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Quantifying the relative importance of multiple indices when predicting fire severity in the Western US.

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Environmental Systems

by

Alisa Renae Keyser

Committee in charge:
Professor Anthony LeRoy Westerling, Chair
Professor Jessica Blois
Professor Elliott Campbell
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2016

The Dissertation of Alisa Renae Keyser is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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University of California, Merced
2016

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This Dissertation is dedicated to my mother and my sister.

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No great journey is ever a truly sole endeavor; the successful completion of this dissertation journey is no exception. I have had the privilege of working in the company of many exceptional scientists and thinkers both during and prior to my dissertation. I have been fortunate to have the support of family, friends and colleagues. I would like to acknowledge some of the people who have shaped this dissertation in one way or another.

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I and my dissertation also benefitted from the exceptional group of scientists who served on my committee: Jessica Blois, Dan Cayan, Elliott Campbell, Lara Kueppers. Thanks to all of them for their time and efforts. A special thanks goes to Jessica Blois for joining at the end, and asking questions and providing suggestions that improved the clarity of the dissertation so much. Thanks to Lara Kueppers for allowing me to participate in her lab group sharing discussions and getting feedback on methods and presentation. Each member of my committee brought unique suggestions and insights that made the dissertation document richer in information content, clearer in language and higher quality overall. I learned from each of them and am incredibly fortunate to have had their input into my work.

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CONFERENCE PRESENTATIONS

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Abstract of the Dissertation

Quantifying the relative importance of multiple indices when predicting fire severity in the Western US.

by

Alisa Renae Keyser

Doctor of Philosophy, Environmental Systems
University of California Merced, 2016
Dr. Anthony LeRoy Westerling, Chair

A long history of fire suppression by federal land management agencies has interrupted fire regimes in much of the western United States. Many forest types that historically burned frequently have undergone significant changes in species composition and have heavy accumulations of surface and canopy fuels. Fuel quantity and flammability are important local predictors of fire severity. The climate system operates at both broad and fine spatial and temporal scales to favor conditions that increase fuel loading through biomass accumulation and accelerate drying of fuels; and maintain active fires under favorable concurrent atmospheric conditions. Observed increases in large fire occurrence and area burned in recent decades are explained by warmer, drier, and longer growing season conditions in the West. There has not yet been a large-scale study that examines patterns and controls of high severity fire in the western US. We use a 30 year record of fire severity to identify the controls of high severity fire across the western US, develop statistical probability models for high severity fire occurrence and area burned, and examine the impacts of climate change on high severity fire risk. In examining topography, vegetation and fire-year climate as predictors we found that inclusion of both vegetation and fire-year climate predictors was critical for identifying fires with high fractional fire severity and capturing inter-annual variation in high severity fire occurrence. While a single, west-wide model was able to predict high severity fire occurrence with some accuracy, it was necessary to develop regional models to accurately predict high severity area burned for forests in extreme fire years. A simple generalized Pareto distribution model with maximum temperature the month of fire, annual normalized moisture deficit and location explains forest high severity area burned in a west-wide model, with the exception of years with especially large areas burned with high severity fire: 1988, 2002. With respect to mitigation or management of high severity fire, understanding what drives extreme fire years is critical. For the Northern Rocky Mountains, Sierra Nevada Mountains, and Southwest forests, topography, spring temperature and snowpack condition, and vegetation condition class variables improved our prediction of high severity burned area in extreme fire years. We used the models developed for the Northern Rocky Mountains to examine how fractional area of high severity fire will change with climate. Application of output from global circulation models to large fire occurrence and size models in the Greater Yellowstone Ecosystem indicates that climate conditions by mid-century will result in an increase in

the frequency of large fire events and area burned. We applied GCM output to a set of probabilistic models for high severity fire occurrence and burned area for the Greater Yellowstone Ecosystem. We found that fraction of high severity burned area increases to levels by mid-century that are three times greater than a 1961-1990 reference period. These potential changes in high severity area burned and frequency of occurrence may result in changes to species composition in these high elevation forests. If a goal of management is to mitigate extreme fire events in terms of fire severity, we would conclude that knowledge of fire year climate is essential. All of the models we developed predict high severity fire occurrence and area burned with reasonable accuracy in all years when fire year climate and vegetation predictors are included. The inclusion of fire-year climate variables allows these models to forecast inter-annual variability in areas at future risk of high severity fire, beyond what slower-changing fuel conditions alone can accomplish. This allows for more targeted land management, including resource allocation for fuels reduction treatments to decrease the risk of high severity fire. Models like this will be important tools for assessing interactions between changing climate and fuel profiles under a diverse menu of future climate and management scenarios.

1   Introduction

Fire Severity: Degree to which a site has been altered or disrupted by fire; loosely, a product of fire intensity and residence time (http://www.nwcg.gov glossary of fire terms)

Uncharacteristic Fire: 'fire processes occurring outside their biophysical baseline conditions' (Hardy 2005).

A long history of fire suppression by federal land management agencies has interrupted fire regimes in much of the western United States (US). Many forest types that historically burned frequently have undergone significant changes in species composition and have heavy accumulations of surface and canopy fuels, putting them at risk for severe fires (Agee et al. 1977, Agee and Skinner 2005, McKelvey et al. 1996, Keane et al. 2002). In testimony to the Natural Disasters Roundtable, Cleaves (2001) testified that of ~415 million acres of fire adapted ecosystems in the coterminous US, more than 71 million are considered to be a high risk to human and ecosystem values due to an accumulation of fuels and risk of high severity fire, and more than 141 million are considered a moderate risk.

The year 2000 was a landmark fire year in terms of number, size, and cost of wildfires; since 2000, most years have seen wildfires of increasing size and severity in the western US, many termed 'catastrophic' for their costs to ecosystems and economies. As one example, suppression costs for the Hayman fire in Colorado (2002) were $38 million; real property losses were $24 million; projected rehabilitation costs are greater than $74 million (Graham, 2003). These are just some of the total economic costs. In August 2000, the National Fire Plan was implemented as a response to the 2000 fire season to respond to the increasing threat of severe wildfires with one of five key goals being hazardous fuels reduction; the Healthy Forests Initiative was enacted in 2002 to reduce the risk of severe wildfire (http://www.forestsandrangelands.gov/). Most land management agencies now manage wildlands with the specific goal of reducing the risk of severe fires through fuel reduction treatments (Agee and Skinner 2005, Stephens and Ruth 2005, Reinhardt et al. 2008). However, it is unknown whether fuel reduction treatments alone can mitigate the risk of severe fires.

In order to determine whether fire effects are uncharacteristic requires knowledge of the ecosystem in question, its natural fire regime, and the fuel character and condition. Ecosystem fire regimes are defined by fire frequency and fire severity, with five classes defined for the United States, Table 1.3.1. A low severity fire can have small patches of mixed or high severity fire effects, but the majority of the fire area will exhibit low severity. This type of fire regime is best exemplified by understory or ground fires that predominately reduce surface fuels. A high severity fire is exemplified by a stand replacing fire where most surface and crown fuels are burned and most over-story vegetation is killed. Between these two extremes is a mixed severity fire that results in a heterogeneous landscape mosaic of fire effects (Figure 1.4.1, Agee 1998). Fire regimes also have a time component. Most stand replacing fires occur at longer time intervals; most low or mixed severity fire regimes are characterized by shorter fire return intervals (Table 1.3.1). The ecosystem type plays an important role in determining the fire regime. Generally, higher elevation sites in the WUS support cool moist forests with dense

vegetation and fuels (exemplified by fire regime groups IV or V), whereas lower elevation sites support relatively less productive dry forests (exemplified by fire regime group I) (Table 1.3.1; Agee 1993, Stephenson 1998, Steel et al. 2015, Schoennagel et al. 2005).

Fire and ecosystems are subject to both top-down (climate) and bottom-up controls. Climate primarily exerts control over fire occurrence and behavior through top-down mechanisms. The climate system operates at both broad and fine spatial and temporal scales to favor conditions that increase fuel loading through biomass accumulation and accelerate drying of fuels (broad-scale phenomena); and maintain active fires under favorable concurrent atmospheric conditions, i.e. hot dry weather (fine-scale). Broad-scale drought conditions have been linked to large fires occurring synchronously at regional scales. Recent decades have seen warmer, drier, and longer growing season conditions that explain much of the observed increase in large fire occurrence and area burned in the West (Gedalof et al. 2005, Heyerdahl et al. 2008, Morgan et al. 2008, Swetnam and Anderson 2008, Westerling et al. 2006); these increases are predicted to continue with climate change in the western US (Westerling et al. 2011, Westerling 2016). Total area burned has been correlated to area burned in high severity fire in some regions, with high severity area burned increasing concomitantly with fire size (Cansler and Mckenzie 2014, Dillon et al. 2011, Miller et al 2009, Miller and Safford 2012).

Bottom-up controls of fire occurrence and severity include topography and vegetation/fuels. Together with climate, soils and topography interact to create biophysical settings that determine vegetation composition and productivity. Topographic variables such as slope, aspect, and elevation affect the energy and water available for biomass production and decomposition, and in turn fuel accumulation. Higher elevation sites in the western US support productive, cool moist forests with dense vegetation and fuels; lower elevation sites support relatively less productive dry forests (Agee 1998, Stephenson 1998, Schoennagel et al. 2005). The microclimate created by topography also controls the drying of fuels available to burn. The importance of both bottom-up and top-down controls on fire severity has been quantified at many scales—individual fires, landscapes, and small regions.

In the Sierra Nevada, CA/NV, Miller et al. (2009) found that fire size (mean and maximum) and total area burned increased in the period 1984-2006, and are now above pre-suppression era levels. They also found that the proportion of high severity, stand-replacing fires increased (Miller et. al 2009). The proportional increase in high severity fires was not uniform, but was concentrated in low to mid-elevation forest types where 25-40% of total burned area was classed as high severity. High severity fires are not characteristic of these forest types, indicating that the current fire regime in these ecosystems is outside of historical natural conditions (Agee et. al 1977, Agee 1998, Collins et. al 2009, Moody et al. 2006, Parsons and DeBenedetti 1979).

Whether a fire is uncharacteristic in its effects is dependent on an ecosystem's historic fire regime and the quantity and condition of fuels present on the ground. Large stand replacing fires are characteristic of many forest types in the West, but when fire size and severity are outside the natural range of variability of an ecosystem's fire regime, ecosystem function is put at risk and a fire is considered uncharacteristic. The ability to

predict potential fire severity would allow identification of landscapes where severe fires are probable, and thus provide insight and guidance for mitigation and management.

Prior analyses of fire severity in California forests showed that time since last fire and fire weather conditions predicted fire severity very well, while a larger regional analysis showed that topography and climate were important predictors of high severity fire (Collins et al. 2009, Dillon et al. 2011). There has not yet been a large-scale study that incorporates topography, vegetation and fire-year climate to determine regional scale patterns and controls of high severity fire. In this study, I use a 30 year record of fire severity from the Monitoring Trends in Burn Severity database (www.mtbs.gov) to identify the determinants of high severity fire across the western US, develop prediction models for high severity fire occurrence and area burned, and examine the impacts of climate change on high severity fire risk.

1.1 Organization of the Dissertation

The objectives of this dissertation are presented in three self-contained chapters (2-4) that are written in manuscript format. In Chapter 2, "Climate drives inter-annual variability in probability of high severity fire occurrence in the western United States," my objective was to examine topography, vegetation, and climate in terms of their utility for predicting high severity fire occurrence across eleven western states and to determine how they act separately to influence fire severity and what is their relative importance as co-determinants. Chapter 3, "Using extreme value theory to predict forest area burned in high severity for three regions of the western United States," seeks to answer the question of what determines high severity area burned in forest fires in the western US and in three smaller regions: the Northern Rocky Mountains, the Sierra Nevada Mountains, and Southwest forests. In Chapter 4, "How will climate change impact high severity burned area in the Greater Yellowstone Ecosystem?" I explore the impact of climate change on high severity fire risk for the Greater Yellowstone Ecosystem. All chapters were written using the pronoun 'we' to refer to myself and co-authors of each manuscript.

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1.3 Tables

Table 1.3.1. Standard fire regime groups for the western United States.
(www.landfire.gov)

Fire Regime Group I	≤ 35 Year Fire Return Interval, Low to Mixed Severity
Fire Regime Group II	≤ 35 Year Fire Return Interval, Replacement Severity
Fire Regime Group III	35-200 Year Fire Return Interval, Low to Mixed Severity
Fire Regime Group IV	35-200 Year Fire Return Interval, Replacement Severity
Fire Regime Group V	> 200 Year Fire Return Interval, Any Severity

1.4 Figures

Figure 1.4.1 The spatial patterns of fire effects that result from different fire regimes. Low severity fires can have small patches of mixed or high severity fire. Moderate (mixed) severity fires exhibit a mosaic of low, mixed and high severity fire patches. High severity fires are dominated by high severity patches reflecting stand replacing fire. (Taken from Agee, J.K. 1998)

2 Climate drives inter-annual variability in probability of high severity fire occurrence in the western United States

2.1 Abstract

A long history of fire suppression in the western United States has significantly changed forest structure and ecological function, leading to increasingly uncharacteristic fires in terms of size and severity. Fuel quantity and flammability are important local predictors of fire severity. Prior analyses of fire severity in California forests showed that time since last fire and fire weather conditions predicted fire severity very well, while a larger regional analysis showed that topography and climate were important predictors of high severity fire. There has not yet been a large-scale study that incorporates topography, vegetation and fire-year climate to determine regional scale occurrence of high severity fire. In this study, we create a model to predict the probability of occurrence of high severity fire for the western US. We find it is possible to predict high severity fire occurrence with some accuracy, and identify the relative importance of predictor classes in determining the probability of high severity fire. The inclusion of both vegetation and fire-year climate predictors was critical for model skill in identifying fires with high fractional fire severity. The inclusion of fire-year climate variables allows this model to forecast interannual variability in areas at future risk of high severity fire, beyond what slower-changing fuel conditions alone can accomplish. This allows for more targeted land management, including resource allocation for fuels reduction treatments to decrease the risk of high severity fire. Models like this will be important tools for assessing interactions between changing climate and fuel profiles under a diverse menu of future climate and management scenarios.

2.2 Introduction

More than 70 years of fire suppression has significantly changed forest structure and ecological function in much of the western United States (WUS), leading to increasingly uncharacteristic fires in terms of size and severity. Many claim this partially due to the build up of fuels due to missed fire cycles in formerly open canopy forests with predominately surface fire regimes (Keane et al. 2002, Miller et al. 2009). The number and size of large wildfires have been steadily increasing in the Western US in recent decades, with a resulting increase in annual average area burned on public lands (Stephens 2005, Westerling et al. 2006, Dennison et al. 2014, Westerling 2016). These changes have resulted in a rapid increase in firefighting costs; for example, federal appropriations for fighting fires averaged $2.9 billion for the period 2001-2007, up from a period average of $1.2 billion for 1996-2000 (GAO-07-922T). Not yet fully quantified is the impact of this history on patterns of fire severity and high severity fire occurrence in the WUS.

Recent research has shown that climate is a strong predictor of large fire occurrence (Preisler and Westerling 2007, Swetnam and Anderson 2008, Westerling et al. 2006, Westerling and Bryant 2008), and that future, warmer conditions may result in continued increases in total area burned (Westerling and Bryant 2008, Westerling et. al 2009, Westerling et al. 2011). Climate primarily exerts control over fire occurrence and severity through top-down mechanisms. The climate system operates at both broad and fine

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spatial and temporal scales to favor conditions that increase fuel loading through biomass accumulation and accelerate drying of fuels (broad-scale phenomena) and to maintain active fires under favorable concurrent atmospheric conditions, i.e. hot dry weather (fine-scale). Broad-scale drought conditions have been linked to large fires occurring synchronously at regional scales and recent decades have seen warmer, drier, and longer growing season conditions that explain much of the large fire occurrence in the West (Gedalof et al. 2005, Westerling et al. 2006, Heyerdahl et al. 2008, Morgan et al. 2008, Swetnam and Anderson 2008, Westerling 2016).

Bottom-up controls of fire occurrence and severity include topography and vegetation/fuels. Together with climate, soils and topography interact to create biophysical settings that determine vegetation composition and productivity. Topographic variables such as slope, aspect, and elevation affect the energy and water available for biomass production and decomposition, and in turn fuel accumulation. Generally, higher elevation sites in the WUS support cool moist forests with dense vegetation and fuels, whereas lower elevation sites support relatively less productive dry forests (Agee 1998, Stephenson 1998, Schoennagel et al. 2005, Steel et al. 2015). The microclimate created by topography also controls the drying of fuels available to burn. The importance of both bottom-up and top-down controls on fire severity has been quantified at many scales— individual fires, landscapes, and small regions.

Findings in the Colorado Front Range and forests in the Southwest indicate that high severity fire occurrence is a function of extreme weather conditions (top-down) rather than cover type or woody fuel quantity (Holden et al. 2007, Sheriff et al. 2014). Collins et al. (2007, 2009) found that fire severity occurrence was controlled by top down and bottom up predictors in the Sierra Nevada. Both climate at the time of fire and time since last fire were important for predicting patterns of fire severity. The time since last fire determines the amount of biomass and fuel buildup on a site. The importance of top-down controls on high severity fire in these regions contrasts with findings in the Northwest.

In the North Cascade Range, Washington, bottom-up controls appeared to mediate burn severity in areas with historical low to moderate severity fire regimes, and top-down controls were most evident in areas where they determine the historical fire regime— high elevation, cool moist forests (Cansler and McKenzie 2014). In an examination of 42 forest fires in central Idaho and western Montana, Birch et al. (2015) also found that bottom up controls, specifically topography and existing vegetation, best predicted daily burn severity values over daily weather and fuel moisture.

There is no consistent picture that emerges of controls on fire severity occurrence among these small-scale studies (individual fires to small regions). Dillon et al. (2011) performed the broadest spatial analysis to date and modeled high severity fire occurrence for ecoregions in the northwestern and southwestern US. They found that both bottom-up and top-down controls were important for predicting high severity fire occurrence, but concluded that topographic controls were relatively more important than climate variables, with the relative importance of variable classes unique to each region (Dillon et al. 2011).

While existing studies have informed our understanding of high severity fire occurrence at small scales, there has not yet been a large-scale study that incorporates topography, vegetation, and fire year climate to determine regional scale occurrence of high severity fire. In this study we develop a model of high severity fire occurrence for the western US that can be applied to predict future risk of occurrence. Our objectives are to:

1.   examine topography, vegetation, and climate in terms of their utility for predicting the occurrence of high severity fire across the WUS.
2.   determine how these factors act separately to influence fire severity and their relative importance as co-determinants of fire severity.

2.3 Methods

2.3.1 Spatial and Temporal Domain of Analysis

The spatial domain of our analysis is a 1/8th degree latitude / longitude grid (~12km resolution) west of −120.0625 longitude encompassing eleven western states: WA, OR, CA, ID, UT, NV, MT, WY, CO, NM, AZ. The spatial resolution of the data used in this study varies from 30m (e.g. observed high severity burned area, vegetation characteristics) to ~12km (e.g. climate, topography, simulated severity). To maintain the information in the finer scale data, we calculated the fractional area of each variable within each 1/8th degree modeling pixel for all data with higher resolution.

The temporal domain of analysis was determined by the burn severity data, which is produced using Landsat images. Our burn severity database begins in 1984 and ends in 2007; this was the most recent year of complete burn severity mapping for all eleven western states at the start of the project. Because our hydroclimate predictor variables and fire ignition (discovery) events were monthly, we modeled probability of occurrence of high severity fire over the Western US at a monthly time step. While individual fire records contain the date of discovery, which in many cases is proximate to the date of ignition, it may often be the case that the fires were ignited earlier and smoldered undetected for some time before being discovered. The month of discovery is useful because it is likely indicative of the onset of conditions conducive to rapid fire spread (Westerling et al. 2006). Likewise, many larger fires likely continue to burn in subsequent months, but the fire history data queried here do not describe fire progression. Consequently, our climate variables keyed to the month of discovery may miss important climatic variability driving fire severity to the extent that conditions observed during the month of discovery may not represent the conditions that actually pertain during the period of high severity burn.

2.3.2 Burn Severity Data

We acquired burn severity data from the Monitoring Trends in Burn Severity database (MTBS, http://www.mtbs.gov; accessed December 2008). We downloaded data for all fires in the Western US for the period1984-2007, resulting in a dataset with a total of 4493 fires. We chose the thematic burn severity images for this study so that our data would be comparable across space and time. We used ESRI Arc Macro Language (ESRI, 1999) to intersect the burn severity data with our 1/8th degree reference grid to assign each fire to the grid cell in which the majority of the fire area occurred. After

assigning each fire to a modeling grid cell, we calculated the fractional area of each severity class in each voxel (latitude, longitude, year, month) for analysis: unburned to low severity, low severity, moderate severity, high severity, increased greenness, unclassified (Eidenshink et al. 2007). In addition to severity, each MTBS fire record also contains the date of fire discovery (month, year). Many burn severity records also have information on the area burned in different vegetation types using the National Land Cover Database class levels one and two, i.e. herbaceous, shrubland, forest, wetlands, water, developed, barren, and cultivated (Homer et al. 2007).

