Evaluating multi-scaled patterns, trends, and drivers of fire severity to inform adaptive management of western North American forests

Gina Rosa Cova

A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2024

Reading Committee:

Van R. Kane, Chair

Susan J. Prichard

Harold S.J. Zald

Program Authorized to Offer Degree:

School of Environmental and Forest Sciences

University of Washington

Abstract

Evaluating multi-scaled patterns, trends, and drivers of fire severity to inform adaptive management of western North American forests

Gina Rosa Cova

Chair of the Supervisory Committee:

Van R. Kane

School of Environmental and Forest Sciences

In the last several decades, profound changes in wildfire activity influenced by climate change, exclusion of Indigenous stewardship, and changes in land management have had enormous impacts on forest ecosystems across much of western North America. Of particular interest to managers and ecologists are observed shifts in fire severity (i.e., the magnitude of ecological change caused by fire, typically measured by vegetation killed), which have important implications for carbon storage and sequestration, wildlife habitat, economic and cultural resources, and post-fire forest regeneration under a warming climate. To develop management strategies aimed at adapting forests to changing wildfire regimes under climate change, information about both the causes and consequences of shifting fire severity patterns is critical. In this dissertation, I used remote sensing datasets to evaluate

drivers, trends, and spatial patterns of fire severity from the scale of individual burn patches to ecoregions that encompass hundreds of recent wildfires in California, Oregon, and Washington. In Chapter 1, I evaluated trends, spatial patterns, and cumulative impacts of fire severity across a range of unburned, low-moderate, and high severity burn patches to evaluate implications for post-fire management in recent California wildfires. I found that a small number of large fires disproportionately contributed to increases in high severity effects, but simultaneously presented an opportunity for managers to use areas burned with low and moderate severities as an initial "treatment" to be followed by additional post-fire fuel treatments. Chapter 2 of this dissertation examined the drivers of changing severity patterns, with a focus on understanding how existing management practices influence fire effects. I found that land ownership designation as a proxy for general management practices was a strong predictor of fire severity across the study area along with other 'bottom-up' controls such as pre-fire forest structure. Finally, in Chapter 3, I evaluated patterns and drivers of fire severity to inform adaptive management strategies within the Northwest Forest Plan, which directs the management of federal forests across nearly 10 million ha within the study area. I found that historically frequent-fire dry forest types – particularly mixed conifer forests, mixed evergreen forests, oak woodlands, and pine-oak woodlands – have faced the greatest impacts in terms of stand-replacing fire. Although fire weather was the most important predictor of fire severity at the regional scale, factors such as pre-fire forest cover and topography exerted strong local controls. Collectively, this dissertation work contributes to enhanced understanding of adaptive forest management strategies for both pre-fire and post-fire forest conditions in increasingly fire-prone landscapes of western North America.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

The completion of this dissertation would not have been possible without the support and friendship of so many key people.

First, a heartfelt thank you to my advisory committee. Van Kane, thank you for your support and encouragement throughout this process. I am forever grateful for the opportunity you provided me to join the folks within the Forest Resilience Lab and Precision Forestry Cooperative. Susan Prichard, thank you for the mentorship, guidance, and endless opportunities you have offered me. Knowing you has made me a better scientist and a better person, and working with you has been so much fun. Harold Zald, thank you for your feedback, thoughtful questions, and willingness to dive deep into the data weeds with me. Our conversations – that often went much longer than we intended! – were always a high point in my week. Monika Moskal, thank you for your leadership and advocacy throughout this process. Our many conversations have helped to broaden my perspective on research, academia, and my career. Abby Swann, thank you for your commitment to ensuring this process was smooth and fair. Working with you has been a joy.

Thank you to the members of the Forest Resilience Lab, who have offered so much support and levity throughout the last few years: Liz van Wagtendonk, Caden Chamberlain, Astrid Sanna, Pratima KC, Hannah Redford, Iris Mire, Bryce Bartl-Geller, and Jonathan Kane. You all have been such a great group of people to work with.

An enormous thank you to my friends who have provided so much encouragement and cheerleading throughout this process. Veronica and Marco, somehow we've lived half a world away for nearly two years now, but you've been such constant sources of support throughout this process.

Thank you for the laughter, comfort, and deep friendship you both provide. Wendy, thank you for making Seattle truly feel like home. I couldn't imagine what living here would be like without you. Elena and Tyler, thank you for your friendship, support, and many Thursday evenings spent together over a shared meal and bottle of wine. I will always be grateful that we got to live down the street from one another for a moment in time. Lisa, thank you for being such a huge cheerleader throughout this process, and for being one of my dearest friends for so many years now. Saba, our many text messages exchanging support, solidarity, and laughter over absurdities kept me sane throughout this process. I'm so glad our paths crossed in Seattle. Tram, you have been such a huge source of advice, guidance, and inspiration in my grad school journey. I am so grateful that we were randomly paired as roommates all those years ago at Berkeley.

Most importantly, I want to extend an enormous thank you to my little family: my husband Thomas and our dog Topo. Topo, thank you for the comfort and playfulness you've brought to my life. And to Thomas – there is no thank you that could ever be big enough. I could not have completed this journey without your relentless support and encouragement. Sharing my life with you is the greatest privilege.

PUBLISHED MATERIALS

A portion of the materials presented in this dissertation have been published through the peer review process. This article is reproduced in full here as Chapter 1 and is reprinted from Elsevier in the journal Forest Ecology and Management.

Cova, G., Kane, V.R., Prichard, S., North, M., Cansler, C.A., 2023. The outsized role of California's largest wildfires in changing forest burn patterns and coarsening ecosystem scale. Forest Ecology and Management 528, 120620. https://doi.org/10.1016/j.foreco.2022.120620

INTRODUCTION

Globally, wildland fire is an important ecological process that shapes forest biodiversity (Pausas and Ribeiro, 2017), dynamically alters vegetation structure and composition (Bond et al., 2005), and regulates carbon and nutrient cycles (Pellegrini et al., 2018). Biota in fire-prone forests are adapted to the general frequency, extent, seasonality, and magnitude of fires (Bowman et al., 2009), but shifting fire regimes influenced by climate change, exclusion and criminalization of Indigenous burning practices, and changes in land management and land use have altered the role of wildfire in many regions (Hagmann et al., 2021; Hessburg et al., 2019; Jain et al., 2021; Senande-Rivera et al., 2022). In western North America, recent increases in annual area burned and extreme fire events have rapidly altered forest cover, posing enormous challenges to forest management to sustain ecological, cultural, and economic values at risk (Dennison et al., 2014; Keeley and Syphard, 2021; Reilly et al., 2022; Stephens et al., 2022; Wang and Lewis, 2024; Welch, 2012).

Of particular concern to both ecologists and land managers are observed shifts in fire severity – or the magnitude of ecological change caused by fire, typically measured by vegetation killed (Keeley, 2009) – which have broad implications for the persistence of forests across the region. Fire severity is an important component of fire regimes that shapes a variety of forest characteristics, from forest structure (Kane et al., 2019) and wildlife habitat (Robinson et al., 2013) to carbon storage (North and Hurteau, 2011) and resilience to future wildfire and drought (Hessburg et al., 2019). Within an individual fire perimeter, a range of fire impacts to forest vegetation may be observed, from negligible impacts on understory fuels to contiguous high-severity areas with complete tree mortality (Agee, 1996; Sugihara et al., 2006).

Following a long absence of fire across western North America (Marlon et al., 2012), there has been an eight-fold increase in total forested area burned with high severity effects since the mid-1980s (Parks and Abatzoglou, 2020), concomitant with increases in the size of individual high severity patches (Cansler and McKenzie, 2014; Reilly et al., 2017). Although high severity fire is a component of many historical fire regimes, uncharacteristically large patches of high severity beyond historical ranges of variability may alter patterns of post-fire tree regeneration, successional pathways, carbon dynamics, and other ecosystem functions (North and Hurteau, 2011; Steel et al., 2022a; Stevens et al., 2017). Rising summer temperatures under climate change and severe drought conditions may further challenge forest regeneration in large high severity burn patches following extreme fire events (Coop et al., 2020; Stevens-Rumann et al., 2022). Areas burned with low and moderate severity effects – which can range from minimal understory fuel consumption to moderate levels of canopy mortality (Miller and Thode, 2007) – can reduce surface and ladder fuel loads (Stephens et al., 2009), shift forests from closed canopy to more open structural conditions (Chamberlain et al., 2023; Churchill et al., 2022), and mitigate the severity of subsequent fires (Taylor et al., 2022). At the lowest end of the fire severity spectrum, unburned and minimally burned areas following wildfire serve important functions such as wildlife habitat refugia (Meddens et al., 2018b), informational and material legacies (Krawchuk et al., 2020), and seed sources that facilitate tree regeneration in nearby high severity patches (Coop et al., 2019). The amount and spatial configuration of a full range of fire effects – more than total area burned – drive the post-fire environment and forest resilience to subsequent disturbance events (Coppoletta et al., 2016; McKenzie et al., 2011).

Patterns of fire severity result from many interacting factors at multiple spatial and temporal scales. Fine-scale variations in topography, for example, influence site moisture, temperature, and vegetation structure, in turn influencing wildland fire behavior and effects (Merschel et al., 2018). Likewise, long-term climate trends may influence fire severity directly by increasing overall fuel aridity or indirectly by affecting vegetation productivity (Parks et al., 2016). Severe weather such as dry wind events may result in extreme fire behavior and daily fire spread, exacerbating fire severity and overriding 'bottom-up' controls such as topographic setting (Lydersen et al., 2017). Forest management practices such as the use of fuel treatments (Cansler et al., 2022; Prichard and Kennedy, 2014), fire suppression and legacies of Indigenous fire exclusion (Collins et al., 2011), and intensive plantation forestry for timber production (Levine et al., 2022; Zald and Dunn, 2018) are additionally important influences on fire severity as factors that alter fuel structure and composition.

Across western North America, climate adaptation strategies have become a major emphasis of contemporary forest and wildland fire management (Gaines et al., 2022; Hessburg et al., 2015, 2021; North et al., 2015b, 2021; Prichard et al., 2021). Previous studies have examined a range of place-based strategies and their relative effectiveness at mitigating fire behavior and severity, including the use of prescribed and cultural burning (Cansler et al., 2022; Long et al., 2021), mechanized treatments (Brodie et al., 2024; Johnston et al., 2021), managed wildfire (Larson et al., 2013; North et al., 2021), and strategic firefighting operations (Calkin et al., 2014; Thompson et al., 2018). Amid rapid environmental change, however, developing appropriate wildfire and climate adaptation strategies requires integrating information on how fire severity is changing, as well as how existing management approaches have influenced wildfire outcomes. As such, implementing robust methods to evaluate comprehensive, up-to-date information about both the patterns and drivers of fire severity is key.

In this dissertation, I evaluated multi-scaled drivers and spatial patterns of fire severity in hundreds of recent wildfires across forested landscapes in California, Oregon, and Washington. I leveraged remote sensing datasets and geospatial analyses to investigate changing wildfire regimes from the burn patch to the ecoregional scale. A central question guided this dissertation: *What are the adaptive management implications of recent fire severity trends in fire-prone forests?* Through a landscape ecology lens, each chapter addresses a component of this question in temperate forest ecosystems: in Chapter 1, I analyze changing patterns in recent fire severity; Chapter 2 evaluates drivers of severity; and in Chapter 3, I examine what recent trends mean for adaptive management within the Northwest Forest Plan area. While previous studies have addressed elements of this central question, efforts have often been constrained to single fires or groups of fires within single ecoregions (Lydersen et al., 2014; Povak et al., 2020; Taylor et al., 2021; Zald and Dunn, 2018), or have focused on limited facets of fire severity such as stand-replacing patches or unburned areas (Meddens et al., 2018a; Parks et al., 2018a; Singleton et al., 2021; Steel et al., 2018). This body of work evaluates spatial and temporal patterns, trends, and drivers of fire severity over a range of post-fire effects, four major ecoregions, several decades, thousands of fires, and millions of hectares burned.

In Chapter 1, I analyzed trends, spatial patterns, and cumulative impacts of fire severity across a full range of unburned, low-moderate, and high severity effects in recent California wildfires to evaluate implications for post-fire management. To date, existing studies on fire severity trends have overwhelmingly focused on spatial patterns of stand-replacing fire (Harvey et al., 2016; Parks and Abatzoglou, 2020; Singleton et al., 2021; Steel et al., 2022a; Stevens et al., 2017). While high severity trends undoubtedly have major implications for forest management, an emphasis on high severity alone may overshadow the beneficial 'work' of recent wildfires (*sensu* Churchill et al., 2022). Low and moderate severity fire effects, for example, can alter forest structure by reducing fine fuel loads and live tree densities, both of which are generally consistent with principles of ecological restoration associated with increased resilience to subsequent fire in frequent-fire forests (Hessburg et al., 2015;

Jeronimo et al., 2019; Kane et al., 2019). Despite recent increases in annual area burned, many frequent-fire forests across western North America are significantly departed from their historical conditions and remain in an overall fire deficit (Hagmann et al., 2021; Parks et al., 2015). As increases to the pace and scale of current forest treatments are needed to accomplish ecological restoration (Kolden, 2019; North et al., 2021), evaluating a full range of post-fire effects is critical to inform adaptive management of post-fire landscapes.

Chapter 2 evaluates the drivers of changing severity patterns across northern California, Oregon, and Washington, with a focus on understanding how existing management practices influence fire effects. While previous studies have evaluated how fuels, topography, and weather work in concert to drive fire severity (Birch et al., 2015; Dillon et al., 2011; Estes et al., 2017; Kane et al., 2015), the influence of forest management practices on fire severity remains poorly understood. Fire-prone forests of western North America typically consist of different landowners, administrative units, and land use designations that may have different – and sometimes conflicting – management goals (Miller et al., 2022). Developing adaptive management strategies and cohesive plans to manage wildfire more holistically across jurisdictional boundaries requires not only understanding the management implications of fire severity trends, but also the influence of management as well.

Finally, Chapter 3 of this dissertation builds on analyses within Chapters 1 and 2 and evaluates patterns and drivers of fire severity to inform adaptive management strategies within the Northwest Forest Plan, which guides the management of federal forests across nearly 10 million hectares in California, Oregon, and Washington states. While its adoption in 1994 marked a pivotal moment for forest conservation (Johnson et al., 2023), concerns around recent forest losses and fragmentation following wildfire have prompted a call for Plan revisions to incorporate climate change adaptations and promote wildfire resilience (US Forest Service, 2022). While this chapter focuses on a specific forest management plan, the findings of this study can inform reserve-driven forest conservation strategies more broadly. By quantifying the range of fire severity impacts and drivers across the study region, the combined findings from these three chapters can inform adaptive management of both pre-fire and post-fire forest conditions.

CHAPTER 1. THE OUTSIZED ROLE OF CALIFORNIA'S LARGEST WILDFIRES IN CHANGING FOREST BURN PATTERNS AND COARSENING ECOSYSTEM SCALE

1.1 ABSTRACT

Although recent large wildfires in California forests are well publicized in media and scientific literature, their cumulative effects on forest structure and implications for forest resilience remain poorly understood. In this study, we evaluated spatial patterns of burn severity for 18 exceptionally large fires and compared their cumulative impacts to the hundreds of smaller fires that have burned across California forests in recent decades. We used a burn severity atlas for over 1,800 fires that burned in predominantly conifer forests between 1985 and 2020 and calculated landscape metrics to evaluate spatiotemporal patterns of unburned refugia, low-moderate-severity, and high-severity post-fire effects. Total annual area burned, mean annual fire size, and total annual core area burned at high severity all significantly increased across the study period. Exceptionally large fires (i.e., the top 1% by size) were responsible for 58% and 42% of the cumulative area burned at high and low-moderate severities, respectively, across the study period. With their larger patch sizes, our results suggest that exceptionally large fires coarsen the landscape pattern of California's forests, reducing their fine-scale heterogeneity which supports much of their biodiversity as well as wildfire and climate resilience. Thus far, most modern post-fire management has focused on restoring forest cover and minimizing ecotype conversion in large, high-severity patches. These large fires, however, have also provided extensive areas of low-moderate severity burns where managers could leverage the wildfire's initial "treatment" with follow-up fuel reduction treatments to help restore finer-scale forest heterogeneity and fire resilience.

1.2 INTRODUCTION

Under historical fire regimes, California's northern and Sierra Nevada low- to mid-elevation forests typically experienced regular fires (< 25-year return interval) with a range of ecological effects (Safford and Stevens, 2017; Stephens et al., 2007). These typically frequent, low- to moderate-intensity fires shaped complex, fine-grained patterns of burn severity patches and forest structure, which conferred greater resilience – or the ability to adapt, reorganize, and maintain basic ecosystem structure and function (Walker et al., 2004) – to disturbances such as subsequent wildfire and drought (Hessburg et al., 2019; Kane et al., 2019; Stephens et al., 2018). Following Euro-American colonization and over a century of fire exclusion, changes in land use patterns have led to profound shifts in forest structure and fire regimes throughout fire-prone forest ecosystems of western North America (Hagmann et al., 2021). Coupled with a changing climate and more frequent days of extreme fire weather, increased availability of fuels has led to a well-documented increase in total annual area burned across the western United States in the last four decades (Abatzoglou and Williams, 2016; Dennison et al., 2014; Holden et al., 2018; Jain et al., 2021; Safford et al., 2022; Westerling, 2016).

While large wildfires are not unknown historically in California, the rate and scale of recent large fire events is novel (Keeley and Syphard, 2021; Safford et al., 2022). In the last several years, wildfires have rapidly increased in both size and occurrence across the state. Fourteen of the state's top 20 largest recorded wildfires occurred in the last decade; nine of which occurred in the last two years (CAL FIRE, 2022). Many of these recent large fires have burned through fuel-laden forests under extremely dry, wind-driven conditions, resulting in major community impacts and property losses (Rosenthal et al., 2021), hazardous smoke impacts (Enayati Ahangar et al., 2022), and severe fire impacts to forests over large swaths of land (Safford et al., 2022; Stephens et al., 2022).

Compounded by the effects of severe drought, these fires have contributed to the erosion of mature conifer forest cover in areas such as the southern Sierra Nevada (Steel et al., 2022b). These exceptionally large fires are often at the center of public and scientific narratives about the impacts of wildfires on California forests, with a dominant focus on areas of forest that experience complete or near-complete tree mortality, termed "stand-replacing fire" (Levine et al., 2022; Miller et al., 2012; Stevens et al., 2017). Recent large fires across the state have been characterized by the unprecedented size of their stand-replacing area, falling far outside the historical range of variation in these forests (Steel et al., 2018; Stephens et al., 2022). The size and spatial patterns of these stand-replacing patches have important implications for post-fire tree regeneration and successional pathways, carbon storage, and other ecosystem services and functions (North and Hurteau, 2011; Stevens et al., 2017). These trends are consistent with broader patterns identified across western North American forests, where studies from other regions have suggested increases to fire size and stand-replacing area (Cansler and McKenzie, 2014; Harvey et al., 2016; Reilly et al., 2017).

While insights into patterns and trends of stand-replacing fire are critical to understand threats to forest resilience, emphasis on stand-replacing fire alone may overshadow more complex landscape patterns shaped by large fires. Although recent studies have found that public perceptions of wildfire are changing (Miller et al., 2020; Toman et al., 2014; Weill et al., 2020), popular media descriptions of unplanned large fires tend to rely on single narratives of the disaster and destruction caused by these events (Keane et al., 2008; McCaffrey et al., 2020). While these large wildfires often have catastrophic impacts on humans and undesirable impacts on ecosystems within large high-severity patches, disentangling their more moderate effects is critical to inform land management strategies. Even with recent wildfire trends, many California forests remain in a fire deficit, and a vast increase to the pace and scale of current treatments is needed to restore forest resilience (North et al., 2021). As fire activity is projected to increase under longer and drier fire seasons caused by a warming climate (Abatzoglou et al., 2021), understanding the full range of post-fire ecological effects can inform adaptive management of large, fire-impacted landscapes.

Despite the attention it receives, total area burned is generally a poor predictor of post-fire forest conditions (Birch et al., 2014). Within an individual fire perimeter, a range of fire-caused ecological effects – hereafter, fire severity – may be present at different proportions and configurations across the landscape. At one end of the spectrum, the size and shape of stand-replacing (high-severity) patches have important implications for the capacity of forests to regenerate following fire (Stevens et al., 2017; Stevens-Rumann and Morgan, 2019). At the other, unburned or minimally burned areas of forest serve as refuge for wildlife habitat (Robinson et al., 2013), act as seed sources for regeneration in nearby stand-replacing patches (Coop et al., 2019; Schwilk and Keeley, 2006), and contribute to the overall forest structural heterogeneity across the post-fire landscape (Kolden et al., 2017; Meddens et al., 2018b). Between these two extremes, a wide range of low to moderate severity fire effects – from patchy consumption of forest floor fuels to up to 75 percent tree mortality – may be present. Low- to moderate-severity fire effects can shape forest structure by reducing tree density and fuel loads, bolstering forest resilience to future disturbances (Hessburg et al., 2015; Jeronimo et al., 2019; Kane et al., 2014, 2019; North et al., 2021, 2022), biotic mortality agents (Hood et al., 2015), and drought (van Mantgem et al., 2021, 2016). More than total fire size, mosaics of these fire effects govern the post-fire forest environment and subsequent fire events (Coppoletta et al., 2016; McKenzie et al., 2011; Peterson, 2002).

In this paper, we examine the landscape patterns of large wildfires across California forests. A central question guided this study: *what is the cumulative impact of exceptionally large wildfires in terms of their area burned at different severities, and how does the impact of large fires differ from the hundreds of smaller fires that* *have burned across California forests in recent decades?* We address this question using a dataset of over 1,800 fires that have burned across California forests between 1985 and 2020. We begin by providing a definition for exceptionally large fires within our dataset and contextualize their emergence over the last four decades in California forests. We evaluate their cumulative impacts using landscape metrics to calculate their area burned, interior (core) area burned, and mean patch sizes across the gradient of unburned, low-moderate, and high-severity effects. We compare these impacts to smaller fires and discuss the role of exceptionally large wildfires in reshaping California forests. We consider cumulative impacts in both spatial and temporal dimensions and focus the interpretation of our findings on potential impacts to forest resilience. Specifically, we analyze the impacts of exceptionally large wildfires through the following objectives:

1. Analyze temporal trends in wildfire size and annual area burned across the study area.
2. Compare spatial patterns of exceptionally large fires to other fires, in terms of cumulative area burned and spatial configurations by severity class.
3. Assess temporal trends in high-severity fire effects and unburned refugia, and evaluate the role of exceptionally large wildfires in these trends.

1.3 METHODS

1.3.1 Study Area

We evaluated fires that burned predominantly in conifer forests of the Klamath, Cascades, and Sierra Nevada ecoregions in California between 1985 and 2020 (Figure 1.1). Combined, these regions contain over 7.3 million hectares of conifer forest and account for more than 70 percent of the state's total conifer forest cover. Our study area is dominated by yellow pine and mixed-conifer forests with variable assemblages of ponderosa pine *(Pinus ponderosa*), Jeffrey pine *(P. jeffreyi)*, sugar pine *(P. lambertiana),* Douglas-fir *(Pseudotsuga menziesii var. menziesii)*, white fir *(Abies concolor)*, incense cedar *(Calocedrus decurrens)*, and black oak *(Quercus kelloggii)* at low- to mid-elevations. In higher elevations, our study area supports upper montane forests with diverse assemblages of red fir *(Abies magnifica),* western white pine *(P. monticola)*, and lodgepole pine *(P. contorta)*. Prior to Euro-American colonization, these forests, which comprise the majority of the area burned by wildfire, supported a predominately low- to moderate- severity fire regime through a combination of frequent natural ignitions and Indigenous burning (Anderson and Moratto, 1996; Meyer and North, 2019; Safford and Stevens, 2017). Over the last century, full suppression has been the primary management response across much of the region, with a smaller subset of areas (such as Yosemite National Park) permitting the use of managed wildfire to allow naturally-ignited fires to burn (Keeley et al., 2021; van Wagtendonk, 2007).

1.3.2 Fire Perimeters and Severity Data

We used a geospatial dataset of historical fire perimeters maintained by the California Department of Forest and Fire Protection (CAL FIRE) Fire and Resource Assessment Program (FRAP) to identify fires that burned between 1985 and 2020 within the study area. The FRAP dataset represents a comprehensive catalog of wildfire history across multiple land ownerships and is considered the best-available data for California. To identify fires that burned predominantly in conifer forests, we selected full fire perimeters where the following criteria were met: 1) the centroid of the fire perimeter was located in the Klamath, Cascades, or Sierra Nevada ecoregions; and 2) the fire burned over at least 50 percent conifer forest according to the LANDFIRE Biophysical Settings potential vegetation dataset (Rollins and Frame, 2006). We retained perimeters only where the total fire area was at least 4 ha to ensure each burn severity image contained a sufficient number of pixels to calculate landscape metrics. A total of 1,809 fires met these criteria.

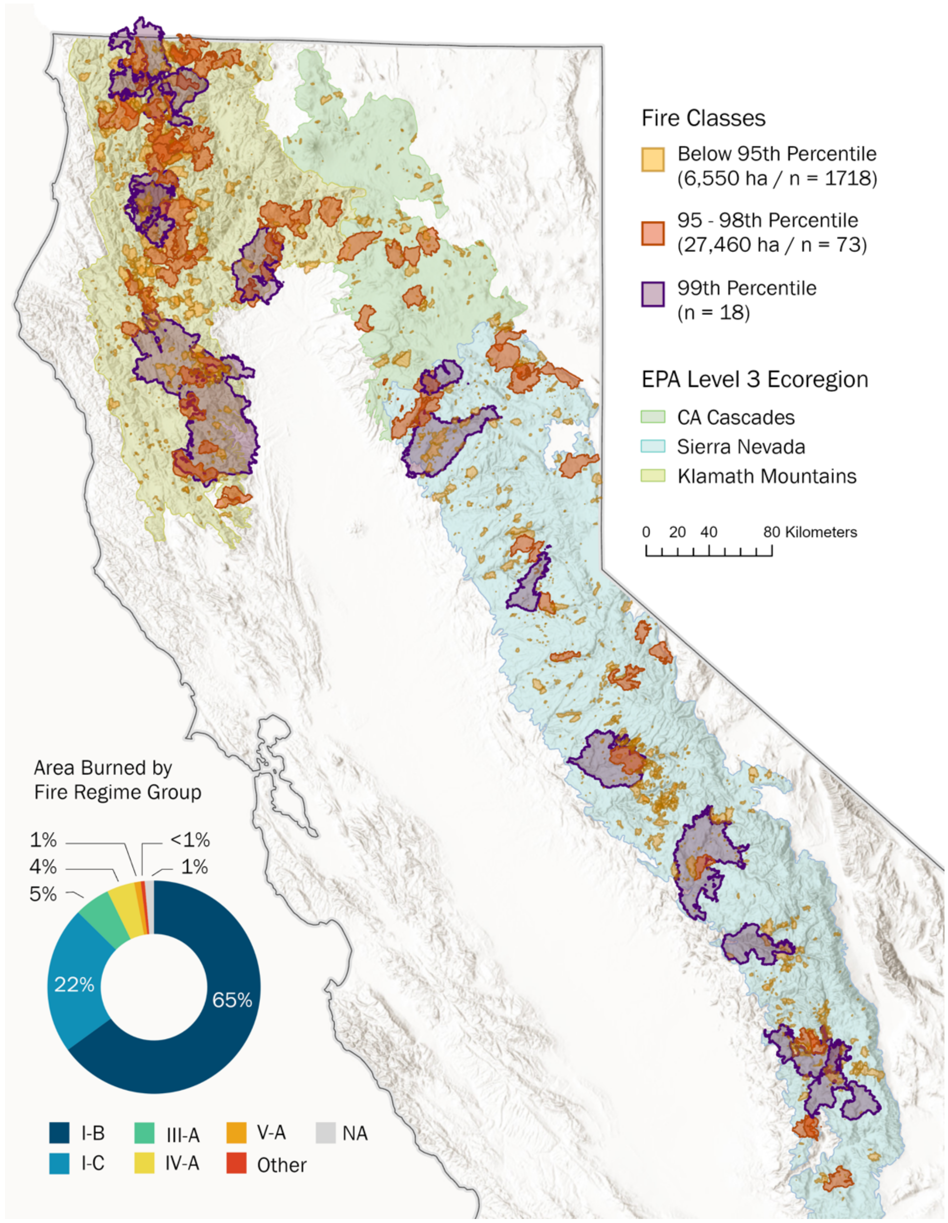

Figure 1.1. Map of the study region in California, USA showing locations of 1,809 fires that burned in predominantly conifer forests between 1985 and 2020 in the Klamath (yellow-green), Cascades (green), and Sierra Nevada (blue) EPA Level III ecoregions (Omernik and Gallant, 1987). Spatial patterns of fires were analyzed by their size class: fires below the 95th percentile by size (light orange), fires between the 95th and 98th percentile by fire size (red orange), and exceptionally large 99th percentile fires by size (purple). The majority (87%) of area burned within our study area is concentrated in historically low-to-moderate, frequent fire regimes (LANDFIRE, 2020). Additional regime types in our study area are found primarily as dispersed pixels, mainly in riparian areas and on north-facing slopes. The graph at the bottom left shows the distribution of burned area across the study area and study period by LANDFIRE Fire

Regime Groups: I-B: Percent replacement fire less than 66.7%, fire return interval 6-15 years (65% of the study area); I-C: Percent replacement fire less than 66.7%, fire return interval 16-35 years (22% of the study area); III-A: Percent replacement fire less than 80%, fire return interval 36-100 years (5% of the study area); IV-A: Percent replacement fire greater than 80%, fire return interval 36-100 years (4% of the study area); V-A: Any severity, fire return interval 201-500 years (1% of the study area). The "Other" category captures a range of fire regime types but accounts for less than 1% of the study area. An additional 1% of the study area is classified as "Not Applicable" due to sparse or no vegetation cover.

We obtained Landsat-derived (30-m resolution) burn severity images for each full fire perimeter (all pixels regardless of vegetation type) by implementing a methodology developed by Parks et al. (2019) within Google Earth Engine (GEE) (Gorelick et al., 2017). This method employs spectral indices (including Normalized Difference Vegetation Index, Mid-Infrared Bi-Spectral Index, and Relativized Burn Ratio), climatic variables, latitude, and a dataset of composite burn index (CBI) values (Key and Benson, 2006) from over 8,000 field sampling plots to produce predicted CBI values via Random Forest modeling (Breiman, 2001). We chose to use predicted CBI rather than other commonly used satellite-derived measures of burn severity (such as the Relativized delta Normalized Burn Ratio or Relativized Burn Ratio) because 1) it is a more meaningful metric of ecological change compared to unitless spectral indices, and 2) exploratory analysis showed that predicted CBI values had a closer relationship with field measurements of CBI (Picotte et al., 2019) than RBR or RdNBR. Field-based CBI measurements incorporate information about fire impacts to substrates, but the index is heavily weighted towards assessments of post-fire tree mortality and vegetation change (Miller and Thode, 2007).

We classified our continuous CBI values into three categories of fire severity for each fire: unburned-very low severity (CBI values below 0.1), low-moderate severity (CBI values 0.1 - 2.25) and high severity (CBI values 2.25 and above) (Miller and Thode, 2007). Although the standardized CBI breaks distinguish between low and moderate severity, previous work has also found that remotely sensed measurements of moderate severity capture a wide range of post-fire conditions and are relatively uncertain in their measurements of post-fire tree mortality and vegetation condition (Furniss et al., 2020). Because of this, we chose to combine low and moderate severity into a single class. We recognize that this single class captures a range of overstory mortality, and measurements of moderate severity in particular can be unclear in their ecological interpretations. However, we interpret our low-moderate severity class as the range of post-fire effects that reshape forests closer to resilient conditions (Collins et al., 2018; Jeronimo et al., 2019; Kane et al., 2019; Taylor et al., 2022).

1.3.3 Exceptionally Large Fires

Definitions of large fires vary widely across studies and are named somewhat arbitrarily (Barbero et al., 2014; Gill and Allan, 2008; Linley et al., 2022; Tedim et al., 2018). Barbero et al. (2014) defined *very large fires* as greater than 5,000 ha; Keeley and Syphard (2021) described *large fires* as greater than 10,000 ha; Stavros et al. (2014) used a threshold of 50,000 acres (20,234 ha) to define *very large wildfires*; Stephens et al. (2014) defined *mega-fires* as those greater than 10,000 ha. Large fire definitions are highly context dependent: they may be relative to geographic regions, vegetation types, socio-economic impacts, or individual datasets. Rather than a predefined threshold of area burned, we adopted the 99th percentile of fire sizes in our dataset (27,460 ha) to describe *exceptionally large fires* (Table 1.1). We focus on this top 1 percent (n = 18 fires) when discussing the cumulative impacts of exceptionally large fires on California forests. Throughout this study, we often contextualize their impacts by contrasting to those of an adjacent fire size group: fires between the 95th and 98th percentile by size, which equates to fires between 6,550 ha and 27,460 ha (n = 73 fires). Because of steep increases in area burned by large wildfires across California in recent years, we concluded that the fires in this adjacent group were not large enough to warrant the distinction of *exceptionally large*; rather, they provide a transitional space with which to evaluate the continuum of fire effects across fire sizes.

Table 1.1. Rank by size, fire name, year burned, ecoregion, total area burned, and area burned by severity class for each of the 18 exceptionally large wildfires (> 27,460 ha) in this study. Percentages in parentheses represent the percentage of area burned at that fire severity class as a function of the total area burned for that fire event. Table continues on next page.

Exceptionally large wildfires in California: top 1% of forest fires by size (n = 18)							
Rank	Fire Name	Year	Ecoregion	Total Area Burned (ha)	High Severity Area (ha)	Low-Moderate Severity Area (ha)	Unburned-Very Low Severity Area (ha)
1.	August Complex	2020	Klamath	419,825	190,728 (45%)	222,713 (53%)	6,384 (2%)
2.	Creek	2020	Sierra Nevada	154,672	66,077 (43%)	85,222 (55%)	3,374 (2%)
3.	Claremont-Bear	2020	Sierra Nevada	129,136	80,692 (62%)	47,437 (37%)	1,007 (1%)
4.	Rim	2013	Sierra Nevada	104,191	36,952 (36%)	62,677 (60%)	4,562 (4%)
5.	Carr	2018	Klamath	93,422	37,931 (41%)	53,550 (57%)	1,941 (2%)
6.	Castle	2020	Sierra Nevada	70,089	30,270 (43%)	38,044 (54%)	1,775 (3%)
7.	Slater	2020	Klamath	64,324	38,176 (59%)	24,161 (38%)	1,987 (3%)
8.	Rough	2015	Sierra Nevada	61,811	15,086 (24%)	40,875 (66%)	5,850 (10%)
9.	McNally	2002	Sierra Nevada	60,934	17,750 (29%)	37,231 (61%)	5,953 (10%)
10.	Red Salmon Complex	2020	Klamath	58,716	17,995 (31%)	39,920 (68%)	800 (1%)
11.	Frying Pan	2014	Klamath	54,323	17,667 (33%)	34,638 (64%)	2,018 (3%)
12.	Megram	1999	Klamath	50,935	9,247 (18%)	36,675 (72%)	5,014 (10%)

13.	King	2014	Sierra Nevada	39,947	20,854 (52%)	17,676 (44%)	1,417 (4%)
14.	Oak	2017	Klamath	37,390	12,101 (32%)	23,333 (63%)	1,956 (5%)
15.	Manter	2000	Sierra Nevada	32,257	11,391 (35%)	15,943 (49%)	4,922 (15%)
16.	Chips	2012	Sierra Nevada	31,122	9,385 (30%)	20,203 (65%)	1,534 (5%)
17.	River Complex	2015	Klamath	27,874	5,014 (18%)	20,238 (73%)	2,622 (9%)
18.	King Titus	1987	Klamath	27,688	2,993 (11%)	22,462 (81%)	2,233 (8%)

1.3.4 Landscape Metrics

Patterns of fire severity have ecological implications at multiple scales. For example, at the individual patch scale, high-severity patch size and interior core area (the area within a patch that is at least a given distance from the patch edge) serve as a proxy for distance to live seed source and govern regeneration potential of trees (Collins et al., 2017b; Stevens et al., 2017). At broader regional scales, the area and configuration of patches belonging to different fire severity classes influences post-fire successional dynamics and overall forest structure heterogeneity (Hessburg et al., 2019, 2016). We calculated five landscape metrics across three dimensions of spatial pattern to evaluate the cumulative impacts of exceptionally large fires: area burned by severity class, core area burned by severity class, and average patch size (Table 1.2). All metrics were calculated with the landscapemetrics package in R (Hesselbarth et al., 2019).

Table 1.2. Description and interpretation of landscape metrics calculated for 1,809 fires that burned between 1985 and 2020 in the Klamath, Cascades, or Sierra Nevada ecoregions of California. All metrics were calculated using the landscapemetrics package in R (Hesselbarth et al., 2019). Table adapted from Singleton et al. (2021).

Metric	**Acronym**	**Description**	**Interpretation of low values**	**Interpretation of high values**	**Units**	**Range**
Class Area (Total)	CA	*Area burned:* Total area belonging to severity class *i*.	Less area burned	More area burned	Hectares	CA ≥ 0
Class Area (Proportional)	PLAND	*Percentage of landscape of class:* Measure of landscape composition. Percentage of total fire area belonging to severity class *i*.	Less proportional area burned	More proportional area burned	Percentage	0 ≤ PLAND ≤ 100
Patch Area	AREA_AM	*Area-weighted mean patch size:* Measure of patch size for each class *i*	Generally smaller patch sizes, with few or no large patches	Generally larger patch sizes, or few large patches among many smaller patches	Hectares	AREA_AM ≥ 0
Patch Area	AREA_MN	*Arithmetic mean patch size:* Measure of patch size for each class *i*	Many smaller patches, with few or no large patches	Many larger patches, or few large patches among few small patches	Hectares	AREA_MN ≥ 0
Core Area (Total)	TCA	*Total core area:* Total core area of class *i* > 120 m from patch edge. Only calculated for high-severity class.	Less interior area burned	More interior area burned	Hectares	TCA ≥ 0

Patch level (two metrics) – We calculated area-weighted mean patch size (AREA_AM) and arithmetic mean patch size (AREA_MN) using the 8-neighbor rule for each severity class present within each fire. The former weights each patch by its proportional contribution to the total area of all patches while the latter gives equal weight to each patch (Li and Archer, 1997). Many of the largest fires in our analysis burned under a combination of wind-driven and fuel-laden conditions and may contain exceptionally large, continuous patches representing days of large fire spread. We chose to calculate both area-weighted mean and arithmetic mean patch sizes to characterize the effect of these large patches. Specifically, in fires with many small patches and a few, exceptionally large patches (right-skewed distributions), we would expect the area-weighted mean patch size to be larger, and arithmetic mean patch size to be smaller. Fires with similar area-weighted and arithmetic mean patch sizes would indicate general homogeneity of patch sizes – either many small patches or few large patches across the fire, depending on the value.

Class level (three metrics) – For each severity class within individual fires, we calculated the total area burned in hectares (class area, CA) and proportional area burned (PLAND). Class area was used to assess the cumulative impact of exceptionally large fires, and proportional area burned enables direct comparisons of patterns of fire severity across the broader population of fire sizes in our dataset.

Lastly, we calculated total core area (TCA). Core area is the area of all patches in severity class *i* greater than a specified distance from each patch edge. We included core area specifically as a way to evaluate potential non-serotinous conifer tree regeneration failures in the high-severity class; as a result, we defined core area by a distance threshold of 120 m (four pixels) from the patch edge, or the distance at which wind-driven seed dispersal becomes very unlikely for most mixed-conifer trees within our study area (Clark et al., 1999). We did not evaluate core area of the unburned or low-moderate severity class.

1.3.5 Impacts of Exceptionally Large Fires

Temporal Trends in Area Burned

We evaluated the role of exceptionally large fires in temporal trends of annual mean fire size and total annual area burned between 1985 and 2020 with a Theil-Sen (TS) slope estimator. TS slope estimators are a nonparametric technique to calculate the median overall slope across a time series from the pairwise slopes between each timestep. Previous work has established statistically significant increases in annual area burned across the study area in the last several decades (Parks and Abatzoglou, 2020; Steel et al., 2018). However, to date, there have been few studies that have evaluated the role of exceptionally large fires in recent wildfire trends. Following the critical value cutoff used in previous studies, we assessed the statistical significance of slopes using a p-value of 0.10 (Dennison et al., 2014; Holden et al., 2018; Parks and Abatzoglou, 2020). All slopes were calculated using the "trend" package in R (Pohlert, 2019).

Spatial Patterns of Exceptionally Large Fires

We evaluated spatial patterns of exceptionally large fires by assessing both their cumulative area burned and their individual configurations by severity class. We calculated cumulative area burned by severity class across all fires to evaluate the role of exceptionally large wildfires in shaping California forests. Previous work examining fire severity in California forests has largely focused on overall trends, with a dominant focus on high-severity effects (Mallek et al., 2013; Miller et al., 2012; Steel et al., 2018; Stevens et al., 2017). While analyses of temporal trends are invaluable to understand shifting fire regimes, we calculated cumulative totals to evaluate the overall footprint of exceptionally large fires across the landscape. We present these totals for each severity class to assess the role of exceptionally large fires in both maintaining and degrading forest resilience.

We focused on two aspects of spatial configuration to evaluate patterns and impacts of individual exceptionally large fires: proportional area burned and patch size. We performed a principal component analysis (PCA) on the proportional area burned (PLAND) of unburned-very low, low-moderate, and high-severity effects present in each fire to understand their ranges of ecological effects. We used ordination plots to visualize patterns of burn severity proportions of exceptionally large fires and directly compare those to the hundreds of smaller fires across our dataset. To understand patch-level effects of exceptionally large fires, we compared area-weighted (AREA_AM) and arithmetic (AREA_MN) mean patch sizes between exceptionally large fires and smaller fires across each severity class. We did not conduct statistical tests of significance among the means or distributions of area-weighted and arithmetic mean patch sizes between fire size groups because our dataset 1) represented the population of fires across our study area and study period and 2) contained substantial differences in sample size and variance between groups.

Temporal Trends in High-Severity Fire Effects and Unburned Area

We evaluated temporal trends in total annual core area burned in high-severity patches to understand the role of exceptionally large wildfires in threats to forest regeneration. We evaluated temporal trends in total area of unburned refugia within fire perimeters to evaluate potential implications for wildlife habitat, carbon storage, and seed sources left behind by exceptionally large fires. We used Theil-Sen regression to analyze the statistical significance of trend slopes.

1.4 RESULTS

1.4.1 Temporal Trends in Area Burned

The majority of exceptionally large fires in our dataset occurred in the last decade (14 of 18), with 2020 containing both the highest number and the largest fires. Between 1985 and 2020, there was a statistically significant increase in total annual area burned, with a trending (fitted) increase of 3,258 ha burned annually per the Theil-Sen model (Table 1.3, Figure 1.2). This represents over an 1100 percent increase in annual area burned over the 35-year study period. Trends in mean annual fire size were likewise statistically significant; according to the model, mean fire size increased from 211 ha to 1,701 ha over the entire study period (47 ha annually), or an eight-fold increase from 1985 to 2020.

Table 1.3. Results of Theil-Sen slope estimator for mean annual fire size and total annual area burned between 1985 and 2020 across the study period. Slopes indicate the estimated annual increase (positive slopes) or decrease (negative slopes) in units of hectares burned. Asterisks indicate statistically significant trends.

	Z statistic	Sen's slope (ha)	p-value	**1985 fit**	**2020 fit**
Mean Annual Fire Size*	3.50	47.26	0.00046*	211 ha	1,701 ha
Total Annual Area Burned*	3.39	3,257.88	0.00069*	10,146 ha	124,172 ha

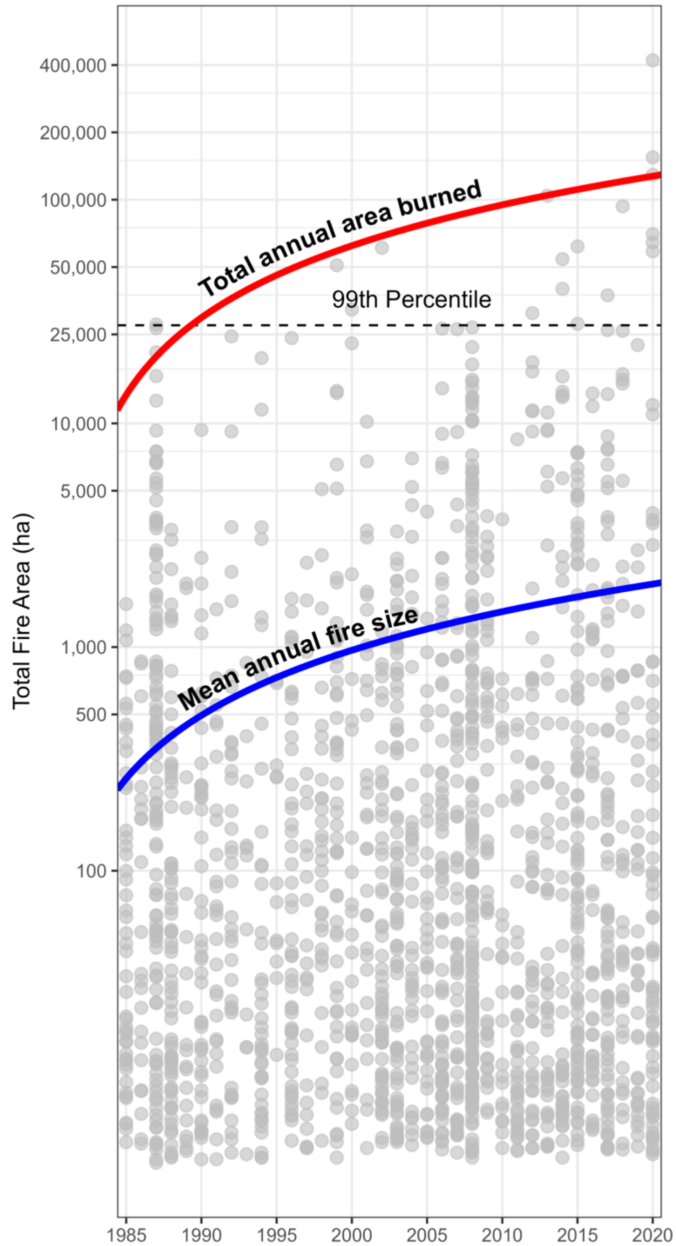

Figure 1.2. Trends in mean annual fire size (blue line) and total annual area burned (red line) per Theil-Sen slope estimators. Each gray dot represents a single fire in the corresponding year. The dashed line represents the cutoff of 99th percentile of fires (exceptionally large fires) by size. Trends in mean annual fire size and total annual area burned are statistically significant.

1.4.2 Spatial Patterns of Exceptionally Large Fires

Between 1985 and 2020, a total of 3,259,701 ha burned across the study area, of which 502,796 ha (15.4 percent) burned more than once. Within the 18 exceptionally large fires, 299,864 ha (19.8 percent) burned more than once. These 99th percentile fire sizes accounted for 47 percent of the total area burned across the study period (Table 1.4). The top 5 percent of fires accounted for 77 percent of the total area burned in this study.

Within all fire perimeters, 215,731 ha were unburned or burned at very low severity (Figure 1.3). It is important to note that our calculations do not explicitly account for overlaps in fire perimeters, and these numbers may capture fire refugia that persist over multiple fire events. Exceptionally large fires accounted for 26 percent of this unburned refugia total; fires below the 99th percentile accounted for 74 percent of area unburned or burned at very low severity.

The majority (60.7 percent) of area burned across all fires between 1985 and 2020 burned at low-moderate severity, for a total of 1,979,773 ha (Figure 1.3). This is nearly double the area burned at high severity and over 9 times the area of unburned-very low severity. The 18 exceptionally large fires accounted for 42 percent (843,000 ha) of the total area burned with low-moderate severity effects; large fires between the 95th and 98th percentile by size accounted for 32 percent of this total. Smaller fires below the 95th percentile – 1,718 fires total – accounted for just 26 percent of the area burned at low-moderate severity.

