Title: Influence of topography and fuels on fire refugia probability under varying fire weather in forests of the US Pacific Northwest

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Abstract:
Fire refugia–locations that burn less severely or frequently than surrounding areas–support late-successional and old-growth forest structure and function. This study investigates the influence of topography and fuels on the probability of forest fire refugia under varying fire weather conditions. We focus on recent large fires in Washington and Oregon, USA (*n* = 39 fires >400 ha, 2004-2014). Our objectives are to (1) map fire refugia as a component of the burn severity gradient; (2) quantify the predictability of fire refugia as a function of pre-fire fuels and topography under moderate and high fire weather conditions; (3) map the conditional probability of fire refugia to illustrate their spatial patterns in old-growth forests. Fire refugia exhibited higher predictability under relatively moderate fire weather conditions. Pre-fire live fuels were strong predictors of fire refugia, with higher refugia probability in forests with higher pre-fire biomass. In addition, fire refugia probability was higher in topographic settings with relatively northern aspects, steep catchment slope, and concave topographic position. Conditional probability maps revealed consistently higher fire refugia probability under moderate versus high fire weather scenarios. Results from this study inform conservation planning by determining late-successional forests most likely to persist as fire refugia despite increasing regional fire activity.

Keywords: biological legacies, burn severity, fire refugia, late-successional forests, Pacific Northwest

Introduction

The spatiotemporal patterns of wildfires have important implications for biodiversity conservation throughout the world. In forest ecosystems of western North America, following decades of fire exclusion, wildfire activity has increased recently in association with climate and land use change (Barbero et al. 2015; Abatzoglou and Williams 2016), sparking stakeholder concerns about potential impacts on threatened and endangered species (Davis et al. 2016). Fire refugia—locations that burn less frequently or severely than surrounding areas (Krawchuk et al. 2016)—are a key component of forest disturbance mosaics, particularly in regions supporting substantial late-successional and old-growth (hereafter "old") forests (e.g., the US Pacific Northwest; Spies et al. 2018). Given projected increasing likelihood of large fires (Davis et al. 2017), some old forests that historically functioned as fire refugia may become more vulnerable to stand-replacing fire. Concurrently, fire refugia may persist due to numerous protective factors, including complex terrain, vegetation resistance associated with old trees, stochastic weather patterns, and varying intensity of fire suppression efforts. Quantifying and disentangling these interactive drivers of fire behavior and effects are urgent research priorities because understanding the probability and predictability of fire refugia is integral for effective management of old-growth forest function and persistence.

Although fuels, topography, and weather interact to influence fire behavior and associated refugia, some fire regimes are dominated by endogenous, bottom-up drivers such as fuels and topography, whereas other fire regimes are dominated by exogenous, top-down drivers such as climate and weather (Pyne et al. 1996). Fuel components, including ground, surface, ladder, and canopy fuels, are a function of vegetation composition and structure, which also influence fire spread, fire effects, and post-fire responses (Parks et al. 2018b; Zald and Dunn 2018). For example, tree size and species are strong predictors of fire-induced mortality and post-fire structural complexity, particularly in forests with mixed-severity fire effects, fire-tolerant species, and large, long-lived trees (Kane et al. 2015; Dunn and Bailey 2016). Although weather is more difficult than fuels to estimate at a fine spatial scale, recent studies have quantified fire weather in a spatially explicit fashion, leveraging interpolation methods to assign daily fire weather within fire perimeters (e.g., Parks 2014; Parks et al. 2018b; Zald and Dunn 2018). Topography also plays a key role across landscape gradients, wherein fire refugia are associated with topographic features like valley bottoms with high moisture, cold air pooling, or dense vegetation in some cases (Leonard et al. 2014; Krawchuk et al. 2016; Wilkin et al. 2016) and steep terrain at headwaters with limited fuel in other cases (Rogeau et al. 2018). Such examples illustrate how topography also influences vegetation/fuels and local fire weather, underscoring the multi-way interactions among these factors. Because topographically mediated fire refugia may be more stable and predictable than stochastic fire refugia associated with fire weather and management activities (Meddens et al. 2018a), topography may represent a key anchor point for forest conservation initiatives.

Recent studies have mapped fire refugia patterns and quantified drivers with large geospatial databases and innovative quantitative approaches. Mapping studies typically have employed Landsat imagery to identify fire refugia within recent fire events as locations including both unburned and low-severity fire effects where fire results in low mortality to dominant trees (e.g., Krawchuk et al. 2016; Meddens et al. 2016; Haire et al. 2017; Meigs and Krawchuk 2018; Collins et al. 2019; Walker et al. 2019; Chapman et al. 2020). Functionally, these remote sensing approaches identify fire refugia as locations exhibiting minimal spectral change relative to the broader burn mosaic. Though spectrally similar, such locations may have highly variable pre-fire fuel conditions, which translate into very different outcomes in terms of fire effects or severity (e.g., differing vegetation mortality in non-forest vs. young forest vs. old forest; Meigs and Krawchuk 2018; Zald and Dunn 2018; Lesmeister et al. 2019). Here, we leverage pre- and post-fire Landsat imagery to quantify fire refugia as part of the overall burn severity mosaic. Although these recent fire refugia represent only one characterization of refugia, which also can include climate refugia at longer time scales (Meddens et al. 2018b), contemporary fire refugia are directly applicable to forest policy and management. Indeed, land managers often utilize Landsat-based burn severity maps as a primary tool to assess fire effects, implement post-fire management activities, and assess conservation outcomes (Morgan et al. 2014; Davis et al. 2016; Meigs and Krawchuk 2018; Harvey et al. 2019).

Mapping recent spatiotemporal patterns of fire can inform regional perspectives on historical and contemporary fire effects (e.g., Reilly et al. 2017), but stakeholders, including land managers, also require information on specific drivers of fire refugia and maps of fire refugia probability under different combinations of fuels, topography, and weather. Prior studies have used machine learning algorithms, such as boosted regression trees (BRT), to assess the probability of fire refugia (Krawchuk et al. 2016; Rogeau et al. 2018), high-severity fire (Parks et al. 2018b), or drought refugia (Cartwright 2018). In this study, we employ BRT modeling to quantify fire refugia probability as a function of topography and pre-fire live fuels under varying fire weather conditions. In addition to quantitatively assessing the key predictors of fire refugia, it is important to evaluate the spatial patterns of predicted refugia across fire-prone landscapes containing heterogeneous forest conditions, including old forests embedded in a matrix of younger forests (Thompson et al. 2007; Spies et al. 2018; Zald and Dunn 2018). Here, we advance an approach to map the spatial patterns of fire refugia probability across numerous, heterogeneous fire events under scenarios representing relatively moderate versus high fire weather, and we highlight implications for old forest management.

Contemporary conservation policies and wildfire activity in the US Pacific Northwest (Oregon and Washington, hereafter “PNW”) make it an ideal location to study and characterize fire refugia in old forests. By definition, old forests develop in locations relatively protected from stand-replacing disturbance, and fire refugia represent an important factor for old forest development in regions where fire is a common disturbance. In western Oregon, Washington and Northern California, old forests occupy a small portion of their historical extent due to widespread timber harvest, underscoring the significance of their unique structural features, including large, old trees and complex forest architecture, which provide habitat for threatened and endangered flora and fauna (Davis et al. 2016). In the PNW, old forest habitats have been the focus of intensive public interest and conservation planning, most notably with the implementation of the Northwest Forest Plan (Spies et al. 2018; Stephens et al. 2019). Despite a general cessation of old forest harvest on federal land since 1994, these forests have recently experienced widespread fire activity (Davis et al. 2017; Reilly et al. 2017), underscoring the urgency of understanding factors conducive to old forest persistence (i.e., as fire refugia). The few studies that have explicitly assessed old forest fire refugia in the PNW suggest that refugia are associated with specific topographic and vegetation/fuel conditions (Camp et al. 1997; Kolden et al. 2017; Meigs and Krawchuk 2018; Lesmeister et al. 2019). Despite concerns about fire effects on late-successional forest habitats, species, and ecosystem services (Camp et al. 1997; Davis et al. 2016), fire refugia in old forests have not been mapped and evaluated across numerous large fire events in the PNW region.

