

UC Merced

UC Merced Previously Published Works

Title

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

Permalink

<https://escholarship.org/uc/item/638538n0>

Journal

Environmental Research Letters, 12(6)

ISSN

1748-9318

Authors

Keyser, Alisa

Westerling, Anthony LeRoy

Publication Date

2017-05-01

DOI

10.1088/1748-9326/aa6b10

Peer reviewed

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

This content has been downloaded from IOPscience. Please scroll down to see the full text.

2017 Environ. Res. Lett. 12 065003

(<http://iopscience.iop.org/1748-9326/12/6/065003>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 64.118.100.182

This content was downloaded on 06/07/2017 at 01:31

Please note that [terms and conditions apply](#).

You may also be interested in:

[Modeling very large-fire occurrences over the continental United States from weather and climate forcing](#)

R Barbero, J T Abatzoglou, E A Steel et al.

[How will climate change affect wildland fire severity in the western US?](#)

Sean A Parks, Carol Miller, John T Abatzoglou et al.

[The spatially varying influence of humans on fire probability in North America](#)

Marc-André Parisien, Carol Miller, Sean A Parks et al.

[Projected changes in daily fire spread across Canada over the next century](#)

Xianli Wang, Marc-André Parisien, Steve W Taylor et al.

[Controls on interannual variability in lightning-caused fire activity in the western US](#)

John T Abatzoglou, Crystal A Kolden, Jennifer K Balch et al.

[Is proportion burned severely related to daily area burned?](#)

Donovan S Birch, Penelope Morgan, Crystal A Kolden et al.

[How much global burned area can be forecast on seasonal time scales using sea surface temperatures?](#)

Yang Chen, Douglas C Morton, Niels Andela et al.

[Fire activity as a function of fire–weather seasonal severity and antecedent climate across spatial scales in southern Europe and Pacific western USA](#)

Itziar R Urbieto, Gonzalo Zavala, Joaquín Bedia et al.

Environmental Research Letters



LETTER

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

OPEN ACCESS

RECEIVED

31 October 2016

REVISED

30 March 2017

ACCEPTED FOR PUBLICATION

4 April 2017

PUBLISHED

26 May 2017

Original content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



Alisa Keyser¹ and Anthony LeRoy Westerling

Sierra Nevada Research Institute, University of California Merced, 5200 N. Lake Rd., Merced, CA 95340, United States of America

¹ Author to whom any correspondence should be addressed.

E-mail: akeyser@ucmerced.edu

Keywords: fire severity, moisture deficit, logistic regression

Supplementary material for this article is available [online](#)

Abstract

A long history of fire suppression in the western United States has significantly changed forest structure and ecological function, leading to increasingly uncharacteristic fires in terms of size and severity. Prior analyses of fire severity in California forests showed that time since last fire and fire weather conditions predicted fire severity very well, while a larger regional analysis showed that topography and climate were important predictors of high severity fire. There has not yet been a large-scale study that incorporates topography, vegetation and fire-year climate to determine regional scale high severity fire occurrence. We developed models to predict the probability of high severity fire occurrence for the western US. We predict high severity fire occurrence with some accuracy, and identify the relative importance of predictor classes in determining the probability of high severity fire. The inclusion of both vegetation and fire-year climate predictors was critical for model skill in identifying fires with high fractional fire severity. The inclusion of fire-year climate variables allows this model to forecast inter-annual variability in areas at future risk of high severity fire, beyond what slower-changing fuel conditions alone can accomplish. This allows for more targeted land management, including resource allocation for fuels reduction treatments to decrease the risk of high severity fire.

1. Introduction

Fire activity is changing in western United States (WUS) forests, with increasing area burned and fire season length partially attributed to warming (Stephens 2005, Westerling *et al* 2006, Dennison *et al* 2014, Westerling 2016, Abatzoglou and Williams 2016). A century of fire suppression has also altered forest structure and ecological function in parts of the WUS. A build-up of fuels due to missed fire cycles in formerly open canopy forests with predominately surface fire regimes likely contributed to increasingly uncharacteristic fires in terms of size and severity (Keane *et al* 2002, Allen *et al* 2002, Miller *et al* 2009). These changes increased firefighting costs: federal firefighting appropriations averaged \$2.9 billion for 2001–2007, up from \$1.2 billion for 1996–2000 (Nazzaro 2007). The impacts of this history on WUS fire severity have not been fully quantified.

Climate is a significant predictor of large fire occurrence and size (Westerling *et al* 2006, Preisler and Westerling 2007, Swetnam and Anderson 2008, Westerling 2016). Climate controls fire occurrence and severity at broad and fine spatial and temporal scales to promote fuel loading through biomass accumulation and accelerate drying of fuels, and to maintain active fires under favorable concurrent atmospheric conditions, i.e. hot dry weather. Broad-scale drought is linked to regionally synchronous large fires, and recent decades have seen warmer, drier, and longer growing seasons that explain much of WUS large forest fire occurrence (Gedalof *et al* 2005, Westerling *et al* 2006, Heyerdahl *et al* 2008, Morgan *et al* 2008, Swetnam and Anderson 2008, Westerling 2016).

Additional controls on fire occurrence and severity include land surface characteristics such as topography and vegetation (Alexander *et al* 2006, Thompson

et al 2007, Gill and Taylor 2009). Together with climate and soils, topography (e.g. slope, aspect, elevation) affects energy and water available for biomass production and decomposition, and thus fuel accumulation. Microclimate created by topography also influences fuel flammability. Generally, higher elevation WUS sites support cool moist forests with dense vegetation and fuels, whereas lower elevation sites support relatively less productive dry forests (Agee 1993, Stephenson 1998, Schoennagel *et al* 2004).