A total of 1,065,197 ha burned with high-severity effects across the study period (Figure 1.3). Exceptionally large fires accounted for the majority (58 percent) of this area with 620,307 ha burned; fires between the 95th and 98th percentiles accounted for 28 percent. The 1,718 smaller fires below the 95th percentile accounted for 148,653 ha – just 14 percent of the total high-severity area.

Table 1.4. Cumulative area burned in hectares by fire size group for 1,809 fires that burned across predominately conifer forests in California between 1985 and 2020. Percentages in parentheses are summed by columns and indicate the percentage of the total area burned in that severity class (CA) across all fire size groups.

	n	**High (ha)**	**Low-Moderate (ha)**	**Unburned-Very Low (ha)**	**Total Area (ha)**
99th percentile	18	620,307 *(58%)*	843,000 *(42%)*	55,349 *(26%)*	1,517,656 *(47%)*
95 – 98th percentile	73	296,237 *(28%)*	628,593 *(32%)*	66,589 *(31%)*	991,419 *(30%)*
Below 95th percentile	1,718	148,653 *(14%)*	508,180 *(26%)*	93,793 *(43%)*	750,626 *(23%)*
All fires	1,809	1,065,197 *(100%)*	1,979,773 *(100%)*	215,731 *(100%)*	3,259,701 *(100%)*
Percentage of total area		*32.7%*	*60.7%*	*6.6%*	*100%*

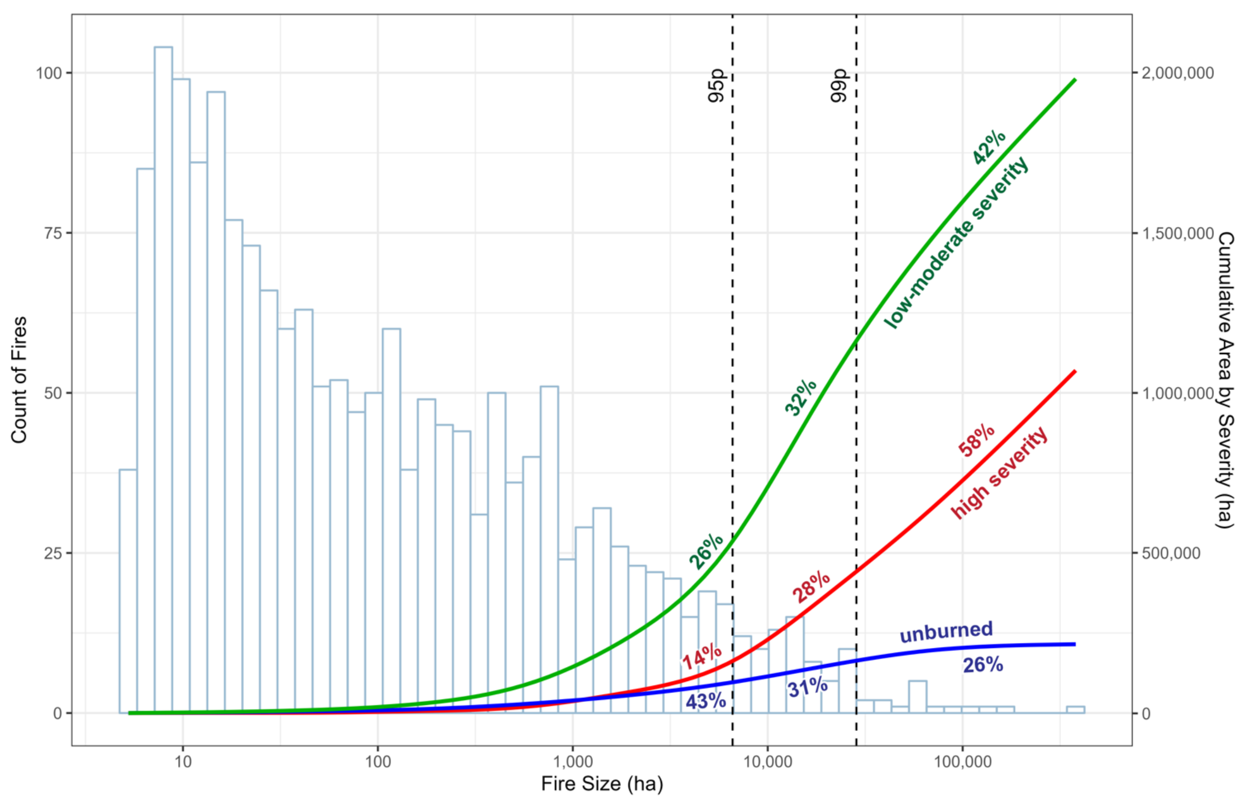

Figure 1.3. Histogram of fires by size (left y-axis) for 1,809 fires that burned across conifer-dominated forests in California between 1985 and 2020. Lines represent the cumulative area

burned (right y-axis) by severity class (CA), where the bottom blue line is unburned-very low severity, the middle red line is high severity, and the top green line is low-moderate severity. The dashed lines represent the 95th percentile and 99th percentile cutoffs of fires by size.

Principal component analysis of proportional area burned by fire severity class (PLAND) differentiated fires primarily by proportional burned and unburned area (Figure 1.4). Fires with greater proportions of unburned area – entirely smaller fires – were associated with the first PC axis (61.5 percent of variation). Fires with greater proportions of low-moderate and high-severity area were associated with the second PC axis (38.5 percent of variation). All exceptionally large fires fell along the second axis, as they typically contained proportionately more high and low-moderate severity effects (Table 1.1). Of the 18 exceptionally large fires, 10 fires contained less than 5 percent area unburned refugia. Fifteen of 18 fires contained proportionally more low-moderate than high-severity area; fourteen of these fires were composed of over half low-moderate severity.

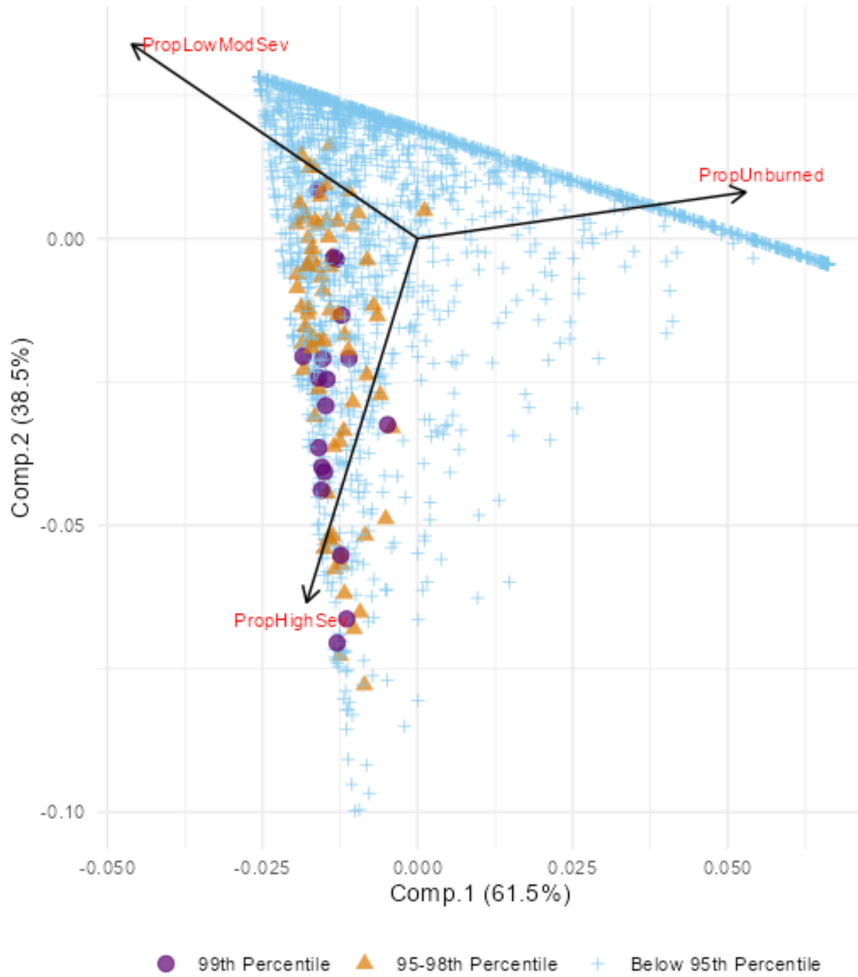

Figure 1.4. Ordination of principal component analysis (PCA) of proportional area burned (PLAND) by fire severity class. Fire size groups are overlaid on the plot to show the range of spatial patterns of fire severity in exceptionally large fires (n = 18) and fires between the 95th and 98th percentiles by size. The threshold line of solid points at the top of the ordination represents smaller fires with proportionally greater area unburned.

Area-weighted mean patch sizes (AREA_AM) varied widely between fire severity classes and fire size groups (Figure 1.5). Patch sizes generally increased with fire size but increases in low-moderate and high-severity patches were much greater than unburned-very low patches. The average area-weighted patch size of unburned refugia in smaller fires was 3.9 ha; in exceptionally large fires, this increased to 44.9 ha. In the low-moderate severity class, smaller fires had average area-weighted patch sizes of 12.9 ha – orders of magnitude smaller than the average patch size of 5,077 ha in exceptionally large fires. In the high-severity class, the contrasts were also pronounced – smaller fires had an average area-weighted patch size of just 1.3 ha, while exceptionally large fires had average patch sizes of 2,301 ha.

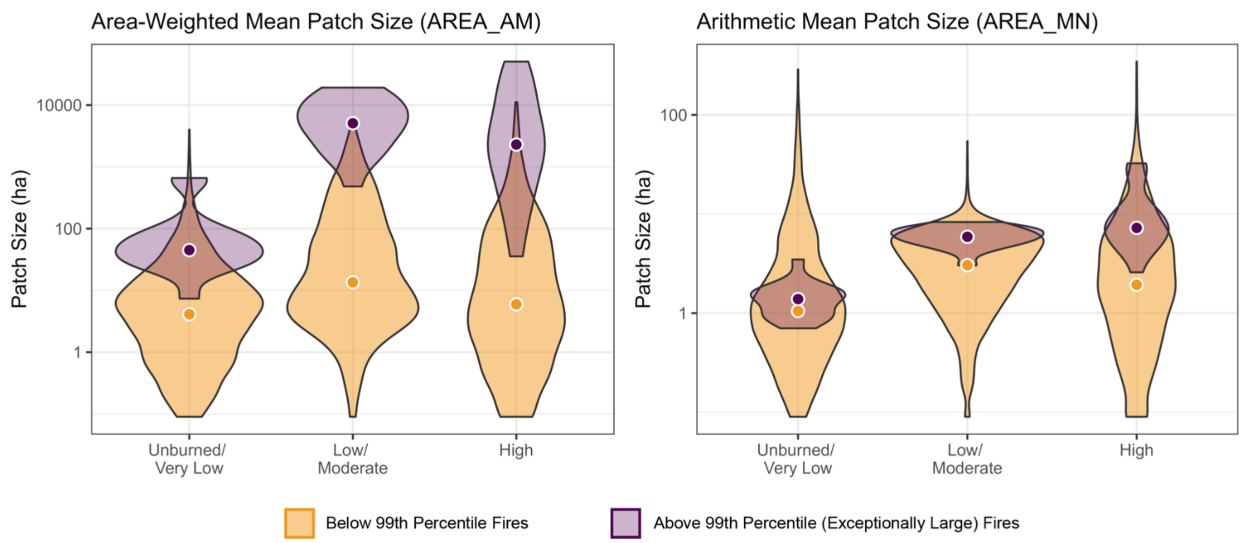

Figure 1.5. Distributions of area-weighted mean patch size (AREA_AM, left) and arithmetic mean patch size (AREA_MN, right) by fire for unburned-very low, low-moderate, and high-severity classes as a function of fire size.

By contrast, arithmetic mean patch sizes were more comparable between smaller and exceptionally large fires across all severity classes, but overall, exceptionally large fires overall contained larger mean patch sizes. Mean arithmetic patch sizes of unburned refugia were 1.1 ha in smaller fires and 1.4 ha in exceptionally large fires. Smaller fires had an arithmetic mean low-moderate-severity patch size of 3 ha; in exceptionally large fires, this mean size was 5.9 ha. In the high-severity class, mean high-severity patch size in smaller fires was 2.3 ha compared to 7.2 ha in exceptionally large fires.

1.4.3 Temporal Trends in High-Severity Fire Effects and Unburned Area

Across all fires, there was a statistically significant positive trend in total annual interior core area (TCA) burned at high severity across the study period, with a nearly 35-fold increase in area according to the Theil-Sen fitted models (Figure 1.6, Table 1.5). Between 1985 and 2020, 378,521 ha of interior core high-severity area (i.e., greater than 120 m from the patch edge) burned. Of this, 256,912 ha (68 percent) burned in exceptionally large fires.

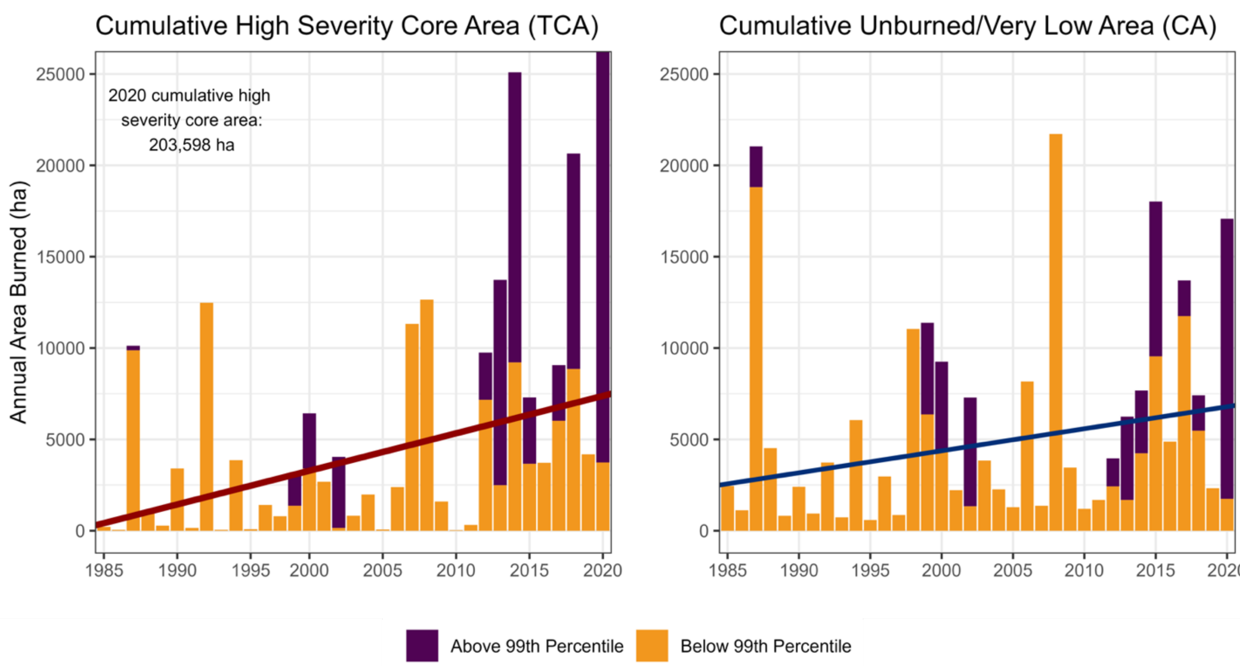

Figure 1.6. Trends in total annual interior core area of high severity (TCA, left panel) and total annual unburned refugia/very low severity (CA, right panel) between 1985 and 2020 across the study area. Trend lines represent Theil-Sen slope estimations of high-severity core area (left panel, red line) and total unburned area (right panel, blue line). Note that for the year 2020, total core area burned at high severity (left panel) extends beyond the y-axis limits; the total amount is noted at the top left of the plot.

Table 1.5. Results of Theil-Sen slope estimator for total annual high-severity core area (TCA) burned and total annual unburned area (CA) between 1985 and 2020 across the study area. Slopes indicate the estimated annual increase (positive slopes) or decrease (negative slopes) in units of hectares. Asterisks indicate statistically significant trends.

	Z stat	Sen's slope (ha)	p-value	**1985 fit**	**2020 fit**
High-severity core area	3.04	204.87	0.00239*	211 ha	7,375 ha
All unburned-very low severity area	2.08	120.56	0.037*	2,448 ha	6,668 ha

Model fits also indicated a statistically significant increase in unburned/very low severity area (CA) – from 2,448 ha to 6,668 ha – across the study period. In total, there were 215,731 ha of unburned-very low severity area across all fires in this study, with exceptionally large fires accounting for 55,348 ha, or 26 percent, of the total unburned-very low severity area.

1.5 DISCUSSION

This study examined the spatial patterns and cumulative impacts of exceptionally large fires on California forests and places those impacts within the spatial and temporal context of the hundreds of smaller fires that have burned across the state from 1985 to 2020. Consistent with previous studies (Parks and Abatzoglou, 2020; Steel et al., 2018; Stevens et al., 2017), we found increasing trends in mean annual fire size, annual area burned, and the interior core area of high-severity patches, of which the latter is associated with large-scale non-serotinous conifer tree regeneration failures, persistent vegetation type conversion, diminished wildlife habitat, and loss of carbon storage (North and Hurteau, 2011; Stephens et al., 2016; Stevens-Rumann and Morgan, 2019). Across the study period, we found that the top 5 percent of fires by size were responsible for the vast majority (74 percent) of area burned with low- to moderate-severity effects, which can reduce fuel loads and tree densities, edging forests towards more resilient conditions (Hessburg et al., 2015; Jeronimo et al., 2019; Kane et al., 2019). Notably, we also found that exceptionally large fires contain much larger low-moderate and high-severity patches than smaller fires (Figure 1.7), indicating a 'coarsening' of the spatial grain size between contrasting severity classes. This coarsening may erode fine-scale patterns of forest structure historically reinforced by smaller fires and the ecological processes that rely on them.

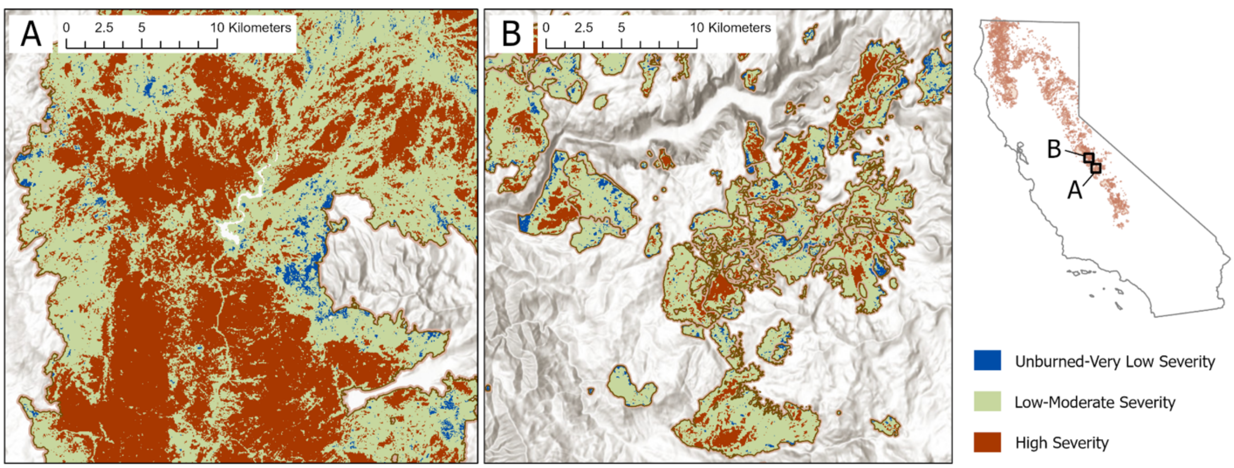

Figure 1.7. Impacts of one exceptionally large fire (Panel A, left) versus dozens of smaller fires (Panel B, right) on California forests. Panel A shows the 2020 Creek Fire in the Sierra Nevada, which contains some of the largest single patches of high and low-moderate severity (> 20,000 ha) in this analysis. Panel B shows a mosaic of 80 small fires ranging from 4 ha to 3,470 ha that burned between 1985 and 2020 just south of Yosemite Valley in the Sierra Nevada. In both panels, dark blue represents unburned-very low severity, light green represents low-moderate severity, and dark red represents high severity. Both panels are at the same spatial scale and have the same areal extent.

1.5.1 Temporal Trends in Area Burned

We observed clear trends in increasing total annual area burned and mean annual fire size over the last four decades. Exceptionally large fires drove these trends – the majority of the top 1 percent of fires by size (14 of 18 fires) burned within the last decade, and the top 3 largest fires in our analysis burned in 2020, the final year of the study period. Previous studies have linked broad trends in annual area burned to severe drought conditions and warmer temperatures, which are expected to intensify under a rapidly changing climate (Dennison et al., 2014; Holden et al., 2018; Westerling, 2016). If wildfires continue to burn dense, homogenized forests, annual area burned and mean fire size driven by rapid fire spread events are likely to continue increasing, and the exceptionally large fires included in this analysis may become more characteristic of future norms (Coop et al., 2022). Assessing the dynamics and drivers of these increases, including where reburned areas may exacerbate or mitigate subsequent fire severity, will be critical topics of future research as fire-on-fire interactions become more frequent.

It is important to note that increases in total annual area burned and fire size alone are not intrinsically a cause for concern. It is widely recognized that over a century of fire exclusion, including suppression policies and curtailment of Indigenous burning, has led to a profound fire deficit across much of California's forests (Hagmann et al., 2021; Hessburg et al., 2019; Mallek et al., 2013; Marlon et al., 2012; Parks et al., 2015). In areas with low to moderate overstory tree mortality following fire, increases in annual area burned certainly address this deficit. However, the observed spatial patterns of severity – including historically unprecedented trends in high-severity core area and patch size configurations – within recent exceptionally large fires suggest that these fires represent an emerging fire regime distinct from historical norms.

Specifically, we found that recent exceptionally large fires have higher mean burn severities than smaller fires, and contain large patches of all fire severities that leave behind markedly different patterns of forest structure than the fine-scale heterogeneity produced by historic fires (Collins and Roller, 2013; Fry et al., 2014; Perry et al., 2011). In areas of forest where these exceptionally large events were the first fire following an extended fire-free period – i.e., first-entry fires – these novel spatial patterns of fire severity may be self-reinforcing in future fires without appropriate post-fire management. In our study area, spatial patterns of fire severity tend to follow the patterns of previous wildfires – that is, in mixed conifer forests, low severity in previous fires typically begets low severity in subsequent fires, and areas that previously burned at high severity may subsequently burn at high severity due to accumulations of snags, coarse woody debris, and regeneration of flashy fuels such as shrubs and grasses (Parks et al., 2014b; Prichard et al., 2017; Taylor et al., 2021, 2022). As areas within existing exceptionally large fires are reburned in subsequent wildfire, assessing whether these self-reinforcing patterns are present should be a focus of future work.

1.5.2 Spatial Patterns of Exceptionally Large Fires

We found that the largest fires (greater than the 95th and 99th percentiles by size) were distinct from the population of smaller fires in their proportions of area burned at different severities (Figure 1.4). Unlike smaller fires, these largest fires contained relatively smaller proportions of unburned refugia and were dominated by area burned at low-moderate and high severity. The 18 exceptionally large fires, representing the top 1 percent of fires by size, were associated with greater proportions of high severity in particular, consistent with previous work that has found greater proportions of stand-replacing effects in large wildfires (Keane et al., 2008; Lydersen et al., 2014; Safford et al., 2022; Stephens et al., 2022; Taylor et al., 2022). These patterns reflect the extreme conditions in which these large fires have typically burned – for example, wind-driven or plume-dominated events such as the 2020 Creek fire exhibit extreme fire behavior under hot and dry conditions that often result in widespread tree mortality (Stephens et al., 2022).

Exceptionally large fires were responsible for the majority of high-severity fire effects across California forests (Table 1.5, Figure 1.6), and our assessment of mean patch sizes suggests that these effects are concentrated in large, contiguous patches (Figure 1.5). The top 1 percent of fires by size accounted for 58 percent of the cumulative area burned at high severity between 1985 and 2020 for a total of 620,307 ha. We found that exceptionally large fires contained larger mean high-severity patches than smaller fires regardless of whether arithmetic or area-weighted calculations were used, producing a distinct spatial signature uncharacteristic of the fine-scale patch heterogeneity historically found in fires prior to widespread fire exclusion (Fry et al., 2014; Perry et al., 2011; Safford and Stevens, 2017). These larger mean patch sizes in exceptionally large fires reflect the influence of both *overall* larger high-severity patches (i.e., even the smallest high-severity patches in large fires tend to be larger than those of smaller fires) and the presence of a handful of extremely large patches in exceptionally large fire events (i.e., the 2020 August Complex and Creek fires, which each contained homogenous high-severity patches roughly 20,000 ha in area (Stephens et al., 2022)). These large contiguous patches inherently contain greater interior core area, which is associated with increased distance to live seed source and likelihood of tree regeneration failure leading to persistent vegetation type-conversion, loss of carbon storage, and diminished wildlife habitat (Earles et al., 2014; Stevens et al., 2017).

While their large stand-replacing patches and associated severe ecological consequences cannot be understated, we also found that exceptionally large wildfires were responsible for the majority of low- to moderate-severity fire effects. The largest 18 fires across the study period were responsible for 42 percent of the area burned with low to moderate severity effects across California forests, and the top 5 percent of fires by size were responsible for 74 percent. Smaller fires – though large in number – had a small cumulative impact by area. We found that exceptionally large fires contained large patches of low-moderate severity effects – often as large as their high-severity patches – suggesting that these fires leave behind contiguous areas of forest (see Figure 1.7) with markedly different post-fire trajectories and management needs than from high-severity patches. It is important to note that our low-moderate severity category captures a broad range of fire effects, from consumption of predominantly understory vegetation with minimal effects on overstory trees to mortality of mid-sized trees resulting in significant reductions to live tree density (Collins et al., 2018; Lydersen et al., 2016). There is likely to be more forest structural heterogeneity within the low-moderate severity class than can be described by the categorization used in this study. Still, these effects mimic a range of treatments that cumulatively push forests closer to resilient conditions and positive ecological outcomes such as maintaining biodiversity and stabilizing carbon storage (Collins et al., 2017b, 2018; Stephens et al., 2020).

Because smaller fires inherently contain less area for large patches, large fires would be expected to contain larger mean patch sizes. We therefore do not suggest that higher mean patch sizes in larger fires is unusual, but rather underscore the novel ecological impacts of their size and spatial patterns. For example, fine-scale mosaics of unburned, low-moderate, and high severity patches in smaller fires shape heterogeneous patterns of individual trees, tree clumps, and openings that can impede the spread of pathogens and insect outbreaks across a forest stand (Churchill et al., 2013; Fettig et al., 2007; Goheen and Hansen, 1993). Forest structural heterogeneity additionally provides a variety of habitat niches that enhance species richness, persistence, and opportunities for divergent adaptations of plant and animal species (Laszlo et al., 2018; Stein et al., 2014; Tews et al., 2004; Weisberg et al., 2014). Fires dominated by larger patches fundamentally shape forests at a much coarser scale, and though a range of post-fire ecological effects may still be present within the full fire perimeter, their configurations may fail to support the biodiversity and ecological processes that benefit from finer-scale mosaics (Figure 1.7) (North et al., 2009).

Although our 18 largest fires share common characteristics such as large patch sizes, they are still distinct in their individual ecological signatures based on their proportions of burn severities

(Table 1.1, Figure 1.4) and warrant evaluation on a case-by-case basis. There are a number of reasons why a fire may become exceptionally large. For example, the 2013 Rim fire – the fourth largest fire in this study – partially burned under extreme conditions and 35 percent of the fire's total area burned within a two-day period (Povak et al., 2020). By contrast, the 2020 August Complex fire, which is both the largest fire in this study and the largest fire on record for all of California, originated as 38 separate lightning-ignited fires that eventually coalesced over the course of several weeks (National Weather Service - Eureka Office, 2021). The second largest fire in this study, the 2020 Creek fire, burned rapidly through severely drought-affected forests but experienced its greatest growth on days largely within the normal range of variation for weather at the time of burning (Stephens et al., 2022). Due to the broad spatial extent and temporal breadth of our study, our dataset captures a range of burning conditions and incident response scenarios that directly inform resulting patterns of fire severity. Regardless of their size, each exceptionally large wildfire shaped forests in distinct ways and warrant discrete post-fire management strategies.

1.5.3 Temporal Trends in High-Severity Fire Effects and Unburned Area

Across the 36-year study period, we observed sharp increases in the interior core area of high-severity fire effects (Figure 1.6). The 18 exceptionally large wildfires within our study were responsible for a majority – 68 percent – of this total over the entire study period. This is somewhat expected, because large fires generally burned under more extreme fire weather conditions than small fires (Meyer, 2015; Singleton et al., 2021; Steel et al., 2018; Stevens et al., 2017). Extreme burning conditions that result in large, contiguous areas of overstory tree mortality are often the same conditions that escape initial fire suppression response and result in days of large fire spread (Coop et al., 2022). Cumulatively, smaller fires were responsible for only a minor portion of the total core area of high-severity fire, in part due to their small size and more moderate weather conditions under which they typically burned.

Though we observed relatively low proportions of unburned area in exceptionally large wildfires, our Theil-Sen slope analysis revealed statistically significant increases in total annual area of unburned refugia over the study period. This increase largely reflects coincident increases in total annual area burned, as large fires tended to have larger patches across all severity classes, including unburned islands. Although cumulative area of unburned refugia increased over the study period, it increased at about half the rate as increases to high-severity interior core area. These unburned islands – though they technically occupied more area in 2020 than they did in 1985 – are still overwhelmed by surrounding high-severity patches in exceptionally large fires (Figure 1.7). Our results suggest that although the extent of unburned refugia has increased over time, these patches may grow increasingly fragmented and isolated as annual area burned and fire sizes continue to increase. This is consistent with Steel et al. (2018), who found that patches of unburned refugia in California mixed-conifer fires that burned between 1984 and 2015 have become increasingly disaggregated.

Although this study focused on fires within California conifer forests, the spatial and temporal patterns identified in our analyses are consistent with broader regional trends across western North American forests. Increasing high-severity patch sizes and increased homogenization of patch structures in large fires that burned between 1984 and 2008 were identified in the northern Cascade Range of Washington state (Cansler and McKenzie, 2014). Across warm and dry conifer forests in the broader Pacific Northwest, proportions of high-severity effects in fires that burned between 1985 and 2010 were greater than historical ranges of variation, and nearly half of this high-severity area occurred in large patches greater than 100 ha (Reilly et al., 2017). In the northern Rocky

Mountains, trends in high-severity patch structures within fires that burned between 1984 and 2010 suggested shifts towards larger, more homogenous patches with greater interior core area, though they were not statistically significant (Harvey et al., 2016). Given recent increases in annual area burned and mean fire severity (Parks and Abatzoglou, 2020) and a number of record-breaking large fires across western North American forests since the aforementioned studies were conducted, the ecological implications of our findings – presented here within the context of California forests – may be more broadly applicable to warm and dry, fire-suppressed conifer forests across the west.

1.5.4 Management Implications

Coarser-scale patterns of fire severity on the order of hundreds to thousands of hectares – like those of the exceptionally large wildfires in this study – are significantly departed from the natural range of variation of frequent fire regimes in our study area. Modern studies in US National Parks with restored fire regimes (Collins et al., 2007) and analysis of historical forest conditions prior to widespread fire exclusion (Safford and Stevens, 2017) suggest that California dry mixed-conifer forests frequently burned in complex mosaics of unburned, low-, moderate-, and high-severity patches typically no larger than a few hectares. These patch mosaics shaped patterns of highly heterogeneous forest structure that regulated the forest's ability to maintain function following subsequent disturbances (Koontz et al., 2020). Small patches of previously burned areas served as 'fences' to subsequent fire spread, and unburned areas or areas of forest that had not recently burned acted as 'corridors' of fire spread, reinforcing a shifting mosaic of forest structures and a regime of frequent, predominately low- to moderate-severity fire (Moritz et al., 2011). As larger fires produce coarser-grained patterns of severity, these patterns may become self-reinforcing, and the ecological memory of forests rooted in fine-scale self-regulation may begin to erode (Taylor et al., 2021).

In frequent-fire ecosystems, historic fire regimes often set the scale and habitat variability that influences the evolution of ecological processes and endemic wildlife (Falk et al., 2011; Pausas and Parr, 2018). Shifting landscape patterns induced by changes in patch sizes may have cascading effects on ecological processes that are associated with fine-scale structural heterogeneity. Forest structural diversity, for example, drives microclimates that regulate subcanopy temperatures, snowpack accumulation and ablation, and thermal refuges, in turn influencing water availability, soil nutrient cycling, plant species biodiversity, and habitat suitability for small terrestrial animals (Kemp et al., 2014; Milling et al., 2018; Tews et al., 2004; Varhola et al., 2010; Wolf et al., 2021). As patterns of structural heterogeneity coarsen, this patchwork of microclimates may erode, fragmenting wildlife habitat, threatening keystone species, and altering understory vegetation composition (Jones et al., 2020; Steel et al., 2022a; Stephens et al., 2021).

While exceptionally large fires often burned with low- to moderate-severity effects, the landscape pattern of burned areas represents a novel configuration for which there is no historical analog. Recent studies have underscored the importance of post-wildfire management responses to these novel landscapes, including post-burn thinning, fuel reduction, and variable-density tree planting (Meyer et al., 2021; North et al., 2019; Stevens et al., 2021). Post-fire patch sizes and configurations are also important considerations for adaptive management (Hessburg et al., 2019, 2016). Introducing additional structural variation at finer spatial scales will be a critical component of adaptive management, not only within patches that burned at high severity but also within unburned islands and areas that burned at low and moderate severity that are outside the range of variation for historical patch sizes. More pre- and post-burn fuel reduction, particularly with prescribed fires for its creation of 'fence' and 'corridor' heterogeneity, may be the most durable and effective means of reducing the self-reinforcing pattern of large high-severity patches (Knapp et al., 2017; Taylor et al., 2022).

These large fires with their unprecedented patch sizes create new challenges and potential opportunities for managers. For the past three decades, much of the focus in the scientific literature and management discussion has been on increasing the pace and scale of treatments to reduce tree density and fuels left by a century of logging and fire exclusion. However, this study demonstrates that the rapidly increasing area and severity of recent wildfires overwhelms the area treated by management agencies (North et al., 2021). While much of the current post-fire management focus has been on salvage logging and replanting in high-severity patches, these large fires have also left extensive forest swaths of low- to moderate-burn severities. In these areas, managers could leverage the wildfire's 'work', and use thinning to remove remaining ladder fuels (Collins et al., 2018) and create or accentuate the spatial pattern of individual trees, clumps of trees, and openings (i.e., ICO, Churchill et al., 2013), that increases forest resilience to wildfire (Koontz et al., 2020; Ng et al., 2020). Seven to twelve years after the fire, when large fuels accumulate as snags fall over, prescribed fire could be applied to reduce surface fuels (Ritchie et al., 2013). With this additional fuel reduction 'hardening' of the low-moderate severity patches, they could be used as anchors for wider use of managed wildfire or prescribed burns, implementing a pyrosilviculture approach to landscape management (North et al., 2021).

1.6 CONCLUSION

Exceptionally large fires are complex and contain a range of both desirable and undesirable ecological effects on California forests. The largest fires in our analysis contained proportionally greater amounts of high-severity fire and contributed to significant increases in high-severity interior core area, but were also responsible for the vast majority of low-moderate severity effects that reshape and can help restore resilience to mixed-conifer forests (Collins et al., 2011). Configurations of very large high-severity and low-moderate-severity patches with little area of unburned refugia represent an emerging fire regime that may alter the fine-scale forest structural heterogeneity historically created by smaller fires. Because fires in our study area tend to follow the spatial patterns of previous fires (Parks et al., 2014b; Prichard et al., 2017; Taylor et al., 2022), future fire patterns may become self-reinforcing, further eroding fine-scale mosaics of forest structure heterogeneity. These post-fire landscapes may present novel challenges for forest managers as they leave behind large, contiguous areas of stand-replacing fire and yet also contain patches of low- and moderate-severity effects that, with subsequent targeted fuels reduction, can move burned forests towards greater resilience to climate change and future fire events.

CHAPTER 2. LAND OWNERSHIP EXERTS STRONG CONTROLS ON FIRE SEVERITY IN CALIFORNIA, OREGON, AND WASHINGTON FORESTS

2.1 ABSTRACT

Understanding the influence of landowner forest management on fire severity is important to inform cohesive management strategies for ecological and community resilience. Although past research has evaluated general drivers of fire severity, less is known about how land ownership and associated forest management practices interact with biophysical factors to influence fire effects. In this study, we evaluated drivers of fire severity for large fires (> 500 ha) that burned from 2001 to 2020 within four major forested ecoregions of California, Oregon, and Washington states. We used a hierarchical modeling framework to analyze fire severity as a function of fire growth and daily weather, topography, pre-fire forest structure, disturbance history, and land ownership to first examine drivers of fire severity at the individual fire level, then evaluate model coefficients across all fires to assess general drivers of fire severity across the full study system. Land ownership type was the most important predictor of fire severity across our full study area, and private industrial land ownership was associated with higher fire severity relative to other ownerships where industrial forests had likely reached greater canopy closure and had greater fuel continuity. Our results inform perceptions of risk in multi-owner landscapes and underscore the importance of cohesive management strategies that prioritize shared governance, long-term perspectives on forest management, and collaborations across individual landowners.

2.2 INTRODUCTION

Climate change is accelerating landscape changes across western North America with increased fire activity and area burned (Abatzoglou and Williams, 2016). Recent wildfire trends are also associated with compounding factors such as changes in land use (Haas et al., 2013; Mell et al., 2010), the consequences of past management and fire exclusion (Hagmann et al., 2021), and current forest management practices (Barros et al., 2021). The frequency, extent, and severity of wildfires across the region have increased in the last several decades (Cova et al., 2023; Dennison et al., 2014; Reilly et al., 2017; Steel et al., 2018), contributing to profound losses to communities (Paveglio et al., 2016; Rosenthal et al., 2021), hazardous smoke impacts (Enayati Ahangar et al., 2022; Liu et al., 2021), erosion of mature forest wildlife habitat (Ayars et al., 2023; Steel et al., 2022b), rapid conversion to non-forest vegetation (Coop et al., 2020), and steep reductions in forest carbon stores (Liang et al., 2017a). These trends are expected to intensify through the next century (Abatzoglou et al., 2021), underscoring a critical need to understand factors influencing fire severity to inform proactive management alternatives under a warming climate and changing fire regimes.

Although past research has evaluated drivers of fire severity, less is known about how forest management practices interact with biophysical factors to influence fire effects. Previous research has evaluated the influence of 'bottom-up' factors such as fuels (Cansler et al., 2022; Lydersen et al., 2017; Prichard and Kennedy, 2014) and landform on fire severity (Birch et al., 2015; Dillon et al., 2011; Kane et al., 2015) and how these interact with 'top-down' factors such as weather (Birch et al., 2015; Estes et al., 2017; Povak et al., 2020) to influence post-fire effects. While these studies have provided valuable insights on the ecological mechanisms influencing wildfire outcomes, it is critical to account for other known factors influencing fire severity to develop appropriate management strategies that bolster both ecological and social resilience in coupled human and natural systems

(Spies et al., 2014). Forest management practices such as industrial timber harvesting (Griffey et al., 2021), fuel treatments (Stephens et al., 2012), and active fire suppression (Hagmann et al., 2021) impart strong influences on forest structure and composition, which in turn result in variable responses to wildfire within different biophysical contexts (Harris et al., 2021; Parks et al., 2018a; Povak et al., 2020; Prichard and Kennedy, 2014; Taylor et al., 2021).

Because fire does not recognize administrative boundaries, understanding the influence of forest management practices on fire severity across multiple ownerships is particularly important to inform cohesive strategies for landscape and community resilience (Steelman and Nowell, 2019). The multiple landowners, administrative units, and land use designations within fire-prone forests of western North America often represent different – and sometimes conflicting – management objectives (Essen et al., 2023; Miller et al., 2022). Developing cross-jurisdictional plans and policies to more holistically manage for wildfire through activities such as thinning, prescribed burning, or fire suppression requires a quantitative evaluation of how management influences fire severity to inform perceptions of risk and collective action for risk reduction (Charnley et al., 2020). These evaluations are challenged, however, by the availability of standardized datasets that consistently catalog fuel treatments, harvests, and other management activities across both private and public lands (Knight et al., 2022b). In absence of comprehensive, multi-owner datasets, land ownership designations (i.e., US Forest Service, designated wilderness, private industrial timberland) can serve as a proxy for different management regimes and priorities (Barros et al., 2021; Griffey et al., 2021; Levine et al., 2022; Zald and Dunn, 2018)

There is ongoing discourse in the media, policy arenas, and scientific literature about the influence of land ownership and associated forest management practices on fire severity and fire occurrence (Ayesh, 2020; Evans et al., 2022; Schwartz et al., 2020; Siegel et al., 2022; Starrs et al., 2018). Federally designated wilderness areas and reserves, for example, emphasize the preservation of natural resources (and in many areas, enhancing late successional and old-growth forest conditions), but in fire-prone landscapes, fire exclusion through loss of Indigenous burning practices and active wildfire suppression (van Wagtendonk, 2007) has resulted in fuel accumulations linked to increased fire probability and severe fire effects (North et al., 2015; Starrs et al., 2018). Management aimed at preserving static forest conditions within federal lands has been called into question as changing climatic and wildfire regimes rapidly reshape forest landscapes (Gaines et al., 2022; North et al., 2015b). Outside of designated wilderness areas, federal forest lands (i.e., US Forest Service and Bureau of Land Management) are managed for multiple objectives such as recreation, forest products, and wildlife habitat. Although forest thinning and prescribed burning occur within these federal lands, rates of prescribed burning and mechanized treatments are generally below the pace and scale needed to restore fire-resilient landscapes (Kolden, 2019; North et al., 2015a; Vaillant and Reinhardt, 2017), and continued fire exclusion within fire-prone forests has contributed to fuel accumulations and forest conditions associated with extreme fire behavior (Povak et al., 2020; Stephens et al., 2022).

By contrast, private land managed for industrial timber production prioritizes the growth and yield of wood products, and typically relies on intensive plantation forestry practices and aggressive fire suppression to protect commercial assets (Binkley et al., 2005). On these lands, homogenous, even-aged stand structures and continuous canopy fuels associated with plantation forestry can contribute to extreme fire behavior and increased probability of high severity effects (Duane et al., 2021; Levine et al., 2022; Zald and Dunn, 2018). Discussions on the role of landowner management practices in influencing fire severity have frequently centered on contrasting the intensive management practices of industrially managed forests with the more passive management approaches of federal public lands (Ayesh, 2020; Levine et al., 2022; National Review, 2020; Schwartz et al., 2020).

Previous efforts to evaluate drivers of fire severity within the context of land ownership have been limited in scope but offer important insights into how forest management can influence wildfire outcomes. In a study of multi-ownership landscapes in California, Levine et al. (2022) found that industrially managed forests had increased probability of high severity fire relative to federal lands. Similarly, intensive plantation forestry on private industrial forestland was associated with higher fire severity compared to adjacent federal lands within the 2013 Douglas fire complex in southwestern Oregon (Zald and Dunn, 2018). By contrast, intensively managed young plantations were associated with lower fire severity in the eastern Cascade mountains of Washington where fuels-reducing site preparations had occurred (Lyons-Tinsley and Peterson, 2012).

To support climate adaptation strategies across a rapidly changing western North American forest landscape, a cross-regional study of fire severity drivers in multi-owner landscapes is needed. Evaluating the influence of known factors on fire severity across broad areas is challenged by the consistency, spatial scale, and correlation of explanatory datasets. Specifically, consistent input datasets are needed to develop a system-level understanding of fire severity across ownerships and regions. Further, regional-scale assessments of fire severity that rely on spatially coarse and autocorrelated input datasets with strong elevational or climatic gradients may result in models that mask important signals from smaller subsets of fires or bottom-up processes at more local scales (Dormann et al., 2007). By contrast, consistent models (i.e. models that use the same explanatory datasets) standardized and constructed for numerous individual fires across a broad study area can enable understanding of general drivers across the full study system (hereinafter, general system behavior) while informing more regional management strategies by allowing direct evaluations and comparisons of drivers within individual fires or across groups of fire events.

In this study, we evaluated drivers of fire severity for large fires (> 500 ha) that burned from 2001 to 2020 within the major forested ecoregions of California, Oregon, and Washington states. We leveraged cloud-based processing of geospatial data on fire severity, fire progression and daily weather, topography, pre-fire forest structure, pre-fire disturbance history, and land ownership to first examine drivers of fire severity using consistent models at the individual fire level, then evaluated model coefficients across all fires to assess general system behavior. We examined three specific research questions: 1) Across the study region, what are the most prominent drivers of fire severity?; 2) Do drivers of fire severity differ between intensively managed systems (i.e., private industrial forest land) and federal public lands?; and 3) Is private industrial forest land associated with higher fire severity?

2.3 METHODS

2.3.1 Study Area

We evaluated fires that burned within four major forested ecoregions of the western United States (Figure 2.1): forests along the western slopes of the Cascade mountains in Oregon and Washington and along the Pacific coast (Western Cascades and Coastal), forests of the Klamath Mountains and southern Cascades within northern California and southwestern Oregon (Klamath and Southern Cascades), forests east of the Cascade crest in Oregon and Washington (Eastern Cascades), and the Sierra Nevada of California. Forests across this biophysically diverse region vary in structure, composition, and dominant fire regime across gradients of climate, topography, and management history (Hessburg et al., 2019), but are unified in that they are largely conifer dominated, are characterized by mosaics of land ownerships, and have faced recent increases in wildfire activity (Nelson et al., 2010; Parks and Abatzoglou, 2020; Reilly et al., 2022).

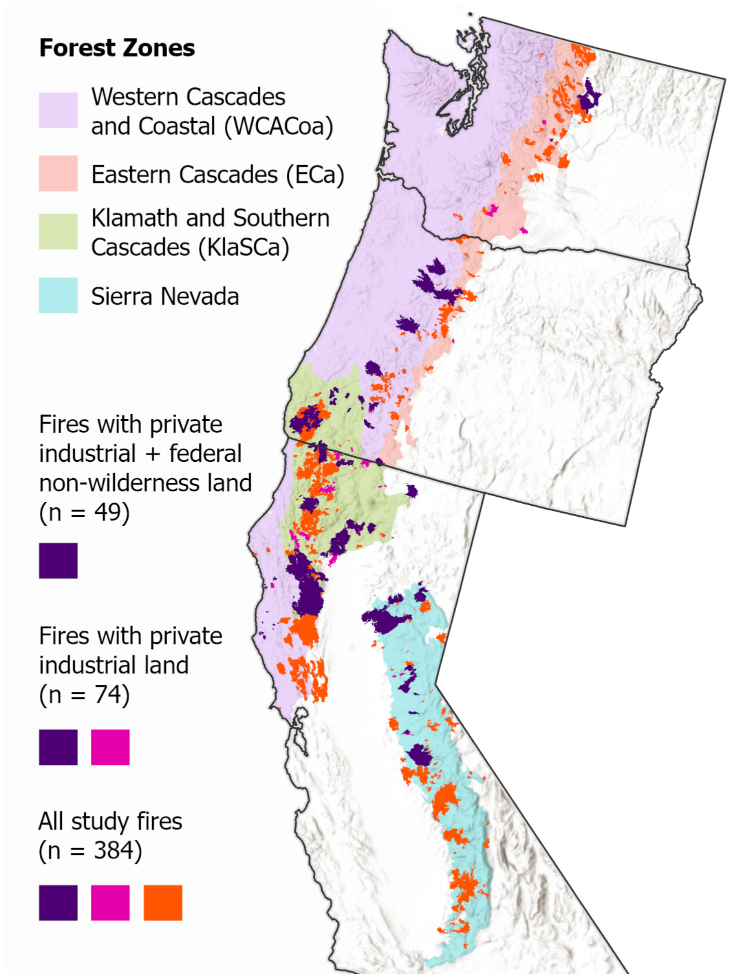

Figure 2.1. Map of the study region in Washington, Oregon, and California, USA showing locations of fires analyzed as part of this study. Drivers of fire severity were analyzed for three groups of fires greater than 500 ha: (1) all study fires regardless of landowner designation (dark purple, pink, and orange, n = 384 fires); (2) fires containing private industrial land and any other landowner designation (dark purple and pink, n = 74 fires); and (3) fires containing private industrial and federal non-wilderness (i.e., public) lands (dark purple, n = 49 fires). Major forested zones include the Western Cascades and Coastal zone (light purple), the Eastern

Cascades (light red), the Klamath and Southern Cascades (green), and the Sierra Nevada (light blue).

