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Spatial patterns of vigor by stand density across species groups and its drivers in a pre-harvest ponderosa pine-dominated landscape in northern California

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ABSTRACT

Information on spatial patterns of forest health and stand vigor in historical forests is quite limited, particularly for forests of North America, which have been subsequently harvested. We used forest inventory data from 1934, which pre-dated early 20th century timber harvest, to reconstruct patterns of vigor in overstory trees. Across 4,000 ha of ponderosa pine-dominated forests in the Blacks Mountain Experimental Forest (BMEF), we described the spatial patterns of pre-harvest (1934) forests using a stand density index (SDI) and accounting for different species and vigor classes. We then identified topo-edaphic variables associated with pre-harvest SDI. To do so, we first calculated SDI for two species groups: 1) ponderosa pine (*Pinus ponderosa* Laws.) and Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.), and 2) incense-cedar (*Calocedrus decurrens* (Torr.) Florin) and white fir (*Abies concolor* (Grod. and Glend.)) as well as for seven vigor classes within these two groups. Second, using Moran's I, we found four spatially aggregated clusters (Moran's I = 0.35): 1) ponderosa pine-high vigor, 2) ponderosa pine-low vigor, 3) mixed species-high vigor, and 4) mixed species-low vigor. Most of the pre-harvest landscape consisted of high vigor ponderosa pine clusters with low SDI (relative density (RD) < 0.25). High elevation sections consisted of mixed species clusters of both high and low vigor with high SDI (RD > 0.35). Using classification and regression tree analysis, we identified elevation (m), surface-soil depth (cm), and sub-soil depth (cm) were related to the clusters. A multinominal logistic regression model (kappa = 0.44; classification accuracy = 64.4 %) identified surface stoniness, available water capacity at 150 cm depth and its interaction with sub-soil depth as important variables that were related to clusters. Within ponderosa pine-dominated forests, managers consider dense stands of low vigor trees to be at-risk of insect, disease, and fire. Thus, our results can be used by managers as representative baselines for characterizing (pre-harvest) stand conditions to guide management treatments to support high vigor and low density forest conditions.

1. Introduction

Prior to Euro-American settlement, ponderosa pine (*Pinus ponderosa* Laws.) dominated forests had overstory stand structures, which facilitated resilience to fire, insect, and disease (Stephens et al., 2008). Selective timber harvesting in the early 1900 s has since altered these original (hereafter referred to as "pre-harvest") stand conditions. Conventional descriptions of overstory stand structure in pre-harvest forests are based on stand-level attributes such as average stand density (trees ha^{-1}) and basal area (m^2/ha) (Boyden et al., 2005). Largely missing from the study of historical and pre-harvest forests is an understanding of tree vigor, which reflects the ability of trees to ward off insect and/or disease attacks (Dunning, 1928; Keen, 1936). Understanding pre-harvest forests, in terms of tree vigor and the spatial patterns of trees, where spatial patterns are defined as clusters of stands at various stand densities (Getzin et al., 2006), can be used by foresters to identify and prioritize contemporary stands in need of restoration (Patton et al., 2021). However, spatial patterns of trees and tree vigor in pre-harvest forests are difficult to ascertain due to a paucity of spatially explicit information for pre-harvest forests across large landscapes (Lydersen et al., 2013).

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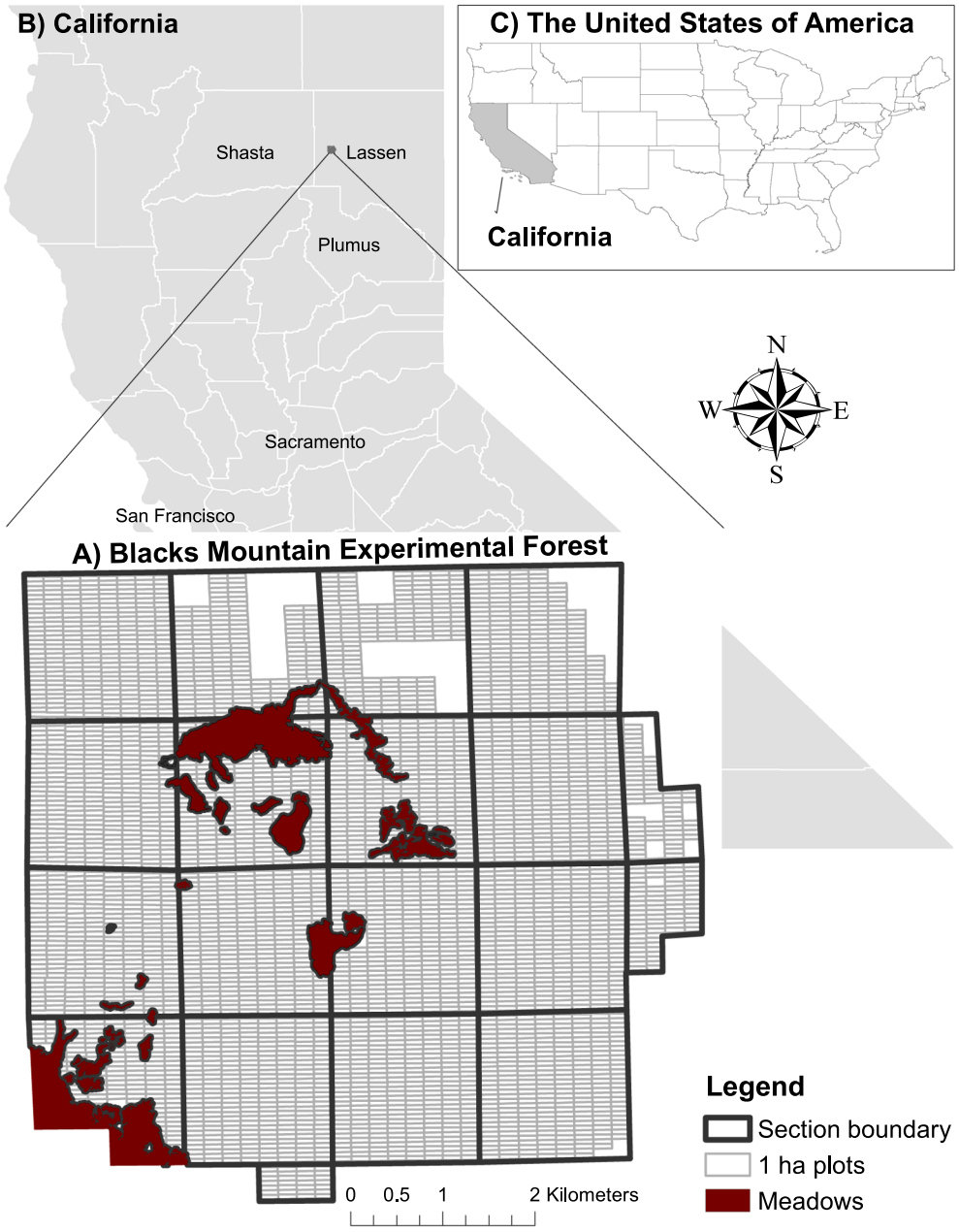

Fig. 1. The figure shows A) the sections and 1 ha plots of Blacks Mountain Experimental Forest in B) northern California in C) the United States of America.

The pre-harvest ponderosa pine-dominated forests in northern California, United States of America (USA), consisted of open, park-like overstory stand structures with low stand density (50–130 trees ha^{-1}) (Cooper, 1961; Fitzgerald, 2005). In these forests, elevation and moisture gradients in conjunction with fire and fire frequency influenced the spatial patterns of species and stand densities (Youngblood et al., 2004). Specifically, low to mid-elevation (<1700 m) and arid sites consisted of forests with low tree density (~36–88 trees ha^{-1}) dominated by ponderosa pine and Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.) (Collins et al., 2021; Hagmann et al., 2013). Low stand densities at lower elevation were maintained by high frequency fires with return intervals of 12–15 years (Norman and Taylor, 2005; Taylor, 2000). In contrast, white fir (*Abies concolor* (Grod. and Glend.) and incense-cedar (*Calocedrus decurrens* (Torr.) Florin) increase at higher elevation (1900–2200 m), mesic sites that experienced more infrequent fires at mean fire return interval > 20 years (Show and Kotok, 1924), achieving abundance and tree densities > 200 trees ha^{-1}. In addition to elevation and moisture, the spatial patterns of stand density is also influenced by environmental processes such as regeneration, mortality, and competition (Stephens, 2000; Youngblood et al., 2004). Therefore, the spatial patterns of density provide important insights on patterns of tree establishment (Boyden et al., 2005), resource utilization, and growth at a given location (Olsen et al., 1995).

