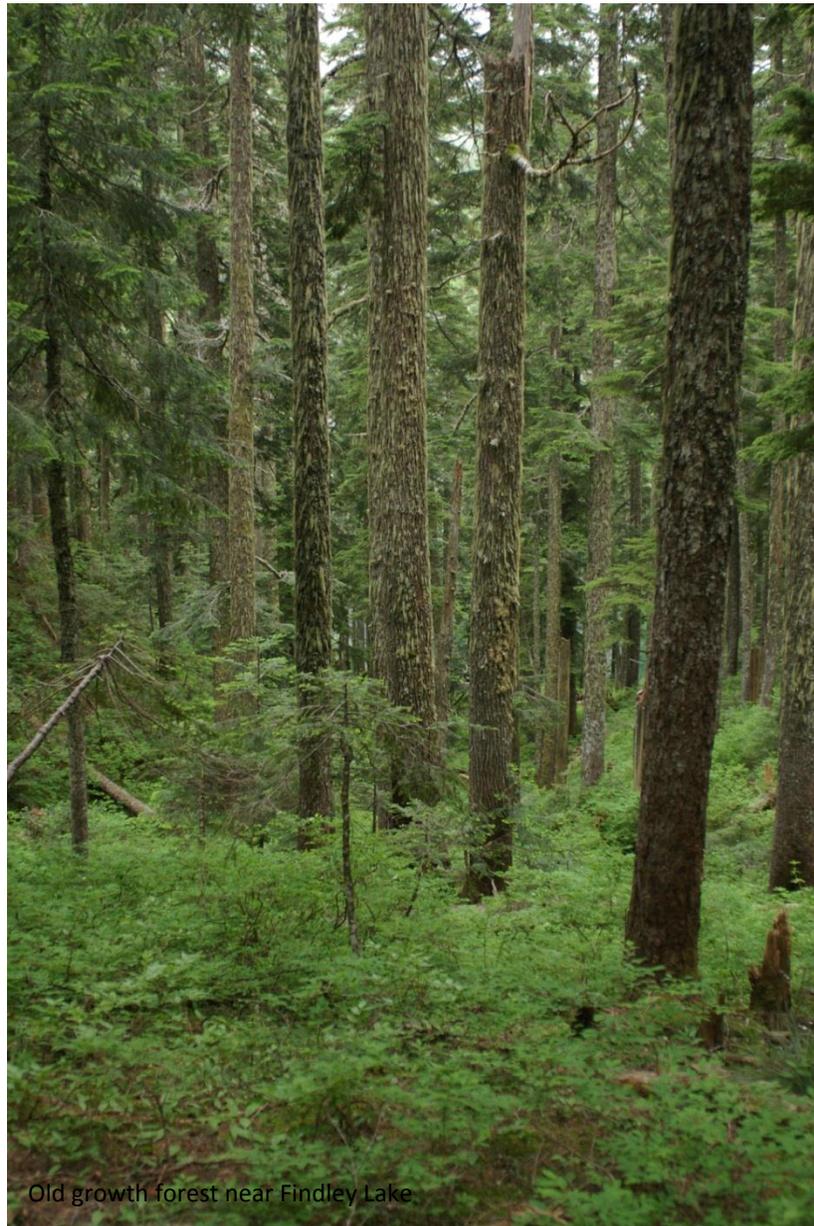


# A Structurally-Based Classification Of Old-Growth Forest in the Cedar River Municipal Watershed

---



Old growth forest near Findley Lake

David Chapin

Ecosystems Management Team  
Watershed Services Division

Seattle Public Utilities

March 2013

## **Executive Summary**

There are approximately 14,000 acres of old-growth forest in the Cedar River Municipal Watershed (CRMW), which is defined here as native, unharvested conifer forest greater than 190 years of age. This report discusses an ecological classification of old-growth forest in the CRMW that incorporates structural attributes for the purpose of determining habitat value for old-growth dependent species. Such a classification is a commitment of the Cedar River Watershed Habitat Conservation Plan (HCP) Watershed Landscape and Habitat Research and Monitoring Program.

The objectives of this work conducted in 2012 were to (1) compile and review previous efforts of classifying old-growth in the CRMW; (2) to extend these efforts by incorporating information and classification tools that have been recently developed; and (3) based on this information, to provide an old-growth classification that fulfills the HCP objective.

### **Previous Old-Growth Classification Efforts**

There were three previous efforts that indirectly or directly addressed classification of old growth in the CRMW. The first was conducted by Lucinda Tear (2006), a consulting statistician, who used a multivariate statistical approach to analyze data from all of the Permanent Sampling Plots (PSPs), including those in old-growth forest. The second was by Bill Richards (2007), an Ecosystems staff member of the SPU Watershed Services Division, who focused on assessing habitat suitability of old-growth areas for marbled murrelet and northern spotted-owl. A third effort was that of Van Kane, then a graduate student at the College of the Environment at the University of Washington, who developed metrics of forest structure from LiDAR data to classify forests across the watershed, including old-growth areas. Kane published three journal articles from this work (Kane et al. 2010a, 2010b, 2011).

### **2012 Old-Growth Classification Effort**

The 2012 classification effort took two approaches: The first was to use the PSP data to evaluate variation in two old-growth structural indices; the second was to map variation in old-growth structure by applying LiDAR-derived structural metrics developed by Kane across old-growth areas in the CRMW.

### **Analysis of PSP Data Using Indices of Old-Growth Habitat Structure**

Two indices of old growth were applied to classifying PSPs: one developed by Acker et al. (1998) to describe the development of old-growth structural characteristics in Douglas-fir dominated forests and the second developed by Washington Department of Natural Resources (WDNR 2005) as a basis for identifying old-growth areas in western Washington conifer forests. Both indices are based on reference values for structural characteristics of west-side Oregon and

Washington Douglas-fir dominated old-growth forests published in Spies and Franklin (1991). The Acker (1998) index of old growth is based on four structural variables: (1) standard deviation of tree DBH (diameter at breast height), (2) density of trees > 100 cm DBH, (3) mean tree DBH, and (4) density of all trees. The WDNR index uses five structural variables to derive a score ranging from 0 to 100 to determine the degree to which stands have old-growth characteristics: density of trees > 100 cm, density of large standing dead trees, volume of down woody debris, tree size diversity, and stand age.

The scores for the two indices were highly correlated and indicated that most CRMW old growth is generally less well-developed structurally than typical Douglas-fir old growth in the western Cascades, which is not surprising since most old-growth stands in the CRMW are in the silver fir zone at higher elevations than most Douglas-fir dominated forests. However, there were some PSPs in old growth that had structural characteristics comparable to the structurally most developed reference stands reported in Spies and Franklin (1991).

### **LiDAR Classification and Mapping of Old-Growth Habitat**

Characterization of old-growth forest using the PSP data and the two structural indices is useful for describing the variation in CRMW old growth, but it does not show how that variation is distributed across old-growth areas. To produce such a map, a raster data set of 30-m pixels of LiDAR<sup>1</sup> structural classes that Van Kane developed for the entire watershed was applied just to old-growth areas. The LiDAR structural classes were based on LiDAR-derived variables for canopy complexity, height, and density. The derivation of the classification by Kane was first replicated across the entire watershed and then replicated using just pixels from old-growth areas to validate its representation of structural variation in old growth alone. From the Kane classification, a set of simplified structural classes were identified that were specific to old-growth forest and used to develop a map that emphasized old-growth structural variation.

This map showed that there was no watershed-scale pattern of structural complexity in old growth. Rather, different levels of structural complexity occur in mosaics in most old-growth patches, indicating that CRMW old-growth habitat is variable even at small scales. Taking the watershed as a whole, 57% of old-growth habitat was in the high to highest complexity classes and 26% in the moderate complexity class. Among old-growth patches there was variation in the proportion of different complexity classes. The heterogeneity of old-growth structural complexity on a stand scale evident from LiDAR data suggests that Richards' approach in mapping suitability of marbled murrelet and northern spotted owl habitat using polygon classes based on topography, aspect, and soils does not capture the variability in habitat quality that stems from smaller scale variation in structure. The nine structural classes ranked based on complexity and on height were strongly correlated to both the ranked WDNR and Acker index

---

<sup>1</sup> LiDAR stands for "Light Detection and Radar" and is a remote sensing technology that measures distance from the sensor to the object (e.g., ground, forest canopy) by illuminating a target with a laser and analyzing the reflected light.

(Spearman's rank correlation coefficient = 0.556 and 0.569, respectively, with  $P < 0.001$ ). However, the LiDAR classification did not appear to resolve areas of old-growth forest known to have exceptionally high complexity from other areas of high complexity.

### **Relating Old Growth Indices and LiDAR Classification to Wildlife Habitat Value**

Relating the WDNR and Acker indices of old-growth structure to habitat suitability classes of PSPs identified by Richards showed no relationship to northern spotted owl habitat suitability but showed some correlation to marbled murrelet habitat suitability. With respect to the relationship between the three LiDAR structural variables and habitat suitability, there was no evident trend of canopy complexity versus suitability class for northern spotted owl, but there was evidence of such a trend for marbled murrelet. There was a significant relationship between canopy height and both northern spotted owl and marbled murrelet habitat suitability class. This very limited analysis suggests there may be some utility in using the distribution of Kane structural complexity classes as a way to differentiate habitat suitability for marbled murrelet, but not as much for northern spotted owl. Rather than applying the two old-growth indices and the maps of LiDAR derived metrics to identifying habitat suitability for individual species, a more appropriate use is likely to be in differentiating habitat value more generally for old-growth dependent species.

# Classification Of Old-Growth Forest in the Cedar River Municipal Watershed

---

## Table of Contents

Executive Summary .....	ii
Background and Objectives .....	1
Previous Efforts .....	1
Analysis of PSP Data .....	2
Mapping of Habitat Suitability for Marbled Murrelet and Spotted Owl .....	3
Characterization and Mapping of Forest Structure from LiDAR Data.....	4
2012 Efforts .....	5
Analysis of PSP Data Using Indices of Old-growth Habitat Structure .....	5
Acker Old-growth Index .....	6
WDNR Index .....	7
Application of LiDAR Characterization and Mapping.....	12
Kane’s Analysis of LiDAR Variables.....	12
Applying Kane’s Analysis to Old Growth Forest Only.....	13
A Map of Old-Growth Structural Characteristics.....	15
Relating Old Growth Indices and LiDAR Classification to Wildlife Habitat Value.....	22
Conclusions.....	27
Literature Cited .....	28
Appendix A – Attributes of Permanent Sampling Plots occurring in old-growth forest in the CRMW .....	30

## Background and Objectives

Completing an ecological classification of old-growth forest is a component of the Cedar River Watershed Habitat Conservation Plan (CRW HCP) Watershed Landscape and Habitat Research and Monitoring Program. As stated in the HCP, this classification is intended to incorporate structural attributes for the purpose of determining habitat value for old-growth dependent species:

*This new classification will not be based solely on chronological age, but will include structural attribute characteristics such as snag density, large woody debris density, and horizontal and vertical complexity. The purpose of more specifically classifying old-growth forest is to determine the relative habitat value of the remaining late-successional and old-growth forests in the watershed for both selected individual species and groups of species of concern, especially those threatened and endangered species dependent on old-growth ecosystems, such as marbled murrelets and spotted owls. (HCP, p. 4.5-33)*

There are approximately 14,000 acres of what is typically referred to as old-growth forest in the Cedar River Municipal Watershed (CRMW). For purposes of the HCP and for this analysis, old growth is defined as native, unharvested conifer forest greater than 190 years of age. Almost all old growth in the CRMW is in the higher elevation, more mountainous, upper watershed (i.e., upstream of Cedar Falls). Since remaining old growth in the watershed has yet to be harvested, it represents a biased sample of the pre-settlement conifer forest of the watershed. It is a biased sample due to its distribution at higher elevations and largely hillslope topographic position, excluding almost all of the most productive forests occupying lower elevations and valley bottoms (i.e., mostly lower watershed downstream of Cedar Falls, but also valley bottoms upstream of Cedar Falls). Thus, the old-growth forest now present in the watershed is likely a smaller-statured remnant of what was left unharvested toward the end of the 20<sup>th</sup> century. Nonetheless, these remaining old-growth stands provide some of the highest value habitat in the watershed for a variety of old-growth dependent flora and fauna species and provide important reference conditions for restoration actions.

Since the HCP was approved in April 2000, there have been previous efforts that directly or indirectly contributed to classifying old-growth forest in the CRMW, and the work documented here is a continuation of those efforts. The objectives of this work conducted in 2012 were to (1) compile and review the previous efforts of classifying old-growth in the CRMW; (2) to extend these efforts by incorporating new information and classification tools that have been developed more recently; (3) based on this information, to provide an old-growth classification that fulfills the HCP objective stated above; and (4) develop materials that can be used to describe variation in CRMW old-forest, such as on the CRMW HCP website.

## Previous Efforts

There have been three previous efforts that have addressed classification of old growth in the CRMW. The first was conducted by Lucinda Tear (2006), a consulting statistician, who used a

multivariate statistical approach to analyze data from all of the Permanent Sampling Plots (PSPs)<sup>2</sup>, including those in old-growth forest. The second was by Bill Richards (2007), an Ecosystems staff member of the SPU Watershed Services Division, who focused on assessing habitat suitability of old-growth areas for marbled murrelet and spotted-owl. A third effort was that of Van Kane (2010a, 2010b, 2011), then a graduate student at the College of the Environment at the University of Washington, who developed metrics of forest structure from LiDAR data to classify forests across the watershed, including old-growth areas.

### Analysis of PSP Data

The analysis conducted by Lucinda Tear was directed at identifying patterns of vegetation and physical variables in the data from 113 PSP plots distributed across the watershed in both second growth and old-growth forest. The analysis and report were never finalized, but it appears from the documentation available that she largely completed her analysis (Tear 2006). As stated in her unfinished draft report:

*The objectives of this data analysis project were to compile and describe the currently available PSP data, to stratify the dataset for growth analysis, and to compare the strata with a regional classification system based on vegetation zones and plant associations.*

Tear's effort was divided into three tasks: (1) review of data and classification systems, (2) PSP data exploration and plot stratification, and (3) comparing classification systems. The analysis included all age classes represented in the PSP data set, which was simplified as being either second- or old-growth forest for the purpose of examining results of multivariate statistical analysis.

