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Weather, fuels, and topography impede wildland fire spread in western US landscapes

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ABSTRACT

As wildland fire activity continues to surge across the western US, it is increasingly important that we understand and quantify the environmental drivers of fire and how they vary across ecosystems. At daily to annual timescales, weather, fuels, and topography are known to influence characteristics such as area burned and fire severity. An understudied facet, however, concerns how these factors inhibit fire spread and thereby contribute to the formation of fire boundaries. We evaluated how weather, fuels, and topography impeded fire spread in four large study areas in the western US, three in the Northern Rockies and one in the Southwest. Weather and fuels were the most important factors in the Northern Rockies, whereas fuels and topography were dominant in the Southwest. Within the categories of weather, fuels, and topography, we also evaluated which specific variables were most influential in impeding fire spread. We explicitly accounted for the presence and age of previous burns within the fuels category. We found that: (1) temperature was the most influential weather variable in the Northern Rockies; (2) previous burns (particularly those that were ⩽5 years old) were moderately to highly influential in all study areas; and (3) valley bottoms and ridgetops were moderately to highly associated with fire boundaries in all study areas. Our results elucidate the regionally varying roles of weather, fuels, and topography in impeding fire spread, emphasizing each ecosystem's unique biophysical setting and fire regime.

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1. Introduction

Wildland fire was historically a pervasive ecological process in many regions of the world (Bowman et al., 2009), influencing a wide range of ecosystem components and processes such as wildlife habitat, nutrient cycling, hydrology, carbon dynamics, as well as disease and insect outbreaks (Falk et al., 2011; Collins and Stephens, 2007). Since about 1900, however, human activities and infrastructure (e.g., livestock grazing, fire suppression, and roads) have largely removed fire from many fire-adapted forested regions in the United States (Savage and Swetnam, 1990; Heyerdahl et al., 2001). For example, only an estimated 0.4% of ignitions were allowed to burn as managed wildfires during the most recent decade (ending in 2008) (North et al., 2015), and more than 97% of all fires are extinguished before they reach 120 ha (Calkin et al., 2005). This so-called fire deficit (cf. Marlon et al., 2012; Parks et al., 2015c) has resulted in forested landscapes across the West that have more fuel, are more homogeneous, and contain more shade-tolerant trees compared to historical reference periods (Keane et al., 2002; Taylor and Skinner, 2003). Consequently, contemporary forests are now prone to uncharacteristically large and severe wildland fire (Stephens et al., 2014; Calkin et al., 2015), particularly in low and middle-elevation forests with relatively frequent fire regimes (Hessburg et al., 2005; Safford and Van de Water, 2014). In recent years, however, an increased emphasis on restoring wildland fire to forested landscapes (e.g., Hessburg et al., 2015) has underscored the need to better understand the principal drivers of fire regimes. In fact, numerous studies conducted over a variety of spatial and temporal scales have made substantial inroads to identifying the environmental factors that facilitate or inhibit wildland fire's distribution, occurrence, frequency, and severity (e.g., Heyerdahl et al., 2001; Krawchuk et al., 2006; Beaty and Taylor, 2008; Dillon et al., 2011; Bigio et al., 2016).

Over the last few decades, our understanding of environmental drivers of fire has increased greatly. At broad temporal and spatial scales (continental to global), fire regimes are controlled by biomass availability, climate, and ignition sources (Krawchuk et al., 2009; Pausas and Ribeiro, 2013). At finer temporal and spatial scales (regional to subcontinental), annual variability in climate is often recognized as the key driver (Westerling et al., 2006; Littell et al., 2009), as warm and dry years generally correspond to increased fire activity, although the influence of vegetation cannot be discounted (Krawchuk et al., 2006; Parisien et al., 2014).

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At even finer scales (meso-scale; 50–5000 ha; Moritz et al., 2011), weather, fuels, and topography are often cited as the main factors controlling fire characteristics such as intensity, rate of spread, and severity (Abatzoglou and Kolden, 2013; Birch et al., 2015). Less attention, however, has been paid towards identifying factors that regulate where fire perimeters occur on landscapes, or put another way: where and why do fires stop burning? Although recent studies have noted that fire perimeters are often adjacent to previously burned areas (Collins et al., 2009; Price et al., 2014; Parks et al., 2015a) or near roads (Narayanaraj and Wimberly, 2011), we are not aware of any study that broadly identifies the factors most responsible for observed patterns of fire perimeters. Consequently, there is a substantial knowledge gap regarding the influence of weather, fuels, and topography in impeding fire spread. A better understanding of what extinguishes fire in natural landscapes across different ecosystem types should help inform efforts (i.e., fire and fuel planning) to restore successional patterns and ecological resiliency in fire-prone forests. It should also help in assessing risk and achieving ecological benefits during active fire management.