Recent large fires in forests spanning variable forest composition, structure, and age, coupled with new geospatial datasets and computational tools, enable novel assessments of fire effects and probability of fire refugia in the PNW. This study assesses fire events in the Western Cascades ecoregion, which contains a substantial amount of old forests and is located centrally within the PNW region. Our specific objectives are to:

1. Map fire refugia as a component of the overall burn severity gradient in recent large fire events using Landsat satellite-based estimates of fire-induced tree mortality.
2. Quantify the predictability of fire refugia as a function of pre-fire fuels and topography under moderate and high fire weather conditions to better understand the enduring topographic drivers of fire refugia.

3. Derive maps of the conditional probability of fire refugia to illustrate spatial patterns of likely refugia in old forests under moderate and high fire weather scenarios.

Methods

Study area

This study focuses on the West Cascades ecoregion and its immediate surroundings (10 km buffer) in the Cascade Mountain Range of the US PNW (Figure 1; Olson and Dinerstein 2002). Precipitation and temperature vary across the study area, but a consistent climatic feature is relatively high winter precipitation and low summer precipitation conducive to natural disturbances, especially fire (Littell et al. 2010; Meigs et al. 2015). The West Cascades are typified by rugged terrain, soils derived from volcanic parent material, and productive conifer forests, including mature and old forests. Tree species composition varies within different forest types from low-elevation Douglas-fir (*Pseudotsuga menziesii* [Mirb.] Franco) and western hemlock (*Tsuga heterophylla* [Raf.] Sarg.) up to mid-elevation pacific silver fir (*Abies amabilis* [Douglas ex Loudon] Douglas ex. Forbes) and higher elevation subalpine fir (*Abies lasiocarpa* [Hook.] Nutt.), mountain hemlock (*Tsuga mertensiana* [Bong.] Carrière), and lodgepole pine (*Pinus contorta* Douglas ex. Loudon) (Franklin and Dyrness 1973). In southern and eastern portions of the ecoregion and adjoining areas, ponderosa pine (*Pinus ponderosa* P. Lawson & C. Lawson), sugar pine (*Pinus lambertiana* Douglas), grand fir (*Abies grandis* (Douglas ex. D. Don) Lindl.), incense-cedar (*Calocedrus decurrens* [Torr.] Florin), and other fire-tolerant tree species are more prevalent, as well as some important hardwood species (Dunn and Bailey 2016). Historical fire regimes were variable, including a combination of infrequent, stand-replacing fire and relatively frequent, non-lethal surface fire, with more frequent fire in southern and eastern parts of the study area (Weisberg and Swanson 2003; Tepley et al. 2013; Davis et al. 2017; Metlen et al. 2018; Spies et al. 2018).

West Cascades forests and surrounding areas are centrally located within the range of the northern spotted owl *(Strix occidentalis caurina)*, which defines the geographic scope of the Northwest Forest Plan (NWFP) and underscores the sociopolitical importance of old forest conservation within the ecoregion (Figure 1; Davis et al. 2016). In general, these forests are managed by US federal agencies for multiple resource objectives or by private industrial landowners for timber production. Like many landscapes in western North America, West Cascades forests have experienced important land-use changes, including logging, grazing, fire exclusion, and associated fuel accumulations (Hessburg et al. 2016). Fire extent has increased in recent decades in conjunction with climate change, particularly in the southern and eastern portions of the study area (Reilly et al. 2017), where the West Cascades ecoregion blend with floristic elements of the Klamath Mountains and East Cascades ecoregions, respectively (Figure 1).

Geospatial data acquisition and preparation

Sample fires and sample points for data analysis

We conducted geospatial and statistical analyses across all forest conditions within the West Cascades ecoregion and adjacent areas to map recent fire effects and quantify predictors of fire refugia (Objectives 1 and 2), and we focused on old forests to illustrate fire refugia spatial patterns (Objective 3). We identified old forests using existing maps of areas containing forest equivalent to or exceeding an old-growth structural index of 200 years (OGSI-200) based on gradient nearest neighbor (GNN) imputation (Ohmann et al. 2012). We acquired fire perimeters from the Monitoring Trends in Burn Severity (MTBS) program (https://www.mtbs.gov/; Eidenshink et al. 2007), selecting all large fires (>400 ha) that occurred between 2004 and 2014 in the West Cascades ecoregion, including an adjacent 10 km buffer to account for transitional forests within the boundary of the NWFP (Figure 1). We selected this time period to coincide with MODIS satellite imagery and associated fire weather data used for analyses.

We also excluded portions of fires that burned more than once during the Landsat era (i.e., since 1984). These basic criteria yielded 39 large fires, which collectively burned ca. 100,000 ha of forest within the study area (Figure 1).

We extracted spatial data (Table 1) and developed statistical models based on a 5% random sample of the total area within the selected fires, which are a subset of the sample points analyzed by Parks et al. (2018b) across the western US. We built statistical models combining points from all forest types to enable interpretation and mapping across the range of conditions represented in the study area. We subsequently assessed old forest fire refugia within a subset of locations that were late-successional or old-growth forests before recent fires (details below). We sampled locations identified as forest by three ancillary vegetation maps: the Landsat Time Series Stacks–Vegetation Change Tracker (Huang et al. 2010) and Existing Vegetation Cover and Environmental Site Potential from LANDFIRE (Rollins 2009; Parks et al. 2018b). We excluded points ≤100 m of fire perimeters to reduce potential edge effects (Stevens-Rumann et al. 2016). These processing steps yielded a large, representative sample for statistical modeling (n = 46,103).

Burn severity mapping and development of fire refugia response variable

Our response variable for statistical analyses was the binary occurrence of fire refugia (refugia/non-refugia) within the study fires described above, resulting in a sample of 10,696 refugia and 35,407 non-refugia points. We also mapped refugia locations as one of five classes across the full gradient of burn severity to provide the full ecological context of the study fires (Objective 1). We created these burn severity maps by combining Landsat imagery, plot-based tree mortality, and maps of pre-fire forest conditions following the workflow described in Figure 1 of Meigs and Krawchuk (2018). Specifically, we estimated fire-induced change with the relative differenced normalized burn ratio (RdNBR; Miller and Thode 2007) derived from pre- and post-fire NBR, which we in turn developed from Landsat time series using the LandTrendr algorithm (Kennedy et al. 2010). In essence, LandTrendr segmentation identifies vegetation disturbance and recovery by distilling potentially noisy annual time series into a simplified set of segments and vertices to capture the salient features of spectral trajectories while omitting most false changes (Kennedy et al. 2010; Meigs et al. 2015). In this study, we used LandTrendr processing to compile annual time series of the NBR, which combines near-infrared and mid-infrared wavelengths of the Landsat TM/ETM+ sensor (Miller and Thode 2007). These NBR time series were centered around the Landsat imagery median date (generally 1 August) at the pixel scale, thereby reducing seasonal variability associated with phenology and sun angles. This process resulted in consistent annual mosaics of NBR covering the full study area. We then computed RdNBR using two-year intervals to ensure consistent pre- and post-fire coverage for all pixels within each fire event (Meigs et al. 2016). RdNBR captures the relative change in dominant vegetation and is appropriate for assessing fire effects across numerous events spanning heterogeneous pre-fire conditions (Miller and Thode 2007; Cansler and McKenzie 2014), especially in the forest types within our study region (Meigs and Krawchuk 2018).

To classify fire refugia and other burn severity classes, we first clipped regional RdNBR mosaics within the MTBS fire perimeters for the 39 study fires. We then applied a regression equation developed by Reilly et al. (2017) that relates RdNBR to relative tree mortality, estimated using forest inventory plots across the PNW study region:

$$y = 134.87 + 259.38x + 567.68x^2 \qquad \text{(Equation 1)}$$

where y is continuous RdNBR and x is the percent basal area mortality based on the change in live tree basal area (BA) before and after fire at 304 inventory locations. We defined fire refugia as locations with very low RdNBR values equivalent to ≤10% tree basal area mortality (RdNBR ≤166). Although negative RdNBR can be associated with enhanced greenness (Miller and Thode 2007), only 54 (0.12%) of our sample points had RdNBR values less than -150 (Kane et al. 2015); a parallel analysis excluding these sample points did not affect our analysis (results not shown). We defined the remaining burned pixels as non-refugia and applied the same thresholds as Meigs and Krawchuk (2018) to evaluate the abundance of low- (10-25% BA mortality; RdNBR = 166-235), moderate- (25-75% BA mortality; RdNBR = 235-648), high- (75-90% BA mortality; RdNBR = 648-828), and very high-severity (>90% BA mortality; RdNBR ≥828). These classes are symmetrical between the low and high ends of the burn severity gradient and provide a more nuanced ecological context than frameworks with fewer severity classes. Given the challenges inherent in remote sensing of fire effects at the low end of the burn severity spectrum (Meddens et al. 2016), we assumed that locations with ≤10% tree mortality within one year of burning included both lightly burned and unburned areas.