Fire was historically an important disturbance process across the entire study area, but its role varied both spatially and temporally across different forest types and ecoregions. In general, Western Cascades and Coastal zone moist forests such as those dominated by western hemlock (*Tsuga heterophylla*) and silver fir (*Abies amabilis*) are highly productive with high biomass accumulation. Large wildfires in this region were typically infrequent due to high fuel moisture and lack of ignitions; when large wildfires did occur under more extreme conditions (i.e. severe drought or wind events), high severity effects were common (Agee, 1996; Reilly et al., 2022; Weisberg and Swanson, 2003). Though this region is often characterized as an infrequent fire regime, mixed-severity fires intentionally applied through frequent Indigenous burning in this region were common (Johnston et al., 2023; Lorimer et al., 2009).

Klamath and Southern Cascades, Eastern Cascades, and Sierra Nevada dry forest types dominated by mixed conifers, ponderosa pine (*Pinus ponderosa)*, or Jeffrey pine *(Pinus jeffreyi*) were historically characterized by frequent fire activity (Hessburg et al., 2019; Safford and Stevens, 2017; Skinner et al., 2018; Skinner and Taylor, 2018). In these ecoregions, lightning ignitions and Indigenous stewardship maintained open forest structures that reinforced a low- to moderate-severity regime resilient to subsequent fires and seasonal drought (Greenler et al., 2024; Knight et al., 2022a). Although fire is the dominant process shaping forests across the entire study area, contemporary management practices by different landowners have imparted additional variability in forest structure (Griffey et al., 2021).

2.3.2 Data Sources

We analyzed fire severity as a function of predictor variables representing pre-fire forest structure, disturbance history, fire progression and daily weather, topography, and land ownership (Figure 2.2, Table 2.1) in large fires (> 500 ha) that burned between 2001 and 2020 across the study area. In previous work, predictor variables, input datasets, and statistical modeling approaches used to quantify drivers of fire severity have varied widely (i.e., Birch et al., 2015; Harris and Taylor, 2017; Povak et al., 2020; Taylor et al., 2021), limiting cross-comparisons of results across individual studies. To assess system-level drivers of fire severity across this large, multi-ownership study area, we developed models using the same input predictor variables and statistical modeling approach for each fire in our study area (statistical modeling details provided below). To select predictor variables used for each fire, we initially gathered 29 datasets (Appendix A, Table 2.7) representing one of each category of our predictors (i.e., pre-fire forest structure, weather, etc.). We eliminated potential variables by assessing multicollinearity among predictors and evaluating accuracy assessments of predictors derived from modeling (where available from the original data source). Following the methods of Meigs et al. (2016), we then further refined our predictors by evaluating a subset of test models constructed for 15 sample fires representing the range of fire conditions in our dataset. Our final set of predictors balanced ecological interpretability (i.e., does at least one predictor describe a component of the fire behavior triangle of fuels, topography, and weather) with data consistency (i.e., is the dataset available for every fire) and model parsimony as identified by the Akaike Information Criterion (AIC) for the 15 sample fire models.

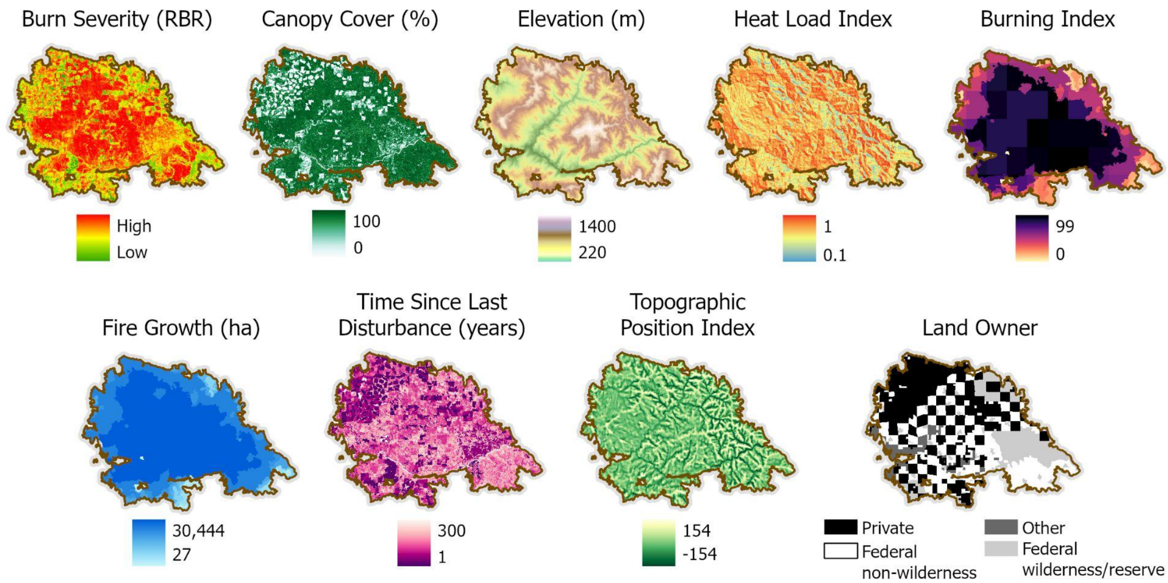

Figure 2.2. Sample input datasets used for statistical modeling before subsampling. Burn severity (RBR) is the response variable; all other variables are predictors. Example fire shown is the 2020 Archie Creek fire in southwest Oregon (53,255 ha).

Table 2.1. Predictor datasets used for statistical modeling of burn severity (RBR).

Predictor	**Source**	**Resolution**
Canopy cover (%)	(Ohmann and Gregory, 2002)	30 m
Elevation (m)	(Farr et al., 2007; Gorelick et al., 2017)	30 m
Heat load index	(Evans and Murphy, 2021)	30 m
Burning index / Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Fire growth (ha)	(Parks, 2014)	30 m
Time since last disturbance (years)	(Healey et al., 2018)	30 m
Topographic Position Index (TPI)	(Evans and Murphy, 2021)	30 m, calculated at 990 m window
Landowner	California Department of Forest and Fire Protection; WA Department of Natural Resources; OR Department of Forestry	30 m

We used geospatial datasets of historical fire perimeters maintained by the California Department of Forest and Fire Protection (CAL FIRE) Fire and Resource Assessment Program (FRAP), Washington Department of Natural Resources (WA-DNR), and the National Interagency Fire Center (NIFC) to identify large fires that burned at least partially within the four major forested ecoregions of the study area (n = 384). We quantified fire severity using the Relativized Burn Ratio (Parks et al., 2014a) derived from one year pre- and post-fire composite Landsat imagery (30 m resolution) following the methodology developed by Parks et al. (2018b) in Google Earth Engine (GEE). Because extremely low and extremely high RBR values may be induced by spectral reflectance errors, we omitted values below and above the 0.5 and 99.5 percentiles, respectively, prior to analysis. Continuous RBR values were used as our response variable for fire severity in our statistical models.

We quantified forest structure for the year prior to each fire using 30-m maps of canopy cover (%) originally created for the Northwest Forest Plan Monitoring Program (Davis et al., 2015; Ohmann et al., 2012) and developed using the gradient nearest neighbor method (GNN), relating forest structure response variables derived from plot data from the U.S. Forest Service Forest Inventory and Analysis Program to various predictors such as climate, topography, and spectral imagery (Ohmann and Gregory, 2002). To further characterize pre-fire forest condition, we mapped time since the last pre-fire disturbance (in years) for each fire using a combination of data from the Landscape Change Monitoring System (LCMS, Healey et al., 2018) and GNN. We used the LCMS change attribution dataset to identify the year of any spectrally detected disturbance (including fire, harvest, insect/drought stress, and other) in 30-m Landsat-derived pixels that occurred between 1985 and the year prior to each fire. For pixels where no disturbance after 1985 was detected, we used GNN-derived maps of forest stand age as a supplement.

Topographic conditions were represented using elevation (m), heat load index, and topographic position index (TPI) derived from a 30-m digital elevation model (Farr et al., 2007). Heat load index was calculated as a function of slope, aspect, and latitude following McCune and Keon (2002) using the 'hli' function in the spatialEco package in R (Evans and Murphy, 2021), where values near 0 indicate the coolest pixels (such as those on northeastern slopes) and values near 1 indicate the hottest pixels (i.e., southwestern slopes). TPI was calculated as the difference between the elevation of a pixel and the mean surrounding elevation within a 990 m moving window using the 'tpi' function in the spatialEco package in R (Evans and Murphy, 2021). Low TPI values correspond to valley bottoms and topographically low features while higher values indicate upper slopes and ridges.

Fire weather is an important driver of fire severity (Birch et al., 2015; Lydersen et al., 2017; Zald and Dunn, 2018), but acquiring temporally accurate weather variables requires knowing the exact date on which a pixel burned. We created 30-m maps of daily fire progression for each fire by interpolating MODIS fire detection points (NASA MCD14ML product) using the methodology developed by Parks (2014). Fire progression maps were used in two ways: first, to create a 'fire growth' predictor variable (defined as the total area (ha) of daily fire growth for a given pixel for the day on which that pixel burned), and second, to acquire gridded surface meteorological data from GRIDMET (Abatzoglou, 2013) and develop downscaled 30-m composite maps of daily weather corresponding to the appropriate day of fire spread. We used burning index (BI) as our final fire weather predictor variable (Bradshaw et al., 1984), as it incorporates information on rate of spread, windspeed, slope, and fuel moisture, and was frequently present in our most parsimonious models during preliminary model testing.

Land ownership designations for each fire were derived from combined geospatial data representing fee lands and ownership boundaries from the California Protected Areas Database

(GreenInfo Network, 2022), CAL FIRE (CAL FIRE, 2019), WA-DNR (WA DNR, 2021), Oregon Department of Forestry (ODF, 2022), and the Protected Areas Database of the United States (USGS GAP Analysis Project, 2022). We grouped ownership types into four broad designations representing Federal Wilderness and Reserves, Federal Non-Wilderness, Private Industrial, and Other lands. 'Other' as an ownership category encompassed a variety of lands including private nonindustrial, state, and tribal entities that combined accounted for less than 15% of the area burned across the study area.

2.3.3 Statistical Modeling and Analysis

We used a hierarchical framework based on the approach of Meigs et al. (2016) to first quantify drivers of fire severity at the individual fire level (that is, one model for each fire), then evaluate standardized model coefficients across all fires to assess general system behavior. For each of our fire-level models, we used scaled Generalized Least Squares Estimators (GLSEs) with an exponential spherical correlation structure to account for spatial autocorrelation (Dormann et al., 2007). GLSE techniques are similar to Ordinary Least Squares regression analyses but are more appropriate for data with unknown covariance matrices, suitable for fitting linear models on datasets that may exhibit heteroskedasticity (Kariya and Kurata, 2004), and are generally recommended for datasets that exhibit spatial autocorrelation (Beguería and Pueyo, 2009). To further minimize effects of spatial autocorrelation as well as any potential georeferencing errors between input datasets, we subsampled our data for each fire by overlaying a grid of points 270 m apart to extract mean response and predictor variables using a 3x3 30-m pixel window centered on each sample point (Kane et al., 2015). We sampled only points that fell within forested pixels as defined by a GNN forest mask. All models were constructed using the nlme package in R (Pinheiro et al., 2023).

2.3.4 Across the study region, what are the most prominent drivers of fire severity?

To evaluate the most prominent drivers of fire severity across the study region, we used GLSEs to model RBR as a function of pre-fire forest structure, disturbance history, topography, fire progression, and fire weather for all study fires regardless of ownership (n = 384 models for n = 384 fires). Input variables for each fire were scaled by converting samples to z-scores prior to analysis to enable direct comparisons of model results across the full set of 384 fires. We excluded ownership as a predictor variable in these models because not all fires contained the same number and type of ownership designations, which precluded inclusion to maintain consistency in predictor variables across all models. We then evaluated measures of central tendency (i.e., mean, standard deviation, and range) of standardized model coefficients across the entire study area and within our four ecoregional groups.

2.3.5 Do drivers of fire severity differ between private industrial and federal public lands?

We evaluated the influence of private industrial versus federal public land ownership designations on fire severity in two distinct ways: first, we tested for *differences* in the relative importance of biophysical predictor variables by land ownership designation for each fire; second, we evaluated the *effect* of each ownership type by including a binary ownership variable as a predictor in our models.

To test for differences in fire severity drivers by land ownership designation, we first identified all study fires that contained both private industrial (intensively managed) and federal non-wilderness (public land) designations (n = 49 fires). We then stratified each fire into two separate GLSE models: a 'private industrial' model subset to only sample points on private industrial land within a given fire, and a 'public land' model subset to the federal non-wilderness sample points within that same fire for a total of 98 models (2 models per fire). We excluded federal wilderness and reserve lands from our 'public land' models for two primary reasons: 1) federal wilderness lands within our fires tended to exist at higher elevations and in more remote settings than private industrial and federal non-wilderness land, precluding a fair comparison of drivers across ownership types; and 2) few fires contained all three (private industrial, federal non-wilderness, and federal wilderness) designations. We did not evaluate a model for the "Other" land ownership category. We tested for differences in mean effect size of each coefficient between land ownership designations using Mann-Whitney-Wilcoxon tests.

To evaluate the standardized effect of land ownership designation on fire severity, we constructed a single GLSE model for each fire containing both private industrial and federal non-wilderness lands (n = 49 models for n = 49 fires). We constrained each model to samples *only* on private industrial and federal non-wilderness land designations within each fire. RBR was modeled as a function of pre-fire forest structure, disturbance history, topography, fire progression, fire weather, and a binary land ownership predictor describing either private industrial (1) or federal non-wilderness (0) land.

2.3.6 Is private industrial forest land associated with higher fire severity?

Few studies have explicitly tested the effect of land ownership designation on fire severity; those that have found private industrial land to be associated with higher severity effects than other ownerships (Levine et al., 2022; Zald and Dunn, 2018). To evaluate if private industrial forestry is associated with higher fire severity across our study area, we first identified all fires containing private industrial land ownership (n = 74). All sample points outside of private industrial ownership (federal wilderness and reserve, federal non-wilderness, and other) were aggregated into a single 'other' ownership category within each fire. We constructed a final set of models to calculate the fixed effect of our eight biophysical predictor variables (Figure 2.2) as well as a binary land ownership category describing either private industrial (1) or other (0) lands. Finally, we predicted the mean RBR value in each fire by ownership type (private industrial versus other) in each of the four major ecoregions after accounting for the mean value of our eight other predictors in our models using the AICcmodavg package (Mazerolle, 2023).

2.4 RESULTS

2.4.1 Across the study region, what are the most prominent drivers of fire severity?

Our analysis of large fires across the entire study area (Figure 2.1) indicates that fire severity (as measured by RBR) was generally highest in forests with greater pre-fire canopy cover and on steep gradient slopes and ridges (Figure 2.3, Table 2.2). Fire severity was reduced with increasing time since pre-fire disturbance such as insect and drought stress, harvest, or fire; it was higher on larger fire growth days and on days with extreme fire weather. On average, higher elevation forests were associated with greater fire severity, though our model results indicate a bimodal distribution of elevation coefficients with reduced severity at the highest elevations. Though our results suggest an average negligible effect of heat load on fire severity, coefficients were also bimodally distributed around zero.

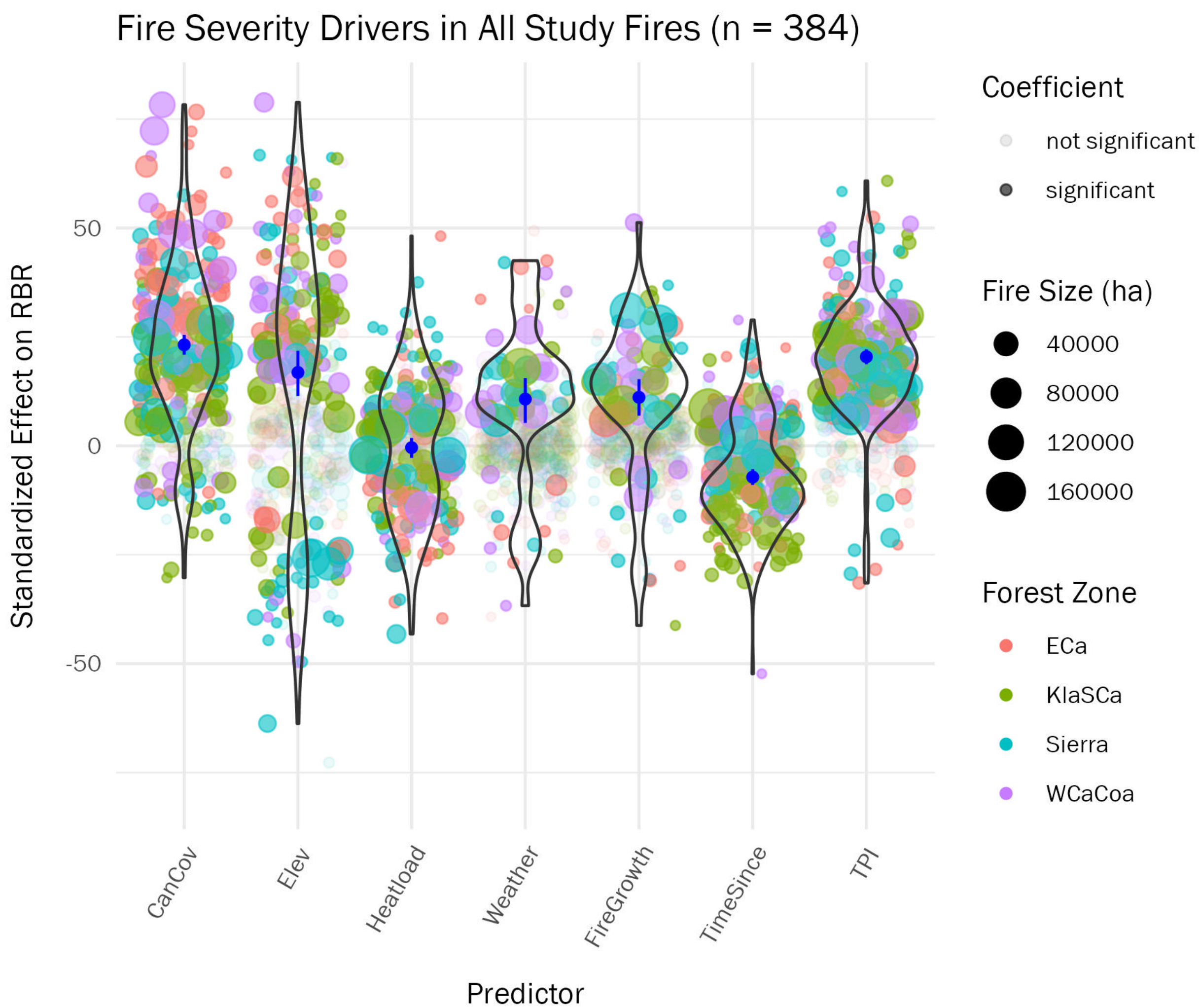

Figure 2.3. Effect of pre-fire forest structure, topography, disturbance history, fire progression, and fire weather on fire severity (RBR) in all study fires (n = 384). Points are symbolized by forest zone (color), statistical significance of the coefficient (transparency), and fire size (point size). Violin plots display the distribution of statistically significant coefficients only. See Figure 2.2, Table 2.1. Predictor datasets used for statistical modeling of burn severity (RBR). for full predictor information. ECa: Eastern Cascades; KlaSCa: Klamath and Southern Cascades; Sierra: Sierra Nevada; WCaCoa: Western Cascades and Coastal. TPI: Topographic position index.

Table 2.2. Mean standardized effect of 7 predictor variables on fire severity across the entire study area (n = 384 fires) and by dominant ecoregion: Western Cascades and Coastal fires (WCaCoa, n = 72), Eastern Cascades fires (ECa, n = 89), Klamath and Southern Cascades fires (KlaSCa, n = 112), and Sierra Nevada (n = 111). Means are calculated from the effect sizes of statistically significant ($p < 0.05$) model coefficients only; the number of statistically significant coefficients for a given predictor is listed in parentheses (i.e., out of 89 models run for 89 fires in the Eastern Cascades, canopy cover was a statistically significant predictor in 74 models with a mean standardized effect of 34.61). Positive mean coefficients indicate that as severity increases, the predictor also increases; negative coefficients indicate that severity decreases as the predictor increases. Larger coefficients (greater magnitude, positive or negative) indicate stronger influences on severity.

	All fires (384 fires)	**WCaCoa** (72 fires)	**ECa** (89 fires)	**KlaSCa** (112 fires)	**Sierra** (111 fires)
Canopy cover	23.18 (254)	25.91 (43)	34.61 (74)	12.89 (69)	19.44 (68)
Elevation	19.66 (164)	25.98 (35)	32.64 (29)	21.32 (55)	4.36 (45)
Heat load	-0.40 (175)	2.03 (28)	-9.52 (37)	1.73 (56)	2.38 (54)
Weather	12.75 (50)	10.69 (14)	20.36 (10)	11.43 (12)	10.49 (14)
Fire growth	8.78 (62)	13.34 (10)	-0.58 (14)	12.57 (18)	9.64 (20)
Time since disturbance	-7.23 (177)	-3.66 (31)	-2.38 (42)	-13.71 (68)	-3.73 (36)
TPI	20.49 (243)	22.42 (53)	15.61 (43)	21.77 (81)	20.55 (66)

Model results within each of our four ecoregions suggest similar importance of drivers as those of our entire study area, with some key differences (Table 2.2). Based on mean standardized effect values, fire severity in WCaCoa forests was generally higher with greater pre-fire canopy cover, at higher elevations, and along upper slopes and ridges. Fire severity in this region also increased under more severe fire weather, on greater fire growth days, and with increasing heat load, though the effects of the latter are less pronounced. Fire severity in WCaCoa forests increased following recent disturbance on average, but the effect was more marginal relative to other drivers. In ECa forests, model results suggest that increased fire severity was primarily driven by greater pre-fire canopy cover, higher elevation, and to a slightly lesser extent, severe fire weather. Fire severity in ECa forests generally increased along upper slopes and ridges with greater TPI values, but was generally lower in areas of higher high load index values. The mean effect of fire growth and time since the most recent disturbance on fire severity were marginally negative. In the KlaSCa forests, fire severity was primarily driven by and positively associated with elevation and TPI. Fire severity in the KlaSCa increased to a lesser extent with greater fire growth, under more extreme fire weather, and with greater pre-fire canopy cover; fire severity also increased in areas that had been recently disturbed. In the Sierra, fire severity increased with greater pre-fire canopy cover and TPI. Fire weather and fire growth were the next most prominent drivers of fire severity. Effects of elevation, heat load, and time since the most recent disturbance were less pronounced.

2.4.2 Do drivers of fire severity differ between intensively managed systems and federal public lands?

Drivers of fire severity on private industrial lands were similar to those on federal non-wilderness land across the 49 fires containing both ownership designations (Table 2.3, Appendix A, Figure 2.8). Generally, pre-fire canopy cover was an important predictor of fire severity across both land ownership designations but had a much larger effect on private industrial lands than on federal non-wilderness lands (mean effect of 40.02 versus 23.45, respectively). Fire severity also increased on large fire growth days, under extreme fire weather, and with greater TPI values on both land ownership designations with similar mean effect sizes. Although the mean effect of elevation on fire severity varied widely between private industrial land and federal non-wilderness land, the distribution of coefficients on both land ownership designations were quite broad, and the difference in means was not statistically significant. Fire severity generally increased in areas that had been recently disturbed on both ownership types, but the mean effect was greater on federal non-wilderness land than private industrial land.

Table 2.3. Mean standardized effect of 7 predictor variables on fire severity across fires containing both private industrial and federal non-wilderness land (n = 49). Models were constructed and are presented by land ownership designation. Means are calculated from the effect sizes of statistically significant ($p < 0.05$) model coefficients only; number of statistically significant coefficients for a given predictor is listed in parentheses. Predictors listed with an asterisk (*) are statistically significantly different ($p < 0.05$) between Private Industrial and Federal Non-Wilderness land per Mann-Whitney-Wilcoxon tests.

	Private Industrial (49 fires)	**Federal Non-Wilderness (49 fires)**
Canopy cover*	40.02 (39)	23.45 (32)
Elevation	-5.65 (16)	19.21 (20)
Heat load	-0.8 (15)	1.36 (17)
Weather	15.95 (10)	18.82 (11)
Fire growth	23.81 (12)	20.44 (13)
Time since disturbance*	-0.22 (13)	-6.81 (25)
TPI	23.44 (35)	25.31 (34)

Of the 49 fires that contained both private industrial and federal non-wilderness designations, our models revealed that, on average, land ownership had a stronger effect on fire severity relative to all other predictors (Figure 2.4, Table 2.4). Pre-fire canopy cover was the second most important predictor in our models, and was statistically significant in 37 of 49 fires. Differences between the mean effect of canopy cover and the mean effect of land ownership were not statistically significant.

Figure 2.4. Effect of pre-fire forest structure, topography, disturbance history, fire progression, fire weather, and land ownership on fire severity (RBR) on private industrial and federal non-wilderness land in fires containing both ownership types (n = 49). Landowner was incorporated as a binary categorical variable where private industrial land was coded as 1, and federal public lands were coded as 0. Points are symbolized by forest zone (color), statistical significance of the coefficient (transparency), and fire size (point size). Violin plots indicate the distribution of statistically significant coefficients only. See Figure 2.2, Table 2.1 for full predictor information. ECa: Eastern Cascades; KlaSCa: Klamath and Southern Cascades; Sierra: Sierra Nevada; WCaCoa: Western Cascades and Coastal. TPI: Topographic position index.

Table 2.4. Mean standardized effect of 8 predictor variables on fire severity across fires containing both private industrial and federal non-wilderness land (n = 49). Means are calculated from the effect sizes of statistically significant ($p < 0.05$) model coefficients only; number of statistically significant coefficients for a given predictor is listed in parentheses.

	Private Industrial and Federal Non-Wilderness (49 fires)
Canopy cover	30.09 (37)
Elevation	2.11 (23)
Heat load	-1.92 (25)
Landowner	31.92 (16)
Weather	11.57 (10)
Fire growth	17.36 (12)
Time since disturbance	-2.28 (27)
TPI	2.47 (40)

2.4.3 Is private industrial forestry associated with higher fire severity?

Across the study area, land ownership was generally the most important predictor of fire severity in 74 models containing private industrial land, but was closely followed by pre-fire canopy cover (Figure 2.5, Table 2.5). By region, land ownership was also the most important predictor of fire severity in Sierra and KlaSCa forests, though in the latter, differences between the effects of land ownership, canopy cover, fire growth, and TPI were not statistically significant. In WCaCoa forests, canopy cover was the most important predictor of fire severity, followed by land ownership. In ECa forests, elevation was the most important predictor of severity, followed by land ownership, but both predictors were only statistically significant in a single model for the ecoregion. After accounting for mean pre-fire forest structure, topography, fire weather, and disturbance history in each fire, predicted mean fire severity (as measured by RBR) was generally higher on private industrial land than other land ownership designations in KlaSCa, Sierra, and WCaCoa forests

(Figure 2.6, Table 2.6). Predicted mean fire severity was generally lower on private industrial lands in ECa forests (Figure 2.6, Table 2.6).

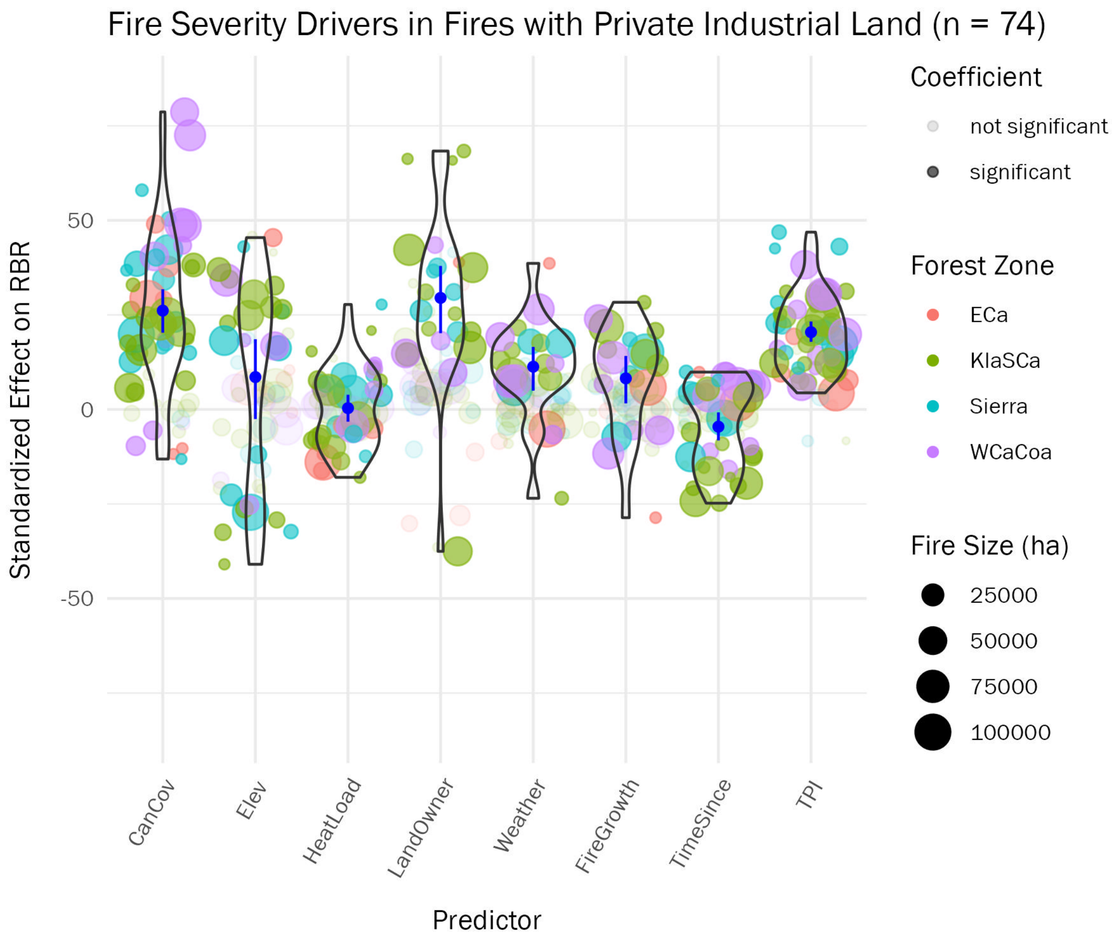

Figure 2.5. Effect of pre-fire forest structure, topography, disturbance history, fire progression, fire weather, and land ownership on fire severity (RBR) in fires containing private industrial land ownership (n = 74). Landowner was incorporated as a binary categorical variable where private industrial land was coded as 1, and all other ownership types were coded as 0. Points are symbolized by forest zone (color), statistical significance of the coefficient (transparency), and fire size (point size). Violin plots indicate the distribution of statistically significant coefficients only. See Figure 2.2, Table 2.1 for full predictor information. ECa: Eastern Cascades; KlaSCa: Klamath and Southern Cascades; Sierra: Sierra Nevada; WCaCoa: Western Cascades and Coastal. TPI: Topographic position index.

Table 2.5. Mean standardized effect of 8 predictor variables on fire severity in fires containing private industrial ownership (n = 74 fires) across the entire study area and by dominant ecoregion: Western Cascades and Coastal fires (WCaCoa, n = 11), Eastern Cascades fires (ECa, n = 7), Klamath and Southern Cascades fires (KlaSCa, n = 36), and Sierra Nevada (n = 20). Means are calculated from the effect sizes of statistically significant ($p < 0.05$) model coefficients only; number of statistically significant coefficients for a given predictor is listed in parentheses.

	All fires (74 fires)	**WCaCoa** (11 fires)	**ECa** (7 fires)	**KlaSCa** (36 fires)	**Sierra** (20 fires)
Canopy cover	25.74 (55)	37.32 (9)	22.58 (7)	21.53 (24)	27.00 (15)
Elevation	11.03 (31)	12.19 (5)	45.44 (1)	11.95 (16)	4.91 (9)
Heat load	-0.63 (42)	6.61 (6)	-10.24 (5)	-2.68 (20)	3.52 (11)
Landowner	27.80 (26)	21.58 (4)	38.91 (1)	21.64 (14)	42.11 (7)
Weather	11.20 (21)	11.02 (6)	16.72 (2)	8.95 (9)	13.79 (4)
Fire growth	9.58 (20)	3.62 (6)	-11.38 (2)	19.6 (8)	8.92 (4)
Time since disturbance	-5.35 (40)	-0.84 (10)	2.31 (4)	-12.69 (18)	1.68 (8)
TPI	20.71 (61)	20.68 (10)	11.81 (6)	19.67 (30)	26.36 (15)

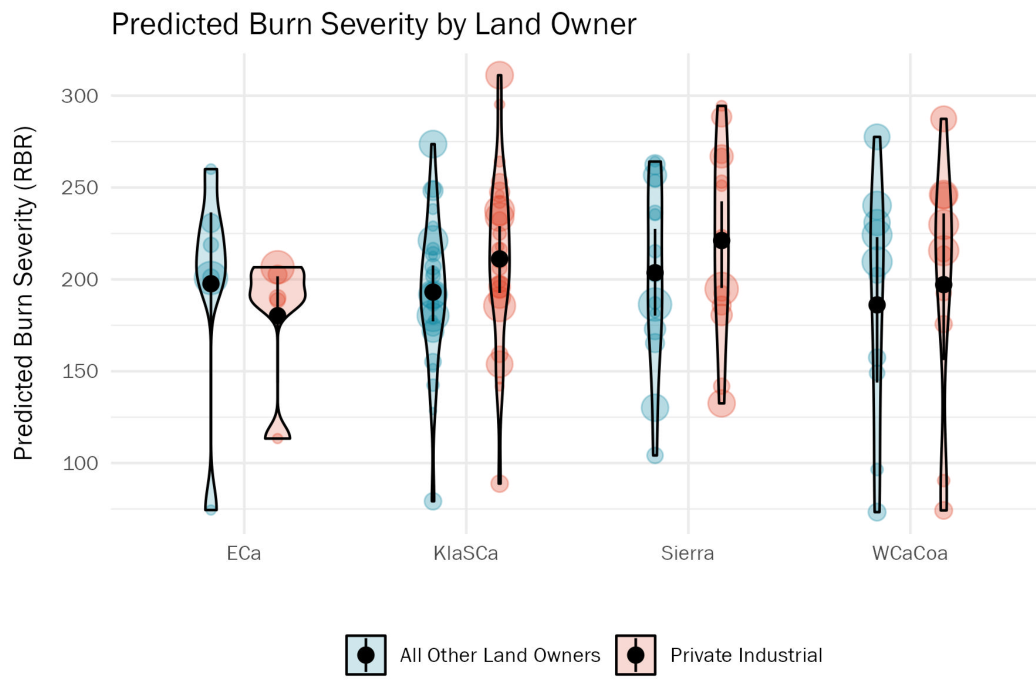

Figure 2.6. Predicted mean fire severity (RBR) by landowner and dominant ecoregion after accounting for pre-fire forest structure, topography, fire weather, and disturbance history within each fire. Each dot represents predicted mean RBR value for a given fire. ECa: Eastern Cascades; KlaSCa: Klamath and Southern Cascades; Sierra: Sierra Nevada; WCaCoa: Western Cascades and Coastal. TPI: Topographic position index.

Table 2.6. Predicted mean fire severity (RBR) by landowner and dominant ecoregion after accounting for pre-fire forest structure, topography, fire weather, and disturbance history within each fire.

	WCaCoa (11 fires)	**ECa** (7 fires)	**KlaSCa** (36 fires)	**Sierra** (20 fires)
Private Industrial	187.48	197.28	199.25	224.18
Other	181.72	205.84	187.04	199.39

2.5 DISCUSSION

This study evaluated drivers of fire severity in the context of land ownership designation, forest canopy cover, topography, fire growth and weather, and past disturbances across four major forested ecoregions in California, Oregon, and Washington. We first examined drivers of fire severity *at the individual fire level* (one model per fire) using consistent, standardized, and directly comparable generalized least squares estimators that used the same set of predictors for each fire. We analyzed fire severity as a function of fire growth and daily weather, topography, pre-fire forest structure, disturbance history, and land ownership in each fire. We then evaluated model coefficients across all fires – focusing on the mean effect of each predictor – across our full study area as well as the four ecoregions within it: Western Cascades and Coastal, Eastern Cascades, Klamath and Southern Cascades, and Sierra Nevada forests. We used this hierarchical modeling framework to assess *general* drivers of fire severity across our study system (hereinafter, general system behavior).

Across our study area, land ownership designation was generally the most important predictor of fire severity, but bottom-up controls associated with pre-fire forest structure and topography were also important, consistent with previous studies (Cansler et al., 2022; Harris and Taylor, 2017; Lydersen et al., 2017; Prichard and Kennedy, 2014; Zald and Dunn, 2018). In mixed-ownership fires, the relative importance of fire severity drivers between private industrial land and federal public lands was quite similar, though pre-fire canopy cover was generally a more important predictor of fire severity on private industrial than on public lands. After accounting for topography, fire growth and fire weather, pre-fire forest structure, and disturbance history in each fire, we found that private industrial land ownership was generally associated with higher fire severity than all other ownership designations in the Western Cascades and Coastal, Klamath and Southern Cascades, and Sierra Nevada ecoregions but was associated with lower fire severity in the Eastern Cascades. Our results suggest that across our study area, ownership designation as a proxy for general management practices is a strong predictor of fire severity, but differences in biomass productivity, forest dynamics, and variations in other prominent drivers across ownerships interact with management activities to govern fire effects.

2.5.3 Across the study region, what are the most prominent drivers of fire severity?

When modeled at the individual fire level, bottom-up influences associated with pre-fire forest structure and topography were generally more important to fire severity than top-down controls of fire growth and fire weather. Weather exerts an important influence on fire severity and was a dominant control in numerous previous studies within our study area (Evers et al., 2022; Lydersen et al., 2017; Zald and Dunn, 2018). While our results indicate that fire severity was indeed generally higher under more extreme weather conditions, the effect of weather was not as pronounced as the effect of pre-fire canopy cover, elevation, and TPI. Bottom-up drivers may mitigate top-down influences on fire severity, even under extreme fire weather conditions (Lydersen et al., 2017; Prichard et al., 2020). However, it is generally recognized that extreme weather such as hot, dry conditions combined with extreme wind events can 'override' bottom-up controls of fuels and topography on resultant fire severity (Graham, 2003; Lydersen et al., 2014; Thompson and Spies, 2010). Across our individual model results, fire weather was rarely more important than bottom-up controls in any ecoregion. While previous studies have shown that pre-fire forest structure, topography, and elevation are indeed important influences on fire severity (Birch et al., 2015; Dillon et al., 2011; Kane et al., 2015; Lydersen et al., 2017), the synoptic nature of fire weather combined with the spatial coarseness of available data confounds the interpretation of our results and may have resulted in its relatively lower effect size in our models. Particularly in ecoregions with climate-limited large wildfires such as the Western Cascades and Coastal forests, extreme weather is frequently attributed as a dominant driver of fire behavior in studies employing regional-scale models (Evers et al., 2022; Reilly et al., 2022). We recognize that while our results indicate that bottom-up controls generally have larger impacts on fire severity relative to weather across our study area, these relationships were revealed with models constructed at the individual fire level, and should not be interpreted as fire weather being unimportant.

It is important to note that this study evaluates general system behavior and presents results through the lens of the *relative importance* of fire severity drivers across the study area – that is, the goal of our models is not to identify an ideal 'recipe' for predicting fire severity. Rather, our hierarchical modeling approach aims to elucidate mean responses and general relationships between consistent (and therefore directly comparable) predictor variables. Across the study area, we found that individual fires had their own unique ecological signatures, and efforts to cluster fires into groups based on the importance of their predictors were not successful. We recognize that the final chosen model for each fire could never be the most parsimonious model for *every* fire – this is evident by the wide range of predictors used across numerous previous analyses of fire severity. For example, average daily temperature was the most important weather variable driving fire severity in the 2002 Biscuit Fire (Thompson and Spies, 2009), while wind speed was the most important weather variable driving severity in the northern Carlton Complex fire of 2014 (Prichard et al., 2020).

2.5.4 Do drivers of fire severity differ between intensively managed systems and federal public lands?

The relative importance of fire severity drivers was generally similar between intensively managed private industrial and federal public lands. In both ownerships, fire severity increased with greater pre-fire canopy cover, with higher topographic positions, and with more extreme weather and on greater fire growth days. Across much of our study area, overall canopy cover on private industrial land was comparable to that of federal land (Appendix A, Figure 2.9, Table 2.8). Yet the mean effect of canopy cover – an important driver on both ownerships – was significantly greater on private industrial land than on federal public lands, and landowner designation was generally the most important predictor of fire severity in our pooled private industrial-versus-federal models. These results suggest that differences in underlying forest structure by landowner significantly influence fire severity.

Multiple mechanisms may explain these differences. Private industrial forests in our study area were generally dominated by younger trees (Appendix A, Figure 2.10), which may be more susceptible to fire-induced tree mortality due to their thin bark and lower crown base heights (Dunn and Bailey, 2016; Stephens and Moghaddas, 2005). In sites where logging residues were not treated either through removal or broadcast burning, surface fuels may also be an important contributor to severe fire effects on plantations where fuels-reducing site preparations have not occurred and surface fire intensity is enough to initiate crown fire (Lyons-Tinsley and Peterson, 2012). Once fire has entered the canopy, homogenous, even-aged forest structure associated with high-yield timber production can enable rapid spread and severe fire effects due to dense canopy connectivity (Duane et al., 2021; Kim et al., 2016; Ritter et al., 2020). Recent studies have likewise suggested that dense horizontal connectivity of fuels can facilitate high surface-to-canopy vertical heat transfer, resulting in large tree consumption and mortality even where ladder fuel loading is relatively low (Ritter et al., 2023).

By contrast, forests on federal public lands in our study area tended to be older (Appendix A, Figure 2.10) in absence of recent disturbance (Appendix A, Figure 2.11), with likely greater variability in tree size and forest structure relative to intensively managed private lands (Griffey et al., 2021). Multi-layered canopies associated with these forests – particularly in fire-excluded, fire-prone systems with dense fuel accumulations – are certainly susceptible to high severity fire (Hessburg et al., 2015; Mallek et al., 2013; Parks et al., 2018a). However, pre-fire canopy cover on federal public lands may have been a less prominent driver of severity than on private lands due to *relatively* reduced canopy connectivity, greater variation in tree age classes, and overall greater structural complexity (Becerril Salas, 2021; Griffey et al., 2021). While pre-fire canopy cover was an important driver of severity on public lands, variables associated with weather and topography were similarly important (Table 2.3). On private industrial lands, canopy cover was significantly more important than other drivers.

2.5.5 Is private industrial forestry associated with higher fire severity?

Land ownership was, on average, the most influential predictor of fire severity when measured as a fixed effect in fires containing private industrial land across the study area. Observed fire severity on private industrial lands (as measured by RBR) was marginally higher than other land ownership designations across much of our study area (Figure 2.7). However, after accounting for pre-fire forest structure, fire weather, topography, and disturbance history in each fire, intensively managed private forests were associated with overall higher predicted fire severity in Klamath and Southern Cascade forests, Western Cascades and Coastal forests, and the Sierra Nevada, but was associated with lower predicted fire severity in the Eastern Cascades. Our results suggest that variations in other important drivers of fire severity across land ownership designations interact with general landowner activities (i.e., management regimes) to influence post-fire outcomes.

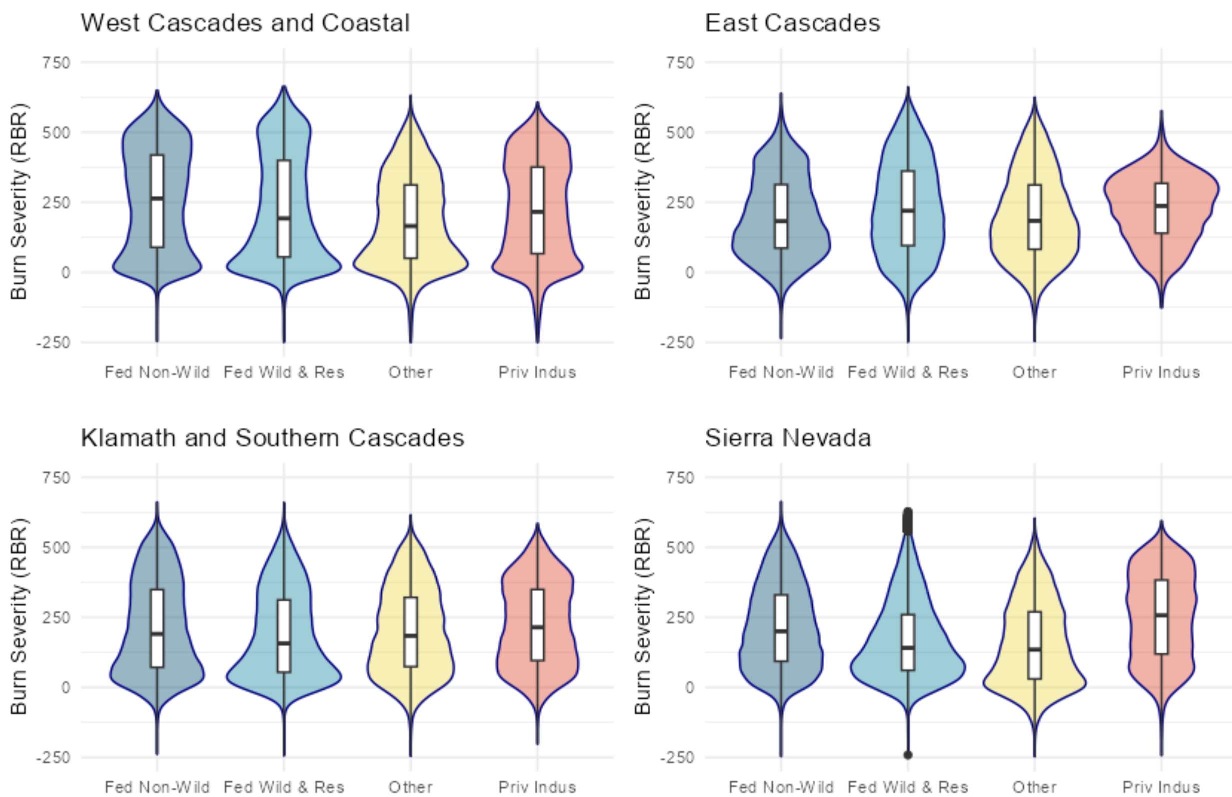

Figure 2.7. Distribution of fire severity (RBR) by major land ownership designation across ecoregions of the study area.

Our use of land ownership as proxy for management enables broad inferences on likely forest conditions informed by previous studies (Becerril Salas, 2021; Chamberlain et al., 2023; Griffey et al., 2021), but it is important to acknowledge that our study does not incorporate explicit measurements and metrics of surface, ladder, and canopy fuel biomass and structure, which greatly influence fire severity (Cansler et al., 2022; Kobziar et al., 2009; Prichard and Kennedy, 2014). However, observed differences in canopy cover and time since disturbance across landowner designations – combined with overall differences in biomass productivity – may explain variations in our results across ecoregions where explicit fuel information is not available.

