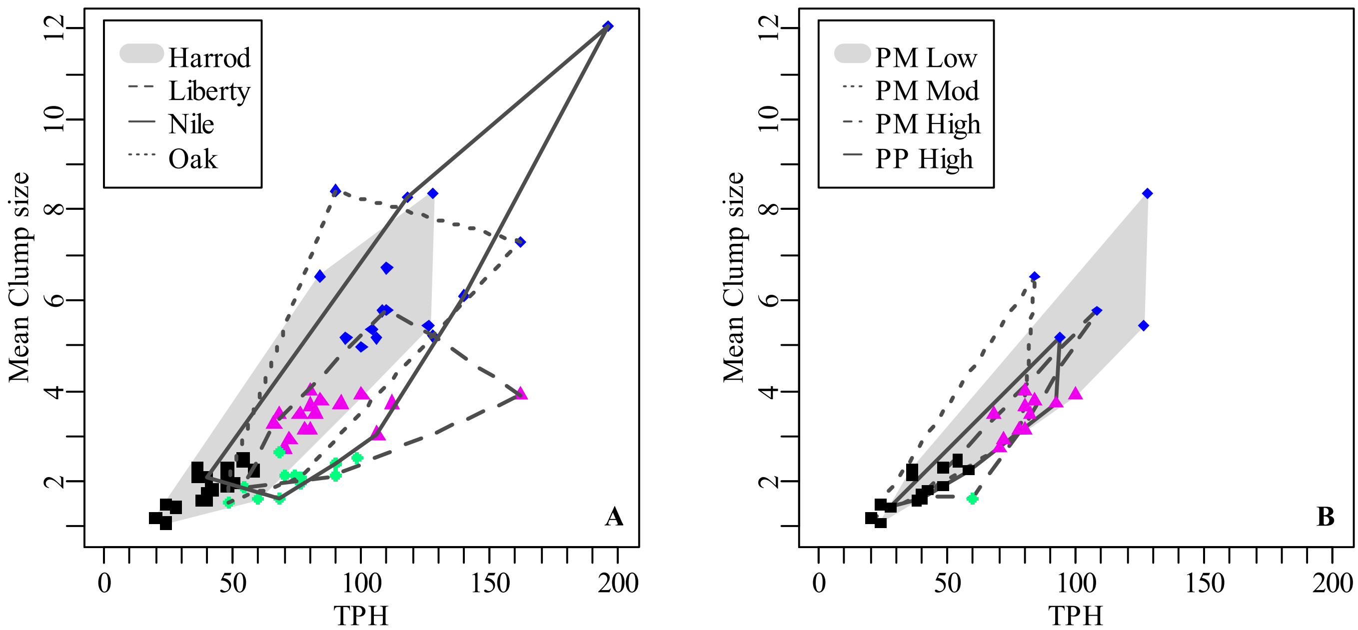
A1.1. Distribution of group means for 50 draws of sub-plot locations on 3 big plots. Panel A is mean clump size, panel B is openings quantified by the proportion of the area in the plot greater than 9m from a tree, and panel C is density in trees per hectare. For each draw, ten 100m x 50m sub-plots were taken from each big plot on a fixed 200x250 grid. The lower left corner of the fixed grid was randomized for each draw.



A2.2: Scatter plots of simplified pattern metrics. Colors correspond to 4 pattern groups.

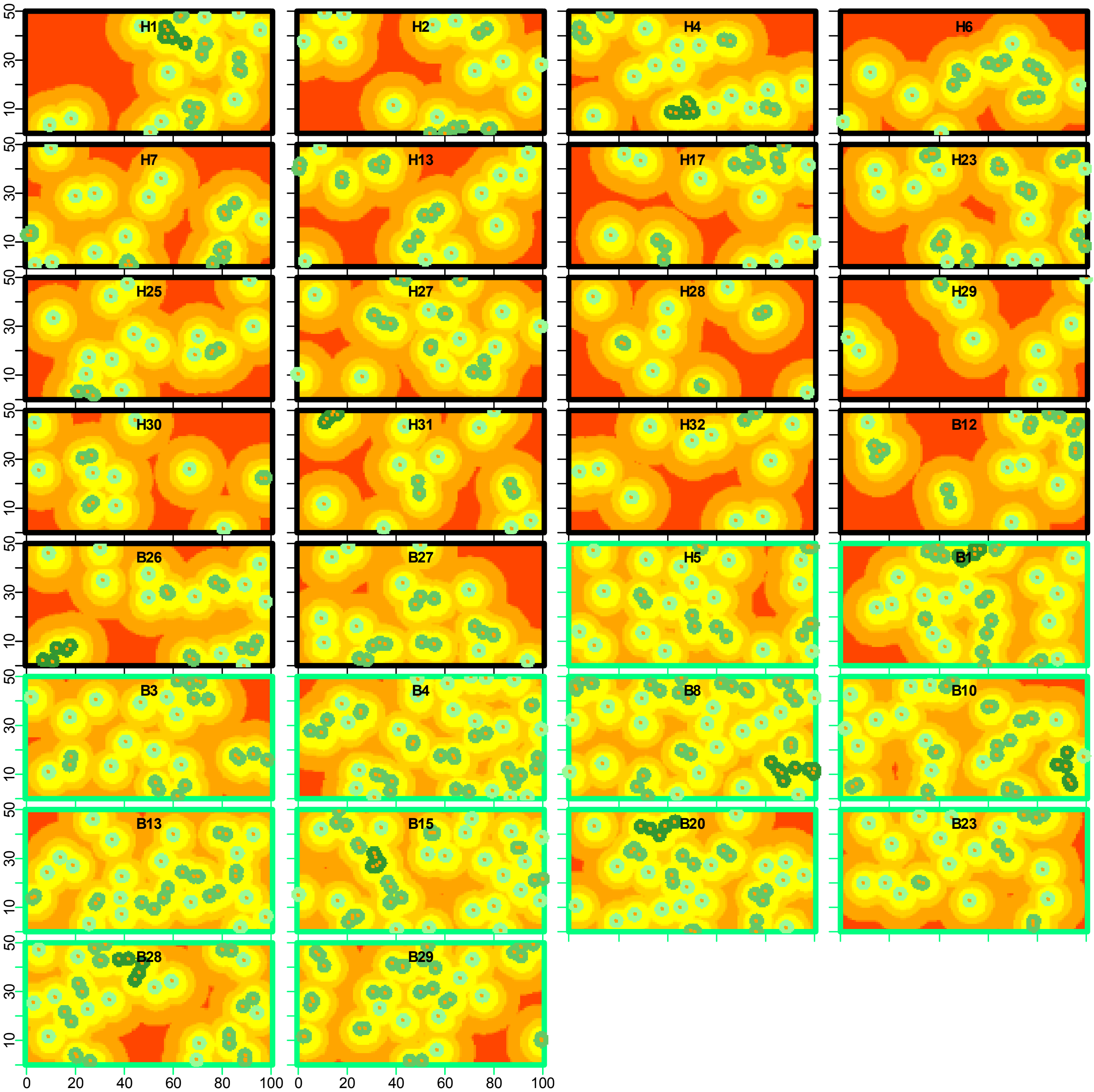


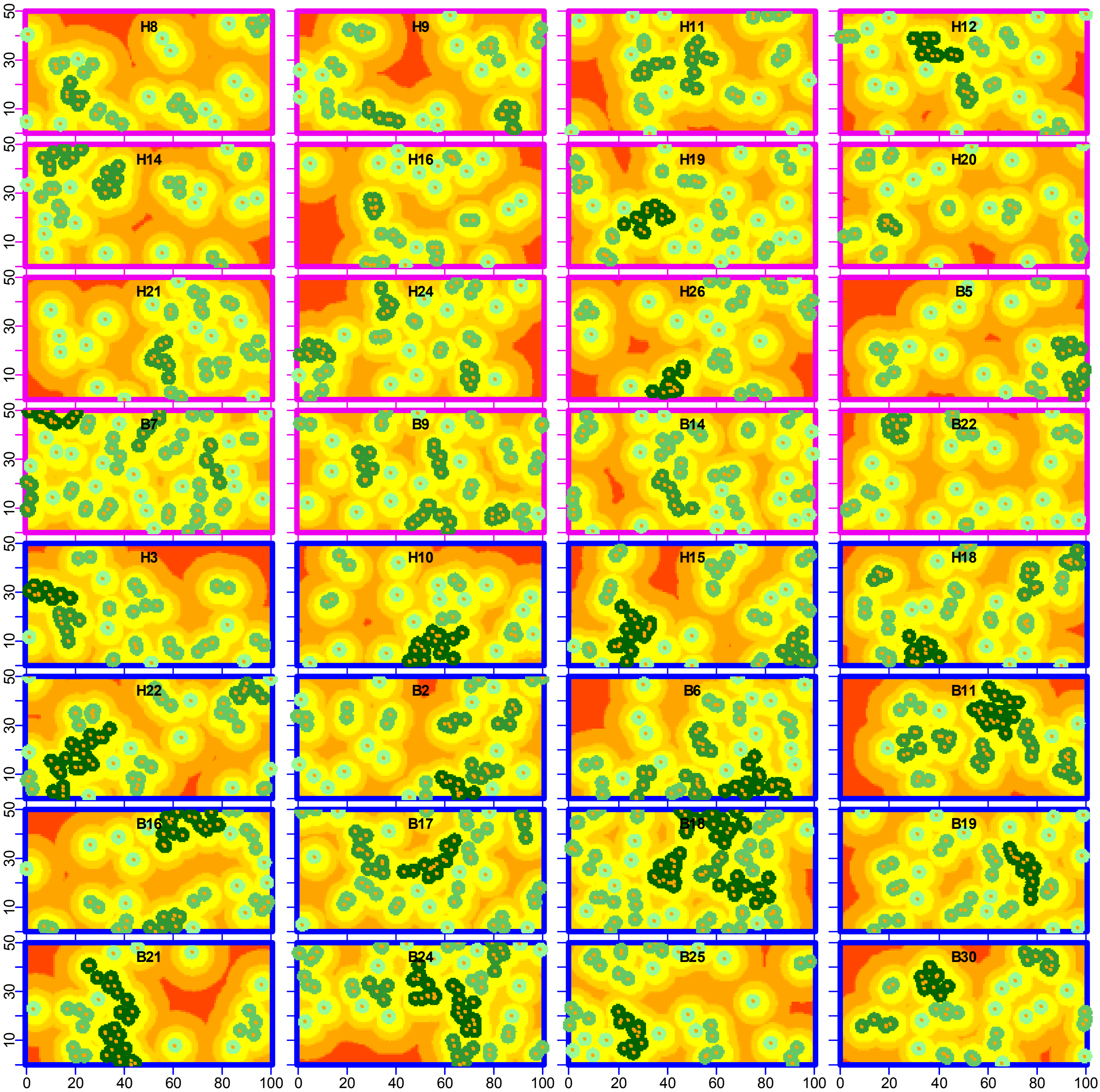
A1.3: Scree plot from hierarchical cluster analysis of combined 62 plots.



A1.4: Hulls showing pattern envelopes. Panel A compares pattern envelopes for 32 dispersed plots (Harrod), and 10 sub-plots on each of the three 6 ha contiguous plots. Plot symbols and colors correspond to 4 pattern groups. Panel B compares envelopes of 4 plant association groups in the Harrod dataset. Plant association groupings are: PIPO High: *Pinus ponderosa/Purshia tridentata/Agropyron spicatum;* PSME High *Pseudotsuga menziesii/Purshia-tridentata/Agropyron spicatum;* PSME Moderate: *P. menziesii/Symphoricarpos albus/Calamagrostis rubescens,* and *P.menziesii/Calamagrostis rubescens*, PSME Low: *P. menziesii/Symphoricarpos oreophilus, P.menziesii/Spirea-betulifolia/ Calamagrostis rubescens,* and *P.menziesii/Carex geyeri.*

A1.5: The following 2 pages show stem maps of all 62 plots, organized by pattern group. Within groups, plots are ordered by plot number.




H8
H9
H11
H12
H14
H16
H19
H20
H21
H24
H26
B5
B7
B9
B14
B22
H3
H10
H15
H18
H22
B2
B6
B11
B16
B17
B18
B19
B21
B24
B25
B30
50
30
10
0
20
40
60
80
100

A1.6: Discussion of spatial pattern metrics and the Pair Correlation Function

On a general level, our results show that metrics quantifying density, tree clumps, and open space effectively characterized and differentiated the range and distribution of the historical pattern envelope. Our spatial metrics performed better at distinguishing different types of tree patterns than the pair correlation function, g(*t*) (Figs. 5-7). This is primarily because our metrics were specifically chosen to quantify tree clumping and openings in dry Forests, whereas g(*t*) is a general point pattern statistic used in a wide range of disciplines (Stoyan and Stoyan 1994, Wiegand and Moloney 2004, Illian et al. 2008). The g(*t*) quantifies statistical clustering (departure from CSR) across a range of inter-tree distances (Diggle 2003). Our clump size distribution, on the other hand, focuses on the distances (e.g. 6m) at which trees form continuous patches of canopy (White 1985). It is strongly related to statistical clustering up to the maximum clump distance but does not quantify statistical clustering at longer distances. Beyond the maximum clump distance, we rely on the F-distribution to quantify clustering or how packed the clumps are. In short, the g(*t*) curve quantifies statistical clustering at both short, medium, and longer distances, while our methods separates out parts of the distribution into different metrics that are directly related to ecologically important structures: individuals, tree clumps, and openings. Another major difference is the direct inclusion of density in our metrics. The g(*t*) function is normalized by density; hence patterns with very different densities can display similar g(*t*) curves (Fortin and Dale, 2005).

The g(*t*) function, and its progenitors Ripley's K(*t*) and L(*t*) (Ripley 1988), have been extensively used to quantify tree patterns in multiple forest types (Kenkel 1988, Moeur 1993, Camarero et al. 2000, Condit et al. 2000, Larson and Churchill 2012). They are useful tools for exploratory analyses of point patterns and for testing against a null model, such as CSR or other models based on clumping parameters (Sánchez Meador et al. 2009) or regeneration patterns (Wiegand et al. 2007b). They are also powerful tools to test bivariate relationships among different size classes, species, or live and dead trees (Boyden et al. 2005, Getzin et al. 2008, Larson et al. 2012). Used alone, however, the g(*t*) offers only a partial description of pattern, as does reliance on any single metric (Dale et al. 2002, Perry et al. 2006). We do not suggest abandoning the g(*t*) function; in fact, we rely on it heavily in our own research (Larson et al. 2012, e.g. Churchill et al. 2013). However, we show that by adding our metrics, variation in pattern in dry forests can be quantified in terms of ecologically meaningful elements: individuals, clumps and openings (Fortin and Dale 2005, Perry et al. 2006). This helps improve our understanding of how these forest spatial mosaics were structured, how they functioned, and how to restore them.

Chapter 2: Stands as Patch Hierarchies

Abstract

Concepts of scale and patch hierarchy are increasingly being used to understand and manage forest ecosystems. Stands are being viewed as the patches that make up watersheds and also contain smaller-scale patches of tree clumps and openings. In frequent-fire forests of Western North America, restoring these mosaic patterns has become a focus of ongoing management efforts. We reconstructed and stem-mapped pre-settlement era conditions on 3 x 6 ha plots in the Eastern Cascades to investigate whether fine-scale, gap phase dynamics dominated or whether there was also evidence of larger scale processes creating spatially dependent aggregations tree clumps and openings. We characterized variation in stand level structure by sub-dividing plots into 30m pixels and then: (1) quantified spatial pattern in terms of widely spaced individual tree, clumps, and openings in each pixel; (2) combined pattern metrics with diameter distributions in hierarchical cluster analysis to group 30m pixels into 4 patch types; (3) tested for spatial dependence of the patch types using join count statistics and Moran-I, and Ripley's L. Contiguous sub-patches (>2ha) of low density forest (0-80 tph) dominated the plots with 40% of trees as individuals and 45-50% in small clumps. However, 7 -16% of the plot area consisted of dense areas with clumps of 10-19 trees that were often aggregated into sub-patches up to 0.5 ha in size. Patterns of tree clumps and openings were spatially dependent on all three plots. We inferred that the underlying heterogeneity in disturbance regime and biophysical conditions across the plots played a role in structuring pattern. Silvicultural treatments intended to restore resilient conditions should consider leaving denser sub-patches and larger openings (>0.4ha), in addition to providing for fine-scale variability in the form of isolated trees and clumps of various sizes.

1. Introduction

Managing for resilience, complexity, and heterogeneity at multiple scales has become a major objective in forest management in many parts of the world (Franklin et al. 2007, Messier and Puettmann 2011, Gustafsson et al. 2012, Kuuluvainen and Grenfell 2012). Management in this direction has required incorporating concepts of scale and patch hierarchy from landscape ecology into forestry (Kotliar and Wiens 1990, Peterson and Parker 1998, Spies and Turner 1999, Wu 1999, Hessburg et al. 2004). The traditional view of stands as the basic organizational unit used in conceptualizing and managing forests is being replaced with a view of stands as patches embedded in a landscape hierarchy (Lertzman and Fall 1998, Puettmann et al. 2009). Stands are the patches that make up watersheds but also contain smaller-scale sub-patches of tree clumps and openings (Urban et al. 1987).

This transition in perspective from stand-centric silviculture to management for complexity at multiple spatial scales is well underway in ponderosa pine and dry mixed-conifer forests of interior western North America (*hereinafter* “dry forests”) (Allen et al. 2002, North et al. 2009, Stephens et al. 2010, Franklin and Johnson 2012). A patch hierarchy with four basic levels has been defined that embeds stands within a multi-scale framework (Hessburg et al. 2004, 2013). At the highest level are regional landscapes or ecological sub-regions that are differentiated by differences in climate, geomorphology, and vegetation types (Hessburg et al. 2000). The patterns and variability within regions come from local landscapes, typically 5th or 6th field watersheds (Seaber et al. 1987), no two of which are the same. Watersheds in turn are mosaics of successional patches or stands (O’Hara et al. 1996). Stands are 4 – 1000+ ha patches of vegetation with similar composition, structure, and topo-edaphic conditions that contain variable patterns of tree neighborhoods. Tree neighborhoods are the lowest level of the hierarchy and consist of sub-patches within stands that have similar arrangements of tree spatial patterns and growing environments (Frelich et al. 2002, Boyden et al. 2012)

At stand and tree neighborhood levels, pre-settlement era and contemporary dry forests with intact fire regimes have been found to be complex, uneven-aged mosaics of widely spaced individual trees, clumps of 2-20+ trees, and openings (Larson and Churchill 2012; references within). Methods to quantify tree neighborhood patterns in terms of individuals, clumps, and openings were developed in chapter 1 and by others (Abella and Denton 2009, Sánchez Meador et al. 2011). A defined envelope of tree neighborhood patterns was found. This envelope ranged from (1) low density patterns with few clumps and high opening levels, to (2) patterns with a mid-range of density and varying levels of clumping, and (3) high density, highly clumped patterns with few openings.

How these patterns of tree clumps and openings are organized across stands is not known, however. Hierarchy theory and the hierarchical patch dynamic paradigm (HPDP) hold that the characteristic scale and pattern of the biota, biophysical conditions, and disturbance regimes create a predictable patch structure at each level (Kotliar and Wiens 1990, Levin 1992, Wu and Loucks 1995). Stand level pattern is shaped by fine-scale interactions between vegetation and frequent, low-severity disturbances (Kaufmann et al. 2007). Meso-scale variation in topography, soil productivity, micro-climate, and species composition also play an important role directly and indirectly by creating greater variability in fire behavior (Agee 1993, Hessburg et al. 2007). Broad scale patterns of biota, geology, geomorphic processes, and climate provide top-down constraints, occasionally overriding bottom up controls and resetting stand-level patterns (Shinneman and Baker 1997, Turner 2010). Patch configurations within stands shift through time and exhibit non-equilibrium behavior (Moritz et al. 2011). This is due to the presence of both stationary and non-stationary properties of disturbance regimes, soils, biotic interactions, and climate.

In regions of the west with low topographic and edaphic complexity (e.g. the pumice zone of Central Oregon), however, frequent, low-severity fire is thought to have been such a dominant force in structuring vegetation that it largely overrode topo-edaphic heterogeneity. These forests are thought to be have been low contrast, fine scale mosaics maintained by a quasi-equilibrium system of gap-phase replacement (Weaver 1943, Cooper 1960, Agee 2003). Clustering of regeneration, species, and mortality produced high variability of small patches (0.01-0.4 ha) (Agee 1998, Larson and Churchill 2012), but the spatial arrangement of these patches was random and no spatial aggregation or dependence of clumps and openings existed across stands (Agee 1998). Tree patterns were stationary at stand scales in the sense that the processes creating pattern and the probability for a large clump or opening to occur were the same across a stand.

In other regions with greater variation in topography and soil productivity (e.g. the northern Rocky Mountains), a broader range of low- to mixed-severity disturbance severities created more variable patch size distributions over time and space (Schoennagel et al. 2004, Hessburg et al. 2007, Klenner et al. 2008, Perry et al. 2011). Pattern was more strongly related to topo-edaphic variation, and thus spatial dependence and aggregation of clumps and openings existed within stands (e.g. >0.4 ha sub-patches of large clumps). Pattern and structure were not stationary or at equilibrium (Turner et al. 1993, Shinneman and Baker 1997).

In the eastern Cascade Range of Washington, the full continuum of gap-phase to mixed-severity dry forests is thought have existed prior to fire suppression (Agee 1998, 2003, Hessburg et al. 2007). These observations were based on numerical simulations, field observations, and empirical reconstructions of pre-management era vegetation conditions and fire severity. However, Harrod et al. (1999) conducted the only spatially explicit reconstruction of pre-settlement dry forest conditions available in eastern Washington and found evidence of gap phase and larger scale influences. Everett et al. (2007) found higher densities in non-spatial plots on similar plant associations and concluded that their sites were a complex mix of structures that varied through time. Hessburg et al. (2007) used aerial photographs from the early 20th century to reconstruct fire severity patch sizes in this region and found that the majority of dry forests were affected by both low and mixed-severity fires. Hence, the extent to which the gap-phase development pathway was dominant in dry forests of the Washington Cascades is not clear.

There is an urgent need to better understand how structure and pattern varied at stand scales considering the large scale of landscape restoration treatments being undertaken (CFLRP 2012, Ager et al. 2013). Managers increasing understand the concept of restoring mosaics of individual trees, tree clumps, and openings (Knapp et al. 2012, Churchill et al. 2013) but need a stronger ecological basis for determining how and when to vary their densities and configurations within stands and across project areas. For example, managers often debate the number and size of patches that should be allowed or encouraged to torch during prescribed fires in order to create snag patches and future openings (North et al. 2009, Powell 2012). Similarly, the proportion of a stand to leave in untreated, dense "skips" in mechanical treatments is often a major operational question (Gaines et al. 2010, North and Sherlock 2012). Almost all reconstruction studies in the interior west have used plots that are too small (<= 1ha) to address these questions. Better understanding of the relationships between pattern, structure, and biophysical variables is also necessary to appropriately use historical reference conditions to guide management as the climate changes (Gärnter et al. 2008).

In this paper, we reconstruct pre-settlement era forest conditions on three stand-scale plots (~6 ha) in the eastern Washington Cascade Range. Our plots are located on sites which historically experienced frequent fire and where gap-phase development was likely. Our objectives in this paper are to: (1) expand the number and size of reconstruction plots in the eastern Washington Cascades; (2) use the conceptual framework of HPDP to quantify stand-level structure and pattern in terms of lower-level patch types; and (3) investigate whether the spatial distribution of structure is consistent with patterns expected under the gap-phase model or whether evidence of larger-scale processes is also present. Our hypotheses are that (1) lower-level patch types with distinct diameter distributions and spatial patterns exist in these stands and (2) no spatial dependence exists between patch types.

2. Methods

2.1 Study Area

This study was conducted at three 5.9-6.7 ha plots on the east slope of Cascade Range in the Yakima River Basin in Washington State (Fig. 1). Sites were subjectively selected to be samples of pre-settlement, old growth, mixed-conifer dry forest that were dominated by frequent, low severity fire. Sites were limited to Douglas-fir (*Pseudotsuga menziesii* var. *glauca*) plant associations (Lillybridge et al. 1995) as drier associations are relatively uncommon in the eastern Cascades (Franklin et al. 2008). The Nile and Liberty plots are in areas where pre-settlement fire-return intervals of 6-7 years (Weibull median probability interval) were reported in fire history studies (Hessl et al. 2004)., Unlogged sites were not available due to pervasive 20th century logging.

Current tree species composition on all three plots consists of ponderosa pine (*Pinus ponderosa*) and interior Douglas-fir with minor components of western larch (Larix occidentalis) and grand-fir (*Abies grandis).* Dominant shrub species include common snowberry *(Symphoricarpos albus)*, shiny-leaf spirea (*Spirea betulifolia)*, and pinegrass (*Calamagrostis rubescens)* and lesser amounts of bitterbrush (*Purshia* *tridentate),* boxwood *(Pachistima* myrsinites), ocean-spray (Holodiscus discolor), and species of rose. The 100 year site index ranges from 25-30m (Barret 1978). Modeled annual precipitation averages between 650-950 mm and occurs mostly as snow between November and April; mean January and July temperatures range from -1.9° to -3.0°C and 14.6°-16.6°C (ClimateWNA 2012). Historical records indicate that grazing occurred from the 1880's until the early 1900's (USFS 1995, 1998, 1998). Fire suppression became effective in the 1930s and has continued to the present. The sites were selectively harvested in the 1930's. Second selective harvests occurred on the Liberty and Oak plots in the early 1970's.

The Liberty plot is located in the Swauk Creek sub-watershed, approximately 50 km NE of the town of Cle Elum. The plot is 1,050-1125 m in elevation, has a SW aspect, and slopes of 20-45%. Soils are deep, well drained and derived from siltstone, sandstone, and volcanic ash (NRCS 2010). The Nile plot is located 25 km NW of Naches in the Dry Orr Creek sub-watershed. It has a NE aspect, slopes ranging from 40-60%, and an elevation of 950 – 1050 m. Soils are derived from conglomerate and tuffs with a mantle of volcanic ash (NRCS 2009). The Oakplot is 20 km W of Naches in the Tieton River sub-watershed, has slopes of 10-30% , and an elevation range of 1275-1300 m. Soils are colluvium and residuum from basalt mixed with volcanic ash and loess (NRCS 2009).

2.2 Reconstructing Structure

The reconstruction protocol of Harrod et al. (1999) was followed to allow for comparison between studies. The approximate year of early selection harvests (1935) was used as the historical reconstruction date, but only trees that established before 1860 were included. This limited our reconstruction to trees that were likely in the upper or mid canopy in 1935, which is similar Youngblood;s (2004) methods in contemporary forests. Densities of trees less than 30cm dbh are underdetermined. Reconstructing diameters to 1860 or 1880 was problematic for several reasons. The maximum lifespan of most ponderosa pine and Douglas-fir logs and snags in these systems is less than 80 and 100 years respectively (Everett et al. 1999). Thus trees that died before 1930 or 1910 are unlikely to have current representation; also, reconstructing 1860 or 1880 diameters would also require counting rings on 1930 era stumps or "growing stumps" back in time using growth rates of current live trees, which were generally in smaller size classes. The 1860 cutoff was chosen to limit inclusion of trees that established after post-settlement fire exclusion and grazing by domestic livestock commenced (Hessburg and Agee 2003) and to allow comparisons with Harrod et al. (1999). Everett et al. (2007) found that tree density began increasing rapidly around 1870 on similar sites in the Washington Cascades.

At each site, all historical (>150 years in age) live trees, stumps, snags, and logs were stem mapped using both line transects and a total station (Nathanson et al. 2006). Bark and crown characteristics were used to determine which live trees were historical using guidelines provided by Van Pelt (2008). All questionable trees were cored and cores counted after drying, mounting, and sanding. Equations from Everett et al. (2007) were used to estimate establishment year of snags and logs based on diameter and decay class (Cline et al. 1980). Harvest year for stumps was estimated from Forest Service records and tree cores taken from a selection of live trees adjacent to stumps. In the two stands that had multiple harvests, each stump was assigned to a harvest year (1935 or 1970) based on species and stage of decay. Trees harvested during early harvests (~1935) were generally large-pine that were clearly established before 1865. For trees harvested in 1970, rings were counted on the stump to ensure establishment before 1865. All questionable stumps, logs, and snags were noted during mapping and later revisited to ensure consistent aging.

We followed methods of North et al. (2007b) to reconstruct breast height diameters of live trees. Approximately 1/3rd of live trees from all diameter classes were cored. Diameters in 1935 were derived from cores after drying and sanding using methods outlined in Bakker (2005) and bark thickness equations (Spada 1960). Regression models for each species were built to estimate 1935 diameter for the rest of the live trees using diameter and a neighborhood competition index from Contreras et al. (2011) as predictor variables (see appendix). For stumps cut in 1970, rings were field counted on 40 stumps per plot to develop a similar regression model. Stump-to-breast-height adjustments were made based on regression equations developed from live trees and from Bones (1960). Time since death for different decay classes of snags and logs was derived from equations in Everett et al. (2007); snags and logs were then grown back to 1935 using models built from the live trees cores.

2.3 Quantifying pattern

We quantified spatial pattern in terms of widely spaced individual trees, tree clumps, and openings using a clump identification algorithm (Plotkin et al. (2002) and the empty space distribution (Diggle 2003). The cluster algorithm partitions a stem map of tree locations into clumps at a specified inter-tree distance (*t*), measured from tree center to tree centerl trees are members of the same clump if they are within distance *t* of at least one other tree in the clump. Trees with no neighbors within distance *t* are termed individuals. This method has been previously used to identify tree clumps in dry forests (Abella and Denton 2009, Sánchez Meador et al. 2011 p. 201, Churchill et al. 2013).

The cluster algorithm can be used in two ways: a single inter-tree distance threshold or modeled crown radius. A single inter-tree distance (typically around 6m) can be used to specify when trees are members of the same clump. This distance is based on the average distance at which mature trees of the dominant species in the study area display interlocking crowns. When using modeled crown radius, trees are members of the same clump if their projected crowns intersect. The crown radius method is a more accurate description of which trees have interlocking canopies (Sánchez Meador et al. 2011) but the single distance is easier to use in the field and for prescriptions (Churchill et al. 2013). We used both methods and compared them.

We ran the cluster algorithm at 4, 5, 6, and 7m. To run the crown radius method, we built allometric equations for Douglas-fir, ponderosa pine, and western larch using tree records from the USFS FIA database. Cumulative clump size distributions were derived for all distances. This distribution quantifies the percent of trees found as individuals and in clumps of different sizes. We tested for significant differences between the fixed distance and crown radius clump size distributions using a two sample K-S test (Zar 1999). Results showed that distributions from the 6m distance and the crown radius method were not statistically different for all three plots (Liberty $p = 0.32$, Nile $p = 0.44$, Oak $p = 0.22$). Thus we used the 6m distance for most subsequent analysis due to its simplicity. Clump sizes were also reported in bins: individuals (1 tree), small clumps (2-4 trees), medium clumps (5-9 trees), and large clumps (10-20+ trees). The percent of total basal area in the different clumps size bins was also calculated to assess the relative size differences of trees in clumps.

