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Predicting increasing high severity area burned for three forested regions in the western United States using extreme value theory

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ABSTRACT

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

1. Introduction

More than 70 years of fire suppression by federal land management agencies has interrupted fire regimes in parts of the western United States (US). Many forest types that historically burned frequently have undergone significant changes in species composition and have heavy accumulations of surface and canopy fuels, putting them at risk for severe fires (Agee et al., 1978; Agee and Skinner, 2005; McKelvey et al., 1996; Keane et al., 2002). Of ~168 million hectares of fire adapted ecosystems in the coterminous US, more than 29 million are considered high risk to human and ecosystem values due to an accumulation of fuels and risk of high severity fire, and more than 57 million are considered a moderate risk (Cleaves, 2001). A high severity fire is exemplified by a stand replacing fire where most surface and crown fuels are burned and most over-story vegetation is killed.

Both the frequency and size of large wildfires have increased in the past 30 years in the western US (Dennison et al., 2014; Littell et al., 2009; Miller et al., 2009; Stephens and Ruth, 2005; Westerling et al., 2006; Westerling, 2016) as has the length of the fire season (Westerling et al., 2006; Jolly et al., 2015; Westerling, 2016). Climate affects area burned through both production of biomass and fuels, enhanced after wet winters and springs, and the drying of fuels, enhanced by drought. Recent work estimates at least half of observed trends in forest wildfire may be due to climate change (Abatzoglou and Williams, 2016). Many studies predict continued increases in large fire occurrence with climate change in western US forests (Spracklen et al., 2009; Littell et al., 2010; National Research Council, 2011; Westerling et al., 2011a, 2011b; Kitzberger et al., 2017).

Area burned in high severity fire has been correlated to total area burned in some regions, and has seen a concomitant increase with increasing fire size (Cansler and Mckenzie, 2014; Dillon et al., 2011; Miller et al., 2009; Miller and Safford, 2012; Abatzoglou et al., 2017). In the North Cascade Range, Cansler and McKenzie found that both total high severity area and patch size increased with total burned area (2014). Bottom-up controls, such as topography and vegetation, appeared to mediate this fire area-burn severity area relationship in some ecosystems with historical low-moderate severity fire regimes (Cansler and McKenzie, 2014).

In the Sierra Nevada Mountains, California and Nevada, Miller et al., found that fire size (annual mean and maximum) and total area burned increased in the period 1984–2006, and are now above pre-suppression levels prior to 1935 (2009). They also found that the proportion of high severity, stand-replacing fires increased (Miller et al., 2009). The proportional increase in high severity fires was not uniform, but was concentrated in low to mid-elevation forest types where 25–40% of total burned area was classed as high severity. High severity fires are not characteristic of these forest types, indicating that the current fire regime in these ecosystems is outside of historical natural

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conditions (Agee et al., 1978; Agee, 1998; Collins et al., 2009; Moody et al., 2006; Parsons and DeBenedetti, 1979).

Previous work (Keyser and Westerling, 2017) indicates that fire year climate is critical to accurately predicting severe fire occurrence, especially for very large fires. While many studies have now sought to explain what controls the occurrence of high severity fire at the individual fire to regional scales, few have looked at what controls the scale at which high severity fire occurs. Abatzoglou et al., (2017) found weak to moderate correlations between metrics of fuel aridity and regional burn severity. The ability to predict the amount of area that is at risk of burning in high severity fire and whether this is changing would improve the implementation of management decisions to mitigate fires with severity that is uncharacteristic in size or for the ecosystem in which it occurs. In this paper, we seek to answer the following questions:

Given that a large fire (> 400 ha) occurs,

1. What is the probability that > 200 ha will burn in high severity?
2. What are the total hectares burned in high severity?
3. What variables determine area burned in high severity?

2. Methods

2.1. Spatial and temporal domain of analysis

As with the presence/absence modeling in Keyser and Westerling, our modeling domain is a 12 km × 12 km latitude/longitude grid of eleven Western US states (2017). We developed models for the Western US as a whole and three smaller regions to determine if we could improve model performance in years with very large high severity area burned in: the Sierra Nevada Mountains (SN), the Northern Rocky Mountains (NR), and mountains in Arizona and New Mexico (hereafter Southwest, SW) (Fig. 1). The data used vary in spatial resolution from 30 m to 12 km; to maintain information content of the higher resolution data, we aggregated it to the 12 km modeling grid by calculating fractional area of each variable.

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

2.2. Burn severity data

We downloaded fire severity data from the Monitoring Trends in Burn Severity (MTBS) project website and used the classified fire severity images to build our models (Eidenshink et al., 2007, http://www.mtbs.gov). The classified images threshold the continuous differenced normalized burn ratio into five severity classes: unburned to low severity, low severity, moderate severity, high severity, increased greenness. For this analysis we selected only forest fires, defined as a fire in which at least 10% of the total burned area was in forest vegetation, following USFS classification standards (Brohman and Bryant, 2005). We used data included with the MTBS data that intersects fire severity pixels with Ecological Systems classifications, based on the National Landcover Data Classification (http://www.mtbs.gov/ProjectDocsAndPowerpoints/projectplan.html; 29 January 2016, Homer et al., 2007). We calculated the fractional fire area, for all classes, in the following broad classifications: barren, developed, forest, herbaceous natural, herbaceous planted, shrubland, water, wetlands. We dropped 41 fires from our classified burn severity data that did not have a matching record in the ancillary vegetation/severity database. Of a total 4591 fire records in the MTBS burn severity and vegetation database files (1984–2006), we retained 1871 fires that were a minimum of 400 ha, had forest cover ≥10% and had matching records in the classified severity and severity by vegetation database files. We intersected the burn severity images with the 12 km grid; if a fire intersected more than one modeling pixel, we assigned it to the pixel containing the majority of the fire area.