Stand densities in ponderosa pine-dominated forests are often related to the availability of growing resources, which influence tree vigor (Patton et al., 2021). An open forest with low tree density has trees with high vigor, increasing its resistance to insect, disease, fire, and drought (Merschel et al., 2021). For example, in pre-harvest ponderosa pine-dominated forests, low tree density resulted in low competition for resources, which resulted in clusters of high vigor (Dunning, 1928; Keen, 1936) and medium-size trees (>27.9–58.4 cm of diameter at breast height, DBH) with few large (i.e., >58.4 cm DBH) fire-resistant, old trees (Churchill et al., 2018; Stephens et al., 2015). Young trees with high vigor (Dunning, 1928; Keen, 1936) can produce more resins than old

Table 1
Overstory and auxiliary variables.

Variables	Source
Overstory variables	
SDIPP#: Stand density index (SDI) by seven Dunning vigor classes (# = 1, …, 7) for ponderosa and Jeffery pine (PP)	1934 Census Survey
SDICF#: SDI by seven Dunning vigor classes (# = 1, …, 7) for incense-cedar and white fir (CF)	1934 Census Survey
Auxillary variables	
Soil variables	
Available water capacity at 50 cm depth (AWC50, cm)	Ecological Unit Inventory (EUI) Map 1991
Available water capacity at 150 cm depth (AWC150, cm)	EUI Map 1991
Sub-soil depth (SBD, cm)	EUI Map 1991
Surface-soil depth (SFD, cm)	EUI Map 1991
Surface stoniness (ST, %)	EUI Map 1991
Topography variables	
Aspect (degree)	Digital Elevation Model (DEM at 1 m resolution)
Slope proportion (SL)	DEM at 1 m resolution
Elevation (ELV, m)	DEM at 1 m resolution
Topographic wetness index (TWI)	DEM at 1 m resolution

trees, providing a defense mechanism against insect attacks (Perrakis et al., 2011). Young trees also potentially recover faster after insect or disease attack (Dunning, 1928; Kolb et al., 2007). In contrast, in ponderosa pine forests with high tree density, competition for resources can produce stands with low vigor, consisting of old and mature slowly-growing trees that are weak competitors for resources and easily killed by insects, disease, and drought (Dunning, 1928; Patton et al., 2021). However, older trees are more fire-resistant than younger trees (Dunning, 1928), provide wildlife habitat (Reynolds et al., 2013), and are living records of past natural disturbances such as fire and drought (Bailey and Idle, 2001).

The information that currently exists about overstory stand density in pre-harvest forests of California often comes from dendrochronological data (Everett, 2008; Taylor and Skinner, 2003) from only a few sites and trees (Stephens et al., 2003). Dendrochronological data often fail to capture the spatial patterns at landscape scales (Finley and Zhang, 2019; Stephens et al., 2003). Several studies capture landscape scale spatial patterns (e.g., Scholl and Taylor, 2010; Beaty and Taylor, 2008) using dendrochronological reconstructions. As reconstructions are derived from contemporary trees, dendrochronological approaches may not capture information from trees that existed during long ago pre-harvest periods (Zhang et al., 2019). Hence, a complete picture of the pre-harvest stand density, species composition, and vigor cannot be depicted using dendrochronological data (Trotsiuk et al., 2018). A reliance on dendrochronology for studying forests of northern California is largely the result of a scarcity of pre-harvest information regarding overstory stand structures at the landscape-scale (Stephens, 2000; Stephens et al., 2015). When such data exist, the exact location of study sites, poorly explained inventory methods, and limited spatial extent are major impediments to depicting landscape-scale spatial patterns of overstory stand structure (Stephens et al., 2015). Thus, there is a knowledge gap that requires field-based measurements of species-level tree vigor information of pre-harvest forest conditions to help managers understand how spatial patterns of overstory stand structures maintain ecosystem processes and function (Churchill et al., 2018).

To fill this knowledge gap, we analyzed a landscape scale (~4,000 ha) census of live trees for the Blacks Mountain Experimental Forest (BMEF) in northern California, USA, containing information about tree vigor for four species: ponderosa and Jeffrey pine, incense-cedar, and white fir (Hasel, 1935). Our goal was to characterize spatial patterns of tree vigor in the pre-harvest ponderosa pine-dominated forests and understand the drivers of such patterns. More specifically, we aimed to: 1) describe the spatial patterns of stand densities by seven vigor classes and two conifer species groups—ponderosa pine with Jeffrey pine and incense-cedar with white fir; and 2) identify the soil and topography variables associated with these pre-harvest forest patterns. We expected to see heterogeneous spatial patterns in reference conditions that were associated with environmental soil and topography variables. Managers can use our results as baseline guide to identify, compare, and contrast stand densities in stands of different vigor classes and identify contemporary stands at-risk of insect, disease, and fire that may benefit from restoration treatments. Such baseline information will help managers design management prescriptions that achieve contemporary forest stand structures that more closely resemble the more open, pre-harvest forests that were more resilient to fire, insect, and disease.

2. Materials and methods

2.1. Location

We conducted this study in BMEF located in northeastern California, USA. BMEF (40°40′ N, 121°10′ W), is managed by the United States Department of Agriculture Forest Service, Pacific Southwest Research Station. BMEF was established in 1934 (Fig. 1A) and covers an area of 4,000 ha within an elevation range between 1700 and 2100 m (Ritchie, 2016). BMEF is dominated by ponderosa pine in lower elevations. Higher elevations include white fir and incense-cedar along with ponderosa pine (Wing et al., 2012). In lower elevations, Jeffrey pine (*Pinus jeffreyi* (Grev. and Balf)) is found within some stands (Oliver, 2000). Western juniper (*Juniperus occidentalis* Hook.) is sparsely distributed as individuals or in small groves in lower elevations of the forest (Oliver, 2000). Frequent fire—5 to 17 years mean fire return interval—once occurred in BMEF and has been effectively excluded from the experimental forest since the late 1800s (unpublished data from Carl Skinner). The disruption of the fire regime was due to widespread sheep grazing followed by aggressive wildfire suppression by the Forest Service in the early 1900s (Ritchie, 2016). In the early 1900s, BMEF had not yet been impacted by timber harvesting due to lack of access. Harvesting and other human management activities in BMEF started in the late 1930s (Ritchie, 2016) after a transportation system had been established. Hence, 1934 data used in this study come from BMEF prior to any timber harvest and active management.

2.2. Data

2.2.1. Overstory data from 1934 census survey

BMEF (Fig. 1A) was divided into sections to conduct a census survey during the fall of 1934 (Hasel, 1935). Within sections, data on overstory trees were collected on a total of 4074 rectangular plots of approximately 1 ha in size (Fig. 1A). All live overstory trees ≥ 9.1 cm (3.6 in) were tallied by species and diameter class (Hasel, 1935). Diameter classes were 5.08 cm (2 in) wide and labeled by even inches (i.e., 4, 6, 8, 10, etc.); the smallest diameter (4 in) class is only 4.1 cm (1.4 in) wide. Tree species were recorded as pine (Jeffrey or ponderosa pine), white fir, and incense-cedar (Hasel, 1935). For this study, we divided trees into two species groups: ponderosa and Jeffrey pine (PP), and incense-cedar and white fir (CF).

In addition, one of the seven Dunning's vigor classes—represented by numbers 1 through 7—was assigned to the individual trees (Dunning, 1928; see Appendix A: Table A.1 for the details). Vigor classes 1, 2, and 6 represent young trees (50–150 years in age), resistant to insects and diseases within dominant and co-dominant crown positions (Dunning, 1928). Vigor class 3 represents mature trees (150–300 years), resistant to insects and disease within a co-dominant crown position (Dunning, 1928). Vigor classes 4, 5, and 7 represent mature trees (150–300 years), with greater susceptibility to insects and disease within the intermediate and the suppressed crown positions (Dunning, 1928). The age in Dunning's classification was determined using visual cues based on tree size, bark thickness and color, crown shape, crown position, and site

productivity (Dunning 1928; pages 758–760). Similarly, vigor was determined using factors such as crown shape, density, color of foliage, degree of dominance, and apparent size-age relationship (Dunning 1928; pages 758–760).

