NRC Research Press

ARTICLE

Influence of topography and fuels on fire refugia probability under varying fire weather conditions in forests of the Pacific Northwest, USA

Garrett W. Meigs, Christopher J. Dunn, Sean A. Parks, and Meg A. Krawchuk

Abstract: Fire refugia — locations that burn less severely or less 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 focused on recent large fires in Oregon and Washington, United States (n = 39 fires > 400 ha, 2004–2014). Our objectives were to (1) map fire refugia as a component of the burn severity gradient, (2) quantify the predictability of fire refugia as a function of prefire fuels and topography under moderate and high fire weather conditions, and (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. Prefire live fuels were strong predictors of fire refugia, with higher refugia probability in forests with higher prefire biomass. In addition, fire refugia probability was higher in topographic settings with relatively northern aspects, steep catchment slopes, and concave topographic positions. 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.

Key words: biological legacies, burn severity, fire refugia, late-successional forests, Pacific Northwest.

Résumé : Les refuges de feu (endroits où la forêt brûle moins sévèrement ou moins fréquemment que dans le territoire environnant) maintiennent la structure et la fonction des forêts en fin de succession et des forêts anciennes. Cette étude examine l'influence de la topographie et des combustibles sur la probabilité de la présence d'un refuge de feu en tenant compte de différentes conditions météorologiques propices aux incendies. Nous avons mis l'accent sur les grands feux récents dans les États de l'Oregon et de Washington, aux États-Unis (n = 39 feux > 400 ha, 2004–2014). Nos objectifs consistaient à (1) cartographier les refuges de feu en tant que composantes d'un gradient de sévérité du feu, (2) quantifier la prévisibilité des refuges de feu en fonction des combustibles présents avant que survienne un feu et de la topographie en tenant compte de conditions météorologiques modérément et très propices aux incendies et (3) cartographier la probabilité conditionnelle de la présence des refuges de feu pour illustrer leur configuration spatiale dans les forêts anciennes. Les refuges de feu étaient plus prévisibles lorsque les conditions météorologiques propices aux incendies étaient relativement modérées. Les combustibles vivants présents avant que survienne un feu étaient de bons prédicteurs de la présence des refuges de feu et la probabilité de la présence d'un refuge de feu était plus élevée dans les forêts contenant une plus grande biomasse avant que survienne un feu. De plus, la probabilité de la présence d'un refuge de feu était plus élevée dans des contextes topographiques caractérisés par des expositions relativement septentrionales, des dénivelés de bassin abrupts et des positions topographiques concaves. Les cartes de probabilité conditionnelle révèlent que la probabilité de la présence des refuges de feu est constamment plus élevée avec les scénarios de conditions météorologiques modérément plutôt que très favorables aux incendies. Les résultats de cette étude contribuent à la planification de la conservation en déterminant les forêts en fin de succession qui ont le plus de chances de persister en tant que refuges de feu malgré l'augmentation régionale des incendies. [Traduit par la Rédaction]

Mots-clés : legs biologiques, sévérité du feu, refuges de feu, forêts en fin de succession, 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 recently increased in association with climate and land-use change (Barbero et al. 2015; Abatzoglou and Williams 2016), fueling stakeholder concerns about potential impacts on threatened and endangered species (Davis et al. 2016). Fire refugia — locations that burn less severely or less frequently 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 (Spies et al. 2018). Given the projected increasing likelihood of large fires (Davis et al. 2017),

Received 15 November 2019. Accepted 10 March 2020.

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 Published at www.nrcresearchpress.com/cjfr on 18 March 2020.

some old forests that historically functioned as fire refugia may become more vulnerable to stand-replacing fire. Concurrently, fire refugia may persist because of 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 bottom-up, endogenous drivers such as fuels and topography, whereas other fire regimes are dominated by top-down, exogenous 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 postfire responses (Parks et al. 2018*b*; Zald and Dunn 2018). For example, tree size and species are strong predictors of fire-induced mortality and postfire 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. 2018*b*; Zald and Dunn 2018). Topography also plays a key role across landscape gradients, wherein fire refugia are associated with topographic features such as 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 multiway 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. 2018*a*), topography may provide functional anchor points for forest conservation initiatives.

