Very large wildfires in the western contiguous United States: probabilistic models for historical and future conditions

Erica Natasha Stavros

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2013

Reading Committee:

Ernesto Alvarado, Chair

Donald McKenzie

Narasimhan Larkin

Program Authorized to Offer Degree:

School of Environmental and Forest Sciences
University of Washington

Dedication

This dissertation and the work therein is dedicated to my Grandma Jean for showing me what it is to be a strong woman with drive and follow-through. She continues to inspire and amaze me as the lessons she taught me unveil their applicability in each stage of my life. Rest in Peace.

Acknowledgements

I would like to acknowledge the funding sources and external work that made this dissertation possible. The Pacific Northwest Research Station, U.S. Forest Service; the EPA-STAR program; and the Joint Fire Science Program, project # 11-1-7-4, have provided funding for Chapter 2. The US Forest Service, Pacific Northwest Research Station, and the Joint Fire Science Program, project 11-1-7-4, provided funding Chapters 3 and 4. I would like to thank Robert Norheim, with the University of Washington, for his hard work designing maps used in the analysis and providing and organizing some of the data. I would also like to acknowledge that **Figures 3.8.2**, **3.8.4**, **3.8.5**, **4.7.4** and **4.7.5** are courtesy of Dr. John Abatzoglou.

On a more personal note, I would like to acknowledge people that have made this dissertation process such a fulfilling opportunity. First, I would like to thank Don McKenzie for being truly the most supportive mentor. I have learned more than I could have ever imagined possible over the last four years, and it is thanks to the wonderful resources he has provided, and the attention, care, and time that he has invested in my success. Next, I would like to acknowledge John Abatzoglou, Sim Larkin, Dave Peterson, and Christian Torgersen for their continued encouragement and support throughout this process. The investment and energy given to me from each of these people has made my time here not only an academic success, but one of appreciation, gratitude, and fulfillment.

To the Fire and Mountain Ecology Lab, for their countless thought-provoking and engaging conversations that have developed my critical thinking skills and ignited a passion about ecology. I would like to especially thank Christina Restaino, Alina Cansler, Keala

Hagmann, Maureen Kennedy, and James Cronan for their conversations both inside and outside of the lab that inspired creative thinking and problem solving as well as advise and camaraderie. Without them, I could not have achieved all that I have.

To my friends, I thank them for their support and much needed distractions. To my parents, who have encouraged, supported, and fed my hunger for intellect that has grown into what it has become. Lastly, to my most loyal and faithful companion, Dakota, for being my rock.

Abstract

Very large wildfires in the western contiguous United States: probabilistic models for historical and future conditions

Erica Natasha Stavros, M.S.

Chair of Supervisory Committee:
Ernesto Alvarado
School of Environmental and Forest Sciences

Wildfires, especially the largest ones, can have lasting ecological and social effects both directly on the landscape and indirectly on the atmosphere and climate. Both climate and fire regimes are expected to change into the future while air quality, the composition of the atmosphere, continues to be regulated. It is necessary to understand how climate, wildfire, and air quality interact to mitigate air quality. Existing studies, however, span spatial and temporal scales necessary for only linking two components at a time (e.g. climate and wildfire or wildfire and air quality). Appropriate scales of data and modeling are required to integrate all three components and understand the system as a whole. To lay the foundation for studying interactions among these three components, I investigated the relationship between climate and very large wildfires, here defined as megafires (≥ 50,000 ac ~ 20,234 ha), at spatial and temporal scales appropriate for future work to bridge results into air quality modeling. In this dissertation, I demonstrated, using a systematic approach, that broad spatial and fine temporal resolutions are the best scales

by which to understand how climate, wildfire, and air quality interact. Thus, using broad wildfire data aggregated to the spatial scale of eight US National Interagency Fire Center Geographic Area Coordination Centers (GACCs) across the western contiguous US, and daily and monthly climate data, I developed logistic regression models to predict the probability that a megafire will occur in a given week. Significant climate predictors of megafires vary by GACC and are similar to those found by other studies for aggregate annual area burned. Thus megafires may influence the analysis of aggregate statistics substantially. For all eight GACCs, projecting these models showed a significant ($p \leq 0.05$) difference between the historical period from 1979 to 2010 and Intergovernmental Panel on Climate Change future scenarios, representative concentration pathways (RCPs) 4.5 and 8.5, during 2031 to 2060. Generally, with the exception of the Southwest and Northern California, megafires will be more likely both throughout the fire season and from year to year, with more pronounced patterns under RCP 8.5 than RCP 4.5. This work investigates the effects of a changing climate on megafires at scales that can aid policy and management to mitigate their effects. It also provides a foundation by which to improve understanding of the climate and carbon systems. Lastly, it illuminates the need to investigate how fire statistics are aggregated and how this affects climate associations.

Table of Contents

List of Acronyms

AUC	Area under the curve
BI	Burning Index
CFFDRS	Canadian Forest Fire Danger Rating System
CH_4	Methane
CO	Carbon monoxide
CO_2	Carbon dioxide
DMC	Duff Moisture Code
EGB	Easter Great basin
ERC	Energy Release Component
FFMC	Fine Fuel Moisture Code
FM100	100 hour fuel moisture
FM1000	1000 hour fuel moisture
FP	False positive
GACC	Geographic Area Coordination Center
GCM	Global climate model
GHG	Greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
MTBS	Monitoring Trends in Burn Severity
NAAQS	National Ambient Air Quality Standard
NCAL	Northern California
NFDRS	National Fire Danger Rating System
NO_x	Nitrogen oxides
NROCK	Northern Rocky Mountains
O_3	Ozone
PDSI	Palmer Drought Severity Index
$PM_{2.5}$	Particulate matter $\leq$ 2.5 micrometers
PNW	Pacific Northwest
PRISM	Parameter-elevation Regressions on Independent Slopes Model
PSA	Predictive Service Area
RCP	Representative Concentration Pathway
RM	Rocky Mountains
SCAL	Southern California
SW	Southwest
TEMP	Average monthly temperature
TP	True positive
USA	United States of America
VOC	Volatile organic compound
WGB	Western Great basin
WUI	Wildland urban interface

List of Figures

Figure 3.8.5. Weekly composite plots from six weeks prior to discovery of fire and six weeks following. Solid lines denote mean conditions where red is megafires, and blue is all other large fires (>405 ha), and gray is weeks in the fire season with no fire. The shaded regions represent a 95 percent confidence interval. The dashed line is the megafire week as defined by day of year, with week 1 = Jan 1-7. The x-axis shows weeks from discovery week. The lighter shaded regions denote the 95 percent confidence interval of the mean. The numbers at the top are the ratios of number of megafire weeks to number of large fire weeks to number of weeks with no fire.

Figure 3.8.6. Trade-offs between precision and recall of two characteristic GACCs: Eastern Great Basin and Northern California, for each of the three megafire-size thresholds. The x-axis is the probability threshold for classifying a megafire (i.e. a probability >0.2 is a megafire). Blue represents normalized precision (how well do the models predict megafires), and red represents recall (how often do the models miss megafires that actually happened). The numbers on the right of each graph denote the percentage of non-megafire weeks. For a complete list of precision and recall values, see **Appendix**.

Figure 3.8.7. Proportion of annual area burned across the contiguous United States by megafires (gray) and by all large fires including megafires (black), by the criteria defined on this study. This illustrates that in many years, the largest fires constitute a substantial proportion of the annual area burned.

Figure 3.8.8. Scatterplot of annual area burned and number of megafires for each GACC.

Figure 4.7.1. The study domain over the western contiguous United States, divided by Geographic Area Coordination Centers (GACCs), excluding subsections of GACCs with predominantly agricultural fires, represented here as white areas within the GACCs.

Figure 4.7.2. Proportional change of the probability that in a given week a megafire will occur from the observed mean probability. The plots show a five- year moving average. Dashed vertical lines denote the from modeled values from the observed period (1979-2010) to those from the future (2011- 2099). Each shaded line denotes one of 14 GCMs used, and the bold line denotes the ensemble mean of all 14 models.

Figure 4.7.3. The seasonality of P(megafire) from 1979-2099. The historical modeled ensemble is used for 1979 to 2010. The ensemble mean of the14 GCMs is used for scenarios RCP 4.5 and RCP 8.5 from 2011 to 2099.

Figure 4.7.4. Change in the means 2031-2060 minus 1971-2000 averaged over 14 GCMs for June-September under RCP 4.5. Gray regions signify area of high uncertainty across models, are areas with <10 of 14 model agreement. Indices represent the index value at daily (ERC, BI, FM1000, FM100, FFMC, and DMC) and monthly (PDSI and mean temperature) resolution. For ease, examining the spatial distribution of changes in FM100 and FM1000 used inverted categorized color spectrums. FM100 and FM1000 decrease with increased fire danger, in contrast to all other variables, which increase with increased fire danger. Therefore, the color spectrums used for spatial investigation of the changes in climate space represent the same for all indices such that red denotes increased fire danger.

Note: PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

Figure 4.7.5. Projected changes, under RCP 4.5, in the number of days or months that exceed the threshold defined by the upper/lower decile of days or months from 1979-2010 to 2031-2060 for each index. Changes are expressed as a percentage change from baseline conditions (e.g., +100 means a doubling). Regions where the signal is not robust, i.e. regions of high uncertainty across models, areas with <10 of 14 model agreement are gray. For ease, examining the spatial distribution of changes in FM100 and FM1000 used inverted categorized color spectrums. FM100 and FM1000 decrease with increased fire danger, in contrast to all other variables, which increase with increased fire danger. Therefore, the color spectrums used for spatial investigation of the changes in climate space represent the same for all indices such that red denotes increased fire danger.

Note: PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

List of Tables

proportional change in ensemble model average over the time period (where historical is 1979-2010 and future is 2031-2060) from the mean observed. AUC is the area under the receiver operating characteristic curve for the GLMs for each GACC.

Chapter 1

Introduction

Wildfires create major environmental changes, locally, regionally, and globally. Local effects include changes in vegetation structure and composition, ecological processes such as nutrient cycling and hydrology, and loss of air quality from smoke emissions, with potential adverse effects on public health. Broader-scale effects include reduced air quality downwind and changes to the global radiation budget from aerosols and to the carbon budget. Across all scales, the largest fires, here called "megafires", are responsible for a significant proportion of these changes.

Megafires can significantly degrade air quality in turn modifying some aspects of climate. For example, Jaffe et al. (2008) found that across the western US, summer wildfires account for a substantial fraction of the annual regulated amount of fine particulate matter (particles $\leq$ 2.5 micrometers, $PM_{2.5}$). $PM_{2.5}$ is responsible for human health problems, regional haze, and has a less certain effect on radiative forcing on climate (Bond et al. 2013). Estimates for summer enhancements of $PM_{2.5}$ approximately double during large wildfire years (Jaffe et al. 2008). Variation in Northern Hemisphere carbon monoxide (CO), a regulated pollutant under the US National Ambient Air Quality Standard (NAAQS), is associated with annual area burned (Kasischke et al. 2005), of which large wildfires constitute a substantial portion in Canada (Jiang and Zhuang 2011) and the United States (Calkin et al. 2005). These associations, along with projections of increased annual area burned under a changing climate (Flannigan et al. 2009, Littell et al. 2010), suggest that more very large wildfires will continue to affect the feedback loop among climate, wildfire, and air quality.

Here I first propose a systematic approach to studying feedbacks within and across these components by providing a conceptualization of processes in the climate-wildfire-air quality system across spatial and temporal scales (Chapter 2). This comprehensive systematic approach identifies key processes integrating climate, wildfire, and air quality to be at broad spatial scales (e.g., square kilometers) and fine temporal resolution (e.g., daily or weekly). This conceptual framework motivates this dissertation and is the basis of its scientific contributions as it provides a foundation from which to understand emergent behavior (McKenzie and Kennedy 2011, p. 29) of individual events (i.e., megafires) that affect the complex climate-wildfire-air quality system. By studying and modeling megafires and climate at characteristic scales of key processes linking climate, wildfire, and air quality (Chapter 3), future work can focus on how any changes within the system (e.g., climate (IPCC 2007) and fire regime (Chapter 4)) affect other components of the system (e.g., air quality).

1.1. Effects of wildfires

Wildfires, especially the largest ones, can have lasting ecological and social effects. Wildfires affect air quality, climate, and atmospheric and terrestrial processes such as hydrology and autotrophic productivity. Wildfire emissions and smoke affect air quality, which can have adverse effects on both ecosystems and human health. Smoke effects include decreased forest growth (Fenn et al. 2011), increased tree mortality (Fenn et al. 2011), increased susceptibility to disease (Wohlgemuth et al. 2006), loss of sensitive species (Reich and Amundson 1985, Peterson and Parker 1998, Wohlgemuth et al. 2006), and increased presence of invasive species (Fenn et al. 2011). Furthermore, wildfire smoke, even from distant sources, can affect human health, particularly by aggravating respiratory illness (Wotawa and Trainer 2000, Jaffe et al. 2004, Langmann et al. 2009). Effects on climate include those from aerosol and greenhouse gas emissions, such as water vapor, carbon dioxide, carbon monoxide, and methane. Other wildfire effects include altering hydrology such as increasing runoff thus leading to erosion (Colombaroli and Gavin 2010), affecting soil processes such as nutrient cycling (Kilgore 1973), facilitating vegetation succession (Sprugel 1991, Littell et al. 2010), affecting ecosystem resilience depending on the severity of the fire (Peterson 2002), and increasing the rate at which carbon is sequestered through growth (McDowell et al. 2003).

Because wildfire affects climate and air quality, the three components, climate, wildfire, and air quality, play into many feedback loops creating a complex system spanning many spatial and temporal scales. The main feedback loop linking these three components is as follows. Climate can affect fire regimes by increasing the likelihood of conditions conducive for combustion (Price and Rind 1994) and by affecting regeneration after disturbance (Peterson 2002, Bond and Keeley 2005, Littell et al. 2010). Climate affects fuel conditions and combustion as well as fire regimes, which affect the amount of available fuels. Thus, climate affects the amount and types of emissions produced during wildfire (McKenzie et al. 2012), which then further affect the climate by altering surface albedo, cloud formation, and radiative forcing (Bond et al. 2013). This broad-scale feedback loop is integral to understanding the climate and carbon systems, two systems that have been of growing concern over the last several decades because of recent and continued projected changes in climate (IPCC 2007). Nevertheless, this feedback loop among climate, wildfire, and air quality has not yet been well studied as a whole.

1.2. A Systematic approach

Rather than studying three-way interactions among climate, wildfire, and air quality, existing research has focused on two components at a time: climate and wildfire (e.g., Littell et al. 2010, Abatzoglou and Kolden 2013), wildfire and air quality (e.g., Randerson et al. 2006, Strand et al. 2011), and climate and air quality (e.g., Pfister et al. 2008, Larkin et al. 2009, Wegesser et al. 2009). Studying this system as a whole, however, has practical implications for mitigating some of the effects of wildfire such as air quality degradation from wildfire and meeting regulations under a changing climate. Air quality standards are intended to regulate the chemical composition of the air to protect human and ecosystem health. There are both direct and indirect managerial strategies to meet these standards, even during natural disasters like wildfires. Direct strategies include mechanical or chemical fuel treatments to reduce fuel loads, prescribed burning to create fuel breaks and to control the timing of the burn to mitigate smoke effects, and suppression. Although the largest wildfires escape suppression efforts, during times of high fire danger, smaller fires can be suppressed to avoid growth. An indirect managerial strategy is to restrict allowable anthropogenic pollution, so that when natural disasters do occur, there is more leeway before exceeding the permitted air quality standard. Applying a systems approach to untangle complex interactions among climate, wildfire, and air quality requires identifying key processes and their spatial and temporal scales.

Scientific implications for studying three-way interactions among climate, wildfire, and air quality include improving understanding of the climate and carbon systems. Although this analysis does not specifically aim to improve understanding of these systems, it does however fill a specific niche in science by analyzing the relationship between climate and wildfire such that results can be used to analyze the system. By better understanding climatic drivers of wildfires at spatial and temporal scales appropriate for further analysis with air quality modeling, we can improve predictive climate models by integrating the feedback loop between climate, wildfire, and air quality.

1.3. Defining megafire

In this dissertation, very large wildfires will be denoted as *megafires*. Generally megafire is a socio-political term applied to wildfires with a lot of attention because of significant economic, social, or ecological damages. There is, however, no database documenting the economic, social, and ecological cost of damages for most fires across a region over several decades (to relate to climate). Instead, a quantitative definition of megafire based on size is used. Large fires are defined as those fires that reach or exceed a threshold of 1000 acres (~ 404 hectares), and megafires as those fires that reach or exceed a threshold of 50,000 acres (~ 20,234 hectares). These definitions are chosen because they resonate with the land management community that commonly uses acres as a unit of measure. This threshold for megafire also corresponds to the top two percent of all large wildfires in the western contiguous United States, and accounts for approximately 33 percent of all annual area burned by large wildfires in this region from 1984 to 2010. In this way my definition for megafires matches other work such as Alvarado et al. (1998) that suggest examining the upper percentiles of large fires when studying extreme fires. Although these thresholds for megafire and large fires have been developed in acres to meet the needs of land management, the rest of this work will be done in standard units.

1.4. Data

In developing a probabilistic occurrence model for megafires a variety of disparate data is used and interrelated. Specifically, datasets of collected historical fires are used, along with datasets that describe historical and future climate in a series of calculated biophysical metrics.

Fire data gathered across the US from remote sensing imagery classified by the US Forest Service is used to develop the database Monitoring Trends in Burn Severity (MTBS, http://www.mtbs.gov, data acquired 1 Oct 2012). MTBS documents the date of discovery, as well as the fire perimeter of area burned divided into classifications of burn severity of wildfires from 1984 to present. All wildfires that exceed 404 hectares in the western contiguous United States are included.

Historical climate data is needed to examine relationships between weather, climate, and moisture and megafire occurrence over the observed record (1984-2010). Two datasets are used: (1) data from Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al. 2008) to calculate monthly Palmer Drought Severity Index (PDSI) and mean temperature; (2) downscaled meteorology from Abatzoglou (2013) to calculate daily US National Fire Danger Rating System (NFDRS) and Canadian Forest Fire Danger Rating System (CFFDRS) metrics.

Future climate data is used to project probabilities for two different future climate scenarios from the Intergovernmental Panel on Climate Change (IPCC) - representative concentration pathways (RCPs) 4.5 and 8.5. RCPs represent radiative forcing in 2100 as defined by the number, e.g. RCP 4.5 denotes the target radiative forcing of 4.5 watts per meter squared (van Vuuren et al. 2011). Output from 14 global climate models (GCMs) is used for each RCP. The use of multiple RCPs and GCM simulations helps account for uncertainty, and allows for results to be analyzed by individual models, across all models for a given RCP, and across RCPs. More detail on these models and scenarios is provided in Chapter 4.

1.5. Analyses

A binomial logistic regression model is used to relate climate at or near the time of ignition to the probability that a fire will grow to be a megafire. These models are created at the regional scale of the Geographic Area Coordination Center (GACC) run by the U.S. National Interagency Fire Center the models varied by GACC. Model selection involved minimizing

Akaike Information Criterion (AIC) by way of backward elimination. AIC was used to avoid incorrect estimations of p-values when the data is highly imbalanced. Models are then assessed using area under the [receiver operating characteristic] curve (AUC) and statistics for exactness (i.e., precision) and completeness (i.e., recall). The sensitivity of the definition of megafire by using alternative size thresholds is also investigated. These models are then used to examine the potential future occurrence of megafires under different climate change scenarios. Temporal changes over the 21st century and the seasonality of increased likelihood of megafire as well as spatial changes in the future climate space are examined.

One difficulty of studying rare events, like megafires, is that they occur infrequently and there is often not a large enough sample size for most statistics to be robust. This results in imbalanced data, which is an imbalance in the class distributions (He and Garcia 2009). Imbalanced data require special consideration when selecting a modeling approach because traditional statistics and algorithms assume balanced class distributions; rare or extreme events are often considered outliers that can be omitted because they skew results (He and Garcia 2009). Similarly, more frequent events can skew results when focusing analysis on extreme events. For example, when there is many more of one class than another, then the model may assume a probability that favors the majority class despite the effect of external conditions. To further complicate analyses, imbalanced data of rare events not only biases traditional statistical approaches, but also are of limited sample size thus weakening the robustness of conclusions. Generalized linear models (GLMs) and accuracy statistics have, however, been adapted to handle a larger proportion of zeros than expected (Barry and Welsh 2002), and are thus used in this analysis.

Another difficulty is that MTBS can be transcribed into presence-only binary data. Presence-only data are occurrence distributions that show only where fire occurs and not absences. Presence-only datasets suffer drawbacks limiting their use and validity in statistical modeling (Zaniewski et al. 2002). For example, with presence-only data there is often a sampling bias toward common versus rare occurrences. However, presence-only data is often all that is available because it is easier to show where an occurrence happened, rather than where an occurrence will not. This further reinforces the use of binomial logistic regression (a type of GLM) to quantify the probability of occurrence because it uses binary data and has been adapted to incorporate presence-only data (Zaniewski et al. 2002).

Other approaches to handling rare and class imbalanced data were also considered. Some of these approaches include extreme value theory (Grissino-Mayer 1999, Draghicescu and Ignaccolo 2009), sampling methods, cost-sensitive methods, kernel-based methods, and assessment statistics like F-measure or G-mean (He and Garcia 2009). Nevertheless, logistic regression was selected for this analysis because (1) simpler models have broader applicability (Elith et al. 2002) and are especially useful for meeting prediction objectives and (2) simpler models are easier to communicate for developing inferences.

Although logistic regression is the most appropriate analysis for this research, it has some limitations. For example, usual test statistics, like accuracy and error rate, are heavily influenced by class distributions in the data. However, some test statistics such as precision and recall can be used to evaluate exactness and completeness (respectively). The formula for precision leaves it sensitive to class distributions, although this is not true for its inverse, recall (He and Garcia 2009). Alternatively, one can use AUC to represent the relative costs and benefits of classifying data. Ideally, this work will inspire future research to conduct multiple analyses to compare and contrast, or verify, the results found here.

1.6. Dissertation structure

I propose a systematic approach to studying feedbacks within and across climate, wildfire, and air quality by providing a conceptualization of processes in the climate-wildfire-air quality system across spatial and temporal scales (Chapter 2). This comprehensive systematic approach identifies the spatial and temporal scales of key processes integrating climate, wildfire, and air quality. I identify that data at broad spatial scales (e.g., square kilometers) and fine temporal resolution (e.g., daily or weekly) are necessary for linking climate, wildfire, and air quality. This conceptual framework of the climate-wildfire-air quality system is the motivation and foundation of the scientific contributions of this dissertation.

Using identified scales for linking climate, wildfire, and air quality (Chapter 2), a model of megafire occurrence based on the historical record of megafires and historical climate conditions (Chapter 3) is developed, which is then used to project future megafire occurrence using future climate simulations (Chapter 4). The focus is on developing a model that can function at the highly resolved temporal scales required for understanding air quality, and that functions at a regional spatial scale (Chapter 3). Specifically the following questions are asked:

1. What is the spatial and temporal distribution of megafires from 1984 to 2010 across the western contiguous US?
2. Do antecedent and concurrent fuel conditions and climate for the occurrence of megafire differ from those for the occurrence other large wildfires?
3. How does this spatial and temporal variation affect the probability that a megafire will occur?

Using the derived historical relationships of megafire with climate conditions, the likelihood of how megafire will change over the 21st century and within the annual year is analyzed. Also changes in how the climate space affects certainty in these estimates are examined (Chapter 4). Specifically the following questions are addressed:

1. Will megafires be more likely in the future?
2. Will seasons of increased likelihood of megafire change in the future?
3. How do key climate predictors of megafire change across space going into the future?

This work not only investigates new scientific ground relating climate to specific megafires, but has practical importance for policy and management as projections can be used to proactively mitigate the effects of megafires. Although other studies have related and projected into the future annual area burned and fire danger indices thus demonstrating average behavior of ecological mechanisms, none have projected the likelihood of megafires as individual events. Examining the relationship of climate and individual megafires at characteristic spatial and temporal scales allows for analysis of emergent behavior of megafires within a more complicated system such as the climate-wildfire-air quality system. Simulating emergent behavior of megafires provides a foundation for creative and adaptive policy development and management strategies (McKenzie and Littell 2011) that inform the mitigation of their effects such as smoke.

Chapter 2

The climate-wildfire-air quality system: interactions and feedbacks across spatial and temporal scales

This work is adapted from work originally submitted as: Stavros EN, McKenzie D, Larkin NK (2013) The Climate-wildfire-air quality system: interactions and feedbacks across spatial and temporal scales. *Frontiers in Ecology and the Environment.*

2.1. Summary

Future climate change and its effects on social and ecological systems present challenges for preserving valued ecosystem services, including local and regional air quality. Wildfire is a major source of air-quality impacts in some locations, and a substantial contributor to pollutants of concern, including nitrogen oxides and particulate matter, which are regulated to protect public and environmental health. Since climate change is expected to increase total area burned by wildfire and wildfires affect air quality, which is regulated, there is a need to define and study climate, wildfire, and air quality as one system. This review defines ecological processes acting across space and time within the climate-wildfire-air quality system and provides a foundation for future research to identify the spatial and temporal domain for assessing impacts of climate on air-quality degradation from wildfire.

2.2. Introduction

Many studies have shown warming temperatures and longer periods of drought will increase area burned by wildfire in North America (Flannigan et al. 2009, Littell et al. 2010). Increased area burned will likely mean more fuel consumed and emissions produced. The latter contribute a positive feedback to greenhouse warming from greenhouse gases (GHGs) and both positive and negative feedbacks from aerosols (IPCC 2007). From here forward, the term *feedback* is used when component A affects B, and B feeds back to A, whereas feedback loop refers to the bidirectional effect of A and B on one another.

Studying these types of feedbacks within the environment requires merging multiple scientific disciplines at multiple scales across space and time. Studies have focused on separate components of this system independently, but few have integrated the components (McKenzie et al. 2006, Chen et al. 2009). Existing research focuses mainly at characteristic spatial and temporal scales of understanding, e.g., how climate affects wildfire (Littell et al. 2009), how wildfire affects air quality (Pfister et al. 2008, Larkin et al. 2009, Wegesser et al. 2009), or how wildfire affects climate (Randerson et al. 2006), but does not incorporate cross-scale analysis necessary for quantifying feedbacks and interactions among system components (**Figure 2.7.1).**

Here I compile and synthesize the latest research on climate, wildfire, and air quality to define interactions and feedbacks and propose a cross-scale approach to studying the system as a whole. I seek to identify the appropriate spatial and temporal domains for modeling the effects of climate on air-quality degradation from wildfire. Interactions and feedbacks within and across system components are placed in an ecological context using examples from North America. Conceptual understanding of the system, however, applies broadly in other regions. Lastly, I discuss broader ecological, social, and scientific implications for studying the system as a whole.