Using the 1934 overstory data, we calculated the stand density index (SDI) by seven vigor classes for the two species groups, which resulted in 14 overstory variables for each 1 ha plot (Table 1). For the SDI calculations, we used the summation method proposed by Long and Daniel (1990) for uneven-aged and mixed-species forests.

$$SDI_{ij} = \sum TPH_{ij}\left(\frac{DBH_{ij}}{25}\right)^{1.6}$$

where SDI_{ij} represents the stand density index of trees in the i^{th} vigor class and j^{th} species group. TPH_{ij} and DBH_{ij} represent, respectively, the trees per hectare and the midpoint of the diameter class for the trees in the i^{th} vigor class and j^{th} species group. The exponent of 1.6 was used in this study, because it is a commonly used exponent for ponderosa pine-dominated mixed-species forests in northern California, USA (Youngblood et al. 2004). Due to the diameter classes, SDI is bound to 9.1 cm (3.6 in.) at the lower end (Curtis, 2010).

Some of the plots within BMEF fell along mountain ridges or bordered meadows, which resulted in the plot area being <1 ha in size. In our exploratory analysis, we found that plots <0.3 ha in size often had inflated tree density and basal area per hectare values due to the small plot size. Therefore, 244 plots <0.3 ha in size were dropped, which resulted in a new total of 3830 plots used in our analysis. The plot locations within BMEF were defined by the coordinates of the center of the plot and were obtained from a plot map provided by the Pacific Southwest Research Station, Redding, California, USA.

2.2.2. Auxiliary soil and topography variables

Auxiliary variables consisted of two groups—soil and topography (Table 1).

Soil variables—A shape-file of an ecological unit inventory (EUI) map for BMEF (Alexander, 1994) had soil information stored as categorical variables (Table 1) for each EUI polygon. The plot map was overlaid with the EUI map and the intersect function in ArcMap 10.4.1 was used to extract the EUI polygons related to the plots (Reed et al., 2016). If a plot straddled multiple polygons from the EUI map, the midpoint of the soil variables from the EUI polygon that covered the maximum area within the plot was assigned to the plot. We did not use a weighted average, because not every plot straddled multiple EUI polygons. Therefore, we did not have multiple soil variable values to work with, and hence the maximum area approach was the best choice.

Topography variables—We extracted average elevation, slope, and aspect (Table 1) for each plot from a digital elevation model (DEM) at 1 m resolution provided by the Pacific Southwest Research Station, Redding, USA, using the zonal statistics function in ArcMap 10.4.4. (Wilson, 2012). Slope was converted to slope proportion. The topographic wetness index (TWI) was calculated based on slope, using the equations provided by Beven and Kirkby (1979). TWI indicates the effect of local topography on runoff flow direction and accumulation, which overall gives the moisture index of a given area (Beven and Kirkby, 1979). TWI is calculated by evaluating the flow direction, flow accumulation, and slope of an area using a DEM as follows:

$$I = ln\frac{\alpha}{tan\beta}$$

where I is the index value, ln is the natural logarithm, α is the local upslope contributing area, and tan β is the local slope calculated using a 1 m DEM.

2.3. Analysis

2.3.1. Principle component analysis to reduce data dimension

Principal component analysis (PCA; Hotelling, 1933) was used to reduce the dimension of our 14 overstory variables—SDI by two species groups—that were calculated for each of the 3830 plots. PCA reduced the 14 overstory variables into non-correlated principal components (PCs) using the "vegan" package (Oksanen et al., 2022) in R version 3.2.6 (R Core Team, 2020). PCs were retained if the observed eigenvalues (Kaiser, 1960) from the PCA exceeded the eigenvalues generated by the broken-stick distribution (Jackson, 1993; MacArthur, 1957). The broken-stick distribution assumes that the total variance in data—sum of eigen values—can be broken into pieces, where the length of each piece represents the variance explained by each principal component (Jackson, 1993). Therefore, if an observed eigenvalue from a PC exceeds the eigenvalue from the broken-stick distribution then all the PCs smaller than the observed eigenvalues are retained (Jackson, 1993).

2.3.2. Cluster analysis

The retained PCs for the 3830 plots were used to perform k-means clustering (Jain and Dubes, 1988) using the function "kmeans" in R version 3.2.6 (R Core Team, 2020). We set the cluster size from k = 2 to 10. We followed methods described in Plant (2012) and Roel and Plant (2004) to select a cluster size k, which we determined to be k = 4 (see details in Appendix B). Based on cluster size k = 4, we interpreted clusters based on their SDI values as described below.

Interpretation of clusters based on SDI values—In this study, for the selected cluster size k, SDI values of clusters were compared and interpreted in relation to the maximum SDI (hereafter referred to as "$SDI^{"}_{max}$) of 1000 trees ha^{-1} for the Californian dry forests (Oliver, 1995). Our study area also consisted of white fir and incense-cedar as minor species components, however, BMEF was ponderosa pine-dominated, hence we used 1000 as the max SDI. We converted the SDI of each cluster into relative density (RD) for easier interpretation. RD is calculated by dividing the given SDI by SDI_{max} (Woodall et al., 2005). A cluster with a mean RD $\leq$ 0.25 was interpreted as open forest, and a cluster with a mean RD between $>$ 0.25 and $<$ 0.35 was interpreted as a dense forest which is at the stage of tree competition initiation (Long, 1985; Long and Shaw, 2005). A cluster with RD $\geq$ 0.35 was an indication of a lower limit of full site occupancy and a dense forest with trees competing for resources (Long, 1985).

2.3.3. Association between clusters and auxiliary variables

We used classification and regression tree analysis (CART, Breiman et al., 1984) and multinomial logistic regression (Hosmer and Lemeshow, 2000) to associate clusters with auxiliary variables using the "rpart" and "nnet" packages, respectively, in R version 3.2.6. (R Core Team, 2020).

Classification and regression tree—CART analysis results in a decision tree with root nodes and leaf nodes that respectively represent the input auxiliary variables (Table 1) and cluster (Breiman et al., 1984; Roel and Plant, 2004). We used a complexity parameter of 0.01 to prune the tree and find the optimal tree size (Breiman et al., 1984) using the inbuilt 'cp' function in the 'rpart' package of R version 3.2.6. (R Core Team, 2020).

Multinomial logistic regression—Prior to the model-building exercise, aspect and slope were incorporated into the model using the transformations presented by Stage (1976). The transformations allowed for the cosine shift on the optimum aspect and amplitude of the slope using the coefficients from the linear model that would allow for the interaction effect of aspect and slope (Stage, 1976). The model building process used in this study held ~ 30 % of the data for validation and ~ 70 % for training (Shoot et al., 2021). In our first step, using the training data, we fit multivariable multinomial logistic regression models separately for the soil and topography variable groups using a forward stepwise selection with cluster as the response (Hosmer and Lemeshow, 2000). From the two auxiliary variable groups, variables that gave