Recent studies have mapped fire refugia patterns and quantified drivers with large geospatial databases and innovative quantitative approaches. Mapping studies have typically employed Landsat imagery to identify fire refugia within recent fire events as locations including both unburned and low-severity fire effects where fire resulted 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 prefire fuel conditions, which translate into very different outcomes in terms of fire effects or severity (e.g., differing vegetation mortality in nonforest versus young forest versus old forest; Meigs and Krawchuk 2018; Zald and Dunn 2018; Lesmeister et al. 2019). Here, we leverage pre- and postfire 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 can also include climate refugia over longer time scales (Meddens et al. 2018*b*), 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 postfire management activities, and assess conservation outcomes (Morgan et al. 2014; Davis et al. 2016; Meigs and Krawchuk 2018; Harvey et al. 2019).

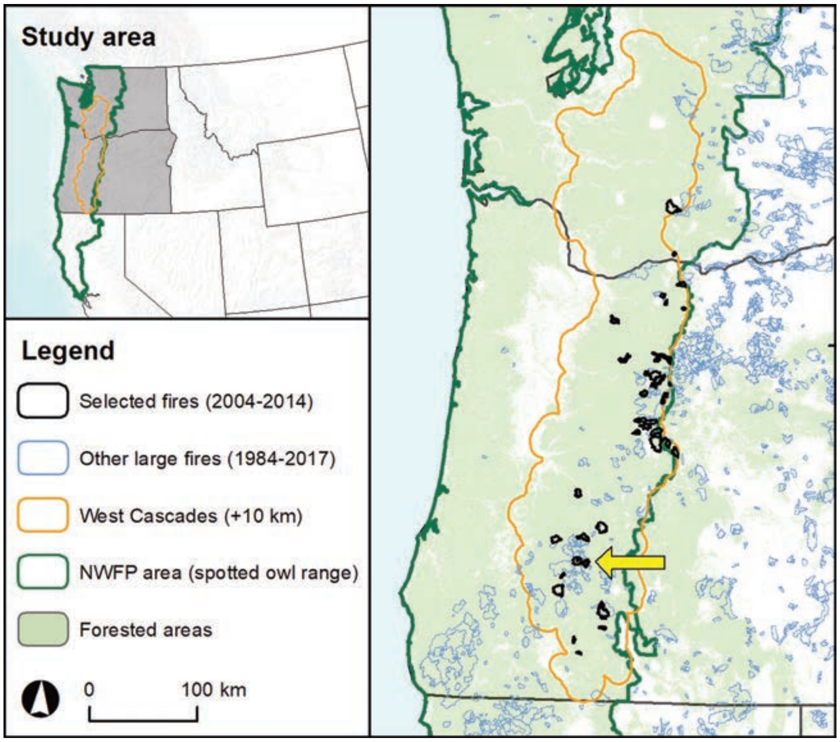
Mapping recent spatiotemporal patterns of fire can inform regional perspectives on both historical and contemporary fire effects (e.g., Reilly et al. 2017), but stakeholders, including land managers, also require information on specific drivers of fire refugia and maps of fire refugia probability under different combinations of fuels, topography, and weather. Prior studies have used machine-learning algorithms such as boosted regression tree (BRT) models to assess the probability of fire refugia (Krawchuk et al. 2016; Rogeau et al. 2018), high-severity fire (Parks et al. 2018*b*), or drought refugia (Cartwright 2018). In this study, we employ BRT modeling to quantify fire refugia probability as a function of topography and prefire 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 (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 or high fire weather conditions, 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 forest succession in fire-prone regions. In western Oregon, Washington, and Northern California, old forests occupy a small portion of their historical extent because of 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 (NWFP) (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 data sets and computational tools, enable novel assessments of fire effects and probability of fire refugia in the PNW. This study assesses fire events in the West Cascades ecoregion, which contains a substantial amount of old forests and is located centrally within the PNW region. Our specific objectives were as follows:

1. Map fire refugia as a component of the overall burn severity gradient in recent large fire events using Landsat-based estimates of fire-induced tree mortality.
2. Quantify the predictability of fire refugia as a function of prefire 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.