2.3. Defining the system: Terminology

For discussion here, it is useful to define the terms needed to understand the climate-wildfire-air quality system (**Figure 2.7.1**).

Climate describes daily, annual (e.g., seasons), and decadal (e.g., El Niño-Southern Oscillation or Pacific Decadal Oscillation) variation in *weather*, such as wind, rain, temperature, and relative humidity. A change in climate is defined as a long-term change in one or more of these variables. The term "climate change" commonly applies to increasing global temperatures and changes in precipitation gradients (IPCC 2007).

Wildfire is a cross-scale phenomenon (Figure 2.7.1; Moritz et al. 2005, Falk et al. 2007). At the finest temporal (seconds to hours) and spatial (10^{-3}-10^{3} square meters) scales, consider fire as the *flame*. To sustain combustion, a flame requires oxygen, fuel, and heat (Agee 1993). *Individual fire events* reside at intermediate temporal (days to months) and spatial (10^{4}-10^{8} square meters) scales, with fire behavior typically characterized in a triangle with legs for fuels, weather, and topography (Agee 1993). Each leg, and its interaction with the others, influences fire behavior. At broader spatial ($\geq 10^{9}$ square meters) and temporal (years to centuries) scales, wildfire can be characterized by the *fire regime*, which consists of many individual fire events over time and is commonly define by multiple attributes: fire frequency, seasonality, fireline intensity (the energy released), fire severity (effect of fire on biological and physical components of the system), fire type (e.g., crown fire, surface fire, ground fire), areal extent of fire perimeter, and spatial complexity (spatial variability of fire severity). These properties depend on interactions between climate, vegetation, and ignition source (Agee 1993).

At the broad scales associated with fire regimes -- landscape (~10^{6} m^{2}) to sub-continental -- vegetation is aggregated to classes (Agee 1993). Ignition sources are either anthropogenic or natural (i.e., spontaneous combustion or lightning). Anthropogenic ignitions are either by accident, arson, or a result of management. For example, in western North America, Native Americans burned the land for thousands of years to sustain food sources (Wright and Bailey 1982, Bowman et al. 2009), thereby altering fire regimes. Currently, managers use prescribed fire to reduce fuel loads, maintain ecological function, and control amount and seasonality of emissions.

Air quality is a measure or standard of the maximum acceptable pollutant concentrations in air. The air is composed of a "cocktail" of compounds (e.g., oxygen and carbon dioxide); pollutants are too much of any one compound that has detrimental effects to both human and ecosystem health. The United States government has established national standards to regulate hazardous gases, some of which are GHGs, and others are aerosols. *GHGs* act as a blanket around the Earth absorbing long-wave radiation and increasing global temperatures. *Aerosols* are solid or liquid microscopic particles dispersed in a gas (Malm 1999), in this case air. An aerosol of particular concern for health is fine particulate matter (PM) (Section 2.5.).

In the following discussion, *feedback loop* refers to the cyclic or bi-directional effect between two (sub)components within the system. Subcomponents are the terms in Figure 2.7.1 that are colored by each component: wildfire, climate, and air quality.

2.4. Interactions and feedbacks

The feedback loop that defines the climate-wildfire-air quality system proceeds as follows: climate change caused by global warming from increased GHGs in the atmosphere increases annual wildfire area, inducing changes in the disturbance regime through vegetation shifts (Peterson 2002, Littell et al. 2010, Kitzberger et al. 2012) and increasing emissions of GHGs and aerosols. Both of these effects feed back to climate, altering temperature and precipitation gradients and indirectly increasing the number of fire ignitions (Price and Rind 1994).

Figure 2.7.2 illustrates the over-arching feedback loop in the climate-wildfire-air quality system. Using Randerson et al. (2006) estimates of radiative forcing, I convert estimates into a percentage of the total net radiative forcing on climate from a boreal forest wildfire in the interior of Alaska. Randerson et al. (2006) focused on one specific fire interval, however, thereby quantifying only the effect on radiative forcing and not the complete feedback loop (represented by the dashed arrow), i.e., fire-caused forcing of climate in turn changes the fire regime. A more comprehensive analysis of the system involves this complete loop, along with resolving scale issues (e.g., radiative forcing is global, but local climate is what affects fire).

2.4.1. Wildfire component

Feedback loops occur at fine and intermediate scales between individual fire events and fuels, and at broad scales between fire regimes and vegetation. Although many tree species' ecological niches are defined by climate (Peterson and Peterson 2001, McKenzie et al. 2003), disturbance regimes can affect the type of vegetation that regenerates (Littell et al. 2010, Kitzberger et al. 2012). Fire is an important disturbance regime to many communities, supporting ecosystem processes (Stephens and Ruth 2005, Noss et al. 2006, Keane et al. 2008). For example, fire affects gap dynamics for regeneration, which affect stand structure, composition, and age (Stephens 1998, Kolb et al. 2007). Some vegetation that depends on fire for recruitment is flammable (e.g., some chaparral species) and thus perpetuates fire-dependent communities (Bond and Keeley 2005). Similarly, wildfire can affect soil through physical, chemical, and biotic processes and can alter erosion (Agee 1993, Kasischke et al. 1995), thereby affecting how vegetation grows and the available fuels.

The effect of vegetation on the type of fuels present (i.e. fuel type) acts across scales within the wildfire component of the climate-wildfire-air quality system. Fuel characteristics depend not only on the type of vegetation present (i.e. vegetation type), but also on the biophysical environment and the spatial patterns of biomass (Langmann et al. 2009). Vegetation type does affect the type and quantity of live and dead fuels available. Furthermore, different vegetation types have different chemical compositions, thus affecting the (McKenzie et al. 2007, 2012) smoke chemistry and aerosol emissions from fires (Yamasoe et al. 2000). Hierarchical spatial variation exists across scales such that although vegetation types can be clumped at broad scales (>10^9 m^2) (Neilson 1995), there is heterogeneous fuel composition at intermediate scales (10^6-10^9 m^2). Similarly, clustered fuel types at intermediate scales have heterogeneous spatial variation in fuel composition and structure at finer scales (10^1-10^6 m^2) (McKenzie et al. 2007, Keane et al. 2012).

2.4.2. Climate component

There are two processes acting across temporal and spatial scales within the climate component. First is the effect of climate on weather. There are many feedbacks within the climate system that affect how the climate changes and consequently affect weather. For example, as the climate warms the overall locations of the jet stream change, causing different air masses to be transported into and out of a given region, thus affecting storm tracks and local weather variables like wind, temperature, and precipitation patterns (IPCC 2007).

Second is the feedback loop between weather and heat from combustion. Weather typically provides the initial heat required for combustion at finer spatial and temporal scales, and heat from the flame affects local weather at intermediate scales. At the mesoscale (~10^9 m^2) a heat release from wildfire of 10 Wm^{-2} has no detectable affect on local weather, but a heat release of 100 Wm^{-2} has a statistically noticeable influence on weather (Miranda 2004). Further complicating the system, the amount of heat produced from the fire is not uniform (which affects the plume rise, vertical mixing, and emissions dispersal) and is largely dependent on the type and structure of fuel loadings (Larkin et al. 2009).

2.4.3. Interactions between climate, wildfires, and air quality components

Interactions between climate, wildfire, and air quality motivate studying the three components as one system. These interactions are shown in **Figure 2.7.1** as arrows between components (between colored text). There exists one internal feedback loop between heat, oxygen, and fuel. Otherwise interactions are discussed in this section under three sub-categories: wildfire and air quality, climate and air quality, and wildfire and climate. Wildfire and air quality includes the effect of fuels on air quality and the feedback loop between vegetation and air quality. Climate and air quality includes the feedback loop between weather and air quality and the feedback loop between air quality and climate. The last category, wildfire and climate, include the effect of climate on fire regime, the feedback loop between weather and individual fire events, and the feedback loop between vegetation and weather, the effect of topography on climate and weather.

Internal feedback loops between oxygen, heat, and fuel link all three components of the climate-wildfire-air quality system. The internal feedback loops are defined by the process of combustion, which has four phases: (a) preheating, (b) distillation and combustion of volatiles, (c) distillation and combustion of residual charcoal, and (d) cooling (Agee 1993). During the preheating phase, fuels trap heat. As the fuels heat-up and moisture evaporates, the ignition process moves to phase (b). Fed by the fuel, the flame grows and produces more heat, thus drying any surrounding fuel in the preheating phase (a) and increasing flammability resulting in combustion (b). Provided there is enough oxygen, fuel, and heat to sustain a flame, the process of combustion will continue.

2.4.3.1. Wildfire and air quality

The effect of fuels on air quality depends on the moisture content, composition, and structure of fuels, which determine the type of emissions (Langmann et al. 2009). The moisture content of the fuels not only affects flammability, but also the amount of water vapor produced during combustion. Also, the amount of methane emitted can affect the amount of water vapor from wildfire as oxidized methane can produce water vapor. Water (H_2O) is a greenhouse gas with substantial affects on radiative forcing (IPCC 2007, Swann et al. 2010). The composition of the emissions cocktail produced (**Table 2.8.1**) depends on the type, structure, and chemical composition of fuels burned as well as the completeness and efficiency of the combustion process (Ward and Hardy 1991, Langmann et al. 2009, Larkin et al. 2009, Bond et al. 2013). For example, incomplete combustion of fuels, which is normally the case in wildfires, leaves behind carbonaceous materials (Agee 1993, Bond et al. 2013) either as charcoal on the ground, coarse particulate matter, or as aerosols.

The feedback loop between vegetation and air quality proceeds as follows: poor air quality can alter productivity of some plant species, while plant productivity can affect the quality of the air. For example, tropospheric ozone (O_3), a secondary pollutant formed in ultraviolet light through reactions between nitrogen oxides (NO_x) and volatile organic compounds (VOCs), which are emissions from wildfire and fossil fuels (Hu et al. 2008), can decrease productivity of some plant species, especially under high concentrations (Reich and Amundson 1985). To complete the feedback, VOCs are also produced by vegetation (Guenther et al. 2000), while carbon dioxide (CO_2) is a key input for photosynthesis.

2.4.3.2. Climate and Air Quality

There is a feedback loop from air quality to weather. Ambient weather, fire-released energy, and moisture (atmospheric or from drying of fuels during a fire) affect the injection height of emissions into the atmosphere and consequently emissions transport and diffusion (Miranda 2004, Wohlgemuth et al. 2006, Larkin et al. 2009). Depending on the injection height (Langmann et al. 2009) and the weather, emissions can have a shorter or longer life. Dry weather is conducive to longer life and farther transport of emissions, while wet deposition removes the aerosols and improves air quality. Aerosols emitted from wildfire can alter cloud formation both by acting as cloud condensation nuclei (increasing) or absorbing light (decreasing), thus affecting precipitation (Liu 2005, Langmann et al. 2009), while the amount of water vapor (which depends in part on temperature) affects the amount of moisture available for precipitation (IPCC 2007). Furthermore, the amount of available light, which is affected by cloud cover, affects the photochemical reaction between CO, methane (CH_4), and VOCs and NO_x, which form ozone, a monitored and regulated gas (Section 2.5.).

Degraded air quality from wildfires is thought to be a substantial positive feedback loop to the climate system (Bowman et al. 2009, Bond et al. 2013). As mentioned, the emissions such as CO_2 and CH_4 both from anthropogenic sources and wildfires, are GHGs. Aerosol emissions from wildfire have a less certain effect on the climate system as per the extent to which they absorb and scatter radiation because not only do aerosol species' properties differ, but also the effect of the source on those species can produce net cooling or net warming (IPCC 2007, Bowman et al. 2009, Bond et al. 2013). In turn, climate can affect the spatial and temporal distribution of GHGs and aerosols such that it affects air quality (Bowman et al. 2009). For example, during times of high fire activity in Canada, transported emissions from wildfire increase background pollutant levels, tropospheric O_3 in particular, in the United States (Wotawa and Trainer 2000). The transport and later deposition of aerosols can also alter sea ice and snow surface albedo, which affect radiative forcing and its consequent effect on climate (**Figure 2.7.2**) (Randerson et al. 2006).

2.4.3.3. Wildfire and Climate

Climate affects the fire regime both directly and indirectly. Directly, climate influences fire regime by affecting flammability (Kitzberger et al. 2012), fuel availability, fire season-length, and ignitions. These direct effects are projected to increase annual area burned (Flannigan et al. 2009, Littell et al. 2010) and number of lightning ignited fires (Price and Rind 1994) in a warming climate. Over time, climate affects fire regimes indirectly through its control of vegetation. For example, in the dry southwestern US, the strongest predictors of area burned are variables associated with the previous year's climate, which controls fuel availability and connectivity across landscapes (Littell et al. 2009). Over longer temporal scale, through the Holocene in Alaska, vegetation type mediated climatic controls on fire regimes (Higuera et al. 2009).

A feedback loop exists between weather and fire at both fine and intermediate scales. In the short term, weather controls wildfire behavior by affecting fine-fuel moisture, fireline intensity, and rate of spread. Fire behavior then affects weather because fire, air temperature, wind, and relative humidity (amount of water vapor in the air) change based on the airshed characteristics and the amount of heat released from the fire (Rothermel 1983, Miranda 2004, Potter 2012). For example, if a fire occurs in a basin and the hot air rises during the fire, the relative humidity gradient in an air column changes because hot air can hold more moisture than cooler air. With warm air rising, vertical mixing and convective winds can change, with further consequences for fire behavior (Heilman and Bian 2010).

The feedback loop between vegetation and weather proceeds as follows: vegetative surface cover influences local wind circulations and the amount of water transpired and evaporated in a region (Pielke et al. 1999, Swann et al. 2010). In turn, the local weather affects the composition, productivity, and mortality of vegetation that grows in the area.

Fire-climate dynamics are mediated globally by topography, which influences climate at broad spatial scales and weather at intermediate spatial scales. For example, topographic (orographic) controls on broad-scale atmospheric circulation over land produce continental climate, thus leading to very different fire regimes than those in maritime climates. At intermediate scales, topography affects the weather by altering the length of time different aspects are shaded, consequently affecting fuel moisture, heat, and convective winds (Rothermel 1983), which are created by air flowing between high and low temperatures. Furthermore, local topography can affect the amount of rainfall received and changes in temperature affect relative humidity, the amount of moisture the air can hold.

2.5. Ecological, social, and scientific implications

In an ecological context, fire as a disturbance alters the succession of vegetation (Sprugel 1991, Littell et al. 2010), affects autotrophic productivity (Fenn et al. 2011), and ecosystem resilience (Peterson 2002). Fire can catalyze vegetational succession in communities adapting to a changing climate (Barrett et al. 2011). Alternatively, management can use fire in conservation and restoration efforts (Reinhardt et al. 2008). For example, fire affects gap dynamics for regeneration, which affect stand structure, composition, and age (Stephens 1998, Kolb et al. 2007), and can alter the disturbance regime. This produces a feedback between landscape pattern and processes like fire, depending on the strength of ecological memory (Peterson 2002, McKenzie et al. 2011). Post-fire regeneration provides ecosystem services such as carbon sequestration by increasing growth (McDowell et al. 2003) and nutrient cycling (Kilgore 1973, Ghimire et al. 2012), and affects timber resources, biodiversity, and soil fertility (Fenn et al. 2011).

Wildfire effects on air quality can counteract the ecological benefits of fire, and emissions from wildfire that affect air quality depend on type of vegetation system burned. For example, Fenn et al. (2011) describe the adverse effects of pollutants on ecosystems, such as decreased forest growth, increased tree mortality, increased susceptibility to disease (Wohlgemuth et al. 2006), loss of sensitive species (Reich and Amundson 1985, Wohlgemuth et al. 2006), and increased presence of invasive species. The dominant source of the pollutants discussed by Fenn et al. (2011) is anthropogenic, but wildfires can account for some of these pollutants (e.g. NO_x and tropospheric O_3). In a global study, van der Werf et al. (2006) show that inter-annual variability in emissions follows that of area burned in forests, thus demonstrating how the type of vegetation system can affect air quality.

The climate-wildfire-air quality system has social significance as wildfires can affect humans directly through emissions harmful to health. Emissions from wildfire in the form of CO, and particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) as well as secondary pollutants like tropospheric O_3 can have particularly grave consequences for human health. Ward and Hardy (2001) found that the sum of CO_2 and CO accounts for 90 to 95 percent of carbon released during the combustion phase of burning. CO can alter pollutant levels, particularly of tropospheric O_3, across large distances (Wotawa and Trainer 2000, Jaffe et al. 2004, Langmann et al. 2009). Not only can CO affect tropospheric O_3 concentrations, but wildfires can directly affect both nearby and distant-downwind surface tropospheric O_3 levels, sometimes exceeding current health standards (Pfister et al. 2008). Surface tropospheric O_3 concentrations can irritate the respiratory system, reducing lung function, aggravating asthma, and increasing susceptibility to lung infection and inflammation of lung tissues. Besides tropospheric O_3, wildfires emit PM. The amount of $PM_{2.5}$ emitted is particularly important because when such small particles are inhaled, they can penetrate deep down into the human lung causing similar symptoms as tropospheric O_3 (Ward and Hardy 1991). Furthermore, PM emitted from wildfire is more toxic than equal levels of PM concentration from ambient air without wildfire (Wegesser et al. 2009).

Smoke from wildfires has social consequences including reduced visibility on roads and at scenic vistas (**Figure 2.7.3**, IPCC 2007). Besides their effects on radiative forcing, aerosols emitted from wildfires, affect visibility (**Figure 2.7.3)**, thus contributing to nuisance smoke and regional haze. Aerosols can come from many sources, but wildfires contribute substantially to annual aerosol emissions, particularly on the worst days. For example, in the western United States, wildfire emissions during summer constitute a significant fraction of the regulated annual NAAQS for $PM_{2.5}$, which reduces visibility (Jaffe et al. 2008). At shorter time scales, following or during a burning a fire, there is nuisance smoke. Nuisance smoke is considered smoke that interferes with the rights or privileges of members of the public (Hardy et al. 2001), such as smoke that reduces visibility on roadways or clouds visibility for air traffic. At longer time scales, aerosols like $PM_{2.5}$ can reduce visibility by producing haze. Haze is the accumulation of microscopic aerosols, at sufficient concentrations to restrict visibility (Hardy et al. 2001). Haze obscures the view at scenic vistas in parks or when looking at a city from a distance.

As area burned increases (Flannigan et al. 2009, Littell et al. 2010), air quality may become less manageable (McKenzie et al. 2013), especially during extreme weather. As larger fires become harder to anticipate and manage, so will smoke effects, such as respiratory illness and heart attacks, nuisance smoke on roadways (Hardy et al. 2001), and reduced visibility over broad areas, including those noted for pristine air quality. Studying climate, wildfire, and air quality systematically across scales will help quantify the cumulative impact of climate change on the diverse physical, ecological, and social processes I have referred to here.

A systems approach can also evaluate the success of meeting air-quality standards. Two national air quality standards in effect for the United States are (1) the National Ambient Air Quality Standard (NAAQS), which regulates pollutants considered harmful to human health and the environment, and (2) the Regional Haze Rule, which requires national parks and other wilderness areas to reduce visibility impairment. Visibility provides ecosystem services such as aesthetic appeal, which determines the value that many observers place on wilderness areas (Malm 1999) and consequently the funding and political support required to maintain them (Hyslop 2009). Direct management strategies to maintain air quality include prescribing fires during seasons and conditions that reduce smoke effects, mechanical pre-thinning of fuels to reduce emissions, and fire suppression when expected emissions endanger health. Indirect management strategies include restricting emissions from anthropogenic pollution sources, such that more emissions from wildfire must occur before exceeding air quality standards.

In a broader scientific context, studying climate, wildfire, and air quality as one system can improve understanding of the carbon cycle and the climate system as a whole. The climate-wildfire-air quality dynamic influences the carbon cycle by (1) releasing carbon to the atmosphere; (2) changing successional patterns that influence biomass carbon storage (Lorenz and Lal 2010); (3) providing improved soil nutrients and gaps for regeneration (kashian et al. 2006); and (4) affecting fire frequency, which determines the amount of total carbon sequestered

(Kasischke et al. 1995, Raymond and McKenzie 2012). Furthermore, because some wildfire emissions have substantial feedbacks to the climate system (Bowman et al. 2009), future studies can integrate modeling frameworks not only by quantifying the impact of climate on air quality from wildfires, but also by including feedbacks to the climate system explicitly, thereby improving the predictive capabilities of climate models.

2.6. Conclusion

This overview of recent literature and synthesis of system dynamics provides a foundation by which to identify appropriate spatial and temporal scales to link climate, wildfire, and air quality, a subject that has only just begun to be assessed. I propose selecting appropriate scales to address specific research objectives, but in general climate and wildfire affect air quality at broad spatial scales as fire regime, climate, and smoke can span across long distance (e.g., regional) and at fine temporal resolution as pollutants and fire can change in short time spans (e.g., hours). Future research of climate and wildfire interactions at these scales will be useful for studying the climate-wildfire-air quality system (McKenzie et al 2006). Research is needed to quantify interactions among these components to evaluate impacts such that managers and decision-makers have more information to address existing regulations or shape new policy. Lastly, by studying the climate-wildfire-air quality system as a whole, scientists can better understand carbon budgets and their potential effect on the climate system.

Moving forward, research should focus on integrating existing models or developing new ones to fill the unique spatial and temporal scales appropriate for linking climate, wildfire, and air quality. In the following two chapters, I develop, assess, and apply wildfire-climate models at broad spatial scales with fine temporal resolution. This work is intended to create a foundation from which to build modeling frameworks that can link climate, wildfire, and air quality. By identifying the scales necessary for capturing specific interactions, models and data sets can be merged to bridge knowledge gaps between disciplines such as climatology, meteorology, fire ecology and behavior, and atmospheric physics and chemistry.

2.7. Figures

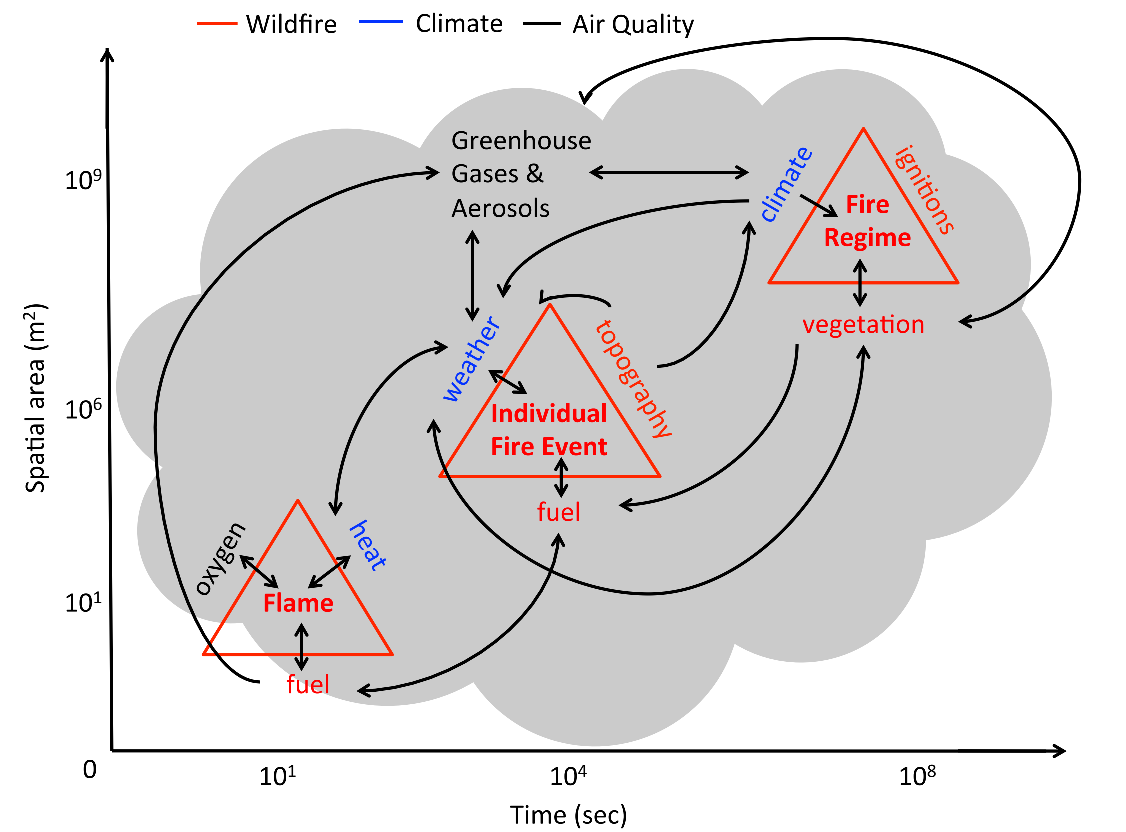

Figure 2.7.1. Conceptual space-time diagram of the climate-wildfire-air quality system with components: air quality (black), climate (blue), and wildfire (red). Modified from Moritz et al. (2005), with permission, to include the air quality and climate components, the feedback loops (double-pointed arrows), and effects (single-pointed arrows) of the climate-wildfire-air quality system across scales.

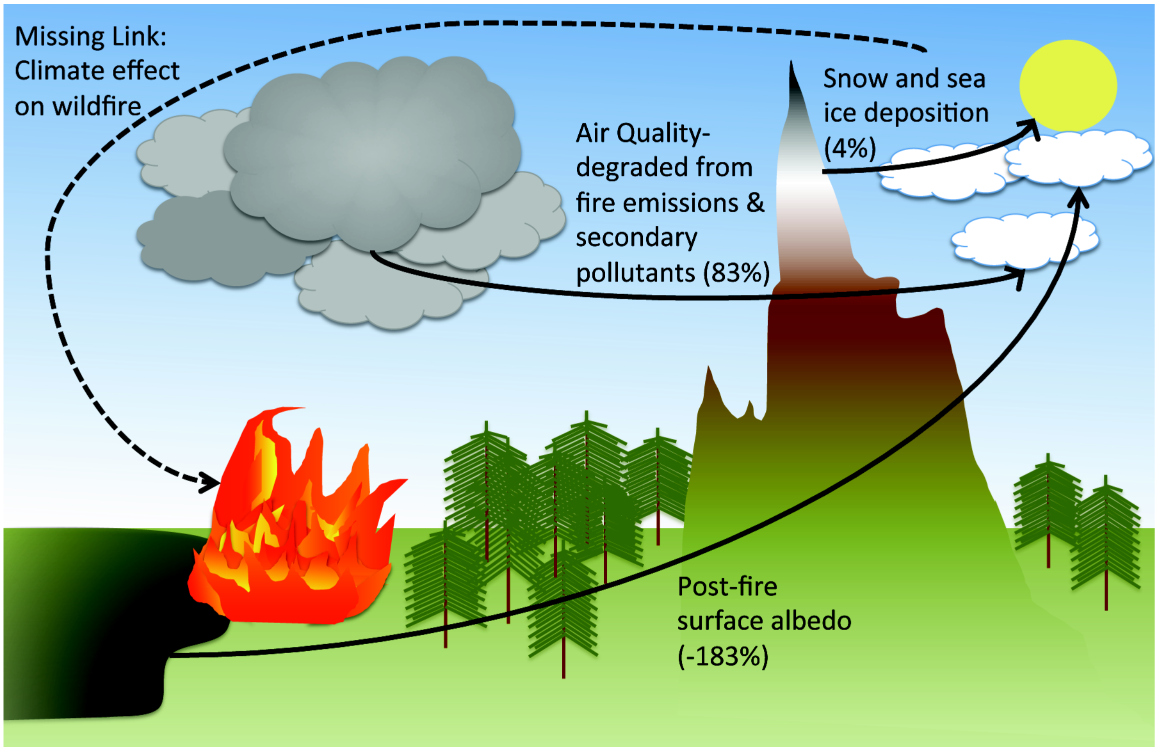

Figure 2.7.2. Mean radiative forcing over an 80-year fire cycle in the boreal forest of interior Alaska (adapted from findings in Randerson et al. 2006). Numbers are the percentage of total net radiative forcing from each component. Positive numbers represent increased forcing (i.e., positive feedback to climate change); negative numbers are decreased forcing. The dashed line represents the change in climatic forcing of fire regimes, thus closing the feedback loop.