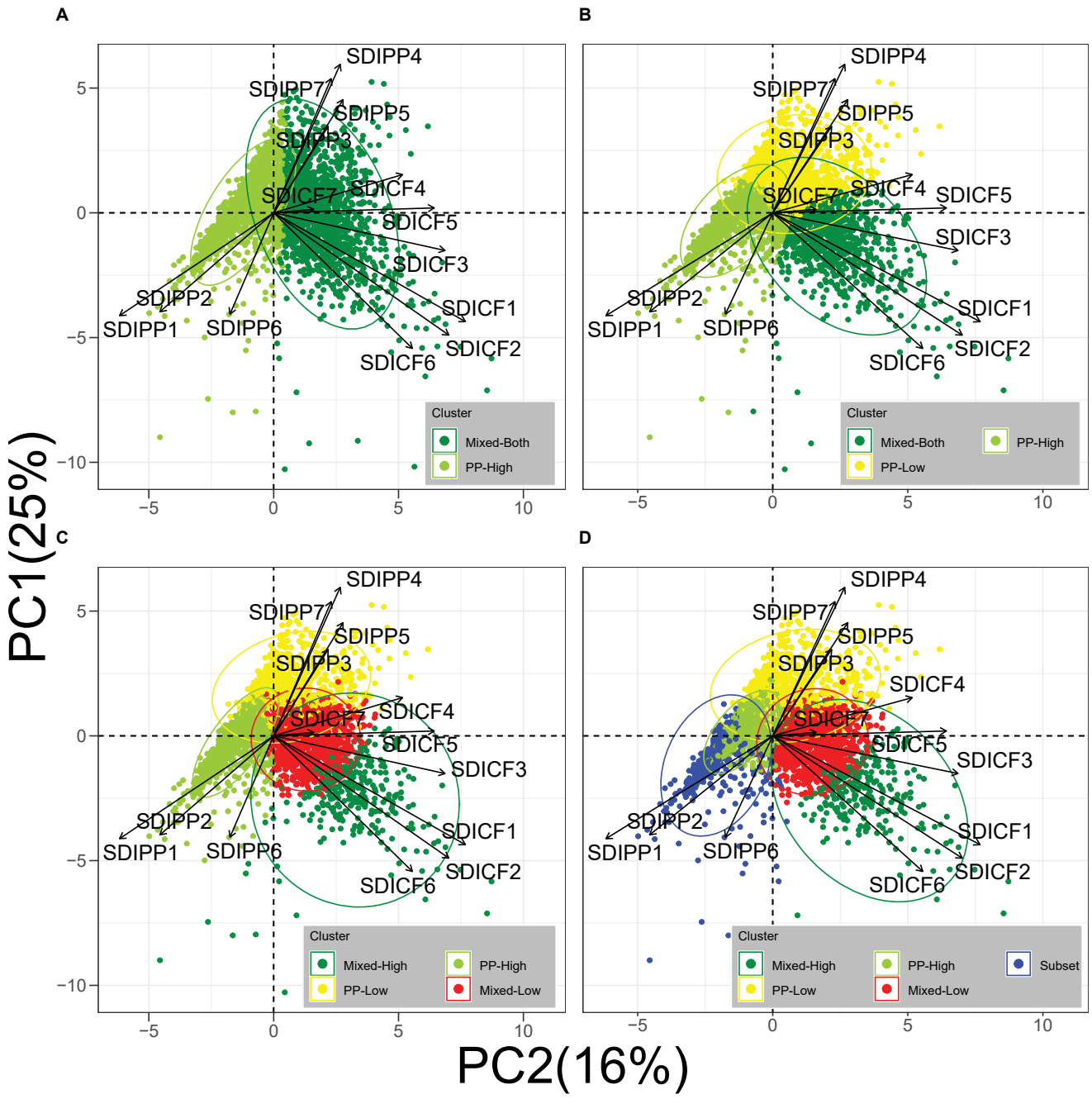

Fig. 2. Results from PCA biplot and cluster analysis for cluster sizes A) k = 2, B) k = 3, C) k = 4, and D) k = 5. SDI: stand density index, PP = ponderosa pine, and Jeffrey pine group, CF = incense-cedar and white fir group, number corresponds to seven Dunning vigor classes, where 1, 2, 3, and 4 are high and 4, 5, and 7 are low vigor classes.

evidence of importance (p-value < 0.05), gave the lowest Akaike Information Criterion (AIC, Akaike, 1973), and a high percentage of correctly classified plots were retained (Hosmer and Lemeshow, 2000). We also calculated the kappa coefficient (Cohen, 1960) using the validation data to assess the degree of agreement between the predicted and the actual cluster for each model (kappa: -1 to 1; 1 perfect agreement, < 0 indicates no better agreement than expected by chance). Kappa was calculated using the following formula provided by (Kuhn, 2008):

$$kappa = \frac{Observed\ cluster\ category - Expected\ cluster\ category}{1 - Expected\ cluster\ category}$$

In our second step, we combined the variables that were retained from the soil and topography groups in a single multivariable model (Hosmer and Lemeshow, 2000). Variables that were not statistically significant previously were considered for entry back into the combined multivariable models to check for further improvement of the models (Hosmer and Lemeshow, 2000; Ferster et al., 2016). Interactions between auxiliary variables were evaluated for the combined multivariable model (Hosmer and Lemeshow, 2000). The model with the lowest AIC value (Akaike, 1973), a high percentage of correctly classified plots, and a high value for the kappa coefficient was selected as our final model.

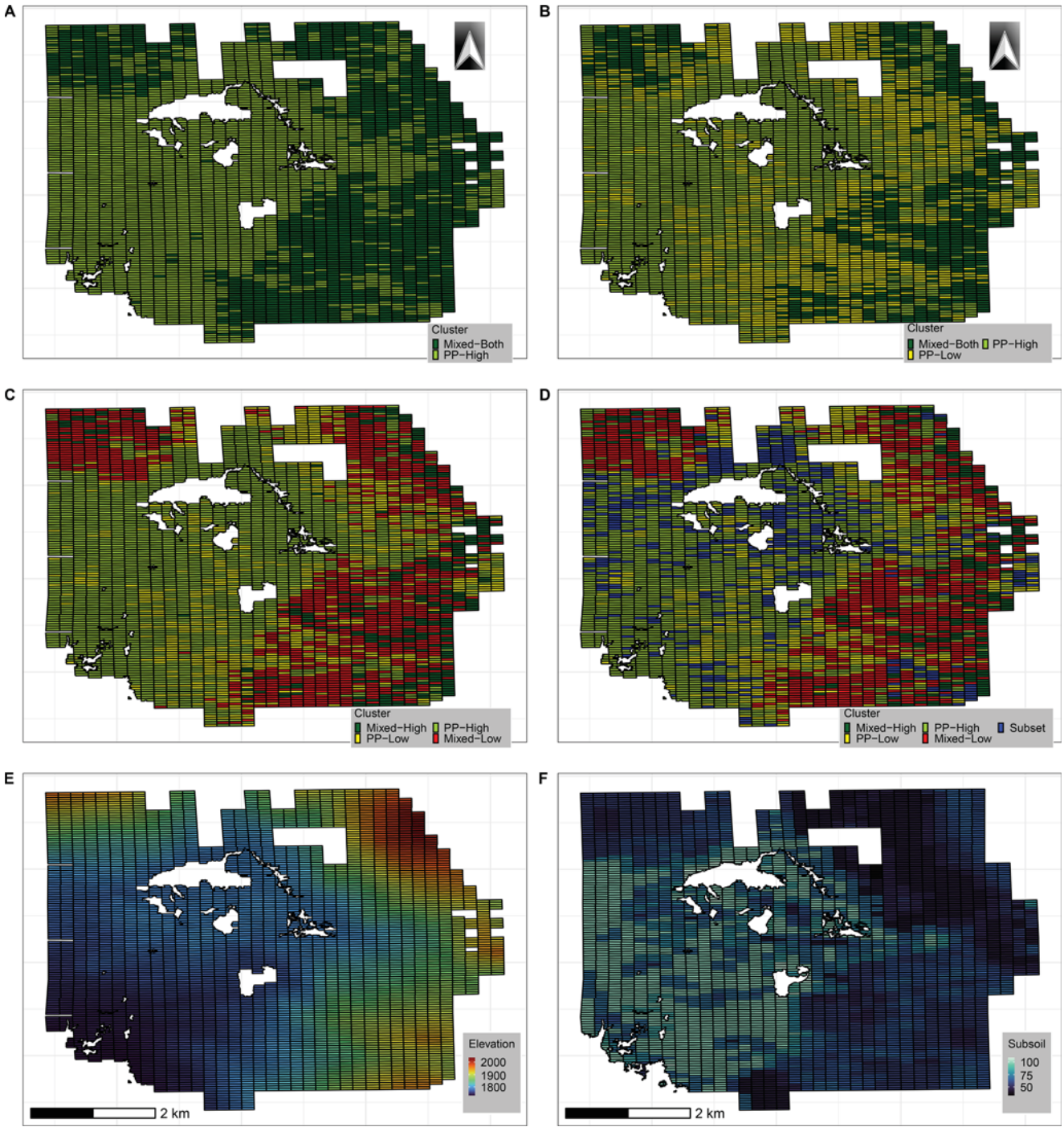

Fig. 3. Cluster analysis results for cluster sizes A) k = 2, B) k = 3, C) k = 4, and D) k = 5 with E) elevation (m) gradient and F) sub-soil depth (cm) gradient for BMEF. Cluster size k = 4 was chosen a s it was internally consistent, spatially structured and lack hierarchical arrangement.

3. Results

3.1. Principal components 1 and 2 explained the variance in the data

PC1 and PC2, which were retained, explained 41 % of the variance in our data (Fig. 2) and had higher eigenvalues compared to eigenvalues from the broken-stick distribution (Appendix B: Table B.1). PC1 captured most information on the SDI and vigor for the PP group. PC1 was strongly correlated with the SDI values of the PP group in high vigor classes 3 and 6 along with low vigor classes 4, 5, and 7 (Fig. 2). PC2 captured most of the information on the SDI and vigor for the CF group (Fig. 2). PC2 was strongly correlated with the SDI values of the CF group in high vigor classes 1 and 3 along with low vigor classes 4, 5, and 7 (Fig. 2).