Fig. 1. Map of the study area in the Pacific Northwest, United States, and fires included in statistical analysis (n = 39). Fire perimeters are from the Monitoring Trends in Burn Severity (MTBS) program (https://mtbs.gov). The West Cascades ecoregion is based on Olson and Dinerstein (2002) plus a 10 km buffer. Forest areas are based on analysis by the Gap Analysis Project (GAP; https://gapanalysis.usgs.gov). The yellow arrow indicates the location of an example fire event: the 2009 Boze Fire in the Umpqua River Basin. Fires are listed in Supplementary Table S1.[1] The inset map shows terrain from Esri's world terrain base map (service layer credits: Esri, U.S. Geological Survey (USGS), and the National Oceanic and Atmospheric Administration (NOAA)). NWFP, Northwest Forest Plan. [Color online.]



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 (Fig. 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 J. Forbes) and, at higher elevations, 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, fire-tolerant tree species are more prevalent, including ponderosa pine (*Pinus ponderosa* Douglas ex P. Lawson & C. Lawson), sugar pine (*Pinus lambertiana* Douglas), grand fir (*Abies grandis* (Douglas ex D. Don) Lindl.), and incense cedar (*Calocedrus decurrens* (Torr.) Florin), 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, nonlethal 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* (Merriam, 1898)), which defines the geographic scope of the NWFP and underscores the sociopolitical importance of old-forest conservation within the ecoregion (Fig. 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 blends with floristic elements of the Klamath Mountains and East Cascades ecoregions, respectively (Fig. 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 spatial patterns of fire refugia (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-

[1]Supplementary data are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfr-2019-0406.

Table 1. Predictor and stratification variables for boosted regression tree (BRT) analysis.

Variable	Description (units)	Source
Live fuel		
EVI	Prefire vegetation greenness from Landsat imagery (spectral vegetation index scaled from 0 to 1000)	Parks et al. 2018*b*
Biomass	Prefire 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
Catchment flow path	Length of hydrologic flow path (m), which is related to watershed area and complexity	30 m DEM
Catchment slope	Mean slope of hydrological catchment (rad), which captures more general slope steepness than local slope	30 m DEM
Local aspect	Direction of slope at local scale (rad), which influences fuel moisture and wind patterns	30 m DEM
Local slope	Steepness of slope at local scale (°), which influences fire spread and fuel preheating	30 m DEM
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
TCI	~6–20; increases with potential for cold-air pooling, which influences fuel moisture and vegetation composition and structure	30 m DEM
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		
ERC	Integrates fuel moisture and potential energy release at flaming front of a fire	Preisler et al. 2016; Jolly and Freeborn 2017; Parks et al. 2018*b*

Note: The response variable for all BRT modeling is a binary (refugia or nonrefugia) classification of burn severity based on Landsat satellite mapping (see Methods). EVI, enhanced vegetation index; TCI, topographic convergence index; SWI, SAGA wetness index; ERC, energy release component; GNN, gradient nearest neighbor; DEM, digital elevation model. DEM is a subset of the US National Elevation Dataset (acquired from the US LANDFIRE program: https://www.landfire.gov/NationalProductDescriptions7.php).

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 (Fig. 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 approximately 100 000 ha of forest within the study area (Fig. 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. (2018*b*) 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 (detailed in the next section). 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. 2018*b*). We excluded points ≤100 m from 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 or nonrefugia) within the study fires previously described, resulting in a sample of 10 696 refugia and 35 407 nonrefugia 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 prefire forest conditions following the workflow described in fig. 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 postfire 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 2-year intervals to ensure consistent pre- and postfire 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 prefire 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:

$$(1) \qquad y = 134.87 + 259.38x + 567.68x^2$$

where y is continuous RdNBR and x is the percent basal area (BA) mortality based on the change in live tree BA before and after fire at 304 inventory locations. We defined fire refugia as locations with very low RdNBR values equivalent to ≤10% tree BA 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 nonrefugia 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 (>90% BA mortality; RdNBR ≥ 828) severities. 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 1 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 in the next section). 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 (Fig. 1).