Controls on fire severity have been quantified at many scales—individual fires, landscapes, and small regions. Findings in Colorado Front Range and Southwest forests indicate high severity fire occurrence is a function of extreme weather, rather than vegetation or woody fuel quantity (Holden *et al* 2007, Sherriff *et al* 2014). Collins *et al* (2007, 2009) found that both climate and time since last fire best predicted patterns of fire severity in the Sierra Nevada; time since last fire is correlated with biomass and fuel buildup on a site. Lutz *et al* (2009) found snowpack anomalies (top-down) mediated lightning ignitions, area burned, and fire severity in Yosemite National Park.

The importance of climate controls in these regions contrasts with findings in parts of the Northwest. In the North Cascade Range, Washington, topographic and vegetation characteristics appeared to mediate burn severity on sites with historically low to moderate severity fire regimes, while climate controls were most evident in high elevation, cool moist forests (Cansler and McKenzie 2014). In central Idaho and western Montana, Birch *et al* (2015) also found topography and vegetation best predicted daily burn severity values over daily weather and fuel moisture.

No consistent picture emerges of controls on severity among these small-scale studies (individual fires to small regions). Dillon *et al* (2011) performed the broadest spatial analysis to date, modeling high severity fire occurrence for northwestern and southwestern US ecoregions. They found both climate and topography important for predicting high severity fire occurrence, but concluded that topographic controls were more important; their predictability was low in extreme years with many large fires (Dillon *et al* 2011).

While existing studies examined high severity fire occurrence at small scales, there has not yet been a large-scale study that incorporates topography, vegetation, and climate to predict regional scale high severity fire occurrence. Here we describe a model for the WUS that predicts high severity fire occurrence, conditional on large fire occurrence, and use it to examine the relative importance of topography, vegetation, and climate.

2. Methods

2.1. Spatial and temporal domain of analysis

Our spatial domain is a 1/8th degree latitude/longitude modeling grid (~12 km resolution) west

of -102.0625 longitude encompassing eleven states: WA, OR, CA, ID, UT, NV, MT, WY, CO, NM, AZ. The spatial resolution of data varies from 30 m (e.g. observed high severity burned area, vegetation) to ~12 km (e.g. climate, topography). For higher resolution variables, we calculated fractional area of each variable within each modeling pixel.

The temporal domain was limited by Landsat image-derived burn severity data (1984–2014). Using land surface and hydroclimate predictors and monthly fire discovery events, we model gridded high severity fire occurrence at a monthly time step. Individual fire records contain the discovery date, which often approximates the ignition date and conditions likely conducive to rapid fire spread (Westerling *et al* 2006).

The California Energy Commission specified 1961–1990 as a reference period for the four California state climate and vulnerability assessments to date, to reflect average climate conditions prior to significant climate change impacts. We retain the 1961–1990 normal period for consistency and comparability of results with prior work by the authors.

2.2. Burn severity data

We acquired burn severity data from the Monitoring Trends in Burn Severity database (MTBS Data Access 2009, www.mtbs.gov; accessed 12/2008 and 9/2016), resulting in a dataset with a total of 6808 fires (4493 through 2006) coded by discovery date (month, year), using thematic burn severity images comparable across space and time. We used ESRI Arc Macro Language (ESRI 1999) to intersect burn severity data with a 1/8th degree grid, assigning each fire to the grid cell where a majority of area burned. We then calculated fractional area burned in six severity classes (unburned to low severity, low severity, moderate severity, high severity, increased greenness, or unclassified) by voxel (latitude, longitude, year × month) (Eidenshink *et al* 2007).

2.3. Landscape data

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

We aggregated LANDFIRE existing vegetation type (EVT) and fire regime condition class (FRCC) variables to the modeling grid (Keane and Rollins 2007, www.landfire.gov). We used a reclassification of the EVT layer, extracting only the fractional area of forest types characterized by stand replacing fire regimes (Westerling *et al* 2011a). FRCC is a metric widely used to prioritize fuel treatments and characterizes ecosystem departure, in terms of vegetation

structure and composition, from historical conditions (Hann 2004, Lavery and Williams 2000). We extracted the fractional area of each FRCC class: FRCC1 (departure <33%), FRCC2 ($\geq 33\%$ departure <66%), and FRCC3 (departure $\geq 67\%$) (Holsinger *et al* 2006, Keane and Rollins 2007). For this study, FRCC is fixed in time, reflecting year 2000 observed conditions.

2.4. Climate and hydrologic data

We obtained hydrologic variables simulated with the Variable Infiltration Capacity (VIC) model and gridded climate data used to force VIC from the University of Washington National Hydrologic Prediction System (NHPS) (www.hydro.washington.edu/forecast/westwide/) (Liang *et al* 1994, Wood and Lettenmaier 2006). VIC calculates daily surface water and energy balances, estimating evaporation from vegetation canopy, bare soil surface, and transpiration by vegetation classes in each grid cell.

Climate data include temperature (Tmax, Tmin, Tave) and precipitation (PPT), while moisture deficit (MD), antecedent moisture deficit derivatives (e.g. 6 month prior moisture deficit), relative humidity (Rh), soil moisture, and snow water equivalent (SWQ) were derived from VIC and the Penman-Monteith equations (Penman 1948, Monteith 1965) on a monthly time step from 1915 present (Westerling *et al* 2011a, Westerling *et al* 2011b).

Stephenson (1998) showed that long term average MD and actual evapotranspiration (AET) are biologically meaningful drivers of the spatial distribution of vegetation types over multiple spatial scales. We used these and related variables as proxies for spatial variability in ecosystem and disturbance regime sensitivity to climate, including 30 years (1961–1990) means and standard deviations for Tave, PPT, cumulative MD, and AET. Standard deviations characterize inter-annual climate variability; for instance, higher precipitation standard deviation indicates locations with more dynamic precipitation regimes. We also created a thin plate spline interacting 1961–1990 average MD and AET to indicate biophysical site conditions for plant growth: different forest types fall along the gradient of MD and AET (Hastie *et al* 2001, Stephenson 1998).