2.3.3. Landscape Data

Our predictors included topographic and ecosystem data. Topographic data (minimum, mean, maximum and standard deviation of elevation; slope; aspect) are 1/8th degree products derived from the GTOPO30 global 30 Arc Second (1km) Elevation Data Set accessed online from the North American Land Data Assimilation System (LDAS) (http://ldas.gsfc.nasa.gov, Mitchell et al. 2004).

We aggregated ecosystem information relevant to fire severity developed by the Landfire project to the 1/8th degree grid used for this analysis: existing vegetation type and fire regime condition class (FRCC) (Keane et al. 2007, www.landfire.gov). We used a reclassified version of LANDFIRE existing vegetation data from another study, specifically extracting the fractional area of forests with stand replacing fire regimes (Westerling et al. 2011).

Fire regime condition class (FRCC) is a metric widely used by land managers to prioritize fuel treatments and is a characterization of how much ecosystem condition has departed from the historical natural range of conditions (Hann 2004, Laverty and Williams 2000). Historical conditions are estimated with a landscape succession model (LANDSUM) that simulates succession under historic fire regimes (Keane et al. 2006, Pratt et al. 2006). A continuous departure value is calculated by subtracting the similarity of current vegetation condition from the simulated median reference condition (Holsinger et al. 2006). The Landfire departure metric refers only to vegetation composition and does not incorporate changes in fire regime. Departure is categorized into three classes—FRCC1 (departure <33%), FRCC2 (≥33% departure <66%), FRCC3 (departure ≥67%) (Holsinger et al. 2006, Keane et al. 2007). We calculated the fractional area of fire regime condition classes 1, 2, and 3 in each modeling pixel and normalized the fractions with a log function.

2.3.4 Climate and Hydrologic Data

We obtained hydrologic variables produced from the Variable Infiltration Capacity (VIC) model and the gridded climate data used to force VIC (Liang et al. 1994). The VIC model calculates surface water and energy balance for large-scale applications. It is unique in that it incorporates sub-grid scale vegetation characteristics by calculating evaporation from the vegetation canopy, bare soil surface, and transpiration at a daily time step for each vegetation class in the modeling grid cell. We used the 1km University of Maryland vegetation map developed for the North American Land Data Assimilation System (LDAS) (http://ldas.gsfc.nasa.gov, Mitchell et al. 2004) and gridded daily climate data (Mauer et al. 2002) as inputs to parameterize VIC at 1/8th degree.

Output from VIC includes temperature extrema and average (Tmax, Tmin, Tave), precipitation (PPT), moisture deficit (MD), antecedent moisture deficit derivatives (e.g. 6 month prior moisture deficit), relative humidity (Rh), soil moisture, and snow water equivalent (SWQ) on a monthly time step from 1915-present (Westerling et al. 2009).

We calculated 30yr means and standard deviations for 1961-1990 Tave, PPT, cumulative moisture deficit (MD), and AET. We also created a thin plate spline of 1961-1990 MD and AET. The spline creates a surface of the interaction between these two variables; this interaction is an indicator of biophysical site conditions for plant growth. Stephenson (1998) showed that MD and AET are biologically meaningful drivers of the spatial distribution of vegetation types over a broad range of spatial scales. We used these variables as a proxy for spatial variability in ecosystem and disturbance regime sensitivity to climate.

The hydroclimatic datasets were initially developed for a project completed for the California Climate Change Center; a full description can also be found in Westerling et al. (2009). The dataset has been updated to the year 2015.

2.3.5 Occurrence Modeling

We employed a multi-step process in modeling the presence of high severity fire. Previous research using parts of this dataset and similar questions have used both logistic regression and classification and regression tree (CART) methods, individually and together (Collins et al. 2007, Collins et al. 2009, Dillon et al. 2011, Preisler and Westerling 2007, Westerling et al. 2008, Westerling et al. 2009). The total number of independent predictor variables available for this analysis was 85. In order to limit the number of variables that we would use in building a predictive model, we first used a CART (Random Forest package in R; Liaw and Wiener 2002) model to identify the most important variables in predicting fractional high severity. The 10-20 most important variables were selected from the Random Forest output as the initial predictor set for two conditional logistic regression models.

2.3.6 Logisitic Regression

We developed two conditional logistic regression models to predict high severity fire occurrence. It is important to note that because the MTBS data contains only fires >=400 ha, there exists an implicit condition to our models. Each model is first conditional on the occurrence of a 400 ha fire. Within this, we first need to determine the presence of high severity fire pixels; we set this condition equal to the median value of high severity fraction, 0.042. Then, given occurrence of high severity fire pixels, we set a threshold for high severity fire fraction equal to the upper quartile cutoff, 0.1732. We define any fire with high severity fraction above this upper threshold as a high severity fire. These definitions result in two binary dependent variables.

To model the probability of high severity fire presence, we use the logged odds, or logit:

Model Pa : Logit (P | f > 0.042) = $\ln(P_{\text{pa}i} / (1-P_{\text{pa}i})) = \sum(b_0 + b_j X_{ij})$

Where X_j is the set of independent predictor variables best fit to the model, P_{pai} is the probability of high severity fire presence, defined as the fraction f of high severity fire greater than 0.042 for a given month and grid cell indexed by *i*.

Similarly, the model for occurrence of high severity fraction greater than 0.1732 is:

Model Hi : Logit (P | f > 0.1732 | f > 0.042) = $\ln(P_{hii} / (1-P_{hii})) = \sum(b_0 + b_jX_{ik})$

Where X_k is the set of predictors best fit to Logit Hi. The probability of high severity fire occurrence for any given month and location is then the product of these two model probabilities: $P_{pai} * P_{hii}$.

We are interested in predicting the probability of high severity fire occurrence on the landscape. Even with the perception that fires are becoming more severe, these fires remain relatively rare. The determination of thresholds to declare presence of high severity fire is necessarily arbitrary. Our goal was to be as objective as possible, while defining thresholds that were meaningful. We examined the distribution of high severity fire area in our dataset and used that as our guide. Our models specifically address the question:

Given that a fire burns to at least a thousand acres, and given that high severity fire is present, what is the probability that this fire is a high severity fire (i.e. in the upper quartile of high severity burned area)?

We use the Aikake Information Criterion (AIC) to evaluate model performance (Aikake, 1974, 1981).

$$AIC= -2(\ln(likelihood)) + 2N$$

where *likelihood* is the probability of the data given a model and N is the number of parameters in the model (predictors and intercept). The best model is a model that balances model fit to the data with number of parameters. The AIC essentially penalizes models for excess predictive parameters. The AICs are evaluated as the difference between individual model AIC and the minimum AIC from all models. There is no test to compare AICs, but a general rule of thumb is that for a change in AIC < 2, the models are not significantly different in their skill; delta AIC > 10 is a significant difference in model skill (Burnham and Anderson 2004, Hare and McGarigal 2010). Once we chose the model with the lowest AIC vs. number of parameters, we performed a leave one out cross-validation assess predictive skill and the stability of model parameter estimates.

2.3.7 Mapping probability of high severity fire occurrence

For each month and year in the dataset, we applied the two conditional logistic regression models to all pixels in the western US. We then calculated an annual probability of high severity fire occurrence for each pixel by taking the average of the twelve monthly values. We also calculated the coefficient of variation (CoV) in the probability values for each pixel for the period 1984-2007. To calculate the CoV, we first summed the twelve monthly probability values for each year for each pixel. The equation for calculating CoV of these annual sums is:

$$CoV = \sqrt{\mathrm{var}(\sum \mathrm{Pr})} / mean(\sum \mathrm{Pr})$$

where ΣPr is the annual sum of monthly probabilities and var is the variance. The coefficient of variation provides a measure of how sensitive the model probabilities are to interannual variation; for our models, this will quantify the sensitivity to the fire-year climate variables.

2.4 Results

2.4.1 Trends in high severity fire occurrence

We did not find a significant trend in high severity fire occurrence in the period 1984-2007. We evaluated potential trend for the entire region, for each state, and for each month. While the some studies have shown an increase in fire season length, we saw no increase in high severity fire occurrence in the months May through October (Figure 2.9.2). We found no correlation between the fraction of high severity fire and total fire size, meaning that an increase in fire size or occurrence does not necessarily result in an increase in the fractional area of high severity fire.

As we would expect, high severity fire occurrence peaks at the peak of the fire season in the Western US (Figure 2.9.2). The distribution of high severity fires is quite variable. California and Idaho consistently experience the largest number of large fires and high severity fire occurrence, but many fires have no presence of high severity fire as we have defined it. Both Montana and Wyoming experience fewer large fires with no high severity fire present than the other western states (Figure 2.9.3).

2.4.2 Occurrence Modelling

The suite of predictor variables that produced the best predictive models for presence of high severity fire is dominated by biophysical factors that include topography, climate normals and vegetation variables (Table 2.8.1). The mean and maximum elevations within the modeling pixel are the only topographic variables in the final model. Climate normals include the standard deviation of 1961-1990 cumulative annual water year precipitation and moisture deficits and a thin plate spline of moisture deficit and evapotranspiration. The standard deviation predictors indicate the degree of variability in annual precipitation and moisture deficits in each pixel; for instance, a higher standard deviation indicates a location with a highly dynamic precipitation regime. The thin plate spline creates a surface of the interaction between two variables. In this instance we are using the 30 yr average moisture deficit and 30 yr average actual evapotranspiration; this interaction is an indicator of biophysical site conditions for plant growth. Different forest types fall along the gradient of moisture deficit and evapotranspiration (Stephenson et al. 1998).

While the spline indicates relative site conditions for plant growth, we have two direct vegetation variables that are included in our final model. The fractional area of forest types with a stand replacing fire regime was important for both conditional models. Additionally, the fractional area of FRCC class 3 (current vegetation highly departed from

what we would expect with historical fire regime, hereafter FRCC3) was important only in the presence/absence model (Model Pa).

Four variables specific to the year that the fire occurred were important: average Spring temperature, average temperature for month of fire, normalized moisture deficit for month of fire, and moisture deficit for the previous November.

When we remove within-year climate variables, our model under-predicts the number of high severity fire occurrences for most years with a larger number of high severity fire events (>60) (Figure 2.9.4). For years with fewer high severity fire events (<60) our model tends to over-predict when we remove within year climate (Figure 2.9.4). Removing vegetation variables does not significantly alter the predicted vs. observed number of high severity fire occurrences. In other words, without fire-year climate, our models cannot predict interannual variability in the presence of high severity fire. Site-specific variables that do not vary with time merely allow us to estimate a constant spatial distribution in the probability of high severity fire presence, which is essentially equivalent to identifying the location and average recurrence rates for fire regimes where high severity fire can occur. While all model iterations perform well with regard to prediction vs. observation for locations with fires, the R^2 of regressing predicted vs. observed number of high severity fire occurrences is higher for the full model (Table 2.8.2). The difference in model skill becomes evident when we apply the model to all pixels in the western US.

2.4.3 Mapping probability of high severity fire occurrence

To illustrate the effect of removing variable classes, we chose two years with few (1991 [N = 16] and 2007 [N = 10]) and many (1996 [N = 75] and 2000 [N = 88]) high severity fire occurrences. For both pairs of years, removing within year climate variables produces a probability map with a shift to greater probability values (and a decrease in spread) for high severity fire occurrence, with distinct regional differences (Figure 2.9.5). The probability of occurrence decreases over California when we remove within year climate, which is likely where the under-prediction we see in Figure 2.9.4 is occurring. This California pattern is opposite of the Northern Rocky Mountain and North Cascade regions where probabilities increase when we remove within year climate. Note again that our model predictions are conditional on the presence of a large fire occurring. We are predicting the presence of high severity fire greater than a specific threshold given that a large fire is already occurring.

In California, much of the Sierra Nevada is classified as a mixed severity fire regime, and we interpret our model results to imply that the presence of substantial fractions of high severity fire in large Sierra Nevada fires requires more extreme climatic conditions. In mixed severity fire regimes, fire-year climate can increase or decrease the fractional area expected to experience high severity fire. Conversely, in regions that are dominated by forests characterized by high severity fire regimes (such as the North Cascades and Northern Rocky mountains), fire-year climate acts more as a control on the occurrence of fire through fuel flammability (of any severity). Others found that fire year climate was less important than topography and vegetation as a predictor of high severity fire occurrence in the North Cascades and Northern Rocky Mountain regions (Cansler and McKenzie 2014, Birch et al. 2015, Dillon et al 2011). Our model results seem to indicate

that in these systems with a propensity for high severity fire, fire-year climate still modulates high severity fire occurrence.

Removing the two vegetation variables does not have as strong an effect on predictive accuracy. As would be expected, the effect is dependent on year. The changes are most pronounced in mountainous areas, as one of the variables is cover of forests with high severity fire regimes. We see a general decrease in probability in the Sierra Nevada, western Nevada, and the Northern Rocky Mountains. Both the Colorado Rocky Mountains and the Northern Cascades in Washington generally show a higher probability of high severity fire occurrence when we remove the vegetation. Recall, however, that without within-year climate variables, this model produces constant predictions of high severity fire presence conditional on the occurrence of a large fire, i.e. probabilities vary only in space, not time. Since the number of observed large fires varies from year to year, the predictions of high severity presence still vary inter-annually, even with the climate variables removed. Essentially, the observed fires are re-sampling fixed probabilities of high severity fire presence each year.

While the spatial probability maps generally predict greater probabilities of high severity fire occurrence in the locations that we would expect—in the mountainous regions of the western US—the interannual variability is quite pronounced. The inclusion of predictors that vary interannually is critical for capturing high probability episodes in areas where fire severity is highly variable, especially in California (CoV = 0.224) and the Southwest, where the coefficient of variation is high. (Figure 2.9.6) Conversely, in regions that are dominated by cool moist forests with high severity fire regimes, the coefficient of variation is low—Northern Rocky Mountains (CoV = 0.133) and Pacific Northwest forests.

2.5 Discussion

2.5.1 Trends in high severity fire occurrence

The lack of trend in our fire severity data is likely due to the short length of the record. The data record for fire severity begins more than seventy years after the start of fire suppression. Without a record of fire severity that includes fires before and after the initiation of the policy of fire suppression, we can't directly quantify a change in fire severity due to suppression. Ecosystems with a short fire return interval (7-10yrs) may have missed up to 10 fire cycles by the time our fire severity record begins, while those with longer fire return intervals my have missed few or none. This means that even with a long record of fire severity data to study, we would still only expect to see changes in severity due to fire suppression and fuel buildup on some of the landscape. We hoped that the use of FRCC could be a proxy for changes in fire severity due to suppression. If it was an important predictor in high severity fire occurrence, it could point us to areas that are burning severely that might not under a historical fire regime.

The other factor that can modify fire severity is climate change. Others have shown an increase in the length of the fire season and an increase in large fire occurrence due to climate change (Dennison et al. 2014, Jolly et al. 2015, Westerling et al. 2006, Westerling 2016,). Again, the short length of our record precludes us from quantifying a trend in fire severity due to climate change. Our results highlight the importance of

interannually varying climate on high severity fire occurrence. For each fire, we calculated the anomaly of the within year climate variables from 1961-1990. For the two month of fire predictors (average temperature and moisture deficit), most anomalies are positive, and the mean anomalies are quite high (Figure 2.9.8). The other with year climate variables also had positive anomalies for most years. Conditions under which the fires in our record burned were warmer and drier than the 1961-1990 reference period. It is possible that the patterns of high severity fire in our record are a result of a changing climate and management activities, but without earlier data, we can't quantify a trend per se.

2.5.2 Modeling and mapping high severity fire occurrence.

Our best model included predictors with both bottom-up and top-down influence on fire severity. When we examine performance of the model on removal of vegetation and within year climate predictors, the impact is subtle. Considering first the removal of temporally fixed predictors such as fractional area in FRCC condition class 3 and forest types with high severity fire regimes, model performance (in terms of interannual variability) is not significantly affected (Figure 2.9.4). When we remove within year climate variables, our AIC score goes up significantly (higher AIC values indicate lower skill), and we can see that our model generally under-predicts the number of high severity occurrences at values over 60 (recall that the model predictions still vary interannually because the number of large fires varies according to the observed record). However, the overall model fit for these two models could still be considered robust (Table 2.8.2).

The impact of removing these variables is more evident when we apply the model to the entire western US. We chose two years with few high severity fire occurrences (low years) and two with many occurrences (high years) to evaluate the impact of removing variable classes. When we remove within year climate variables, the probability of high severity fire decreases in California and Nevada, but increases in the Pacific Northwest and Northern Rocky Mountain regions. Many of the ecosystems in the Pacific Northwest and Northern Rocky Mountains are dominated by cool moist forests with historically infrequent stand replacing fire regimes (Agee et al. 1977, Agee 1998, Cansler and McKenzie 2014, Schoennagel et al. 2005). These forests have abundant fuels, but are rarely hot and dry enough to burn. The increase in probabilities in these regions when we remove within year climate reflects the importance of climate in determining whether these forests will burn and supports findings that current year climate controls severity occurrence in this forest type (Cansler and Mckenzie 2014, Schoennagel et al. 2005).

For the low fire year 1991, removing within-year climate variables increases the mean west-wide probability of high severity fire by approximately 2%, but the maximum predicted probability increases from 79% to 90%. For 1996, a high occurrence year, removing within-year climate increases the mean probability by 0.7%, but increases the maximum from 76% to 90%. When we look at the probability maps, we can see that within year climate shifts probability both positively and negatively—it either amplifies or moderates the probability of high severity fire. Average spring temperature anomalies, while high for most of this time period, are highest for many of the high occurrence fire years (Figure 2.9.8). This is also true for anomalies in MD0, MD2 and Tave.

The MD2 variable is an indicator for moisture stress at the beginning of the water year, in November. The anomalies for this variable correspond most closely with high occurrence years. Van Mantgem et al. (2013) found that high pre-fire climatic water deficit is related to an increase in post-fire tree mortality. While the average temperature anomalies are high for the entire fire record, many of the years with high severity fire occurrences have unusually high average temperature anomalies for the month the fire burned. These variables are capturing interannual weather conditions that increase flammability of fuels and create conditions for fire spread, given ignitions.

While the inclusion of within year climate variables was important for capturing the years with a large number of high severity fire occurrences, the vegetation variables used did not have a large impact on the model. We expected that the inclusion of FRCC3 would be important for predicting high severity fire occurrence. Removing the vegetation variables did have an effect on the patterns of predicted probability of high severity fire over the western US, but did not change the range of predicted probability as much as the removal of within year climate variables did. The probability of high severity fire occurrence increases in the Pacific Northwest and Colorado Rocky Mountains when FRCC3 is removed from the model, but decreases in the Northern Rocky Mountains and California. This indicates that it might be reflecting increased risk in areas where low elevation forest structure has been modified due to fire suppression (Agee 1978, Miller and Safford 2012, Steel et al. 2015).

The FRCC variable is limited in its utility as a less productive forest type with a historically frequent fire return interval might be highly departed from missing many fire cycles but still have less fuel buildup than a more productive forest that missed fewer fire cycles and received a less departed classification (Stephens and Ruth, 2005). The latter would likely be at higher risk for high severity fire, which the FRCC metric might not capture. Also, the FRCC category reflects more than fire suppression and a category of three does not imply increased fire hazard; with the data we have, we can only infer the role of FRCC as a predictor. Last, it is also possible that FRCC was not more important to our models because of how we employed it. We use the fractional values for the $1/8^{th}$ degree pixel, which tells us the nature of the condition class distribution in the pixel that our fire is located in, but not necessarily the distribution within the fire perimeter.

It is important to note that the model probabilities used to create the predictive maps are conditional on a large (>400 hectare) fire occurring. While the predictive maps for years like 1991 and 1996 look very similar in terms of *conditional* probability of high severity fire occurrence, the actual fire record is quite different. The number of fires in the MTBS record for 1991 was 75 total (16 high severity) vs. 272 total (75 high severity) fires for 1996. While the number of ignitions that results in a large fire occurring were small, the probability map shows us that had conditions that control ignition or fire size been conducive to a large fire occurring, high severity fire would have been likely in 1991.

Our results are similar to Dillon et al. (2011) with respect to the importance of topography, but are quite different with respect to the importance of within year climate variables. This is likely due to both methodological approach and data availability. In our study, we determined the actual fraction of each fire that burned as high severity, using every large fire in the MTBS database. For each fire, we had hydroclimate variables for the voxel that the majority of the fire area occurred in. Dillon et al. (2011) selected a

random subset of individual fire pixels classified to high severity, 0/1. There is a fundamental difference in the dependent variable used for analysis between our study and the Dillon et al. study (2011). Our definition of high severity fire occurrence is dependent on high severity fractional area for each fire, so that each fire is classified as a high severity fire, 0/1. This means that Dillon et al. (2011) could have two pixels from a single fire with different classification, because their pixel selection process was random.