We developed a similar edge correction method to Sanchez Meador et al., (2011), but with some important differences. In the field, we purposely mapped trees outside of our plots that were part of clumps within the plot using the longest realistic distance to define clumps (7m). This resulted in an expanded plot from our original layout. The cluster algorithm was then run with the expanded plot. We then used a reduced sample edge correction in which all trees outside of the original plot boundaries were dropped from the tree list. However, the clump sizes of the trees within the plots still reflected the trees outside the plot that were dropped. For example, for a 10 tree clump with 5 trees inside the original plot and 5 trees outside, the 5 “in” trees would be tabulated as being in a 10 tree clump.

The empty space function was used to quantify openings in our plots (Diggle 2003). The *F(t)* function generates a grid of points, set to 0.5 m, and then derives the distance from each grid point to the nearest tree, and is used to quantify the amount of separation between trees. Distances are pooled to create a cumulative distribution. We compared observed distributions against envelopes of simulated random patterns to determine if there was a process creating openings, similar to methods using with Ripley's K(t) (Moeur 1993). A graphical plot of this function was created. We used a similar edge correction in which *F(t)* was first run for the expanded boundaries. We then removed the grid points outside of the original plot from the F(t) distribution

The empty space function does not delineate individual gaps, however. We initially used PatchMorph for this purpose (Girvetz and Greco 2007). PatchMorph is a recently developed tool to delineate patches in raster grid. The tool identifies openings based on a threshold separation distance from tree crowns and a closing distance that pinches openings into defined "gaps". We found long closing distances were needed to delineate gaps (>18m), which created arbitrary gap boundaries. We chose not to use the PatchMorph approach, but include our exploratory analysis in an appendix.

2.4 Quantifying lower level patch types

To evaluate whether distinct, smaller scale patch types existed within our plots, we first partitioned each plot into 30 x 30m subplots or grid cells. For each 30m cell, we calculated clump size and F(t) distributions and basic structural metrics. To avoid large edge effects with such small cells, we applied the edge corrections described above to each 30m cell so that the trees surrounding each cell influenced F(t) and the clump size distribution. We chose to use 30m cells for a number of reasons. First, we explored two methods that delineate individual patches based on local structural and patterns metrics: Gettis G (Getis and Franklin 1987) and spatially constrained clustering, (Fortin and Drapeau 1995). These methods produced patch configurations that varied widely depending on input parameters. Creating patches with these methods proved to be very subjective. Thirty meter pixels are more straightforward and allow for comparison with recent 30m structural classifications done using LiDAR from active fire sites in the Sierra Nevada (Kane et al. 2013, In review) and 0.1 ha field plots (Stephens and Gill 2005, Scholl and Taylor 2010). Also, tree neighborhood interactions occur at this level (Boyden et al. 2012).

The plot boundaries permitted a 7x8 30m grid on the Liberty and Oak plots and an 8x8 grid on the Nile plot. The plots were larger than these grids, however, and so a portion of each plot had to be dropped. To select the grid location, we ran 100 randomly located grids for each of the 3 plots and analyzed spatial pattern metrics for the 30m cells within each grid. We selected the grid location that had the widest range of tree density for each plot to capture the full range of structure/pattern groups. This had the effect of centering a grid cell around the lowest density 30 x 30m area in the plot.

To identify common structural vegetation patterns within the smaller 30x30m grid cells across the three sites, we used hierarchical cluster analysis (McCune and Grace 2002) to create groups of structure and pattern, similar to chapter 1 and other studies (Stephens and Gill 2005, Scholl and Taylor 2010). We expanded methods from chapter 1 to include structural as well as pattern variables. We selected 7 variables to construct the distance matrix: (1) the average of the mean clump size at 4, 5, 6, and 7m; (2) total plot area greater than 9m away from the nearest tree ($F > 9$m); (3) tph <40cm dbh; (4) tph 40-59.9cm; (5) tph 60-79.9 cm; (6) tph 80 +cm; and (7) total tph. We established in prior analyses that the $F > 9$m and average mean clump size metrics are good descriptors of the clump size and $F(t)$ distributions (chapter 1). All variables were standardized by the 95% percentile value instead of maxima to reduce the effects of extreme values. Euclidean distances and the “Ward” method of evaluating clusters were used. The combined 176 cells from all three plots were analyzed together. To check that the groups were balanced between the plots, we used a *Pearson's chi-squared* test on a contingency table of the number of cells in each groups on each plot.

Meaningful differences in structure and pattern between the groups were assessed by analyzing the relationships between input variables and the groups using Principal Components Analysis ordination (McCune and Grace 2002). We also inspected the correlation matrix of the 7 input variables (see appendix). Boxplots of the two summary pattern metrics and range of common structure metrics were generated to compare groups. We calculated Kurtosis and Skewness to capture differences in diameter distributions. To test our first hypothesis that statistically different structure and pattern groups were present on our sites, we used Permanova (Anderson 2001) with the full set of 7 variables. Contrast tests were then used to test for differences between individual groups. The 4 diameter distribution metrics alone were also run to test whether groups had different diameter distributions. We did not include species composition in the distance matrix, but instead tested for significant differences in the relative proportion of ponderosa pine, Douglas-fir, and western larch between the groups. The proportions were not normally distributed and sample sizes were unbalanced; thus we used a non-parametric, Permanova. A distance matrix was created for this purpose using the proportion of total basal occupied by each species.

2.5 Testing for spatial dependence of patch types

A sequential set of methods was used to test our second hypothesis of no spatial dependence between 30 m patch types on each 6 ha plot. First, the join count statistic was used to assess spatial dependence of 30 m structure types. This statistic tests for negative or positive spatial autocorrelation by assessing whether the adjacency of cells from a particular categorical group in a grid are departed from a random distribution (Cliff and Ord 1973). Tests for each group were run using the "queen" spatial weights setting. A permutation approach was used where the join count statistic from the observed pattern was ranked against 2000 random permutations of the same grid. We also used Moran's I with permutation to test for spatial dependence of tph values of cells (Cliff and Ord 1973). Tree density was selected as it was highly correlated with the other pattern and structure metrics (see appendix).

To ensure that any observed spatial dependence was not an artifact of how the plots were subdivided into cells, we employed the *L(t)* function. *L(t)* is a transformation of Ripley's K(*t)* and is commonly used with a Monte Carlo simulation envelope of random patterns (CSR) to detect significant clustering or inhibition up to a certain inter-tree distance (Ripley 1988, Moeur 1993). For this application, we use *L(t)* to visually assess whether the overall spatial pattern of trees is clustered at distances beyond which tree to tree interactions occur (>15 m). An increasing *L(t)* function at distances > 15m indicates clustering at longer distances and the inference that larger scale heterogeneity in biophysical conditions is affecting pattern (Perry et al. 2006, Wiegand et al. 2007a). We used Cramer–von Mises goodness-of-fit test from Loosmore and Ford (2006) with the *L(t)* curves to formally test for clustering between 15-40 m for each pattern.

3. Results

3.1 Stand level pattern and structure

We inferred from our historical reconstructions that the plots we studied represented low-density stands dominated by large diameter ponderosa pine and Douglas-fir trees (Fig. 2, Table

1). Basal area ranged from 19 to 24 m^2ha^{-1} and total canopy cover was 24-25% among the plots. The Oak plot had a relatively flat diameter distribution with the fewest tph, 72% of its basal area in trees >60cm, and 8 tph of trees >90cm. The Nile and Liberty plots had more small diameter trees and steeper, bell-shaped diameter distributions (Fig. 2). All three plots were dominated by ponderosa pine with Douglas-fir comprising 1/3rd to 1/4th of the basal area.

The three plots were spatially heterogeneous with a similar range of clump sizes: 21-26% of trees were individuals, 36-38% were in small clumps (2-4 trees), and 17-27% were in medium clumps (5-9 trees) (Table 2). The Nile and Oak plots had a higher proportion of trees in large clumps (19%) than the Liberty plot (10%) and a higher mean clump size (Table 2, Fig. 3). Maximum clump size using the 6m distance was similar for all plots (16-19 trees). The clump size distributions derived from the crown radius method and the 6m fixed distance were very similar across most of the clump size distribution (Fig. 3) but the crown radius method identified a larger maximum clump size for the Nile and Oak plots (24 and 22). The proportion of basal area in the different clump sizes was similar to the proportion of trees (Table 2) but with a higher percent in individual trees and fewer in large clumps. Still, only a third of the basal area was in individual trees and 6-12% was in large clumps. This indicates that mean diameters were lower in the large clumps, but not dramatically so.

All three plots had F(t) distributions that were more "open" than random patterns, especially the Nile and Oak plots (Fig. 4). The total plot area greater than 9m away from the nearest tree (F > 9m) was 17% for Liberty, 22% for Nile, and 24% for Oak. A visualization of the F(t) approach to quantifying openings is shown in Fig 5.

3.2 Lower level patch types

The hierarchical cluster analysis produced groups or patch types of 30m cells that were ecologically meaningful. We selected 4 groups based on the dendrogram and PCA ordination (Fig. 5), The first PCA axis explained 50% of the variation and separated groups primarily based on density, especially of trees <60cm (Table 3). Clumping and F>9m were also drivers in the first axis but these are both correlated with density (see correlation matrix in the appendix). The second axis explained an additional 17% of the variation and separated groups based on large trees (>60cm) and to a lesser extent lower levels of F>9m. The third axis split groups by very large trees (>80cm) in one direction and large trees in the other (60-80cm).

We rejected the null hypothesis of no difference in structure and pattern between patch types. Contrast tests with Permanova showed that the groups were all statistically different from each other ($p<0.001$ for the overall test of group differences and for each between group test). Density was the main driver of differences between the groups (Fig. 6). Mean clump size, F>9m, mean DBH, and the shape of the diameter distributions were also distinct, but with some overlap between groups (Fig. 6). Inspection of stem maps with an overlay of the cells and group membership illustrates differences between the groups (Fig 8). Contrast tests with Permanova also indicated that diameter distributions were significantly different between each group ($p < 0.001$) (Fig. 8.).

The first group, which we call "Open", had the lowest density (0-100 tph) and was characterized by higher levels of large openings (F >9m) than the other groups (Fig. 6 - 8). A few of the cells had no trees. The group generally had low levels of clumping and many widely-spaced individual trees and small clumps. However some cells had moderately-sized clumps and moderate density but still had large openings. Some of this is attributable to the edge correction we used. Diameter distributions were mostly flat (i.e., more uniform compared to a Gaussian curve) (Fig. 8). Average species composition was 70% pine and 30% Douglas-fir, although individual cells varied from 100% pine to 85% Douglas-fir.

The second group, which we call "Park-like", had low to moderate density (50-120 tph) with mostly individual trees and small clumps (Fig. 6). Trees were generally well distributed across the plot, which accounts for the relatively low amount of open space in larger openings. This group had the highest numbers of large trees with relatively flat diameter distributions (Fig. 8). Species composition was similar to the Open type.

The third group, which we call "Moderate clump", had moderate to high densities (100-200 tph), moderate clumping, and almost no F >9m. These cells generally had trees from all size classes and diameter distributions that were bell shaped in most cases (Fig. 8) but flat in others. Moderately-sized clumps (5-9 trees) were the most distinguishing characteristic of this group. Douglas-fir was slightly more prevalent than ponderosa pine (Fig. 6).

The final group, called "Dense clump", had the highest tree density (150-300 tph), total canopy cover, and smallest mean diameters. Almost all the large clumps (10-20 trees) on the plots were located in these cells resulting in a higher mean clump size (Fig. 6). Diameter distributions were generally bell shaped and dominated by 20-60 cm trees (Fig. 8). Large trees were present on many of the cells, but at low overall densities. Species composition was statistically different in this group compared to the other three groups: Douglas-fir made over 40% of the average basal area, although some individual cells were 100% pine.

All four patch-type groups were represented on each of the 3 plots (Fig. 10). The overall distribution of group membership between the plots was not different than expected under a chi-squared distribution ($p=0.12$). The plots were dominated by Open and Park-like cells, with 63-

80% of the cells in these two groups (Fig. 10). Nile had the most cells in the Dense-clump group (18%) while Liberty had only 7%.

3.3 Spatial dependence of patch types

We rejected our hypothesis of no spatial dependence of patch types for all three plots based on the results from the join count, Moran's-I, and L(*t*) analyses. We inferred from the join count statistic that positive spatial dependence between the cell types was present for the Moderate-clump patch type on the Liberty and Oak plots, and the Open, Park-like, and Dense clump types on the Nile plot (Table 4). Results from Moran's-I showed spatial dependence of cell tph values on the Nile and Oak plots, but not at Liberty ($p = 0.001$, 0.03, 0.23 respectively). Clear clustering of trees at short distances in all three plots (<6 m) was inferred from the L(*t*) function, which clearly departed from CSR patterns (Fig. 9). Increasing L(*t*) distributions that were much steeper than the CSR envelopes all the way to 40m were found on the Nile and Oak plots at distances longer than 6 m. Patterns were statistically different from CSR from 15 to 40 m (Cramer–von Mises GoF test, p=0 .005). This strongly supports an inference that trees are aggregated into some 15-40m regions of the plot, forming high density zones larger than tree clumps (Wiegand et al. 2007a). The *L(t)* distribution of the Liberty plot did not rise as steeply after 6m but was still statistically different from CSR from 15-40m (p=0.025) (Fig. 9).

Some large-scale patterns are evident on at least two of the plots. An aggregation of 6 Dense clump cells forming a patch larger than 0.4 ha is evident from an inspection of the Nile stem map (Fig 8). On the other side of the plot there are 7 Open cells that form a ~0.6 ha opening with scattered trees. A directional trend in density from is confirmed by the increasing *L(t)* curve. A similar large scale pattern occurs on the Oak plot with a concentration of Moderate-clump and dense-clump cells in the lower right and Open and Park-like cells covering most of the left half of the plot. The different patch types are more evenly distributed on the Liberty plot (Fig. 7) and density was not spatially dependent but aggregation of the Moderate-clump group is apparent on the stem map (Fig. 7), which we confirmed by the join count and *L(t)* results.

4. Discussion

4.1 Stands as patch hierarchies

Our results provide new, initial evidence that some pre-settlement dry forest stands were not only comprised of tree clumps and openings of various sizes, but that tree clumps and opening spaces were also spatially aggregated (Weaver 1943, Cooper 1960, White 1985, Kaufmann et al. 2007). Use of Hierarchical Patch Dynamics theory (HPDP) (Kotliar and Wiens 1990, Wu and Loucks 1995) as a framework for conceptualizing pattern and structure in dry forests is supported by these results. HPDP is commonly used at the landscape level in fire prone forests (Keane et al. 2009, Perry et al. 2011); our work extends and connects it to stand- and tree-neighborhood levels of the landscape hierarchy. Tree neighborhood patch types are the organizing elements that make up stands (Urban et al. 1987).

Differences in stands, such as among our three plots, can be understood in terms of different proportions and spatial arrangements of these tree neighborhood patch types (Wu 1999, Kane et al. 2011). All three of our plots were dominated by Open or Park-like patch types, but with different amounts of and aggregations of Dense-clump patches (Fig. 10). The Nile and Liberty plots had a different internal spatial configuration of tree neighborhoods (Fig. 7), even though stand average tph, basal areas, and diameter distributions were very similar (Table 1, Figure 2). Our data are limited to an exploratory analysis of pattern on only 3 plots, however, so these conclusions should be interpreted as initial findings.

The notion of stands as mosaics of low-level patches is supported by theories and models of gap dynamics (Watt 1947, Shugart 1984, Botkin 1993) and of neighborhood effects (Frelich et al. 2002). The core idea is that a level of organization exists in forest patches at a scale where individual trees and tree groups interact (~ 0.05 – 0.5 or 0.6 ha or more), but below the level of stands (Boyden et al. 2012). Pattern at this scale is often driven by chronic endemic insect and disease, windthrow, and low or mixed severity fire disturbances which kill individual trees and tree groups, thereby provide new growing space for new cohorts (Bormann and Likens 1979, Agee 1998, Franklin et al. 2002). Processes operating at larger spatial and temporal scales affect most forest ecosystems as much or more than fine-scale processes (Turner 2010). Yet, conceptualizing, modeling, and managing forests simply as homogenous stands - without incorporating the tree neighborhood scale -- may overlook key patterns, interactions, and processes that effect ecological function at larger spatial scales (Frelich and Reich 1999a).

Clear spatial boundaries or breaks in structural conditions between patches types are rare in dry forests stands, however. Instead, boundaries are fuzzy and often occur as a gradient of changing conditions (McGarigal et al. 2009). Our attempt to delineate openings with PatchMorph illustrates this challenge (see appendix). We found in our hierarchical clustering analysis that group membership for some cells switched with small changes to the input variables. The overlap between groups in the PCA ordination confirms the fuzzy edges between groups (Fig. 6). Shifting the grid of 30m cells by 5 or 10 meters also resulted in somewhat different arrangements and proportions of cell types. However, the basic nature of the 4 groups did not change. The group membership of most cells was stable, especially the Dense-clump and Open groups. Cells only shifted to adjacent groups (e.g. Open – Parklike; Parklike – Moderate, Moderate -Dense).

A key qualification of these observations is the uncertainty in the numbers of small trees (<~30cm) due to the limitations of reconstruction (Fule et al. 1997, Taylor 2004, North et al. 2007b). We only considered trees that were 75 years old in 1935. The fact that large clumps were relatively common in our plots suggests that thickets of regeneration did exist as large clumps generally start out as regeneration thickets (Lydersen and North 2012). However, Everett et al. (2007) found that only 5-10 tph per decade made it past the sapling stage in the 100 years prior to cessation of frequent fire. In Arizona, comparison of reconstructions with actual historical records found that total density estimates were within 10% (Moore et al. 2004). Early 1900th century accounts and inventories of dry forest do not show huge numbers of small trees (10-30m) and sharp inverse J diameter distributions (Lyderson, submitted, Munger 1912, Sánchez Meador et al. 2009). Regeneration thickets were common, however (Larson and Churchill 2012). Thus our density estimates for trees 10-30 cm are likely accurate enough to describe the basic structure-pattern types across the plot.

4.2 Sub-patches, spatial dependence and stationarity

Our results indicate that there is some underlying heterogeneity that cannot be explained by fine-scale, vegetation and disturbance dynamics alone (Perry et al. 2006, Getzin et al. 2008). In statistical terms, the assumption of stationarity is not valid for these plots (Illian et al. 2008). The stand-level mosaics of individual trees, clumps, and openings on the three plots contain non-random, aggregations, or sub-patches of large and moderate clumps in some areas and open cells in others (Fig. 7). Clear clustering of trees at inter-tree distances beyond those of tree neighborhoods (>15m) is also present (Fig. 9). This suggests that the underlying parameters of the processes creating pattern vary in different parts of the plot (Fortin and Dale 2005, Perry et al. 2006, Getzin et al. 2008). Stationarity is a necessary assumption for standard point pattern statistics, although corrections exist for non-stationary patterns (Illian et al. 2008)

All 25 studies of pattern in frequent fire forests that we reviewed assumed stationarity (Larson and Churchill 2012). They implicitly assumed that the underlying dynamics of the vegetation and disturbance regime were the same across their plots and that the probability for a large clump or opening to occur is the same across the plot. Some heterogeneity in biophysical conditions certainly existed but this was overwhelmed by frequent fire (Wright and Agee 2004) or distributed randomly across the plot. These assumptions appear to be valid in past studies for several reasons. First, almost of these plots are small (<=1.0 ha), so variability in underlying conditions is less likely. Second, inspection of Ripley's *K(t)* and *L(t)* curves and point patterns from these studies shows that in almost all cases, there is no increasing trend at distances >15m (Arno et al. 1997, Harrod et al. 1999, Youngblood et al. 2004, North et al. 2007b, Sánchez Meador et al. 2009). The conclusion that the observed variation in pattern was caused by fine-scale gap dynamics at the spatial extent of these plots is therefore reasonable.

In contrast, we infer from our analyses that the assumption of stationarity is not valid on our plots and that the probability of different disturbance severities was not uniform across our plots due to topography, the legacies of past disturbances, or other factors. For example, the aggregation of Dense-clump cells on the Nile plot may be the result of a past patch of mortality caused by a fire that crowned, potentially related to Douglas-fir dwarf mistletoe (*Arceuthobium douglasii)* infection which was present on the plot. The steeper slopes (40-60%) of the Nile plot could also have contributed to more variable fire behavior. Another factor could be thin soils in some areas that limit potential of vegetation moving past the Open-dense patch type. We did not directly evaluated the ecological processes driving pattern, however, so can only speculate about the causes of the spatial aggregation of tree clumps and openings we observed.

Stationarity depends on the spatial and temporal scale of observation (Illian et al. 2008). Dry forests across the west are clearly influenced by biophysical variability and decadal or longer climatic patterns (Swetnam and Betancourt 1998, Hessl et al. 2004, Kaufmann et al. 2007). On a 1ha plot, the likelihood of observing pure gap-phase dynamics is high. As one increases the spatial extent, there is increasingly likelihood of observing non-stationary behavior in spatial pattern caused by heterogeneity in disturbance regimes and biophysical conditions (Turner et al. 1993). Non-stationary patterns are inevitable at a sufficiently large spatial or temporal scales of observation.

Our plots are the largest that have been reconstructed in western frequent-fire forests insofar as we know (Larson and Churchill 2012). Hence, it is not surprising that we observed non-stationary patterns where other studies have not. It is notable that we found these patterns in a relatively small area of dry forest that historically experienced frequent fires (Everett et al. 2000). Non-stationary patterns are even more likely to be observed in more mesic parts of the Cascade Range, where biophysical variation and productivity gradients are wider. However, it is also possible that stationarity existed in some dry forest stands, likely those with gentle topography. Installing additional plots across a wider range of biophysical settings is necessary to better understand how both fine and meso-scale factor influence spatial pattern within stands.

4.4 Management implications

There is a growing scientific consensus that to increase resilience, managers should consider the functional importance of spatial heterogeneity in dry forests (Allen et al. 2002, Franklin and Johnson 2012, Hessburg et al. 2005, Moore et al. 1999, North et al. 2009, Jain et al.

2008, Perry et al. 2011, Stephens et al. 2010), in addition to retaining large and old fire-tolerant trees and following other resilience principles (Agee and Skinner 2005, Peterson et al. 2011). Pre-settlement era conditions are commonly used as reference systems to provide targets for spatial heterogeneity as these forests were adapted to frequent fire and shifting climatic conditions (Landres et al. 1999, Keane et al. 2009). Based on the results of this study, we recommend that heterogeneity be approached on two spatial scales - tree neighborhoods and stands.

Within tree neighborhoods (< 0.4 ha), managers can retain or create fine-scale heterogeneity by incorporating targets for individual trees and different sizes of tree clumps into marking or cutting guidelines (Churchill et al. 2013). At stand scales, aggregating tree clumps and openings into large sub-patches should be considered. This can be accomplished by incorporating untreated "skips" or "complex patches" in stands as a part of mechanical thinning and prescribed fire treatments, as well as larger openings (>0.4 ha) (Gaines et al. 2010, Powell 2012).

In this study the 7-16% range in occurrence of Dense-open patches is comparable to the common recommendation of leaving 10-20% of stands in skips (Franklin et al. In Press). However, the Dense-clump cells were not 0.5 ha patches of closed canopy, high density forest but, rather, had 150-300 tph and 40-60% of maximum stocking with some small openings (Fig. 6). Allowing prescribed fire to burn through some skips may be warranted, especially in dense stands (300+ tph). Similarly, the Open cells had scattered individuals and small clumps of trees; only a few cells were completely lacking in trees.

Finally, we emphasize that the dense, highly clumped areas made up a small portion of these plots. The majority of the area (65-80%) in our plots was low-density, park-like forest (Fig. 10). Each plot contained contiguous blocks (2+ha) of low-density forest with 40% of trees as individuals and 45-50% in small clumps (Open and Park-like groups) (Fig. 6 & 7). These areas likely also contained some thickets of regeneration. We caution, however, that size or frequency distributions of sub-patches for dry forests in Eastern Washington cannot be inferred from our study. We only examined 3 plots covering 18 ha. The boundaries of many of the sub-patches were on edge of our plots (Fig 7a & 7b); thus it impossible to know their actual size.

The functional rationale for including heterogeneity as goal in restoration treatments should always be considered, rather than doing it simply to replicate historic patterns (Millar et al. 2007). From the perspective of resiliency, creating or maintaining variable patterns and structures will set up different probabilities of disturbance severity across the stand – i.e., creating a "gradient of resistance". Within spatial heterogeneous stands, future disturbances will be more likely to produce variable levels of mortality and perpetuate the pattern and structure of these mosaics over time (Moritz et al. 2011). These complex adaptive systems will have greater potential to reorganize and adapt to changing altered environmental conditions (Stephens et al. 2010, Messier and Puettmann 2011). Historic forests were sculpted by centuries of fluctuation in fire regimes, drought, disturbances from insects and diseases, and change (Swetnam et al. 1999, Keane et al. 2009). The lower-level patch types of dry forests are the basic building blocks that have been rearranged and reshuffled through time. Different proportions and spatial arrangements may be necessary in the future, but these basic building blocks and patch hierarchies are the structural "memory" of these forests that has proven resilient over many centuries (Peterson 2002).

Tables

Table 1: Summary metrics of three reconstruction plots.

	Liberty	Nile	Oak
Plot size (ha)	5.9	6.7	6.2
Density and Size			
Trees per ha	94	100	78
Trees > 60 cm per ha	21	23	33
Mean dbh (cm)	47.9	48.3	58.5
Quadr. Mean dbh (cm)	49.5	49.9	61.1
Basal Area (m^2/ha)	19.1	20.7	24.2
% BA in Trees > 60 cm	45%	49%	72%
Stand Density Index[1]	306	331	364
Canopy Cover	24%	25%	25%
Species Composition			
PIPO (%BA)	65%	64%	74%
PSME (%BA)	35%	34%	26%
LOAC (%BA)	0%	2%	0%

Table 2: Proportion of tree density and basal area in different clump sizes. Clumps are defined using a 6m inter-tree distance.

	Proportion of Trees				Proportion of Basal Area					
	Inviduals	Small Clumps (2-4)	Medium Clumps (5-9)	Large Clumps (10-20+)	Inviduals	Small Clumps (2-4)	Medium Clumps (5-9)	Large Clumps (10-20+)	Mean Clump Size	Max Clump Size
Liberty	0.22	0.4	0.29	0.09	0.24	0.41	0.28	0.07	4.4	16
Nile	0.19	0.38	0.25	0.18	0.26	0.39	0.22	0.13	5.6	17
Oak	0.21	0.36	0.28	0.15	0.24	0.38	0.28	0.1	5.6	19

Table 3: Loadings and variance explained for the Principle Components Analysis

Variable	PC1	PC2	PC3	PC4
TPH <40cm	0.44	-0.27	0.14	-0.31
TPH 40-60cm	0.42	-0.09	-0.04	0.54
TPH 60-80cm	0.12	0.67	-0.57	-0.35
TPH 80+	-0.12	0.55	0.78	-0.04
TPH	0.52	0.06	0.07	-0.04
Mean Clump Size	0.43	-0.09	0.19	-0.50
F > 9m	-0.38	-0.38	0.00	-0.47
Prop. Variance	0.51	0.17	0.13	0.10
Cumulative Prop.	0.51	0.68	0.81	0.90

Table 4: Join count statistics for different patch types in each plot. Shaded boxes are significant p<0.05.

	Lower Level Patch Type			
	Open	Park-like	Mod. Clump	Dense Clump
Liberty	0.25	0.93	0.009	0.4
Nile	0.04	0.02	0.13	0.005
Oak	0.41	0.08	0.03	0.3

Figures

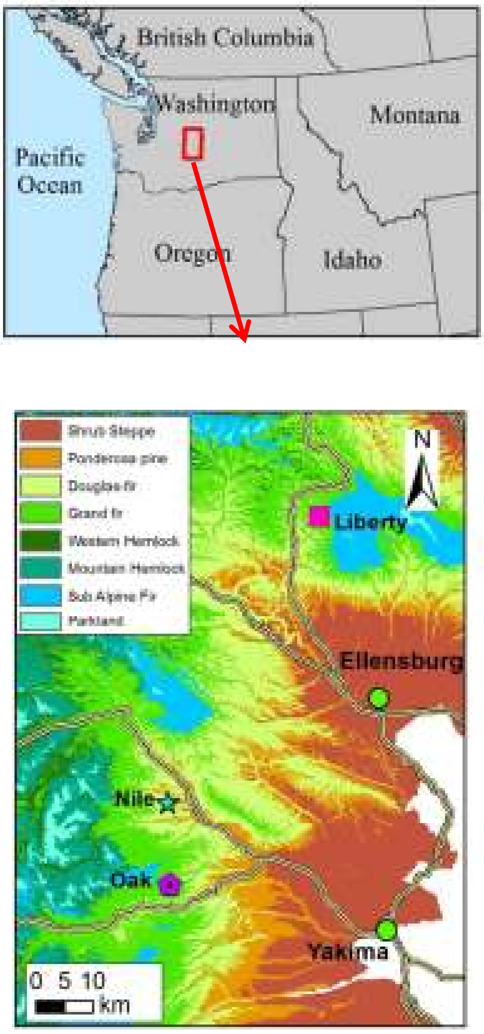


Fig. 1: Map showing locations of study sites and plant association groups.

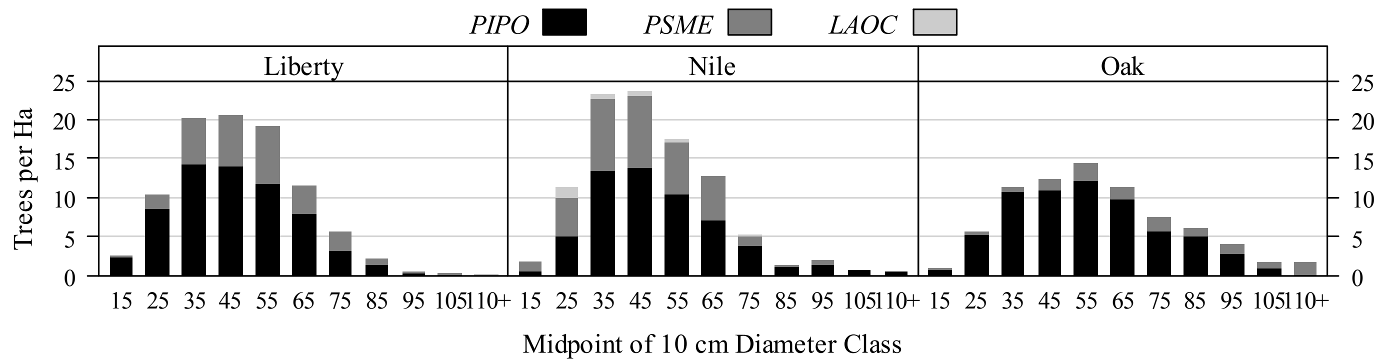


Fig. 2: Diameter distributions of three plots.