Following these computations, we assessed the absolute and relative abundance of mapped fire refugia and other burn severity classes across the study fires (Objective 1). We summarized these maps of estimated fire effects for the portions of burned areas that were old and other forests prior to the study period using OGSI-200 maps (old-growth structural index equivalent of 200 years; Ohmann et al. 2012). We also compared burn severity distributions between different fire weather conditions (described below). Finally, we illustrated spatial patterns of recent fire effects in an example fire in the southern portion of the study area: the 2009 Boze Fire in the Umpqua River Basin (Figure 1).

Predictor and stratification variables: fuels, topography, and weather

We developed a statistical modeling framework to quantify the influence of pre-fire fuels and topography on fire refugia predictability under moderate and high fire weather conditions (Objective 2) (Table 1). We used two variables to assess pre-fire fuel conditions. First, we utilized Landsat imagery from 2002 to compute the enhanced vegetation index (EVI), which is an indicator of total live vegetation biomass (i.e., a key indicator of live fuels) and a strong predictor of Landsat-based severity (Parks et al. 2018a; Parks et al. 2018b). Second, we used maps of estimated live biomass from 2002 based on GNN maps, which integrate data from federal forest inventory plots (n ≈ 17,000), spatial predictors, and Landsat time series to impute numerous plot-level attributes for forested locations across the PNW

(Ohmann et al. 2012; available online: https://lemma.forestry.oregonstate.edu/data). For both live fuel variables, we used maps representing the year 2002 to ensure that they pre-dated the earliest fires in our study period.

To assess potential topographic drivers of fire refugia, we computed eight variables based on digital elevation models (30-m resolution) after Krawchuk et al. (2016): 1) local aspect (radians), 2) local slope (degrees), 3) catchment area (m^2), 4) catchment flowpath length (m), 5) catchment slope (radians), 6) relative topographic position (0-1, lower to higher elevation within 500-m radius reflecting concave to convex terrain), 7) topographic convergence index (~6-20, a metric of cold air drainage that increases with potential for cold air pooling), and8) SAGA wetness index (~1-12, a metric of hydrologic pooling that increases with potential soil wetness). These eight variables capture distinct elements of local- or watershed-scale topography that account for processes (e.g., solar insolation, cold air pooling) influencing fuel moisture and fire behavior (Table 1, Figure S1). Correlation among all predictor variables was generally low ($r < |0.4|$), with the exception of the slope, wetness, and convergence indices (Figure S1). All topographic metrics were calculated using the raster (Hijmans 2015) and RSAGA (Brenning and Bangs 2016) packages in the R statistical environment (R Core Team 2019).

Recognizing that fire weather is a dominant driver of fire behavior and effects (Pyne et al. 1996), we developed separate statistical models for two categories of daily fire weather (moderate vs. high). We estimated daily fire weather using energy release component (ERC) on a percentile scale. This metric represents the fuel moisture and potential energy release of a spreading fire and is used commonly in fire management (Table 1; Schlobohm and Brain 2002; Parks et al. 2018b). To match a given location with its associated daily ERC value, we assigned day of burn to each pixel by leveraging daily fire progression maps based on MODIS hotspot fire detection (Parks 2014). We then extracted ERC percentiles for each burned pixel from existing daily ERC maps, which are described in detail by Preisler et al. (2016) and Jolly and Freeborn (2017). For this study, we converted absolute ERC values to percentile values within an empirically estimated fire season for the West Cascades ecoregion over a 25-year period (1990-2014) (Parks et al. 2018b). Finally, we divided the sample data into two roughly equivalent bins according to ERC percentiles ≤90% (low/moderate fire weather *n* = 22,427 (49% of dataset)) and >90% (high/extreme *n* = 23,676 (51% of dataset)).

Statistical analyses: boosted regression tree model implementation and assessment

We modeled the probability of fire refugia (Objective 2) using boosted regression trees (BRT), a machine-learning approach that can accommodate complex, nonlinear relationships (Elith et al. 2008). For two initial model runs, we contrasted fire refugia predictability under moderate versus high fire weather using all eight topographic variables (hereafter "TOPO" models) (Table 1). For two additional model runs, we included the eight topographic variables plus the two live pre-fire fuel variables (hereafter "TOPO+FUELS" models) (Table 1). We parameterized each of the four BRT model runs after Krawchuk et al. (2016) using random subsets of the data to obtain at least 1000 trees (learning rate = 0.001, tree complexity = 5, bag fraction = 0.5). We evaluated model performance based on the area under the curve of the receiver-operator characteristic (hereafter "AUC") and five-fold cross-validated correlation based on sample pixels. The AUC provides a synthetic metric of a model's ability to predict the presence and absence of refugia. An ideal, fully predictive model would have an AUC value of 1.0, whereas a model with no predictive ability, that is, random, would have a value of 0.5. We interpreted values of >0.6-0.7 as fair, >0.7-0.8 as good, >0.8-0.9 as very good, and >0.9 as excellent (Krawchuk et al. 2016). We also interpreted model results by assessing the relative influence and partial-dependence plots of predictor variables. Variables with higher relative influence are more important drivers of fire refugia probability, and the partial-dependence plots show the distribution-wide association between each predictor variable and fire refugia probability after accounting for the other predictors in a given model run. We conducted BRT modeling using R with the gbm (Ridgeway 2015) and dismo (Hijmans et al. 2016) packages.

Spatial predictions of fire refugia probability

Based on these four model runs (TOPO or TOPO+FUELS under moderate or high fire weather conditions), we created conditional fire refugia probability maps to assess spatial patterns of predicted fire refugia (Objective 3). These maps display refugia probability on a scale from 0 to 1 at 30-m resolution and are based on the combined influence of the predictor variables in a given statistical model. Because they are derived directly from the statistical models, these maps represent reference scenarios where an entire area is assumed to burn under either moderate or high fire weather, but it is important to recognize that the actual fire weather that generated the burn mosaic for any individual fire varies within this range across both space and time. We compared maps of statistically modeled fire refugia probability under moderate versus high fire weather scenarios by differencing those maps and evaluating the locations associated with low and high fire refugia probability for each model run. In addition, we illustrated landscape patterns of our spatial predictions within a focal fire event: the 2009 Boze Fire in the Umpqua River Basin. Finally, we assessed old forest fire refugia probability by focusing on spatial predictions within the same OGSI-200 maps used for summarizing fire refugia and burn severity distributions in Objective 1 (Ohmann et al. 2012).

Results

Fire refugia and burn severity across recent large fires in the West Cascades

Large fires occurred primarily in the southern and eastern portions of the study area between 2004 and 2014 (Figure 1). The 39 fires in our study area encompassed 102,154 ha, ranging in individual extent from 591 ha to 18,008 ha (Table S1). 28% of these fires occurred in old forests (28,655 ha), with the remaining 72% occurring in other forests (Figure 2). Fire refugia accounted for 8,331 ha of burned old forests and 18,933 ha of other forests, representing 29% and 26% of each forest type, respectively (Figure 2).

The overall distribution of severity classes was similar between the moderate and high fire weather classes, although the high fire weather class had a larger percentage of very high severity than the moderate fire weather class (34% vs. 20%) (Figure 3). Fire refugia were a substantial component of locations that experienced both moderate and high fire weather in old and other forests. Under moderate fire weather, fire refugia represented 32% and 25% of old and other forests, respectively (Figure 3). Under high fire weather, fire refugia occupied a smaller portion of the area within fire perimeters, representing 22% and 20% of old and other forests, respectively (Figure 3).