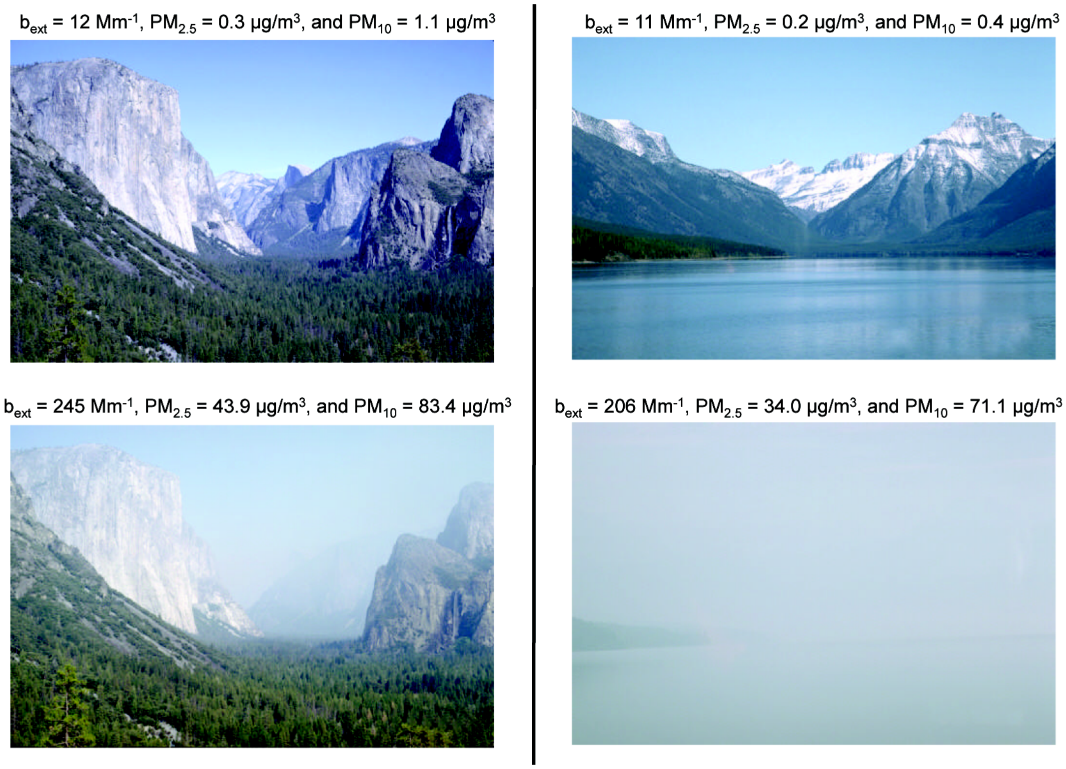

Figure 2.7.3. Examples of pristine air quality (top panels) and degraded air quality (bottom panels) in Yosemite National Park (California, USA) (left) and Glacier National Park (Montana, USA) (right). b_{ext} represents light extinction whereby low values are typical for clear conditions and high are typical of degraded visibility. Photos are courtesy of IMPROVE (http://vista.cira.colostate.edu/improve/) and used with permission.

2.8. Tables

Table 2.8.1. Table of some of the emissions and secondary pollutants from wildfire (Agee 1993) as well as classification as a greenhouse gas (GHG) or aerosol and the typical spatial and temporal extent. Spatial and temporal scales are defined as fine (10^{-3}-10^{3} square meters or seconds-days), intermediate (10^{4}-10^{8} square meters or weeks-months), and broad (($\geq 10^{9}$ square kilometers or years-centuries).

Emission from Wildfire	Greenhouse Gas (GHG) or Aerosol	Spatial Scale	Temporal Scale
Carbon Monoxide (CO)	Neither	Fine	Fine
Carbon Dioxide (CO_2)	GHG	Fine to Broad	Broad
Methane (CH_4)	GHG	Fine to Broad	Fine to Intermediate
Water vapor (H_2O)	GHG	Fine to Broad	Fine to Intermediate
Nitrogen Oxides (NO_x)	GHG	Fine to Broad	Constant
Volatile Organic Compounds (VOCs)	Neither	Fine	Fine
Particulate matter (PM_{10}) ^{2} 10 µm	Aerosol	Fine to Intermediate	Fine
Particulate matter ($PM_{2.5}$) ^{2} 2.5 µm	Aerosol	Fine to Broad	Fine
Secondary pollutants			
Tropospheric ozone (O_3)	GHG	Fine to Broad	Fine to Intermediate

Chapter 3

Climate and megafires in the contiguous Western United States

This work is adapted from work originally submitted as: Stavros EN, Abatzoglou J, Larkin NK, McKenzie D, Steel EA (2013) Megafires: An analysis of climatic factors associated with very large wildfires in the western contiguous United States. *International Journal of Wildland Fire.*

3.1. Summary

Very large wildfires can cause significant economic and environmental damage, including destruction of homes, adverse air quality, firefighting costs, and even loss of life. I examine how climate enables very large wildfires (≥ 50,000 ac ~ 20,234 ha) in the western contiguous US. For simplicity, I refer to such fires as "megafires", as they account for the top two percent of all fires and represent 33% of all area burned. Multiple megafires often occur in one region during a single fire season, suggesting that regional climate is a driver. I used composite records of climate and fire to investigate the spatial and temporal variability of the megafire climatic space. I developed logistic regression models to predict the probability that a megafire will occur in a given week, with separate models for each of eight US National Interagency Fire Center Geographic Area Coordination Centers (GACCs) across the western contiguous United States (US). Accuracy was good (Area Under the Curve: AUC > 0.80) for all eight models, but significant climate predictors of megafires vary by GACC, suggesting that broad-scale ecological mechanisms associated with megafires also vary across regions. These mechanisms associated are very similar to those found by previous analyses of annual area burned, thus reflecting how the largest fires drive annual aggregate statistics. By predicting individual megafires, however, instead of annual area burned, I provide a means for anticipating extreme fire events and thereby possibly mitigating their risk and associated damage.

3.2. Introduction

Throughout the western contiguous United States in the past several years, very large wildfires have set modern records for the largest fires in several states (e.g. Long Draw in Oregon (2012), Wallow Fire in Arizona (2011), and the Whitewater Baldy Complex in New Mexico (2012); http://www.nifc.gov). Such fires may have dramatic and lasting socio-economic, environmental, and health effects including property damage, firefighting costs, loss and degradation of habitat, and air-quality reductions (Jaffe et al. 2008) that lead to respiratory illness or even premature mortality. Fires also contribute to global warming, including greenhouse gas emissions, aerosols and other secondary pollutants (Randerson et al. 2006, Bond et al. 2013). During very large wildfire events, particularly if there are multiple large fires in a region, firefighting resources within the region may become strained and additional resources may be needed from other areas, if they are even available.

Investigation of the mechanisms and climatic drivers of these very large fires is a first step to reducing or managing their effects. Past studies have focused on quantifying the factors influencing total annual area burned within a region including the influence of fuel loading, climate, and weather (e.g., Westerling et al. 2002, McKenzie et al. 2004, Flannigan et al. 2005, Flannigan et al. 2009, Littell et al. 2009), the probability of a fire, of any size, across North America (Parisien et al. 2012), or a single-day fire growth event (Podur and Wotton 2011). These studies have aggregated fires in a region over an entire fire season, without addressing individual large wildfires, and do not provide information at adequate temporal resolution for management strategies, such as suppression, or policy, such as air quality regulation.

Studies investigating fire probability or fire behavior across a range of fire sizes may fail to capture relationships between fuels, climate, and large fires because large fires may behave differently than smaller fires (Alvarado et al. 1998), and are often the consequence of uncommon circumstances, e.g., extreme fire weather with abundant fuels and limited resources for suppression in their early stages. Consequently the largest fires are subsumed into analysis of aggregate properties such as annual area burned (Littell et al. 2009). Studies that have addressed individual large fires have been geographically specific (Abatzoglou and Kolden 2011, Irland 2013, San-Miguel-Ayanz et al. 2013, Tedim et al. 2013), not extending across the western contiguous US, or have examined only fire danger without linking it to actual entire events (Liu et al. 2013). My study addresses this knowledge gap by specifically predicting the probability of very large wildfires across the western US.

I assess how antecedent and concurrent climate is associated with very large wildfire events, specifically those with total area burned over 50,000 acres (~20,234 hectares). For simplicity, I refer to such fires here as “megafires”. I recognize that the term “megafires” has been used loosely in scientific and popular literature, with multiple underlying meanings. Here I apply a simple and consistent quantitative definition based on total burned area in the fire. Fires this size and above constitute roughly 33 percent of annual area burned across the West (figure from data used in this analysis). Such fires have probably escaped attempts at suppression, contribute disproportionately to degraded air quality, present danger to communities, and have great economic costs. I hypothesize that these fires are associated with an identifiable climatology, that is, they can be quantitatively linked to specific climate and weather.

To examine climate associations with megafires and develop a set of regional predictive models useful for management and policy, I use the Monitoring Trends in Burn Severity (MTBS) database of fire perimeters and burn severity that has fire date of discovery, perimeter, and burn-severity classifications from 1984 to present, along with climate data for the same period. These data sets meet the broad spatial and fine temporal resolutions required for investigating climate, wildfire, and air quality (Chapter 2). I focus on three questions. (1) What is the spatial and temporal distribution of megafires from 1984 to 2010 across the western contiguous US? (2) Do antecedent and concurrent fuel conditions and climate for megafire (≥ 50,000 ac ~ 20,234 ha) occurrence differ from those for other large wildfire (≥ 1000 ac ~ 405 ha but <20.234 ha) occurrence? (3) How does this spatial and temporal variation affect the probability that a megafire will occur? Although this research does not specially integrate predictive models into smoke modeling to investigate the Climate-Wildfire-Air Quality system (Chapter 2), it provides a foundation for such future research.

3.3. Study area

My analysis grouped climate and fire information within existing operational management boundaries across the western US (**Figure 3.8.1**). Specifically, I examined the geographic areas defined by the US National Interagency Fire Center as Geographic Area Coordination Center (GACC). GACCs are management units and do not coincide directly with ecological boundaries (most of which are subjectively defined) or vegetative fuel types (which vary at much finer scales than acknowledged in classification – Keane et al. 2012). Each GACC includes multiple Predictive Service Areas (PSAs) (last acquired 1 Oct 2011 from http://psgeodata.fs.fed.us/data/gis_data_download/static/PSA_2009.zip). PSAs, used for both operational decision-making and regional forecasting in air-quality management, are spatial polygons defined by distinct climate and weather that affect fire occurrence and behavior. Because my goal was to understand wildfires, I excluded PSAs within each GACC for which large fires are primarily agricultural, notably within the Great Plains (defined by the Terrestrial Ecoregion L1 boundaries, Olson et al. 2001). There are eight GACCs in the study area: Southern

California (SCAL), Northern California (NCAL), Pacific Northwest (PNW), Northern Rockies (NROCK), Rocky Mountains (RM), Western Great Basin (WGB), Eastern Great Basin (EGB), and the Southwest (SW). I modeled megafires at the GACC scale because the rarity of megafires makes finer-scale analyses difficult, with sample sizes too small to develop predictive models, and because GACCs do define operationally important fire management boundaries.

3.4. Data and methods

3.4.1. Fire data

For fire area, I used fire perimeters from the Monitoring Trends in Burn Severity (MTBS) dataset produced by the US Forest Service (http://www.mtbs.gov, data acquired 1 Oct 2012). As used, MTBS spans 1984-2010 and includes area burned and burn-severity data within nearly 6,000 individual large fire perimeters exceeding 405 ha across the western contiguous US. Unburned islands (anything categorized as "unburned/unchanged" by MTBS) within the fire perimeter were not included in the burned area calculations to achieve a more accurate estimate of the total area burned (Kolden et al. 2012).

I used past records of fire discovery date to define the core fire season within each GACC. Statistical analyses often assume that data classes are balanced, however, this is not the case with rare events (He and Garcia 2009), such as megafires. Consequently, I reduced each year to the core fire season to create a more balanced data set and improve inference from statistical analyses. The core fire season was defined as the time window within which fires accounting for the middle 95% of the area burned were within each GACC in an average year over the record (**Figure 3.8.2**, i.e., Abatzoglou and Kolden 2013). Fires with discovery dates outside of the core fire season were excluded from the analysis. I classified each week of the core fire season in which at least one megafire was discovered, as a "megafire week", weeks in which at least one large fire was discovered but no megafires as a "large fire week", and weeks in which no large fires occurred as a "no fire week". Because megafires are rare, there were many fewer megafire weeks than weeks in which no megafires occurred (e.g. the RM GACC has only three megafire weeks out of 621 weeks available for analysis). Analysis was aggregated to weeks for the following reasons. In keeping with Chapter 2, I wanted to conduct the analysis at "fine temporal resolution" in order for the models to eventually be applied to air quality modeling. Unfortunately, daily resolution created even more of an imbalance in the data, and was more subject to temporal autocorrelation. In addition, MTBS provides dates of discovery, but there is some uncertainty in that estimate. Therefore, aggregating data to the week made the most sense.

3.4.2. Climate data and derived indices

Climate data were averaged spatially across all pixels (800-m for monthly data, 4-km for daily data) within each GACC perimeter (excluding PSAs within the Great Plains). This aggregation assumes homogeneity of fire regime, vegetation, climate, and weather within a GACC. Two gridded climate datasets were considered: (1) monthly temperature and precipitation from Parameter-elevation Regressions on Independent Slopes Model (PRISM - Daly et al. 2008), and (2) daily surface meteorological data from Abatzoglou (2013). Multiple biophysical metrics were also calculated and available with these data sets. Palmer Drought Severity Index (PDSI), a time-averaged measure of drought believe to track soil moisture, is calculated from the monthly climate data, and fire danger indices of the National Fire Danger Rating System (NFDRS) and the Canadian Forest Fire Danger Rating System (CFFDRS) are calculated from the daily surface meteorological data. NFDRS calculations used fuel model G (dense conifer stand with heavy litter accumulation) to maintain consistency with previous studies (Andrews et al. 2003) and used greenup dates defined by the first day of each year when the normalized growing season index exceeds 0.5 (Jolly et al. 2005; M. Jolly, personal communication). NFDRS and CFFDRS are compared in **Figure 3.8.3**. Both NFDRS and CFFDRS are used because each classification system has been shown to be more effective in different areas.

I used six indices from the NFDRS and CFFDRS. From NRFDRS: (1) NFDRS- 100-hour fuel moisture (FM100) represents the moisture content of dead fuels 2.5-7.6 centimeters in diameter or roughly the moisture content of 1.9-10.2 centimeters of soil. (2) NFDRS- 1000-hour fuel moisture (FM1000) represents moisture content of dead fuels 7.6-15.2 centimeters in diameter. Lower values of FM100 and FM1000 represent drier conditions. (3) NFDRS- energy release component (ERC) represents the daily potential worst-case scenario of total available energy per unit area within the flaming front at the head of a fire. Higher values represent higher fire danger. (4) NFDRS- burning index (BI) represents the potential difficulty of fire control as a function of spread rate and ERC. Higher values represent higher fire danger. (5) CFFDRS- fine fuel moisture content (FFMC) represents the relative ease of ignition and flammability of litter and other fine fuels. Higher values represent drier conditions. (6) CFFDRS- duff moisture code (DMC) represents average moisture content of loosely compacted organic layers of moderate soil depth. Higher values represent drier conditions. These indices were selected because *a priori* data analysis of the data sets suggested that these indices had strong associations with the fire data.

3.4.3. Large fire vs. megafire climatology

A composite analysis was used to answer my second question: Do antecedent and concurrent fuel conditions and climate differ for megafires and other large wildfires and for weeks during the fire season without large fires? Composite analysis calculates biophysical metrics for fires classified as large versus megafire and plots them relative to the date of discovery. This allows one to see the difference in mean (and 95 percent confidence intervals) of biophysical conditions for all fires within a given classification for a GACC from ten weeks before to ten weeks following the discovery of the fire. Composite analysis includes lead-lag temporal composites of (1) weekly fire danger index percentiles over a 13-week period centered on the discovery week, and (2) monthly temperature and PDSI for the year prior to and concurrent to the discovery week. Temperature and PDSI were used to examine fire climatologies up to a year prior to discovery and to provide insight to longer-term lagged effects of climate. The composite analysis staggers climate and fire danger index percentiles (to aid comparisons between GACCs) relative to the discovery week of fires (when x-axis is zero) within each GACC. The analysis is aggregated to the discovery week of each fire (weeks are defined by day-of-year, e.g. week 1 = January 1-7), because of challenges in temporal overlap of individual fires and inconsistencies in the reported discovery date of each fire. The 95% confidence intervals of the composite means are estimated using bootstrapping (N=1000).

3.4.4. Probability of a megafire week

I built logistic regression models for each GACC to estimate the probability of a megafire week, i.e. a week when at least one megafire occurred within a fire season. Potential predictor variables included climate and fire danger indices as described in section 3.4.2. The hypothesized mechanisms relating each potential predictor variable to megafire probability suggest a variety of potential time lags. For example, climate several weeks in advance of ignition could influence fire risk through reduced fuel moisture. Climate after ignition could also influence megafire probability via spread from wind and lack of significant precipitation. To allow for these time lags during the model building, I used the composite graphs to identify predictor variables at multiple time lags (section 3.2). Note that PDSI and temperature (TEMP) are monthly indices that were assigned to all days of the month. Furthermore, explanatory variables used in this analysis are raw values rather than the percentiles applied by managers for fire danger ratings. Percentiles are tied strictly to the model database used to generate them, thus using them over-calibrates models to the dataset used to generate them.

I applied the following binomial logistic regression model selection procedure independently for each GACC. I built models using forward stepwise procedure by minimizing Akaike Information Criterion (AIC), then removing insignificant ($p>0.05$) variables one at a time, rebuilding the model after each elimination. Next, I examined the resultant models for any correlated indices (Pearsons correlation coefficient ≥ 0.8) or any indices that were included over multiple time windows, retaining the first occurrence (e.g., if FFMC the week prior to discovery was used, no other FFMC variable was allowed). I confirmed that all predictor variables retained in the model still met the significance criteria ($p<0.05$). Although there are many cautions when using forward stepwise regression (Anderson et al. 2000, Mundry and Nunn 2009), in this case we have a very large data set and the models are used for prediction, consequently inferences from these models are fairly direct (Anderson and Burnham 2002). Moreover, the use of AIC avoids the corruption of alpha levels when forward selection is used with significance testing. I used standard odds ratios to estimate each predictor's influence on the probability of a megafire week. To understand how sensitive model selection and accuracy statistics were to the choice of megafire threshold, I built an additional two models for each GACC using alternative definitions of megafire (10,000 ac ~ 4,047 ha and 25,000 ac ~10,117 ha).

I evaluated each model using a combination of precision, recall, and Area Under the [receiver operating characteristic] Curve (AUC). Precision is "a measure of exactness" returning the probability of correctly classifying a megafire, where as recall is “a measure of completeness” returning the probability of correctly classifying a megafire that is actually a megafire (He and Garcia 2009). There is generally a trade-off between precision and recall. To calculate precision and recall, I converted the model output, probability of a megafire week, into binary predictions of megafire week (**Table 3.9.1**). I used a sliding classification criterion, in increments of 0.05, to translate model output into binary megafire predictions. For example, if one applies a classification criterion of $p \geq 0.5$, then any modeled predictions greater than or equal to 0.5 would be considered a prediction that a megafire would occur in that week. I evaluated model predictive accuracy across all thresholds, using AUC, which quantifies the relative trade-offs between true positives (TP; benefits) and false positives (FP; costs) (He and Garcia 2009). An AUC of 0.5 indicates that the model predicts no better than random, whereas a value of 1.0 indicates that the model makes perfect predictions (Harrell 2001).

3.5. Results

3.5.1. Large fire vs. megafire climatology

In all GACCs, unlike monthly PDSI values, monthly temperature anomalies are highly variable and show limited evidence of meaningful differences in conditions between megafires and large fires (**Figure 3.8.4**). One exception is that fire-season temperature coincident with megafires in the NROCK and RM GACCs appear warmer than temperatures associated with large fires. In contrast to the highly variable temperature anomalies, PDSI values for megafires in several GACCs show a transition from moist conditions the year before the fire year to moisture deficits concurrent with the fire season. Most notably, megafires in the WGB occur a year following pluvial conditions as evident from PDSI values >2 (wet) the year prior to the fire, and approach normal values during the fire season of the fire year. Though not as dramatic, similar patterns were seen the year prior to megafires in the EGB and SCAL GACCs. Megafires in the SW and RM occurred during periods of negative PDSI and after periods of negative PDSI during the prior summer and winter, respectively. However, there is a limited sample size for these GACCs. Megafires in the NROCK appear to occur during concurrent drought.

In contrast to the limited and disparate relationships observed for megafires using monthly temperature and PDSI, strong commonality across GACCs was observed in the composite analysis for weekly fire danger indices (**Figure 3.8.5**). Megafires generally experienced elevated fire danger concurrent to and up to three weeks post discovery week. The fire danger indices with slower response times (i.e., FM1000, ERC, DMC) sustain conditions in the upper decile in the weeks following the discovery week. For other large wildfires, fire danger indices were more moderate and typically subsided the week following fire discovery. In many of the GACCs, large differences in climate that desiccate fuels and increase fuel availability are apparent two weeks prior to the discovery week. These differences both before and after fire discovery provide a basis for defining time durations of calculated indices that can be used to define explanatory variables driving fire growth.

3.5.2. Probability of a megafire week

Models to predict the probability of a megafire week and the effect of predictors on the output probability differed by GACC (**Table 3.9.2** and **3.9.3**). In general, models predicting megafire probability for all GACCs included seasonal drought signals (FM100, low FM1000, high ERC, high BI, and high DMC). Models for only a few GACCs included variables indicative of short-term and long-term moisture signals. Models for EGB and NROCK included short-term fire-weather signals (high FFMC). Models for EGB and WGB included long-term moisture signals (PDSI).

Odds ratio (**Table 3.9.3**) demonstrates the effect size of any one predictor variable on the response when holding all other predictors constant. In general, models for all GACCs show that hotter, drier conditions have an odds ratio >1, therefore increasing the probability of a megafire week. EGB and WGB show PDSI with an odds ratio >1, thus increased long-term moisture increases the probability of a megafire week. The NROCK model also includes FFMC and DMC, which have odds ratios <1 denoting that wetter conditions increase the probability of a megafire.

Models for all GACCs have AUC greater than 0.8 suggesting that the models have high predictive ability (Harrell 2001), but examining the trade-offs between precision and recall demonstrates that model probabilities drop to near zero very quickly (**Figure 3.8.6**). Because of the large number of zeros in the data being modeled, the model can achieve reasonably high predictive ability by simply predicting a probability of zero. This phenomenon is most obvious when the percentage of non-megafire weeks ≥ 98 (e.g., NCAL, SCAL and SW at 20,234 ha and RM at 10,117 and 20,234 ha). This bias toward zero affects AUC for nearly all GACCs (with the exception of EGB).

Models predicting the odds of a megafire using smaller fire-size thresholds with more fire weeks are more balanced (smaller portion of zeros), and may be more robust because they included a larger sample of megafires. I identified similar predictor variables for models across the three fire-size thresholds within a region in all GACCs except NCAL and PNW (**Table 3.9.2** and **3.9.4**).

3.6. Discussion

3.6.1. Megafires across space and time

The spatial and temporal distributions of megafires show three patterns. First, mapping the number of fires and percentage area burned by megafires (**Figure 3.8.1**) shows that although models were developed at the GACC scale, there is finer-scale variability at the PSA scale. There are many PSAs with no megafire occurrence at all. PSAs with the most fires are also PSAs with the most megafire occurrences. Furthermore, the PSAs with megafires have a substantial percentage of annual fire area was burned by megafires. Second, fire seasons are qualitatively different among GACCs (**Figure 3.8.2)**, and with exception of the SW, megafires occur throughout the fire season. Third, years with the most annual area burned ("megayears") are years with not only a substantial fraction of hectares burned by megafires (**Figure 3.8.7**), but also an increased number of megafires (**Figure 3.8.8**).

3.6.2. Megafire climate space

This analysis focuses on climate conducive to the occurrence of megafires (≥ 50,000 ac ~ 20,234 ha) in the western contiguous US. Previous studies focusing on annual area burned provide less specific information, thus making it difficult to prepare for and mitigate the lasting ecological and social effects of individual fires. I focus on climate-fire relationships, because although there are other controls on fire size such as fuel abundance and connectivity and topographic complexity (Littell et al. 2009, Kennedy and McKenzie 2010, Hessburg et al. 2000), extreme climate and weather can neutralize the effects of other controls (Turner and Romme 1994, Bessie and Johnson 1995). I compared findings from this analysis to those for annual area burned in previous studies. Similar broad-scale ecological mechanisms were associated with megafires as with annual area burned, thus suggesting that the megafire size class may be substantially influencing the associations found in aggregate analyses.