The independent climate/weather variables that Dillon et al. (2011) used are also very different from those we used, which could lead to the different conclusions on importance in each model. For each fire, we had hydroclimate variables for the 1/8th degree voxel that the majority of the fire area occurred in. Dillon et al. (2011) interpolated monthly temperature and precipitation for the central latitude and longitude and mean elevation for each fire from a climatic spline model. The soil moisture data they used are from the VIC model, as are our hydroclimate variables, but at a coarser scale. The fire weather variables are from the North American Regional Reanalysis dataset. While our weather and climate variables are much coarser in scale than the fire severity data, the scale is, for some, finer than the Dillon variables. We also have a larger set of hydroclimate variables, many of which integrate climate effects on vegetation.

2.6 Conclusions

Opportunities with this model

Because our models include within year climate, we can use them to predict year-to-year changes in the probability of high severity fire occurrence. While the risk of high severity fire occurrence is partially determined by biophysical setting and existing vegetation and fuels, our model demonstrates that fire year weather is an important component that amplifies or moderates risk of high severity fire occurrence given ignition and growth to at least 1000 acres. We see distinct differences in probability maps between years, showing the influence of the within year climate. These models could be used in tandem with models that predict large fire occurrence to plan for resource allocation or mitigation efforts. We can also use these models to look at how the probability of high severity fire occurrence might change in a changing climate.

Limitations of the model

The scale of the hydroclimate data we used is quite coarse at 1/8th degree. The importance of these variables, especially fire year climate, suggests that improvements could be made with finer scale data. This would be especially true in mountainous terrain where climate varies greatly with topography. The hydroclimate variables are also modeled with a static vegetation layer for all years. Sensitivity analysis to evaluate the impact of including a dynamic vegetation layer in VIC did not result in significant changes in MD or AET (unpublished, A.L. Westerling *personal communication*). Additionally, FRCC that more closely represents individual fires or that could be combined with fuel availability might improve its performance as a predictor.

Because these probabilities are conditional on a large fire occurring, they would need to be coupled with the probability of a large fire occurring in order to be utilized for any forecasting effort. As with all models, ours has limitations, but its performance is robust.

This is the first study to use every large fire in the MTBS database to examine patterns in high severity fire, identify the importance of within year climate, and predict high severity fire occurrence.

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2.8 Tables

Table 2.8.1. List of final predictors for two conditional logistic regression models.

Variable Description	Model PA	Model HI
Elevation		
maximum	✓	
minimum		
mean	✓	
standard deviation		
1961-1990:		
Average temperature: mean and standard deviaiton	✓	
Cumulative annual moisture deficit: standard deviaiton		✓
Cumulative water year precipitation deficit: standard deviation	✓	✓
Previous November moisture deficit	✓	✓
Normalized moisture deficit month of fire (41 yr)	✓	
Spring average temperature (March, April, May)	✓	✓
April snow water equivalent		
Fractional cover of vegetation with stand replacing fire regime	✓	✓
Fraction of FRCC 3	✓	
Thin plate spline of 30yr average moisture deficit and evapotranspiration	✓	✓

Table 2.8.2. Performance statistics for logistic regression models. The ΔAIC value is the difference between the full model and models with variables removed.

		AIC	ΔAIC	Adjusted R^2	Cross validated Adjusted R^2	Cross validated r Predicted v Observed
Full Model	Model PA	5353.7	-	0.9241 (p 5.17e-14)		
	Model Hi	3033.9	-	0.9602 (p < 2.2e-16)	0.9211 (p 7.92e-14)	0.9615
No Vegetation	Model PA	5409.1	55.4			
	Model Hi	3036.7	2.8	0.9292 (p 2.39e-14)		
No Fire Year Climate	Model PA	5518.9	165.2	0.8294 (p 3.99e-10)		
	Model Hi	3069.3	35.4			
No Veg/No Climate	Model PA	5566	212.3	0.8311 (p 3.57e-10)		
	Model Hi	3075.8	41.9			

Table 2.8.3 Results from trend analysis of mean annual fraction of high severity fire (high severity acres / total acres) and annual count of fires with high severity fraction >= 0.1732 (*Count*) for the period 1984-2014. * *p* <0.05. We looked for trends in all large fires in the western US and for trends in fires by state. Standard Error values are in parentheses.

Parameter	Slope	*p*
Westwide		
Mean Annual Fraction	-1.31e-3 (5.52e-4)	0.025*
Count Over Threshold	0.04 (0.53)	0.947
Arizona		
Mean Annual Fraction	-1.66e-3 (8.21e-4)	0.052
Count Over Threshold	-0.04 (0.06)	0.540
California		
Mean Annual Fraction	-7.39e-4 (8.08e-4)	0.368
Count Over Threshold	-0.14 (0.14)	0.340
Colorado		
Mean Annual Fraction	3.27e-4 (3.27e-3)	0.921
Count Over Threshold	0.12 (0.04)	0.009*
Idaho		
Mean Annual Fraction	7.76e-4 (1.11e-3)	0.490
Count Over Threshold	0.15 (0.12)	0.240
Montana		
Mean Annual Fraction	-3.02e-3 (2.28e-3)	0.197
Count Over Threshold	0.12 (0.15)	0.432
New Mexico		
Mean Annual Fraction	-1.71e-4 (0.001)	0.887
Count Over Threshold	-4.43e-3 (0.07)	0.948
Nevada		
Mean Annual Fraction	-4.02e-3 (1.44e-3)	0.009*
Count Over Threshold	-4.03e-3 (0.11)	0.971
Oregon		
Mean Annual Fraction	-1.73e-3 (1.15e-3)	0.142
Count Over Threshold	-0.03 (0.07)	0.658
Utah		
Mean Annual Fraction	-2.06e-3 (2.48e-3)	0.415
Count Over Threshold	0.12 (0.07)	0.079
Washington		
Mean Annual Fraction	-9.21e-4 (2.20e-3)	0.678
Count Over Threshold	0.03 (0.03)	0.289
Wyoming		
Mean Annual Fraction	-3.65e-3 (2.66e-3)	0.187
Count Over Threshold	0.13 (0.07)	0.055

2.9 Figures
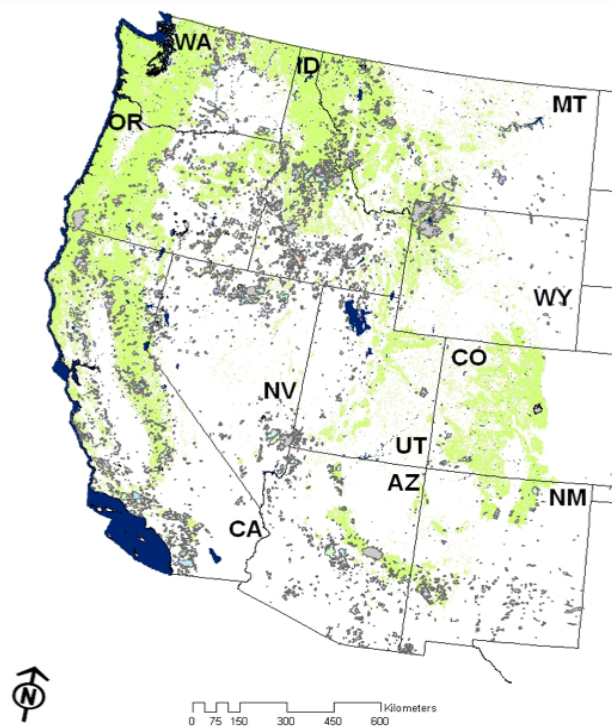
Figure 2.9.1. Locations (grey polygons) of large fire occurrence in the Western US form 1984-2006. All fires >1000 acres were classified for fire severity by the Monitoring Trends in Burn Severity project (www.mtbs.gov). The area highlighted in green is classified as forest in the LDAS data.
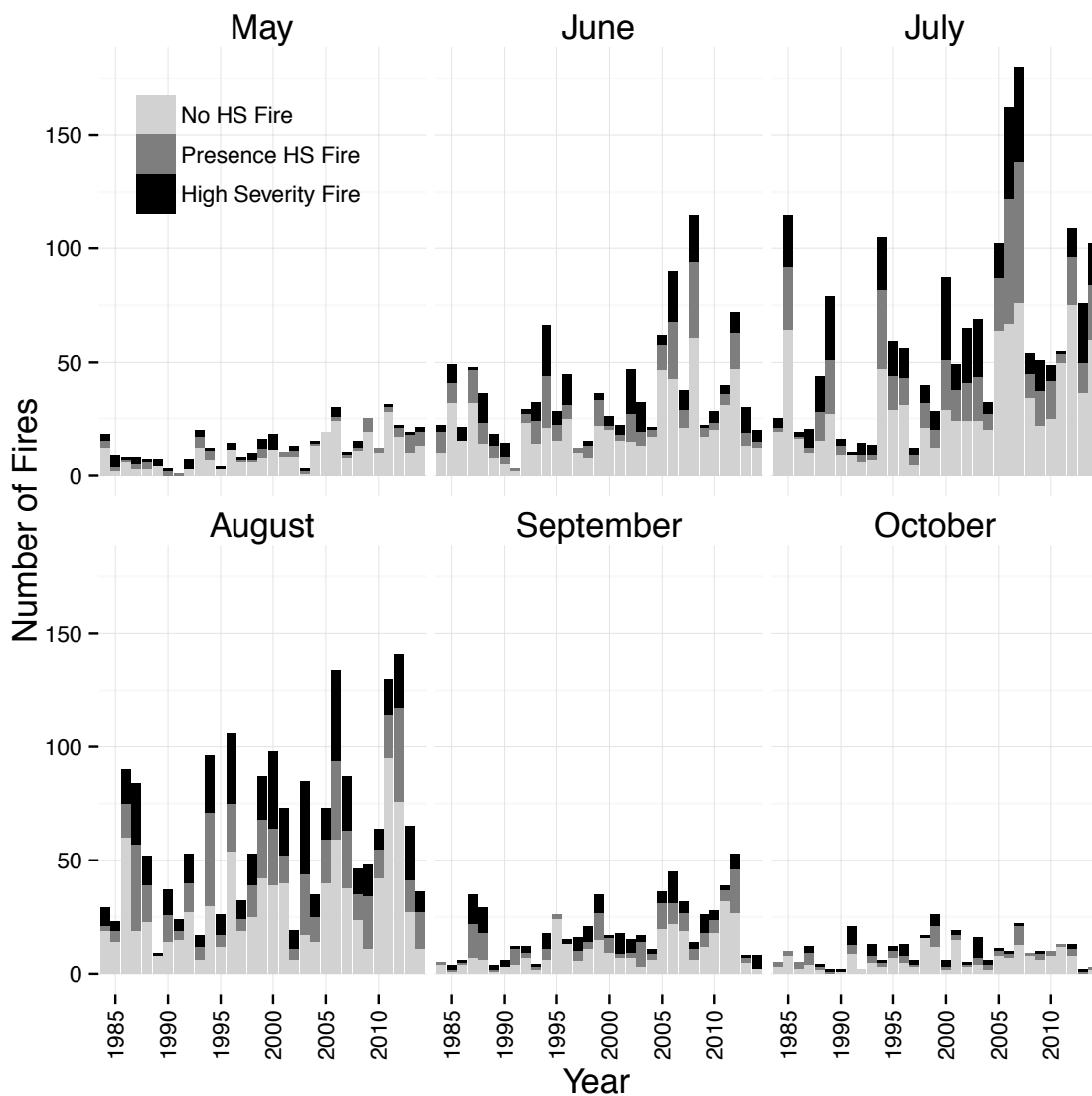
Figure 2.9.2 Frequency of fires by severity class for May-October, 1984-2014. Light gray bars are large fires with no presence of high severity fire; medium gray bars are fires that met the threshold for presence (high fraction ≥ 0.042); black bars are fires classified as high severity with fraction exceeding the high fraction ≥ 0.1732 threshold.
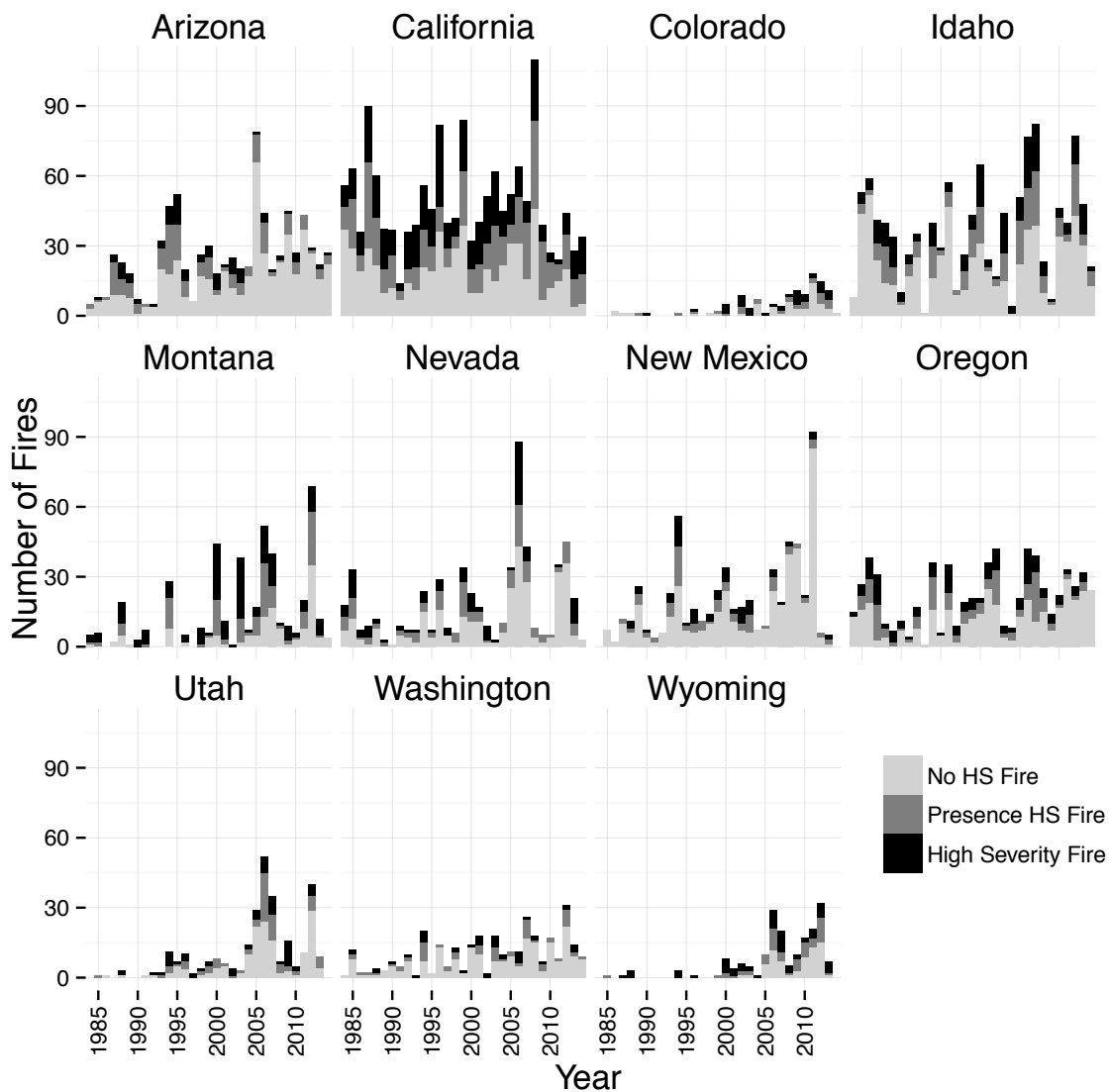
Figure 2.9.3. Frequency of fires by severity class for each state for 1984-2014. Light gray bars are large fires with no presence of high severity fire; Medium gray are fires that met the threshold for presence (high fraction ≥ 0.042); black are fires classified as high severity with fraction exceeding the high fraction ≥ 0.1732 threshold.
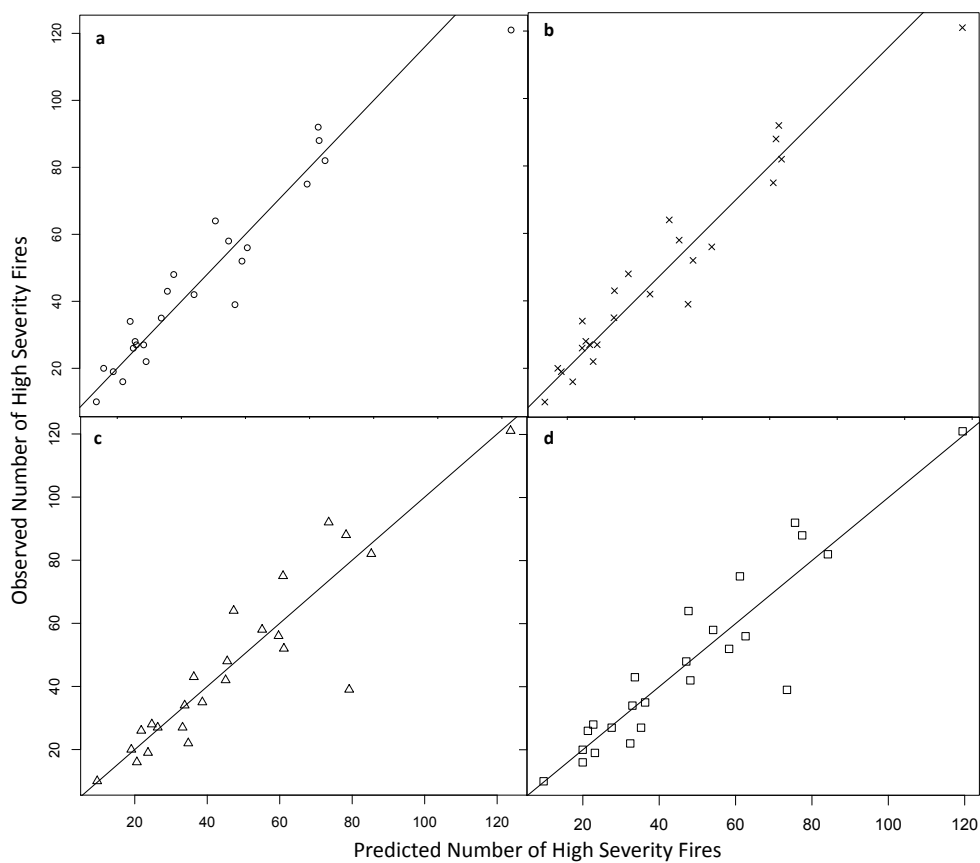
Figure 2.9.4. Predicted versus observed number of fires with high severity fraction>= 0.1732 for a) full model [AIC 3033.9] b) model with vegetation variables removed [AIC 3036.7] c) model with within year climate variables removed [AIC 3069.3] d) model with within year climate and vegetation variables removed [AIC 3075.8].
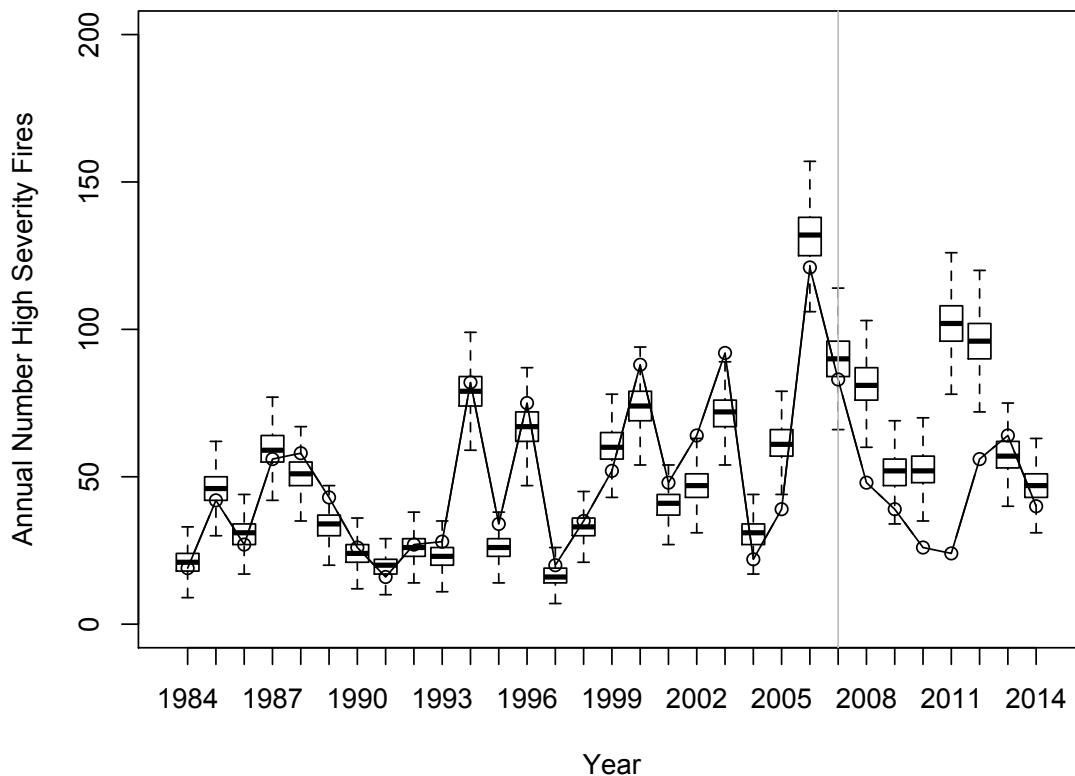
Figure 2.9.5. Observed number of fires with high severity fraction >= 0.1732 (line) plotted against 1000 draws from the cross-validated full variable conditional logistic regression probability distribution (boxes show inter-quartile range and whiskers 1.5x inter-quartile range) for all voxels with high severity fire. The model was built with data through 2006 and applied to 2007-2014. The cross-validated Adjusted R^2 = 0.82, p < 0.001.
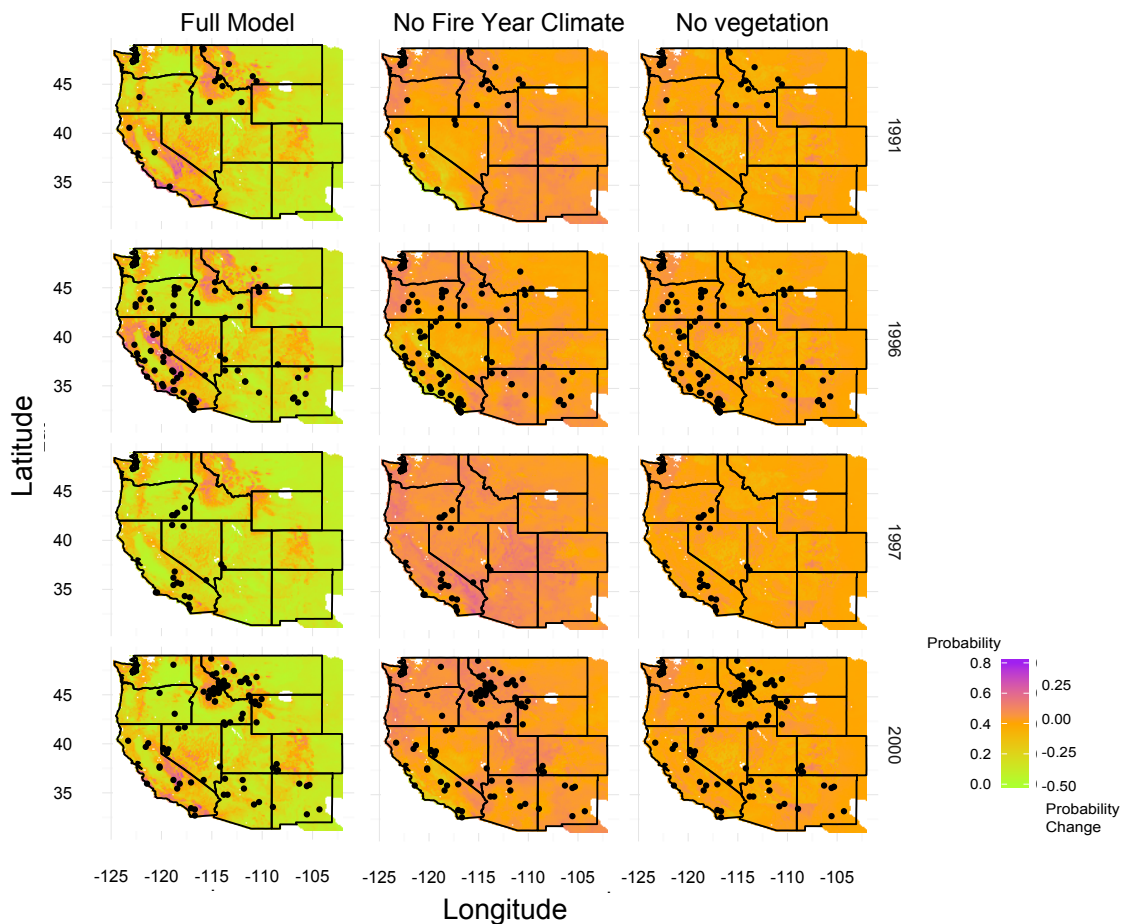
Figure 2.9.6. Probability of high severity fire occurrence over the Western US for two low fire years (1991, 1997) and two high fire years (1996, 2000) with actual high severity fire events shown. Circles are large fires with high severity fraction >0.1732. The left column shows the probabilities for the full model. Difference maps for the models with fire year climate and vegetation variables removed are shown. Positive difference values indicate that the probability increased when the predictor set was removed; negative values indicate a decrease in probability.
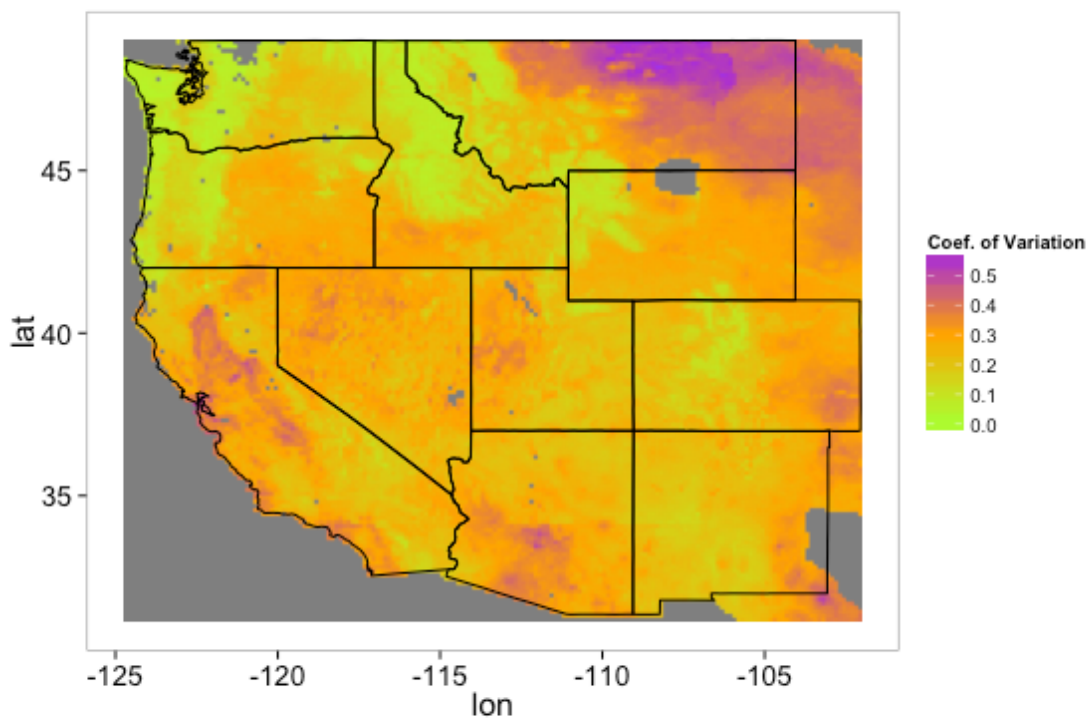
Figure 2.9.7. The coefficient of variation of annual number of high severity fire occurrences (sum of monthly probabilities) for 1984-2007. Higher values show us where the probability of high severity fire occurrence is more sensitive to annually varying climate.
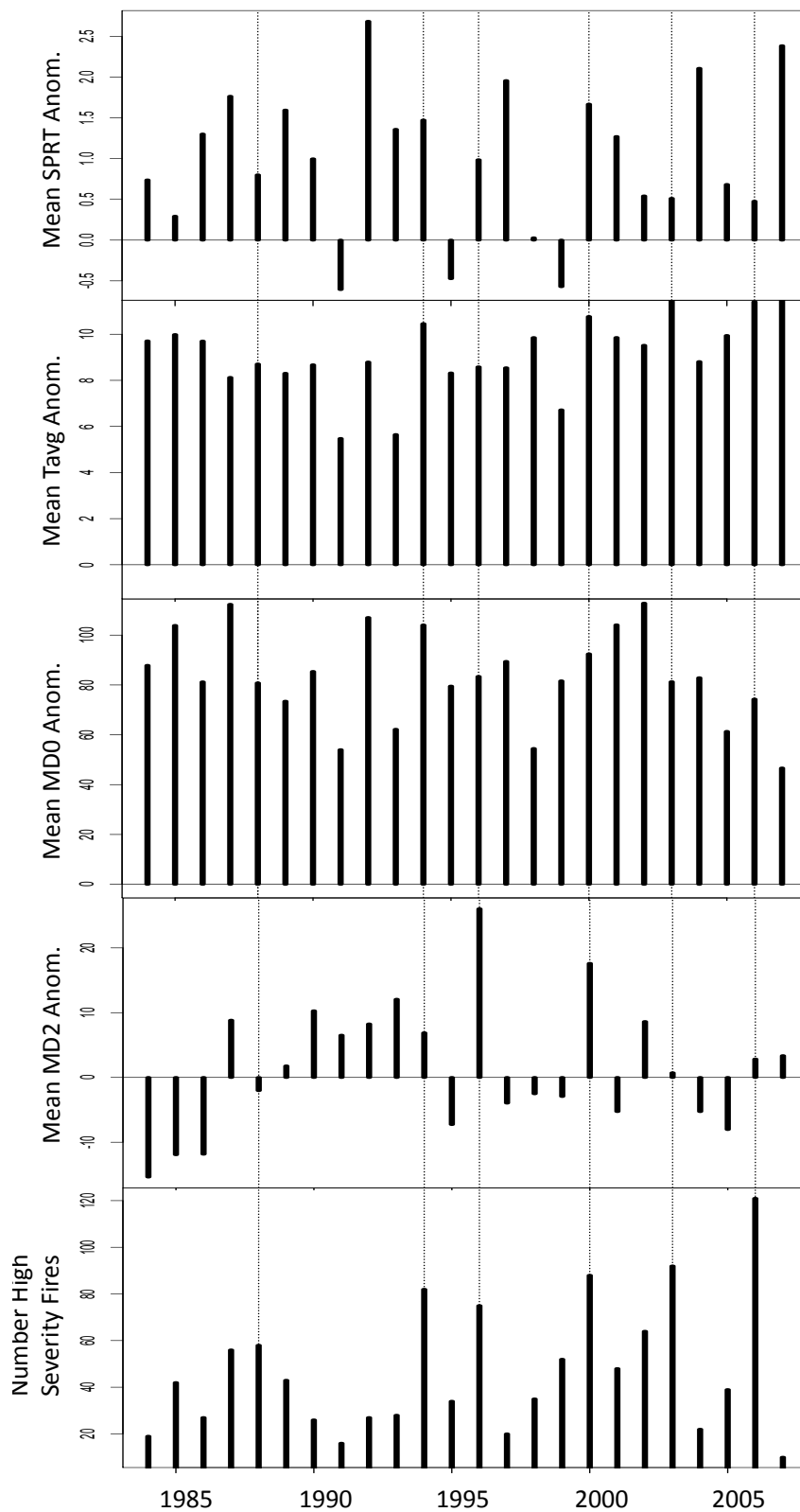
Figure 2.9.8. Yearly number of high severity fire occurrences and mean annual anomalies (from 1961-1990 mean) of within year climate predictor variables. The anomalies are calculated for each voxel (month-year-location) that contained a high severity fire occurrence and the annual mean for all fire events is presented. Years with a large number of high severity fire events are highlighted with dotted lines.