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

2.3. Landscape data

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

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

2.4. Climate and hydrologic data

We obtained a suite of hydroclimate predictor variables output from the Variable Infiltration Capacity model (VIC) and the gridded climate data used to force it. The VIC model calculates surface and energy water balances and is designed for large-scale applications; it has a simplified soil-vegetationatmosphere-transfer scheme with a two-layer soil module (Liang et al., 1994). A unique feature of VIC is its ability to account for sub-grid scale variability in vegetation characteristics; it

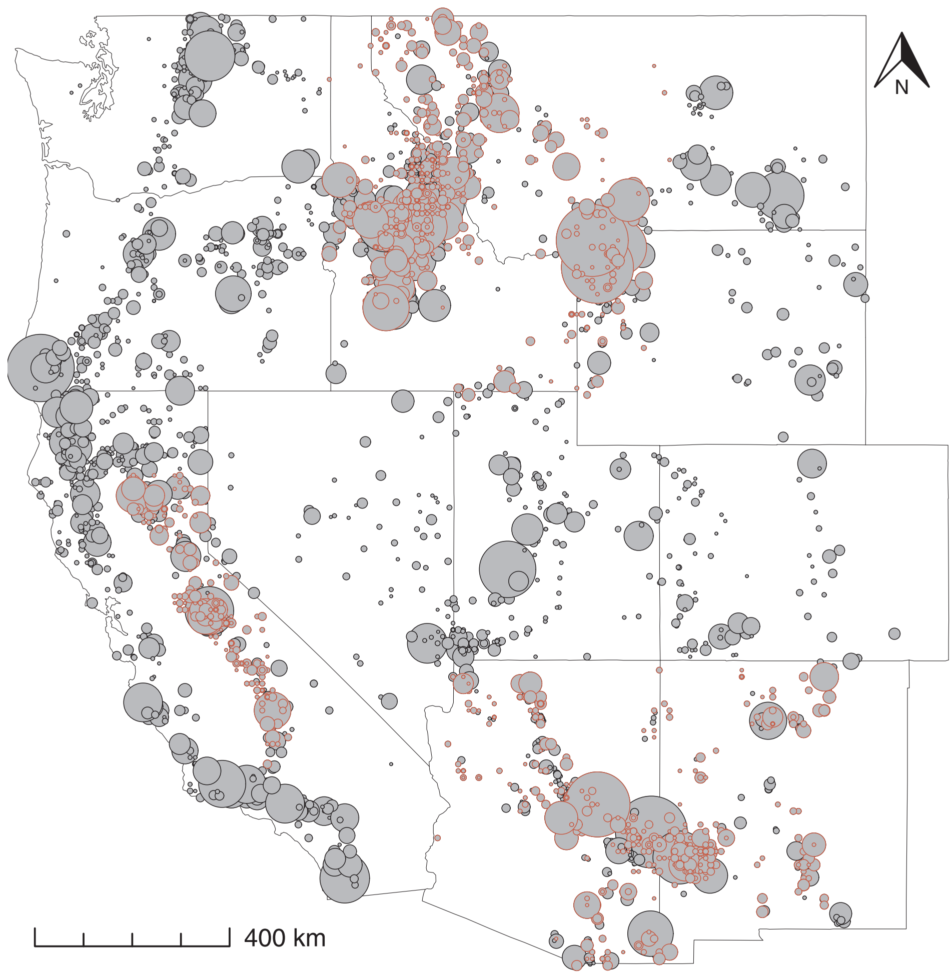

Fig. 1. Fires with > 10% forest cover from the MTBS database 1984–2014. Circle area is proportional to fire size. Fires in three model development sub-regions are outlined in red: the Northern Rocky Mountains (MT, ID, WY), the Sierra Nevada Mountains (CA), the Southwest (AZ, NM). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

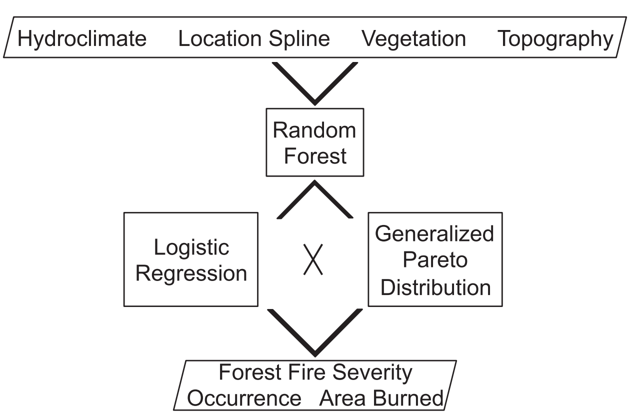

Fig. 2. Modeling framework. Predictor variables are winnowed using Random Forest. Logistic regression was used to predict the probability of meeting the threshold of > 200 ha and generalized Pareto distribution is used to predict the area burned in high severity fire.

calculates evapotranspiration from the vegetation and evaporation from bare soil surfaces at a daily time step for each vegetation class in the modeling grid cell and returns a weighted area sum. Our VIC data was produced with gridded daily climate at ~12 km (Maurer et al., 2002) and a 1 km vegetation layer from the North American Land Data Assimilation System produced by the University of Maryland (http://ldas.gsfc.nasa.gov, Mitchell et al., 2004). The vegetation layer is composed of coarse plant functional types, e.g. Evergreen needle leaf forest, deciduous broadleaf forest.

The VIC output is returned as monthly averages from 1915 to 2014 and includes: temperature extrema and average (Tmax, Tmin, Tave), precipitation (PPT), relative humidity (Rh), snow water equivalent (SWQ), evapotranspiration (ET), moisture deficit (MD), and antecedent moisture deficit derivatives (Westerling et al., 2009). Moisture deficit is the difference between potential ET and actual ET, or the unmet water demand of vegetation. For antecedent MD derivatives, we use the VIC output for 0–15 months prior to the current month, based on a water year. We calculated 30-year means and standard deviations for 1961–1990 for Tave, PPT, cumulative MD, and ET. Month of fire and cumulative annual MD variables were normalized relative to the 1961–1990 average and standard deviation.

2.5. Modeling framework

We employed a tiered modeling approach, first using Random Forest to winnow our predictor set. We then used logistic regression to determine the probability of a fire meeting our severity threshold and generalized Pareto distribution modeling to predict actual area burned in high severity fire. The product of these models is the potential area burned in high severity fire (Fig. 2). This framework was repeated for the west-wide model and each regional model.

2.5.1. Logistic regression modeling

We defined the presence of high severity fire for this analysis as 200 ha (as above). We used the Random Forest package in R to predict both the fraction of high severity fire (high severity hectares divided by total fire hectares) and high severity burned area (hectares classified as high severity) (Liaw and Wiener, 2002; R Core Team, 2015). We used the top 10–20 predictors from Random Forest as an initial predictor set to perform logistic regression analysis on presence of high severity fire > 200 ha. The model building and evaluation was iterative starting with a core set of variables and removing insignificant variables and evaluating changes in the AIC until we achieved the most parsimonious model with the best explanatory power.

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

$$\text{LogitP200} = \ln(\text{P200}/(1-\text{P200})) = \beta \times [1 + \text{X}j]$$

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

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

$$\text{AIC} = -2(\ln(\textit{likelihood})) + 2\text{N}$$

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

2.5.2. Generalized Pareto distribution modeling

We estimated generalized Pareto distributions (GPD) for fire severity area burned with a threshold value of 200 ha and used these to model the log of area burned in high severity fire. The GPD is a points over threshold model. The choice of threshold was made by evaluating a mean residual life (or sample mean excess function) plot. A threshold was chosen above which the mean residual life plot was linear, meaning that the GPD is providing a valid approximation of the distribution (Coles, 2001). The GPD can be estimated with and without covariates. Generally, if the data vary spatially or temporally, the inclusion of covariates is necessary to obtain a good model fit (Coles, 2001). We estimated GPDs with and without covariates using the *ismev* function in **R**, initializing with the same set of predictors used in the logistic regression model. Model specifications were evaluated with the AIC ((Akaike, 1974, 1981).