In Task 1, Tear summarized useful information about the characteristics of PSPs, including old growth. Old-growth PSPs range in elevation from 2,252 ft to 4,469 ft above sea level and primarily occurred on midslopes (25 of 37 plots) as opposed to the lower or upper third of slopes, ridge tops, or flatter land forms (benches, planes, or valley bottoms). The old-growth PSPs tend to be in lower quality sites with respect to soils, with 23 plots in site classes 4 and 5. Nineteen of the old-growth PSPs are in the *Abies amabilis* (Pacific silver fir) forest zone (elev. 2,800 to 4,000 ft), 16 are in the *Tsuga heterophylla* (western hemlock) zone (< 2,800 ft), and three in the high elevation *Tsuga mertensiana* (mountain hemlock) zone (> 4,000 ft).

The multivariate analysis in Task 2 derived a variety of ordinations, primarily using Principle Components Analysis (PCA) to examine gradients among various combinations of physical and biological variables. Old-growth PSPs tended to be on steeper slopes and at higher elevations compared to second-growth forests, which is likely a result of the pattern of harvest history (i.e., forests on lower slopes were generally harvested before those on higher, steeper slopes). In the ordinations of tree basal area (in which Tear used PCA and two other ordination techniques), the axis accounting for the most variation found that the old-growth PSPs represented a species-

---

<sup>2</sup> A system of 115 upland habitat Permanent Sampling Plots were established throughout the CRMW from 2003 through 2005, 37 of which were located in old-growth forest. Locations of plots in both old-growth and second-growth forest were selected randomly from a set of evenly spaced grid points.

composition gradient from dominance by Douglas-fir to that of silver fir, with old-growth PSPs falling mostly in the middle to silver fir end of the gradient.

The cluster analysis identified four groups, which varied by the number of old-growth (OG) PSPs in each: one dominated by western hemlock (7 OG PSPs), a second transitional between western hemlock and silver fir (12 OG PSPs), a third dominated by Douglas-fir (5 OG PSPs), and a fourth dominated by silver fir (14 OG PSPs).

In general, the Lucinda Tear analysis does not directly contribute much to the classification of the old-growth PSPs with respect to ecological characteristics. It primarily is useful in confirming the impression that old-growth relative to second-growth PSPs primarily represent higher elevation forests having lower site index that tend to have a higher abundance of western hemlock and silver fir. However, the multivariate analysis indicates that there is considerable variation among the old-growth PSP plots, suggesting that a classification based on structural features might also show a range of variation.

### **Mapping of Habitat Suitability for Marbled Murrelet and Spotted Owl**

The classification conducted by Bill Richards (Richards 2007) was intended to classify old-growth areas primarily for the purpose of identifying potential habitat for marbled murrelet (*Brachyramphus marmoratus*) and northern spotted owl (*Strix occidentalis caurina*). Richards utilized GIS data to identify polygons within old-growth areas according to criteria of site class, aspect, and elevation. He then used data from the 37 PSP plots located in old-growth stands to classify each of these derived polygons.

For northern spotted owl, Richards used a habitat classification of suitable nesting, foraging, and dispersal habitat, which was a simplified version of northern spotted owl habitat types used by the Washington Department of Natural Resources Forest Practice Rules (WAC 222-16-085). Habitat suitability was based on tree size/density and snag size/density and resulted in classifying each PSP into one of the three northern spotted owl habitat types. Since the 37 PSPs represented only 24 of the 50 polygon types (that were based on site class, aspect, and elevation), the PSP sample set was not sufficient to classify each of the polygon types, although unrepresented polygon types were only a small fraction of the total old-growth forest area.<sup>3</sup> Richards took a conservative approach and classified each polygon according to the best PSP habitat found in each polygon, which provided a guide to focus future survey efforts. This classification resulted in a map of northern spotted owl habitat suitability for old-growth polygons, which included 8,136 acres of nesting habitat (I type), 5,349 acres as foraging habitat (II type), 0 acres as dispersal habitat (III type), and 660 acres as non-suitable habitat (N type).

---

<sup>3</sup> Only five percent of old-growth (704 acres) was in polygon types not represented by PSPs, mostly because site class was unknown. These polygons were assigned suitability based on similarity to represented polygon types with respect to known attributes.

Richards applied a similar approach to mapping marbled murrelet suitable habitat. Based on the number of large limbs (> 8 inch diameter at trunk); tree size, density, and species; and distance from marine habitat, he defined three classes of marbled murrelet habitat suitability (high, medium, and low) and assigned each PSP to one of the three classes. He classified each old-growth polygon by the average marbled murrelet habitat suitability found in each polygon. He produced a map of old-growth forest classified by marbled murrelet suitability class, and found 0, 5,134, and 9,012 acres, respectively for high, medium, and low marbled murrelet habitat suitability in CRMW old-growth areas.

### **Characterization and Mapping of Forest Structure from LiDAR Data**

Van Kane's dissertation research used LiDAR (Light Detection and Ranging) and PSP data from the CRMW to examine how remotely sensed LiDAR data could be used for characterizing forest structure on a landscape scale. He published three papers on this work:

- Kane et al. 2010a examined how field data (from PSPs) compared to LiDAR-based measures of stand structural complexity. He evaluated six LiDAR-based metrics (mean height, standard deviation [SD] of height, canopy density, 95<sup>th</sup> percentile canopy height, coefficient of variation of height, and rumple [ratio of canopy outer surface area to ground surface area]) and four field metrics (mean diameter at breast height [DBH], SD of DBH, tree density, and trees > 100 cm DBH density). He found generally good correlation between field and LiDAR metrics and between PCA ordinations of those metrics. He chose three variables that best characterized different aspects of forest structure: 95th percentile height as a height variable, rumple as a canopy structural complexity variable, and canopy density as a measure of canopy gaps and leaf area.
- Using the three LiDAR variables above, Kane et al. (2010b) conducted a hierarchical clustering analysis and PCA ordination of all the PSPs to examine canopy structural complexity across forest ages and elevations. He identified two precanopy closure classes, and six postcanopy closure classes.<sup>4</sup> He further classified the six postcanopy closure classes into two that were low-complexity and four that were high complexity. While the most complex classes included primarily old-growth PSPs and the least complex primarily second-growth PSPs, the intermediate classes included mixtures of both old-growth and second-growth PSPs. This indicates considerable overlap in the complexity of old-growth and second-growth forest in the CRMW, as described by LiDAR data. He also found that complexity was not associated with elevation.
- Kane et al. (2011) used LiDAR data to examine horizontal heterogeneity and patch structure of forest in the CRMW. He classified 48 9-ha sites (300x300m) in both old growth and second growth for within-stand patch structure and three 64-ha sites within second-growth forest for

---

<sup>4</sup> Precanopy closure refers to young stands that have not yet entered the competitive exclusion stage of forest development following stand initiation. Postcanopy closure includes a wide range of age classes from relatively young, dense forest in competitive exclusion to structurally complex old-growth forest.

variance in patch structure at larger scales. He identified six classes of within-stand structure that corresponded to different developmental stages: stand establishment, competitive exclusion, maturation, high elevation structural complexity, and shifting patch mosaics (2 classes). For the 9-ha sites, rumple was the variable that most strongly differentiated structural classes, and canopy closure was the second strongest. At larger scales he identified three patch mosaic stages of late-seral forest development.

In addition to the published work that Van Kane did regarding the use of LiDAR-derived metrics to characterize forest structure, he used the same LiDAR-derived metrics to develop a “first-cut” classification of forest structural complexity across the watershed (Van Kane, personal communication). Kane’s work essentially developed a methodology for classifying forest structure on a landscape scale. In the 2012 efforts I conducted and describe below, I used the approach that Kane et al. (2010a, 2010b) developed and his “first-cut classification to classify old-growth areas by LiDAR structural characteristics.

## **2012 Efforts**

After review of previous work on classifying old-growth habitat in the CRMW, I took two approaches to carry this work further. The first was to use the PSP data in evaluating variation in two indices of old-growth structural characteristics; the second was to map variation in old-growth structure by applying Van Kane’s LiDAR-derived structural metrics across old-growth areas in the CRMW.

### **Analysis of PSP Data Using Indices of Old-growth Habitat Structure**

The PSP data were used in all three previous approaches to characterizing old-growth habitat and were further explored here using two indices of old growth – one developed by Acker et al. (1998) to describe the development of old-growth structural characteristics in Douglas-fir dominated forests and the second developed by Washington Department of Natural Resources (WDNR 2005) as a basis for identifying old-growth areas in western Washington conifer forests. The two indices are both based on reference values for structural characteristics of west side Oregon and Washington old-growth forests (n = 96 plots) published in Spies and Franklin (1991), which focused on how structural characteristics differed among young (< 80 yr), mature (80-195 yr), and old-growth (> 195 yr) Douglas-fir forests, and which characteristics best differentiated old-growth from younger forests.

The indices essentially provide a way of quantifying “old-growthness”, and thus are useful for characterizing the variation in the structural characteristics in CRMW old growth. While the indices are not specific with respect to habitat features needed by individual species, they do provide a measure of how a particular PSP compares to average old-growth structure across Douglas-fir-dominated forests of western Oregon and Washington.

## Acker Old-growth Index

The Acker (1998) index of old growth is based on four structural variables: (1) SD of tree DBH (diameter at breast height), (2) density of large trees (> 100 cm DBH), (3) mean tree DBH, and (4) density of all trees (the same variables that Kane et al. [2010a] used in correlating LiDAR to field data). The Acker index is essentially a measure of where a plot falls in structural characteristics between young forests regenerating after clearcutting and well-developed old-growth conditions. It uses an algorithm to create a score, termed  $I_{og}$ , calculated as follows:

$$I_{og} = 25 \sum [(x_{i,obs} - x_{i,young}) / (x_{i,old} - x_{i,young})]$$

Where:

$x_{i,obs}$  = observed (i.e., PSP) value of each of the four structural variables;

$x_{i,young}$  = mean value of each of the four structural variables from the young stands in Spies and Franklin (1991);

$x_{i,old}$  = mean value of each of the four structural variables from the old-growth stands in Spies and Franklin (1991).

There is also a caveat that for variables 1 through 3, values are given the mean old-growth value if greater than the mean old-growth value and for variable 4 are given the mean old-growth value if less than the mean old-growth value. This prevents the  $I_{og}$  from getting uncharacteristically large. The  $I_{og}$  ranges from 0 to 100 for plots with mean characteristics equivalent to the young and old forests, respectively, evaluated by Spies and Franklin (1991). The study plots analyzed by Acker et al (1998), which were distributed across National Forests in western Oregon and Washington and were 120 to 155 yrs since stand initiation, had  $I_{og}$  ranging from 43 to 67 with a mean of 54.

Summary statistics for  $I_{og}$  calculated for all the old-growth PSPs in the CRMW ( $n = 37$ ) are shown in Table 1 ( See Appendix A for values calculated for each PSP). Although the minimum  $I_{og}$  value for CRMW PSPs was lower than the plots analyzed by Acker et al. (1998), the mean and maximum were higher. Not all of the old-growth PSPs had age data, but the age range of those that have been dated was 223 to 308, except for one plot having an age of 699. Since the PSP age range is substantially older than that of the Acker plots, it is not surprising that the CRMW plots had higher mean and maximum  $I_{og}$  values. Since a  $I_{og}$  of 100 represents mean conditions for western Oregon and Washington old-growth forest, the CRMW has some old growth with structure similar to average old-growth conditions in western Oregon and Washington dominated forests (seven PSPs with scores of 100), however, most old growth in the CRMW does not have structure as well developed as that of Douglas-fir dominated old growth.

The wide range of  $I_{og}$  values for PSPs supports the impression that there is substantial variation in structural characteristics within CRMW old-growth forest, with some areas less “old-growth like” than others. Although the Acker index was calibrated to data from Douglas-fir dominated forest, it

is nonetheless a consistent measure of forest structure regardless of dominant species. For purposes of describing structural variation in CRMW PSPs, whatever the dominant species, the Acker index should provide a meaningful measure of forest structure that incorporates tree size, variation in tree size, and tree density. Mean  $I_{og}$  for Douglas-fir (n=5), western hemlock (n=18), and Pacific silver fir (n=10) dominated PSPs was 81, 73, and 59, respectively. The ranking of these values is generally consistent with what one would expect in these different types of stands. There was a significant relationship between  $I_{og}$  and elevation, but the correlation was relatively low (adjusted  $r^2 = 0.093$ ) (Figure 1, Appendix A). Of the seven PSPs with  $I_{og} = 100$ , three were in the upper Rex River basin, with one each in the Seattle and Lindsay creek basins, and two in the slopes north and south of Chester Morse Lake (Figure 3).

### WDNR Index

The WDNR index uses five structural variables to derive a score ranging from 0 to 100 to determine the degree to which stands have old-growth characteristics. These variables are:

1. Large trees (number of trees per ha > 100 cm),
2. Large snags (number of standing dead trees per hectare > 50 cm DBH and > 15 m tall),
3. Volume of down woody debris (cubic meters per hectare),
4. Tree size diversity, and
5. Stand age (years).

The methods for developing scores for each variable generally entail scaling the score to the values for each variable in the Douglas-fir dominated old-growth forest reported by Spies and Franklin (1991) (i.e. the same old-growth reference conditions used by Acker [1998]), with the average score of all variables combined providing the old-growth habitat index. Calculating tree size diversity is somewhat more involved than the other variables, as it scaled the density of different size classes and weighted the larger size classes more heavily. The WDNR index differs from the Acker (1998) index in that it includes a different set of variables, except for density of large trees, and thus captures a wider variety of old-growth structural features. The method combines scores from the different variables into three different indices:

- Standard Old Growth Habitat Index (OGHI), which is just the average of the five scores;
- Modified OGHI, which excludes stand age making the index purely structural; and
- Weighted OGHI, which is also based on only the four structural variables, with each variable weighted by a relativized Spearman's rank correlation coefficient between each variable and stand age.