Of the three principal factors (weather, fuels, and topography) that likely influence where and why fires stop burning, weather is generally considered the most dynamic (Jolly et al., 2015). Weather affects fire spread indirectly via its influence on fuel moisture and directly via wind direction (Rothermel, 1972; Finney, 2005), such that fire spread is more likely when weather is hot, dry, and windy (Chang et al., 2013; Sedano and Randerson, 2014). Fire spread is also influenced by fuels, or lack thereof (Peterson, 2002). Fuels are partially a function of productivity (Schoennagel et al., 2004; Krawchuk and Moritz, 2011), and vary both temporally as vegetation grows, and spatially within and among regions. Fuels are also consumed by fire such that previous burns impede subsequent fire spread (Collins et al., 2009; Parks et al., 2015a) where the strength of this effect decays over time as fuels re-accumulate, and varies according to each ecosystem's climate and productivity (Schoennagel et al., 2004). Lastly, topography (e.g., slope position, topographic roughness), the most static of environmental drivers, *indirectly* influences fire spread via fuel moisture and the type and arrangement of fuels (Guyette et al., 2002; Taylor and Skinner, 2003). For example, fuel moisture and fuel amount may be higher on north vs. south facing slopes in the US Rocky Mountains (Rollins et al., 2002), and consequently, the interface between contrasting aspects (i.e., valley bottoms and ridge tops) may act as barriers to fire spread (Iniguez et al., 2008; Flatley et al., 2011). Topography also *directly* modulates fire spread, where energy transfer from flaming fronts to upslope fuels accelerates fire spread (Rothermel, 1983).

In this study, we retrospectively examined the influence of weather, fuels, and topography in impeding fire spread. We were especially interested in quantifying the influence of these three factors across ecosystems and identifying the particular environmental predictors of fire cessation. To this end, we evaluated ~200 fires across four large study areas in the western US. All study areas were comprised of designated wilderness or national park and, consequently, largely unaffected by anthropogenic factors that may influence fire cessation (e.g., roads). Fire suppression continues to be practiced to some degree but policies over the last 30–40 years have facilitated a large-scale reintroduction of fire to wilderness areas (Hunter et al., 2014), providing some of the best available landscapes for observing natural processes such as fire disturbance (Collins et al., 2009; Lutz et al., 2009; Teske et al., 2012; Morgan et al., 2014; Parks et al., 2016). We used matched case-control (MCC) logistic regression to quantify the influence of weather, fuels, and topography, and selected a suite of variables to represent each factor. We expected that all three factors would be predictive of where fires stopped, but relative influences would vary among study areas due to differences in biophysical environments and ecosystems. We also expected that the relative importance of individual variables within each factor (e.g., elevation complexity vs. topographic position) would vary by study area, again reflecting characteristics unique to each ecosystem. Lastly, we expected that previous burns would be strongly associated with fire perimeters, but associations would diminish with age of burn and vary depending on ecological context (i.e., climate and productivity of each ecosystem). The results of our study should benefit managers who seek to better understand biotic and abiotic controls that produce fire boundaries and to better manage for resilient natural landscapes.

2. Methods

2.1. Study areas

We conducted our investigation in four fire-prone study areas in the western U.S (Fig. 1). Because wilderness areas have experienced little to no vegetation management (e.g., logging), confounding effects of human disturbances are reduced. Furthermore, although some fires are suppressed in these areas, many have been allowed to burn for resource benefit in recent decades. Similarly, fire suppression is likely to be less effective in wilderness due to lack of road access and safety concerns. Consequently, these areas serve as appropriate natural laboratories for this study, and have experienced substantial fire activity over the last few decades, providing ample data for identifying factors inhibiting fire spread.

2.1.1. Crown of the Continent Ecosystem

The CCE is the largest study area (10,331 km^2) and comprises Glacier National Park and the Great Bear, Bob Marshall, and Scapegoat wilderness areas in Montana. Elevations range from 950 m to over 3100 m. In this rugged study area, alpine glacial canyons and cirques drain into major river valleys (Barrett et al., 1991; Keane et al., 1994). Areas of ponderosa pine and mixed-conifer forest compose a relatively small proportion of CCE (15%) (Rollins, 2009) and were historically maintained by low and mixed severity regimes (Arno et al., 2000). Most of the study area (60%), however, is comprised of subalpine forest types and characterized by a mixed to high severity fire regime. The amount of area burned in the CCE in recent history (1972–2012) is estimated at nearly 3000 km^2, amounting to about 30% of the landscape; this is low relative to the other study areas.