For example, in the Western Cascades and Coastal ecoregion, private industrial forests associated with higher predicted fire severity had generally high canopy cover (Appendix A, Figure 2.9) despite their relatively young stand ages after recent harvest across much of the ecoregion (Appendix A, Figure 2.10). Forests in this moist region are highly productive, and private industrial lands emphasizing timber yield may be particularly susceptible to high severity fire with their dense single-cohort fuel structures dominated by age classes younger than 60 years (Schillinger et al., 2003). While dense, shaded canopy cover can facilitate microclimates that maintain moist understory fuels (Agee and Skinner, 2005), decreased precipitation associated with seasonally dry summers and drought can overwhelm these effects, leading to a negligible effect of canopy shading on moderating fire behavior during periods of high fire danger (Bigelow and North, 2012; Estes et al., 2012). Federal forests of this ecoregion, by contrast, had similar levels of canopy cover but were overall much older, with likely greater heterogeneity in horizontal and vertical fuel structure due to natural regeneration processes and stand development (Donato et al., 2012; Franklin et al., 2002). Larger, mature trees within these older forests may additionally be important influences on fire severity with their relatively fire-resistant, thick bark and higher canopy base heights compared to younger, smaller trees (Peterson and Ryan, 1986).

Likewise, private industrial lands associated with greater predicted fire severity in both the Klamath and Southern Cascades and Sierra Nevada ecoregions had generally high canopy cover (Appendix A, Figure 2.9). While these fire-prone forests are generally less productive than moist Western Cascades and Coastal forests, private industrial forests in these regions also tended to be relatively older prior to wildfire (Appendix A, Table 2.8), likely enabling enhanced canopy connectivity and fuel continuity associated with high severity fire effects (Ritter et al., 2023).

By contrast, private industrial land in the Eastern Cascades – associated with lower predicted fire severity relative to other landowner designations – was dominated by young forests but had generally lower canopy cover compared to all other landowner designations in the region (Figure 2.9, Table 2.8). Eastern Cascade forests are generally lower productivity relative to other ecoregions within our study area, and private industrial forests concentrated at lower to mid-elevations may be slower to accumulate biomass and reach canopy closure following harvest, likely resulting in lower resultant fire severity (Hungerford et al., 1991). This differs from likely conditions present on much of the federal lands throughout the ecoregion, where legacies of fire exclusion and greater disturbance-free intervals have resulted in profound departures in forest structure and accumulation of fuels associated with widespread tree mortality (Hagmann et al., 2021).

Differences in site-preparation and management of post-harvest surface fuels on private industrial forest lands may additionally explain variations in predicted severity across ecoregions. For example, logging slash left behind after harvest can result in higher fire severity than adjacent forests that have higher pre-fire fuel loads but greater heterogeneity in fuel distribution (Lyons-Tinsley and Peterson, 2012; Stone et al., 2004). By contrast, site preparations such as soil scarification in frequent-fire young plantations can reduce subsequent fire severity years after the initial treatment occurred (Lezberg et al., 2008). Without explicit and consistent information on past management activities and fuel treatments, the exact mechanisms driving differences in predicted severity across ownership designations and ecoregions remains unclear.

2.5.6 Limitations and Considerations

Our study represents, to our knowledge, the most robust assessment of how landowner designation interacts with fuels, topography, and weather to influence fire severity. However, it is important to recognize key limitations of our study. Broad categories of landowner designation types are helpful for describing general management regimes and landowner behavior (Barros et al., 2021), but landowners are not a monolith, and individual landowner actions may have discrete impacts on fire behavior and effects. Landowner designation alone cannot discern differences in management activities (i.e., site preparation, partial thinning, pile burning, broadcast burning, fuel treatments, etc.), which can influence resultant fire severity (Cansler et al., 2022; Kobziar et al., 2009; Lezberg et al., 2008; Lyons-Tinsley and Peterson, 2012; Prichard and Kennedy, 2014). Additionally, while we found that private industrial forest ownership was associated with higher fire severity relative to other ownerships across much of our study area, this should not be interpreted as a blanket criticism of management practices on all private industrial lands, nor an endorsement of all forest management practices in non-private industrial agencies. Particularly in fire-prone federal forests, legacies of fire exclusion and curtailment of Indigenous stewardship have resulted in forests profoundly departed from their historical conditions (Hagmann et al., 2021), and a vast increase in the pace and scale of fuel treatments is needed to restore forests to more resilient conditions (North et al., 2015a, 2021). Regardless of landowner designation, thinning combined with surface fuel reduction treatments are a long-recognized mean of reducing fire severity and moderating fire behavior at stand scales in fire-prone forests (Brodie et al., 2024; Davis et al., 2024; Lydersen et al., 2017).

There are additional limitations inherent to remote sensing-based analyses that apply to this study. While Landsat-derived methods are widely used and well-established for estimating fire severity and forest change, coarse-scale satellite imagery is most likely to detect forest conditions and fire-induced changes in the uppermost strata of vegetation when traditional NBR-derived severity indices are employed (Hoy et al., 2008; Zhu et al., 2006). In forests, this implies that remotely sensed measurements of fire severity most likely reflect fire effects on tree crowns, especially in denser forests where subcanopy fuels and substrates may be obstructed. Additionally, our use of Landsat-derived predictor datasets such as GNN and LCMS do not explicitly capture information on surface and ladder fuels, which strongly influence fire behavior and effects (Agee and Skinner, 2005). Lastly, our methods used to calculate satellite-derived fire severity rely on imagery collected one year post-fire, following established methods applied consistently across our fires (Howe et al., 2022; Parks et al., 2018b). However, we recognize that post-fire tree mortality may temporally vary between immediate post-fire salvage and delayed mortality several years following fire, and new methods are emerging to quantify this (Filip et al., 2007; Reilly et al., 2023).

2.5.7 Management Implications

Understanding how land ownership influences fire severity is particularly important in today's fire environment, where recent trends in increasing frequency and extent of wildfires (Cova et al., 2023; Dennison et al., 2014; Parks and Abatzoglou, 2020) could reasonably increase the likelihood of fires burning over complex, multi-owner landscapes. This study demonstrates a strong influence of bottom-up controls such as pre-fire forest structure on fire severity, and provides evidence that private industrial land ownership is often associated with higher fire severity, consistent with previous studies in the southern Oregon Cascades of a single fire event (Zald and Dunn, 2018) and Sierra Nevada (Levine et al., 2022). These findings have important implications for fire governance strategies that aim to increase both social and ecological resilience across landscapes.

Fire-prone landscapes of western North America often consist of multiple landowners with competing goals, practices, and policies (Miller et al., 2022). Despite increasingly large and severe wildfires that do not adhere to administrative boundaries, wildfire governance systems reinforce the behavior of individual landowners that prioritize short-term risk aversion at the expense of needed treatments to mitigate long-term fire risk (Fischer et al., 2016). For example, concerns about property losses, public safety, and liability may result in an individual landowner being less likely to conduct needed prescribed burns or other fuel reduction treatments and instead rely on risk reduction activities of nearby landowners or agencies (Busby and Albers, 2010). Our results inform these perceptions on sources of risk in multi-owner landscapes and underscore the importance of landowner behavior in driving post-fire effects. Cohesive management strategies that involve collaborations across ownerships and prioritize long-term perspectives on forest and fire management are needed to improve social and ecological wildfire outcomes (Essen et al., 2023; Fischer et al., 2016; McCaffrey, 2004). More work is needed to develop and understand the impact of alternative management practices that meet owner-specific objectives while improving socioecological resilience at broader landscape scales.

2.6 CONCLUSION

Overall, landowner designation was the most important predictor of fire severity across our study area, and bottom-up controls including pre-fire canopy cover interacted with landowner management regimes to govern fire effects. Private industrial land ownership was associated with higher fire severity relative to other ownerships where industrial forests had reached greater canopy closure, but was associated with lower fire severity relative to other landowners where industrial forests had more open canopies and likely lower surface fuel accumulations and greater within-stand spatial heterogeneity. Our findings expand upon insightful but limited previous studies that found private industrial forestry to be associated with higher fire severity in the Klamath Mountains and Sierra Nevada (Levine et al., 2022; Zald and Dunn, 2018), and have important implications for forest management in multi-owner landscapes. Specifically, cohesive management strategies that prioritize shared governance, long-term perspectives on forest management, and collaborations across landowners are needed to improve social and ecological wildfire outcomes.

2.7 APPENDIX A: SUPPLEMENTARY MATERIAL

Table 2.7. Predictor variables gathered and initially considered for models. Variable selection was completed through an iterative process based on predictor collinearity, accuracy assessments of predictors (where available), preliminary analysis of test models for a representative set of 15 fires, and ecological interpretability of predictors. TPI is topographic position index. Predictors with an asterisk (*) were retained in final models. Table continues on next page.

Datasets considered for model selection			
Predictor	Category	Source	Resolution
TPI fine - 270 m	Topography	(Evans and Murphy, 2021)	30 m
TPI moderate - 990 m*	Topography	(Evans and Murphy, 2021)	30 m
TPI coarse - 2070 m	Topography	(Evans and Murphy, 2021)	30 m
Slope	Topography	(Farr et al., 2007; Gorelick et al., 2017)	30 m
Aspect	Topography	(Farr et al., 2007; Gorelick et al., 2017)	30 m
Elevation*	Topography	(Farr et al., 2007; Gorelick et al., 2017)	30 m
Heat load index*	Topography	(Evans and Murphy, 2021)	30 m
Stand age of dominant trees	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Stand age of dominant trees - no remnant trees	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Proportional basal area of live conifers	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Component Ratio Method biomass of live trees	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Canopy cover*	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Canopy cover - conifers	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Diameter diversity index	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Downed wood volume	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Old growth structural index	Forest Structure	(Ohmann and Gregory, 2002)	30 m
Snag volume	Forest Structure	(Ohmann and Gregory, 2002)	30 m

Magnitude of most recent disturbance	Forest Structure	(Healey et al., 2018)	30 m
Time since most recent disturbance*	Forest Structure	(Healey et al., 2018)	30 m
Most recent disturbance type	Forest Structure	(Healey et al., 2018)	30 m
Fire growth*	Weather	(Parks, 2014)	30 m
Wind velocity	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Vapor pressure deficit	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Maximum temperature	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Minimum relative humidity	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
100-hr fuel moisture	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
1000-hr fuel moisture	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Energy resource component	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m
Burning index*	Weather	(Abatzoglou, 2013)	4km, downscaled to 30 m

Table 2.8. Median and standard deviation (in italicized parentheses) of predictors by ecoregion and dominant land ownership designation in our study area. Units for each predictor are given in parentheses except where units are index values (heat load index, weather - burning index, and TPI - topographic position index). Table continues on next page.

	WCaCoa			
	Fed Non-Wild	Fed Wild & Res	Other	Priv Indus
Canopy cover (%)	77.96 *(16.84)*	79.85 *(16.67)*	59.43 *(20.27)*	72.64 *(28.61)*
Elevation (m)	795.11 *(364.31)*	1086.13 *(440.26)*	465.11 *(418.78)*	718.83 *(232.57)*
Heat load	0.71 *(0.17)*	0.72 *(0.19)*	0.71 *(0.15)*	0.72 *(0.17)*
Weather	62.00 *(18.61)*	52.58 *(15.81)*	59.93 *(15.27)*	60.27 *(16.20)*
Fire Growth (ha)	16365.24 *(14488.10)*	1555.65 *(10527.27)*	6725.88 *(16122.80)*	22737.60 *(12185.33)*
Time Since (years)	100.46 *(88.22)*	153.24 *(94.51)*	64.61 *(52.65)*	20.00 *(53.24)*
TPI	0.54 *(34.56)*	-0.08 *(39.37)*	-0.70 *(28.12)*	1.17 *(34.78)*
	ECa			
	Fed Non-Wild	Fed Wild & Res	Other	Priv Indus
Canopy cover (%)	50.55 *(20.96)*	62.33 *(20.12)*	44.69 *(23.90)*	36.22 *(15.10)*
Elevation (m)	1198.11 *(301.36)*	1546.43 *(355.87)*	1086.07 *(320.58)*	1175.86 *(158.46)*
Heat load	0.67 *(0.17)*	0.68 *(0.19)*	0.66 *(0.13)*	0.70 *(0.10)*
Weather	53.32 *(12.35)*	51.00 *(10.58)*	55.00 *(11.90)*	55.31 *(11.45)*
Fire Growth (ha)	1358.37 *(11939.61)*	1117.80 *(3091.59)*	1617.30 *(10790.42)*	4951.98 *(13583.93)*
Time Since (years)	84.08 *(54.58)*	104.80 *(66.78)*	80.37 *(53.31)*	38.33 *(35.47)*
TPI	0.83 *(32.80)*	-2.04 *(35.62)*	-0.67 *(25.01)*	-0.12 *(14.98)*
	KlaSCa			
	Fed Non-Wild	Fed Wild & Res	Other	Priv Indus
Canopy cover (%)	71.31 *(18.94)*	71.57 *(20.04)*	59.87 *(20.57)*	69.57 *(19.60)*
Elevation (m)	997.97 *(343.03)*	1085.92 *(416.49)*	770.98 *(334.40)*	1026.30 *(369.02)*
Heat load	0.75 *(0.18)*	0.74 *(0.18)*	0.72 *(0.16)*	0.74 *(0.17)*
Weather	56.00 *(12.64)*	55.50 *(12.71)*	56.14 *(10.38)*	58.00 *(10.27)*
Fire Growth (ha)	2972.34 *(14345.45)*	2094.48 *(10495.96)*	4962.42 *(14053.59)*	2517.57 *(11106.67)*
Time Since (years)	27.00 *(72.01)*	18.00 *(80.78)*	19.00 *(50.30)*	29.00 *(58.21)*
TPI	1.45 *(37.80)*	0.19 *(40.60)*	-0.95 *(30.94)*	0.17 *(35.91)*
	Sierra			
	Fed Non-Wild	Fed Wild & Res	Other	Priv Indus
Canopy cover (%)	55.87 *(19.44)*	50.37 *(19.46)*	45.08 *(19.31)*	62.73 *(19.94)*

Elevation (m)	1579.03 *(522.81)*	2164.83 *(367.94)*	662.96 *(510.21)*	1449.94 *(333.47)*
Heat load	0.78 *(0.16)*	0.80 *(0.14)*	0.77 *(0.13)*	0.77 *(0.12)*
Weather	63.95 *(14.95)*	59.00 *(12.35)*	72.02 *(26.02)*	69.65 *(22.32)*
Fire Growth (ha)	2499.48 *(5762.25)*	1041.12 *(3171.66)*	7795.53 *(12182.23)*	3187.98 *(8932.63)*
Time Since (years)	66.73 *(59.69)*	22.00 *(77.73)*	69.66 *(39.96)*	39.39 *(55.37)*
TPI	-0.16 *(34.48)*	-1.46 *(31.78)*	-0.83 *(27.11)*	1.12 *(25.45)*

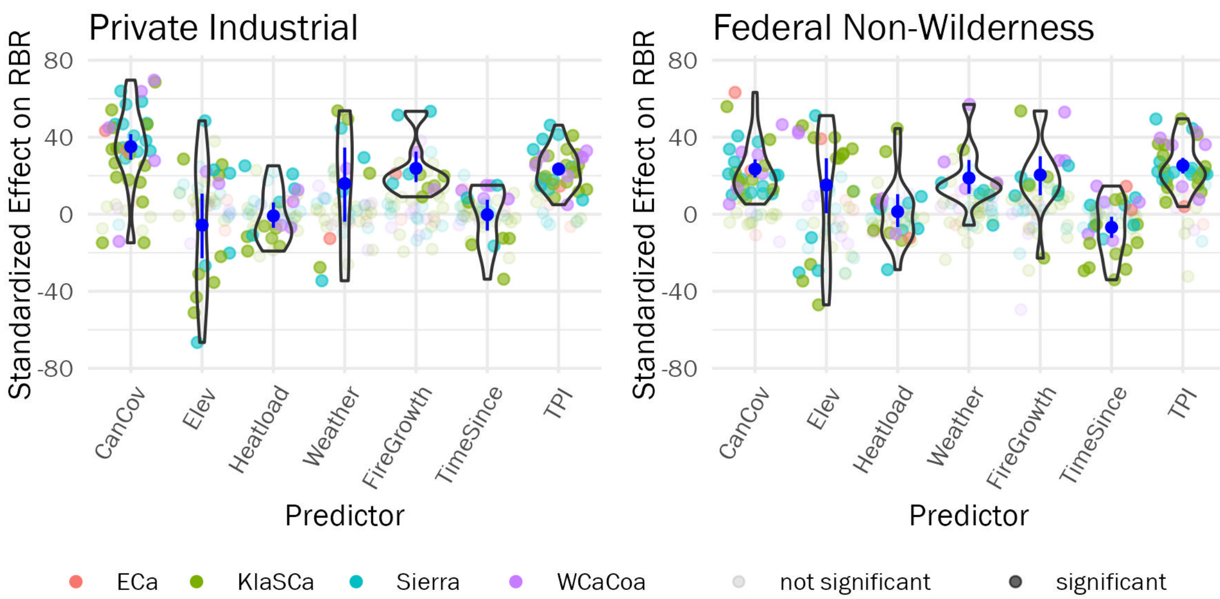

Figure 2.8. Effect of pre-fire forest structure, topography, disturbance history, fire progression, and fire weather on fire severity (RBR) across fires containing both private industrial and federal non-wilderness land (n = 49). Models were constructed and are presented by land ownership designation. Points are symbolized by forest zone (color) and statistical significance of the coefficient (transparency). Violin plots indicate the distribution of statistically significant coefficients only. See Figure 2.2, Table 2.1 for predictor information.

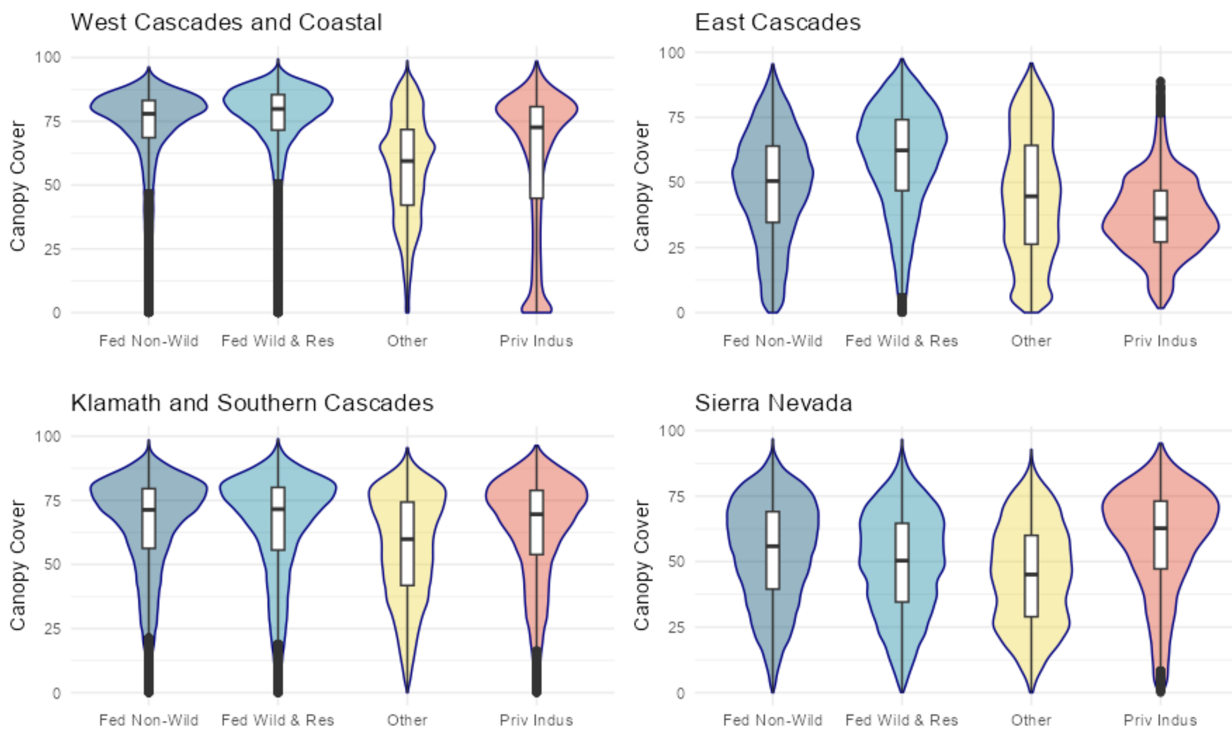

Figure 2.9. Canopy cover by ecoregion and dominant land ownership designation in our study area.

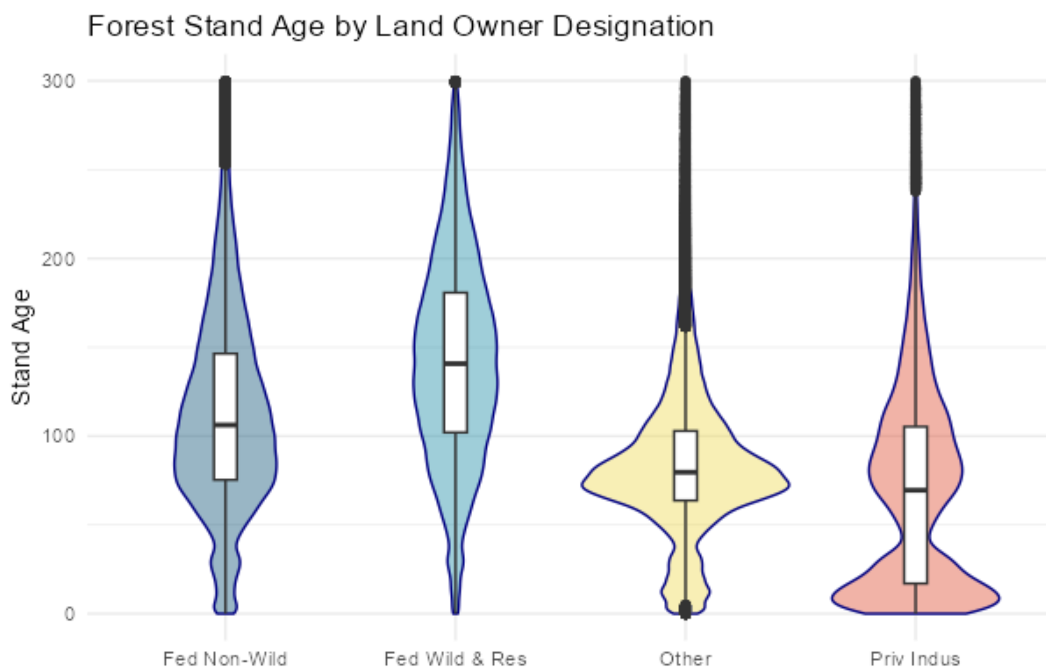

Figure 2.10. Stand age by dominant land ownership designation.

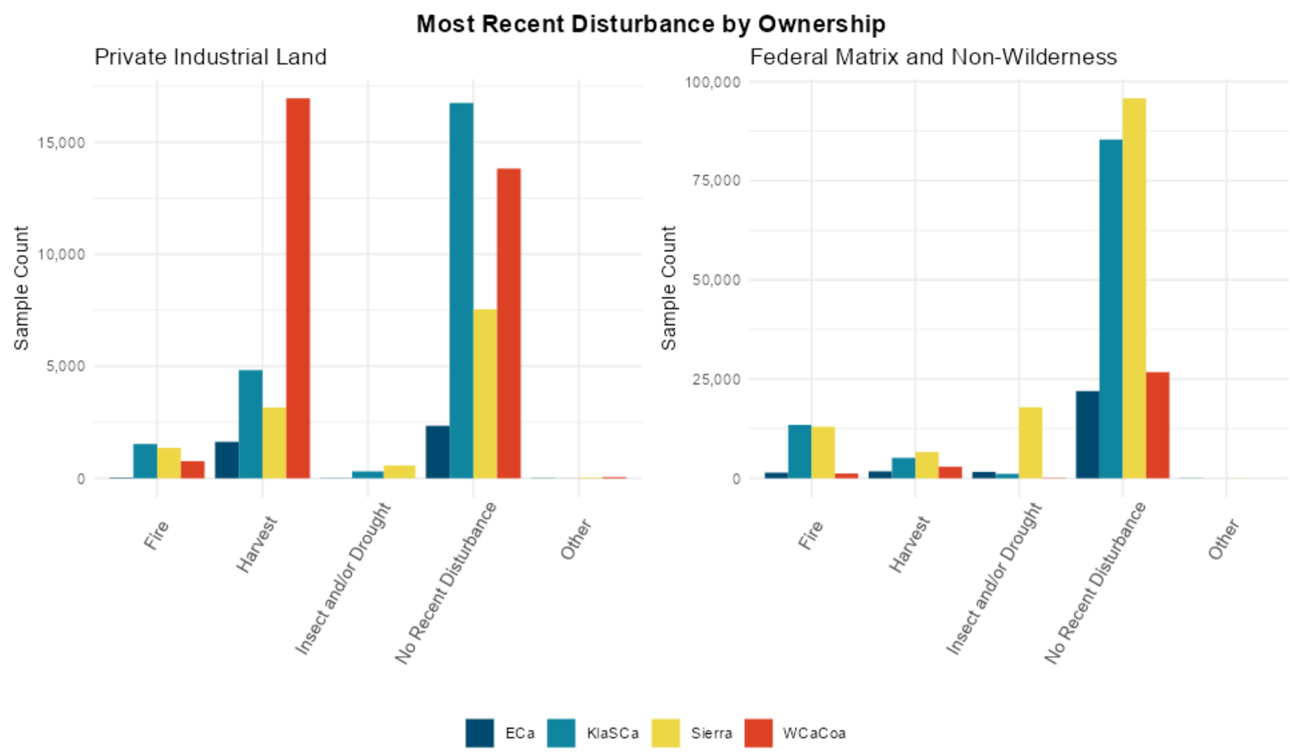

Figure 2.11. Most recent disturbance type by land ownership designation and major ecoregion across the study area.

CHAPTER 3. IMPLICATIONS OF RECENT WILDFIRES FOR FOREST MANAGEMENT ON FEDERAL LANDS IN THE PACIFIC NORTHWEST, USA

3.1 ABSTRACT

Adoption of the Northwest Forest Plan in 1994 marked a pivotal moment in federal forest management in the Pacific Northwest, shifting focus away from intensive timber harvest toward ecosystem management that emphasized late-successional forest habitat across nearly 10 million ha in Washington, Oregon, and northern California. The primary strategy of the NWFP was the creation of a network of conservation reserves to maintain and restore old forest habitat across moist and dry forest zones, but effects of climate change and shifting wildfire regimes were not directly considered in the initial Plan. Thirty years after its adoption, concerns over recent forest loss and fragmentation by wildfires and a changing climate have prompted discussions of Plan revisions, but the ecological effects and drivers of recent fires in NWFP forests is not well understood. In this study, we evaluated over 2,200 fires that have burned in the NWFP area over the last four decades to inform conservation efforts and recommendations for Plan amendments. Using landscape metrics and statistical modeling, we quantified patterns and drivers of fire severity across different land use allocations and major forest zones within the NWFP. We found that annual area burned and mean high severity patch size increased across the entire study area, and historically frequent-fire forest types including dry mixed conifer forests, mixed evergreen forests, and pine-oak woodlands experienced the most severe wildfire effects. Although moist forest types were less affected by wildfire, we observed large-scale erosion of forest cover in late successional reserves. Weather was a prominent driver of fire severity across much of the study area, but bottom-up influences including

vegetation cover type, topography, and pre-fire forest structure exerted strong bottom-up controls outside of large high severity patches. Our results can inform NWFP revisions aimed at integrating adaptive management. Potential amendments to the NWFP could include adapting existing reserve design and management, expansion of wildland fire use in dry forests, increased pre- and post-fire forest restoration activities, and identification of monitoring 'triggers' that inform adaptive strategies for the conservation of old forests within the Plan area.

3.2 INTRODUCTION

Globally, forests are changing rapidly as wildfire seasons grow longer and more severe (Flannigan et al., 2013; Parks and Abatzoglou, 2020) and forests are further challenged by severe drought (Dai, 2013; Swain, 2015), widespread insect outbreaks (Raffa et al., 2008), expansion of the wildland urban interface (Radeloff et al., 2018), and resource extraction (Laurance et al., 2000). In response to accelerating threats to forests, dominant conservation strategies throughout much of the last century aimed to protect mature and old forest habitat through the designation of wilderness areas and reserves (Massip, 2020). While reserved areas play a vital role in combating forest losses to development and commercial exploitation (Talty et al., 2020), a warming climate and shifting disturbance regimes have continued to reshape forest landscapes (Seidl et al., 2017). As climate change is expected to amplify existing forest stressors in the coming decades (Abatzoglou et al., 2021; Cook et al., 2018; Keenan, 2015), there is significant need to assess the role of static reserve systems in achieving forest conservation goals (Bengtsson et al., 2003; Hessburg et al., 2021; North et al., 2015b). To restore dynamic forest landscapes and adapt them to climate change, implementing proactive and innovative management strategies is key (Prichard et al., 2021; Wildland Fire Mitigation and Management Commission, 2023).

In the Pacific Northwest, the Northwest Forest Plan (hereafter, the NWFP or the Plan) specifies the management of federal forests across nearly 10 million ha in Washington, Oregon, and northern California. Implementation of the Plan in 1994 marked a pivotal moment following the 'timber wars' – intense conflict between conservation groups and timber companies over the fate of remaining old growth forests – and decades of debate about the primary purpose of public land management in the region (Johnson et al., 2023; Winkel, 2014). Unprecedented in its geographic scale and complexity, the Plan represented the most ambitious forest management, conservation, and monitoring effort ever implemented for the US national forest system, and shifted focus away from intensive timber harvest toward ecosystem management that emphasized late-successional forest habitat for threatened and endangered species (Johnson et al., 2023; Thomas et al., 2006). A network of conservation reserves dispersed across both moist and fire-frequent dry forest zones was the primary strategy to maintain and restore forest habitat of species such as the northern spotted owl (*Strix occidentalis caurina*) and marbled murrelet (*Brachyramphus marmoratum*).

Across the NWFP, management guidelines and objectives for federal forests are determined by a set of land use allocations developed as part of the Plan. A range of management strategies are represented across allocations, ranging from Congressional Reserves (lands designated by US Congress, including wilderness areas and national parks where active forest management is restricted) to Matrix lands (non-reserved forests where the majority of silvicultural and harvest activities were expected to occur). Of particular importance to the Plan's forest conservation strategy are forests allocated as Late Successional Reserves (LSRs), where management goals emphasize the protection and enhancement of late-successional and old-growth forest conditions to primarily support wildlife habitat connectivity (Johnson et al., 2023). While potential impacts from natural disturbances such as wildfire were considered as part of the NWFP's reserve design – particularly in the dry forest zone – the effects of climate change were not directly considered in the initial Plan (Gaines et al., 2022; Spies et al., 2019).

Thirty years after its adoption, the Plan is now being reviewed for updates to address the effects of climate change and implement adaptation strategies to better sustain old forests and the cultural significance, economic and resource values, habitat, and carbon sequestration they provide (US Forest Service, 2023). Concerns surrounding forest loss, fragmentation, and mounting threats from climate change and recent wildfires prompted the federal government to issue a recent executive order aimed at conserving old and mature forests nationally (Exec. Order 14072, 2022). Following this, a Federal Advisory Committee was formed in 2023 to draft recommendations that will be used to inform Plan revisions to promote climate change adaptations and wildfire resilience (US Forest Service, 2022).

Wildfire is currently the driving agent of changing forest conditions across the diverse landscapes of the NWFP (Davis et al., 2022, 2015). Increasingly large and severe recent fires have rapidly reshaped fire-prone dry forests of the region, consistent with broader trends observed across western North America (Cansler and McKenzie, 2014; Cova et al., 2023; Harvey et al., 2016; Parks and Abatzoglou, 2020; Reilly et al., 2017; Steel et al., 2018). The unprecedented scale of large, stand-replacing patches observed within these fires presents critical challenges to the regeneration and persistence of future forests, particularly in a warming climate (Coop et al., 2020; Davis et al., 2019). Moist forests within the region have likewise recently burned in large and severe fires, though these events are generally more consistent with historical fire regimes of the moist forest zone (Reilly et al., 2022).

It is critical that management efforts aimed at conserving forests – particularly old forests – account for the effects of these recent wildfires. This is pertinent across a range of post-fire effects, including areas where forest succession across large areas may have been reset by stand-replacing events, in areas where forests are maintained through more frequent wildfires with low and mixed severity ecological effects (Spies et al., 2006), and in patches of unburned fire refugia (Meddens et al., 2018b). Analysis of trends and drivers (i.e., fuels, topography, and weather) of wildfire effects on forests can be used to inform future conservation and stewardship strategies that consider recent forest loss, prioritize stewardship of remaining forests, and anticipate post-fire effects in a future with more frequent fire (Abatzoglou et al., 2021; Dye et al., 2024).

In this study, we evaluated recent wildfires within the NWFP to inform conservation efforts and recommendations for Plan amendments. We analyzed satellite burn severity images for over 2,200 fires that have burned across the region over the last four decades, using landscape metrics and statistical modeling to quantify patterns and drivers of fire severity across different land use allocations and major forest zones. Our study was guided by three central research questions: 1) What have been the ecological effects of recent wildfires on NWFP forests across land use allocations and forest zones?; 2) Within the NWFP area, what are the primary drivers (in terms of fire weather, fuels, and topography) of fire severity across land use allocations and forest zones?; and 3) What are the management and policy implications of these trends?

3.3 METHODS

3.3.1 Study Area

We evaluated fires that burned at least partially within the administrative boundaries of the NWFP spanning forests in Washington, Oregon, and northern California (Figure 3.1). Forests across this region span diverse gradients of climate and topography, and include a broad range of forest types from coastal rainforests to historically frequent-fire dry mixed-conifer forests and pine-oak woodlands (Hessburg et al., 2019). We evaluated fires across two broad physiographic regions as defined in the NWFP: a moist forest zone encompassing forests west of the Cascade Mountain crest and along the coast of northern California, and a dry forest zone comprised of the forests east of the Cascade Mountain crest and within the Klamath Mountain ecoregion of southwestern Oregon and interior northern California (Franklin and Johnson, 2012).

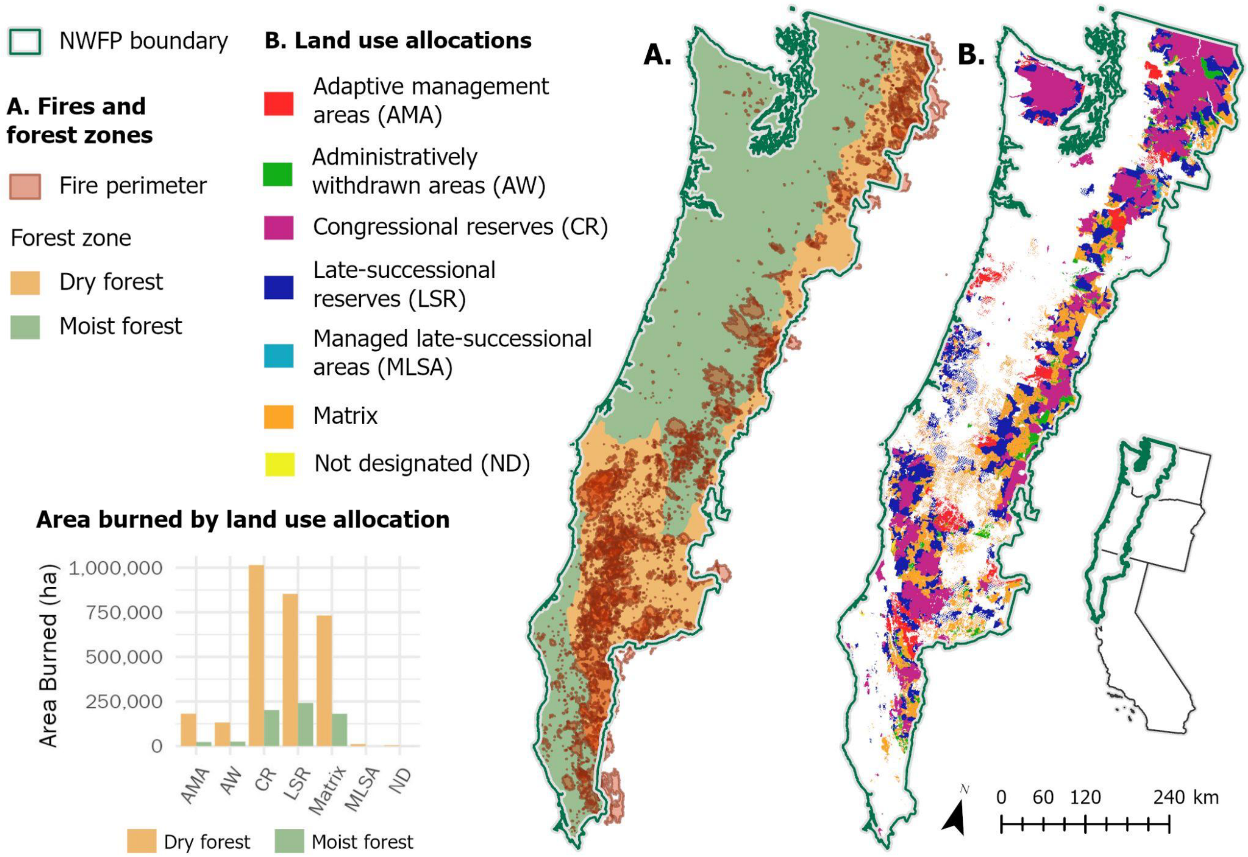

Figure 3.1. Map of the study area spanning the bounds of the Northwest Forest Plan (NWFP) across federal lands in Washington, Oregon, and northern California, USA. Map A (left): major physiographic forest zones and over 2,200 wildfires that have burned between 1985 to 2022 at least partially within the bounds of the NWFP. Map B (right): federal land use allocations designated within the NWFP. Total area burned by land use allocation and major forest zone (dry versus moist) is shown in the bottom left. The majority of area burned occurred in congressional reserves (CR), late successional reserves (LSR), and Matrix designations.

The moist forest zone of the NWFP is largely characterized by high-biomass, highly productive conifer forests and rainforests dominated by western hemlock (*Tsuga heterophylla*), Douglas-fir (*Pseudotsuga menziesii*), western red cedar (*Thuja plicata*), and Sitka spruce (*Picea sitchensis*), with abundance of bigleaf maple (*Acer macrophyllum*), black cottonwood (*Populus trichocarpa*), and red alder (*Alnus rubra*) (Franklin and Dyrness, 1973). Along the coast in northern California, long-lived coastal redwoods (*Sequioia sepervirens*) are present. At higher elevations, cold forests are dominated by Pacific silver fir (*Abies amabilis*), mountain hemlock (*Tsuga mertensiana*), and subalpine fir (*Abies lasiocarpa*). Although moist conifer, moist mixed conifer, and temperate rainforests comprise the majority of the area of this zone, drier mixed conifer forests, riparian hardwoods, and dry mixed evergreen forests are also present. The moist forest zone is broadly characterized by mild, wet winters and a pronounced summer dry season, where large fires were historically infrequent due to high fuel moisture (Agee, 1996; Weisberg and Swanson, 2003); when large fires did occur – often under extreme dry east wind events – high severity fire effects were common (Reilly et al., 2022). Though the region is often described as an infrequent fire regime, low- to moderate-severity fires applied through Indigenous burning were historically frequent (Lorimer et al., 2009). Along with lightning ignitions, Indigenous stewardship practices including fuel harvesting and cultural burning played an important role in the development of local- to landscape-scale patches of forest and non-forest vegetation such as meadows and grasslands (Charnley et al., 2008; Kimmerer and Lake, 2001; Lorimer et al., 2009).

The dry forest zone of the NWFP is dominated by dry mixed conifer forests – particularly in the Klamath ecoregion – with areas of cold forests, mixed evergreen forests, and moist mixed conifer forests present across the region. Riparian forests, pine-oak woodlands, pine savannas, and oak woodlands are also present in the region, but are less abundant. In the southern Cascades, mixed conifer forests contain Jeffrey pine (*Pinus jeffreyi*), incense cedar (*Calocedrus decurrens*), sugar pine (*Pinus lambertiana*), and white fir (*Abies concolor*) (Skinner et al., 2018). From the central Cascades of Oregon to northern Washington state, dry zone mixed conifer forests are dominated by variable assemblages of fire-tolerant Douglas-fir, ponderosa pine (*Pinus ponderosa*), and western larch (*Larix occidentalis*), intermixed with aspen (*Populus tremuloides*) and grand fir (*Abies grandis*) (Franklin and Dyrness, 1973; Sorenson, 2012). At higher elevations, forests dominated by mountain hemlock are prevalent in the north, with red fir (*Abies magnifica*) common in the south. The dry forest zone is the more frequent-fire region of the NWFP; historical fire regimes were broadly characterized by low- to moderate-severity fire effects dominated by frequent (less than 35 year) return intervals and mixed-severity fires with fire return intervals less than 75 years (Agee, 1996; Hessburg et al., 2016; Perry et al., 2011).

The original NWFP recognized a potential need for different management strategies and reserve design between forest zones (Franklin and Johnson, 2012). In moist forest zone LSRs, wildfire impacts were generally not considered, but management activities such as forest thinning to accelerate old forest structural characteristics and promote ecological diversity in young (< 80 years) second-growth forests were permitted (USFS and BLM, 1994). In the dry forest zone, LSRs were designed as larger, more contiguous areas than in the moist forest zone to maintain a baseline level of wildlife habitat connectivity while anticipating potential wildfire effects that could erode forest cover (Johnson et al., 2023). The Plan additionally recognized that more active management, including forest thinning and prescribed burning, would be required to maintain ecological function in frequent-fire dry forest landscapes. While proactive management of dry forest zone LSRs was an intent of the initial Plan, rates of restoration treatments such as thinning and burning are generally below the levels needed to maintain resilience of dry forest landscapes, and implementing adaptive management strategies in these designations has proven challenging (Franklin and Johnson, 2012; Gaines et al., 2022).

3.3.2 Fire Perimeters

We compiled a dataset of historical fire perimeters from datasets maintained by the California Department of Forest and Fire Protection (CAL FIRE) Fire and Resource Assessment Program, the Washington Department of Natural Resources, and the National Interagency Fire Center. We identified all recorded fires that burned between 1985 and 2022 within the administrative boundaries of the Plan, retaining all fires greater than 4 ha to minimize potential data entry errors and ensure each burn severity image contained a sufficient number of pixels to analyze spatial patterns of burn severity. Although the NWFP was adopted in 1994, we chose to evaluate severity for all possible fires in the modern Landsat satellite record – back to 1985 – to provide a more complete picture of how forests within the NWFP have fared following wildfire. A total of 2,254 fires met our criteria; 352 fires burned prior to 1994 representing 7% of the total area burned across the study period.

3.3.3 Patterns of Fire Severity

We generated a Landsat-derived burn severity image for each of the 2,254 fires in our dataset using a methodology developed by Parks et. al (2019) in Google Earth Engine (Gorelick et al., 2017). The workflow produces a 30-m resolution predicted Composite Burn Index (CBI) image for a given fire by combining the Relativized Burn Ratio (Parks et al., 2014a) – a spectral index used to measure burn severity developed from pre- and post-fire Landsat imagery – with climatic variables, latitude, and other spectral indices such as the Normalized Difference Vegetation Index and Mid-Infrared Bi-Spectral Index in a Random Forest model (Breiman, 2001) calibrated by over 8,000 field sampling plots. For ecological interpretability, continuous predicted CBI values were classified into categories using established thresholds: unburned/very low severity - CBI values below 0.1; low severity - values 0.1 to 1.25; moderate severity - values 1.25 to 2.25; and high severity - values greater than 2.25 (Miller and Thode, 2007). Because CBI is a field-based sampling protocol developed to evaluate severity in forests (Key and Benson, 2006), all non-forested pixels were removed from our burn severity images using a forest/non-forest mask originally developed as part of the NWFP Monitoring Program (Ohmann et al., 2012). Additionally, because we were interested specifically in forests managed as part of the NWFP, we excluded non-federal lands from our analysis.

Patterns of fire severity have important implications for a variety of ecological processes, including potential post-fire successional dynamics, loss of forest cover and wildlife habitat, and possible regeneration failures following stand-replacing fire (Collins et al., 2017b; Stevens et al., 2017; Stevens-Rumann and Morgan, 2019). To evaluate the ecological effects of recent wildfires on NWFP forests, we evaluated patterns of fire severity using four landscape metrics: total area burned by severity class, core area of high severity fire patches, mean patch size of contiguous areas of high severity and combined low and unburned (unburned-low) patches, and connectivity of unburned-low patches (Table 3.1). Across the NWFP, we observed the majority of area burned within congressional reserves (CRs), LSRs, and matrix designations (Figure 3.1); because of this, we focused our analysis on these three land use allocations. All landscape metrics were calculated using the landscapemetrics package in R (Hesselbarth et al., 2019).

Table 3.1. Landscape metrics calculated for 2,254 fires to evaluate the ecological effects of recent wildfires on NWFP forests. All metrics were calculated by land use allocation and major forest zone (dry versus moist). Table adapted from Singleton et al. (2021) and Cova et al. (2023).

Metric	**Description**	**Interpretation of low values**	**Interpretation of high values**	**Units**	**Range**
Class Area	*Area burned:* Total area belonging to severity class *i*.	Less area burned	More area burned	Ha	Class Area ≥ 0
Patch Size	*Area-weighted mean patch size:* Measure of mean patch size for class *i*. Only calculated for high-severity and combined low and unburned (unburned-low) patches.	Generally smaller patch sizes with few or no large patches	Generally larger patch sizes or few large patches among many smaller patches	Ha	Patch Size ≥ 0
Core Area	*Total core area:* Total core area of class *i* > 120 m from patch edge. Only calculated for high-severity class.	Less interior area burned	More interior area burned	Ha	Core Area ≥ 0
Connectivity	*Aggregation Index:* The number of like adjacencies of patches for class *i* divided by the theoretical maximum possible number of like adjacencies for that class. Only calculated for unburned-low patches.	Disaggregated patches with lower landscape-level connectivity.	Aggregated patches with higher landscape-level connectivity.	None / Index	100 ≥ Connectivity ≥ 0

Class Area - We calculated total area burned by severity class (unburned/very low, low, moderate, and high severity) to assess the ecological effects of recent wildfires in forests of the NWFP. Fire severity was evaluated across the full study period by land use allocation (CR, LSR, and Matrix), forest zone (dry versus moist), and major forest type based on LANDFIRE Biophysical Settings potential vegetation types (Appendix B, Table 3.4, Rollins and Frame, 2006). We additionally evaluated trends in annual area burned by land use allocation and forest zone. Trends were tested for statistical significance using Theil-Sen (T-S) slope estimators – a nonparametric technique to evaluate the median slope across a time series – via the 'trend' package in R (Pohlert, 2019). Following previous studies, we evaluated the statistical significance of trends using a p-value of 0.10 (Cova et al., 2023; Dennison et al., 2014; Holden et al., 2018; Parks and Abatzoglou, 2020).

Patch Size - We evaluated trends in area-weighted mean annual patch size by forest zone using an 8-cell neighborhood to define a patch. Area-weighted means weight each patch by their proportional contribution to the total area of all patches, and are generally preferred for ecological interpretations of mean patch size as they better reflect the largest patches present on the landscape (Li and Archer, 1997). Patch size trends were assessed for the high severity and unburned-low classes, and tested for statistical significance using T-S slope estimators. Because large patches often span designations, we did not evaluate patch size by land use allocation. We focused on high severity patches because they are associated with high (> 75%) tree mortality and can have strong effects on forest recovery and successional dynamics (Coop et al., 2020). We analyzed unburned-low patches (corresponding to areas that have likely experienced less than 25% overstory tree mortality, Miller and Thode, 2007) as they serve important functions as biological legacies (Johnstone et al., 2016; Meddens et al., 2018b), habitat refugia (Robinson et al., 2013), and are an important component of restoring fire-resilient structure and composition in dry forests (Becker and Lutz, 2016; Hood et al., 2015).