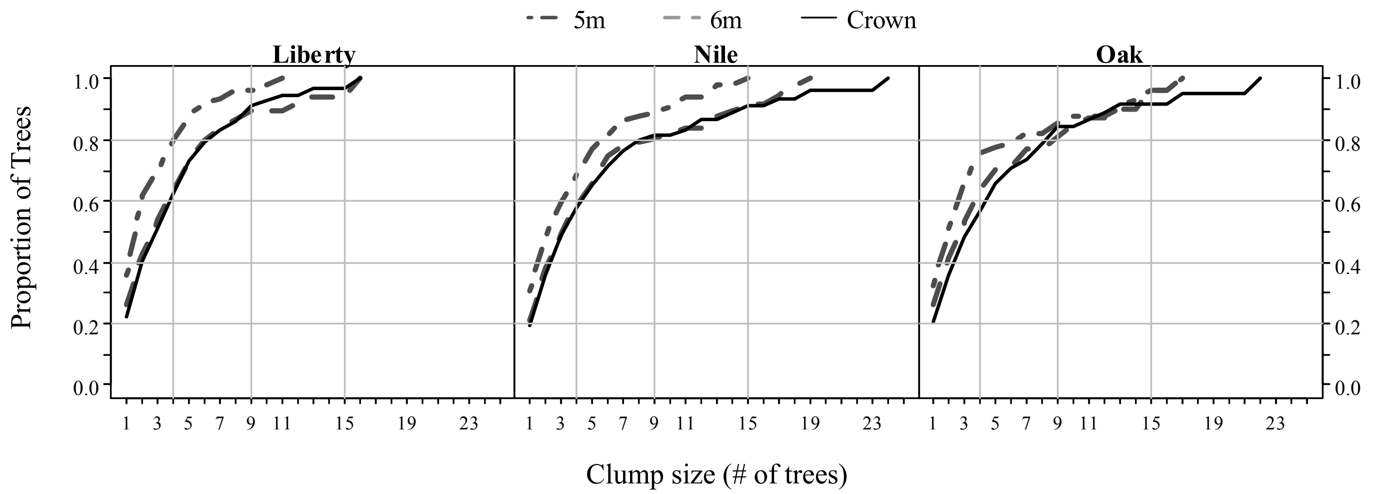


Fig. 3: Clump size distributions of three plots for 5 and 6m inter-tree distances, plus crown radii method. The 6m and crown radii distributions are not statistically different (KS test: Liberty p = 0.32; Nile p = 0.44; Oak p = 0.22).

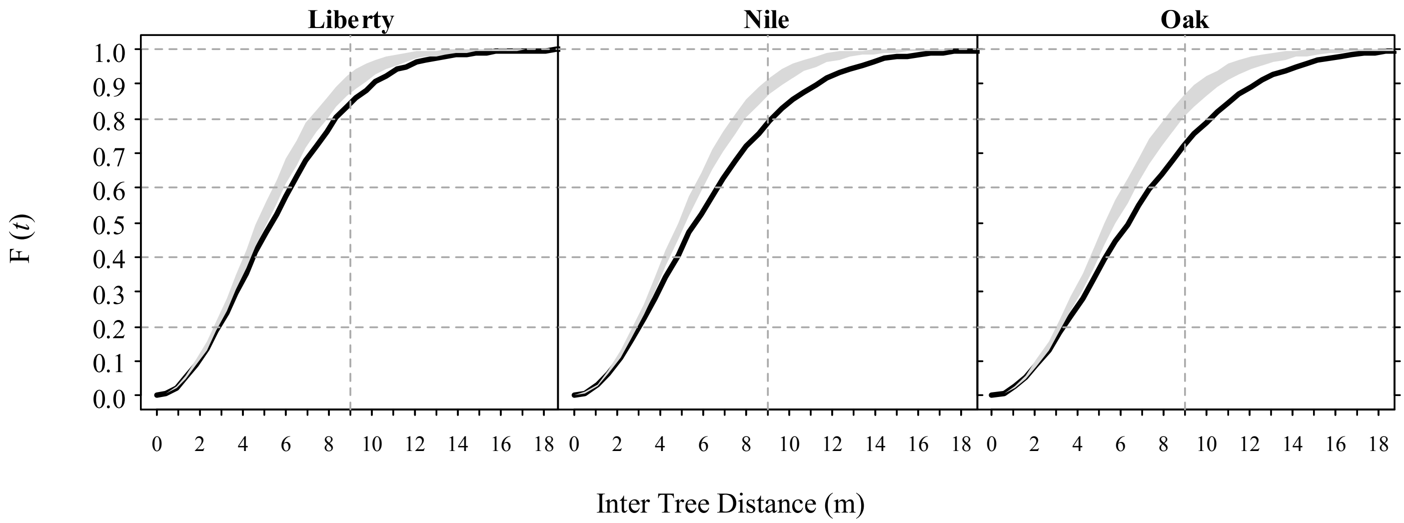


Fig. 4: Empty space distributions for the three plots, *F(t)*. Shaded envelopes are 200 random patterns (CSR). Rightward shifted curves indicate greater area in larger size openings. *F(t)* values at 9m (vertical dashed line) are the total area of a plot less than 9m away from the nearest tree. 1 – this value is the area greater than 9m away from the nearest tree (F > 9m).

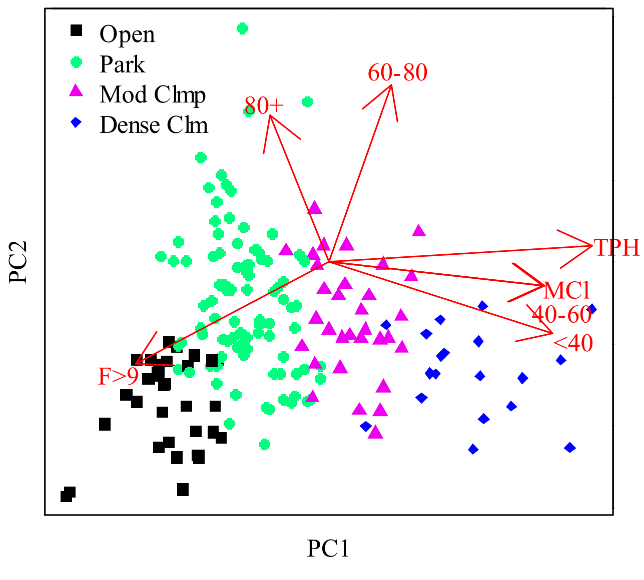


Fig. 5: Principal Components ordination of structural and pattern metrics from 30m cells. Input variables are: mean clump size (MCl); total plot area greater than 9m away from the nearest tree (F > 9m); tph <40cm dbh; tph 40-59.9cm; tph 60-79.9 cm; tph 80 +cm; and total tph.

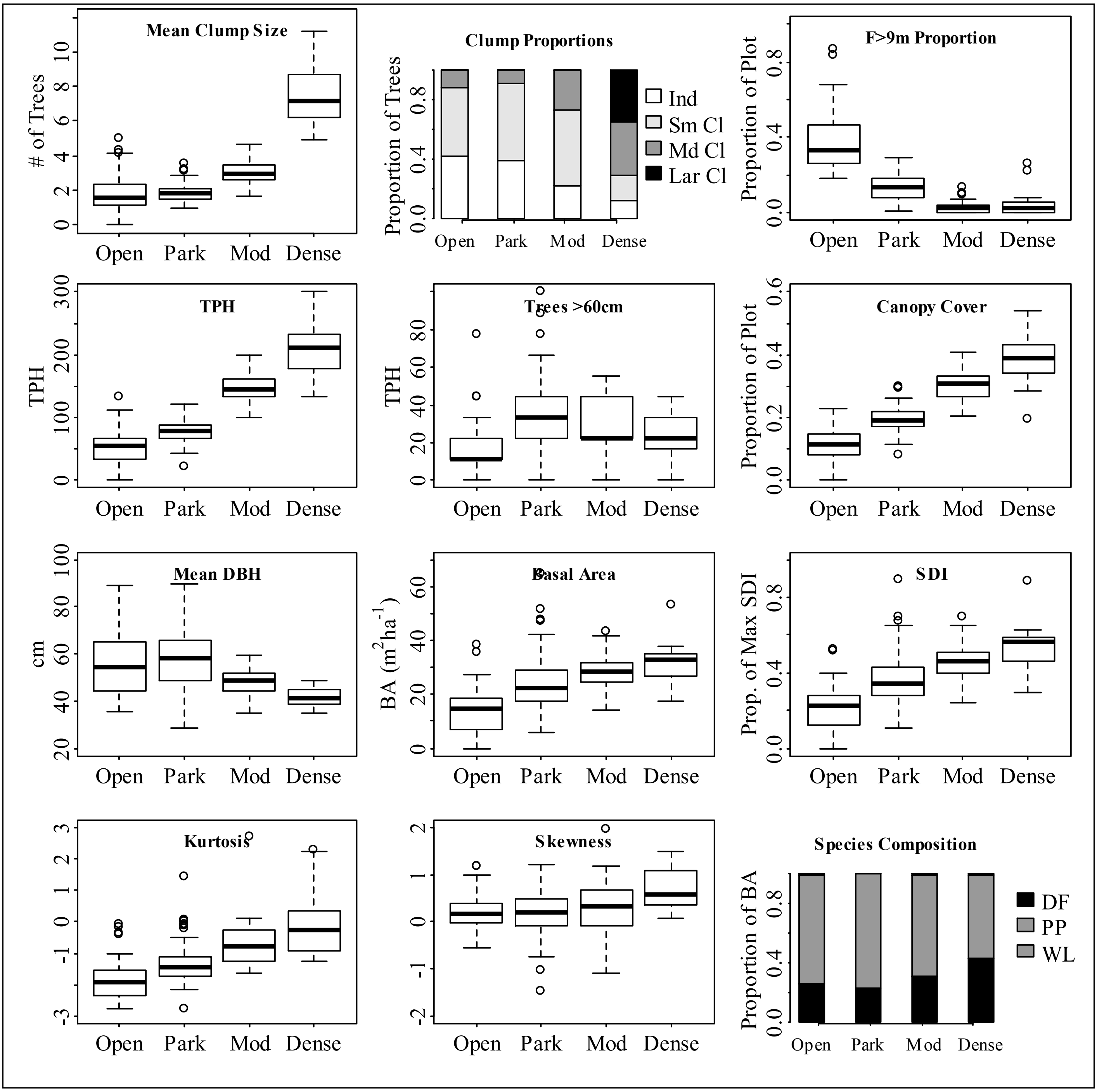


Fig. 6: Boxplots and barcharts of summary metrics for 4 groups or lower-level patch types.

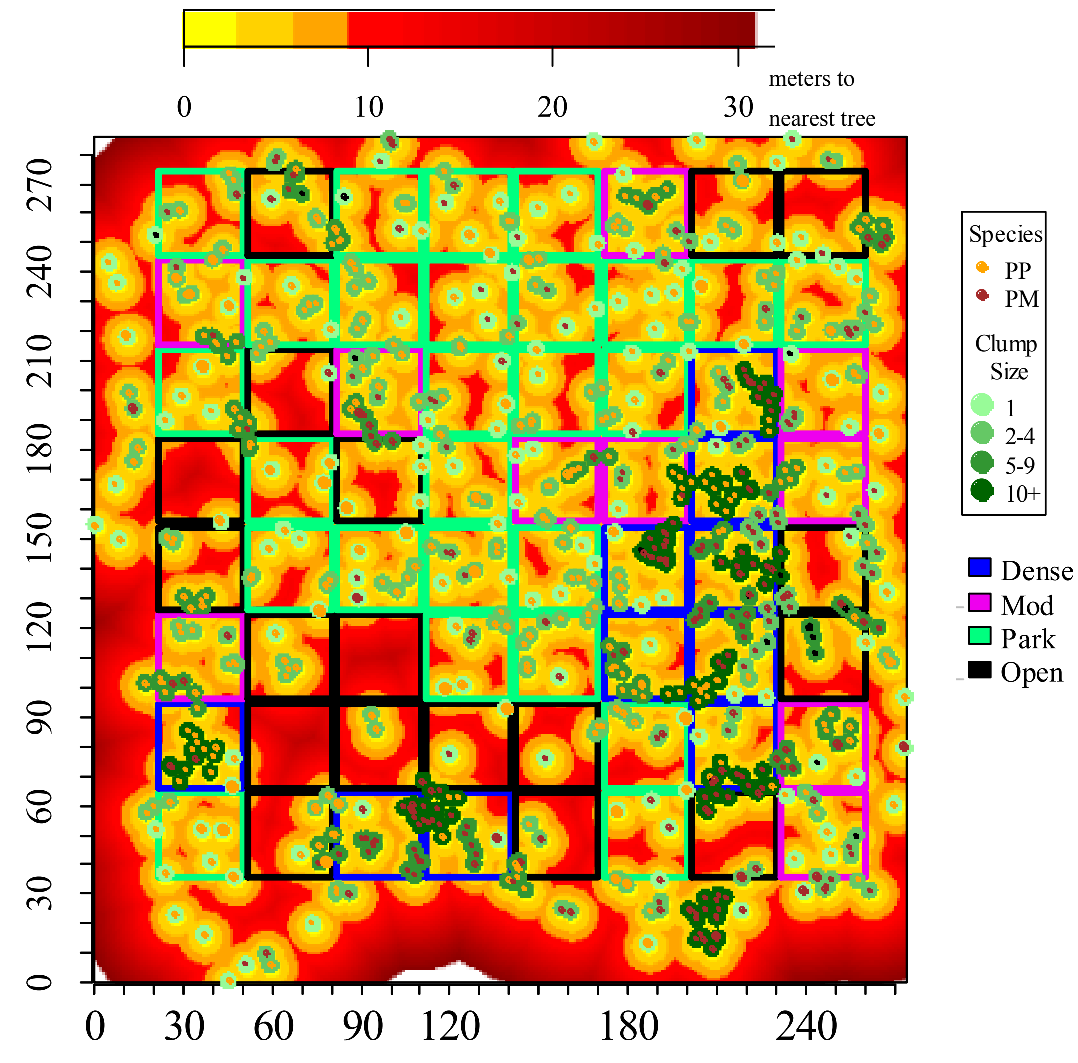


Fig. 7a: Stem map of 6.7 ha Nile plot with overlay of 30m cells. Outline colors of cells indicate patch type. Axes are in meters. Tree boles are scaled to diameter.

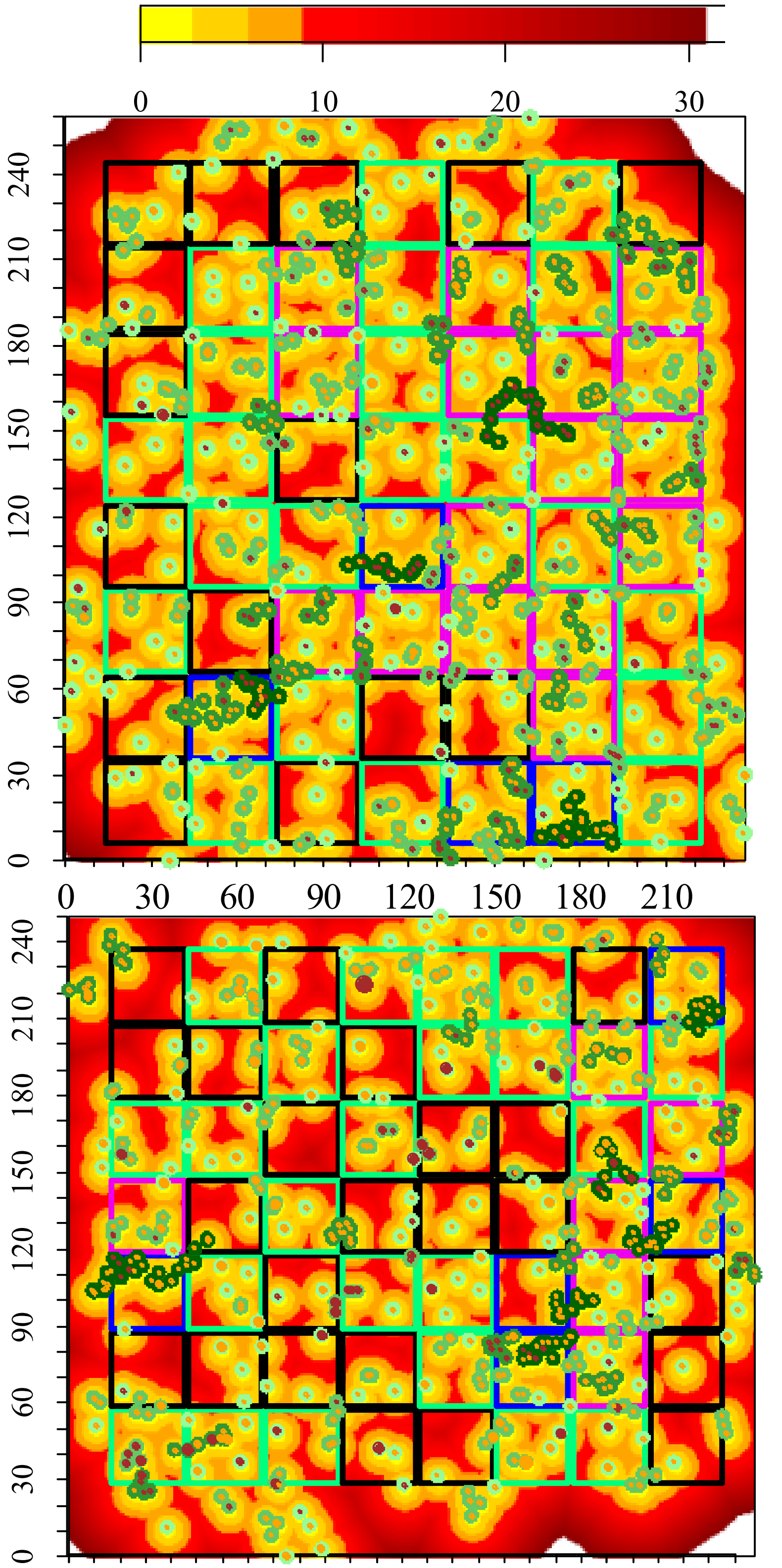

0
10
20
30
0
30
60
90
120
150
180
210
240
0
30
60
90
120
150
180
210
240
0
30
60
90
120
180
240

Fig. 7b: Stem maps of Liberty (upper panel) and Oak (lower panel).

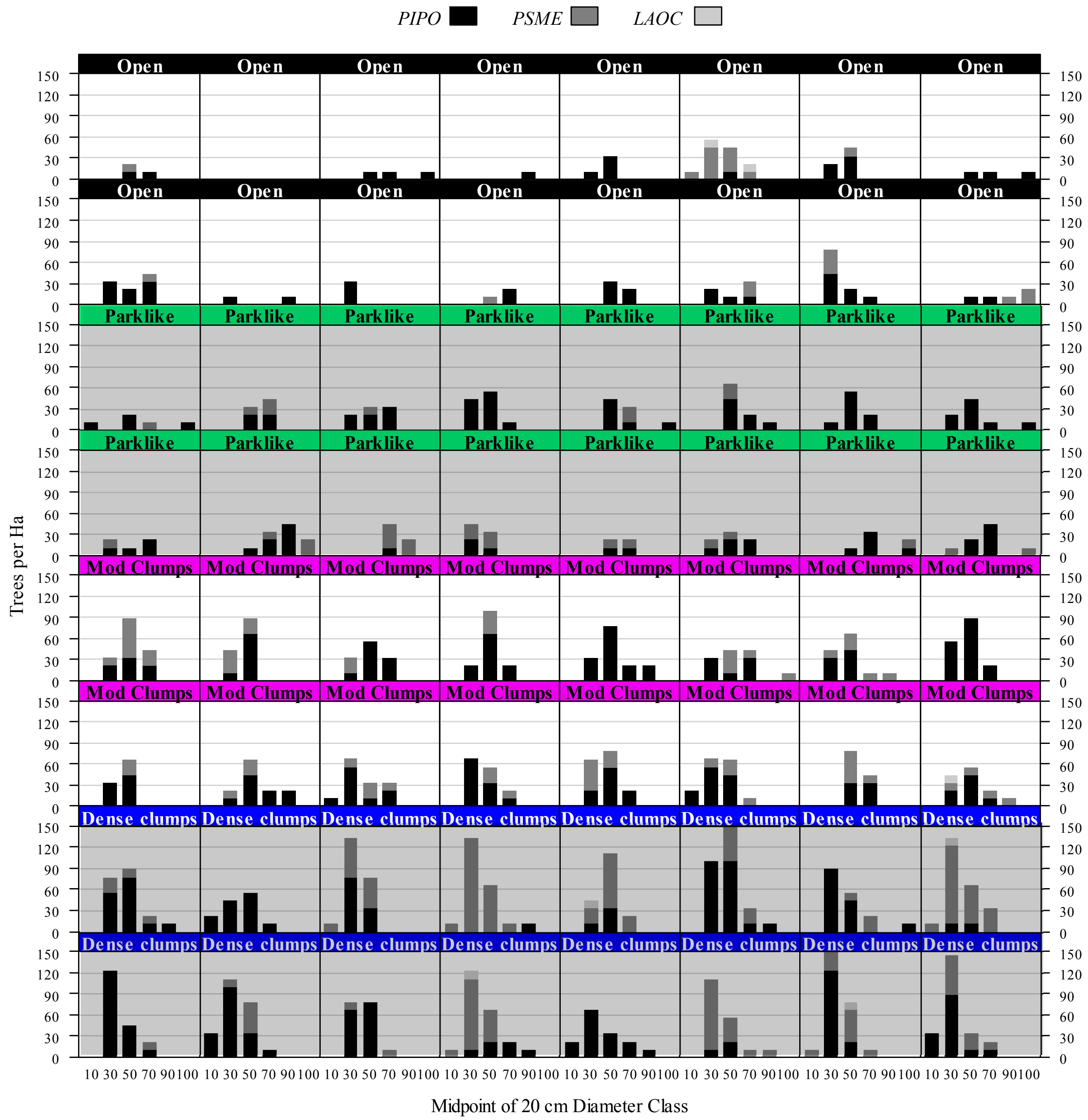


Fig. 8 Diameter distributions for 16 randomly selected cells from each lower-level patch type. The upper diameter class is 100-180cm.

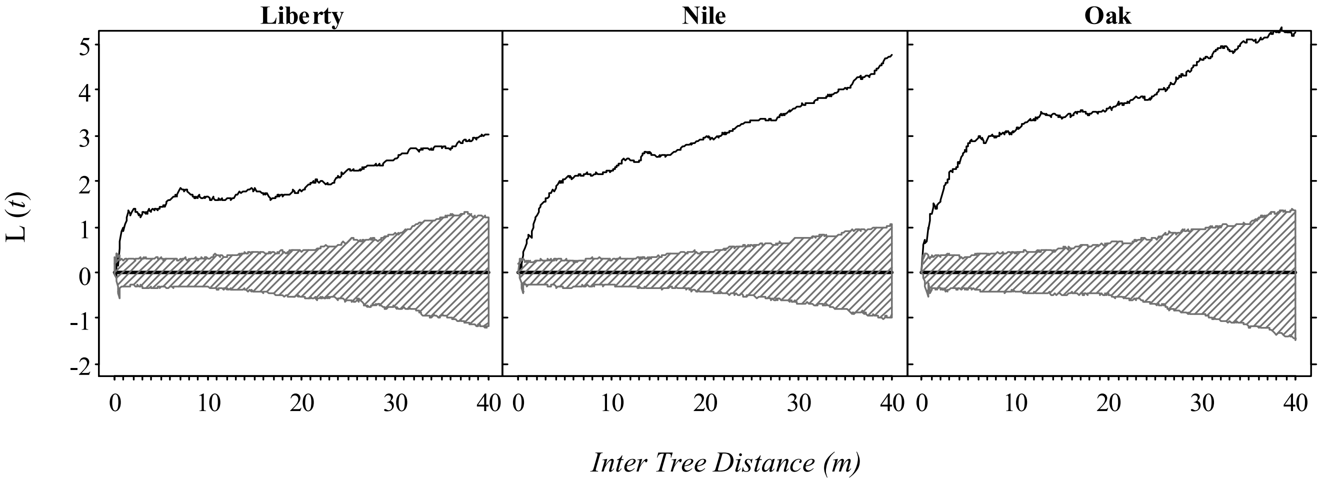


Fig. 9: *L(t)* curves for three plots with CSR envelopes (hatched). All *L(t)* curves were departed from CSR from 15-40m ($p<0.05$).

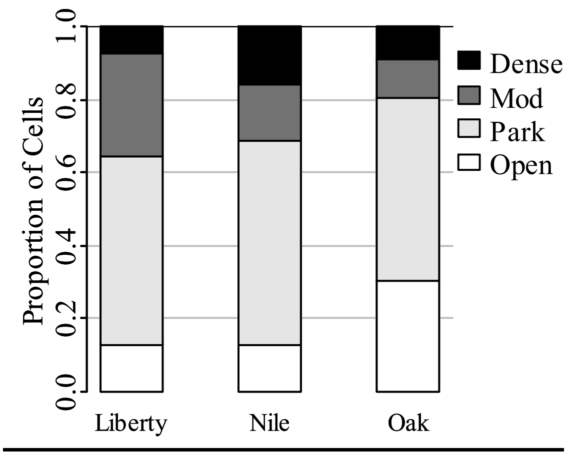
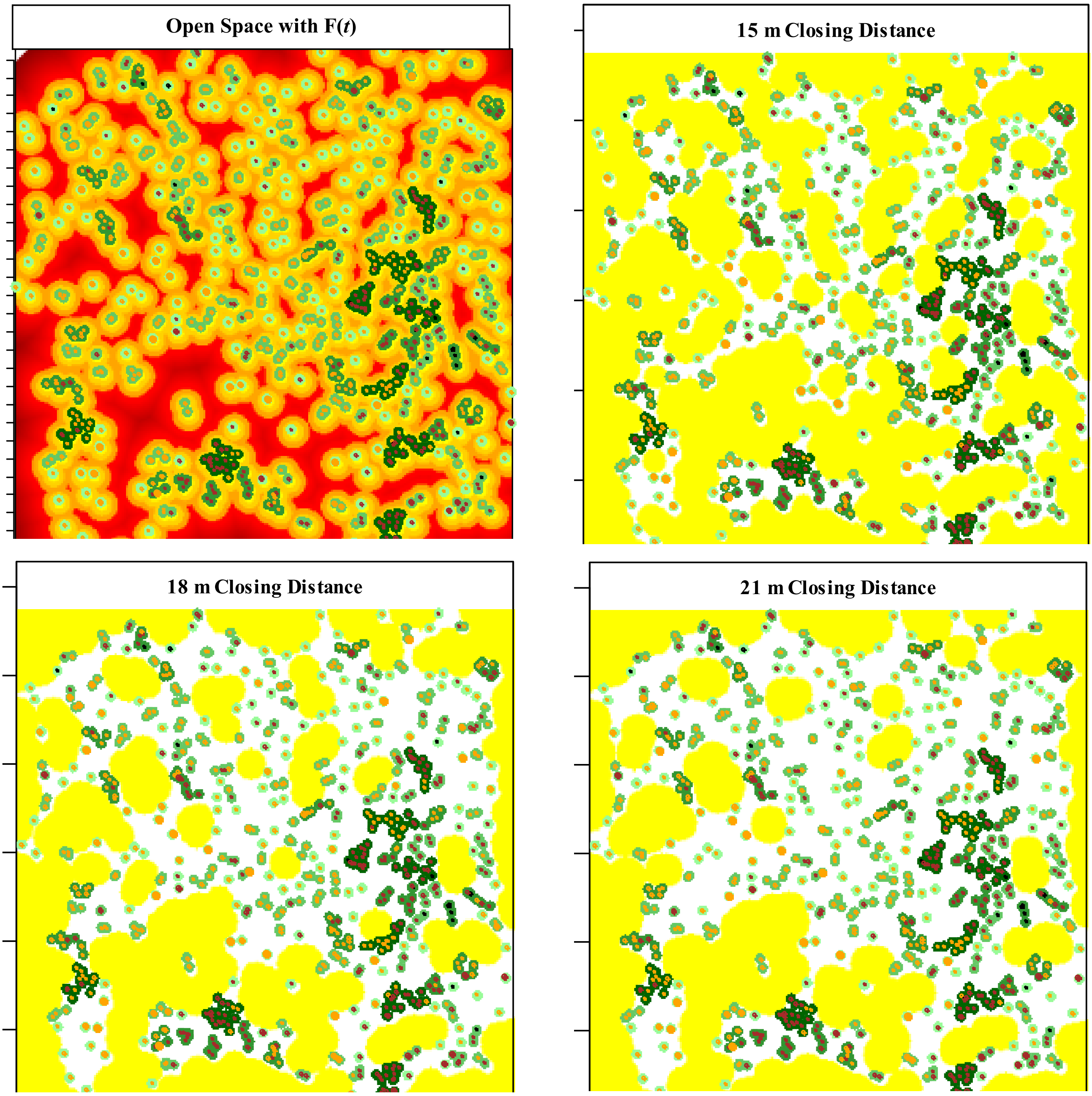


Fig.10: Proportion of cells from each plot in the four different patch type groups. The table underlying this proportions was not different from an expected chi-squared distribution ($p = 0.12$).

Appendices



A2.1: Comparison of open space, *F(t),* method of visualizing openings with PatchMorph. Three examples of the PatchMorph method are shown using closing distances of 15, 18, and 21m. The closing distance is the distance between trees that close off a gap edge. The Stem map is from the 6.7 ha Nile plot. See discussion below.
Discussion on Quantifying openings

Opening sizes in stands represent a significant information gap existsin dry forest ecology (Larson and Churchill 2012). Our attempts with PatchMorph to delineate individual gaps (Fig. A2.1) demonstrated the challenges of quantifying openings in forests with low canopy cover (McGuire et al. 2001). Very few delineated "gaps" occur at a closing distance of 15m. Instead, we see openings representing linear, sinuous, and amorphous shapes that weave through the plot. At 18 and 21 meters, more "gaps" are present but the line between gaps and inter-tree space becomes more arbitrary. Investigators have successfully used PatchMorph to quantify gaps in other frequent-fire forests but those forests had higher densities (Conlins per comm.). We propose that there is a threshold density after which defined canopy "gaps" transition into open space that becomes the background "matrix" for individual trees and clumps. The concept of a tree-fall gap (e.g. Canham et al. 1990) or group selection opening (e.g. Bigelow et al. 2011) no longer works once this threshold is passed. We hypothesize that this threshold is between 150-200 tph depending on clumping levels.