2.6. West-wide modeling

In our first stage of model estimation, we used all forest fires in the western US. Our success in creating models of high severity fire occurrence across the western US led us to first estimate GPDs for the entire region (Keyser and Westerling, 2017). These models performed well, with the exception of years with extremely large areas burned in high severity fire: 1988, 2002. The utility of our models lies in the ability to understand the conditions that lead to exceptional years in terms of high severity area burned. The years where our model performed poorly are years that saw regional differences in extreme fire activity, indicating that there are unique regional-scale controls on high severity fire area burned across western US forests in these years. We hypothesize that these are related to vegetation-mediated differences in the climate sensitivity of regional fire regimes that are not fully captured by the covariates we used. Previous work indicated that high severity fire occurrence requires more extreme climate conditions in regions where high severity fire occurrence is highly variable, such as California and the Southwest, than in areas dominated by cool moist forests with high severity fire regimes (Keyser and Westerling, 2017). We chose the Northern Rocky Mountains, Sierra Nevada Mountains, and Southwest forest areas to generate regional GPD models of high severity area burned in an attempt to improve model performance in extreme years and capture this variability across a large bioclimatic gradient.

2.7. Regional modeling

The Northern Rocky Mountain region experienced very large high severity area burned in the years 1988 and 2000; forests of the Southwest experienced the same in 2002, while 1987 and 2002 were high in the Sierra Nevada. We defined the Northern Rocky Mountains as area in Montana, Idaho, and Wyoming bound by latitudes (41.1875, 48.9375) and longitudes (−117.1875, −108.8125). We defined the Sierra Nevada Mountains using latitude (37.0, 40.5) and longitude (−122, −117.5) within California. For the Southwest, we took all forest fires in Arizona and New Mexico (Fig. 1).

3. Results

3.1. Trends in high severity burned area

High severity burned area was positively correlated to total burned area in the WUS and in individual states; the fraction of high severity burned area had weak to no correlation to total burned area (Table 1, Fig. 3). We looked for 1984–2014 trends in both high severity burned area and in the number of fires with > 200 ha high severity for the western US as a whole, for individual states, for our three modeling regions, and for months in the fire season. We found no trend in total annual high severity hectares burned from 1984 to 2014 (Table 2). There was, though, a corresponding trend in the number of fires with high severity hectares > 200.

Both the WUS and Wyoming experienced significant increases in the annual number of fires with high severity hectares > 200 from 1984 to 2014 ($p < 0.05$, Figs. 4 and 5, Table 2). This increase has occurred during the summer fire season in June, July, and August, all with significant increases in the number of high severity fires (Fig. 6).

For the three sub-regions we modeled, there were no significant trends in high severity burned area, fraction of high severity fire, or number of high severity fires (Table 3). The annual minimum fraction of high severity burned area per fire increased significantly in the Sierra Nevada; this means that severity of the least severe fire has increased (Fig. 7).

3.2. West-wide models

3.2.1. Logistic regression of high severity occurrence > 200 ha

There were 815 forest fires that met the threshold of 200 ha burned in high severity. A combination of vegetation condition class, location, temperature and moisture deficit variables best explained presence of high severity fire over our threshold (Table 4). The final model fit the observations well, Fig. 8 ($r = 0.95$, p-value < 0.001), and has the form:

Table 1
Pearson's correlation coefficients for high severity hectares burned and fraction of high severity hectares burned to total fire hectares. $^*p$ values < 0.05.

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

Table 2
Results from trend analysis of total annual high severity hectares burned and annual count of fires with high severity hectares > 200 (*Count*) for the period 1984–2014. $^*p < 0.05$. We looked for trends in all forest fires in the western US and for trends in forest fires by state. Standard Error values are in parentheses.

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

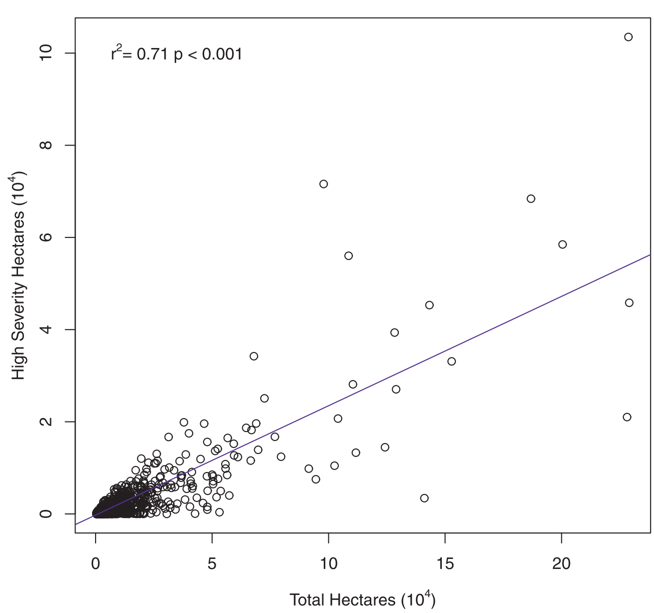

Fig. 3. Total area burned vs. high severity area burned for all fires in the western US, 1984–2014. Blue line is linear model fit to the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

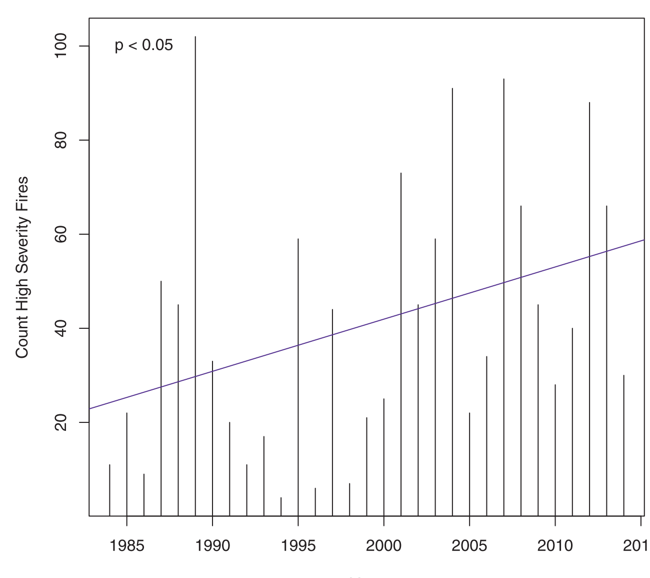

Fig. 4. Annual number of fires with high severity area exceeding the 200 ha threshold for 1984–2014 for all fires in the western US. The blue line is a fit of the statistically significant trend in number of high severity fires. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

