Characterizing and Ranking the Importance of Fire Refugia in the Northwestern US

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Authorization to Submit Thesis

This thesis of Anthony J. Martinez, submitted for the degree of Master of Science with a Major in Natural Resources and titled "Characterizing and Ranking the Importance of Fire Refugia in the Northwestern US," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

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Abstract

Fire refugia are ecologically important features on the landscape. Fire refugia are becoming an increasingly popular topic in the discussion of how to improve forest resiliency in the face of shifting fire regimes. Presently, land managers have not been able to utilize fire refugia in their management plans largely due to the challenges associated with locating and prioritizing them. In this thesis, I aimed to address these knowledge gaps by identifying and characterizing high-value fire refugia in the Pacific Northwest of the United States.

Using an existing database of unburned islands from 1984 to 2014, I identified fire refugia that remain unburned over multiple fires. I sampled points in both these persistent fire refugia and in areas burned by wildfire. At these sample points in both persistent fire refugia and in areas burned by wildfire, I compared several topographical and other geospatial metrics of these groups. The analysis revealed that the biophysical setting underlying persistent unburned islands differs between forests and rangelands, and differs from burned areas.

I then investigated the perceived importance of criteria used to identify high-value fire refugia by surveying land managers within the US Pacific Northwest. Participants scored a predetermined list of criteria by their importance for determining the value of fire refugia. The results indicate that respondents generally organized criteria into two groups: human infrastructure and wildlife habitat. However, there was little consensus among respondents in their scoring of fire refugia importance criteria, suggesting that a single fire refugia ranking model for the entire region is not feasible. More targeted approaches that reduce the scale or scope of the ranking model are required.

Finally, I developed a reduced-scope fire refugia importance ranking model for the northern spotted owl (*Strix occidentalis caurina*) using a multi-criteria decision analysis framework. I then applied the model to four fires in the East Cascades and compared the patch shape, topography, and forest structure of high importance fire refugia and low importance fire refugia. The research shows that higher ranked refugia tended to have structures that were more characteristic of later successional stage forests than lower ranked refugia.

This thesis provides the basis for the identification of high-value fire refugia, potentially allowing land managers to prioritize high-value fire refugia for restoration activates after a fire. Further research is needed to improve their applicability of reduced-scope and reduced-scale fire refugia ranking models to land management.

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Dedication

To my family, especially my wife Jessica, for their unyielding encouragement and love.

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List of Abbreviations

AGB	Aboveground biomass
BLM	US Bureau of Land Management
CART	Classification and regression tree
CosAsp	Cosine of the aspect
D	Kolmogorov-Smirnov test statistic
DBH	Diameter at breast height
dNBR	Differenced Normalized Burn Ratio
DNR	Washington state Department of Natural Resources
DP	Degree of persistence
EEMS	Environmental Evaluation Modeling System
ETM	Enhanced Thematic Mapper
FRAC	Fractal dimension index
FRG	Fire regime group
GAP	Gap Analysis Program
GIS	Geographic information system
IDL	Idaho Department of Lands
IFTDSS	Interagency Fuel Treatment Decision Support System
KDE	Kernel density estimation
MCDA	Multiple criteria decision analysis
MTBS	Monitoring Trends in Burn Severity
NBR	Normalized Burn Ratio
NED	National Elevation Dataset
NGO	Non-governmental organization
NNE	North-northeast
NPS	US National Park Service
ODFW	Oregon Department of Fish and Wildlife
PDF	Probability density function
PGIS	Participatory geographic information system (GIS)
RdNBR	Relativized differenced Normalized Burn Ratio
SRTM	Shuttle Radar Topography Mission
SSW	South-southwest

TM	Thematic Mapper
TNC	The Nature Conservancy
TPI	Topographic position index
TRASP	Transformed aspect
TRI	Terrain ruggedness index
TWI	Topographic Wetness Index
USFS	US Forest Service
USFWS	US Fish and Wildlife Service
USGS	US Geological Survey
WFDSS	Wildland Fire Decision Support System

Statement of Contribution

The work in this thesis represents a collaboration between multiple authors: me, Anthony Martinez (AJM), Arjan Meddens (AJHM), Crystal Kolden (CAK), Andrew Hudak (ATH), and Eva Strand (EKS). While all authors contributed to the work, I, Anthony Martinez, am primarily responsible for the authorship of this work. The specific contributions of all authors are described below.

Chapter 2: AJM, EKS, and AJHM conceptualized the idea. AJM, AJHM, and EKS developed the methodology. AJM developed the software. AJM performed the data validation. AJM performed the formal analysis. AJM performed the investigation. AJM and AJHM provided the resources. AJM performed the data curation. AJM wrote and prepared the original draft. AJHM, CAK, EKS, and ATH reviewed and edited the manuscript. AJM created the visualizations. AJHM supervised the project. AJM administered the project. AJHM and CAK acquired the funding.

Chapter 3: AJM and AJHM conceptualized the idea. AJM, AJHM, and C.A.K developed the methodology. AJM developed the software. AJM performed the data validation. AJM performed the formal analysis. AJM performed the investigation. AJM and AJHM provided the resources. AJM performed the data curation. AJM wrote and prepared the original draft. AJHM, ATH, and CAK reviewed and edited the manuscript. AJM created the visualizations. AJHM supervised the project. AJM administered the project. AJHM and CAK acquired the funding.

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Chapter 1: Introduction

Fire is a dominant driver of ecological change throughout the forests of the Pacific Northwest (Agee 1993). While ecosystems are well-adapted to recover from disturbances under natural disturbance regimes (Peterson et al. 1998), disturbance regimes, and fire regimes have changed since Euro-Americans settled in the West. Both the area burned and total number of wildfires across the western United States have increased over the last century (NIFC 2019) due to land use changes (Hessburg et al. 2005), fire exclusion (Rollins et al. 2001), an increasing wildland urban interface (Radeloff et al. 2018), and anthropogenic climate change (Abatzoglou and Williams 2016). Recent research has provided evidence that these changes have resulted in forests' decreasing ability to respond to and recover from these disturbances (Stevens-Rumann et al. 2018). As declining forest resiliency becomes an increasingly pressing issue for land managers, one potential mechanism for maintaining or enhancing forest resiliency is the promotion of fire refugia (Lindenmayer et al. 2006; Meddens et al. 2018b).

As fire burns across the landscape, changes in vegetation composition and structure, topography, and weather conditions create a heterogeneous mosaic of fire effects (Cumming 2001). This mosaic—created by heterogeneity in vegetation age, species composition, and disturbance history—facilitates biodiversity and ecological functioning of associated ecosystems. Fire refugia are defined as patches of vegetation that are less severely or less frequently affected by fire, relative to the surrounding matrix, and which are important for the persistence of biota (Meddens et al. 2018b). These fire refugia serve an important ecological function by containing unique habitat conditions not present in the directly surrounding forest matrix (Delong and Kessler 2000). During a fire, they promote organisms' survival by providing shelter from flames and radiant heat (Robinson et al. 2013). After a fire, refugia can allow for longer-term ecological persistence and recolonization of vegetation by acting as seed sources (Viedma et al. 1997; Charron and Greene 2002; Burton et al. 2008) and as wildlife habitat (Delong and Kessler 2000; Franklin et al. 2000b).

Although they serve important ecological functions, fire refugia have generally not been included in forest management plans for two primary reasons: 1) fire refugia are a novel concept in land management and have not yet been prioritized by land managers (Meddens et al. 2018b), and 2) a method for identifying high-value fire refugia does not yet exist (Meddens et al. 2018a). Meddens et al. (2016, 2018a) compiled a database of unburned islands within the inland Pacific Northwest. Their model used remotely sensed data and classification trees to identify patches of unburned vegetation within the perimeter of wildland fires that burned between 1984 and 2014 (Meddens et al. 2016). While this provided an effective means for identifying unburned areas, it did not enable assessment of the patches' ecological value. To identify high-value fire refugia from these unburned areas, it is necessary to develop a ranking system to assess the importance of each of these unburned areas.

In this thesis, I aimed to identify and characterize high-value fire refugia in order to address these gaps within the scientific literature. I used geographic information systems (GIS), spatial modeling, survey questionnaires, and multicriteria decision analysis (MCDA) to address the question: where are high-value fire refugia located and how are they characterized?

In Chapter 2, I address persistent fire refugia and evaluate how they differ from the surrounding landscape. To produce these findings, I identified persistent fire refugia by determining the intersection of overlapping fire refugia from multiple fires within the Inland Northwest, then exploring the spatial and temporal characteristics of persistent unburned areas. Additionally, I examined multiple patch shape, topographic, and fuel type characteristics of persistent unburned islands and compared them to characteristics of the surrounding landscape. This chapter is currently in press at the peer-reviewed journal: *Fire Ecology*.

In Chapter 3, I present findings on the criteria land managers consider important for ranking the importance of fire refugia. To collect relevant data, I surveyed 33 land managers in the Pacific Northwest using an online questionnaire. I asked them to identify criteria that they would consider important for fire refugia and compared the results across demographic groups. I have submitted this chapter to the peer-reviewed journal *Fire*, and it is currently under review.

In Chapter 4, I provide a fire refugia importance ranking model for the northern spotted owl (*Strix occidentalis caurina*). I developed the model using a multi-criteria decision analysis framework with a user-friendly interface, and with model parameters that can be easily changed to meet the needs of a specific end user. I applied the model to four fires in the eastern Cascades and compared the patch shape, topography and forest structure of high importance fire refugia to low importance fire refugia. I intend to submit this chapter for inclusion in a peer-reviewed journal.

In Chapter 5, I present the overall conclusions of the thesis. This includes a summary of the important results, the context of these results within the fire ecology field, management implications, and directions for future research.

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Chapter 2: Characterizing persistent unburned islands within the Inland Northwest

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Abstract

In the Inland Pacific Northwest of the United States, fire is a dominant driver of ecological change. Within wildfire perimeters, fire effects often vary considerably and typically include remnant patches of unburned islands. As fires reburn the landscape, some unburned islands remain persistently unburned. These persistent unburned islands can serve an important ecological function as fire refugia; however, their characteristics have not been quantified. The objective of this study was to assess the characteristics of persistent unburned islands and compare them to the burned areas that surround them. Using an existing database of unburned islands from 1984 to 2014, overlapping unburned islands were delineated. We sampled points in both persistent unburned islands and in areas burned by wildfire. At these sample points we derived several topographical and other geospatial metrics, and we compared the characteristics of these groups. Because the study area covers many ecosystems, we stratified the analysis by different fire regime groups.

Our analysis revealed that persistent unburned islands are not randomly distributed across the landscape. While the topography and vegetation fuel type that underlie persistent unburned islands differ from burned areas, these differences are dependent upon fire regime group and are less pronounced than what other studies have found. The topographic features that differed the most between persistent unburned islands and burned areas were terrain ruggedness, slope, and transformed aspect. We also found that as unburned islands increased in persistence (i.e., remained unburned for an increasing number of overlapping fires), they decreased in size and shape complexity.

Our research shows that the biophysical setting underlying persistent unburned islands differs between forests and rangelands, and also differs from burned areas, which has potential applications for fire refugia prediction and management. Characterizing fire refugia and understanding the

processes that contribute to their creation and maintenance will be important for land management as climate changes and increasingly large areas are affected by wildfire.

1. Introduction

The northwestern United States has experienced a considerable increase in fire activity due to anthropogenic climate change, largely due to summertime drying and warming conditions (Abatzoglou and Williams 2016). This trend is expected to continue, yielding increased frequency of megafires (Barbero et al. 2015). Such increases are worrisome not only due to the greater potential for disasters and negative impacts to humans (Bowman et al. 2017), but also because changing fire regimes may have considerable cascading ecological consequences (Smith et al. 2016a). As such, there is great concern for a loss of forest resilience associated with these fires leading to land cover transitions and loss of biodiversity and ecosystem services (Vaillant et al. 2016; Stevens-Rumann et al. 2018); this is magnified for areas where repeat wildfires alter forest recovery trajectories (Stevens-Rumann and Morgan 2016). Within these repeat fire scars, however, there are unburned islands that, through multiple fires, have escaped or perhaps resisted burning. Persistent unburned islands may yield critical insights to restoring and maintaining forest resilience (Kolden et al. 2015a), but little is known about what makes them persistent, nor the attributes of such landscape features. In general, areas that function as refugia from fire continue to be under-analyzed in the ecological literature, despite the desire to manage ecosystems to support formation of such resilient features (Meddens et al. 2018b). This knowledge gap highlights a critical need that must be addressed to better understand fire interaction with ecosystems, particularly as climate change amplifies the effects of changing ecological disturbance regimes.

Fire regimes in the coniferous forests of the Pacific Northwest vary greatly in response to the top-down (e.g., steep climatic gradients associated with the complex topography of the region) and bottom-up controls (e.g., wide range of variation in local topography and vegetation types; Gill and Taylor 2009). In biophysical settings that support cooler and moister forest types (i.e., higher elevation, northerly aspects), the fire regime is typified by lower frequency, higher intensity, stand-replacing fires; whereas forests that occur in warmer, drier settings (i.e., lower elevation, southerly aspects) are adapted to more frequent, lower intensity surface fires (Agee 1993). This general fire regime pattern was altered by anthropogenic factors over the past century. At lower elevations in particular, fire exclusion policies during the mid-20th century effectively lengthened fire return intervals relative to the historical norm, thus accumulating fuels to induce more stand-replacing fires (Rollins et al. 2001; Morgan et al. 2008, 2017). A warming and drying climate and longer fire seasons since the latter 20th century (Higuera et al. 2015) have been exacerbating the size of fires and area burned in the western USA, and these trends are forecasted to continue (Littell et al. 2009; Westerling 2016).

Fire frequency and its inverse, fire return interval, are important fire regime attributes for characterizing burn area and reburn dynamics. An increase in fire activity and area burned during the past century has fueled research related to how often areas burn in repeated fires and how historical fires impact subsequent fires (Harvey et al. 2016; Stevens-Rumann and Morgan 2016; Stevens-Rumann et al. 2016; Prichard et al. 2017). Research in the Northern Rocky Mountain forests supports the hypothesis that burn severity is lower in wildfires burning in relatively short succession (< 10 years) following a previous fire (Harvey et al. 2016). Stevens-Rumann and Morgan (2016) found that lower severity levels in subsequent fires could be observed for as long as three decades in mixed conifer forests, and Morgan et al. (2017) found evidence for such legacy fire effects persisting for decades longer in higher elevation forests. Because the legacy of fires can alter the consequences of subsequent fires and may even serve as a barrier to fire spread (Prichard et al. 2017), legacy fire perimeters have been suggested as useful in fire suppression tactics (Stevens-Rumann and Morgan 2016). In other ecosystems, areas that have reburned exhibit greater burn severity (van Wagtendonk et al. 2012) due to the accumulation of fuels and conversion to a different fuel type. This emphasizes the need for further study of reburns and their associated effects on organisms and ecosystem processes (Prichard et al. 2017). At the landscape scale, quantifying reburns, fire return interval, and time between individual subsequent wildfires is commonly estimated from spatial fire atlas data (e.g., Eidenshink et al. 2007; Gibson et al. 2014) by overlaying historical fire perimeters to determine the number of times an area has burned or the time between subsequent fires. A shortcoming of spatial fire perimeter data is their inability to provide information about unburned areas within the fire perimeter (Kolden and Weisberg 2007; Kolden et al. 2015b). Advances in remote sensing of wildfire heterogeneity, however, have improved detection of fire edges (e.g. Smith et al. 2016b), facilitating studies to accurately delineate unburned islands over large areas (Meddens et al. 2016).

Recent research has focused on quantifying the unburned area within fire perimeters (Kolden et al. 2012; Meddens et al. 2016), and both characterizing these islands across space and time (Meddens et al. 2018a) and determining predictors of fire refugia formation (Krawchuk et al. 2016). One of the limits of such studies, however, is that the formation of unburned islands is a function of both relatively static and highly dynamic environmental conditions. While topography and geomorphology remain relatively static over decades to centuries, fuels fluctuate considerably in both structure and mass over the same period. Similarly, fuels vary little on an annual temporal scale, but weather and climate are highly dynamic over comparatively short periods, from hours to months. These factors all contribute to the formation of both ephemeral (single-event) and persistent (multiple-event) unburned islands and fire refugia (Meddens et al. 2018b). For example, some unburned islands form due to persistently wet topographic depressions (Krawchuk et al. 2016), while others form where vegetation has not yet matured enough to become fuel. In one study, fire refugia from a prior event burned more severely than the surrounding vegetation in a subsequent fire due to fuel maturity (Kolden et al. 2017), while Kolden et al. (2015a) highlighted the geographic differences between unburned islands associated with antecedent versus coincident climatic conditions (e.g., winter snowpack supporting vegetation growth versus summer drought making it available to burn). Further complicating attempts to identify drivers of unburned island formation is the role of fire management; some islands have formed entirely because humans used wildfire suppression actions or fuel breaks to prevent advancement and consumption (Kolden and Abatzoglou 2018 in review). As such, studies assessing formation of ephemeral refugia following a single fire event are less conclusive. Thus, there is a critical gap in identifying the factors that contribute to formation of persistent unburned islands and fire refugia through multiple wildfires across regions. Kolden et al. (2017) found that prior fire refugia failed to persist through a 2012 wildfire, and their limited study of a single fire is the only one to date to assess refugia persistence through multiple fire events. The unburned island database developed by Meddens et al. (Meddens et al. 2018a) provides an opportunity to fill this knowledge gap.

Our objectives in this study were to (1) compare the patch metrics of persistent unburned islands (i.e., unburned landscape patches that have remained unburned through at least two fires) to areas that were classified as unburned only once, (2) explore the spatial and temporal characteristics of overlapping fires and their persistent unburned areas, and (3) evaluate differences in landscape characteristics (e.g., topography, land cover type, fuel type) between persistent unburned areas and areas that were burned at least once over the study period (1984–2014).

2. Methods

2.1 Study Area

The study area is located within the Inland Pacific Northwest, including Washington and Oregon east of the Cascade Crest and Idaho (Figure 2.1). Because this study makes use of their unburned island database, the extent matches that of Meddens et al. (Meddens et al. 2018a). The study area (approximately 499,200 km^2) is covered by 35% forest, 42% rangeland (including grassland, shrublands, and semi-desert), with the remaining 23% including water, agriculture, and urban development (US Geological Survey Gap Analysis Program 2011). The high elevations in the west (Cascade Mountains) and the east (Rocky Mountains) of the study area are predominantly covered with subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.) and Engelmann spruce (*Picea engelmannii* Parry ex Engelm.) forests, whereas the middle elevations are primarily covered with mixed-conifer forests, transitioning to ponderosa pine forest at lower elevations. The Columbia Basin, in the middle of the study area, is primarily rangeland (including grass and shrub-dominated areas) and includes a substantial amount of agricultural lands (Franklin and Dyrness 1973). From 1984 to 2014, 16.5% of the study area has burned at least once, and 9.9% of the total area remained unburned within fire perimeters through at least one fire.

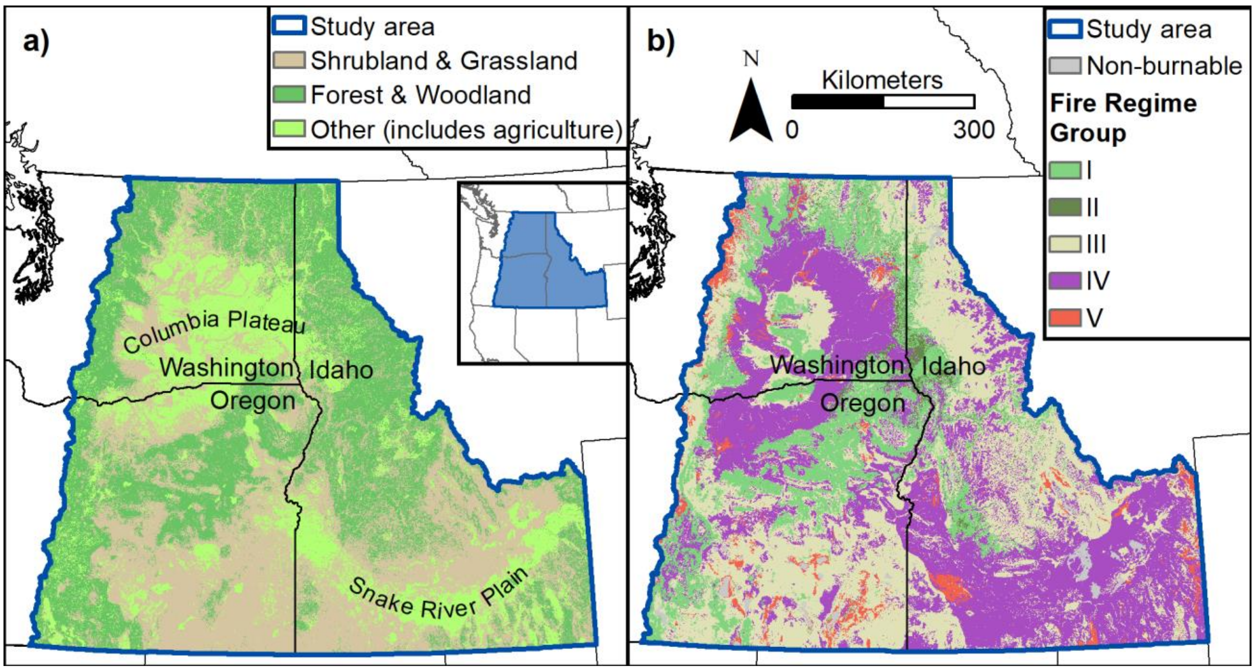

Figure 2.1. The study area, encompassing the Inland Northwest. The inset map shows the study area location within the western United States. (a) Landcover was aggregated from the USGS GAP landcover data (30-m resolution). (b) Fire regime groups (FRGs) across the study area. Note: The Snake River Plains and Columbia Plateau are predominantly agricultural lands, so their fire regime groups are uncertain and may change over time.

2.2 Datasets

The datasets used for this study include a recently developed unburned island database (Meddens et al. 2018a), a Landsat-based land cover type dataset (US Geological Survey Gap Analysis Program 2011), topographical indices derived from a digital elevation model, and fire regime groups (FRG; Barrett et al. 2010; LANDFIRE 2011a; see Figure 1.1b) and fuel models (Anderson 1982; LANDFIRE 2011b) acquired from LANDFIRE. All raster datasets used in this analysis were 30-m resolution products. Meddens et al. (Meddens et al. 2018a) developed a database of unburned islands for the Inland Pacific Northwest for fires from 1984 to 2014 using classification trees (CART; Breiman et al. 1984) and spectral vegetation indices derived from Landsat data. They used fire perimeters obtained from Monitoring Trends in Burn Severity (MTBS; Eidenshink et al. 2007), which records wildland fires > 404 ha (1000 acres). While MTBS fire perimeter polygons were used, the classification of burned and unburned pixels by Meddens et al. (Meddens et al. 2018a) for their database was completed following methods described in Meddens et al. (2016) and did not utilize the MTBS burn severity raster data. Unburned islands were detected with a minimum size threshold of two Landsat pixels (0.18 ha). Their algorithm identified 701,188 unburned islands within 2,318 fires (including 100 prescribed fires) with an overall accuracy of a subset of fires of 89% (Meddens et al. 2016).