2.5. Occurrence modeling

We employed a multi-step process in modeling high severity fire occurrence. Previous research using parts of this dataset and similar questions used both logistic regression and classification and regression tree (CART) methods, individually and together (Collins *et al* 2007, Collins *et al* 2009, Dillon *et al* 2011, Preisler and Westerling 2007, Westerling and Bryant 2008, Westerling *et al* 2011a, Westerling *et al* 2011b). The number of potential predictor variables available for this analysis was 85. In order to limit the number of variables in building a predictive model, we first used a

CART (Random Forest package in R; Liaw and Wiener 2002) model to identify the 20 most important variables in predicting fractional high severity. These provided the potential predictor set for developing conditional logistic regression models.

2.5.1. Logistic regression

We developed two conditional logistic regression models to predict high severity fire occurrence. Because MTBS contains only fires >400 ha, there exists an implicit *a priori* condition for our models: the occurrence of a >400 ha fire. Given this, we set a threshold for the presence of high severity equal to the median value of high severity fraction in the MTBS data, 0.042. Then, given presence of high severity fire, we set a threshold equal to the upper quartile cutoff, 0.1732. We define fires with high severity fraction above this threshold as high severity fires.

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

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

where X_j is the set of predictor variables best fit to Model Pa, P_{Pai} is the probability of high severity fire presence, defined as the fraction f of high severity fire >0.042 for a given month and grid cell indexed by i .

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

$$\begin{aligned} \text{Model Hi: Logit}(P|f > 0.1732|f > 0.042) \\ = \ln(P_{\text{Hii}}/(1 - P_{\text{Hii}})) = \sum (b_0 + b_j X_{ik}) \end{aligned}$$

where X_k denotes predictors best fit to Model Hi, where P_{Hii} is as P_{Pai} above. The probability of high severity fire occurrence (conditional on >400 total ha burned) for any month and location is the product of these two model probabilities: $P_{\text{Pai}} * P_{\text{Hii}}$.

The thresholds for high severity fire presence and occurrence are necessarily arbitrary. Our goal was to be as objective as possible, while defining meaningful thresholds for relatively rare events, and to demonstrate the predictability of high severity fires. Our models specifically address the question:

Given that a fire burns >400 ha, and given that high severity fire is present, what is the probability that this is a high severity fire (i.e. in the upper quartile of high severity burned area)?

We use the Aikake Information Criterion (AIC) to evaluate model performance (Aikake 1974, Aikake 1981). The best model optimizes model fit (minimizes AIC) while penalizing excess predictive parameters. We performed leave-one-out cross-validation of the best model. We tested variable importance by calculating probabilities and testing model performance after removing variable groups.

Table 1. List of predictors used in two conditional logistic regression models.

Variable Group and Description	Model Pa	Model Hi
TOPOGRAPHY		
Elevation:		
maximum	y	
mean	y	
CLIMATE		
1961–1990:		
Average temperature, mean and standard deviation	y	
Cumulative annual moisture deficit, standard deviation		y
Culuative water year precipitaion, standard deviation	y	y
Thin plate spline of 30 years average moisture deficit and evapotranspiration	y	y
Previous November moisture deficit	y	y
Normalized moisture deficit, month of fire	y	
Spring average temperature	y	y
VEGETATION		
Fractional cover of forest with stand replacing fire regime	y	y
Fraction of FRCC3	y	

2.5.2. Mapping probability of high severity fire occurrence

We applied both conditional logistic regression models to all WUS voxels, 1984–2014 and calculated annual probability of high severity fire occurrence for each pixel by summing monthly values. We also calculated the coefficient of variation (CoV) in the annual probability values for each grid cell for the period 1984–2014. Here CoV measures inter-annual variability in conditional probabilities, quantifying spatially varying sensitivity to fire-year climate variables.

3. Results

3.1. Trends in high severity fire occurrence

We tested trends for WUS, each state, and each month. We found no significant trend in WUS high severity fire occurrence over 1984–2014, except for Colorado (table S1 available at stacks.iop.org/ERL/12/065003/mmedia). While some studies have shown increasing fire season length, we saw no significant increase in high severity fire occurrence by month, May through October (figure S1). We found no correlation between fraction of high severity fire and total fire size, meaning increasing large fires does not necessarily increase fractional high severity fire area.

Seasonal occurrence of high severity fire coincided with WUS burned area (figure S1). However, the fine-grained distribution of high severity fire is quite variable. California and Idaho had the largest number of large fires and high severity fire occurrence, but many fires had no presence of high severity fire. Both Montana and Wyoming experienced fewer large fires than other states, often with no high severity fire present (figure S2).

3.2. Occurrence modeling

The best predictive models for high severity fire presence included all variable groups—climate,

topography, and vegetation (table 1). Pixel mean and maximum elevations are the only topographic variables in the best model. Climate normals include standard deviation of 1961–1990 cumulative annual water-year precipitation and moisture deficits and the thin plate spline interacting long term average MD and AET. Fire-year climate variables included average spring temperature (SPRT), average monthly temperature and normalized monthly moisture deficit at fire discovery (MD0), and MD the previous November (MD2).

Our best models included two vegetation variables. Fractional area of forest types with stand replacing fire regimes was important for Models Pa and Hi, while fractional area of FRCC3 was significant only in Model Pa.