3   Using extreme value theory to predict forest area burned in high severity for three regions of the western United States.

3.1 Abstract

More than 70 years of fire suppression by federal land management agencies has interrupted fire regimes in much of the western United States. The result of missed fire cycles is a buildup of both surface and canopy fuels in many forest ecosystems, increasing the risk of severe fire. The frequency and size of fires has increased in recent decades, as has the area burned with high severity in some ecosystems. A number of studies have examined the controls of high severity fire occurrence, but none have yet determined what controls the extent of high severity fire. We developed statistical models predicting high severity area burned for the western United States and three sub-regions—the Northern Rocky Mountains, Sierra Nevada Mountains, and Southwest. A simple model with maximum temperature the month of fire, annual normalized moisture deficit and location explains area burned in high severity fire in our west-wide model, with the exception of years with especially large areas burned with high severity fire: 1988, 2002. With respect to mitigation or management of high severity fire, understanding what drives extreme fire years is critical. For the sub-regional models, topography, spring temperature and snowpack condition, and vegetation condition class variables improved our prediction of high severity burned area in extreme fire years. Fire year climate is critical to predicting area burned in high severity fire, especially in extreme fire years. If a goal of management is to mitigate extreme fire events in terms of fire severity, then knowledge of fire year climate and its effect on fire severity is essential. The models developed here can be used to predict high severity area burned in the near term and with a changing climate.

3.2 Introduction

More than 70 years of fire suppression by federal land management agencies has interrupted fire regimes in much of the western United States (US). Many forest types that historically burned frequently have undergone significant changes in species composition and have heavy accumulations of surface and canopy fuels, putting them at risk for severe fires (Agee et al. 1978, Agee and Skinner 2005, McKelvey et al. 1996, Keane et al. 2002). In testimony to the Natural Disasters Roundtable, Cleaves testified that of ~168 million hectares of fire adapted ecosystems in the coterminous US, more than 29 million are considered to be a high risk to human and ecosystem values due to an accumulation of fuels and risk of high severity fire, and more than 57 million are considered a moderate risk (2001).

Both the frequency and size of large wildfires have increased in the past 30 years in the western US (Dennison et al. 2014, Littell et al. 2009, Miller et al. 2009, Stephens et al. 2005, Westerling et al. 2006, Westerling 2016) as has the length of the fire season (Jolly et al. 2014, Westerling, 2016). Climate, especially drought severity, exerts strong control over area burned through production of biomass and fuels and the drying of fuels. Many studies predict continued increases in large fire occurrence with climate change in the western US (Westerling et al. 2011a,b, Westerling 2016).

Area burned in high severity fire has been correlated to total area burned in some regions, and has seen a concomitant increase with increasing fire size (Cansler and Mckenzie 2014, Dillon et al. 2011, Miller et al 2009, Miller and Safford 2012). In the North Cascade Range, Cansler and McKenzie found that both total high severity area and patch size increased with total burned area (2014). Bottom up controls appeared to mediate this fire area-burn severity area relationship in some ecosystems with historical low-moderate severity fire regimes (Cansler and McKenzie 2014).

In the Sierra Nevada, CA/NV, Miller et al. found that fire size (annual mean and maximum) and total area burned increased in the period 1984-2006, and are now above pre-suppression levels (2009). They also found that the proportion of high severity, stand-replacing fires increased (Miller et. al 2009). The proportional increase in high severity fires was not uniform, but was concentrated in low to mid-elevation forest types where 25-40% of total burned area was classed as high severity. High severity fires are not characteristic of these forest types, indicating that the current fire regime in these ecosystems is outside of historical natural conditions (Agee et. al 1977, Agee 1998, Collins et. al 2009, Moody et al. 2006, Parsons and DeBenedetti 1979).

Previous work (Chapter 2) indicates that fire year climate is critical to accurately predicting severe fire occurrence, especially for very large fires. While many studies have now sought to explain what controls the occurrence of high severity fire at the individual fire to regional scales, none have looked at what controls the scale at which high severity fire occurs. The ability to predict the amount of area that is at risk of burning in high severity fire and whether this is changing would improve the implementation of management decisions to mitigate fires with severity that is uncharacteristic in size or for the ecosystem in which it occurs. In this paper, we seek to answer the following questions:

> Given that a large fire (> 400 hectares) occurs,
> 1. What is the probability that > 200 hectares will burn in high severity?
> 2. What are the total hectares burned in high severity?
> 3. What variables determine area burned in high severity?

3.3 Methods

3.3.1 *Spatial and Temporal Domain of Analysis*

As with the presence/absence modeling in Chapter 2, our modeling domain is a 12km x 12km latitude/longitude grid. We developed models for eleven contiguous Western US states as a whole and three smaller regions to determine if we could improve model performance in years with very large high severity area burned in: the Sierra Nevada Mountains (SN), the Northern Rocky Mountains (NR), and mountains in Arizona and New Mexico (hereafter Southwest, SW) (Figure 3.9.1). The data used vary in spatial resolution from 30m to 12km; to maintain information content of the higher resolution data, we aggregated it to the 12km modeling grid by calculating fractional area of each variable.

The temporal domain of analysis is determined by the availability of burn severity data, which is produced with Landsat imagery. Our models are built on data from 1984-2006, the latest year of completed burn severity mapping when we started our project. We have since obtained data from 2007-2014; trends in fire severity metrics are calculated for 1984-2014. Both our hydroclimate predictor variables and dates within the burn severity database are monthly. We modeled the monthly probability of high severity fire area over 200 hectares and total high severity burned area in the Western US and summed to annual values from 1984-2006. The ignition date of the fire is provided with the burn severity data, but there is no data on length of fire activity; we used the ignition month to link our hydroclimate predictor variables. Our predictors represent the month that the fire started, but may not represent the exact conditions when high severity fire occurred as many large fires burn for more than one month. Any climatic variability that might drive fire behavior, and thus severity, in a fire burning outside the month of discovery will not be captured in our data.

3.3.2 *Burn Severity Data*

We downloaded fire severity data from the Monitoring Trends in Burn Severity (MTBS) project website and used the classified fire severity images to build our models (Eidenshink 2007, http://www.mtbs.gov). The classified images threshold the continuous differenced normalized burn ratio into five severity classes: unburned to low severity, low severity, moderate severity, high severity, increased greenness, For this analysis we selected only forest fires, defined as a fire in which at least 10% of the total burned area was in forest vegetation, following USFS classification standards (Brohman and Bryant 2005). We used data included with the MTBS data that intersects fire severity pixels with Ecological Systems classifications, based on the National Landcover Data Classification (http://www.mtbs.gov/ProjectDocsAndPowerpoints/projectplan.html; 29 January 2016, Homer et al. 2007). We calculated the fractional fire area, for all classes, in the following broad classifications: barren, developed, forest, herbaceous natural, herbaceous planted, shrubland, water, wetlands. We dropped 41 fires from our classified burn severity data that did not have a matching record in the ancillary vegetation/severity database. Of a total 4591 fire records in the MTBS burn severity and vegetation database file, we retained 1871 fires that were a minimum of 400 hectares, had forest cover ≥ 10% and had matching records in the classified severity and severity by vegetation database files. The burn severity images were intersected with the 12km grid; if a fire intersected more than one modeling pixel, we assigned it to the pixel containing the majority of the fire area.

We set the presence of high severity fire hectares > 200 as the threshold for this analysis. Of the 1871 forest fires, 815 exceeded the 200 hectare high severity threshold. The 200 hectare threshold was selected for the generalized Pareto distribution models for area exceeding that threshold using graphical analysis to fall within the range where the sample mean excess function is a linear function of the threshold value (*see* Coles 2001; Holmes, Huggett, and Westerling 2008).

3.3.3 *Landscape Data*

Topographic variables derived from the GTOPO30 global 30 Arc Second (1km) Elevation Data Set data were aggregated to our 12km modeling resolution. These were accessed online from the North American Land Data Assimilation System (LDAS) (http://ldas.gsfc.nasa.gov, Mitchell et al. 2004). The variables include minimum, maximum, mean and standard deviation of elevation within each modeling pixel. Mean slope and aspect are also included. The standard deviation of elevation reflects the topographic complexity within each modeling pixel. We also created a two dimensional surface spline of latitude and longitude to use as a smoothed spatial dummy variable for site-specific characteristics (*as in* Preisler and Westerling 2007).

We aggregated fire regime condition class (FRCC) data from the LANDFIRE project (accessed online at http://www.landfire.gov) as the fractional coverage of each class within the 12km modeling pixels; we then normalized the FRCC fractions using the log function. Fire regime condition class is a widely used metric to identify the impact of land management decisions on ecosystems. It quantifies differences in current vegetation composition from the range of variability under historical natural fire regimes; the departure value is a continuous value 0-100 (Hann 2004, Laverty and Williams 2000). The historical range of variability is determined using the LANDSUM disturbance and succession model run with historic fire regimes (Keane et al. 2006, Pratt et al. 2006). The LANDFIRE departure metric refers only to vegetation composition and does not incorporate changes in fire regime. The departure values are categorized into three FRCC classes: FRCC1 is within historical range (departure <33%); FRCC2 is moderately departed (33% ≥ departure < 66%); FRCC3 is highly departed, or outside the historical range of variability (departure ≥ 67%) (Holsinger et al. 2006, Keane et al. 2007). We are using the FRCC as a proxy variable to reflect the effects of fire suppression.