Land cover data were classified from the USGS GAP land cover analysis dataset (US Geological Survey Gap Analysis Program 2011). The GAP land cover classifications were determined using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) acquisitions.

To calculate the topographical indices (Table 2.1), we used the 30-m resolution National Elevation Dataset (NED) which is derived from the best-available local digital elevation data, including lidar or Shuttle Radar Topography Mission (SRTM) data.

Table 2.1. Definitions for the shape and topographic indices used in this analysis.

Index	**Abbrev.**	**Formula**	**Notes**	**Reference**
Fractal Dimension Index	FRAC	$\frac{2\ln(.25\, p_{ij})}{\ln(a_{ij})}$	Shape complexity, from less complex to more complex	(McGarigal and Marks 1995)
Topographic Position Index	TPI	Difference between the value of a cell and the mean elevation of the surrounding cells		(Weiss 2001)
Topographic Wetness Index	TWI	$\ln\frac{upslope\ drainage}{\tan(slope)}$	Measure of hydrologic pooling potential	(Beven and Kirkby 1979)
Terrain Ruggedness Index	TRI	Mean of the absolute differences between the elevation of a cell and the elevation of the surrounding cells		(Riley et al. 1999)
Slope	Slope	Slope in degrees	Steepness	–
Cosine of the aspect	CosAsp	$\cos(Aspect)$	Gradient from north to south aspects	–
Transformed aspect	TRASP	$\frac{-\cos(Aspect - 30) + 1}{2}$	Gradient from northeastern to southwestern aspects	(Roberts and Cooper 1989)

Notes:
p_{ij}= perimeter (m) of patch ij
a_{ij} = area (m2) of patch ij
TPI and TRI were calculated with a 7x7 focal window (90 m in each direction)
Aspect is azimuth in degrees

The Topographic Position Index (TPI; Weiss 2001; De Reu et al. 2013) identifies where, topographically, each raster cell exists by comparing the elevation of each cell with the mean elevation of the surrounding cells. A TPI ≈ 0 indicates a constant or near-constant slope, which includes flat areas, mid-slopes and saddles. TPI > 0 indicate ridges and upper slopes and TPI < 0 indicate valleys and lower slopes. The TWI (Topographic Wetness Index; Beven and Kirkby 1979; McKenzie and Ryan 1999) is an indicator of soil and water movement and has been shown to be highly correlated to soil moisture. Greater TWI indicates more runoff and less water accumulation, while lower TWI values indicate less runoff and more water accumulation. The Terrain Ruggedness Index (TRI; Riley et al. 1999) identifies the degree of topographic ruggedness by comparing the mean of the absolute differences between the elevation of each cell and that of the surrounding cells. Greater TRI indicates greater topographic ruggedness. TPI and TRI were calculated with a 7x7 focal window, 90 m in each direction. For these indices, focal frames had third order queen contiguity including all diagonals (Figure A.1). Two aspect-derived indices were used to explore the aspect of the persistent unburned islands: the cosine of the aspect (Figure A.2) and the transformed aspect (TRASP; Roberts and Cooper 1989). While the cosine of the aspect was considered for analysis, TRASP was used as the primary aspect-derived index for visualization. This aspect transformation, a gradient from north-northeast (generally the coolest and wettest orientation in the study area) to south-southwest (generally the hottest and driest), is an indicator of solar radiation and localized climate (Moisen and Frescino 2002; Hudak et al. 2008).

Note that these datasets have certain characteristics associated with them which limit our analysis. The unburned islands database and all raster datasets (including the fuel model data) have a 30-m spatial resolution which masks fine-scale variability. Fire perimeter mapping is subjective, frequently resulting in mapping error (Kolden and Weisberg 2007), including numerous surface conditions in which remotely sensed data would incorrectly identify unburned areas (Kolden et al. 2012). Further, delimiting unburned islands using spectral reflectance data resulted in an 11% error rate (Meddens et al. 2016).

2.3 Data analysis

The areas where unburned islands overlap across multiple fires were identified as persistent fire refugia. After converting the unburned island database (Meddens et al. 2018a) to a shapefile, the unburned polygons were overlaid in a geographic information system (GIS), and any overlapping areas were converted into unique polygons (see Figure 2.2). The degree of persistence (DP; the number of fires through which an unburned island has remain unburned) was then assigned to each of these overlapping areas. We assumed that the status of each 900 m^2 Landsat pixel was either unburned or burned, and the status of the pixel was uniform across the pixel.

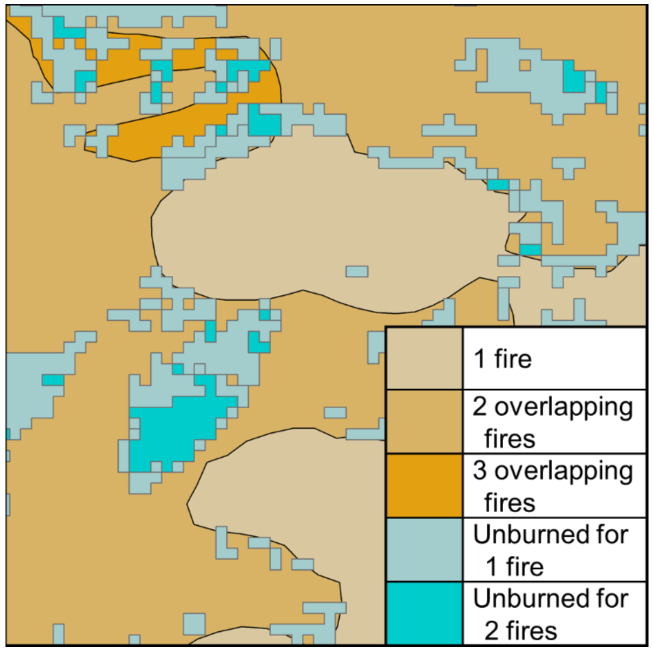

Figure 2.2. Conceptual diagram of unburned island persistence calculations. Fire perimeters are shown in semi-transparent brown, unburned islands shown in semi-transparent cyan. The degree of persistence, the number of fires a patch has remained unburned, is labeled on each unburned island patch.

2.3.1 Patch metrics

To assess the patch metrics of individual unburned areas, we extracted two unburned patch metrics for each unburned patch within the database: patch area (m^2) and Fractal Dimension Index (FRAC; McGarigal and Marks 1995). FRAC has a range from one to two; as FRAC approaches two, patches have perimeters that become highly convoluted; as FRAC approaches one, patches become simpler (more round or square). The distributions of unburned island areas for each DP were compared to one another in a series of two-sample Kolmogorov-Smirnov tests. This test reports the maximum difference between the two cumulative density distributions (*D*). It can detect differences in medians, variances, and distributions (Corder and Foreman 2014). This allowed us to assess if there were truly differences in the areas of unburned islands as they remain unburned for additional fires. These tests were repeated on the FRAC data to asses if there were also differences in patch shape complexity as islands remained unburned over additional fires.

For each patch shape characteristic, kernel density estimations were plotted along with the median value for visualization. Kernel density estimation is a nonparametric method of estimating the probability density function (PDF) of a given variable (Hollander et al. 2014). When integrated over a given range, the area under the PDF curve is the probability within the specified range (Shynk 2012). They are useful for visualizing the distribution of these data and have the advantage over histograms of showing a continuous probability density estimate, whereas histograms jump from bin to bin

(Hollander et al. 2014). The median was selected over the arithmetic mean to show central tendency because many of these datasets are highly right-skewed with extreme outliers and heavy tails.

2.3.2 Spatial patterns

To identify the locations that were subject to heightened fire activity (i.e., reburning) and increased proportions of (persistent) unburned areas, we calculated the proportion of area covered by fire perimeters and unburned islands for all fire perimeters and unburned islands in the database. These proportions were summarized within 6-km by 6-km grid cells. We present the proportion of area burned at least once and the proportion of area burned at least twice (i.e., reburned). Likewise, we present the proportion of area of both unburned islands and persistent unburned islands. By intersecting the yearly MTBS wildfire polygons and the yearly unburned island polygons, we calculated the degree of overlap for both fire perimeters and unburned areas (Eidenshink et al. 2007). The proportion of area burned was determined by summing the total area within fire perimeters and dividing it by the area of each 6-km by 6-km grid cell (36 km^2). The same process was used to determine the proportion of area burned at least twice, except that areas that were burned only once were removed from the analysis. The process was repeated for unburned islands (unburned $\geq$ 1 time) and persistent unburned islands (unburned $\geq$ 2 times).

To assess whether the spatial distributions of overlapping fire perimeters and unburned islands were randomly distributed or showed some degree of spatial co-occurrence, we calculated the observed versus the expected fire perimeter and unburned island areas. The observed fire perimeter areas were calculated by summing the fire perimeter area for each patch by the degree of reburn and the number of fires that have burned over an area previously burned. The expected reburn area ($Reb\widehat{urnA}rea$) was estimated using the equation:

$$Reb\widehat{urnA}rea_t = TotFireArea \times (P_{reburn})^t \tag{1}$$

where *t* is degree of reburn (the number of times a patch has reburned) and P_{reburn} is the proportion of area that reburned once and *TotFireArea* is the total area burned within the entire dataset (8,223,980 km^2). P_{reburn} was calculated by dividing the total area reburned by the total area within fire perimeters (0.195). Absent from any spatial influences, we assumed that the proportion of area that burned would remain constant, so that 19.5% of the area reburned would reburn again and so on.

The same process was used to calculate observed and expected areas of unburned islands by their degree of persistence, the number of fires which each patch has remained unburned. The expected unburned area ($Unb\widehat{urnA}rea$) was estimated using the equation:

$$Unb\widehat{urnA}rea_q = TotFireArea \times (P_{unburn})^q \tag{2}$$

where q is the degree of persistence (the number of fires through which each patch has remained unburned) and P_{unburn} is the proportion of area with fire perimeters that remained unburned and the $TotFireArea$ is the total area burned within the entire dataset (8,223,980 km^2). P_{unburn} was calculated by dividing the total area of unburned islands (DP ≥ 1) by the total area within fire perimeters (0.099). Absent from any external influences, we would expect that the proportion of area that burns will remain constant, so that 9.9% of the area unburned will not be burned again and so on. We then compared both the expected reburn area and the unburned area by degree of reburn/persistence with the observed areas within the database.

2.3.3 Vegetation characteristics

To assess the difference in vegetation composition of persistent unburned islands and burned area, the frequency of each of the 13 fuel types was compared between burned and persistent unburned areas by sampling 51,704 pixels, half from burned areas, half from persistent unburned islands ($n = 51,704$; $n_1 = n_2 = 25,852$). We used the 13 Anderson Fire Behavior Fuel Models (Anderson 1982) to classify vegetation fuel types. This model was chosen over other models, such as the 40 Scott and Burgan Fire Behavior Fuel Models (Scott and Burgan 2005), for two reasons: (1) with only 13 fuel types, it simplified comparison and interpretation, and (2) the added precision of additional fuel models becomes unnecessary when identifying patterns at such a coarse scale and within broad groups, such as the five Fire Regime Groups (FRG). To determine whether the fuel type is dependent or independent of the burn status, Pearson's chi-squared test for independence using equal sample sizes ($n_1 = n_2 = 25,852$) was applied.

2.3.4 Topographic characteristics

To compare the underlying topography of persistent unburned islands and areas that burned within fire perimeters, seven topographic indices were investigated (Table 2.1). For the topographic analysis, 60,000 pixels were sampled; 30,000 each from burned areas and persistent unburned islands. The data were stratified by the FRG (Table 2.2) to parse out differences in unburned islands between vegetation types with similar fire regimes. For each index, the kernel density estimations were plotted along with the median value. Two-sample Kolmogorov-Smirnov tests were calculated to investigate the differences in frequency distributions between persistent unburned and burned pixels.

Table 2.2. Fire regime groups (FRG; adapted from Malesky et al. 2018).

Fire regime group	**Frequency**	**Severity**	**Severity description**	**Example cover type from study area**
I	0 – 35 years	Low/Mixed	Generally low-severity fires replacing less than 25% of the dominant overstory vegetation; can include mixed-severity fires that replace up to 75% of the overstory (typical of perennial grasslands)	Ponderosa pine; dry mixed conifer forest
II	0 – 35 years	Replacement	High-severity fires replacing greater than 5% of the dominant overstory vegetation (annual grasslands and some forests with frequent surface fires)	Grassland
III	35 – 200 years	Mixed/low	Generally mixed-severity; can also include low-severity fires (many forests and shrublands)	Big sagebrush, lodgepole pine
IV	35 – 200 years	Replacement	High-severity fires (forests and shrublands)	Big sagebrush, lodgepole pine
V	200 + years	Replacement/ any severity	Generally, replacement severity; can include any severity type in this frequency range (some moist forests, tundra, and deserts)	Very sparse big sagebrush steppe; spruce-fir forest

3. Results

Across all 2,318 fires there were up to seven overlapping fires (reburned six times), which resulted in areas that were unburned up to four times (max DP = 4; Figure 2.3). Of the total fire area within the fire perimeter (8,223,980 km^2), 15.1% of the area reburned and 9.9% was unburned. Of the unburned area, 97% remained unburned through one fire event, 2.7% through two fire events, 0.1% through three fire events, and < 0.01% through four fire events (Figure 2.3).

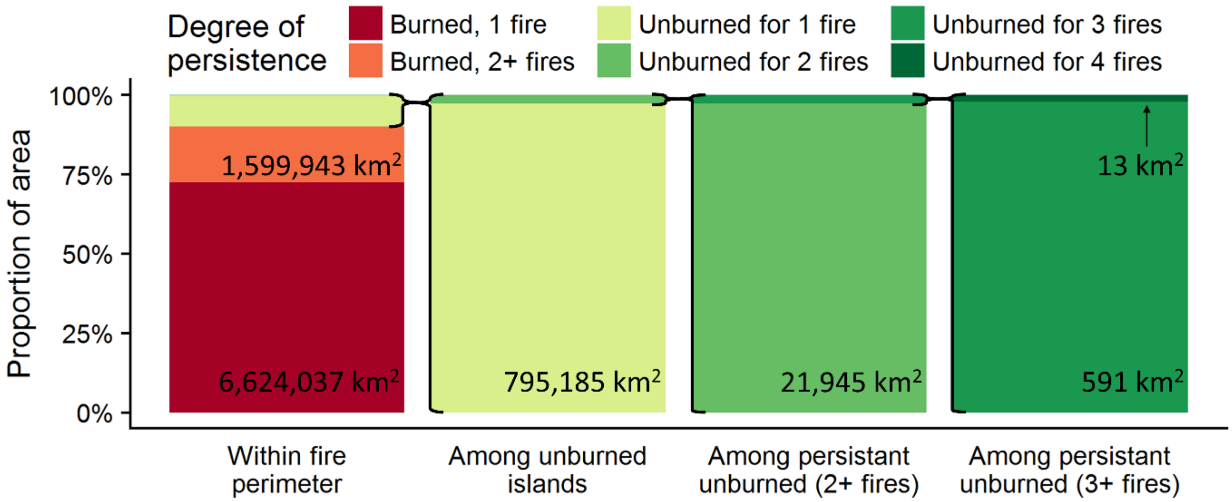

Figure 2.3. The distribution of unburned islands (area) by the degree of persistence. The proportional area of decreases exponentially with each additional fire an island remains unburned.

3.1 Patch metrics

Patch area of unburned islands decreases with each additional fire (i.e., as the DP increases; Figure 2.4a; Table 2.3). The median patch area of unburned islands decreased by: 33% from one to two fires (D = 0.3570, P < 0.001); 50% from two to three fires (D = 0.1357, P < 0.001). There was no significant difference in patch area from three to four fires (D = 0.1202, P = 0.1748).

With each successive fire that a patch remains unburned, the patch shape becomes rounder and simpler (Figure 2.4). The median FRAC decreased by 0.02 from one to two fires (D = 0.3533, P < 0.001); by 0.01 from two to three fires (D = 0.1324, P < 0.001; there was no significant difference in patch shape complexity distribution from three to four fires (D = 0.1166, P = 0.2018).

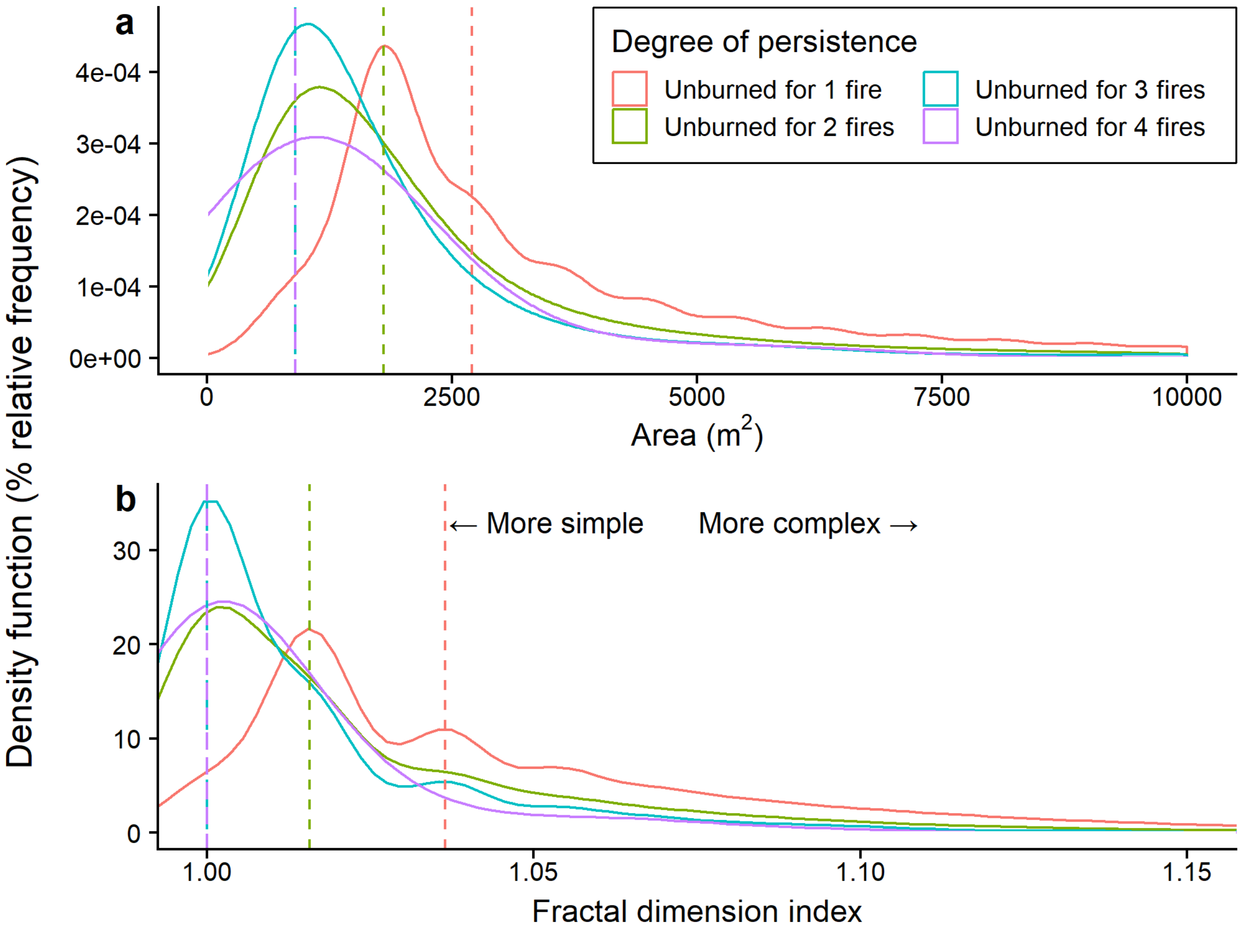

Figure 2.4. The distribution of shape characteristics by the degree of persistence. The median value is shown with a dashed line of the same color. (a) The patch size (area) decreases as the degree of persistence increases (DP) until DP = 4, which have the same area as unburned islands with DP = 3. (b) The fractal dimension index is a measure of shape complexity: higher values indicate more complex shapes; lower values indicate more simple shapes (round or square). With each successive fire an island remains unburned, the island becomes rounder and simpler until DP = 4 which have the same FRAC as DP = 3.

Table 2.3. Two-sample Kolmogorov-Smirnov D statistic and P-values to test significance of difference between the distributions of shape metrics among unburned islands based on their degree of persistence. Red highlights indicate P > 0.05.

Degree of Persistence		**Area**	**FRAC**	**Number of observations**
1 vs. 2	D	0.357	0.3533	n_1 = 749,179
	P	< 0.001	< 0.001	n_2 = 64,765
1 vs. 3	D	0.4927	0.4857	n_1 = 749,179
	P	< 0.001	< 0.001	n_3 = 2,771
1 vs. 4	D	0.6129	0.6023	n_1 = 749,179
	P	< 0.001	< 0.001	n_4 = 87
2 vs. 3	D	0.1357	0.1324	n_2 = 64,765
	P	< 0.001	< 0.001	n_3 = 2,771
2 vs. 4	D	0.2559	0.249	n_2 = 64,765
	P	< 0.001	< 0.001	n_4 = 87
3 vs. 4	D	0.1202	0.1166	n_3 = 2,771
	P	0.1748	0.2018	n_4 = 87

3.2 Spatial patterns

The highest density of fire events and areas burned through at least two fire events occurs near the intersection of Owyhee and Twin Falls counties in southwestern Idaho (Figure 2.5a and b). This area is classified as the Owyhee Uplands section of the Intermountain Semi-desert ecosystem province (Bailey 2016). The highest densities of unburned islands occur in patches throughout this region (Figure 2.5c), and persistent unburned islands appear in the highest densities in areas of high unburned islands (Figure 2.5c-d).

After estimating the overall change in reburning ($P_{reburn} = 0.1945$; i.e. 19.5% of burned area burning again), the area that actually reburned according to our database was higher than expected for all degrees of reburn other than those reburned once (Figure 2.6a, c). There is 14% more area reburned than expected for areas being reburned twice; 40% for three times; 47% for four times; 55% for five times; and 5% for six times, indicating that areas that have already burned are more likely to burn again.

The chance of an area being unburned within a given fire perimeter was 9.9% (or $P_{unburn} = 0.099$); the area of persistent unburned islands was lower than expected (Figure 2.6b, d). There is 72% less persistently unburned area within fire perimeters for areas remaining unburned for two fires; 93% for three fires; and 98% for four fires, indicating that areas that have been unburned are more likely to burn than to remain unburned in a subsequent fire.