Predictor and stratification variables: fuels, topography, and weather

We developed a statistical modeling framework to quantify the influence of prefire fuels and topography on fire refugia predictability under moderate and high fire weather conditions (objective 2) (Table 1). We used two variables to assess prefire 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. 2018*a*, 2018*b*). Second, we used maps of estimated live biomass from 2002 based on GNN maps, which integrate data from federal forest inventory plots ($n \approx 17\,000$), spatial predictors, and Landsat time series to impute numerous plot-level attributes for forested locations across the PNW (Ohmann et al. 2012; https://lemma.forestry.oregonstate.edu/data). For both live-fuel variables, we used maps representing the year 2002 to ensure that they predated 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): (*i*) catchment area (in square metres), (*ii*) catchment flow path length (in metres), (*iii*) catchment slope (in radians), (*iv*) local aspect (in radians), (*v*) local slope (in degrees), (*vi*) relative topographic position (0–10, lower to higher elevation within a 500 m radius reflecting concave to convex terrain), (*vii*) topographic convergence index (TCI; ~6–20, a metric of cold-air drainage that increases with potential for cold-air pooling), and (*viii*) SAGA wetness index (SWI; ~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 and cold-air pooling) influencing fuel moisture and fire behavior (Table 1; Supplementary Fig. S1[1]). Correlation among all predictor variables was generally low ($r < |0.4|$), with the exception of the slope, wetness, and convergence indices (Supplementary Fig. S1[1]). All topographic metrics were calculated using the raster (Hijmans et al. 2019) and RSAGA (Brenning et al. 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 and 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 commonly used in fire management (Table 1) (Schlobohm and Brain 2002; Parks et al. 2018*b*). 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. 2018*b*). Finally, we divided the sample data into two roughly equivalent bins according to ERC percentiles ≤90% (low or moderate fire weather, n = 22 427 (49% of data set)) and >90% (high or extreme fire weather, n = 23 676 (51% of data set)).

Statistical analyses: BRT model implementation and assessment

We modeled the probability of fire refugia (objective 2) using 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 and 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 prefire live-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 operating characteristic (hereafter "AUC") and fivefold 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 (i.e., 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 importance and partial-dependence plots of predictor variables. Variables with higher relative importance are more influential 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 the gbm (Greenwell et al. 2019) and dismo (Hijmans et al. 2017) packages in R.

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 in which 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

Fig. 2. Burn severity and fire refugia extent across selected fires in the West Cascades study region (n = 31). Classification is based on Landsat change detection (relative differenced normalized burn ratio (RdNBR)) and regional forest inventory plots; severity classes correspond to estimated tree basal area (BA) mortality: refugia ≤ 10%, low = 10%–25%, moderate = 25%–75%, high = 75%–90%, and very high ≥ 90% (Meigs and Krawchuk 2018). [Color online.]

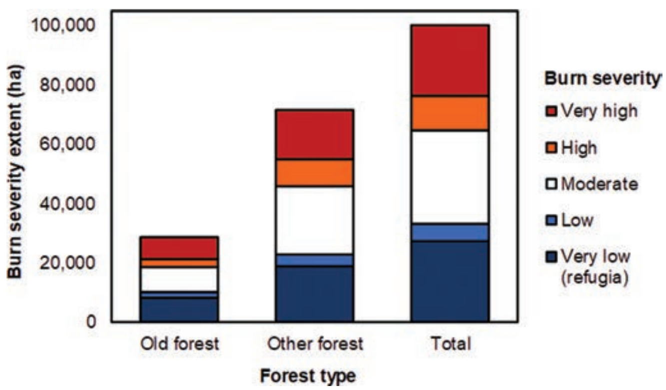
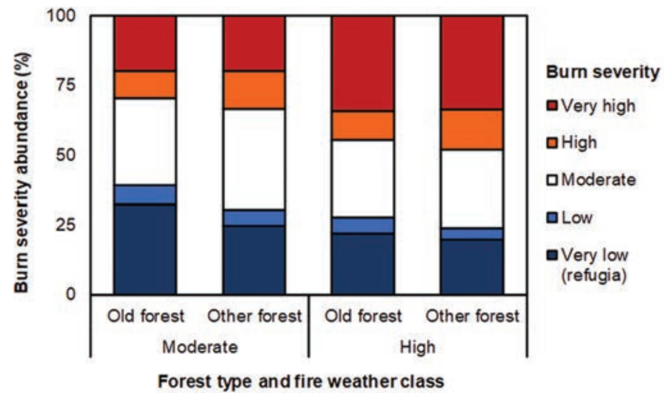


Fig. 3. Burn severity and refugia relative abundance across forested sample points used for statistical analysis by fire weather class. Moderate fire weather includes points that burned with energy release component (ERC) ≤ 0.9, and high fire weather includes points that burned with ERC > 0.9. Burn severity and fire refugia classification is described in the caption of Fig. 2. [Color online.]



moderate and 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 (Fig. 1). The 39 fires in our study area encompassed 102 154 ha, ranging in individual extent from 591 to 18 008 ha (Supplementary Table S1[1]). Of these fires, 28% occurred in old forests (28 655 ha) and the remaining 72% occurred in other forests (Fig. 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 (Fig. 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% versus 20%) (Fig. 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 (Fig. 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 (Fig. 3).