3.2. Cluster analysis

3.2.1. Cluster size k = 4 was internally consistent, spatially structured, and lacking hierarchical arrangement

The gamma statistic (γ) was highest for cluster size k = 5 followed by cluster sizes k = 2 and k = 4 which indicated that clusters partitioned in each of the 10 replications for any given cluster size k were identical and internally consistent (Appendix B: Table B.2). Cluster size k = 2 was most spatially aggregated with plots of similar SDI, vigor, and species

Table 2
Summary statistics for each cluster given as mean SDI with standard deviation in parentheses and RD by species and vigor group for clusters in cluster size k = 4.

Clusters (n)	Ponderosa pine and Jeffrey pine (PP)		Incense-cedar and white fir (CF)		Cluster's mean SDI	min SDI	max SDI	RD	RD < 0.25 (% of plots)	RD > 0.35 (% of plots)
	High vigor	Low vigor	High vigor	Low vigor						
Mixed-High (304)	93.9 (62.7)	112.8 (46.2)	102.2 (35.4)	45.6 (35.3)	354.5 (74.8)	172.4	634.5	0.36	6.2	51.0
PP-Low (723)	119.6 (50.4)	191.5 (64.3)	16.3 (15.8)	28.3 (26.1)	356.0 (71.0)	100.8	667.5	0.36	4.2	49.7
PP-High (1821)	119.2 (57.2)	99.3 (55.4)	2.7 (7.7)	2.3 (7.6)	223.6 (84.5)	164.7	723.4	0.22	61.0	6.1
Mixed-Low (982)	83.9 (41.7)	225.9 (53.8)	43.8 (19.8)	47.0 (33.6)	316.8 (72.2)	61.8	643.6	0.32	16.8	32.1
Total: 3830										

SDI = stand density index; PP = ponderosa pine group; CF = incense-cedar and white fir group; RD: Relative density of a given cluster, min: minimum SDI value within the given cluster, max: maximum SDI value within the given cluster; n: number of plots.

group next to each other followed by cluster sizes k = 3 and k = 4 as indicated by Moran's I values (Appendix B: Table B.2). Cluster size k = 2 had higher γ and Moran's I values than cluster size k = 4, however, two clusters could only capture the information on SDI by the two species groups (Fig. 2A). In contrast, four clusters in cluster size k = 4 captured the information on SDI by vigor across the two species group (Fig. 2A vs C). As the cluster size increased to k ≥ 5, both γ and Moran's I decreased (Appendix B: Table B.2). In addition, the new cluster in cluster size k ≥ 5 was hierarchically arranged, being a subset of cluster 3 from cluster size k = 4. Therefore, we selected cluster size k = 4 for further CART and multinomial logistic regression analyses.

3.2.2. *Spatially aggregated clusters of different stand density index and tree vigor*

Within cluster size k = 4, there were 4 distinctive clusters: ponderosa pine-high vigor (PP-High), ponderosa pine-low vigor (PP-Low), mixed species-high vigor (Mixed-High), and mixed species-low vigor (Mixed-Low) (Figs. 2C and 3C). The PP-High cluster contained most of the plots (47.5 %), followed by Mixed-Low (25.6 %) (Fig. 3C, Table 2).

PP-High—The PP-High cluster had low RD (≤ 0.25) and mostly consisted of the PP species group in the high vigor classes 1, 2 and 6 with a substantial amount of vigor class 3 trees (Table 2, Appendix C: Table C.1). Within the PP-High cluster, 61 % of plots had RD ≤0.25, while 6 % of plots had RD ≥ 0.35 (Table 2). The PP-High cluster dominated the central and southwestern sections of BMEF that were in low elevation with greater sub-soil depth (Fig. 3C, E, and F). The presence of incense-cedar and white fir was low (Table 2, Appendix C: Table C.1). This cluster represented an open, high vigor forest at low elevation (Table 2).

PP-Low—Within the PP-High cluster, mostly in the southern-central section of BMEF, were small, spatially aggregated patches of the PP-Low cluster (Fig. 3C, E, and F). The average RD of the PP-Low cluster was high compared to the PP-High cluster and mostly consisted of the PP species group in the low vigor classes 4, 5, and 7 (Table 2, Appendix C: Table C.1). Within, the PP-Low cluster, 49.7 % of plots had RD ≥ 0.35, while only 4.2 % of plots had RD ≤ 0.25 (Table 2). The presence of incense-cedar and white fir was low (Table 2, Appendix C: Table C.1). Since the majority of forest was > 0.25 RD, this cluster represented a dense, low vigor forest at low elevation compared to the PP-High cluster (Table 2).

Mixed-High—The average RD of the Mixed-High cluster was comparable with the PP-Low cluster (Table 2). However, the Mixed-High cluster consisted of trees from the two species groups while the PP-Low had mostly ponderosa pine species group (Table 2). Within the Mixed-High cluster ~ 6 % of plots had RD ≤ 0.25, while ~ 61 % of plots had RD ≥0.35. The Mixed-High cluster dominated the northeastern, northwestern, and southeastern sections of BMEF that were high elevation areas with shallow sub-soil depth (Fig. 3C, E, and F). High vigor trees in Dunning classes 1, 2, 3, and 6 in the CF group were mostly present in the Mixed-High cluster (Table 2, Appendix C: Table C.1).

Mixed-Low—Within the Mixed-High cluster, throughout the northeastern, northwestern, and southeastern sections of BMEF, were small, spatially aggregated patches of the Mixed-Low cluster (Fig. 3C, E, and F), which mostly included trees in the CF group, that were low vigor trees in Dunning classes 4, 5, and 7 (Table 2). Within the Mixed-Low clusters, ~17 % of plots had RD ≤ 0.25, while ~ 32 % of plots had RD ≥0.35 (Table 2). The trees in the PP group in both Mixed-High and Mixed-Low clusters were mostly low vigor trees in Dunning class 5 (Appendix C: Table C.1).

3.3. *Elevation, surface-soil depth, and sub-soil depth were associated with clusters*

Based on both CART analysis and multinomial logistic regression, we found that elevation, surface-soil depth, and sub-soil depth were the important variables that were related to clusters in cluster size k = 4 (Fig. 4, Table 3). The CART analysis also suggested that elevation, sub-soil depth, and surface-soil depth were related to clusters (Fig. 4). For example, the PP-High cluster aggregated at lower elevation (<1806 m) at high surface-soil depth (Fig. 4, node 1), while the Mixed-Low cluster aggregated at high elevation (>1806 m) at low sub-soil depth (Fig. 4, node 6). In addition to the CART results, our final multinomial model suggested that surface stoniness, available water capacity at 150 cm depth, and its interaction with sub-soil depth were also related to clusters (Table 3, Model 15). Our final model resulted in the highest classification accuracy, the highest kappa coefficient, and the lowest AIC value (Table 3, Model 15). Our final model showed an interaction of sub-soil depth and available water capacity (AWC) at 150 cm, which was consistent with results from the CART analysis. Both CART results and the interaction term in our final model suggested that at high elevations, areas where the sub-soil depth was high, the AWC at 150 m decreased resulting in low tree vigor clusters (Fig. 4, Table 3). Including the slope-aspect transformation and the topographic wetness index in our models did not increase model performance substantially (Table 3, Model 14 vs Models 17–18).

4. Discussion

Before timber harvest activity in 1934, within the Blacks Mountain Experimental Forest (BMEF) nearly half of the plots consisted of low density stands, with distinct stand density patterns by tree vigor and species groups. The high vigor ponderosa pine stands (PP-High) were aggregated at lower elevations of the central and southwestern sections of BMEF, and occurred in lower densities. In contrast, low vigor PP stands and incense-cedar and white fir groups (CF-Low) were aggregated at high elevations in the southeastern, northeastern, and northwestern sections of BMEF, and occurred at higher densities. The spatial patterns of stand densities based on tree vigor and species groupings showed strong associations with elevation, soil moisture content, and sub-soil depth throughout the BMEF.