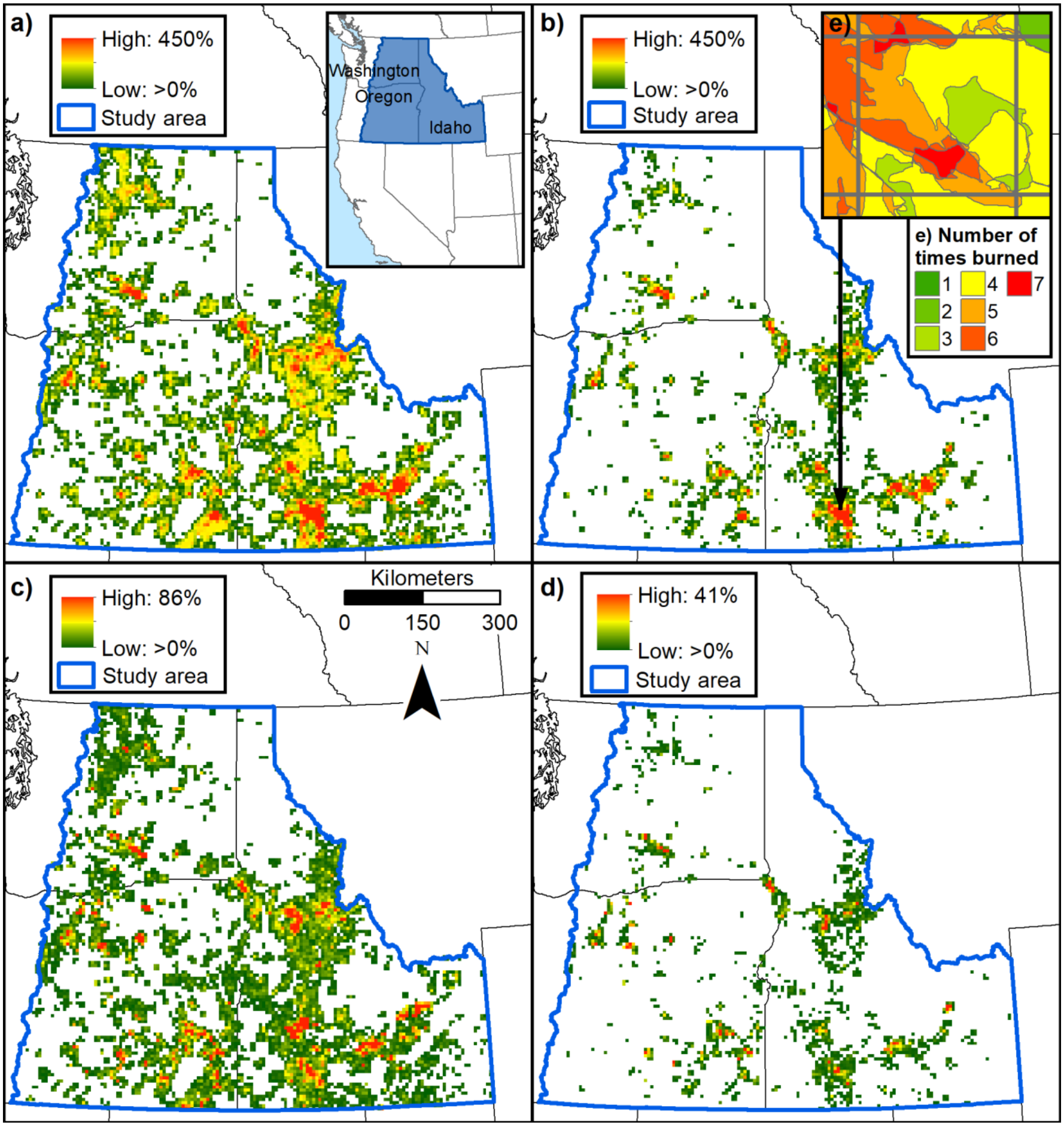

Figure 2.5. Maps illustrating the proportional area of each 6 km x 6 km grid cell that is covered by a) fire perimeters (including reburns, such that the proportion is cumulative and can exceed 100% of the pixel area), b) overlapping fire perimeters (i.e. at least 2 fire perimeters or reburn only), c) all unburned islands (including persistent unburned islands), and d) persistent unburned islands (i.e. patches that have remained unburned through at least 2 fires). e) The inset illustrates the number of overlapping fire perimeters (the degree of overlap) in the most highly burned grid cell.

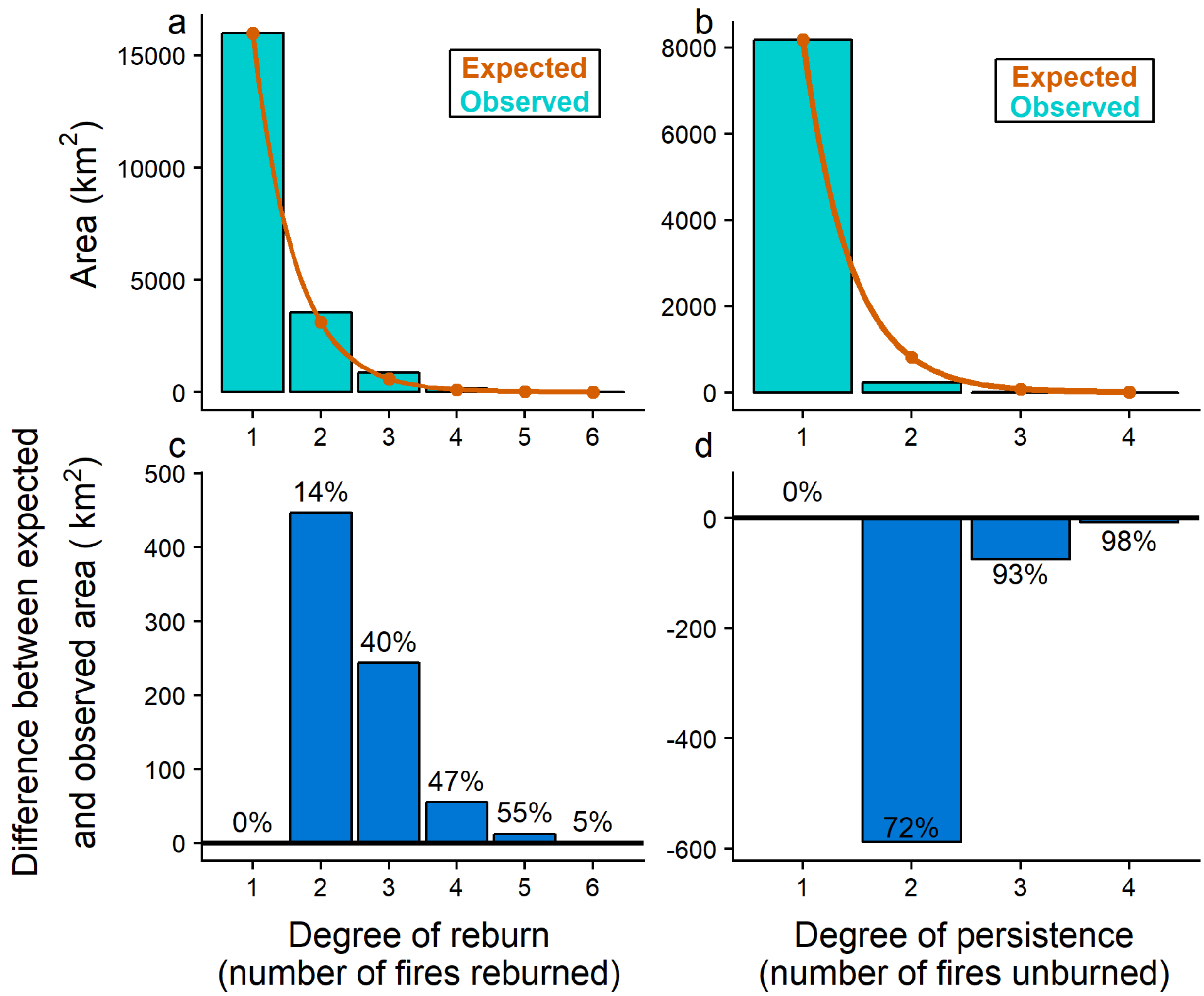

Figure 2.6. a) The observed fire perimeter area by degree of reburn compared to the expected fire perimeter area by degree of reburn, and b) the observed unburned island area by the degree of persistence compared to the expected unburned island area by the degree of persistence. c) The difference between the observed area and the expected area by the degree of reburn., and d) the difference between the observed area and the expected area by the degree of persistence.

3.3 Vegetation characteristics

There were significant differences between burned versus persistent unburned areas by fuel type (χ^2 = 1323.3, df = 12, P < 0.001; Figure 2.7). Generally, persistent unburned islands were more likely to be found in fuel limited areas, such as in grass dominated vegetation types, and were less likely to be found in areas that were fuel abundant, such as heavy brush and forests.

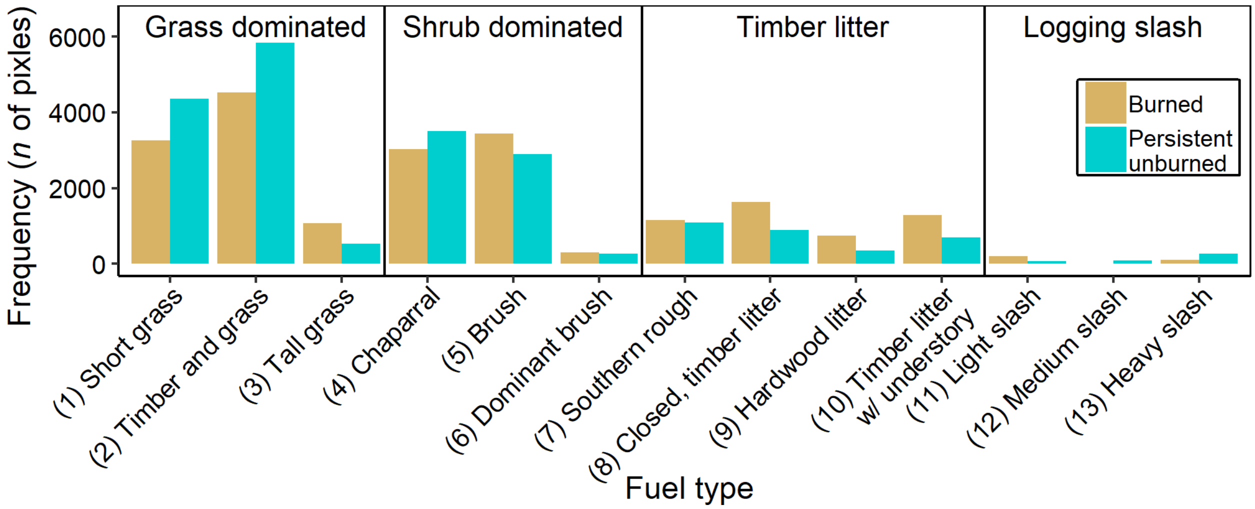

Figure 2.7. Frequency of each of the Anderson fuel types, by burn status. Note: while Fuel Model 7 (Southern Rough) was initially created to describe Palmetto-gallberry understory-pine overstory sites in the southern US, this group can describe other ecosystem types such as areas of tall sagebrush steppe and high montane conifer forests within our study area.

3.4 Topographic characteristics

In FRGs I-IV, persistent unburned islands were more likely than burned areas to be located at the foot of slopes and valleys (Table 4; $P < 0.0001$ for FRG I-IV). In FRG V, persistent unburned islands were slightly more likely to be found on slope shoulders and ridges ($P = 0.0035$). The greatest difference in median TPI between persistent unburned islands and burned areas was in FRG II, which includes annual grasses and dry ponderosa pine forests (Figure 2.8).

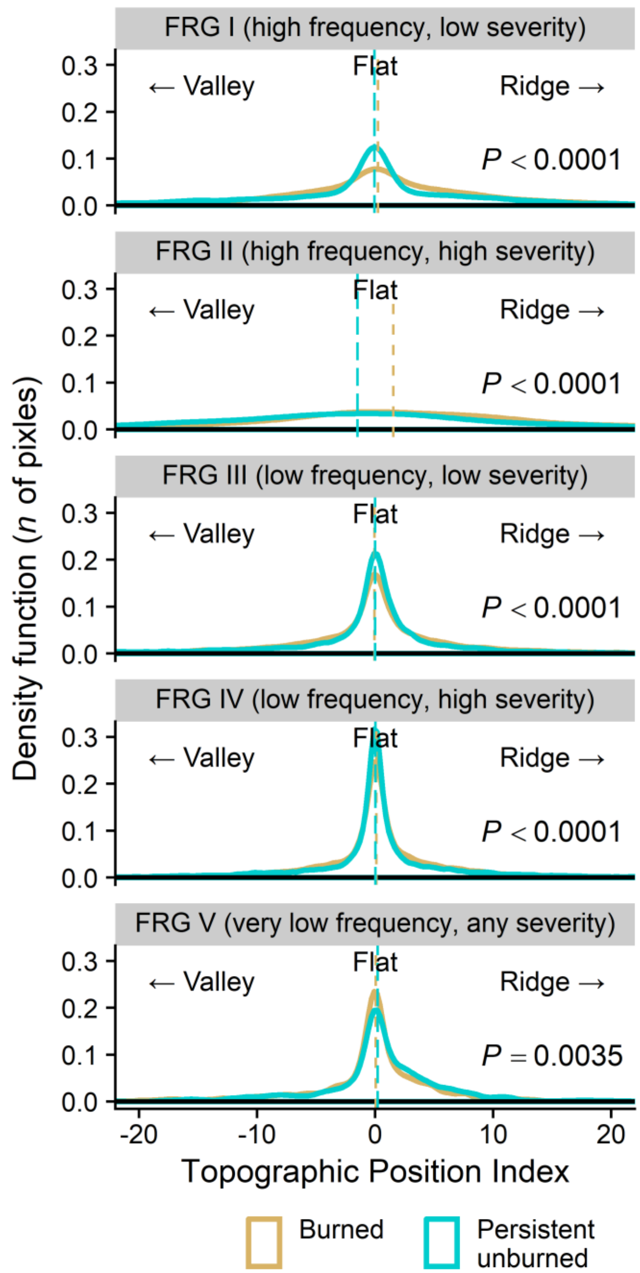

Figure 2.8. Kernel density estimation illustrating the distribution of Topographic Position Index (TPI), an indication of the position of a pixel relative to the surrounding topography, by burn status and fire regime group (FRG) with a dashed line of the same color indicating the median for each distribution.

Similarly, persistent unburned islands were more likely to be found in areas with lower runoff and a higher likelihood of water accumulation than in burned areas in FRGs I, II, and IV (Table 4; $P < 0.0001$), while persistent unburned islands were more likely to be found in areas of higher runoff in FRG V ($P = 0.0082$; Figure 2.9). There was no significant difference in the distributions of TWI values for persistent unburned islands and burned areas for FRG II ($P = 0.1234$).

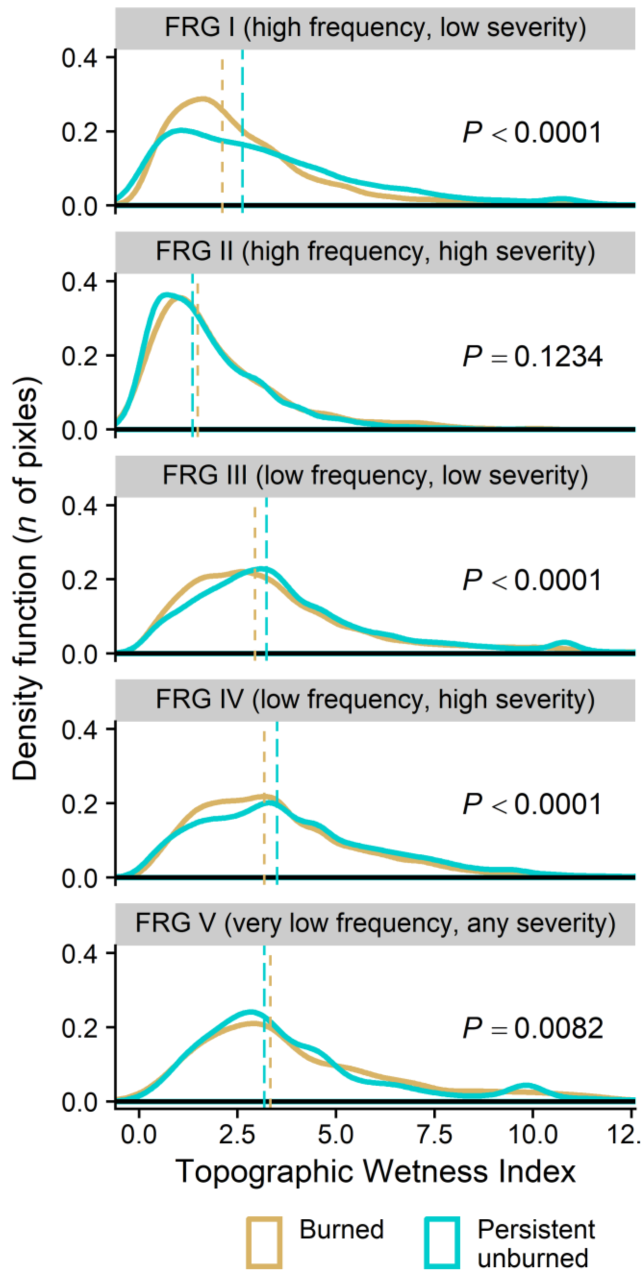

Figure 2.9. Kernel density estimation illustrating the distribution of Topographic Wetness Index (TWI), an indication of the tendency for water runoff vs. accumulation, by burn status and fire regime group (FRG) with a dashed line of the same color indicating the median for each distribution.

Persistent unburned islands were more likely to be found in more rugged areas for FRGs I and II (high frequency fire regimes; $P < 0.0001$), while they were more likely to be found in less rugged areas in FRGs III and IV (low frequency fire regimes; $P < 0.0001$). There was no significant difference between the distributions in FRG V (Figure 2.10; $P = 0.0736$).

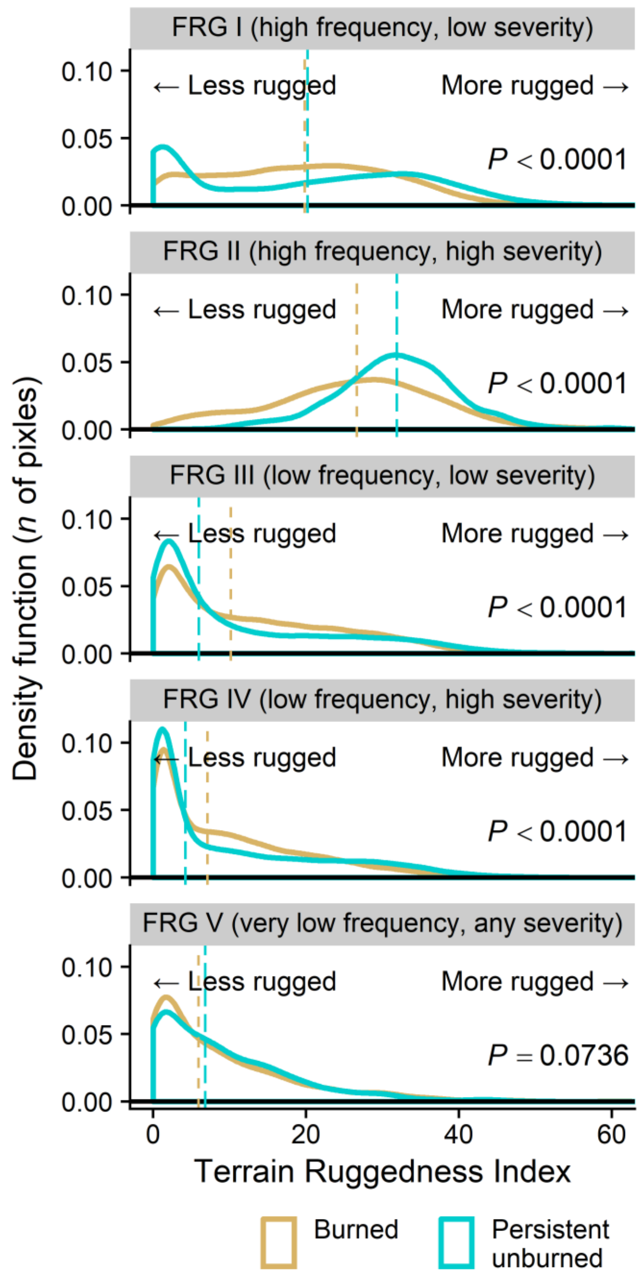

Figure 2.10. Kernel density estimation illustrating the distribution of Terrain Ruggedness Index (TRI), an indication of the terrain ruggedness (or roughness) of the area surrounding a pixel, by burn status and fire regime group (FRG) with a dashed line of the same color indicating the median for each distribution.

Persistent unburned islands were more likely to be found on flatter slopes in FRGs I, III, and IV (Figure 2.11; $P < 0.0001$); however, persistent unburned islands were more likely to be found on steeper slopes in FRGs II and V (P < 0.0001 and P = 0.0429, respectively).

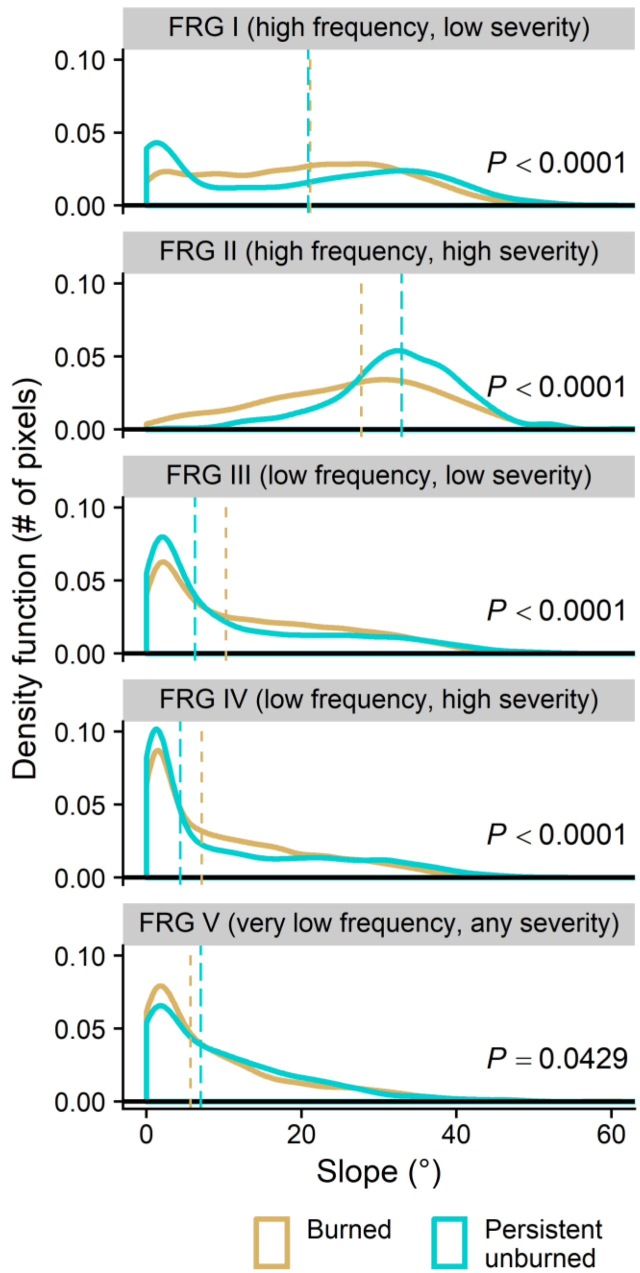

Figure 2.11. Kernel density estimation illustrating the distribution of slope, the degree of incline of a pixel by burn status and fire regime group (FRG) with a dashed line of the same color indicating the median for each distribution.