The Boze Fire, which burned ca. 4,000 ha in 2009 in the Umpqua National Forest, provided an illustrative example of pre-fire biomass, topography, and fire effects in a medium-large fire that occurred under relatively high fire weather conditions (68% of sample points within fire perimeter). Pre-fire biomass varied substantially within the fire perimeter, primarily due to recent timber harvest, with dark green areas in Figure 4a representing generally old forests (i.e., exceeding the estimated 200-year-old threshold of the OGSI-200 map). Aspect mapped at 30-m resolution within the fire perimeter indicated important topographic features, including north-facing slopes, ridge tops, and valley bottoms (Figure 4b). Finally, burn severity patterns illustrated relatively large patches of stand-replacing fire (Figure 4c), presumably driven primarily by fire weather.

Predictability of fire refugia as a function of pre-fire fuels and topography under different fire weather conditions

In the TOPO and TOPO+FUELS statistical model runs, the abundance of refugia (percentage of response variable) was 26% and 20% under the moderate and high fire weather conditions, respectively (Table 2). Overall model performance was best (i.e., higher predictability of fire refugia) when including estimates of pre-fire live fuel abundance with topography variables (TOPO+FUELS), yielding AUC values of 0.75 and 0.69 under moderate and high fire weather, respectively (Table 2). Although topography alone did not produce a model with as strong predictive power, yielding AUC of 0.65 and 0.63 for the TOPO models under moderate and high fire weather, respectively (Table 2), the locations identified as topographic fire refugia may play a particularly important role for persistent and predictable old forests.

In terms of specific predictor variables, all four models exhibited similar relative influence of predictor variables under both moderate and high fire weather conditions (Table 3). For the TOPO+FUELS models, pre-fire EVI and pre-fire biomass exhibited the highest relative influence on the probability of fire refugia, and both variables were generally positively associated with fire refugia probability (Figure 5). For the TOPO models, the three variables with the highest relative importance were local aspect, catchment slope, and relative topographic position (Table 3). These three variables were also the topographic variables with the highest relative importance in the TOPO+FUELS models (Table 3). Across all model runs, northern aspects were positively associated with fire refugia probability, and southern aspects were negatively associated with fire refugia probability (Figure 4, Figure S2). Steeper catchment slopes were positively associated with fire refugia probability, as were terrain locations quantified as very low relative position (i.e., concavities within the context of a 500-m radius surface) (Figure 4, Figure S2). The relative influence of particular topographic variables varied somewhat among model runs, for example with catchment slope being more important than relative position under moderate fire weather and vice versa under high fire weather (Table 3). Finally, the BRT models illustrated interactions of predictor and stratification variables, with topography exhibiting a smaller relative influence on fire refugia probability during high fire weather (Table 3, Figure 4).

Maps of fire refugia probability in all forests and old forests under moderate and high fire weather scenarios

The spatial predictions of fire refugia probability revealed systematic landscape-scale differences between moderate and high fire weather scenarios (i.e., if a given fire were to occur entirely under either moderate or high fire weather). For the TOPO+FUELS models, mean refugia probability across all mapped fires was higher under moderate (0.72) than high (0.67) fire weather conditions despite substantial variability (Table 4).

Within the example fire event (Boze Fire), mapped fire refugia probability was consistently higher under moderate versus high fire weather scenarios (Figure 6). Predicted fire refugia spatial patterns were associated with topographic features, including aspect, ridges, and valley bottoms, particularly in the moderate fire weather scenario (Figure 4b, Figure 6a). Specific locations with lower fire refugia probability were especially evident in the difference map (Figure 6c), and some of these locations were associated with low pre-fire biomass (regeneration in past timber harvest patches, non-forest areas; Figure 4a).

As illustrated by the Boze Fire, old forest fire refugia with relatively high pre-fire biomass represented only a portion of the modeled landscapes (Figure 4, Figure 6). Fire refugia that actually resulted from the Boze Fire were relatively patchy and discontinuous (dark blue areas in Figure 4c), whereas the conditional probability of fire refugia under the two fire weather scenarios varied at relatively fine spatial scales associated with the underlying topography and pre-fire live fuels (Figure 6).

As with all other forested areas (Figure 6a-c), old forest fire refugia probability was both higher and more variable under moderate fire weather conditions (Figure 6d-f).

Discussion

Influence of topography and fuels on forest fire refugia under variable fire weather

In this study, we developed spatially explicit methods to quantify the occurrence, drivers, and conditional probability of fire refugia as a function of fuels, topography, and fire weather in forests of the US Pacific Northwest. We developed statistical models and maps across all lands within fire perimeters and subsequently highlighted spatial patterns of fire refugia probability in old forests. We found that fire refugia predictability is related to multiple metrics of pre-fire live fuels and topography and that fire refugia probability is lower under higher fire weather conditions. Specifically, we determined that high biomass forests on northwest-facing slopes have the highest refugial capacity, even when burning during periods of relatively high fire weather. In addition, the fundamental relationships between fire refugia probability and the topographic predictor variables assessed here were relatively consistent across fire weather scenarios. Because fire refugia predictability and probability both were lower under high fire weather, our findings suggest that the abundance and stability of fire refugia may decline as wildfire activity increases with projected climate change (Barbero et al. 2015). Moreover, because the likelihood of large wildfires also is projected to increase with climate change within the study area (Davis et al. 2017), more of the landscape will experience fire. However, despite recent large fire years, many PNW forests are still in a fire deficit relative to historical fire regimes (Haugo et al. 2019). Low-severity fire has been a substantial component of contemporary fire in the PNW region (Reilly et al. 2017), indicating a high potential for fire refugia to persist despite increasing fire extent.

Our findings are generally consistent with recent spatially explicit, boosted regression tree analyses of fire refugia, fire effects, and refugia from other disturbances in western North America. The top three topographic variables in our study—aspect, catchment slope, and relative position—were also important predictor variables with similar partial-dependence relationships in an analysis of large fires in the Western Cordillera of Canada, which is relatively colder and more topographically rugged than the West Cascades (Krawchuk et al. 2016). Our study applies the same general analytical approach and variables as Krawchuk et al. (2016), providing models and maps applicable to research and management in the PNW. Another BRT analysis in Canada utilized historical landscape photos to delineate fire refugia as forest patches that survived large fires in headwater drainages and near upper tree line, highlighting the refugial capacity of high elevation sites close to non-fuel conditions (Rogeau et al. 2016). In another recent burn severity assessment using the same sampling scheme and some of the same data and methods as our study, Parks et al. (2018b) found that pre-fire live fuels (EVI) were a strong predictor of high-severity fire probability in the West Cascades and across the western US (Parks et al. 2018b). Finally, a recent analysis close to our study area determined that a combination of topographically shaded slopes, low biomass forests, and low soil bulk density was associated with drought and insect/drought refugia (Cartwright 2018). Collectively, these studies demonstrate the value of integrating multiple variables representing fuels or vegetation, topography or landscape context, and weather or climate to quantify refugia probability or persistence, as well as the importance of geographic variation among study regions.

Despite similarities among analyses and regions, there are important distinctions between the relatively temperate, moist forests in the West Cascades and forests in colder or drier ecosystem types. For example, our finding that pre-fire EVI (i.e., live fuel) is positively associated with fire refugia is consistent with findings from the 2013 Douglas Complex, which burned to the west of our study area in the PNW (Zald and Dunn 2018; Lesmeister et al. 2019). In contrast, our results differ from observations of lower burn severity (i.e., tree mortality) in young forest stands with lower pre-fire fuels following the 2006 Tripod Complex in the northern PNW (Lyons-Tinsley and Peterson 2012). Our findings also contrast with an assessment of numerous fires in the southwestern US that found that low-severity fire was more likely in locations with lower pre-fire EVI, particularly in cooler or wetter years (Parks et al. 2018a). Consequently, further research is warranted on the influence of pre-fire fuels on burn severity and fire refugia, particularly studies that contrast the relatively warm, moist PNW with drier, less productive forests.

Within the US Pacific Northwest, prior field-based studies that explicitly focused on fire refugia in older forests showed how refugial conditions are associated with particular topographic settings at a plot scale, including northerly aspects, stream confluences, and within highly dissected terrain (Camp et al. 1997; Kolden et al. 2017). These fire refugia, located within the federally protected Swauk late-successional reserve in Washington, exhibited characteristic vegetation composition and structure, including fire-intolerant species, old trees, multi-layered canopies, and downed coarse wood (Camp et al. 1997). Although these fire refugia sites were relatively buffered from prior stand-replacing fire, they also contained abundant fuel for a recent large fire, the Table Mountain Fire of 2012, which resulted in marginally higher overstory tree mortality in refugial than in non-refugial sites (Kolden et al. 2017). At the same time, non-stand-replacing fire was abundant in mixed-conifer forests within that fire event (Meigs and Krawchuk 2018), likely supporting the retention of large live trees, large dead wood, and other old forest elements. Such non-stand-replacing fire effects are a fundamental driver of old forest structural development pathways in the study region (Tepley et al. 2013).