2.1.2. Selway-Bitterroot Wilderness

The SBW (5471 km^2) is the third-largest wilderness area in the contiguous US and is located in western Montana and north central Idaho. Elevations range from 531 m to over 3000 m. Sub-alpine forest types compose the large portion of the study area (50%), followed by Douglas fir and mixed-conifer forests (30%) (Rollins, 2009). The fire regime is categorized as mixed: lower severity surface fires are common in lower elevations; patchy, stand replacing fires become common as elevation increases; and during extremely dry years, stand replacing fires can occur (Brown et al., 1994). Between 1972 and 2012, wildland fire burned ~3300 km^2, a moderate amount relative to the other study areas, and equivalent to 60% of the landscape.

2.1.3. Frank Church-River of No Return Wilderness (FCW)

The FCW (9777 km^2) is located in central Idaho and is the second largest wilderness area in the contiguous US. Elevations range from 600 to 3136 m and topographic features include river breaks, deep canyons, mountains, and glaciated basins (USDA Forest Service, 2003). Vegetation is dominated by mixed-conifer (40%)

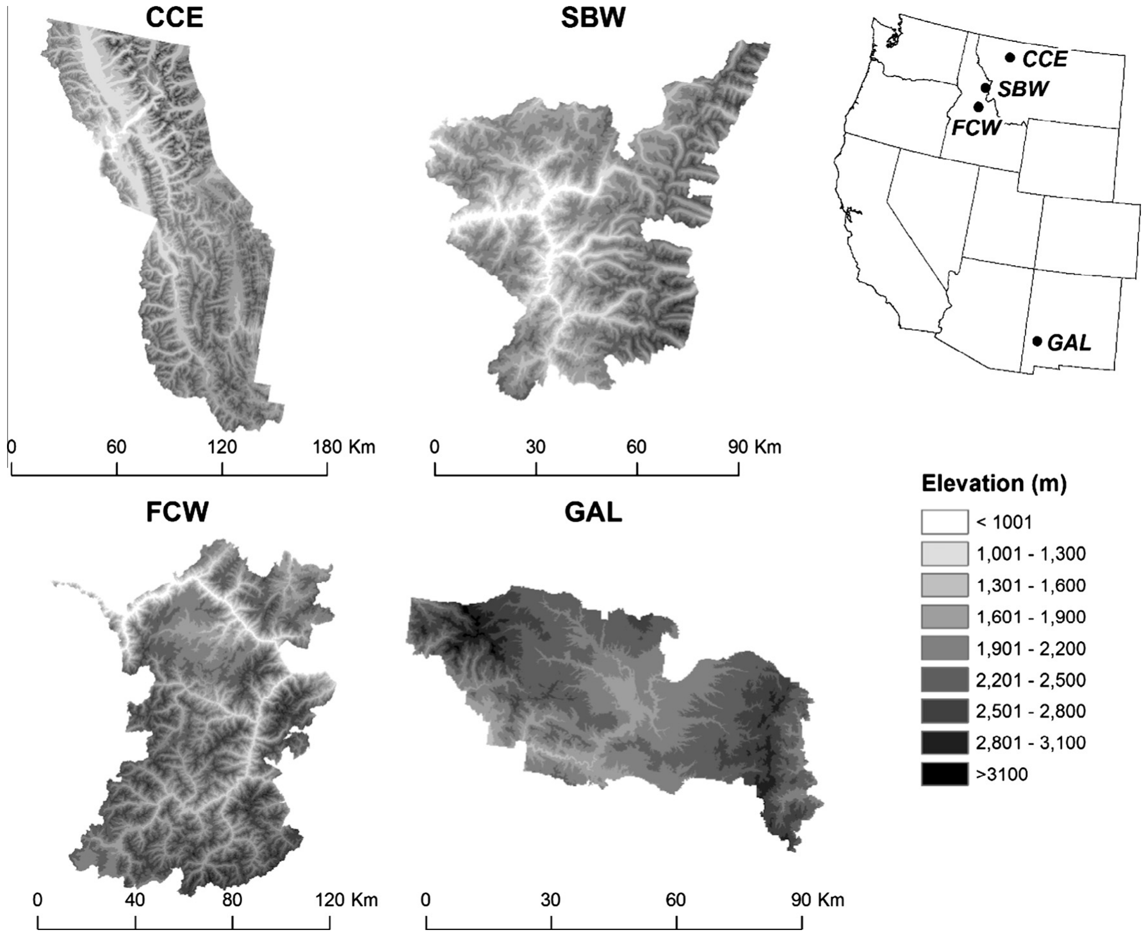

Fig. 1. Locations of study areas in the western US. CCE, Crown of the Continent Ecosystem; SBW, Selway-Bitterroot Wilderness; FCW, Frank Church-River of No Return Wilderness; GAL, Gila and Aldo Leopold Wilderness.