Persistent unburned islands were more likely to be found on more SSW aspects in FRGs I, III, IV, and V (Figure 2.12; $P < 0.0001$). The difference between the TRASP distributions for persistent unburned islands and burned areas in FRG II was insignificant ($P = 0.3906$).

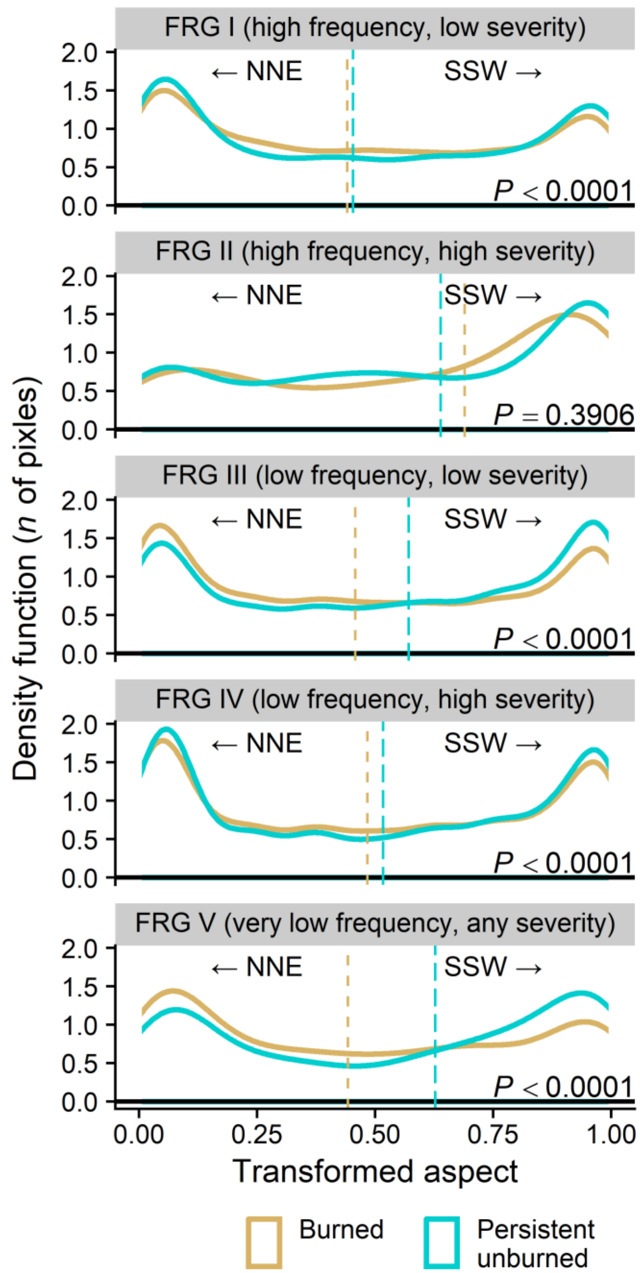

Figure 2.12. Kernel density estimation illustrating the distribution of Transformed Aspect (TRASP), which describes the gradient from NNE aspects (0 = 30° azimuth) to SSW aspects (1 = 210° azimuth), by burn status and fire regime group (FRG) with a dashed line of the same color indicating the median for each distribution.

4. Discussion

Our analysis revealed that there were locations that experienced up to seven overlapping fire events (i.e., reburned six times) in our 31-year study period (mean fire return interval of 4.43 years). In these frequently burned areas, primarily in southern Idaho, there were persistent unburned islands that remained unburned through up to four fires. As might be expected, persistent unburned islands decrease in number, size and shape complexity for each additional fire it remains unburned. The dramatic decrease in the number of refugia (Figure 2.3) is supported by Kolden et al. (2017), who found that areas previously identified as fire refugia burned at higher severity and intensity 20 years later. For unburned islands that persist through multiple fires, presumably, the biophysical factors that caused them to remain unburned during a previous burn act again to allow them to remain unburned through these additional fires. However, the additional fires burn the edges of a given persistent unburned island, shrinking and simplifying them, until they are completely consumed. Persistent unburned islands were not randomly distributed across the landscape. Their location was dependent not only on the existence of fires, but multiple, overlapping fire perimeters. Further, these fire locations were not randomly distributed across the landscape.

In this study, the greatest number of both overlapping fires and persistent unburned islands within those fires occurred in Idaho, but in two very different ecosystems: (1) the two central Idaho wilderness areas (Frank Church-River of No Return and Selway-Bitterroot) and (2) the Snake River Plain (Figure 2.5). In the central Idaho wilderness areas, the primary ignition source is high-frequency lightning (Abatzoglou et al. 2016), and the primary vegetation is forest broken by stretches of exposed granite above tree line and talus slopes. As most of the persistent islands are concentrated along the deep Salmon River canyon, it is likely that the exposed walls and steep terrain of the canyon itself contribute to erratic fire behavior, creating persistent islands.

By contrast, the density of repeat fires and persistent unburned islands in southern Idaho is likely primarily a function of biological invasion and climatologically strong winds, in conjunction with a higher degree of human ignitions than elsewhere in the study area (Abatzoglou et al. 2016). Across much of the Snake River Plain in Idaho and into the southeastern portion of Oregon, the annual grass cheatgrass (*Bromus tectorum*) has partially replaced the native shrub-steppe and fundamentally altered the fire regime by dramatically increasing fire frequency (Balch et al. 2013). The highest density of both fires and persistent unburned islands occurs in the Bruneau Desert, a large plateau west of Twin Falls, Idaho, that is incredibly remote and difficult to access but has a relatively high rate of human ignitions and a high density of cheatgrass (Bradley et al. 2018), facilitating large fire growth (Figure 2.5e). Cheatgrass invasion into lower elevation, relatively steep river canyons (where narrow canyon walls also support high winds) across the study is potentially responsible for several of the concentrations of persistent islands across the study area, including much of the Snake River Plain, Hells Canyon (Snake River) along the Idaho-Oregon border, the Salmon River canyon in central Idaho, the Deschutes and John Day River canyons in central Oregon, and the Columbia River gorge in north-central Washington. By contrast, the other cluster of persistent unburned islands in central Washington is associated with the Hanford Reach section of the Columbia River, which is a vast riparian zone (Figure 2.5d).

The results of our topographic analysis are counter to what previous fire refugia research has found. While many authors have found fire refugia in valley bottoms and gullies (Romme and Knight 1981; Leonard et al. 2014; Krawchuk et al. 2016), in our study area we found that, although there was a significant relationship between topographic position and persistent unburned islands, the effect was small (Figure 2.8). However, prior studies focused on forests whereas our study area encompasses forests, shrublands, and arid grasslands. Likewise, forest-centric fire refugia studies have found fire refugia to be more prevalent on the cooler and wetter aspects (north and east in the northern hemisphere, south and east in the southern hemisphere; Roberts and Cooper 1989; Wood et al. 2011; Krawchuk et al. 2016). Our analysis reveals the opposite to be true in our study area for most of the FRGs, except FRG II (predominantly grasslands, where there was no significant relationship; Figure 2.12). We hypothesize that this is in large part due to the sparser vegetation on these warmer and drier aspects, particularly as described above in relation to canyons in the Columbia basalt plateau, resulting in higher likelihood of unburned areas. In addition, while there is evidence that fuel types and topographic features differ in persistent unburned islands and burned areas, these features only partially explain what causes their formation. Fire behavior, the ultimate determinant of the formation of unburned islands, also is driven by fire weather, not just topography and fuel type (Román-Cuesta et al. 2009).

Our results show that the forest-centric paradigm often used when investigating fire refugia is not sufficient when considering arid grasslands or shrublands. We suggest that in the arid, non-forest ecosystems of the Inland Northwest, fire refugia are predominantly caused by fuel limitations and wind-dominated behavior, rather than the cool, mesic fire refugia found in forests. Because of the water limitation in these ecosystems, fuels are discontinuous, resulting in a patchy fire mosaic (Littell and Gwozdz 2011).

There are several key limitations of our data that affect our ability to characterize persistent unburned islands. Although there was a large number of persistent unburned islands identified across our study area, the temporal range of our dataset was limited. While our dataset covers decades, the fire return interval of many of the ecosystems in our study area is greater than 31 years, so the likelihood of experiencing more than one fire is very low. This means that many of the unburned islands identified as only persisting through a single fire event may have persisted or will persist through several more fires prior to 1984 and following 2014 (the range of our dataset). Additionally, the 30-m resolution of many of our datasets likely masks fine-scale variability. Fire refugia exist at a range of scales, and the resolution of our data does not capture smaller fire refugia that still may be ecologically significant (Krawchuk et al. 2016). Further, the error inherent in classifying unburned islands from remotely sensed data carries forward to analyses of persistence (Kolden et al. 2012). Finally, we note that our dataset included 100 prescribed fires that likely burned under different conditions than wildfires, including ignition patterns based on subjective decisions. However, these prescribed fires were not separated in our analysis and, therefore, differences in unburned island formation between wildfires and prescribed fires were not tested.

While unburned islands are a useful proxy for fire refugia (Robinson et al. 2013), they are not equivalent. For example, roads or rock piles may be classified as unburned islands; however, they may have little ecological value and may not function as fire refugia. Even among fire refugia, some may hold greater ecological significance than others. To address these issues, the ecological importance of unburned islands should be assessed to identify the most ecologically valuable fire refugia. This would allow for land managers and ecologists to make better informed decisions regarding the preservation of important fire refugia.

Characterizing persistent fire refugia allows us to better understand the biophysical factors that contribute to their formation. These key insights have implications for land management, especially when considering the impact of global climate change. Land managers may find that preserving and protecting fire refugia on the landscape helps them to meet their management objectives, whether by naturally revegetating the burned landscape surrounding them (Viedma et al. 1997; Charron and Greene 2002), or allowing for the persistence and recolonization of fauna after a fire event (Delong and Kessler 2000). They also may aid in restoring and maintaining forest resilience (Kolden et al. 2015a), which may become increasingly important as our climate continues to change, fires become more extreme, and reburning occurs in shorter intervals. Land managers looking to capitalize on the benefits of fire refugia may find it beneficial to consider techniques to encourage the formation or the persistence of unburned islands on their lands. While it has been previously acknowledged that managing for refugia is an important land management principle (Lindenmayer et al. 2006), little research exists on how land managers might accomplish this; future research is needed on management techniques that may promote the formation or persistence of unburned islands (Meddens et al. 2018a).

5. Conclusion

Our study provides evidence that persistent unburned islands are related to certain topographic characteristics, but these characteristics differ between fire regime group and fuel type. These findings are important for management activities that focus on maintaining important persistent unburned islands (fire refugia) on the landscape. Fire refugia are essential to the persistence of fire sensitive taxa within fire prone ecosystems. As the global climate continues to change and wildland fires are predicted to become larger and more frequent, fire refugia and their characteristics are expected to change with them, such that fire refugia will play an increasingly important role in the recovery and resilience of fire prone landscapes.

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Chapter 3: Land managers' rankings of fire refugia importance criteria

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Submitted to *Fire*

Abstract

There is evidence that forest resiliency is declining in the western US due to the increases in wildfire area burned and the number of large fires in recent decades. Fire refugia may increase forest resiliency, but for land managers to incorporate fire refugia into their management plans, methods need to be developed to identify and rank criteria for what make fire refugia important. As part of a larger effort to build a spatially-explicit ranking model for an unburned islands database in the inland northwestern US, we investigate the perceived importance of criteria used to inform a ranking model to identify high-value fire refugia. We developed a survey targeting land managers within the US Pacific Northwest. Participants were asked to score a predetermined list of criteria by their importance for determining the value of fire refugia. These scores were analyzed to identify trends among respondents that could be used to develop a fire refugia ranking model. The results indicate that respondents generally organized criteria into two groups: human infrastructure and wildlife habitat. However, there was little consensus among respondents in their scoring of fire refugia importance criteria, suggesting that a single fire refugia ranking model for the entire region is not feasible; more research with a larger sample size is needed to develop targeted ranking models.

1. Introduction

In recent decades, wildfire area burned and the number of large wildfires have increased across the western United States despite decreased total ignitions (NIFC 2019) and relatively stable burn severity trends (Picotte et al. 2016). This is in large part due to human influence: directly, with increased human activity in wildland areas resulting in increased human ignitions (Balch et al. 2017; Nagy et al. 2018); and indirectly, by way of fire and land management practices (Ryan et al. 2013) and anthropogenic climate change (Abatzoglou and Williams 2016). Further, more large fires are projected in the future (Barbero et al. 2015). While ecosystems are well-adapted to recover from disturbances under natural disturbance regimes (Peterson et al. 1998), there is indication that altered disturbance regimes are already reducing forest resiliency, for example by way of reduced tree regeneration in burned areas (Stevens-Rumann et al. 2018).

Fire refugia are areas which are disturbed less frequently or less severely by wildfire relative to the surrounding vegetation matrix, making them important for the persistence of organisms (Meddens et al. 2018b). Fire refugia are one example of biological refugia: microhabitats providing spatial and/or temporal protection from disturbances (Keppel et al. 2012), such as climate change, drought, floods, or glaciation (Mackey et al. 2002). While the concept of biological refugia has been around for 60 years, Camp et al. (1997) were the first to analyze fire refugia across a landscape. Fire refugia serve an important ecological function by containing unique habitat conditions not present in the adjacent forest matrix (Delong and Kessler 2000). During a fire, fire refugia promote survival of organisms by providing shelter from flames and radiant heat (Robinson et al. 2013). After a fire, they can allow for longer-term persistence and act as 'lifeboats' for recolonization (Franklin et al. 2000b) of vegetation by acting as seed sources (Viedma et al. 1997; Charron and Greene 2002; Burton et al. 2008), as wildlife habitat (Delong and Kessler 2000; Franklin et al. 2000b), and as safe havens for other organisms including soil fungi (Hart et al. 2005). As many fire refugia are associated with topographic features that produce fire-resilient microclimates (Krawchuk et al. 2016), some fire refugia may be at risk from climate change, land management, and fire management practices (Meddens et al. 2018b).

Although the maintenance of fire refugia on the landscape has been identified as an important management need for over a decade (Lindenmayer et al. 2006), a specific and comprehensive strategy for managing fire refugia to support ecological function and ecosystem services currently does not exist (Meddens et al. 2018b). Meddens et al. (2016, 2018a) developed a database of unburned islands within the interior northwestern US; however, while their unburned island detection model is effective at identifying unburned patches, it does not assess the ecological (or conservation) value of these unburned islands. Therefore, there is a critical need to develop methods that characterize the overall 'refugia value' or 'refugia importance' for these unburned islands (Perera and Buse 2014; Meddens et al. 2018a).

Ranking the value of landscape patches by their ecological importance is well-established throughout the ecological literature. Individual landscape patches have been ranked by their importance for general wildlife habitat (Endries et al. 2003), as well as the for the habitat of individual species (Stauffer et al. 2004). There have also been studies ranking habitat patches by specific features such as connectivity (Bodin and Saura 2010).

As part of a larger effort to build a spatially-explicit ranking model for an unburned islands database in the inland northwestern US, we sought here to investigate the importance of criteria used to inform a fire refugia ranking model. We developed an online survey that solicited information on the weight of several criteria for this ranking model. Although the ranking model method is inherently value-based, by surveying natural resource managers directly, the resulting ranking system will better reflect the values of land managers and is, therefore, more directly relevant to management actions. We investigated whether there was clear separability in survey responses related to respondent managed ecosystem type, occupational category, key refugial wildlife species of interest, agency, and management type. Our survey allowed managers to contribute to the development of decision models that are ultimately intended to assist land managers in carrying out their duties.

2. Methods

2.1 Sampling methodology

We targeted participants in the US Pacific Northwest (i.e., Washington, Oregon, and Idaho) employed by the primary land management agencies: US Forest Service (USFS), US Bureau Land Management (BLM), US Fish and Wildlife Service (USFWS), National Park Service (NPS), local tribal nations, Washington Department of Natural Resources (DNR), Idaho Department of Lands (IDL), Oregon Department of Fish and Wildlife (ODFW), and the Nature Conservancy (TNC). This survey was distributed using a combination of two non-probability sampling techniques: purposive sampling (Battaglia 2008) and snowball sampling (Morgan 2008). Initial participants were identified using purposive sampling; we identified individuals who were natural resource managers and professionals who might be interested in participating in our survey based on prior engagement in workshops and collaborative projects. A snowball sampling approach was then employed by asking those initial potential participants to identify other natural resource professionals who may be interested, and then asking all subsequent potential participants to identify others; respondents were also asked to provide the name and email of potential participants at the end of the survey. A total of 70 individuals were identified and invited to participate in this survey as a result.

We developed an online survey instrument using Qualtrics (Qualtrics, Provo, UT, USA). We emailed each potential respondent with information about the study and a unique link to participate in the survey. All potential participants who had not already responded to the survey or expressly declined to participate were contacted one additional time and asked again (Dillman et al. 2014). The survey asked participants to score a predetermined list of criteria (Table 1) by their importance for determining the value of fire refugia. Respondents were asked to score these using a 5-point Likert scale from “not important” to “extremely important,” which were then coded from 0 to 4. Respondents also had the option to add their own criteria and score them in a Likert format. In addition to the criteria scoring section, there were two additional sections of the survey: 1) a participatory GIS (PGIS) (Abbot et al. 1998) portion where participants identified the locations of known fire refugia using Google Earth and 2) a questionnaire about management actions to protect or preserve fire refugia. However, these additional sections are not analyzed here. The survey concluded with several demographic questions, including participant's job title and employer. The survey was expected to take 15 – 30 minutes to complete, depending on the level of detail participants provided.

2.2 Survey analysis

We first removed several respondents from the analysis (listwise deletion) because they did not answer all questions, because we used multivariate statistical analysis methods that do not support missing data. Questions asking respondents to rate "Other" criteria where the respondent supplied their own criteria were excluded because these criteria were non-uniform across respondents. The only additional criterion supplied by a respondent was a refugium's ability to "function for ecosystem services." Surveys that were not fully completed by participants were excluded.

Factor analysis was used to reduce the number of variables (i.e., the refugia importance criteria) by identifying correlation among the measured variables within the dataset and combining them into fewer "common" variables. Factors represent "hidden" or latent variables that were not directly measured but are influencing the data in aggregate (Fabrigar and Wegener 2011). Factors can be approximately identified and named by observing patterns in the responses of observed variables using the factor loadings. The optimal number of factors was determined considering the scree test (Cattell 1966). K-means nearest neighbor analysis of the factor scores was used to group respondents with similar responses. The optimal number of clusters was determined using the silhouette method (Rousseeuw 1987).

After the factor analysis identified (two) clusters, we divided the responses of these clusters into two distinct groups, investigated their differences, and characterized each cluster by their main themes of survey response. In addition to the factor analysis, we stratified our respondents into several categories to see whether patterns would arise. These categories were: ecosystem type (forest versus non-forest/rangeland), occupation type (ecologist versus manager), refugial species of concern (sage grouse , spotted owl, other), employer (USFS, BLM, USFWS, Tribes, DNR, IDL, TNC, NPS, and OFW), and management type (fire manager, land manager, other (agency) and other (non-agency)).

3. Results

3.1 Respondent demographics

Of the 70 individuals identified as potential participants, 33 responded in total (Response rate = 47.1%). However, nine respondents had to be excluded from the analysis due to omitted questions, so the effective response rate was 34.2%. We categorized the respondents by occupations as follows (Figure 3.1): 33% ecologist/biologist; 33% fire/fuels manager; 18% land manager; 6% researcher; and 9% other (including a soil scientist, science coordinator, and chief of cultural resources). The employers of the respondents were: 76% federal government; 9% state or local government; 6% nonprofit or NGO; 6% university or educational institution; and 3% other (retired federal government).

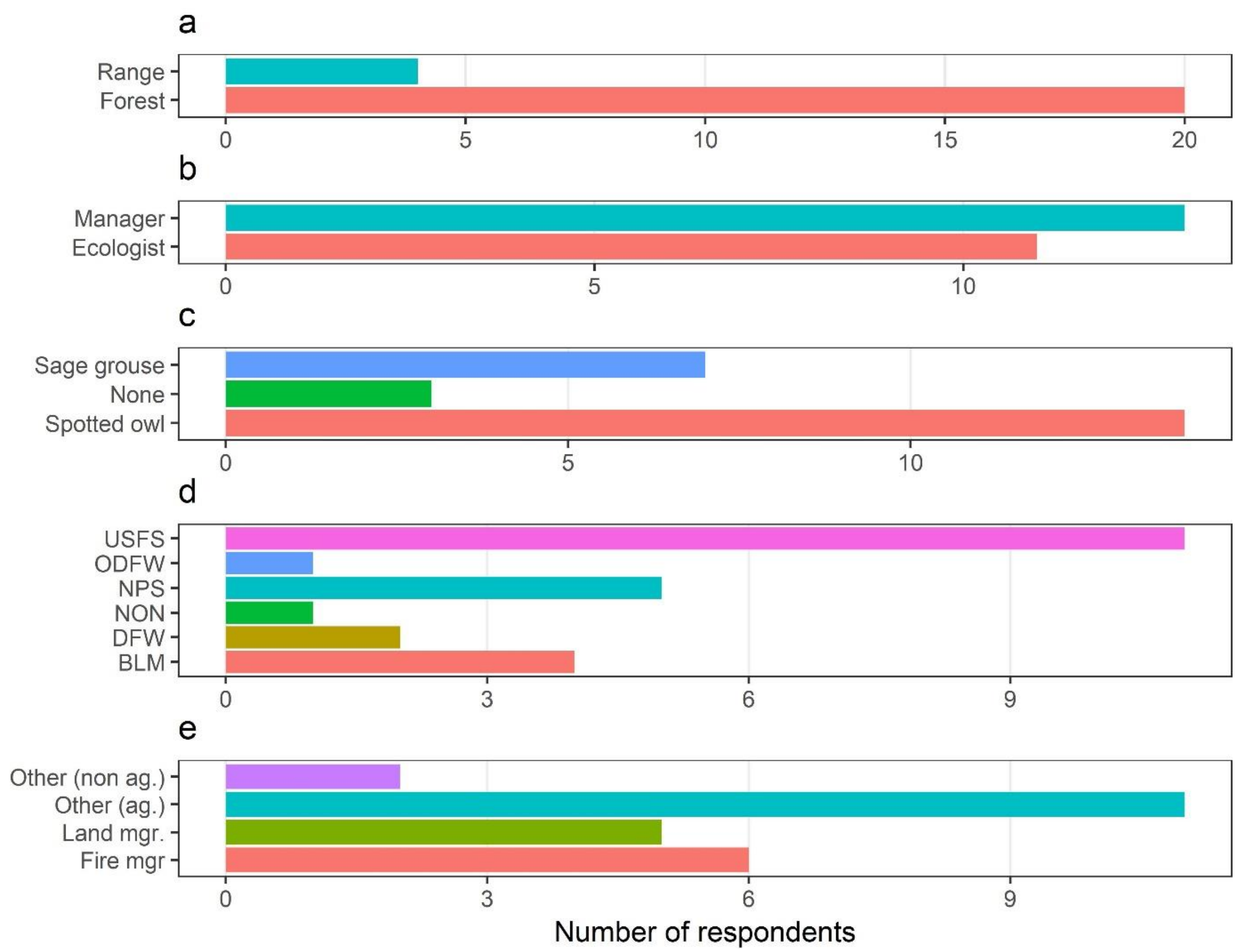

Figure 3.1. Demographic makeup of survey respondents by a) ecosystem type, b) occupational category, c) refugia species of concern, d) agency, and e) management type.