3.3.4 *Climate and Hydrologic Data*

We obtained a suite of hydroclimate predictor variables output from the Variable Infiltration Capacity model (VIC) and the gridded climate data used to force it (Liang et al. 1994). The VIC model calculates surface and energy water balances and is designed for large-scale applications; it has a simplified soil-vegetation-atmosphere-transfer scheme with a two-layer soil module. A unique feature of VIC is its ability to account for sub-grid scale variability in vegetation characteristics; it calculates evapotranspiration from the vegetation and evaporation from bare soil surfaces at a daily time step for each vegetation class in the modeling grid cell and returns a weighted area sum. Our VIC data was produced with gridded daily climate at ~12km (Mauer et al. 2002) and a 1km vegetation layer from the North American Land Data Assimilation System produced by the University of Maryland (http://ldas.gsfc.nasa.gov, Mitchell et al. 2004). The vegetation layer is composed of coarse plant functional types, e.g. Evergreen needle leaf forest, deciduous broadleaf forest.

The VIC output is returned as monthly averages from 1915-present and includes: temperature extrema and average (Tmax, Tmin, Tave), precipitation (PPT), relative humidity (Rh), snow water equivalent (SWQ), evapotranspiration (ET), moisture deficit (MD), and antecedent moisture deficit derivatives, e.g. 0-12 month prior (Westerling et

al. 2009). We calculated 30-year means and standard deviations for 1961-1990 for Tave, PPT, cumulative MD, and ET. Month of fire and cumulative annual MD variables were normalized relative to the 1961-1990 average and standard deviation.

3.3.5 *Logistic Regression Modeling*

We defined the presence of high severity fire for this analysis as 200 hectares (as above). We used the Random Forest package in R to predict both the fraction of high severity fire (high severity hectares divided by total fire hectares) and high severity burned area (hectares classified as high severity). We used the top 10-20 predictors to perform logistic regression analysis on presence of high severity fire >200 hectares. We used all combinations of variables to determine the best-fit model.

To model the probability of high severity fire presence, we use the logged odds, or logit:

$$\text{Logit } P_{200} = \ln(P_{200} / (1 - P_{200})) = \beta \times [1 + X_j]$$

Where P_{200} is the probability of a fire having >200 hectares classified as high severity; note that implicit in this is that a fire of at least 400 hectares burned. The Logit P_{200} is the logarithm of the odds ratio $P_{200} / (1 - P_{200}))$; β is a vector of maximum likelihood estimated parameters from the data; X_j is the set of independent predictor variables best fit to the model. The threshold of 200 hectares to determine presence was chosen as it is the threshold chosen for the generalized Pareto distribution model; to predict area burned over our threshold of 200 hectares, we need first to know the probability that this many hectares would burn.

We use the Aikake Information Criterion (AIC) to evaluate model performance (Aikake, 1974, 1981).

$$AIC = -2\big(\ln(likelihood)\big) + 2N$$

where *likelihood* is the probability of the data given a model and N is the number of parameters in the model (predictors and intercept). The best model is a model that balances model fit to the data with number of parameters. The AIC penalizes models for excess predictive parameters. The AICs are evaluated as the difference between individual model AIC and the minimum AIC from all models. There is no test to compare AICs, but a general rule of thumb is that if ΔAIC < 2, the models are not significantly different in their skill; ΔAIC > 10 is a significant difference in model skill (Burnham and Anderson 2004, Hare and McGarigal 2010). Once we chose the model with the lowest AIC vs. number of parameters, we performed a leave one out cross-validation.

3.3.6 *Generalized Pareto Distribution Modeling*

We estimated generalized Pareto distributions (GPD) for fire severity area burned with a threshold value of 200 hectares and used these to model the log of area burned in high severity fire. The GPD is a points over threshold model. The choice of threshold was made by evaluating a mean residual life (or sample mean excess function) plot. A threshold was chosen above which the mean residual life plot was linear, meaning that

the GPD is providing a valid approximation of the distribution (Coles, 2001). The GPD can be estimated with and without covariates. Generally, if the data vary spatially or temporally, the inclusion of covariates is necessary to obtain a good model fit (Coles, 2001). We estimated GPDs with and without covariates using the *ismev* function in **R**, initializing with the same set of predictors used in the logistic regression model (R Core Team 2015). Model specifications were evaluated with the AIC (Aikake, 1974, 1981).

West-wide Modeling

In our first stage of model estimation, we used all forest fires in the western US. Our success in creating models of high severity fire occurrence across the western US led us to first estimate GPDs for the entire region (Chapter 2). These models performed well, with the exception of years with extremely large areas burned in high severity fire: 1988, 2002. The utility of our models lies in the ability to understand the conditions that lead to exceptional years in terms of high severity area burned. The years where our model performed poorly are years that saw regional differences in extreme fire activity, indicating that there are unique regional-scale controls on high severity fire area burned across western US forests in severe fire years. We hypothesize that these are related to vegetation-mediated differences in the climate sensitivity of regional fire regimes that are not fully captured by the covariates we used. We chose the Northern Rocky Mountains, Sierra Nevada Mountains, and Southwest forest areas to generate regional GPD models of high severity area burned in an attempt to improve model performance in extreme years.

Regional Modeling

The Northern Rocky Mountain region experienced very large high severity area burned in the years 1988 and 2000; forests of the Southwest experienced the same in 2002, while 1987 and 2002 were high in the Sierra Nevada. We defined the Northern Rocky Mountains as area in Montana, Idaho, and Wyoming bound by latitudes (41.1875,48.9375) and longitudes (-108.675, -104.1875). We defined the Sierra Nevada Mountains using latitude (37.0,40.5) and longitude (-122, -117.5) within California. For the Southwest, we took all forest fires in Arizona and New Mexico (Figure 3.9.1).

3.4 Results

3.4.1 Trends in high severity burned area

High severity burned area is positively correlated to total burned area in the WUS and in individual states; the fraction of high severity burned area has weak to no correlation to total burned area (Table 3.8.1, Figure 3.9.2). We looked for 1984-2014 trends in both high severity burned area and in the number of fires with >200 hectares high severity for the western US as a whole, for individual states, for our three modeling regions, and for months in the fire season. There is no trend in total annual high severity hectares burned from 1984-2014 (Table 3.8.2). There was, though, a corresponding trend in the number of fires with high severity hectares > 200.

Both the WUS and Wyoming experienced significant trends in the annual number of fires with high severity hectares > 200 from 1984-2014 ($p < 0.05$, Figures 3.9.3 and 3.9.4,

Table 3.8.2). This increase is occurring during the summer fire season in June, July, and August, all with significant increases in the number of high severity fires (Figure 3.9.5).

For the three regions we modeled, there were not significant trends in high severity burned area or number of high severity fires. The Sierra Nevada did have a significant increase in the annual minimum fraction of high severity burned area; this means that there are now fewer years without any severe fire (Figure 3.9.5).

3.4.2 West-wide Models

Logistic regression of high severity occurrence >200 hectares

There are 815 forest fires that meet the threshold of 200 hectares burned in high severity. A combination of vegetation condition class, location, temperature and moisture deficit variables best explain presence of high severity fire over our threshold (Table 3.8.4). The final model fits the observations well, Figure 3.9.7 (r = 0.95, p-value < 0.001), and has the form:

$$\text{Logit}(P_{200}) = \beta \times [1 + \text{Tavg.mu} + \text{Tavg.sd} + \text{Tmax} +$$
$$\text{MD10} + \text{MD00n} + \text{FRCC3} + X(\text{Lat, Lon})]$$

where Tavg.mu and Tavg.sd are the 1961-1990 mean and standard deviation, respectively of annual average temperature; Tmax is maximum temperature the month of fire occurrence, MD10 is July moisture deficit of the year of fire, MD00n is normalized cumulative annual moisture deficit in the year of fire; FRCC3 is fractional area in fire regime condition class 3; and X() is a matrix describing a west-wide two-dimensional basis spline. The surface spline of latitude and longitude was important for predicting occurrence of high severity fire for all west-wide and regional models.

Generalized Pareto distribution modeling

The addition of covariates to the stationary generalized Pareto distribution (GPD) model significantly improved model fit (Figure 3.9.8a). A fairly simple model with maximum temperature the month of fire, cumulative annual moisture deficit and location explains area burned in high severity fire in most years (Table 3.8.4).

Our west-wide model performs well with the exception of years with especially large areas burned with high severity fire: 1988, 2002. In the Northern Rocky Mountains, 1988 experienced large and severe fire in the greater Yellowstone region; forests of the Southwest and Sierra Nevada experienced large and severe burns in 2002. In these years, our model greatly under-predicts the area burned in high severity fire; regional GPD models identified location specific covariates that best explained total area burned in high severity fire in these extreme years.

3.4.3 Regional Models

Logistic regression of high severity occurrence > 200 hectares

Regional models all performed well with highly significant correlations between predicted and observed high severity fire occurrence (Figure 3.9.9). The primary difference in regional versus west-wide occurrence modeling is the importance of topographic and climate variables in the final regional models (Table 3.8.4). In the Northern Rocky Mountains (NRM), minimum and mean elevation in the modeling pixel were important (r = 0.94, p-value < 0.001); maximum elevation was important for the Southwest (SW, r = 0.84, p-value < 0.001), and average slope was important in the Sierra Nevada (SN, r = 0.79, p-value < 0.001). The NRM was the only region for which vegetation condition class (FRCC) was not important in the best-fit occurrence models.

Generalized Pareto distribution modeling

Our regional models explained extreme years with large areas burned in high severity, each with unique covariates. For the NRM, the following covariates were important: minimum and mean elevation, average spring temperature, 1961-1990 average temperature, maximum temperature in the month of fire occurrence, relative humidity, March snow water equivalent, and cumulative annual moisture deficit. When these variables are included, we achieve much better predictions of area burned for 1988 and 2000, the years with largest areas burned in high severity fire in this region (Figure 3.9.8b, Table 3.8.4).

For Southwest forests, 2002 was an extreme year with respect to area burned in high severity fire (224023 hectares vs. a 24 year mean of 19577 hectares; the next highest value is 46380 hectares). Our regional model slightly under-predicts 2002, but the value falls within the range of 1000 random draws from the GPD (Figure 3.9.8c, Table 3.8.4). Maximum elevation, average spring temperature, relative humidity, and moisture deficit in the month of fire occurrence were significant covariates for area burned in high severity.

The best GPD model for the Sierra Nevada Mountains included climate, topographic, and vegetation condition covariates (Figure 3.9.8d, Table 3.8.4). The variability in long term moisture deficit and average temperature, slope, and fraction in FRCC1 were included. Annual climate variables of maximum temperature the month of fire, annual average spring temperature, April snow water equivalent, and cumulative water year moisture deficit were also included. The years 1987 and 2002 account for most of the area burned in high severity. We were not able to fit a model that captured both years well. In 1987, two weeks of dry lightning storms at the end of summer resulted in a record number of fire starts and all of the high severity fires in our data started in the first three days of this period (http://www.fire.ca.govdownloads/redbooks//1987_BW.pdf). In 2002, almost all of the hectares burned in high severity (37642 of 47064 total hectares) in our dataset are from one fire, the McNally fire, that started as a result of an illegal campfire. Without the McNally fire, 2002 would not have been a remarkable year in terms of high severity hectares burned, and we were not able to fit any model that matched this year well, though our model does fit well to the other two fires that burned in 2002 (results not shown).

3.5 Discussion

3.5.1 Trends in high severity burned area

Our finding that high severity burned area is positively correlated to total burned area is in agreement with other smaller scale studies (Cansler and McKenzie, 2014, Dillon et al. 2011). While larger fires are associated with more hectares burned in high severity, this does not necessarily mean that larger fires are more severe as there is not a corresponding association with the proportion of total fire area burned in high severity. The increases in large fire occurrence and area burned that have been observed and are predicted with a changing climate will likely result in increases in total high severity fire area in the future (Littell et al. 2009, Stephens 2005, Westerling et al. 2006, 2009, Westerling 2016).

Our record of high severity fire is likely to short to record a significant trend in high severity burned hectares. Without a longer record of severity, we can't with certainty say whether the amount of severity has increased significantly. For many ecosystems in the WUS, enough fire cycles may have been missed due to fire suppression by the time our fire severity record began to impact fuel availability and severity, while others would not have missed any. Our only sub-setting of fires was by relatively large sub-regions that include many forest types and historical fire regimes. It is possible that individual forest types (i.e. those with short fire return intervals) may have experienced an increase in high severity area burned, as recorded in California and Southwest forests, but these increases are not evident when all forest fires are examined together (Dillon et al. 2011, Miller and Safford 2012). While we did not find a significant trend in total high severity hectares, there was a significant west-wide trend in number of fires that meet our high severity threshold.

The significant trend in the number of fires meeting our severity threshold indicates that there is an overall increase in the number of large severe fires since 1984. This is likely a result of the aforementioned correlation between area burned and high severity area burned and the observed increases in number of large fires in recent decades (Dennison et al. 2014, Littell et al. 2009, Westerling et al. 2006, Westerling 2016). While there is evidence for an increase in the length of the fire season in the western US (Jolly et al. 2015, Westerling et al. 2006, Westerling 2016), our increases in high severity fire occurrence occur in the middle of the fire season, June-August, indicating that the increases are likely due to changes in burning conditions or fuels rather than in the lengthening of the fire season (Figure 3.9.5).

3.5.2 Models of high severity burned area

Our west-wide models for both presence of high severity fire and log area burned in high severity fire have three classes of explanatory variables—biophysical setting, climate, and vegetation condition class. The spline of latitude and longitude used here is substituting for the spline of MD/ET that we used in previous work (Chapter 2). The MD/ET spline is a proxy for biological site conditions suitable for plant growth (Stephenson 1998). We substituted the latitude and longitude spline as we would like these models to be readily usable with GCM model output; it also performed better than the MD/ET spline. The importance of the normalized fraction of FRCC in our model

indicates that historical management of fire, primarily as fire suppression, has affected the probability that high severity fire will occur in the presence of a large fire. Last, the maximum temperature and normalized moisture deficit in the month of fire occurrence are important, especially for predicting area burned in high severity fire. The importance of within-year climate variables for predicting high severity fire area in these models is supported by the results from Chapter 2; when we removed within year variables, our ability to predict fires with a high fraction of high severity burned area was limited.

While the west-wide model did well in most years, and the predictor variables are supported by our previous research, the relatively simple model did not explain years with very large high severity burned area. With respect to mitigation or management of high severity fire, understanding what drives extreme fire years is critical. Many variables that were important west-wide were also important in the regional models; in addition to the spline variable, topographic position variables were important biophysical setting predictors in the regional models.

Topographic position is an important determinant of the overall energy balance of a site, impacting vegetation distribution and productivity and, concomitantly, fuel availability. High elevation sites, especially those with north aspects, support cool moist forests that typically burn infrequently, but with high severity. In contrast, low elevation sites with south aspects will support drier open forests that burn more frequently. The importance of topographic parameters in our regional models is supported by smaller scale studies. Elevation was important in the Southwest and Northern Rocky Mountain regions in both logistic regression and GPD models. Previous regional studies from these areas also found topographic variables to be important. Dillon et al. created predictive models for the Northern Rocky Mountains and Southwest and found that topographic position was a dominant predictor of fire severity occurrence and was more important than climate variables (2011). Birch et al. also looked at fire severity in Idaho and Montana (NRM) and found that topography and existing vegetation were more important than climate in predicting burn severity (2015). Both of these studies used finer scale and more complex topographic variables nearer the scale of the burn severity data, which could explain the difference in importance. Including climate variables improved the Dillon et al. models, especially in the Southwest (2011).

Fire year climate variables were more important in predicting area burned in high severity fire (GPD models) than in occurrence of high severity over a threshold. The Northern Rocky Mountains and Sierra Nevada Mountains had more complex models than the Southwest. This is likely because these two regions support a broader range of ecosystems and historic fire regimes. Models for both regions include seasonal and month of fire climate variables. Average spring temperature was important in all regions. Warmer springs lead to earlier snowmelt and can lead to an earlier start of the fire season, especially in dry years. Snow water equivalent in the spring was also important for the NR and SN; snowmelt provides the majority of growing season moisture available for plant growth in these regions. Years with earlier snowmelt and/or less snowpack will impact fuel quantity and flammability. Less available growing season moisture will result in lower production of fine fuel biomass and increased flammability due to fuel drying. In addition to temperature and moisture conditions antecedent to the fire season, the maximum temperature and relative humidity in the month of fire (NR only) were important for predicting area burned in high severity fire. The combination of less

seasonal moisture availability and hot, dry conditions at the time of ignition further increases flammability and risk for severe fire.

For the Southwest, area burned in high severity is best explained with average spring temperature and month of fire relative humidity and normalized moisture deficit. Holden et al. found that fire season precipitation patterns influence fire severity in the Gila Wilderness, NM (2007). The climate of this region is monsoonal, with much of the precipitation occurring during the growing season. Southwest climate is also strongly impacted by the El Nino Southern Oscillation (ENSO); large fire years correspond to high phase ENSO (La Nina) and spring drought conditions. The climate conditions that produce large fires are also important for creating conditions conducive to severe fires via increasing the flammability of vegetation and fuels.

We expected that fire regime condition class would be an important predictor of high severity fire. While it was important in the west-wide logistic regression model, it wasn't consistently important in the GPD or regional models. In forested ecosystems, FRCC indicates how departed the current vegetation is from what would be expected under a historical fire regime. Areas in the highly departed condition class 3 should burn in higher severity given a buildup in fuels and changes in species composition due to fire suppression. The fraction of FRCC3 was important only in the Southwest forests, for both logistic regression and GPD models. The historic fire regime in many Southwest forests was one of frequent low severity fires; the importance of FRCC3 in these models is likely capturing the impact of suppression (Covington et al. 1997,Swetnam and Baisan 1996). In the Sierra Nevada, FRCC1 was important for both models, but FRCC3 was not important. Substituting FRCC3 and FRCC2+3 into our SNC model resulted in decreased model performance as evaluated with AIC and the variable was not significant.

The Sierra Nevada forests are dominated historically by a mixed severity fire regime. Studies have shown an increase in fire severity in some mixed conifer forests (fuel limited fire regimes) over the period of record studied here; they did not find the same in climate limited fire regimes (Miller and Safford 2012, Steel et al. 2015). Fire severity increased in areas that experienced increased time since fire due to fire suppression, as we would expect, in the fuel limited forests in the Sierra Nevada. Collins et al. also found that time since fire was important in predicting fire severity in the Sierra (2007, 2009). With quantitative evidence that fire frequency is important in controlling severity in fuel limited ecosystems, we would expect that FRCC would be a significant predictor as a proxy for fuel buildup due to fire suppression. Perhaps the distribution of FRCC classes in this region is such that FRCC1 better captures fire severity here.

A limitation to our use of FRCC is that our modeling pixels are very large and we have calculated the fraction of each severity class in these to maintain as much information as possible. However, the FRCC fractions don't necessarily reflect the exact FRCC fraction within any given fire perimeter. Instead, they are an indication of fuel conditions proximate to the ignition site of a fire.

3.5.3 Climate Change and High Severity Burned Area

Climate change will create warmer conditions over the western US, while precipitation changes will be more variable. The Southwest is projected to be both warmer and drier,

with increasing drought severity (Cayan et al. 2013). The Sierra Nevada will be very sensitive to changes in the timing of snowmelt due to warming temperatures, regardless of precipitation changes, and is projected to be drier overall (Cayan et al. 2013). The Northern Rockies are likely to be warmer and drier (Westerling et al. 2011a). The importance of annual moisture deficit, monthly maximum temperature, spring temperature and snow water equivalent in our regional models of high severity area burned indicate that there could be more extreme fire years in the future. The combination of our predictors being more likely and the increase in large fires will likely be and increase in extreme fire years in terms of size and severity.

The length of the fire season (Jolly et al. 2014, Westerling, 2016) and large fire occurrence have increased over the past three decades (Dennison et al. 2014, Littell et al. 2009, Miller et al. 2009, Stephens and Ruth 2005, Westerling et al. 2006, Westerling 2016). Our models are conditional on large fires burning, and many studies predict continued increases in large fire occurrence with climate change in the western US (Westerling et al. 2011a,b, Westerling 2016).