and subalpine forest types (30%) (Rollins, 2009). The FCW has a mainly mixed severity fire regime where low elevation, open ponderosa pine forests typically experience frequent, low intensity fires, and, generally, fire frequency decreases and severity increases with increasing elevation, moisture, and tree density (Crane and Fischer, 1986). About 5300 km^2 of the FCW has burned from 1972 to 2012, or about 54% of the study area.

2.1.4. Gila and Aldo Leopold Wilderness (GAL)

The GAL (3087 km^2) comprises the Gila and Aldo Leopold Wilderness Areas in western New Mexico. Elevations range from 1462 to 3314 m and topographic features include mountains, broad valleys, steep canyons and extensive mesas. Vegetation in GAL is comprised mainly of ponderosa pine forest (30%), juniper-pinyon pine woodland (40%), and mixed conifer forest types (20%) (Rollins, 2009). Fires in GAL are generally frequent, low severity surface fires, but severity tends to increase with elevation (Swetnam and Dieterich, 1985) and varies with aspect, incident radiation and topographic position (Holden et al., 2009). The GAL has relatively high amounts of fire, with about 3100 km^2 burned from 1972 to 2012, equivalent to over 100% of the landscape.

2.2. Sampling design

We sampled fire atlas data (Parks et al., 2015b) including only large fires ($\geqslant$400 ha) between 2001 and 2012 (209 fires in total, Table 1), to coincide with the spatial resolution and temporal coverage of Moderate Resolution Imaging Spectrometer (MODIS)

Table 1
Number and sizes (mean, minimum, maximum) of sampled fires (2001–2012) and number of edge/core pairs in each study area, and Area under the Receiver Operating Characteristic (ROC) from the full multiple logistic regression model.

Study area	No. of fires	Fire size (ha)			No. of pairs	ROC
		Mean	Min	Max		
CCE	51	5,818	421	29,627	1,108	0.91
SBW	70	4,782	403	164,007	856	0.89
FCW	62	11,480	428	294,571	1,305	0.89
GAL	26	12,531	415	121,347	553	0.87

data (1 km^2, record starting in 2001) used to derive weather (details follow). We built MCC logistic regression models for each study area to describe the relationship between fire boundaries and fuels, weather, and topography. This statistical approach, widely used in biomedical research (Balasubramanian et al., 2014), and increasingly in ecological studies (Whittington et al., 2005) including wildland fire (Narayanaraj and Wimberly, 2011), is a powerful technique for analyses with many potentially confounding variables. It matches 'cases' with 'controls', and measures their difference for all explanatory variables.

In this study, we identified each 'case' by systematically sampling pixels at 3-km intervals along each fire perimeter (~1% sampling frequency) to reduce spatial autocorrelation (Parks et al., 2015a). For each fire perimeter sample or hereafter referred to as 'edge', we selected the nearest (by Euclidean distance) location in the fire's interior or 'core' sample to match as a pair for the