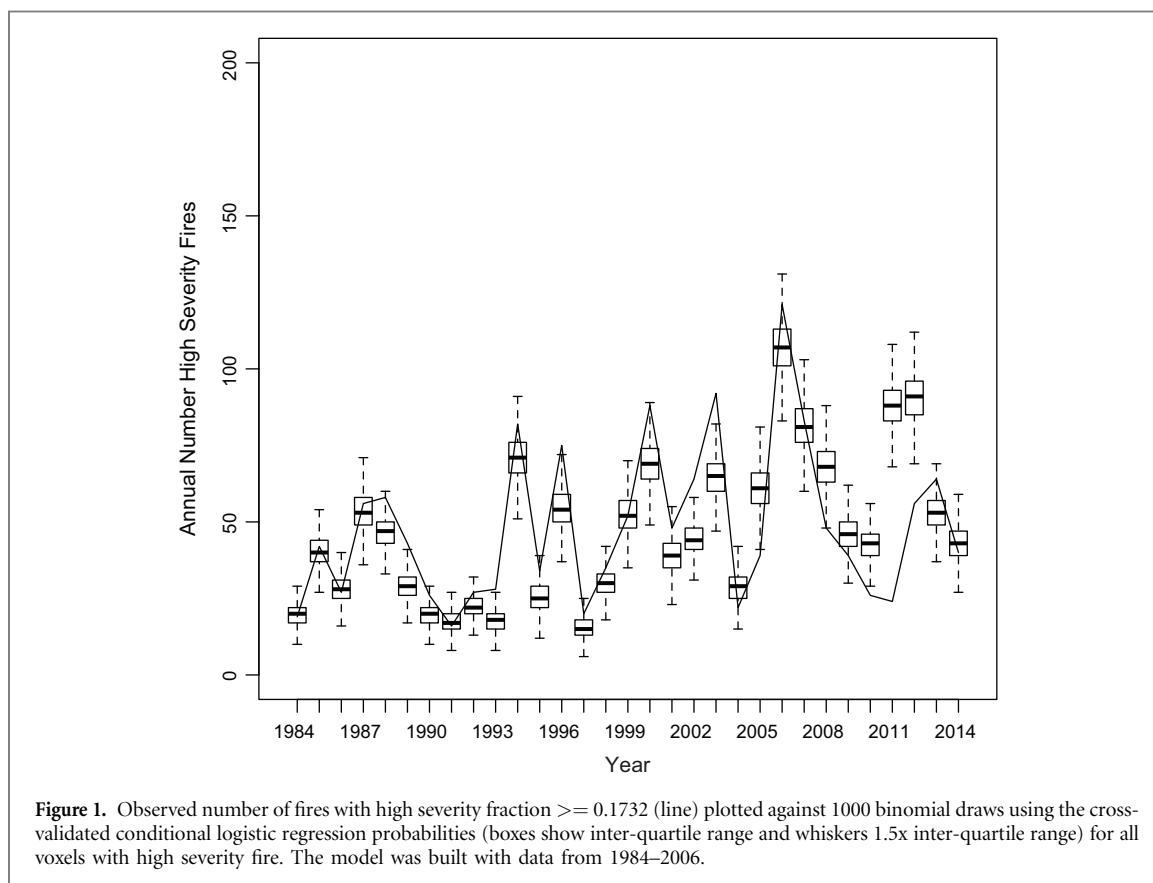
Removing fire-year climate, our models do not predict extremes in inter-annual variability of high severity fire occurrence. Removing vegetation variables does not significantly alter predicted vs. observed high severity fire occurrences (high severity fire occurrence in vegetation-only models still varies with time because it is conditional on observed fires). Fixed site-specific variables describe a constant spatial distribution for probability of high severity fire given a large fire, identifying location and average recurrence rates for fire regimes where high severity fire occurs. While all model iterations perform well with regard to prediction vs. observation for locations with fires, the AIC is lowest for the full model (table 2, figure 1).

3.3. Mapping probability of high severity fire occurrence

To illustrate effects of variable groups, we mapped differences for two years with few (1991 [$N = 16$] and 1997 [$N = 10$]) and two years with many (1996 [$N = 75$] and 2000 [$N = 88$]) high severity fires (figure 2). Removing fire-year climate produces probability maps with a negligible shift in WUS average probabilities for high severity fire occurrence, but with distinct regional

Table 2. Performance statistics for logistic regression models. The delta AIC value is the difference between the full model and models with variables removed. Lower AICs indicate better model performance.

		AIC	Δ AIC	Adjusted R^2	Cross validated Adjusted R^2	CV pearsons r Predicted ν Observed
Full Model	Model PA	7799	—	0.811 (p 3.16e-12)	0.715 (p1.32e-9)	
	Model Hi	6425	—	0.647 (p 2.99e-8)	0.438 (p 3.0e-5)	0.676
No Vegetation	Model PA	7888	89	0.820 (p 1.60e-12)		
	Model Hi	6554	129	0.575 (p 4.70e-7)		
No Fire Year Climate	Model PA	7943	144	0.817 (p 1.99e-12)		
	Model Hi	6534	109	0.633 (5.47e-8)		
No Veg/No Climate	Model PA	8030	231	0.821 (p 1.40e-12)		
	Model Hi	6690	265	0.582 (p 3.68e-7)		



differences (figure 2). For the low year 1991, removing fire-year climate increases the maximum predicted probability from 79% to 90%. For 1996, a high occurrence year, removing fire-year climate increases the maximum from 76% to 90%. Probability of occurrence decreases over California; this pattern is opposite the Northern Rocky Mountain and North Cascade regions, where probabilities increase when we remove fire-year climate.