Core Area - The interior core area of high severity patches is often used as a proxy for understanding where forest regeneration may be threatened following wildfire due to distance from live seed sources at the patch edge (Collins et al., 2017a, 2017b; Stevens et al., 2017). We evaluated the core area of high severity patches by forest zone in CRs, LSRs, and matrix designations to understand how recent wildfires may influence post-fire successional dynamics. Because a single high severity patch may span multiple designations, this metric represents the *amount* of core area within a given land use allocation, and not necessarily the *size* of the entire patch core. We define core area as the interior of a high severity patch at least 120 m from the patch edge, where wind-driven seed dispersal for non-serotinous and relatively heavy-seed species such as ponderosa pine becomes unlikely (Clark et al., 1999). Because seed dispersal distances vary widely and can exceed 120 m for tree species with wind-borne seeds (Laughlin et al., 2023), we recognize our core area threshold as a conservative proxy for challenges to tree regeneration, particularly in moist forests.

Connectivity - Late successional reserves of the NWFP were arranged to provide a network of late-successional habitat connectivity for focal wildlife species such as the Northern Spotted Owl (NSO) (Johnson et al., 2023). In the dry forest zone, LSRs were designated in larger areas than in the moist forest zone to preserve a baseline level of wildlife habitat connectivity while anticipating that fires may alter or erode forest cover within reserves. Information on the connectivity of unburned-low patches can inform where habitat may have been retained following fire, and how it may have shifted over time. To evaluate post-fire patterns of potential habitat, we calculated an aggregation index for unburned-low patches of both dry and moist forest zone LSRs and tested for statistical significance of annual trends in aggregation using T-S slope estimators. The aggregation index is a unitless metric that measures the number of within-class patch adjacencies divided by the theoretical maximum possible number of adjacencies for that class (He et al., 2000; McGarigal and Marks, 1995).

3.3.4 Drivers of Fire Severity - Datasets

We evaluated drivers of fire severity as a function of predictor variables representing fuels, topography, and weather by forest zone separately in CRs, LSRs, and matrix designations (Table 3.2). Because many of our predictor variables included datasets derived from satellites with shorter temporal time spans or coarser spatial resolutions than Landsat (i.e., daily fire progression maps used to acquire weather variables are derived from MODIS satellite data and are not available before 2000), we constrained our models to the 407 large fires (> 500 ha) that burned between 2001 and 2021. We used continuous fire severity values from the Relativized Burn Ratio (Parks et al., 2014a) as the response variable in our models.

Table 3.2. Predictor variables used to assess drivers of fire severity by forest zone (dry versus moist) and land use allocation (congressional reserves, late successional reserves, and matrix designations).

Category	Variable	Source	Resolution
Topography	Topographic position index (TPI) fine - 270 m	(Evans and Murphy, 2021)	30 m
	TPI coarse - 2070 m	(Evans and Murphy, 2021)	30 m
	Slope	(Farr et al., 2007; Gorelick et al., 2017)	30 m
	Aspect	(Farr et al., 2007; Gorelick et al., 2017)	30 m
	Elevation	(Farr et al., 2007; Gorelick et al., 2017)	30 m
	Heat load index	(Evans and Murphy, 2021)	30 m
Forest structure	Cover type	(Rollins and Frame, 2006); see Appendix B, Table 3.4 for crosswalk	30 m
	Stand age of dominant trees (Stand age)	(Ohmann and Gregory, 2002)	30 m
	Component Ratio Method biomass of live trees (Biomass)	(Ohmann and Gregory, 2002)	30 m
	Canopy cover	(Ohmann and Gregory, 2002)	30 m
	Diameter diversity index (DDI)	(Ohmann and Gregory, 2002)	30 m
	Old growth structural index (OGSI)	(Ohmann and Gregory, 2002)	30 m
	Snag volume (Snag)	(Ohmann and Gregory, 2002)	30 m
	Time since most recent disturbance (Time since)	(Healey et al., 2018)	30 m
	Most recent disturbance type (Disturbance)	(Healey et al., 2018)	30 m
Weather	Wind velocity (Wind)	(Abatzoglou, 2013)	4km, downscaled to 30 m
	Vapor pressure deficit (VPD)	(Abatzoglou, 2013)	4km, downscaled to 30 m
	Energy resource component (ERC)	(Abatzoglou, 2013)	4km, downscaled to 30 m

Topographic datasets on elevation, slope, aspect, heat load index, and topographic position index (TPI) were generated for each fire derived from a 30-m digital elevation model (Farr et al., 2007). Slope and aspect were calculated using the terra package in R (Hijmans et al., 2024). Heat load index was calculated using the spatialEco package in R (Evans and Murphy, 2021) and derived from slope, aspect, and latitude following McCune and Keon (2002), where values near 0 represent cooler and wetter pixels and values near 1 represent warmer and drier pixels. TPI was calculated as the difference between the elevation of a given pixel and the mean surrounding elevation within a moving window surrounding the pixel; we calculated two separate TPI variables using a fine- (270 m) and coarse- (2070 m) scale moving window using the spatialEco package (Evans and Murphy, 2021).

We obtained variables on pre-fire canopy cover, biomass per hectare, stand age of dominant trees, snag volume, diameter diversity index, and old growth structural index (OGSI) developed as part of the NWFP Monitoring Program using the gradient nearest neighbor method which integrates Forest Inventory Analysis plots, spectral data, topographic data, and climate data (Ohmann et al., 2012; Ohmann and Gregory, 2002). We used a change attribution dataset developed by the Landscape Change Monitoring System (Healey et al., 2018) to map the most recent disturbance type prior to each fire (one of fire, harvest, insect/drought stress, other, or no detected disturbance) and years since the most recent disturbance. LCMS datasets are developed from spectral changes and are only available for the modern Landsat record; where no disturbance was detected since 1985, we used stand age from GNN to attribute years since the most recent disturbance. Finally, we incorporated a predictor variable for major forest type by grouping LANDFIRE Biophysical Settings potential vegetation types into broad categories of vegetation (Appendix B, Table 3.4, Rollins and Frame, 2006).

Information on daily fire weather was obtained by first producing MODIS-derived interpolated day-of-burn maps for each fire using a methodology developed by Parks (2014), then acquiring gridded surface meteorological data from GRIDMET (Abatzoglou, 2013) for the corresponding day and area burned. We used this workflow to produce downscaled 30-m maps of daily wind velocity, vapor pressure deficit (VPD), and energy resource component (ERC) for each fire. VPD is calculated as the difference between the amount of moisture in the atmosphere and the amount of maximum moisture it can hold and has strong effects on wildfire behavior (Abatzoglou and Williams, 2016), and ERC is a composite fuel moisture index and can be used to gauge fuel dryness.

3.3.5 Drivers of Fire Severity – Statistical Modeling

To minimize effects of short-distance spatial autocorrelation in our statistical models, we extracted mean response and predictor variables within a 3x3 pixel window on a grid of points spaced 270 m apart across the whole study area (Kane et al., 2015). We used tree-based Random Forest (RF) machine learning algorithms within the ranger package in R (Wright et al., 2023) to model relationships between our subsampled predictor datasets and RBR response variable. Separate RF models were constructed for each forest zone (dry versus moist) and land use allocation (CR, LSR, and matrix designations) for a total of six models. For each of the six models, we first evaluated predictor variable importance by running RF with all 18 predictor variables (Table 3.2) and calculating the percent increase in mean squared error (MSE) for each predictor variable present in the model. We then applied a variable selection for interpretation workflow implemented in the Variable Selection Using Random Forests (VSURF) package in R to refine our predictors (Genuer et al., 2015). A final set of RF models were run using only the selected predictors from the variable selection step and evaluated using out-of-bag error. We ran all RF models at each step using 1,000 bootstrapped samples in which one-third of the predictor variables were randomly selected and evaluated at each node split of the decision tree. We visualized relationships between individual predictor and response variables for each model using partial dependence plots. Lastly, we used Shapley additive explanation (SHAP) values to explore the local importance of our predictors at the individual pixel-level. SHAP values are based on cooperative game theory and, for each sample, quantify the impact of each predictor variable (positive or negative) on the response. To provide spatial nuance and contextualize our results, we created categorical maps of the most influential driver (greatest magnitude SHAP value, positive or negative) of severity at the pixel-level for a representative sample of fires. SHAP values were calculated using the treeShap package in R (Komisarczyk et al., 2024).

3.4 RESULTS

3.4.1 What have been the ecological effects of recent wildfires on NWFP forests across land use allocations and forest zones?

Between 1985 and 2022, over 3.6 million hectares of forest burned within the NWFP area, with most of that (90%) occurring in CRs, LSRs, and Matrix land allocations (Table 3.3). Within each of these allocations, the dry forest zone accounted for 4-5 times the area burned than the moist forest zone, with the greatest difference observed in CRs. The greatest fire activity was observed in dry forest CRs and dry forest LSRs – 67.5% (1,015,009 ha) of all dry forest CR area and 59.4% (853,469 ha) of dry forest LSR area burned over the study period. Over one-fifth (22%, 330,850 ha) of the total dry forest CR area – including burned and unburned area – experienced high severity fire effects, and 19% of the total dry forest LSR area (273,816 ha) experienced stand-replacing high severity fire. Of the moist forest zone land use allocations, the most area burned was in LSRs at

16.9% (241,083 ha). However, Matrix lands experienced the most severe proportional wildfire impacts in the moist first zone, with 5.4% of the total Matrix land area burning as high severity fire (60,197 ha).

Table 3.3. Area burned by severity class (in hectares) by land use allocation and major forest zone. Values in the "% total area burned" columns describe the proportion of area burned in each severity class as a function of total burned area - e.g., in dry forest zone Congressional Reserves, 27.5% of the total area burned was low severity effects. The next column ("% total CR area") describes the proportion of area burned in each severity class as a function of the total available area (both burned and unburned) in that forest zone and allocation - e.g., in dry forest zone Congressional Reserves, 18.5% of the entire area within dry forest zone Congressional Reserves burned with low severity effects. Table continues on the next page.

Congressional Reserves (CRs)

	Dry forest zone			Moist forest zone			All CRs		
	Area burned (ha)	% total area burned	% total CR area	Area burned (ha)	% total area burned	% total CR area	Area burned (ha)	% total area burned	% total CR area
Unburned/ Very Low	89,369	8.8	5.9	23,696	11.7	1.4	113,065	9.3	3.5
Low	278,636	27.5	18.5	46,771	23.2	2.8	325,407	26.7	10.2
Moderate	316,154	31.1	21.0	52,467	26.0	3.1	368,621	30.3	11.5
High	330,850	32.6	22.0	78,906	39.1	4.7	409,756	33.7	12.8
Total Area Burned	**1,015,009**	**-**	**67.5**	**201,839**	**-**	**11.9**	**1,216,848**	**-**	**38.1**
Total CR Area		**1,503,937**			**1,689,768**			**3,193,705**	

Late Successional Reserves (LSRs)

	Dry forest zone			Moist forest zone			All LSRs		
	Area burned (ha)	% total area burned	% total LSR area	Area burned (ha)	% total area burned	% total LSR area	Area burned (ha)	% total area burned	% total LSR area
Unburned/ Very Low	64,179	7.5	4.5	40,317	16.7	2.8	104,496	9.5	3.6
Low	240,742	28.2	16.7	80,670	33.5	5.6	321,412	29.4	11.2
Moderate	274,732	32.2	19.1	64,508	26.8	4.5	339,240	31.0	11.8
High	273,816	32.1	19.0	55,589	23.0	3.9	329,405	30.1	11.5
Total Area Burned	**853,469**	**-**	**59.4**	**241,083**	**-**	**16.9**	**1,094,552**	**-**	**38.2**
Total LSR Area		**1,437,790**			**1,430,048**			**2,867,838**	

Matrix

	Dry forest zone			Moist forest zone			All Matrix		
	Area burned (ha)	% total area burned	% total Matrix area	Area burned (ha)	% total area burned	% total Matrix area	Area burned (ha)	% total area burned	% total Matrix area
Unburned/ Very Low	47,140	6.4	3.0	31,836	17.6	2.9	78,977	8.6	3.0
Low	169,894	23.2	11.0	45,520	25.1	4.1	215,415	23.6	8.1
Moderate	248,895	34.0	16.1	43,771	24.1	3.9	292,666	32.0	11.0
High	266,472	36.4	17.2	60,197	33.2	5.4	326,668	35.8	12.3
Total Area Burned	**732,401**	**-**	**47.4**	**181,325**	**-**	**16.3**	**913,726**	**-**	**34.4**
Total Matrix Area	**1,545,594**			**1,110,071**			**2,655,665**		

From 1985 to 2022, annual area burned increased in each forest zone and land use allocation, with the greatest area burning in the last decade (Figure 3.2). In dry forests, fire activity was observed across the entire study period, with only 1995 and 1997 containing no area burned in dry forest CRs and dry forest LSRs, respectively. Relative to the dry forest zone, little fire activity was observed in moist zone forests from 1985 to 2015, with a pronounced increase in annual area burned between 2015 and 2022. Temporal trends in annual area burned were statistically significant in each forest zone and land use allocation per T-S slope estimators.

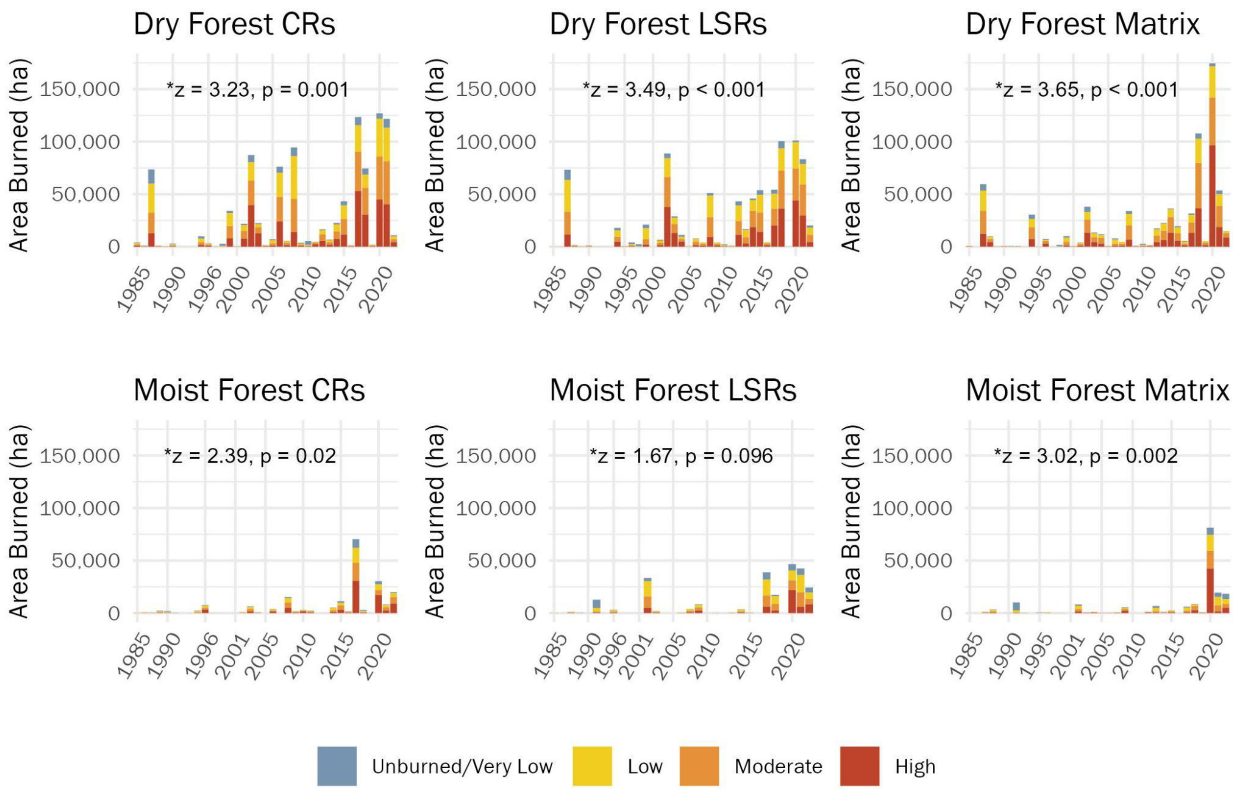

Figure 3.2. Trends in annual area burned by severity class in dry forest zone (top row) and moist forest zone (bottom row) across land use allocations. CRs - Congressional Reserves, leftmost column; LSRs - Late Successional Reserves, middle column; Matrix - Matrix land designation, rightmost column. Z statistic and p-value printed on plots represent model outputs from Theil-Sen slope estimators to assess statistically significant trends in annual area burned. Asterisks (*) represent plots with statistically significant trends. Statistical significance was assessed at $p < 0.1$ following previous studies (Dennison et al., 2014; Holden et al., 2018; Parks and Abatzoglou, 2020).

Area burned in the moist forest zone was concentrated in moist mixed conifer, moist conifer/rainforest, and cold forest cover types (Figure 3.3, Appendix B, Table 3.4), but represented an overall small proportion of the total forested area relative to the dry forest zone. In moist forest zone LSRs, for example, moist mixed conifer forests dominated by Douglas-fir, western hemlock, and Pacific silver fir burned 132,564 ha but accounted for only 26% of the total moist mixed conifer area within the allocation. In moist forest zone CRs and Matrix lands, less than 20% of the total area of moist conifer/rainforest and moist mixed conifer forest types burned over the study period, and less than 7% of this area burned with high severity effects.

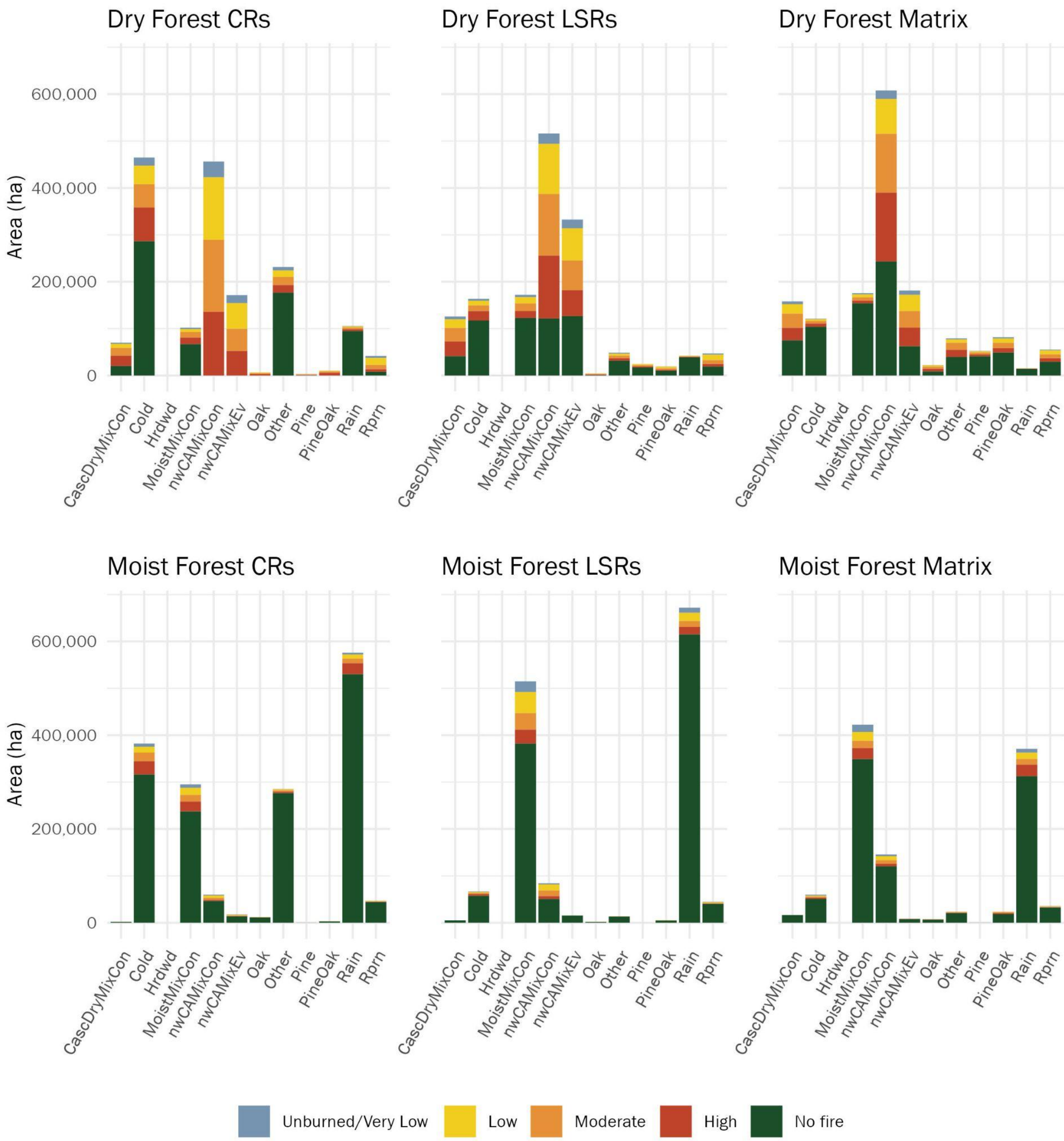

Figure 3.3. Area burned by severity class within each forest type by dry (top row) and moist (bottom row) forest zones and land use allocations (CRs: Congressional Reserves, left column, LSRs: Late Successional Reserves, middle column; Matrix: Matrix land allocation, right column). The height of each bar represents the total area (both burned and unburned) of each forest type. Dark green represents the area within that forest type that has not burned at all; the remaining colors are symbolized by severity class. CascDryMixCon - dry mixed conifer forests within the Cascade mountain range; Cold - cold forests; Hrdwd - hardwood forests;

MoistMixCon - moist mixed conifer forests; nwCAMixCon - mixed conifer forests in northwestern California; nwCAMixEv - mixed evergreen forests in northwestern California; Oak - oak woodlands, Other - non-forest or other forest; Pine - pine forests and savannas; PineOak - pine-oak woodlands, Rain - temperate rainforests; Rprn - riparian forests. For a full breakdown of these forest type groups, see Appendix B, Table 3.4.

Area burned was distributed over a wide variety of forest types in the dry forest zone (Figure 3.3). Although dry forest CRs are dominated by cold forests and northwest California (nwCA) mixed conifer cover types, we observed large (> 40,000 ha) extents of area burned in the Cascades dry mixed conifer, nwCA mixed conifer, cold forest, nwCA mixed evergreen, and 'other' cover types (where 'other' was dominated by high elevation barren rock, shrubland, and grassland, Appendix B, Table 3.4). Dry forest LSRs contained large areas burned in cold forests, moist mixed conifer, Cascades dry mixed conifer, nwCA mixed evergreen, and nwCA mixed conifer cover types. In dry forest Matrix land, large area burned was observed in the Cascades mixed conifer, nwCA mixed evergreen, and nwCA mixed conifer forest types. The greatest extent of high severity area burned in each dry forest zone allocation was the nwCA mixed conifer cover type, which burned 146,701 ha in Matrix, 135,659 ha in CRs, and 134,068 ha in LSRs.

We observed the greatest high severity impacts in pine-oak woodlands, oak woodlands, pine forests, nwCA mixed conifer, nwCA mixed evergreen, and Cascades dry mixed conifer forest types (Figure 3.3). Pine-oak woodlands in dry forest zone CRs experienced the greatest proportional impacts, where 61% of their total area within the allocation (both burned and unburned) burned at high severity. Over half (54%) of all oak woodlands within dry forest zone CRs burned with high severity effects, and 41% of nwCA mixed conifer extent in the allocation burned at high severity. In dry forest zone LSRs, oak woodlands had the greatest proportional impacts (32% of the total extent burned at high severity), followed by nwCA mixed conifer (26% burned at high severity) and Cascades dry mixed conifer (25% burned at high severity). In Matrix lands, 25% of all oak woodlands burned with high severity effects, and 24% of nwCA mixed conifer and 22% of nwCA mixed evergreen burned at high severity.

Mean high severity patch size increased over the study period in both dry and moist forest zones (Figure 3.4A). T-S model fits indicated a nearly 4-fold increase in dry forest zone mean high severity patch size (from 40.1 ha in 1985 to 154.1 ha in 2022), and a 6-fold increase in the moist forest zone (6.12 ha in 1985 to 39.79 ha in 2022). Both trends were statistically significant. In the moist forest zone, annual mean size of unburned-low severity patches (Figure 3.4B) significantly increased over the study period (from a predicted mean patch size of 5.3 ha in 1985 to 51.8 ha in 2022 per T-S models). There was no discernible trend in annual mean size of unburned-low severity patches in the dry forest zone over the study period. In dry forest zone LSRs, unburned-low severity patches grew increasingly disaggregated over the study period and trends were statistically significant (Figure 3.4C). There were no significant trends in aggregation of unburned-low severity patches in moist forest zone LSRs.

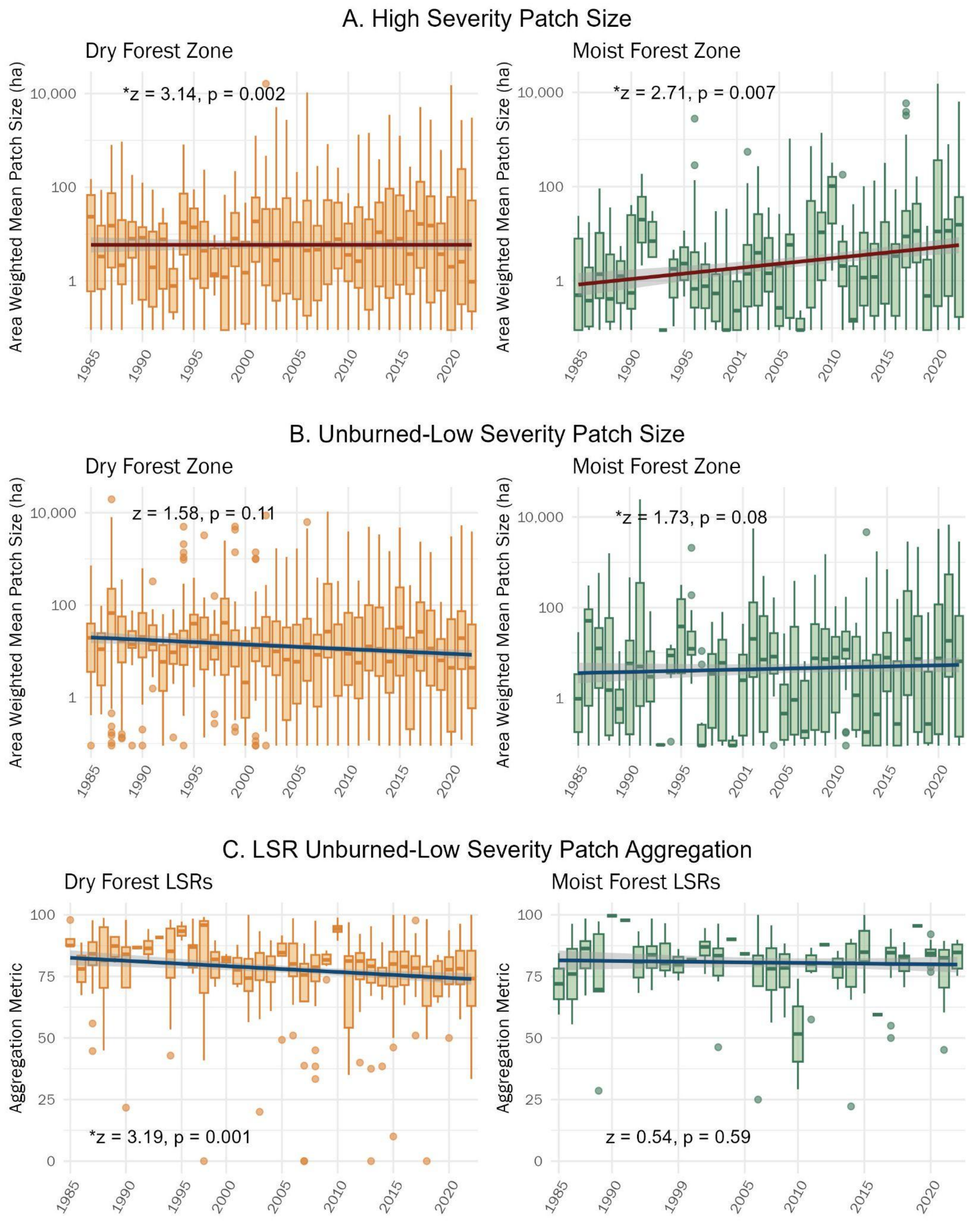

Figure 3.4. Patch configurations in dry forest zone (left column) and moist forest zone (right column) fires. Panel A (top row): Annual mean high severity patch size (area-weighted), regardless of land use allocation; Panel B (middle row): Annual mean size (area-weighted) of unburned and low severity patches combined, regardless of land use allocation; Panel C

(bottom row): Annual mean aggregation index of unburned and low severity patches combined in LSRs only. High aggregation index values indicate patches that are more aggregated; low index values indicate patches that are more isolated.

Across the study area, high severity interior core area was distributed in many small patches with relatively few large patches (Figure 3.5). Dry forest zone allocations overall contained both a greater number of patches and larger cumulative extent of high severity core area than moist forest zone allocations. Moist forest zones had generally wider patch size distributions (i.e., a relatively greater proportion of large patches) than dry forest zones. In all forest zones and allocations, a relatively small number of the largest patches accounted for the greatest cumulative area burned.

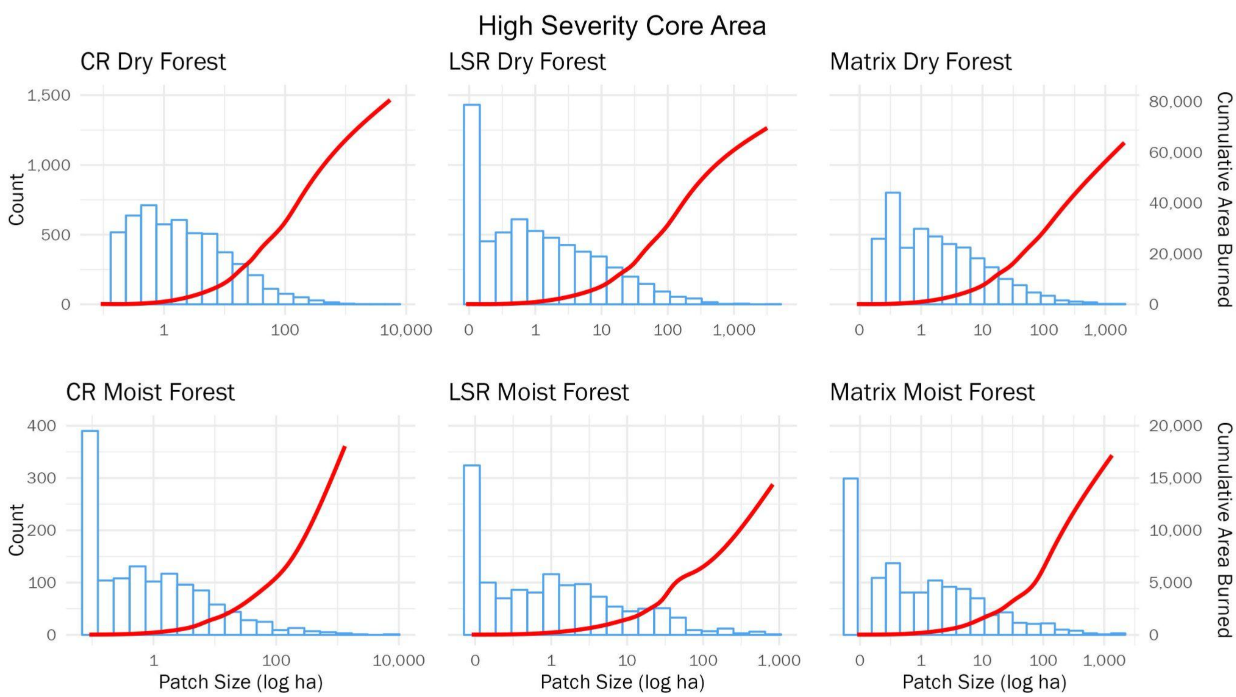

Figure 3.5. Histogram of high severity core area patches (left axis) and cumulative area burned within high severity core area (red line, right axis) by dry forest zone (top row) and moist forest zone (bottom row) by allocation. CR - congressional reserve; LSR - late successional reserve; Matrix - matrix designation. Note that a single contiguous high severity patch can span multiple designations - therefore "patch size" here does not necessarily refer to whole patches (i.e., a 100 ha patch present in LSR moist forests may actually be part of a larger 500 ha patch).

3.4.2 Within the NWFP area, what are the primary drivers (in terms of fire weather, fuels, and topography) of fire severity across land use allocations and forest zones?

Our variable selection workflow retained between 6 and 9 predictors for each final RF model (Figure 3.6). Weather variables (wind, VPD, and ERC) were the most important predictors of fire severity (RBR) in all models except for the dry forest zone CR model, in which cover type, elevation, biomass, and canopy cover were more important than weather. Wind was associated with the greatest increase in model MSE across the study area (116% in the moist forest Matrix model). Elevation was the second most important variable driving severity in the dry forest CR model, and the most important predictor after weather variables in all other models. Cover type was an important predictor in the dry forest CR (increasing MSE by 29.9%), dry forest LSR (16.3%), moist forest CR (35%), and moist forest Matrix models (13.3%). Time since the last pre-fire disturbance, biomass, and canopy cover were also important predictors across the study area, but exact order of importance varied by model. Coarse-scale TPI was selected as a final variable only in moist forest zone models, increasing MSE by 13.4% in moist CR, 12.1% in moist LSR, and 12.9% in moist Matrix models. DDI was only selected in the final model for moist forest CRs, increasing MSE by 17.6%. Aspect, fine scale TPI, most recent disturbance type, OGSI, heat load, and stand age were generally less important and were not selected in final models. RF models explained 55% of the variability in RBR across moist forest zone CRs, 44% in moist forest zone LSRs, 52% in moist forest zone Matrix, 39% in dry forest zone CRs, 43% in dry forest zone LSRs, and 50% in dry forest zone Matrix.

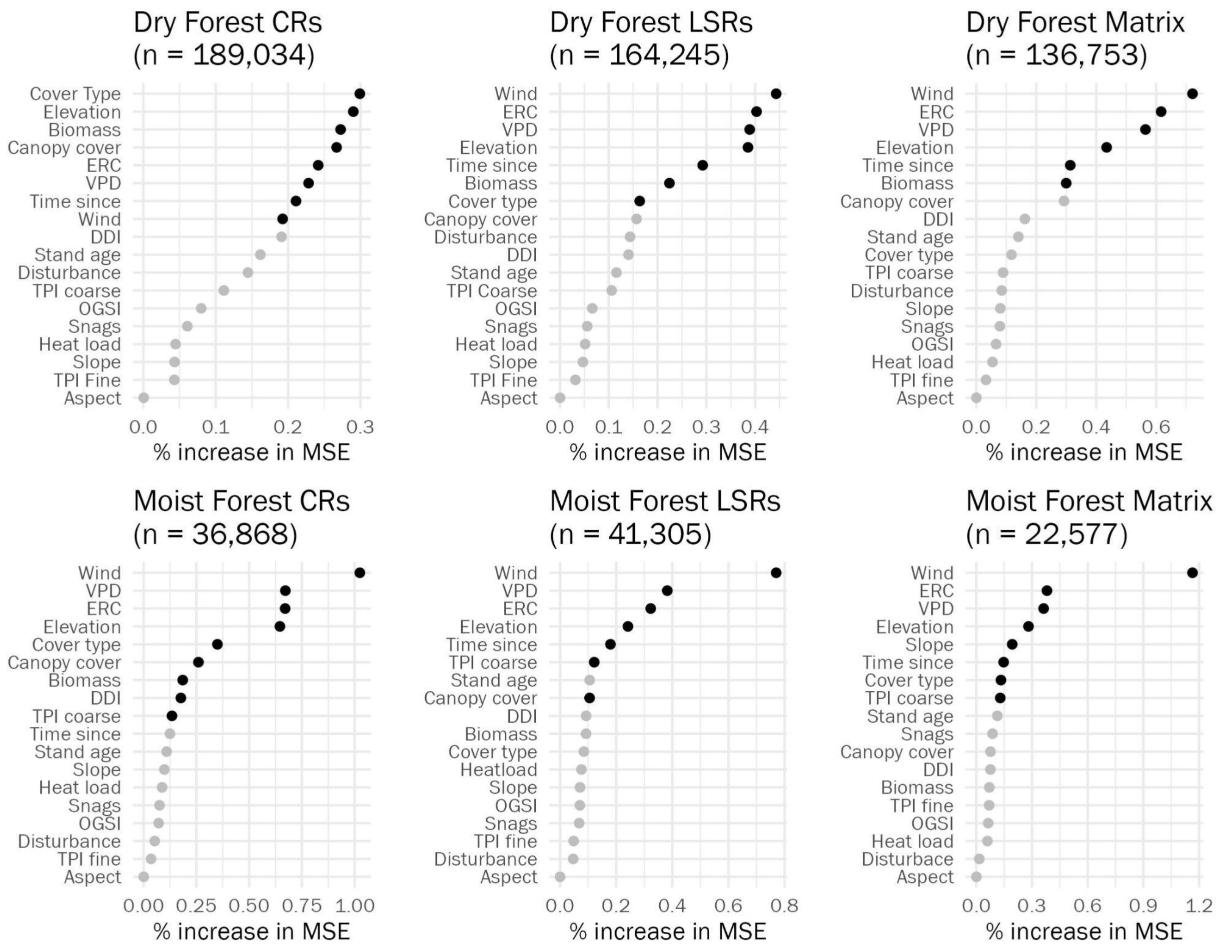

Figure 3.6. Variable importance plots for predictor variables from Random Forest (RF) models of RBR for dry forest (top row) and moist forest (bottom row) zones and allocations. Black circles denote variables retained in the variable selection process; gray circles denote variables removed from the final RF models during variable selection. ERC - energy resource component; VPD - vapor pressure deficit; Time since - time (years) since last pre-fire disturbance; DDI - diameter diversity index; TPI - topographic position index; OGSI - old growth structural index; MSE, Mean Squared Error.

Partial dependence plots revealed relationships between continuous predictor variables and our fire severity (RBR) response variable (Figure 3.7-Figure 3.12). In all models, RBR increased as wind velocity and VPD increased. Relationships between RBR and ERC across the study area were more variable – particularly at the tail ends of the distribution of ERC values – but suggested a general increase in severity as ERC increased across much of the study area. In all models, RBR generally increased with elevation, but tended to plateau or decrease above elevations around 2000 m (Figure 3.7, Figure 3.10). RBR steadily increased with pre-fire canopy cover in moist and dry forest zone CRs; in moist forest LSRs, RBR increased as canopy cover increased between 0 and 20%, plateaued between 20 and 80%, then increased again between 80 and 100% cover (Figure 3.8). In all models containing pre-fire biomass as a predictor, RBR increased with biomass up to 250,000 kg/ha, where severity then plateaued or decreased as biomass increased. RBR increased in all models as time since disturbance increased for the first 25 years. In moist forest models, RBR then decreased between 25-75 years following disturbance, then continually increased; in dry forest models, RBR continued to decrease with increasing time since disturbance after the first 25 years.

Relationships between RBR and cover type, a categorical predictor variable, were also described by the partial dependence plots (Figure 3.7, Figure 3.9, Figure 3.10, Figure 3.11). In moist forest zone models where cover type was selected as a final predictor (Matrix and CR), cold forests, moist mixed conifer, and rainforest cover types were associated with the highest severity. The 'other' cover type (dominated by high elevation shrublands and grasslands) was associated with high severity in the moist Matrix model, and Cascades dry mixed conifer forests were associated with high severity in the moist CR model, though both cover types represented a small proportion of total land area in each designation. In dry forest zone models, Cascades dry mixed conifer, cold forests, moist mixed conifer, and rainforests were associated with the greatest RBR values. Hardwood forests were additionally associated with high severity, but comprised less than 0.1% of the total area burned. Northwest California (nwCA) mixed conifer, nwCA mixed evergreen, oak woodlands, pine forests, pine-oak woodlands, and the 'other' category were also associated with increased RBR, though not to the extent of the aforementioned cover types.

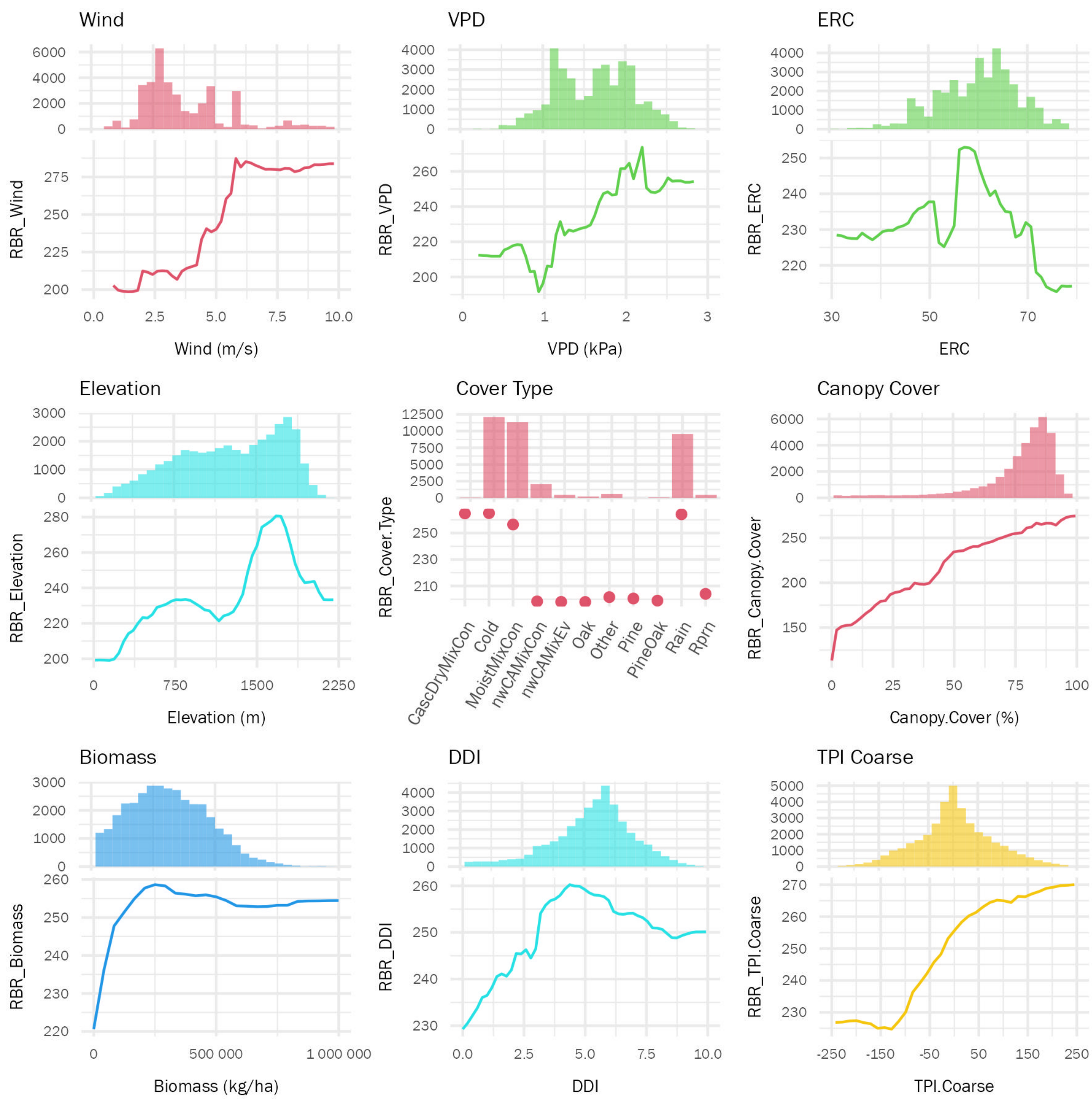

Figure 3.7. Partial dependence plots showing relationships between 9 predictor variables and fire severity (RBR) in the moist forest zone Congressional Reserve (CR) model.

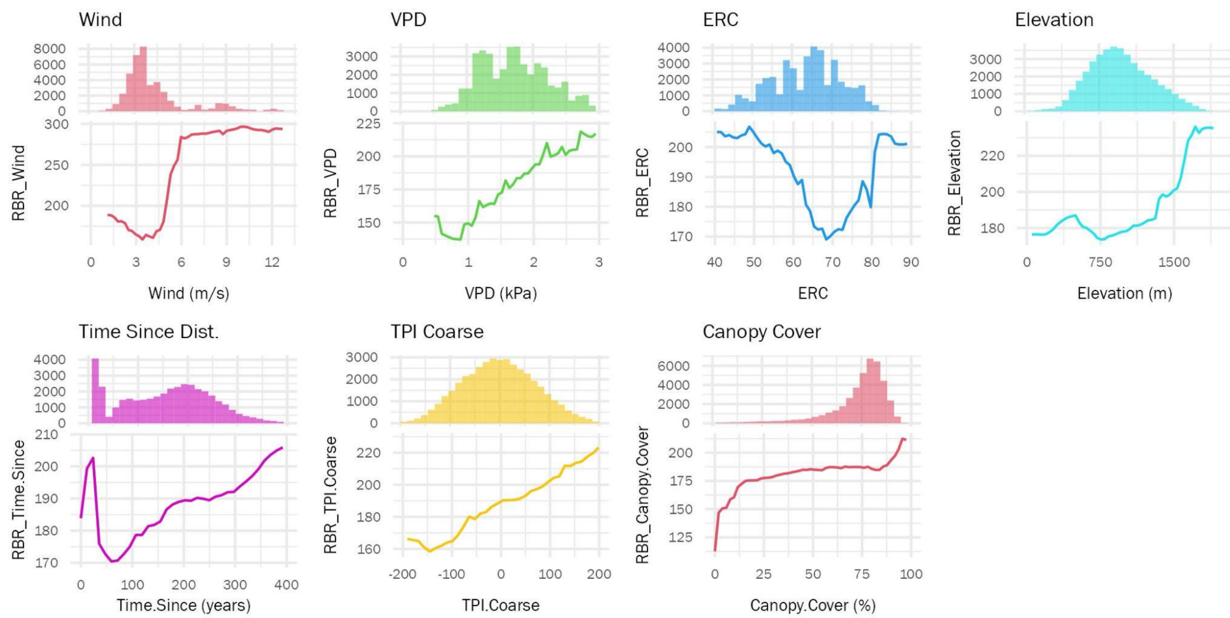

Figure 3.8. Partial dependence plots showing relationships between 7 predictor variables and fire severity (RBR) in the moist forest zone Late Successional Reserve (LSR) model.