The Boze Fire, which burned approximately 4 000 ha in 2009 in the Umpqua National Forest, provided an illustrative example of prefire 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). Prefire biomass varied substantially within the fire perimeter, primarily because of recent timber harvest, with dark green areas in Fig. 4*a* 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, ridgetops, and valley bottoms (Fig. 4*b*). Finally, burn severity patterns illustrated relatively large patches of stand-replacing fire (Fig. 4*c*), presumably driven mainly by fire weather.

Predictability of fire refugia as a function of prefire 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 prefire 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 values 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 importance of predictor variables under both moderate and high fire weather conditions (Table 3). For the TOPO+FUELS models, prefire EVI and prefire biomass exhibited the highest relative influence on the probability of fire refugia, and both variables were generally positively associated with fire refugia probability (Fig. 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 (Fig. 4; Supplementary Fig. S2[1]). 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) (Fig. 4; Supplementary Fig. S2[1]). The relative importance of particular topographic variables varied somewhat among model runs; for example, catchment slope was 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 influence on fire refugia probability during high fire weather (Table 3; Fig. 6).

Fig. 4. Landscape-scale maps of example predictor variables and response variable for one fire event: the Boze Fire. (*a*) Prefire biomass (2002) based on gradient nearest neighbor (GNN) imputation modeling. Black areas indicate nonforest 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 is described in the caption of Fig. 2. Green areas indicate nonforest conditions. Fire location is indicated by the yellow arrow in Fig. 1. [Color online.]

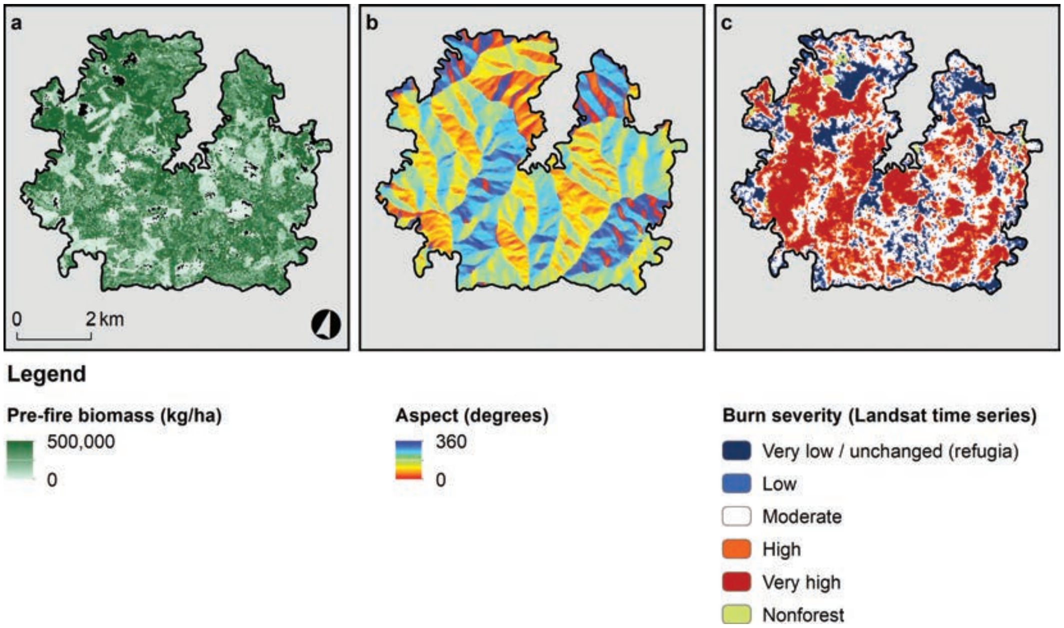


Table 2. BRT model metrics and performance.