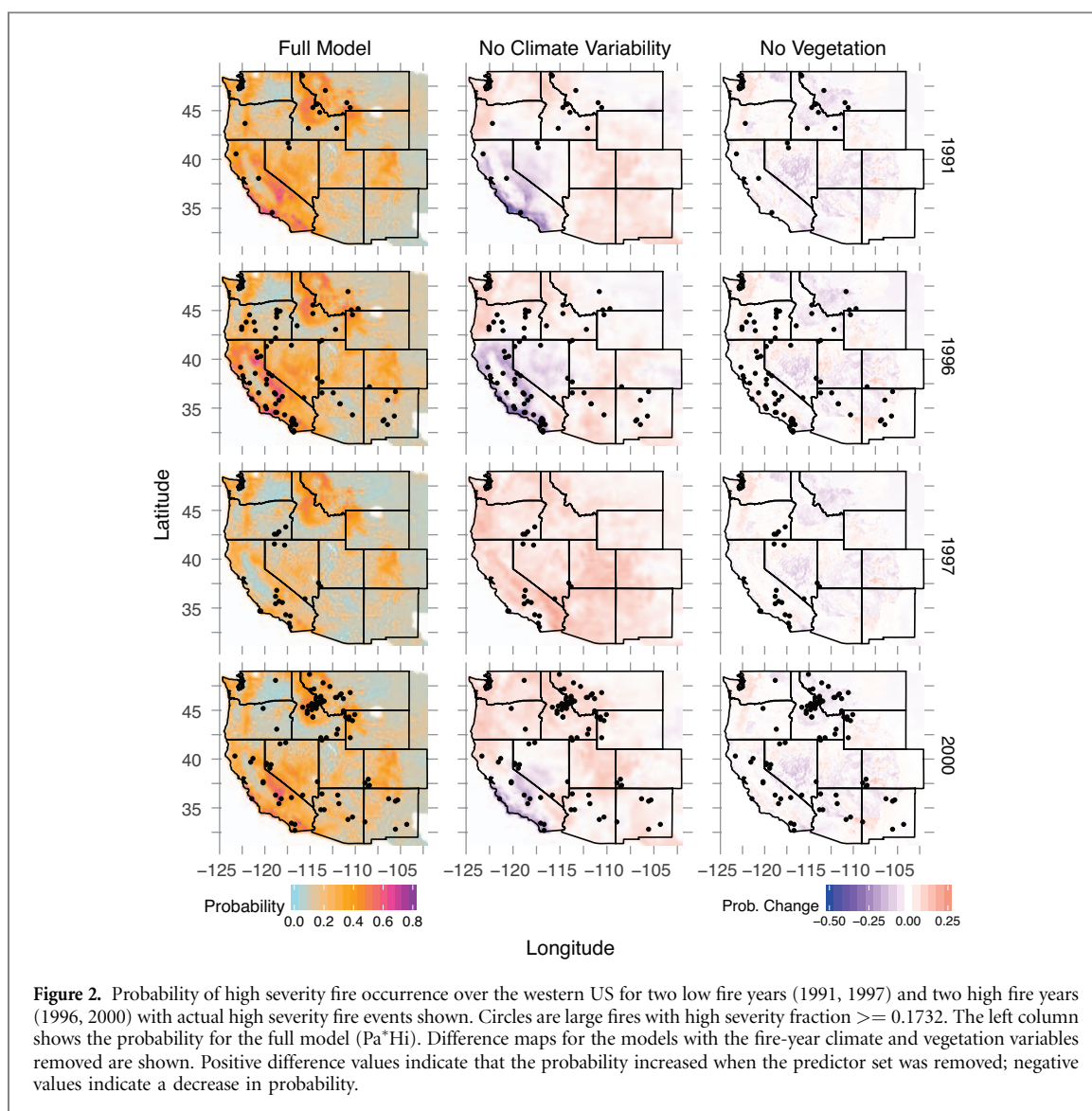
4. Discussion

4.1 Inter-annual variability and trends in high severity fire occurrence

Our results highlight the importance of inter-annually varying climate for high severity fire occurrence. Fire-

year climate significantly modified conditional probabilities of high severity fire occurrence across the WUS, though with stronger effects in Sierra Nevada and Southwest forests with mixed-severity fire regimes than in Northwest and Northern Rockies forests with high severity fire regimes.

Others have shown a lengthening fire season and increasing large fire occurrence and burned area due to climate change (Westerling *et al* 2006, Dennison *et al* 2014, Jolly *et al* 2015, Westerling 2016). While conditions under which high severity fires in our record burned were warmer and drier than the long term average (figure S3), the lack of observed trends in fire severity occurrence (table S1) may be at least in part due to the short record, which begins right at the time of the largest temperature-driven increase in WUS forest burned area (Westerling *et al* 2006).



