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LETTER

High-severity fire: evaluating its key drivers and mapping its probability across western US forests

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Abstract

Wildland fire is a critical process in forests of the western United States (US). Variation in fire behavior, which is heavily influenced by fuel loading, terrain, weather, and vegetation type, leads to heterogeneity in fire severity across landscapes. The relative influence of these factors in driving fire severity, however, is poorly understood. Here, we explore the drivers of high-severity fire for forested ecoregions in the western US over the period 2002–2015. Fire severity was quantified using a satellite-inferred index of severity, the relativized burn ratio. For each ecoregion, we used boosted regression trees to model high-severity fire as a function of live fuel, topography, climate, and fire weather. We found that live fuel, on average, was the most important factor driving high-severity fire among ecoregions (average relative influence = 53.1%) and was the most important factor in 14 of 19 ecoregions. Fire weather was the second most important factor among ecoregions (average relative influence = 22.9%) and was the most important factor in five ecoregions. Climate (13.7%) and topography (10.3%) were less influential. We also predicted the probability of high-severity fire, were a fire to occur, using recent (2016) satellite imagery to characterize live fuel for a subset of ecoregions in which the model skill was deemed acceptable ($n = 13$). These 'wall-to-wall' gridded ecoregional maps provide relevant and up-to-date information for scientists and managers who are tasked with managing fuel and wildland fire. Lastly, we provide an example of the predicted likelihood of high-severity fire under moderate and extreme fire weather before and after fuel reduction treatments, thereby demonstrating how our framework and model predictions can potentially serve as a performance metric for land management agencies tasked with reducing hazardous fuel across large landscapes.

Introduction

Wildland fire is a critical natural disturbance and ecological process in many ecosystems around the globe, particularly in the forested regions of the western US (Agee 1993, Bond *et al* 2005). Fire affects a wide range of ecosystem components and processes such as post-fire successional trajectories, nutrient cycling, hydrology, and carbon dynamics (Turner 2010, McKenzie *et al* 2011, Larson *et al* 2013). Wildland fire often exhibits high inter-and intra-fire heterogeneity, generally burning with varying degrees of severity (Lentile *et al* 2007) depending on fuel load, dominant vegetation type, topography, climate, and weather (Cansler and McKenzie 2014, Harvey *et al* 2016). Fire severity is defined here as the amount of fire-induced change to physical ecosystem components such as vegetation and soil (Key and Benson 2006,

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Morgan *et al* 2014). The need to better understand those factors controlling fire severity (e.g. Dillon *et al* 2011) are invoked by concerns about public safety, infrastructure, critical wildlife habitat, watershed health, and successional trajectories (e.g. Savage and Mast 2005, Moody *et al* 2013, Calkin *et al* 2014). Such concerns are heightened in forests with a legacy of past logging and fire exclusion, where significant shifts in ecosystem composition, structure, and function have triggered fuel conditions at greater risk for high-severity fire (Mallek *et al* 2013, Hessburg *et al* 2015).

Over the last decade, our understanding of factors that influence fire severity has improved, but the relative importance of these factors remains unclear. Topography, for example, is clearly an influential factor (Holden *et al* 2009, Dillon *et al* 2011), as is the amount and composition of live vegetation and dead fuel (Fang *et al* 2015, Harris and Taylor 2015). A limited number of studies also indicate that long-term climate (i.e. 30-year climate normals) is an important factor driving fire severity (Parks *et al* 2014c, Kane *et al* 2015a), although many suggest that climate likely has an indirect influence via its effect on productivity and dominant vegetation type (e.g. Miller and Urban 1999a, Pausas and Bradstock 2007, Krawchuk *et al* 2009). Surprisingly, empirical evidence is extremely varied pertaining to the importance of fire weather as a driver of high-severity fire; some studies have shown that its influence is marginal (Fang *et al* 2015, Birch *et al* 2015) whereas others have concluded it is a highly influential factor (Keyser and Westerling 2017, Lydersen *et al* 2017). Other factors that influence fuel, such as vegetation management activities (Thompson *et al* 2007, Prichard and Kennedy 2014) and the presence of previous wildland fire (Parks *et al* 2014b, Stevens-Rumann *et al* 2016), have also been shown to influence fire severity.

Research to date pertaining to the key drivers of high-severity fire has been either comprehensive in ecological scope but geographically limited, or geographically broad but lacking important environmental components. Dillon *et al* (2011) conducted perhaps the most comprehensive evaluation (in terms of geographic scope and number of fires) of the drivers of high-severity fire using data from three ecoregions in the northwestern US and three in the southwestern US (~1500 total fires). Dillon *et al* (2011), however, did not evaluate some of the factors likely responsible for high-severity fire such as fuel, thereby making it difficult to interpret their findings from an ecological perspective. Keyser and Westerling (2017) also conducted a comprehensive evaluation of fire severity in the western US, but their unit of analysis was coarser—at the individual fire (i.e. fires were categorized as either 'high-severity' or 'other'). Conversely, most studies to date (and this study) evaluated pixels within individual fires as the unit of analysis, thereby preserving and analyzing intra-fire variability. Some studies have evaluated a more inclusive set of environmental drivers but were often conducted at disparate temporal and spatial scales, ranging from those of individual fires (Thompson *et al* 2007, Harris and Taylor 2015) to landscapes with ~50–100 fires (Fang *et al* 2015, Birch *et al* 2015), thereby making broader-scale generalizations challenging. Differences in methodology among these studies also complicate interpretation. An evaluation using consistent data and methods across the broad geographic range of forested landscapes of the western US will allow for an improved understanding of the most influential factors driving fire severity and will provide forest managers with highly relevant information for planning and mitigation purposes.