After accounting for pre-fire live fuels, three topographic variables were consistently important across all four statistical models: aspect, catchment slope, and relative position. The positive association between fire refugia probability and northerly aspects is intuitive because they are generally cooler and retain moisture longer into the fire season, supporting higher fuel moisture and large, fire-resistant trees than south-facing aspects. In contrast, the positive association between fire refugia and catchment-scale slope is less intuitive given the expectation of faster spread rates and higher burn severity when fire spreads up steep slopes (Pyne et al. 1996). However, the catchment slope variable may also be capturing terrain ruggedness and associated fuel breaks at a landscape scale (e.g., rocky ridges, cliffs, and outcrops). Finally, the negative association between fire refugia probability and relative topographic position highlights the refugial role of convergent valley bottoms, cold air pooling, and riparian forest composition, structure, and moisture (Leonard et al. 2014). We recognize that these topographic conditions interact with fuel/vegetation type and abundance as well as weather dynamics, which underscores the value of integrating multiple metrics of fuels, topography, and weather, as well as their interactions. We also note that although topography alone did not produce the strongest predictive models, the variability that topography *does* explain could be very important for identifying enduring, persistent fire refugia for old forest habitats.

Uncertainties and future research

The topic of fire refugia has been gaining interest in research and management arenas, especially in the context of climate change, but many uncertainties remain regarding the different ways that refugia have been conceived, defined, and measured across spatial, temporal, and taxonomic scales (Meddens et al. 2018b). Each objective of this study—mapping of recent fire refugia and burn severity, statistical modeling of refugia predictability, and spatial predictions of fire refugia conditional probability—depends on key assumptions and could be improved for future assessments. Quantifying burn severity with satellite imagery presents multiple challenges, including spatial variability (e.g., sub-pixel fire effects), temporal variability (e.g., delayed tree mortality), and the inherent disconnect between remote and ground-based metrics of burn severity (Morgan et al. 2014, Dunn and Bailey 2016, Harvey et al. 2019). Nevertheless, Landsat-based RdNBR mapping is valuable as a relative indicator of fire-induced change across numerous fire events spanning heterogeneous conditions, particularly when interpreted in the context of field-measured fire effects like tree mortality (Reilly et al. 2017; Chapman et al. 2020). We recognize that the fire refugia threshold of 10% basal area mortality is subjective, and future studies could test other refugia thresholds or leverage additional spectral information in Landsat imagery (Meddens et al. 2016; Collins et al. 2019), as well as finer-resolution satellite and aerial imagery (Walker et al. 2019; Chapman et al. 2020). Future studies also could integrate field observations to distinguish low-severity from truly unburned refugia (Meddens et al. 2016) and to quantify the distinctive composition and structure in old forests, particularly in the West Cascades where large, fire-resistant Douglas-fir trees are prevalent.

As with any statistical analysis, BRT modeling requires making assumptions and decisions about specific variables and model parameters. For example, fuel and fire weather metrics are difficult to characterize consistently at the fine spatial and temporal scales where they influence fire behavior and effects, as described in detail by Parks et al. (2018). Also, many other predictor variables could be incorporated to assess fire refugia, including fire weather indices other than ERC (e.g., burning index, temperature, precipitation, wind speed and direction), climatic conditions (i.e., drought), fire season, and spatial variables that capture the landscape context of refugia (e.g., forest patch size and edge effects, distance to roads, ridges, and other known fuel breaks). Additionally, BRT is a very powerful machine learning approach, but it also is prone to overfitting, and nonlinear partial-dependence plots can hinder model interpretation and spatial prediction, especially when sample size is low at the margins of fitted functions (Figure S3). In particular, the spatial predictions of conditional probability (Figure 6) represent unique combinations of interacting variables, and it is challenging to discern direct relationships between mapped fire refugia probability and specific predictors. Finally, although spatial predictions are one of the most powerful outputs from BRT modeling, we caution against overinterpreting the specific values of conditional fire refugia probability (Table 4, Figure 6), suggesting that the relative difference among models and fire weather scenarios is more informative.

Implications for fire refugia monitoring and management

This study provides methods and results that are directly applicable to forest monitoring and management efforts in the PNW and other fire-prone regions. The fire refugia and burn severity maps illustrate the landscape mosaic of fire effects within recent large fires. Although the prevalence of large fires in the southern and eastern portions of the greater West Cascades study area was not surprising given the sub-regional variation in forest composition, historical fire regimes, and lightning ignitions, the low relative abundance of stand-replacing fire across all fires indicates that fire refugia can occur across much of the region. The role of bottom-up, endogenous drivers of fire behavior, including the intrinsic fire resistance of old Douglas-fir trees in this study region (Dunn and Bailey 2016) and the cool/moist microclimates supported by old forests, is a key factor that supports fire managers using wildfire to meet resource objectives under moderate fire weather conditions. In fact, wildfires burning under moderate conditions potentially could enhance the refugial capacity of old forests by effectively thinning less fire-resistant trees and ladder fuels, similar to the ecological effects of prescribed fire (North et al. 2012; Walker et al. 2018).

At the same time, most of the northern and western portions of our study area have not burned for decades to centuries. These cooler and moister forests represent a broader scale of fire refugia associated with fire frequency rather than severity, reflecting top-down, exogenous drivers of fire behavior. Because wind-driven fire events in these cooler, wetter Douglas-fir dominated forests were typified historically by large patches of stand-replacing fire (Halofsky et al. 2018), mitigation of anthropogenic ignitions and rapid mobilization of firefighting resources could continue to play an important role in protecting old forests that are vulnerable to fire under extreme fire weather conditions. The residual old forests in much of the study region typically occur in patches surrounded by younger forests regenerating from timber harvest (Franklin and Dyrness 1973), underscoring how the spatial patterns of land ownership and management intensity have strong effects on fire spread, burn severity (Zald and Dunn 2018), and associated fire refugia capacity.

Moving forward, our statistical modeling and mapping approaches could be expanded and enhanced to address the broader range of forest conditions and management applications throughout the PNW and other regions. Old forest persistence and spotted owl conservation are timely issues with complicated tradeoffs among fire exclusion, restoration thinning, and increasing fire activity, especially in the more fire-prone portions of the study area (Davis et al. 2016; Spies et al. 2018; Lesmeister et al. 2019; Stephens et al. 2019). Spatial predictions of fire refugia probability could help land managers identify specific locations for forest restoration or habitat conservation, depending on management objectives and policy constraints (Wilkin et al. 2016). Another key application of this research is that all refugia are not equivalent. Persistent fire refugia represent a critical subset of old forests, and our study demonstrates that some persistent fire refugia can be predicted based on enduring topographic features. Although these old forests have persisted for centuries in a relatively fire-prone region, we have entered a new era of anthropogenically dominated landscapes that are projected to experience increasing fire activity (Barbero et al. 2015; Davis et al. 2017). As such, landscape and regional maps of locations most likely to persist as fire refugia—particularly in old forest environments critical to the survival of threatened and endangered species—will support adaptive management, forest plan revisions, and ongoing conservation initiatives.

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Tables

Table 1: Predictor and stratification variables for boosted regression tree analysis.