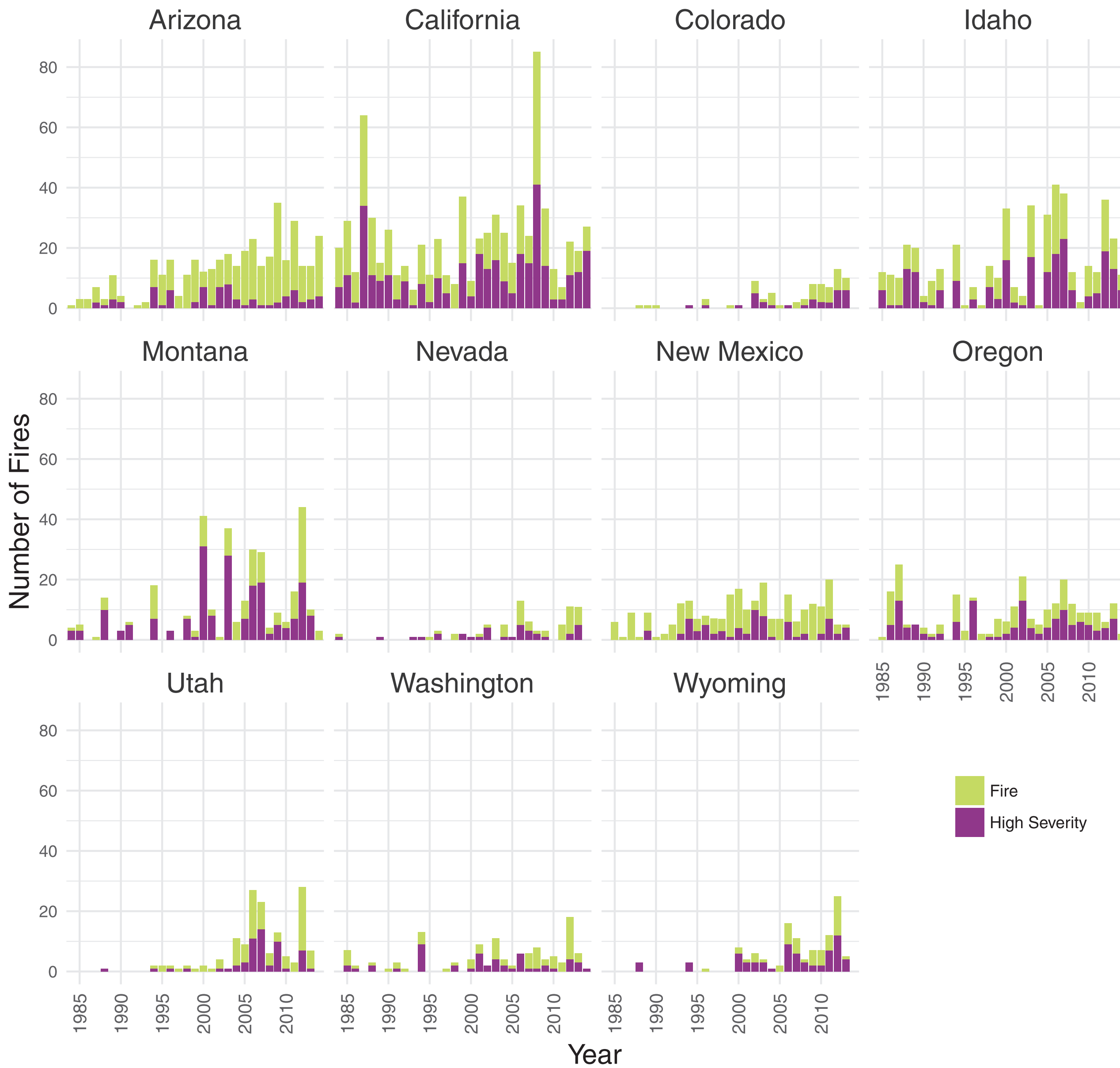

Fig. 5. Frequency of fires above and below our 200 ha threshold for each state. Green bars are the annual number of large fires with no presence of high severity fire; purple bars are the annual number of large fires classified as high severity, i.e. high severity hectares exceeding the 200 ha threshold. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\mathrm{Logit(P200)} = \beta \times [1 + \mathrm{Tavg.\ mu} + \mathrm{Tavg.\ sd} + \mathrm{Tmax} + \mathrm{MD10} + \mathrm{MD00n} + \mathrm{FRCC3} + \mathrm{X(Lat,\ Lon)}]$$

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

3.2.2. Generalized Pareto distribution modeling

The addition of covariates to the stationary generalized Pareto distribution (GPD) model significantly improved model fit (Fig. 9a). A fairly simple model with maximum temperature the month of fire, cumulative annual moisture deficit and location explains area burned in high severity fire in most years (Table 4).

Our west-wide model performed well with the exception of years with especially large areas burned in high severity fire: 1988, 2002. In the Northern Rocky Mountains, 1988 experienced large and severe fires in the greater Yellowstone region; forests of the Southwest and Sierra Nevada experienced large and severe burns in 2002. In these years, our model greatly under-predicts the area burned in high severity fire. While we theoretically should be able to specify a single west-wide model that captures these years as well as regional models do, it is difficult in practice because the R library for fitting GPD distributions with covariates somewhat constrains the functional form. It is also possible that the data we have available at this spatial scale do not fully capture differences in forest types across the regions. By fitting GPD distributions to different regions, we were better able to characterize the climate-fire-vegetation interactions across forest types—especially in extreme years—than with a single west-wide model.