The somewhat linear, sinuous nature of the openings we observed represesnt canopy discontinuities that weave through most of the stand. Several authors have suggested that such openings probably impede the spread of crown fire, insect disturbances, and fungal pathogens (Goheen and Hansen 1993, Fettig et al. 2007, Cassagne et al. 2011). The sinuous and complex nature of the openings also reduces sighting distances compared with large circular gaps, which is important for a number of wildlife species (Roberts et al. 2008). The empty space approach is a technique that quantifies this permeability and complexity and eliminates the need to subjectively decide where gaps begin and end. A similar concept is used in variable retention harvesting to quantify the amount of area beyond the "tree influence zone", typically one tree height from a retention patch (Baker and Read 2011). It is less intuitive than gap size, however, especially for marking crews on the ground. More work is needed to further Additional research is needed to provide tools for quantification of open space in dry forests and to understand the processes that create them.

A2.2: Correlation matrix for input variables used in hierarchical cluster analysis and PCA ordination. Cariables are: mean clump size (MCl); total plot area greater than 9m away from the nearest tree (F > 9m); tph <40cm dbh; tph 40-59.9cm; tph 60-79.9 cm; tph 80 +cm; and total tph

	<40	40-60	60-80	80+	TPH	MCl	F>9
<40	1.00	0.46	-0.04	-0.27	0.84	0.70	-0.45
40-60	0.46	1.00	0.04	-0.24	0.77	0.53	-0.55
60-80	-0.04	0.04	1.00	0.01	0.26	0.13	-0.33
80+	-0.27	-0.24	0.01	1.00	-0.11	-0.09	-0.04
TPH	0.84	0.77	0.26	-0.11	1.00	0.76	-0.68
MCl	0.70	0.53	0.13	-0.09	0.76	1.00	-0.35
F>9	-0.45	-0.55	-0.33	-0.04	-0.68	-0.35	1.00

A2.3: Parameters for regression models used to predict basal area increment from listed year to 1935 in $cm^{2.}$ Model for live trees was the year 2010. Models for prior years were used for snags and downed logs from there year of death. All parameters were significant ($p<0.05$).

Model form :

$$BAI = e^{a + b*\ln(DIA) + c*NI}$$

DIA is inside bark diameter at breast height

NI is a neighborhood index from Contreras et al. (2011) that measures the competitive environment of the tree using an 8m radius:

$$\sum_{i=1}^{n} (d_i/d) \times \arctan(d_i/dist_i)$$

d is the diameter of the subject tree. n is the number of trees within a 8m radius of the subject tree. d_i is the diameters of i^{th} neighbor. $dist_i$ is the distance from the i^{th} neighbor to the subject tree.

		Parameters			
Plot	**Year**	**a**	**b**	**c**	**Adj R^2**
Nile	2010	3.060	1.323	-0.018	0.74
Nile	2005	3.436	1.227	-0.022	0.70
Nile	2000	3.528	1.196	-0.024	0.70
Nile	1995	3.625	1.161	-0.026	0.69
Nile	1990	3.695	1.135	-0.028	0.68
Nile	1985	3.749	1.109	-0.031	0.67
Nile	1980	3.751	1.090	-0.034	0.67
Nile	1975	3.643	1.097	-0.036	0.67
Nile	1970	3.427	1.126	-0.037	0.67
Nile	1965	3.381	1.114	-0.042	0.67
Nile	1960	3.259	1.107	-0.046	0.66
Nile	1955	2.985	1.126	-0.053	0.65
Nile	1950	3.247	0.976	-0.063	0.62
Nile	1945	2.626	1.004	-0.062	0.60
Nile	1940	1.178	1.153	-0.054	0.54
Oak	2010	1.389	1.788	0	0.85
Oak	2005	1.517	1.748	0	0.85
Oak	2000	1.517	1.737	0	0.85
Oak	1995	1.472	1.735	0	0.85
Oak	1990	1.439	1.727	0	0.86
Oak	1985	1.328	1.734	0	0.87
Oak	1980	1.140	1.759	0	0.88
Oak	1975	0.596	1.869	0	0.88
Oak	1970	-0.195	2.040	0	0.86

Oak	1965	-0.389	2.061	0	0.85
Oak	1960	-0.613	2.080	0	0.83
Oak	1955	-0.785	2.067	0	0.81
Oak	1950	-0.647	1.950	0	0.79
Oak	1945	-0.832	1.899	0	0.78
Oak	1940	-1.314	1.870	0	0.73
Lib	2010	2.074	1.584	0	0.70
Lib	2005	2.783	1.375	0	0.69
Lib	2000	3.104	1.283	0	0.69
Lib	1995	3.318	1.215	-0.028	0.69
Lib	1990	3.563	1.135	-0.032	0.69
Lib	1985	3.820	1.048	-0.037	0.69
Lib	1980	4.174	0.925	-0.044	0.68
Lib	1975	4.249	0.870	-0.046	0.67
Lib	1970	4.292	0.826	-0.049	0.66
Lib	1965	3.606	1.000	-0.054	0.64
Lib	1960	4.438	0.705	-0.058	0.62
Lib	1955	4.673	0.577	-0.063	0.60
Lib	1950	4.635	0.493	-0.066	0.56
Lib	1945	3.257	0.691	-0.055	0.50
Lib	1940	2.761	0.622	-0.053	0.45

Chapter 3: Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring

Abstract

Stand-level spatial pattern influences key aspects of resilience and ecosystem function such as disturbance behavior, regeneration, snow retention, and habitat quality in frequent-fire pine and mixed-conifer forests. Reference sites, from both pre-settlement era reconstructions and contemporary forests with active fire regimes, indicate that frequent-fire forests are complex mosaics of individual trees, tree clumps, and openings. There is a broad scientific consensus that restoration treatments should seek to restore this mosaic pattern in order to restore resilience and maintain ecosystem function. Yet, methods to explicitly incorporate spatial reference information into restoration treatments are not widely used. In addition, targets from reference conditions must be critically evaluated in light of climate change. We used a spatial clump identification algorithm to quantify reference patterns based on a specified inter-tree distance that defines when trees form clumps. We used climatic water balance parameters, downscaled climate projections, and plant associations to assess our historical reference sites in the context of projected future climate and identify climate analogue reference conditions. Spatial reference information was incorporated into a novel approach to prescription development, tree marking, and monitoring based on viewing stand structure and pattern in terms of individuals, clumps, and openings (ICO) in a mixed-conifer forest restoration case study. We compared the results from the ICO approach with simulations of traditional basal area and spacing-based thinning prescriptions in terms of agreement with reference conditions and functional aspects of resilience. The ICO method resulted in a distribution of tree clumps and openings within the range of reference patterns,

while the basal area and spacing approaches resulted in uniform patterns inconsistent with known reference conditions. Susceptibility to insect mortality was lower in basal area and spacing prescriptions, but opportunities for regeneration and in-situ climate adaptation were fewer. Operationally, the clump identification method struck a balance between providing clear targets for spatial pattern directly linked to reference conditions. The ICO method, especially when used in combination with climate analogue reference targets, offers a practical approach to restoring spatial patterns that are likely to enhance resilience and climate adaptation.

1. Introduction

Increasing ecological resilience has become a central objective in management of public forestlands due to the combined effects of past management and projected climate change (Baron et al. 2009, Joyce et al. 2009). Ecological resilience (hereafter, resilience) includes the capacity to persist through and re-organize after disturbance, adapt to shifting environmental conditions, and maintain basic ecosystem structure and function over time (Walker et al. 2004). There is increasing evidence that spatial heterogeneity at multiple scales, in addition to forest structure and composition, is a critical component of ecosystem resilience (Levin 1998, Moritz et al. 2011, North et al. 2009, Stephens et al. 2008). General frameworks that incorporate ecologically-based guidelines for spatial pattern have been developed for some forest ecosystems (Carey 2003, Franklin and Johnson 2012, Hessburg et al. 2004, 1999b, Franklin et al. 2007, Mitchell et al. 2006 p. 20). A major remaining task is the identification of spatial pattern targets for specific ecosystems that are empirically linked to resilience, climate adaptation, and desired ecological functions (Puettmann et al. 2009). A related challenge is translating such targets into operationally-efficient prescriptions and monitoring protocols (North and Sherlock 2012, O'Hara et al. 2012)

In frequent-fire pine and mixed-conifer forests in western North America (hereafter, *dry forests*), pre-settlement era forests are commonly used as reference systems to inform treatment targets (Larson and Churchill 2012). Contemporary dry forests with minimally altered or restored fire regimes are increasingly being used as reference sites as well (Lydersen and North 2012, Stephens et al. 2008, Taylor 2010). At the stand level, tree patterns in these forests are commonly characterized by an uneven-aged mosaic of individual trees, clumps ranging from 2 to more than 20 trees, and openings (Kaufmann et al. 2007, Larson and Churchill 2012). Such mosaics persisted for centuries in a dynamic system of fine-scale, gap-phase replacement driven primarily by frequent fire and insect mortality (Agee 1993, Cooper 1960). Patch size and within-patch heterogeneity varied temporally at individual sites, and across different biophysical environments (Kaufmann et al. 2007). Infrequent moderate to high-severity disturbances did occasionally reset these stand-level patterns as well (Arno et al. 1995, Hessburg et al. 2007). Here, we refer to stands as patches embedded in a hierarchy of landscape organization; smaller than sub-watersheds and larger than the largest tree clumps and openings (Urban et al., 1987). Historical patch size distributions of stands in dry forests ranged from 1 to $10^{\wedge 4}$ ha (Perry et al. 2011), different from the traditional view of stands as 10-50 ha management units.

The fine-scale mosaic pattern is thought to be a key factor underpinning the resilience of dry forest ecosystems (Allen et al. 2002, Binkley et al. 2007, Stephens et al. 2010). Irregular tree patterns, large openings, and resulting variation in surface fuels inhibit the spread of crown fire and perpetuate variable post-fire patterns (Beaty and Taylor 2007, Pimont et al. 2011, Stephens et al. 2008), analogous to strategic placement of fuel treatments at larger spatial scales (Finney et al. 2007). Heterogeneous stand structures impede the buildup of epidemic insect outbreaks by disrupting pheromone plumes and breaking up the continuity of susceptible species, as well as age and size classes (Fettig et al. 2007).

Similarly, openings create barriers to the spread of dwarf mistletoes and fungal pathogens (Goheen and Hansen 1993, Hawksworth et al. 1996, Shaw et al. 2005). Likewise, openings and frequent disturbances facilitate periodic tree regeneration in dry forests (Boyden et al. 2005, Sánchez Meador et al. 2009), which is thought to be partly responsible for high levels of local genetic diversity of trees (Linhart et al. 1981, Hamrick et al. 1989). Snow retention is highest where canopy openings are large enough reduce canopy interception, but small enough to be shaded and protected from wind (Varhola et al. 2010). In addition, the contrasting light, moisture, and soil nutrient environments in heterogeneous stands increase understory plant abundance and diversity (Dodson et al. 2008, Moore et al. 2006).

There is a growing scientific consensus that to increase resilience, mechanical and prescribed-fire treatments should seek to restore the range of mosaic patterns found in reference stands (Allen et al. 2002, Franklin et al. 2008, Hessburg et al. 2005, Moore et al. 1999, North et al. 2009, Perry et al. 2011), in addition to retaining large and old fire-tolerant trees and following other resilience principles (Table 1). Widespread adoption of prescription approaches based on spatial reference information has been slow, however, despite numerous operational-level research studies (e.g. Graham et al. 2007, Knapp et al. 2012, Lynch et al. 2000, USFS 2008, Waltz et al. 2003).

The fundamental challenge facing managers is the mismatch between the grain and variation of pattern found in dry forests and the tools commonly used to quantify and manage them. Most silvicultural methods are based on stand-average density metrics originally designed to create homogenous stands (Puettmann et al. 2009). Modifying these approaches to manage for within-stand spatial variability requires re-conceptualizing “stands” as mosaics of variably sized canopy patches (Puettmann et al. 2009). This shift—and the associated changes in mensuration tools, operational methods, and contractual mechanisms—can be initially complex and time consuming (Knapp et al. 2012, North and Sherlock 2012). Thus, many managers continue to employ stand-average basal area or spacing-based approaches (e.g. Powell 2010). There is concern that these approaches create evenly spaced stands inconsistent with ecologically important fine-scale processes, and may have unintended negative effects to wildlife and disturbance behavior. The tradeoffs between the costs of transitioning to new approaches and gains in ecological functionality and resilience are unknown, however.

Projected changes in climate and related shifts in disturbance behavior present an additional challenge to the use of historical reference conditions (Franklin et al. 1991, McKenzie et al. 2011, Williams et al. 2007). Pre-settlement-era dry forests developed from pattern-process linkages that persisted through centuries of frequent disturbances and climatic fluctuation and thus serve as a general guide for increasing resilience (Fule 2008, Keane et al. 2009, Moritz et al. 2011). Restoration approaches based on reference conditions follow almost all of the strategies recommended for climate adaptation (Table 1). Restoring historical spatial pattern, composition, and density for a specific site, however, may not ensure resilience. Targets derived from reference conditions must be critically evaluated, and potentially modified, based on projected future climates and ecological knowledge to provide operative targets for restoration (Keane et al. 2009, Spies et al. 2010, Stephens et al. 2010). Climate analogue reference sites offer a constructive approach to evaluating and using historical reference conditions. A climate analog site is one that developed in a climate similar to the projected future climate of the treatment site

(Gärnter et al. 2008). Climate analogues provide an empirical basis for integrating climate adaptation with ecosystem restoration and can provide ecologically based targets for resilience, response, or realignment adaptation strategies (Stephens et al. 2010).

In this paper we address two central challenges of dry forest restoration: managing for resilient spatial patterns consistent with reference sites, and the use reference conditions in conjunction with climate change adaptation. We employ a spatial clump identification algorithm to quantify reference patterns in terms of individual trees and clumps (Plotkin et al. 2002). We assess our historical reference sites in the context of projected future climate using climatic water balance parameters (annual Actual Evapotranspiration and Deficit), plant associations, and downscaled climate model outputs. We then introduce a novel method to incorporate reference spatial pattern targets into silvicultural prescriptions and tree marking guidelines, which we term the ICO method (for individuals, clumps, openings), in an operational case study. We evaluate the practical utility of the ICO method, and compare it with simulated basal area and spacing-based prescriptions in terms of alignment with reference conditions and effects on several functional aspects of resilience. We hypothesized that: (1) the pattern created using the ICO method would fall within the range of variation, or envelope, of past and climate analogue reference patterns; and (2) basal area and (3) spacing-based prescriptions would be outside of these envelopes.

2. Methods

2.1 Background and Study Area

In 2008, managers from the Okanagan-Wenatchee National Forest (OWNF) selected a 30 ha harvest unit within the Wildcat Timber Sale to test stand-level implementation of the OWNF Restoration Strategy (Gaines et al. 2010). The project area is located within the Tieton River drainage in the eastern Cascade Mountains, 30 miles west of Yakima, Washington and immediately north of Rimrock Reservoir. The site lies on a south-facing aspect with slopes of 10-45%, at an elevation of 975 m to 1060 m. Soils are derived from volcanic ash deposits layered over basalt colluvium (NRCS 2010), and are deep (>150 cm), well drained, and moderately productive (100 year site index, 29 m) (Barret 1978). Modeled precipitation from 1971-2000 averaged 1103 mm annually, falling mostly as snow between November and April (ClimateWNA 2012). Mean January and July temperatures were -2.1°C and 15.7°C.

Forest structure, composition, and management history in the project area is representative of dry-forest biophysical environments common throughout the Eastern Cascades of Washington and Oregon. Tree species consist of ponderosa pine (*Pinus ponderosa*) and interior Douglas-fir (*Pseudotsuga menziesi* var. *glauca*) with a minor component of grand fir (*Abies grandis).* The dominant plant association is Douglas-fir/shiny-leaf spirea (*Spirea betulifolia))*/pinegrass (*Calamagrostis rubescens)* (Lillybridge et al. 1995). Members of the Yakama Nation extensively utilized the area prior to Euro-American settlement in the 1880's. Intensive grazing by sheep and cattle occurred from the 1880's until the early 1900's (USFS 1998), followed by logging in the 1930's and 1970's that removed almost all large-diameter ponderosa pines and spaced out residual overstory trees . Fire exclusion and suppression began at the turn of the century and has continued to the present. Current forest structure is dominated by trees established between 1890 and 1930. A pre-settlement multi-age structure with the oldest trees greater than 250 years was inferred from field ring counts of stumps. Pre-settlement disturbance was likely dominated by low and mixed severity fire, with a return interval of 5-20 years (USFS 1998), and native insect and pathogen disturbances as well (Hessburg et al. 1994).

2.2 Tree Clump Identification

To characterize within-stand tree patterns, we use a clump identification algorithm from Plotkin et al. (2002). The algorithm partitions a stem map of tree locations into clumps at a specified inter-tree distance (*t*), measured from tree center to tree center. Trees are members of the same clump if they are within distance *t* of at least one other tree in the clump. Trees with no neighbors within distance *t* are termed individuals. This method has been previously used to identify tree clumps in dry forests (Abella and Denton 2009, Sánchez Meador et al. 2011 p. 201) and to compare silvicultural treatments with patterns from reference old-growth forests (Larson and Churchill 2008, Larson et al. 2012).

We elected not to use any edge correction method following Plotkin et al. (2002). Yamada and Rogerson (2003) explored the effects of edge correction methods and concluded that there is no advantage in using corrections when the goal is to describe an observed pattern. However, the use of edge correction is important when testing for departure from a null pattern with point pattern statistics. Sánchez Meador et al. (2011) developed an edge correction technique for the clump identification, where clumps that have trees within distance *t* of the edge are removed. We implemented this correction for comparison.

2.3 Climate Analogue Reference Conditions

The pre-settlement era reference conditions used to guide prescription development were based on a 100 m × 100 m stem-map plot installed within the Wildcat project area as well as 32, 50 m × 100 m plots from Harrod et al. (1999), (hereafter, Harrod sites). Harrod et al. (1999) is the only spatially explicit reconstruction of pre-settlement conditions from the eastern Cascade Range of Washington. The Harrod sites reside approximately 85 km northeast of the harvest unit, and display similar biophysical conditions, forest types, and pre-settlement era disturbance regimes; however, approximately half of the 32 plots are in plant associations that are warmer and/or drier than the plant association in the Wildcat unit (Lillybridge et al. 1995).

Our rationale for using the two reference datasets was to compare the reference plot from the Wildcat site against a known range of variation of structure and pattern. This allowed us to determine that the Wildcat site was not an outlier and also compare its pattern and structure with warmer and drier sites. We followed the reconstruction protocols used by Harrod et al. (1999) for the Wildcat reference plot. All live trees, stumps, snags, and logs that were estimated to have originated before 1865 were considered "historical" and mapped. The plot was subjectively located in an area with relatively homogenous slopes, aspects, and soil conditions that were typical of the project area, where stumps, snags, and logs from the pre-settlement forest were well preserved. The slope and aspect of the plot location was compared in GIS with the overall project area to ensure it was not anomalous.

To assess whether the Harrod locations were suitable climate analogue reference sites, we compared current climate (1971-2000) from the Harrod sites to the projected climate of the Wildcat site for three future time periods (2011-2040, 2041-2070, 2071-2100). We used current and projected temperature and precipitation from the Climate WNA database (ClimateWNA 2012). The Climate WNA methodology downscales projections from general circulation models (GCM) by combining PRISM downscaling methods (Daly et al. 2008) for 800 m grid cells with local lapse rates to account for elevation differences (Wang et al. 2012). We used an ensemble of 15 general circulation models (GCMs) to capture the variability in GCM predictions and create an envelope of future climatic conditions (see Appendix for a list of the 15 GCMs). We chose the

A1B and A2 emissions scenarios (IPCC 2007) as they reflect the most likely scenarios given current trends (Rogelj et al. 2009).

To compare the climate regimes of the sites, we used temperature, precipitation, and soil water-holding capacity to calculate annual actual evapotranspiration (AET) and annual climatic water deficit (Deficit), the difference between potential evapotranspiration (PET) and AET. AET and Deficit have been shown to be good predictors of species presence/absence and growth rates (Littell et al. 2008, McKenzie et al. 2003, Stephenson 1998, 1990); and have been used to project shifts in species distributions and disturbance regimes (Littell et al. 2010, Lutz et al. 2010, Shafer et al. 2001). We used a Thornthwaite-type model for PET (Lutz et al. 2010, Thornthwaite et al. 1957) and a soil water balance model from Dingman (2002) based on soil water-holding capacity in the top 150 cm of the soil profile (NRCS 2010).

We added a multiplier to the PET equation for solar radiation similar to the approach used by Stephenson (1998) and Lutz et al. (2010) to account for differences introduced by aspect, slope, and latitude. We calculated solar gain at each Harrod plot center in ArcMAP v10 (ESRI 2012). We then normalized PET using the ratio of solar gain of each plot to the average value for the study area, which was derived from a 90m × 90m grid of points distributed across the 6,500 ha study area. Plant associations from Lillybridge et al. (1995) were used to assess the ecological significance of relative AET and Deficit and evaluate which of the Harrod sites and respective plant associations represented appropriate climate analogues for the Wildcat site. Plant associations were used as indicators of site potential in terms of productivity (site index), carrying capacity (SDI levels for full stocking), and species viability (whether sites can support Douglas-fir and grand fir) not as stationary communities (Daubenmire 1976). After assessing the AET and Deficit of plant associations, we combined similar associations to more easily compare the current and projected climates of the Wildcat site against the current climate of Harrod sites. Plant associations were combined into four groups based on defining tree species, proximity of average AET and Deficit values, and overlap of ranges of Deficit values. The four groups were PIPO High, PSME High; PSME Moderate, and PSME Low.

2.4 Prescription Development using the ICO Method

Translation of the reference spatial patterns into prescription guidelines was done by using the Plotkin et al. (2002) clump algorithm to derive clump size distributions for the reference plots. This distribution summarizes the percent of trees arranged as individuals and in clumps of different sizes at a specified inter-tree distance (Table 2). We selected a single inter-tree distance threshold of 6 m to define tree clumps based on the observed distance at which most mature ponderosa pine trees (>120 years) in our study area display interlocking crowns and form patches of continuous canopy (Graham et al. 2007). Crown radius data from the US Forest Service Forest Inventory and Analysis database for similar plant associations on the OWNF were consistent with distances between 5 m and 7 m. The 6 m distance represented the 33rd percentile of crown diameter for ponderosa pine. Abella and Denton (2009) and Sánchez Meador et al. (2011) used a similar process to derive a clump distance and used 6 and 5.3-6.6m, respectively. We then generated cumulative clump size distributions using the 6 m threshold to compare the Wildcat and Harrod sites and to assess differences in clump size distributions among plant associations. Visual inspection of these distributions revealed no major difference in pattern between the associations, and the distribution from the Wildcat reference site lay in the middle third of the Harrod distributions.

The next step in prescription development was to determine the average leave tree density and pattern to be approximated in tree marking. We choose 100 trees ha^{-1} (tph) based on the desired range of 50-75 tph in dry, old forest structure described in the OWNF restoration strategy (Gaines et al. 2010) and allowance for post-treatment mortality from prescribed fire, inter-tree competition, and ongoing insect and pathogen disturbance. We then multiplied the proportion of trees each clump size from the Wildcat reference pattern by the target of 100 tph to generate the target number of tph in each clump size.

To facilitate marking and tracking of clumps in the field, we grouped clump sizes together into three bins: individual trees (clump size = 1), 2-4 tree clumps, and 5+ tree clumps. We divided the target number of trees in each bin by the average number of trees for that bin (3 for 2-4 tree clumps and 6 for 5+ tree clumps) to derive the target number of clumps per hectare for each bin (Table 3). To ensure that large clumps would exist in the future, the target for 5+ tree clumps was increased by 30% because we expected more density-dependent bark beetle mortality in large clumps vs. individuals. Bin size was based on observed functional differences between clump sizes: for example, 5+ clumps typically contain "interior trees" that are more susceptible to competitive stress and insect related mortality (Olsen et al. 1996); smaller clumps do not. Moreover, understory shading and micro-climatic effects begin occurring in larger clumps (~5+ trees), which can affect understory development, wildlife use, and fire behavior (Dodd et al. 2006, Ma et al. 2010). Individual trees have faster growth rates and distinct crown architecture which can affect bark thickness, fire and insect resistance, resin response to wounding, and sensitivity to climatic fluctuation (Carnwath et al. 2012).

The purpose of the prescription was not to replicate the clump size distribution of the reference stand on every hectare but to promote a mosaic pattern of individual trees, clumps, and gaps within the envelope of historic conditions. Consequently, the per hectare targets for individuals and clumps were not rigid targets but, approximate averages to be obtained over the entire unit. The marking guidelines also included instructions to retain all trees >110 years old, generally thin from below, favor ponderosa pine, and leave trees with live crown ratios >40% (see Appendix for complete marking guidelines). The overall goal was to work with existing stand conditions to achieve the approximate individual tree and clump targets, while meeting the other criteria. We assumed that leaving over 50% of the target density in clumps would result in the desired range of opening sizes and thus did not provide explicit instructions to create openings. Leave tree marking was used with crews tallying the number of residual individuals and clumps by bin size. The results were tallied after the marking was completed, so no adjustments were made during marking. This treatment was called the ICO treatment (individuals, clumps, and openings).

2.5 Monitoring and simulated treatment alternatives

To monitor and evaluate the implementation of the prescription, we installed a 2 ha plot (141 m × 141 m) prior to harvest, in which all trees >15 cm dbh were mapped. The 15cm cutoff was based on a commercial thinning minimum diameter threshold. We derived clump size distributions at 6 m and determined that too few large clumps were retained; this presented an opportunity for adaptive learning through simulation of an adaptive management marking scenario. In this scenario, we adapted the initial mark to better achieve the 5+ tree clump targets, and create larger openings that better reflected conditions of the reference plot. This simulated marking scenario was labeled the adaptive management (AM) treatment and was intended to be an example of how tallying clump totals during marking could have been used to make adjustments to the original ICO treatment.

We also simulated basal area- (BA) and spacing-based (Space) prescriptions to compare our method with these more standard thinning approaches. The BA simulated marking scenario sought to achieve a uniform target basal area throughout the 2 ha monitoring plot, with a +/- 50% allowance for natural openings and denser areas. The target basal area was the same as that retained on the 2 ha plot in the actual marking. Variable radius plots were simulated on a 20 m × 20 m square grid within the 2 ha using a basal area factor of 4.59. The same leave tree criteria used in the actual treatment, minus the clump targets, were followed on each plot until the basal area target was met. Ponderosa pine was selected for retention over Douglas-fir if dwarf mistletoe (*Arceuthobium douglasii)* infections were present, or if the pines were similar in diameter (within 5 cm dbh). The BA simulation was implemented in sequential strips within the stem map, similar to how a marking crew ordinarily moves through a stand.

The third simulated marking scenario (Space) followed a spacing-based prescription where all trees within 6.7 m of a larger tree were cut, while retaining all ponderosa pine >50 cm dbh. The distance of 6.7 m was calculated to achieve the same tph as the actual treatment. This approach, called Designation by Description (DxD), is used in some contemporary dry, mixed conifer forests in the Pacific Northwest and northern Rockies (Wynsma and Keyes 2010). The BA and Space treatments resulted in post-treatment basal areas (16.9 and 17.5 $m^2 \cdot ha^{-1}$) and stocking levels (30% and 31% of maximum SDI) similar to other dry forest fuel reduction and restoration treatments conducted in the region (Larson et al. 2012, Powell 1999 p. 200, Prichard et al. 2010, Youngblood et al. 2006).

2.6 Comparing treatment alternatives and reference plots

We used a combination of global and local point pattern analysis methods to provide a robust evaluation (sensu G. L. W. Perry et al., 2006) of whether the field ICO treatment and the three simulated treatments fell within the envelope of spatial patterns found in the Wildcat and Harrod reference plots . The pair correlation function, g(*t*), was selected as the primary global pattern statistic (Wiegand and Moloney 2004). The g(*t*) function is a non-cumulative form of Ripley's *K(t)* (Ripley 1988), and is calculated by taking the derivative of the kernel smoothed *K(t)* distribution (Wiegand and Moloney 2004). The g(*t*) function avoids the problem of "cumulative effects" associated with *K(t)* or *L*(*t*), where patterns at short *t* values can lead to incorrect assessments of clumping, randomness, or inhibition at longer *t* values (Fortin and Dale 2005, Perry et al. 2006, Illian et al. 2008). We generated reference pattern envelopes from the Harrod plots using the g(*t*) function at a range of *t* distances from 0 to 12.5 m, or 1/4 of the distance of the shortest length of the plots (Diggle 2003). Results of the g(*t*) function from the Wildcat reference site and four treatments were then plotted against the reference envelopes to visually assess departure.

To test our hypotheses of no differences between the reference and treatment patterns, we tested all patterns against a null hypothesis of complete spatial randomness (CSR) across a specified range of t values. This allowed us to infer statistical differences even though patterns were not directly tested against each other (Fortin and Dale 2005, Perry et al. 2006, Illian et al. 2008). We first tested for overall departure from CSR at 0-12.5 m using the Cramer–von Mises goodness-of-fit (GoF) test from Loosmore and Ford (2006) with *g(t).* Values of the test pattern were ranked against the *g(t)* values of 1000 simulated CSR patterns based on the squared difference from the mean of the CSR patterns. The null hypothesis, no departure from CSR, was tested with a one tailed test using the rank of the test pattern with critical value of 0.05. We then inferred clustering, randomness, or inhibition (even spacing) at specific inter-tree distances based on where g*(t)* values of the test pattern were above, within, or below the 95th percentile of 1000 CSR patterns respectively (Wiegand and Moloney 2004). We applied an isotropic (Ripley 1988) edge correction to all g(*t*) tests based on an analysis of edge correction methodologies by Yamada and Rogers (2003).

We plotted clump size distributions at 6 m to visually assess departure of the treatment patterns from reference pattern envelopes, and also used a modified version of the Loosmore and Ford (2006) GoF test. To quantify departure, the Harrod plots were used as the null pattern distribution in place of simulated CSR patterns (Illian et al. 2008). Ranks were based on the sum of differences between the test pattern and the mean cumulative proportion of trees in 1 to 18 tree clumps; 18 was the largest observed clump size. Ranks were converted to percentiles with the 100th percentile representing the pattern with the highest proportion of trees as individuals and in small clumps, while the lowest percentile indicated the pattern with the greatest proportion in large clumps. This test was also done at 5 m and 7 m to assess how using a different threshold distance for defining clumps would affect the results.

As the Harrod et al. (1999) plots were 0.5 ha (100 × 50 m), we partitioned the 1 ha Wildcat reference plot and the 2 ha treatment plot into three and six 100 m × 50 m subplots, respectively, using a moving window with 10-20 m of overlap. This subsampled local variation in pattern across the treatment plots and provided comparisons at the same spatial extent. We also plotted the Harrod clump size distributions by plant association grouping to assess relationships between AET/Deficit and levels of clumping. Finally, we derived clump size distributions at 2 m and 10 m distances to compare patterns at multiple scales of observation.