In this study, we assessed a comprehensive suite of potential drivers of high-severity fire using a consistent, repeatable approach that was not only geographically extensive but also predictive in nature. We built a statistical model describing high-severity fire for each ecoregion in the contiguous western United States (hereafter western US) with the exception of those with insufficient data (e.g. Sonoran Desert was excluded; see Methods). We defined high-severity fire as those that are stand-replacing as inferred by the relativized burn ratio (RBR) (Parks *et al* 2014a), a gridded satellite-based fire severity metric. Our evaluation included explanatory variables representing live fuel, topography, climate, and fire weather. The models we developed have the potential to support fire and fuel management (cf Hessburg *et al* 2007) because several of the explanatory variables are dynamic (i.e. varying on daily to annual time scales), such as those representing live fuel and daily fire weather. Consequently, raster maps representing predictions of high-severity fire (cf Holden *et al* 2009) can be updated annually and under different weather scenarios to assess, for example, the potential for high-severity fire in an upcoming fire season. Such products may facilitate the development of more adaptive strategies for addressing the contemporary challenges of wildland fire management. Similarly, model predictions have the potential to monitor and quantify potential changes in the probability of high-severity fire resulting from management actions, such as fuel reduction treatments.

Our overarching objectives were three-fold. First, we aimed to identify the most influential factors driving high-severity fire for each ecoregion in the western US. Second, we designed a quantitative framework such that the model predictions for each ecoregion can be updated annually using recent (e.g. 2016) satellite imagery and implemented to evaluate the probability of high-severity fire (were a fire to occur) under a range of potential weather scenarios. Third, we incorporated the capability for model predictions to assess and monitor the effectiveness of fuel treatments in changing the probability of high-severity fire.

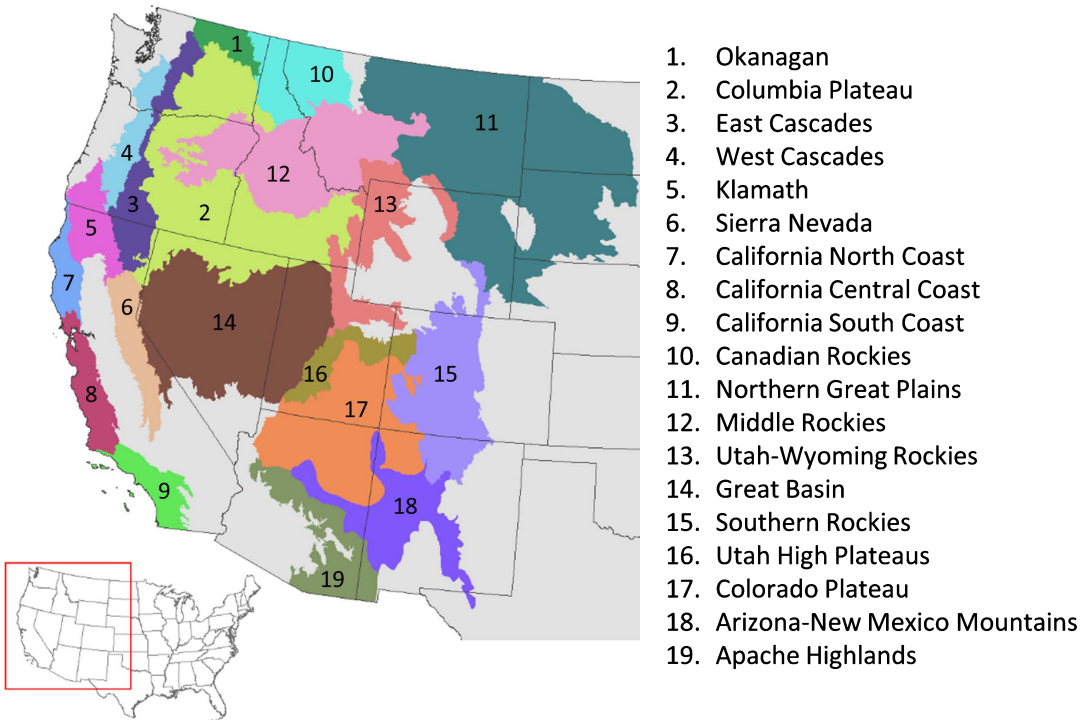

Figure 1. Ecoregions in the western US for which we built models describing the probability of high-severity fire.

Methods

This is an abridged version—see appendix A available at stacks.iop.org/ERL/13/044037/mmedia for a detailed description of the Methods.

Data

We built a statistical model describing high-severity fire for each ecoregion in the western US (Olson and Dinerstein 2002) (figure 1). Fire severity was measured using the relativized burn ratio (RBR), a satellite measure of fire severity (resolution = 30 m) that differences pre-and post-fire Landsat data. We classified the RBR into binary categories representing high-severity (RBR $\geq$ 298) and other severity (RBR $<$ 298) (Parks *et al* 2014a). High-severity fire can be considered stand-replacing fire in the context of this study.

We evaluated 16 explanatory variables in the model for each ecoregion which can be categorized into four groups representing live fuel, topography, climate, and fire weather (table 1). The fuel group is comprised of three satellite vegetation indices: NDVI, NDMI, and EVI (table 1). These metrics implicitly incorporate management activities and disturbances such as fuel reduction treatments and wildland fire. Inclusion of 'static' fuel metrics such as vegetation type or cover (e.g. www.landfire.gov) (cf Birch *et al* 2015, Keyser and Westerling 2017) was not considered since such products are only updated periodically and are thus not sensitive to annual dynamics. The variables representing topography, climate, and fire weather are summarized in table 1; see appendix A for further details.