4.1. *Low stand density was associated with tree vigor*

The low stand density (RD ≤ 0.25) for the PP-High cluster, found in the central and southwestern section of BMEF, supports previous assertions that pre-harvest ponderosa pine forests of California were open,

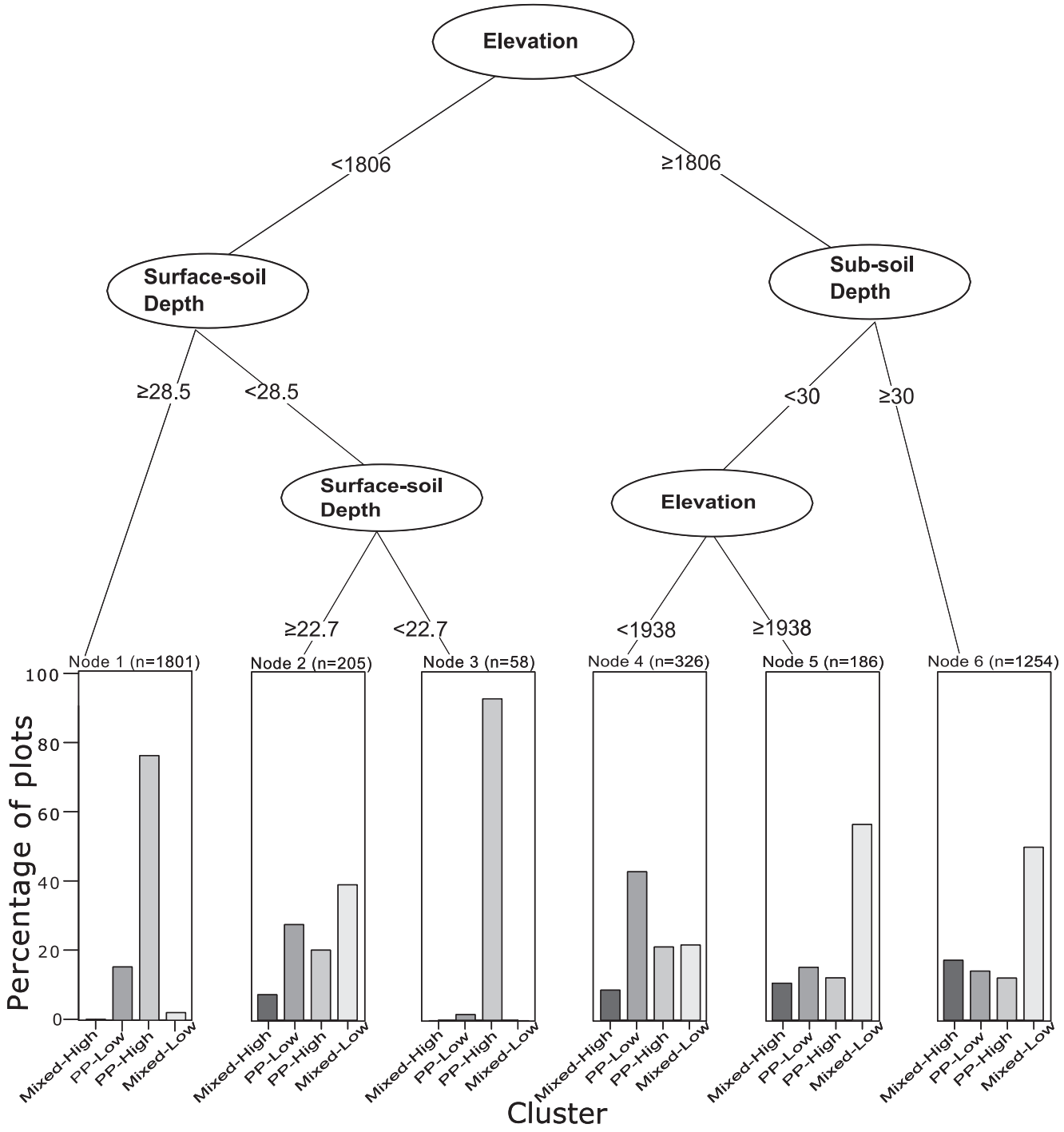

Fig. 4. Decision tree to find the auxiliary variables predicting each of the four clusters in cluster size k = 4. The root nodes represent the value of variables above or below which the split occurs. The number in parentheses represents the number of plots used in the classification for a given leaf node.

park-like structures (Collins et al., 2021; North et al., 2022). Low-density stands are maintained by the repeated occurrence of low intensity and high frequency fire (10–12 years fire return interval; Fitzgerald, 2005). Similar to Stephens et al. (2015), low density PP-High clusters within the southwestern section of BMEF could be the result of a frequent fire regime that existed before active fire suppression, which began in the early 1990s (Fitzgerald, 2005; Norman and Taylor, 2005).

The presence of trees in high vigor classes (classes 1, 2, 3, and 6) within the PP-High cluster in the southwestern section of BMEF supports the notion that at low stand density (RD $\leq$ 0.25), there is little tree competition within the forest (Oliver, 1995; Long, 1985), which likely enhances tree vigor (Cochran et al., 1994). The presence of high vigor trees in the PP-High cluster in the southwestern and central section of BMEF is an indication of potentially resilient overstory stand structures, as a lack of suitable tree hosts for pine beetles to spread may support resilience (Oester et al., 2018; Olsen et al., 1995). Under bark beetle attack, the open overstory stand structure (RD $\leq$ 0.25) likely limits dispersal of insects among trees making a forest resilient against insects (Churchill et al., 2018). In addition, the southwestern section also contains mature ponderosa pine trees (vigor class 3) with thick bark (Dunning, 1928; Keen, 1936). Thick bark, which peels off upon burning, helps prevent the spread of fire into the canopy, creating a fire-resilient

Table 3
Summary of Akaike Information criteria (AIC) value, kappa coefficient, percentage of correctly classified plots (% correct) for multivariable models across the auxiliary variables group.

Auxiliary variables	Model	AIC	% correct	Kappa
Multivariable models for soil				
ST + SBD	1	7962	57.3	0.31
AWC_{150} + SBD	2	7986	57.6	0.32
ST + SFD + SBD	3	7900	56.1	0.29
ST + SBD + SFD + AWC_{150}	4	7850	62.3	0.41
ST + SBD + AWC_{150}	5	7909	62.3	0.41
Multivariable models for topography				
ELV + TWI	6	7517	59.3	0.32
ELV+{SL + cos(aspect) + sin(aspect)}	7	7503	59.4	0.33
ELV + TWI+{SL + cos(aspect) + sin(aspect)}	8	7497	59.3	0.32
Combined models for soil and topography				
ELV+{SL + cos(aspect) + sin(aspect)} + ST + SBD + TWI + AWC_{150}	9	7148	61.9	0.38
ELV+{SL + cos(aspect) + sin(aspect)} + ST + SBD + TWI	10	7188	60.4	0.36
ELV+{SL + cos(aspect) + sin(aspect)} + ST + SBD + AWC_{150}	11	7150	62.1	0.39
ELV + ST + SBD + TWI + AWC_{150}	12	7152	61.6	0.38
ELV + ST + SBD + AWC_{150}	13	7176	62.0	0.38
Combined models with interaction				
ELV + ST + TWI + SBD + AWC_{150} +(SBD*AWC_{150})	14	6921	65.5	0.44
ELV + ST + SBD + AWC_{150} +(SBD*AWC_{150})	**15**	**6752**	**66.3**	**0.46**
ELV + ST + SBD + AWC_{150} +(SBD*AWC_{150})+(ELV*SBD)	16	6933	64.5	0.43
ELV+{SL + cos(aspect) + sin(aspect)} + ST + SBD + AWC_{150} +(SBD*AWC_{150})	17	6922	64.7	0.43
ELV+{SL + cos(aspect) + sin(aspect)} + ST + SBD + AWC_{150} +(SBD*AWC_{150})+(ELV*SBD)	18	6903	64.5	0.43

Highlighted bold is the multinomial logistic regression model selected in each model building step, ELV: elevation (m), ST = surface stoniness, SBD = sub-soil depth (cm), SFD = surface-soil depth (cm), AWC150 = available water capacity at 150 cm soil depth (cm), TWI = topographic wetness index, SL = proportion of slope, cos (aspect) = cosine of aspect, sin(aspect) = sine of aspect, {SL + cos(aspect) + sin(aspect)} = Stage (1976) transformation.

overstory (Fitzgerald, 2005). Thick bark also acts as an insulator, preventing heat transfer into the cambium and thus minimizing scorching injuries (Fitzgerald, 2005).