2.7 Evaluating functional attributes of resilience

To assess the potential implications for climate adaptation of the different treatment alternatives, we quantified several functional attributes of resilience. First, species composition and diameter distributions were compared to determine the extent to which treatments favored drought- and fire-tolerant species and larger size classes (Table 1). Second, potential susceptibility to mountain pine beetle (MPB; *Dendroctonus ponderosae)* was compared by characterizing inter-tree competition using Stand Density Index (SDI). We derived critical MPB mortality thresholds for the different plant association groupings using methods from Cochran (1994), with data from Lillybridge et al. (1995), and results from other empirical studies (Negron and Popp 2004, Olsen et al. 1996). SDI was calculated around each individual ponderosa pine using an 8 m radius following methods of Negron and Popp (2004). SDI is commonly used to quantify density relative to maximum carrying capacity (Reineke 1933) and is an adequate predictor of BA increment (Contreras et al. 2011) and bark beetle vulnerability (Fettig et al. 2007).

A third aspect of resilience we quantified was the amount and size of openings. Delineating and quantifying individual gaps in forests with low canopy cover is challenging due to irregular gap shapes and lack of clear boundaries. Instead, we used the empty space function *F(t)* to quantify openings in terms of distance from the nearest tree, or distance from the nearest gap edge. The *F(t)* function generates a grid of cells, set to 1 m in our case, and then derives the distance from the center of each grid cell to its nearest tree. We created histograms of binned F(*t)* distances for all the grid cells, using 3m bins. This quantified the proportion of the total plot area in the different bin sizes. A graphical plot of this function was also created to visually assess the spatial distribution of cells in the 3 m bins across each treatment. We defined large openings as those with distances ≥15 m from the nearest tree or gap edge, based on minimum light requirements for ponderosa pine growth and associated gap sizes (Gersonde et al. 2004, York et al. 2004). Openings of this width are also likely to impede the spread of active or independent crown fire (Peterson et al. 2005).

All analyses were implemented in R v.2.8.1.and made use of functions in the *spatstat* package (Baddeley and Turner 2005). The R code for the Plotkin et al. (2002) algorithm is available upon request and instructions for implementing it in ArcMAP v10 are provided in the Appendix.

3. Results

3.1 Climate analogue reference conditions

Annual AET and Deficit values at the Harrod sites were generally consistent with the productivity and moisture gradients of the respective plant associations described in Lillybridge et al. (1995). Ponderosa pine associations had the highest Deficit followed by the Douglas-fir/bitterbrush/bunchgrass (*Purshia-tridentata/Agropyron-spicatum*; PSME-High). Ponderosa pine associations are found on low productivity sites, too droughty for Douglas-fir, while the PSME-High association is found at the dry end of the Douglas-fir ecotone (Lillybridge et al. 1995). The PSME-Moderate and PSME-Low groups contained plant associations found on cooler and moister sites, with generally higher productivity and carrying capacity (Fig. 1).

The present-day Deficit value for the Wildcat site fell well within the range of the same plant association on the Harrod sites (Douglas-fir/shiny-leaf spirea-pinegrass) although AET values were higher. Deficit projections for the Wildcat site for the 2011-2040 period were within AET-Deficit levels for the PSME-Moderate group. By the 2041-70 period, the Wildcat AET-

Deficit projections were similar to the ponderosa pine and PSME-High groupings. At the end of the 21st century, only the lowest Wildcat Deficit projections were similar to current ponderosa pine sites. The variability of the AET and Deficit projections increased through time due to increasing difference between the A2 and A1B emissions scenarios and the GCM projections in the second half of the century (IPCC 2007).

3.2 Prescription development, implementation, and adaptive management

After initial training period, the marking crew implemented the prescription efficiently and created a mosaic pattern of clumps and openings (Fig. 2). The proportion of trees left in 2-4 tree clumps closely approximated the target; 34 to 37% respectively, however, an insufficient number of trees were left in 5+ tree clump (4% vs. the target of 21%). Results from the 2 ha monitoring plot were similar (Fig. 3), but 10% of trees were left in 5+ tree clumps. Through discussions with the marking crew, we learned that the crew had difficulty deciding when to thin from below and when to leave smaller trees to form larger clumps. In addition, we had not defined the upper range of clump size for the 5+ tree clumps. Consequently, the crew left mostly 5 to 6 tree clumps and no clumps with more than 8 trees. Most importantly, tracking results were not tallied until after marking was completed, so bias was not detected early in the implementation process when corrections could have been made. There was also some confusion as to whether stream buffer zones (no-entry “skips”) should count as large clumps. Finally, our assumption that large openings would occur as a result of creating clumps did not prove correct (Fig. 2). Crews were uncomfortable with creating large openings, especially when it required marking large trees for removal.

3.3 Treatment alternative and reference pattern envelopes

We accepted the hypothesis of no difference between the ICO treatment pattern and those of Harrod sites, as well as the hypotheses that the BA and Space treatment patterns were different than the Harrod sites. Most Harrod plots (23 out of 32) showed statistically significant, deviance from complete spatial randomness (CSR) in the GoF test, and were clustered patterns. The remaining 9 plots displayed no difference from CSR, and none were uniform (see Appendix). The ICO treatment was also different from CSR and clustered, but was close to being a random pattern (p= 0.048) (Table 4, Fig. 4). Both the Wildcat reference site and the simulated AM treatment were different than CSR and clearly clustered (p= 0.001 and p=0.002 respectively). The two patterns also followed a similar pattern of clustering and randomness at short (<6 m), intermediate (6-12 m), and long intermediate distances (>12m). The BA and Space treatments displayed significant deviance from CSR and were uniform, although the BA pattern was close to random (p= 0.047). Compared directly to the Harrod g(*t*) pattern envelope as opposed to a CSR envelope, the BA and Space treatments were near the boundary, or outside, of the Harrod envelope (Fig. 4B).

Comparison of the cumulative clump size distributions and the modified GoF rankings confirmed the results of the GoF tests (Table 4 & Fig. 5). Of the treatment patterns, the AM treatment was the most clumped, and was on the high end of clumping relative to the Harrod envelope (40th percentile). Approximately 1/3rd of the trees in this treatment were individuals, 1/3rd were in small clumps (2-4 trees), and 1/3rd were in medium clumps (5-9) (Fig. 3). It displayed high variation in the subsample of 0.5 ha plots laid out across the 2 ha plot (Figs. 2 & 5). The ICO treatment was less clumped relative to the Harrod envelope (65th percentile), with 52% of trees as individual trees, 40% in small clumps, and 8% in medium clumps; and more modest variation in the 0.5 ha subsamples. In the BA treatment, 70% of the trees were individuals trees with the remainder in small clumps. The pattern had little variation in the 0.5 ha subsamples, and was near the low clumping boundary of the Harrod envelope (95th percentile). The Space treatment created a pattern outside the Harrod envelope (100th percentile) with 90% of the trees as individuals, and no variation in the 0.5 subsamples. The percentile rankings of the four treatments varied somewhat using clump size distributions based on 5 and 7 m distances, but results were generally the same (Table 4).

Finally, the cumulative clump size distributions of the Harrod plots were plotted by AET/Deficit plant association group to assess the effect of AET/Deficit on pattern (Fig. 5). Patterns dominated by medium to large clumps (10+ trees), as well as patterns with mostly individual trees and small clumps, were found in all of the plant association groupings. The ponderosa pine grouping had only one medium clump pattern, however, with the rest containing predominantly individuals and small clumps (2-4 trees).

3.4 Functional attributes of resilience

By design, density and average diameter measures were similar among the ICO and three simulated treatments (Table 4). A major difference was the greater retention of small and mid-size pine in the ICO and AM treatments compared to the BA and Space treatments (Fig. 6). In the AM treatment, removing additional large trees (>65 cm dbh) was necessary to create openings. This resulted in retention of 7.5 vs. 10 large (>65 cm dbh) Douglas-fir tph and 7.5 vs. 8 large pine tph in the AM vs. ICO treatments, respectively. Large trees were also cut in the BA and Space treatments, but to achieve uniform spacing. The proportion of pine to Douglas-fir basal area was 10% higher in the ICO and AM treatments compared with the BA and Space treatments, but was still 25% less than the reference plot (Table 4).

The BA and Space treatments resulted in zero pine susceptible to mountain pine beetle mortality based on the critical SDI thresholds from the Wildcat site (Fig. 7). If the lower SDI thresholds from the High-Deficit PIPO and PSME plant associations on the Harrod sites are considered, approximately 25% of the pine were susceptible (the extent of the boxplot above the threshold lines in Fig. 7). In the ICO and AM treatments, approximately 50 and 66% of the pine were susceptible, respectively, using the lower SDI thresholds. Trees in the Harrod plots, pooled by plant association grouping, and the Wildcat reference site showed a wider range of inter-tree competitive conditions than any of the treatments. In all groupings, 30-45% of the pines were above their site specific critical SDI thresholds (Fig. 7). Extreme SDI values (2000+) caused by large clumps of large diameter trees were not uncommon in the reference stands.

The spatially explicit plots and histograms of the *F(t)* function showed differences in the total area, size, and shape of openings among the patterns (Fig. 2). Large openings, defined as those with the opening center ≥15 m from a tree or gap edge, were generally sinuous, ill-defined, and lacked distinct boundaries. The shape and approximate area of large openings can be estimated by examining the background color surfaces of the stem maps in Fig. 2. Approximately 21% of the area in the Wildcat reference plot was > 15 m from a tree or gap edge, while the AM and ICO treatments displayed 10% and 2%, respectively. The BA and Space treatments did not contain any area >15 m from a gap edge.

4. Discussion

4.1 Prescription development, implementation, and adaptive management

The ICO method proved to be a useful framework for conceptualizing stands as mosaics of individuals, clumps and openings. Spatially assessing variation in tree density in terms of individuals and clumps instead of basal area or spacing required training, but resulted in a more intuitive and concrete way for the marking crew to understand and create the desired heterogeneity. Use of a single distance based on crown interlock was necessary to clearly define tree clumps and make implementation operationally tractable. There is no single correct crown overlap distance (Sánchez Meador et al. 2011), however, and choosing a 5 m or 7 m distance would have resulted in somewhat different target proportions for clumps and individuals. Selecting a 5, 6, or 7m distance would have resulted in highly similar patterns, as the proportion of trees in small, medium, and large clumps increased in a roughly linear fashion with inter-tree distances from 4 m to 7 m (Fig. 2).

The insufficient number of large clumps and openings in the initial ICO mark demonstrated the need for monitoring and adaptive learning when transitioning to new approaches (Knapp et al. 2012). In subsequent restoration projects, we have added a bin for larger clumps and now use four: individual trees, small clumps (2-4 trees), medium clumps (5-9 trees) and large clumps (10-20 trees). We also created a simple tracking system for both leave and cut tree marking that provides real time feedback during marking. Crews are now consistently meeting the clump targets in ongoing projects based on results from this tracking system. Once crews are familiar with the methods, we are finding that it takes a similar amount of time to implement as more traditional marking approaches. More details on implementing the method are available at: http://www.cfc.umt.edu/forestecology/files/ICO_Manager_Guide.pdf

Another lesson learned was the need to provide explicit direction for the creation of large openings. Retaining large, fire tolerant trees is a key principle of dry forest restoration and increasing resilience (Agee and Skinner 2005, Hessburg and Agee 2003, Taylor and Skinner

2003), and removal of pre-settlement era trees (old trees) is not necessary to restore pattern (Franklin and Johnson 2012). However, we concur with others that rigid diameter limits, with no flexibility for young trees or fire intolerant species, can conflict with restoration of spatial pattern and other objectives (Abella et al. 2006, North et al. 2007a). Other factors to consider when creating openings are edaphic conditions such as shallow soils and disturbance processes, including prescribed fire. Refining methodologies to quantify openings in reference patterns is also needed to provide more explicit guidelines for openings.

The ICO method is one approach to implementing variable density (Carey 2003, O'Hara et al. 2012) or free thinning (Tappeiner et al. 2007). A key challenge for any approach that seeks to create within-stand heterogeneity is to balance the needs for (1) concrete, ecologically based targets for spatial pattern that can be objectively monitored, (2) sufficient flexibility to achieve other structural and compositional objectives (e.g., Table 1), and (3) operational simplicity and efficiency (North and Sherlock 2012, O'Hara et al. 2012). In designing the ICO method, we explicitly sought to balance these needs by combining elements of other approaches that use spatial information from dry forest reference conditions. The direct, transparent link to reference conditions is similar to the methods of Covington et al. (1997) and Waltz et al. (2003), who used the locations of pre-settlement stumps, snags, and downed logs to guide spatial patterns of tree retention. However, the ICO method is not based off the pre-settlement locations of clumps and thus does not require that evidence of pre-settlement pattern be present. Our approach seeks a middle ground between direct reliance on pre-settlement structures and more flexible "free selection" methods (Lynch et al. 2000, Graham et al. 2007, Jain et al. 2008, Mitchell et al. 2006), which typically lack concrete targets for spatial pattern, require more judgment to implement, and can result in stands that are overly clumped relative to reference conditions (North et al.

2007a). Our method is similar to approaches that prescribe a target distribution of basal area or SDI and instruct marking crews to create patches of different densities while incorporating other leave tree criteria (Harrod et al. 1999, USFS 2008). Similar to Knapp et al. (2012), we have found that identifying and tracking tree clumps is more intuitive and efficient than using basal area. Finally, the ICO method is conceptually similar to several uneven-age, multi-cohort management approaches (e.g. Bailey and Covington 2002, O'Hara 1996), and would benefit from more rigorous quantification of growing space allocation using tools from these approaches.

No prescription approach is optimal for all stand conditions, operational systems, and objectives. The ICO method works best in even-age stands simplified by past management. It may not be the right tool in stands with serious forest health issues, poor live crown ratios, or where a major shift in species composition is needed. In stands with large numbers of live pre-settlement era trees, simply retaining these trees can restore spatial pattern (Larson et al. 2012, Lutz et al. 2012), although the ICO method can be useful for managing younger cohorts in such stands.

Another challenge is obtaining stem map data. Stem maps are not mandatory to implement the method, however. Regional reference datasets exist for most areas of the interior western US (Larson and Churchill 2012). An effort is underway to quantify regional reference pattern envelopes through a meta-analysis of all existing reference stem maps and make the information available to managers in a user friendly format. Additional 3-10ha stem maps will be needed to ensure that existing datasets indeed capture the range of variation in pattern across the dry forest landscape. Use of remote sensing tools in areas with minimally altered or intact fire regimes to derive reference clump and opening size distributions over larger spatial extents is needed to examine variation in pattern relative to shifts in biophysical conditions, as well as to ensure that the upper range of clump and opening sizes is captured. Field methods to sample clump and opening size distributions without a full stem map are also needed. Finally, further examination of the edge effects on clump size distributions is warranted.

4.2 Climate analogue reference conditions

Climate analogue reference conditions offer a way of utilizing information from pre-settlement era conditions while factoring in climate change projections (Gärnter et al. 2008, Keane et al. 2009). By modeling the climate envelopes of plant associations instead of species presence/absence, we were able to show that future projected AET-Deficit of our study site may be within the range of the Harrod sites, at least through the middle of the century. This suggests that Douglas-fir and ponderosa pine will likely be viable species in this area for multiple decades, although productivity and carrying capacity may decline. Other studies have found similar results using climate envelope models (Littell et al. 2010, Rehfeldt et al. 2006), as well as mechanistic models (Coops and Waring 2011, Griesbauer et al. 2011). Deficit is also a major driver of the two primary disturbance agents in this ecosystem: fire occurrence and severity (Littell et al. 2009, Westerling et al. 2006) and insect related mortality (Littell et al. 2010).

As forest structure and spatial pattern at this scale are shaped by the interaction of vegetation types, fine-scale biophysical variables, disturbances, and climate (Moritz et al. 2011), we assumed that the Harrod sites on moderate and high Deficit plant associations (Fig 1) were reasonable climate analogue reference sites. The plots on these plant associations encompassed almost the full range of the spatial patterns found in the Harrod reference envelope (Fig. 5), whereas the plots on ponderosa pine associations contained predominantly individual trees and small clumps, with only one large clump of 11 trees. This suggests that moisture and site productivity limited pattern only on the harshest Harrod sites, which are currently at the forest and shrub-steppe ecotone (Lillybrige et al., 1995). Abella and Denton (2009) also found reduced clumping on soils with lower moisture and nitrogen levels in ponderosa pine forests in Northern Arizona and attributed it to limitations on tree establishment. Based on the observed relationships between plant association groupings, clump size distributions, and AET-Deficit relations, the full Harrod pattern envelope is a reasonable reference pattern envelope for the Wildcat site through the first climate projection period (2010-2040). After that, the ability of the site to support large clumps may be diminished.

As with all climate change projections, our conclusions must be interpreted and applied in the context of the associated model uncertainty. Climate change models and projected ecological effects are best interpreted at watershed (10,000+ ha) or larger scales (McKenzie et al. 2011). Downscaling climate data to the stand scale introduces additional error, especially in complex terrain with strong orographic and microsite effects, such as in our study area (Lundquist and Cayan 2007). Our method does not factor in localized and fine-scale weather patterns such as cold air drainage and pooling (Daly et al. 2010). Furthermore, changes in other climate variables such as growing season timing and length and minimum winter temperatures may result in additional physiological stress and maladaptation issues (Chmura et al. 2011, Griesbauer et al. 2011). Climate envelope approaches such as ours rely on the assumption that current species ranges are constrained primarily by climate, a top-down spatial control, and that past and future climates will feature similar climate envelopes for each species.

Despite these limitations, use of climate analogue reference conditions translates climate projections into site-specific information for managers that is based on empirical relationships between the predicted climate, potential species viability, and site potential. The fact that AET and Deficit captured differences among plant associations reasonably well confirm that they are good composite variables for the components of the biophysical environment that affect plant distributions (Stephenson 1998). Perhaps most importantly, the climate analogue approach facilitates a forward-looking forest restoration paradigm that is not based on recreating historical conditions, but seeks to utilize historical information to restore pattern-process relationships appropriate to specific climatic conditions.

While recommended, we stress that climate analogue reference conditions are not required to use the ICO approach. The ICO method is a way to incorporate spatial reference information into prescriptions and marking guidelines, while the climate analogue approach is a framework for selecting climate-appropriate reference conditions. Dry forest treatments based on historical reference conditions alone are generally a positive step towards climate adaptation and resilience (Keane et al. 2009, Spies et al. 2010).

4.3 Treatment alternatives and reference pattern envelopes.

The BA and Space simulated treatments resulted in patterns that differed from the Harrod reference envelopes and the AM and ICO treatments in two key ways. First, the BA and Space patterns were uniform *and* had relatively high densities (tph). Many of the Harrod patterns (30%) were random and the rest clustered, similar to other reconstruction studies (Abella and Denton 2009, Binkley et al. 2008, North et al. 2007a, Youngblood et al. 2004). A few were close to being statistically uniform, but these had much lower densities than the 64-70 tph of the treatment alternatives (see Appendix). The higher densities, combined with more regular spacing, explain why the BA and Space patterns are statistically different from the Harrod patterns using the GoF test, but within part or all of the Harrod envelopes for the g(t) and clump size distributions. As density increases, the “additional” trees are more likely to be found in larger clumps rather than spaced out evenly across the stand. This is an intuitive result given that regeneration in dry forests is typically clumped and often associated with patchy mortality of overstory trees (Sánchez Meador et al. 2009). The BA and Space patterns also lack of variation in the 0.5 ha subsamples across the 2 ha plot (Fig. 5). Regularly spaced, individual trees are indeed a component of reference patterns. However, the Harrod plots, along with other studies (Abella and Denton 2009, Youngblood et al. 2004), suggest that regularly spaced trees rarely cover more than 0.5 ha of contiguous area at densities >50 tph.

It is clear that applied over entire stands, or especially multiple contiguous stands, stand-average basal area and spacing based prescriptions do not restore the range of patterns that existed when frequent fire occurred. Over time, prescribed fire, natural disturbances, and post-treatment stand development will cause mortality, openings, regeneration, and new clump formation (Stephens et al. 2009, Waltz et al. 2003). These processes will likely nudge the BA and Space patterns into the reference envelope over time. However, it may take a long time for natural processes to create openings, and clumps of overstory trees will take many decades to re-form if eliminated during treatments. Basal area and spacing approaches can be modified to leave a greater range of density (e.g. USFS 2008), but explicitly prescribing the creation of openings and retention of large clumps in such prescription may be necessary to achieve the desired pattern.

4.4 Managing for Resilience

The primary objective of the treatment was not to recreate the pre-settlement forest, but to enhance resilience. Tree patterns in the AM treatment displayed a steeper "gradient of resistance" to different disturbance agents across the plot (*sensu* Moritz et al., 2011), similar to many of the Harrod plots. At one end of this gradient are "fences" of high resistance that may slow or stop the spread of high intensity disturbance, such as openings or areas of widely spaced trees. At the other end of the gradient are patches of potential instability that can lead to decadence, mortality, and subsequent regeneration of early-seral species (Odion and Sarr 2007). Examples include high density clumps that are well above critical beetle thresholds, mistletoe patches, or multistory tree clumps conducive to torching. The steeper gradient of resistance in the AM pattern compared to the other patterns predisposes it to higher variation in disturbance effects and post-disturbance development pathways (Parisien et al. 2010, Thaxton and Platt 2006, Waltz et al. 2003). In theory, patterns with more fences and corridors are less susceptible to high severity disturbances that reset entire stands (North et al. 2009, Stephens et al. 2010) and initiate non-linear shifts to new system states (Messier and Puettmann 2011, Paine et al. 1998). As the pattern of past disturbances influences future distances (Collins et al. 2009, Peterson 2002), the mosaic will theoretically be more likely to replenish itself and maintain its basic pattern elements over time through fine-scale, gap phase replacement even as the climate changes. Larger scale climate drivers and disturbances will occasionally override the effects of stand level patterns, however (Turner 2010).

Tree patterns in the BA and Space treatments contain fewer ponderosa pines susceptible to mortality from mountain pine beetle attack due to more uniform spacing and a lower proportion of pine to Douglas-fir. Higher clumping levels in the AM treatment would likely sustain higher endemic levels of bark beetle mortality, especially during drought periods (Olsen et al. 1996) and where warming trends lead to non-linear changes in beetle life histories and survivorship (Bentz et al. 2010). However, the fact that 30-45% of pines were above beetle thresholds in the Harrod plots demonstrates that many old trees are able to persist in high density clumps, embedded in a mosaic of individuals and openings, for multiple centuries. High severity insect outbreaks did occur historically (Weaver 1961).

From a climate adaptation standpoint, ongoing tree mortality from endemic levels of insects and pathogens is an important element of resilience and system adaptation. Periodic mortality and subsequent regeneration pulses likely select for genotypes adapted to a wider range of climate regimes than regeneration that establishes quickly after a single severe disturbance event, thereby taping into the high level of local genetic variability in ponderosa pine and Douglas-fir (Hamrick et al. 1989, Linhart et al. 1981). The larger openings in the AM pattern and potential for "time release mortality" of clumps and subsequent regeneration may lead to higher levels of establishment and faster growth of seedlings (Boyden et al. 2005, Fajardo et al. 2006, Sánchez Meador et al. 2009, York et al. 2004). Regeneration will thus more quickly attain size classes capable of reproduction, which may facilitate a gradual *in situ* shift to Douglas-fir and pine genotypes adapted to new climates (Chmura et al. 2011). More uniform treatments may result in less mortality in the short run, but if implemented over large areas may lead to landscapes that have less capacity to adapt to new climates.

There is no single, optimal stand-level approach to maximizing resilience and adaptive capacity for all future conditions. As the climate changes, shifts in the interactions among the vegetation, disturbances, and the climate are likely to give rise to evolving communities and pattern-process relationships (McKenzie et al. 2009, Williams et al. 2007). A resilience strategy that maximally conserves options is prudent. Thus, it is sensible to vary patterns and structure types between stands, thereby varying risk levels and functional tradeoffs among different organisms and processes, as well as economic and social factors. Applying any single treatment type over a large area will increase risks of unintended consequences. Selection of specific strategies and targets for individual stands first requires planning over larger spatial extents in order to link stand-level prescriptions to larger scale resilience strategies (Gaines et al. 2010, Keane et al. 2009, McKenzie et al. 2011, Spies et al. 2010). In many cases, disparate stands may need to be blended together into larger patches to restore resilient patch size distributions (Hessburg et al. 2004, Moritz et al. 2011). In other cases, stands may need to be broken up into smaller patches. Stand-level reference envelopes can be used to accomplish this, while also providing ecologically based targets for within-stand heterogeneity. For example, reference patterns that contain high levels of clumping and openings can be used to guide prescriptions for some stands and less clumped patterns used for others. Varying overall density and species composition targets, guided by bio-physical setting (North et al. 2009), will also enhance resilience.

4.5 Conclusion

Managing dry forest landscapes to increase resilience in the face of changing climatic and fire regimes poses an immense challenge. Considerable research confirms that dry forest landscapes were heterogeneous at multiple scales prior to the period of fire suppression, and that this heterogeneity was an important driver of the resilience of these systems. This research identified methods that (1) quantified a range of spatial reference patterns to provide concrete targets for stand-level restoration treatments, (2) translated these ranges into operationally efficient marking guidelines, and (3) facilitate monitoring and evaluation of treatment effectiveness. Furthermore, we developed a tractable method to critically evaluate historical reference targets in light of climate change based on empirical correlations between pattern and biophysical conditions, expressed through site water balance and plant association groups. Climate envelope modeling can indicate a site's projected future water balance, thereby allowing managers to select treatment targets from reference sites that are analogous to the projected future conditions of the treatment site. But with or without a climate analogue assessment, restoring mosaics of individual trees, clumps, and openings can make future forests more resilient by re-establishing pattern-process linkages. Minimizing treatments that result in spatial homogeneity over large areas can avoid conditions that are likely more susceptible to large-scale, high severity disturbance events. The ICO method provides a quantitative framework to vary pattern both within and among stands that is directly related to reference conditions that can be tailored to the current and future conditions of specific stand. Although initially challenging, managing for spatial heterogeneity can be done.

Tables

Table 1: Comparison of three stand-level treatment approaches in dry-mixed conifer forests: fuels treatments and hazard reduction, restoration of pre-settlement or current reference conditions, and climate adaptation/resilience management. Treatment targets for different strategies may vary considerably between the three different approaches.

Recommended Strategies	Fuels Treatments[1]	Restoration[2]	Resilience/ Adaptation[3]
1. Reduce surface and ladder fuels; increase crown base height.	x	x	x
2. Reduce and maintain lower tree densities; decrease crown bulk density.	x	x	x
3. Increase relative composition of fire and drought tolerant species.	x	x	x
4. Increase mean tree diameter and individual tree vigor by generally retaining larger trees with healthy crowns.	x	x	x
5. Conserve existing species and genetic diversity, including pre-settlement trees.		x	x
6. Restore horizontal spatial heterogeneity of forest structure, including openings where early-seral species can establish.		x	x
7. Re-introduce fire to reduce fuel loads, stimulate understory species, and maintain desired fuel beds.	x	x	x
8. Reduce and/or maintain appropriate levels of pathogens, insects, and other disturbances in order to create decadence, mortality, and interactions with fire that lead to regeneration of new tree cohorts and diverse understories.		x	x
9. Replant desired native species, especially after high severity disturbances.			x
10. Plant new genotypes and/or species.			x
11. Monitor key processes such as mortality, regeneration, growth, fuel accumulation, and new species colonization to inform future management.	x	x	x

[1] Agee & Skinner 2005, Graham et al. 2004, Peterson et al. 2005

[2] Allen et al. 2002, Covington and Moore 1997, Franklin and Johnson 2012

[3] Chmura et al. 2011, Peterson et al 2011, Spies et al. 2010, Stephens et al. 2010. These include resistance, resilience, response, and realignment options

Table 2: Proportional clump size distribution for 1 ha Wildcat reference plot.

	Cluster Size (# of trees)									
t	1	2	3	4	5	6	7	8	9	10
	Percent of total trees									
1m	96	4	0	0	0	0	0	0	0	0
2m	67	21	12	0	0	0	0	0	0	0
3m	60	17	6	0	0	0	0	17	0	0
4m	58	8	6	8	0	0	0	0	19	0
5m	52	12	6	8	0	0	0	0	0	21
6m	42	17	12	8	0	0	0	0	0	21
7m	35	17	19	8	0	0	0	0	0	21
8m	35	17	19	8	0	0	0	0	0	21
9m	33	17	19	0	10	0	0	0	0	21
10m	31	17	19	0	0	12	0	0	0	21
	Percent of total trees with edge correction									
6m	32	18	9	12	0	0	0	0	0	29
	Percent of total plot basal area									
6m	51	17	11	4	0	0	0	0	0	17
	Mean dbh of trees (cm)									
6m	90	81	77	57	0	0	0	0	0	73

t is the inter-tree distance.

Table 3: Derivation of prescription targets for clumps from proportional clump size distribution of reference plot at 6m.

	Clump Size (# of trees)		
	1	**2-4**	**5+**
Percent of trees in clumps in reference plot	42%	37%	21%
Rx target for trees per ha.	42	37	21
Rx target for clumps per ha	42	12	5*

* The target for 5+ tree clumps was increased by 30% to hedge against higher anticipated rates of mortality in large clumps vs. individual trees.

Table 4: Summary information for 1 ha reference plot and different patterns on 2 ha monitoring plot

	Plot/Pattern					
	Reference	*Pre-Treat*	*ICO*	*AM*	*BA*	*Space*
Density and Size						
Trees per ha	48	221	64	70	67	65
Mean dbh (cm)	77.5	40.4	55.6	53.1	54.5	56.6
Basal Area (m^2/ha)	24.9	32.7	16.7	16.9	16.9	17.5
% Max Stocking[1]	40%	64%	30%	31%	30%	31%
Species Composition						
PIPO (%BA)	74%	35%	48%	49%	42%	39%
PSME (%BA)	26%	65%	52%	51%	58%	61%
PCF results:						
Pattern Type:	Clumped	Clumped	Clumped	Clumped	Uniform	Uniform
P-value	0.001	0.001	0.048	0.002	0.048	0.008
Distances (m)	0.1-6.7 & 9.8-12.5	0.1-9.3 & 14.0-15.1	0.3-3.7	0.1-5.8 & 6.7-10.2	0.1- 2.2 & 3.5-6.4 & 11.2-12.5	0.1-7.7
Harrod Percentile Rank						
5 m	22%		68%	49%	95%	97%
6 m	35%		65%	41%	95%	100%
7 m	46%		49%	39%	81%	100%

ICO (individuals, clumps, and openings) is actual field treatment. AM is adaptive management, BA is basal area. Percent of maximum stocking is calculated in Stand Density Index with a maximum value of 800. PIPO: *Pinus ponderosa*. PSME: *Pseudtosuga menziesii*. PCF (pair correlation function) p-values are derived from a Monte Carlo goodness of fit test to test for significant difference from complete spatial randomness (CSR) from 0-12.5m. Distances are the inter tree distances at which the pattern differs from the maximum or minimum envelope of 1000 CSR patterns. Harrod percentile ranks are the percentile rank of the pattern relative to the 32 Harrod patterns; lower values are more clumped and higher values are more uniform.