Sampling design and statistical models

We sampled individual 30 m pixels within fires that occurred from 2002–2015. Each ecoregion was modeled separately. We only sampled pixels identified as forest (i.e. forest, woodland, and savanna). We removed all pixels $<$100 m from the fire perimeter to reduce edge effects common at fire boundaries (Stevens-Rumann *et al* 2016). All analyses and predictions were conducted using the native resolution of the response variable (30 m). For each ecoregion, we used boosted regression trees (BRT) using the 'gbm' package in R to model high-severity fire (binary response) as a function of live fuel, topography, climate, and fire weather (table 1). A handful of ecoregions were not evaluated because they contained a low proportion of forest or did not have enough fire data (e.g. Sonoran Desert and North Cascades ecoregion, respectively) (appendix A).

In an effort to reduce overfitting and build the most parsimonious model for each ecoregion, we employed a cross-validated stepwise procedure in which specific variables were removed if they did not provide unique information that improved model fit. Models for each ecoregion were evaluated with five-fold cross validation that was spatially and temporally structured such that 20% of fires (as opposed to pixels) within an ecoregion were held out in each iteration. Specifically, we built a model for each ecoregion using the full suite of variables (table 1) and evaluated it with the area under curve (AUC) statistic derived from the receiver operating characteristic curve as measured with the 'verification' package in R. We then built an additional set of models for each ecoregion in which each explanatory variable was removed and calculated the

Table 1. Variables used as predictors in modeling the probability of high-severity fire in forests of the western US.

Group	Variable name	Description	Source
Live fuel	NDVI	Normalized differenced vegetation index. Calculated using pre-fire imagery distributed by the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink *et al* 2007).	Pettorelli *et al* (2005)
	NDMI	Normalized differenced moisture index. Calculated using pre-fire imagery distributed by MTBS (Eidenshink *et al* 2007).	McDonald *et al* (1998)
	EVI	Enhanced vegetation index. Calculated using pre-fire imagery distributed by MTBS (Eidenshink *et al* 2007).	Huete (2002)
Topography	DISS	Dissection index with a 450 meter radius. DISS is a measure of topographic complexity.	Evans (1972)
	TPI	Topographic position index with a 2000 meter radius. TPI is a measure of valley bottom vs. ridge top.	NA
	SRAD	Solar radiation, as calculated using the SOLPET6 model.	Flint *et al* (2013)
	Slope	Slope angle	NA
Climate	CMD	Climatic moisture deficit (Wang *et al* 2016). Mean over the 1981–2010 time period.	Wang *et al* (2016), https://adaptwest.databasin.org/
	ET	Evapotranspiration (i.e. Eref—CMD). Mean over the 1981–2010 time period.	Wang *et al* (2016), https://adaptwest.databasin.org/
	T.sm	Average summer temperature. Mean over the 1981–2010 time period.	Wang *et al* (2016), https://adaptwest.databasin.org/
Fire weather	BI.day	Burning index; a measure of fire intensity. Raw value converted to per-pixel percentile.	Preisler *et al* (2016) Jolly and Freeborn (2017)
	ERC.day	Energy release component; an index describing the amount of heat released per unit area at the flaming front of a fire. Raw value converted to per-pixel percentile.	Preisler *et al* (2016) Jolly and Freeborn (2017)
	Tmax.day	Maximum daily temperature. Raw value converted to per-pixel percentile.	Abatzoglou (2013)
	HM.ann	Heat moisture for the year in which the fire occurred. HM is calculated as follows: (annual temperature + 10) / (annual precipitation/1000). Raw value converted to per-pixel *z*-score.	Climate NA software package; Wang *et al* (2016)
	Temp.ann	Mean annual temperature for the year in which the fire occurred. Raw value converted to per-pixel *z*-score.	Climate NA software package; Wang *et al* (2016)
	CMD.ann	Climatic moisture deficit for the year in which the fire occurred. Raw value converted to per-pixel *z*-score.	Climate NA software package; Wang *et al* (2016)

AUC as previously described. If the cross-validated AUC *increased* when any given variable was removed from the model, it indicates that the model is overfit and that the variable does not provide any unique information. In these cases, the variable that resulted in the largest increase in AUC was permanently removed and the process was repeated until all variables resulted in a decreased AUC when removed from the model. As such, all variables in the final models provided unique information and ensured that our models were spatially and temporally transferable.

Once the final model for each ecoregion was identified, the relative influence of variable groups was calculated using the AUC of a five-fold cross validation using a process that excluded all variables from a particular group. Specifically, we compared the five-fold cross validated AUC of the full model to models that iteratively excluded all variables representing live fuel, topography, climate, and fire weather. The specific equation was as follows:

$$\text{Relative influence}_i = \frac{\text{AUC.full} - \text{AUC.no.var}_i}{\sum_{i=1}^{i=4}(\text{AUC.full} - \text{AUC.no.var}_i)} \times 100$$

where AUC.full was the AUC of the full model, AUC.no.var was the AUC of the model excluding any particular variable group, and i represented one of the four variable groups.

Model implementation and map production

From the BRT models, we produced wall-to-wall raster maps (objective 2) depicting the probability of high-severity fire, if a fire were to occur, for each ecoregion in which the cross-validated AUC $\geq$0.70. For the fuel inputs (NDVI, NDMI, and EVI), satellite imagery from 2016 spanning the entirety of each ecoregion was obtained using Google Earth Engine (GEE; https://developers.google.com/earth-engine/). Consequently, these raster predictions represent fairly current fuel conditions across each ecoregion. Predictions theoretically range from zero to one and depict the probability of high-severity fire.