For purposes of this analysis, I used the weighted index (WOGHI).

The values for WOGHI for the 37 PSPs ranged from 38 to 89, indicating that there is a wide range of forest structural conditions in CRMW old growth, similar to what was found with the range of Acker  $I_{og}$  scores. Despite the differences in methodology, the Acker and the WDNR WOGHI were very similar in result, although WOGHI values were less than the Acker  $I_{og}$  for almost all PSPs. A

regression of the two scores had an  $r^2 = 0.83$  (Figure 2). Comparing the scores for old-growth PSPs dominated by different species, Douglas-fir and western hemlock PSPs both had mean WOGHI = 51, which was considerably higher than that for Pacific silver fir dominated PSPs (mean WOGHI = 35). As with the Acker index, however, correlation of WOGHI to elevation was significant ( $P = 0.022$ ) but with relatively low correlation (adjusted  $r^2 = 0.117$ ) (Figure 1).

The minimum, 25% quartile, median, and 75% quartile scores for CRMW old-growth PSPs were well below those found in 40 plots located in Douglas-fir dominated old-growth stands of the western Washington Cascade Range evaluated by Spies and Franklin (1991) and reported in WDNR (2005) (Table 1). However, the maximum WOGHI score for PSPs was very similar to the WDNR maximum based on the Spies and Franklin data from the western Washington Cascades. Similar to the Acker  $I_{og}$ , the CRMW WOGHI scores indicate that most CRMW old growth is generally less well-developed structurally than typical Douglas-fir old growth in the western Cascades, which is not surprising given that there is no remaining old growth in the CRMW that is located in more productive lower elevation and valley bottom sites. However, three PSPs had OGHI > 80, which is comparable in structure to the most structurally complex old growth in Washington. Two PSPs had exceptionally high OGHI ( $\geq 88$ ), one was in the upper Rex River basin and the other in Fish Creek basin (Figure 4). Four other PSPs with relatively high OGHI ( $\geq 76$ ) were located in the upper Rex basin (2), Lindsay Creek basin (1), and Seattle Creek basin (1).

Table 1. Values for  $I_{og}$  and WOGHI calculated for CRMW PSPs. Also shown are values for  $I_{og}$  and WOGHI reported in Acker et al. (1998) and WDNR (2005), respectively.

	<b>Index</b>	<b>min</b>	<b>25% quartile</b>	<b>mean</b>	<b>median</b>	<b>75% quartile</b>	<b>max</b>
CRMW old-growth PSPs	$I_{og}$	36	54	72	64	93	100
Acker et al. (1998) plots	$I_{og}$	43	---	54	---	---	67
CRMW old-growth PSPs	WOGHI	19	30	48	39	64	89
WDNR (2005) plots <sup>1</sup>	WOGHI	38	62	---	77	81	89

<sup>1</sup> The WDNR plots are old growth plots in Washington from Spies and Franklin (1991).

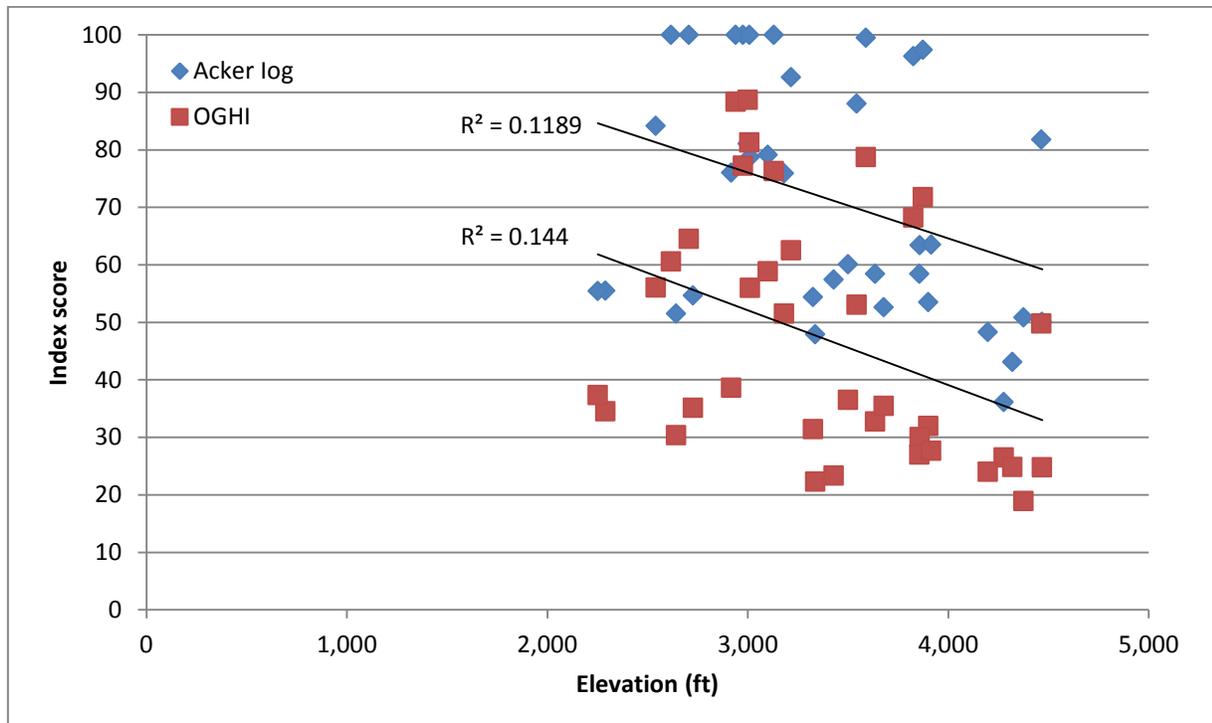


Figure 1. Relationship of Acker  $I_{og}$  and WOGHI values for CRMW PSPs to elevation.

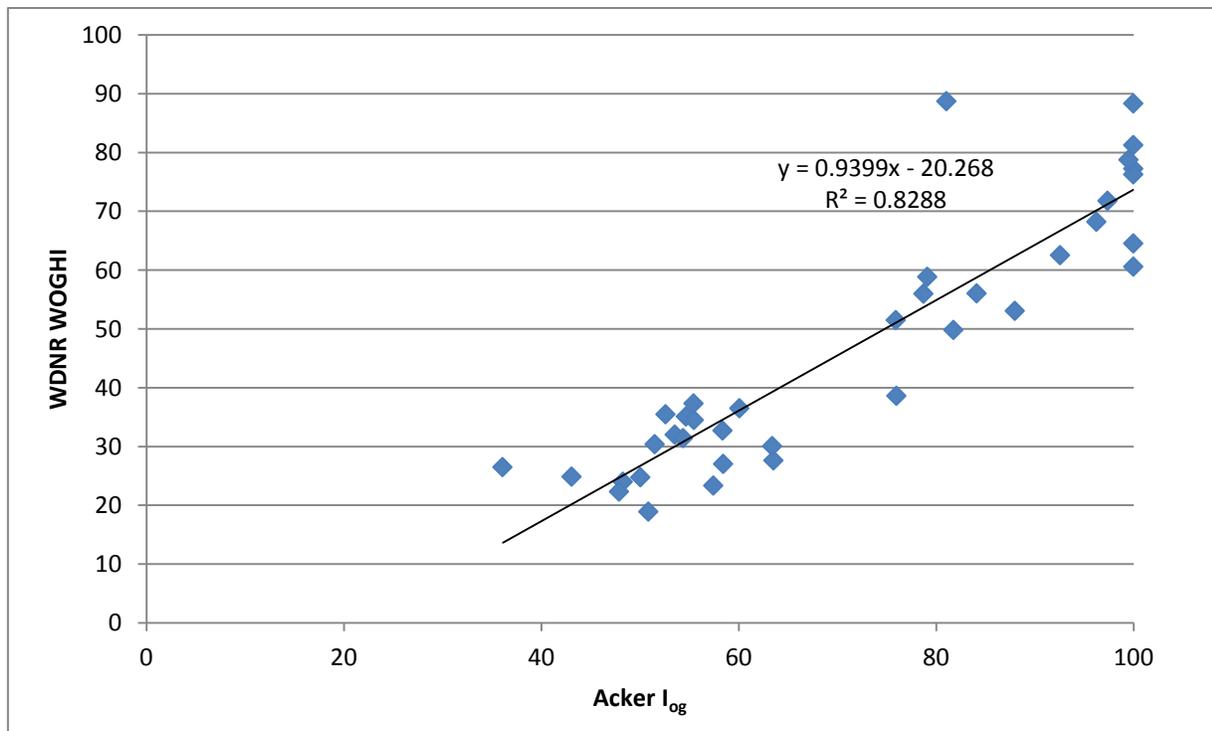


Figure 2. Correlation of Acker  $I_{og}$  and the WOGHI for old-growth PSPs in the CRMW.

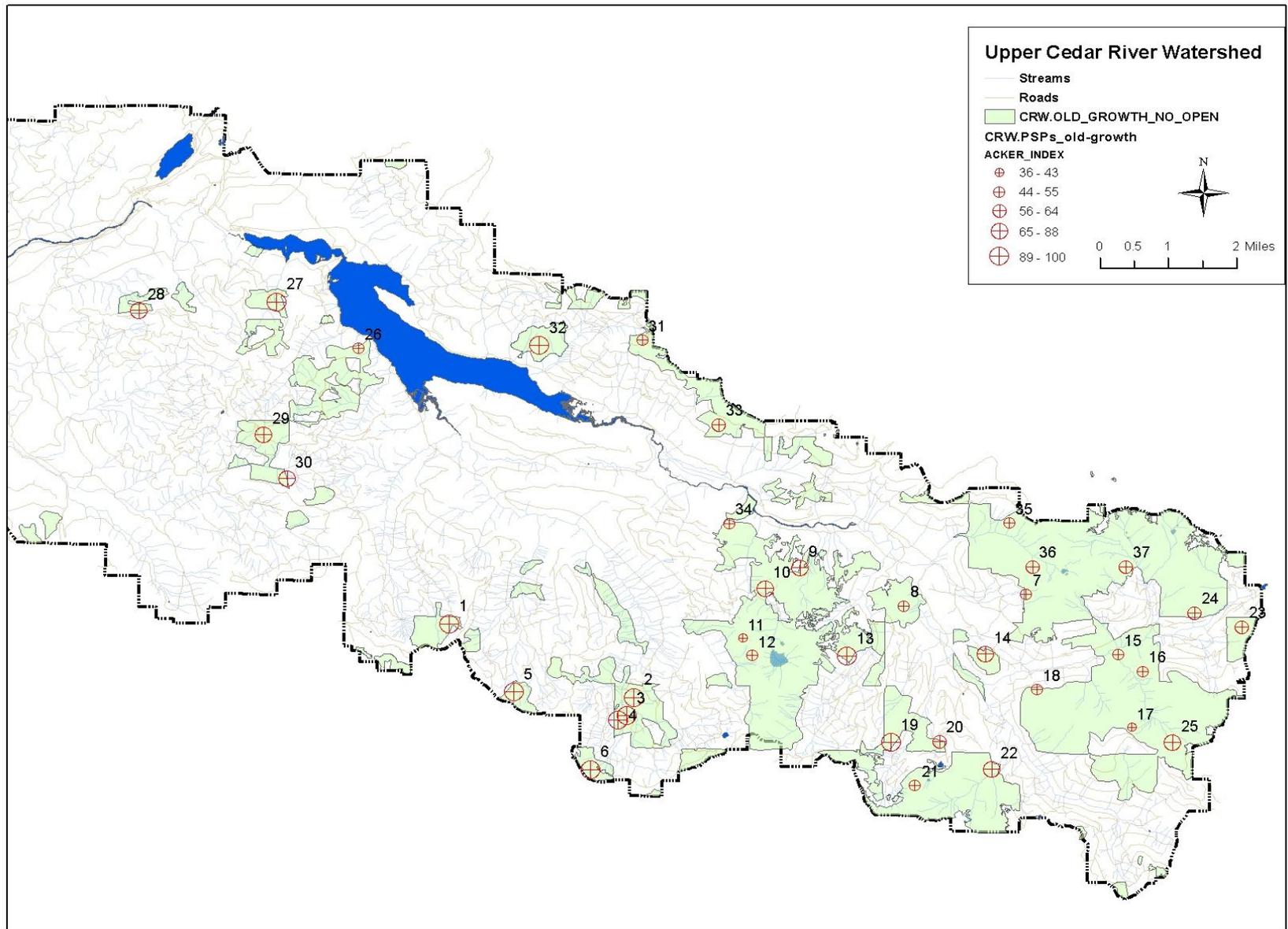


Figure 3. Permanent sample plots (PSPs) in old-growth forest within the CRMW, with symbols scaled by Acker  $I_{og}$  value. Numbers by symbols identify PSP by key shown in Appendix A.