High stand densities (RD $\geq$ 0.35) were found for the PP-Low, Mixed-High, and Mixed-Low clusters. Even though the mean relative density on these clusters seems similar, there were differences in percentage of the plots that were at RD $\leq$ 25 and the plots that were at RD $\geq$ 0.35. In addition, there were also differences in the species that dominate each cluster. For example, there was a substantial presence of low vigor trees (classes 4, 5, and 7) in the CF groups in the Mixed-High cluster compared to PP-Low cluster, which included low vigor PP groups. Low vigor trees in the CF group in Mixed-High and Mixed-Low clusters indicate competition-induced stress associated with high stand density (Larsson et al., 1983; Olsen et al., 1995). On the other hand, the density of the ponderosa pine species in vigor class 5 was relatively high in all clusters except PP-High, which indicated the existence of old and mature ponderosa pine trees within 1934 BMEF (Dunning, 1928). Their presence possibly was an indication of the fire-resistant nature of old and mature ponderosa pine trees (Fitzgerald, 2005). However, the low vigor in those old and mature ponderosa pine trees indicated that they are weak competitors of resources and hence experience more competition stress compared to incense-cedar and white fir trees (Graham and Jain, 2005).

4.2. Spatial patterns of vigor in BMEF indicate a resilient forest ecosystem

Unlike other studies (e.g., Churchill et al., 2017; Hessburg et al., 1994), the overall spatial pattern of the four types of forested clusters identified in 1934 BMEF represents a landscape with unique and heterogenous spatial structures in terms of stand density, tree vigor, and species composition as suggested by Merschel et al. (2021). In addition, where other studies (e.g., North et al., 2022) relied on SDI alone to make inferences about forest resiliency, one of the most unique attributes of our data set is the tree vigor information assessed during the 1934 inventory. The vigor information collected during the inventory allowed us to link the relative SDI with tree vigor to capture the spatial patterns of heterogeneous and resilient landscapes in accurate details. This heterogeneous spatial pattern is indicative of forest stands that are resilient to insect and disease (e.g., Merschel et al., 2021). In general, heterogeneous spatial structures can reduce the spread of disease and insects when suitable tree hosts are only in patches dispersed throughout the landscape (Merschel et al., 2021). A patchy occurrence of suitable tree hosts lacks connectivity in both the roots and crowns, thus limiting the infestations to small localized tree groups or stands rather than the entire forest, hence, making the landscape resilient to insect and disease (Merschel et al., 2021).

4.3. Elevation and soil characteristics influenced tree vigor

The influence of elevation on vegetation types within ponderosa pine-dominated landscapes in northern California has long been recognized (Show and Kotok, 1924), and the association of greater pine dominance at low elevations has also been observed (Fites-Kaufman et al., 2007, Lydersen and North, 2012, Skinner and Taylor, 2018). Within BMEF, the elevation gradient influenced the species composition and stand density for the given spatial patterns of clusters. Similar to our results, within southern Sierra Nevada ponderosa pine forests (circa 1911), clumps of ponderosa pine forest occurred at elevations $\leq$ 1800 m, while mixed-species forest (of incense-cedar and white fir) were aggregated at elevations around $\geq$ 1850 m (Stephens et al., 2015). What is new however, is our understanding of tree vigor patterns, summarized next.

Ponderosa pine dominance at lower elevations in pre-harvest forests of California has been observed elsewhere (Show and Kotok, 1924; Stephens et al., 2015). However, we further discerned relationships between soil characteristics and spatial patterns of vigor in pre-harvest forests. The amount of water at depth of 150 cm, sub-soil depth, and surface stoniness can vary with soil types (Hatfield et al., 2017) and influence the spatial patterns of tree species and vigor (McCullough and Wagner, 1987). For example, mollisols have high available water capacity at 150 cm, greater sub-soil depth, and less surface stoniness (Hatfield et al., 2017). Therefore, the southwestern section of BMEF is made up of deep mollisols or andisols (Alexander, 1994), which has a high moisture content, that likely favored the growth of the PP group observed in the PP-High cluster. In addition, ponderosa pine under deep soil conditions also develops a well distributed tap root system (Zouhar, 2001) that is likely related to their drought resistance and make them less susceptible to insect and disease attack, hence high vigor (Merschel et al., 2021). On the contrary, species such as white fir and incense-

cedar, which were intermixed within the Mixed-High and Mixed-Low clusters, are likely of low vigor compared to ponderosa pine, because of their shallow rooting habitat, which makes them susceptible to root diseases that additionally cause moisture stress and increase insect susceptibility (Zou et al., 2008; Zouhar, 2001). However, shallow rooting habitat, which is needed for plants to establish under frigid and shallow mollisols conditions of higher elevation within the northeastern and southeastern sections of BMEF (Alexander, 1994), could be the reason for the dominance of the CF group in these areas in our study (Zouhar, 2001). Our findings are consistent with (North et al., 2002), who detected a cluster of incense-cedar and white fir within shallow outcrop areas in the southern Sierra Nevada, USA.

The difference in soil moisture indicated by available water capacity at 150 cm pertaining to various soil characteristics and competition for resources such as light likely influenced the tree vigor in various clusters within BMEF. For example, low tree vigor in the PP-Low, Mixed-High, and Mixed-Low clusters compared to the PP-High cluster could likely be the result of soil moisture stress (McCullough and Wagner, 1987). In low soil moisture conditions, more carbohydrates are allocated for the repair of roots than towards the crown development, which substantially depletes the carbohydrate reserve and reduces tree vigor (Grulke et al., 2020; McCullough and Wagner, 1987). In addition, under the high stand density (Mixed-High, Mixed-Low, and PP-Low) at high elevation, competition for resources such as light likely resulted in a decrease in chlorophyll content and other photosynthetic pigments, eventually reducing photosynthesis and tree vigor (Kocher and Harris, 2007; Schubert, 1974). Also, at high elevation, where the sub-soil depth increases, moisture becomes the limiting factor as moisture exists in deeper soil depth (Zouhar, 2001). As moisture becomes available at greater depth, the shallow rooting habit of the incense-cedar and white fir species prevents them from drawing moisture from greater sub-soil depth causing moisture stress and improper growth and development (Zou et al., 2008; Zouhar, 2001). Therefore, our results from the CART analysis and the interaction term in the multinomial logistic regression model suggested that the Mixed-Low cluster was apparent in high elevation areas with higher sub-soil depth and low available water capacity at 150 cm depth.

4.4. Management implications

Our analysis of the pre-harvest forest inventory is unique in terms of the details captured regarding overstory stand structures at a landscape scale and provides one of the first notable records of pre-harvest conditions of ponderosa pine-dominated forests in northern California (Oliver, 2000). At the time of original data collection in 1934, BMEF had not yet been harvested (Oliver, 2000) and fire suppression had been implemented only since the late 1800s (Unpublished data from Carl Skinner). Hence, the spatial patterns we identified for 1934, represent a relatively intact forest, undisturbed by Euro-American settlers. Such forest still exhibited the overstory stand structures, species composition, and patterns of vigor structure expected in an ecosystem subjected to frequent fire. Thus, our results provide a reasonable baseline and context to guided monitoring of forest change within BMEF and similar ponderosa pine forests in northern California.

The variation in the spatial patterns of overstory stand structures in our study conveys an important message to managers on landscape-scale heterogeneity that existed prior to any active human management. The entire BMEF landscape was heterogenous and non-uniform in terms of the spatial patterns of forest cluster types. Thus, our results on the pre-harvest spatial patterns of vigor by SDI can be used to improve management guidelines to develop spatially heterogeneous, resilient forests in the face of environmental change (Stephens et al., 2015). For example, within the ponderosa pine dominated forests, managers can aim at reducing the RD below 0.25 by retaining high vigor trees in clumps, like PP-High clusters in the southwestern section of our study area, which is more resilient compared to the rest of the BMEF. In addition, quantifying the spatial patterns of tree vigor by SDI, prior to any management treatments, could help identify dense low vigor stands at risk of insect, disease, and fire where management treatments can be prioritized.

Our study comes with several limitations. First, we cannot evaluate spatial patterns at a scale finer than 1 ha due to the design of the 1934 census. This could be important from a wildlife perspective (Larson and Churchill, 2012). Second, excluding trees < 9.1 cm (3.6 in) DBH leaves out the regeneration that was established around the early 1900s, which may have influenced tree vigor due to understory and overstory resources competition (Riegel et al., 1992). Our study does not incorporate any data on disturbances such as fire and climate, which could have affected the spatial patterns in 1934 BMEF. Hence, our results provide an incomplete picture of the pre-harvest spatial patterns of the overstory stand structures of frequent fire ecosystems (Lydersen et al., 2013). Even in the areas where the fire regimes were still intact, due to the patchy nature of fire (Show and Kotok, 1924), small trees might still be present within BMEF, which might substantially alter the spatial patterns of the overstory.

5. Conclusions

The management of current dry forest ecosystems depends on the comprehensive understanding of pre-harvest spatial patterns based on the three important components of overstory, which are stand density, tree species, and vigor.