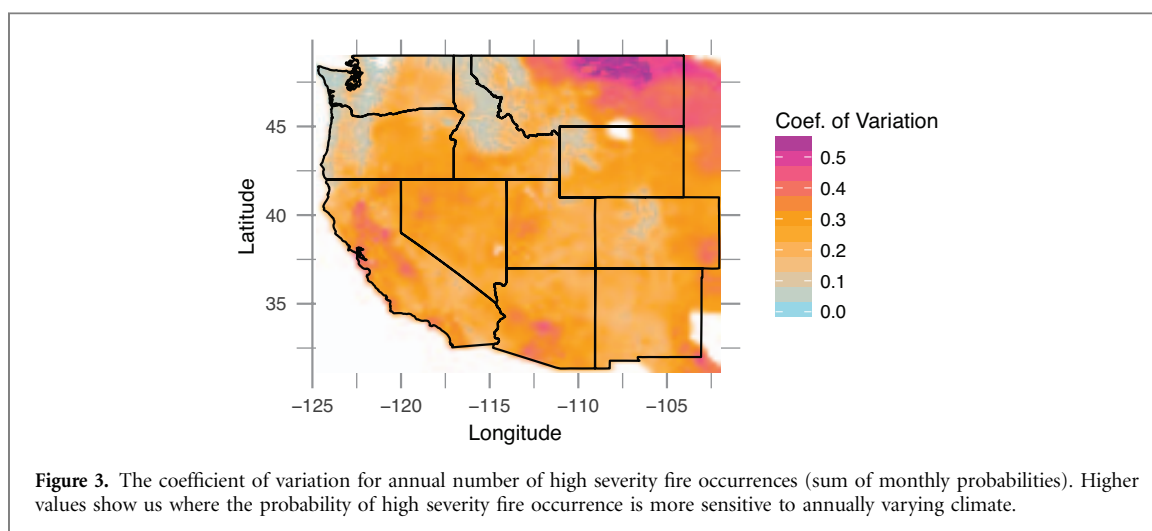
Similarly, the record for fire severity begins >70 years after the start of fire suppression. Ecosystems with short fire return intervals (7–10 years) may have missed up to 10 fire cycles by the time the MTBS severity record begins, while those with longer fire return intervals may have missed few or none, so we would only expect to see changes in severity due to fire suppression and fuel buildup on some of the landscape. Observed patterns of high severity fire occurrence may be influenced by changing climate and management, but without more observations, we can not quantify significant trends in high severity fire occurrence.

4.2. Mapping high severity fire occurrence

Our best models included both climate and land surface characteristics, e.g. topography and vegetation, to predict fire severity. The impact of removing vegetation or fire-year climate predictors is subtle. Considering first removing temporally fixed predictors such as fractional area in FRCC3 and in forest types with high severity fire regimes, inter-annual variability

of model predictions is not significantly affected. Spatially, effects are most pronounced in mountainous areas, as one of the variables is forest fraction with high severity fire regimes (figure 2). We see a general decrease in probability of occurrence in the Sierra Nevada, western Nevada, and Northern Rocky Mountains. Both the Colorado Rocky Mountains and the Northern Cascades in Washington generally show a higher probability of high severity fire occurrence when we remove vegetation variables.

When we remove fire-year climate variables, conditional probabilities of high severity fire generally decrease in California and Nevada, but increase in the Pacific Northwest and Northern Rocky Mountain regions (figure 2). Many of the ecosystems in the Pacific Northwest and Northern Rocky Mountains are dominated by cool moist forests with historically infrequent stand replacing fire (Agee *et al* 1977, Agee 1993, Cansler and McKenzie 2014, Schoennagel *et al* 2004). These forests have abundant fuels, but are rarely hot and dry enough to burn. Increased probabilities in these regions after removing fire-year climate reflect



climate's importance in determining whether these forests will burn and supports findings that fire-year climate controls severity occurrence in this forest type (Cansler and McKenzie 2014, Schoennagel *et al* 2004). Previous studies found fire-year climate less important than topography and vegetation as a predictor of high severity fire occurrence in the North Cascades and Northern Rocky Mountains (Cansler and McKenzie 2014, Birch *et al* 2015, Dillon *et al* 2011). Our results indicate that in these systems with a propensity for high severity fire, fire-year climate still modulates high severity fire occurrence.

Probability maps show fire-year climate both amplifies and moderates probabilities of high severity fire based on biophysical site characteristics. Fire-year climate anomalies are highest for many high occurrence fire years: Tave, SPRT, MD0, MD2 (figure S3). November MD (MD2) is an indicator for moisture stress early in the water year; Van Mantgem *et al* (2013) found that high pre-fire climatic water deficit is related to increased post-fire tree mortality. These variables all indicate high severity occurrence years are drier and hotter than average, conditions that increase fuel flammability and enhance conditions for fire spread.

While climate variability significantly affected conditional probabilities of high severity fire, those probabilities are conditional on fires >400 ha. Though the predictive maps for years like 1991 and 1996 look very similar in terms of *conditional* probability of high severity fire occurrence, the actual fire record is quite different. The number of fires in the MTBS record for 1991 was 75 total (16 high severity) v. 272 total (75 high severity) fires for 1996. While ignitions resulting in large fires were few, modeled probabilities indicate that had more large fires occurred, high severity fire would have been likely in 1991.

The inclusion of inter-annually varying climate is critical for capturing high probability episodes in areas where fire severity is highly variable, especially California and the Southwest, where the coefficient of variation (thus influence of climate) is higher

(figure 3). Our models imply substantial fraction high severity fire in mixed severity fire regimes requires more extreme climatic conditions. Conversely, in the Northern Rocky Mountain and Pacific Northwest, regions that are dominated by cool moist forests with high severity fire regimes, the coefficient of variation (and effect of climate) is lower.

Our results are similar to Dillon *et al* (2011) regarding the importance of topography, but differ with respect to the importance of fire-year climate and the ability to predict extremes in high severity fire occurrence. This is likely due to differences in methodology and data. In our study each fire is classified as a high severity fire or not. Dillon *et al* (2011) selected a random subset of individual 30 m fire pixels classified to high severity or not. This means that they could select multiple pixels from a single fire with different classification, whereas their climate data would be identical for pixels from a given fire.

Dillon *et al* (2011) tested different independent climate variables, which could also lead to the differing conclusions. For each fire, we used hydroclimate variables for the voxel where the majority of area burned. Dillon *et al* (2011) interpolated monthly temperature and precipitation for the central latitude, longitude and mean elevation of each fire. Their soil moistures were simulated with VIC, as were our hydroclimate data, but at coarser scale. We also test a larger set of hydroclimate variables. Comparing approaches, we expect theirs would have more power to describe topographic controls on fire severity, whereas the present study may be better suited to demonstrating climatic controls.