We aimed to produce these severity predictions representing the average weather conditions under which fires burn. This is somewhat challenging, however, given that weather is spatially and temporally dynamic. Consequently, we produced 100 initial predictions and varied the weather for each of these predictions; all other inputs across each ecoregion (fuel from 2016, topography, and climate) were held static. To vary the weather, we randomly selected 100 records from our fire severity datasets. Each record represents one burned pixel with a unique combination of observed

Table 2. Cross-validated AUC and the relative influence for each of the four groups of variables used to model the probability of high-severity fire in 19 ecoregions in the western US.

			Relative influence			
Region ID	Ecoregion name	Cross-validated AUC	Live fuel	Topography	Climate	Weather
1	Okanagan	0.66	40.5	14.4	29.9	15.2
2	Columbia Plateau	0.67	35.3	3.1	17.4	44.2
3	East Cascades	0.68	60.7	12.4	5.6	21.2
4	West Cascades	0.71	40.7	2.3	14.6	42.5
5	Klamath	0.68	38.8	25.0	0	36.2
6	Sierra Nevada	0.67	58.7	15.7	19.1	6.5
7	California North Coast	0.70	5.1	19.6	9.1	66.2
8	California Central Coast	0.73	64.6	22.3	13.1	0
9	California South Coast	0.72	40.6	9.4	0	50.1
10	Canadian Rockies	0.71	53.9	14.0	24.0	8.1
11	Northern Great Plains	0.69	43.4	9.7	29.3	17.6
12	Middle Rockies	0.72	46.2	14.8	34.9	4.1
13	Utah-Wyoming Rockies	0.75	99.0	1.0	0	0
14	Great Basin	0.76	63.6	7.0	17.6	11.8
15	Southern Rockies	0.72	57.4	12.5	22.9	7.3
16	Utah High Plateaus	0.76	93.2	5.1	0.2	1.5
17	Colorado Plateau	0.81	39.0	6.9	2.1	52.0
18	Arizona-New Mexico Mountains	0.79	75.0	0.2	9.7	15.0
19	Apache Highlands	0.75	53.3	1.0	9.9	35.9
	AVERAGE	**0.72**	**53.1**	**10.3**	**13.7**	**22.9**

fire weather. We used the observed fire weather from each random record for each of the 100 initial predictions. We then averaged the 100 initial predictions over each 30 m pixel, resulting in one raster map depicting the probability of high-severity fire under average weather conditions in which fires burn. An important consideration here is that the severity predictions do not represent 'average weather conditions', but the 'average weather conditions *under which fires burn*'. That is, because fires often burn under more extreme fire weather, our predictions implicitly incorporate weather associated with high fire activity. This consideration also pertains to our mapped predictions under moderate and extreme fire weather, as described in the next paragraph.

For those ecoregions in which the relative influence of fire weather ≥15%, we produced two additional raster maps, one depicting the probability of high-severity fire under conditions representing moderate weather and the other under conditions representing extreme weather. To do so, we calculated the 50th and 95th percentile *for each pixel* out of the 100 previously described initial predictions. While these maps represent the 50th and 95th percentile in predicted outcomes for each pixel, we use them to represent the outcomes of moderate and extreme fire weather, respectively. Neither says anything specific about the percentile of weather conditions under which they occurred, but they can be interpreted as resulting from moderate and extreme fire weather conditions.

To illustrate how our models can potentially be used to monitor changes in the probability of high-severity fire due to fuel treatments (objective 3), we made pre- and post-treatment predictions using the BRT model from the Arizona—New Mexico Mountains ecoregion. We obtained imagery representing the live fuel variables using GEE for the years 2007 (pre-treatment) and 2011 (post-treatment). Again, we produced two sets of predictions for each time period (pre-and post-treatment) representing moderate and extreme fire weather, as previously described.

Results

We incorporated data from over 2000 fires across all ecoregions to describe and explain the probability of high-severity fire (appendix B). On average, the BRT models performed moderately well for the 19 ecoregions for which we modeled (table 2). The average spatially and temporally independent cross-validated AUC statistic was 0.72 and ranged from 0.66 (Okanagan) to 0.81 (Colorado Plateau). Following Mason and Graham (2002), all five cross-validated models were statistically significant ($p < 0.01$) for each of the 19 ecoregions.

Although there was substantial variation across ecoregions (table 2), live fuel was the most important variable group, with an average relative influence of 53.1% among ecoregions; this ranged from 5.1% (California North Coast) to 99.0% (Utah—Wyoming Rockies). Fire weather was the second most influential variable group (22.9% average), ranging from 0% (California Central Coast and Utah – Wyoming Rockies) to 66.2% (California North Coast). Climate was the third most influential variable group (13.7% average) and topography the least influential (10.3% average) (table 2). The cross-validated variable selection approach reduced overfitting and produced parsimonious models (i.e. all variables provided unique information) (table 3).

Raster maps depicting the probability of high-severity fire were built for the 13 ecoregions in which the cross-validated AUC ≥0.70 (figure 2; appendix C). These gridded probabilities represent fuel conditions (i.e. as measured with Landsat imagery) in 2016 and

Table 3. Final models for each ecoregion. Variables were selected through a cross-validated stepwise procedure to ensure that each variable provides unique information and improves the cross-validated AUC (see Methods).