3.6 Conclusion

Based on this and our previous work (Chapter 2), we conclude that fire year climate is critical to predicting area burned in high severity fire, especially in extreme fire years. Our ability to accurately predict high severity area burned in extreme fire years requires, though, creating regional models that are more complex than the west-wide models.
If a goal of management is to mitigate extreme fire events in terms of fire severity, then knowledge of fire year climate and its effect on fire severity is essential. Most of the variables that were important in the best fit models are readily available, meaning that we can use our models to forecast future fire severity and how high severity area burned might change in a changing climate.

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3.8 Tables

Table 3.8.1 Pearson's correlation coefficients for high severity hectares burned and fraction of high severity hectares burned to total fire hectares. * *p* values < 0.05.

	Correlation	
Parameter	r	p
Westwide		
High Severity Acres	0.84	<0.001*
Proportion High Severity	0.12	<0.001*
Arizona		
High Severity Acres	0.81	<0.001*
Proportion High Severity	0.12	0.0169*
California		
High Severity Acres	0.83	<0.001*
Proportion High Severity	0.21	<0.001*
Colorado		
High Severity Acres	0.93	<0.001*
Proportion High Severity	0.09	0.4343
Idaho		
High Severity Acres	0.93	<0.001*
Proportion High Severity	0.14	0.002*
Montana		
High Severity Acres	0.80	<0.001*
Proportion High Severity	0.07	0.2021
New Mexico		
High Severity Acres	0.84	<0.001*
Proportion High Severity	0.10	0.09242
Nevada		
High Severity Acres	0.94	<0.001*
Proportion High Severity	-0.03	0.802
Oregon		
High Severity Acres	0.93	<0.001*
Proportion High Severity	0.03	0.6609
Utah		
High Severity Acres	0.45	<0.001*
Proportion High Severity	-0.01	0.9469
Washington		
High Severity Acres	0.79	<0.001*
Proportion High Severity	0.12	0.176
Wyoming		
High Severity Acres	0.93	<0.001*
Proportion High Severity	0.13	0.1743

Table 3.8.2. Results from trend analysis of total annual high severity hectares burned and annual count of fires with high severity hectares > 200 (*Count*) for the period 1984-2014. * *p* <0.05. We looked for trends in all forest fires in the western US and for trends in forest fires by state. Standard Error values are in parentheses.

Parameter	Slope	*p*
Westwide		
High Severity Acres	6412 (4586)	0.173
Count Over Threshold	1.11 (0.53)	0.047*
Arizona		
High Severity Acres	-417.7 (720.5)	0.567
Count Over Threshold	0.05 (0.01)	0.309
California		
High Severity Acres	2402 (1352)	0.086
Count Over Threshold	0.12 (0.18)	0.530
Colorado		
High Severity Acres	181.1 (357.6)	0.619
Count Over Threshold	0.07 (0.06)	0.259
Idaho		
High Severity Acres	2591 (1490)	0.093
Count Over Threshold	0.20 (0.14)	0.162
Montana		
High Severity Acres	-349.5 (1315.4)	0.793
Count Over Threshold	-0.22 (0.19)	0.253
New Mexico		
High Severity Acres	471.2 (319.4)	0.152
Count Over Threshold	0.01 (0.06)	0.907
Nevada		
High Severity Acres	-43.24 (241.76)	0.860
Count Over Threshold	0.02 (0.04)	0.723
Oregon		
High Severity Acres	-1129.5 (745.6)	0.141
Count Over Threshold	-0.03 (0.08)	0.740
Utah		
High Severity Acres	412.4 (481.8)	0.403
Count Over Threshold	0.16 (0.14)	0.248
Washington		
High Severity Acres	117.7 (412.4)	0.778
Count Over Threshold	-0.02 (0.05)	0.743
Wyoming		
High Severity Acres	-347.7 (4356.7)	0.933
Count Over Threshold	0.24 (0.10)	0.039*

Table 3.8.3. Results from trend analysis of total annual high severity hectares burned and annual count of fires with high severity hectares > 200 (*Count*) for the period 1984-2014. *p <0.05. We looked for trends in all forest fires in the western US and for trends in forest fires by modeled sub-region. Standard Error values are in parentheses.

	Slope	p
Westwide		
High Severity Acres	6412 (4586)	0.173
Count Over Threshold	1.11 (0.53)	0.047*
Northern Rocky Mountains		
High Severity Acres	53.18 (3408.92)	0.988
Count Over Threshold	0.44 (0.30)	0.150
Sierra Nevada Mountains		
High Severity Acres	205.3 (411.1)	0.621
Count Over Threshold	0.07 (0.06)	0.280
Southwest		
High Severity Acres	-111.0 (930.6)	0.906
Count Over Threshold	-0.05 (0.10)	0.649

Table 3.8.4. The final predictor variables for the logistic regression (presence/absence) and generalized Pareto distribution (GPD) models for the western US and three sub-regions.

| Variable Description	Westwide logistic regression	Westwide GPD	NR logistic regression	NR GPD	SW logistic regresssion	SW GPD	SN logistic regression	SN GPD
Elevation								
Minimum			✓	✓				
Maximum					✓	✓		
Mean			✓	✓				
Slope							✓	✓
1961-1990:								
Cumulative water year moisture deficit, standard deviaiton								✓
Cumulative water year evapotranspiration, mean					✓			
Average temperature, mean	✓		✓	✓				
Average temperature, std.devn.	✓						✓	✓
Month of Fire:								
Maximum temperature	✓	✓		✓			✓	✓
Average spring temperature				✓		✓	✓	✓
Average relative humidity				✓		✓		
March snow water equivalent				✓				
April snow water equivalent								✓
Moisture deficit June					✓			
Moisture defiict July	✓							
Fraction of FRCC1							✓	✓
Fraction of FRCC2							✓	
Fraction of FRCC3	✓				✓	✓		
Month of fire normalized moisture deficit					✓	✓		
Normalized cumulative water year moisture defiicit	✓	✓	✓	✓				✓
Latitude-longitude spline	✓		✓	✓	✓	✓	✓	

3.9 Figures
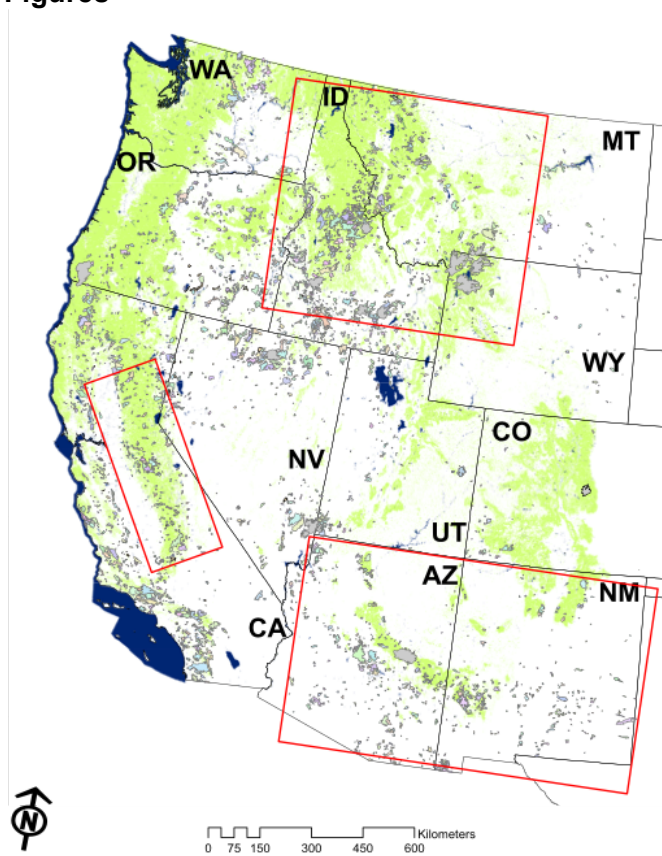
Figure 3.9.1 Fire perimeters of large fires 1984-2006. Forested areas are green. Three model development sub-regions are outlined: the Northern Rocky Mountains (MT, ID, WY), the Sierra Nevada Mountains (CA), the Southwest (AZ, NM).
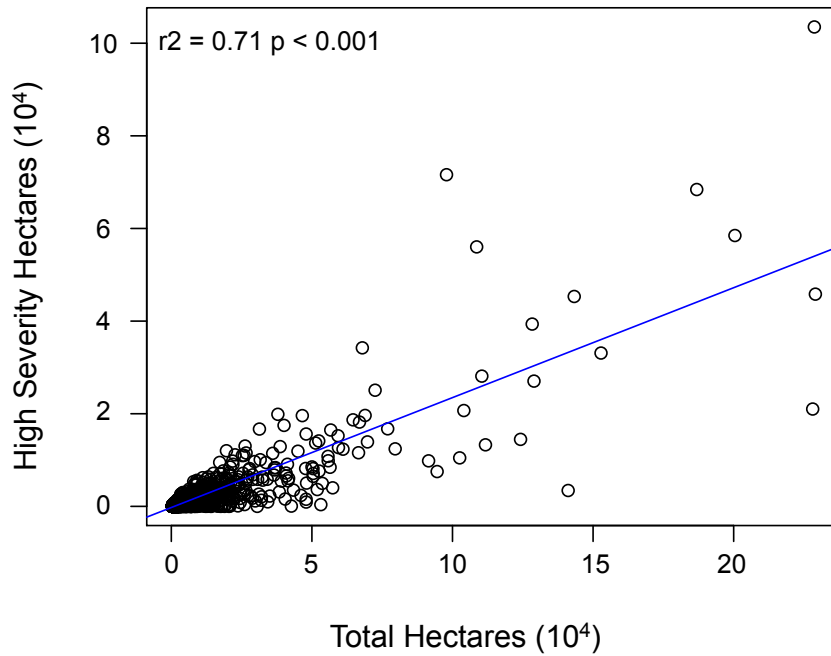
Figure 3.9.2 Total area burned vs. high severity area burned for all fires in the western US, 1984-2014. Blue line is linear model fit to the data.
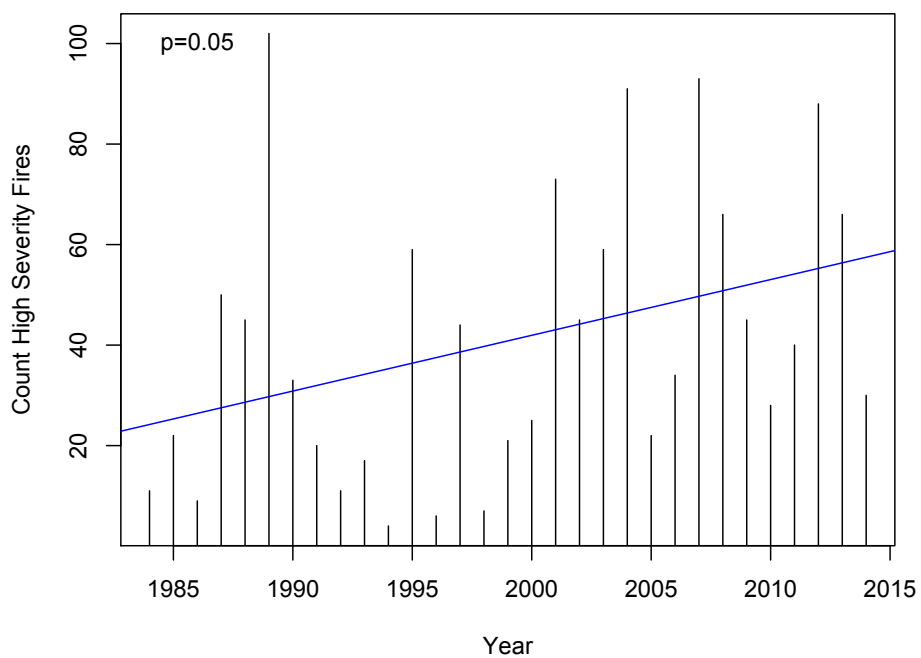
Figure 3.9.3. Annual number of fires with high severity area exceeding the 200 hectare threshold for 1984-2014 for all fires in the western US. The blue line is a fit of the statistically significant trend in number of high severity fires.

Figure 3.9.4. Frequency of fires above and below our 200 hectare threshold for each state. Green bars are the annual number of large fires with no presence of high severity fire; purple bars are the annual number of large fires classified as high severity, i.e. high severity hectares exceeding the 200 hectare threshold.
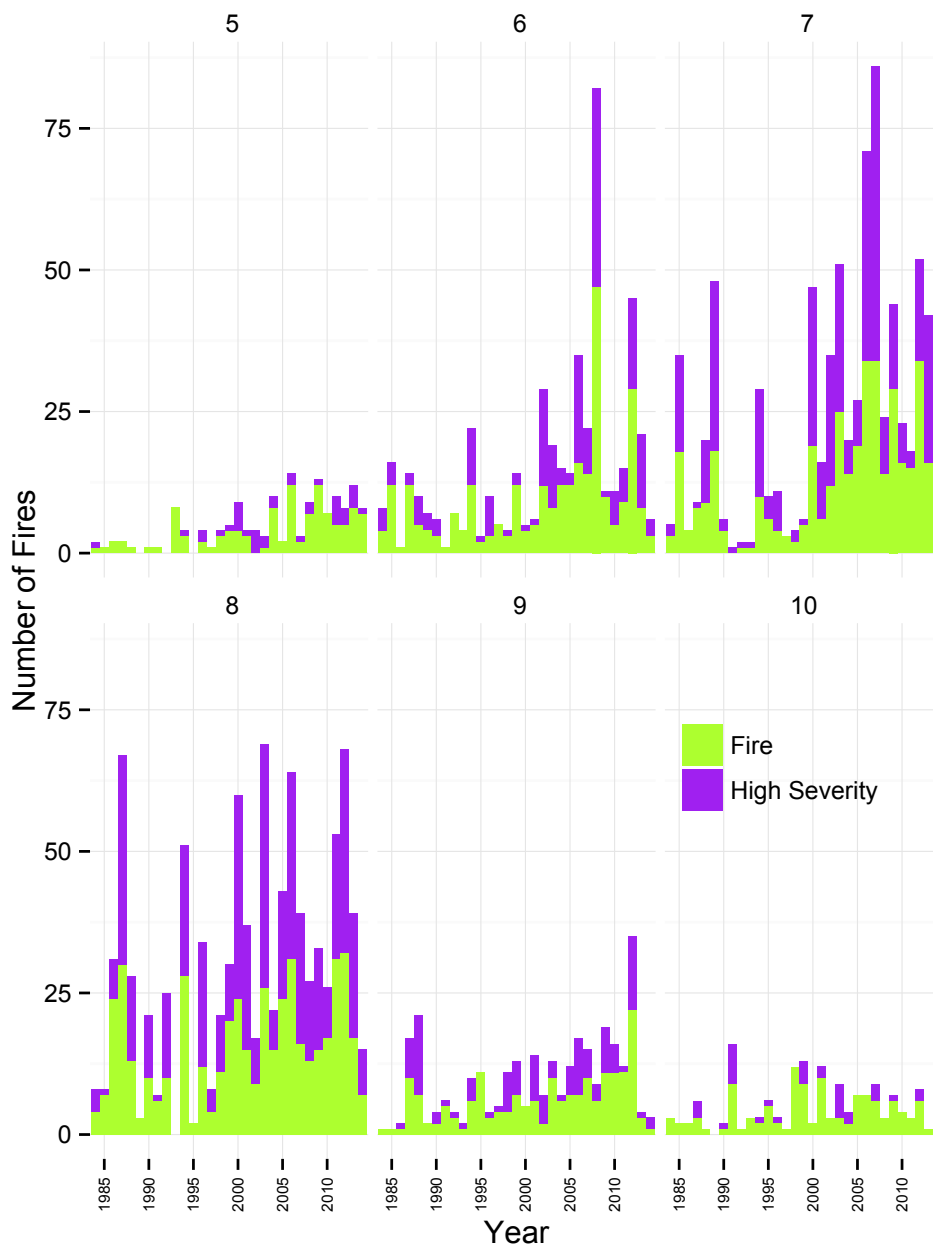
Figure 3.9.5 Frequency of fires by severity class for May (5) – October (10). Green bars are the annual number of large fires with no presence of high severity fire; purple bars are the annual number of fires classified as high severity, with high severity hectares > 200 hectare threshold. June, July, and August all experienced statistically significant increases in number of high severity fires from 1984-2014 (p = 0.015, p=0.043, p=0.057, respectively).
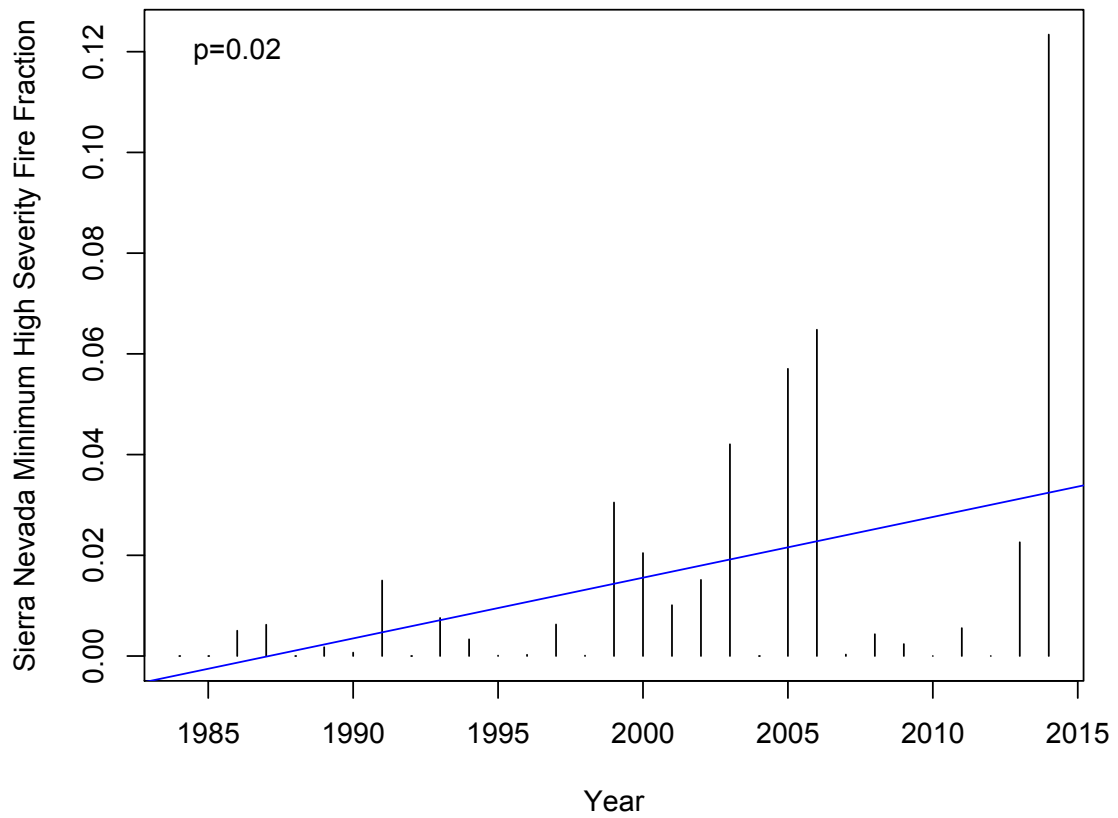
Figure 3.9.6. Sierra Nevada annual minimum high severity fraction for years 1984-2014 with trend line in blue.
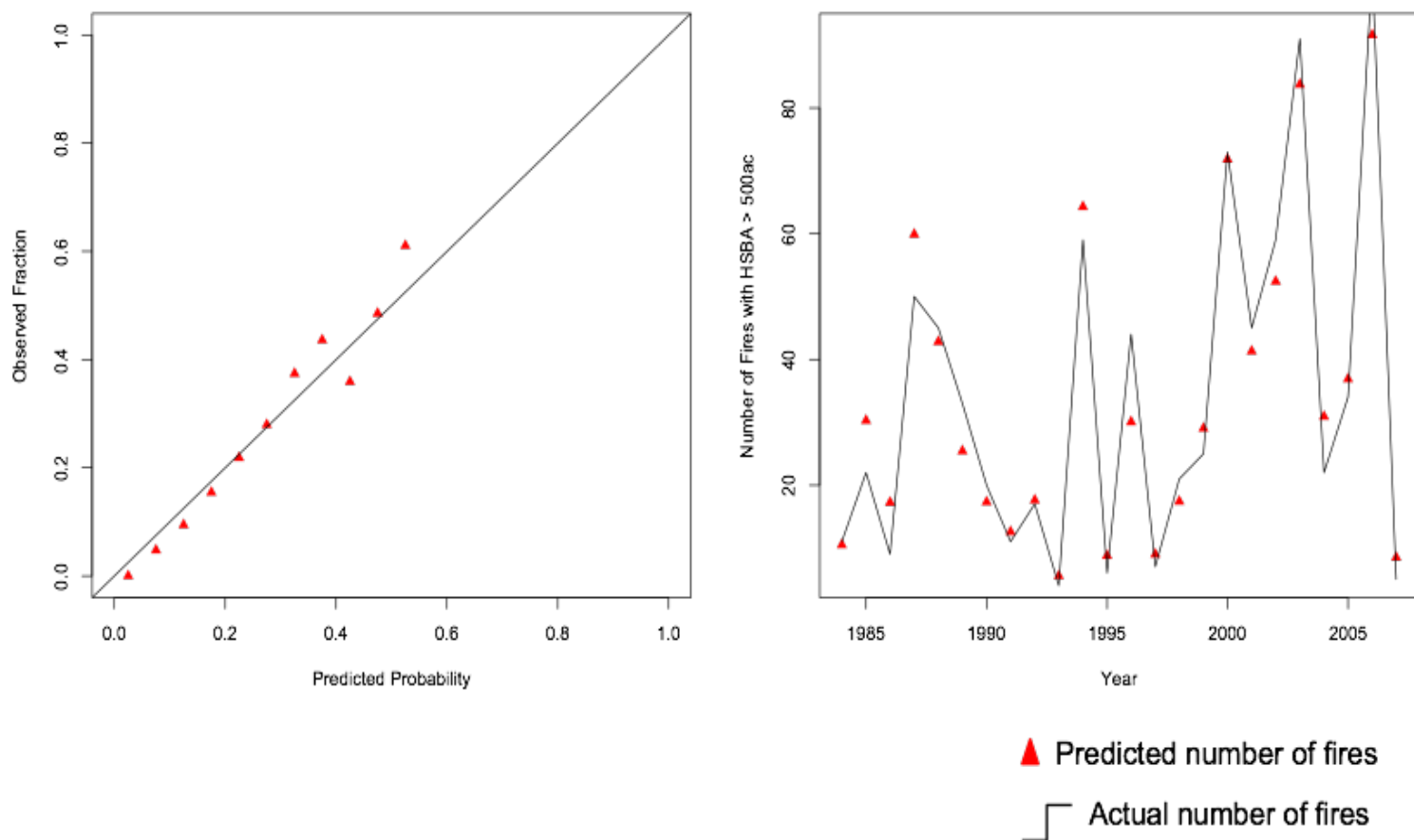
Figure 3.9.7 a) Probability of occurrence of high severity fire >200 hectares vs. observed fraction from logistic regression analysis for the Western US. b) Predicted vs. observed annual number of fires meeting threshold of 200 hectares.
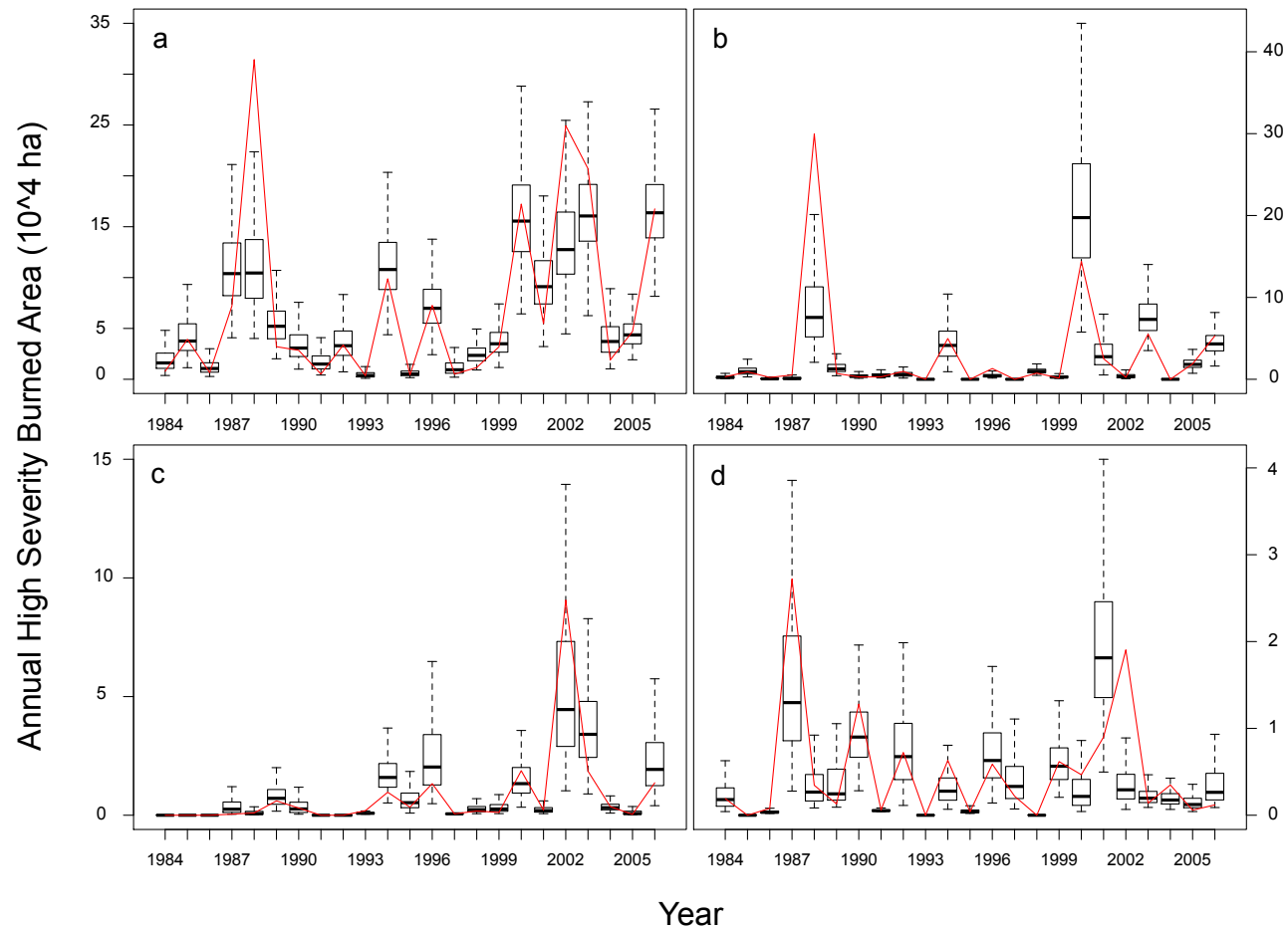
Figure 3.9.8. Observed high severity hectares burned (line) versus 1000 simulations generated with a generalized Pareto Distribution with covariates for a) the Western United States, b) the Northern Rocky Mountains, c) the US Southwest, d) the Sierra Nevada Mountains. Developing regional models improved predictions for years with regionally specific high severity fire occurrence: 1988 and 2000 for the Northern Rocky Mountains, 2002 for the Southwest, and 1987 for the Sierra Nevada.