	TOPO		TOPO+FUELS	
Metric	Moderate fire weather	High fire weather	Moderate fire weather	High fire weather
Sample size (number of pixels)	22 427	23 676	22 427	23 676
Refugia (%)	26	20	26	20
Number of regression trees	4 050	4 800	9 450	8 600
AUC	0.65	0.63	0.75	0.69
Cross-validated correlation	0.24	0.21	0.4	0.31

Note: TOPO, eight topography variables; TOPO+FUELS, eight topography variables plus two metrics of prefire live fuel; AUC, area under the curve of the receiver operating characteristic.

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 fire weather conditions (0.72) than under high fire weather conditions (0.67), despite substantial variability (Table 4).

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

As illustrated by the Boze Fire, old-forest fire refugia with relatively high prefire biomass represented only a portion of the modeled landscapes (Figs. 4 and 6). Fire refugia that actually resulted from the Boze Fire were relatively patchy and discontinuous (dark-blue areas in Fig. 4*c*), 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 prefire live fuels (Fig. 6). As with all other forested areas (Figs. 6*a*–6*c*), old-forest fire refugia probability was both higher and more variable under moderate fire weather conditions (Figs. 6*d*–6*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 PNW. 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 prefire 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

Table 3. Relative importance of predictor variables in BRT analysis across four model scenarios.

Moderate fire weather		High fire weather	
Variable	Relative influence	Variable	Relative influence
TOPO			
Catchment slope	36.3	Relative position	27.2
Local aspect	23.3	Catchment slope	21.5
Relative position	12.0	Local aspect	18.0
SWI	10.2	SWI	11.3
Local slope	7.9	Local slope	6.4
Catchment area	4.0	Catchment flow path	5.5
Catchment flow path	3.5	TCI	5.4
TCI	2.8	Catchment area	4.9
TOPO+FUELS			
EVI (prefire live fuel)	32.2	EVI (prefire live fuel)	22.5
Biomass (prefire live fuel)	20.2	Biomass (prefire 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	SWI	7.6
SWI	3.7	TCI	7.2
TCI	2.2	Local slope	6.9
Catchment area	1.3	Catchment area	2.8
Catchment flow path	1.2	Catchment flow path	2.2

Note: Variables and units are defined in Table 1.

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 is also 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.

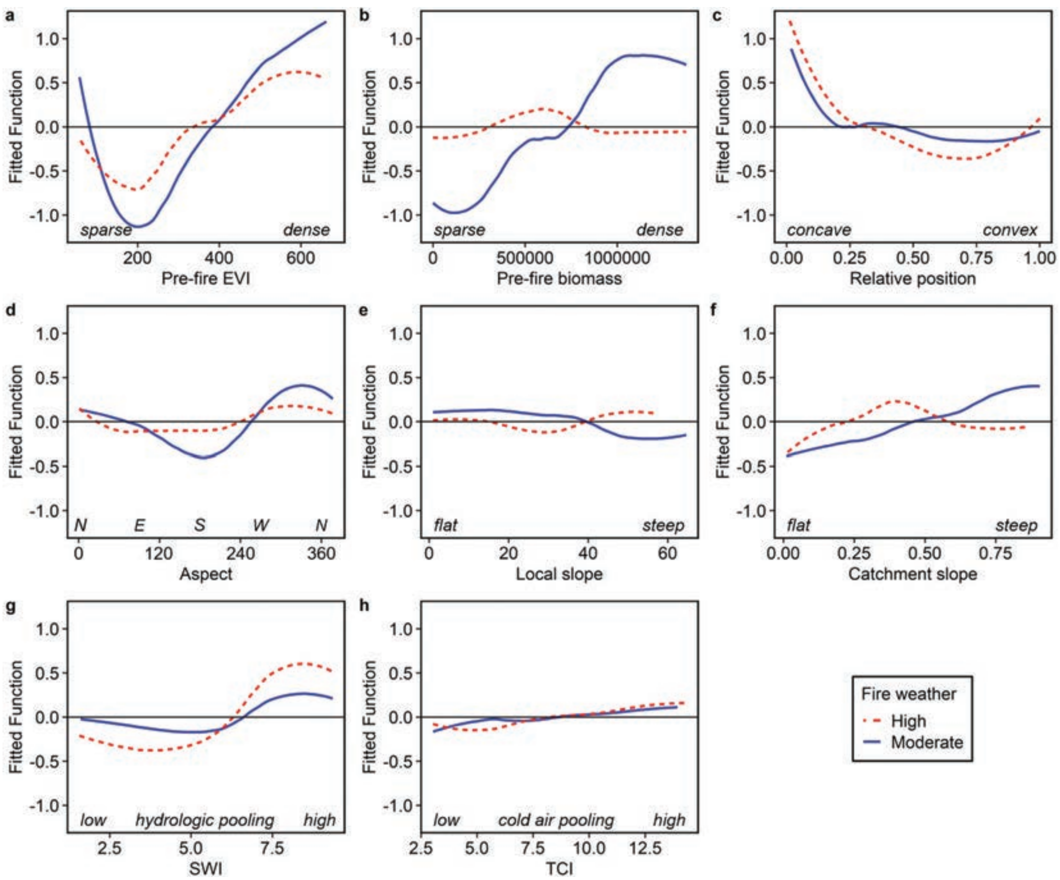
Our findings are generally consistent with recent spatially explicit BRT analyses of fire refugia, fire effects, and refugia from other disturbances in western North America. The top three topographic variables in our study — aspect, catchment slope, and relative position — were also important predictor 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 photographs 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 nonfuel conditions (Rogeau et al. 2018). 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. (2018*b*) found that prefire live fuels (EVI) were a strong predictor of high-severity fire probability in the West Cascades and across the western US (Parks et al. 2018*b*). Finally, a recent analysis close to our study area determined that topographically shaded slopes, low-biomass forests, and low soil bulk density were associated with refugia from drought and insect outbreaks (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 prefire EVI (i.e., live fuel) is positively associated with fire refugia is consistent with findings from the 2013 Douglas Complex Fire, 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 prefire fuels following the 2006 Tripod Complex Fire 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 prefire EVI, particularly in cooler or wetter years (Parks et al. 2018*a*). Consequently, further research is warranted on the influence of prefire fuels on burn severity and fire refugia, particularly studies that contrast the relatively warm, moist PNW with drier, less productive forests.