Region ID	Ecoregion name	Fuel	Topography	Climate	Weather
1	Okanagan	EVI NDMI	Slope	ET	Tmax.day
2	Columbia Plateau	NDVI EVI NDMI	DISS TPI SRAD Slope	CMD ET T.sm	Tmax.day ERC.day HM.ann Temp.ann
3	East Cascades	NDVI EVI NDMI	DISS TPI SRAD Slope	T.sm	ERC.day Tmax.day HM.ann
4	West Cascades	NDVI EVI NDMI	DISS TPI Slope	ET T.sm	ERC.day HM.ann
5	Klamath	EVI NDMI	DISS TPI Slope	—	BI.day ERC.day HM.ann Temp.ann
6	Sierra Nevada	NDMI	DISS SRAD Slope	ET T.sm	ERC.day Tmax.day HM.ann CMD.ann Temp.ann
7	California North Coast	NDVI EVI NDMI	DISS TPI SRAD	T.sm	Tmax.day HM.ann
8	California Central Coast	NDVI EVI NDMI	DISS TPI Slope	T.sm	—
9	California South Coast	NDVI EVI NDMI	DISS Slope	—	HM.ann CMD.ann Temp.ann
10	Canadian Rockies	EVI NDMI	DISS SRAD Slope	T.sm	BI.day Tmax.day HM.ann
11	Northern Great Plains	NDVI NDMI	DISS TPI SRAD Slope	CMD ET T.sm	BI.day ERC.day
12	Middle Rockies	NDVI EVI NDMI	DISS SRAD Slope	CMD ET T.sm	BI.day ERC.tay Temp.day
13	Utah-Wyoming Rockies	NDVI EVI	DISS	—	—
14	Great Basin	NDVI EVI	DISS SRAD Slope	CMD T.sm	HM.ann CMD.ann Temp.ann
15	Southern Rockies	NDVI EVI NDMI	DISS SRAD Slope	ET T.sm	HM.ann CMD.ann Temp.ann
16	Utah High Plateaus	NDVI EVI NDMI	DISS TPI SRAD Slope	T.sm	ERC.day Tmax.day
17	Colorado Plateau	NDVI NDMI	DISS SRAD Slope	ET	ERC.day Tmax.day HM.ann Temp.ann

Table 3. *Continued.*

Region ID	Ecoregion name	Fuel	Topography	Climate	Weather
18	Arizona-New Mexico Mountains	EVI NDMI	TPI	CMD ET	BI.day Tmax.day HM.ann CMD.ann
19	Apache Highlands	NDVI EVI	TPI	CMD	Tmax.day CMD.ann

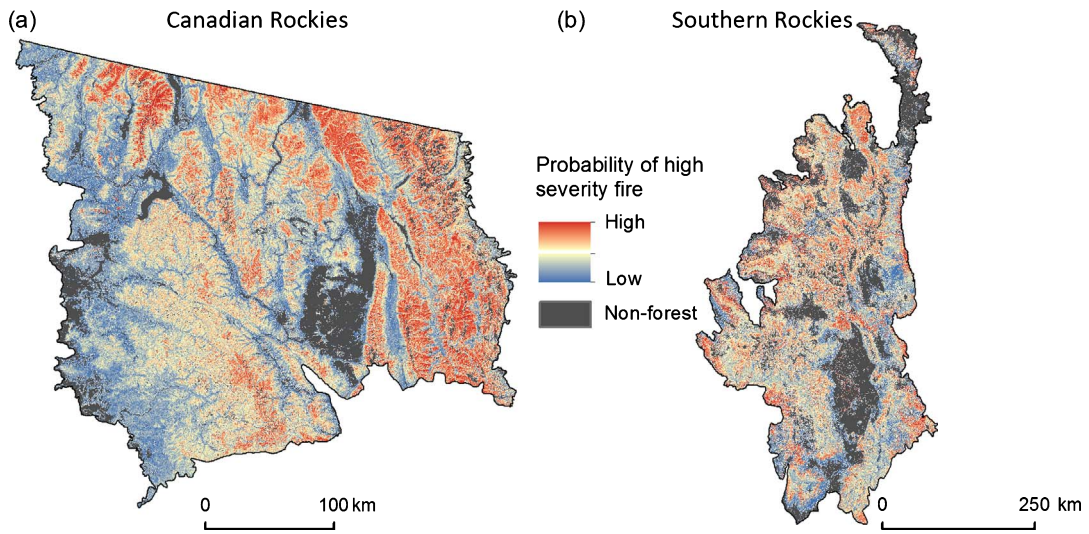

Figure 2. Maps depict the probability of high-severity fire (were a fire to occur) in the Canadian Rockies (*a*) and Southern Rockies (*b*) ecoregions. We used satellite imagery from 2016 to represent live fuel. See figure 1 to reference ecoregion locations. Predictions for other ecoregions available in appendix C.

average weather conditions under which fires burn and show substantial spatial variability in the probability of high-severity fire. For ecoregions in which the relative influence of weather ≥15% ($n = 6$), we produced two additional raster maps depicting the probability of high-severity fire under conditions representing moderate and extreme fire weather (figure 3; appendix D).

Maps of pre-and post-treatment predictions provide an example of how our models and approach can potentially be used to quantify and monitor changes in the probability of high-severity fire due to fuel treatments (figure 4). This example shows that, under conditions representing both moderate and extreme fire weather, there is an overall reduction in the probability of high-severity fire within treatment units.

Discussion

High-severity fire is often of high ecological and societal consequence, thereby motivating increasing attention and research towards better understanding its drivers and distribution (Cansler and McKenzie 2014, Whitman *et al* 2015, Morgan *et al* 2017, Reilly *et al* 2017). Research to date has been either comprehensive in ecological scope but geographically limited or geographically broad but capturing only a subset of the key elements affecting fire severity. Our study expands upon these previous investigations of fire severity by (a) including a more complete suite of relevant explanatory variables, (b) evaluating fires over a large geographic extent (i.e. forests of the western contiguous US) at fine spatial resolution (30 m), and (c) including a high number of fires in our models ($n = 2061$ unique fires among all ecoregions; appendix B). Our results show that fuel is the most important driver of high-severity fire in forested regions of the western US, followed by fire weather, climate (i.e. 30 year normals), and topography. Our results are supported by the findings of past research but also contrast with several previous studies (see below) and provide important new insights regarding the drivers of high-severity fire. Our study is also a substantial step forward by providing a modelling framework that enables the prediction for high-severity fire while incorporating fuel and fire weather inputs. In particular, this framework involves the inclusion of fuel and fire weather inputs as dynamic variables (i.e. those that change over time) and gives us the ability to produce maps depicting the probability of high-severity fire, were a fire to occur, over entire ecoregions (e.g. figures 2 and 3). This framework also provides the means to evaluate changes in the probability of high-severity fire due to fuel treatments (e.g. figure 4).