5. Conclusions

While conditional probabilities of high severity fire occurrence are partially determined by biophysical setting, existing vegetation and fuels, our models demonstrate fire-year climate amplifies or moderates risk of high severity fire occurrence given ignition and

growth to at least 400 ha burned area, and is important for predicting extremes in high severity fire occurrence. These models could be used with others that predict large fire occurrence to plan for resource allocation or mitigation efforts, or to assess how high severity fire occurrence might respond to changing climate and fuels management.

The importance of hydroclimate variables, especially fire-year climate, suggests further improvements could be achieved with finer scale, more realistic data, especially in mountainous terrain where climate varies greatly with topography. Hydroclimate was simulated in VIC with a static vegetation layer. Sensitivity analyses of large vegetation changes in VIC did not result in large changes in MD or AET (unpublished, AL Westerling *personal communication*); newer-generation hydrologic models might improve simulations. Additionally, FRCC that more closely represents individual fires or that could be combined with fuel availability might improve its value as a predictor.

Because probabilities modeled here are conditional on large fire occurrence, they need to be coupled with models of large fire occurrence in order to predict high severity fire occurrence. As with all models, ours has limitations, but its performance is robust. This is the first study to use the entire MTBS database to examine patterns in high severity fire, identify the importance of fire year climate, and predict extremes in high severity fire occurrence conditional on large fire occurrence.

Acknowledgments

This research was supported by the California Nevada Applications Program under NOAA grant no. NA110AR4310150, California Energy Commission grant no. 500-14-005, and by the USDA Forest Service under award no. 14 CS-11052006-025. We thank Jeanne Milostan for assistance in processing hydroclimate data. We thank Jessica Blois and Lara Kueppers for thoughtful comments that improved the manuscript. We also thank the reviewers for their insight to better the manuscript. Any errors or omissions are our own.

References

- Abatzoglou J T and Williams A P 2016 Impact of anthropogenic climate change on wildfire across western US forests *Proc. Nat. Acad. Sci.* **113** 11770–5
- Agee J K, Wakimoto R H and Biswell H H 1977 Fire and fuel dynamics of Sierra Nevada conifers *For. Ecol. Manage.* **1** 255–65
- Agee J K 1993 *Fire Ecology of Pacific Northwest Forests* (Washington, DC: Island Press) p 505
- Akaike H 1974 A new look at the statistical model identification *IEEE Trans. Autom. Control* **19** 716–23
- Akaike H 1981 Likelihood of a model and information criteria *J. Econ.* **16** 3–14
- Alexander J D, Seavy N E, Ralph C J and Hogoboom B 2006 Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California *Int. J. Wildland Fire* **15** 237–45
- Allen C D, Savage M, Falk D A, Suckling K F, Swetnam T W, Schulke T, Stacey P B and Morgan P 2002 Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective *Ecol. Appl.* **12** 1418–33
- Birch D S, Morgan P, Kolden C A, Abatzoglou J T, Dillon G K, Hudak A T and Smith A M S 2015 Vegetation, topography and daily weather influenced burn severity in central Idaho and western Montana forests *Ecosphere* **6** 17
- Cansler A C and McKenzie D 2014 Climate, fire size, and biophysical setting control fire severity and spatial pattern in the northern cascade range USA *Ecol. Appl.* **24** 1037
- Collins B M, Kelly M, van Wagtenonk J W and Stephens S L 2007 Spatial patterns of large natural fires in Sierra Nevada wilderness areas *Landscape Ecol.* **22** 545–57
- Collins B M, Miller J D, Thode A E, Kelly M, van Wagtenonk J W and Stephens S L 2009 Interactions among wildland fires in a long-established Sierra Nevada natural fire area *Ecosystems* **12** 114–28
- Dennison P E, Brewer S C, Arnold J D and Moritz M A 2014 Large wildfire trends in the western United States, 1984–2011 *Geophys. Res. Lett.* **41** 2928–33
- Dillon G K, Holden Z A, Morgan P, Crimmins M A, Heyerdahl E K and Luce C H 2011 Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006 *Ecosphere* **2** 130
- Eidenshink J, Schwind B, Brewer K, Zhu Z, Quayle B and Howard S 2007 A project for monitoring trends in burn severity *Fire Ecology* **3** 3–21
- ESRI Editors and Editors of ESRI Press, editors 1999 *Arc Macro Language version 7.1.1: Developing ARC/INFO Menus and Macros with AML, for UNIX and Windows NT* 2nd edn (Redlands, CA: ESRI Press)
- Gedalof Z, Peterson D L and Mantua N J 2005 Atmospheric, climatic, and ecological controls on extreme wildfire years in the northwestern United States *Ecol. Appl.* **15** 154–74
- Gill L and Taylor A H 2009 Top-down and bottom-up controls on fire regimes along an elevational gradient on the east slope of the Sierra Nevada, California, USA *Fire Ecol.* **5** 57–75
- Hann W J 2004 Mapping fire regime condition class: a method for watershed and project scale analysis *Proc. 22nd Tall Timbers Fire Ecology Conf., Fire in Temperate, Boreal and Montane Ecosystems* ed R T Engstrom, K E M Galley and W J De Groot (Tall Timbers Research Station) pp 22–44
- Hastie T J, Tibshirani R and Friedman J 2001 *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (New York: Springer) 533 pp
- Heyerdahl E K, McKenzie D, Daniels L D, Hessel A E, Littell J S and Mantua N J 2008 Climate drivers of regionally synchronous fires in the inland Northwest (1651–1900) *Int. J. Wildland Fire* **17** 40–9
- Holden Z A, Morgan P, Crimmins M A, Steinhorn R K and Smith A M S 2007 Fire season precipitation variability influences fire extent and severity in a large southwestern wilderness area, United States *Geophys. Res. Lett.* **34** L16708
- Holsinger L, Keane R E, Steele B, Reeves M C and Pratt S 2006 Using historical simulations of vegetation to assess departure of current vegetation conditions across large landscapes ed M G Rollins and C K Frame Tech eds. 2006. The LANDFIRE Prototype Project: nationally consistent and locally relevant geospatial data for wildland fire management *Gen. Tech. Rep. RMRS-GTR-175* (Fort Collins, CO: US Department of Agriculture)
- Jolly W M, Cochrane M A, Freeborn P H, Holden Z A, Brown T J, Williamson G J and Bowman D M J S 2015 Climate induced variations in global wildfire danger from 1979 to 2013 *Nat. Commun.* **6** 7537