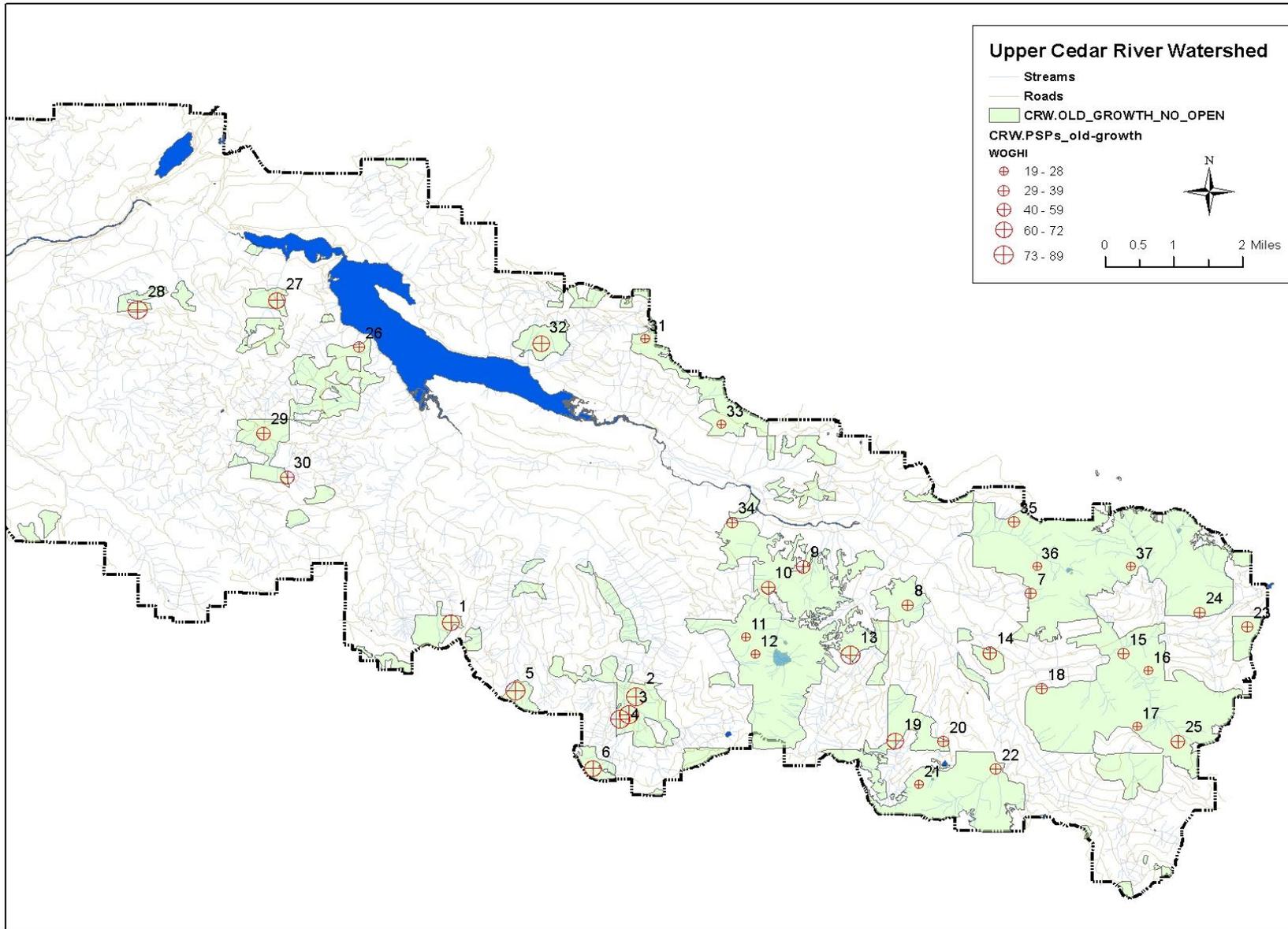


Figure 4. Permanent sample plots (PSPs) in old-growth forest within the CRMW, with symbols scaled by WOGHI value. Numbers by symbols identify PSP by key shown in Appendix A.

## Application of LiDAR Characterization and Mapping

Characterization of old-growth forest using the PSP data and the two structural indices is useful for describing the variation in CRMW old growth, but it does not show how that variation is distributed across all the remaining old-growth areas. A map showing the variation in structure across all the old-growth forest in the CRMW has several possible applications, such as showing the scale at which variation occurs and identifying where areas of high structural complexity are located. To produce such a map, I applied the unpublished map that Kane developed of LiDAR structural classes across the entire watershed to old-growth areas. I first validated how it was derived and how well it represented structural variation in old growth alone, then identified a set of simplified structural classes that were specific to old-growth forest for developing a map that emphasized old-growth structural variation.

## Kane's Analysis of LiDAR Variables

Kane identified nine structural classes using agglomerative hierarchical cluster analysis and PCA of a random selection of 10,000 30-m pixels across forested habitat in the watershed. He then mapped these classes to all 30-m pixels of LiDAR data using the Random Forest algorithm (Van Kane, personal communication). Random Forest is a method for developing a classification tree from different variables (in this case, the three LiDAR variables of 95 percentile height, rumple, and canopy cover) that consists of many decision trees and outputs the class that is the mode of the classes developed for individual trees (Breiman 2001). Although not published by Kane, a graphic of the cluster analysis and PCA ordination from a Powerpoint file he provided is shown in Figure 5.

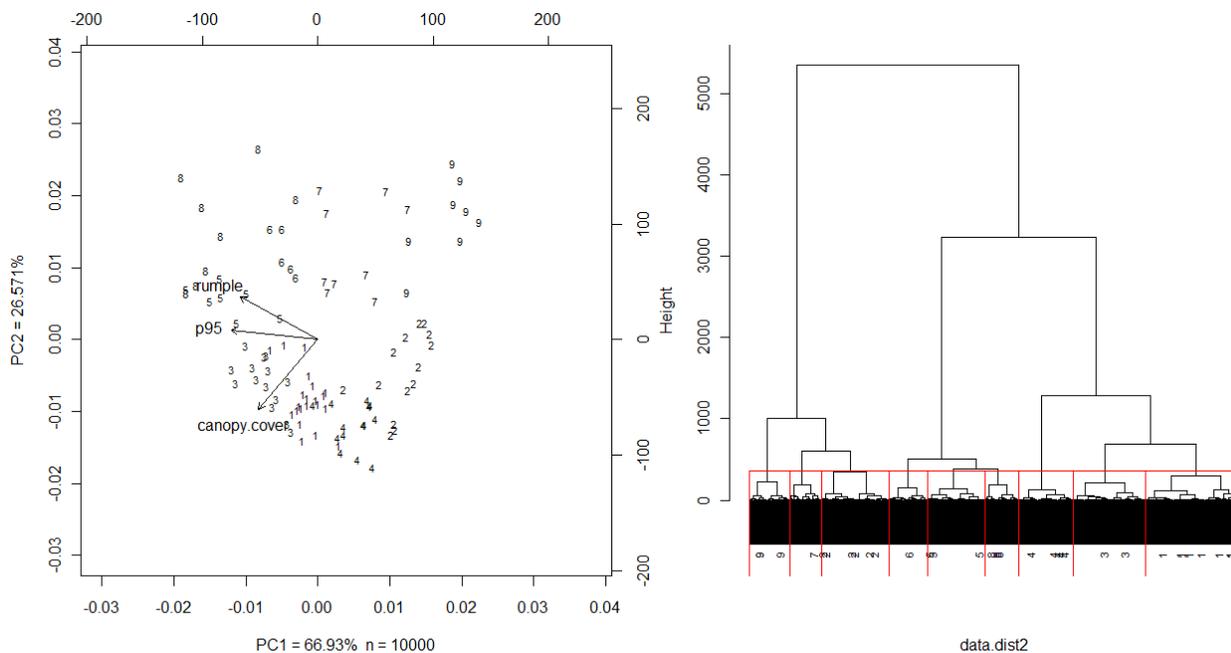


Figure 5. PCA ordination (left) and cluster analysis (right) of 10,000 random pixels across the CRMW based on three LiDAR metrics: 95 percentile height, rumple, and canopy cover. For clarity, only a small sample of the sampled pixels are shown in the PCA ordination. The numbers in the PCA ordination correspond to the nine-classes identified by the cluster analysis and the vectors indicate strength and degree of correlation of the LiDAR variables with each PCA axis. (Source: Van Kane Powerpoint file *CRMW structure classification 2012020.ppt*)

## Applying Kane's Analysis to Old Growth Forest Only

Although Kane's analysis included old-growth habitat, I thought it necessary to first evaluate how well the nine structural classes differentiated the variation of structural characteristics within just old-growth forest. To do this I first replicated the process that Kane followed for developing the nine structural classes by using data from the entire CRMW to ensure that my analysis would achieve the same result and then, second, conducted the same analysis with old-growth habitat only.

Using GIS raster layers of the nine structural classes and the three LiDAR variables provided by Kane, I (with the help of SPU GIS analyst Mark Joselyn), derived a sample of 10,000 pixels from across the CRMW (excluding water bodies and the Cedar Falls headquarters area). With the three LiDAR variables from this 10,000 pixel sample, I then conducted an agglomerative hierarchical cluster analysis using Euclidian distances and Ward's linkage method (as did Kane) in the PC-ORD multivariate statistics package (McCune and Mefford 2006) and ran PCA on the sample (also with PC-ORD). The PCA ordination of this sample was very similar to the one Kane produced, both in the distribution of classes along the two axes and in the direction of the vectors showing correlation of each LiDAR variable to the axes (Figure 6).

Using a random selection of 2,000 pixels from old-growth forest (there were about 12,000 pixels total for all CRMW old growth), I again conducted the hierarchical cluster analysis and PCA, grouping the samples in the PCA using the nine-classes as before. The results of this PCA ordination were very similar to both Kane's PCA ordination and the one I did using a 10,000 sample of pixels across the CRMW, with respect to both the distribution of classes within the ordination and in the LiDAR variable vectors (Figure 7).

The close correspondence between Kane's analysis for the entire CRMW and my replication of those analyses using a sample from just old-growth forest indicates that the nine structural classes that Kane mapped using the Random Forest algorithm for the entire watershed should also reasonably represent structural variation in old growth considered alone. However, the classification of old-growth forest using this approach might be refined by running the Random Forest algorithm on old-growth data only, which might better differentiate the range of structural complexity found across just the old-growth forest in the CRMW.

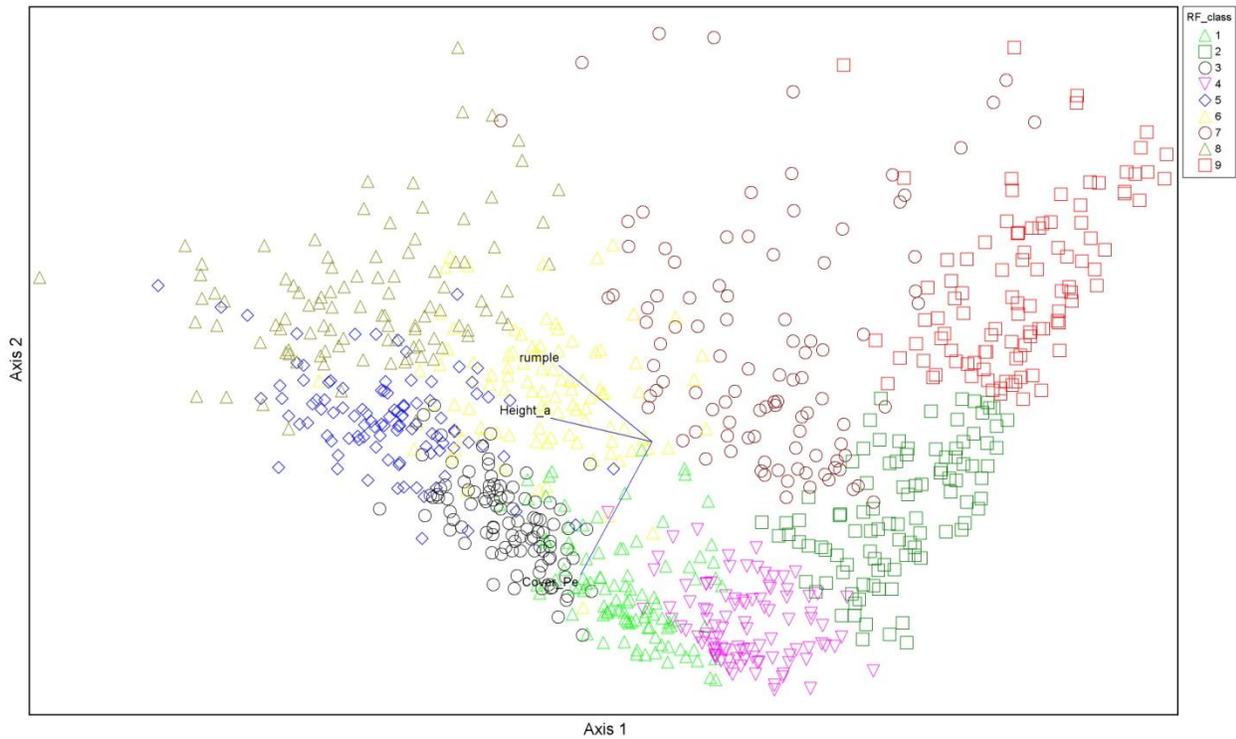


Figure 6. PCA ordination of a random selection of pixels across the CRMW based on three LiDAR metrics: 95 percentile height, rumple, and canopy cover. For clarity, only 900 of the 10,000 sample are shown here. Class number shown in legend are the same as used in Kane's PCA ordination shown in Figure 5.