3.2 Analysis

The optimal number of factors was determined to be two (Figure A.3). These two factors account for 58.5% of the variance in the survey responses. The two Factors broadly describe "ecological habitat" (Factor 1; 40.5% of the variance) and "human infrastructure" (Factor 2; 18.0% of the variance; Figure 3.2; Table A.1). By plotting the respondents' factor regression scores and grouping them by various demographic measures, several patterns in the respondents' scores emerge (Figure 3.3). For example, NPS employees did not prioritize human infrastructure in refugia valuation as high as USFS employees Figure 3.3d). Respondents that worked in rangeland areas were likely to prioritize both ecological habitat and infrastructure, whereas respondents working in forested areas gave more variable responses (Figure 3.3). As apparent from large overlapping polygons, there was no clear separability of groups for ecosystem type (forest versus rangeland), occupation type (ecologist versus manager), refugial species of concern (sage grouse, spotted owl, other), and management type (fire manager, land manager, other (agency) and other (non-agency)).

For the k-means cluster analysis, the optimal number of clusters was determined to be two (Figure A.4). Respondents were clustered by their responses (Figure 3.4), and their average ratings for each criterion were plotted (Figure 3.4b). No additional patterns could be identified from the demographic makeup of the survey respondents by cluster.

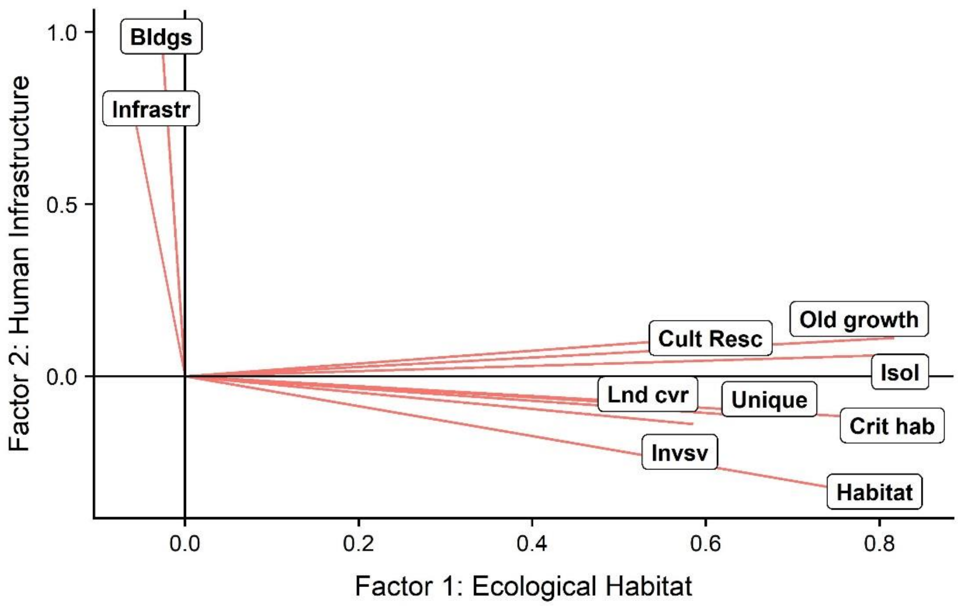

Figure 3.2. Factor loadings for each variable. Latent variables can be approximated by identifying the distribution patterns of observed variables along each axis. See Table A.1 for descriptions of the abbreviations of the variables.

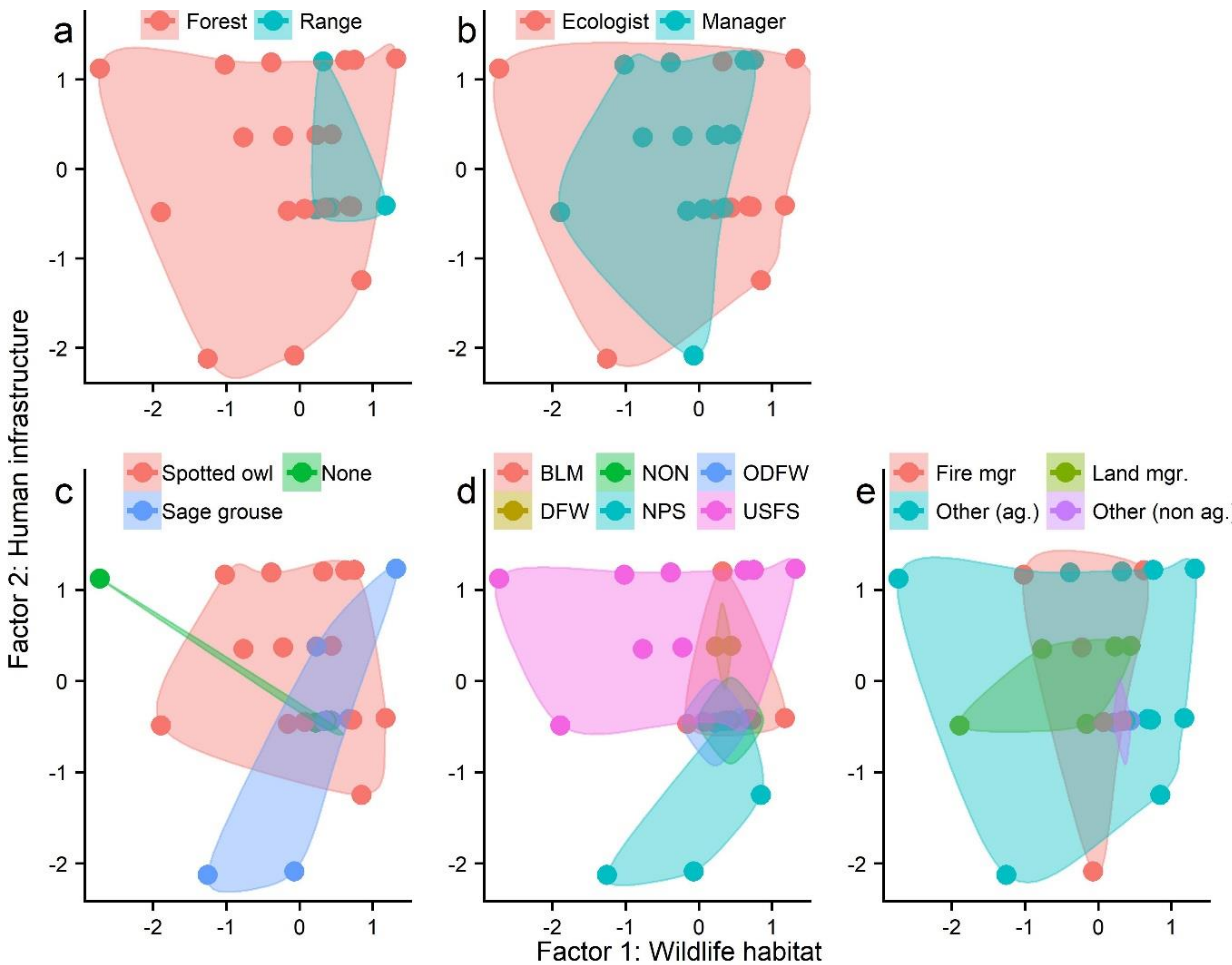

Figure 3.3. Plots of the respondents' factor scores grouped by a) ecosystem type, b) occupational category, c) refugia species of concern, d) agency, and e) management type. Polygons were plotted to encircle all points within each group.

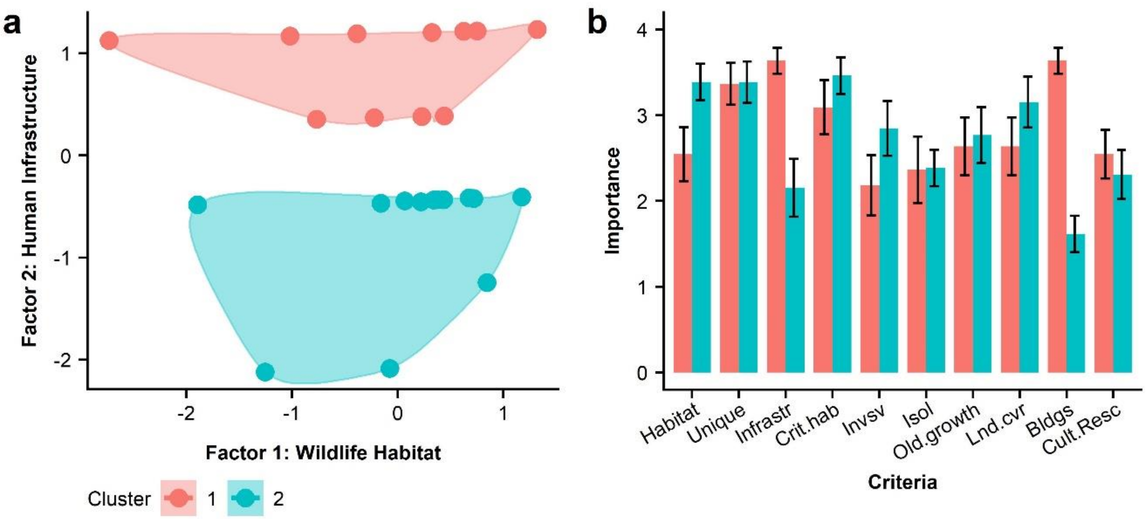

Figure 3.4. Respondent scores by cluster: a) respondents plotted along first and second principal components, grouped by cluster; b) mean and standard error of respondent importance rankings, by cluster. See Table A.1 for descriptions of the abbreviations of the variables.

4. Discussion

While there were only a few discernable patterns that emerged from the participants' raw responses, we did find two distinct clusters of respondents (Figure 3.4). Respondents in Cluster 1 were predominantly USFS employees. These individuals valued human infrastructure higher than average, and there was a range of human infrastructure values. Respondents in Cluster 2 represented many different agencies. These individuals valued human infrastructure less than average and tended to value habitat higher than Cluster 1. This is particularly interesting because USFS does not have responsibility for private infrastructure on or near USFS lands, but there has been considerable scientific and gray literature over the past few decades aligning the USFS fire suppression and management mission specifically with protecting private infrastructure on adjacent lands (Calkin et al. 2014). This is perhaps best encapsulated by Calkin et al. (Calkin et al. 2014), who argue that the primary means of reducing home loss in wildfire disasters is reducing fire risk on adjacent public lands. Our survey results suggest this mentality has carried over into more conversation-focused management strategies such as managing for fire refugia as well.

Our analysis revealed that, overall, there was little consensus among the respondents in their scoring of fire refugia importance criteria. This is in line with previous research that indicates that values and objectives vary greatly among forest owners (Ní Dhubháin et al. 2007) and even within public land management agencies (Martin and Steelman 2004). This lack of consensus among land managers suggests that a single "one-size-fits-all" approach to refugia importance ranking will likely not be effective, and aligns with prior research advocating for place-based strategies that rely on local and/or traditional ecological knowledge to inform fire management strategies, in this case to promote fire refugia (Ray et al. 2012).

There are a variety of management objectives that not only differ among agencies or occupation, but also among individuals and their local units. Rather, ranking models that are targeted to a single species of interest (e.g., sage grouse [*Centrocercus urophasianus*], northern spotted owl [*Strix occidentalis caurina*]) or an ecosystem function (e.g., forest recovery) may be a more suitable approach. These ranking models should reflect several of the underlying drivers of land management objectives within the region.

The inclusion of land manager input through the survey provided a mechanism for us to conclude that our initial approach was inadequate for capturing the real-world intricacies of land management decision-making. It further revealed that if a truly management-driven solution to ranking fire refugia was desired, it would require a co-produced ranking model, with land manager input at every step of the process (Roux et al. 2006). This would require not only the ranking of the criteria used for determining the importance of fire refugia, but the identification of the precise objectives of the land managers and all the criteria they consider when making management decisions for a given management unit.

There are several limitations to the data we gathered from this survey. The most notable limitation is the small sample size. Relatively few managers responded to our survey, and several of those that did provided data that was unusable. Additionally, there was poor representation from many agencies (particularly state agencies) and regions (particularly rangeland areas). Another limitation is the small cluster size of two clusters. With few participants, adding additional clusters becomes less effective.

5. Conclusions

Fire refugia are critical for preserving critical ecosystem functions in the fire-impacted landscapes. We initially aimed to use a survey targeted toward land managers to develop a model that ranked unburned islands by their importance throughout the entire Inland Pacific Northwest region. The analysis of the survey data revealed highly variable responses from land manager respondents, suggesting a wide range of land management objectives and values throughout the region. This suggests that a single fire refugia ranking model for the entire region is not feasible. Further research is needed in developing targeted refugia ranking models, either by specific value (e.g. spotted owl or sage grouse habitat) or a variety of values at a much smaller spatial scale.

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Chapter 4: Ranking the importance of unburned islands: a case study of northern spotted owls in the eastern Cascades

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Abstract

While wildfire helps to maintain landscape heterogeneity which promotes quality northern spotted owl (*Strix occidentalis caurina*) habitat, there is evidence that the total area of spotted owl nesting and roosting habitat has been decreasing over the last 25 years and that fire is the primary cause. One way to help promote spotted owl habitat is to prioritize the value of fire refugia within fire perimeters. In this study, we developed a fire refugia ranking model that assesses the importance of fire refugia for spotted owl nesting/roosting habitat. We then applied the model to four fires in the eastern Cascades of the United States and compared patch shape, topographic and forest structure metrics between the highest-value fire refugia and the remaining fire refugia. We found that the highest-ranking refugia had forest structure characteristics that more resembled old-growth characteristics than the remaining fire refugia. We also found that topographically, there were few differences between the highest ranked 10% refugia and the remaining refugia that were consistent across the four fires. This modeling framework could be easily adapted for use by land managers for new fires and with altered model parameters or additional criteria to identify high-value refugia, not just for spotted owl habitat, but for any other resource.

1. Introduction

In the eastern Cascades of Washington, the primary cause of nesting/roosting habitat loss of the northern spotted owl (*Strix occidentalis caurina*; hereafter “spotted owl”) from 1993 to 2012 was wildfire (Davis et al. 2016). While fire has caused significant losses of spotted owl habitat in the Eastern Cascades, spotted owl fitness is associated with a mosaic of older forest and open vegetation patches caused by mixed-severity fire, particularly in the dry eastern Cascades (DellaSala et al. 2015). Mixed-severity fires are beneficial to the maintenance of owl habitat through the creation of crucial landscape heterogeneity (Franklin et al. 2000a): low and moderate severity fires maintain forest that provides opportunities for nesting and roosting habitat, while high severity fire burned forest provides opportunities for owl foraging habitat (Baker 2015). While there is disagreement of the current risk of spotted owl habitat loss due to wildfire (Davis et al. 2016; Lee 2018), it is clear that a mosaic of early seral foraging habitat and late-successional nesting/roosting habitat is key to maintaining northern spotted owl populations.

The management of spotted owl habitat has been an important, albeit controversial, aspect of forest management in the Pacific Northwest. The Northwest Forest Plan, which provides management direction for all federally administered forests in the Pacific Northwest, is largely driven by the preservation and promotion of habitat suitable for the spotted owl (Thomas et al. 2006). Because of this, land managers in this region must prioritize the conservation and management of spotted owl habitat when developing management plans.

Within burned areas, particularly those of large, high-severity "mega-fires," identifying the unburned or low-severity patches—also referred to as *fire refugia* (Meddens et al. 2018b)—that are suitable nesting/roosting habitat within fire perimeters may be an effective strategy for maintaining spotted owl populations (DellaSala et al. 2015). Fire refugia are landscape patches that are disturbed less frequently or less severely by wildfire relative to the surrounding vegetation matrix which are important to biota (Meddens et al. 2018b). Within forests, these remnants of older forest within a younger forest matrix (Camp et al. 1997) can be the "threads of continuity" that allow for the persistence of old-forest obligate species (Franklin et al. 2000b), such as the spotted owl whose habitat is partially defined by the presence of old-growth conifer forest structures (Ripple et al. 1997).

To start identifying fire refugia, Meddens et al. (2016) developed a method for detecting unburned islands within fire perimeters across the inland Pacific Northwest. While this is useful, these unburned islands cannot be directly used to identify spotted owl fire refugia within a fire, as the model does not assess the ecological value of these patches (Martinez et al., in press). For example, some unburned islands have remained unburned because they were unburnable roads or piles of rocks, whereas others may truly be biological refugia. Additionally, within a single fire perimeter there can be hundreds or thousands of unburned islands comprising approximately 9.6% of any given fire (Meddens et al. 2018a), which could make conserving all unburned islands infeasible and impractical. Given the limitations of resources available for managing post-fire NSO habitat, a system to rank the value of unburned islands by their importance for spotted owl habitat is necessary.

There are a variety of different methods that rank the importance of habitat patches for different species and habitat types. Rossi and Kuitunen (1996) ranked 26 defined habitat types across the entirety of Finland to determine their overall importance in order to inform land use decisions. They based their importance ranking on a habitat value (HV), calculated for each habitat by considering the species present, the threat category of the species, and their likeliness to be within a specific habitat. Endries et al. (2003) developed a habitat ranking model that assesses the overall habitat value for all fish and wildlife across the state of Florida. To calculate their wildlife importance index, they summed the values of equally weighed, scaled (0-1) criteria (e.g., species richness, distance to roads), which resulted in a 30-m raster dataset. Stauffer et al. (2004) developed an approach for ranking old-growth forest stands by their importance for marbled murrelet (*Brachyramphus marmoratus*) habitat by using occupancy estimates as a measure of nesting activity. The scales and objectives of these projects all varied greatly but provide a range of examples of the practical application of habitat ranking.

The objectives of this study are to: (1) develop a tool to rank unburned islands within fire perimeters by their importance for spotted owl habitat, and (2) to apply that tool to 4 fires in the eastern Cascades and characterize the most important spotted owl fire refugia. To achieve this, we developed a multiple-criteria model that ranks the importance of known unburned islands by their importance for spotted owl habitat. After applying the model to four fires in the eastern Cascades, we compared patch shape, topographic, and forest structure metrics between the highest-value fire refugia with the remaining fire refugia.

2. Methods

2.1 Study area

We considered four fires that occurred at the intersection of several datasets used in this analysis: 1) the unburned island database (Meddens et al. 2018a), 2) the spotted owl habitat suitability model (Davis et al. 2016), and 3) available lidar datasets (Hudak et al., in prep). Specifically, these fires are the B&B fire (Oregon, Aug. 2003), the Davis fire (Oregon, June 2003), the Poison fire (Washington Sep. 2012), and the Pole Creek fire (Oregon, Sep 2012).

These fires occurred on the eastern slope of the Cascades, near the eastern extent of the spotted owl's range (Figure 4.1). The Oregon fires (B&B, Davis, and Pole Creek) all occurred in the Deschutes National Forest, while the Poison fire burned predominantly in the Okanogan-Wenatchee National Forest. The Oregon fires ranged in elevation from about 1000 to 2000 m and had annual precipitations ranging from 33 (near the Pole Creek fire) to 165 cm (near B&B fire; Arguez et al. 2010). The Poison fire ranged in elevation from about 300 to 1000 m and had annual precipitation of about 22 cm (Arguez et al. 2010). Fire regimes in the eastern Cascades range from low-severity regimes with three-year fire return intervals in Ponderosa pine (*Pinus ponderosa*) dominated forests, to mixed-severity regimes with fire return intervals greater than 300 years in subalpine fir (*Abies lasiocarpa*) dominated forests (Agee 2003).

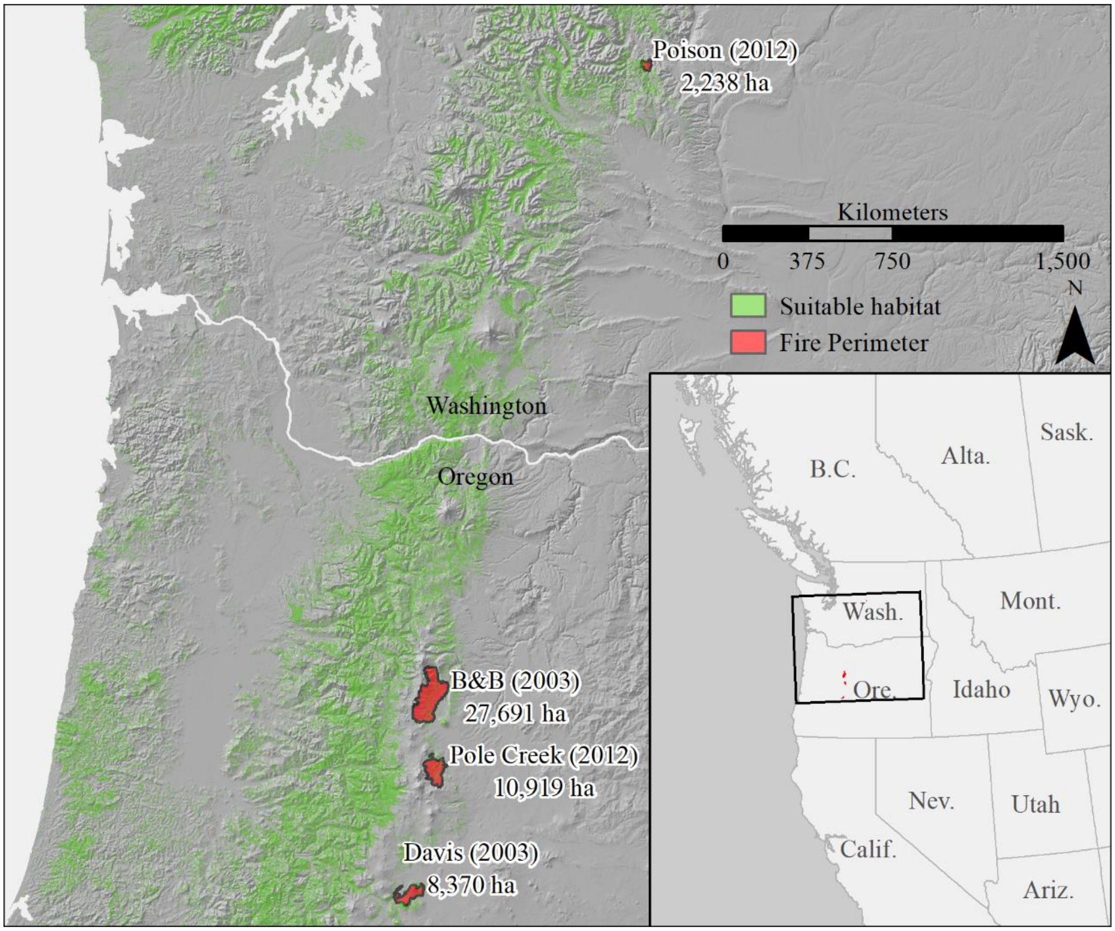

Figure 4.1. The study area includes four fires across the East Cascades of Washington and Oregon. The burn areas are shown in red. Areas that are suitable (or highly suitable) for spotted owl nesting/roosting habitat (Davis et al. 2016) are shown in green.