Variable	Description (units)	Source
Live fuel: Enhanced vegetation index	Pre-fire vegetation greenness from Landsat imagery (spectral vegetation index scaled from 0 to 1000)	Parks et al. 2018
Live fuel: Biomass	Pre-fire biomass based on GNN imputation mapping (kg ha^{-1})	Ohmann et al. 2012
Topography: Catchment area	Extent of hydrological catchment (m^2)	30-m DEM*
Topography: Catchment flowpath	Length of hydrologic flowpath (m), which is related to watershed area and complexity	30-m DEM
Topography: Catchment slope	Mean slope of hydrological catchment (radians), which captures more general slope steepness than local slope	30-m DEM
Topography: Local aspect	Direction of slope at local scale (radians), which influences fuel moisture and wind patters	30-m DEM
Topography: Local slope	Steepness of slope at local scale (degrees), which influences fire spread and fuel pre-heating	30-m DEM
Topography: Relative position	Relative topographic position (0-10); lower to higher elevation within 500-m radius, which captures the landscape position of a given site	30-m DEM
Topography: Topographic convergence index (TCI)	TCI (~6-20); increases with potential for cold air pooling, which influences fuel moisture and vegetation composition and structure	30-m DEM
Topography: Saga wetness index (SWI)	SWI (~1-12); a metric of hydrologic pooling that increases with potential soil wetness, which influences fuel moisture and vegetation composition and structure	30-m DEM
Fire weather: Energy release component	Integrates fuel moisture and potential energy release at flaming front of a fire	Preisler et al. 2016, Jolly and Freeborn 2017, Parks et al. 2018b

Notes: The response variable for all BRT modeling is a binary refugia/non-refugia classification of burn severity based on Landsat satellite mapping (see Methods). *Digital elevation model subset of the US National Elevation Dataset (acquired from US Landfire program: https://www.landfire.gov/NationalProductDescriptions7.php).

Table 2. Boosted regression tree model metrics and performance.

	TOPO (eight topography variables)		TOPO+FUELS (eight topography variables plus two metrics of pre-fire live fuel)	
Fire weather	Moderate	High	Moderate	High
Sample size (number of pixels)	22427	23676	22427	23676
Refugia (percent)	26	20	26	20
Number of regression trees	4050	4800	9450	8600
AUC	0.65	0.63	0.75	0.69
Cross-validated correlation	0.24	0.21	0.4	0.31

Table 3. Relative importance of predictor variables in boosted regression tree analysis across four model scenarios.

TOPO			
Moderate fire weather		High fire weather	
Variable name	Relative influence	Variable name	Relative influence
Catchment slope	36.3	Relative position	27.2
Local aspect	23.3	Catchment slope	21.5
Relative position	12.0	Local aspect	18.0
Wetness index	10.2	Wetness index	11.3
Local slope	7.9	Local slope	6.4
Catchment area	4.0	Catchment flowpath	5.5
Catchment flowpath	3.5	Convergence index	5.4
Convergence index	2.8	Catchment area	4.9
TOPO+FUELS			
Moderate fire weather		High fire weather	
Variable name	Relative influence	Variable name	Relative influence
EVI (pre-fire live fuel)	32.2	EVI (pre-fire live fuel)	22.5
Biomass (pre-fire live fuel)	20.2	Biomass (pre-fire live fuel)	17.0
Local aspect	16.8	Relative position	13.8
Catchment slope	10.2	Catchment slope	10.1
Relative position	6.4	Local aspect	10.0
Local slope	5.8	Wetness index	7.6
Wetness index	3.7	Convergence index	7.2
Convergence index	2.2	Local slope	6.9
Catchment area	1.3	Catchment area	2.8
Catchment flowpath	1.2	Catchment flowpath	2.2

Notes: Variables and units are defined in Table 1.

Table 4. Summary statistics of mapped fire refugia conditional probability across four model runs.

	TOPO (eight topography variables)		TOPO+FUELS (eight topography variables plus two metrics of pre-fire live fuel)	
Fire weather	Moderate	High	Moderate	High
Minimum	0.40	0.28	0.27	0.16
Maximum	0.66	0.75	0.88	0.81
Mean	0.54	0.59	0.72	0.67
Stand dev	0.02	0.02	0.02	0.05

Notes: Statistics based on spatial distribution of modeled fire refugia probability across all fire perimeters combined throughout the study region. Values (minimum, maximum, mean, standard deviation) represent the conditional probability of fire refugia, assuming all pixels burn under a given fire weather scenario.

Figure captions

Figure 1. Study area map and fires included in statistical analysis (*n* = 39). Fire perimeters from the MTBS program (https://mtbs.gov). West Cascades ecoregion based on Olson and Dinerstein (2002) plus 10 km buffer. Forest areas based on GAP analysis (https://gapanalysis.usgs.gov). Yellow arrow indicates location of example fire event, the 2009 Boze Fire in the Umpqua River Basin. Fires are listed in Table S1. Inset map shows terrain from ESRI world terrain base map (service layer credits: Esri, USGS, NOAA).

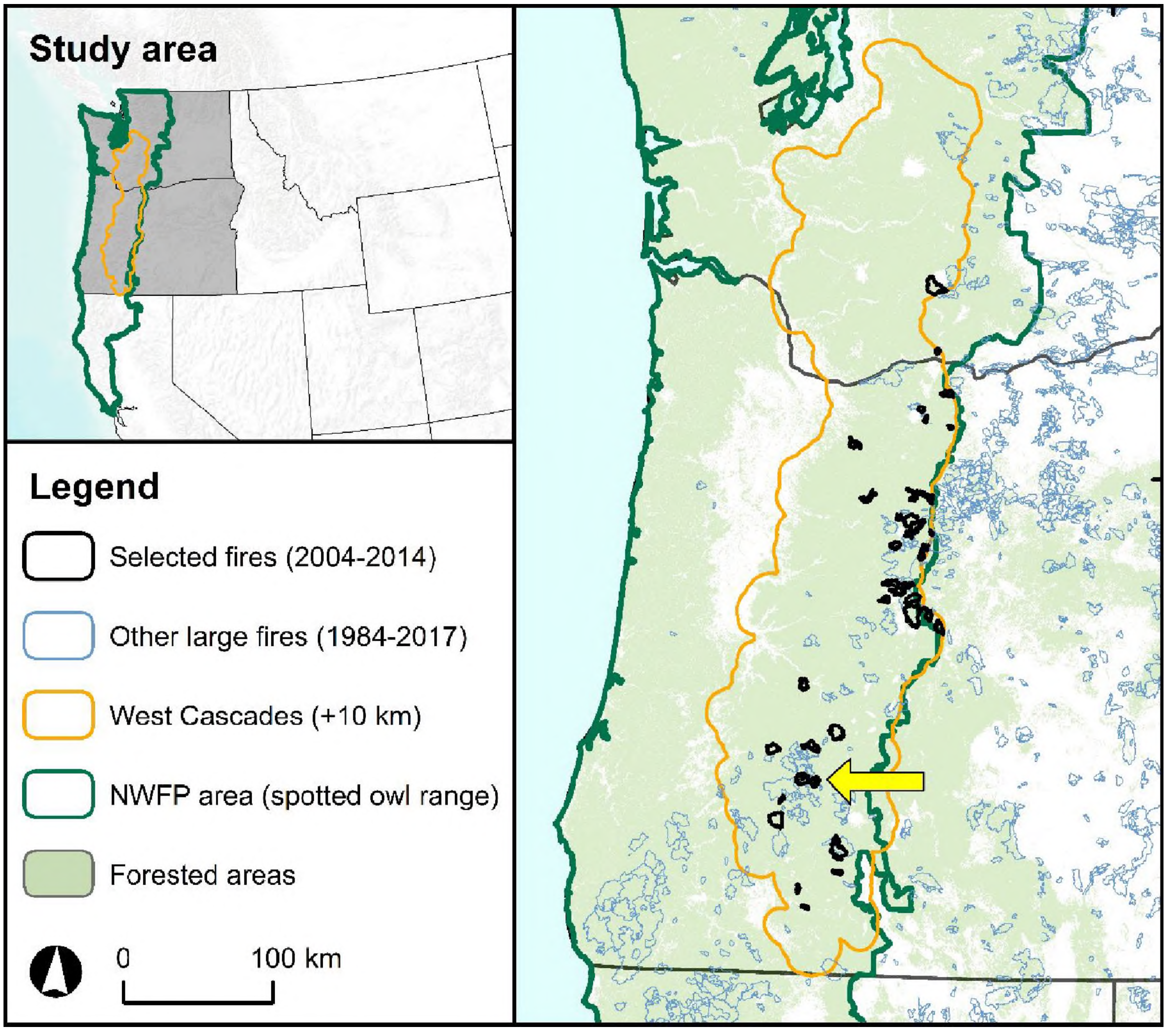
Figure 2. Burn severity and fire refugia extent across selected fires in West Cascades study region (*n* = 31). Classification is based on Landsat change detection (RdNBR) and regional forest inventory plots, where the severity classes correspond to estimated tree basal area mortality: refugia ≤10%, low = 10-25%, moderate = 25-75, high = 75-90%, very high ≥90% (Meigs and Krawchuk 2018).