Figure 3.9.9 From logistic regression, the predicted probability vs. observed fraction of high severity fire burned area > 200 hectare for a) Western US b) Northern Rocky Mountains c) Southwest d) Sierra Nevada Mountains

4   How will climate change impact high severity burned area in the Greater Yellowstone Ecosystem?

4.1 Abstract

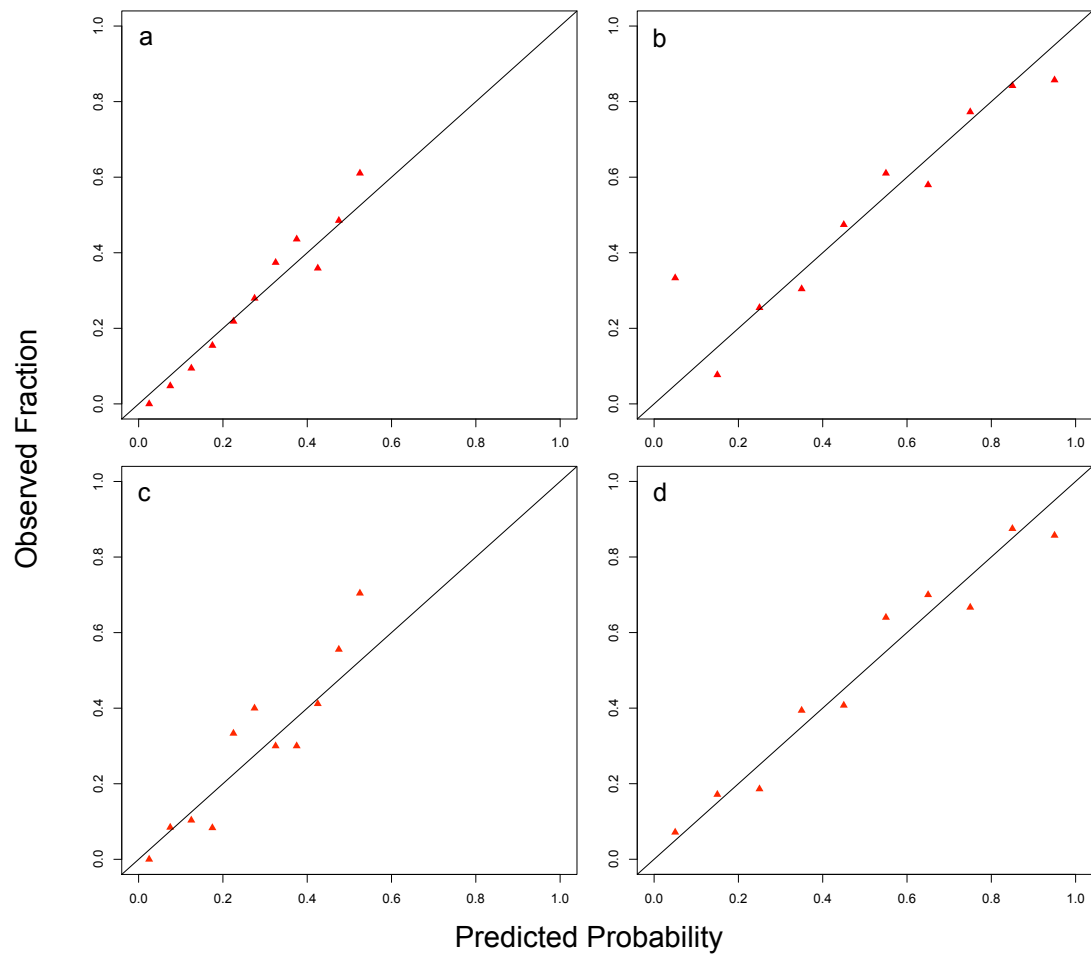Fire season length and large fire occurrence and area burned have increased in recent decades. These increases are expected to continue with climate change, and are concomitant with forests that have a buildup of fuels due to fire suppression. How fire size and severity will respond to climate change is uncertain. The western United States is expected to get warmer, with the Northern Rocky Mountain region expected to get drier as well. Application of output from global circulation models to large fire occurrence and size models in the Greater Yellowstone Ecosystem indicates that climate conditions by mid-century will result in an increase in the frequency of large fire events and area burned. 1988 was an extreme year in terms of historic climate and fire activity in the Yellowstone ecosystem, but years like it will be common by mid-century. We applied GCM output to a set of probabilistic models for high severity occurrence and burned area for the Greater Yellowstone Ecosystem. We found that fraction of high severity burned area increases to levels by mid-century that are three times greater than a 1961-1990 reference period. These potential changes in high severity area burned and frequency of occurrence may result in changes to species composition in these high elevation forests.

4.2 Introduction

Recent decades have seen an increase in the length of the fire season and occurrence and size of large fires in the western United States (US; Dennison et al. 2014, Jolly et al. 2016, Littell et al. 2009, Westerling et al. 2006, Westerling 2016). Climate change models predict rising temperatures and moisture deficit across the region, increasing the likelihood of large fire occurrence.

Westerling et al. (2011) applied probabilistic models of large fire occurrence and area burned to climate change scenarios for the Greater Yellowstone Ecosystem (GYE). They found that fire area burned increased across the region for three different general circulation model (GCM) scenarios. 1988 was a unique year in terms of fire area burned in the GYE, with no other year in the recent historical or modern record surpassing it (Despain et al. 1989, Romme and Despain 1989, Schoennagel et al. 2003, Romme et al. 2011). The most recent fire equivalent in size occurred in the 1700's; the fire return interval is ~300 years for most of the forests in the GYE. Westerling et al. (2011) found that fire season comparable to 1988 conditions will occur more frequently by midcentury.

An important component of how ecosystem fire regimes will be impacted by climate change is fire severity. Fire suppression resulted in an increase in fuels in many ecosystems of the western US, increasing the risk of high severity fire (Keane et al. 2002). High severity area has also been found to correlate to fire size in some regions (Cansler et al. 2014, Chapter 3). We found that high severity fire occurrence and area burned can be predicted with topographic, vegetation and climate variables across the western US, with some regional differences in predictor composition (Chapters 2 and 3). For years that are extreme in terms of fire size and high severity area burned, fire year climate variables were critical to model fit.

Here we use the fire size predictions for the GYE in Westerling et al. (2011) to explore how climate change might impact high severity area burned in this ecosystem. Because our models are conditional on a large fire occurring, we are using existing data that will provide us with a statistical probability of large fire occurrence to constrain our model predictions to future potential.

4.3 Methods

4.3.1 Study Area

The Greater Yellowstone Ecosystem (GYE), covering approximately 80,000km^2, sits at the intersection of the northwest corner of Wyoming, Montana and Idaho. It is centered on Yellowstone National Park, additionally encompassing Grand Teton National Park and multiple national forests (Figure 4.7.1). Much of the GYE is forested, with lodgepole pine (*Pinus contorta* var*. latifolia* Engelm.), Englemann spruce (*Picea engelmanii*), subalpine fir (*Abies lasiocarpa*), and whitebark pine (*Pinus albicaulis*) dominating higher elevations and Interior Douglas-fir (*Pseudotsuga menziesii*) the lower elevations.

4.3.2 *Climate and Hydrologic Data*

We used the Variable Infiltration Capacity model (VIC) to generate a suite of hydroclimate predictor variables, as in Chapters 2 and 3 (Liang et al. 1994). The set of predictors includes monthly climate, snow water equivalent, evapotranspiration (ET) and moisture deficit (MD) variables. We also created a two dimensional surface spline of latitude and longitude to use as a smoothed spatial dummy variable for site-specific characteristics (as in Preisler and Westerling 2007, Chapter 3).

We used temperature and precipitation inputs to force the VIC model that were output from the Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1 GCM scenario downscaled to 1/8th degree from the Intergovernmental Panel on Climate Change Fourth Assessment, medium high (SRES A2) emission pathway (IPCC 2007; for fuller description see Westerling et al. 2011). We chose the GFDL CM2.1 for this study as it was used in Westerling et al. (2011) to generate estimates of area burned. We clamped all predictor variables to fall within the range of historical values over the GYE.

4.3.3 Large fire occurrence modeling

Our GCM driven VIC output provides 147 years of monthly data, 1953-2099. Westerling et al. (2011) developed probabilistic statistical models of large fire occurrence for the GYE in a changing climate. A logistic regression model predicts the probability of large (>200ha) fire occurrence for each voxel (latitude, longitude, month, year); a Poisson log-normal model predicts the number of large fire occurrences conditional on one occurrence. Last, the area burned in large fires is predicted using a generalized Pareto distribution (GPD) fit to observed historical fires over the 200ha threshold (see Westerling et al. 2011). The overall approach for predicting large fire occurrence is:

$$\text{Expected Area Burned} = P(\Theta(X)) * \hat{C}(\Theta | \text{fire>0}) * \hat{A}(X | \text{fire=1})$$

Where Θ is the estimator of a logistic regression on variables X, and P is the probability of fire where

$$P = \exp(\Theta)/(1+\exp(\Theta)),$$

$\hat{C}$ (Θ| fire>0) is the expected number of fires given one occurrence via a Poisson lognormal model on Θ; and $\hat{A}$ is the expected burned area per fire estimated by a GPD with covariates X, given at least one large fire. For each month in 147 years, one thousand draws were made from the binomial (logistic), GPD, and Poisson (count) distributions for each GCM output set. These outputs then provided the framework for modeling high severity fire occurrence and area burned.

As the severity models developed here are conditional on a large (400 ha/1000 acre) fire occurring, we first had to determine the probability of large fire occurrence and predicted fire size. From the 1000 simulation output of the Westerling GPD model, we counted how many times each month that a fire > 400ha burned; we also summed the total area burned in fires > 400ha for each month. This gave us estimates for occurrence of large fire and total area burned.

4.3.4 High severity burned area modeling

We first fit a logistic regression model to our Northern Rocky Mountain (NRM) fire severity data to determine probability of high severity occurrence within a large fire (see Chapter 3). Our criterion for presence of high severity area here is 200ha (500acre), the threshold for the GPD modeling. Using the logistic regression model from Chapter 3, we estimated the probability of high severity acres exceeding 200ha with a thousand draws from the binary distribution for each month, 1953-2099, using future climate predictors.

We then ran 1000 simulations with our NRM GPD model for each month; any output that was greater than the largest high severity burned area in the historical record was clamped to that historical maximum. The GPD model used in this analysis is modified from the model developed for the Northern Rocky Mountains in Chapter 3 by the removal of the relative humidity parameter. Removing relative humidity decreases model skill in predicting high severity area burned in the two large fire years in the Northern Rocky Mountains, 1988 and 2000. We removed this variable due to concerns with how it is calculated in the VIC hydrologic model; the relationship used is invalid for use with GCM model output due to the radiative properties assumption (*personal communication* Westerling, Pierce et al. *In revision*).

After we created a set of 1000 simulations from our two models for estimating high severity area burned, we combined them with the predicted models for fire area burned to predict potential high severity area burned and fractional high severity area burned for each month. The overall model framework is:

Estimated High Severity Area Burned (HSBA) = $P_h(\theta(X)|N>0) * \hat{A}_h(X' | N>0)$,

where Θ is the estimator of the logistic regression on X and P_h is the probability of high severity area > 200ha where

$$P_h = \exp(\Theta)/(1+\exp(\Theta)),$$

N is the count of Estimated Area Burned (EAB) > 400ha; $\hat{A}_h$ is the estimated high severity area burned per fire with covariates X'. We randomly sampled N probability and high severity area burned values from our 1000 simulations and estimated high severity area burned for each month. We divided our estimates of HSBA by the total area burned in N fires > 400ha from the EAB data to derive an estimate of fractional high severity burned area for each month.

We calculated averages for the following time periods: 1961-1990, 2005-2034, 2035-2064, 2070-2099 to look at changes in high severity burned area and fraction through time. We calculated 30year mean values for each pixel, and used 1961-1990 as a reference period to estimate relative differences.

4.4. Results and Discussion

The distributions of large fire (> 400ha) occurrences and fraction HSBA increased consistently for each summary period (Figure 4.5.3). In the 1961-1990 reference period, the maximum 30 year average fraction of HSBA was 15% (note that individual voxel values were greater, up to 100%) and by the end of the century the maximum 30 year average was 54%; the mid century maximum was 33% (Figure 4.5.4). Results past mid-century cannot be considered realistic as our model does not incorporate changes in landscape composition due to time or disturbance; the impacts of both will be evident by the mid-21st century.

By mid-century 50% of the GYE could experience a three-fold increase in fractional HSBA; this number increases to five-fold by the end of the century (Figure 4.5.5). The greatest increase in fractional HSBA occurs the southeast region of the GYE.
High elevation spruce-fir forests dominate this area. The historical fire regime of most of the high elevation forests in the GYE is one of infrequent stand replacing fires (~300yr interval), generally controlled by top down factors (Romme and Despain 1989, Schoennagel et al. 2003). Fuels are abundant in these systems, but are rarely dry enough to burn except under extreme climatic conditions. The large increase in fractional HSBA predicted for these regions indicates that climatic conditions which were once rare will become much more common.

The 1988 fires had the largest high severity area burned in our historical fire severity record, yet the fraction high severity was only 0.45. The scale of the 1988 fires was not unprecedented for this region, but the most similar prior event occurred in the 1700's (Romme and Despain 1989). While extreme climate conditions made the scale of the 1988 fires possible, bottom up controls of topography and fuels mediated burn severity resulting in a mosaic of fire severity on the landscape (Christensen et al. 1989, Romme and Despain 1989, Romme et al. 2011, Turner et al. 1994).

The models used to predict large fire occurrence indicate a significant decrease in the fire return interval and fire rotation by mid-century (Westerling et al. 2011). With the return interval of large fires shortening, and the fraction of high severity acres within them increasing, there is likely to be a disturbance driven shift in vegetation composition on the landscape.

Both the time between and severity of fires impact vegetation composition and structure and fuel availability. High severity fires result in new stand establishment. If fires return before trees become large enough to survive, even a low intensity fire could result in repeated stand replacement and/or a shift in vegetation composition. The predicted changes in fire rotation by mid-century along with our predicted changes in high severity fraction are dependent on fuel availability, which is not represented dynamically in our models. Using a forest succession and disturbance model, Henne et al. (2016) found that a future with increased fire frequency and area burned resulted in an overall shift to younger stands across the GYE, from mean ages of 112-191 years (historical fire frequency) to 31-92 years. They also predicted expansion of lodgepole pine (*Pinus contorta*) stand area and contraction of spruce-fir (*Picea engelmanii - Abies lasiocarpa*) stand area.