Within the US PNW, 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 locations with northerly aspects, stream confluences, and 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, multilayered 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 sites than in nonrefugial 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 deadwood, 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 prefire 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 north-facing aspects are generally cooler and retain moisture longer into the fire season, supporting higher fuel moisture and large, fire-resistant trees compared with 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 vegetation (fuel) 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.

Fig. 5. Partial-dependence plots for the top eight predictor variables of TOPO+FUELS models under moderate (blue solid line) and high (red dashed line) fire weather conditions. The *y* axes indicate logit probability of fire refugia after accounting for interactions among predictor variables. All variables and units are defined in Table 1. Relative importance values are shown in Table 3. Relationships are similar for TOPO models (see Supplementary Figs. S2 and S3[1]). EVI, enhanced vegetation index; SWI, SAGA wetness index; TCI, topographic convergence index. [Color online.]



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. 2018*b*). 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., subpixel 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 such as tree mortality (Reilly et al. 2017; Chapman et al. 2020). We recognize that the fire refugia threshold of 10% BA 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 could also integrate field observations to distinguish low-severity from truly unburned refugia (Meddens et al. 2016) and 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 at which they influence fire behavior and effects, as described in detail by Parks et al. (2018*b*). 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, and 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, edge effects, and 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 (Supplementary Fig. S3[1]). In particular, the spatial predictions of conditional probability (Fig. 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; Fig. 6), suggesting that the relative difference among models and fire weather scenarios is more informative.

Fig. 6. Landscape-scale maps of refugia probability for an example fire event: the Boze Fire. Refugia conditional probability under (*a* and *d*) moderate and (*b* and *e*) high fire weather (ERC) and (*c* and *f*) the 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 are shown for the TOPO+FUELS model with eight topography variables plus prefire biomass and prefire reflectance (EVI). Fire location is indicated by the yellow arrow in Fig. 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. [Color online.]