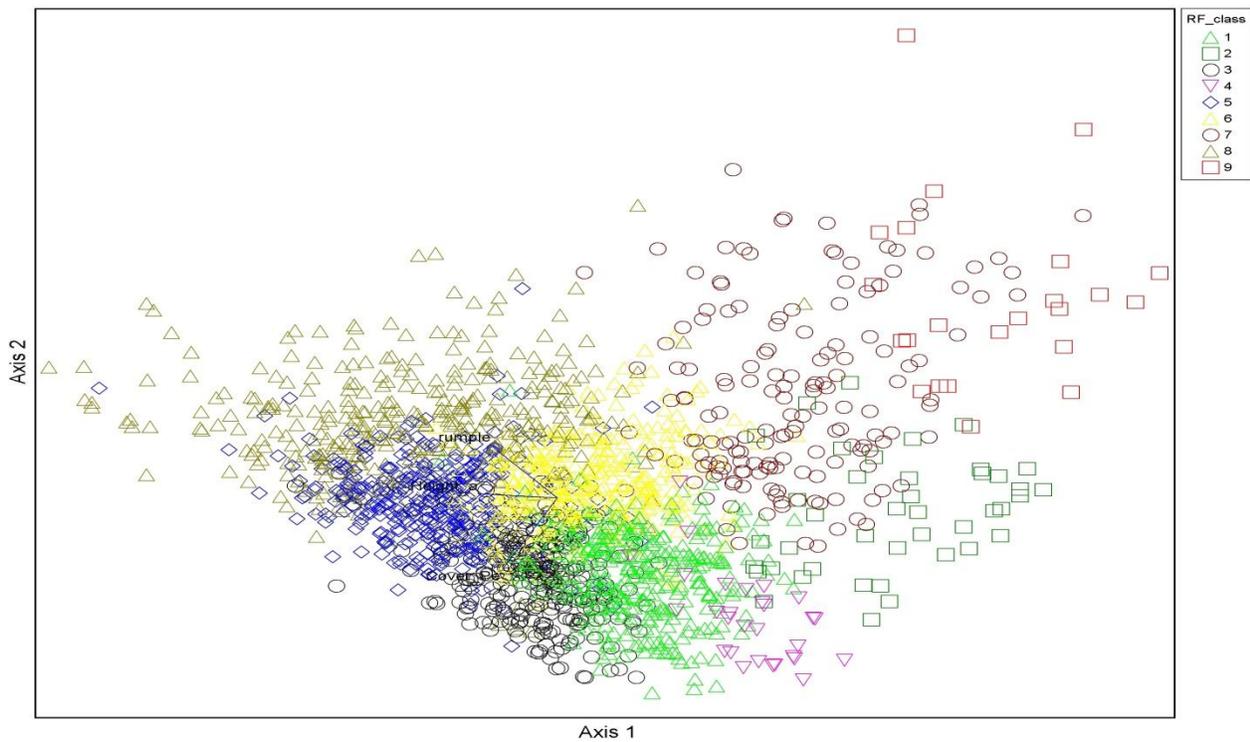


Figure 7. PCA ordination of a random selection of 2000 pixels from old-growth forest in the CRMW based on three LiDAR metrics: 95 percentile height, rumple, and canopy cover. Class number shown in legend are the same as used in Kane's PCA ordination shown in Figure 5.

## A Map of Old-Growth Structural Characteristics

Having demonstrated that the map of the forest structural classification that Kane developed reasonably represents variation in CRMW old-growth structure, I next examined how variation in structural complexity is distributed in old-growth forest stands across the upper watershed and produced graphic displays of the classification to show that variation.

To describe each of these classes, I derived median and quartile values for each of the three LiDAR variables for each of the nine structural classes across all old-growth pixels (Figures 8). Comparing the median and quartile values among classes, I ranked rumple and canopy cover into four levels and 95 percentile height into five levels for each structural class (Table 2). These ranked levels of the different LiDAR variables were used to describe each of Kane's classes in terms of the level of structural complexity (based on rumple), height (based on 95 percentile height), and canopy closure (based on canopy density).

To display these classes on a map, the color symbology of the nine classes was simplified by lumping six of the nine classes into three classes, based first on rumple (complexity) and second on height and cover, resulting in six color symbols on the map. Table 2 shows descriptions of each class and how they were lumped in the map symbology. Maps of the LiDAR-derived structural classes are shown in Figure 9 (with separate pages for the western, central, and eastern portion of the upper CRMW).

Table 2. Descriptions of nine structural classes of CRMW old-growth forest. Color scheme is that used in maps of old-growth structural complexity (Figures 2 and 3)

Kane class number	Kane class ranking	Ranking Category			
		Rumple	95 percentile height	Canopy cover	Color scheme
8	1	highest	tallest	moderate	darkest green
5	2	high	tallest	high	dark green
6	3	high	tall	moderate	dark green
3	4	moderate	tall	high	lighter green
1	5	moderate	moderate	high	lighter green
7	6	moderate	low	low	very light green
4	7	low	low	high	yellow-green
2	8	low	very low	moderate	yellow-green
9	9	low	very low	very low	light yellow

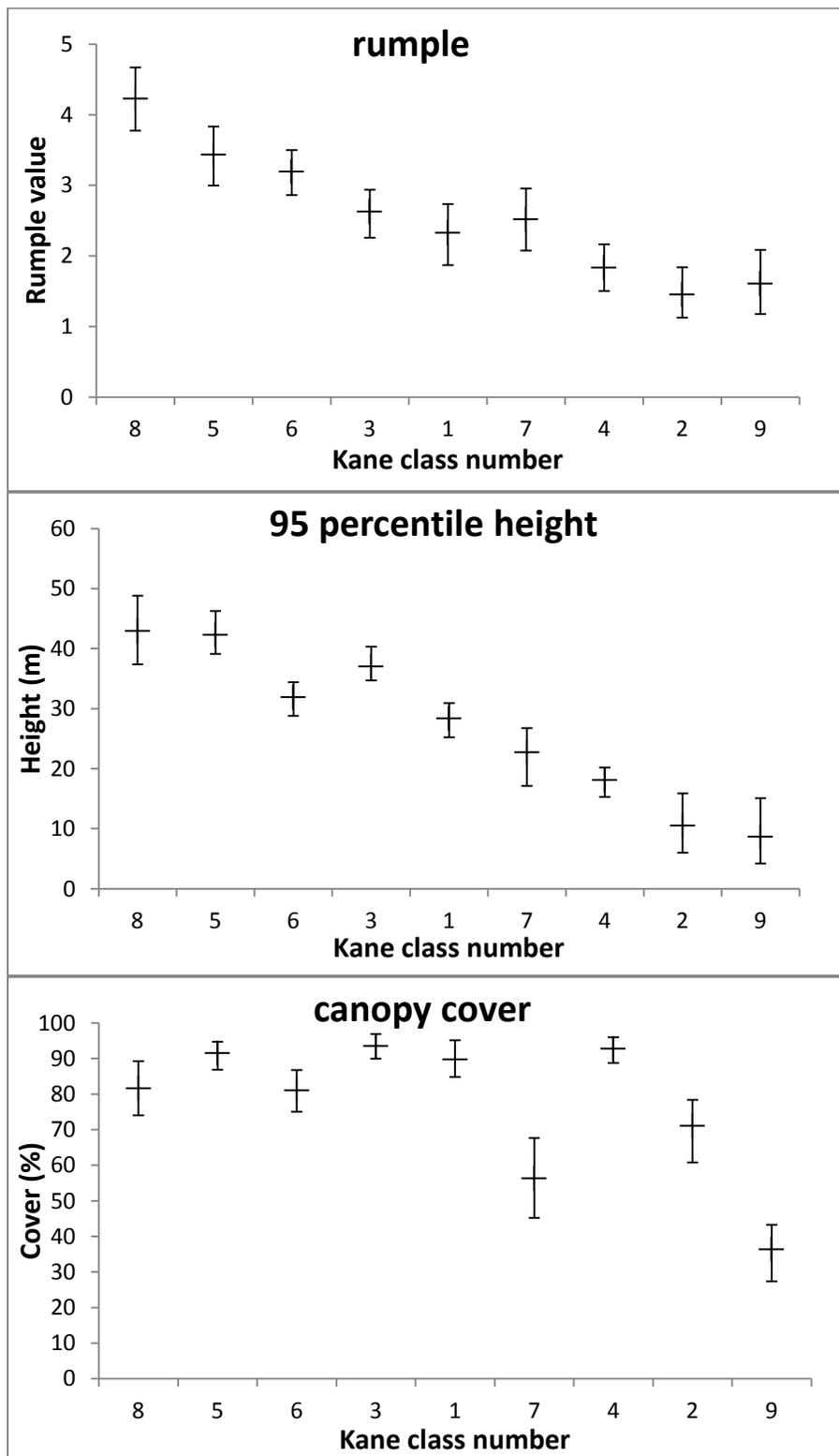


Figure 8. Median (horizontal line), 25 percentile (lower error bar), and 75 percentile (upper error bar) values of three LiDAR variables for all pixels in CRMW old-growth forest in each of nine structural classes identified by Van Kane.

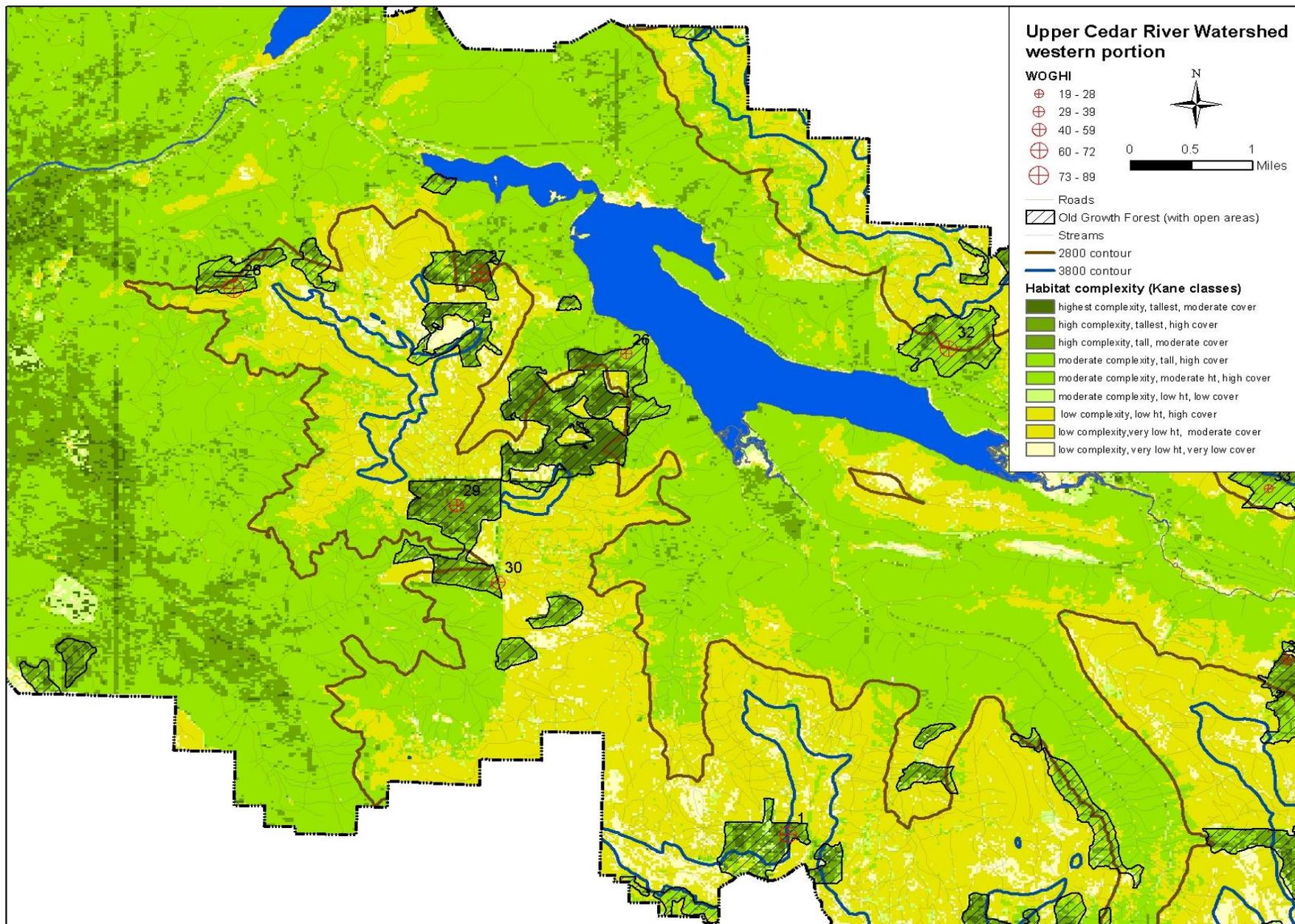


Figure 9a. Map of habitat complexity classes developed by Kane for the upper CRMW, western portion. Old-growth PSP symbols scaled by WOGHI value as in Figure 4. Numbers by symbols identify PSP by key shown in Appendix A.

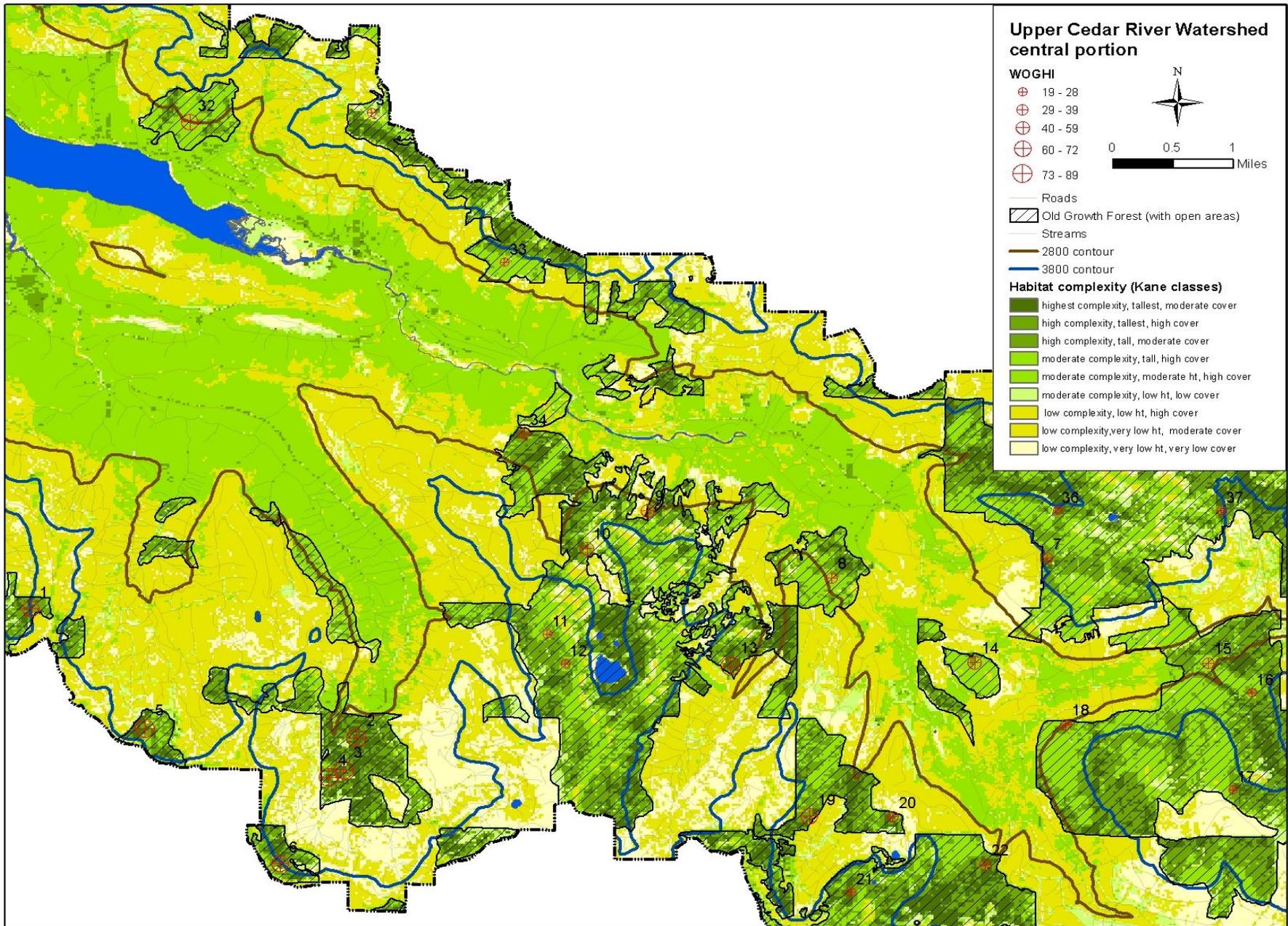


Figure 9b. Map of habitat complexity classes developed by Kane for the upper CRMW, central portion. Old-growth PSP symbols scaled by WOGHI value as in Figure 4. Numbers by symbols identify PSP by key shown in Appendix A.