- Keane R E, Ryan K C, Veblen T T, Allen C D, Logan J A and Hawkes B 2002 The cascading effects of fire exclusion in Rocky Mountain ecosystems *Rocky Mountain Futures: An Ecological Perspective* ed J Baron (Washington DC: Island Press) 325 pp
- Keane R E, Rollins M and Zhu Z 2007 Using simulated historical time series to prioritize fuel treatments on landscapes across the United States: the LANDFIRE prototype project *Ecol. Modelling* **204** 485–502
- Laverty L and Williams J 2000 Protecting people and sustaining resources in fire-adapted ecosystems—a cohesive strategy *Response to GAO Report GAO/RCED* (Washington, DC: USDA Forest Service) 67479–511
- Liang X, Lettenmaier D P, Wood E F and Burges S J 1994 A simple hydrologically based model of land surface water and energy fluxes for general circulation models *J. Geophys. Res.* **99** 415–28
- Liaw A and Wiener M 2002 Classification and regression by random Forest *R News* **2** 18
- Lutz J A, Van Wagtenonk J W, Thode A E, Miller J D and Franklin J F 2009 Climate lightning ignitions, and fire severity in Yosemite National Park, California, USA *Int. J. Wildland Fire* **18** 765–74
- MTBS Data Access: Fire Level Geospatial Data 2009 MTBS Project (USDA Forest Service/U.S. Geological Survey) (<http://mtbs.gov/dataquery/individualfiredata.html>) (Accessed: December 2009, September 2016)
- Miller J D, Safford H D, Crimmins M and Thode A E 2009 Quantitative evidence for increasing forest fire severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA *Ecosystems* **12** 16–32
- Mitchell K E 2004 The multi-institution North American land data assimilation system (NLDAS): utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system *J. Geophys. Res.* **109** D07S90
- Monteith J L 1965 Evaporation and environment *Symp. Soc. Exp. Biol.* **19** 205–34
- Morgan P, Heyerdahl E K and Gibson C E 2008 Multi-season climate synchronized forest fires throughout the 20th century, Northern Rockies *Ecology* **89** 717–28
- Nazarro R M 2007 Management improvements could enhance federal agencies' efforts to contain the costs of fighting fires. *Testimony Report GAO-07-922T*
- Penman H L 1948 Natural evaporation from open water, bare soil and grass *Proc. R. Soc. Lond. A Math Phys. Sci.* **193** 120–45
- Preisler H K and Westerling A L 2007 Statistical model for forecasting monthly large wildfire events in western United States *J. Appl. Meteor. Climatol.* **46** 1020–30
- R Core Team 2015 *R: A Language and Environment for Statistical Computing* (Vienna, Austria: R Foundation for Statistical Computing)
- Schoennagel T, Veblen T T and Romme W H 2004 The interaction of fire, fuels, and climate across rocky mountain forests *Bioscience* **54** 661–76
- Sherriff R L, Platt R V, Veblen T T, Schoennagel T L and Gartner M H 2014 Historical, observed, and modeled wildfire severity in montane forests of the Colorado Front Range *PLoS One* **9** e106971
- Stephens S L 2005 Forest fire causes and extent on United States forest service lands *Int. J. Wildland Fire* **14** 213–22
- Stephenson N 1998 Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales *J. Biogeog.* **25** 855–70
- Swetnam T W and Anderson R S 2008 Fire climatology in the western United States introduction to special issue *Int. J. Wildland Fire* **17** 1–7
- Thompson J R, Spies T A and Ganio L M 2007 Reburn severity in managed and unmanaged vegetation in a large wildfire *Proc. Natl Acad. Sci.* **104** 10743–748
- van Mantgem P J, Nensmith J C B, Keifer M, Knapp E E, Flint A and Flint L 2013 Climatic stress increases forest fire severity across the western United States *Ecol. Lett.* **16** 1151–6
- Westerling A L, Hidalgo H G, Cayan D R and Swetnam T W 2006 Warming and earlier spring increase western US forest wildfire activity *Science* **313** 940–3
- Westerling A L and Bryant B P 2008 Climate change and wildfire in California *Clim. Change* **87** S231–49
- Westerling A L, Turner M G, Smithwick E H, Romme W H and Ryan M G 2011a Continued warming could transform Greater Yellowstone fire regimes by mid-21st Century *Proc. Natl Acad. Sci.* **108** 13165–70
- Westerling A L, Bryant B P, Preisler H K, Holmes T P, Hidalgo H, Das T and Shrestha S 2011b Climate change and growth scenarios for California wildfire *Clim. Change* **109** 445–63
- Westerling A L R 2016 Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring *Phil. Trans. R. Soc. B* **371** 20150178
- Wood A W and Lettenmaier D P 2006 A testbed for new seasonal hydrologic forecasting approaches in the western US *Bull Am. Meteorol. Soc.* **87** 1699–712