Disturbance will not be the only driver of future vegetation change; climate change will also impact vegetation through modification of site potential. A future that is warmer and drier in the GYE will likely result in a shift in species distribution. Habitat suitable for current subalpine species, especially whitebark pine (*Pinus albicaulis*) is likely to shrink (Bartlein et al. 1997, Schrag et al. 2007, Chang et al. 2014, Hansen et al. 2016). Lower elevation sites could support new tree species and/or expansion of existing ponderosa pine (*Pinus ponderosa*) habitat. It is likely that the combination of warmer drier climate combined with increased fire frequency and severity will result in a shift of tree species composition in the GYE. Models with disturbance and climate change driven vegetation changes both indicate a decrease in habitat suitability for subalpine species and an increase in habitat for species suited to warmer and drier climates with more frequent fire return. How the two will feedback on one another is unknown.

Parks et al. (2016) developed a statistical model for high severity fire occurrence using actual evapotranspiration and climatic water deficit (WD, analogous to our moisture deficit variable) and used it to predict changes in fire severity in a changing climate. They found that future increases in WD resulted in a decrease in the probability of high severity fire occurrence. They interpret increases in WD across the western US to be a proxy for changes in vegetation, namely lower vegetation productivity leading to less fuel biomass. The findings of Parks et al. (2016) contrast with our prediction of an increase in high severity fire area fraction, though both models are primarily constructed with climatic predictors. Unlike our results, Parks et al. (2016) estimated probabilities for two time periods, historic and end of century, and calculated the difference. Our models are generating probabilities through time. In essence Parks et al. (2016) are describing where changes in fire severity risk might terminate, but our models are describing how severity might change through time.

A limitation of our approach is that we do not account for vegetation changes due to fire or climate change. The inputs to the VIC hydrologic model include a static vegetation layer. Sensitivity analyses performed on VIC to test the impact of changes in vegetation also did not have a significant impact on total moisture deficit output (Westerling, *personal communication*). Our HSBA models for the Northern Rockies have only one predictor related to vegetation, normalized cumulative moisture deficit for the 1961-1990 period. Our models are primarily driven by climate, so changes in vegetation due to climate change are not likely to influence our prediction for HSBA.

4.6 Conclusions and Future Research

Historical high severity burned area in the Northern Rocky Mountains was predominantly controlled by climate. Application of our high severity burned area prediction models using the GFDL A2 scenario results in a significant increase in the fraction of high severity burned area over the GYE in the 21st century. The GFDL model used produces a hotter and drier future for this region than other GCMs, so our results reflect a worse case scenario.

We will improve this application by using three GCM models to produce a range of possible future scenarios. We will also use the most recent IPCC GCM model outputs (AR5). We will be able to refine the scale of analysis as we have these data, and resulting VIC model outputs, downscaled to 1/16th degree. Application of our model outputs should produce better quality predictions of high severity burned area given the importance of within year climate variables in our model.

4.4. References

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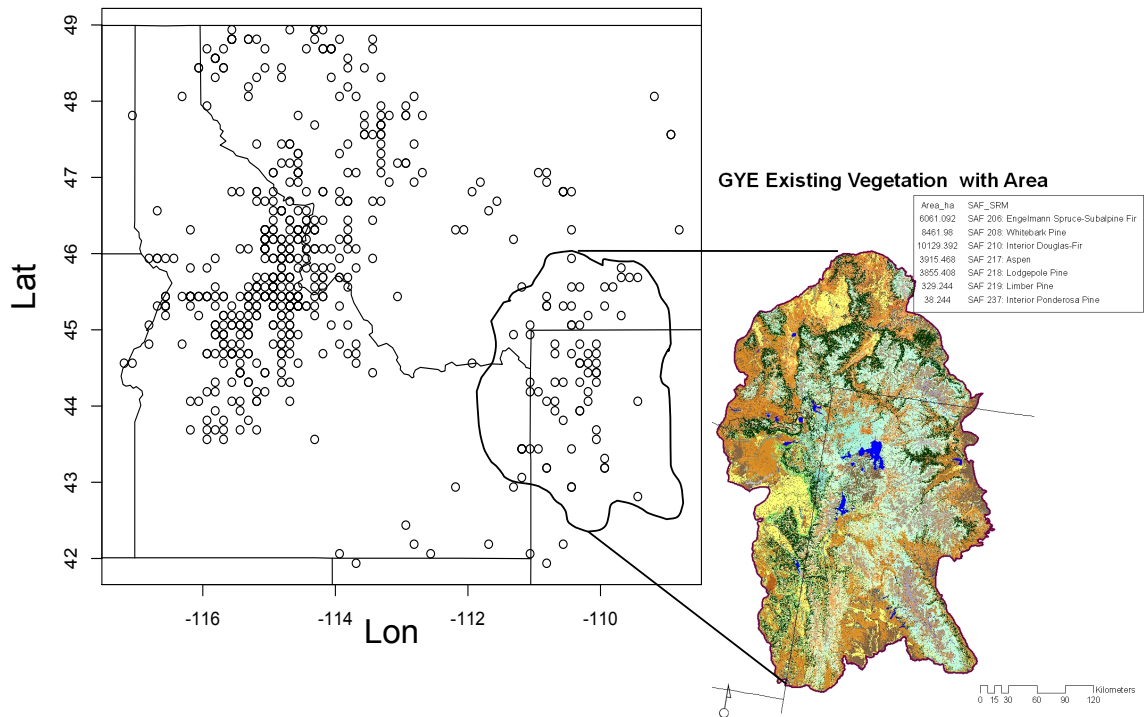
4.5 Figures

Figure 4.5.1. Locations of historical large fires used to create statistical models for the Northern Rocky Mountains. Inset map of existing vegetation in the Greater Yellowstone Ecosyst
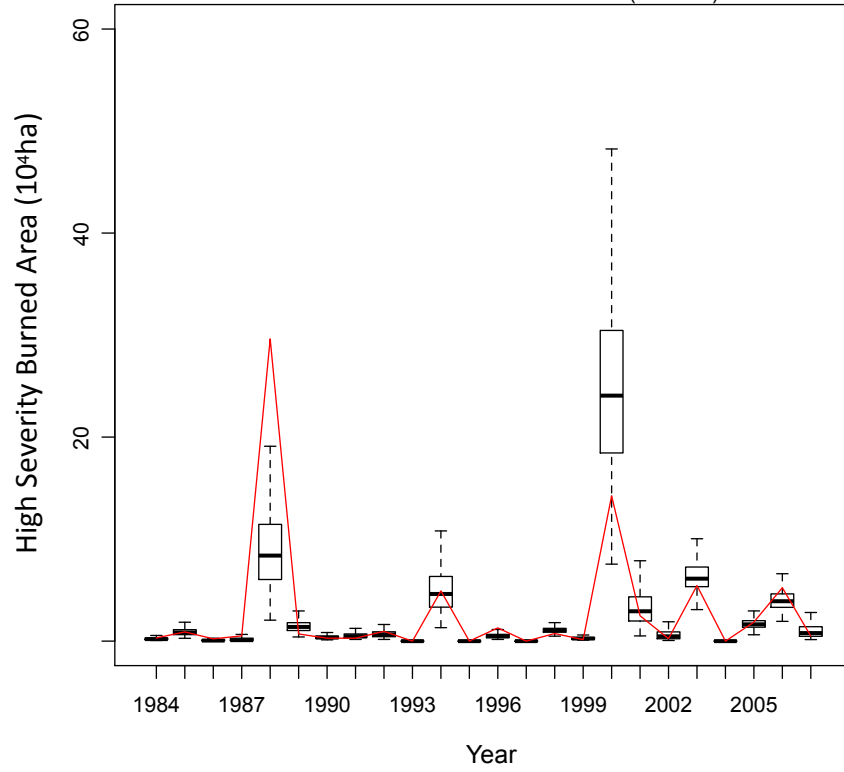
Figure 4.5.2. Boxplot of 1000 draws from the generalized Pareto distribution for the Northern Rocky Mountain generalized Pareto distribution model. (See Chapter 3 for details on model development).
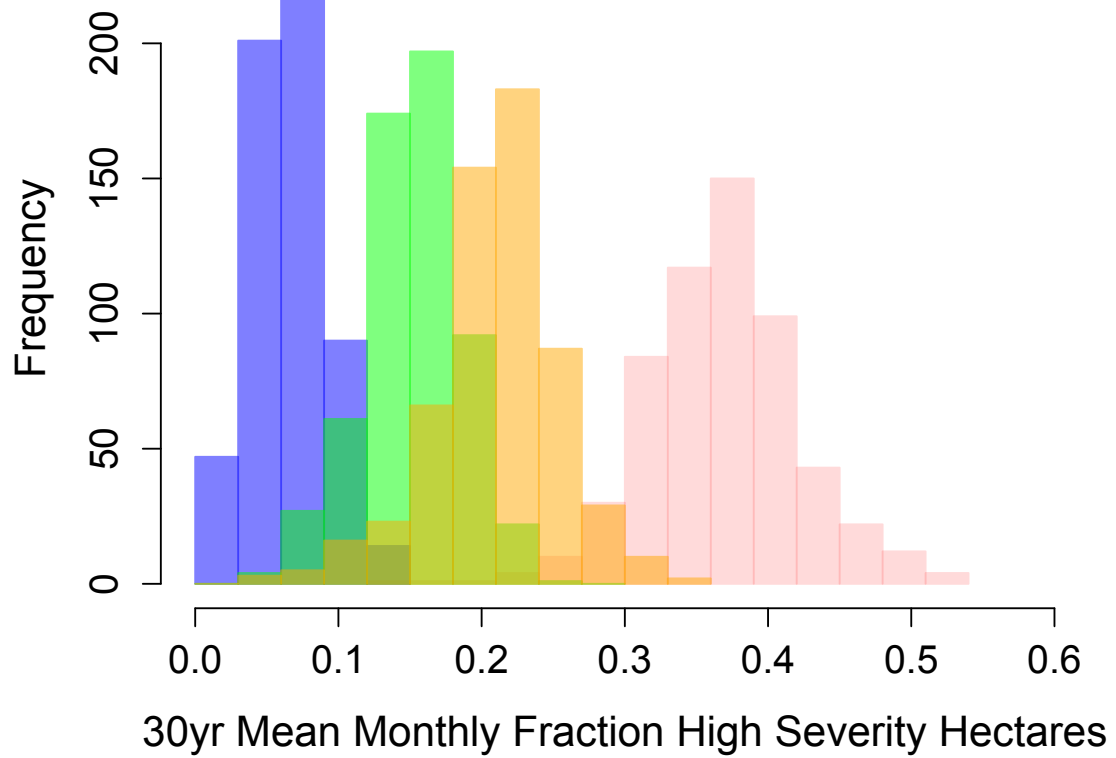
Figure 4.5.3 Distribution of 30year average fraction high severity area burned for 1961-1990 reference period (blue), 2005-2034 (green), 2035-2064 (orange), 2070-2099 (red)
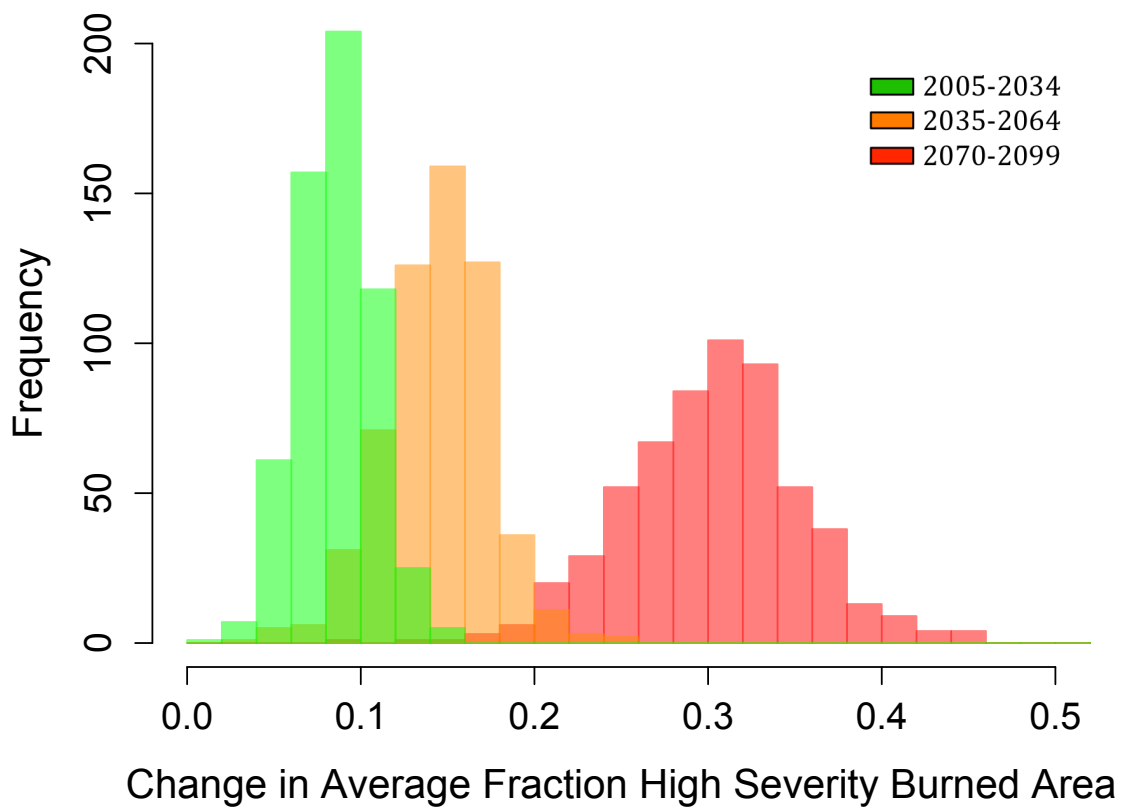
Figure 4.5.4. Change in high severity burned area fraction from the 1961-1990 reference period for 2005-2034, 2035-2064, 2070-2099.
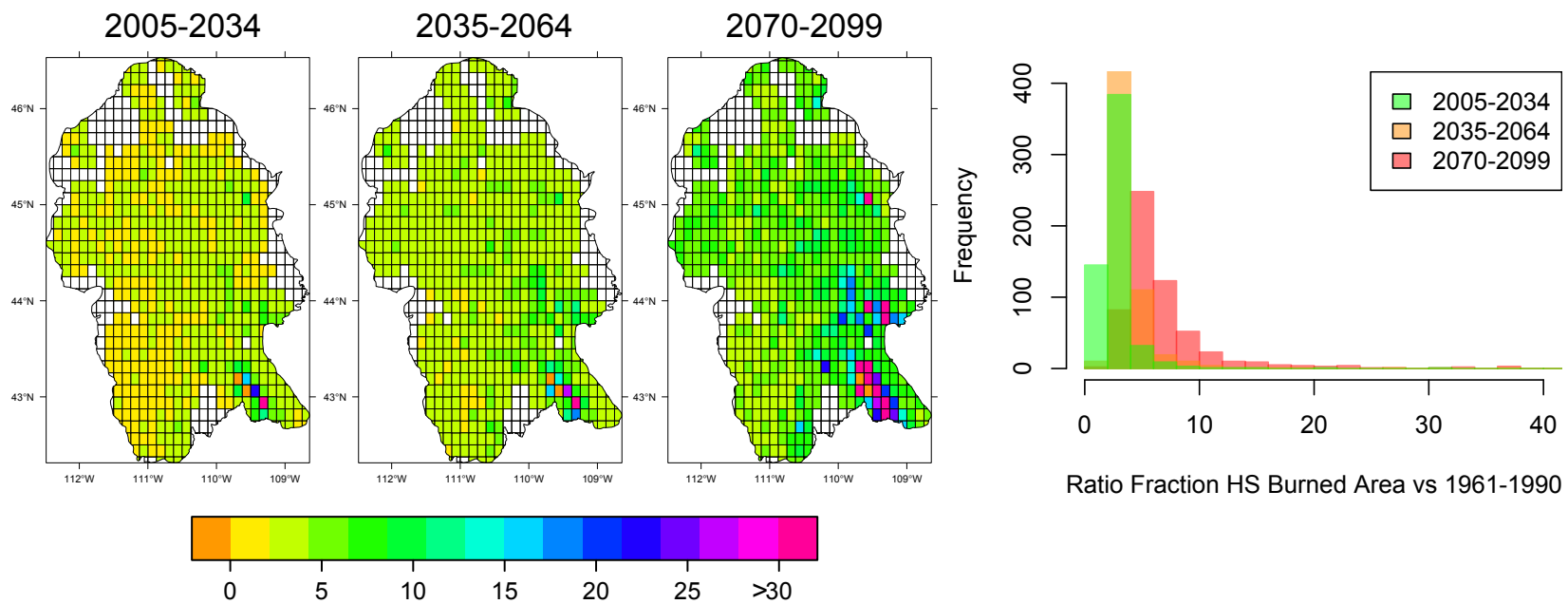
Figure 4.5.5. Spatial distribution of changes in high severity burned area relative to the 1961-1990 reference period.

5   Conclusion

The overall objective of my dissertation was to understand recent patterns of fire severity in the western US in order to inform potential management decisions. A long history of fire suppression has led to fuel buildup in many ecosystems in the western US, increasing risk of severe fire; I therefore focused my objectives on high severity fire occurrence and area burned. I first sought to develop predictive models of high severity occurrence using topography, vegetation, and climate. A secondary objective was to determine relative importance of these three predictor classes. Success in predicting occurrence led to predicting area burned in high severity fire. With successful probabilistic models of high severity fire occurrence and area burned, I explored the impact of climate change on high severity fire risk for the Greater Yellowstone Ecosystem.

The only trend I found in high severity metrics was in the number of fires that had more than 200ha burned in high severity; high severity area burned is also positively correlated with total area burned. I can't attribute any increase in severe fire due to past fire suppression from my data. The record of high severity fire is likely too short to record a significant trend in high severity burned area. Without a longer record of severity, we can't with certainty say whether the amount of severity has increased significantly. I also included every large fire in the MTBS data in the analysis. For many ecosystems in the WUS, enough fire cycles may have been missed due to fire suppression by the time our fire severity record began to impact fuel availability and severity, while others would not have missed any.

In Chapter 2, I found that it was possible to predict the annual number of high severity fire occurrences using logistic regression. High severity fire occurrence is driven by large-scale biophysical factors, but the inclusion of fire year climate was crucial for capturing years with a large number of high severity fire occurrences and fires with high fractional fire severity. The inclusion of inter-annually varying predictors was especially important for capturing high probability episodes in areas where severity is highly variable—California and the Southwest. While removal of fire year climate variables impacted successful prediction of high severity fire occurrence, removal of vegetation variables had minimal impact on model skill. My findings on the importance of fire year climate (top down control) are in contrast to smaller scale regional studies that found bottom-up factors largely determined high severity fire occurrence.

Success in developing a west-wide model for high severity fire occurrence was not matched in Chapter 3. Development of one model for predicting high severity area burned in forests was successful for all years except those with very large high severity area burned, 1988 and 2002. My ability to accurately predict high severity area burned in forests in extreme fire years required creating regional models that are more complex than the west-wide model. As with Chapter 2, fire year climate variables were more important than vegetation variables in predicting years with large area burned in high severity. The fire year climate variables important for predicting high severity area burned were regionally specific, but most are readily available. Climate change will likely result in climate conditions that will increase potential high severity area burned that was

historically infrequent. The availability of climate variables important to our models will facilitate forecasting of future risk of high severity forest fire.

Historical high severity burned area in the Northern Rocky Mountains was predominantly controlled by climate. When I simulated future potential for high severity fire in the Greater Yellowstone Ecosystem (GYE), I found a significant increase in the fraction of high severity burned area in the 21st century. The climate in the GYE will be significantly warmer and drier than the historical record, and these increases could result in a three-fold increase in fractional high severity area burned. The increases are largest in high elevation spruce fir forests; the combination of disturbance and climate change will likely result in changes in species composition in this ecosystem in the future.

The most important finding in my dissertation is the importance of within year climate for predicting high severity fire, especially in extreme fire years. I was able to successfully model both high severity fire occurrence and high severity burned area for all fires and forest fires, respectively, in the western US. The significant trend in the number of fires meeting our severity threshold indicates that there is an overall increase in the number of large severe fires since 1984. It is likely that warmer, drier future fires seasons will continue to see more large severe fires. Most of the variables that were important in the best fit models are readily available, meaning that we can use our models to forecast future fire severity and how high severity area burned might change in a changing climate. If a goal of management is to mitigate extreme fire events in terms of fire severity, then knowledge of fire year climate and its effect on fire severity is essential.