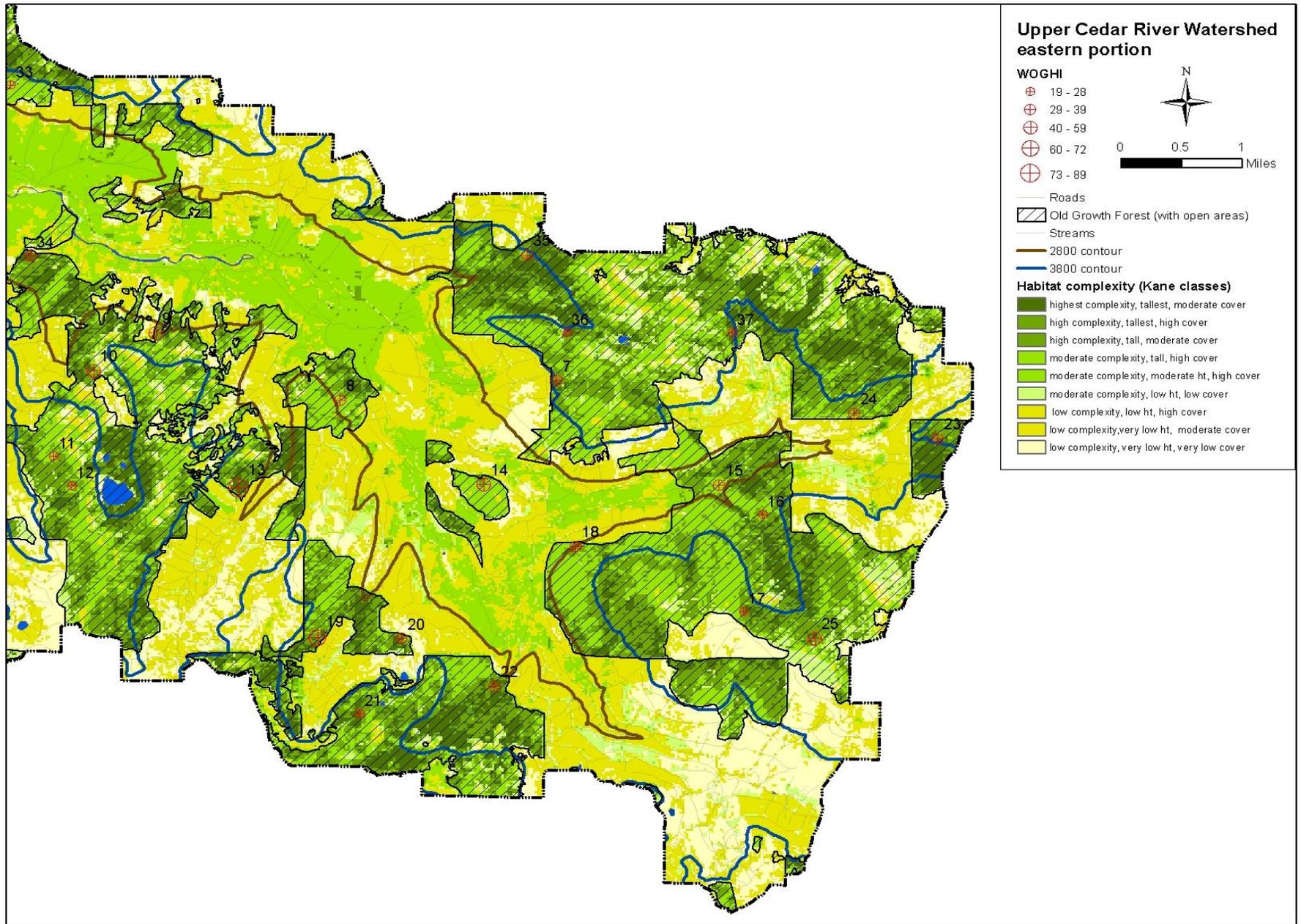


Figure 9c. Map of habitat complexity classes developed by Kane for the upper CRMW, eastern portion. Old-growth PSP symbols scaled by WOGHI value as in Figure 4. Numbers by symbols identify PSP by key shown in Appendix A.

It is clear from Figure 9 that old-growth stands with high structural complexity are well distributed across the upper watershed. There does not appear to be any watershed-scale pattern of structural complexity, rather different levels of structural complexity occur in mosaics in most old-growth patches, indicating that old-growth habitat in the CRW is quite variable even at a relatively small scale. This small-scale variability undoubtedly is part of the horizontal heterogeneity in forest structure, which Kane et al (2011) described. Taking the watershed as a whole, 57% of old-growth habitat is in the high to highest complexity classes and 38% in the moderate complexity class (Figure 10). Not only is there variation in complexity across all old growth, there is also variation among patches in the proportion of different complexity classes. For example, 34% of the upper Rex basin old-growth patch is in the highest complexity class, whereas only 12% of the North Fork Cedar River – Meadow Mountain patch is in the highest complexity class, with 19% of all old-growth forest in that class.

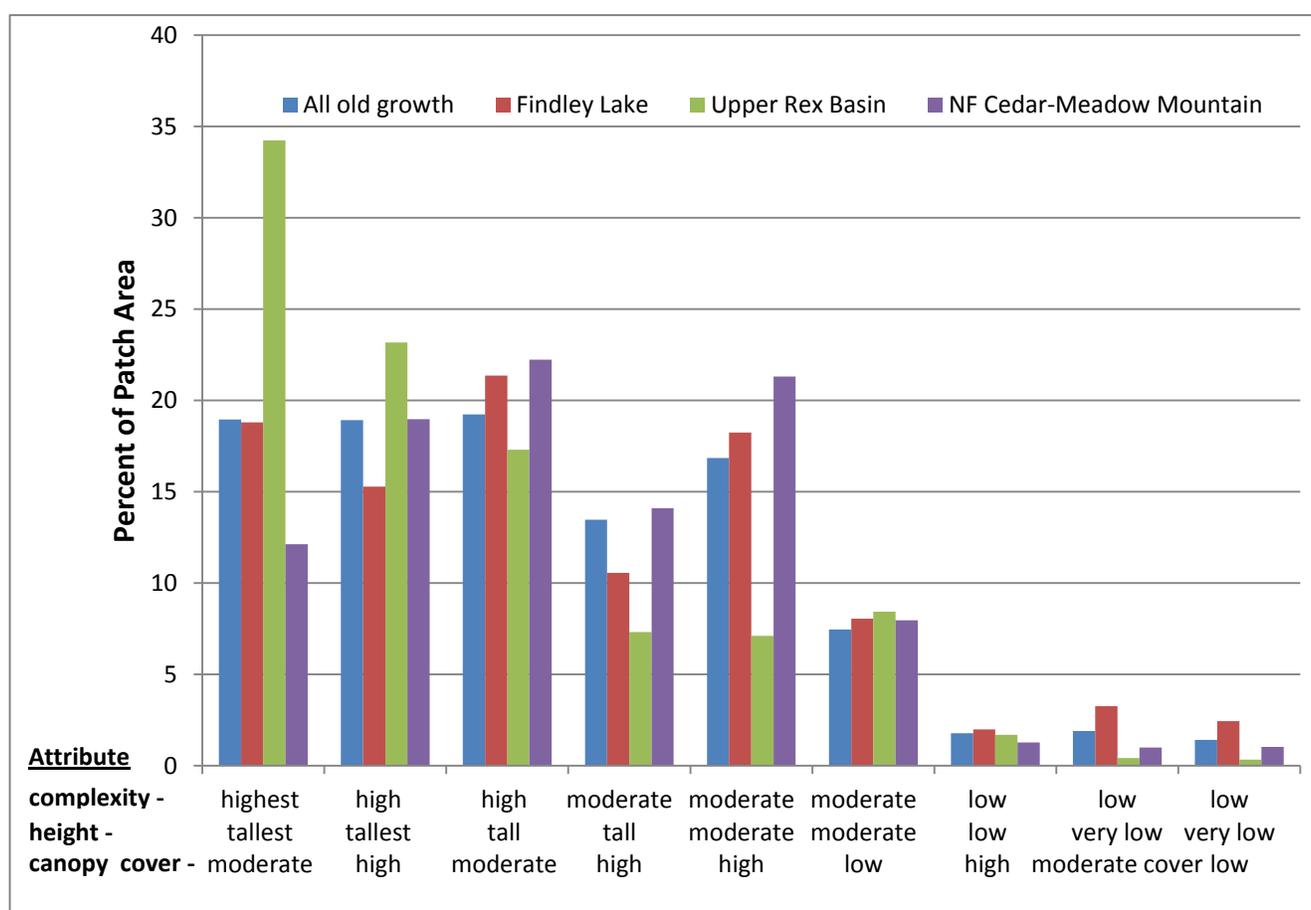


Figure 10. Percentage of all old-growth forest and three representative patches of old-growth forest in each of the nine Kane complexity classes.

Such small scale variability would not appear to be related closely to soil type, site index, elevation, or aspect, which tend to vary on larger scales; rather, it more likely reflects different intensity or time since stand-replacing disturbance, the pattern of disturbance during stand development, or a combination of these disturbance characteristics. The heterogeneity of old-growth structural complexity on a stand scale evident from LiDAR data suggests that Richards' approach in mapping

suitability of marbled murrelet and northern spotted owl habitat using classes does not capture the variability in habitat quality that stems from smaller scale variation in structure. Richards based the habitat suitability of sub-polygons within old-growth polygons on PSPs occurring in similar combinations of elevation, aspect, and site class, which do not appear to relate closely to variability in structural complexity evident from LiDAR data.

Although there are areas within old-growth polygons mapped as low complexity, these are typically not forest habitat but rather are open areas of rock, meadow, or wetland shrub, which further add to the habitat heterogeneity of CRMW old growth.<sup>5</sup> Interestingly, there are substantial areas of second-growth forest that are mapped as the highest complexity structural class, which was pointed out in Kane et al. (2010b, 2010c) (e.g., forest along the Cedar River in the upper left of Figure 9a). This suggests that older (> 90 years) second-growth forests on high productivity sites have developed some attributes of size and complexity comparable to existing old-growth forest in the upper CRMW. This is not necessarily unexpected, as existing old-growth forest in the watershed tends to be at higher elevations with lower site index (Tear 2006). With time, perhaps in less than a hundred years, the lower elevation second-growth forests would be expected to acquire structural complexity greater than most of the remaining CRMW old growth.

The highest complexity class appears to group areas of an exceptionally high complexity old-growth forest with that of high, but not as high, complexity. For example, the area in the upper Rex River basin around PSPs labeled 2, 3, and 4 (likely the oldest old-growth patch remaining in the watershed with trees dated to over 800 years old) is known to have exceptionally high complexity for the watershed, but is not classified by the LiDAR data separately from areas known to have very high, but less complex structure (e.g., old growth near Sutton Lake around PSP labeled 20 in Figure 7c, lower left). However, as shown in Figure 10, the upper Rex River old-growth patch has a substantially higher amount of the most complex structural class, compared to all old growth and two other relatively large old-growth patches. This suggests that the proportion of high complexity within a stand is also important to consider in evaluating forest structure. It is possible that a classification of structure based on an analysis of just old-growth forest, leaving out all second growth, might better resolve these areas of exceptional complexity, as opposed to this classification developed by Kane based on all forest habitat in the CRMW. And a classification that included horizontal heterogeneity in structure might further differentiate the most structurally complex forest in the watershed. This classification, thus, should be considered to be a conservative estimate of complexity in the most structurally complex forests in the CRMW.

To evaluate how well the mapped structural classes correlated to structural complexity indices calculated for the old-growth PSPs, I recorded the map structural class at the location of each old-growth PSP in the GIS and examined how they were correlated to the WOGHI and Acker  $I_{og}$  values for

---

<sup>5</sup> The old-growth habitat GIS layer used in Figure 9 (CRW.OLD\_GROWTH\_NO\_OPEN) does not exclude small open areas, as does a more restrictive layer (CRW.OLD\_GROWTH). Because these small excluded non-forest areas are often inter-mixed and confusing to interpret at relatively large scales, such as in Figure 9, the layer with the small open areas included was used here for analysis and presentation.

each PSP<sup>6</sup>. The rank of Kane’s nine structural classes based on complexity and on height (Figure 8, Table 2) is significantly correlated to both the ranked WOGHI (Spearman’s rank correlation coefficient ( $r_s$ ) = 0.556,  $P < 0.001$ ) and Acker  $I_{og}$  ( $r_s$  = 0.569,  $P < 0.001$ ). However, there are certainly many PSPs that do not align well between rank of structural class and one or both of the two indices (Appendix A). Since Kane found good correlation between LiDAR and field metrics (Kane et al. 2010a), the latter of which were the same variables used in the Acker  $I_{og}$  (Table 3), a strong correlation between Acker  $I_{og}$  and the ranked structural classes (perhaps even higher than the  $r_s$  = 0.569 found here) is expected. However, it is somewhat surprising that the correlations of structural class rank to WOGHI and the Acker are so similar, since the WOGHI is based on two similar but also two different metrics (down wood and snags), neither of which are captured directly by the LiDAR metrics.