Identifying the megafire climate space requires both examining the fire climatologies and interpreting the effect of predictors on the probability of a megafire week. Fire climatologies provide insight about climate beyond that which is identified in the explanatory variables. Interpreting the effect of predictors on the probability of a megafire week cannot be done directly by examining the sign and magnitude of coefficients, even standardized coefficients, because the daily and monthly indices averaged to create predictor variables are calculated using nonlinear relationships between meteorological data and are not completely independent. For this reason, odds ratios (**Table 3.9.3**) provide a basis for quantitatively measuring the effect size of a predictor variable on the response by calculating each predictor variable's influence while holding the others constant.

The climate space of megafires across the West shows very different fire danger leading up to and concurrent to discovery of megafires than with large wildfires. Despite commonality among GACCs, there is variability by GACC that reflects either fuel-limited or flammability-limited fire regimes. In extremely hot and dry climates, fire regimes are fuel limited in that fuel accumulation and connectivity are enabled by wet conditions in the previous year, and abundant fuels become flammable in the succeeding dry year (Veblen et al. 2000). On the other hand, areas with more moderate climate, and forest vegetation, are flammability limited (Littell et al. 2009) because there is always sufficient fuel to burn under the right conditions. It is difficult to classify a fire regime for entire GACCs, however, because of climatic differences and finer-scale variability of ecotypes (i.e. grouping of similar ecosystems) and fire regimes within them (**Figure 3.8.1**, Littell et al. 2009, Littell et al. 2010).

The composite plots show that mountainous and Northern regions are generally flammability-limited, in agreement with the conceptual model of annual area burned and climate

(Littell et al. 2009). For example, in the PNW, the most influential predictor as defined using the magnitude of the odds ratio, is temperature the week following discovery. This is in agreement with findings from Littell et al. (2010), which show annual area burned increase with low summer precipitation and high temperature. When temperature increases, the probability of a megafire week increases, and under wetter conditions (FM1000 increases), the probability decreases (**Table 3.9.3**). Keane et al. (2008) found that the PNW large fires are characterized by seasonal drought (represented in this analysis by FM1000) and easterly winds. In the NROCK, my models and the composite graphs suggest that drying of both fine (FFMC) and medium-sized fuels (FM100 and DMC) during the discovery week and increased temperature leading up to it, as well as how hot and fast the fire grows (BI), influence the occurrence of megafires. Using the odds ratios (**Table 3.9.3**), when BI and temperature increase, so does the probability of a megafire week, and when FM100 increases (i.e. wetter conditions), the probability decreases. Counter-intuitively, however, when FFMC and DMC increase (i.e. drier conditions), the probability decreases. An increase in FFMC probably decreases the probability because the model uses both FM100 and FFMC, which are correlated (Pearsons correlation coefficient = 0.55) enough to have interacting effects on the predicted probability, but not enough so to be excluded from the model. Although an increase in DMC decreases the probability of a megafire, the odds ratio for DMC is very close to 1 and thus does not heavily influence the output probability. In the RM, drying of medium-sized fuels (DMC) post-discovery influences the occurrence of megafires. In NCAL, drying of large fuels (FM1000) following discovery of the fire is the dominant predictor of the occurrence of megafires.

Dry fuel-limited areas such as the WGB and parts of the EGB show similar dominant predictors with both long-term and short-term precipitation influencing the occurrence of megafires, in agreement with findings from previous studies (Westerling and Swetnam 2003, Littell et al. 2009). In the WGB, seasonal drought (FM100) (i.e., dry conditions over the season) peaking the week of discovery, and PDSI are the dominant predictors of the occurrence of megafires. In the EGB, increased short-term and seasonal drought (FFMC and DMC) during and up to three weeks after the discovery week increases the probability of megafire, with odds ratios >1. Temperature, the dominant predictor, and PDSI, also increase the probability of megafire. The odds ratios for both WGB and EGB show that as PDSI increases, so does the probability of a megafire. This may seem counter-intuitive because positive PDSI indicates wetter conditions. Studies, however, have shown that PDSI has an e-folding time (i.e., natural logarithmic analog of doubling time) of approximately 10 months (Cook et al. 2007). The composite plots show positive PDSI for at least a year prior to the month of megafire discovery in the WGB and for a year to six months before discovery in the EGB. Previous studies have shown area burned in non-forested areas of the EGB and WGB had significant correlations to the previous years moisture (Littell et al. 2009, Abatzoglou and Kolden 2013). EGB also showed significant correlations between area burned in forested areas and in-season fire danger (Abatzoglou and Kolden 2013), thus demonstrating the mixed fire regime of the EGB between fuel and flammability limited.

Similar to the EGB, the SW has an intermediate fire regime (Swetnam and Baisan 1996, Littell et al. 2009), but some studies have shown indirectly that drought, periods of prolonged dryness, has been and continues to be a primary influence on the occurrence of wildfires (Williams et al. 2013). In concurrence, my model shows that increased seasonal drought (DMC) peaking the week of discovery is the dominant predictor of the probability of a megafire week. There is a sharp decline in fire danger indices in the SW the month following discovery of all fires in the dataset, especially megafires (**Figure 3.8.5**), which is likely attributable to monsoonal moisture which may be responsible for curtailing fire growth. In correspondence, **Figure 3.8.2** shows that most megafires occur in the hot and dry months before the monsoon.

Drivers of wildfire in SCAL differ from the rest of the contiguous US. In general, wildfires are driven by either Foehn-type winds known as Santa Anas (Sergius et al. 1962, Westerling et al. 2004, Keane et al. 2008, Parisien and Moritz 2009) or low spring precipitation (Littell et al. 2009). My models do not include wind as a direct predictor, rather a component of the calculated indices (e.g. BI) used to define explanatory variables. Nevertheless, in agreement with the understanding that seasonal drought influences the occurrence of wildfire, my models found that the potential for how hot the fire burns (ERC), a function of seasonal drought the week following the week of discovery, has a positive relationship with the probability of a megafire week.

All of the models had higher accuracy (AUC $\geq$ 0.8) at the highest megafire size threshold than with smaller fire-size thresholds. Similarity in models across fire-size definitions, however, provides confidence that my models are robust to the specification of particular megafire thresholds and to heavy zero-inflation in the largest threshold (20,234 ha).

3.6.3. Domain of model applicability

Besides the intrinsic difficulties of modeling rare events (Alvarado et al. 1998, Coles 2001), other factors limit the domain of applicability of these models. First, these models assume that area burned approximately equates fire effects and thus size thresholds can be used to define megafires. What defines a "megafire", however, goes beyond area burned (Kasischke et al. 2005) to include lives lost, structures destroyed, economic cost, and degradation of air quality, which can be very different for two fires of similar size. Second, other factors, besides climate and weather, control wildfires. Large fires can occur because of large areas of continuous fuels, merging of multiple fires, time available for spread, and ineffectiveness of suppression (Gill and Allan 2008), which can be taxed if there are multiple coincident wildfires. In all GACCs, there was at least one megafire week in which more than one megafire burned, but there are no indices or metrics in this analysis that account for preparedness or availability of suppression resources. Third, the biophysical metrics used here to regress the binary occurrence of a megafire in a given week do not include all climate influences, e.g. atmospheric stability (Werth et al. 2011). Fourth, there is an element of uncertainty in these models associated with ignitions and discovery date. For example, Jiang and Zhuang (2011) reported that lightning-caused and human-caused fires have very different fire behavior, something not accounted for in this study. These statistics are different perhaps because human-caused fires generally start close to the wildland urban interface (WUI) where there is increased land-use fragmentation and a higher motivation for suppression efforts (Jiang and Zhuang 2011). My models do not account for proximity to the WUI or the time between the fire start and initial attack of suppression efforts (Gill and Allan 2008), which can vary widely depending on the number of concurrent fires burning and proximity of resources needing protection. Furthermore, multiple ignitions at different times can merge into one large fire (Gill and Allan 2008), referred to as a complex fire, thus there is some uncertainty around classifying the discovery date of a megafire.

A principle effect of these confounding factors is to limit the domain of applicability of these models to the coarse scale of the GACCs. Predicting megafires at finer scales will require explicit fire-spread modeling, whether probabilistic or mechanistic, and acceptance of even greater uncertainty around climatic and other factors that produce a megafire. Still, my models provide a foundation for investigating very large wildfires specifically, rather than using aggregate statistics such as annual area burned.

3.7. Conclusions

Because large wildfires have lasting ecological and social effects, and future projections under a changing climate estimate increased annual area burned (Flannigan et al. 2009, Littell et al. 2010) and more extreme events in general (Coumou and Rahmstorf 2012, Hansen et al. 2012) there is a need to understand how climate influences the occurrence of very large wildfires. This analysis assesses the spatial and temporal domain of megafires (area burned ≥ 20,234 ha ~ 50,000 ac) and related climate patterns. In general, hotter, drier conditions increase the probability of a megafire in the western contiguous US. Climate drivers of megafires are similar (but not the same as) to those of annual area burned, which is largely attributable to broad-scale ecological mechanisms driving wildfire, e.g. xeric areas require wet conditions the year prior to wildfire to increase fuel connectivity. Furthermore, "megayears" or years with high area burned have more megafires and a substantial portion burned is by megafires.

Predicting these very large wildfires emphasizes the difficulty and importance of studying these events individually, rather than in annual aggregates. This analysis provides a good example of how larger aggregates, like annual area burned, can be influenced by individual events, like megafires that compose a substantial portion of the aggregate, despite any imbalance in the size of the class distribution.

A future enhancement of this analysis could be to define megafires by severity rather than simply by an area threshold. Data sets like MTBS are useful for breaking down area burned into fire-severity classes, and can be used to improve assessments of the ecological consequences of megafire in particular. Other data sets may be needed to refine the assessment of megafire to include political and social consequences.

A focus on individual fire events can aid managerial preparedness; e.g., to keep smaller fires small when the probability of a megafire occurrence in a given week is high (Tedim et al. 2013). Short-term management responses are more reactive than proactive. For short-term responses, management may use fire danger indices (Xiao-rui 2005) or the probability that fire will spread in a given day (Podur and Wotton 2011). The models in this study, however, may provide a foundation from which proactive fire management can be developed. For example, by projecting these models into future climate space, we can determine how the likelihood of a megafire is going to change. If the probability of a megafire week is going to increase into the future, we may need policy that supports proactive carefully placed fuel reductions so as to avert the climatic potential of a megafire occurrence (Williams 2013).

Projecting these models into the future will require consideration of a changing climate space and non-stationarity of megafire-climate relationships as vegetation (fuels) configurations within the GACCs change. These models produce a probability representative of the climatic potential for megafire, and consequently naïve projections into the future would assume that relationships between climate and megafires remain the same despite changes in fuels, land-use, and natural resource policy or management. By using multiple future climate scenarios (IPCC 2007), however, we could still use these models to constrain the variability of future megafire occurrence, which can then be used to inform policy decisions, while recognizing intrinsic uncertainties associated with non-climatic factors.

3.8. Figures

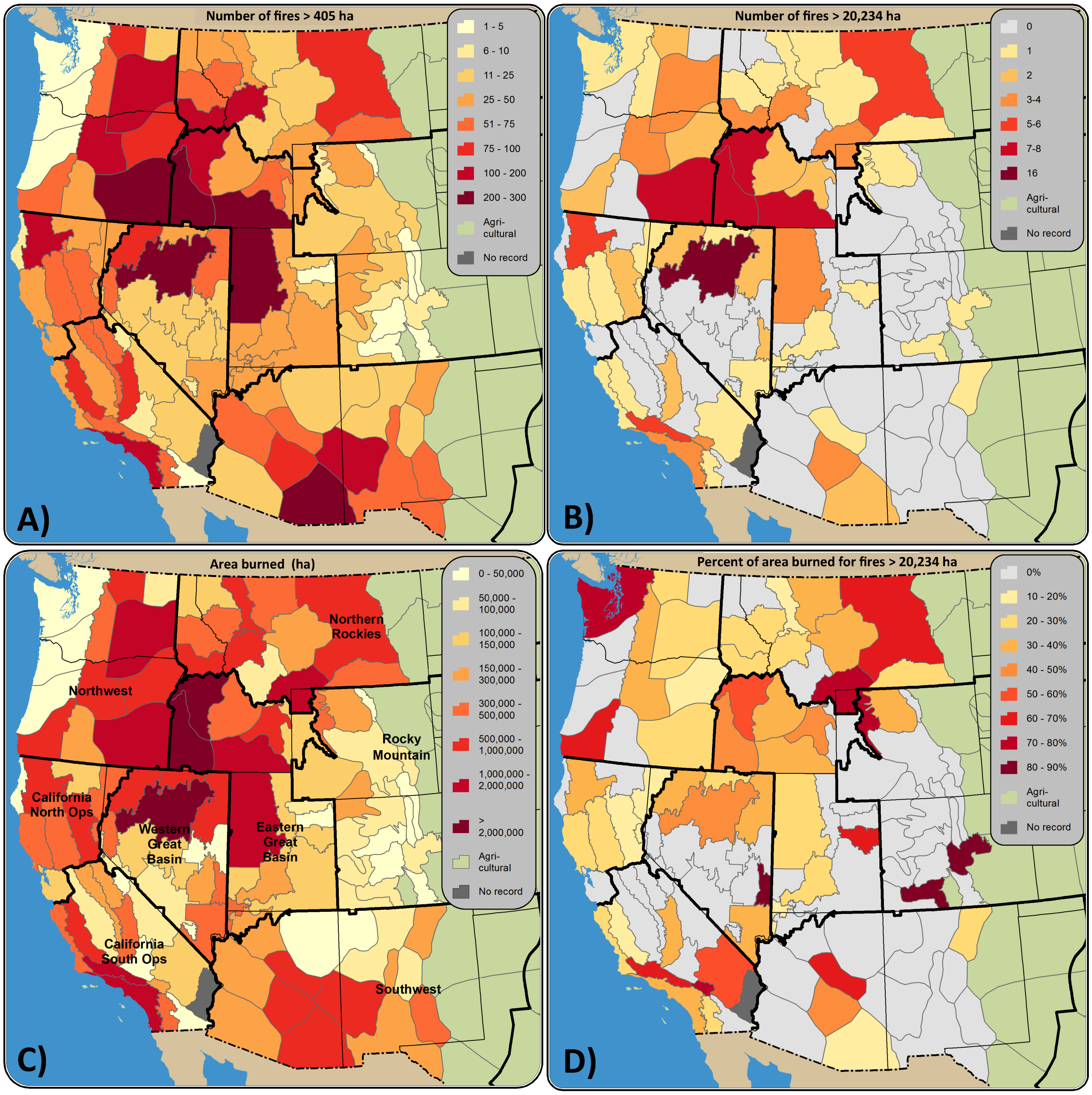

Figure 3.8.1. Spatial patterns of four fire statistics across the study domain from 1984 to 2010. Smaller polygons indicate PSAs by which statistics are calculated to show finer-scale variability, whereas larger polygons in bold indicate GACCs: a) total number of fires in MTBS >=404 ha, b) number of fires in MTBS >= 20,234 ha, c) hectares burned in climatological record in MTBS, and d) total area burned in 25 years for fires > 20,234 ha divided by total area burned by all fires.

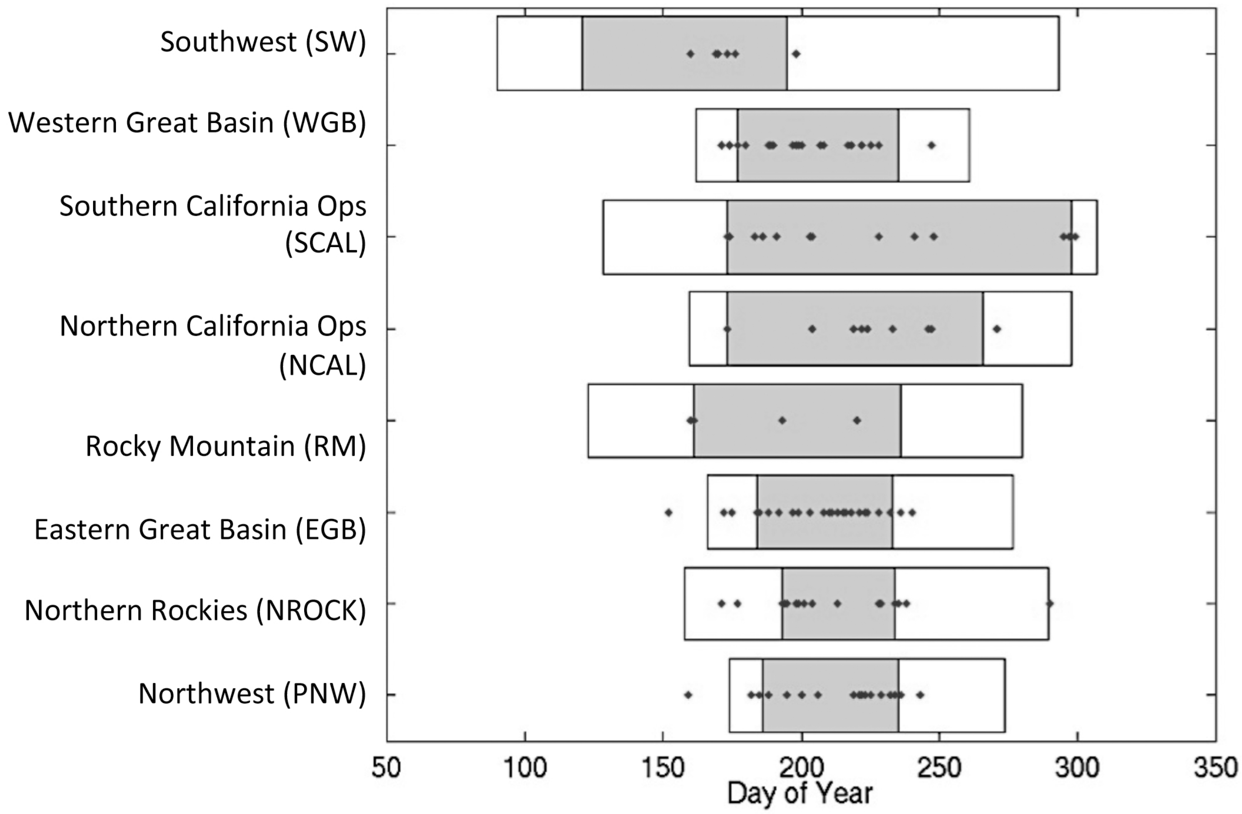

Figure 3.8.2. Core fire season and extended fire season by GACC. Seasons are defined by the average middle 95% of annual area burned (inside white rectangle) in the historical record. The shaded gray region denotes the middle 75% of annual area burned. The points represent megafire events by discovery date.

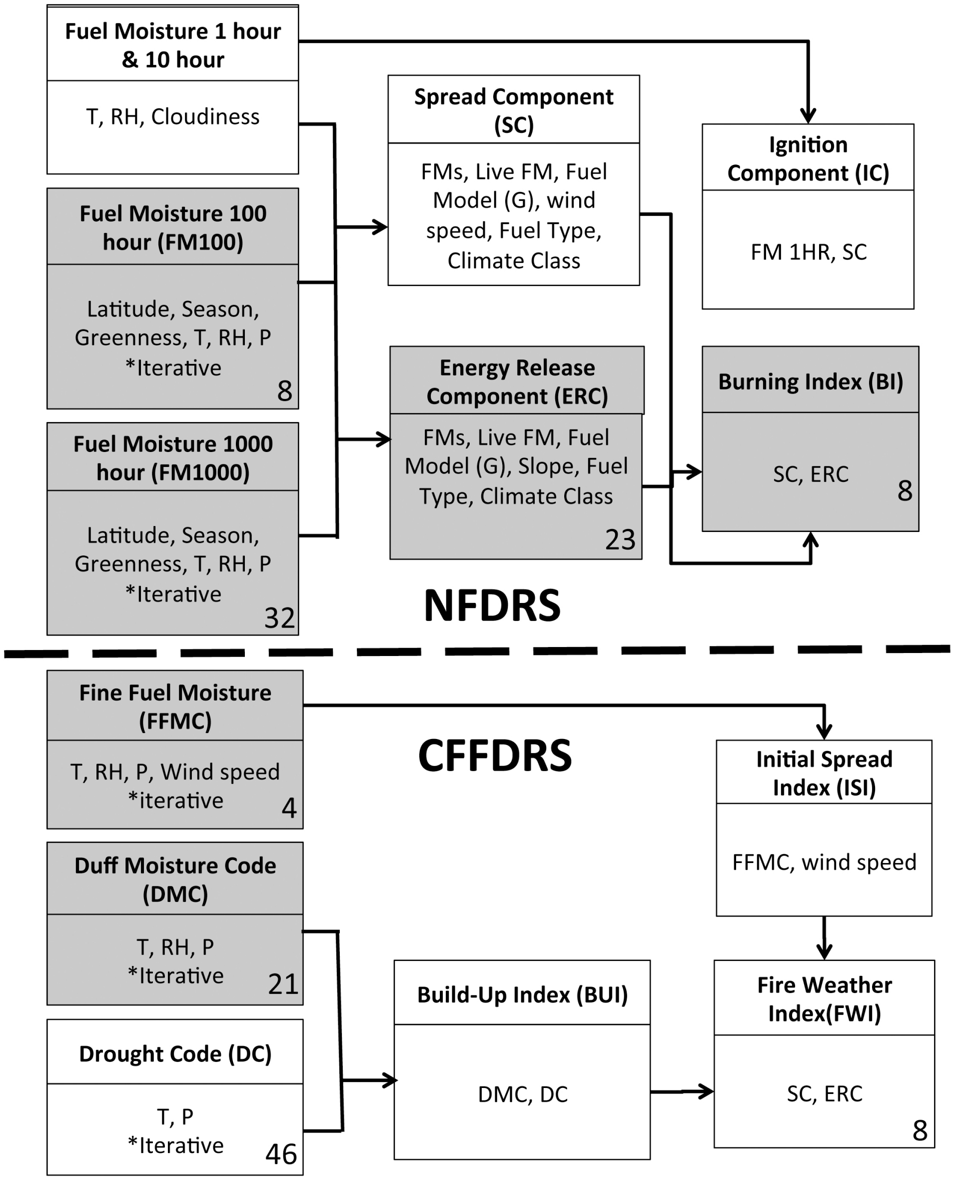

Figure 3.8.3. Computational flow chart of the United States National Fire Danger Rating System (NFDRS) vs. the Canadian Forest Fire Danger Rating System (CFFDRS). Similar positions in the flow charts indicate similar metrics (Xiao-rui et al. 2005). The number in the lower right corner represents the residence time in days that any given calculated index has an effect on subsequent calculated indices. The gray shaded indices denote those used in this analysis.
Note: T = temperature, RH = relative humidity, P = precipitation, FM = fuel moisture

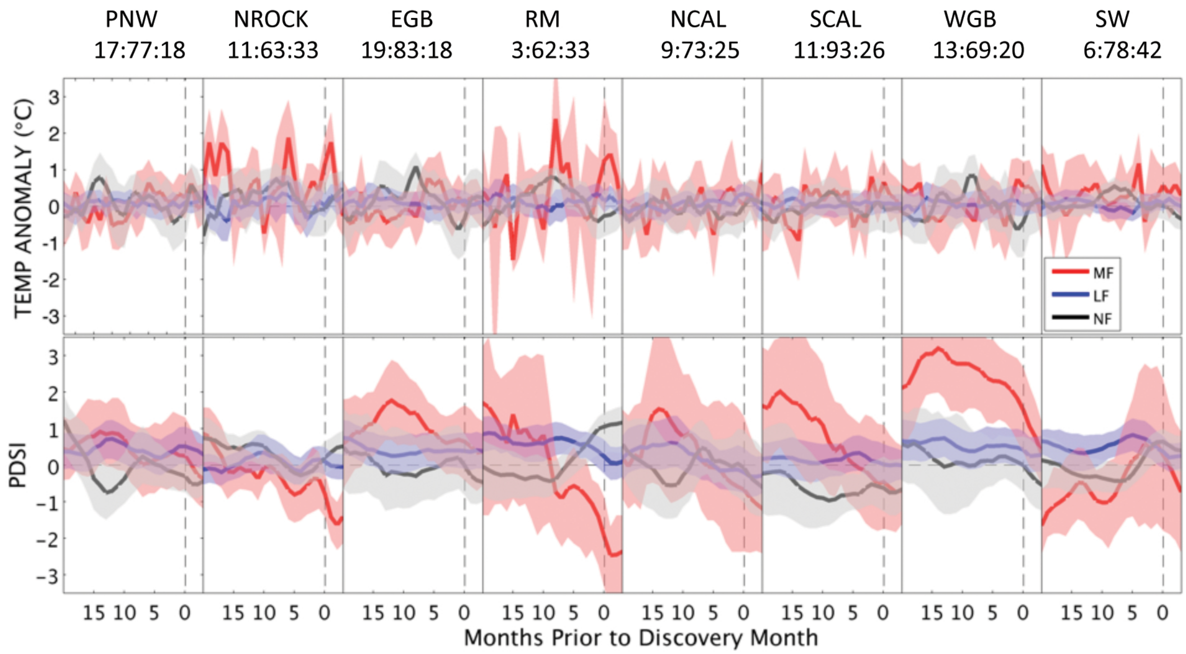

Figure 3.8.4. Monthly composite plots of temperature anomaly and PDSI up to 21 months prior to and two months post the month of discovery. Red lines denote mean conditions during megafires, and blue lines denote all other fires, with a 95 percent confidence interval (shaded pink and blue respectively). The dashed line is the megafire month. The numbers at the top are the ratios of the number of megafire months to number of large fire months to number of megafire months with no fire.