Figure 3. Burn severity and refugia relative abundance across forested sample points used for statistical analysis by fire weather classes. Moderate fire weather includes points that burned with ERC ≤0.9, and high fire weather includes points that burned with ERC >0.9. Burn severity and fire refugia classification based on Landsat change detection (RdNBR) and regional forest inventory plots, where the severity classes correspond to estimated tree basal area mortality: refugia ≤10%, low = 10-25%, moderate = 25-75, high = 75-90%, very high ≥90% (Meigs and Krawchuk 2018).

Figure 4. Landscape-scale map of example predictor variables and response variable for one fire event, the Boze Fire, which burned in 2009 in the Umpqua River Basin. (a) Pre-fire biomass (2002) based on GNN imputation modeling, where black areas indicate non-forest conditions. (b) Aspect (direction of slope) based on digital elevation model. Blue and red represent northerly and southerly aspects, respectively. (c) Burn severity and fire refugia classification based on Landsat change detection (RdNBR) and regional forest inventory plots, where the severity classes correspond to estimated tree basal area mortality: refugia ≤10%, low = 10-25%, moderate = 25-75, high = 75-90%, very high ≥90% (Meigs and Krawchuk 2018). Fire location indicated by yellow arrow on Figure 1.

Figure 5. Partial-dependence plots and relative importance values for top eight predictor variables of TOPO+FUELS models under moderate (blue solid line) and high (red dashed line) fire weather conditions. Y-axis indicates logit probability of fire refugia after accounting for interactions among other predictor variables. All variables and units are defined in Table 1. Relationships are similar for TOPO models (see Figure S2 and Figure S3).

Figure 6. Landscape-scale map of refugia probability for an example fire event, the Boze Fire, which burned in 2009 in the Umpqua River Basin. Refugia conditional probability under (a, d) moderate and (b, e) high fire weather (ERC) and (c, f) difference between fire weather conditions. Values indicate the probability that a given location (30-m pixel) will experience very low burn severity if it burns under a given fire weather scenario. Results shown from TOPO+FUELS model with eight topography variables plus pre-fire biomass and pre-fire reflectance (EVI). Fire location indicated by yellow arrow in Figure 1. Insets (black squares in panels a-c) indicate location of zoom maps (panels d-f) showing spatial patterns of refugia probability within old forests. Mapped areas in panels d-f exceed the threshold of old-growth structural index ≥200 (see Methods), whereas less structurally complex forests are masked out as black areas.



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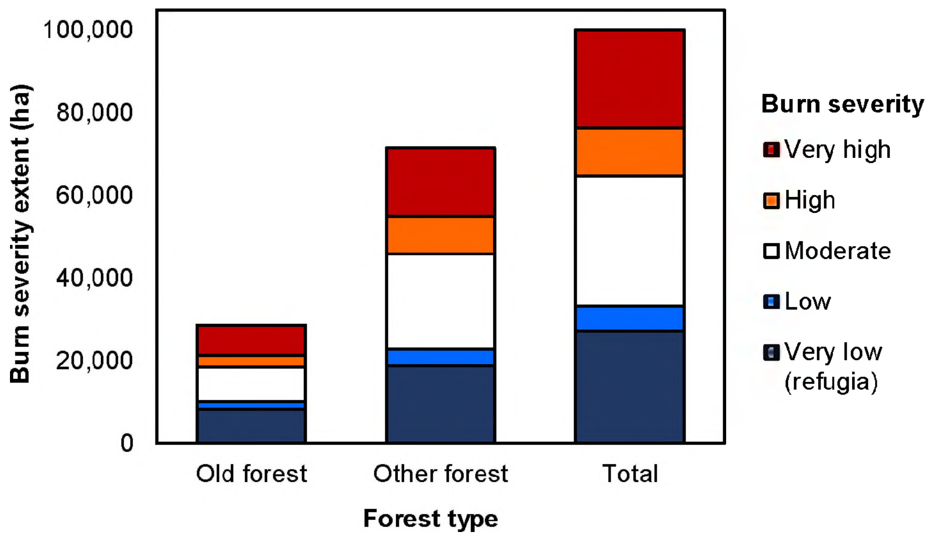

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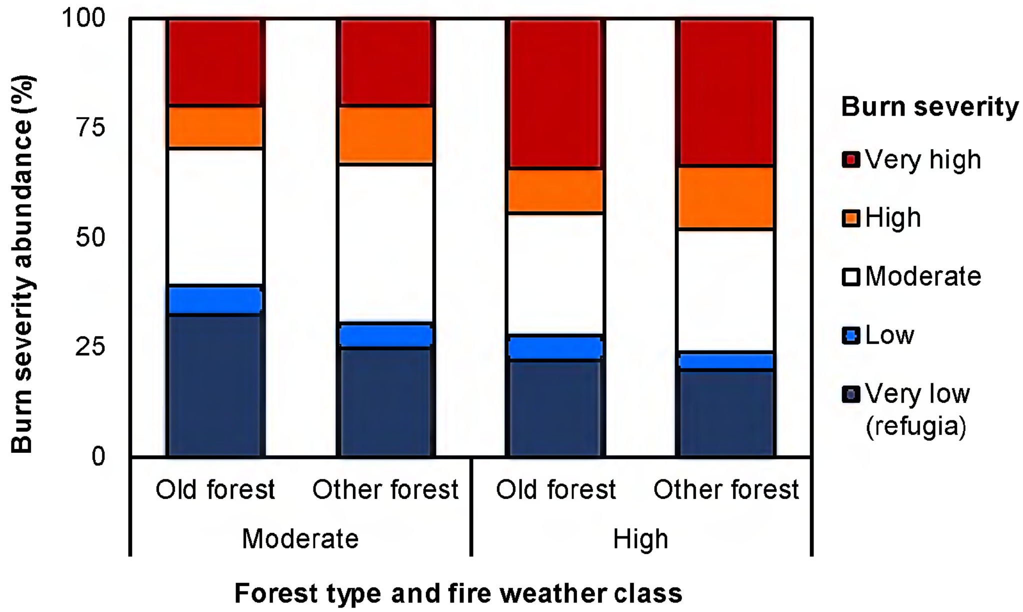

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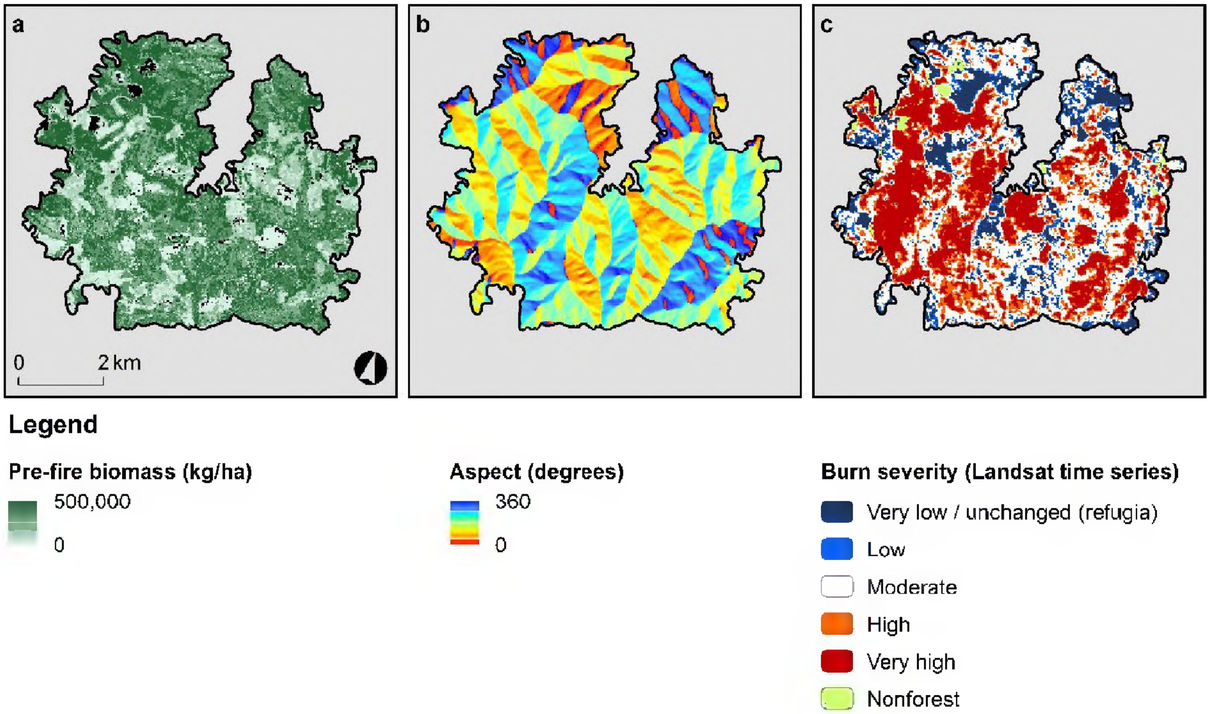