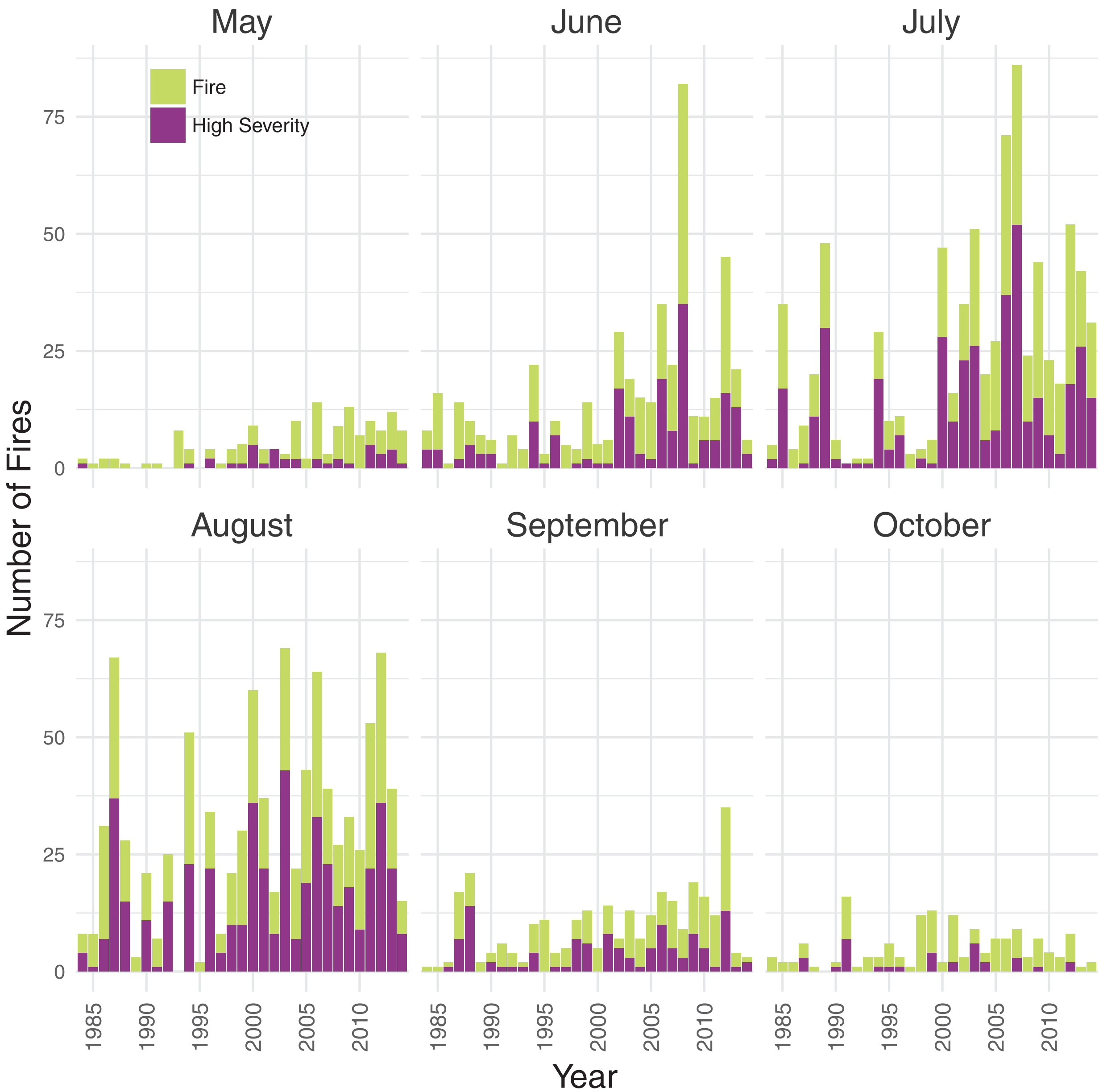

Fig. 6. Frequency of fires by severity class for May – October . Green bars are the annual number of large fires with no presence of high severity fire; purple bars are the annual number of fires classified as high severity, with high severity hectares > 200 ha threshold. June, July, and August all experienced statistically significant increases in number of high severity fires from 1984 to 2014 ($p = 0.015$, $p = 0.043$, $p = 0.057$, respectively). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.3. Regional models

3.3.1. Logistic regression of high severity occurrence > 200 ha

Regional models all performed well with highly significant correlations between predicted and observed high severity fire occurrence (Fig. 10). The primary difference in regional versus west-wide occurrence modeling was the importance of topographic and climate variables in the final regional models (Table 4). In the Northern Rocky Mountains (NRM), minimum and mean elevation in the modeling pixel were important ($r = 0.94$, p-value < 0.001); maximum elevation was important for the Southwest (SW, $r = 0.84$, p-value < 0.001), and average slope was important in the Sierra Nevada (SN, $r = 0.79$, p-value < 0.001). The NRM was the only region for which vegetation condition class (FRCC) was not important in the best-fit occurrence models.

3.3.2. Generalized Pareto distribution modeling

Our regional models explained extreme years with large areas burned in high severity, each with unique covariates. For the NRM, the following covariates were important: minimum and mean elevation, average spring temperature, 1961–1990 average temperature, maximum temperature in the month of fire occurrence, relative humidity, March snow water equivalent, and cumulative annual moisture deficit. When these variables are included, we achieve much better predictions of area burned for 1988 and 2000, the years with largest areas burned in high severity fire in this region (Fig. 9b, Table 4).

For Southwest forests, 2002 was an extreme year with respect to area burned in high severity fire (224,023 ha vs. a 24 year mean of 19,577 ha; the next highest value is 46,380 ha). Our regional model slightly under-predicts 2002, but the value falls within the range of 1000 random draws from the GPD (Fig. 9c, Table 4). Maximum elevation, average spring temperature, relative humidity, and moisture deficit in the month of fire occurrence were significant covariates for

Table 3
Results from trend analysis of total annual high severity hectares burned and annual count of fires with high severity hectares > 200 (*Count*) for the period 1984–2014. *$p < 0.05$. We looked for trends in all forest fires in the western US and for trends in forest fires by modeled sub-region. Standard Error values are in parentheses.

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

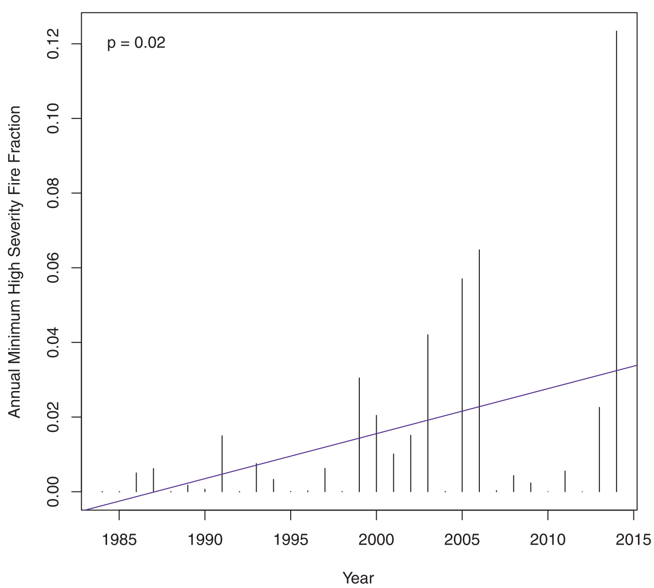

Fig. 7. Sierra Nevada annual minimum high severity fraction for years 1984–2014 with trend line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

area burned in high severity.