2.2 Model development

2.2.1 Data

We developed a fire refugia ranking model that assessed the importance of fire refugia by their importance for spotted owl nesting/roosting habitat. This model primarily made use of three datasets: 1) an unburned island database, 2) a spotted owl habitat suitability model, and 3) a spotted owl habitat type model.

A database of unburned islands within fires from 1984 – 2014 was compiled by Meddens et al. (Meddens et al. 2018a). They used classification trees (Breiman et al. 1984) of spectral indices for fire perimeters obtained from Landsat data and fire perimeters from the Monitoring Trends in Burn Severity (MTBS) data set, which includes wildland fires 404 ha (1000 acres) or greater in the western US (Eidenshink et al. 2007; Meddens et al. 2016). Unburned islands were detected with a minimum size threshold of 2 Landsat pixels (0.18 ha in area). Their algorithm identified 701,188 unburned islands within 2,729 fires with an 89% accuracy (Meddens et al. 2016).

A northern spotted owl nesting/roosting habitat model was developed by Davis et al. (2016) using maximum entropy species distribution modeling. This 30-m raster dataset classified areas of habitat suitability as: unsuitable, marginal, suitable, or highly suitable. Their model considered nine forest structure, age, and species composition variables to determine spotted owl habitat suitability (Table A.2). The model used a bootstrapping procedure that utilized 75% of owl presence data to train the model and the remaining 25% to test the model. The model performed well, with AUCs ranging from 0.78 to 0.87.

To assess habitat fragmentation, a northern spotted owl nesting/roosting habitat pattern-type model was developed by Davis et al. (2016) based on their habitat suitability data. This 100-m raster dataset classified spotted owl habitat type as: background, edge, core-edge, and core. Core habitat was habitat which was greater than 100 m from non-habitat. Edge habitat was habitat adjacent (< 100 m) to non-habitat. Core-edge habitat was the edge habitat along the periphery of core habitat. Background was non-habitat.

To ensure that areas within the fire perimeters that burned at high severity were not considered suitable nesting/roosting habitat, we masked high severity areas. High severity burns were identified by classifying relative differenced Normalized Burn Ratio (RdNBR) values ≥ 703 as high severity. The equation for RdNBR is as follows:

$$RdNBR = \frac{\left(NBR_{prefire} - NBR_{postfire}\right) - dNBR_{offset}}{\sqrt{\left|NBR_{prefire}/1000\right|}} \tag{3}$$

where NBR is the Normalized Burn Ratio and $dNBR_{offset}$ is the average differenced NBR (dNBR) value of nearby unburned vegetation (Miller and Thode 2007). The threshold of 703 was the threshold identified by Cansler and McKenzie (2012) for high severity burns in the Northern Cascade Range. RdNBR values were obtained from MTBS (www.mtbs.gov) RdNBR 30-m rasters.

To analyze the topography and forest structure of the fire refugia, data derived from three different lidar acquisitions were used (Table 4.1). The lidar datasets had average pulse densities ranging from 9.4 to 12.3 pulse/m^2. These three acquisitions were flown in 2011 and 2015. Lidar data was acquired after all four fires; for the Pole Creek fire, the lidar was also flown pre-fire. However, since we were interested in the unburned islands, the fire should have had minimal effect on the lidar returns. Lidar was delivered as a series 30-m rasters, the outputs of the FUSION GridMetrics, and TopoMetrics tools (McGaughey 2018). Additionally, modeled aboveground biomass predictions were applied to these lidar acquisitions (Hudak et al., in prep).

Table 4.1. List of lidar data sources.

Fire	Date started	State	Lidar Year	Average pulse density (pulse/m^2)
B&B	19 Aug 2003	OR	2011[1], 2015[2]	9.4, 10.2
Davis	28 Jun 2003	OR	2011[1]	9.4
Poison	8 Sep 2012	WA	2015[3]	12.3
Pole Creek	9 Sep 2012	OR	2011[1]	9.4

[1]http://www.oregongeology.org/pubs/ldq/reports/Deschutes_Report_ALL_AREAS_PLUS_METOLIUS.pdf
[2]https://www.oregongeology.org/pubs/ldq/reports/OLC_Lane_County_2015.pdf
[3]https://pugetsoundlidar.ess.washington.edu/lidardata/proj_reports/2015_OLC_Chelan_FEMA_Data_Report.pdf

2.2.2 Ranking model

To determine the ranking of unburned islands by their importance for spotted owl habitat, we used a multiple criteria analysis (MCDA) system called the Environmental Evaluation Modeling System (EEMS; Sheehan and Gough 2016). MCDA allows for the optimization of the decision output by analyzing multiple criteria. MCDA has been widely used for many decades in scientific fields of business management, healthcare, and manufacturing, but has only recently become more commonly applied in forestry and environmental science (see reviews Kangas and Kangas 2005; Ananda and Herath 2009; Huang et al. 2011).

EEMS is a platform-independent fuzzy logic MCDA modeling framework, developed specifically to provide environmental decision support (Sheehan and Gough 2016). This system works by evaluating the degree of truth or falseness of hierarchically arranged propositions, linked and combined with operators (AND, OR, etc.). For this model, the final proposition to be evaluated for each unburned island with the given fire perimeter is "*this unburned island is important for spotted owl habitat*." By determining the degree of truth of the final proposition for each unburned island, a ranking can be calculated using multiple criteria. For each of these criteria, EEMS uses a scale from -1 to 1: -1 being fully false, 1 being fully true, and the values between representing the spectrum of truth. The user defines threshold values for each criterion when a proposition is fully true or fully false.

To determine the ranking of each unburned island, a fuzzy logic tree was created (Figure 4.2) to hierarchically group criteria. Propositions occur at the tree nodes, and the final proposition is at the root node; fuzzy values are input at terminal nodes. Fuzzy values are calculated by linearly mapping input criteria values along the true/false gradient established by assigning fully true and fully false thresholds (Table 4.2; Figure A.5). The hierarchy was developed heuristically by grouping similar criteria and determining a shared characteristic among them.

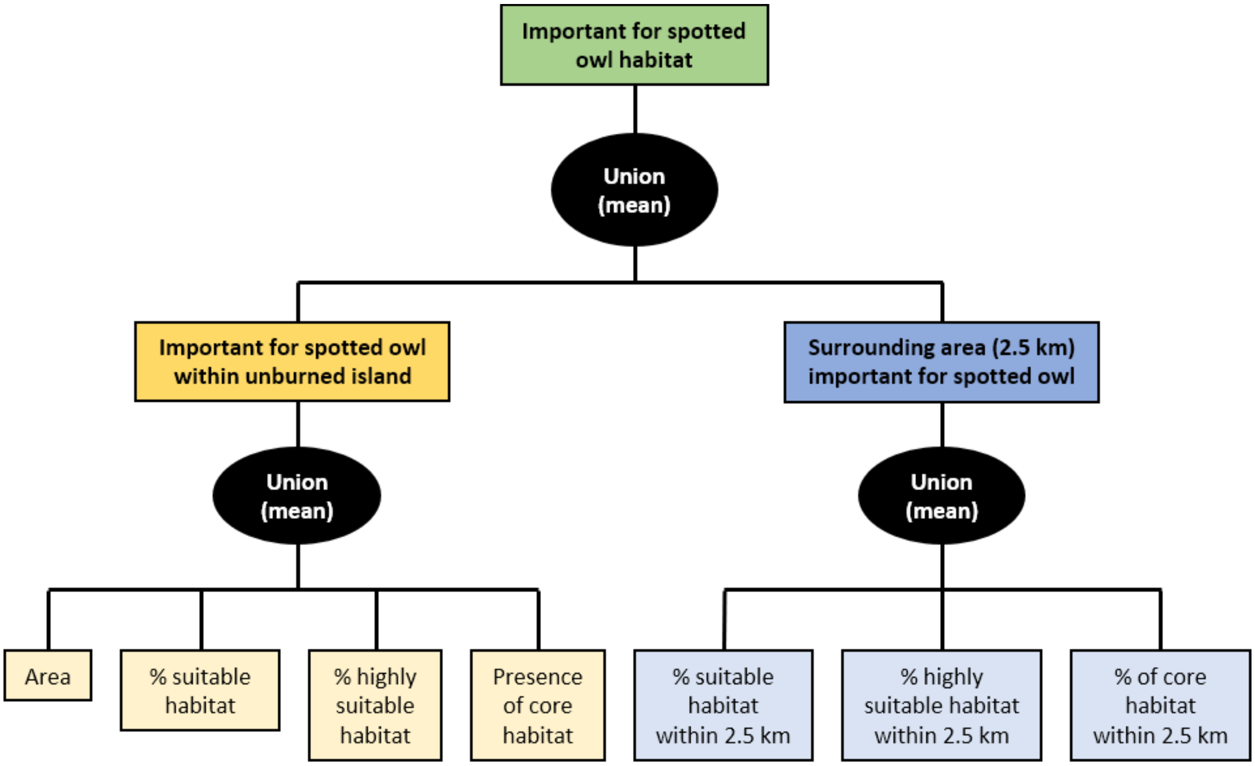

Figure 4.2. Fuzzy logic tree for spotted owl habitat ranking model. The final proposition (green) is a union of the two intermediate propositions (yellow and blue). The terminal nodes are the input criteria (light yellow and light blue).

Table 4.2. Criteria used to determine the importance of unburned islands for spotted owl habitat using the Environmental Evaluation and Modeling System (EEMS) model. The false thresholds represent the point when a criteria values are fully false; true thresholds represent the point when criteria values are fully true. Any value less than the false value will be assigned a fuzzy value of -1; any value greater than the true value will be assigned a fuzzy value of 1. Values between the true and false values will be assigned a fuzzy value proportionally along the true/false gradient. See the text in section 2.2.2 for explanation of threshold value determination.

	Threshold	
Criteria	**False**	**True**
Within unburned island		
Area (of unburned island)	0.18 ha	418 ha
% of suitable (+ highly suitable) habitat	0 %	100 %
% of highly suitable habitat	0 %	100 %
Presence of core (or core edge) habitat	Absent (0)	Present (1)
Surrounding unburned island		
% suitable (+ highly suitable) habitat	0 %	75 %
% highly suitable habitat	0 %	75 %
% core (+ core-edge) habitat	0 %	50 %

We arranged the criteria in two categories: those describing the unburned island itself and those describing the area surrounding the unburned island being evaluated. To describe the unburned island itself we considered four variables. We considered the area of each unburned island, with area being positively correlated to owl management importance. The minimum threshold for unburned island area is the minimum size for unburned islands (0.18 ha; Meddens et al. 2016), and the maximum threshold was set at the mean average spotted owl nest patch area (418 ha) described by Ripple et al. (418 ha; 1997). The proportion of suitable (and highly suitable) habitat within an unburned island was considered positively correlated with owl management importance. This was calculated by calculating the proportion of each unburned island that overlaid suitable or highly suitable spotted owl habitat. Thresholds were set at 0% and 100% to reflect the desirability of increased nesting/roosting habitat within a fire refugium. Additionally, the presence of core habitat within an unburned island was considered positively correlated to owl management importance (Dugger et al. 2005). This was simply calculated by determining if each unburned island overlaid any spotted owl core habitat. These thresholds were set at 0 and 1 because of the binary presence/absence criteria.

For the criteria describing the area surrounding unburned islands, a 2.5-km radius was used. This radius corresponds to the maximum foraging distance of spotted owls (Carey et al. 1992). The proportion of suitable (and highly suitable) habitat surrounding unburned islands was considered positively correlated to owl management importance, with thresholds at 0% and 75%. The maximum threshold at 75% accounts for owl's preference for a heterogeneous forest cover, while also roughly approximating suitable habitat connectivity. The proportion of core habitat (including core-edge) within 2.5 km was considered positively correlated to owl management importance, with thresholds at 0% and 50%.

The criteria were combined using a "weighted union" operator (weighted mean) into the two intermediate propositions "unburned island important for spotted owl" and "surrounding area important for spotted owl" (Figure 4.2). These were combined using a weighted union operator to determine the final importance score. All criteria were weighted equally. Refugia were then ranked by importance based on the final refugia importance scores.

In addition to a spotted owl refugia ranking model, we wanted to develop a tool that was customizable to the needs of individual end users. To accomplish this, the tool was built using the "Shiny" package of the R open source statistical programming language (Chang et al. 2018). This offered both a user-friendly web app interface and the spatial statistical analysis functionality of R. Use of the app does not require advanced statistical or computer programming knowledge to operate. While the thresholds for converting criteria into fuzzy values and the weights for the weighted union operators are set as the default values for the model, the web app allows for users to alter those parameters. The model is hosted through the Shiny website at https://ajmartinez.shinyapps.io/NSO_Refugia_Ranking/ (Figure 4.3).

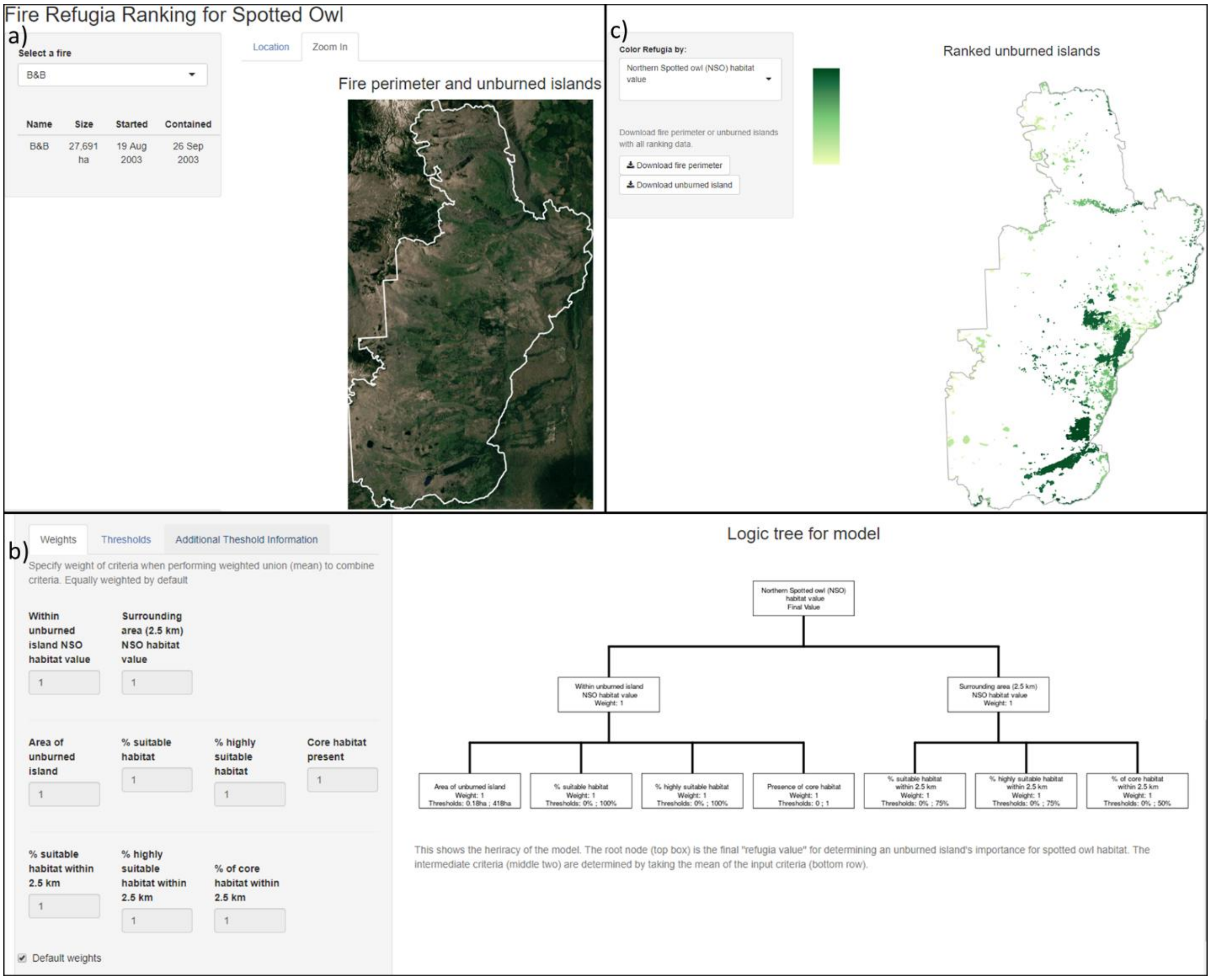

Figure 4.3. Screenshots of online fire refugia ranking model tool. a) Fire selection with, with the four fires analyzed in this study. b) Parameter selections and the associated logic tree showing the model hierarchy. c) The mapped fire refugia with options on how fire refugia should be colored for the visualization. Here is where an ESRI shapefile of ranked refugia can be downloaded.

2.3 Model application

We ran the ranking model for the four selected fires using the default parameters. Ranked refugia were then combined with the lidar datasets to compute the topographic and forest structure metrics. These were extracted from the rasters by computing the mean value of each lidar metric for each unburned island.

To assess the characteristics of the top ranked fire refugia, we analyzed differences in patch shape, topography, and forest structure across unburned islands between the top 10% of refugia scores and the remaining bottom 90% of the unburned islands within a fire.

To assess differences in patch shape we compared the area and Fractal Dimension Index (FRAC; McGarigal and Marks 1995). FRAC has a range from one to two: a value of one indicates a simple shape with a round or square perimeter; a value of two indicates a highly complex shape with a long perimeter given the area of the shape. While this metric is a measure of the perimeter to area ratio, it has the benefit of controlling for shape size, which the perimeter to area ratio does not.

To assess differences the topography underlying the unburned islands, we compared the elevation, transformed aspect (TRASP; Roberts and Cooper 1989), and slope. TRASP is a linear transformation of the aspect that measures a continuous gradient from the colder and wetter NNE (0 = 30°) to the hotter and drier SSW (1 = 210°). These data were obtained from numerous lidar datasets (see Table 4.1).

To assess differences in the forest structure of the unburned islands, we compared the aboveground biomass, mean height of first return, and 95th percentile height of first return. Aboveground biomass (AGB) was used because we anticipated that highly valuable spotted owl habitat occurs in older stands with an increased amount of AGB as compared to forest patches less suitable for spotted owl habitat with less AGB. The mean height of first returns was used because it is strongly correlated with the mean diameter at breast height (DBH) of forest plots (Kane et al. 2010). The 95th percentile height of first return was used because it is related to the canopy height of dominant trees within forest plots (Lefsky et al. 2005; Kane et al. 2010).

In all these analyses, non-parametric two-sample Kolmogorov-Smirnov tests were used to test for differences among the distributions of metrics analyzed. This non-parametric test compares two distributions by assessing the maximum difference between their cumulative density functions (Corder and Foreman 2014). For visualization, kernel density estimations (KDE) were used. KDEs provide an estimate of the probability density function within a dataset (Hollander et al. 2014). Central tendency for these plots was shown using distribution means.

3. Results

While the possible refugia scores ranged from -1 to 1, among the four fires tested the refugia scores ranged from -1 to -0.16. The distributions of the scores were right skewed, with the mean less than -0.75 for each fire (Figure 4.4-Figure 4.7). When mapped, the most notable pattern observable among the unburned islands was the highly influential positive effect that the size of the fire refugia has upon the refugia importance score. Higher valued refugia also tended to be distributed nearer to the edges of the fire perimeter. The patch shape and topographic metrics were generally not highly correlated, while the forest structure metrics were all highly correlated with one another (Table A.3).

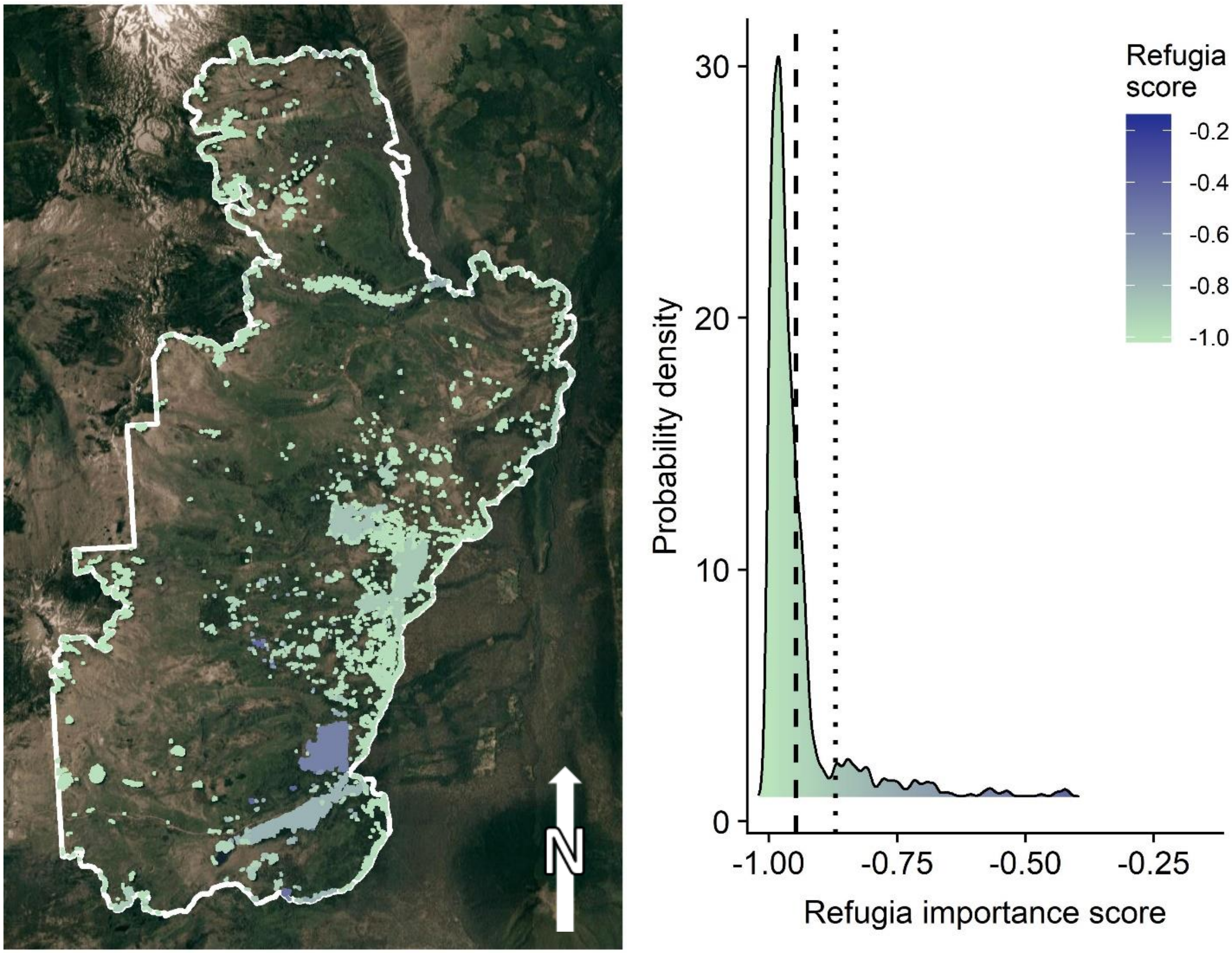

Figure 4.4. Mapped fire refugia colored by refugia importance score (left) and the distributions of scores (right) for the B&B fire. The dashed lines are distribution means. The dotted lines indicate the lower boundary of the top 10th percentile. Background imagery from Google Maps. Note: fire refugia are mapped with a border for easier viewing; they are smaller than they appear.