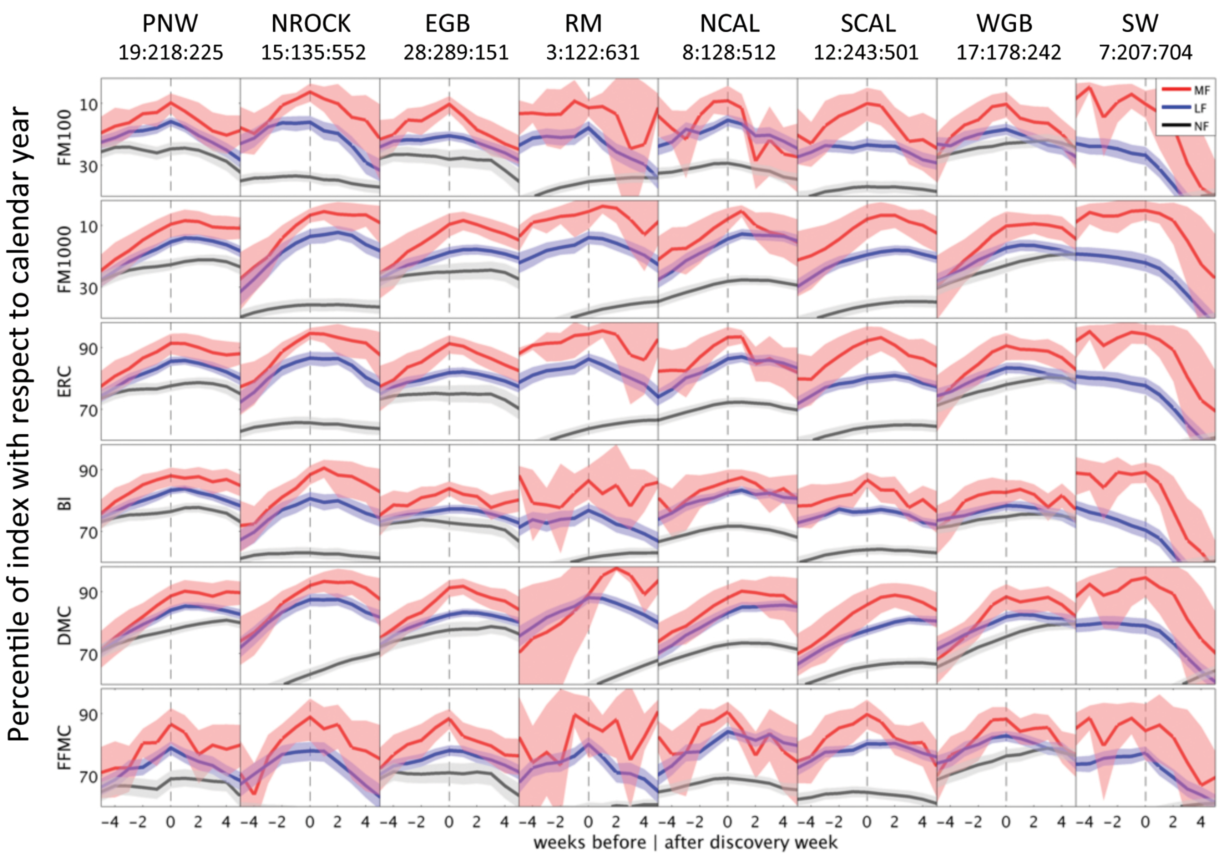

Figure 3.8.5. Weekly composite plots from six weeks prior to discovery of fire and six weeks following. Solid lines denote mean conditions where red is megafires, and blue is all other large fires (>405 ha), and gray is weeks in the fire season with no fire. The shaded regions represent a 95 percent confidence interval. The dashed line is the megafire week as defined by day of year, with week 1 = Jan 1-7. The x-axis shows weeks from discovery week. The lighter shaded regions denote the 95 percent confidence interval of the mean. The numbers at the top are the ratios of number of megafire weeks to number of large fire weeks to number of weeks with no fire.

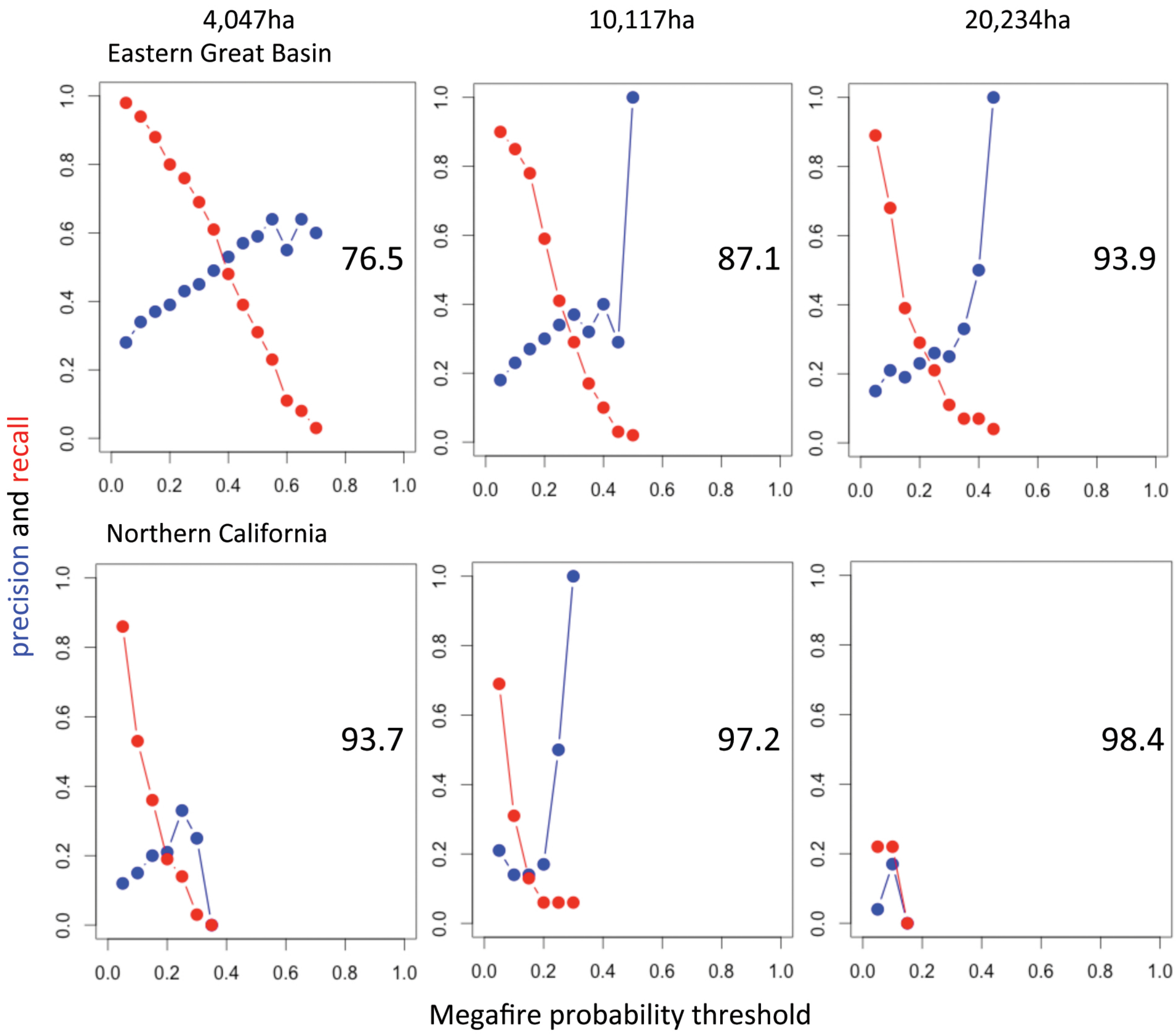

Figure 3.8.6. Trade-offs between precision and recall of two characteristic GACCs: Eastern Great Basin and Northern California, for each of the three megafire-size thresholds. The x-axis is the probability threshold for classifying a megafire (i.e. a probability >0.2 is a megafire). Blue represents normalized precision (how well do the models predict megafires), and red represents recall (how often do the models miss megafires that actually happened). The numbers on the right of each graph denote the percentage of non-megafire weeks. For a complete list of precision and recall values, see **Appendix**.

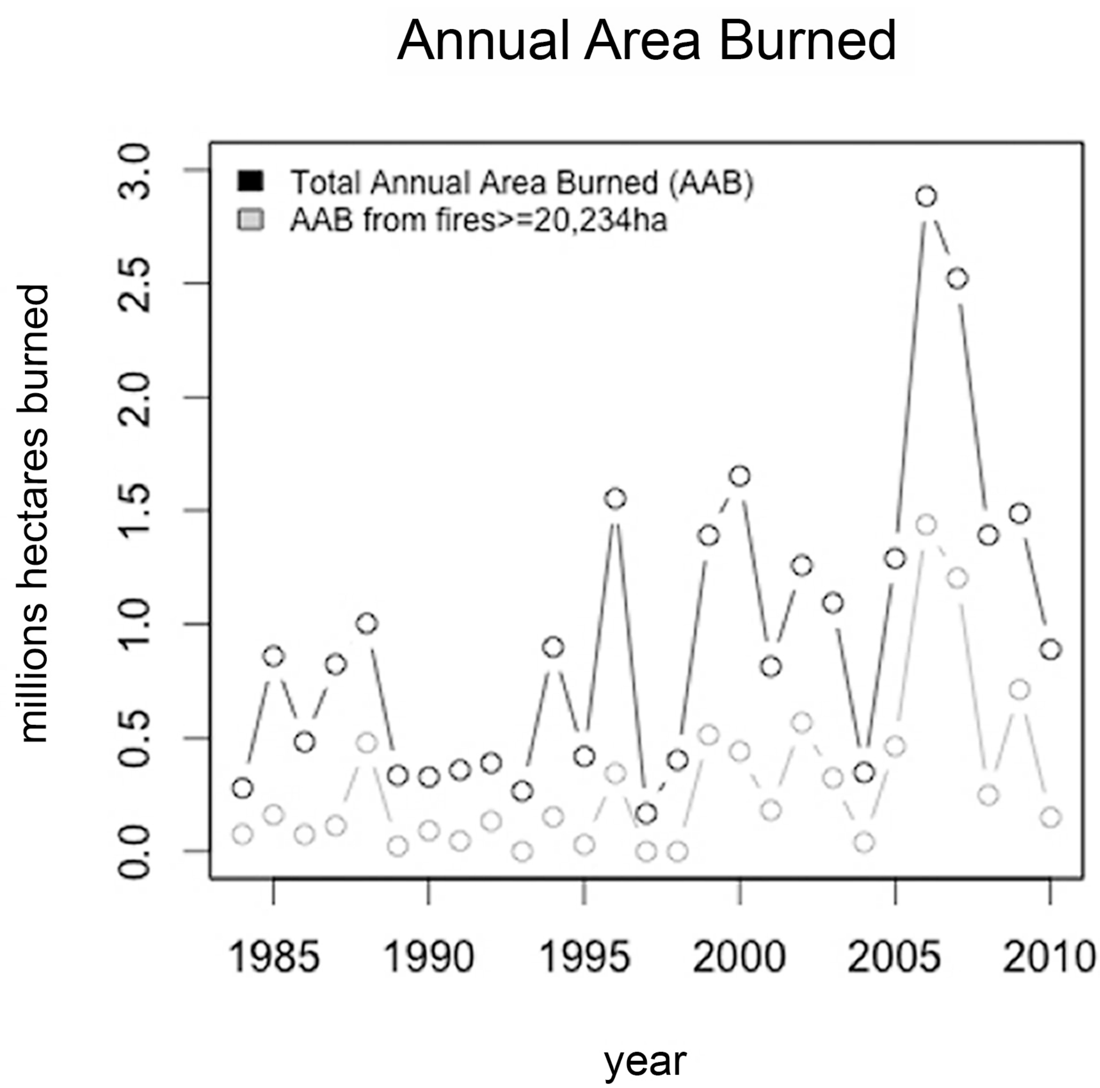

Figure 3.8.7. Proportion of annual area burned across the contiguous United States by megafires (gray) and by all large fires including megafires (black), by the criteria defined on this study. This illustrates that in many years, the largest fires constitute a substantial proportion of the annual area burned.

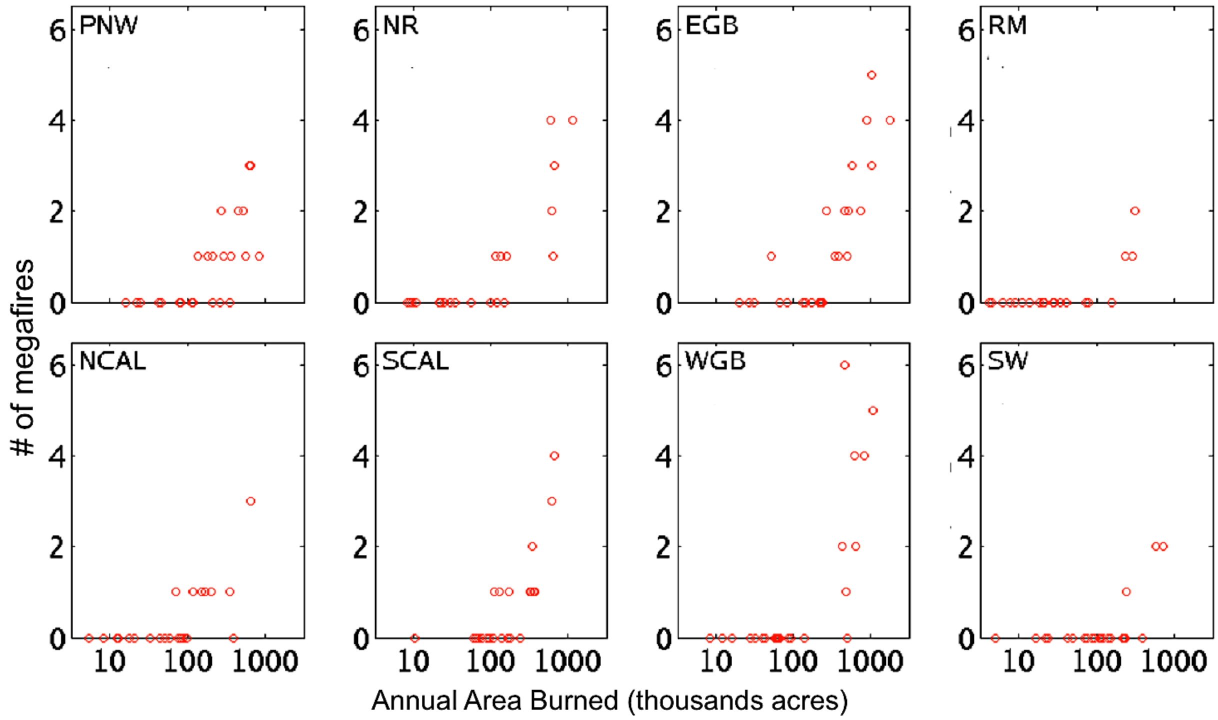

Figure 3.8.8. Scatterplot of annual area burned and number of megafires for each GACC.

3.9. Tables

Table 3.9.1. Contingency table structure and associated model accuracy statistics precision and recall. Recall = TP/(TP +FN) = p(predicting a megafire that is actually a megafire). Precision = TP/(TP + FP) = p(correctly classifying a megafire).

		observed	
		megafire	large fire
predicted	megafire	True Positive (TP)	False Positive (FP)
	large fire	False Negative (FN)	True Negative (TN)

Table 3.9.2. Models by GACC to calculate the probability of conditions during a given week being conducive for fire growth to megafire size. AUC is the area under the receiver operating characteristic curve.

Note: I defined explanatory variables as the calculated index averaged over the suffix such that ".1" denotes the week prior to discovery, ".dw" is the discovery week, and ".n#" is the number of weeks post discovery week. PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

GACC	Megafire Size (ha)	P(Megafire) = 1/(1+eb) where b =	AUC
EGB	20234	31.033 - 0.226*FFMC.dw - 0.260*TEMP.dw - 0.015*DMC.n3 - 0.238*PDSI.n1	0.84
NCAL	20234	-8.500 + 1.290*FM1000.n1	0.86
NROCK	20234	-13.951 - 0.309*BI.n3 + 0.672*FM100.dw + 0.334*FFMC.n1 + 0.026*DMC.dw - 0.366*TEMP.1	0.93
PNW	20234	6.664 - 0.514*TEMP.n1 + 0.468*FM1000.n1	0.86
RM	20234	11.930 - 0.057*DMC.n3	0.97
SCAL	20234	18.660 - 0.193*ERC.n1	0.80
SW	20234	8.430 - 0.017*DMC.dw	0.92
WGB	20234	-4.532 + 1.279*FM100.dw - 0.392*PDSI.dw	0.86

Table 3.9.3. Table of odds ratio, i.e. effect size, of each explanatory variable get GACC model. Odds ratio >1 indicates a positive relationship that an increase in the predictor results in an increase in the probability of a megafire week. Odds ratio <1 indicates a negative relationship that an increase in the predictor results in a decrease in the probability of a megafire week.

GACC	Explanatory Variables Odds Ratio					
EGB	variable	FFMC.dw	TEMP.dw	DMC.n3	PDSI.n1	
	odds ratio	1.25	1.3	1.01	1.27	
	95% CI	(0.98,1.61)	(1.05,1.60)	(1.00,1.03)	(1.02,1.58)	
NCAL	variable	FM1000.n1				
	odds ratio	0.28				
	95% CI	(0.12,0.64)				
NROCK	variable	BI.n3	FM100.dw	FFMC.n1	DMC.dw	TEMP.1
	odds ratio	1.36	0.51	0.72	0.97	1.44
	95% CI	(1.14,1.63)	(0.28,0.92)	(0.58,0.89)	(0.96,0.99)	(1.06,1.97)
PNW	variable	TEMP.n1	FM1000.n1			
	odds ratio	1.67	0.63			
	95% CI	(1.15,2.43)	(0.44,0.89)			
RM	variable	DMC.n3				
	odds ratio	1.06				
	95% CI	(1.02,1.10)				
SCAL	variable	ERC.n1				
	odds ratio	1.21				
	95% CI	(1.10,1.33)				
SW	variable	DMC.dw				
	odds ratio	1.02				
	95% CI	(1.01,1.02)				
WGB	variable	FM100.dw	PDSI.dw			
	odds ratio	0.28	1.48			
	95% CI	(0.15,0.50)	(1.15,1.90)			

Table 3.9.4. Models by GACC to calculate the probability of conditions during a given week being conducive for fire growth to megafire size for alternate size thresholds defining megafire. AUC is the area under the receiver operating characteristic curve.
Note: I defined explanatory variables as the calculated index averaged over the suffix such that ".1" denotes the week prior to discovery, ".dw" is the discovery week, and ".n#" is the number of weeks post discovery week. PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

GACC	Megafire Size (ha)	P(Megafire) = 1/(1+eb) where b =	AUC
EGB	10,117	0.004 + 0.501*FM1000.n3 - 0.165*TEMP.n1 - 0.181*PDSI.n3	0.78
	4,047	-1.393 + 0.550*FM1000.n2 - 0.161*TEMP.n1 - 0.202*PDSI.dw	0.80
NCAL	10,117	64.410 - 0.594*FFMC.dw - 0.120*BI.dw	0.84
	4,047	12.211 - 0.153*ERC.dw	0.79
NROCK	10,117	4.67 - 0.158*BI.n3 + 0.567*FM100.dw	0.93
	4,047	-8.822 - 0.192*BI.n2 + 0.133*FM100.dw + 0.278*FFMC.n1 - 0.021*DMC.n3 - 0.199*TEMP.n1	0.93
PNW	10,117	3.759 + 0.584*FM100.dw - 0.322*TEMP.n1 - 0.010*DMC.n3	0.88
	4,047	0.761 + 0.450*FM100.dw - 0.103*BI.n3	0.81
RM	10,117	9.640 - 0.045*DMC.n1	0.93
	4,047	1.450 - 0.033*DMC.n2 + 0.483*FM1000.1	0.92
SCAL	10,117	-1.53680 -0.158*ERC.n1 + 0.175*FFMC.1	0.75
	4,047	10.460 - 0.141*ERC.n1 + 0.101*TEMP.n3	0.74
SW	10,117	-2.938 + 0.753*FM1000.n2	0.89
	4,047	-1.500 + 0.599*FM1000.n1 - 0.080*TEMP.n3	0.86
WGB	10,117	14.596 - 0.012*DMC.dw - 0.180*TEMP.n2 - 0.345*PDSI.dw - 0.080*BI.n2	0.81
	4,047	40.910 - 0.366*FFMC.dw – 0.296*PDSI.dw - 0.069*BI.n2	0.76

Appendix

Tables of each GACC providing the numerical values of precision and recall given different probability thresholds for classifying a megafire. Percent Imbalance is the percent of non-megafire weeks in the analysis.

GACC		EGB					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		93.9		87.1		76.5	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.15	0.89	0.18	0.90	0.28	0.98
	0.10	0.21	0.68	0.23	0.85	0.34	0.94
	0.15	0.19	0.39	0.27	0.78	0.37	0.88
	0.20	0.23	0.29	0.30	0.59	0.39	0.80
	0.25	0.26	0.21	0.34	0.41	0.43	0.76
	0.30	0.25	0.11	0.37	0.29	0.45	0.69
	0.35	0.33	0.07	0.32	0.17	0.49	0.61
	0.40	0.50	0.07	0.40	0.10	0.53	0.48
	0.45	1.00	0.04	0.29	0.03	0.57	0.39
	0.50			1.00	0.02	0.59	0.31
	0.55					0.64	0.23
	0.60					0.55	0.11
	0.65					0.64	0.08
	0.70					0.60	0.03
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		NCAL					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		98.4		97.2		93.7	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.04	0.22	0.21	0.69	0.12	0.86
	0.10	0.17	0.22	0.14	0.31	0.15	0.53
	0.15	0.00	0.00	0.14	0.13	0.20	0.36
	0.20			0.17	0.06	0.21	0.19
	0.25			0.50	0.06	0.33	0.14
	0.30			1.00	0.06	0.25	0.03
	0.35					0.00	0.00
	0.40						
	0.45						
	0.50						
	0.55						
	0.60						
	0.65						
	0.70						
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		NROCK					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		97.0		94.4		91.5	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.18	0.81	0.23	0.90	0.27	0.89
	0.10	0.26	0.75	0.29	0.80	0.33	0.78
	0.15	0.32	0.69	0.37	0.73	0.39	0.72
	0.20	0.42	0.59	0.39	0.63	0.46	0.70
	0.25	0.35	0.44	0.42	0.57	0.51	0.65
	0.30	0.50	0.38	0.44	0.50	0.55	0.63
	0.35	0.67	0.25	0.52	0.47	0.54	0.56
	0.40	0.67	0.25	0.62	0.43	0.58	0.50
	0.45	0.80	0.25	0.67	0.40	0.63	0.48
	0.50	0.80	0.25	0.64	0.30	0.71	0.44
	0.55	1.00	0.25	0.56	0.17	0.83	0.41
	0.60	1.00	0.25	0.67	0.13	0.81	0.37
	0.65	1.00	0.19	0.60	0.10	0.88	0.30
	0.70	1.00	0.06	1.00	0.10	0.92	0.26
	0.75	1.00	0.06	1.00	0.07	1.00	0.17
	0.80					1.00	0.11
	0.85					1.00	0.09
	0.90						
	0.95						
	1.00						

Appendix

GACC		PNW					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		95.8		91.7		80.8	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.12	0.83	0.21	0.94	0.25	0.95
	0.10	0.18	0.61	0.24	0.78	0.29	0.90
	0.15	0.21	0.33	0.27	0.61	0.35	0.86
	0.20	0.21	0.17	0.32	0.53	0.38	0.78
	0.25	0.22	0.11	0.33	0.39	0.44	0.71
	0.30	0.00	0.00	0.34	0.33	0.46	0.58
	0.35	0.00	0.00	0.44	0.33	0.51	0.53
	0.40			0.50	0.31	0.51	0.39
	0.45			0.53	0.25	0.57	0.31
	0.50			0.83	0.14	0.61	0.27
	0.55			0.75	0.08	0.61	0.13
	0.60			0.67	0.06	0.60	0.07
	0.65			1.00	0.03	0.60	0.04
	0.70					0.00	0.00
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		RM					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		99.5		98.9		96.9	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.00	0.00	0.13	0.57	0.20	0.84
	0.10	0.00	0.00	0.13	0.29	0.25	0.74
	0.15	0.00	0.00	0.22	0.29	0.29	0.58
	0.20	0.00	0.00	0.00	0.00	0.29	0.32
	0.25			0.00	0.00	0.33	0.26
	0.30			0.00	0.00	0.40	0.21
	0.35			0.00	0.00	0.50	0.21
	0.40					0.50	0.16
	0.45					0.50	0.11
	0.50					0.50	0.11
	0.55					0.33	0.05
	0.60					0.33	0.05
	0.65					0.33	0.05
	0.70					0.50	0.05
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		SCAL					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		98.0		95.4		90.2	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.09	0.50	0.10	0.72	0.14	0.93
	0.10	0.27	0.29	0.18	0.41	0.17	0.67
	0.15	0.29	0.14	0.28	0.22	0.20	0.44
	0.20	0.20	0.07	0.39	0.16	0.28	0.30
	0.25	0.00	0.00	0.17	0.03	0.31	0.16
	0.30			0.00	0.00	0.35	0.10
	0.35					0.46	0.07
	0.40					0.38	0.04
	0.45					0.50	0.01
	0.50						
	0.55						
	0.60						
	0.65						
	0.70						
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		SW					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		99.1		97.4		90.9	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.13	0.43	0.12	0.76	0.21	0.93
	0.10	0.18	0.29	0.10	0.29	0.27	0.87
	0.15	0.17	0.14	0.10	0.14	0.29	0.68
	0.20	0.25	0.14	0.23	0.14	0.31	0.53
	0.25	0.33	0.14	0.50	0.10	0.32	0.43
	0.30	0.33	0.14			0.35	0.37
	0.35	0.00	0.00			0.36	0.28
	0.40					0.41	0.19
	0.45					0.57	0.16
	0.50					0.69	0.12
	0.55					0.88	0.10
	0.60					1.00	0.03
	0.65						
	0.70						
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Appendix

GACC		WGB					
Megafire Size (ha)		20,234		10,117		4,047	
Percent Imbalance		96.3		92.6		84.2	
Accuracy Statistic		precision	recall	precision	recall	precision	recall
Probability Threshold (for classifying a megafire)	0.05	0.12	0.67	0.15	0.90	0.19	0.98
	0.10	0.21	0.47	0.21	0.60	0.23	0.89
	0.15	0.27	0.40	0.25	0.40	0.27	0.73
	0.20	0.31	0.33	0.31	0.37	0.30	0.59
	0.25	0.30	0.20	0.32	0.27	0.39	0.50
	0.30	0.50	0.13	0.40	0.20	0.52	0.34
	0.35	0.33	0.07	0.33	0.10	0.47	0.22
	0.40	0.33	0.07	0.33	0.10	0.50	0.14
	0.45	0.00	0.00	0.33	0.07	0.43	0.09
	0.50	0.00	0.00	0.00	0.00	0.40	0.06
	0.55			0.00	0.00	0.17	0.02
	0.60					0.00	0.00
	0.65					0.00	0.00
	0.70					0.00	0.00
	0.75						
	0.80						
	0.85						
	0.90						
	0.95						
	1.00						

Chapter 4

Regional projections of the likelihood of megafires under a changing climate in the contiguous Western United States

This work is adapted for submission: Stavros EN, Abatzoglou J, Larkin NK, McKenzie D (2013) Regional projections of the likelihood of megafires under a changing climate in the contiguous Western United States. *Climatic Change*.