The best GPD model for the Sierra Nevada Mountains included climate, topographic, and vegetation condition covariates (Fig. 9d, Table 4). The variability in long term moisture deficit and average temperature, slope, and fraction in FRCC1 were included. Annual climate variables of maximum temperature the month of fire, annual average spring temperature, April snow water equivalent, and cumulative water year moisture deficit were also included. The years 1987 and 2002 account for most of the area burned in high severity. We were not able to fit a model that captured both years well. In 1987, two weeks of dry lightning storms at the end of summer resulted in a record number of fire starts and all of the high severity fires in our data started in the first three days of this period (http://www.fire.ca.govdownloads/redbooks//1987_BW.pdf). In 2002, 43.7% of the high severity hectares (15233.3 of 34891.7 total hectares) in our dataset are from a single fire, the McNally fire. Without the McNally fire, 2002 would not have been a remarkable year in terms of high severity hectares burned, and we were not able to fit any model that matched this year well, though our model does fit well to the other fires that burned in 2002 (results not shown).

4. Discussion

4.1. Trends in high severity burned area

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

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

The significant trend in the number of fires meeting our severity threshold indicates that there is an overall increase in the number of large severe fires since 1984. This is likely a result of the aforementioned correlation between area burned and high severity area burned and the observed increases in number of large fires in recent decades (Dennison et al., 2014; Littell et al., 2009; Westerling et al., 2006; Westerling, 2016). While there is evidence for an increase in the length of the fire season in the western US (Jolly et al., 2015; Westerling et al., 2006; Westerling, 2016), our increases in high severity fire occurrence occur in the middle of the fire season, June-August, indicating that the increases are likely due to changes in burning conditions or fuels rather than in the lengthening of the fire season (Fig. 6).

4.2. Models of high severity burned area

Our west-wide models for both presence of high severity fire and log area burned in high severity fire have three classes of explanatory variables—biophysical setting, climate, and vegetation condition class. The spline of latitude and longitude used here is substituting for the spline of MD/ET that we used in previous work (Keyser and Westerling, 2017). The MD/ET spline is a proxy for biological site conditions suitable for plant growth (Stephenson, 1998). We substituted the latitude and longitude spline as we would like these models to be readily usable with GCM model output; it also performed better than the MD/ET spline. The importance of the normalized fraction of FRCC in our model indicates that historical management of fire, primarily as fire suppression, has affected the probability that high severity fire will occur in the presence of a large fire. Last, the maximum temperature and normalized moisture deficit in the month of fire occurrence are important, especially for predicting area burned in high severity fire. The importance of within-year climate variables for predicting high severity fire area in these models is supported by the results from Keyser and Westerling (2017); when we removed within year variables, our ability to predict fires with a high fraction of high severity burned area was limited.

Table 4
The final predictor variables for the logistic regression (presence/absence) and generalized Pareto distribution. (GPD) models for the western US and three sub-regions (*MOF = monh of fire).

Variable Description	Westwide logistic regression	Westwide GPD	NR logistic regression	NR GPD	SW logistic regression	SW GPD	SN logistic regression	SN GPD
Elevation								
Minimum			✓	✓				
Maximum					✓	✓		
Mean			✓	✓				
Slope							✓	✓
Climate Normals (1961–1990):								
Cumulative water year moisture deficit, standard deviation								✓
Cumulative water year evapotranspiration, mean					✓			
Average temperature, mean	✓		✓	✓				
Average temperature, std. devn.	✓						✓	✓
Fire Year Climate:								
Maximum temperature (*MOF)	✓	✓		✓			✓	✓
Average spring temperature				✓		✓	✓	✓
Average relative humidity (*MOF)				✓		✓		
Normalized moisture deficit (*MOF)					✓	✓		
March snow water equivalent				✓				
April snow water equivalent								✓
Normalized cumulative water year deficit	✓	✓	✓	✓				✓
Moisture deficit June					✓			
Moisture deficit July	✓							
Fraction of FRCC1							✓	✓
Fraction of FRCC2							✓	
Fraction of FRCC3	✓				✓	✓		
Latitude-longitude spline	✓	✓	✓		✓	✓	✓	

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

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

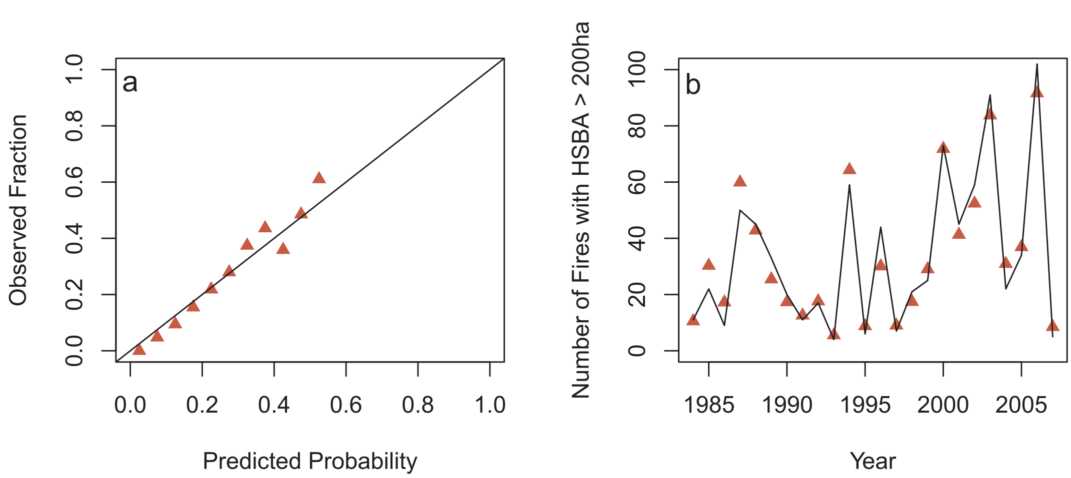

Fig. 8. (a) Probability of occurrence of high severity fire > 200 ha vs. observed fraction from logistic regression analysis for the Western US. (b) Predicted (triangle) vs. observed (line) annual number of fires meeting threshold of 200 ha.