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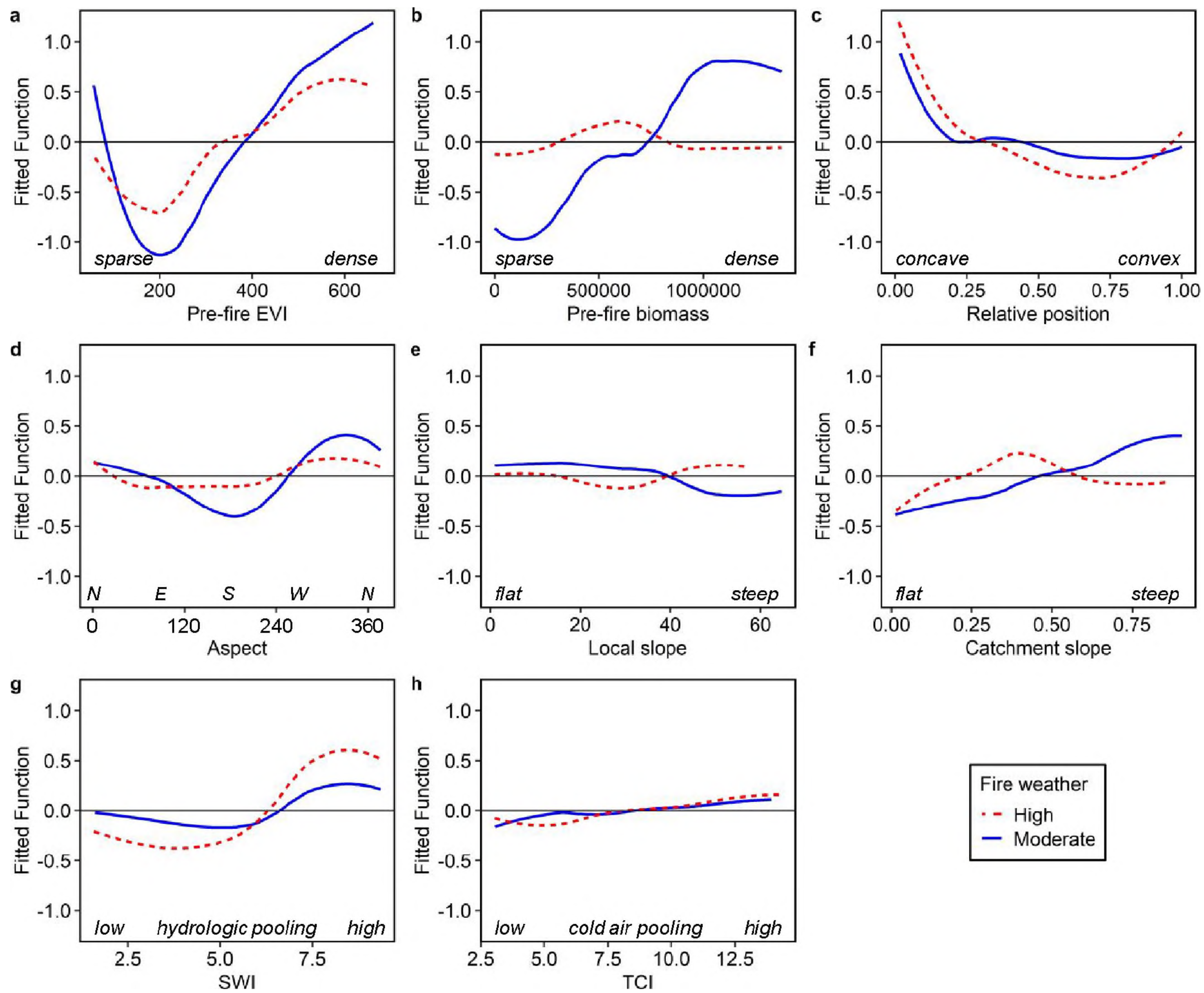

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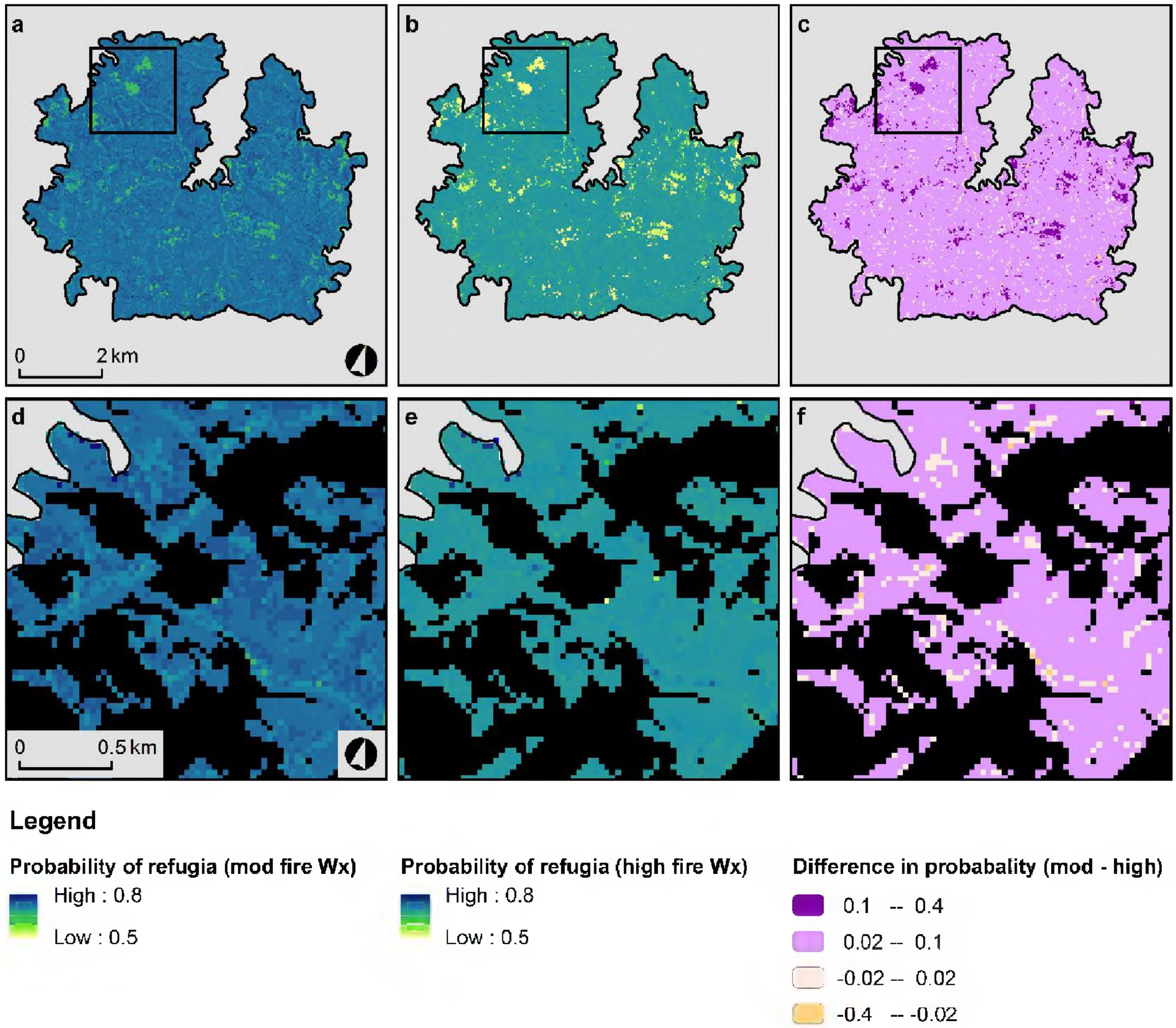

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