4.1. Summary

A warming climate will likely increase wildfire activity. To anticipate future fire events, projections of individual fires are necessary. Wildfires that account for a disproportionate amount of damage are classified as megafires, here defined quantitatively as fires that burn ≥ 50,000 ac ~ 20,234 ha. This research evaluates long-term and seasonal changes in the climatic potential for megafire occurrence across the western contiguous United States using binomial regression models projected onto two Intergovernmental Panel on Climate Change representative concentration pathways (RCPs). The Eastern Great Basin, the Northern Rockies, the Pacific Northwest, the Rocky Mountains, and the Southwest show increasing proportional changes over time in the probability of a megafire. There was a significant ($p \leq 0.05$) difference between the historical modeled ensemble mean proportional difference in megafire probability from 1979-2010 and both RCP 4.5 and 8.5 means during 2031-2060. Generally, with the exception of the Southwest and Northern California, there are higher probabilities of megafire occurrence more frequently and for longer periods both throughout the fire season and from year to year, with more pronounced patterns under RCP 8.5 than RCP 4.5. My results provide a quantitative foundation for management strategies to mitigate the effects of megafires.

4.2. Introduction

In a warming climate, we expect increases in lightning ignition (Price and Rind 1994), area burned (Flannigan et al. 2009, Littell et al. 2010), fire intensity (Flannigan et al. 1998, Liu et al. 2013), and severity (Flannigan et al. 2013). Wildfires can have substantial ecological, social, and economic effects. However, the many studies that project annual averages of area burned (Westerling et al. 2002, McKenzie et al. 2004, Flannigan et al. 2005, Flannigan et al. 2009, Littell et al. 2009) or the potential for fire occurrence (Parisien et al. 2012), do not capture fire-climate relationships at a temporal resolution suitable for predicting individual fire events. Individual fire events are challenging to predict (Chapter 3), but if it is done successfully it can provide key information necessary for facilitating fire management in mitigating the effects of wildfire.

Ecological, social, and economic effects of wildfires include ecosystem effects, property loss especially along the wildland urban interface (WUI), destruction of natural resources, significant degradation of air quality (Jaffe et al. 2008), suppression expenditures (Calkin et al. 2005), and loss of human life. Also, wildfires are a part of a feedback loop between climate, wildfire, and air quality (Chapter 2) as they produce carbon emissions and aerosols that contribute to global warming (Bond et al. 2013). Individual wildfires that cause significant damage are classified as "megafires". Although the term megafire can have socio-political connotations, I use a simple quantitative definition of megafire, assuming these effects, as wildfires ≥ 50,000 acres ~ 20,234 hectares (Chapter 3).

Understanding the potential for megafires in the future is important for both planning and mitigation. Megafires may be unavoidable, but projecting models of megafire climatic drivers (Chapter 3) into the future can identify spatial and temporal patterns of increased potential of megafire, thereby controlling risk, enhancing opportunities for management, and developing policy using both direct and indirect strategies. Direct strategies include fuel management and fire suppression. Areas with large-scale fuel reduction have successfully reduced "suppression costs, private property loss, environmental damages, and wildfire fatalities" over the long-term from megafire events (Williams 2013). If we can determine where and when megafires are more likely in the future, then we can allocate resources proactively to regions most at risk. Although megafires, by definition, are wildfires that escape initial and extended suppression efforts, it may be possible to suppress smaller fires that might become megafires when the likelihood is very high (Podur and Wotton 2011, Tedim et al. 2013), provided that multiple megafires in a region do not constrain suppression resources. Indirect strategies to mitigate the effects of megafires include, for example, reducing anthropogenic emissions (e.g., fossil fuels), so that when there is a wildfire, more emissions must occur before exceeding air-quality standards (Bedsworth 2011).

For this study, I examine three fundamental questions about the future likelihood of megafire occurrence at scales appropriate for management and policy planning using models developed by Stavros (2013a). First, will megafires be more likely in the future? Second, will seasons of increased likelihood of megafire change (e.g., timing and duration of the season) in the future? Third, how will key climate predictors of megafire change across space in the future?

4.3. Data and methods

4.3.1. Study area

The analysis is divided regionally based on existing operational management in the western contiguous United States. Regions are defined by the firefighting command centers, Geographic Area Coordination Centers (GACC), run by the U.S. National Interagency Fire Center (**Figure 4.7.1**, last acquired 1 Oct 2011 from http://psgeodata.fs.fed.us/download.html/GACC_2009.zip). Aggregating to this broad spatial scale assumes homogeneity of fire regimes, vegetation, climate, and weather within the GACC; discussion of what these assumptions mean for our results and interpretation is given in Section 4.5.2. GACCs are used for operational decision-making and regional forecasting in air-quality management. There are eight GACCs in the study area: Southern California (SCAL), Northern California (NCAL), Pacific Northwest (PNW), Northern Rockies (NROCK), Rocky Mountains (RM), Western Great Basin (WGB), Eastern Great Basin (EGB), and the Southwest (SW). To focus the analysis on wildfires, I excluded Predictive Service Areas (PSAs), subdivisions of GACCs, within each GACC for which large fires are primarily agricultural, notably within the Great Plains (defined by the Terrestrial Ecoregion L1 boundaries, Olson et al. 2001).

4.3.2. Climate Data

The study uses observed climate data over 1979-2010 and modeled climate data from 14 Global Climate Models (GCMs) over 1979-2099. Using the same data set as Abatzoglou and Kolden (2013), climate data over the observed period 1979-2010 comes from two gridded data sets: (1) 800-m monthly temperature and precipitation from Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly et al. 2008), and (2) 4-km daily surface meteorology from Abatzoglou (2013).

Climate predictions have three sources of uncertainty: model uncertainty, scenario uncertainty, and internal variability (Hawkins and Sutton et al. 2009). To address model uncertainty, this analysis uses 14 global climate models (GCMs, **Table 4.8.1**). By examining ensembles from the 14 models rather than on any one model, I focus on trends rather than internal temporal variability in projections of the climate system. To include a range of scenarios, future modeled climate data come from 14 GCMs under two future scenarios: representative concentration pathways (RCPs) 4.5 and 8.5 for 2010 to 2099. RCPs are the new set of scenarios introduced for the upcoming fifth Intergovernmental Panel on Climate Change Assessment Report. These two RCPs are representative of the larger set used by IPCC, and are back-engineered from cumulative radiative forcing in 2100, in watts per square meter (van Vuuren et al. 2011). In RCP 4.5, total radiative forcing is stabilized before 2100. Clarke et al. (2007) and Wise et al. (2009) detail the associated drivers, technology strategies, and land use and terrestrial carbon emissions. In RCP 8.5, greenhouse gas emissions continue to increase through the 21st century. Riahi et al. (2007) details the underlying scenario drivers and the resulting development path of the older SRES A2r scenario (Nakicenowicz and Swart 2000) from which RCP 8.5 is based.

From the gridded climate datasets, the Palmer Drought Severity Index (PDSI, a metric of drought believed to track soil moisture) and six indices from the United States National Fire Danger Rating System (NFDRS, using fuel model G) and the Canadian Forest Fire Danger Rating System (CFFDRS) were available. Indices from NFDRS include the moisture content of fuels 2.5-7.6 centimeters in diameter (100-hour fuel moisture- FM100), the moisture content of fuels 7.6-15.2 centimeters in diameter (1000-hour fuel moisture- FM1000), how hot a fire could burn (energy release component- ERC), and the potential difficulty of controlling a fire as a function of spread rate and ERC (burning index- BI). Indices from CFFDRS include the relative ease of ignition and flammability of fine fuels (fine fuel moisture content- FFMC), and the average moisture of loosely compacted organic layers (duff moisture code- DMC). For all indices but FM100 and FM1000, the higher the index value, the higher the fire danger.

Because the cumulative distribution function of simulated data may be different from the observed, modeled data were bias-corrected. I received the climate data sets bias-corrected for both historical and future simulated data to match quantiles of the observed cumulative distribution function, using a non-parametric quantile mapping transformation (Michelangeli et al. 2009). Bias correction was also applied on the calculated indices. The calculated fire danger indices were bias-corrected to match the quantiles of the downscaled data over the historical model runs to the observed data. The same transformation was applied to future projections with the assumption that any biases are stationary in time, thereby preserving the differences between the projections and historical model runs.

4.3.3. Methods

To investigate the three questions posed for this analysis, I use time-series plots, Welch's t-test comparisons of the historical to the future, contour plots of how the probability of a megafire varies by season and by year, and spatial GIS mapping of key megafire predictors. First, I define megafire quantitatively as wildfires ≥ 50,000 acres ~ 20,234 hectares in keeping with Chapter 2. Climate data were then integrated into megafire models defined per GACC, thereby projecting the probability that in a given week, a megafire will occur (**Table 4.8.2**, Chapter 3). The models produced in Chapter 2 were selected because they focus explicitly on extremely large wildfires.

To compare the observed likelihood of megafire to the future, I examined time series of the proportional change in probabilities and performed Welch's t-test for statistical comparison. For each RCP ensemble from 1979 to 2099 and for the observed ensemble 1979 to 2010, I used five-year moving averages each divided by the mean of the observed record to determine the proportional change in probability. Future proportional change projections for 2031-2060 were then compared both as ensembles and by individual GCMs to the historical modeled proportional change using Welch's pairwise t-test assuming unequal variances. I chose 2031-2060 for two reasons. First, the mean from 2010-2030 is very similar between future scenarios and I wanted projections far enough into the future to detect any changes and capture the differences between a radiative forcing of 4.5 versus 8.5 Wm^{-2}. Second, as I project into the future beyond 2060, there is more uncertainty associated with vegetation shifts and its feedback to fire climatology that may change the climate-megafire associations used to build the models in this analysis. Nevertheless, time series were extended out to 2100 to capture the full potential difference qualitatively in probability of a megafire between RCP scenarios.

Two other analyses included (1) a plot of megafire seasonality and (2) the spatial distribution of the change in climate space from the observed record to the future. First, I plotted seasonality by examining the probability of a megafire by week of year (y-axis) for each year from 1979 to 2010 (x-axis). Second, I examined the spatial distribution in the change of climate space by plotting the change in all calculated indices across the domain from the baseline conditions (1979-2010) to the future RCP 4.5 scenario for 2031-2060. For qualitative analysis of the climate space, I used RCP 4.5 as it is a more conservative representation of any future changes that may occur. I examined both the change in mean calculated index for months June to September between the future and the baseline period, and frequency of extremes. Regions where fewer than ten of the 14 models agree on the sign of change were excluded from the analysis. To see changes in extreme climate, I used the percentage change in days or months (depending on the predictor variable) with extreme conditions. Extreme conditions are defined as exceeding the upper decile of the observed calculated index from 1979-2010 for ERC, BI, FFMC, DMC and Temperature. Because large fires have a proclivity for occurring during drought and low fuel moisture, the bottom decile was used as the threshold for classifying extreme for FM100, FM1000, and PDSI.

4.4. Results

4.4.1. Long-term temporal change

Five of the eight GACCs show relatively steep positive slopes in the long-term trend in probability of megafire regardless of the future scenario used (**Figure 4.7.2**). The GACCs that do show positive slopes in the trend of proportional change of the probability of a megafire are the EGB, the NROCK, the PNW, the RM, and the SW. These GACCs have much more variability in predicted probabilities by model than those that do not show such changes. NCAL, SCAL, and WGB ensembles do not show steep slopes in proportional change in the probability of a megafire, and appear to have one or two models as outliers. This is particularly true for future scenario RCP 8.5. Inter-decadal variability is well captured by individual GCMs and the projected probabilities. The historical modeled probabilities show more inter-decadal variability than do the observed, with the exception of the NROCK and RM. The NROCK shows periodic increases and decreases in the observed probability of a megafire. In the RM, however, inter-decadal variability is visible when probabilities are fit to individual GCMs, but not for the ensemble mean.

The proportional change in the mean probabilities for the future was significantly different from the proportional change in the historical modeled mean for all GACCs (**Table 4.8.3**). In all but the SW GACC, means increased from the historical modeled probabilities to RCP 4.5 and then to RCP 8.5. In the SW, RCP 4.5 has a slightly higher mean proportional change in the probability of a megafire than the mean for RCP 8.5. Examining **Figure 4.7.2** shows that RCP 8.5 begins to exceed the proportional change projected by RCP 4.5 towards the end of the period over which the means were calculated. For all these observations, we see strong model agreement in that the difference observed between the ensembles is true for at least 9 of the 14 GCMs, with the exceptions of NCAL and RM for RCP 8.5.

The baseline period from 1979 to 2010 showed significant ($p<0.05$) differences between the historical modeled ensemble and the observed probabilities for the EGB, PNW, RM, and WGB GACCs. With the exception of the RM, these GACCs had high agreement among GCMs that there was a significant difference between the historical modeled divided by the mean observed and the observed probabilities divided by the mean observed.

4.4.2. Annual temporal change

There is variation in how the probability of megafire will change by GACC, but in general, both throughout the fire season and from year to year, the likelihood of a megafire is higher and more frequent in the future than from the baseline (**Figure 4.7.3**). With the exception of NCAL, the likelihood of a megafire is more frequent under RCP 4.5, and more exaggerated under RCP 8.5.

In EGB, NROCK, and PNW, the likelihood of megafire increases in magnitude, frequency within a year, and length of megafire season under both RCP 4.5 and RCP 8.5. Under RCP 4.5, we see increased probabilities throughout the fire season of each year that continue increasing into the future. This trend is more pronounced under RCP 8.5. Over the baseline period and under RCP 4.5, the season for megafire is between mid-June to early August, but under RCP 8.5 the season lengthens from early June to early October.

Similarly to the EGB, NROCK, and PNW, the RM and SCAL show increased likelihood of a megafire more frequently within a fire season and from year to year. The fire season typically covers early June through early September under RCP 4.5, but extends as late as October under RCP 8.5. The magnitude of increased probability is not as exaggerated as EGB, NROCK, and PNW, however, and follows a less consistent pattern both throughout the season and from year to year.

In the SW, the length of the megafire season remains consistent, but the likelihood of a megafire is higher, and more frequent both throughout the season and from year to year. In the WGB, the fire season lengthens and shows increased consistency in increased probability of a megafire both throughout the megafire season and from year to year. The megafire season for 1979-2010 was from late June through July, but under both future RCP 4.5 and RCP 8.5 it extends from early June through mid to late August. NCAL shows no indication under either RCP 4.5 or RCP 8.5 that the fire season length or consistency of increased probability of megafire will change. This may because the availability of fire prone areas is projected to retreat in some areas of NCAL in the future (Krawchuk et al. 2009).

4.4.3. Changes in the climate space

We examined spatial patterns of the change in climate space by examining changes in the means of calculated indices and in changes in the frequency of extreme conditions. The spatial patterns of change in the mean of climatic indices from 1979 to 2010 and the mean from 2031 to 2060 are not universal, but patterns that do exist do not have strong model agreement (**Figure 4.7.4**). Increases in the number of days or months of extreme climate are more universal with more model agreement than the change in means of predictors of megafire (**Figure 4.7.5**). For most predictors of megafire by GACCs, there is either no change or an increase in the frequency of exceeding the decile threshold classified as “extreme” from 1979-2010 to 3031-2060, but there are areas where more than three of the 14 GCM models disagree on such increases.

4.5. Discussion

4.5.1. Long-term trends and seasonal change

Although studies have projected annual area burned under a changing climate space (Flannigan et al. 2009, Littell et al. 2010), these do not specifically address the likelihood of megafire events, which constitute a disproportionate amount of annual area burned and have long-lasting social and environmental effects. By understanding the effect of climate on the occurrence of megafires specifically, management can allocate resources more appropriately than from annual-scale projections of area burned potential. We used previously developed logistic regression models on each of the eight GACCs in the western contiguous US (**Table 4.8.2**, Chapter 3) to explore long-term trends of and seasonal changes in the likelihood of megafire occurrence.

In general, all GACCs show a significantly ($p<0.05$) increased potential for megafire occurrence from the baseline period 1979-2010 to the future 2031-2060 under both RCP 4.5 and again under RCP 8.5. In the SW, however, the proportional change in mean probability of a megafire is not greater under RCP 8.5 (**Figure 4.7.2**) until after 2070 when the scenarios diverge and radiative forcing continues to increase under RCP 8.5. Results show periodic fluctuations in climate being reflected in the changing probability of a megafire, although attributing probabilities to specific future years would constitute false precision that ignores the stochastic elements in climate models. Mapping the proportional change in probability of a megafire across 14 GCMs (**Figure 4.7.2**) shows the worst and best case scenarios. GACCs with the largest spread of projected proportional change, EGB, NROCK, PNW, RM, and SW, generally have the most models that agree that megafires will be more likely in the future. This is in conceptual agreement with Kitzberger et al. (2012) who found that fire size distributions (log-transformed) shifted to more large fires as climatic variability increased. It is worth noting, however, that the EGB, PNW, RM, and WGB show significant differences between the 14 GCM ensemble mean probability and the observed. Of these models, RM does not have high model agreement of this difference. Down-scaled GCM meteorological data used in the models for this analysis, over predict the probability of a megafire for the EGB, PNW, and the WGB. Consequently, assuming stationarity, these models of the likelihood of megafire over-predict the likelihood of megafire.

A unique feature of this study is that it specifically projects the likelihood of individual megafires rather than the aggregate statistic of annual area burned. By temporally partitioning the probability into seasonality of megafires, and further into megafire weeks, we enable more timely anticipation of megafire events. Projecting models into the future, there is variation in how the probability of megafire will change seasonally by GACC, but generally (with the exception of the SW and NCAL) the likelihood of a megafire is higher more frequently both within a fire season and from year to year. Patterns are generally more pronounced for RCP 8.5 than RCP 4.5.

With enhanced predictability of individual events, we can draw on proposed mechanisms for increased future wildfire to improve megafire predictions. For example, one hypothesis about future fire season in the western United States is that warming temperatures will facilitate earlier snow-melt and green-up, desiccating fuels earlier and creating a longer fire season (Westerling et al. 2006). Spatial variation in earlier snowmelt could be used to refine predictions of the onset of conditions conducive to megafires, complementing more volatile predictors like fire-danger indices, which only rarely can be estimated more than a few days in advance.

4.5.2. Projection considerations

There are two key limitations to our projections. First, biophysical variables provide better correlations for fire potential than do individual variables like temperature and precipitation (Abatzoglou and Kolden 2013), but their calculation uses temperature, precipitation, relative humidity, and wind (Xiao-rui et al. 2005), not all of which are estimated with the same certainty by climate models (IPCC 2007). Second, the response of vegetation and wildfire patterns to climate change is not simple. For example, extreme environments are unsuitable for wildfire (Parisien and Moritz 2009), e.g., very hot and dry climates that lack fuel connectivity to carry wildfire or cold and wet climates where fuels are rarely flammable. Further complicating future fire climatology is uncertainty about how vegetation, and the fire regimes it supports (Abatzoglou and Kolden 2013), will change (McKenzie and Littell 2011). Such uncertainties could affect megafire-climate correlations, weakening or changing the predictors used to calculate the probability of megafire.

Generally, the climate space for each GACC is expected to have more days and months with “extreme” conditions than the observed period. Because GCMs have varying degrees of uncertainty, especially for moisture metrics, there are places where at least three GCMs produce inconsistent results from the rest and do not agree that days and months with extreme conditions will increase. The EGB, PNW, NROCK RM, and the SW experienced at least a 150% increase in the mean proportional change in probability of a megafire (**Table 4.8.3**). The PNW and RM both have over a four-fold increase in probability of a megafire, and are both classified as areas with a flammability-limited fire regime (Littell et al. 2009, Chapter 3). Consequently, these areas require hot and dry weather for fire to occur. It follows logically that as the climatic extremes of hot and dry become more likely in these areas, there will also be more fire. The EGB, NROCK and SW have mixed fire regimes constituting both fuel and flammability limited (Littell et al.

2009). It is likely that the increase in probability of a megafire is driven by areas within the GACC that are flammability limited, but such inference lies beyond the scope of this study. SCAL, NCAL, and the WGB have a less steep change in probability of a megafire. Non-forested areas within these GACCs are mostly fuel limited (Littell et al. 2009, Chapter 3, Abatzoglou and Kolden 2013). Consequently, more days of extremely hot and dry conditions are unlikely to increase the probability of a megafire, which in these GACCs depends on fuel connectivity. This supports the hypothesis by Parisien and Moritz (2009) that wildfire is less likely under climatic extremes.

The change in climate space with regard to changes in the mean predictors of megafire, specific to each GACC, is much less agreed upon across GCMs than percentage change in days or months with "extreme climate". Other studies have found similar shifts in the distribution of extreme climate with an increase in temperatures at the high end of the probability distribution (Hansen et al. 2012). Probable explanations for more pronounced and agreed upon changes in extremes versus means are that the fire season means were defined from June to September, but not all GACCs have such a long fire season (e.g. NROCK, EGB, and PNW (Abatzoglou and Kolden 2013)), nor does this period capture the peak fire season for all GACCs (e.g. SW). Consequently, the means may be "washed-out", whereas the extremes are counts of days or months with conditions exceeding a threshold. Calculated values of extremes are less certain and may not be as well defined because they reside in the tail of the distribution with many fewer samples.

4.6. Conclusions

Because megafires have lasting and damaging effects socially and environmentally, understanding future changes can inform decision makers on how best to prepare for such events. This analysis, the first of its kind over the western contiguous US, addresses key questions about how the likelihood of megafires is projected to change over the 21st century. Unlike other studies that project annual area burned (Flannigan et al. 2005, Littell et al. 2010) into the future, this study focuses on how the climatic potential for megafires changes both seasonally and over the 21st century.

In general, across the western contiguous US, the likelihood of a megafire will both increase over the long-term, but also in duration and frequency throughout the fire season. Specifically, my analysis showed that the climatic potential of a megafire will increase through the 21st century in the Eastern Great Basin, the Northern Rockies, the Pacific Northwest, the Rocky Mountains, and the Southwest. For all eight GACCs within the domain, there was a significant ($p \leq 0.05$) difference between the historical modeled ensemble mean megafire probability during 1979 to 2010 and the mean for both RCP 4.5 and 8.5 during 2031 to 2060. With the exception of the Southwest and Northern California, our results show more frequent and longer durations of increased probability of megafire occurrence both throughout the fire season and from year to year, with more pronounced patterns under RCP 8.5 than RCP 4.5.

Although these models may not predict actual megafire occurrence, rather the climatic potential for a megafire, these results can be used to shape new fire policy including fuel and air-quality management. Large-scale fuel management may mitigate the effects of megafires (Williams 2013) because high biomass and fuel accumulations also contribute to megafires. Areas with previous fuel treatments have lower tree mortality with decreased fire behavior and reduced spread rates (Williams 2013), thus large-scale fuel reduction may reduce suppression costs, private property loss, environmental damages, and fatalities from megafires (Williams 2013). Fuel treatments, depending on the relationship between fire hazard and stand age, may also suppress a cycle of megafires as they provide fuel breaks, preventing large burned areas from regenerating into even-aged stands (Williams 2013). This work can also aid air-quality policy. Because this work is at a broad spatial scale and uses climate data at fine temporal resolution, it can be integrated into air quality modeling frameworks, e.g. BlueSky (Larkin et al. 2009), to understand potential effects of megafires on regulated air quality.

There are still many questions, however, that should be addressed moving forward. First, what is the effect of multiple disturbances on the likelihood of megafire? For example, beetle kill, which is affected by climate, can increase fuel availability and connectivity affecting wildfire patterns (Lynch et al. 2006, Jenkins 2008). Second, how does uncertainty in GCM projections affect the projected probabilities of megafire? This question arises when considering that moisture-specific metrics, many of which are incorporated into the probability models, are less robust than temperature-specific metrics. Future research could partition the variance found in projected probabilities to investigate this uncertainty. Third, the IPCC scenarios used in this analysis represent target radiative forcing per square meter, such that many combinations of different population growth, technological developments, and land-use scenarios meet the same RCP "budget", whose differing components may affect the probability of megafire beyond that which can be predicted by examining the climatic potential for a megafire (D'Andrea et al. 2010). Further investigation is required to understand how these components will interact to affect the occurrence of megafires. The projections from this study can still be used as a baseline for future research and policy and management decision-making.

4.7. Figures

Figure 4.7.1. The study domain over the western contiguous United States, divided by Geographic Area Coordination Centers (GACCs), excluding subsections of GACCs with predominantly agricultural fires, represented here as white areas within the GACCs.

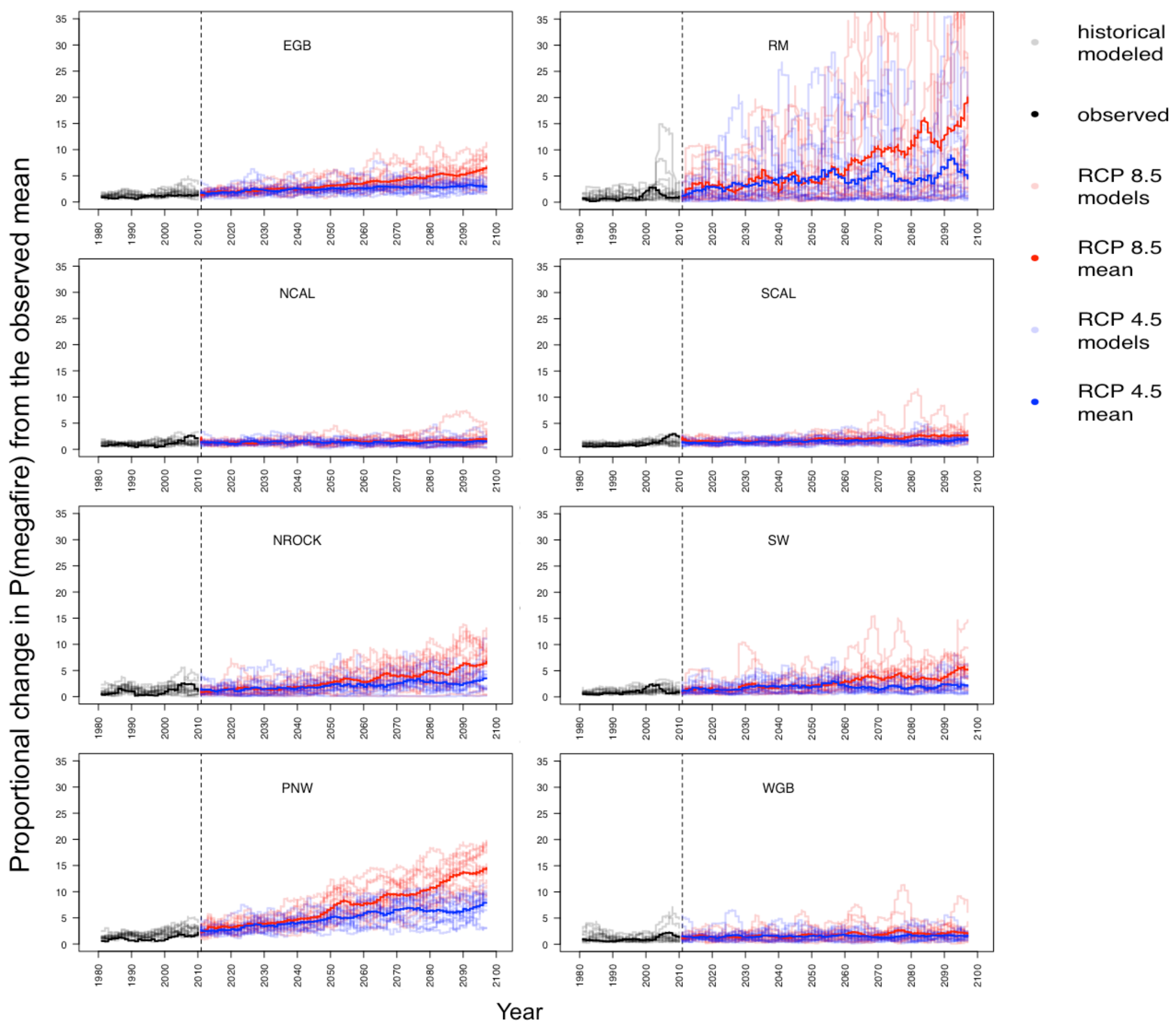

Figure 4.7.2. Proportional change of the probability that in a given week a megafire will occur from the observed mean probability. The plots show a five-year moving average. Dashed vertical lines denote the from modeled values from the observed period (1979-2010) to those from the future (2011-2099). Each shaded line denotes one of 14 GCMs used, and the bold line denotes the ensemble mean of all 14 models.