Figures

Fig. 1: Actual evapotranspiration (AET) and climatic water deficit (Deficit) for the contemporary climate (1971-2000) for Harrod sites, and current and projected future climates for the Wildcat site. Climate projections include A2 and A1B emissions scenarios from 15 GCMs. See Stephenson (1998) for a detailed explanation of the relationship between AET and Deficit. Plant association groupings are: PIPO High: *Pinus ponderosa/Purshia tridentata/Agropyron spicatum;* PSME High *Pseudotsuga menziesii/Purshia-tridentata/Agropyron spicatum;* PSME Moderate: *P. menziesii/Symphoricarpos albus/Calamagrostis rubescens,* and *P.menziesii/Calamagrostis rubescens*, PSME Low: *P. menziesii/Symphoricarpos oreophilus, P.menziesii/Spirea-betulifolia/ Calamagrostis rubescens,* and *P.menziesii/Carex geyer.*

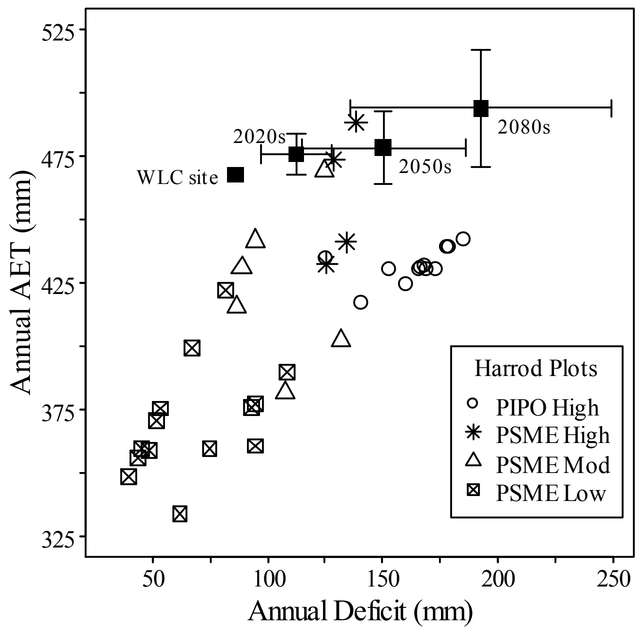
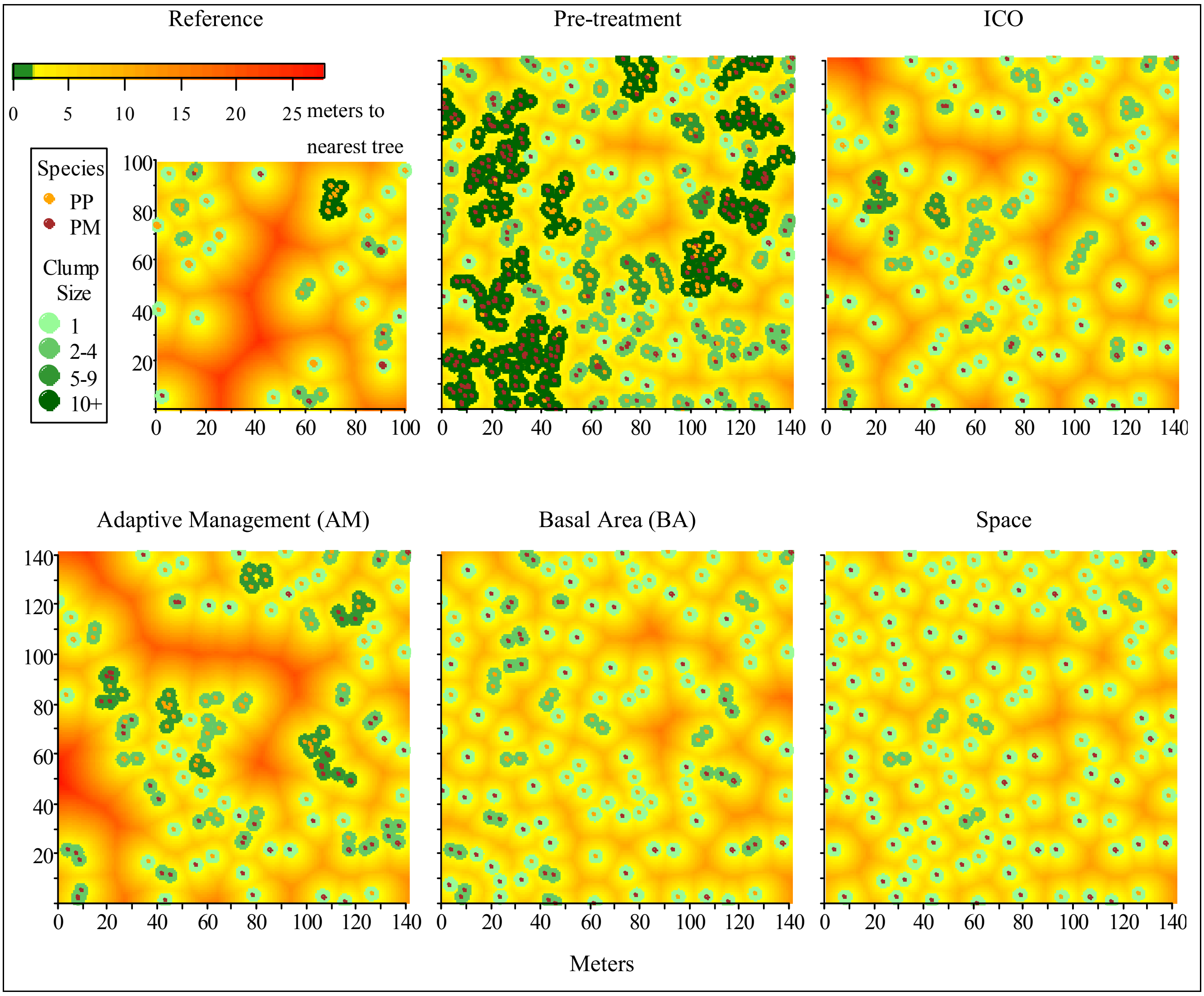


Fig. 2: Upper panel displays tree spatial patterns for reference plot (100 m × 100 m) and 4 treatment alternatives in the 2 ha monitoring plot (141 m ×141 m). ICO: individuals, clumps, and openings. PP: *Pinus ponderosa.* PM: *Pseudtosuga menziesii*. Projected crown radii are 3 m to indicate interlocking crowns and clump formation. Larger clump sizes are shown in darker green colors. Background coloration indicates the distance to nearest tree or gap edge from the centers of a 1m cell grid- a graphical representation of the empty space function. The areas colored dark orange in plots are areas that are approximately 15 m from the nearest tree or gap edge. An opening with a relatively circular center of dark orange, such as in the Pre-treatment plot, has an approximate area of 0.07ha (the area of a circle with a radius of 15m). The long, sinuous opening the AM pattern, for example, has dark red in the middle indicating that it is roughly 50m wide (2x 25 m distance to the gap edge). The lower panel displays histograms that show the proportion of area in 3 m distance to nearest tree bins with corresponding colors. Bin labels are maximum values (e.g. 6 m = 3.01 - 6 m)



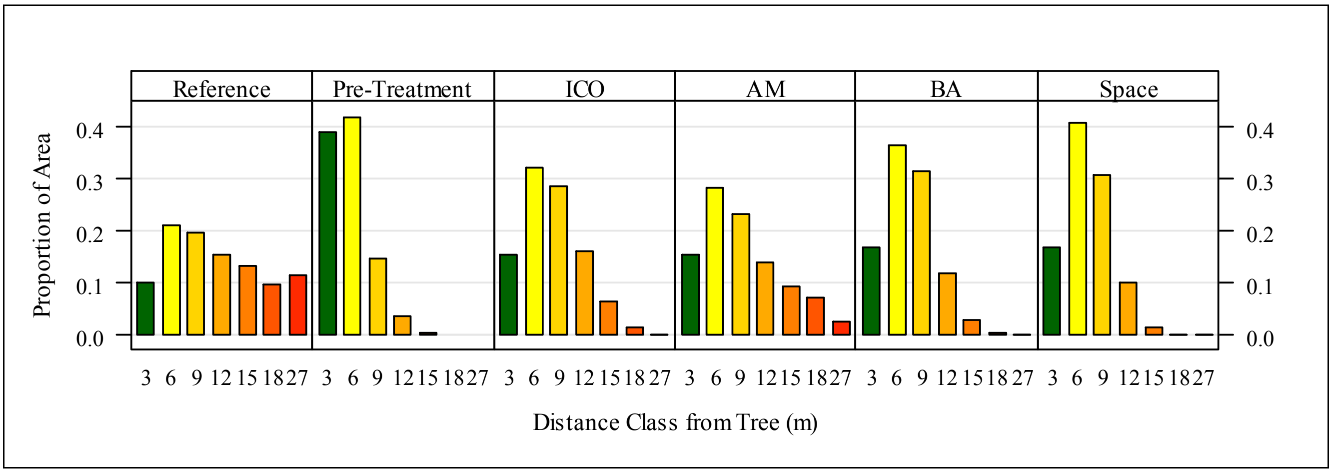


Fig. 3: Proportion of trees in different clump size bins across different inter-tree distances in the 1 ha reference plot and pre-treatment and four treatment alternatives on the 2 ha monitoring plot: the actual treatment (ICO), a adaptive management (AM), basal area (BA), and spacing based (Space). Clump size is defined as the number of trees comprising the clump. Six meters was used to define tree clumps in subsequent analyses (Fig. 5).

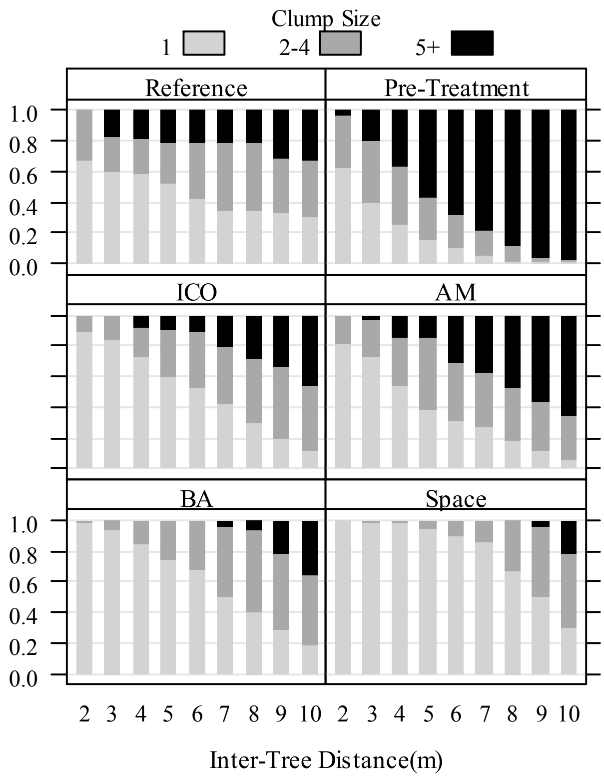


Fig. 4: Point pattern statistics for study plots and Harrod et al. (1999) plots. Panels A & B compare envelopes of the pair correlation function of 32 Harrod et al. (1999) plots with the reference plot, field treatment (ICO), and 3 simulated treatments: adaptive management (AM), basal area (BA), and spacing based (Space). The majority (72%) of the Harrod plots display clustered tree patterns, while the remainder are random (panel A) based on a Monte Carlo goodness of fit test evaluated patterns from 1 m to 12.5 m. Panels C & D show pair correlation functions of study plots with 95th percentile CSR envelopes. Distances at which curves are within CSR envelopes indicate spatially random tree patterns, while curves above or below CSR envelopes indicate clustered or uniform patterns, respectively. The CSR envelope of reference plot (panel C) is larger due to its lower point density .

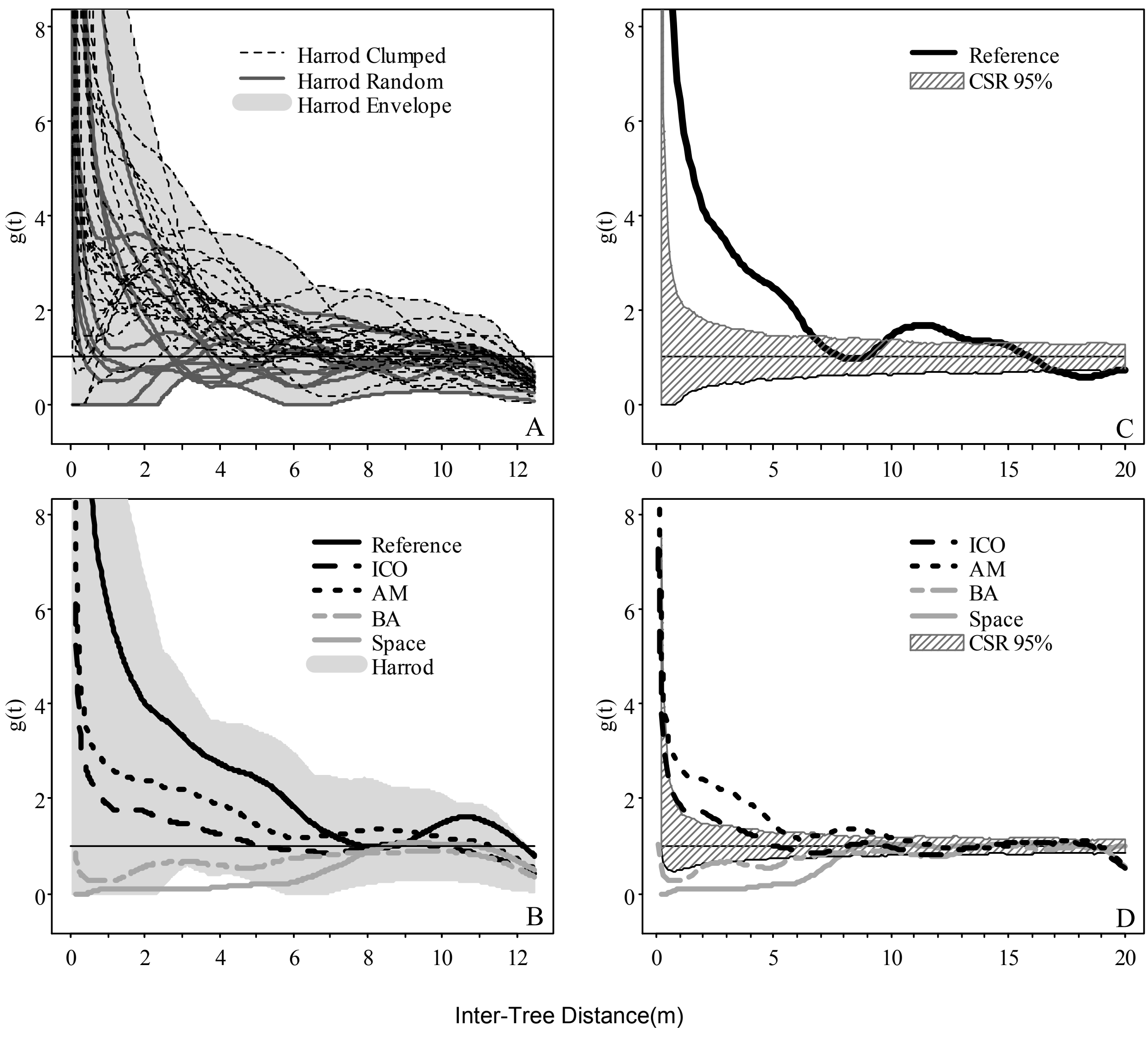


Fig. 5: Comparison of the cumulative clump size distributions for reference and treatment plots against shaded envelope of Harrod (1999) plots. Top row compares plots from Harrod et al. (1999) by plant association groupings from Fig. 1. Bottom row displays the reference plot, and four treatment alternatives: actual treatment (ICO), adaptive management (AM), basal area (BA), and spacing based (Space). In bottom row, bold lines show the distributions of the whole plots. Narrow lines are 0.5 ha sub-plots taken across each large plot using a 0.5ha (100 m x 50 m) moving window. Clump size is the number of trees in a clump and is based on a 6 m inter-tree distance.

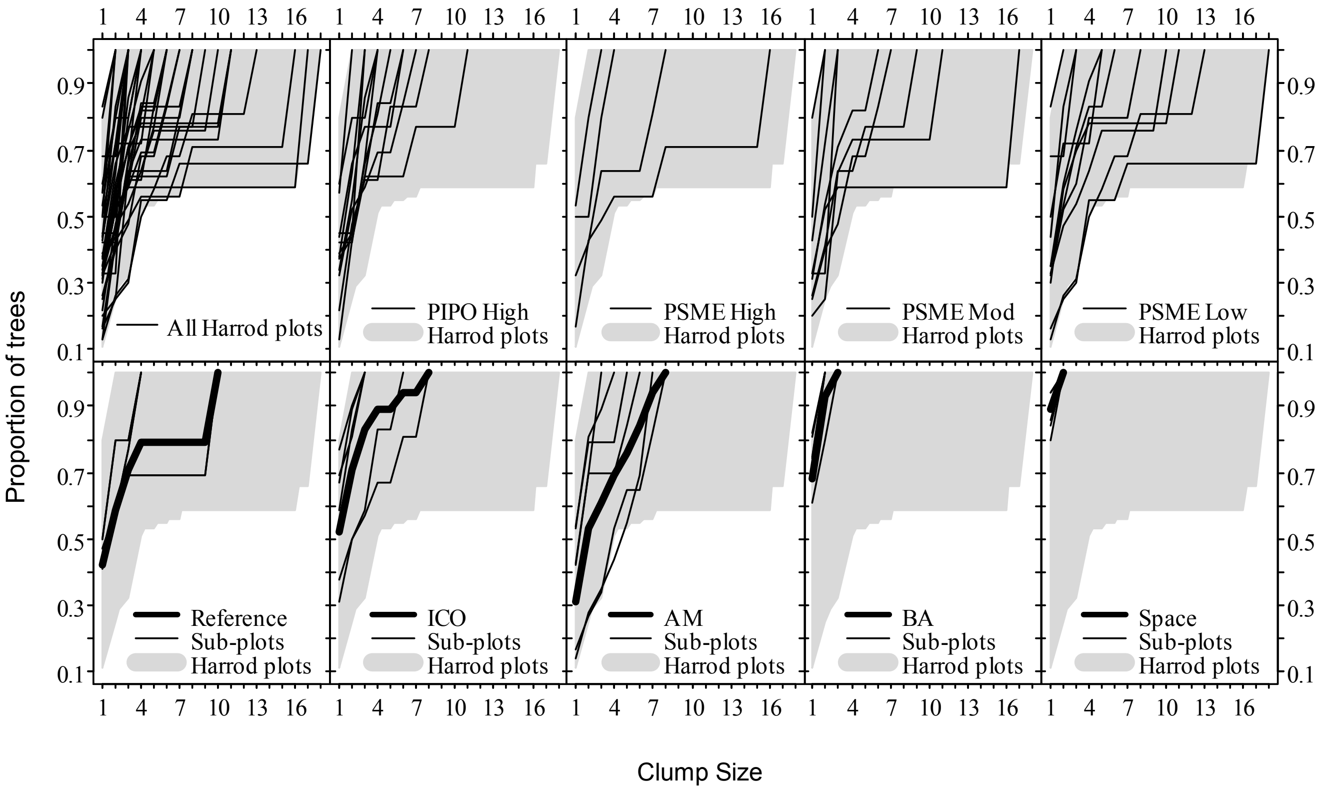


Fig. 6: Diameter distributions of reference plot, ICO treatment, and 3 simulated treatment alternatives: adaptive management (AM), basal area (BA), and spacing based (Space). Only leave trees are shown.

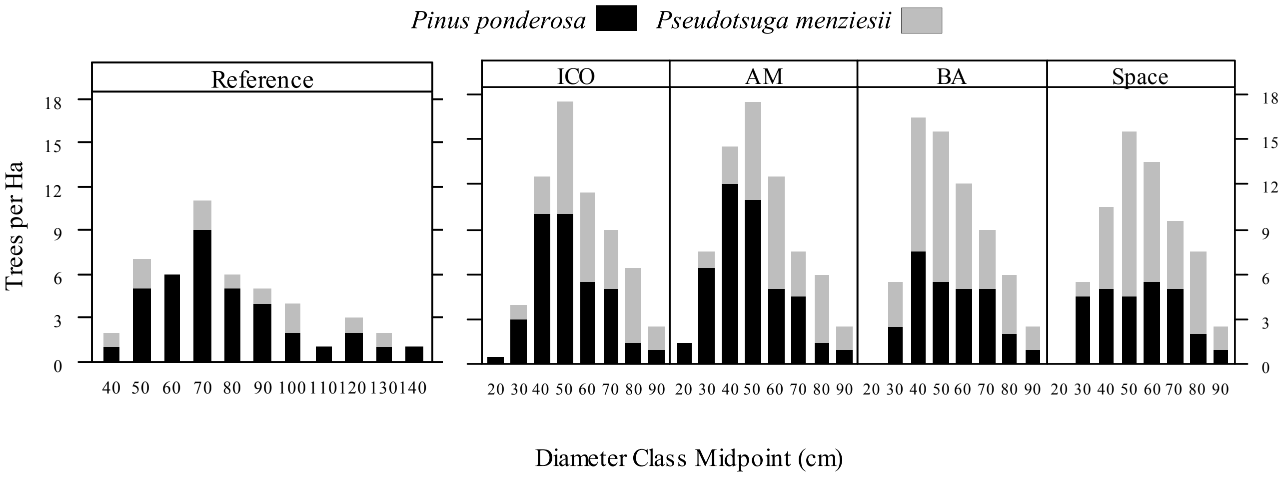
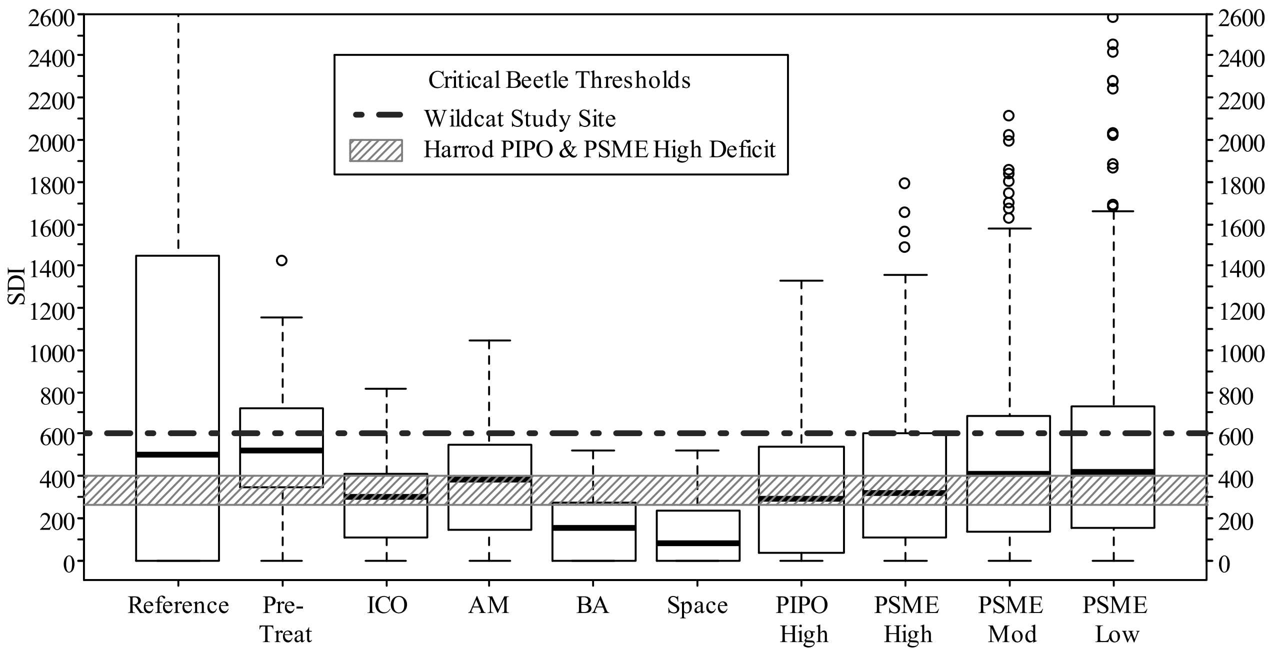


Fig. 7: Boxplot showing distribution of Stand Density Index values for 8 m radius plots placed around all ponderosa pine trees for reference plot; four treatment alternatives; and plots from Harrod et al. (1999) grouped by plant association/water balance deficit level from Fig. 1. Black lines in center of boxes are medians, boxes show the interquartile range (25-75%) and whiskers show the 10-90% range. Critical threshold values are for mountain pine beetle mortality. SDI values are in metric units; to convert to English units divide by 2.47. The proportion of trees above the thresholds for a plot (as shown by the intersection of the respective boxplot and the threshold line) is the proportion of trees considered at risk to mountain pine beetle mortality.



Appendices

A3.1 Marking Guidelines for the Wildcat Unit, Okanagon-Wenatchee National Forest:

Spacing:

- Leave an average of 100 tph (40 tpa)
- Leave an average of 12 clumps/ha w/2-4 trees, and 2 with 5+ trees. Clumps have trees w/in 6 m (20 ft) of another tree.
- Leave 42 tph (18 tpa) as individuals with average spacing about 9m (30 ft) with a range of 6-12 m.

Leave Tree Criteria:

- Retain all old trees, established before about 1900. Note, that is younger than Van Pelt (2008) rating greater than 6 for PP and 7 for DF
- Around old PP, remove 100yr age class DF for 1-2 driplines—OK to keep 1-2 large/vigorous DF occasionally-use judgement.
- Thin from below removing mostly trees <21 inch to meet tree density/LCR objectives. Removal of trees >63cm (25”) isn’t expected. Maybe on east end as needed to prevent mistletoe spread to the west. Remove DF w/LCR <40 (Can go to <35 for clumping,check growth). Retain occasional understory w/LCR > 40 (+- 2/ac)
- Remove 100 yr PP w/LCR <30% or with Van Pelt fig.69 form C or D.

Insect and Disease**:**

- Retain only old trees that are mistletoe infected and isolate them as clumps or individuals with a 40-50 foot host-free (80-100%) buffer beginning at the last visible sign of infection.
- Keep DF mistletoe on east end from moving into unit.

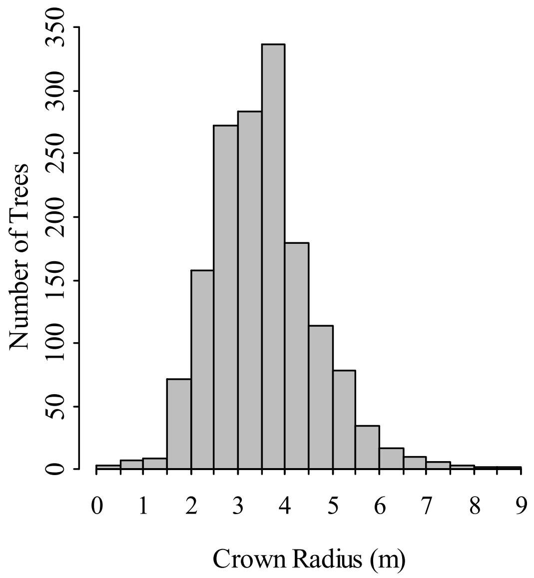
Snags/Down Wood & Size**:**

- Protect existing decay class 3 or less snags > 20 inches with a no-cut buffer.
- Retain at least 1-2 of the 15-19 and all > 20 inch trees with dead, forked, or broken tops

Wildlife**:**

- Retain about 15% of stand in no-entry complex patches—counting no-cut riparian areas and patch in SW corner wet area.

A3.2 Frequency distribution of crown radii for trees between 39 and 139 cm dbh. Data are from the USFS Forest Inventory and Analysis database using plots in the eastern Washington Cascades, n = 1584 trees. Bins are 0.5m width.



A3.3 List of GCM's used to derive climate variables for both A2 and A1B emissions scenarios. Detailed information on each GCM is available at the IPCC website: http://www.ipcc-data.org/ar4/gcm_data.html. Downscaled model projections for these GCM's were downloaded from Climate WNA: http://www.genetics.forestry.ubc.ca/cfcg/ClimateWNA/ClimateWNA.html.

BCCR:BCM2
CCCMA:CGCM3
CNRM:CM3
CSIRO:MK3
GFDL:CM2
GFD: CM2_1
NASA:GISS-EH
INM:CM3
IPSL:CM4
NIES:MIROC3_2
ONS:ECHO-G
MPIM:ECHAM5
MRI:CGCM2_3_2
NCAR:CCSM3
UKMO:HADCM3

A3.4 Harrod Reference Plot Summary Information:

Summary density metrics, proportional clump size distributions, and pattern type of Harrod et al. (1999) reference plots. Plant association groupings are based on calculated water balance deficits for each plot. SDI is Stand Density index and is in metric units; to convert to English units, divide by 2.47. Pattern types and p-values are derived from a Monte Carlo goodness of fit test to test for significant difference from complete spatial randomness from 0-12.5m using the pair correlation function.