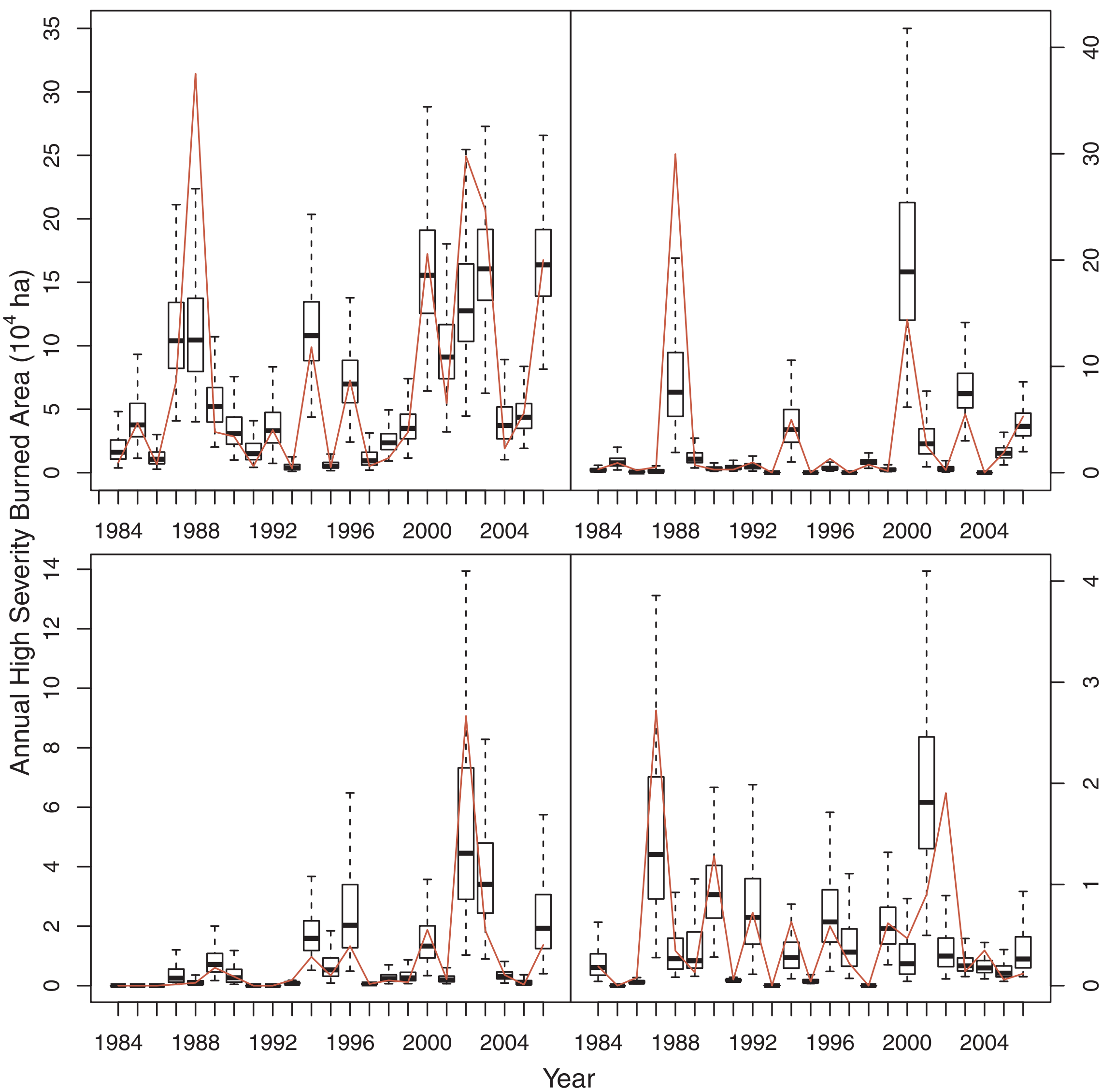

Fig. 9. Observed high severity hectares burned (line) versus 1000 simulations generated with a generalized Pareto Distribution with covariates for (a) the Western United States, (b) the Northern Rocky Mountains, (c) the US Southwest, (d) the Sierra Nevada Mountains. Developing regional models improved predictions for years with regionally specific high severity fire occurrence: 1988 and 2000 for the Northern Rocky Mountains, 2002 for the Southwest, and 1987 for the Sierra Nevada.

the difference in importance. Including climate variables improved the Dillon et al. models, especially in the Southwest (2011).

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

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

We expected that fire regime condition class would be an important predictor of high severity fire. While it was important in the west-wide logistic regression model, it wasn't consistently important in the GPD or regional models. In forested ecosystems, FRCC indicates how departed the current vegetation is from what would be expected under a historical fire regime. Areas in the highly departed condition class 3 should burn in higher severity given a buildup in fuels and changes in species composition due to fire suppression. The fraction of FRCC3 was