Table 3. List of LiDAR and field metrics used by Kane (2010a) and field metrics used in calculating the Acker  $I_{og}$  and WOGHI for CRMW PSPs.

<b>Kane LiDAR metrics</b>	<b>Kane field metrics</b>	<b>Acker <math>I_{og}</math></b>	<b>WOGHI</b>
rumple	SD of DBH	SD of tree DBH	tree size diversity
rumple, 95 percentile height	density of trees > 100 cm DBH	density of trees > 100 cm DBH	density of trees > 100 cm DBH
95 percentile height	mean DBH	mean tree DBH	
canopy cover	tree density	tree density	
			large snags
			volume of down woody debris

### Relating Old Growth Indices and LiDAR Classification to Wildlife Habitat Value

The WDNR habitat index (WOGHI) and the Acker index of old-growth habitat ( $I_{og}$ ) are useful for characterizing the degree to which the forest structure in old-growth PSPs, as representative of old-growth habitat in the CRMW, compares to that of reference stands of old-growth forest structure (i.e., 96 plots of old-growth Douglas-fir dominated forest occurring in western Oregon and Washington, reported by Spies and Franklin [1991]). LiDAR-derived structural attributes provide information to create a relatively high resolution map (30 m pixels) of variation in forest structure across the entire CRMW landscape. There is still the question, however, as to how these two approaches to characterizing old-growth habitat capture relative habitat suitability for old-growth dependent species.

As a first step to answering that question, I examined how the two indices and the three LiDAR variables used in developing the map of habitat structural complexity (Figure 9) were related to habitat suitability for northern spotted owl and marbled murrelet as found by Richards (2007). As shown in Figure 11, the mean values for WOGHI and  $I_{og}$  of all PSPs among each of the northern spotted owl suitability classes are not significantly different (Kruskal-Wallis non-parametric test due to unequal sample sizes). For the marbled murrelet suitability classes, only the difference between the Medium and Low classes was tested (two-sample t-test), as there were only two plots in the High suitability class. The Medium and Low classes were found to be significantly different for both WOGHI and  $I_{og}$ ,

<sup>6</sup> Because Kane’s structural classes are fixed ranks, a standard parametric correlation isn’t appropriate. Consequently, I also ranked WOGHI and Acker  $I_{og}$  values and used the non-parametric Spearman’s rank correlation coefficient.

with the mean of the two PSPs in the High class (which were not included in the t-test) being substantially higher than that of the Medium and Low classes.

With respect to the LiDAR variables, only the 95 percentile height variable showed significant differences among northern spotted owl suitability classes (Kruskal-Wallis non-parametric test due to unequal sample sizes)(Figure 12). For marbled murrelet (again just examining Medium versus Low suitability classes), there were significant differences for both 95 percentile height and canopy density. Though not included in the t-test, the mean rumple value of the two High PSPs was considerably higher than the Medium and Low classes, as was found with the old-growth index values of the two High PSPs for marbled murrelet habitat. Although the mean rumple value in these two High suitability PSPs was higher, it is interesting that rumple does not otherwise differentiate among habitat suitability types for either species. One would expect rumple to be more strongly related to the old-growth indices, as structural complexity is typically associated with characteristics determining both northern spotted owl and marbled murrelet habitat suitability (e.g., density of large trees). Compared to rumple, the stronger relationship of 95 percentile height to habitat suitability found in this analysis may be a consequence of it being an indicator that is more directly related of tree size (e.g., mean DBH).

To examine the relationship of the Kane structural complexity classification map to northern spotted owl and marbled murrelet habitat suitability, I counted the number of PSPs in two different complexity groups – high and highest complexity combined and moderate complexity. There were no old growth PSPs that occurred in low complexity pixels. If there were a strong relationship between structural complexity classes and habitat suitability, one would expect that the percent of PSPs in the high-highest group would decrease as habitat suitability decreased (and conversely the percent of the moderate complexity group would increase). As shown in Figure 13, there was no evident trend of complexity versus suitability class for northern spotted owl, however there was evidence of such a trend for marbled murrelet. This very limited analysis suggests there may be some utility in using the distribution of Kane structural complexity classes as a way to differentiate habitat suitability for marbled murrelet, but not for northern spotted owl.

In summary, it appears that the two old-growth indices do not distinguish different suitability classes for northern spotted owl, but may have utility in differentiating classes of marbled murrelet suitability, although the low number of PSPs in the High marbled murrelet class limits our ability to draw any definitive conclusions. The 95 percentile height variable seems to be the most promising LiDAR-derived variable as an indicator of both northern spotted owl and marbled murrelet habitat suitability. The LiDAR-based structural classification map of old-growth habitat appears to be applicable to marbled murrelet, but not northern spotted owl, habitat suitability.

Rather than applying the two old-growth indices and the maps of LiDAR derived metrics to identifying habitat suitability for individual species, a more appropriate use is likely to be in differentiating habitat value more generally for old-growth dependent species. Since the WOGHI and Acker  $I_{og}$  integrate several metrics that have been found to best differentiate the degree to which a sampled forest resembles the structure of well-developed western Oregon and Washington Douglas-fir forests, they should be good indicators of habitat features important to a wide variety of old-growth

dependent species. Kane (2010a) showed that the LiDAR-derived metrics were highly correlated with the same variables used in the old-growth indices, which suggests that these should also be good, albeit less direct, indicators of general habitat value for old-growth dependent species. There appears to be some association of overall stand complexity to marbled murrelet, though not northern spotted owl, habitat suitability (Figure 13), but this analysis indicates that 95 percentile height is perhaps the most useful single LiDAR metric for describing general old-growth habitat value on a landscape scale. Although tree height is only one component of old-growth structure important to wildlife, it's likely to be correlated with a number of other important habitat characteristics and can be accurately quantified by LiDAR. The use of 95 percentile height as an indicator of habitat value, however, is not likely to be as useful in second-growth forest, where trees can reach considerable height before the stand differentiates and develops the complexity associated with late-seral or old-growth conditions.

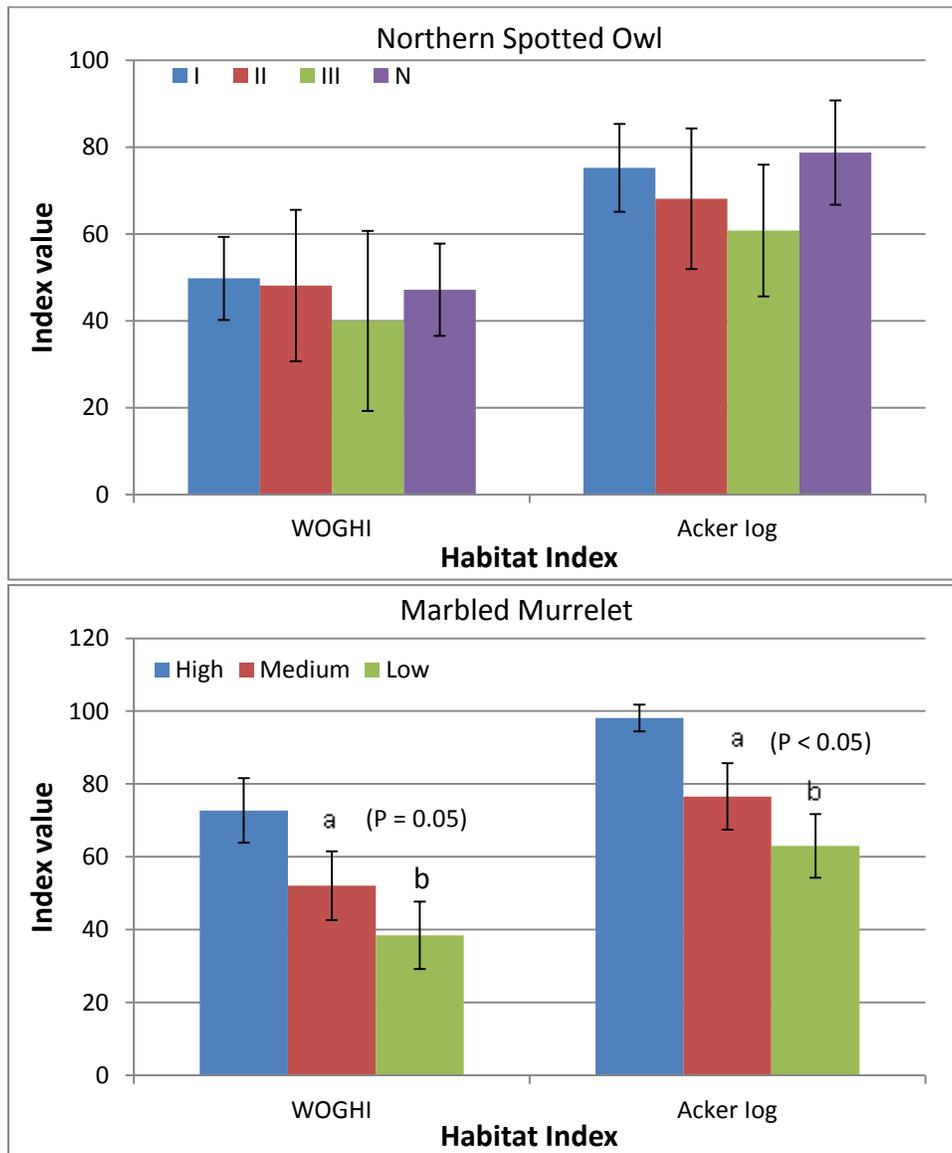


Figure 11. Mean value ( $\pm$  95% CI) of WOGHI and Acker  $I_{og}$  from old-growth PSPs for different habitat suitability classes of northern spotted owl (upper graph) and marbled murrelet (lower graph). Means are of all PSPs classified into a given northern spotted owl or marbled murrelet suitability class (see Appendix A). Number of PSPs in each northern spotted owl class are: I (nesting):  $n = 13$ ; II (foraging):  $n = 9$ ; III (dispersal):  $n = 7$ ; N (not suitable):  $n = 8$ . Number of PSPs in each marbled murrelet class are: high:  $n = 2$ ; medium:  $n = 18$ ; low:  $n = 17$ . Different letters above bars with P values indicate significant differences between classes.

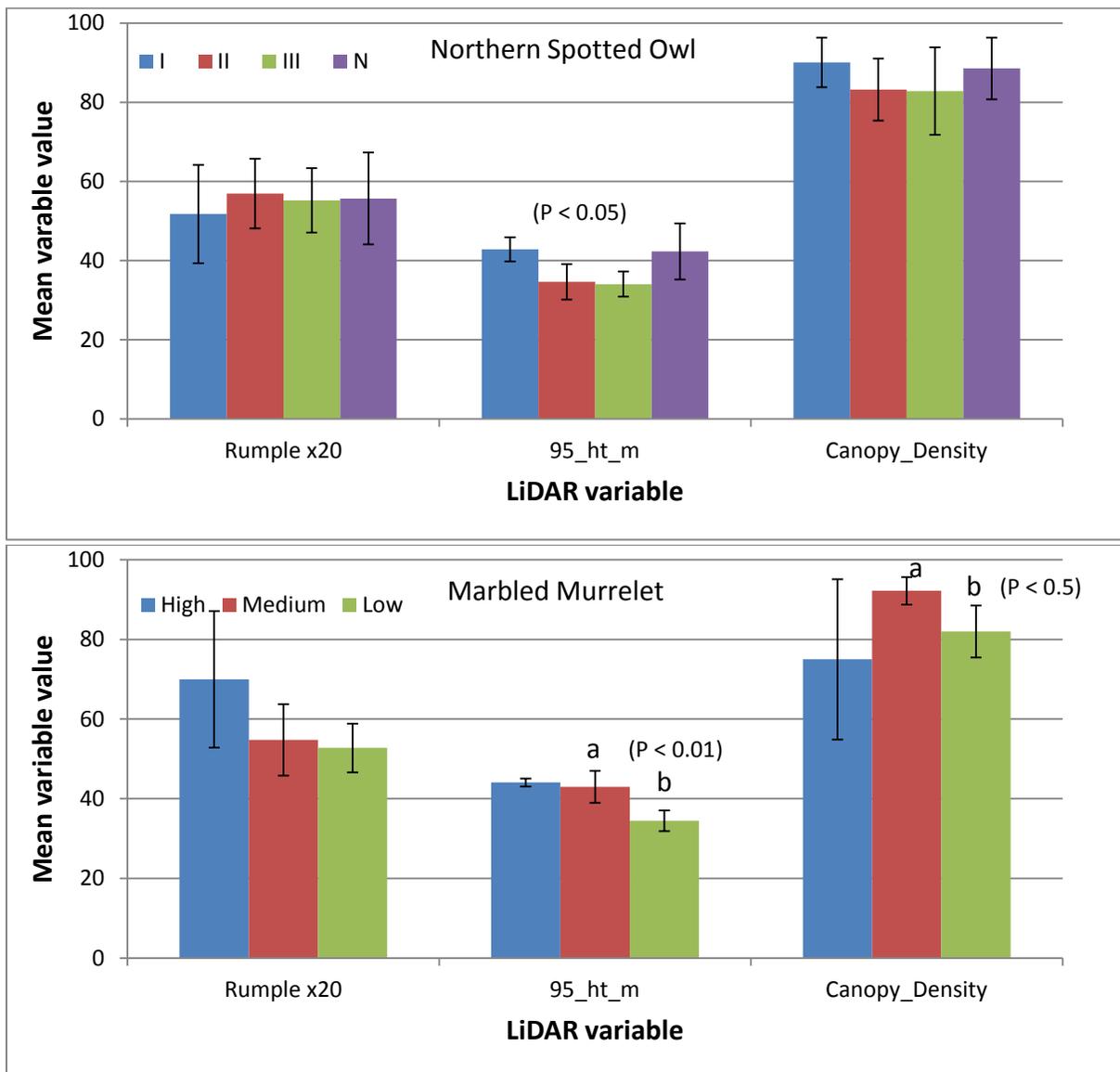


Figure 12. Mean value ( $\pm$  95% CI) of rumple (x20), 95 percentile height (m), and canopy density (%) from old-growth PSPs for different habitat suitability classes (high, medium, low) of northern spotted owl (upper graph) and marbled murrelet (lower graph). Means are of all PSPs classified into a given northern spotted owl or marbled murrelet suitability class (see Appendix A). Number of PSPs in each northern spotted owl class are: I (nesting):  $n = 11$ ; II (foraging):  $n = 9$ ; III (dispersal):  $n = 7$ ; N (not suitable):  $n = 7$ . Number of PSPs in each class are: high:  $n = 2$ ; medium:  $n = 18$ ; low:  $n = 17$ . Different letters above bars with P values indicate significant differences between classes.