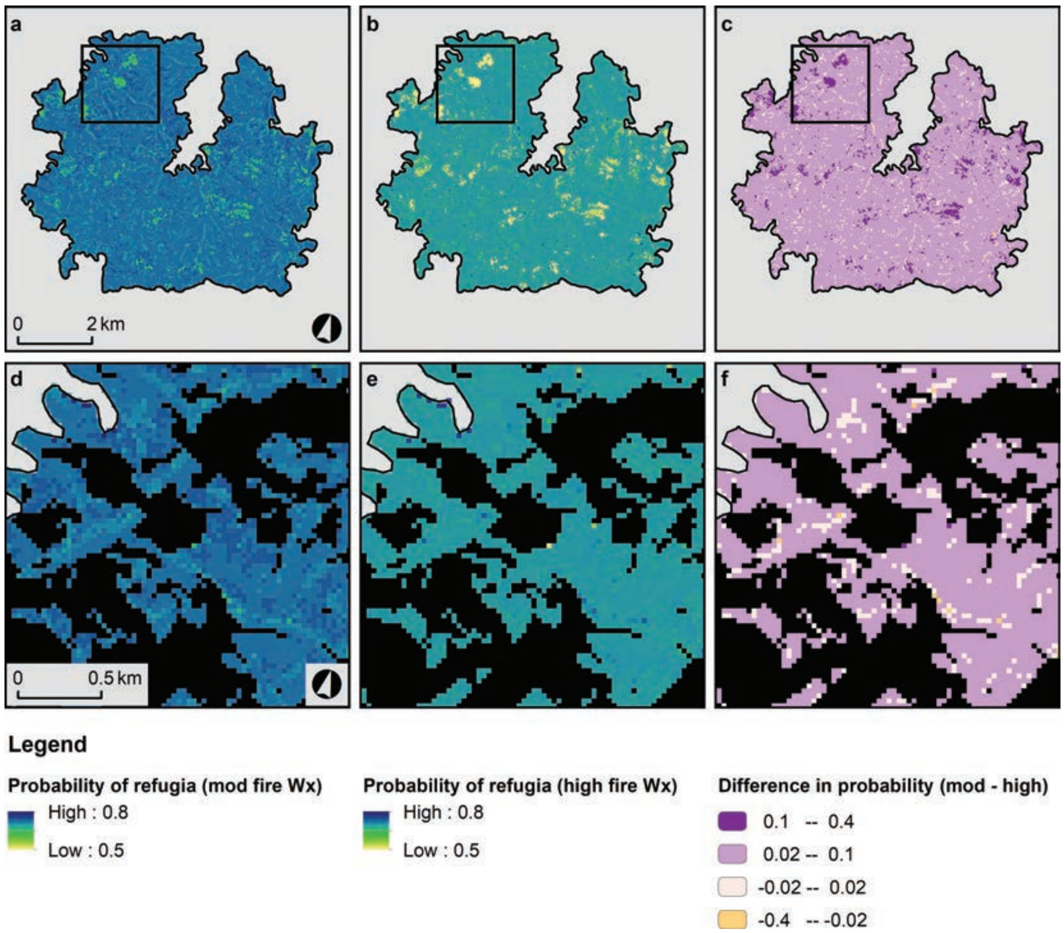


Table 4. Summary statistics of mapped fire refugia conditional probability across four model runs.

	TOPO		TOPO+FUELS	
Statistic	Moderate fire weather	High fire weather	Moderate fire weather	High fire weather
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
SD	0.02	0.02	0.02	0.05

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

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 ecoregion was not surprising given the subregional variation in forest composition, historical fire regimes, and lightning ignitions, the low relative abundance of stand-replacing fire across the study area shows how low-severity fire refugia can occur throughout much of the PNW. 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 and associated topography — 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 could potentially enhance the refugial capacity of old forests by effectively thinning smaller trees, less fire-tolerant 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 historically resulted in very large patches of stand-replacing fire (Halofsky et al. 2018), mitigation of anthropogenic ignitions and rapid mobilization of firefighting resources could continue to play essential roles 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 trade-offs 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.

Acknowledgements

This research was possible because of funding from the U.S. Department of the Interior Northwest Climate Adaptation Science Center (U.S. Geological Survey Cooperative Agreement G18AC00242). The authors thank Jennifer Cartwright, Matthew Gregory, Sandra Haire, and Lisa Holsinger for assistance with database development and analysis. David Bell, Raymond Davis, and David Wiens assisted with framing applications to forest management in the study region. Jonathan Coop, Will Downing, Sandra Haire, Carol Miller, and three anonymous reviewers provided valuable feedback that substantially improved this manuscript.

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