Plot ID	Plant Association Grouping	Trees Ha^{-1}	Mean DBH (cm)	BA m^2/Ha	SDI	Proportion of trees by Clump size (# of trees)				Pattern Type	P-Value
						1	2-4	5-9	10-20		
CD1	PIPO High	48	66.3	17	256	0.42	0.58	0	0	Clustered	0.005
CD7	PIPO High	58	46.4	11	181	0.34	0.66	0	0	Clustered	0.015
CD8	PIPO High	92	46.5	17	276	0.22	0.39	0.39	0	Clustered	0.005
CD9	PIPO High	28	54.1	7	112	0.57	0.43	0	0	Random	0.245
CD14	PIPO High	48	62.1	16	236	0.38	0.63	0	0	Clustered	0.020
HD1	PIPO High	82	60.4	26	385	0.37	0.44	0.19	0	Clustered	0.005
HD2	PIPO High	72	43.0	12	193	0.39	0.45	0.17	0	Clustered	0.005
HD3	PIPO High	22	71.4	10	138	0.45	0.55	0	0	Clustered	0.020
HD4	PIPO High	40	53.8	9	148	0.6	0.4	0	0	Random	0.130
HD5	PIPO High	94	51.0	21	330	0.13	0.49	0.15	0.23	Clustered	0.005
WD1	PIPO High	54	73.3	26	361	0.44	0.33	0.22	0	Clustered	0.020
HD6	PSME High	60	57.4	17	264	0.53	0.47	0	0	Random	0.235
HD7	PSME High	82	50.3	18	279	0.32	0.32	0.37	0	Clustered	0.010
HD8	PSME High	108	52.4	25	387	0.17	0.39	0.15	0.3	Clustered	0.005
HD9	PSME High	40	57.0	11	171	0.5	0.5	0	0	Random	0.090
CD3	PSME Mod	80	63.7	29	426	0.25	0.43	0.33	0	Clustered	0.005
CD4	PSME Mod	78	54.3	19	295	0.26	0.38	0.36	0	Clustered	0.010
CD6	PSME Mod	24	67.6	9	137	0.5	0.5	0	0	Random	0.115
CD13	PSME Mod	80	63.0	28	408	0.2	0.53	0	0.28	Clustered	0.005
WM1	PSME Mod	36	65.5	13	187	0.33	0.67	0	0	Clustered	0.035
WM2	PSME Mod	42	65.3	15	222	0.43	0.58	0	0	Random	0.075
WM3	PSME Mod	20	75.2	10	137	0.8	0.2	0	0	Random	0.560
WM4	PSME Mod	70	61.6	23	338	0.31	0.51	0.17	0	Clustered	0.005
CD2	PSME Low	68	70.6	28	406	0.35	0.48	0.18	0	Clustered	0.005
CD5	PSME Low	84	50.6	18	292	0.33	0.31	0.12	0.24	Clustered	0.005
CD10	PSME Low	36	69.5	15	216	0.5	0.22	0.28	0	Clustered	0.005
CD11	PSME Low	24	54.8	6	98	0.83	0.17	0	0	Random	0.870
CD12	PSME Low	38	76.1	18	260	0.68	0.32	0	0	Clustered	0.040
WD2	PSME Low	126	58.5	37	557	0.13	0.37	0.31	0.21	Clustered	0.005
WD3	PSME Low	100	57.4	28	429	0.3	0.48	0	0.22	Clustered	0.020
WD4	PSME Low	80	59.3	24	359	0.32	0.48	0.2	0	Clustered	0.020
WD5	PSME Low	128	52.8	30	466	0.16	0.39	0.11	0.34	Clustered	0.005

Concluding Chapter

Managing dry forest landscapes to increase resilience and adaptive capacity in the face of changing climatic and fire regimes poses an immense challenge. Considerable research confirms that dry forest landscapes were heterogeneous at multiple scales prior to the period of fire suppression, and that this heterogeneity was an important driver of the resilience of these systems (Hessburg et al. 1999b, Keane et al. 2009, Perry et al. 2011, Larson and Churchill 2012). Concepts of scale and hierarchical patch dynamics from landscape ecology are increasingly being used to understand and restore the multi-scale heterogeneity associated with frequent fire forests (Peterson and Parker 1998, Spies and Turner 1999, Hessburg et al. 2004). Stands are increasingly viewed as patches embedded in a landscape hierarchy rather than as units of forest management with similar tree structure and composition (Lertzman and Fall 1998). Stands are the patches that make up watersheds but also contain smaller-scale patch mosaics of tree clumps and openings (Urban et al. 1987). Restoring the range of mosaic patterns found in reference stands is becoming a major objective for managers and collaborative stakeholders involved in dry forest restoration (North et al. 2009, CFLRP 2012, Franklin and Johnson 2012). However, restoration targets for heterogeneity derived from reference conditions must be critically evaluated, and potentially modified, based on projected future climates and ecological knowledge to provide operative targets for restoration that are best suited to increase resilience and adaptive capacity (Spies et al. 2010, Stephens et al. 2010).

This dissertation focused on quantifying, understanding, and restoring within-stand spatial pattern and structure in pre-settlement dry forests of the Eastern Cascades of Washington. In chapter 1, I developed a new set of spatial metrics to quantify within-stand pattern in terms of widely spaced individual trees, tree clumps, and openings. I used these metrics to characterize patterns of tree clumps and openings within 0.5 ha tree neighborhoods. I found a strong relationship between increasing density, higher clumping levels, and decreased large openings. I also found clear evidence that a definable range and distribution, or envelope, of pattern and structure was present. This envelope ranged from low density patterns with few clumps and high opening levels, to patterns with a mid-range of density and varying levels of clumping, to high density, highly clumped patterns with few openings. Low to moderate density patterns were the most prevalent. The envelope was constrained by an upper limit of clump size, maximum density levels well below site potential, and the presence of at least some clumping in all plots (ie. no uniform patterns were found). Results indicate if restoration prescriptions get the clump size distribution with historic ranges for a specific density level, the appropriate amount of open space will result as a by-product, although guidelines for large openings may be necessary.

In chapter 2, I analyzed how tree neighborhood patterns of clumps and openings were arranged across 3 x 6ha plots; a spatial extent approximating the size of stands. I found that patterns of tree clumping and openings were spatially dependent and aggregated into sub-patches. Aggregations of large clumps in portions of 6 ha plots formed sub-patches with somewhat clear boundaries that occupied 7-16% of the plots. Sub-patches of large openings and scattered individual trees and small clumps were also present, although the boundaries were less distinct. A gradient of low to moderate density with low levels of clumping was found on the remainder of each plot (60-80%). Evidence that spatial point patterns were non-stationary was present at this spatial extent. These results suggest that a mix of fine-scale (<0.4 ha) vegetation and low-severity disturbance processes and meso-scale (>1ha) topographic, edaphic, and/or disturbance factors were shaping pattern. These results provide an ecological basis for adding patches of higher density (e.g. untreated “skips”) and larger openings (>0.4 ha) to treatments, in addition to fine scale variability of individual trees, clumps, and small to medium openings.

In chapter 3, I developed and conducted a case study of a silvicultural approach to restoring spatial patterns from reference stands. Clump size distributions from reference pattern envelopes were translated into operationally efficient marking and monitoring guidelines. Treatments using the Individuals, Clumps, and Openings (ICO) approach resulted in a distribution of tree clumps and openings within the range of reference envelopes, while simulated basal area and spacing approaches resulted in uniform patterns outside of reference envelopes. Susceptibility to insect mortality was lower in basal area and spacing prescriptions, but openings and corresponding opportunities for regeneration and in-situ climate adaptation were fewer. Operationally, the clump identification method struck a balance between providing clear targets for spatial pattern directly linked to reference conditions, sufficient flexibility to achieve other restoration objectives, and implementation efficiency. I also developed a tractable method to critically evaluate historical reference targets in light of climate change based on empirical correlations between pattern and biophysical conditions that are expressed through site water balance and plant association groups. Climate envelope modeling can indicate a site’s projected future water balance, thereby allowing managers to select treatment targets from climate analog reference sites that are similar to those projected future conditions of the treatment site. The concept of climate analog reference conditions enables a practical, forward-looking restoration approach that confronts challenges and limitations associated with using historical reference data to inform contemporary restoration targets. The ICO method combined with the climate analogue approach provides a quantitative framework to vary pattern both within and among stands that is directly related to reference conditions which can be tailored to the current and future conditions of a specific stand.

This dissertation developed new methods and reference information to quantify and restore spatial heterogeneity in dry forests. The functional rationale for making heterogeneity a goal in restoration treatments must remain central, rather than using it simply to replicate historic patterns (Millar et al. 2007). The primary goal of dry forest restoration is to increase resilience and adaptive capacity to projected climate driven increases in drought stress, higher fire frequency and severity, and altered insect behavior (Spracklen et al. 2009, Waring et al. 2009, Littell et al. 2010). From the perspective of resiliency the fine-scale, “clumpy gappy” patterns of historic dry forests are the emergent pattern that evolved from forests adapting to a frequent and variable wildfire regime; a range of insect, pathogenic and abiotic disturbances; and shifting climatic conditions at decadal to century temporal scales (Allen et al. 2002, Kaufmann et al. 2007). The tree neighborhood patterns of tree clumps and openings are the basic building blocks that have been rearranged and reshuffled through time. Different proportions and spatial arrangements may be necessary in the future, but these basic building blocks and patch hierarchies built upon them are the structural “memory” of these forests. They thus provide a strong ecological basis for enhancing their resilience and adaptive capacity.

The fine-grained mosaic pattern of individual trees, clumps, and openings appears to be a common emergent pattern of frequent fire forests across the west (Larson and Churchill 2012), despite differences in climate, soil types, topographic complexity, ignition sources, disturbance regimes, and plant communities that affect dry forest ecosystems across the west (Kaufmann et al. 2007). Fire is such a dominant structuring agent in these systems that it dampens the influence of biophysical differences (Agee 1993). However, the extent to which tree neighborhood (< 1 ha) pattern types and envelopes are consistent across different regions of the west is unknown. Re-analysis of existing stem map reconstruction datasets from dry forests using methods developed in this dissertation would address this question, as well as analysis of stem map data from contemporary forests with active fire regimes. At stand scales (>4 ha), the proportion different tree neighborhood patterns within stands and the extent they are aggregated into sub-patches is less understood. The 6 ha plots in this study are the largest reconstruction plots that have been analyzed in the west. However, even larger plots using a combination of ground sampling and remotely sensed data (e.g. historical photographs or LiDAR of active fire regime areas) are necessary to understand pattern at stand scales.

Finally, our understanding of relationships between pattern and biophysical conditions is still primitive. It is not clear whether, or at what threshold, low productivity constrains clump sizes, for example. New reconstruction or contemporary datasets are needed in more mesic, low to mixed-severity systems where higher variation in pattern is likely, as well as in drier areas that can serve as climate analog reference sites. Expanding reference datasets across a wider range of biophysical conditions is necessary to provide managers with a more robust basis for restoring specific pattern types that are likely to be resilient and adaptive to changing climates. Fortunately, this effort is underway in many areas across the west.

References

Abella, S. R., and C. W. Denton. 2009. Spatial variation in reference conditions: historical tree density and pattern on Pinus ponderosa landscape. Canadian Journal of Forest Research 39:2391–2403.

Abella, S. R., P. Z. Fule, and W. W. Covington. 2006. Diameter caps for thinning southwestern ponderosa pine forests: Viewpoints, effects, and tradeoffs. Journal of Forestry 104:407–414.

Agee, J. K. 1993. Fire Ecology of Pacific Northwest Forests. . Island Press, Washington D.C.

Agee, J. K. 1998. The Landscape Ecology of Western Forest Fire Regimes. Northwest Science 72:24–34.

Agee, J. K. 2003. Historical range of variability in eastern Cascades forests, Washington USA. Landscape Ecol. 18:725–74.

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Ager, A. A., N. M. Vaillant, and A. McMahan. 2013. Restoration of fire in managed forests: a model to prioritize landscapes and analyze tradeoffs. Ecosphere 4:art29.

Allen, C. D., M. Savage, D. A. Falk, K. F. Suckling, T. W. Swetnam, T. Schulke, P. B. Stacey, P. Morgan, M. Hoffman, and J. T. Klingel. 2002. Ecological restoration of Southwestern ponderosa pine ecosystems: A broad perspective. Ecological Applications 12:1418–1433.

Anderson, M. J. 2001. A new method for non-parametric multivariate analysis of variance. Austral Ecology 26:32–46.

Arno, S. F., J. H. Scott, and M. G. Hartwell. 1995. Age-class structure of old growth ponderosa pine/Douglas-fir stands and its relationship to fire history. USDA Forest Service: Intermountain Research Station. Research Paper INT-RP-481.

Arno, S. F., H. Y. Smith, and M. A. Krebs. 1997. Old growth ponderosa pine and western larch stand structures: influences of pre-1900 fires and fire exclusion. USDA Forest Service: Intermountain Research Station INT-RP-495.

Baddeley, A. J., and R. Turner. 2005. Spatstat: An R package for analyzing spatial point patterns. Journal of Statistical Software 12:1–42.

Bailey, J. D., and W. W. Covington. 2002. Evaluating ponderosa pine regeneration rates following ecological restoration treatments in northern Arizona, USA. Forest Ecology and Management 155:271–278.

Baker, S. C., and S. M. Read. 2011. Variable retention silviculture in Tasmania's wet forests: Ecological rationale, adaptive management and synthesis of biodiversity benefits. Australian Forestry 74:218–32.

Bakker, J. D. 2005. A new, proportional method for reconstructing historical tree diameters. Canadian Journal of Forest Research 35:2515–2520.

Baron, J., L. H. Gunderson, C. Allen, E. Fleishman, D. McKenzie, L. Meyerson, J. Oropeza, and N. L. Stephenson. 2009. Options for National Parks and Reserves for Adapting to Climate Change. Environmental Management 44:1033–1042.

Barret, J. W. 1978. Height growth and site index curves for managed, even-aged stands of ponderosa pine in the Pacific Northwest. USDA Forest Service: Pacific Northwest Research Station Research Paper PNW-RP-232.

Beaty, M. R., and A. H. Taylor. 2007. Fire disturbance and forest structure in old-growth mixed conifer forests in the northern Sierra Nevada, California. Journal of Vegetation Science 18:879–890.

Bentz, B. J., J. Regniere, C. J. Fettig, E. M. Hansen, J. L. Hayes, J. A. Hicke, R. G. Kelsey, J. F. Negron, and S. J. Seybold. 2010. Climate Change and Bark Beetles of the Western United States and Canada: Direct and Indirect Effects. Bioscience 60:602–613.

Bigelow, S. W., M. P. North, and C. F. Salk. 2011. Using light to predict fuels-reduction and group-selection effects on succession in Sierran mixed-conifer forest. Canadian Journal of Forest Research 41:2051–2063.

Binkley, D., B. Romme, and T. Cheng. 2008. Historical forest structure on the Uncompahgre Plateau: informing restoration prescriptions for mountainside stewardship. . Colorado Forest Restoration Institute, Colorado State University.

Binkley, D., T. Sisk, C. Chambers, J. Springer, and W. Block. 2007. The role of old-growth forests in frequent-fire landscapes. Ecology and Society 12:18.

Bones, J. T. 1960. Estimating D. B. H, from Stump Diameter in the Pacific Northwest. USDA Forest Service: Pacific Northwest Research Station, Research Note PNW-RN-186.

Bormann, F. H., and G. E. Likens. 1979. Pattern and process in a forested ecosystem. . Springer-Verlag, New York.

Botkin, D. B. 1993. Forest dynamics: an ecological model. . Oxford University Press, USA.

Boyden, S., D. Binkley, and W. Shepperd. 2005. Spatial and temporal patterns in structure, regeneration, and mortality of an old-growth ponderosa pine forest in the Colorado Front Range. Forest Ecology and Management 219:43–55.

Boyden, S., R. Montgomery, P. B. Reich, and B. Palik. 2012. Seeing the forest for the heterogeneous trees: stand-scale resource distributions emerge from tree-scale structure. Ecological Applications 22:1578–1588.

Camarero, J. J., E. Gutiérrez, and M. J. Fortin. 2000. Spatial pattern of subalpine forest-alpine grassland ecotones in the Spanish Central Pyrenees. Forest Ecology and Management 134:1–16.

Canham, C. D., J. S. Denslow, W. J. Platt, J. R. Runkle, T. A. Spies, and P. S. White. 1990. Light regimes beneath closed canopies and tree-fall gaps in temperate and tropical forests. Can. J. For. Res. 20:620–631.

Carey, A. B. 2003. Biocomplexity and restoration of biodiversity in temperate coniferous forest: inducing spatial heterogeneity with variable-density thinning. Forestry 76:127–136.

Carnwath, G. C., D. W. Peterson, and C. R. Nelson. 2012. Effect of crown class and habitat type on climate–growth relationships of ponderosa pine and Douglas-fir. Forest Ecology and Management 285:44–52.

Cassagne, N., F. Pimont, J.-L. Dupuy, R. R. Linn, A. Mårell, C. Oliveri, and E. Rigolot. 2011. Using a fire propagation model to assess the efficiency of prescribed burning in reducing the fire hazard. Ecological Modelling 222:1502–1514.

CFLRP. 2012. People Restoring America's Forests: 2012 Report on the Collaborative Forest Landscape Restoration Program. . The Nature Conservancy.

Chmura, D. J., P. D. Anderson, G. T. Howe, C. A. Harrington, J. E. Halofsky, D. L. Peterson, and D. C. Shaw. 2011. Forest responses to climate change in the northwestern United States: Ecophysiological foundations for adaptive management. Forest Ecology and Management 261:1121–1142.

Churchill, D. C., A. J. Larson, M. C. Dalhgreen, J. F. Franklin, P. F. Hessburg, and J. A. Lutz. 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. Forest Ecology and Management 291:442–457.

Cliff, A. D., and J. K. Ord. 1973. Spatial autocorrelation. Pion, London, UK.

ClimateWNA. 2012. ClimateWNA: A program to generate climate normal data for genecology and climate change studies in western North America. http://www.genetics.forestry.ubc.ca/cfcg/ClimateWNA/ClimateWNA.html (Accessed April 10,2012).

Cline, S. P., A. B. Berg, and H. M. Wight. 1980. Snag characteristics and dynamics in Douglas-fir forests, western Oregon. The Journal of Wildlife Management:773–786.

Cochran, P. H. 1994. Suggested stocking levels for forest stands in northeastern Oregon and southeastern Washington. USDA Pacific Northwest Research Station Reseach Note PNW-RN-513.

Collins, B. M., J. D. Miller, A. E. Thode, M. Kelly, J. W. van Wagtendonk, and S. L. Stephens. 2009. Interactions Among Wildland Fires in a Long-Established Sierra Nevada Natural Fire Area. Ecosystems 12:114–128.

Condit, R., P. S. Ashton, P. Baker, S. Bunyavejchewin, S. Gunatilleke, N. Gunatilleke, S. P. Hubbell, R. B. Foster, A. Itoh, J. V. LaFrankie, H. S. Lee, E. Losos, N. Manokaran, R. Sukumar, and T. Yamakura. 2000. Spatial patterns in the distribution of tropical tree species. Science 288:1414–1418.

Contreras, M. A., D. Affleck, and W. Chung. 2011. Evaluating tree competition indices as predictors of basal area increment in western Montana forests. Forest Ecology and Management 262:1939–1949.

Cooper, C. F. 1960. Changes in vegetation, structure, and growth of southwestern pine forests since white settlement. Ecological Monographs 30:130–164.

Coops, N. C., and R. H. Waring. 2011. Estimating the vulnerability of fifteen tree species under changing climate in Northwest North America. Ecological Modelling 222:2119–2129.

Covington, W. W., and M. M. Moore. 1994. Southwestern ponderosa forest structure - changes since euro-american settlement. Journal of Forestry 92:39–47.

Dale, M. R. T., P. Dixon, M. J. Fortin, P. Legendre, D. E. Myers, and M. S. Rosenberg. 2002. Conceptual and mathematical relationships among methods for spatial analysis. Ecography 25:558–577.

Daly, C., D. R. Conklin, and M. H. Unsworth. 2010. Local atmospheric decoupling in complex topography alters climate change impacts. International Journal of Climatology 30:1857–1864.

Daly, C., M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, and P. P. Pasteris. 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. International Journal of Climatology 28:2031–2064.

Daubenmire, R. 1976. Use of vegetation in assessing productivity of forest lands. Botanical Review 42:115–143.

Diggins, C., P. Z. Fulé, J. P. Kaye, and W. W. Covington. 2010. Future climate affects management strategies for maintaining forest restoration treatments. International Journal of Wildland Fire 19:903–913.

Diggle, P. J. 2003. Statistical analysis of spatial point patterns. . Academic Press, New York, NY.

Diggle, P. J., V. Gómez-Rubio, P. E. Brown, A. G. Chetwynd, and S. Gooding. 2007. Second-order analysis of inhomogeneous spatial point processes using case–control data. Biometrics 63:550–557.

Diggle, P. J., N. Lange, and F. M. Benevs. 1991. Analysis of variance for replicated spatial point patterns in clinical neuroanatomy. Journal of the American Statistical Association 86:618–625.

Diggle, P. J., J. Mateu, and H. E. Clough. 2000. A comparison between parametric and non-parametric approaches to the analysis of replicated spatial point patterns. Advances in Applied Probability 32:331–343.

Dingman, S. L. 2002. Physical hydrology. . Prentice Hall, Upper Saddle River, NJ.

Dodd, N. L., R. E. Schweinsburg, and S. Boe. 2006. Landscape-scale forest habitat relationship to tassel-eared squirrel populations: implications for ponderosa pine forest restoration. Restoration Ecology 14 14:537–547.

Dodson, E. K., D. W. Peterson, and R. J. Harrod. 2008. Understory vegetation response to thinning and burning restoration treatments in dry conifer forests of the eastern Cascades, USA. Forest Ecology and Management 255:3130–3140.

Donato, D. C., J. L. Campbell, and J. F. Franklin. 2011. Multiple successional pathways and precocity in forest development: can some forests be born complex? Journal of Vegetation Science:n/a.

ESRI. 2012. ArcGIS Desktop 10 - An overview of the Solar Radiation tools. http://help.arcgis.com/en/arcgisdesktop/10.0/help (Accessed May 12, 2012).

Everett, R. J., R. Lehmkuhl, P. Schellhass, P. Ohlson, D. Keenum, H. Riesterer, and D. Spurbeck. 1999. Snag dynamics in a chronosequence of 26 wildfires on the east slope of the Cascade Range in Washington State, USA. International Journal of Wildland Fire 9:223–234.

Everett, R. L., D. Baumgartner, P. Ohlson, R. Schellhaas, and R. J. Harrod. 2007. Development of current stand structure in dry fir-pine forests of eastern Washington. J. Torrey Bot. Soc. 134:199–214.

Everett, R. L., R. Schellhaas, D. Keenum, D. Spurbeck, and P. Ohlson. 2000. Fire history in the ponderosa pine/Douglas-fir forests on the east slope of the Washington Cascades. Forest Ecology and Management 129:207–225.

Fajardo, A., J. M. Goodburn, and J. Graham. 2006. Spatial patterns of regeneration in managed uneven-aged ponderosa pine Douglas-fir forests of Western Montana, USA. Forest Ecology and Management 223:255–266.

Falk, D. A. 2006. Process-centred restoration in a fire-adapted ponderosa pine forest. Journal for Nature Conservation 14:140–151.

Falk, D. A., C. Miller, D. McKenzie, and A. E. Black. 2007. Cross-scale analysis of fire regimes. Ecosystems 10:809–823.

Fettig, C. J., K. D. Klepzig, R. F. Billings, A. S. Munson, T. E. Nebeker, J. F. Negrón, and J. T. Nowak. 2007. The effectiveness of vegetation management practices for prevention and control of bark beetle infestations in coniferous forests of the western and southern United States. Forest Ecology and Management 238:24–53.

Finney, M. A., R. C. Seli, C. W. McHugh, A. A. Ager, B. Bahro, and J. K. Agee. 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. International Journal of Wildland Fire 16:712–727.

Fortin, M. J., and M. R. T. Dale. 2005. Spatial Analysis: A Guide for Ecologists. . Cambridge University Press, Cambridge, UK.

Fortin, M. J., and P. Drapeau. 1995. Delineation of ecological boundaries: comparison of approaches and significance tests. Oikos:323–332.

Franklin, J. F., M. A. Hemstrom, R. Van Pelt, and J. B. Buchanan. 2008. The Case for Active Management of Dry Forest Types in Eastern Washington: Perpetuating and Creating Old Forest Structures and Function. . Washington State Department of Natural Resources Report, Olympia, WA.

Franklin, J. F., and K. N. Johnson. 2012. A restoration framework for federal forests in the Pacific Northwest. Journal of Forestry 110:429–439.

Franklin, J. F., N. K. Johnson, D. C. Churchill, K. Hagmann, D. Johnson, and J. Johnston. In Press. Restoration of Dry Forests in Eastern Oregon: A Field Guide. . The Nature Conservancy of Oregon, Portland, OR.

Franklin, J. F., R. J. Mitchell, and B. J. Palik. 2007. Natural Disturbance and Stand Development Principles for Ecological Forestry. USDA Forest Service Northern Research Station General Technical Report NRS-GTR-19:1–44.

Franklin, J. F., T. A. Spies, P. R.V., A. B. Carey, D. A. Thornburghd, D. R. Berg, D. B. Lindenmayerf, M. E. Harmond, K. W.S., 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 and Example. Forest Ecology and Management 5624:p 1–25.

Franklin, J. F., F. J. Swanson, M. E. Harmon, D. A. Perry, T. A. Spies, V. H. Dale, A. McKee, W. K. Ferrel, and J. E. Means. 1991. Effects of global climatic change on forests in northwestern North America. Northwest Environmental Journal 7:233–254.

Frelich, L. E., and P. B. Reich. 1999a. Neighborhood effects, disturbance severity, and community stability in forests. Ecosystems 2:151–166.

Frelich, L. E., and P. B. Reich. 1999b. Neighborhood Effects, Disturbance Severity, and Community Stability in Forests. Ecosystems 2:151–166.

Frelich, L. E., S. Sugita, P. B. Reich, M. B. Davis, and S. K. Friedman. 2002. Neighbourhood effects in forests: implications for within-stand patch structure. Journal of Ecology 86:149–161.

Fry, D. L., and S. L. Stephens. 2010. Stand-level spatial dependence in an old-growth Jeffrey pine - mixed conifer forest, Sierra San Pedro Martir, Mexico. Canadian Journal of Forest Research 40:1803–1814.

Fule, P. Z. 2008. Does It Make Sense to Restore Wildland Fire in Changing Climate? Restoration Ecology 16:526–531.

Fule, P. Z., W. W. Covington, and M. M. Moore. 1997. Determining reference conditions for ecosystem management of southwestern ponderosa pine forests. Ecological Applications 7:895–908.

Gaines, W. L., R. J. Harrod, and M. C. Dalhgreen. 2010. The Okanogan-Wenatchee National Forest Restoration Strategy: a process for guiding restoration projects within the context of ecosystem management. . Okanogan-Wenatchee National Forest, Wenatchee, WA.

Gärnter, S., K. M. Reynolds, P. F. Hessburg, S. Hummel, and M. Twery. 2008. Decision support for evaluating landscape departure and prioritizing forest management activities in a changing environment. Forest Ecology and Management 256:1666–1676.

Gersonde, R., J. J. Battles, and K. L. O'Hara. 2004. Characterizing the light environment in Sierra Nevada mixed-conifer forests using a spatially explicit light model. Canadian Journal of Forest Research 34:1332–1342.

Getis, A., and J. Franklin. 1987. 2ND-ORDER NEIGHBORHOOD ANALYSIS OF MAPPED POINT PATTERNS. Ecology 68:473–477.

Getzin, S., T. Wiegand, K. Wiegand, and F. L. He. 2008. Heterogeneity influences spatial patterns and demographics in forest stands. Journal of Ecology 96:807–820.

Girvetz, E. H., and S. E. Greco. 2007. How to define a patch: a spatial model for hierarchically delineating organism-specific habitat patches. Landscape ecology 22:1131–1142.

Goheen, D. J., and E. M. Hansen. 1993. Effects of pathogens and bark beetles on forests. Pages 175–196 *in* T. D. Schowalter and G. M. Filip, editors. Beetle-Pathogen Interactions in Conifer Forests. . Academic Press, London, UK.

Graham, R., T. Jain, and J. Sandquist. 2007. Free selection: a silvicultural option. Pages 121–156 *in* R. F. Powers, editor. Restoring fire-adapted ecosystems: proceedings of the 2005 national silviculture workshop. . USDA Forest Service, Pacific Southwest Research Station General Technical Report. GTR-PSW-203.

Griesbauer, H. P., D. S. Green, and G. A. O'Neill. 2011. Using a spatiotemporal climate model to assess population-level Douglas-fir growth sensitivity to climate change across large climatic gradients in British Columbia, Canada. Forest Ecology and Management 261:589–600.

Gunderson, L. H., and C. S. Holling. 2002. Panarchy: understanding transformations in human and natural systems. . Island Press, Washington, D.C., USA.

Gustafsson, L., S. C. Baker, J. Bauhus, W. J. Beese, A. Brodie, J. Kouki, D. B. Lindenmayer, A. Lõhmus, G. M. Pastur, C. Messier, M. Neyland, B. J. Palik, A. Sverdrup-Thygeson, J. A. Volnery, A. Wayne, and J. F. Franklin. 2012. Retention Forestry to Maintain Multifunctional Forests: A World Perspective. BioScience 62:633–645.

Hagmann, K., J. F. Franklin, and K. N. Johnson. In review. Historical structure and composition of ponderosa pine and mixed-conifer forests in south-central Oregon. Forest Ecology and Management.

Halpern, C. B., J. A. Antos, J. M. Rice, R. D. Haugo, and N. L. Lang. 2010. Tree invasion of a montane meadow complex: temporal trends, spatial patterns, and biotic interactions. Journal of Vegetation Science 21:717–732.

Hamrick, J., H. Blanton, and K. Hamrick. 1989. Genetic-Structure of Geographically Marginal Populations of Ponderosa Pine. American Journal of Botany 76:1559–1568.

Harrod, R. J., B. H. McRae, and W. E. Hartl. 1999. Historical stand reconstruction in ponderosa pine forests to guide silvicultural prescriptions. Forest Ecology and Management 114:433–446.

Hawksworth, F. G., D. Wiens, B. W. Geils, and R. G. Nisley. 1996. Dwarf mistletoes: biology, pathology, and systematics. . Agricultural Handbook 709. USDA, Forest Service, Washington, D.C.

Hessburg, P. F., and J. K. Agee. 2003. An environmental narrative of Inland Northwest United States forests, 1800-2000. Forest Ecology and Management 178:23–59.

Hessburg, P. F., J. K. Agee, and J. F. Franklin. 2005. Dry forests and wildland fires of the inland Northwest USA: Contrasting the landscape ecology of the pre-settlement and modem eras. Forest Ecology and Management 211:117–139.

Hessburg, P. F., R. G. Mitchell, and G. M. Filip. 1994. Historical and current roles of insects and pathogens in eastern Oregon and Washington forested landscapes. Pacific Northwest Research Station General Technical Report PNW-GTR-327.

Hessburg, P. F., K. M. Reynolds, R. B. Salter, J. D. Dickinson, W. L. Gaines, and R. J. Harrod. 2013. Landscape Evaluation for Restoration Planning on the Okanogan-Wenatchee National Forest, USA. Sustainability 5:805–840.

Hessburg, P. F., R. B. Salter, and K. M. James. 2007. Re-examining fire severity relations in pre-management era mixed conifer forests: inferences from landscape patterns of forest structure. Landscape Ecology 22:5–24.

Hessburg, P. F., R. B. Salter, M. B. Richmond, and B. G. Smith. 2000. Ecological subregions of the Interior Columbia Basin, USA. Applied Vegetation Science 3:163–180.

Hessburg, P. F., B. G. Smith, S. D. Kreiter, C. A. Miller, R. B. Salter, C. H. McNicoll, and W. J. Hann. 1999a. Historical and current forest and range landscapes in the interior Columbia River basin and portions of the Klamath and Great Basins. Part 1: Linking vegetation patterns and landscape vulnerability to potential insect and pathogen disturbances. Pacific Northwest Research Station Gen. Tech. Rep. PNW-GTR-458.

Hessburg, P. F., B. G. Smith, S. D. Kreiter, and M. B. Richmond. 2004. Using a decision support system to estimate departures of present forest landscape patterns from historical conditions: An example from the Inland Northwest Region of the United States. Pages 158–175 *in* A. H. Perera, L. J. Buse, and M. G. Weber, editors. Emulating Natural Forest Landscape Disturbances: Concepts and Applications. . Columbia University Press, New York, NY.

Hessburg, P. F., B. G. Smith, and R. B. Salter. 1999b. Detecting change in forest spatial patterns from reference conditions. Ecol. Appl. 9:1232–1252.