Live fuel, as measured with Landsat vegetation indices, was on average the most important group of

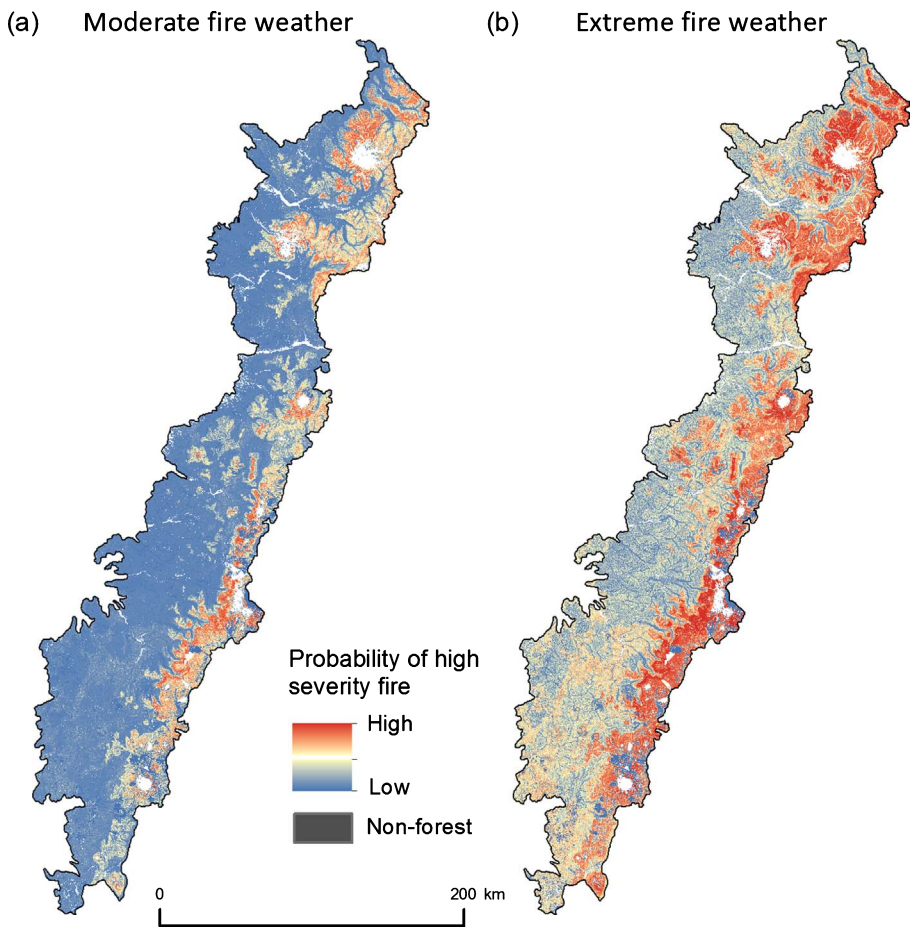

Figure 3. Maps depict the probability of high-severity fire (were a fire to occur) for the West Cascades ecoregion under weather conditions representing moderate (i.e. 50th percentile prediction) (*a*) and extreme (i.e. 95th percentile prediction) (*b*). We used satellite imagery from 2016 to represent live fuel. See figure 1 to reference ecoregion location. Predictions for other ecoregions available in appendix D.