Our study quantified the spatial patterns of stand density index (SDI) across vigor classes in two conifer species groups using landscape scale (~4000 ha) 1934 field data from BMEF. We found that high vigor forests with ponderosa pine as dominant species were spatially aggregated at low SDI, while low vigor forests were spatially aggregated with a mixture of incense-cedar, white fir, and ponderosa pine trees at high SDI. We also found that the spatial patterns of stand density index by vigor and species groups were associated with elevation, soil moisture, and soil depth.

Forest managers in California use pre-harvest forest conditions, which were resilient against insect, fire, and disease, as a guide to inform their management decisions. Our results will help forest managers to understand that resiliency against insects, disease, and fire in the pre-harvest mixed-species dry forest came from the spatial patterns of species vigor and was influenced by environmental factors. Forest managers can use our results as a baseline to make an informed decision regarding management prescriptions that will allow them to retain a tree species at various SDI and vigor combinations within different environmental gradients in a landscape.

The results from our study are unique as they include the information on tree vigor, which is an underrepresented component of forest stand structure in the current body of literature. In addition, studies on pre-harvest spatial patterns often come from reconstruction and dendrochronological studies, and the current body of literature lacks research on spatial patterns based on field data. Hence, this research pioneers the description of pre-harvest spatial patterns using actual field data in a large landscape of 4,000 ha.

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CRediT authorship contribution statement

Sushil Nepal: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Bianca N.I. Eskelson:** Conceptualization, Funding acquisition, Methodology, Resources, Supervision, Writing – review & editing. **Martin W. Ritchie:** Conceptualization, Data curation, Project administration,

Resources, Writing – review & editing. **Sarah E. Gergel:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Brief description of each Dunning's vigor classes (Dunning 1928).

Class	Age	Crown position	Crown size	Vigor	Crown height
1	Young or Thrifty (50–150)	Isolated or dominant	Average or wider	good	60 % or more of total height
2	Young or Thrifty (50–150)	Codominant	Average or narrower	Good or moderate	<60 % of total height
3	Mature (150–300)	Isolated or dominant	Average or wider	Moderate	65 % or more of total height
4	Mature (150–300)	Codominant	Average or narrower	poor	<65 % of total height
5	Over mature (>300)	Isolated or dominant	Any size	Poor	<65 % of total height
6	Young or Thrifty (50–150)	Intermediate or suppressed	Any size	Good	<65 % of total height
7	Mature or Over mature	Intermediate or suppressed	Any size	Poor	<65 % of total height

Appendix B

Process of cluster size determination

The cluster size k determines how many clusters are identified as part of the cluster analysis. For example, the analysis where cluster size is set to k = 4 resulted in four clusters of plots, where each plot belonged to one of the four clusters. We then evaluated the results for each cluster size k with regards to internal consistency, spatial structure, and hierarchical arrangement of the plots within each cluster following Plant (2012) and Roel and Plant (2004). The results from the cluster analysis for each cluster size k were translated into two-dimensional PCA-biplots of the first two principal components (Hancock and Zvelebil, 2004).

Gamma statistic to assess the internal consistency of the clusters—Internal consistency indicates the similarity of plots within a cluster for a given cluster size k in terms of their Euclidean distance and the values of their overstory variables (Plant, 2012; Roel and Plant, 2004). To calculate the gamma statistic, for each cluster size k, we replicated the cluster analysis with ten different initial seeds (Plant, 2012). For a given cluster size k, internal consistency is achieved when the plots are partitioned into the same cluster in each replication (Plant, 2012; Roel and Plant, 2004). Internal consistency was measured using the gamma statistic (γ) for each cluster size k = 2 to 10 (Plant, 2012; Roel and Plant, 2004). Values of γ closer to 1 indicate that a given cluster size k resulted in internally consistent clusters. Values closer to 0 indicate a lack of internal consistency (Plant, 2012; Roel and Plant, 2004).

Moran's I to assess spatial autocorrelation of the clusters—We calculated Moran's I (Moran, 1950) for each of the cluster sizes k = 2 to 10 to detect spatial autocorrelation as an indicator of spatial aggregation of plots belonging to a cluster. Moran's I ranges from −1 to 1. Values between 0 and 1 indicate positive spatial autocorrelation, meaning that plots similar in SDI by species group and vigor classes are aggregated together. A value of 0 indicates perfect spatial randomness of plots belonging to a cluster (Moran, 1950).

Visual assessment for indication of hierarchical arrangement—Moran's I and γ may be high for cluster size k + 1 compared to cluster size k, yet clusters in cluster size k + 1 may be hierarchically arranged (Plant, 2012; Roel and Plant, 2004). When the cluster size switched from k to k + 1, we looked at whether the additional cluster in cluster size k + 1 was a subset of the existing cluster in the cluster size k as an indication of hierarchical arrangement (Roel and Plant, 2004). We selected a cluster size for which the clusters were not hierarchically arranged.

Table B1
Summary of observed and broken-stick model eigenvalues along with variance explained by the first ten principal components.

Principal components (PC)	Eigenvalue		Variance percentage	Cumulative variance
	Observed	Broken Stick Model		
PC1	3.45	3.25	24.66	31.51
PC2	2.25	2.24	16.04	40.70
PC3	1.74	1.75	12.45	53.16
PC4	1.07	1.41	7.71	60.87
PC5	0.96	1.16	8.87	67.74
PC6	0.83	0.96	5.93	73.67
PC7	0.75	0.80	5.38	79.06
PC8	0.58	0.65	4.19	83.26
PC9	0.52	0.53	3.77	87.03
PC10	0.46	0.42	3.71	90.75

Table B2
Summary of gamma statistics (γ) and Moran's I for cluster sizes k = 2 to 10.

Cluster size k	Gamma statistic (γ)	Moran's I
2	0.99	0.59
3	0.59	0.51
4	**0.63**	**0.31**
5	1.00	0.10
6	0.54	0.14
7	0.47	0.12
8	0.41	0.25
9	0.51	0.10
10	0.29	0.09

Appendix C

Table C1
Mean stand density index (SDI) by seven vigor classes for two species group: ponderosa pine (PP) and cedar-fir (CF) with standard deviation in parentheses.

Ponderosa pine Clusters	**SDIPP1**	**SDIPP2**	**SDIPP3**	**SDIPP4**	**SDIPP5**	**SDIPP6**	**SDIPP7**	**Number (%)**
Mixed-High	35.53 (31.33)	17.13 (15.91)	32.67 (24.60)	10.70 (11.37)	100.70 (43.29)	8.61 (8.26)	1.42 (2.11)	304 (8)
PP-Low	30.94 (16.61)	13.66 (10.17)	71.17 (41.77)	38.02 (20.32)	147.29 (59.58)	3.91 (4.22)	6.28 (4.27)	723 (19)
PP-High	62.55 (31.85)	22.53 (15.88)	28.82 (26.06)	8.18 (10.06)	90.21 (50.81)	5.34 (6.12)	0.95 (1.74)	1821 (47)
Mixed-Low	29.58 (17.30)	12.04 (8.15)	39.14 (30.18)	11.61 (10.19)	128.87 (52.95)	3.16 (3.01)	1.53 (1.34)	982 (26)
Total	158.60	65.36	171.80	68.51	467.06	21.02	10.17	3830
Cedar-fir								
	SDICF1	**SDICF2**	**SDICF3**	**SDICF4**	**SDICF5**	**SDICF6**	**SDICF7**	**Number (%)**
Mixed-High	40.80 (18.82)	28.75 (14.56)	19.13 (13.87)	7.47 (6.8)	37.56 (26.88)	13.54 (11.26)	0.57 (0.37)	304 (8)
PP-Low	6.40 (7.19)	3.38 (4.94)	5.86 (9.26)	7.16 (12.73)	20.98 (18.56)	0.73 (0.68)	0.23 (0.45)	723 (19)
PP-High	1.36 (4.11)	0.66 (2.17)	0.51 (2.19)	0.20 (1.23)	2.13 (7.14)	0.24 (1.06)	0.00 (0.00)	1821 (47)
Mixed-Low	19.46 (11.43)	10.82 (8.49)	11.11 (9.27)	4.15 (5.98)	42.70 (33.03)	2.49 (2.45)	0.18 (0.14)	982 (26)
Total	68.02	43.61	36.62	18.98	103.37	17.00	0.98	3830

SDI: stand density index; PP = ponderosa pine; CF = incense-cedar and white fir, number in the subscript to the seven Dunning vigor classes, where 1, 2, 3, and 4 are high and 4, 5, and 7 are low vigor classes.

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