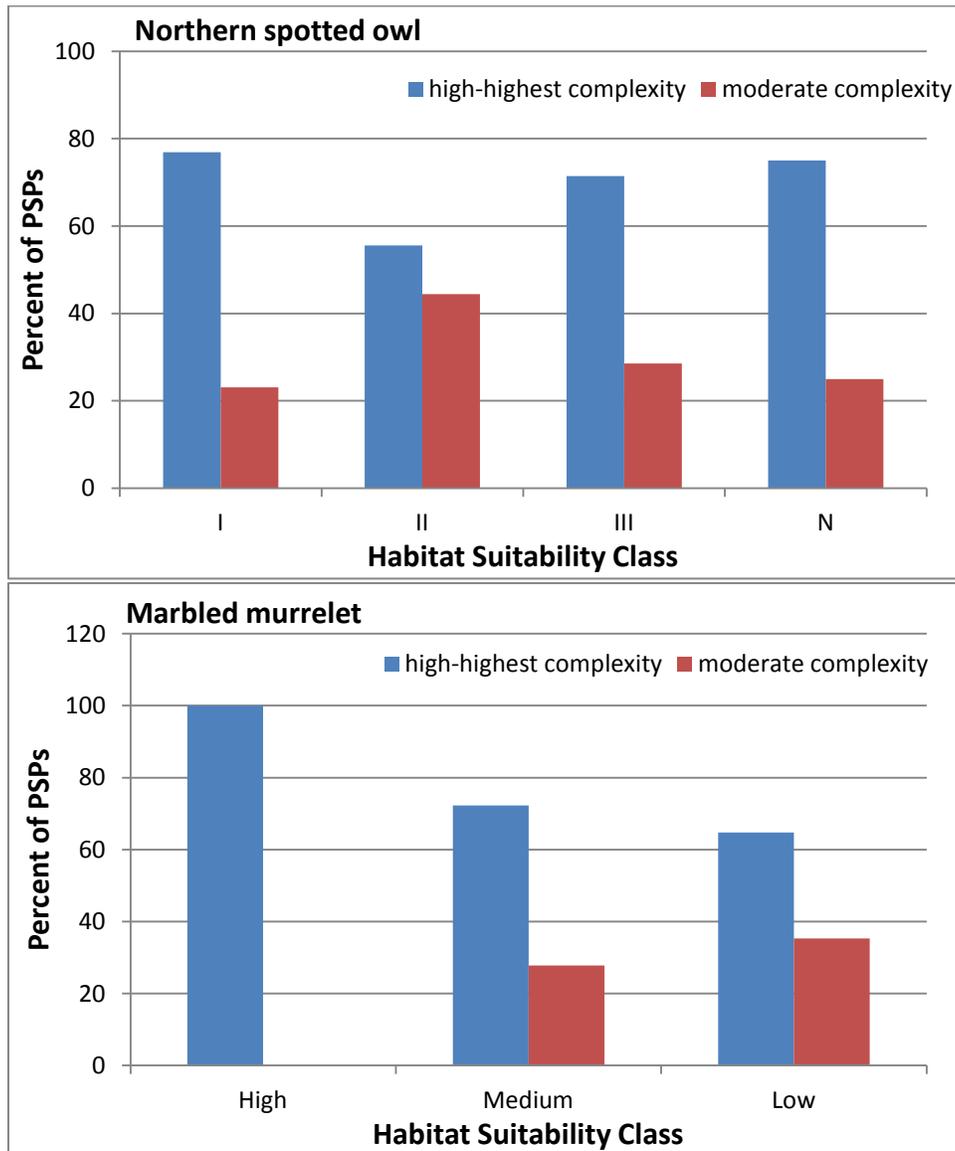


Figure 13. Percent of PSPs within a given suitability class for northern spotted owl (upper graph) and marbled murrelet (lower graph) that were either in the high-highest or moderate structural complexity classes defined by Kane (Figure 9). Number of PSPs in each northern spotted owl class are: I (nesting): n = 11; II (foraging): n = 9; III (dispersal): n = 7; N (not suitable): n = 7. Number of PSPs in each class are: high: n = 2; medium: n = 18; low: n = 17.

## Conclusions

This and previous work by Richards (2007) and Kane (2010a, 2010b, 2011, unpublished) provide a basis to differentiate old-growth structural variability using both field data (i.e., PSPs) and LiDAR-derived data. PSP data are useful for characterizing the range of variability in structural complexity of old growth, but have limited direct value in producing spatially-explicit maps of habitat suitability. Using either single or combining multiple LiDAR-derived variables that have been shown to be

correlated to field data of important old-growth structural characteristics, high resolution (i.e., 30 m pixel) maps of habitat structure were produced in this analysis that show considerable variation in habitat structure across old-growth forest in the CRMW, with that variation correlated to habitat suitability for at least one important wildlife species, marbled murrelet. However, use of the LiDAR-derived maps of habitat structure is limited when applied to individual species, unless the LiDAR variables used are fairly direct measures of structural attributes important in determining habitat suitability for a given species, such as 95 percentile tree height. The LiDAR-derived map of forest structure produced here from the data and classification provided by Van Kane are more appropriately used for characterizing old-growth forest habitat on a general basis with respect to suitability for a variety of old-growth dependent species.

I would conclude that we have only partially fulfilled the purpose of an old-growth forest classification as stated in the HCP ( "...to determine the relative habitat value of the remaining late-successional and old-growth forests in the watershed for both selected individual species and groups of species of concern..."). This and previous efforts have been successful at determining "relative" habitat value for old-growth dependent species and to some degree for marbled murrelet. However, it is evident from this analysis that the goal of classifying old-growth habitat on a landscape scale with respect to habitat suitability for a variety of individual wildlife species is not likely to be achieved with high accuracy, given the current information and technology available.

## Literature Cited

- Acker, S.A., T.A. Sabin, L.M. Ganio, and W.A. McKee. 1998. Development of old-growth structure and timber volume growth trends in maturing Douglas-fir stands. *Forest Ecology and Management* 104: 265-280.
- Franklin, J.F., T.A. Spies, and R. Van Pelt. 2005. Definition and inventory of old growth forests on DNR-managed state lands. Publication of Washington State Department of Natural Resources. June ([http://www.dnr.wa.gov/Publications/lm\\_ess\\_westside\\_oldgrowth\\_rpt.pdf](http://www.dnr.wa.gov/Publications/lm_ess_westside_oldgrowth_rpt.pdf))
- Kane, V.R., R.J. McGaughey, J.D. Bakker, R.F. Gersonde, L.A. Lutz, and J.F. Franklin. 2010a. Comparison between field- and LiDAR-based measures of stand structural complexity. *Canadian Journal of Forest Research* 40: 761-773.
- Kane, V.R., J.D. Bakker, R.J. McGaughey, L.A. Lutz, R.F. Gersonde, and J.F. Franklin. 2010b. Examining conifer canopy structural complexity across forest ages and elevations with LiDAR data. *Canadian Journal of Forest Research* 40: 774-787.
- Kane, V.R., R.F. Gersonde, L.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.

- McCune, B. and M. J. Mefford. 2006. PC-ORD. Multivariate analysis of ecological data. Version 5.32 MjM Software, Gleneden Beach, Oregon, U.S.A.
- Richards, B. 2007. Old forest classification report: Cedar River Municipal Watershed. Unpublished draft report, Watershed Services Division, Seattle Public Utilities. February.
- Spies, T.A. and Franklin, J.F. 1991. The structure of natural young, mature, and old-growth Douglas-fir forests in Oregon and Washington. Pages 91-109 in: L.F. Ruggiero et al, Wildlife and Vegetation of Unmanaged Douglas-fir Forests, Pacific Northwest Research Station General Technical Report PNWGTR-285.
- Tear, L. 2006. Report of data analysis of permanent sampling plots at Cedar River Municipal Watershed. Unpublished draft report submitted to Watershed Services Division, Seattle Public Utilities. May.

## Appendix A – Attributes of Permanent Sampling Plots occurring in old-growth forest in the CRMW

PSP Number	Map plot number	<i>I</i> <sub>og</sub>	DNR Weighted OGI	Kane class number	Kane class ranking	Rumple	95p ht	Canopy density	Dominant species	Elev (ft)	Northern spotted owl suitability class	Marbled murrelet suitability class	Basin
2109054192	1	96	68	8	1	3.1	85.3	85.3	WH	3,826	I	H	Boulder
2109142128	2	100	77	8	1	3.9	64.7	64.7	RC	2,976	I	H	Rex
2109142222	3	100	88	8	1	3.7	81.0	81.0	WH	2,940	II	L	Rex
2109154010	4	100	81	8	1	3.5	83.1	83.1	WH	3,008	II	M	Rex
2109162102	5	100	79	8	1	3.0	88.4	88.4	SF	3,590	II	L	Lindsay
2109224032	6	97	72	8	1	3.2	82.9	82.9	MH	3,874	III	M	Rex
2110034038	7	54	32	6	3	-----	-----	-----	SF	3,901	I	L	Bear
2110044092	8	52	30	1	5	1.3	100.0	100.0	WH	2,643	I	M	Upper Cedar
2110061128	9	79	59	5	2	1.8	97.1	97.1	WH	3,101	I	M	Upper Cedar
2110062252	10	76	51	5	2	2.9	81.3	81.3	WH	3,182	I	M	Findley
2110073028	11	36	26	1	5	2.4	97.1	97.1	SF	4,278	II	L	Pine

PSP Number	Map plot number	$I_{og}$	DNR Weighted OGI	Kane class number	Kane class ranking	Rumple	95p ht	Canopy density	Dominant species	Elev (ft)	Northern spotted owl suitability class	Marbled murrelet suitability class	Basin
2110073128	12	48	24	1	5	3.1	61.1	61.1	SF	4,199	III	L	Pine
2110083128	13	100	76	8	1	4.7	90.1	90.1	DF	3,130	I	M	Seattle
2110102128	14	84	56	3	4	1.4	93.6	93.6	WH	2,542	I	M	N Fork Cedar
2110121126	15	55	35	3	4	-----	-----	-----	WH	2,727	I	M	N Fork Cedar
2110121230	16	48	22	5	2	3.4	94.4	94.4	DF	3,338	III	M	N Fork Cedar
2110134034	17	43	25	6	3	2.4	86.0	86.0	SF	4,320	III	L	N Fork Cedar
2110141094	18	54	31	5	2	1.9	98.7	98.7	WH	3,326	I	M	N Fork Cedar
2110163128	19	93	63	5	2	2.7	93.1	93.1	WH	3,216	N	M	Goat
2110164128	20	60	37	5	2	3.3	70.1	70.1	WH	3,501	II	L	Goat
2110213128	21	50	25	8	1	2.3	64.2	64.2	SF	4,469	III	L	Goat
2110224026	22	76	39	8	1	4.0	66.4	66.4	WH	2,918	N	L	S Fork Cedar
2111053224	23	63	30	5	2	2.3	92.7	92.7	SF	3,859	N	L	N Fork Cedar
2111064128	24	58	33	6	3	3.3	80.0	80.0	DF	3,636	II	M	N Fork Cedar

PSP Number	Map plot number	<i>I</i> <sub>og</sub>	DNR Weighted OGI	Kane class number	Kane class ranking	Rumple	95p ht	Canopy density	Dominant species	Elev (ft)	Northern spotted owl suitability class	Marbled murrelet suitability class	Basin
2111183128	25	82	50	6	3	2.3	85.4	85.4	SF	4,465	I	L	N Fork Cedar
2208134128	26	55	34	1	5	1.5	96.4	96.4	WH	2,290	II	L	Chester Morse
2208141124	27	100	61	8	1	3.6	96.7	96.7	DF	2,617	N	M	Chester Morse
2208161128	28	81	89	5	2	3.0	100.0	100.0	WH	3,000	III	M	Fish
2208261128	29	88	53	5	2	2.9	100.0	100.0	WH	3,544	I	M	M Fork Taylor
2208264128	30	79	56	3	4	2.3	95.7	95.7	RC	3,011	N	L	M Fork Taylor
2209143098	31	51	19	1	5	2.3	61.1	61.1	MH	4,376	II	L	McClellan
2209164128	32	100	65	3	4	1.4	100.0	100.0	DF	2,706	N	M	Chester Morse
2209243060	33	57	23	1	5	2.0	91.2	91.2	WH	3,430	III	M	Upper Cedar
2209361128	34	55	37	8	1	3.4	84.9	84.9	WH	2,252	N	M	Upper Cedar
2210341128	35	53	35	3	4	2.6	91.7	91.7	WH	3,679	II	L	Bear
2210344128	36	58	27	5	2	2.0	95.0	95.0	SF	3,856	I	L	Bear
2210363128	37	64	28	5	2	2.6	78.9	78.9	SF	3,916	N	L	N Fork Cedar