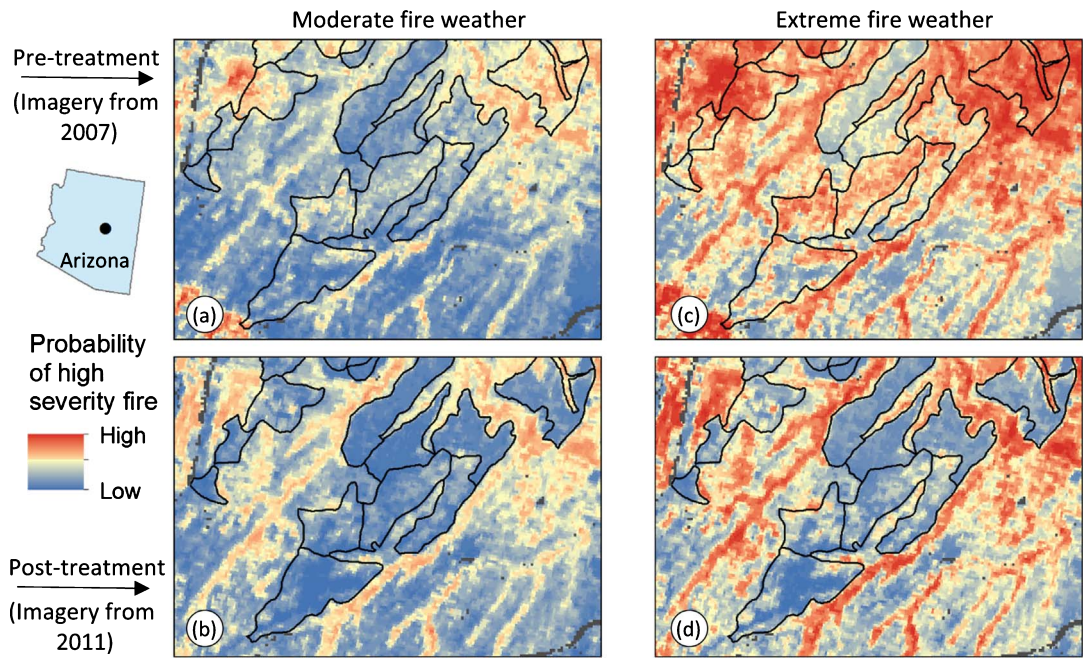

Figure 4. Example shows pre-and post-treatment predictions (top and bottom row, respectively) of the probability of high-severity fire under moderate (50th percentile prediction) (*a*) and (*b*) and extreme (95th percentile prediction) (*c*) and (*d*) fire weather conditions on the Apache-Sitgreaves National Forests, Arizona, USA. Treatment units are represented by the solid black outlines. All treatments are commercial thinning that occurred in 2010 or 2011.

variables driving high-severity fire and was the most important group in 14 out of 19 ecoregions. This finding provides valuable insight pertaining to the ongoing debate as to whether fuel or fire weather are more important in driving fire severity (cf Thompson and Spies 2009). Whereas some studies found fuel was more important (Fang *et al* 2015, Birch *et al* 2015, Harris and Taylor 2015), others concluded weather was more important (Bessie and Johnson 1995, Bradstock *et al* 2010, Price and Bradstock 2010). We found that live fuel was 2.3 times (on average) more influential than fire weather across the 19 ecoregions in the western US we analyzed (but see 'caveats' section). This finding is not trivial in terms of management efforts to reduce fire severity because land managers can control fuel via fuel treatments, prescribed fire, and managed wildland fire (formerly termed wildland fire use) but cannot control fire weather.

Our study found that fire weather was, on average, the second most important variable group driving high-severity fire. Previous studies have reported somewhat conflicting findings pertaining to the relative influence of fire weather in driving fire severity in the western US. Whereas some studies found weather to be moderately to highly influential (e.g. Collins *et al* 2007, Lydersen *et al* 2017), others found that the influence of weather was marginal to negligible (e.g. Kane *et al* 2015a, Harris and Taylor 2015). We posit that the variability we observed pertaining to the influence of fire weather among ecoregions could partly explain the divergent findings of previous studies: the relative influence of fire weather ranged from 0% to 66.2% and was the most important variable group in five out of the 19 ecoregions we analyzed. Although our results show that weather was less influential in driving high-severity fire than fuel, its influence was important in most ecoregions and should not be discounted in terms of managing fuel and fire. For example, the maps we generated (e.g. figure 3) clearly show that the probability of high-severity fire is reduced under moderate vs. extreme fire weather.

On average, climate ranked as the third most influential variable group. This contrasts with some previous studies. For example, Kane *et al* (2015a) found that climate was highly influential in driving fire severity in the Sierra Nevada. However, we suspect that climate was less important in our study because, over broad spatial and temporal extents, climate provides an indirect measure of fuel associated with inherent biophysical environments (Parks *et al* 2014c). More specifically, biomass amount is known to vary along climatic gradients (Meyn *et al* 2007, Krawchuk and Moritz 2011), which implies that climate can serve as an indirect surrogate for biomass. However, satellite-derived vegetation indices such as those used in this study are a more direct measure of biomass (Zhao *et al* 2005). Consequently, when fuel and climate are both included as variables (as was done in our study), climate is ranked as less important. This said, climate was a non-negligible factor in most ecoregions. We suggest, as do others (Miller and Urban 1999b), that climate may indirectly measure factors that were not well accounted for by our variables. We believe that climate may correspond to dominant vegetation type, in that climate promotes particular physiognomic vegetation types and species that are more or less susceptible to fire (Parks *et al* 2018). For example, cooler and wetter climates are more likely to support species that are more susceptible to fire-induced mortality (e.g. Engelmann spruce), whereas warmer and drier climates are more likely to support species that can survive fire (e.g. ponderosa pine) (Lutz *et al* 2010).

Nearly every fire severity study to date has found that topography had a moderate to high influence on fire severity (e.g. Holden *et al* 2009, Dillon *et al* 2011, Fang *et al* 2015, Kane *et al* 2015a, Birch *et al* 2015, Estes *et al* 2017). Conversely, our study indicates that topography is on average the least important variable group. We posit that topography is an indirect measure of fuel, and that because we directly account for fuel (using satellite-derived vegetation indices), topography is deemed a relatively unimportant factor. It is worth noting that many of these previously mentioned studies do not incorporate any measure of fuel or vegetation into their analyses (Holden *et al* 2009, Dillon *et al* 2011, Kane *et al* 2015b), and consequently, the influence of topography may be unintentionally elevated. For example, even though Dillon *et al* (2011) found topography to be the strongest driver of fire severity across large regions of the western US, they clearly stated that topography was serving as a proxy for variation in fuel and bioclimatic variables (i.e. fuel moisture and temperature) which were not accounted for in their study. Since we capture such variability in live fuel using satellite-derived vegetation indices, the influence of topography on its own is greatly diminished.

Caveats

There are several difficulties associated with building statistical models describing fire severity across broad geographic regions. Our ability to characterize fuel, for example, was limited to satellite indices that generally characterize overstory vegetation and have limited capacity to measure live and dead surface and ladder fuels known to drive fire behavior and effects (Rothermel *et al* 1972, Scott and Burgan 2005). Our ability to adequately characterize fire weather was also limited. For example, we estimated the day at which any given pixel burned using MODIS fire detection data. These day-of-burning estimates are not without error (Parks 2014, Veraverbeke *et al* 2014); this error increases uncertainty and likely diminishes our ability to characterize the influence of weather. Also, the temporal and spatial resolution of currently available gridded weather datasets do not necessarily match the realized spatial and temporal weather variability associated with any given fire (Wagenbrenner *et al* 2016). Fires have even been known to generate their own weather

(Potter 2012) and gridded weather datasets do not and will not likely be able to account for such phenomenon in the foreseeable future.