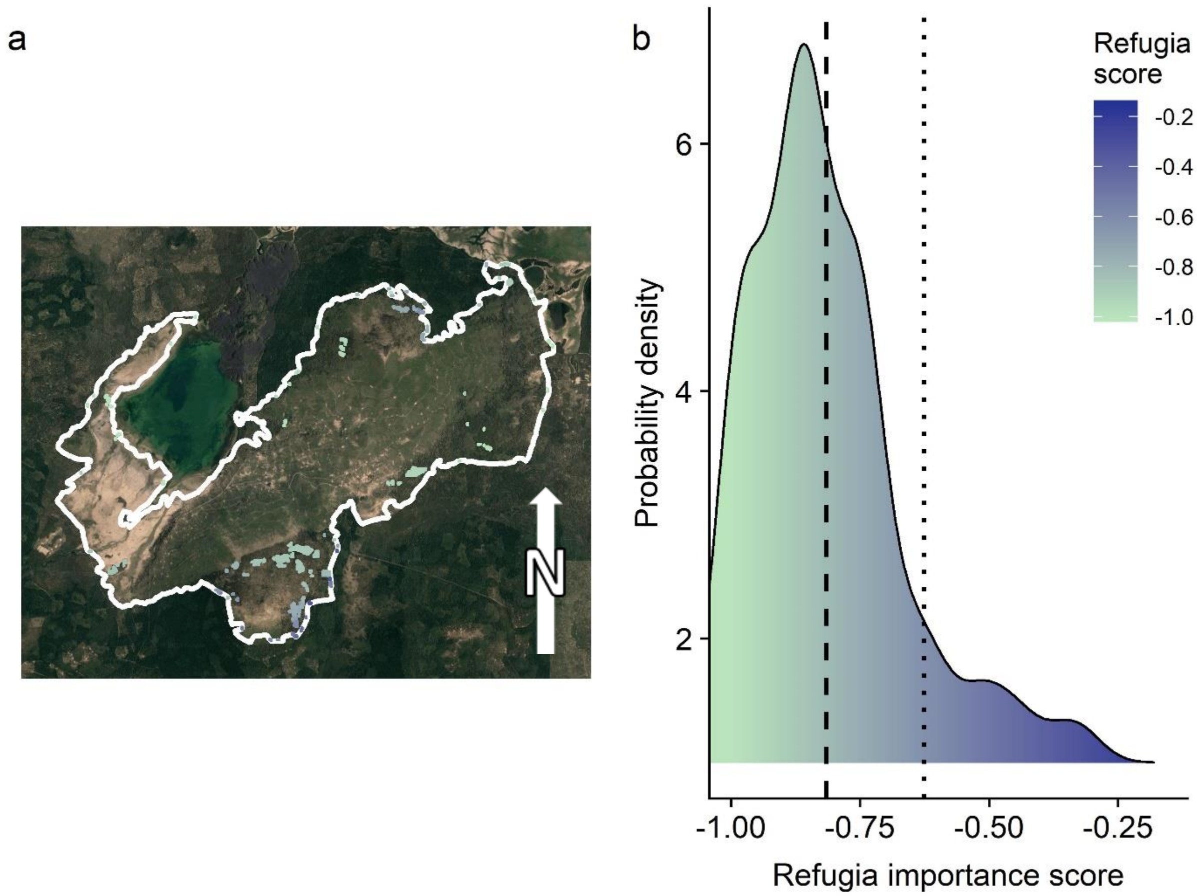

Figure 4.5. Mapped fire refugia colored by refugia importance score (left) and the distributions of scores (right) for the Davis fire. The dashed lines are distribution means. The dotted lines indicate the lower boundary of the top 10th percentile. Background imagery from Google Maps. Note: fire refugia are mapped with a border for easier viewing; they are smaller than they appear.

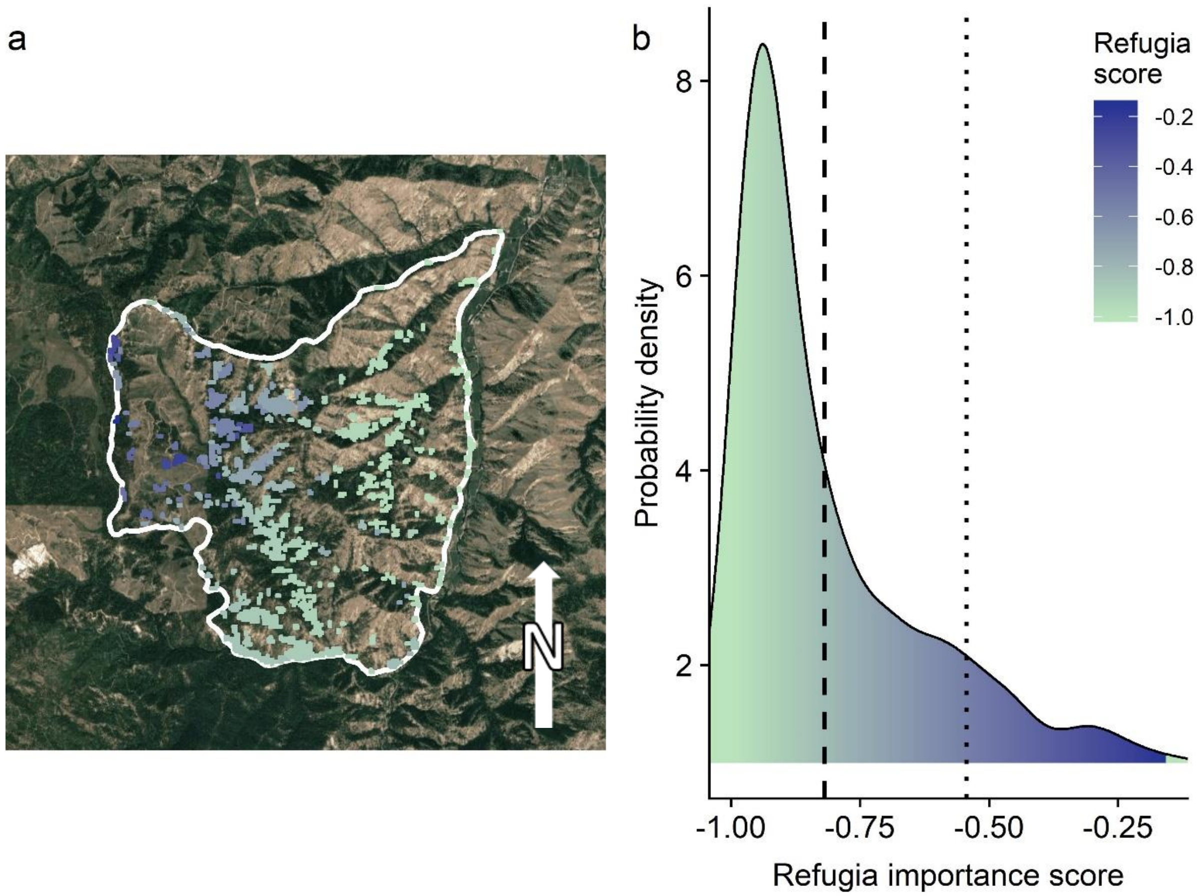

Figure 4.6. Mapped fire refugia colored by refugia importance score (left) and the distributions of scores (right) for the Poison fire. The dashed lines are distribution means. The dotted lines indicate the lower boundary of the top 10th percentile. Background imagery from Google Maps. Note: fire refugia are mapped with a border for easier viewing; they are smaller than they appear.

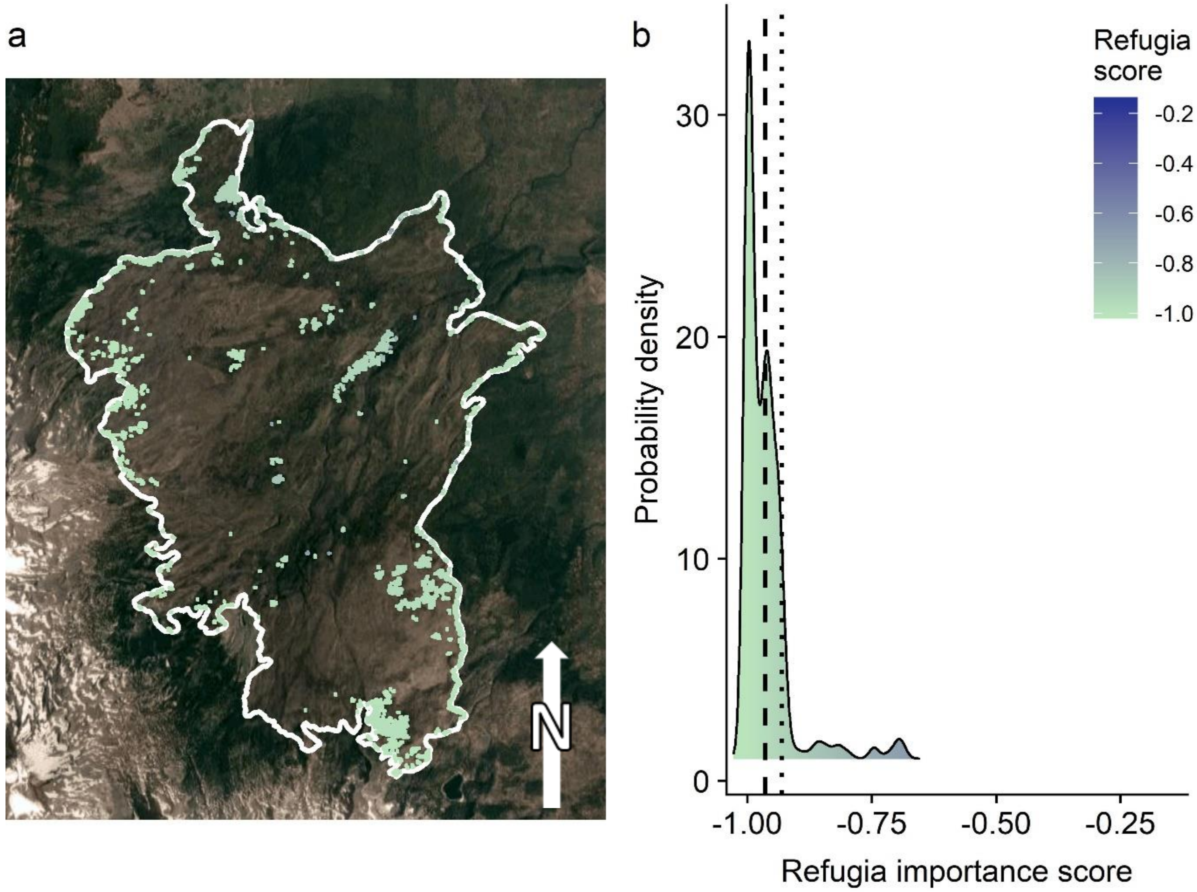

Figure 4.7. Mapped fire refugia colored by refugia importance score (left) and the distributions of scores (right) for the Pole Creek fire. The dashed lines are distribution means. The dotted lines indicate the lower boundary of the top 10^{th} percentile. Background imagery from Google Maps. Note: fire refugia are mapped with a border for easier viewing; they are smaller than they appear.

The distributions of unburned island areas and FRAC was highly right skewed for all fires regardless of refugia scores (Figure 4.4-Figure 4.7). In two of the fires, the Davis and Poison fires, there was a significant difference between the total fire refugia area distributions, with the mean area of the top 10% of fires being less than the mean area of the bottom 90% (Figure 4.8). There were significant differences in the FRAC distributions between the top 10% of unburned islands and the rest, for each of the fires (Figure 4.8b). While the top 10% of refugia in the Davis and Poison fires had higher means than the rest of the unburned islands, the effect was reversed for the B&B and Pole Creek fires.

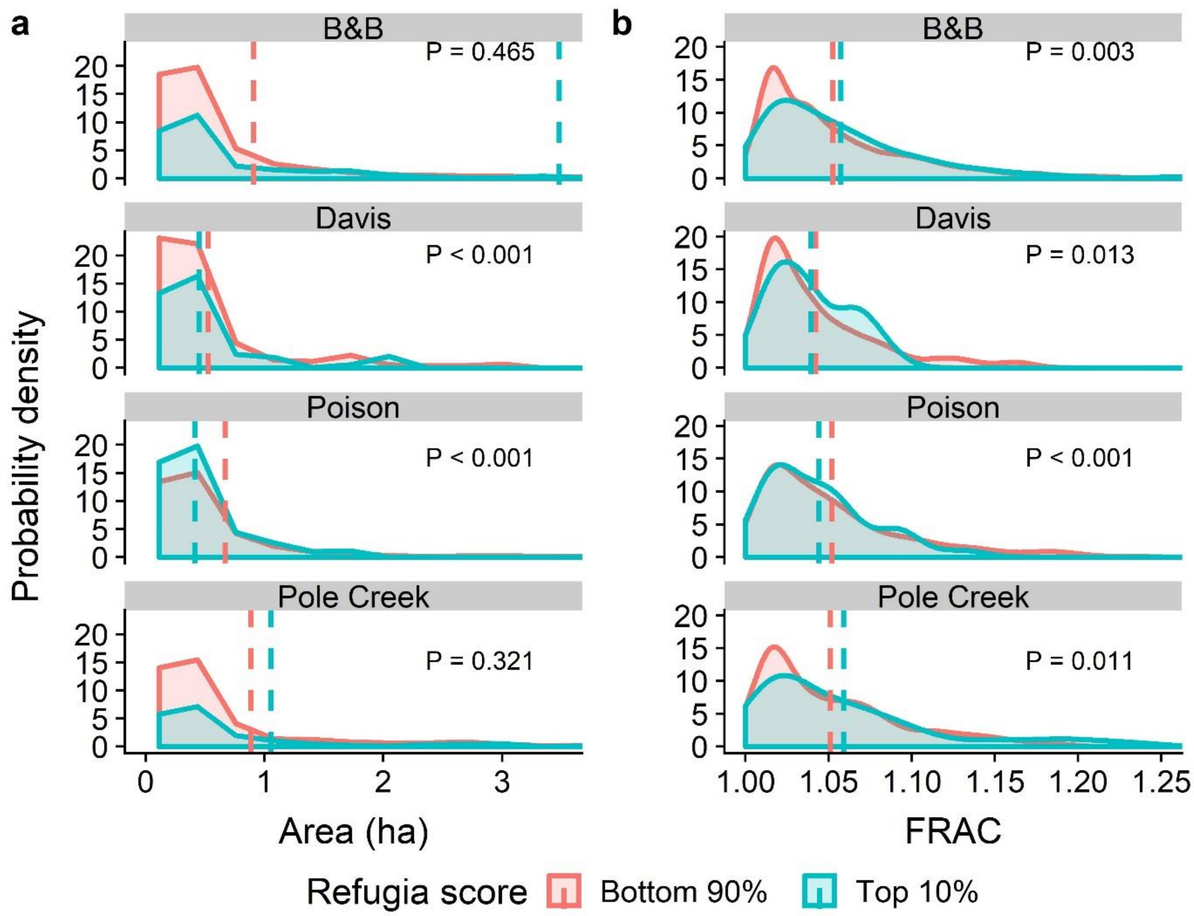

Figure 4.8. Kernel density estimation illustrating the distribution of the a) area (ha) and b) the fractal dimension index (FRAC) of unburned islands, by fire and ranking. The dashed line of the same color indicates the mean for each distribution.

The distributions of unburned island elevation differed significantly in all fires (Figure 4.9a). In the B&B and Pole Creek fires, the mean elevation of the top 10% of fire refugia was lower than the mean elevation of the rest of the unburned islands. In the Davis and Poison fires, the effect was reversed. The transformed aspect differed significantly in the Davis and Pole Creek fires (Figure 4.9b). In the Davis fire, the top refugia tended to be more on SSW aspects, whereas they tended be more on NNE aspects in the Pole Creek fire. The distributions of unburned island slopes differed significantly in all fires (Figure 4.9c). The mean slope of the top 10% of refugia was less than for the resto of the unburned islands in the B&B (although the effect was minimal), Davis, and Pol Creek fires. The effect was reversed in the Davis fire.

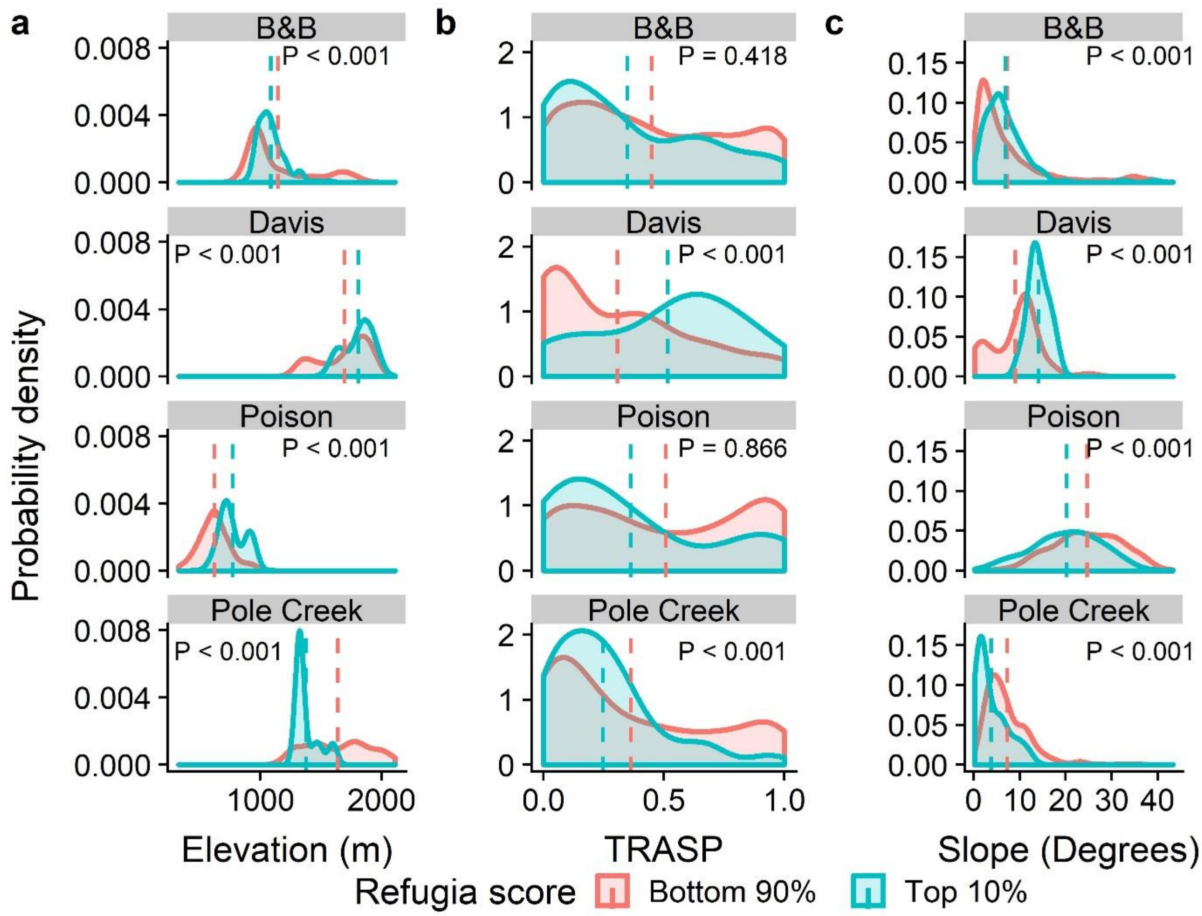

Figure 4.9. Kernel density estimation illustrating, by fire and ranking, the distribution of unburned island topographic metrics: a) elevation (m), b) transformed aspect (TRASP; Roberts and Cooper 1989), and c) slope (degrees). The dashed lines of the same color indicate the means for each distribution.

The distribution of above ground biomass was significantly different between the top 10% of fire refugia and the remaining unburned islands for the Davis and Poison fires (Figure 4.10a). In the Davis fire, the top 10% of fire refugia had higher mean biomass; in the Poison fire, the effect was reversed. The distribution of mean lidar point return elevations was significantly different in all fires except the Davis fire (Figure 4.10). In both the B&B and Pole Creek fires, the mean elevation was higher for the top 10% of refugia than the rest of the unburned islands; the effect was reversed in the Poison fire. The distributions of 95th percentile point return elevation differed significantly between the top 10% of refugia and the remaining unburned islands in all fires (Figure 4.10). In all fires except for the Poison fire, the mean 95th percentile elevation was higher in the top 10% of fire refugia than the remaining unburned islands; in the Poison fire, the effect was reversed.

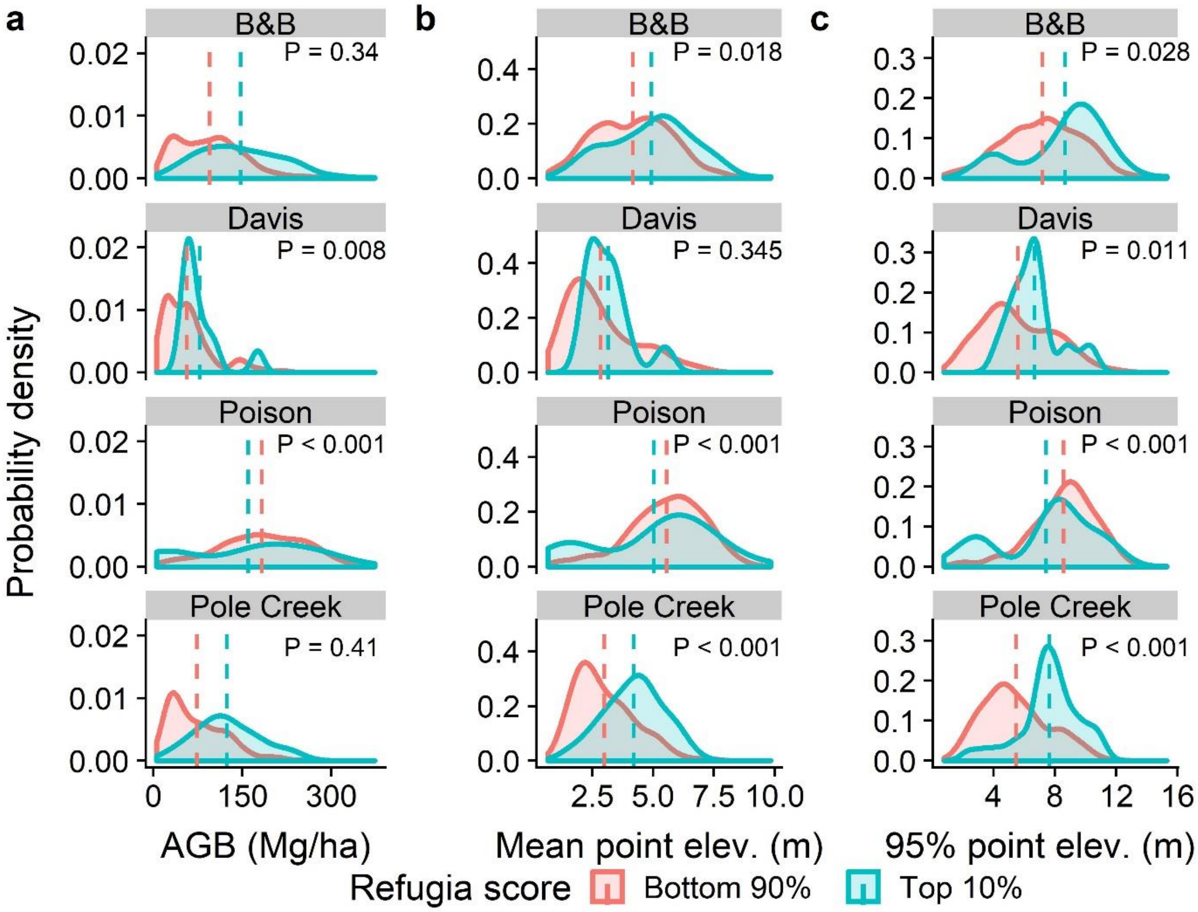

Figure 4.10. Kernel density estimation illustrating, by fire and ranking, the distribution of unburned island canopy metrics: a) aboveground biomass (AGB; mg/ha), b) mean point return height (m above ground surface), and c) height of the 95th percentile point return (m above ground surface). The dashed lines of the same color indicate the means for each distribution.