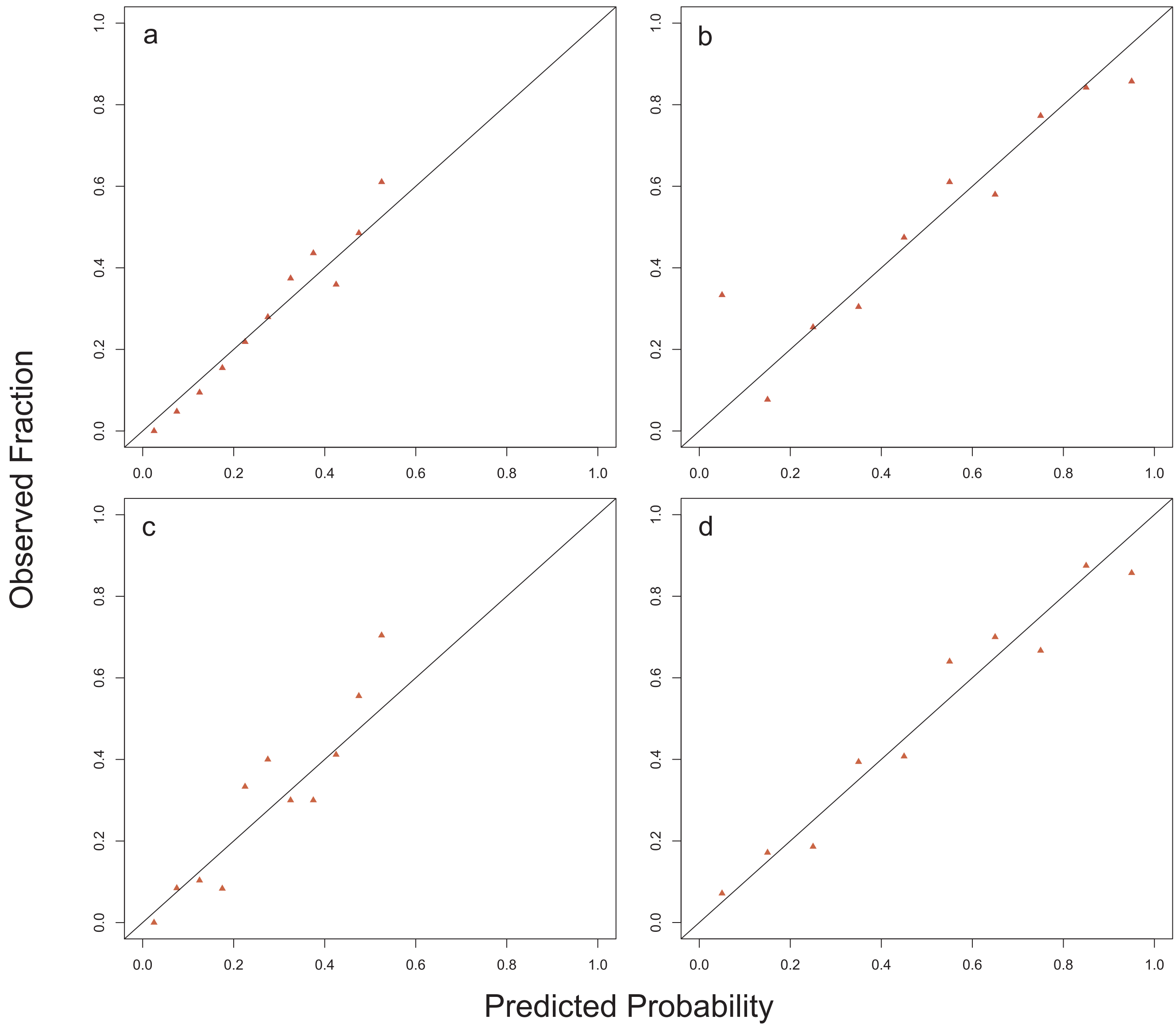

Fig. 10. From logistic regression, the predicted probability vs. observed fraction of high severity fire burned area > 200 ha for (a) Western US, (b) Northern Rocky Mountains, (c) Southwest and (d) Sierra Nevada Mountains.

important only in the Southwest forests, for both logistic regression and GPD models. The historic fire regime in many Southwest forests was one of frequent low severity fires; the importance of FRCC3 in these models is likely capturing the impact of suppression (Covington et al., 1997; Swetnam and Baisan, 1996). In the Sierra Nevada, FRCC1 was important for both models, but FRCC3 was not important. Substituting FRCC3 and FRCC2 + 3 into our SNC model resulted in decreased model performance as evaluated with AIC and the variable was not significant.

The Sierra Nevada forests are dominated historically by a mixed severity fire regime. Studies have shown an increase in fire severity in some mixed conifer forests (fuel limited fire regimes) over the period of record studied here; they did not find the same in climate limited fire regimes (Miller and Safford, 2012; Steel et al., 2015). Fire severity increased in areas that experienced increased time since fire due to fire suppression, as we would expect, in the fuel limited forests in the Sierra Nevada. Collins et al. also found that time since fire was important in predicting fire severity in the Sierra (Collins et al., 2007, 2009). With quantitative evidence that fire frequency is important in controlling severity in fuel limited ecosystems, we would expect that FRCC would be a significant predictor as a proxy for fuel buildup due to fire suppression. Perhaps the distribution of FRCC classes in this region is such that FRCC1 better captures fire severity here. A limitation to our use of FRCC is that our modeling pixels are very large and we have calculated the fraction of each severity class in these to maintain as much information as possible. However, the FRCC fractions don't necessarily reflect the exact FRCC fraction within any given fire perimeter. Instead, they are an indication of fuel conditions proximate to the ignition site of a fire.

4.3. Climate change and high severity burned area

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

The length of the fire season (Westerling et al., 2006; Jolly et al., 2015; Westerling, 2016) and large fire occurrence have increased over the past three decades (Dennison et al., 2014; Littell et al., 2009; Miller et al., 2009; Stephens and Ruth, 2005; Westerling et al., 2006; Westerling, 2016). Our models are conditional on large fires burning, and many studies predict continued increases in area burned or large fire occurrence with climate change in the western US (Westerling and Bryant, 2008; Spracklen et al., 2009; Littell et al., 2010; National Research Council, 2011; Westerling et al., 2011a,b; Kitzberger et al., 2017).

4.4. Implications for forest management

Forest management plans need to incorporate climate change, and models like ours are well suited to impact assessment and scenario analysis. The combination of climate and vegetation variables in our model allows us to examine the separate and interactive effects of climate and fuels management scenarios. Most of the variables that were important in the best-fit models are readily available, meaning that we can simulate how high severity occurrence and extent might respond to a changing climate. Given projected future changes of the climate variables in our model (warmer and drier on average), it is likely that high severity area burned will increase unless fuel availability and structure become a constraint (Cayan et al., 2013; Kitzberger et al., 2017; Westerling et al., 2011a). The spatial distribution of changes in high severity area will be variable and dependent on whether the historical fire regime was more fuel- (Sierra Nevada mixed conifer forests) or climate-limited (Northern Rocky Mountain cool moist forests). Our models can be used to inform managers when and where these increases are most probable, and what the near-term magnitude of change is likely to be.

While climate affects both fuel availability and flammability, past forest management has also affected fuel availability in many western forest ecosystems. For regions where fire regime condition class was an important predictor of high severity area burned, we can explore fuels management scenarios with our models to evaluate their potential for mitigating high severity area burned. In addition, the experimental work presented here could be extended to incorporate other data characterizing fuels conditions where these are available. Krofcheck et al. used the probability of high severity fire to derive fuels treatment scenarios in a spatial, process modeling framework to evaluate the effects of targeted fuels management on Sierra Nevada forest carbon sequestration and resilience (2018). Similarly, we have looked at the potential for fuels treatments to mitigate high severity area burned, and resulting impacts to spotted owl (*Strix occidentalis*) habitat, in the Sierra Nevada in a changing climate (Keyser et al., 2017). Westerling (in preparation) applies this modeling methodology to explore the effects of scenarios for the impact of recent drought-related mortality in Sierra Nevada forests on high severity fire over the next couple of decades. Modeling and scenario analysis studies like these can improve our understanding of how changing climate and fuels might interact to affect area burned in high severity across a landscape and allow managers to target expensive fuel treatments to address multiple objectives, while accounting for a changing climate.

5. Conclusions

Based on this and our previous work (Keyser and Westerling, 2017), we conclude that fire year climate is critical to predicting area burned in high severity fire, especially in extreme fire years. The importance of climate versus vegetation type varies considerably across western US forests, with climate playing a greater role in mixed severity fire regimes such as mid-elevation Sierra Nevada forests. Accurately predicting high severity area burned in extreme fire years requires developing regional models that reflect varying fire-climate-vegetation dynamics across different forest types.

We were deliberate in building our models with predictor variables that are readily available to facilitate their utility to both researchers and managers. With a very low computational cost, we can estimate the probability and area of high severity fire for multiple western US landscapes. Models like these are ideal for scenario analyses, such as: developing adaptive management strategies (e.g. Keyser et al., 2017; Krofcheck et al., 2018), for resource planning, and climate impact assessment (e.g. Westerling et al., 2009, 2011b).

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