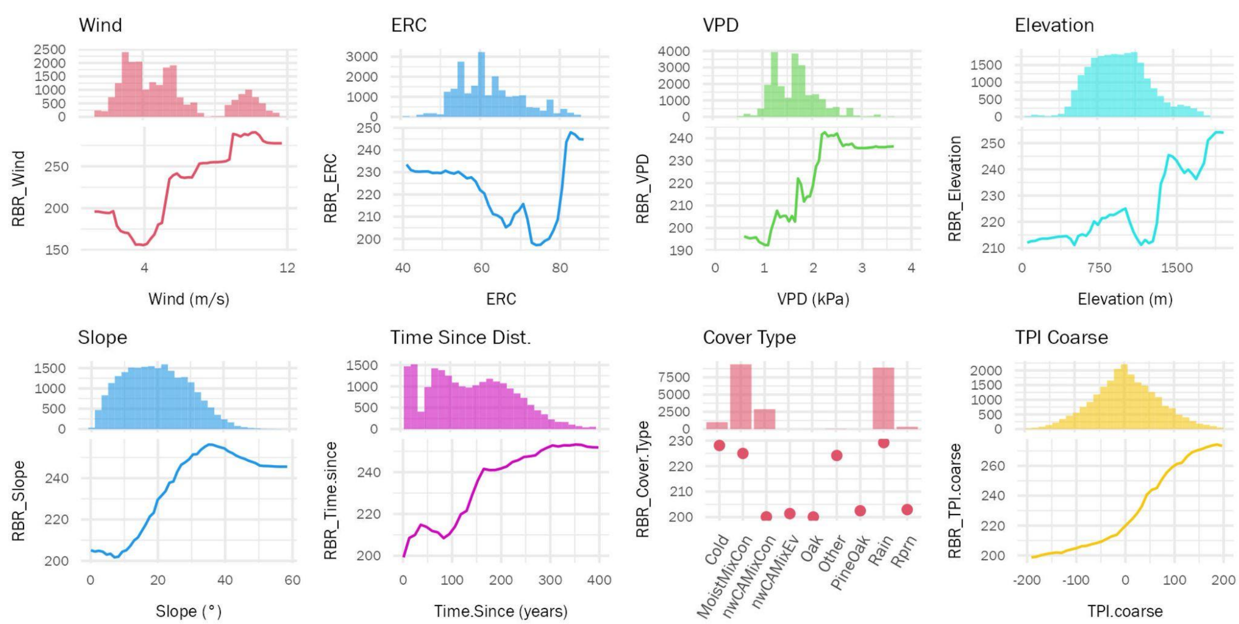

Figure 3.9. Partial dependence plots showing relationships between 8 predictor variables and fire severity (RBR) in the moist forest zone Matrix model.

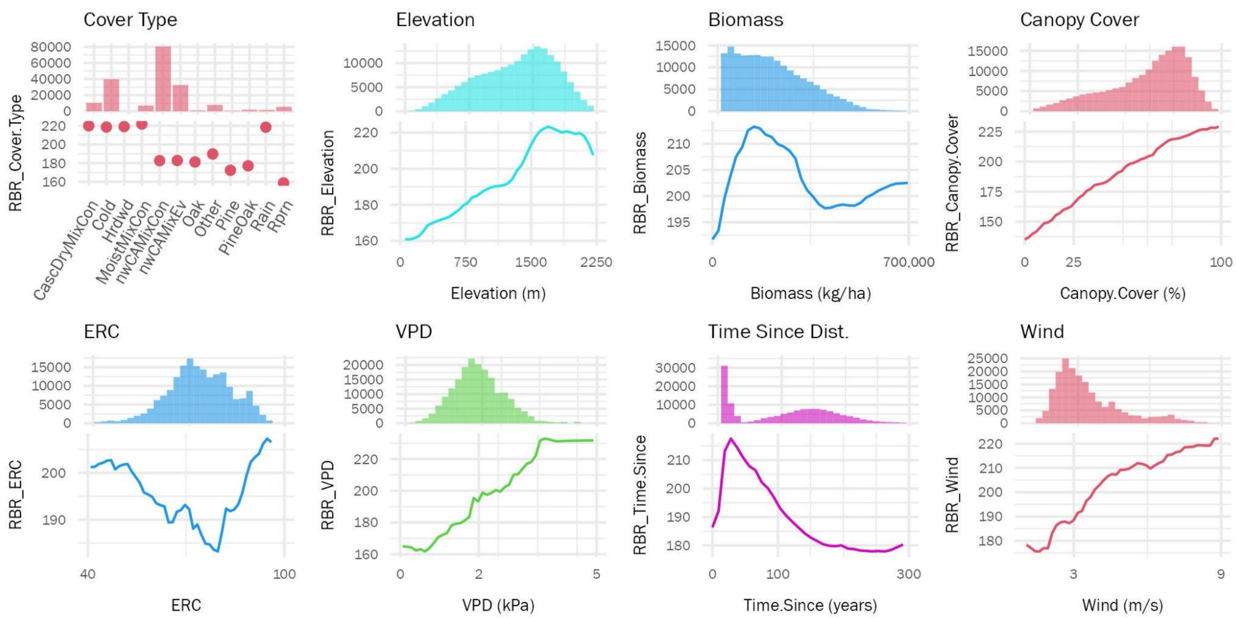

Figure 3.10. Partial dependence plots showing relationships between 8 predictor variables and fire severity (RBR) in the dry forest zone Congressional Reserve (CR) model.

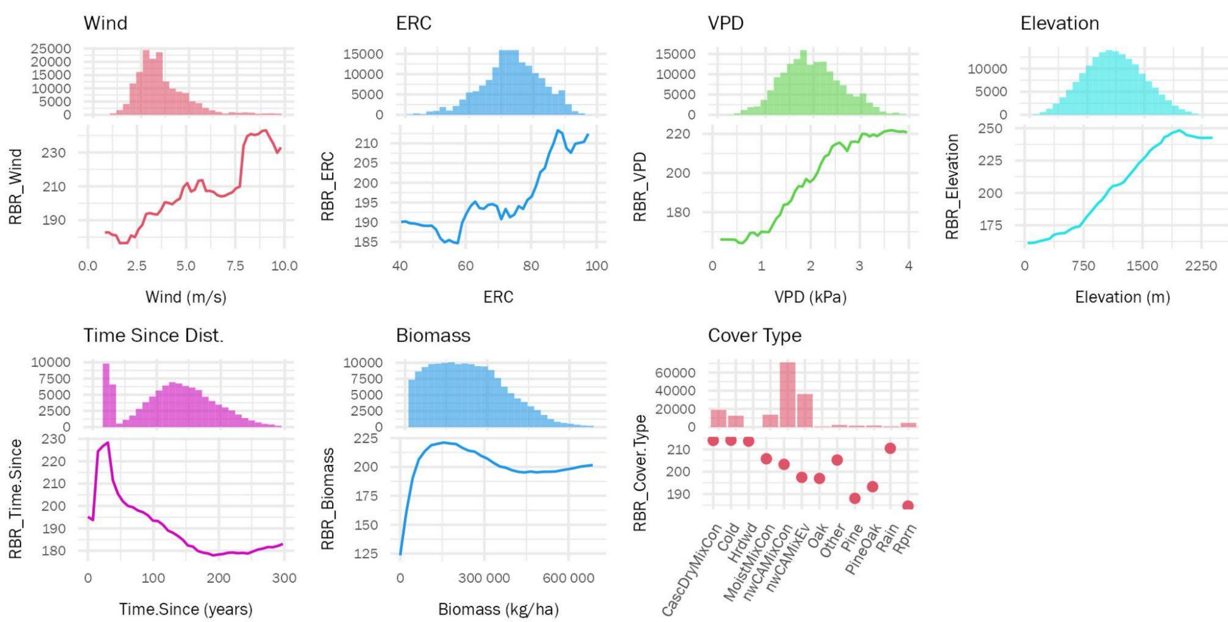

Figure 3.11. Partial dependence plots showing relationships between 7 predictor variables and fire severity (RBR) in the dry forest zone Late Successional Reserve (LSR) model.

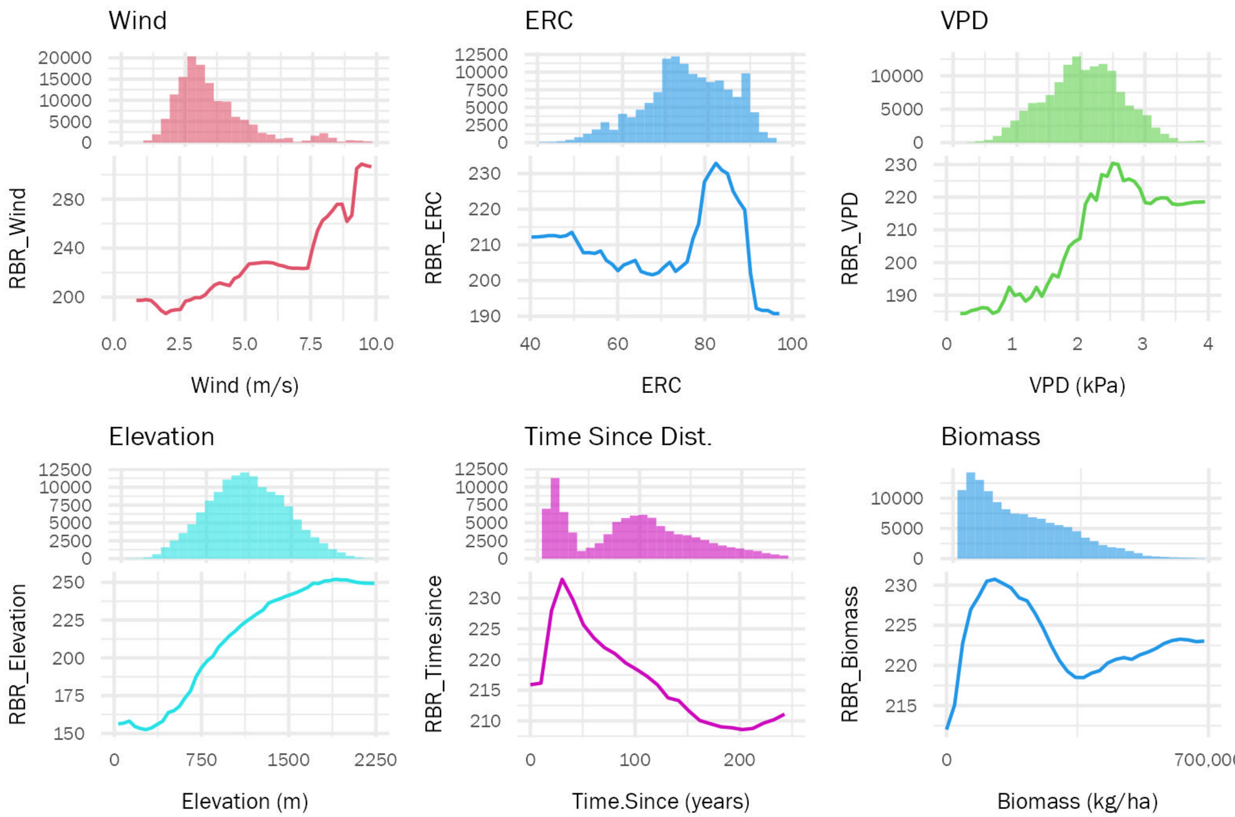

Figure 3.12. Partial dependence plots showing relationships between 6 predictor variables and fire severity (RBR) in the dry forest zone Matrix model.

Maps of SHAP values represent the pixel-level variability of local drivers of fire severity (Figure 3.13). While we observed that many large, high severity patches across the study area were associated with top-down weather drivers, local importance maps also revealed a diversity of bottom-up variables driving severity. In the 2020 Big Hollow fire, for example, large patches of high severity in moist forest zone LSRs were primarily associated with wind in a topographically complex landscape in the western Cascades of Washington (Figure 3.13A). By contrast, in the 2003 Booth fire in the eastern Cascades of Oregon, high severity patches in dry forest zone CRs were driven largely by pre-fire canopy cover and cover type on the leeward side of a large ridge (Figure 3.13B).

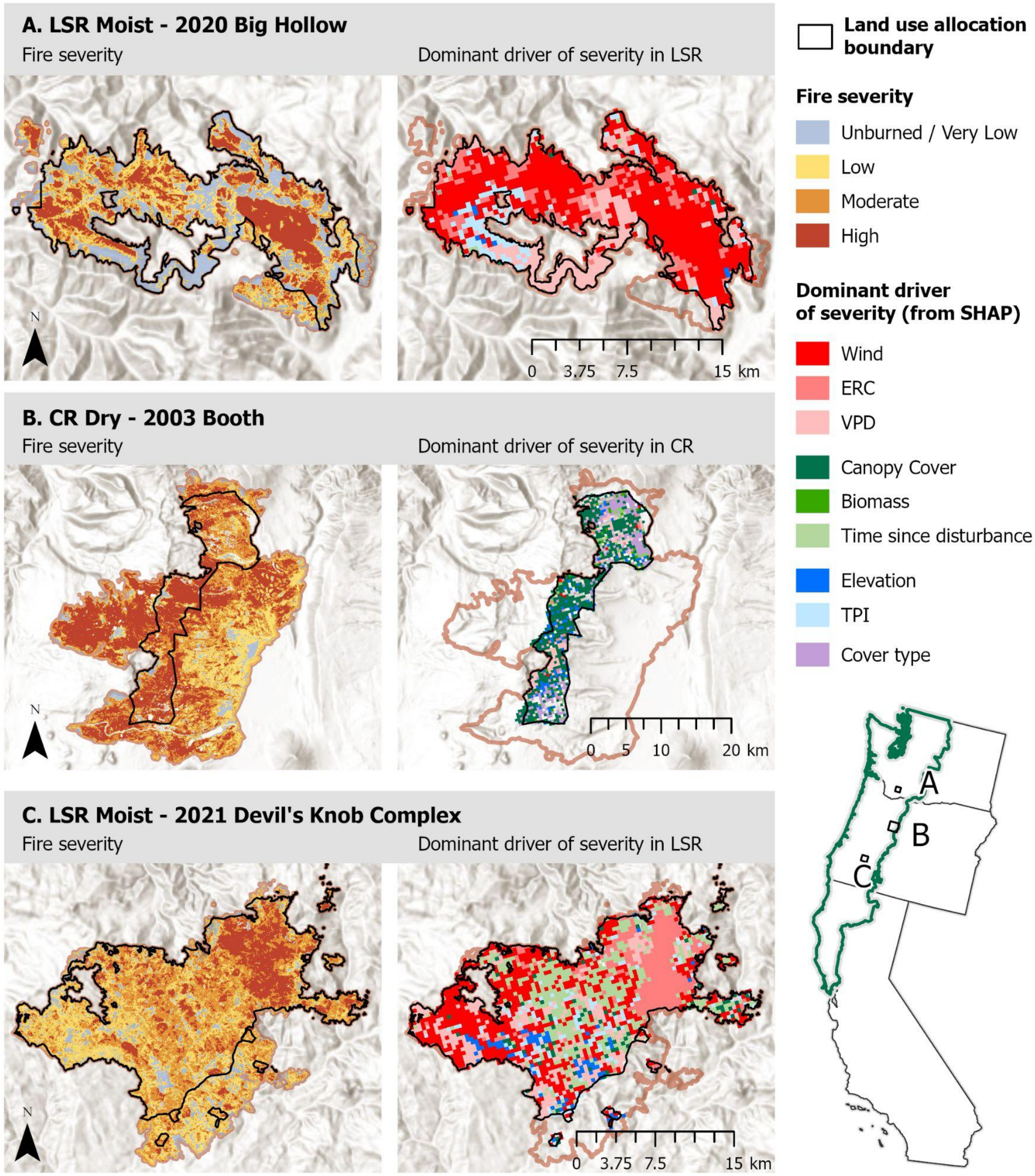

Figure 3.13. Fire severity (left panel) and locally dominant driver of severity at the pixel level (right panel) for three select fires according to SHAP values.

3.5 DISCUSSION

In this study, we examined patterns and drivers of severity in wildfires that have burned between 1985 and 2022 within the NWFP area. We observed significantly greater fire activity and more severe ecological effects in the dry forest zone than moist forest zone (Figure 3.2, Table 3.3), with trends in annual area burned and high severity in the dry forest zone mirroring those of frequent-fire forests in western North America more broadly (Cova et al., 2023; Harvey et al., 2016; Parks and Abatzoglou, 2020; Reilly et al., 2022). While the moist forest zone experienced relatively little fire for the first 30 years of the study period (Figure 3.2), we observed significant shifts in recent wildfire activity and high severity patch sizes that may continue under future climate change (Abatzoglou et al., 2021; Cullen et al., 2023; Rupp et al., 2017). We found that across the study area, forest types with historically frequent fire regimes such as pine-oak woodlands, oak woodlands, and dry mixed conifer forests have experienced the greatest impacts from stand-replacing fire (Figure 3.3), which have important implications for the adaptation of NWFP forests in a warmer climate. Finally, while weather variables were the most influential predictor of severity across much of the study area and exerted strong top-down controls, we observed evidence of bottom-up local controls such as pre-fire canopy cover, biomass, and cover type on severity across the study area.

3.5.1 What have been the ecological effects of recent wildfires on NWFP forests across land use allocations and forest zones?

The original NWFP recognized differences in historical disturbance regimes of dry and moist forests, and anticipated potential wildfire effects – especially in the dry forest zone – that could reduce forest cover and habitat associated with old and mature forest conditions (Franklin and Johnson, 2012). However, initial expected wildfire impacts were based on the area burned in preceding decades leading up to the Plan's adoption in 1994 (Davis et al., 2016, 2011), and did not explicitly account for how fire regimes may shift under a changing climate (Gaines et al., 2022). Past studies have connected trends in annual area burned with severe droughts and higher temperatures, both anticipated to intensify under continued climate change (Dennison et al., 2014; Westerling, 2016). Given that across the NWFP area, fire activity has significantly increased over the last four decades (Figure 3.2) and will likely continue to increase (Abatzoglou et al., 2021), our results suggest that effects of recent wildfires may outpace Plan expectations, especially in the dry forest zone. Within the NWFP area, the dry forest zone experienced substantially greater fire activity and extent of high severity effects from wildfire than the moist forest zone (Table 3.3), with over four times both the total area burned and total high severity area across CRs, LSRs, and Matrix lands.

Observed increases in mean high severity patch size (Figure 3.4A) may additionally challenge Plan expectations and existing reserves. Particularly in the dry forest zone, LSRs boundaries were delineated as contiguous areas designed to withstand large wildfire events over at least the first half century of the Plan, such that unburned portions could maintain a well-connected network of old forest conditions associated with northern spotted owl (NSO) habitat (Johnson et al., 2023). Increasingly large high severity patches – with single patches as large as 10,000 ha in some areas – may challenge this reserve design as multi-storied, closed-canopy forests that are highly valued for NSO habitat (Sovern et al., 2019) face rapid changes following stand-replacing fire and extensive tree mortality. Concomitant with increases in high severity patch size, forest patches that burned with low severity effects or were unburned following wildfire (unburned-low severity patches) grew increasingly disaggregated over the study period in the dry forest zone (Figure 3.4C). It is important to note that we did not evaluate the connectivity of unburned forest patches *outside* of known fire perimeters (i.e, all potential habitat). Likewise, unburned-low severity patches within fire perimeters may not always contain suitable old forest habitat because pre-fire forest conditions within LSRs are variable. However, under current trends, our results suggest that as more forested area burns, old and mature forest habitat will likely erode due to the combined influences of large stand replacing patches and increased fragmentation of unburned areas.

In the moist forest zone, large fire years were relatively rare in the first 30 years of the study period, but recent large wildfires have driven observed increases in annual burned area (Figure 3.2), mean high severity patch size (Figure 3.4A), and extent of high severity interior core area in CRs, LSRs, and Matrix designations (Figure 3.5). Although recent fires are largely consistent with historical fire regimes in the moist forest zone (Reilly et al., 2022), they have had important impacts to NWFP forests, particularly within LSRs. As a whole, only a small fraction (3.9%) of the total LSR network in the moist forest zone experienced stand replacing fire (Table 3.3). However, in some instances, the high severity effects that *did* occur affected large portions of entire LSR units. For example, in the Willamette and Mt. Hood National Forests of western Oregon, several large (>1,000 ha) LSR units burned almost entirely at high severity (Figure 3.14A). Further south in the footprint of the 2020 Archie Creek fire in the Oregon western Cascades, we observed 24 individual small (approx. 40 ha) LSRs burned completely as stand-replacing fire (Figure 3.14B). These severe wildfire effects to entire reserves have important implications for future Plan considerations. Specifically, designations of LSRs in the original Plan were largely driven by where remaining mature and old growth forests still existed following an extended period of widespread timber harvests, informed by the Interagency Scientific Committee's NSO conservation strategy (Thomas et al., 1990). Adapting the design and management of existing reserves may be necessary to meet Plan objectives amid substantial mature and old forest loss.

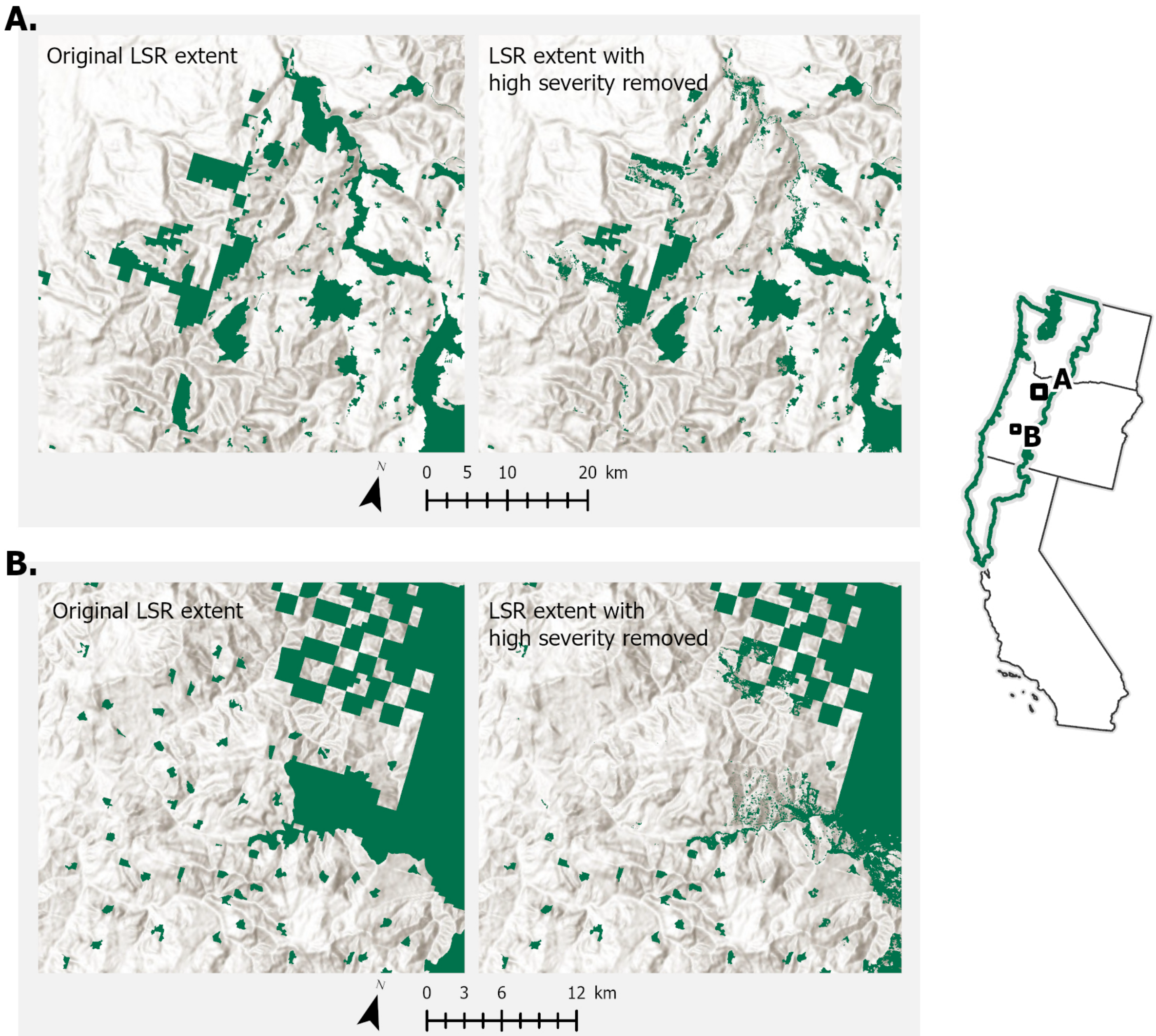

Figure 3.14. Extent of high severity fire effects on Late Successional Reserve (LSR) boundaries. Areas shown in dark green represent LSR designations. The left image of each panel shows the true extent of LSR designations, and the right image of each panel shows what that extent would look like if areas that have burned as high severity (stand-replacing) fire were removed. Panel A (top) shows an area near the Willamette and Mt. Hood National Forests in the Oregon western Cascades; Panel B (bottom) shows an area near the Umpqua National Forest in the Oregon western Cascades.

Oak woodlands, pine forests, pine-oak woodlands, and dry mixed conifer forests consistently had the greatest high severity impacts across the NWFP (Figure 3.3). In some areas – such as pine-oak woodlands in dry forest zone CRs – over half the total forest extent has been impacted by high severity fire. In dry forest types historically characterized by frequent, low-intensity fire regimes, large extents of stand-replacing effects represent significant departures from historical baselines (Agee, 1996; Hessburg et al., 2019; Skinner et al., 2018). In these ecosystems, frequent fire maintained by active Indigenous stewardship and natural lightning ignitions reduced understory fuels and maintained relatively open canopies and dynamic, heterogenous forest structures that conferred resilience to wildfire and drought (Agee, 2003; Chamberlain et al., 2023; Hagmann et al., 2013; Hessburg et al., 2019; Taylor and Skinner, 2003). Dry forests with restored structural characteristics and large, fire-resistant trees are likely to persist under climate change (Liang et al., 2017b; Murphy et al., 2021), but continued fire suppression and loss of cultural burning leave them increasingly vulnerable to conversion to non-forest vegetation (Collins et al., 2011; Coop et al., 2020; Kreider et al., 2024). Active stewardship and ecological restoration treatments to reduce fuels and mitigate severe wildfire risk are important strategies for conserving remaining old and mature dry forest types within the NWFP area (Kalies and Yocom Kent, 2016; Prichard et al., 2021), especially in culturally important and relatively rare ecosystems such as oak woodlands.

3.5.2 Within the NWFP area, what are the primary drivers (in terms of fire weather, fuels, and topography) of fire severity across land use allocations and forest zones?

Fire weather was a dominant driver of severity across much of the study area, with the exception of dry forest zone CRs, in which bottom-up variables associated with forest type, fuels, and topography were more important (Figure 3.6). Synoptic top-down weather patterns exert strong controls on fire behavior, and previous studies have linked increases in vapor pressure deficit (Mueller et al., 2020), wind speed (Prichard et al., 2020), and ERC (Parks et al., 2018a) to large fire growth and severe fire effects. While our findings are consistent with known drivers of severity in other regional studies (i.e., Cansler et al., 2022; Evers et al., 2022), this study evaluated drivers specifically in *large* fires, as 500 ha was the minimum fire size included in our models. Fires that burn under more moderate weather conditions are typically suppressed and remain small (Calkin et al., 2015; Katuwal et al., 2016), reinforcing a 'suppression bias' (*sensu* Kreider et al., 2024) in which fires typically burning under the most extreme conditions are able to grow large. Because of this, our fires – and therefore our model results – likely reflect more extreme weather conditions.

Despite this, bottom-up controls including vegetation cover type, elevation, pre-fire biomass, and pre-fire canopy cover all were more important drivers of fire severity than weather in dry forest zone CRs (Figure 3.6). Cascade dry mixed conifer, nwCA mixed conifer, and nwCA mixed evergreen forests experienced the most severe proportional fire impacts of the forest types present in dry forest zone CRs (Figure 3.3); total area burned in each forest type included 44%, 30%, and 30% high severity effects, respectively. Of these highly impacted forest types, severity increased particularly in Cascade dry mixed conifer forests (Figure 3.10), where the effects of climate change combined with fire exclusion and forest densification (Hessburg et al., 2019) have led to recent large wildfires that have rapidly homogenized forest structure with large extents of stand replacing effects and uncharacteristically large high severity patches (Cansler and McKenzie, 2014; Churchill et al., 2022). Although drivers of fire severity are partly related to broad gradients in climate and elevation (i.e., high-elevation cold forest types associated with stand-replacing fire regimes also burned at higher severity, Figure 3.10), dominance of bottom-up controls within dry forest zone CRs – where the use of prescribed and managed wildfires can be difficult to implement (Miller et al., 2020) – may reflect profound departures in the structure, function, and composition of dry forest types (Hagmann et al., 2021) exacerbated by the effects of climate change.

Strong top-down controls on fire severity were observed across much of the study area, and wind in particular was often the most important driver within large, high severity patches (Figure

3.13A). However, we also observed strong bottom-up controls on severity (Figure 3.13B). Maps produced from SHAP values – representing the unique influence of each predictor variable on the response at the pixel-scale – demonstrated a range of dominant local drivers. Even within regions where weather variables were the most important drivers at the full model level, we observed variation in local dominance of predictors associated with pre-fire fuels, topography, and forest structure. For example, in the moist forest zone LSR model, outside of the largest, wind-driven high severity patch in the 2021 Devil's Knob Complex fire (Figure 3.13C), time since disturbance, topography, and occasionally canopy cover were dominant drivers within smaller high severity patches along upper slopes and valley bottoms. As evidenced by studies on fuel treatment effectiveness, bottom-up controls can mitigate fire severity even under extreme weather conditions (Lydersen et al., 2017; Prichard et al., 2020). Reliance on global variable importance alone may mask signals from important – but underrepresented – fine-scale controls at local scales, and local variables may be important in small domains of a fire but have limited influence on global model results (Dormann et al., 2007; Prichard et al., 2020). Future work incorporating spatially explicit analyses of local drivers – while computationally intensive – may be important tools for fully understanding the strength of bottom-up controls to inform management strategies.

3.5.3 Management and Policy Implications

Adaptive management is the systematic and iterative process of planning and decision-making based on learned outcomes and monitoring that measure the effectiveness of existing management approaches (Holling, 1978). Investments in adaptive management within the NWFP supported a robust monitoring program (Davis et al., 2022, 2016, 2011), but enacting changes to management strategies with monitoring data has been difficult to implement in practice (Gaines et al., 2022; Spies et al., 2018c). To date, adaptive management has been challenging to fully administer due to funding, a legacy of distrust in active management, and staffing (Bormann et al., 2007; Spies et al., 2019, 2018b; Stankey et al., 2003).

Following decades of widespread timber harvest across much of the area, the NWFP was successful in protecting remaining old and mature forests from the threat of logging on federal lands, particularly within LSRs (Spies et al., 2018c). However, climate change and shifts in wildfire activity since the Plan's adoption have profoundly reshaped landscapes across the NWFP area and now threaten the future of old and mature forests (Table 3.3). While disturbances such as episodic drought, insect and pathogen outbreaks, and land development additionally threaten NWFP forests and will likely become increasingly severe under climate change (Halofsky et al., 2020), wildfire is currently the driving agent of forest change across the region (Davis et al., 2022, 2015). As fire frequency, extent, and severity is predicted to continue through at least the next half century (Abatzoglou et al., 2021; Dye et al., 2024; Parks et al., 2016), accounting for and anticipating the effects of wildfire will be critical to conserving forests under the NWFP.

Rapid erosion of mature and old forest cover over substantial portions – or in some cases, the entirety – of LSRs (Figure 3.14) poses grave concerns for critical wildlife habitat connectivity, climate refugia, and remaining old and mature forests (Spies et al., 2019). Current Plan objectives to promote multi-layered, dense forest structures within LSRs are largely in line with the disturbance ecology and historical old-growth forest structures within much of the broader moist forest zone (Agee, 1996; Spies et al., 2018a), but adjustments to the existing design and management of reserves may still be required to meet Plan goals. For example, within moist forest zone LSRs where old forest habitat has been affected by substantial high severity fire effects, managers could implement variable density thinning in remaining second-growth stands to accelerate the development of old growth structural conditions (Halofsky et al., 2018; Spies et al., 2019). Carefully reasoned and site-specific fire suppression may be required to protect old and mature forests from large, high severity fire effects (Halofsky et al., 2018). Where entire LSR units have been impacted by stand-replacing fire, management strategies could alternatively focus on adapting reserve boundaries to emphasize existing mature and old forest habitat on surrounding Matrix lands (Halsey, 2024). Plan revisions that instead ensure greater protection of mature and old forest patches within Matrix designations could additionally promote old forest habitat, independent of LSR boundaries. Alternatively, following the recommendations of the National Cohesive Wildland Fire Management Strategy (DOI and USDA, 2014), an 'all hands, all lands' approach to old and mature forest conservation across land ownerships and could sustain old and mature forests in the region.

In the dry forest zone, management strategies aimed at maximizing dense, multi-layered forest structures are generally inconsistent with maintaining ecological integrity in historically frequent-fire forests (Spies et al., 2019). In these systems, old forest conditions maintained by frequent-fire generally supported more open structures than what the current Plan emphasizes in LSRs, and consisted of large, old trees that served as anchors in a landscape of dynamically shifting burned and unburned areas (Hessburg et al., 2019, 2016). Ecological restoration in dry forest types – including the use of thinning, prescribed and cultural burning, and managed wildfire – can reduce fuel continuity, promote the retention of climate- and fire-resistant large trees, and restore historical fire regimes (Prichard et al., 2021). Restoration of fire- and climate-resilient forest structure and composition is especially relevant for forests that have already been profoundly impacted by high severity fire such as pine-oak woodlands and dry mixed conifer forests (Figure 3.3). Within reserves in the dry forest zone, adaptive management options could maintain existing LSR boundaries and implement proactive, continuous management to maintain ecological integrity and restore the role of frequent understory burning. As an alternative, retention and recruitment of large and old trees could be prioritized independent of land use allocations to promote their persistence through proactive treatments across a broader landscape (Hessburg et al., 2015).

Providing managers with the flexibility to manage wildfires under moderate weather conditions will be key to achieving landscape-scale restoration goals both within and outside the existing reserve network. Particularly in frequent-fire dry forests, the pace and scale of prescribed burning and mechanical treatments is below what is needed to restore forest landscapes across the broader west (North et al., 2021; Prichard et al., 2021). Despite profound high severity effects in NWFP dry zone forests (Figure 3.2, Table 3.3), recent fires have also done a substantial amount of 'work' to reshape forests at low and moderate severities. Low-to-moderate severity fire can have beneficial effects, shifting closed-canopy forests to more fire-resilient open structural conditions via understory fuel consumption and fire-induced thinning of mainly fire-intolerant small and medium-sized trees (Churchill et al., 2022; Lydersen et al., 2016). Allowing fires to burn under moderate weather conditions can maximize this work and accelerate achievement of restoration objectives (North et al., 2021), and has been adopted as an official management strategy in other dry forested regions including areas of the Sierra Nevada (Keeley et al., 2021). In fire-frequent areas that have already burned, allowing managers the flexibility to conduct post-fire fuel treatments such as removing remaining ladder fuels (Collins et al., 2018) and creating or accentuating tree spatial patterns associated with fire and climate resilience will be critical to maximize beneficial outcomes in subsequent fire events (Chamberlain et al., 2023; Churchill et al., 2013; Koontz et al., 2020; Stevens et al., 2021).

Lastly, a key challenge for managers will be identifying adaptive management 'triggers', or predetermined commitments to initiate a shift in management strategy if monitoring data reveals particular undesirable ecological outcomes (Nie and Schultz, 2012). Required management interventions can be difficult to recognize, especially as ecosystems experience "shifting baselines," in which accepted norms for environmental conditions gradually change (Pauly, 1995; Soga and Gaston, 2018). Evaluating trends in the spatial configurations of fire severity to understand impacts to old and mature forest habitat can be valuable tools for these assessments. For example, potential management triggers could incorporate monitoring of high severity patch size, proportion of high severity effects, or erosion of forest cover above a particular threshold (i.e., high severity impacts to greater than a specified proportion of a given forest type over a monitoring period). Indicators used as management triggers could be informed by pre-fire forest conditions, historical ranges of variability, and specific management goals. Assessments of these post-fire patterns at a watershed level can be particularly valuable, as mid-scales are small enough to understand changing local conditions and identify restoration needs and priorities, yet are large enough to evaluate cumulative effects and scale-down broad-scale management directives (Hessburg et al., 2013).

3.6 CONCLUSION

Wildfire has had profound effects on forests across the NWFP area. Across dry and moist forest zones and LSR, CR, and matrix land allocations, annual area burned and mean high severity patch size has significantly increased. The dry forest zone – dominated by dry mixed conifer forests in the Klamath Mountains and eastern Cascades, mixed evergreen forests, and cold forests at high elevations – faced the greatest fire activity in terms of total area burned. Dry mixed conifer forests and relatively rare, culturally important dry forest types such as pine-oak forests and oak woodlands were most severely impacted in terms of proportion of total forest extent burned at high severity. While the moist forest zone had relatively small area burned compared to dry forests, recent fires including the 2020 wildfires in western Oregon resulted in a large-scale erosion of forest cover, particularly in LSRs, with a substantial or complete loss of forest cover in smaller networks of reserves. Our results have important implications for NWFP revisions aimed at integrating adaptive management. We suggest that adapting the design and management of reserves, increased pre- and post-fire forest restoration activities, expansion of wildland fire use, and identification of adaptive management ‘triggers’ will be necessary to achieve Plan goals.

3.7 APPENDIX B: SUPPLEMENTARY MATERIAL

Table 3.4. Crosswalk of major forest types used to evaluate patterns of severity based on LANDFIRE Biophysical Settings potential vegetation types (Rollins and Frame, 2006). Note that not all forest types within this table have necessarily burned in recent fires and may not be included in models. nwCA = northwest California.

Major Forest Type	**LANDFIRE BPS Name**	**Hectares**
Cold forests and meadows	North Pacific Mountain Hemlock Forest-Wet	295,234
	Mediterranean California Red Fir Forest	290,109
	North Pacific Mountain Hemlock Forest-Xeric	251,349
	Northern Rocky Mountain Subalpine Woodland and Parkland	97,939
	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland	90,976
	Klamath-Siskiyou Upper Montane Serpentine Mixed Conifer Woodland	83,410
	North Pacific Maritime Mesic Subalpine Parkland	71,651
	Rocky Mountain Poor-Site Lodgepole Pine Forest	44,185
	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	18,718
	Northern California Mesic Subalpine Woodland	12,799
	Mediterranean California Subalpine Woodland	2,398
	Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	706
Cascade dry mixed conifer	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest	350,319
	North Pacific Dry Douglas-fir(-Madrone) Forest and Woodland	27,960
	Northern Rocky Mountain Foothill Conifer Wooded Steppe	630
Hardwood	Rocky Mountain Aspen Forest and Woodland	224
Moist conifer forest / rainforest	North Pacific Mesic Western Hemlock-Silver Fir Forest	779,418
	North Pacific Maritime Mesic-Wet Douglas-fir-Western Hemlock Forest	778,483
	North Pacific Hypermaritime Western Red-cedar-Western Hemlock Forest	148,083
	North Pacific Hypermaritime Sitka Spruce Forest	83,408

Moist mixed conifer	North Pacific Maritime Dry-Mesic Douglas-fir-Western Hemlock Forest	854,593
	North Pacific Dry-Mesic Silver Fir-Western Hemlock-Douglas-fir Forest	509,861
	East Cascades Mesic Montane Mixed-Conifer Forest and Woodland	323,080
Non-forest / other	Barren-Rock/Sand/Clay	217,800
	North Pacific Dry and Mesic Alpine Dwarf-Shrubland or Fell-field or Meadow	98,760
	California Montane Woodland and Chaparral	63,681
	North Pacific Alpine and Subalpine Dry Grassland	58,367
	Perennial Ice/Snow	57,017
	Northern and Central California Dry-Mesic Chaparral	35,510
	Open Water	34,691
	Northern California Coastal Scrub	17,601
	North Pacific Montane Shrubland	15,364
	California Mesic Chaparral	14,905
	Inter-Mountain Basins Big Sagebrush Steppe	13,998
	North Pacific Avalanche Chute Shrubland	13,000
	Columbia Plateau Steppe and Grassland	12,835
	North Pacific Montane Grassland	7,106
	North Pacific Swamp Systems	6,803
	North Pacific Sparsely Vegetated Systems	3,652
	Columbia Plateau Western Juniper Woodland and Savanna	3,048
	Inter-Mountain Basins Montane Sagebrush Steppe	2,515
	California Xeric Serpentine Chaparral	2,174
	Inter-Mountain Basins Curl-leaf Mountain Mahogany Woodland and Shrubland	2,093
	California Northern Coastal Grassland	1,484
	Inter-Mountain Basins Sparsely Vegetated Systems	1,197
	California Mesic Serpentine Grassland	947
	Rocky Mountain Alpine/Montane Sparsely Vegetated Systems	860

	Inter-Mountain Basins Big Sagebrush Shrubland	725
	North Pacific Broadleaf Landslide Forest and Shrubland	637
	North Pacific Wooded Volcanic Flowage	530
	Mediterranean California Sparsely Vegetated Systems	357
	Pacific Coastal Marsh Systems	352
	Columbia Plateau Low Sagebrush Steppe	288
	Columbia Plateau Scabland Shrubland	241
	California Maritime Chaparral	154
	Mediterranean California Subalpine Meadow	110
	Northern Rocky Mountain Montane-Foothill Deciduous Shrubland	104
	Inter-Mountain Basins Greasewood Flat	38
	NoData	16
	Inter-Mountain Basins Semi-Desert Grassland	7
	Great Basin Pinyon-Juniper Woodland	6
	Great Basin Semi-Desert Chaparral	3
	Northern Rocky Mountain Lower Montane-Foothill-Valley Grassland	1
nwCA mixed conifer	Mediterranean California Mesic Mixed Conifer Forest and Woodland	876,457
	Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	711,464
	Klamath-Siskiyou Lower Montane Serpentine Mixed Conifer Woodland	111,086
	California Coastal Redwood Forest	46,753
	Sierran-Intermontane Desert Western White Pine-White Fir Woodland	7,808
	California Coastal Closed-Cone Conifer Forest and Woodland	50
nwCA mixed evergreen	Mediterranean California Mixed Evergreen Forest-Interior	545,205
	Mediterranean California Mixed Evergreen Forest-Coastal	88,624
Oak savannas, woodlands, and forests	Mediterranean California Mixed Oak Woodland	38,799
	North Pacific Oak Woodland	10,100
	Willamette Valley Upland Prairie and Savanna	5,338
	California Coastal Live Oak Woodland and Savanna	617

Pine savannas, woodlands, and forests	Northern Rocky Mountain Ponderosa Pine Woodland and Savanna-Mesic	56,715
	California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	19,346
	Northern Rocky Mountain Ponderosa Pine Woodland and Savanna-Xeric	4,963
Pine-oak woodlands	Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	91,104
	East Cascades Oak-Ponderosa Pine Forest and Woodland	27,161
	California Lower Montane Blue Oak-Foothill Pine Woodland and Savanna	23,315
	Klamath-Siskiyou Xeromorphic Serpentine Savanna and Chaparral	3,150
Riparian	California Montane Riparian Systems	118,816
	North Pacific Lowland Riparian Forest and Shrubland	64,043
	North Pacific Montane Riparian Woodland and Shrubland-Wet	51,505
	North Pacific Montane Riparian Woodland and Shrubland-Dry	28,969
	Inter-Mountain Basins Montane Riparian Systems	10,415
	Rocky Mountain Montane Riparian Systems	186

CONCLUSION

Fire severity – the magnitude of ecological change caused by fire, often measured as proportion of vegetation killed – is an important component of fire regimes that shapes forest structure, habitat, carbon storage, and forest resilience to climate and subsequent fire. In the last half century, climate change and changes in land use have resulted in significant shifts in fire severity across many regions of western North America, threatening the persistence of forests and the cultural, ecological, and economic values they provide. As such, developing adaptive management strategies aimed at increasing social and ecological resilience to wildfire requires evaluation of the causes and consequences of shifting fire effects, and a deeper understanding of both the management *implications* as well as management *influences* on recent severity trends. In this dissertation, I quantified changing spatial patterns, trends, and drivers of fire severity in hundreds of fires that have burned across California, Oregon, and Washington forests over the last several decades to inform adaptive management. The key findings from this dissertation are presented below.

KEY FINDINGS

In Chapter 1, I analyzed trends, spatial patterns, and cumulative impacts of fire severity in over 1,800 wildfires to evaluate the role of large fires in shaping California forests. Observed increases in annual area burned over the last four decades have been met with steep trends in total annual core area burned at high severity, which may threaten post-fire tree regeneration and the persistence of forest cover under a warming climate (Coop et al., 2020). Recent large wildfires have had an outsized role in driving these trends – over the 36-year study period, the largest one percent of wildfires (n = 18) were responsible for 58% of the total area burned at high severity. Large fires contained overall greater proportions of stand-replacing effects than smaller fires, and in some instances contained single high severity patches as large as 20,000 hectares. These large patches may pose challenges to post-fire management to address the extensive tree mortality and risk of persistent ecotype conversion within them.

While large fires had an outsized impact on high severity trends, they also accounted for a large proportion of the total area burned with low and moderate severity effects across the study area. Low and moderate severity fire can result in reduced understory fuel loads and thinning of fire-intolerant trees, pushing closed canopy forests towards more open structural conditions associated with greater climate and wildfire resilience in dry forest types historically characterized by frequent fire (Kane et al., 2019). In California forests, 18 large wildfires accounted for 42% of the total area burned at low and moderate severity, which often burned in large patches over 1,000 hectares. In large low-to-moderate severity burn patches, managers could leverage the 'work' of these large wildfires (*sensu* Churchill et al., 2022) as an initial forest treatment to be followed by additional post-fire treatments to remove remaining ladder fuels and create or accentuate heterogeneous spatial patterns of trees and forest openings.

Chapter 2 of this dissertation evaluated drivers of fire severity to understand how existing forest management practices influenced fire effects in Sierra Nevada, northern California, Oregon, and Washington forests. I used a hierarchical modeling approach to first model severity at the individual fire level for hundreds of fires, then evaluated model results across the study area to assess general drivers of fire severity. Broad classes of land ownership and designation types – as a proxy for general management practices – had an important influence on fire severity and worked in concert with other bottom-up drivers to influence fire effects. Relative to other predictors describing pre-fire forest structure, topography, and fire weather, land ownership class was the strongest driver of severity at the scale of individual fire events, and moderated the importance of other drivers, even within the same fire. Private industrial forest lands that had reached greater canopy closure and likely had greater fuel continuity prior to wildfire were typically associated with higher fire severity relative to other land ownership types. In multi-ownership landscapes – which characterize many forested areas across western North America – these results underscore the need for cohesive strategies that prioritize shared wildfire governance across administrative boundaries.

Chapter 3 evaluated patterns and drivers of fire severity to inform adaptive management within the Northwest Forest Plan (NWFP), which specifies the management of federal forests across nearly 10 million hectares in northern California, Oregon, and Washington. Forests across both moist and dry forest zones within the NWFP area have been shaped by over 2,200 wildfires between 1985 and 2022, with increased trends in annual area burned and mean high severity patch size. Historically frequent-fire, dry forest types including mixed conifer forests, mixed evergreen forests, pine-oak woodlands, and oak woodlands have been most impacted by these trends – for example, in some areas, over half of the total extent of pine-oak woodlands have been affected by stand replacing fire. Management practices associated with continued fire suppression and departed forest conditions in frequent-fire forests were likewise associated with widespread areas of high severity fire effects. In the moist forest zone, total area burned was much lower compared to the dry forest zone, but recent wildfires – including the 2020 wildfires in western Oregon – contributed to the erosion of forest cover in large portions of late successional reserves.

Weather was a prominent driver of fire severity at regional scales within the NWFP, but bottom-up variables associated with pre-fire forest structure, fuels, and topography exerted strong local controls. Large high severity patches across both moist and dry forest zones within the study area were often associated with top-down weather predictors such as wind velocity, but within smaller patches, variables such as topographic position, pre-fire canopy cover, and pre-fire biomass often drove fire severity. These patterns were observed even within ecoregions where models indicated that weather variables were by far the most important drivers of fire severity; these results demonstrate that reliance on model variable importance alone to interpret drivers of fire severity can mask important signals at finer spatial scales or within smaller spatial domains. More broadly, the findings from this chapter suggest that across the area, adapting the design and management of existing reserves, increasing pre- and post-fire forest restoration activities, and implementing the use of managed wildfire will be necessary to achieve NWFP goals.