It is also worth noting that our data is potentially biased due to undersampling of non-extreme weather conditions, thereby limiting our ability to completely capture the full range of weather conditions conducive to fire and to completely characterize the influence of fire weather. Specifically, fire suppression success rates are higher under less-than-extreme weather conditions (Arienti *et al* 2006, Fernandes *et al* 2016, Beverly 2017), thereby reducing the amount of area burned under more moderate weather; this biases the weather associated with our fire severity data. For example, we found that the relative influence of weather was zero in two ecoregions; this result is more likely an artifact of biased data (and the other caveats mentioned in this section) than an unconditional representation of the relative influence of weather. Simply put, we potentially mischaracterized the relative influence of weather since we could not sample the full range of weather under which fire can burn. We also suggest that more data (i.e. fires) are needed in some ecoregions to better characterize the influence of fire weather and other variables (e.g. the coastal ecoregions in California; see appendix B).

Management implications

Managing for wildland fire has become incredibly complex as we face the nexus of increasingly large and intense wildfires linked to a warming climate and more frequent drought, landscapes with heavy fuel accumulations due to prolonged fire exclusion, and a rapid expansion of the wildland-urban interface (Littell *et al* 2016, Stephens *et al* 2016, Schoennagel *et al* 2017). Land management agencies have a daunting challenge to reduce risks from fire to communities and fire fighters while simultaneously restoring forests to more resilient conditions (www.forestsandrangelands.gov) (Barnett *et al* 2016). In response, land management agencies in the US established a long-term fuel reduction program in which millions of hectares have been treated since 2001 using a variety of methods such as mechanical thinning and prescribed burning (US Congress 2003). Various efforts are underway to assess how to best focus such fuel reduction activities given that land management agencies have limited resources. In particular, spatially explicit planning frameworks have offered an effective means to strategize locating treatments across landscapes (e.g. Ager *et al* 2016, Scott *et al* 2016). These planning frameworks are often built on spatial assessments of quantitative wildfire risk that incorporate the probability of wildfire occurrence across a range of simulated fire intensities, and the effects of fire on specific values at risk (e.g. natural resources, built assets) (Finney 2005, Scott *et al* 2013). We suggest that the modeling framework in this study could complement these efforts and allow predictions of high-severity fire to be integrated with fire occurrence and behavior predictions to provide managers with a more comprehensive set of risk-analysis information to target locations in wildfire mitigation planning.

We also suggest that our models and the resulting predictions of high-severity fire could potentially serve as a performance metric for evaluating hazardous fuel treatments (see figure 4). For example, the US Forest Service often uses 'acres treated' as a performance measure, but this measure does not capture anything about whether treatment objectives have been met (USDA Forest Service 2016). Specifically, the primary objective of most hazardous fuel treatments is to reduce the intensity and resulting severity of potential wildland fires (Hudak *et al* 2011, USDA OIG 2016). Some treatments are quantitatively more effective at achieving this objective than others (Wimberly *et al* 2009, Hudak *et al* 2011, Safford *et al* 2012). Furthermore, although detailed fuel treatment assessments have been conducted at the stand (Johnson *et al* 2011, Noonan-Wright *et al* 2014) and landscape scale (Vaillant *et al* 2009, Collins *et al* 2013), consistent and long-term monitoring methods have yet to be realized. The protocols developed in this study offer a means to provide predictions that are objective, consistent, updateable, spatially detailed (30 m resolution), and spatially extensive as a measurable benchmark to characterize changes in the potential for high-severity fire. We acknowledge, however, that substantial financial resources would be necessary to implement our framework to monitor the potential for high-severity fire, but such a tool is essential if not timely for filling a key information gap in fire management on public lands in the US and elsewhere.

Conclusions

Fuel is on average the most influential factor driving high-severity fire in forests of the western US. Consequently, efforts to reduce fuel will likely reduce the potential for high-severity fire (Pollet and Omi 2002, Stephens *et al* 2009, Arkle *et al* 2012). Our results also indicate that fire weather has a substantial influence on fire severity and highlight that the probability of high-severity fire is reduced under conditions representing moderate vs. extreme fire weather. This finding, when considered with the fact that fire suppression is more effective under less-than-extreme fire weather (Arienti *et al* 2006, Beverly 2017), underscores that land management agencies may be paradoxically selecting for high-severity fire by aggressively suppressing fire (cf Calkin *et al* 2015). Simply put, aggressive fire suppression reduces the occurrence of low severity fire, thereby increasing fuel on the landscape and selecting for higher severity fire when the inevitable fire occurs. This has substantial ecological and social consequences, particularly for dry forests that historically experienced low-and mixed-severity fire. For example,

fire-facilitated conversions from dry forest to non-forest vegetation (shrubland and grassland) are now evident, but it is important to note that such conversions appear to be triggered only by high-severity fire (not low severity) (Savage and Mast 2005, Coop *et al* 2016, Coppoletta *et al* 2016). Consequently, to limit the probability of high-severity fire, fire-facilitated conversions to non-forest, and altered successional trajectories in dry forests (Johnstone *et al* 2016, Walker *et al* 2018), land managers could consider, in addition to traditional fuel reduction treatments, expanding opportunities that allow wildland fires to burn under less-than-extreme weather conditions.

Data accessibility statement

All ecoregional fire severity predictions shown in appendices C and D are available for download in a georeferenced raster format through the Fire Research and Management Exchange System (FRAMES; www.frames.gov/NextGen-FireSeverity).

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