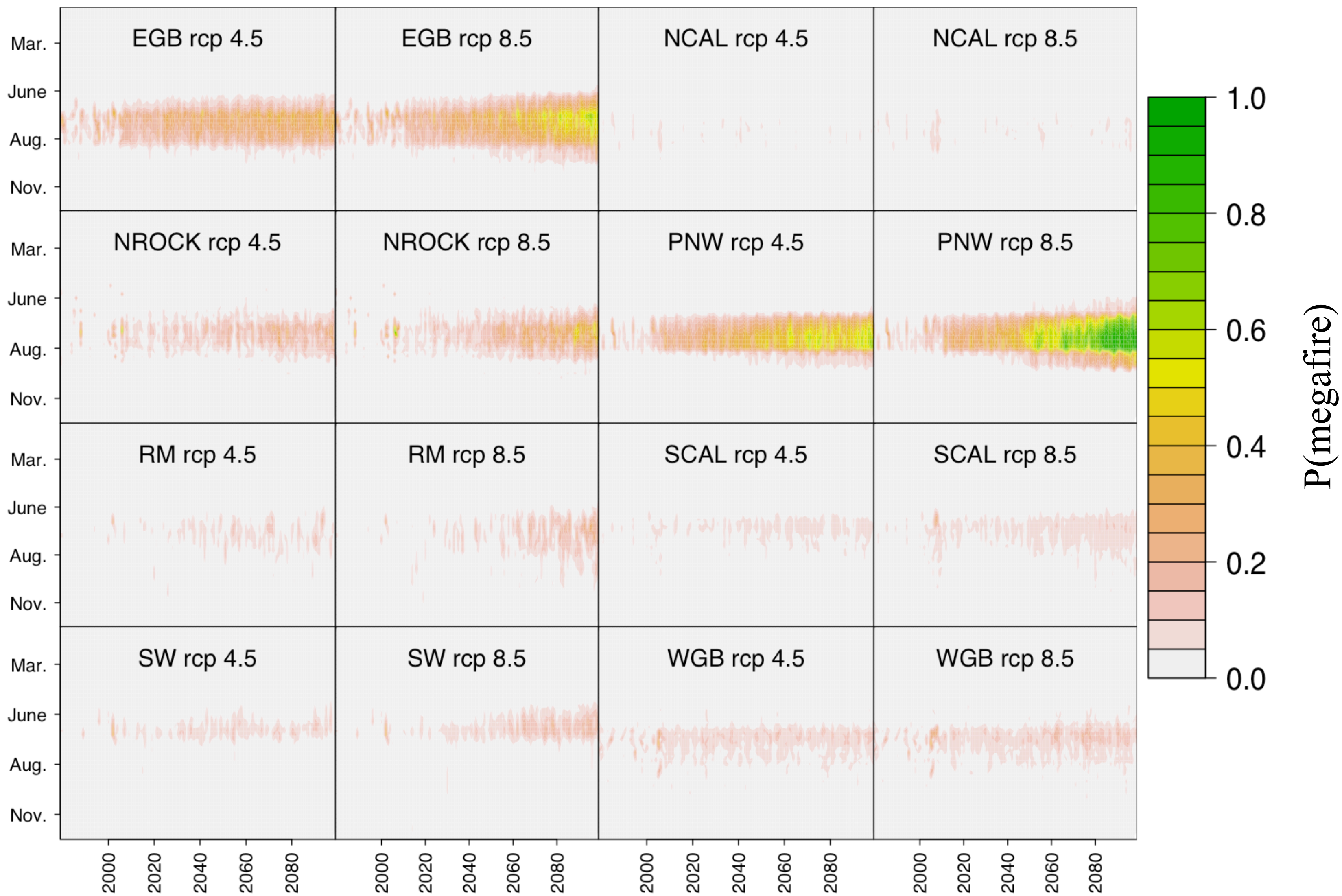

Figure 4.7.3. The seasonality of P(megafire) from 1979-2099. The historical modeled ensemble is used for 1979 to 2010. The ensemble mean of the14 GCMs is used for scenarios RCP 4.5 and RCP 8.5 from 2011 to 2099.

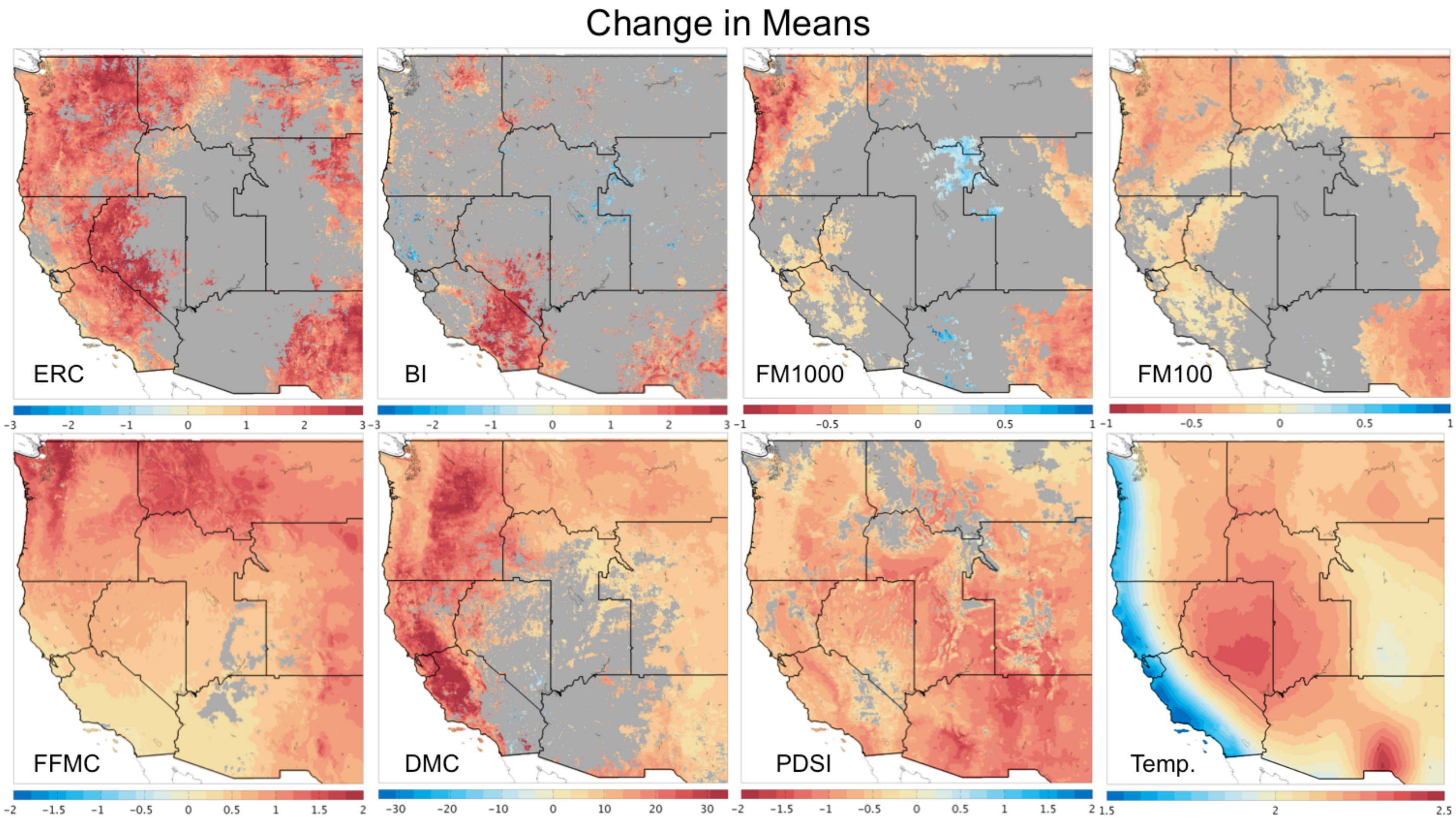

Figure 4.7.4. Change in the means 2031-2060 minus 1971-2000 averaged over 14 GCMs for June-September under RCP 4.5. Gray regions signify area of high uncertainty across models, are areas with <10 of 14 model agreement. Indices represent the index value at daily (ERC, BI, FM1000, FM100, FFMC, and DMC) and monthly (PDSI and mean temperature) resolution. For ease, examining the spatial distribution of changes in FM100 and FM1000 used inverted categorized color spectrums. FM100 and FM1000 decrease with increased fire danger, in contrast to all other variables, which increase with increased fire danger. Therefore, the color spectrums used for spatial investigation of the changes in climate space represent the same for all indices such that red denotes increased fire danger.
Note: PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

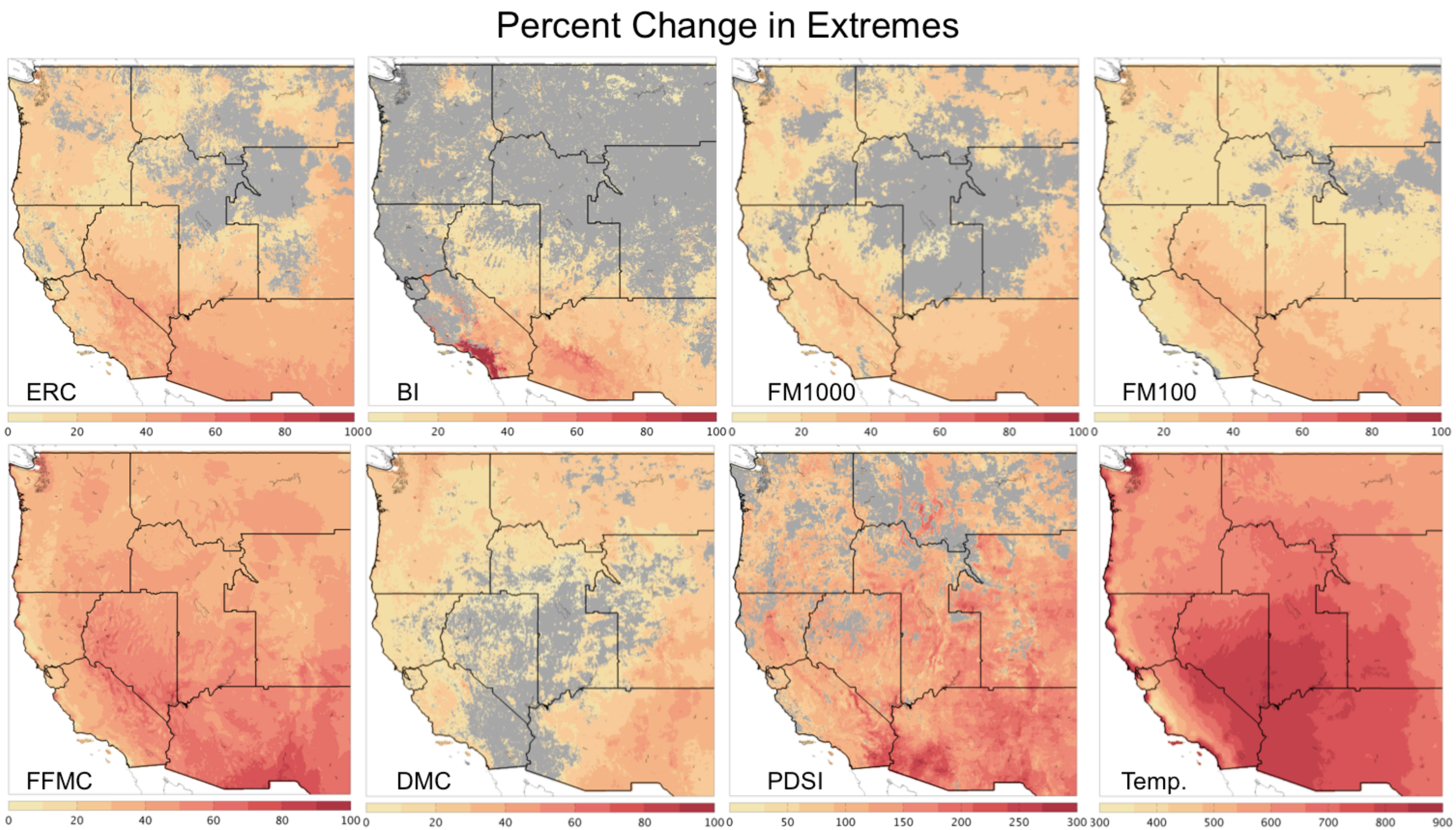

Figure 4.7.5. Projected changes, under RCP 4.5, in the number of days or months that exceed the threshold defined by the upper/lower decile of days or months from 1979-2010 to 2031-2060 for each index. Changes are expressed as a percentage change from baseline conditions (e.g., +100 means a doubling). Regions where the signal is not robust, i.e. regions of high uncertainty across models, areas with <10 of 14 model agreement are gray. For ease, examining the spatial distribution of changes in FM100 and FM1000 used inverted categorized color spectrums. FM100 and FM1000 decrease with increased fire danger, in contrast to all other variables, which increase with increased fire danger. Therefore, the color spectrums used for spatial investigation of the changes in climate space represent the same for all indices such that red denotes increased fire danger.

Note: PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

4.8. Tables

Table 4.8.1. A list of the 14 GCMs used in this analysis listed in descending order of most to least total relative error as a sum of relative errors from many metrics over the PNW as calculated by Rupp et al. (in review).

GCM	*Reference*
CNRM-CM5	Voldoire et al. 2012
GFDL-ESM2M	http://www.gfdl.noaa.gov/earth-system-model
CanESM2	http://www.atmos-chem-phys-discuss.net/11/22893/2011/acpd-11-22893-2011.pdf
MIROC5	Wantanabe et al. 2010
HadGEM2-ES	Martin et al. 2011
GFDL-ESM2G	http://www.gfdl.noaa.gov/earth-system-model
HadGEM2-CC	Martin et al. 2011
CSIRO-MK3-6-0	Collier et al. 2011
inmcm4	Volodin et al. 2010
MIROC-ESM	Wantanabe et al. 2011
MIROC-ESM CHEM	Wantanabe et al. 2011
bcc-csm 1-1	
MRI-CGCM3	Yukimoto et al. 2012
BNU-ESM	http://esg.bnu.edu.cn/BNU_ESM_webs/htmls/data_acc.html

Table 4.8.2. Models by GACC to calculate the probability of conditions during a given week being conducive for fire growth to megafire size. Models taken from Stavros (2013a). Note: We defined explanatory variables as the calculated index averaged over the suffix such that ".1" denotes the week prior to discovery, ".dw" is the discovery week, and ".n#" is the number of weeks post discovery week. PDSI = palmer drought severity index, TEMP = mean temperature, FFMC = fine fuel moisture code, DMC = duff moisture code, FM100 = 100-hr. fuel moisture, FM1000 = 1000-hr. fuel moisture, ERC = energy release component, and BI = Burning index.

GACC	P(Megafire) = $1/(1+e^{b})$ where b = the linear predictor in a binomial GLM =
EGB	31.033 - 0.226*FFMC.dw - 0.260*TEMP.dw - 0.015*DMC.n3 - 0.238*PDSI.n1
NCAL	-8.500 + 1.290*FM1000.n1
NROCK	-13.951 - 0.309*BI.n3 + 0.672*FM100.dw + 0.334*FFMC.n1 + 0.026*DMC.dw -0.366*TEMP.1
PNW	6.664 - 0.514*TEMP.n1 + 0.468*FM1000.n1
RM	11.930 - 0.057*DMC.n3
SCAL	18.660 - 0.193*ERC.n1
SW	8.430 - 0.017*DMC.dw
WGB	-4.532 + 1.279*FM100.dw - 0.392*PDSI.dw

Table 4.8.3. Comparative statistics across GACCs for projections of the GLMs from Stavros (2013) onto historical and future modeled climate spaces under two RCPs. "Mean" refers to the proportional change in ensemble model average over the time period (where historical is 1979-2010 and future is 2031-2060) from the mean observed. AUC is the area under the receiver operating characteristic curve for the GLMs for each GACC.

row		**EGB**	**NCAL**	**NROCK**	**PNW**	**RM**	**SCAL**	**SW**	**WGB**
1	Model AUC	0.840	0.858	0.934	0.859	0.967	0.804	0.918	0.863
2	Historical modeled ensemble mean/ observed mean	1.462	1.086	1.227	1.88	1.447	1.061	1.145	1.190
3	p-value (H_0: row 2 = observed/observed mean)	2.04 e-6	0.308	0.092	3.3 e-11	0.007	0.375	0.206	0.033
4	# models with sig. difference (p<0.05) between each model/mean observed and observed/mean observed	12	2	3	14	3	2	3	9
	RCP 4.5								
5	RCP 4.5 mean/observed mean	2.426	1.278	1.840	4.471	4.557	1.396	2.301	1.472
6	p-value (H_0: row 2 = row 5)	6.9 e-13	0.010	4.6 e-7	5.0 e-22	3.6 e-27	6.3 e-8	4.7 e-18	5.0 e-4
7	# models with sig. difference (p<0.05) between each model and row 2	11	11	11	13	13	9	12	11
	RCP 8.5								
8	RCP 8.5 mean/observed mean	2.901	1.306	2.259	5.901	4.630	1.542	2.280	1.531
9	p-value (H_0: row 2 = row 8)	1.5 e-21	0.004	9.4 e-14	4.6 e-33	1.1 e-26	6.7 e-13	8.9 e-18	2.8 e-5
10	# models with sig. difference (p<0.05) between each model and row 2	14	8	12	14	7	11	11	12

Chapter 5

Conclusion

5.1. Overview

Very large wildfires can have lasting ecological and social effects both directly on the landscape and indirectly on the atmosphere and climate. Understanding these effects requires placing wildfires within the context of feedbacks between the climate-wildfire-air quality system (Chapter 2). There are limited studies, however, conducted at appropriate spatial and temporal scales, for integrating climate, wildfire, and air quality data to understand the system as a whole (McKenzie et al. 2006, Chen et al. 2009). Additionally, there are no studies that specifically examine the occurrence of very large fires (≥ 50,000 ac ~ 20,234 ha), here termed 'megafires' in the western contiguous US. This dissertation has developed, evaluated, and projected regional models of megafire occurrence that can be used at spatial and temporal scales appropriate for integrative studies on climate, wildfire, and air quality across the western contiguous US.

First a systematic framework was created to understand and study climate, wildfire and air quality feedbacks. Appropriate spatial and temporal scales of key processes affecting climate, wildfire, and air quality were identified (Chapter 2). Then climatic drivers for extremely large wildfires (≥ 50,000 ac ~ 20,234 ha, defined here as megafires) were examined across the western US from 1984 to 2010 (Chapter 3) at the identified scales for integrating climate, wildfire, and air quality. Biophysical metrics calculated from climate were used to develop regional probabilistic models of the occurrence of megafires. Finally, the potential occurrence of future megafires was examined under a number climate change scenarios and models by projecting how the identified drivers of megafires are expected to change over time (Chapter 4).

5.2 Findings

5.2.1. Spatial and temporal scales

To understand air quality, the climate-wildfire-air quality system is best modeled at broad spatial scales and fine temporal resolution. Climate, fire regimes, and air quality operate or affect broad spatial scales thus aggregating across similar landscapes captures them and allow for better statistics because megafires are rare events; fine temporal resolution is needed to capture the effects of smoke emissions and transport which. Here megafire was examined from 1979 to 2099 at the broad spatial scale of the National Interagency Fire Center (NIFC) Geographic Area Coordination Center (GACC) regions. GACCs are used to manage fire-fighting resources; there are 8 GACCs covering the western contiguous United States. A weekly temporal resolution was used to meet the fine temporal scale required for linking climate, wildfire, and air quality.

5.2.2. Statistical modeling

Logistic regression was used to examine how climatic and biophysical variables influence the likelihood of a megafire occurrence. Explanatory variables examined include those thought to drive large wildfires and include variables from one week before and up to three weeks after the discovery date. Models varied by GACC and were created using backwards elimination by minimizing AIC. Analyzing these models and the difference between fire climatology between large fires and megafires showed that in general, hotter, drier conditions increase the probability of a megafire in the western contiguous US. These results are similar to those found in area burned analyses, thus demonstrating the influence of broad-scale ecological mechanisms driving wildfires (e.g., fuel versus flammability limited environments). Similar results are probably because the number of megafires and the amount of area burened by megafires correlate with annual area burned.

Projecting these models into the future under IPCC scenarios RCP 4.5 and 8.5 showed significant ($p \leq 0.05$) differences in the mean likelihood of a megafire between the historical period from 1979 to 2010 and the future during 2031 to 2060. Across the West, with the exception of the Southwest and Northern California, megafires will be more likely in the future both throughout the fire season and from year to year, with more pronounced patterns under RCP 8.5 than RCP 4.5.

5.3. Scientific and management context

This work is a significant advance over previous studies that have predicted annual area burned in that it presents models for predicting individual fire events. Although the relationships between climate and megafires are similar to those found for annual area burned, this work provides more specific information as to the seasonality of individual events; thus it is a basis for developing wildfire policy and management strategies.

This research demonstrates the sensitivity of aggregate statistics, like annual area burned, to influential sub-classes, like megafires. Although climate and megafire relationships are similar to those found to predict annual are burned, annual area burned estimates represent average behavior, which suffers from error propagation and produces biased estimates at broad-scales because of the cumulative error from aggregating many individual events (McKenzie and Kennedy 2011, p. 29). This analysis of individual megafires represents emergent behavior, which is defined as the complex behavior of many simple entities operating within a system. Consequently, this analysis was conducted on megafires at specific spatial and temporal scales to capture changes (McKenzie and Kennedy 2011, p. 29) within the more complicated climate-wildfire-air quality system (Chapter 2).

Unfortunately few studies have been conducted at the scales necessary for understanding changes within the climate-wildfire-air quality system. By filling a specific spatial and temporal niche identified in Chapter 2, the models produced in Chapter 3 and applied to future projections in Chapter 4, provide a foundation for investigating system dynamics between climate, wildfire, and air quality (Chapter 2). Furthermore, future megafires can be simulated as part of Earth-system models, informing processes as diverse as aerosol feedbacks to radiative forcing and estimates of carbon soruces or sinks, to better predict and understand the climate and carbon systems.

In a managerial context, this research can be used to shape new fire policy such as fuel management. For example, high biomass and fuel accumulations contribute to megafires, and large-scale fuel management may reduce the effects of megafire including tree mortality, fire behavior, suppression costs, private property loss, environmental damages, and fatalities (Williams 2013). Since megafires are more likely (Chapter 4), governments are better advised to financially and politically support fuel treatments as essential tasks of forest management.

5.4. Future research

By integrating this work into air quality smoke modeling frameworks, e.g. BlueSky (Larkin et al. 2009), we can improve understanding on how megafires degrade air quality and how best to mitigate such effects (McKenzie et al. 2006, 2013). For example, since we project that megafires are more likely in the future (Chapter 4), and they constitute a significant fraction of the annual regulated amount of emissions (Jaffe et al. 2008), urban areas could restrict anthropogenic emissions (e.g. from fossil fuels) allowing for more emissions from prescribed and wildfire to occur before exceeding regulated levels. Such work would require downscaling likelihoods of megafire to create a map of probabilities (*sensu* McKenzie et al. 2006 but with empirically based estimates replacing a heuristic method). Using a Monte Carlo approach with a stochastic simulation the downscaled probabilities could then be converted to megafire occurrences and then integrated into a smoke modeling framework, such as Bluesky (Larkin et al. 2009), to examine how climate will affect air-quality degradation from wildfire.

Consideration for how management strategies will feed back into the likelihood of megafire is especially important as the IPCC scenarios used in this analysis represent target radiative forcing per square meter rather than a particular storyline (van Vuuren et al. 2011). Defining the scenarios as a target radiative forcing means that there are many different combinations of population growth rate, technological developments, and land-use changes that meet the same radiative forcing “budget”. Consequently, further investigation is required to understand how these components and different management strategies interact to affect the likelihood of a megafire beyond climatic potential.

Investigating how sensitive results from this analysis are to the assumptions used is a good first step to bounding the uncertainties in future projections and their consequences. One assumption was that the top two percent of fire sizes, expected to be the most damaging, could be isolated from other large fire with respect to climatic drivers. Future work is required to investigate how climatic predictors change under different definitions of megafire. A second assumption is that the effects of megafires are strongly associated with their extent. Other options for megafire “indicators” are fire severity, which could be evaluated further with the MTBS data set, or political and social metrics such as cost or the medical or aesthetic effects of smoke. A third more subtle assumption is the equal certainty of different output variables in climate projections by GCMs. It has been established that not all meteorological variables are equally well predicted by GCMs (IPCC 2007). For example, temperature-specific metrics are more robust than moisture-specific metrics. Understanding confidence limits for the least certain of megafire predictors in the future is essential for determining the confidence of megafire projections. Sensitivity analyses of projected megafire probabilities such as variance partitioning, would help quantify uncertainties in projections.

This work lays an important foundation for understanding how extreme events, specifically megafires, are affected by climate and may change into the future. The projections from this study provide a baseline for future research including investigation of the assumptions, sensitivity of findings, and air quality modeling. The results suggest the emergence of a changing wildfire environment, one marked by longer seasons and more years with high likelihood of megafire occurrence. Those directing policy and management will be faced with adapting to a changing climate. The results from this research can aid development of management strategies for meeting existing regulations where possible and informing new ones where needed.

References

Abatzoglou J and CA Kolden (2011) Relative importance of weather and climate on wildfire growth in interior Alaska. *International Journal of Wildland Fire* **20**:479-486.

Abatzoglou JT (2013) Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* **33**:121-131.