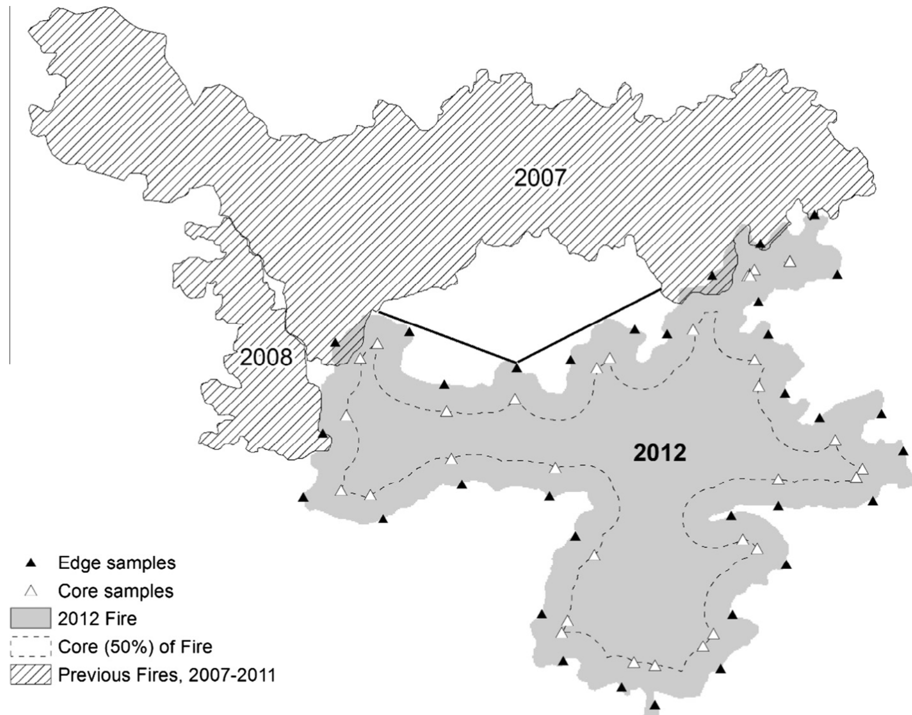

Fig. 2. Example of sampling approach to measure distances to previous burns, for a 2012 fire in the SBW. We measured distances from fire edge samples and corresponding 'matched' core samples to nearest, recent burns from 2007 to 2011. The interior core of each fire is defined as containing 50% of a fire's area. Two solid straight lines illustrate the line-of-sight window for an edge sample, within which distance to previous burn was measured.

matched case-control design. The challenge was spatially pairing nearly 4000 edge samples (Table 1) to a corresponding core sample in an automated and efficient manner. To this end, we defined the core of each fire as the portion containing 50% of the fire's area; that is, we delineated the interior area of each fire using isotropic fixed-distance buffering methods (Mu, 2008) to comprise half of the fire's total area, and with similar shapes and origin to each fire's perimeter (Fig. 2). This was effectively a "reverse buffer" based on each fire's area, which identified the core boundary. Along this core boundary, we assumed that fire had a reasonably high probability of burning freely, and we used it to locate core samples. For the resulting edge/core pairs, we extracted values of all explanatory values (detailed below) and built logistic regression models where the dependent variable was the fire edge vs. its core, and were given values of 1 and 0, respectively. All geospatial operations were performed using the R statistical program (R Core Team, 2015) or ArcMap 10.2 (ESRI, 2014), and regression models were developed using the survival package in R (Therneau, 2015).

2.3. Data sources and selection of explanatory variables

We used a two-tiered approach to select a consistent set of explanatory variables for regression models across all four study areas. First, we consulted wildland fire literature for variables important to occurrence, spread, size, or severity of fire (e.g., Dillon et al., 2011; Flatley et al., 2011; Parks et al., 2015a) and created a list with 21 weather, 10 topographic and 3 fuels-related attributes (Table S1). In selecting a set of variables to include in the models, our overarching goal was to include the exact suite of variables in the model for each study area (thereby facilitating just comparisons among study areas). This required flexibility in how we chose this suite of variables. From the onset, we included all fuel variables in the models (Table 2). To eliminate some of the weather and topographic variables from the exhaustive list (Table S1), we identified which variables were highly correlated (Pearson's $r \geqslant 0.70$). In cases where variables were highly correlated, we *generally* removed from consideration the weaker variable in terms of predicting edge vs. core. Note that, in order to select the exact suite of variables among the models for each study area, we did not always adhere to the 0.7 threshold. We next used a step-wise approach of model selection based on Akaike's Information Criterion (AIC; Burnham and Anderson, 2004) to identify our final model. Specifically, we built an initial logistic regression model only including the fuels variables. We then iteratively added variables and calculated the difference in AIC. Variables producing the highest ΔAIC as well as the most significant P-values in the accompanying model were considered for inclusion. In general, selected variables consistently performed well across all study areas. We explored interactions between pairs of selected variables, and a few contributed substantially (ΔAIC > 2) in one or more study areas. However, none were common across all study areas, and interactions were not included. This selection process resulted in a total of 12 variables (Table 2) described below.