BROADER IMPLICATIONS

The observed trends, spatial patterns, and drivers of fire severity presented throughout this dissertation provide strong evidence that existing management approaches over much of the study area require revision to conserve forests under changing patterns of wildfire and accelerated climate change. In dry forest types that have been profoundly affected by stand-replacing fire, a key challenge for post-fire management will be addressing widespread tree mortality along with potential forest regeneration failures and ecotype conversions in large high severity patches. This will be especially critical under climate change, as future climate conditions may be untenable for restoring pre-fire forest structure and composition, and severe wildfire may catalyze sudden ecosystem changes (Coop et al., 2020; Stevens-Rumann et al., 2022).

Concomitant with the challenges presented by changing patterns of stand-replacing fire, recent trends also present a management opportunity to leverage low-to-moderate severity fire effects as an initial forest 'treatment', especially as much of the broader study area remains in an overall fire deficit, and the current pace and scale of restoration treatments such as prescribed burning and mechanical thinning are generally below the levels needed to restore fire-prone forests across the broader region (Hagmann et al., 2021; Kolden, 2019; North et al., 2015). Adopting the use of managed wildfire as an official policy and expanding its use under moderate weather conditions can maximize the ecological benefits of fire and serve as an important tool to support forest climate adaptation. Analyzing locally dominant drivers of severity at the pixel-scale – an emerging approach demonstrated in Chapter 3 – can provide important context about where bottom-up controls may mitigate fire severity outside of extreme, wind-driven burn days and inform where expanded managed wildfire use may be most effective. In dry forests, frequent managed wildfires can serve as a climate adaptation strategy to support the restoration of historically fire-resilient forest structure and composition (Chamberlain et al., 2023; Larson et al., 2013). In moist forests, managed wildfire under moderate conditions has been suggested as a tool to restore landscape diversity, heterogenous mosaics of forest cover, and early successional habitat, though the long-term climate adaptation benefits of managed wildfire are less clear than in dry forests (Halofsky et al., 2018).

Finally, implementing cohesive, cross-jurisdictional management strategies that prioritize long-term perspectives on forest management will be key to adapting forests to future conditions. A key novel finding of this dissertation is that management approaches tied to different land ownerships and land use allocations have strong influences on fire severity across a range of pre-fire environments, which has important implications for broad-scale forest management. Specifically, many fire-prone landscapes of the study region consist of multiple landowners with conflicting management objectives that prioritize short-term risk aversion (for example, fire suppression to protect property and commercial assets) over conducting forest restoration and fuel treatments that reduce long-term risk exposure to severe wildfire (Fischer et al., 2016). Because fires do not adhere to administrative boundaries, collaborations across ownerships and adaptive management of whole landscapes will be critical to improving wildfire outcomes. Under a more fire-prone future, analyzing the changing spatial patterns and drivers of fire severity across these ownerships will be an important tool for prioritizing and developing cohesive post-fire management strategies.

DIRECTIONS FOR FUTURE RESEARCH

This dissertation advances several lines of research within the field of landscape fire ecology. However, several key knowledge gaps remain that should be addressed in future work. First, it remains unclear what long-term ecological outcomes will be in large, contiguous areas recently affected by stand-replacing fire. While empirical studies and simulation models can provide insights into what successional dynamics *may* occur in these areas, future research to monitor and evaluate post-fire trajectories in large high severity patches is warranted to provide a deeper understanding of stand-replacing fire effects under a warming climate. Likewise, the degree to which current fire severity mapping protocols capture post-fire delayed tree mortality remains poorly understood. Quantifying this uncertainty is an emerging area of research (Busby et al., 2024; Reilly et al., 2023).

Additionally, while previous studies have associated low and moderate severity fire effects with creating and maintaining fire- and climate-resilient forest structures in frequent-fire forests (Chamberlain et al., 2023; Jeronimo et al., 2019; Kane et al., 2019), remotely sensed measurements of moderate severity can capture a range of post-fire changes, tree mortality, and vegetation conditions (Furniss et al., 2020). Similarly, measurements of fire severity can be sensitive to pre-fire canopy cover (Miller and Thode, 2007) and topographic setting (Harvey et al., 2019). Calibrating satellite-derived measurements of fire severity with information on pre-fire forest conditions and field plots to refine fire severity measurements is a critical research need to improve our understanding of fire effects. This is a research area where I, along with several others in the scientific community, intend to focus my efforts.

Finally, as demonstrated in this dissertation, evaluating fire severity is a critical component to developing adaptive management strategies. Despite the wealth of information the research community now has on past fire events, new fires will always occur, and may burn under unique forest conditions, following unique disturbance interactions, or under novel future climates. As such, understanding spatial patterns, trends, and drivers of fire severity will remain an important research endeavor in a disturbance-prone future under climate change.

REFERENCES

Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology 33, 121–131. https://doi.org/10.1002/joc.3413

Abatzoglou, J.T., Battisti, D.S., Williams, A.P., Hansen, W.D., Harvey, B.J., Kolden, C.A., 2021. Projected increases in western US forest fire despite growing fuel constraints. Communications Earth & Environment 2, 227. https://doi.org/10.1038/s43247-021-00299-0

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. PNAS 113, 11770–11775. https://doi.org/10.1073/pnas.1607171113

Agee, J.K., 2003. Historical range of variability in eastern Cascades forests, Washington, USA. Landscape Ecology 18, 725–740. https://doi.org/10.1023/B:LAND.0000014474.49803.f9

Agee, J.K., 1996. Fire Ecology of Pacific Northwest Forests. Island Press, Washington, D.C.

Agee, J.K., Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management, Relative Risk Assessments for Decision–Making Related to Uncharacteristic Wildfire 211, 83–96. https://doi.org/10.1016/j.foreco.2005.01.034

Anderson, M.K., Moratto, M.J., 1996. Native American land-use practices and ecological impacts, in: Sierra Nevada Ecosystem Project: Final Report to Congress. University of California, Centers for Water and Wildland Resources, Davis, CA, pp. 187–206.

Ayars, J., Emmet, R.L., Bassing, S.B., Sanderfoot, O.V., Raby, S., Karambelas, A., James, E.P., Ahmadov, R., Gardner, B., 2023. Camera traps link population-level activity patterns with wildfire smoke events for mammals in Eastern Washington State. Fire Ecology 19, 49. https://doi.org/10.1186/s42408-023-00207-1

Ayesh, R., 2020. Oregon governor: Wildfires are result of climate change and forest mismanagement Axios. https://www.axios.com/2020/09/13/oregon-wildfires-climate-change-forest-mismanagement (accessed 2.15.23).

Barbero, R., Abatzoglou, J.T., Steel, E.A., K Larkin, N., 2014. Modeling very large-fire occurrences over the continental United States from weather and climate forcing. Environmental Research Letters 9, 124009. https://doi.org/10.1088/1748-9326/9/12/124009

Barros, A.M.G., Day, M.A., Spies, T.A., Ager, A.A., 2021. Effects of ownership patterns on cross-boundary wildfires. Scientific Reports 11, 19319. https://doi.org/10.1038/s41598-021-98730-1

Becerril Salas, E., 2021. Exploring forest structure patterns among ownership and federal NWFP land use allocations in the forested western Cascades of Oregon (Thesis). University of Washington, Seatte, WA. https://digital.lib.washington.edu:443/researchworks/handle/1773/48034

Becker, K.M.L., Lutz, J.A., 2016. Can low-severity fire reverse compositional change in montane forests of the Sierra Nevada, California, USA? Ecosphere 7, e01484. https://doi.org/10.1002/ecs2.1484

Beguería, S., Pueyo, Y., 2009. A comparison of simultaneous autoregressive and generalized least squares models for dealing with spatial autocorrelation. Global Ecology and Biogeography - GLOBAL ECOL BIOGEOGR 18, 273–279. https://doi.org/10.1111/j.1466-8238.2009.00446.x

Bengtsson, J., Angelstam, P., Elmqvist, T., Emanuelsson, U., Folke, C., Ihse, M., Moberg, F., Nyström, M., 2003. Reserves, Resilience and Dynamic Landscapes. ambi 32, 389–396. https://doi.org/10.1579/0044-7447-32.6.389

Bigelow, S.W., North, M.P., 2012. Microclimate effects of fuels-reduction and group-selection silviculture: Implications for fire behavior in Sierran mixed-conifer forests. Forest Ecology and Management 264, 51–59. https://doi.org/10.1016/j.foreco.2011.09.031

Binkley, C.S., Aronow, M.E., Washburn, C.L., New, D., 2005. Global Perspectives on Intensively Managed Plantations: Implications for the Pacific Northwest. Journal of Forestry 103, 61–64. https://doi.org/10.1093/jof/103.2.61

Birch, D.S., Morgan, P., Kolden, C.A., Abatzoglou, J.T., Dillon, G.K., Hudak, A.T., Smith, A.M.S., 2015. Vegetation, topography and daily weather influenced burn severity in central Idaho and western Montana forests. Ecosphere. 6(1): Article 17. 6. https://doi.org/10.1890/ES14-00213.1

Birch, D.S., Morgan, P., Kolden, C.A., Hudak, A.T., Smith, A.M.S., 2014. Is proportion burned severely related to daily area burned? Environmental Research Letters 9, 064011. https://doi.org/10.1088/1748-9326/9/6/064011

Bond, W.J., Woodward, F.I., Midgley, G.F., 2005. The global distribution of ecosystems in a world without fire. New Phytologist 165, 525–538. https://doi.org/10.1111/j.1469-8137.2004.01252.x

Bormann, B.T., Haynes, R.W., Martin, J.R., 2007. Adaptive management of forest ecosystems: Did some rubber hit the road? BioScience 57, 186–191. https://doi.org/10.1641/B570213

Bowman, D.M.J.S., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., D'Antonio, C.M., DeFries, R.S., Doyle, J.C., Harrison, S.P., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., Kull, C.A., Marston, J.B., Moritz, M.A., Prentice, I.C., Roos, C.I., Scott, A.C., Swetnam, T.W., van der Werf, G.R., Pyne, S.J., 2009. Fire in the Earth System. Science 324, 481–484. https://doi.org/10.1126/science.1163886

Bradshaw, L.S., Deeming, J.E., Burgan, R.E., Cohen, J.D., 1984. The 1978 National Fire-Danger Rating System: Technical Documentation (General Technical Report No. 169). U.S. Forest Service, Intermountain Forest and Range Experiment Station. Ogden, UT. https://doi.org/10.2737/INT-GTR-169

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32. https://doi.org/10.1023/A:1010933404324

Brodie, E.G., Knapp, E.E., Brooks, W.R., Drury, S.A., Ritchie, M.W., 2024. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. Fire Ecology 20, 17. https://doi.org/10.1186/s42408-023-00241-z

Busby, G., Albers, H.J., 2010. Wildfire risk management on a landscape with public and private ownership: Who pays for protection? Environmental Management. 45: 296-310 45, 296–310. https://doi.org/10.1007/s00267-009-9381-x

California Department of Forestry and Fire Protection (CAL FIRE), 2022. Top 20 Largest California Wildfires. https://www.fire.ca.gov/media/4jandlhh/top20_acres.pdf

California Department of Forestry and Fire Protection (CAL FIRE), 2019. California Land Ownership. https://hub-calfire-forestry.hub.arcgis.com/datasets/f73858e200634ca888b19ca8c78e3aed_0/

Calkin, D.E., Cohen, J.D., Finney, M.A., Thompson, M.P., 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. PNAS. 111(2): 746-751. 746–751. https://doi.org/10.1073/pnas.1315088111

Calkin, D.E., Thompson, M.P., Finney, M.A., 2015. Negative consequences of positive feedbacks in US wildfire management. Forest Ecosystems 2, 9. https://doi.org/10.1186/s40663-015-0033-8

Cansler, C.A., Kane, V.R., Hessburg, P.F., Kane, J.T., Jeronimo, S.M.A., Lutz, J.A., Povak, N.A., Churchill, D.J., Larson, A.J., 2022. Previous wildfires and management treatments moderate subsequent fire severity. Forest Ecology and Management 504, 119764. https://doi.org/10.1016/j.foreco.2021.119764

Cansler, C.A., McKenzie, D., 2014. Climate, fire size, and biophysical setting control fire severity and spatial pattern in the northern Cascade Range, USA. Ecological Applications 24, 1037–1056. https://doi.org/10.1890/13-1077.1

Chamberlain, C.P., Cova, G.R., Cansler, C.A., North, M.P., Meyer, M.D., Jeronimo, S.M.A., Kane, V.R., 2023. Consistently heterogeneous structures observed at multiple spatial scales across fire-intact reference sites. Forest Ecology and Management 550, 121478. https://doi.org/10.1016/j.foreco.2023.121478

Charnley, S., Fischer, A.P., Jones, E.T., 2008. Traditional and local ecological knowledge about forest biodiversity in the Pacific Northwest. Gen. Tech. Rep. PNW-GTR-751. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 52 p. 751. https://doi.org/10.2737/PNW-GTR-751

Charnley, S., Kelly, E.C., Fischer, A.P., 2020. Fostering collective action to reduce wildfire risk across property boundaries in the American West. Environ. Res. Lett. 15, 025007. https://doi.org/10.1088/1748-9326/ab639a

Churchill, D.J., Jeronimo, S.M.A., Hessburg, P.F., Cansler, C.A., Povak, N.A., Kane, V.R., Lutz, J.A., Larson, A.J., 2022. Post-fire landscape evaluations in Eastern Washington, USA: Assessing the work of contemporary wildfires. Forest Ecology and Management 504, 119796. https://doi.org/10.1016/j.foreco.2021.119796

Churchill, D.J., Larson, A.J., Dahlgreen, M.C., Franklin, J.F., Hessburg, P.F., Lutz, J.A., 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. Forest Ecology and Management 291, 442–457. https://doi.org/10.1016/j.foreco.2012.11.007

Clark, J.S., Silman, M., Kern, R., Macklin, E., HilleRisLambers, J., 1999. Seed Dispersal Near and Far: Patterns Across Temperate and Tropical Forests. Ecology, 80(5), 1999, pp. 1475-1494.

Collins, B.M., Everett, R.G., Stephens, S.L., 2011. Impacts of fire exclusion and recent managed fire on forest structure in old growth Sierra Nevada mixed-conifer forests. Ecosphere. 2(4): 1-14 2, 1–14. https://doi.org/10.1890/ES11-00026.1

Collins, B.M., Fry, D.L., Lydersen, J.M., Everett, R., Stephens, S.L., 2017a. Impacts of different land management histories on forest change. Ecological Applications 27, 2475–2486. https://doi.org/10.1002/eap.1622

Collins, B.M., Kelly, M., van Wagtendonk, J.W., Stephens, S.L., 2007. Spatial patterns of large natural fires in Sierra Nevada wilderness areas. Landscape Ecol 22, 545–557. https://doi.org/10.1007/s10980-006-9047-5

Collins, B.M., Lydersen, J.M., Everett, R.G., Stephens, S.L., 2018. How does forest recovery following moderate-severity fire influence effects of subsequent wildfire in mixed-conifer forests? Fire Ecology 14, 3. https://doi.org/10.1186/s42408-018-0004-x

Collins, B.M., Roller, G.B., 2013. Early forest dynamics in stand-replacing fire patches in the northern Sierra Nevada, California, USA. Landscape Ecol 28, 1801–1813. https://doi.org/10.1007/s10980-013-9923-8

Collins, B.M., Stevens, J.T., Miller, J.D., Stephens, S.L., Brown, P.M., North, M.P., 2017b. Alternative characterization of forest fire regimes: incorporating spatial patterns. Landscape Ecol 32, 1543–1552. https://doi.org/10.1007/s10980-017-0528-5

Cook, B.I., Mankin, J.S., Anchukaitis, K.J., 2018. Climate Change and Drought: From Past to Future. Curr Clim Change Rep 4, 164–179. https://doi.org/10.1007/s40641-018-0093-2

Coop, J.D., DeLory, T.J., Downing, W.M., Haire, S.L., Krawchuk, M.A., Miller, C., Parisien, M.-A., Walker, R.B., 2019. Contributions of fire refugia to resilient ponderosa pine and dry mixed-conifer forest landscapes. Ecosphere 10, e02809. https://doi.org/10.1002/ecs2.2809

Coop, J.D., Parks, S.A., Stevens-Rumann, C.S., Crausbay, S.D., Higuera, P.E., Hurteau, M.D., Tepley, A., Whitman, E., Assal, T., Collins, B.M., Davis, K.T., Dobrowski, S., Falk, D.A., Fornwalt, P.J., Fule, P.Z., Harvey, B.J., Kane, V.R., Littlefield, C.E., Margolis, E.Q., North, M., Parisien, M.-A., Prichard, S., Rodman, K.C., 2020. Wildfire-driven forest conversion in western North American landscapes. BioScience. 70(8): 659-673. 70, 659–673. https://doi.org/10.1093/biosci/biaa061

Coop, J.D., Parks, S.A., Stevens-Rumann, C.S., Ritter, S.M., Hoffman, C.M., Varner, J.M., 2022. Extreme fire spread events and area burned under recent and future climate in the western USA. Global Ecol Biogeogr geb.13496. https://doi.org/10.1111/geb.13496

Coppoletta, M., Merriam, K.E., Collins, B.M., 2016. Post-fire vegetation and fuel development influences fire severity patterns in reburns. Ecological Applications 26, 686–699. https://doi.org/10.1890/15-0225

Cova, G., Kane, V.R., Prichard, S., North, M., Cansler, C.A., 2023. The outsized role of California's largest wildfires in changing forest burn patterns and coarsening ecosystem scale. Forest Ecology and Management 528, 120620. https://doi.org/10.1016/j.foreco.2022.120620

Cullen, A.C., Prichard, S.J., Abatzoglou, J.T., Dolk, A., Kessenich, L., Bloem, S., Bukovsky, M.S., Humphrey, R., McGinnis, S., Skinner, H., Mearns, L.O., 2023. Growing convergence research: Coproducing climate projections to inform proactive decisions for managing simultaneous wildfire risk. Risk Analysis 43, 2262–2279. https://doi.org/10.1111/risa.14113

Dai, A., 2013. Increasing drought under global warming in observations and models. Nature Climate Change 3, 52–58. https://doi.org/10.1038/nclimate1633

Davis, K.T., Dobrowski, S.Z., Higuera, P.E., Holden, Z.A., Veblen, T.T., Rother, M.T., Parks, S.A., Sala, A., Maneta, M.P., 2019. Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. Proceedings of the National Academy of Sciences 116, 6193–6198. https://doi.org/10.1073/pnas.1815107116

Davis, K.T., Peeler, J., Fargione, J., Haugo, R.D., Metlen, K.L., Robles, M.D., Woolley, T., 2024. Tamm review: A meta-analysis of thinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. Forest Ecology and Management. 561: 121885. 581, 121885. https://doi.org/10.1016/j.foreco.2024.121885

Davis, R.J., Bell, D.M., Gregory, M.J., Yang, Z., Gray, A.N., Healey, S.P., Stratton, A.E., 2022. Northwest Forest Plan—the first 25 years (1994–2018): status and trends of late-successional and old-growth forests. Gen. Tech. Rep. PNW-GTR-1004. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 82 p. 1004. https://doi.org/10.2737/PNW-GTR-1004

Davis, R.J., Dugger, K.M., Mohoric, S., Evers, L., Aney, W.C., 2011. Northwest Forest Plan—the first 15 years (1994–2008): status and trends of northern spotted owl populations and habitats. Gen. Tech. Rep. PNW-GTR-850. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 147 p 850. https://doi.org/10.2737/PNW-GTR-850

Davis, R.J., Hollen, B., Hobson, J., Gower, J.E., Keenum, D., 2016. Northwest Forest Plan—the first 20 years (1994-2013): status and trends of northern spotted owl habitats. Gen. Tech. Rep. PNW-GTR-929. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 54 p. 929. https://doi.org/10.2737/PNW-GTR-929

Davis, R.J., Ohmann, J.L., Kennedy, R.E., Cohen, W.B., Gregory, M.J., Yang, Z., Roberts, H.M., Gray, A.N., Spies, T.A., 2015. Northwest Forest Plan–the first 20 years (1994-2013): status and trends of late-successional and old-growth forests. Gen. Tech. Rep. PNW-GTR-911. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 112 p. 911. https://doi.org/10.2737/PNW-GTR-911

Dennison, P.E., Brewer, S.C., Arnold, J.D., Moritz, M.A., 2014. Large wildfire trends in the western United States, 1984–2011. Geophysical Research Letters 41, 2928–2933. https://doi.org/10.1002/2014GL059576

Dillon, G.K., Holden, Z.A., Morgan, P., Crimmins, M.A., Heyerdahl, E.K., Luce, C.H., 2011. Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006. Ecosphere 2, art130. https://doi.org/10.1890/ES11-00271.1

Donato, D.C., Campbell, J.L., Franklin, J.F., 2012. Multiple successional pathways and precocity in forest development: can some forests be born complex? Journal of Vegetation Science 23, 576–584. https://doi.org/10.1111/j.1654-1103.2011.01362.x

Dormann, C., McPherson, J., Araújo, M., Bivand, R., Bolliger, J., Carl, G., G. Davies, R., Hirzel, A., Jetz, W., Daniel Kissling, W., Kühn, I., Ohlemüller, R., R. Peres-Neto, P., Reineking, B., Schröder, B., M. Schurr, F., Wilson, R., 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography 30, 609–628. https://doi.org/10.1111/j.2007.0906-7590.05171.x

Duane, A., Castellnou, M., Brotons, L., 2021. Towards a comprehensive look at global drivers of novel extreme wildfire events. Climatic Change 165, 43. https://doi.org/10.1007/s10584-021-03066-4

Dunn, C.J., Bailey, J.D., 2016. Tree mortality and structural change following mixed-severity fire in *Pseudotsuga* forests of Oregon's western Cascades, USA. Forest Ecology and Management 365, 107–118. https://doi.org/10.1016/j.foreco.2016.01.031

Dye, A.W., Reilly, M.J., McEvoy, A., Lemons, R., Riley, K.L., Kim, J.B., Kerns, B.K., 2024. Simulated Future Shifts in Wildfire Regimes in Moist Forests of Pacific Northwest, USA. Journal of Geophysical Research: Biogeosciences 129, e2023JG007722. https://doi.org/10.1029/2023JG007722

Earles, J.M., North, M.P., Hurteau, M.D., 2014. Wildfire and drought dynamics destabilize carbon stores of fire-suppressed forests. Ecological Applications 24, 732–740. https://doi.org/10.1890/13-1860.1

Enayati Ahangar, F., Cobian-Iñiguez, J., Cisneros, R., 2022. Combining Regulatory Instruments and Low-Cost Sensors to Quantify the Effects of 2020 California Wildfires on PM2.5 in San Joaquin Valley. Fire 5, 64. https://doi.org/10.3390/fire5030064

Essen, M., McCaffrey, S., Abrams, J., Paveglio, T., 2023. Improving wildfire management outcomes: shifting the paradigm of wildfire from simple to complex risk. Journal of Environmental Planning and Management 66, 909–927. https://doi.org/10.1080/09640568.2021.2007861

Estes, B.L., Knapp, E.E., Skinner, C.N., Miller, J.D., Preisler, H.K., 2017. Factors influencing fire severity under moderate burning conditions in the Klamath Mountains, northern California, USA. Ecosphere 8, e01794. https://doi.org/10.1002/ecs2.1794

Estes, B.L., Knapp, E.E., Skinner, C.N., Uzoh, F.C.C., 2012. Seasonal variation in surface fuel moisture between unthinned and thinned mixed conifer forest, northern California, USA. Int. J. Wildland Fire 21, 428–435. https://doi.org/10.1071/WF11056

Evans, J., Murphy, M., 2021. spatialEco. https://github.com/jeffreyevans/spatialEco

Evans, S.G., Holland, T.G., Long, J.W., Maxwell, C., Scheller, R.M., Patrick, E., Potts, M.D., 2022. Modeling the risk reduction benefit of forest management using a case study in the Lake Tahoe Basin. Ecology and Society 27. https://doi.org/10.5751/ES-13169-270218

Evers, C., Holz, A., Busby, S., Nielsen-Pincus, M., 2022. Extreme winds alter influence of fuels and topography on megafire burn severity in seasonal temperate rainforests under record fuel aridity. Fire 5, 41. https://doi.org/10.3390/fire5020041

Executive Order 14072: Strengthening the Nation's Forests, Communities, and Local Economies., 2022. https://www.federalregister.gov/documents/2022/04/27/2022-09138/strengthening-the-nations-forests-communities-and-local-economies

Falk, D.A., Heyerdahl, E.K., Brown, P.M., Farris, C., Fulé, P.Z., McKenzie, D., Swetnam, T.W., Taylor, A.H., Van Horne, M.L., 2011. Multi-scale controls of historical forest-fire regimes: new insights from fire-scar networks. Frontiers in Ecology and the Environment 9, 446–454. https://doi.org/10.1890/100052

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., Alsdorf, D., 2007. The Shuttle Radar Topography Mission. Reviews of Geophysics 45. https://doi.org/10.1029/2005RG000183

Fettig, C.J., Klepzig, K.D., Billings, R.F., Munson, A.S., Nebeker, T.E., Negron, J.F., Nowak, J.T., 2007. The effectiveness of vegetation management practices for prevention and control of bark beetle infestations in coniferous forests of the western and southern United States. Forest Ecology and Management 238, 24–53. https://doi.org/10.1016/j.foreco.2006.10.011

Filip, G.M., Schmitt, C.L., Scott, D.W., Fitzgerald, S.A., 2007. Understanding and defining mortality in western conifer forests. Western Journal of Applied Forestry 22, 105–115. https://doi.org/10.1093/wjaf/22.2.105

Fischer, A.P., Spies, T.A., Steelman, T.A., Moseley, C., Johnson, B.R., Bailey, J.D., Ager, A.A., Bourgeron, P., Charnley, S., Collins, B.M., Kline, J.D., Leahy, J.E., Littell, J.S., Millington, J.D., Nielsen-Pincus, M., Olsen, C.S., Paveglio, T.B., Roos, C.I., Steen-Adams, M.M., Stevens, F.R., Vukomanovic, J., White, E.M., Bowman, D.M., 2016. Wildfire risk as a socioecological pathology. Frontiers in Ecology and the Environment 14, 276–284. https://doi.org/10.1002/fee.1283

Flannigan, M., Cantin, A.S., de Groot, W.J., Wotton, M., Newbery, A., Gowman, L.M., 2013. Global wildland fire season severity in the 21st century. Forest Ecology and Management, The Mega-fire reality 294, 54–61. https://doi.org/10.1016/j.foreco.2012.10.022

Franklin, J.F., Dyrness, C.T., 1973. Natural vegetation of Oregon and Washington. Gen. Tech. Rep. PNW-GTR-008. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 427 p 008.

Franklin, J.F., Johnson, K.N., 2012. A restoration framework for federal forests in the Pacific Northwest. Journal of Forestry 110, 429–439. https://doi.org/10.5849/jof.10-006

Franklin, J.F., Spies, T.A., Pelt, R.V., Carey, A.B., Thornburgh, D.A., Berg, D.R., Lindenmayer, D.B., Harmon, M.E., Keeton, W.S., Shaw, D.C., Bible, K., Chen, J., 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. Forest Ecology and Management 155, 399–423. https://doi.org/10.1016/S0378-1127(01)00575-8

Fry, D.L., Stephens, S.L., Collins, B.M., North, M.P., Franco-Vizcaíno, E., Gill, S.J., 2014. Contrasting Spatial Patterns in Active-Fire and Fire-Suppressed Mediterranean Climate Old-Growth Mixed Conifer Forests. PLOS ONE 9, e88985. https://doi.org/10.1371/journal.pone.0088985

Furniss, T.J., Kane, V.R., Larson, A.J., Lutz, J.A., 2020. Detecting tree mortality with Landsat-derived spectral indices: Improving ecological accuracy by examining uncertainty. Remote Sensing of Environment 237, 111497. https://doi.org/10.1016/j.rse.2019.111497

Gaines, W.L., Hessburg, P.F., Aplet, G.H., Henson, P., Prichard, S.J., Churchill, D.J., Jones, G.M., Isaak, D.J., Vynne, C., 2022. Climate change and forest management on federal lands in the Pacific Northwest, USA: Managing for dynamic landscapes. Forest Ecology and Management 504, 119794. https://doi.org/10.1016/j.foreco.2021.119794

Genuer, R., Poggi, J.-M., Tuleau-Malot, C., 2015. VSURF: An R Package for Variable Selection Using Random Forests. The R Journal 7, 19–33. https://journal.r-project.org/archive/2015/RJ-2015-018/index.html

Gill, A.M., Allan, G., 2008. Large fires, fire effects and the fire-regime concept. Int. J. Wildland Fire 17, 688. https://doi.org/10.1071/WF07145

Goheen, D., Hansen, E., 1993. Effects of Pathogens and Bark Beetles on Forests, in: The Bark Beetles, Fuels, and Fire Bibliography. Academic Press, London, UK, pp. 175–196.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, Big Remotely Sensed Data: tools, applications and experiences 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Graham, R.T., 2003. Hayman Fire Case Study (No. RMRS-GTR-114). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ft. Collins, CO. https://doi.org/10.2737/RMRS-GTR-114

GreenInfo Network, 2022. California Protected Areas Database (CPAD). https://calands.org

Greenler, S.M., Lake, F.K., Tripp, W., McCovey, K., Tripp, A., Hillman, L.G., Dunn, C.J., Prichard, S.J., Hessburg, P.F., Harling, W., Bailey, J.D., 2024. Blending Indigenous and western science: Quantifying cultural burning impacts in Karuk Aboriginal Territory. Ecological Applications n/a, e2973. https://doi.org/10.1002/eap.2973

Griffey, V., Kellogg, B., Haugo, R., Kane, V., 2021. Ownership patterns drive multi-scale forest structure patterns across a forested region in southern coastal Oregon, USA. Forests 12, 47. https://doi.org/10.3390/f12010047

Haas, J.R., Calkin, D.E., Thompson, M.P., 2013. A national approach for integrating wildfire simulation modeling into Wildland Urban Interface risk assessments within the United States. Landscape and Urban Planning 119, 44–53. https://doi.org/10.1016/j.landurbplan.2013.06.011

Hagmann, R.K., Franklin, J.F., Johnson, K.N., 2013. Historical structure and composition of ponderosa pine and mixed-conifer forests in south-central Oregon. Forest Ecology and Management 304, 492–504. https://doi.org/10.1016/j.foreco.2013.04.005

Hagmann, R.K., Hessburg, P.F., Prichard, S.J., Povak, N.A., Brown, P.M., Fulé, P.Z., Keane, R.E., Knapp, E.E., Lydersen, J.M., Metlen, K.L., Reilly, M.J., Sánchez Meador, A.J., Stephens, S.L., Stevens, J.T., Taylor, A.H., Yocom, L.L., Battaglia, M.A., Churchill, D.J., Daniels, L.D., Falk, D.A., Henson, P., Johnston, J.D., Krawchuk, M.A., Levine, C.R., Meigs, G.W., Merschel, A.G., North, M.P., Safford, H.D., Swetnam, T.W., Waltz, A.E.M., 2021. Evidence for

widespread changes in the structure, composition, and fire regimes of western North American forests. Ecological Applications 31, e02431. https://doi.org/10.1002/eap.2431
Halofsky, J.E., Peterson, D.L., Harvey, B.J., 2020. Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. Fire Ecology 16, 4. https://doi.org/10.1186/s42408-019-0062-8
Halofsky, J.S., Donato, D.C., Franklin, J.F., Halofsky, J.E., Peterson, D.L., Harvey, B.J., 2018. The nature of the beast: examining climate adaptation options in forests with stand-replacing fire regimes. Ecosphere 9, e02140. https://doi.org/10.1002/ecs2.2140
Halsey, S.M., 2024. Prioritizing new conservation areas during forest plan updates. Forest Ecology and Management 553, 121445. https://doi.org/10.1016/j.foreco.2023.121445
Harris, L., Taylor, A.H., 2017. Previous burns and topography limit and reinforce fire severity in a large wildfire. Ecosphere 8, e02019. https://doi.org/10.1002/ecs2.2019
Harris, L.B., Drury, S.A., Farris, C.A., Taylor, A.H., Harris, L.B., Drury, S.A., Farris, C.A., Taylor, A.H., 2021. Prescribed fire and fire suppression operations influence wildfire severity under severe weather in Lassen Volcanic National Park, California, USA. Int. J. Wildland Fire 30, 536–551. https://doi.org/10.1071/WF20163
Harvey, B.J., Donato, D.C., Turner, M.G., 2016. Drivers and trends in landscape patterns of stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). Landscape Ecol 31, 2367–2383. https://doi.org/10.1007/s10980-016-0408-4
He, H.S., DeZonia, B.E., Mladenoff, D.J., 2000. An aggregation index (AI) to quantify spatial patterns of landscapes. Landscape Ecology 15, 591–601. https://doi.org/10.1023/A:1008102521322
Healey, S.P., Cohen, W.B., Yang, Z., Kenneth Brewer, C., Brooks, E.B., Gorelick, N., Hernandez, A.J., Huang, C., Joseph Hughes, M., Kennedy, R.E., Loveland, T.R., Moisen, G.G., Schroeder, T.A., Stehman, S.V., Vogelmann, J.E., Woodcock, C.E., Yang, L., Zhu, Z., 2018. Mapping forest change using stacked generalization: An ensemble approach. Remote Sensing of Environment 204, 717–728. https://doi.org/10.1016/j.rse.2017.09.029
Hessburg, P.F., Churchill, D.J., Larson, A.J., Haugo, R.D., Miller, C., Spies, T.A., North, M.P., Povak, N.A., Belote, R.T., Singleton, P.H., Gaines, W.L., Keane, R.E., Aplet, G.H., Stephens, S.L., Morgan, P., Bisson, P.A., Rieman, B.E., Salter, R.B., Reeves, G.H., 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecol 30, 1805–1835. https://doi.org/10.1007/s10980-015-0218-0
Hessburg, P.F., Miller, C., Parks, S., Povak, N., North, M., Collins, B., Spies, T., Cansler, C., Battaglia, M., Skinner, C., 2019. Climate, environment, and disturbance history govern resilience of Western North American forests. Frontiers in Ecology and Evolution. 7: 239. 7, 11770. https://doi.org/10.3389/fevo.2019.00239
Hessburg, P.F., Prichard, S.J., Hagmann, R.K., Povak, N.A., Lake, F.K., 2021. Wildfire and climate change adaptation of western North American forests: a case for intentional management. Ecological Applications 31, e02432. https://doi.org/10.1002/eap.2432

Hessburg, P.F., Reynolds, K.M., Salter, R.B., Dickinson, J.D., Gaines, W.L., Harrod, R.J., 2013. Landscape Evaluation for Restoration Planning on the Okanogan-Wenatchee National Forest, USA. Sustainability 5, 805–840. https://doi.org/10.3390/su5030805

Hessburg, P.F., Spies, T.A., Perry, D.A., Skinner, C.N., Taylor, A.H., Brown, P.M., Stephens, S.L., Larson, A.J., Churchill, D.J., Povak, N.A., Singleton, P.H., McComb, B., Zielinski, W.J., Collins, B.M., Salter, R.B., Keane, J.J., Franklin, J.F., Riegel, G., 2016. Tamm Review: Management of mixed-severity fire regime forests in Oregon, Washington, and Northern California. Forest Ecology and Management 366, 221–250. https://doi.org/10.1016/j.foreco.2016.01.034

Hesselbarth, M.H.K., Sciaini, M., With, K.A., Wiegand, K., Nowosad, J., 2019. landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography 42, 1648–1657. https://doi.org/10.1111/ecog.04617

Hijmans, R., Bivand, R., Pebesma, E., Sumner, M., 2024. terra: Spatial Data Analysis. https://rspatial.github.io/terra/

Holden, Z.A., Swanson, A., Luce, C.H., Jolly, W.M., Maneta, M., Oyler, J.W., Warren, D.A., Parsons, R., Affleck, D., 2018. Decreasing fire season precipitation increased recent western US forest wildfire activity. Proceedings of the National Academy of Sciences 115, E8349–E8357. https://doi.org/10.1073/pnas.1802316115

Holling, C.S., 1978. Adaptive Environmental Assessment and Management. John Wiley & Sons.

Hood, S., Sala, A., Heyerdahl, E.K., Boutin, M., 2015. Low-severity fire increases tree defense against bark beetle attacks. Ecology. 96(7): 1846-1855. 96, 1846–1855. https://doi.org/10.1890/14-0487.1

Howe, A.A., Parks, S.A., Harvey, B.J., Saberi, S.J., Lutz, J.A., Yocom, L.L., 2022. Comparing Sentinel-2 and Landsat 8 for Burn Severity Mapping in Western North America. Remote Sensing 14, 5249. https://doi.org/10.3390/rs14205249

Hoy, E.E., French, N.H.F., Turetsky, M.R., Trigg, S.N., Kasischke, E.S., Hoy, E.E., French, N.H.F., Turetsky, M.R., Trigg, S.N., Kasischke, E.S., 2008. Evaluating the potential of Landsat TM/ETM+ imagery for assessing fire severity in Alaskan black spruce forests. Int. J. Wildland Fire 17, 500–514. https://doi.org/10.1071/WF08107

Hungerford, R., Harrington, M., Frandsen, W., Ryan, K., Niehoff, G., 1991. Influence of fire on factors that affect site productivity. Proc. Manage. Prod. Western-Montane Forest Soils 280.

Jain, P., Castellanos-Acuna, D., Coogan, S.C.P., Abatzoglou, J.T., Flannigan, M.D., 2021. Observed increases in extreme fire weather driven by atmospheric humidity and temperature. Nat. Clim. Chang. 1–8. https://doi.org/10.1038/s41558-021-01224-1

Jeronimo, S., Kane, V., Churchill, D., Lutz, J., North, M., Asner, G., Franklin, J., 2019. Forest structure and pattern vary by climate and landform across active-fire landscapes in the montane Sierra Nevada. Forest Ecology and Management 437, 70–86. https://doi.org/10.1016/j.foreco.2019.01.033

Johnson, K.N., Franklin, J., Reeves, G., 2023. The Making of the Northwest Forest Plan: The Wild Science of Saving Old Growth Ecosystems. Oregon State University Press.

Johnston, J.D., Olszewski, J.H., Miller, B.A., Schmidt, M.R., Vernon, M.J., Ellsworth, L.M., 2021. Mechanical thinning without prescribed fire moderates wildfire behavior in an Eastern Oregon, USA ponderosa pine forest. Forest Ecology and Management 501, 119674. https://doi.org/10.1016/j.foreco.2021.119674

Johnston, J.D., Schmidt, M.R., Merschel, A.G., Downing, W.M., Coughlan, M.R., Lewis, D.G., 2023. Exceptional variability in historical fire regimes across a western Cascades landscape, Oregon, USA. Ecosphere 14, e4735. https://doi.org/10.1002/ecs2.4735

Johnstone, J.F., Allen, C.D., Franklin, J.F., Frelich, L.E., Harvey, B.J., Higuera, P.E., Mack, M.C., Meentemeyer, R.K., Metz, M.R., Perry, G.L., Schoennagel, T., Turner, M.G., 2016. Changing disturbance regimes, ecological memory, and forest resilience. Frontiers in Ecology and the Environment 14, 369–378. https://doi.org/10.1002/fee.1311

Jones, G.M., Kramer, H.A., Whitmore, S.A., Berigan, W.J., Tempel, D.J., Wood, C.M., Hobart, B.K., Erker, T., Atuo, F.A., Pietrunti, N.F., Kelsey, R., Gutiérrez, R.J., Peery, M.Z., 2020. Habitat selection by spotted owls after a megafire reflects their adaptation to historical frequent-fire regimes. Landscape Ecol 35, 1199–1213. https://doi.org/10.1007/s10980-020-01010-y

Kalies, E.L., Yocom Kent, L.L., 2016. Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. Forest Ecology and Management 375, 84–95. https://doi.org/10.1016/j.foreco.2016.05.021

Kane, V.R., Bartl-Geller, B.N., North, M.P., Kane, J.T., Lydersen, J.M., Jeronimo, S.M.A., Collins, B.M., Moskal, L.M., 2019. First-entry wildfires can create opening and tree clump patterns characteristic of resilient forests. Forest Ecology and Management 454. https://doi.org/10.1016/j.foreco.2019.117659

Kane, V.R., Cansler, C.A., Povak, N., Kane, J., McGaughey, R., Lutz, J., Churchill, D., North, M., 2015. Mixed severity fire effects within the Rim fire: Relative importance of local climate, fire weather, topography, and forest structure. Forest Ecology and Management 358. https://doi.org/10.1016/j.foreco.2015.09.001

Kane, V.R., North, M.P., Lutz, J.A., Churchill, D.J., Roberts, S.L., Smith, D.F., McGaughey, R.J., Kane, J.T., Brooks, M.L., 2014. Assessing fire effects on forest spatial structure using a fusion of Landsat and airborne LiDAR data in Yosemite National Park. Remote Sensing of Environment, Special Issue on 2012 ForestSAT 151, 89–101. https://doi.org/10.1016/j.rse.2013.07.041

Kariya, T., Kurata, H., 2004. Generalized least squares, Wiley series in probability and statistics. Wiley, Chichester, West Sussex, England ; Hoboken, NJ.

Katuwal, H., Calkin, D., Hand, M.S., 2016. Production and efficiency of large wildland fire suppression effort: A stochastic frontier analysis. Journal of Environmental Management. 166: 227-236. 166, 227–236. https://doi.org/10.1016/j.jenvman.2015.10.030

Keane, R.E., Agee, J.K., Fule, P., Keeley, J.E., Key, C., Kitchen, S.G., Miller, R., Schulte, L.A., 2008. Ecological effects of large fires on US landscapes: benefit or catastrophe? International Journal of Wildland Fire. 17: 696-712. https://doi.org/10.1071/wf07148

Keeley, J.E., 2009. Fire intensity, fire severity and burn severity: a brief review and suggested usage. Int. J. Wildland Fire 18, 116–126. https://doi.org/10.1071/WF07049

Keeley, J.E., Pfaff, A., Caprio, A.C., 2021. Contrasting prescription burning and wildfires in California Sierra Nevada national parks and adjacent national forests. Int. J. Wildland Fire 30, 255. https://doi.org/10.1071/WF20112

Keeley, J.E., Syphard, A.D., 2021. Large California wildfires: 2020 fires in historical context. Fire Ecology 17, 22. https://doi.org/10.1186/s42408-021-00110-7

Keenan, R.J., 2015. Climate change impacts and adaptation in forest management: a review. Annals of Forest Science 72, 145–167. https://doi.org/10.1007/s13595-014-0446-5

Kemp, K., Higuera, P., Morgan, P., 2014. Post-fire tree recruitment in the U.S. Northern Rockies: The influence of seed source proximity and environmental conditions. 99th ESA Annual Convention.

Key, C.H., Benson, N.C., 2006. Landscape Assessment (LA). In: Lutes, Duncan C.; Keane, Robert E.; Caratti, John F.; Key, Carl H.; Benson, Nathan C.; Sutherland, Steve; Gangi, Larry J. 2006. FIREMON: Fire effects monitoring and inventory system. Gen. Tech. Rep. RMRS-GTR-164-CD. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. LA-1-55

Kim, D.-W., Chung, W., Lee, B., 2016. Exploring tree crown spacing and slope interaction effects on fire behavior with a physics-based fire model. Forest Science and Technology 12, 167–175. https://doi.org/10.1080/21580103.2016.1144541

Kimmerer, R., Lake, F., 2001. Maintaining the Mosaic: The role of indigenous burning in land management. Journal of Forestry 99, 36–41.