Hessl, A. E., D. McKenzie, and R. Schellhaas. 2004. Drought and Pacific Decadal Oscillation linked to fire occurrence in the inland Pacific Northwest. Ecological Applications 14:425–442.

HFRA. 2003. Healthy Forests Restoration Act of 2003.

Holling, C. S. 1996. Engineering resilience versus ecological resilience. *in* P. Schulze, editor. Engineering with ecological constraints. . National Academy, Washington D.C.

Illian, J., E. Benson, J. Crawford, and H. Staines. 2006. Principal component analysis for spatial point processes—assessing the appropriateness of the approach in an ecological context. Case Studies in Spatial Point Process Modeling:135–150.

Illian, J., A. Penttinen, H. Stoyan, and D. Stoyan. 2008. Statistical Analysis and Modelling of Spatial Point Patterns Statistics. . John Wiley & Sons, Chichester, UK.

IPCC. 2007. Climate change 2007: WG I The Physical Science Basis. . Cambridge University Press, New York, NY.

Jackson, S. T., and R. J. Hobbs. 2009. Ecological restoration in the light of ecological history. Science 325:567–569.

Jain, T. B., R. T. Graham, J. Sandquist, M. Butler, K. Brockus, D. Frigard, D. Cobb, H. Sup-Han, J. Halbrook, R. Denner, and J. S. Evans. 2008. Restoration of northern Rocky Mountain moist forests: Integrating fuel treatments from the site to the landscape. Pages 147–172 *in* R. L. Deal, editor. Integrated restoration of forested ecosystems to achieve multiple resource benefits: proceedings of the 2007 national silviculture workshop. . USDA Forest Service, Pacific Northwest Research Station General Technical Report. PNW-GTR-733.

Joyce, L. A., G. M. Blate, S. . McNulty, C. I. Millar, S. Moser, N. R.P., and D. L. Peterson. 2009. Managing for Multiple Resources Under Climate Change:National Forests. Environmental Management 44:1022–1032.

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.

Kaufmann, M. R., D. Binkley, P. Z. Fule, M. Johnson, S. L. Stephens, and T. W. Swetnam. 2007. Defining old growth for fire-adapted forests of the Western United States. Ecology and Society 12.

Keane, R. E., P. F. Hessburg, P. B. Landres, and F. J. Swanson. 2009. The use of historical range and variability (HRV) in landscape management. Forest Ecology and Management 258:1025–1037.

Kenkel, N. C. 1988. Pattern of self-thinning in jack pine: testing the random mortality hypothesis. Ecology 69:1017–1024.

Kerby, J. D., S. D. Fuhlendorf, and D. M. Engle. 2007. Landscape heterogeneity and fire behavior: scale-dependent feedback between fire and grazing processes. Landscape Ecology 22:507–516.

Kernan, J. T., and A. E. Hessl. 2010. Spatially heterogeneous estimates of fire frequen-cy in ponderosa pine forests of Washington, USA. Fire Ecology 6:117–135.

Klenner, W., R. Walton, A. Arsenault, and L. Kremsater. 2008. Dry forests in the Southern Interior of British Columbia: Historic disturbances and implications for restoration and management. Forest Ecology and Management 256:1711–1722.

Knapp, E. E., M. P. North, M. Benech, and B. Estes. 2012. The Variable-Density Thinning Study at Stanislaus-Tuolumne Experimental Forest. Pages 127–140 *in* M. P. North, editor. Managing Sierra Nevada Forests. . USDA Forest Service, Pacific SW Research Station General Technical Report. PSW-GTR-237.

Kotliar, N. B., and J. A. Wiens. 1990. Multiple Scales of Patchiness and Patch Structure - a Hierarchical Framework for the Study of Heterogeneity. Oikos 59:253–260.

Kuuluvainen, T., and R. Grenfell. 2012. Natural disturbance emulation in boreal forest ecosystem management—theories, strategies, and a comparison with conventional even-aged management 1 1 This article is one of a selection of papers from the 7th International Conference on Disturbance Dynamics in Boreal Forests. Canadian Journal of Forest Research 42:1185–1203.

Landres, P. B., P. Morgan, and F. J. Swanson. 1999. Overview of the use of natural variability concepts in managing ecological systems. Ecological Applications 9:1179–1188.

Larson, A. J., and D. C. Churchill. 2008. Spatial patterns of overstory trees in late-successional conifer forests with implications for restoration. Canadian Journal of Forest Research 38:2814–2825.

Larson, A. J., and D. C. Churchill. 2012. Tree spatial patterns in fire-frequent forests of western North America, including mechanisms of pattern formation and implications for designing fuel reduction and restoration treatments. Forest Ecology and Management 267:74–92.

Larson, A. J., K. C. Stover, and C. R. Keyes. 2012. Effects of restoration thinning on spatial heterogeneity in mixed conifer forest. Canadian Journal of Forest Research 42:1505–1517.

Lertzman, K. P., and J. Fall. 1998. From forest stands to landscapes: Spatial scales and the roles of disturbances. Pages 339–367 *in* D. L. Peterson and V. T. Parker, editors. Ecological Scale: Theory and Applications. . Columbia University Press, New York, NY.

Levin, S. A. 1992. The Problem of Pattern and Scale in Ecology: The Robert H. MacArthur Award Lecture. Ecology 73:1943–1967.

Levin, S. A. 1998. Ecosystems and the biosphere as complex adaptive systems. Ecosystems 1:431–436.

Lillybridge, T. R., B. L. Kovalchik, C. K. Williams, and B. G. Smith. 1995. Field guide for forested plant associations of the Wenatchee National Forest. USDA Forest Service: Pacific Northwest Research Station General Technical Report PNW GTR-359.

Lindenmeyer, D. B., and J. F. Franklin. 2002. Conserving Forest Biodiversity. . Island Press, Washington, D.C.

Lingua, E., P. Cherubini, R. Motta, and P. Nola. 2009. Spatial structure along an altitudinal gradient in the Italian central Alps suggests competition and facilitation among coniferous species. Journal of Vegetation Science 19:425–436.

Linhart, Y., J. Mitton, K. Sturgeon, and M. Davis. 1981. Genetic-Variation in Space and Time in a Population of Ponderosa Pine. Heredity 46:407–426.

Littell, J. S., D. McKenzie, D. L. Peterson, and A. L. Westerling. 2009. Climate and wildfire area burned in western U. S. ecoprovinces, 1916-2003. Ecological Applications 19:1003–1021.

Littell, J. S., E. E. Oneil, D. McKenzie, J. A. Hicke, J. A. Lutz, R. A. Norheim, and M. M. Elsner. 2010. Forest ecosystems, disturbance, and climatic change in Washington State, USA. Climatic change 102:129–158.

Littell, J. S., D. L. Peterson, and M. Tjoelker. 2008. Douglas-fir growth in mountain ecosystems: water limits tree growth from stand to region. Ecological Monographs 78:349–368.

Loosmore, N. B., and E. D. Ford. 2006. Statistical inference using the G or K point pattern spatial statistics. Ecology 87:1925–1931.

Lundquist, J. D., and D. R. Cayan. 2007. Surface temperature patterns in complex terrain: Daily variations and long-term change in the central Sierra Nevada, California. J. Geophys. Res 112:D11124.

Lutz, J. A., A. J. Larson, M. E. Swanson, and J. A. Freund. 2012. Ecological importance of large-diameter trees in a temperate mixed-conifer forest. PloS one 7:e36131.

Lutz, J. A., J. W. van Wagtendonk, and J. F. Franklin. 2010. Climatic water deficit, tree species ranges, and climate change in Yosemite National Park. Journal of Biogeography 37:936–950.

Lydersen, J., and M. P. North. 2012. Topographic variation in structure of mixed-conifer forests under an active-fire regime. Ecosystems 15:1134–1146.

Lynch, D. L., W. H. Romme, and M. L. Floyd. 2000. Forest restoration in southwestern ponderosa pine. Journal of Forestry 98:17–24.

Ma, S. Y., A. Concilio, B. Oakley, M. North, and J. Q. Chen. 2010. Spatial variability in microclimate in a mixed-conifer forest before and after thinning and burning treatments. Forest Ecology and Management 259:904–915.

McCune, B., and J. Grace. 2002. Analysis of ecological communities. . MjM Software Design, Gleneden Beach, OR.

McGarigal, K., S. Tagil, and S. A. Cushman. 2009. Surface metrics: An alternative to patch metrics for the quantification of landscape structure. Landscape Ecology 24:433–450.

McGuire, J., R. Mitchell, E. Moser, S. Pecot, D. Gjerstad, and C. Hedman. 2001. Gaps in a gappy forest: plant resources, longleaf pine regeneration, and understory response to tree removal in longleaf pine savannas. CANADIAN JOURNAL OF FOREST RESEARCH-REVUE CANADIENNE DE RECHERCHE FORESTIERE 31:765–778.

McKenzie, D., and M. C. Kennedy. 2011. Scaling laws and complexity in fire regimes. Pages 27–49 *in* D. McKenzie, C. Miller, and D. A. Falk, editors. The landscape ecology of fire. . Springer.

McKenzie, D., C. Miller, and D. A. Falk (Eds.). 2011. The Landscape Ecology of Fire. . Springer.

McKenzie, D., D. L. Peterson, and J. S. Littell. 2009. Global warming and stress complexes in forests of Western North America. Pages 319–338 *in* A. Bytnerowicz, M. Arbaugh, C. Andersen, and A. Riebau, editors. Wildland Fires and Air Pollution. Developments in Environmental Science. . Elsevier, Amsterdam, The Netherlands.

McKenzie, D., D. W. Peterson, D. L. Peterson, and P. E. Thornton. 2003. Climatic and biophysical controls on conifer species distributions in mountain forests of Washington state, USA. Journal of Biogeography 30:1093-1108. 30:1093–1108.

Messier, C., and K. J. Puettmann. 2011. Forests as Complex Adaptive Systems: Implications for Forest Management and Modelling. Italian Journal of Forest and Mountain Environments 66:249–258.

Millar, C. I., N. L. Stephenson, and S. L. Stephens. 2007. Climate change and forests of the future: Managing in the face of uncertainty. Ecological Applications 17:2145–2151.

Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode. 2009. Quantitative Evidence for Increasing Forest Fire Severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA. Ecosystems 12:16–32.

Mitchell, R. J., J. K. Hiers, J. J. O'Brien, S. B. Jack, and R. T. Engstrom. 2006. Silviculture that sustains: the nexus between silviculture, frequent prescribed fire, and conservation of biodiversity in longleaf pine forests of the southeastern United States. Canadian Journal of Forest Research 40:596–596.

Moeur, M. 1993. Characterizing spatial patterns of trees using stem-mapped data. Forest Science 39:756–775.

Moore, M. M., C. A. Casey, J. D. Bakker, J. D. Springer, P. Z. Fule, W. W. Covington, and D. C. Laughlin. 2006. Herbaceous vegetation responses (1992-2004) to restoration treatments in a Ponderosa pine forest. Rangeland Ecology & Management 59:135–144.

Moore, M. M., W. W. Covington, and P. Z. Fule. 1999. Reference conditions and ecological restoration: A southwestern ponderosa pine perspective. Ecological Applications 9:1266–1277.

Moore, M. M., D. W. Huffman, P. Z. Fule, and W. W. Covington. 2004. Comparison of historical and contemporary forest structure and composition on permanent plots in southwestern ponderosa pine forests. Forest Science 50:162–176.

Moritz, M. A., P. F. Hessburg, and N. A. Povak. 2011. Native Fire Regimes and Landscape Resilience. Pages 51–88 *in* D. McKenzie, C. Miller, and D. A. Falk, editors. The Landscape Ecology of Fire. . Springer.

Moritz, M. A., M. E. Morais, L. A. Summerell, J. M. Carlson, and J. Doyle. 2005. Wildfires, complexity, and highly optimized tolerance. Proceedings of the National Academy of Sciences of the United States of America 102:17912–17917.

Munger, T. T. 1917. Western yellow pine in Oregon. USDA Bulletin 418.

Nathanson, J., M. T. Lamzafama, and P. Kissam. 2006. Surveying fundamentals and practices.Prentice Hall. Upper Saddle River, New Jersey.

Negron, J. F., and J. B. Popp. 2004. Probability of ponderosa pine infestation by mountain pine beetle in the Colorado Front Range. Forest Ecology and Management 191:17–27.

Van Nes, E. H., and M. Scheffer. 2005. Implications of spatial heterogeneity for catastrophic regime shifts in ecosystems. Ecology 86:1797–1807.

Neyman, J., and E. L. Scott. 1957. On a mathematical theory of population conceived as conglomerations of clusters. Pages 109–120.

North, M., J. Innes, and H. Zald. 2007a. Comparison of thinning and prescribed fire restoration treatments to Sierran mixed-conifer historic conditions. Canadian Journal of Forest Research 37:331–342.

North, M. P., J. Innes, and H. Zald. 2007b. Comparison of thinning and prescribed fire restoration treatments to Sierran mixed-conifer historic conditions. Canadian Journal of Forest Research 37:331–342.

North, M. P., and J. W. Sherlock. 2012. Marking and Assessing Forest Heterogeneity. Pages 95–105 *in* M. P. North, editor. Managing Sierra Nevada Forests. . USDA Forest Service, Pacific SW Research Station General Technical Report. PSW-GTR-237.

North, M. P., P. Stine, K. L. O'Hara, W. J. Zielinski, and S. L. Stephens. 2009. An ecosystem management strategy for sierran mixed- conifer forests. USDA Forest Service: Pacific Southwest Research Station General Technical Report PSW-GTR-220.

NRCS. 2009. Soil Survey of Wenatchee National Forest, Naches Area, Washington, Parts of Kittitas and Yakima Counties. . USDA Natural Resources Conservation Service.

NRCS. 2010. Soil Survey of Kittitas County Area, Washington. . USDA Natural Resources Conservation Service.

O'Hara, K. L. 1996. Dynamics and stocking-level relationships of multi-aged Pondersoa Pine Stands. Forest Science, Monograph 33 42:1–34.

O'Hara, K. L., P. A. Latham, and P. F. Hessburg. 1996. A structural classification of inland Northwest forest vegetation. Western Journal of Applied Forestry 11:97–102.

O'Hara, K. L., L. P. Leonard, and C. R. Keyes. 2012. Variable-Density Thinning and a Marking Paradox: Comparing Prescription Protocols to Attain Stand Variability in Coast Redwood. Western Journal of Applied Forestry 27:143–149.

Odion, D. C., and D. A. Sarr. 2007. Managing disturbance regimes to maintain biological diversity in forested ecosystems of the Pacific Northwest. Forest Ecology and Management 246:57–65.

Olsen, W. K., J. M. Schmid, and S. A. Mata. 1996. Stand characteristics associated with mountain pine beetle infestations in ponderosa pine. Forest Science 42:310–327.

Paine, R. T., M. J. Tegner, and E. A. Johnson. 1998. Compounded perturbations yield ecological surprises. Ecosystems 1:535–545.

Parish, R., J. A. Antos, and M. J. Fortin. 1999. Stand development in an old-growth subalpine forest in southern interior British Columbia. Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere 29:1347–1356.

Parisien, M. A., C. Miller, A. A. Ager, and M. A. Finney. 2010. Use of artificial landscapes to isolate controls on burn probability. Landscape Ecology 25:79–93.

Van Pelt, R. V. 2008. Identifying old trees and forests in Eastern Washington. . Washington Department of Natural Resouces.

Perry, D. A., P. F. Hessburg, C. N. Skinner, T. A. Spies, S. L. Stephens, A. H. Taylor, J. F. Franklin, B. McComb, and G. M. Riegel. 2011. The ecology of mixed severity fire regimes in Washington, Oregon, and Northern California. Forest Ecology and Management 262:703–717.

Perry, G. L. W., B. P. Miller, and N. J. Enright. 2006. A comparison of methods for the statistical analysis of spatial point patterns in plant ecology. Plant Ecology 187:59–82.

Peterson, D. L., J. S. Halofsky, and M. C. Johnson. 2011. Managing and Adapting to Changing Fire Regimes in a Warmer Climate. Pages 249–268 *in* D. McKenzie, C. Miller, and D. A. Falk, editors. The Landscape Ecology of Fire. . Springer.

Peterson, D. L., M. C. Johnson, D. McKenzie, J. K. Agee, T. B. Jain, and E. D. Reinhardt. 2005. Forest structure and fire hazard in dry forests of the western United States. USDA Forest Service, Pacific Northwest Research Station GTR-PNW-628.

Peterson, D. L., and V. T. Parker (Eds.). 1998. Ecological Scale: Theory and Applications. . Columbia University Press.

Peterson, G. D. 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. Ecosystems 5:329–338.

Peterson, G. D., C. R. Allen, and C. S. Holling. 1998. Ecological resilience, biodiversity, and scale. Ecosystems 1:6–18.

Pimont, F., J. L. Dupuy, R. R. Linn, and S. Dupont. 2011. Impacts of tree canopy structure on wind flows and fire propagation simulated with FIRETEC. Annals of Forest Science 68:523–530.

Plotkin, J. B., J. M. Chave, and P. S. Ashton. 2002. Cluster analysis of spatial patterns in Malaysian tree species. American Naturalist 160:629–644.

Powell, D. C. 1999. Suggested Stocking Levels for Forest Stands in Northeastern Oregon and Southeastern Washington: An Implementation Guide for the Umatilla National Fores. USDA Forest Service, Pacific Northwest Region, Umatilla National Forest F14-SO-TP-03-99.

Powell, D. C. 2010. Estimating Crown Fire Susceptibility for Project Planning. Fire Management Today 70:8–15.

Powell, D. C. 2012. Active Management of Dry Forests in the Blue Mountains: Silvicultural Considerations. USDA Forest Service, Pacific Northwest Region, Umatilla National Forest White Paper F14- SO-WP- Silv- 4.

Prichard, S. J., D. L. Peterson, and K. Jacobson. 2010. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. Can. J. For. Res. 40:1615–1626.

Puettmann, K. J., D. K. Coates, and C. Messier. 2009. A Critique of Silviculture: Managing for Complexity. . Island Press, Washington, D.C.

Rehfeldt, G. E., N. L. Crookston, M. V. Warwell, and J. S. Evans. 2006. Empirical analyses of plant-climate relationships for the western United States. International Journal of Plant Sciences 167:1123–1150.

Reineke, L. H. 1933. Perfecting a stand density index for even-aged forests. Journal of Agricultural Research 46:627–638.

Ripley, B. D. 1988. Statistical inference for spatial processes. . Cambridge University Press, Cambridge, U.K.

Roberts, S. L., J. W. van Wagtendonk, A. K. Miles, D. A. Kelt, and J. A. Lutz. 2008. Modeling the effects of fire severity and spatial complexity on small mammals in Yosemite National Park, California. Fire Ecology 4 (2): 83-104. Fire Ecology Special Issue Vol 4:84.

Rogelj, J., B. Hare, J. Nabel, K. Macey, M. Schaeffer, K. Markmann, and M. Meinshausen. 2009. Halfway to Copenhagen, no way to 2 °C. Nature Reports Climate Change:81–83.

Sánchez Meador, A. J., M. M. Moore, J. D. Bakker, and P. F. Parysow. 2009. 108 years of change in spatial pattern following selective harvest of a Pinus ponderosa stand in northern Arizona, USA. Journal of Vegetation Science 20:79–90.

Sánchez Meador, A. J., P. F. Parysow, and M. M. Moore. 2011. A new method for delineating tree patches and assessing spatial reference conditions of ponderosa pine forests in northern arizona. Restoration Ecology 19:490–499.

Schoennagel, T., and C. R. Nelson. 2010. Restoration relevance of recent National Fire Plan treatments in forests of the Western US. Frontiers in Ecology and Environment. 17:742–753.

Schoennagel, T., E. A. H. Smithwick, and M. G. Turner. 2009. Landscape heterogeneity following large fires: insights from Yellowstone National Park, USA. International Journal of Wildland Fire 17:742–753.

Schoennagel, T., T. T. Veblen, and W. H. Romme. 2004. The interaction of fire, fuels, and climate across rocky mountain forests. Bioscience 54:661–676.

Scholl, A. E., and A. H. Taylor. 2010. Fire regimes, forest change, and self-organization in an old-growth mixed-conifer forest, Yosemite National Park, USA. Ecological Applications 20:362–380.

Seaber, P. R., F. P. Kapinos, and G. L. Knapp. 1987. Hydrologic unit maps. . U.S. Geological Survey.

Shafer, S. L., P. J. Bartlein, and R. S. Thompson. 2001. Potential changes in the distributions of western North America tree and shrub taxa under future climate scenarios. Ecosystems 4:200–215.

Shaw, D. C., J. Q. Chen, E. Freeman, and D. Braun. 2005. Spatial and population characteristics of dwarf mistletoe infected trees in an old-growth Douglas-fir/western hemlock forest. Canadian Journal of Forest Research 35:990–1001.

Shinneman, D. J., and W. L. Baker. 1997. Nonequilibrium dynamics between catastrophic disturbances and old-growth forests in Ponderosa pine landscapes of the Black Hills. Conservation Biology 11:1276–1288.

Shugart, H. H. 1984. A theory of forest dynamics. The ecological implications of forest succession models. Springer-Verlag.

Simeoni, A., P. Salinesi, and F. Morandini. 2011. Physical modelling of forest fire spreading through heterogeneous fuel beds. International Journal of Wildland Fire 20:625–632.

Spada, B. 1960. Estimating past diameters of several species in the ponderosa pine subregion of Oregon and Washington. USDA Forest Service Pacific Northwest Forest and Range Experiment Station RN 181.

Spies, T. A., T. W. Giesen, F. J. Swanson, J. F. Franklin, D. Lach, and K. N. Johnson. 2010. Climate change adaptation strategies for federal forests of the Pacific Northwest, USA: ecological, policy, and socio-economic perspectives. Landscape Ecology 25:1185–1199.

Spies, T. A., and M. E. Turner. 1999. Dynamic forest mosaics. *in* M. L. Hunter, editor. Maintaining biodiversity in forest ecosystems. . Cambridge University Press, Cambridge, UK.

Spracklen, D. V., L. J. Mickley, J. A. Logan, R. C. Hudman, R. Yevich, M. D. Flannigan, and A. L. Westerling. 2009. Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. Journal of Geophysical Research-Atmospheres 114:17.

Stephens, S. L., D. L. Fry, and E. Franco-Vizcaino. 2008. Wildfire and spatial patterns in forests in northwestern Mexico: the United States wishes it had similar fire problems. Ecology and Society 13.

Stephens, S. L., and S. J. Gill. 2005. Forest structure and mortality in an old-growth Jeffrey pine-mixed conifer forest in north-western Mexico. Forest Ecology and Management 205:15–28.

Stephens, S. L., C. I. Millar, and B. M. Collins. 2010. Operational approaches to managing forests of the future in Mediterranean regions within a context of changing climates. Environmental Research Letters 5:1–9.

Stephens, S. L., J. J. Moghaddas, C. Edminster, C. E. Fiedler, S. Haase, M. Harrington, J. E. Keeley, E. E. Knapp, J. D. McIver, K. Metlen, C. Skinner, and A. Youngblood. 2009. Fire and fire surrogate treatment effects on vegetation structure, fuels, and potential fire behavior and severity from six western United States coniferous forests. Ecological Applications 19:305–320.

Stephenson, N. L. 1990. Climatic control of vegetation distribution: the role of the water balance. American Naturalist:649–670.

Stephenson, N. L. 1998. Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales. Journal of Biogeography 25:855–870.

Stoyan, D., and H. Stoyan. 1994. Fractals, random shapes and point fields: methods of geometrical statistics. . John Wiley & Sons, Chichester, UK.

Strauss, D. J. 1975. A model for clustering. Biometrika 62:467–475.

Swanson, M. E., J. F. Franklin, R. L. Beschta, C. M. Crisafulli, D. A. DellaSala, R. L. Hutto, D. B. Lindenmayer, and F. J. Swanson. 2011. The Forgotten Stage of Forest Succession: Early Successional Ecosystems on Forest Sites. Frontiers in Ecology and the Environment 9:117–125.

Swetnam, T. W., C. D. Allen, and J. L. Betancourt. 1999. Applied historical ecology: using the past to manage for the future. Ecological applications 9:1189–1206.

Swetnam, T. W., and J. L. Betancourt. 1998. Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. Journal of Climate 11:3128–3147.

Tappeiner, J. C., D. A. Maguire, and T. B. Harrington. 2007. Silviculture and Ecology of Western U.S. Forests. . Oregon State University Press, Corvalis, OR.

Taylor, A. H. 2004. Identifying forest reference conditions on early cut-over lands, Lake Tahoe Basin, USA. Ecological Applications 14:1903–1920.

Taylor, A. H. 2010. Fire disturbance and forest structure in an old-growth Pinus ponderosa forest, southern Cascades, USA. Journal of Vegetation Science 21:561–572.

Taylor, A. H., and C. N. Skinner. 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. Ecological Applications 13:704–719.

Thaxton, J. M., and W. J. Platt. 2006. Small-scale fuel variation alters fire intensity and shrub abundance in a pine savanna. Ecology 87:1331–1337.

Thornthwaite, C. W., J. R. Mather, and D. B. Carter. 1957. Instructions and tables for computing potential evapotranspiration and the water balance. Publications in Climatology 10:181–311.

Turner, M. G. 2010. Disturbance and landscape dynamics in a changing world1. Ecology 91:2833–2849.

Turner, M. G., W. H. Romme, and R. H. Gardner. 1999. Prefire heterogeneity, fire severity, and early postfire plant reestablishment in subalpine forests of Yellowstone National Park, Wyoming. International Journal of Wildland Fire 9:21–36.

Turner, M. G., W. H. Romme, R. H. Gardner, R. V. Oneill, and T. K. Kratz. 1993. A Revised Concept of Landscape Equilibrium - Disturbance and Stability on Scaled Landscapes. Landscape Ecology 8:213–227.

Urban, D. L., R. V. Oneill, and H. H. Shugart. 1987. Landscape Ecology. Bioscience 37:119–127.

USFS. 1995. Mission Creek Watershed Assessment. USDA Forest Service, Okanagon-Wenatchee National Forest.

USFS. 1997. Rattlesnake Creek Watershed Analysis. . USDA Forest Service. Okanagon Wenatchee National Forest, Naches Ranger District, Naches, WA.

USFS. 1998. Upper Tieton Watershed Analysis. USDA Forest Service. Okanagon Wenatchee National Forest, Naches Ranger District, Naches, WA.

USFS. 2008. Glaze Forest Restoration Project, Environmental Assessment. . USDA Forest Service, Deschutes National Forest, Sisters Ranger District, Sisters, OR.

Varhola, A., N. C. Coops, M. Weiler, and R. D. Moore. 2010. Forest canopy effects on snow accumulation and ablation: An integrative review of empirical results. Journal of Hydrology 392:219–233.

Walker, B., C. S. Hollin, S. R. Carpenter, and A. Kinzig. 2004. Resilience, adaptability and transformability in social-ecological systems. Ecology and Society 9.

Waltz, A. E. M., P. Z. Fule, W. W. Covington, and M. M. Moore. 2003. Diversity in ponderosa pine forest structure following ecological restoration treatments. Forest Science 49:885–900.

Wang, T., A. Hamann, D. L. Spittlehouse, and T. Q. Murdock. 2012. ClimateWNA—High-Resolution Spatial Climate Data for Western North America. Journal of Applied Meteorology and Climatology 51:16–29.

Waring, K. M., D. M. Reboletti, L. A. Mork, C. H. Huang, R. W. Hofstetter, A. M. Garcia, P. Z. Fule, and T. S. Davis. 2009. Modeling the Impacts of Two Bark Beetle Species Under a Warming Climate in the Southwestern USA: Ecological and Economic Consequences. Environmental Management 44:824–835.

Watt, A. S. 1947. Pattern and process in the plant community. Journal of Ecology 35:1–22.

Weaver, H. 1943. Fire as an ecological and silvicultural factor in the ponderosa pine region of the pacific slope. Journal of Forestry 41:7–15.

Weaver, H. 1961. Ecological changes in the ponderosa pine forest of cedar valley in southern Washington. Ecology 42:416–420.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam. 2006. Warming and earlier spring increase western US forest wildfire activity. Science 313:940–943.

White, A. S. 1985. Presettlement regeneration patterns in a southwestern ponderosa pine stand. Ecology 66:589–594.

Wiegand, T., S. Gunatilleke, and N. Gunatilleke. 2007a. Species associations in a heterogeneous Sri Lankan dipterocarp forest. The American Naturalist 170:E77–E95.

Wiegand, T., S. Gunatilleke, N. Gunatilleke, and T. Okuda. 2007b. Analyzing the spatial structure of a Sri Lankan tree species with multiple scales of clustering. Ecology 88:3088–3102.

Wiegand, T., and K. A. Moloney. 2004. Rings, circles, and null-models for point pattern analysis in ecology. Oikos 104:209–229.

Williams, J. W., S. T. Jackson, and J. E. Kutzbacht. 2007. Projected distributions of novel and disappearing climates by 2100 AD. Proceedings of the National Academy of Sciences of the United States of America 104:5738–5742.

Wood, S. N. 2004. Stable and efficient multiple smoothing parameter estimation for generalized additive models. Journal of the American Statistical Association 99:673–686.

Wright, C. S., and J. K. Agee. 2004. Fire and vegetation history in the eastern Cascade Mountains, Washington. Ecological Applications 14:443–459.

Wu, J. G. 1999. Hierarchy and scaling: extrapolating information along a scaling ladder. Canadian Journal of Remote Sensing 25:367–380.

Wu, J. G., and S. A. Levin. 1997. A patch-based spatial modeling approach: conceptual framework and simulation scheme. Ecological Modelling 101:325–346.

Wu, J. G., and O. L. Loucks. 1995. From balance of nature to hierarchical patch dynamics: A paradigm shift in ecology. Q. Rev. Biol. 70:439–466.

Wynsma, B., and C. R. Keyes. 2010. Biomass utilization opportunities to achieve diverse silvicultural goals. USDA Forest Service Rocky Mountain Research Station Proceedings RMRS-P-61:135–143.

Yamada, I., and P. A. Rogerson. 2003. An Empirical Comparison of Edge Effect Correction Methods Applied to K-function Analysis. Geographical Analysis 35:97–109.

York, R. A., R. C. Heald, J. J. Battles, and J. D. York. 2004. Group selection management in conifer forests: relationships between opening size and tree growth. Canadian Journal of Forest Research 34:630–641.

Youngblood, A., T. Max, and K. Coe. 2004. Stand structure in eastside old-growth ponderosa pine forests of Oregon and northern California. Forest Ecology and Management 199:191–217.

Youngblood, A., K. L. Metlen, and K. Coe. 2006. Changes in stand structure and composition after restoration treatments in low elevation dry forests of northeastern Oregon. Forest Ecology and Management 234:143–163.

Zar, J. H. 1999. Biostatistical Analysis: fourth edition. . Prentice Hall, Upper Saddle River, New Jersey.