4. Discussion

This research provides a modeling framework for ranking fire refugia for spotted owl habitat importance. This framework, based upon the existing EEMS MCDA modeling environment, determined the importance of fire refugia for spotted owl habitat by analyzing multiple criteria. Although the model was informed by concepts and values found in the literature (e.g., Carey et al. 1992; Dugger et al. 2005; Davis et al. 2016), it is easily adapted to add the current state of knowledge and/or add ancillary inputs from land managers or biologists. We created an online platform which allows users without advanced computer programming or statistical capabilities access to this model. An important aspect of this modeling framework was to create a model that allowed for parameters to be easily altered to meet the specific needs of an end user. Additional criteria could include a more explicit measure of habitat connectivity, an important aspect of owl suitability, or distance to roads, which can be important for management suitability/effectiveness. Using the default parameters, we applied this model to rank the importance of fire refugia for spotted owl habitat.

In our analysis of the four fires in the eastern Cascades, the highest-ranked 10% of fire refugia had forest structure metrics that more resemble late-successional forest characteristics than the remaining fire refugia. These include an increased AGB, increased mean lidar return height (related to increased mean plot DBH), and increased 95th percentile lidar return height (related to canopy height of dominant trees). A notable anomaly is that the forest structure patterns were reversed in the Poison fire. The Poison fire sat at a lower elevation and had a lower annual precipitation than the other fires and was the only fire analyzed which occurred outside of the Deschutes National Forest. These factors all likely contributed to a different forest type, which may explain this irregularity.

While there were significant differences between the topographic metrics of the highest-ranked 10% of fire refugia and the remaining fire refugia, there were not many discernable patterns that held true across the fires. While the model input criteria were primarily based on vegetation characteristics (i.e., no topographical criteria were used as inputs), one may still expect that topography may control the formation of fire refugia. However, these results support recent findings that fire refugia formation may be controlled less by local topography than previously suggested and more by fire weather or fuels (Martinez et al., in press).

The distribution of fire refugia importance scores varies among fires but remains negative for all fire refugia. This indicates that while there is a range in importance for spotted owl habitat among the fire refugia, none of the fire refugia within these fires are currently optimal habitat. This is likely due to two primary factors: 1) even before the fire, owl habitat was not optimal, and 2) the fire itself reduced habitat quality. These fires were chosen for analysis because they are located at the intersection of several datasets, namely the unburned island database, the spotted owl habitat suitability model, and available lidar datasets. This intersection occurs along the eastern edge of the spotted owl's range, because the unburned island database stops at the Cascade crest, which limits the nearby suitable habitat. Further, as the fire burns, it removes nearby areas of previously high-quality spotted owl nesting/roosting habitat.

4.1 Limitations

There are several limitations to this study. First is the hierarchy of the model design. While the hierarchy used was developed logically, it was not based on an existing or established model hierarchy. However, like other parameters in this model, the hierarchy layout can be easily altered.

Another limitation is the detection accuracy of the datasets used as model inputs. While the unburned island detection performed well, especially in forested areas, it also predicted unburned areas conservatively (Meddens et al. 2016). There are likely areas within the fire perimeters, burned at low severity, that would still make suitable spotted owl nesting/roosting habitat yet were not included in the unburned island database. Uncertainty in the spotted owl habitat suitability model is another limitation. While maximum entropy habitat modeling is well established in ecological literature, they have limitations, specifically that sample selection bias of the presence-only data has a very strong effect on them (Elith et al. 2011). The authors of the spotted owl model address this by limiting the number of sampling location in each spotted owl pair territory and by thinning out locations to produce a less clumped dataset (Davis et al. 2011, 2016).

Finally, lidar data were acquired at different times in relation to the fires; all lidar was acquired post-fire, except for the Pole Creek fire, which was collected pre-fire. While this very likely did not impact the analysis of topographic variables, it may have impacted the analysis of the forest structure. However, we were investigating the unburned patches within a fire, so while there were potential low-severity impacts to the understory vegetation, the overstory likely did not change drastically.

4.2 Comparison to other habitat ranking models

While there were similarities between our model and other habitat ranking models from the literature, our model differed from them considerably. The habitat ranking model developed by Endries et al. (2003), in a manner similar to ours, used multiple spatial datasets to assess the importance for wildlife habitat. However, unlike ours, their model did not combine criteria into intermediate criteria or assign weights to different datasets. The Stauffer et al. (2004) modeled habitat importance for marbled murrelets based on field observations of habitat occupancy and recording both the presence and absence of murrelets. While our model did not base importance for spotted owl directly on field observations, it made use of the Davis et al. (2016) spotted owl suitability map which used spotted owl observations (presence only) as inputs. Rossi and Kuitunen (1996) didn't make much use of spatial datasets; however, they did address criteria weighting. Where we assumed equal weighting but gave an option for adjustment, they calculated expected weights of the ordinal threat category data algebraically, by assuming the probability density function for all threat categories was equal.

While these previous models performed as intended, we aimed for an approach that did not assume the requirements of the end users were static. Instead we hoped to develop a model that, while having default parameters that were generalized and ecologically meaningful, could be altered to address other considerations and reflect the values specific to each end user.

4.3 Future research

While we have produced a habitat ranking model, formal evaluation and validation is still required. One possible method for evaluation would compare post-fire owl presence between modeled high-importance and lower-importance refugia. Another method could locate functioning fire refugia occupied by spotted owls and use their locations and characteristics to model high-importance fire refugia.

5. Conclusions

After a fire, our fire refugia ranking model provides an efficient and quantitative method for ranking fire refugia by their importance for spotted owl habitat. As land managers look to improve the resiliency of their forests, prioritization of fire refugia is one method for achieving this. This modeling framework could be adapted for use by land managers for new fires and with altered model parameters or additional criteria. Given the correct inputs, it could be used to identify high-value refugia, not just for spotted owl habitat, but for any other resource.

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Chapter 5: Conclusion

As the forests of the American West have undergone various ecological shifts, scholars and practitioners have expressed considerable concern regarding forests' ability to respond to such changes. Wildfire activity has increased over the past century; this trend is projected to continue in the face of increasing wildland urban interface, continued fire suppression, and a changing climate. To increase forest resilience and maintain ecological functioning in the face of altered fire regimes, the promotion of fire refugia is imperative. While extant scientific literature has addressed the promotion of fire refugia in a theoretical sense, there remains a critical gap in the scientific literature in terms of how to identify and characterize high value fire refugia.

In this thesis, I employed geographic information systems (GIS), spatial modeling, survey questionnaires, and multicriteria decision analysis (MCDA) in order to identify and characterize high-value fire refugia. I aimed to develop an applicable model for ranking the ecological importance of unburned islands to identify high-value fire refugia.

In Chapter 2, I provide evidence that persistent unburned islands differ from the surrounding burned area in certain topographic characteristics; however, these characteristics differ according to fire regime group and fuel type. Previous studies found that fire refugia tend to occur in cooler and wetter areas, such as valley bottoms and on aspects with less solar radiation. In the present study, I largely found the opposite to be true in the Inland Northwest. I hypothesize that this is due to the prevalence of fuel-limited fire refugia in the arid canyon grasslands, rather than in the cool, mesic forest patches described in previous studies. Understanding the characteristics of persistent fire refugia allows for a better understanding of the biophysical factors that contribute to their formation.

In Chapter 3, by surveying land managers in the northwestern US, I determined that a region-wide, single metric fire refugia ranking model was not feasible for management applications because the criteria for determining the importance of fire refugia varied considerably. I categorized respondents' attitudes into two broad groups: 1) those who prioritized human infrastructure (predominantly US Forest Service employees), and 2) those who prioritized wildlife habitat (employees of various organizations). However, this broad clustering did little to explain the variability in the respondents' scoring of fire refugia importance criteria. The lack of consensus about these criteria reflects both the real-world intricacies of land management decision-making and the novelty of considering fire refugia in relation to land management practices.

In Chapter 4, I developed a refugia value ranking model by assessing the importance of fire refugia for northern spotted owl (*Strix occidentalis caurina*) nesting/roosting habitat. I incorporated an existing multi-criteria decision analysis (MCDA) framework into this model; further, I designed an online tool with a user-friendly interface and alterable parameters to enable end users to adapt this model with minimal design barriers. I applied this model to four fires in the East Cascades and characterized the high-value refugia by comparing them to lower valued refugia. Higher ranked refugia tended to have structures that were more characteristic of later successional stage forests than lower ranked refugia. While this model was built to rank fire refugia by their importance for spotted owl habitat, the framework can be applied to other fires to rank the importance of fire refugia for different species and ecosystems.

5.1 Management implications

While promoting fire refugia are one option for improving forest resiliency, it has remained infeasible for land managers due to the difficulty locating them. Using the ranking model framework presented in this thesis in combination with the Meddens et al. (2016, 2018a) unburned island detection model provides an effective avenue for identifying high-value fire refugia. Once identified, managers would be able to prioritize high-value fire refugia for restoration activities after a fire in order to maximize the potential benefit while minimizing the resource cost to perform these activities.

5.2 Future research

To ensure that land managers prioritize fire refugia in their management plans, developing a method for effectively ranking such unburned islands is critical. An effective ranking framework must be broad enough to be applicable to a variety of land managers, but targeted enough to yield results that reflect local values or site conditions. Rather than a single, region-wide model, a more specific approach that reduces the scope or the scale of the ranking model is necessary. In Chapter 4, I presented a framework for a reduced-scope ranking model that considered a single resource. Alternatively, a reduced-scale approach could be used. For example, future research could include the development of a multiple-value model for a smaller management unit. If co-produced with land managers, such a model could reflect the specific values and management considerations of a single management unit. Further research on both approaches is necessary to improve their applicability to land management. Furthermore, land managers could benefit from the incorporation of a fire refugia ranking model into a fire decision support system such as the Wildland Fire Decision Support System (WFDSS) or the Interagency Fuel Treatment Decision Support System (IFTDSS).

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Appendix A - Supplementary materials

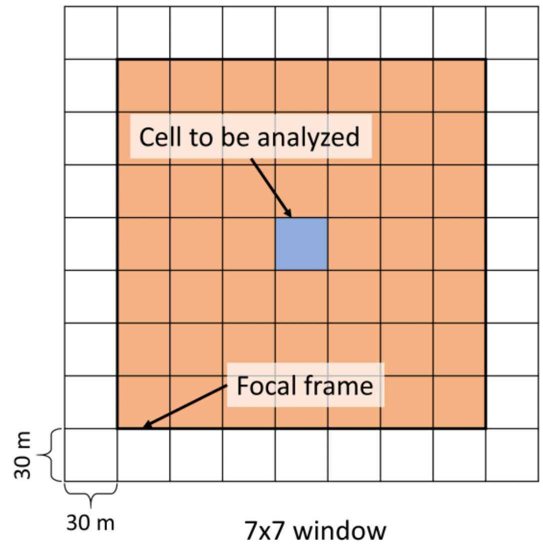

Figure A.1. Neighborhood analysis was used to calculate TPI and TRI. The 7x7 focal frame, which is 90 m in each direction, used third order Queen contiguity, which includes all cells (orange) within the focal frame.

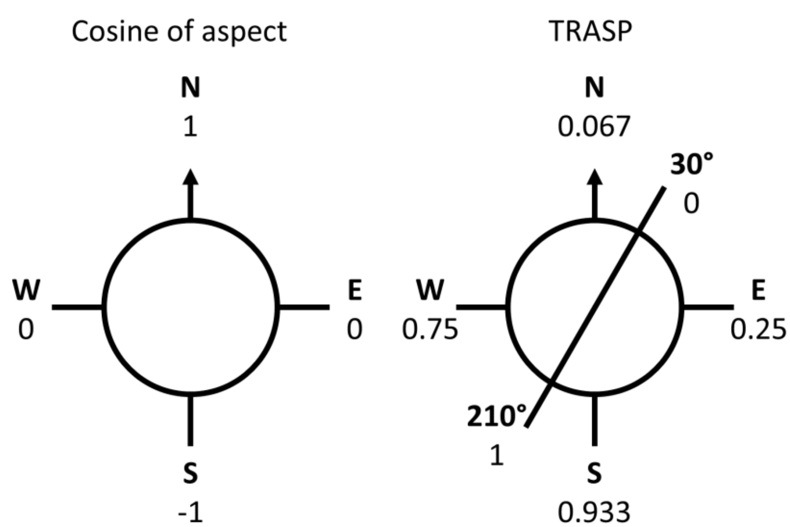

Figure A.2. An illustration of both aspect derived indices analyzed in this study. Transformed aspect (TRASP) was most informative for illustrations, although both were used in the analysis.

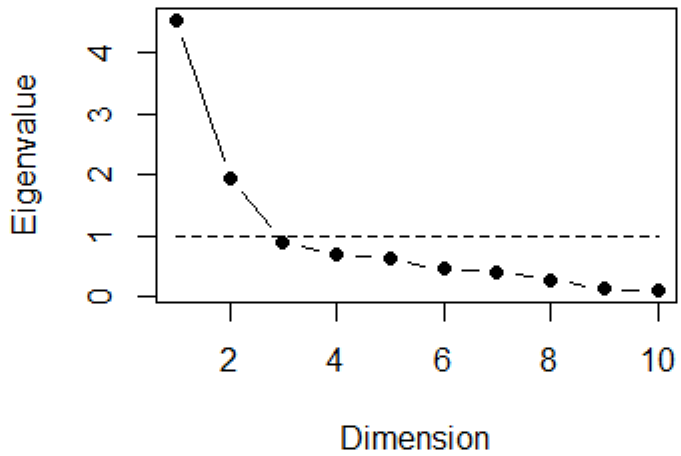

Figure A.3. Scree plot of the survey data used to determine the optimal number of factors to use in the exploratory factor analysis. Retain the number of factors above the inflection point of the curve. Two factors were retained.

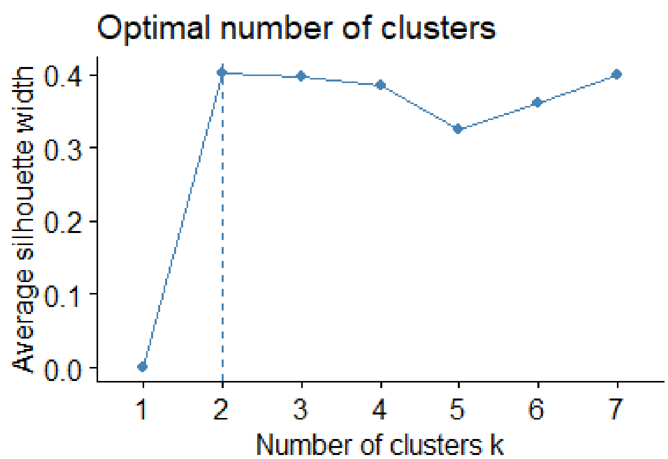

Figure A.4. Plot of average silhouette widths for each number of clusters. The optimal number is 2 clusters.

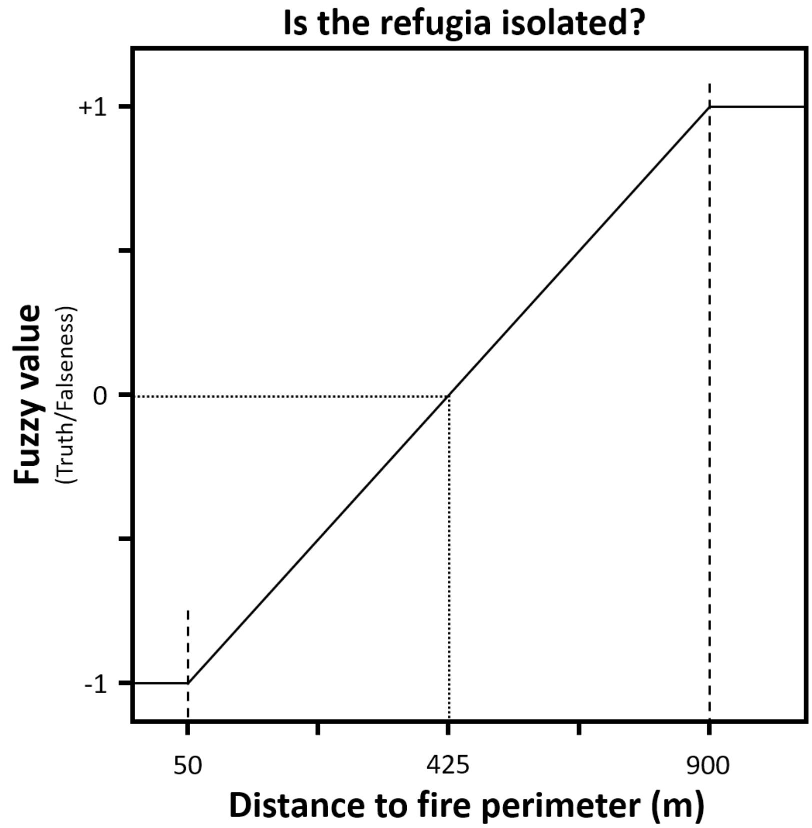

Figure A.5. An example of how fuzzy scores are determined. To determine the fuzzy value indicating the truth of the proposition "the refugia is isolated," its distance (in meters) to the nearest live edge forest edge is compared to the line above. Any distance ≤ 50 m would return -1, or entirely false. Any value ≥ 900 m would return 1 or completely true. Distances between 50 m and 900 m would return a value between -1 and 1, with 425 m returning a fuzzy value of 0 (dotted line). The thresholds (dashed lines) are manually set during the model building process.

Table A.1. Factor loadings for survey response data. Items with loadings >0.7 are bolded to highlight the most meaningful variables that make up each factor.

Criteria (abbreviation)	**Description**	**Factor 1**	**Factor 2**
Habitat (Habitat)	The quality of habitat within a refugium	**0.794**	-0.345
Uniqueness (Unique)	How unique a refugium is among all other refugium	0.620	-0.110
Infrastructure (Infrastr)	The amount of human infrastructure within refugium	-0.060	**0.778**
Critical habitat (Crit hab)	The presence of "critical habitat" in a refugium	**0.827**	-0.127
Invasive species (Invsv)	The absence of invasive species in a refugium	0.585	-0.139
Isolation (Isol)	The isolation of a refugium	**0.804**	0.061
Old growth (Old growth)	The presence of old growth within a refugium	**0.817**	0.112
Lad cover (Lnd cvr)	The rarity of the landcover type of a refugium among all other refugium	0.561	-0.081
Buildings (Bldgs)	The presence of buildings within a refugium	-0.027	**0.997**
Cultural Resources (Cult Resc)	The presence of cultural resources within a refugium	0.609	0.113

Table A.2. Habitat suitability variables. Adapted from Table 1 of Davis et al. (2016). Variables that were not applicable to the Washington Eastern Cascades or Oregon Cascades modeling regions were excluded.

Variable	Description
Forest structure and age	
Diameter diversity index (index)	Measure of structural diversity of forest stand. Positive relationship with habitat suitability.
Conifer canopy cover (%)	Percentage of conifer cover in the canopy as calculated in Forest Vegetation Simulator. Positive relationship with habitat suitability.
Stand height (m)	Average height of dominant height of dominant and codominant trees. Positive relationship with habitat suitability.
Mean conifer diameter (cm)	Basal area weighted mean DBH of all live conifers. Positive relationship with habitat suitability.
Density of large conifers (trees/ac)	Estimated tree density for all live conifers ≥ 30 in DBH Positive relationship with habitat suitability.
Stand age (years)	Average stand age based on field-recorded ages of dominant and codominant tree species (excluding remnant trees). Positive relationship with habitat suitability.
Forest species composition	
Subalpine forest (% of total basal area)	Stand component of Pacific silver fir (*Abies amabilis* Dougl. ex Forbes), subalpine fir (*A. lasiocarpa* (Hook.) Nutt.), noble fir (*A. procera* Rehd.), Shasta red fir (*A. shastensis* (Lemmon) Lemmon), Alaska cedar (*Chamaecyparis nootkatensis* (D. Don) Spach), Engelmann spruce (*Picea engelmannii* Parry ex Engelm.), whitebark pine (*Pinus albicaulis*, Engelm.), and mountain hemlock (*Tsuga mertensiana* (Bong.) Carr.). Negative relationship with habitat suitability.
Pine forest (% of total basal area)	Stand component of lodgepole pine (*Pinus contorta* Dougl. ex Loud.), Jeffrey pine (*P. jeffreyi* Grev. & Balf.), Bishop pine (*P. muricata* D. Don), and ponderosa pine (*P. ponderosa* Dougl. ex Laws.). Negative relationship with habitat suitability.
Oak woodland (% of total basal area)	Stand component of blue oak (*Quercus douglasii* Hook. & Arn.), Oregon white oak (*Q. garryana* Dougl. ex Hook.), and California black oak (*Q. kelloggii* Newb.). Negative relationship with habitat suitability.
Evergreen hardwood (% of total basal area)	Stand component of Pacific madrone (*Arbutus menziesii* Pursh), tanoak (*Lithocarpus densiflorus* Rehd.), California live oak (*Quercus agrifolia* Née), canyon live oak (*Q. chrysolepis* Liebm.), and California laurel (*Umbellularia californica* (Hook. & Arn.) Nutt.). Positive relationship with habitat suitability at lower levels, then negative at higher levels.

Table A.3. Correlation matrix for patch shape, topographic, and forest structure metrics.

Variables	**Area**	**FRAC**	**Elev.**	**TRASP**	**Slope**	**AGB**	**Mean return height**	**95% return height**
Area	1							
Fractional dimension index (FRAC)	0.354	1						
Elevation	-0.022	-0.054	1					
Transformed aspect (TRASP)	-0.006	0.052	-0.119	1				
Slope	-0.041	-0.071	-0.123	0.016	1			
Aboveground biomass (AGB)	-0.011	0.059	-0.491	0.051	0.203	1		
Mean return height	-0.016	0.042	-0.528	0.093	0.082	0.854	1	
95% return height	-0.018	0.04	-0.476	0.062	0.001	0.8	0.931	1