Knapp, E.E., Lydersen, J.M., North, M.P., Collins, B.M., 2017. Efficacy of variable density thinning and prescribed fire for restoring forest heterogeneity to mixed-conifer forest in the central Sierra Nevada, CA. Forest Ecology and Management 406, 228–241. https://doi.org/10.1016/j.foreco.2017.08.028

Knight, C.A., Anderson, L., Bunting, M.J., Champagne, M., Clayburn, R.M., Crawford, J.N., Klimaszewski-Patterson, A., Knapp, E.E., Lake, F.K., Mensing, S.A., Wahl, D., Wanket, J., Watts-Tobin, A., Potts, M.D., Battles, J.J., 2022a. Land management explains major trends in forest structure and composition over the last millennium in California's Klamath Mountains. Proceedings of the National Academy of Sciences 119, e2116264119. https://doi.org/10.1073/pnas.2116264119

Knight, C.A., Tompkins, R.E., Wang, J.A., York, R., Goulden, M.L., Battles, J.J., 2022b. Accurate tracking of forest activity key to multi-jurisdictional management goals: A case study in California. Journal of Environmental Management 302, 114083. https://doi.org/10.1016/j.jenvman.2021.114083

Kobziar, L.N., McBride, J.R., Stephens, S.L., 2009. The efficacy of fire and fuels reduction treatments in a Sierra Nevada pine plantation. Int. J. Wildland Fire 18, 791–801. https://doi.org/10.1071/WF06097

Kolden, C.A., 2019. We're Not Doing Enough Prescribed Fire in the Western United States to Mitigate Wildfire Risk. Fire 2, 30. https://doi.org/10.3390/fire2020030

Kolden, C.A., Bleeker, T.M., Smith, A.M.S., Poulos, H.M., Camp, A.E., 2017. Fire Effects on Historical Wildfire Refugia in Contemporary Wildfires. Forests 8, 400. https://doi.org/10.3390/f8100400

Komisarczyk, K., Kozminski, P., Maksymiuk, S., Kapsner, L., Spytek, M., Krzyzinski, M., Biecek, P., 2024. treeshap: Compute SHAP Values for Your Tree-Based Models Using the "TreeSHAP" Algorithm. https://modeloriented.github.io/treeshap/

Koontz, M.J., North, M.P., Werner, C.M., Fick, S.E., Latimer, A.M., 2020. Local forest structure variability increases resilience to wildfire in dry western U.S. coniferous forests. Ecol Lett 23, 483–494. https://doi.org/10.1111/ele.13447

Krawchuk, M.A., Meigs, G.W., Cartwright, J.M., Coop, J.D., Davis, R., Holz, A., Kolden, C., Meddens, A.J., 2020. Disturbance refugia within mosaics of forest fire, drought, and insect outbreaks. Frontiers in Ecology and the Environment 18, 235–244. https://doi.org/10.1002/fee.2190

Kreider, M.R., Higuera, P.E., Parks, S.A., Rice, W.L., White, N., Larson, A.J., 2024. Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation. Nat Commun 15, 2412. https://doi.org/10.1038/s41467-024-46702-0

LANDFIRE, 2020. Biophysical Settings Layer. https://landfire.gov/bps.php

Larson, A.J., Belote, R.T., Cansler, C.A., Parks, S.A., Dietz, M.S., 2013. Latent resilience in ponderosa pine forest: effects of resumed frequent fire. Ecological Applications 23, 1243–1249. https://doi.org/10.1890/13-0066.1

Laszlo, E., Gyorgy, K.-D., Zoltan, B., Bence, K., Csaba, N., Janos, K.P., Csaba, T., 2018. Habitat heterogeneity as a key to high conservation value in forest-grassland mosaics. Biol. Conserv. 226, 72–80. https://doi.org/10.1016/j.biocon.2018.07.029

Laughlin, M.M., Rangel-Parra, L.K., Morris, J.E., Donato, D.C., Halofsky, J.S., Harvey, B.J., 2023. Patterns and drivers of early conifer regeneration following stand-replacing wildfire in Pacific Northwest (USA) temperate maritime forests. Forest Ecology and Management 549, 121491. https://doi.org/10.1016/j.foreco.2023.121491

Laurance, W.F., Vasconcelos, H.L., Lovejoy, T.E., 2000. Forest loss and fragmentation in the Amazon: implications for wildlife conservation. Oryx 34, 39–45. https://doi.org/10.1046/j.1365-3008.2000.00094.x

Levine, J.I., Collins, B.M., Steel, Z.L., de Valpine, P., Stephens, S.L., 2022. Higher incidence of high-severity fire in and near industrially managed forests. Frontiers in Ecology and the Environment 20, 397–404. https://doi.org/10.1002/fee.2499

Lezberg, A.L., Battaglia, M.A., Shepperd, W.D., Schoettle, A.W., 2008. Decades-old silvicultural treatments influence surface wildfire severity and post-fire nitrogen availability in a ponderosa pine forest. Forest Ecology and Management. 255: 49-61. 49–61. https://doi.org/10.1016/j.foreco.2007.08.019

Li, B.-L., Archer, S., 1997. Weighted mean patch size: a robust index for quantifying landscape structure. Ecological Modelling 102, 353–361. https://doi.org/10.1016/S0304-3800(97)00071-9

Liang, S., Hurteau, M.D., Westerling, A.L., 2017a. Potential decline in carbon carrying capacity under projected climate-wildfire interactions in the Sierra Nevada. Sci Rep 7, 2420. https://doi.org/10.1038/s41598-017-02686-0

Liang, S., Hurteau, M.D., Westerling, A.L., 2017b. Response of Sierra Nevada forests to projected climate-wildfire interactions. Glob Chang Biol 23, 2016–2030. https://doi.org/10.1111/gcb.13544

Linley, G.D., Jolly, C.J., Doherty, T.S., Geary, W.L., Armenteras, D., Belcher, C.M., Bliege Bird, R., Duane, A., Fletcher, M.-S., Giorgis, M.A., Haslem, A., Jones, G.M., Kelly, L.T., Lee, C.K.F., Nolan, R.H., Parr, C.L., Pausas, J.G., Price, J.N., Regos, A., Ritchie, E.G., Ruffault, J., Williamson, G.J., Wu, Q., Nimmo, D.G., Poulter, B., 2022. What do you mean, 'megafire'? Global Ecology and Biogeography n/a. https://doi.org/10.1111/geb.13499

Liu, Y., Austin, E., Xiang, J., Gould, T., Larson, T., Seto, E., 2021. Health Impact Assessment of the 2020 Washington State Wildfire Smoke Episode: Excess Health Burden Attributable to Increased PM2.5 Exposures and Potential Exposure Reductions. GeoHealth 5, e2020GH000359. https://doi.org/10.1029/2020GH000359

Long, J.W., Lake, F.K., Goode, R.W., 2021. The importance of Indigenous cultural burning in forested regions of the Pacific West, USA. Forest Ecology and Management. 500(3): 119597 500, 119597. https://doi.org/10.1016/j.foreco.2021.119597

Lorimer, C.G., Porter, D.J., Madej, M.A., Stuart, J.D., Veirs, S.D., Norman, S.P., O'Hara, K.L., Libby, W.J., 2009. Presettlement and modern disturbance regimes in coast redwood forests: Implications for the conservation of old-growth stands. Forest Ecology and Management 258, 1038–1054. https://doi.org/10.1016/j.foreco.2009.07.008

Lydersen, J.M., Collins, B.M., Brooks, M.L., Matchett, J.R., Shive, K.L., Povak, N.A., Kane, V.R., Smith, D.F., 2017. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. Ecological Applications 27, 2013–2030. https://doi.org/10.1002/eap.1586

Lydersen, J.M., Collins, B.M., Miller, J.D., Fry, D.L., Stephens, S.L., 2016. Relating Fire-Caused Change in Forest Structure to Remotely Sensed Estimates of Fire Severity. fire ecol 12, 99–116. https://doi.org/10.4996/fireecology.1203099

Lydersen, J.M., North, M.P., Collins, B.M., 2014. Severity of an uncharacteristically large wildfire, the Rim Fire, in forests with relatively restored frequent fire regimes. Forest Ecology and Management 328, 326–334. https://doi.org/10.1016/j.foreco.2014.06.005

Lyons-Tinsley, C., Peterson, D.L., 2012. Surface fuel treatments in young, regenerating stands affect wildfire severity in a mixed conifer forest, eastside Cascade Range, Washington, USA. Forest Ecology and Management 270, 117–125. https://doi.org/10.1016/j.foreco.2011.04.016

Mallek, C., Safford, H., Viers, J., Miller, J., 2013. Modern departures in fire severity and area vary by forest type, Sierra Nevada and southern Cascades, California, USA. Ecosphere 4, art153. https://doi.org/10.1890/ES13-00217.1

Marlon, J.R., Bartlein, P.J., Gavin, D.G., Long, C.J., Anderson, R.S., Briles, C.E., Brown, K.J., Colombaroli, D., Hallett, D.J., Power, M.J., Scharf, E.A., Walsh, M.K., 2012. Long-term

perspective on wildfires in the western USA. Proceedings of the National Academy of Sciences 109, E535–E543. https://doi.org/10.1073/pnas.1112839109
Massip, N., 2020. The 1964 Wilderness Act, from "wilderness idea" to governmental oversight and protection of wilderness. Miranda. Revue pluridisciplinaire du monde anglophone / Multidisciplinary peer-reviewed journal on the English-speaking world. https://doi.org/10.4000/miranda.26787
Mazerolle, M., 2023. AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c). https://cran.r-project.org/package=AICcmodavg
McCaffrey, S., 2004. Thinking of Wildfire as a Natural Hazard. Society & Natural Resources 17, 509–516. https://doi.org/10.1080/08941920490452445
McCaffrey, S., McGee, T.K., Coughlan, M., Tedim, F., 2020. Understanding wildfire mitigation and preparedness in the context of extreme wildfires and disasters, in: Extreme Wildfire Events and Disasters. Elsevier, pp. 155–174. https://doi.org/10.1016/B978-0-12-815721-3.00008-4
McCune, B., Keon, D., 2002. Equations for potential annual direct incident radiation and heat load. Journal of Vegetation Science 13, 603–606. https://doi.org/10.1111/j.1654-1103.2002.tb02087.x
McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 122 p 351. https://doi.org/10.2737/PNW-GTR-351
McKenzie, D., Miller, C., Falk, D.A., 2011. Toward a Theory of Landscape Fire, in: McKenzie, D., Miller, C., Falk, D.A. (Eds.), The Landscape Ecology of Fire, Ecological Studies. Springer Netherlands, Dordrecht, pp. 3–25. https://doi.org/10.1007/978-94-007-0301-8_1
Meddens, A.J.H., Kolden, C.A., Lutz, J.A., Abatzoglou, J.T., Hudak, A.T., 2018a. Spatiotemporal patterns of unburned areas within fire perimeters in the northwestern United States from 1984 to 2014. Ecosphere 9, e02029. https://doi.org/10.1002/ecs2.2029
Meddens, A.J.H., Kolden, C.A., Lutz, J.A., Smith, A.M.S., Cansler, C.A., Abatzoglou, J.T., Meigs, G.W., Downing, W.M., Krawchuk, M.A., 2018b. Fire Refugia: What Are They, and Why Do They Matter for Global Change? BioScience 68, 944–954. https://doi.org/10.1093/biosci/biy103
Meigs, G.W., Zald, H.S.J., Campbell, J.L., Keeton, W.S., Kennedy, R.E., 2016. Do insect outbreaks reduce the severity of subsequent forest fires? Environ. Res. Lett. 11, 045008. https://doi.org/10.1088/1748-9326/11/4/045008
Mell, W.E., Manzello, S.L., Maranghides, A., Butry, D., Rehm, R.G., 2010. The wildland–urban interface fire problem – current approaches and research needs. International Journal of Wildland Fire 238–251. https://doi.org/10.1071/WF07131
Merschel, A.G., Heyerdahl, E.K., Spies, T.A., Loehman, R.A., 2018. Influence of landscape structure, topography, and forest type on spatial variation in historical fire regimes, Central Oregon, USA. Landscape Ecol 33, 1195–1209. https://doi.org/10.1007/s10980-018-0656-6

Meyer, M., North, M., 2019. Natural range of variation of red fir and subalpine forests in the Sierra Nevada Bioregion (No. PSW-GTR-263). U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station, Albany, CA. https://doi.org/10.2737/PSW-GTR-263

Meyer, M.D., 2015. Forest Fire Severity Patterns of Resource Objective Wildfires in the Southern Sierra Nevada. Journal of Forestry 113, 49–56. https://doi.org/10.5849/jof.14-084

Meyer, M.D., Long, J.W., Safford, H.D., 2021. Postfire restoration framework for national forests in California. Gen. Tech. Rep. PSW-GTR-270. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station. 204 p. 270. https://doi.org/10.2737/PSW-GTR-270

Miller, B.A., Yung, L., Wyborn, C., Essen, M., Gray, B., Williams, D.R., 2022. Re-Envisioning Wildland Fire Governance: Addressing the Transboundary, Uncertain, and Contested Aspects of Wildfire. Fire 5, 49. https://doi.org/10.3390/fire5020049

Miller, J.D., Skinner, C.N., Safford, H.D., Knapp, E.E., Ramirez, C.M., 2012. Trends and causes of severity, size, and number of fires in northwestern California, USA. Ecological Applications 22, 184–203. https://doi.org/10.1890/10-2108.1

Miller, J.D., Thode, A.E., 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). Remote Sensing of Environment 109, 66–80. https://doi.org/10.1016/j.rse.2006.12.006

Miller, R.K., Field, C.B., Mach, K.J., 2020. Barriers and enablers for prescribed burns for wildfire management in California. Nat Sustain 3, 101–109. https://doi.org/10.1038/s41893-019-0451-7

Milling, C.R., Rachlow, J.L., Olsoy, P.J., Chappell, M.A., Johnson, T.R., Forbey, J.S., Shipley, L.A., Thornton, D.H., 2018. Habitat structure modifies microclimate: An approach for mapping fine-scale thermal refuge. Methods Ecol. Evol. 9, 1648–1657. https://doi.org/10.1111/2041-210X.13008

Moritz, M.A., Hessburg, P.F., Povak, N.A., 2011. Native Fire Regimes and Landscape Resilience, in: McKenzie, D., Miller, C., Falk, D.A. (Eds.), The Landscape Ecology of Fire, Ecological Studies. Springer Netherlands, Dordrecht, pp. 51–86. https://doi.org/10.1007/978-94-007-0301-8_3

Mueller, S.E., Thode, A.E., Margolis, E.Q., Yocom, L.L., Young, J.D., Iniguez, J.M., 2020. Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. Forest Ecology and Management 460, 117861. https://doi.org/10.1016/j.foreco.2019.117861

Murphy, J.S., York, R., Rivera Huerta, H., Stephens, S.L., 2021. Characteristics and metrics of resilient forests in the Sierra de San Pedro Martír, Mexico. Forest Ecology and Management 482, 118864. https://doi.org/10.1016/j.foreco.2020.118864

National Review, 2020. California's Disastrous Forest Mismanagement. https://www.nationalreview.com/2020/09/california-forest-mismanagement-a-disaster/

National Weather Service - Eureka Office, 2021. August Complex, Northern California. https://storymaps.arcgis.com/stories/056a3a9520274896aa4146a57ea9f506

Nelson, M.D., Liknes, G.C., Butler, B.J., 2010. Map of forest ownership in the conterminous United States. [Scale 1:7,500,000]. Res. Map NRS-2. Newtown Square, PA: U.S. Department of

Agriculture, Forest Service, Northern Research Station. 2, 1–2. https://doi.org/10.2737/NRS-RMAP-2

Ng, J., North, M.P., Arditti, A.J., Cooper, M.R., Lutz, J.A., 2020. Topographic variation in tree group and gap structure in Sierra Nevada mixed-conifer forests with active fire regimes. Forest Ecology and Management 472, 118220. https://doi.org/10.1016/j.foreco.2020.118220

Nie, M.A., Schultz, C.A., 2012. Decision-Making Triggers in Adaptive Management. Conservation Biology 26, 1137–1144. https://doi.org/10.1111/j.1523-1739.2012.01915.x

North, M., Brough, A., Long, J., Collins, B., Bowden, P., Yasuda, D., Miller, J., Sugihara, N., 2015a. Constraints on Mechanized Treatment Significantly Limit Mechanical Fuels Reduction Extent in the Sierra Nevada. Journal of Forestry 113, 40–48. https://doi.org/10.5849/jof.14-058

North, M., Hurteau, M., 2011. High-severity wildfire effects on carbon stocks and emissions in fuels treated and untreated forest. Fuel and Energy Abstracts 261, 1115–1120. https://doi.org/10.1016/j.foreco.2010.12.039

North, M., Stephens, S.L., Collins, B.M., Agee, J.K., Aplet, G., Franklin, J.F., Fulé, P.Z., 2015b. Reform forest fire management. Science 349, 1280–1281. https://doi.org/10.1126/science.aab2356

North, M., Stevens, J.T., Greene, D.F., Coppoletta, M., Knapp, E.E., Latimer, A.M., Restaino, C.M., Tompkins, R.E., Welch, K.R., York, R.A., Young, D.J.N., Axelson, J.N., Buckley, T.N., Estes, B.L., Hager, R.N., Long, J.W., Meyer, M.D., Ostoja, S.M., Safford, H.D., Shive, K.L., Tubbesing, C.L., Vice, H., Walsh, D., Werner, C.M., Wyrsch, P., 2019. Tamm Review: Reforestation for resilience in dry western U.S. forests. Forest Ecology and Management. 432: 209-224 432, 209–224. https://doi.org/10.1016/j.foreco.2018.09.007

North, M., Stine, P., O'Hara, K., Zielinski, W., Stephens, S., 2009. An ecosystem management strategy for Sierran mixed-conifer forests (No. PSW-GTR-220). U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station, Albany, CA. https://doi.org/10.2737/PSW-GTR-220

North, M., York, R.A., Collins, B.M., Hurteau, M.D., Jones, G.M., Knapp, E.E., Kobziar, L., McCann, H., Meyer, M.D., Stephens, S.L., Tompkins, R.E., Tubbesing, C.L., 2021. Pyrosilviculture Needed for Landscape Resilience of Dry Western United States Forests. Journal of Forestry 119, 520–544. https://doi.org/10.1093/jofore/fvab026

North, M.P., Tompkins, R.E., Bernal, A.A., Collins, B.M., Stephens, S.L., York, R.A., 2022. Operational resilience in western US frequent-fire forests. Forest Ecology and Management 507, 120004. https://doi.org/10.1016/j.foreco.2021.120004

Ohmann, J.L., Gregory, M.J., 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest- neighbor imputation in coastal Oregon, U.S.A. Can. J. For. Res. 32, 725–741. https://doi.org/10.1139/x02-011

Ohmann, J.L., Gregory, M.J., Roberts, H.M., Cohen, W.B., Kennedy, R.E., Yang, Z., 2012. Mapping change of older forest with nearest-neighbor imputation and Landsat time-series. Forest Ecology and Management, Emerging Methods for Handling Missing Data in Forest Ecology and Management Applications 272, 13–25. https://doi.org/10.1016/j.foreco.2011.09.021

Omernik, J.M., Gallant, A.L., 1987. Ecoregions of the Southwest States. https://gaftp.epa.gov/EPADataCommons/ORD/Ecoregions/ca/ca_eco_l3.htm

Oregon Department of Forestry (ODF), 2022. Oregon Land Management. https://oregon-department-of-forestry-geo.hub.arcgis.com/datasets/51ac085ed5f9457a9b3c9ab47708ea6e_1/

Parks, Holsinger, Koontz, Collins, Whitman, Parisien, Loehman, Barnes, Bourdon, Boucher, Boucher, Caprio, Collingwood, Hall, Park, Saperstein, Smetanka, Smith, Soverel, 2019. Giving Ecological Meaning to Satellite-Derived Fire Severity Metrics across North American Forests. Remote Sensing 11, 1735. https://doi.org/10.3390/rs11141735

Parks, S.A., 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. International Journal of Wildland Fire. 23: 215-223. 215–223. https://doi.org/10.1071/WF13138

Parks, S.A., Abatzoglou, J.T., 2020. Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017. Geophys. Res. Lett. 47. https://doi.org/10.1029/2020GL089858

Parks, S.A., Dillon, G.K., Miller, C., 2014a. A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. Remote Sensing 6, 1827–1844. https://doi.org/10.3390/rs6031827

Parks, S.A., Holsinger, L.M., Panunto, M.H., Jolly, W.M., Dobrowski, S.Z., Dillon, G.K., 2018a. High-severity fire: evaluating its key drivers and mapping its probability across western US forests. Environ. Res. Lett. 13, 044037. https://doi.org/10.1088/1748-9326/aab791

Parks, S.A., Holsinger, L.M., Voss, M.A., Loehman, R.A., Robinson, N.P., 2018b. Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. Remote Sensing 10, 879. https://doi.org/10.3390/rs10060879

Parks, S.A., Miller, C., Abatzoglou, J.T., Holsinger, L.M., Parisien, M.-A., Dobrowski, S.Z., 2016. How will climate change affect wildland fire severity in the western US? Environmental Research Letters. 11: 035002. 11. https://doi.org/10.1088/1748-9326/11/3/035002

Parks, S.A., Miller, C., Nelson, C.R., Holden, Z.A., 2014b. Previous fires moderate burn severity of subsequent wildland fires in two large western US wilderness areas. Ecosystems. 17: 29-42. 29–42. https://doi.org/10.1007/s10021-013-9704-x

Parks, S.A., Miller, C., Parisien, M.-A., Holsinger, L.M., Dobrowski, S.Z., Abatzoglou, J., 2015. Wildland fire deficit and surplus in the western United States, 1984–2012. Ecosphere 6, 1–13. https://doi.org/10.1890/ES15-00294.1

Pauly, D., 1995. Anecdotes and the shifting baseline syndrome of fisheries. Trends Ecol Evol 10, 430. https://doi.org/10.1016/s0169-5347(00)89171-5

Pausas, J.G., Parr, C.L., 2018. Towards an understanding of the evolutionary role of fire in animals. Evol Ecol 32, 113–125. https://doi.org/10.1007/s10682-018-9927-6

Pausas, J.G., Ribeiro, E., 2017. Fire and plant diversity at the global scale. Global Ecology and Biogeography 26, 889–897. https://doi.org/10.1111/geb.12596

Paveglio, T.B., Kooistra, C., Hall, T., Pickering, M., 2016. Understanding the Effect of Large Wildfires on Residents' Well-Being: What Factors Influence Wildfire Impact? Forest Science 62, 59–69. https://doi.org/10.5849/forsci.15-021

Pellegrini, A.F.A., Ahlström, A., Hobbie, S.E., Reich, P.B., Nieradzik, L.P., Staver, A.C., Scharenbroch, B.C., Jumpponen, A., Anderegg, W.R.L., Randerson, J.T., Jackson, R.B., 2018. Fire frequency drives decadal changes in soil carbon and nitrogen and ecosystem productivity. Nature 553, 194–198. https://doi.org/10.1038/nature24668

Perry, D.A., Hessburg, P.F., Skinner, C.N., Spies, T.A., Stephens, S.L., Taylor, A.H., Franklin, J.F., McComb, B., Riegel, G., 2011. The ecology of mixed severity fire regimes in Washington, Oregon, and Northern California. Forest Ecology and Management 262, 703–717. https://doi.org/10.1016/j.foreco.2011.05.004

Peterson, D.L., Ryan, K.C., 1986. Modeling postfire conifer mortality for long-range planning. Environmental Management 10, 797–808. https://doi.org/10.1007/BF01867732

Peterson, G.D., 2002. Contagious Disturbance, Ecological Memory, and the Emergence of Landscape Pattern. Ecosystems 5, 329–338. https://doi.org/10.1007/s10021-001-0077-1

Picotte, J.J., Arkle, R., Bastian, H., Benson, N., Cansler, A., Caprio, T., Dillon, G., Key, C., Klein, R.N., Kopper, K., Meddens, A.J.H., Ohlen, D., Parks, S.A., Peterson, D.W., Pilliod, D., Pritchard, S., Robertson, K., Sparks, A., Thode, A., 2019. Composite Burn Index (CBI) Data for the Conterminous US, Collected Between 1996 and 2018. https://doi.org/10.5066/P91BH1BZ

Pinheiro, J., Bates, D., R Core Team, 2023. nlme: Linear and Nonlinear Mixed Effects Models. https://CRAN.R-project.org/package=nlme

Pohlert, T., 2019. trend: Non-Parametric Trend Tests and Change-Point Detection. https://CRAN.R-project.org/package=trend

Povak, N.A., Kane, V.R., Collins, B.M., Lydersen, J.M., Kane, J.T., 2020. Multi-scaled drivers of severity patterns vary across land ownerships for the 2013 Rim Fire, California. Landscape Ecol 35, 293–318. https://doi.org/10.1007/s10980-019-00947-z

Prichard, S.J., Hessburg, P.F., Hagmann, R.K., Povak, N.A., Dobrowski, S.Z., Hurteau, M.D., Kane, V.R., Keane, R.E., Kobziar, L.N., Kolden, C.A., North, M., Parks, S.A., Safford, H.D., Stevens, J.T., Yocom, L.L., Churchill, D.J., Gray, R.W., Huffman, D.W., Lake, F.K., Khatri-Chhetri, P., 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecological Applications 31, e02433. https://doi.org/10.1002/eap.2433

Prichard, S.J., Kennedy, M.C., 2014. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. Ecological Applications 24, 571–590. https://doi.org/10.1890/13-0343.1

Prichard, S.J., Povak, N.A., Kennedy, M.C., Peterson, D.W., 2020. Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. Ecological Applications 30, e02104. https://doi.org/10.1002/eap.2104

Prichard, S.J., Stevens-Rumann, C.S., Hessburg, P.F., 2017. Tamm Review: Shifting global fire regimes: Lessons from reburns and research needs. Forest Ecology and Management. 396: 217-233 396, 217–233. https://doi.org/10.1016/j.foreco.2017.03.035

Radeloff, V.C., Helmers, D.P., Kramer, H.A., Mockrin, M.H., Alexandre, P.M., Bar-Massada, A., Butsic, V., Hawbaker, T.J., Martinuzzi, S., Syphard, A.D., Stewart, S.I., 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. Proceedings of the National Academy of Sciences 115, 3314–3319. https://doi.org/10.1073/pnas.1718850115

Raffa, K.F., Aukema, B.H., Bentz, B.J., Carroll, A.L., Hicke, J.A., Turner, M.G., Romme, W.H., 2008. Cross-scale Drivers of Natural Disturbances Prone to Anthropogenic Amplification: The Dynamics of Bark Beetle Eruptions. BioScience 58, 501–517. https://doi.org/10.1641/B580607

Reilly, M.J., Dunn, C.J., Meigs, G.W., Spies, T.A., Kennedy, R.E., Bailey, J.D., Briggs, K., 2017. Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985–2010). Ecosphere 8, e01695. https://doi.org/10.1002/ecs2.1695

Reilly, M.J., Zuspan, A., Halofsky, J.S., Raymond, C., McEvoy, A., Dye, A.W., Donato, D.C., Kim, J.B., Potter, B.E., Walker, N., Davis, R.J., Dunn, C.J., Bell, D.M., Gregory, M.J., Johnston, J.D., Harvey, B.J., Halofsky, J.E., Kerns, B.K., 2022. Cascadia Burning: The historic, but not historically unprecedented, 2020 wildfires in the Pacific Northwest, USA. Ecosphere 13, e4070. https://doi.org/10.1002/ecs2.4070

Reilly, M.J., Zuspan, A., Yang, Z., 2023. Characterizing post-fire delayed tree mortality with remote sensing: sizing up the elephant in the room. Fire Ecology 19, 64. https://doi.org/10.1186/s42408-023-00223-1

Ritchie, M.W., Knapp, E.E., Skinner, C.N., 2013. Snag longevity and surface fuel accumulation following post-fire logging in a ponderosa pine dominated forest. Forest Ecology and Management 287, 113–122. https://doi.org/10.1016/j.foreco.2012.09.001

Ritter, S.M., Hoffman, C.M., Battaglia, M.A., Linn, R., Mell, W.E., 2023. Vertical and Horizontal Crown Fuel Continuity Influences Group-Scale Ignition and Fuel Consumption. Fire 6, 321. https://doi.org/10.3390/fire6080321

Ritter, S.M., Hoffman, C.M., Battaglia, M.A., Stevens-Rumann, C.S., Mell, W.E., 2020. Fine-scale fire patterns mediate forest structure in frequent-fire ecosystems. Ecosphere 11, e03177. https://doi.org/10.1002/ecs2.3177

Robinson, N.M., Leonard, S.W.J., Ritchie, E.G., Bassett, M., Chia, E.K., Buckingham, S., Gibb, H., Bennett, A.F., Clarke, M.F., 2013. REVIEW: Refuges for fauna in fire-prone landscapes: their ecological function and importance. Journal of Applied Ecology 50, 1321–1329. https://doi.org/10.1111/1365-2664.12153

Rollins, M.G., Frame, C.K., 2006. The LANDFIRE Prototype Project: nationally consistent and locally relevant geospatial data for wildland fire management (No. RMRS-GTR-175). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ft. Collins, CO. https://doi.org/10.2737/RMRS-GTR-175

Rosenthal, A., Stover, E., Haar, R.J., 2021. Health and social impacts of California wildfires and the deficiencies in current recovery resources: An exploratory qualitative study of systems-level issues. PLOS ONE 16, e0248617. https://doi.org/10.1371/journal.pone.0248617

Rupp, D.E., Li, S., Mote, P.W., Shell, K.M., Massey, N., Sparrow, S.N., Wallom, D.C.H., Allen, M.R., 2017. Seasonal spatial patterns of projected anthropogenic warming in complex terrain: a modeling study of the western US. Clim Dyn 48, 2191–2213. https://doi.org/10.1007/s00382-016-3200-x

Safford, H.D., Paulson, A.K., Steel, Z.L., Young, D.J.N., Wayman, R.B., 2022. The 2020 California fire season: A year like no other, a return to the past or a harbinger of the future? Global Ecology and Biogeography n/a. https://doi.org/10.1111/geb.13498

Safford, H.D., Stevens, J.T., 2017. Natural range of variation for yellow pine and mixed-conifer forests in the Sierra Nevada, southern Cascades, and Modoc and Inyo National Forests, California, USA (No. PSW-GTR-256). U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station, Albany, CA. https://doi.org/10.2737/PSW-GTR-256

Schillinger, R.R., Adams, D.M., Latta, G.S., van Nalts, A.K., 2003. An Analysis of Future Private Timber Supply Potential in Western Oregon. Western Journal of Applied Forestry 18, 166–174. https://doi.org/10.1093/wjaf/18.3.166

Schwartz, M.W., Thorne, J.H., Collins, B.M., Stine, P.A., 2020. "Forest mismanagement" misleads. Science 370, 417–417. https://doi.org/10.1126/science.abe9647

Schwilk, D.W., Keeley, J.E., 2006. The role of fire refugia in the distribution of pinus sabiniana (Pinaceae) in the southern Sierra Nevada. Madroño 53, 364–372. https://www.jstor.org/stable/41425665

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M.J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T.A., Reyer, C.P.O., 2017. Forest disturbances under climate change. Nature Clim Change 7, 395–402. https://doi.org/10.1038/nclimate3303

Senande-Rivera, M., Insua-Costa, D., Miguez-Macho, G., 2022. Spatial and temporal expansion of global wildland fire activity in response to climate change. Nat Commun 13, 1208. https://doi.org/10.1038/s41467-022-28835-2

Siegel, K.J., Larsen, L., Stephens, C., Stewart, W., Butsic, V., 2022. Quantifying drivers of change in social-ecological systems: land management impacts wildfire probability in forests of the western US. Reg Environ Change 22, 98. https://doi.org/10.1007/s10113-022-01950-y

Singleton, M.P., Thode, A.E., Sánchez Meador, A.J., Iniguez, J.M., Stevens, J.T., 2021. Management strategy influences landscape patterns of high-severity burn patches in the southwestern United States. Landscape Ecol 36, 3429–3449. https://doi.org/10.1007/s10980-021-01318-3

Skinner, C.N., Taylor, A.H., 2018. Chapter Twelve. Southern Cascades Bioregion, in: Chapter Twelve. Southern Cascades Bioregion. University of California Press, pp. 195–218. https://doi.org/10.1525/9780520961913-015

Skinner, C.N., Taylor, A.H., Agee, J.K., Briles, C.E., Whitlock, C.L., 2018. Chapter Eleven. Klamath Mountains Bioregion, in: Chapter Eleven. Klamath Mountains Bioregion. University of California Press, pp. 171–194. https://doi.org/10.1525/9780520961913-014

Soga, M., Gaston, K.J., 2018. Shifting baseline syndrome: causes, consequences, and implications. Frontiers in Ecology and the Environment 16, 222–230. https://doi.org/10.1002/fee.1794

Sorenson, D.G., 2012. Chapter 12: Eastern Cascades Slopes and Foothills Ecoregion, in: Status and Trends of Land Change in the Western United States - 1973 to 2000, Professional Paper 1794-A. U.S. Geological Survey.

Sovern, S.G., Lesmeister, D.B., Dugger, K.M., Pruett, M.S., Davis, R.J., Jenkins, J.M., 2019. Activity center selection by northern spotted owls. The Journal of Wildlife Management 83, 714–727. https://doi.org/10.1002/jwmg.21632

Spies, T., Long, J., Charnley, S., Hessburg, P., Marcot, B., Reeves, G., Lesmeister, D., Reilly, M., Cerveny, L., Stine, P., Raphael, M.G., 2019. Twenty-five years of the Northwest Forest Plan: what have we learned? Frontiers in Ecology and the Environment. 35, 1. https://doi.org/10.1002/fee.2101

Spies, T., White, E., Kline, J., Fischer, A., Ager, A., Bailey, J., Bolte, J., Koch, J., Platt, E., Olsen, C., Jacobs, D., Shindler, B., Steen-Adams, M., Hammer, R., 2014. Examining fire-prone forest landscapes as coupled human and natural systems. Ecology and Society 19. https://doi.org/10.5751/ES-06584-190309

Spies, T.A., Hemstrom, M.A., Youngblood, A., Hummel, S., 2006. Conserving Old-Growth Forest Diversity in Disturbance-Prone Landscapes. Conservation Biology 20, 351–362. https://doi.org/10.1111/j.1523-1739.2006.00389.x

Spies, T.A., Hessburg, P.F., Skinner, C.N., Puettmann, K.J., Reilly, M.J., Davis, R.J., Kertis, J.A., Long, J.W., Shaw, D.C., 2018a. Chapter 3: Old growth, disturbance, forest succession, and management in the area of the Northwest Forest Plan. In: Spies, T.A.; Stine, P.A.; Gravenmier, R.; Long, J.W.; Reilly, M.J., tech. coords. 2018. Synthesis of science to inform land management within the Northwest Forest Plan area. Gen. Tech. Rep. PNW-GTR-966. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 95-243. 966, 95.

Spies, T.A., Long, J.W., Stine, P., Charnley, S., Cerveny, L., Marcot, B.G., Reeves, G., Hessburg, P.F., Lesmeister, D., Reilly, M.J., Raphael, M.G., Davis, R.J., 2018b. Chapter 12: Integrating ecological and social science to inform land management in the area of the northwest forest plan. In: Spies, T.A.; Stine, P.A.; Gravenmier, R.; Long, J.W.; Reilly, M.J., tech. coords. 2018. Synthesis of science to inform land management within the Northwest Forest Plan area. Gen. Tech. Rep. PNW-GTR-966. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 919-1020. 966, 919.

Spies, T.A., Stine, P.A., Gravenmier, R., Long, J.W., Reilly, M.J., Mazza, R., 2018c. Synthesis of science to inform land management within the Northwest Forest Plan area: executive summary. Gen. Tech. Rep. PNW-GTR-970. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 186 p. 970. https://doi.org/10.2737/PNW-GTR-970

Stankey, G.H., Bormann, B.T., Ryan, C., Shindler, B., Sturtevant, V., Clark, R.N., Philpot, C., 2003. Adaptive Management and the Northwest Forest Plan: Rhetoric and Reality. Journal of Forestry 101, 40–46. https://doi.org/10.1093/jof/101.1.40

Starrs, C.F., Butsic, V., Stephens, C., Stewart, W., 2018. The impact of land ownership, firefighting, and reserve status on fire probability in California. Environ. Res. Lett. 13, 034025. https://doi.org/10.1088/1748-9326/aaaad1

Stavros, E.N., Abatzoglou, J.T., McKenzie, D., Larkin, N.K., 2014. Regional projections of the likelihood of very large wildland fires under a changing climate in the contiguous Western United States. Climatic Change 126, 455–468. https://doi.org/10.1007/s10584-014-1229-6

Steel, Z.L., Fogg, A.M., Burnett, R., Roberts, L.J., Safford, H.D., 2022a. When bigger isn't better—Implications of large high-severity wildfire patches for avian diversity and community composition. Diversity and Distributions 28, 439–453. https://doi.org/10.1111/ddi.13281

Steel, Z.L., Jones, G.M., Collins, B.M., Green, R., Koltunov, A., Purcell, K.L., Sawyer, S.C., Slaton, M.R., Stephens, S.L., Stine, P., Thompson, C., 2022b. Mega-disturbances cause rapid decline of mature conifer forest habitat in California. Ecological Applications 33, e2763. https://doi.org/10.1002/eap.2763

Steel, Z.L., Koontz, M.J., Safford, H.D., 2018. The changing landscape of wildfire: burn pattern trends and implications for California's yellow pine and mixed conifer forests. Landscape Ecol 33, 1159–1176. https://doi.org/10.1007/s10980-018-0665-5

Steelman, T., Nowell, B., 2019. Evidence of effectiveness in the Cohesive Strategy: measuring and improving wildfire response. Int. J. Wildland Fire 28, 267–274. https://doi.org/10.1071/WF18136

Stein, A., Gerstner, K., Kreft, H., 2014. Environmental heterogeneity as a universal driver of species richness across taxa, biomes and spatial scales. Ecology Letters 17, 866–880. https://doi.org/10.1111/ele.12277

Stephens, S.L., Bernal, A.A., Collins, B.M., Finney, M.A., Lautenberger, C., Saah, D., 2022. Mass fire behavior created by extensive tree mortality and high tree density not predicted by operational fire behavior models in the southern Sierra Nevada. Forest Ecology and Management 518, 120258. https://doi.org/10.1016/j.foreco.2022.120258

Stephens, S.L., Burrows, N., Buyantuyev, A., Gray, R.W., Keane, R.E., Kubian, R., Liu, S., Seijo, F., Shu, L., Tolhurst, K.G., Wagtendonk, J.W. van, 2014. Temperate and boreal forest mega-fires: characteristics and challenges. Frontiers in Ecology and the Environment. 12: 115-122. 115–122. https://doi.org/10.1890/120332

Stephens, S.L., Collins, B.M., Fettig, C.J., Finney, M.A., Hoffman, C.M., Knapp, E.E., North, M.P., Safford, H., Wayman, R.B., 2018. Drought, Tree Mortality, and Wildfire in Forests Adapted to Frequent Fire. BioScience 68, 77–88. https://doi.org/10.1093/biosci/bix146

Stephens, S.L., Martin, R.E., Clinton, N.E., 2007. Prehistoric fire area and emissions from California's forests, woodlands, shrublands, and grasslands. Forest Ecology and Management 251, 205–216. https://doi.org/10.1016/j.foreco.2007.06.005

Stephens, S.L., McIver, J.D., Boerner, R.E.J., Fettig, C.J., Fontaine, J.B., Hartsough, B.R., Kennedy, P.L., Schwilk, D.W., 2012. Effects of forest fuel-reduction treatments in the United States. Bioscience 62:549-560 62, 549–560. https://doi.org/10.1525/bio.2012.62.6.6

Stephens, S.L., Miller, J.D., Collins, B.M., North, M.P., Keane, J.J., Roberts, S.L., 2016. Wildfire impacts on California spotted owl nesting habitat in the Sierra Nevada. Ecosphere 7, e01478. https://doi.org/10.1002/ecs2.1478

Stephens, S.L., Moghaddas, J.J., 2005. Silvicultural and reserve impacts on potential fire behavior and forest conservation: Twenty-five years of experience from Sierra Nevada mixed conifer forests. Biological Conservation 125, 369–379. https://doi.org/10.1016/j.biocon.2005.04.007

Stephens, S.L., Moghaddas, J.J., Edminster, C., Fiedler, C.E., Haase, S., Harrington, M., Keeley, J.E., Knapp, E.E., McIver, J.D., Metlen, K., Skinner, C.N., Youngblood, A., 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western U.S. forests. Ecological Applications 19, 305–320. https://doi.org/10.1890/07-1755.1

Stephens, S.L., Thompson, S., Boisramé, G., Collins, B.M., Ponisio, L.C., Rakhmatulina, E., Steel, Z.L., Stevens, J.T., Wagtendonk, J.W. van, Wilkin, K., 2021. Fire, water, and biodiversity in the Sierra Nevada: a possible triple win. Environ. Res. Commun. 3, 081004. https://doi.org/10.1088/2515-7620/ac17e2

Stephens, S.L., Westerling, A.L., Hurteau, M.D., Peery, M.Z., Schultz, C.A., Thompson, S., 2020. Fire and climate change: conserving seasonally dry forests is still possible. Frontiers in Ecology and the Environment 18, 354–360. https://doi.org/10.1002/fee.2218

Stevens, J.T., Collins, B.M., Miller, J.D., North, M.P., Stephens, S.L., 2017. Changing spatial patterns of stand-replacing fire in California conifer forests. Forest Ecology and Management 406, 28–36. https://doi.org/10.1016/j.foreco.2017.08.051

Stevens, J.T., Haffey, C.M., Coop, J.D., Fornwalt, P.J., Yocom, L., Allen, C.D., Bradley, A., Burney, O.T., Carril, D., Chambers, M.E., Chapman, T.B., Haire, S.L., Hurteau, M.D., Iniguez, J.M., Margolis, E.Q., Marks, C., Marshall, L.A.E., Rodman, K.C., Stevens-Rumann, C.S., Thode, A.E., Walker, J.J., 2021. Tamm Review: Postfire landscape management in frequent-fire conifer forests of the southwestern United States. Forest Ecology and Management 502, 119678. https://doi.org/10.1016/j.foreco.2021.119678

Stevens-Rumann, C.S., Morgan, P., 2019. Tree regeneration following wildfires in the western US: a review. Fire Ecology 15, 15. https://doi.org/10.1186/s42408-019-0032-1

Stevens-Rumann, C.S., Prichard, S.J., Whitman, E., Parisien, M.-A., Meddens, A.J.H., 2022. Considering regeneration failure in the context of changing climate and disturbance regimes in western North America. Can. J. For. Res. 52, 1281–1302. https://doi.org/10.1139/cjfr-2022-0054

Stone, C., Hudak, A., Morgan, P., 2004. Forest Harvest Can Increase Subsequent Forest Fire Severity. USDA Forest Service / UNL Faculty Publications. https://digitalcommons.unl.edu/usdafsfacpub/199

Sugihara, N.G., Van Wagtendonk, J.W., Shaffer, K.E., Fites-Kaufman, J., Thode, A.E., 2006. Fire in California's Ecosystems, 1st ed. University of California Press.

Swain, D.L., 2015. A tale of two California droughts: Lessons amidst record warmth and dryness in a region of complex physical and human geography. Geophysical Research Letters 42, 9999–10,003. https://doi.org/10.1002/2015GL066628

Talty, M.J., Mott Lacroix, K., Aplet, G.H., Belote, R.T., 2020. Conservation value of national forest roadless areas. Conservation Science and Practice 2, e288. https://doi.org/10.1111/csp2.288

Taylor, A.H., Harris, L.B., Drury, S.A., 2021. Drivers of fire severity shift as landscapes transition to an active fire regime, Klamath Mountains, USA. Ecosphere 12. https://doi.org/10.1002/ecs2.3734

Taylor, A.H., Harris, L.B., Skinner, C.N., 2022. Severity patterns of the 2021 Dixie Fire exemplify the need to increase low-severity fire treatments in California's forests. Environ. Res. Lett. 17, 071002. https://doi.org/10.1088/1748-9326/ac7735

Taylor, A.H., Skinner, C.N., 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. Ecological Applications13(3): 704-719 13, 704–719.

Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M.R., Delogu, G.M., Fernandes, P.M., Ferreira, C., McCaffrey, S., McGee, T.K., Parente, J., Paton, D., Pereira, M.G., Ribeiro, L.M., Viegas, D.X., Xanthopoulos, G., 2018. Defining Extreme Wildfire Events: Difficulties, Challenges, and Impacts. Fire 1, 9. https://doi.org/10.3390/fire1010009

Tews, J., Brose, U., Grimm, V., Tielborger, K., Wichmann, M.C., Schwager, M., Jeltsch, F., 2004. Animal species diversity driven by habitat heterogeneity/diversity: the importance of keystone structures. J. Biogeogr. 31, 79–92. https://doi.org/10.1046/j.0305-0270.2003.00994.x

Thomas, J.W., Forsman, E.D., Lint, J., Meslow, E.C., Noon, B.R., Verner, J., United States., United States., United States., U.S. Fish and Wildlife Service, United States., 1990. A conservation strategy for the northern spotted owl. [U.S. Department of the Interior, Fish and Wildlife Service], Portland, Or. : https://doi.org/10.5962/bhl.title.124040

Thomas, J.W., Franklin, J.F., Gordon, J., Johnson, K.N., 2006. The Northwest Forest Plan: Origins, Components, Implementation Experience, and Suggestions for Change. Conservation Biology 20, 277–287. https://doi.org/10.1111/j.1523-1739.2006.00385.x

Thompson, J.R., Spies, T.A., 2010. Factors associated with crown damage following recurring mixed-severity wildlifes and post-fire management in southwestern Oregon. https://doi.org/10.1007/s10980-010-9456-3

Thompson, J.R., Spies, T.A., 2009. Vegetation and weather explain variation in crown damage within a large mixed-severity wildfire. Forest Ecology and Management 258, 1684–1694. https://doi.org/10.1016/j.foreco.2009.07.031

Thompson, M.P., Liu, Z., Wei, Y., Caggiano, M.D., Thompson, M.P., Liu, Z., Wei, Y., Caggiano, M.D., 2018. Analyzing Wildfire Suppression Difficulty in Relation to Protection Demand, in: Environmental Risks. IntechOpen. https://doi.org/10.5772/intechopen.76937

Toman, E., Shindler, B., McCaffrey, S., Bennett, J., 2014. Public acceptance of wildland fire and fuel management: Panel responses in seven locations. Environmental Management. 54(3): 557-570. 54, 557–570. https://doi.org/10.1007/s00267-014-0327-6

US Department of Interior (DOI), US Department of Agriculture (USDA), 2014. National Cohesive Wildland Fire Management Strategy. https://www.forestsandrangelands.gov/strategy/

US Forest Service, 2023. Region 5 and Region 6; California, Oregon, and Washington; Forest Plan Amendment for Planning and Management of Northwest Forests Within the Range of the Northern Spotted Owl, 2023-27742.
US Forest Service, 2022. The Northwest Forest Plan Area Advisory Committee, 87 FR 69249. https://www.federalregister.gov/documents/2022/11/18/2022-25184/the-northwest-forest-plan-area-advisory-committee
U.S. Forest Service (USFS), Bureau of Land Management (BLM), 1994. Standards and Guidelines for Management of Habitat for Late-Successional and Old-Growth Forest Related Species Within the Range of the Northern Spotted Owl. Attachment A to the Record of Decision for Amendments to Forest Service and Bureau of Land Management Planning Documents Within the Range of the Northern Spotted Owl. https://www.fs.usda.gov/r6/reo/library/downloads/documents/NWFP-S&G-1994.pdf
USGS GAP Analysis Project, 2022. Protected Areas Database of the United States. https://doi.org/10.5066/P9Q9LQ4B
Vaillant, N.M., Reinhardt, E.D., 2017. An Evaluation of the Forest Service Hazardous Fuels Treatment Program—Are We Treating Enough to Promote Resiliency or Reduce Hazard? Journal of Forestry 115, 300–308. https://doi.org/10.5849/jof.16-067
van Mantgem, P.J., Caprio, A.C., Stephenson, N.L., Das, A.J., 2021. Forest Resistance to Extended Drought Enhanced by Prescribed Fire in Low Elevation Forests of the Sierra Nevada. Forests 12, 1248. https://doi.org/10.3390/f12091248
van Mantgem, P.J., Caprio, A.C., Stephenson, N.L., Das, A.J., 2016. Does Prescribed Fire Promote Resistance to Drought in Low Elevation Forests of the Sierra Nevada, California, USA? fire ecol 12, 13–25. https://doi.org/10.4996/fireecology.1201013
van Wagtendonk, J., 2007. The History and Evolution of Wildland Fire Use. fire ecol 3, 3–17. https://doi.org/10.4996/fireecology.0302003
Varhola, A., Coops, N.C., Weiler, M., Moore, R.D., 2010. Forest canopy effects on snow accumulation and ablation: An integrative review of empirical results. Journal of Hydrology 392, 219–233. https://doi.org/10.1016/j.jhydrol.2010.08.009
WA Department of Natural Resources (WA DNR), 2021. Washington Parcel and Legal Boundaries. https://data-wadnr.opendata.arcgis.com/datasets/1400dcfcc52a4c56ab1301e3c98d426c_1
Walker, B., Holling, C.S., Carpenter, S., Kinzig, A., 2004. Resilience, Adaptability and Transformability in Social–ecological Systems. Ecology and Society 9. https://doi.org/10.5751/ES-00650-090205
Wang, Y., Lewis, D.J., 2024. Wildfires and climate change have lowered the economic value of western U.S. forests by altering risk expectations. Journal of Environmental Economics and Management 123, 102894. https://doi.org/10.1016/j.jeem.2023.102894
Weill, A.M., Watson, L.M., Latimer, A.M., 2020. Walking through a "phoenix landscape": hiker surveys reveal nuanced perceptions of wildfire effects. Int. J. Wildland Fire 29, 561. https://doi.org/10.1071/WF19053
Weisberg, P.J., Dilts, T.E., Becker, M.E., Young, J.S., Wong-Kone, D.C., Newton, W.E., Ammon, E.M., 2014. Guild-specific responses of avian species richness to LiDAR-derived habitat

heterogeneity. Acta Oecol.-Int. J. Ecol. 59, 72–83. https://doi.org/10.1016/j.actao.2014.06.002

Weisberg, P.J., Swanson, F.J., 2003. Regional synchroneity in fire regimes of western Oregon and Washington, USA. Forest Ecology and Management 172, 17–28. https://doi.org/10.1016/S0378-1127(01)00805-2

Welch, J.R., 2012. Effects of fire on intangible cultural resources: Moving toward a landscape approach [Chapter 8]. In: Ryan, Kevin C.; Jones, Ann Trinkle; Koerner, Cassandra L.; Lee, Kristine M., tech. eds. Wildland fire in ecosystems: effect 42, 157–170.

Westerling, A.L., 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philosophical Transactions of the Royal Society B: Biological Sciences 371, 20150178. https://doi.org/10.1098/rstb.2015.0178

Wildland Fire Mitigation and Management Commission, 2023. ON FIRE: The Report of the Wildland Fire Mitigation and Management Commission. https://www.usda.gov/sites/default/files/documents/wfmmc-final-report-09-2023.pdf

Winkel, G., 2014. When the pendulum doesn't find its center: Environmental narratives, strategies, and forest policy change in the US Pacific Northwest. Global Environmental Change 27, 84–95. https://doi.org/10.1016/j.gloenvcha.2014.04.009

Wolf, K.D., Higuera, P.E., Davis, K.T., Dobrowski, S.Z., 2021. Wildfire impacts on forest microclimate vary with biophysical context. Ecosphere 12, e03467. https://doi.org/10.1002/ecs2.3467

Wright, M., Wager, S., Probst, P., 2023. ranger: A Fast Implementation of Random Forests. https://cran.r-project.org/web/packages/ranger/ranger.pdf

Zald, H.S.J., Dunn, C.J., 2018. Severe fire weather and intensive forest management increase fire severity in a multi-ownership landscape. Ecological Applications 28, 1068–1080. https://doi.org/10.1002/eap.1710

Zhu, Z., Key, C., Ohlen, D., Benson, N., 2006. Evaluate Sensitivities of Burn-Severity Mapping Algorithms for Different Ecosystems and Fire Histories in the United States. Final Report to the Joint Fire Science Program. JFSP Project No. 01-1-4-12. Sioux Falls, SD: USGS, National Center for Earth Resources Observation and Science. 35 p.