Abatzoglou JT and CA Kolden (2013) Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire [online]* http://dx.doi.org/10.1071/WF13019.

Agee JK (1993) Fire Ecology of Pacific Northwest forests. Washington DC: Island Press.

Alvarado E, Sandberg DV, Pickford SG (1998) Modeling large forest fires as extreme events. *Northwest Science* **72**:66-75.

Anderson DR and KP Burnham (2002) Avoiding Pitfalls When Using Information-Theoretic Methods. *The Journal of Wildlife Management* **66**:912-918.

Anderson DR, Burnham KP, Thompson WL (2000) Null Hypothesis Testing: Problems, Prevalence, and an Alternative. *The Journal of Wildlife Management* **64**:912-923.

Andrews PL, Loftsgaarden DO, Bradshaw LS (2003) Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire* **12**:213-226.

Barrett K, McGuire AD, Hoy EE, Kasischke ES (2011) Potential shifts in dominant forest cover in interior Alaska driven by variations in fire severity. *Ecological Applications* **21**:2380-2396.

Barry SC, and AH Welsh (2002) Generalized additive modelling and zero inflated count data. *Ecological Modelling* **157**:179-188.

Bedsworth L (2011) Air quality planning in California's changing climate. *Climatic Change*:1-18. doi:10.1007/s10584-011-0244-0

Bessie WC and EA Johnson (1995) The relative importance of fuels and weather on fire behaior in sub-alpine forests. *Ecology* **76**:747-762.

Bond WJ and JE Keeley (2005) Fire as a global ‘herbivore’: the ecology and evolution of flammable ecosystems. *Trends in Ecology and Evolution* **20**:387-394.

Bond TC, Doherty SJ, Fahey DW, Forster PM et al. (2013) Bouding the role of black carbon in the climate system: a scientific assessment. *Journal of Geophysical Research: Atmospheres* [*online*]. Doi: 10.1002/jgrd.50171.

Bowman D, Blach JK, Artaxo P, Bond WJ et al. (2009) Fire in the Earth system. *Science* **324**:481-484.

Calkin DE, Gebert KM, Jones JG, Neilson RP (2005) Forest Service large fire area burned and suppression expenditure trends, 1970-2002. *Journal of Forestry* 103 (4):179-183

Chen J, Avise J, Lamb B, Salathe E, Mass C et al. (2009) The effects of global changes upon regional ozone pollution in the United States. *Atmospheric Chemistry and Physics* **9**:1125-1141.

Clarke L, Edmonds J, Jacoby H, Pitcher H, Reilly J, Richels R (2007) Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessment Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Department of Energy, Office of Biological and Environmental Research, Washington, 7 DC.

Coles S (2001) An Introduction to Statistical Modeling of Extreme Values. London, United Kingdom: Springer.

Collier MA, Jeffrey SJ, Rotstayn, LD, Wong KK-H, Dravitzki, SM et al. (2011) The CSIRO-Mk3.6.0 Atmosphere-Ocean GCM: participation in CMIP5 and data publication. 19th International Congress on Modelling and Simulation. Perth, Australia. 12-16 December. http://mssanz.org.au/modsim2011

Colombaroli D and DG Gavin (2010) Highly episodic fire and erosion regime over the past 2,000 y in the Siskiyou Mountains, Oregon. *PNAS* **107**(44):18909–18914.

Cook ER, Seager R, Cane MA, Stahle, DW (2007) North American drought: Reconstructions, causes, and consequences. *Earth-Science Reviews* **81**: 93-134.

Coumou D and S Rahmstorf (2012) A decade of weather extremes. *Nature Climate Change* **2**:491-496.

D'Andrea M, Fiorucci P, Holmes TP (2010) A stochastic Forest Fire Model for future land cover scenarios assessment. *Natural Hazards and Earth System Sciences* **10**:2161-2167.

Daly C, Halbleib M, Smith JI, Gibson WP, Doggett MK, Taylor GH, Curtis J, Pasteris PP (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology* **28**:2031-2064.

Draghicescu D and R Ignaccolo (2009) Modeling threshold exceedance probabilities of spatially correlated time series. *Electronic Journal of Statistics* **3**:149-164.

Elith J, Burgman MA, Regan HM (2002) Mapping epistemic uncertainties and vague concepts in predictions of species distribution. *Ecological Modelling* **157**:313-329.

Falk DA, Miller C, McKenzie D, Black AE (2007) Cross-scale analysis of fire regimes. *Ecosystems* **10**:809-823.

Fenn ME, Lambert KF, Blett TF, Burns DA, Pardo LH et al. (2011) Setting limits: using air pollution thresholds to protect and restore U.S. Ecosystems. *Issues in Ecology* ***14***. ISSN: 10928987.

Flannigan M, Cantin AS, de Groot WJ, Wotton M, Newbery A, Gowman LM (2013) Global wildland fire season severity in the 21st century. *Forest Ecology and Management* **294** (0):54-61. doi: http://dx.doi.org/10.1016/j.foreco.2012.10.022

Flannigan MD, Krawchuk MA, de Groot WJ, Wotton BM, Gowman LM (2009) Implications of changing clamate for global wildland fire. *International Journal of Wildland Fire* **18**:483-507.

Flannigan MD, Logan KA, Amiro BD, Skinner WR, Stocks BJ (2005) Future area burned in Canada. *Climatic Change* **72**:1-16.

Flannigan MD, Bergeron Y, Engelmark O, Wotton BM (1998) Future wildfire in circumboreal forests in relation to global warming. *Journal of Vegetation Science* **9**:469-476.

Ghimire B, Williams CA, Collatz GJ, and M. Vanderhoof. 2012. Fire-induced carbon emissions and regrowth uptake in western U.S. forests: documenting variation across forest types, fire severity, and climate regions. *Journal of Geophysical Research* 117, G03036

Gill AM and G Allan (2008) Large fires, fire effects and the fire-regime concept. *International Journal of Wildland Fire* **17**:688-695.

Guenther A, Geron C, Pierce T, Lamb B, Harley P, Fall R (2000) Natural emissions of non-methane volatile organic compounds, carbon monoxide, and oxides of nitrogen from North America. *Atmospheric Environment* **34**:2205-2230.

Grissino-Mayer HD (1999) Modeling fire interval data from the American Southwest with the Weibull distribution. *International Journal of Wildland Fire* **9**:37-50.

Hansen J, Sato M, Ruedy R (2012) Perception of climate change. *Proceedings of the National Academy of Sciences* 109 (37) E2415-E2423.

Hardy CH, Ottmar RD, Peterson JL, Core JE, Seamon P (2001) Smoke Management Guide for Prescribed and Wildland Fire. Boise, ID: National Wildfire Coordination Group. PMS 420-2 NFES 1279.

Harrell FEJ (2001) Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis. Springer-Verlag New York, Inc., New York.

Hawkins ED, Sutton R (2009) The potential to narrow uncertainty in regional climate predictions. *American Meteorological Society* **90** (8): 1095-1107.

He H and EA Garcia (2009) Learning from Imbalanced Data. *Knowledge and Data Engineering, IEE Transactions on* **21**:1263-1284.

Heilman WE and X Bian (2010) Turbulent kinetic energy during wildfires in the north central and north-eastern US. Intern*ational Journal of Wildland Fire* **19**:346-363.

Hessburg PF, Smith BG, Salter RB, Ottmar RD, Alvarado E (2000) Recent changes (1930s-1990s) in spatial patterns of interior northwest forests, USA. *Forest Ecology and Management* **136**(1-3): 53-83.

Higuera PE, Brubaker LB, Anderson PM, Hu FS, Brown TA (2009) Vegetation mediated the impacts of postglacial climate change on fire regimes in the south central Brooks Range, Alaska. *Ecological Monographs* **79**:201–219.

Hyslop NP (2009) Impaired visibility: the air pollution people see. *Atmospheric Environment* **43**:182-195.

Hu YT, Odman MT, Chang ME, Jackson W, Lee S, Edgerton ES, Baumann K, Russell AG (2008) Simulation of air quality impacts from prescribed fires on an urban area. *Environmental Science and Technology* **42**: 3676-3682.

IPCC (2007) Climate change 2007: synthesis report. Conribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland: IPCC.

Irland LC (2013) Extreme value analysis of forest fires from New York to Nova Scotia, 1950-2010. *Forest Ecology and Management* **294**:150-157.

Jaffe D, Bertschi I, Jaegle L, Novelli P, Reid JS, Tanimoto H, Vingarzan R, Westphal DL (2004) Long-range transport of Siberian biomass burning emissions and impact on surface ozone in western North America. *Geophysical Research Letters* **31**:1-4.

Jaffe D, Hafner W, Chand D, Westerling A, Spracklen D (2008) Interannual variations in PM2.5 due to wildfires in the Western United States. *Environmental Science and Technology* **42**:2812-2818.

Jenkins MJ, Hebertson E, Page W, Jorgensen CA (2008) "Bark beetles, fuels, fires and implications for forest management in the Intermountain West." *Forest Ecology and Management* **254**(1): 16-34.

Jiang Y and Zhuang Q (2011) Extreme value analysis of wildfire in Canadian boreal forest ecosystems. *Canadian Journal of Forest Research* **41**:1836-1851.

Jolly WM, Nemani R, Running SW (2005) A generalized, bioclimatic index to predict foliar phenology in response to climate. *Global Change Biology* **11**:619-632.

Kashian DM, Romme WH, Tinker DB, Turner MG, Ryan MG (2006) Carbon storage on coniferous landscapes with stand-replacing fires. *BioScience* **7**: 598-606

Kasischke ES, Hyer EJ, Novelli PC, Bruhwiler LP, French NHF, Sukhinin AI, Hewson JH, Stocks BJ (2005) Influences of boreal fire emissions on Northern Hemisphere atmospheric carbon and carbon monoxide. *Global Biogeochemical Cycles* **19**:GB1012.

Kasischke ES, Christensen NL, Stocks BJ (1995) Fire, global warming, and the carbon balance of boreal forests. *Ecological Applications* **5**:437-451.

Keane RE, Agee JK, Fule R, Keeley JE, Key C, Kitchen SG, Miller R, Schulte LA (2008) Ecological effects of large fires on US landscapes: benefit or catastrophe? *International Journal of Wildland Fire* 17:696-712.

Keane R, Gray K, Bacciu V, Leirfallom S (2012) Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. *Landscape Ecology* **27**:1213-1234.

Kennedy MC and McKenzie D (2010) Using a stochastic model and cross-scale analysis to evaluate controls on historical low-severity fire regimes. *Landscape Ecology* **25**:1561-1573.

Kilgore BM (1973) The ecological role of fire in Sierran conifer forest. *Ecology* **60**:129-142.

Kilgore BM (1973) The ecological role of fire in sierran conifer forests its application to national park management. *Quaternary Research* (Orlando) **3**:496-513.

Kitzberger T, Araoz E, Gowda J, Mermoz M, Morales J (2012) Decreases in Fire Spread Probability with Forest Age Promotes Alternative Community States, Reduced Resilience to Climate Variability and Large Fire Regime Shifts. *Ecosystems* **15**:97-112.

Koenker, R and KF Hallock (2001) Quantile Regression. *Journal of Economic Perspectives* **15**:143-156.

Kolb TE, Agee JK, Fule PZ, McDowell NG, Pearson K, Sala A, Waring RH (2007) Perpetuating old ponderosa pine. *Forest Ecology and Management* **249**:141-157.

Kolden CA, Lutz JA, Key CH, Kane JT, van Wagtendonk JW (2012) Mapped versus actual burned area within wildfire perimeters: Characterizing the unburned. *Forest Ecology and Management* **286**:38-47.

Krawchuk MA, Moritz MA, Parisien M-A, Dorn JV, Hayhoe K (2009) Global pyrogeography: the current and future distribution of wildfire. *PLoS ONE* **4**:e5102.

Langmann B, Duncan B, Textor C, Trentmann J, van der Werf GR (2009) Vegetation fire emissions and their impact on air pollution and climate. *Atmospheric Environment* **43**:107-116.

Larkin NK, O'Neill SM, Solomon R, Raffuse S et al. (2009) The Bluesky smoke modeling framework. *International Journal of Wildland Fire* **18**:906-920.

Littell JS, McKenzie D, Peterson DL, Westerling AL (2009) Climate and wildfire area burned in western U. S. ecoprovinces, 1916-2003. *Ecological Applications* **19**:1003-1021.

Littell JS, O'Neil EE, McKenzie D, Hicke JA, Lutz JA, Norheim RA, Elsner MM (2010) Forest ecosystems, disturbance, and climatic change in Washington State, USA. *Climatic Change* **102**:129-158.

Liu Y (2005) Enhancement of the 1988 northern U.S. drought due to wildfires. *Geophysical Research Letters* **32**:1-4.

Liu Y, Goodrick SL, Stanturf JA (2013) Future U.S. wildfire potential trends projected using a dynamically downscaled climate change scenario. *Forest Ecology and Management* **294**:120-135.

Lorenz K and R Lal (2010) Effects of Disturbance, Succession and Management on Carbon Sequestration. Dordrecht, The Netherlands: Springer.

Lynch HJ, Renkin RA, Crabtree RL, Moorcroft PR (2006) The influence of previous mountain pine beetle (Dendroctonus ponderosae) activity on the 1988 Yellowstone fires. *Ecosystems* ***9***(8), 1318-1327.

Malm WC (1999) Introduction to visibility. Fort Collins, CO: Air Resources Division, National Park Service. CA2350-97-001: T097-04, T098-06.

Marin GM, Bellouin, N, Collins, WJ, Culverwell, ID, Halloran, PR, Hardiman, SC, Hinton, TJ et al. (2011) The HadGEM2 family of met office unified model climate configurations. *Geoscientific Model Development Discussions* **4**(2):765-841.

McDowell N, Brooks JR, Fitzgerald SA, Bond BJ (2003) Carbon isotope discrimination and growth response of old Pinus ponderosa trees to stand density reductions. *Plant Cell and Environment* **26**:631-644.

McKenzie D, Peterson DW, Peterson DL, Thornton PE (2003) Climatic and biophysical controls on conifer species distributions in mountain forests of Washington State, USA. *Journal of Biogeography* **30**:1093-1108.

McKenzie D, Gedalof Z, Peterson DL, Mote P (2004) Climatic change, wildfire, and conservation. *Conservation Biology* **18**:890-902.

McKenzie D, O'Neill SM, Larkin NK, Norheim R (2006) Integrating models to predict regional haze from wildland fire. *Ecological Modelling* **199**:278-288.

McKenzie D, Raymond CL, Kellogg L-KB, Norheim RA, Andreu AG, Bayard AC, Kopper KE, Elman E (2007) Mapping fuels at multiple scales: landscape application of the Fuel Characteristic Classification System. *Canadian Journal of Forest Research* **37**:2421-2437.

McKenzie D and JS Littell (2011) Climate change and wilderness fire regimes. *International Journal of Wilderness* **17**(1):22-27.

McKenzie D, Miller C, Falk DA (2011) Toward a theory of landscape fire. Chapter 1 in: McKenzie D, Miller C, Falk DA (eds) The Landscape Ecology of Fire. Dordrecht, The Netherlands: Springer Ltd.

McKenzie D and M Kennedy (2011) Scaling laws and complexity in fire regimes. Chapter 2 in: McKenzie D, Miller C, Falk DA (eds) The Landscape Ecology of Fire. Dorderecht, The Netherlands: Spring Ltd.

McKenzie D, French NHF, Ottmar RD (2012) National database for calculating fuel available to wildfires. *EOS* **93**:57-58.

McKenzie D, Shankar U, Keane RE, Heilman WE, Stavros EN, Fox DG, Riebau AC, et al. (2013) Smoke consequences of new wildfire regimes driven by climate change. Joint Fire Science Program. Project 12-S-01-2.

Michelangeli PA, Vrac M, Loukos H (2009) Probabilistic downscaling approaches: application to wind cumulative distribution functions. *Geophysical Research Letters* **36** (11):L11708. doi:10.1029/2009GL038401

Mika J, Horváth S, Makra L, Dunkel Z (2005) The Palmer Drought Severity Index (PDSI) as an indicator of soil moisture. *Physics and Chemistry of the Earth, Parts A/B/C* **30**:223-230.

Miranda AI (2004) An integrated numerical system to estimate air quality effects of forest fires. *International Journal of Wildland Fire* **13**:217-226.

Moritz MA, Morais ME, Summerell LA, Carlson JM, Doyle J (2005) Wildfires, complexity, and highly optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of America* **102**:17912-17917.

Mundry R and CL Nunn (2009) Model fitting and statistical inference: Turning noise into signal pollution. *American Naturalist* **173**:119-123.

Nakicenovic N and R Swart (2000) Special Report on Emissions Scenarios (SRES). Cambridge, United Kingdom: Cambridge University Press.

Neilson RP (1995) A model for predicting continental-scale vegetation distribution and water balance. *Ecological Applications* **5**:362.385.

Noss RF, Franklin JF, Baker WL, Schoennagel T, Moyle PB (2006) Managing fire-prone forests in the western United States. *Frontiers in Ecology and the Environment* **4**:481-487.

Olson DM, Dinerstein E, Wikramanayank ED, Burgess ND, Powell GVN, Underwood EC et al. (2001) Terrestrial Ecoregions of the World: A new map of life on Earth. *Bioscience* **51**:933-938.

Parisien M-A and MA Moritz (2009) Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs* **79**:127-154.

Parisien M-A, Snetsinger S, Greenberg JA, Nelson CR, Schnennagel T, Dobrowski SZ, Moritz MA (2012) Spatial variability in wildfire probability across the western United States. *International Journal of Wildland Fire* **21**:313-327.

Peterson DL and T Parker (1998) Dimensions of scale in ecology, reource management, and society *in* D. L. Peterson and T. Parker, editors. Ecological Scale: Theory and Applications. Columbia University Press, New York, NY, USA.

Peterson DW and Peterson DL (2001) Mountain hemlock growth responds to climatic variability at annual and decadal time scales. *Ecology* **82**:3330-3345.

Peterson GD (2002) Contagious disturbance, ecological memory, and the emergency of landscape pattern. *Ecosystems* **5**:329:338.

Pfister GG, Wiedinmyer C, Emmons LK (2008) Impacts of the fall 2007 California wildfires on surface ozone: Integrating local observations with global model simulations. *Geophysical Research Letters* **35**:1-5.

Pielke RA, Walko RL, Steyaert LT, Vidale PL, Liston GE, Lyons WA, Chase TN (1999) The Influence of Anthropogenic Landscape Changes on Weather in South Florida. *Monthly Weather Review* **127**:1663-1673.

Podur J and BM Wotton (2011) Defining fire spread event days for fire-growth modeling. *International Journal of Wildland Fire* **20**:497–507.

Potter BE (2012) Atmospheric interactions with wildland fire behaviour - 1. basic surface interactions, vertical profiles, and synoptic structures. *International Journal of Wildland Fire* **21**:779-801.

Price C and Rind D (1994) The impact of a 2-x-CO_2 climate on lightning-cased fires. *Journal of Climate* **7**:1484-1494.

Randerson JT, Liu H, Flanner MG, Chambers SD et al. (2006) The impact of boreal forest fire on climate warming. *Science* **314**:1130-1132.

Raymond CL and D McKenzie (2012) Carbon dynamics of forests in Washington, USA: 21st century projections based on climate-driven changes in fire regimes. *Ecological Applications* **22**:1589-1611.

Reich PB and Amundson RG (1985) Ambient levels of ozone reduce net photosynthesis in tree and crop species. *Science* **230**:566-570.

Reinhardt ED, Keane RE, Calkin DE, Cohen JD (2008) Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *Forest Ecology and Management* **256**:1997-2006.

Riahi K, Grubler A, Nakicenovic N (2007) Scenarios of long-term socio-economic and environmental development under climate stabilization. *Technological Forecasting and Social Change* **74** (7):887-935. doi: http://dx.doi.org/10.1016/j.techfore.2006.05.026

Rothermel RC (1983) How to predict the spread and intensity of forest and range fires. Boise, ID: National Wildfire Coordinating Group. PMS 436-1 NFES 1573.

Rupp DE, Abatzoglou JT, Hegewisch KC, Mote PE (in review) Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest US. *Journal of Geophysical Research*.

San-Miguel-Ayanz J, Moreno JM, Camia A (2013) Analysis of large fires in European Mediterranean landscapes: Lessons learned and perspectives. *Forest Ecology and Management* **294**:11-22.

Sergius LA, Ellis GR, Ogden RM (1962) The Santa Ana Winds of Southern California. *Weatherwise* **15**:102-121.

Sprugel DG (1991) Disturbance, equilibrium, and environmental variability - What is natural vegetation in a changing environment? *Biological Conservation* **58**:1-18.

Stephens SL (1998) Evaluation of the effects of silvicultural and fuels treatments on potential fire behavior in Sierra Nevada mixed-conifer forests. *Forest Ecology and Management* **105**:21-35.

Stephens SL and LW Ruth (2005) Federal forest-fire policy in the United States. *Ecological Applications* **15**:532-542.

Strand T, Larkin N, Rorig M, Krull C, Moore M (2011) PM2.5 measurements in wildfire smoke plumes from fire seasons 2005-2008 in the Northwestern United States. *Journal of Aerosol Science* **42**:143-155.

Swann ALS, Fung IY, Levis S, Bonan GB, Doney SC (2010) Changes in arctic vegetation amplify high-latitude warming through the greenhouse effect. *PNAS* **107**:1295-1300.

Swetnam T and C Baisan (1996) Historical fire regime patterns in the southwestern United States since AD 1700. In: CD Allen (ed) Fire Effects in Southwestern Forest: Proceedings of the 2nd La Mesa Fire Symposium, pp. 11-32. USDA Forest Service, Rocky Mountain Research Station. General Technical Report RM-GTR-286.

Tedim F, Remelgado R, Borges C, Carvalho S, Martins J (2013) Exploring the occurrence of mega-fires in Portugal. *Forest Ecology and Management* **294**:86-96.

Turner MG and WH Romme (1994) Landscape dynamics in crown fire ecosystems. *Landscape Ecology* **9**:59-77.

van der Werf GR, Randerson JT, Giglio L, Collatz GJ, Kasibhatla PS, Arellano AF Jr. (2006) Interannual variability in global biomass burning emissions from 1997 to 2004. *Atmospheric Chemistry and Physics* **6**:3423-3441.

van Vuuren DP, Edmonds J, Kainuma M, Riahi K et al. (2011) The representative concentration pathways: an overview. *Climatic Change* **109**:5-31.

Veblen TT, Kitzberger T, Donnegan J (2000) Climatic and human influences on fire regims in Ponderosa Pine forests in the Colorado Front Range. *Ecological Applications* **10**:1178-1195.

Voldoire, A, Sanchez-Gomez, E, y Mélia, DS, Decharme, B, Cassou, C, Sénési, S et al. (2012) The CNRM-CM5. 1 global climate model: description and basic evaluation. *Climate Dynamics* **40**:2091-2121.

Volodin, EM, Dianskii, NA, Gusev, AV (2010) Simulating present-day climate with the INMCM4.0 coupled model of the atmospheric and oceanic general circulations. *Atmospheric and Oceanic Physics* **46**(4):414-431.

Ward DE and CC Hardy (1991) Smoke emissions from wildland fires. *Environment International* **17**:117-134.

Watanabe, M, Suzuki, T, O'ishi, R, Komuro, Y, Watanabe, S, Emori, S et al. (2010) Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity. *Journal of Climate* **23**(23):6312-6335.

Watanabe S, Hajima T, Sudo K, Nagashima T, Takemura T, Okajima H et al. (2011) MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments. *Geoscientific Model Development* **4**:845-872.

Wegesser TC, Pinkerton KE, Last JA (2009) California wildfires of 2008: coarse and fine particulate matter toxicity. *Environmental Health Perspectives* **117**:893-897.

Werth PA, Potter BE, Clements CB, Finney MA, Goodrick SL, Alexander ME, Cruz MG, Forthofer JA, McAllister SS (2011) Synthesis of knowledge of extreme fire behavior: Volume I for fire managers. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon. General Technical Report PNW-GTR-854.

Westerling AL, Gershunov A, Cayan DR, Barnett TP (2002) Long lead statistical forecasts of area burned in western US wildfires by ecosystem province. *International Journal of Wildland Fire* **11**:257-266.

Westerling AL and TW Swetnam (2003) Interannual to decadal drought and wildfire in the western United States. *EOS, Transactions American Geophysical Union* **84**:545.

Westerling AL, Cayan DR, Brown TJ, Hall BL, Riddle LG (2004) Climate, Santa Ana winds and autumn wildfires in southern California. *EOS, Transactions American Geophysical Union* **85**:289-296.

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW (2006) Warming and earlier spring increase western US forest wildfire activity. *Science* **313** (5789):940-943. doi:10.1126/science.1128834

Williams J (2013) Exploring the onset of high-impact mega-fires through a forest land management prism. F*orest Ecology and Management* **294**:4-10.

Williams AP, Allen CD, Macalady AK, Griffin D, Woodhouse CA, Meko DM et al. (2013) Temperature as a potent driver of regional forest drought stress and tree mortality. *Nature Climate Change* **3**:292-297.

Wise M, Calvin K, Thomson A, Clarke L, Bond-Lamberty B, Sands R, Smith SJ, Janetos A, Edmonds J (2009) Implications of Limiting CO2 Concentrations for Land Use and Energy. *Science* **324** (5931):1183-1186. doi:10.1126/science.1168475

Wohlgemuth PM, Hubbert K, Abbaugh MJ (2006) Fire and physical environment interactions: soil, water and air. In: Fire in California's ecosystems. Berkeley, CA: University of California Press. pp. 75-93.

Wotawa G and M Trainer (2000) The influence of Canadian forest fires on pollutant concentrations in the United States. *Science* **288**:324-328.

Wright HA and AW Bailey (1982) Fire ecology, United States and southern Canada. New York, NY: Wiley.

Xiao-rui T, McRae D, Boychuk D, Ji-zhong J, Cheng-da G, Li-fu S, Ming-yu W (2005) Comparisons and assessment of forest fire danger systems. *Forestry Studies in China* **7**:53-61.

Yamasoe MA, Artaxo P, Miguel AH, Allen AG (2000) Chemical composition of aerosol particles from direct emissions of vegetation fires in the Amazon Basin: water-soluble species and trace elements. *Atmospheric Environment* **34**:1641-1653.

Yukimoto S, Adachi Y, Hosaka M (2012) A new global climate model of the Meteorological Research Institute: MRI-CGCM3: model description and basic performance (special issue on recent development on climate models and future climate projections). *Journal of the Meteorological Society of Japan* **90**:23-64.

Zaniewski AE, Lehmann A, Overton JM (2002) Predicting species spatial distributions using presence-only data: a case study of native New Zealand ferns. *Ecological Modelling* **157**:261-280.