2.3.1. Weather

Variables included daily temperature (recorded at 13:00) and three fire danger indices: energy release component (ERC), fine fuel moisture code (FFMC), and initial spread index (ISI) (Table 2) calculated using Fire Family Plus software (Bradshaw and McCormick, 2000). ERC is defined as the potential energy at a fire's head, where higher values indicate intensifying fire-conducive weather. FFMC is a moisture index for fine fuels where higher values represent drier conditions. ISI incorporates wind speed and describes rates of spread; higher values represent faster rates. Weather data were obtained from remote automated weather stations (RAWS) within or near each study area (Beaverhead RAWS for GAL, Lodgepole for FCW, Hells Half Acre for SBW, Spotted Bear Ranger Station for CCE).

To associate daily weather data with edge and core samples, we used daily fire progression maps produced using the methods described in Parks (2014). This method uses MODIS fire detection

Table 2
Variables used to model fire boundaries.

Variable name[a]	Description	Reference
Weather		
Temperature	Daily at 13:00 (°C)	http://www.raws.dri.edu/
ERC	Available energy per unit area within flaming front	Andrews et al. (2003)
FFMC	Index of moisture content of litter and other fine fuels	Van Wagner (1987)
ISI	Combines FFMC & wind speed to estimate potential rate of spread	Van Wagner (1987)
Fuel		
Burn	Distance (m) from core/edge points to closest previous fire	
NDVI	Index of productivity	Eidenshenk et al. (2007)
NonFuel	Perennial ice/snow, barren-rock/sand/clay, lakes, streams (percent)	www.landfire.gov
Topography		
TPI2k	Difference between cell & neighborhood elevation in 2000-m radius	Gallant and Wilson (2000)
TPI300	Difference between cell & neighborhood elevation in 300-m radius	Gallant and Wilson (2000)
ERR450	Elevation complexity, as proportion upland to lowland in 450-m radius	Pike and Wilson (1971)
HLI	Accounts for how slope steepness & aspect influence temperature	McCune and Keon (2002)
Rough450	Elevational difference among cells within 450-m radius	Riley et al. (1999)

[a] ERC: Energy Release Component; ISI: initial spread index; FFMC: fine fuel moisture code; NDVI: Normalized Difference Vegetation Index; TPI: topographic position index; ERR: elevation relief ratio; HLI: heat load index; Rough: roughness index.

data (NASA MCD14ML product, Collection 5, Version 1) to interpolate day-of-burning for each 30-m pixel within a fire perimeter. For core samples, we assigned daily weather corresponding to active fire dates (i.e., interpolated day-of-burning). For edge samples, the ideal weather data would be on a finer-temporal-scale (i.e., hourly), which describe diurnal variations in meteorological variables associated with extinguishment (i.e., cooler temperature, higher humidity, inversions and atmospheric stability). We lacked such data and were limited to weather data associated with day-of-burning from MODIS detected *active fire*. Recognizing that temperature on active fire days can differ significantly from temperature on days shortly after fire (Potter, 1996), and that periods of rain and high humidity can extinguish fire (Latham and Rothermel, 1993), we chose to delay weather measurements by one day for edge samples to better estimate conditions related to fire cessation. Although somewhat arbitrary, delaying weather measurements for one day following active fire detection represented a reasonable approximation for quantifying weather conditions less conducive to fire spread.

2.3.2. Fuels

We selected a set of variables to represent three ways in which the fuel mosaic may influence fire spread: previous burns, fuel loading, and unburnable areas (Table 2). To quantify the influence from previous burns, we calculated the distance from each edge and core sample to the nearest previous burn, similar to Narayanaraj and Wimberly (2011). Here, if the nearest previous burn did not intersect with an edge or core sample, distances had positive values, whereas negative values were assigned when the previous burn overlapped (i.e., re-burn). We expected similar distributions of positive and negative values if fire perimeters occurred randomly on the landscape (i.e., no significant influence from previous burns), but mainly positive values if burns hindered subsequent fire (i.e., minimal re-burning). For segments of fires that did not overlap with a previous burn, we measured the distance from sample locations to the nearest burn, but limited the field of analysis to areas outside the fire and within a line-of-sight (i.e., field of view) from the fire edge (ESRI, see Fig. 2 for example). If a segment of fire overlapped an earlier burn, we assumed that the fire's progress was unconstrained and instead measured the Euclidean distance from sample locations to the nearest burn perimeter in the overlapping region. We measured three sets of distances according to age-of-burn: young (1–5 years), intermediate (6–10 years), and old (11–15 years old). We did not report results for ages beyond 15 years since such older fires are less as effective fuel breaks (Parks et al., 2015a), fire records are more limited as fire age increases (i.e., older fires have a shorter available fire history record), and only nominal effects were apparent across all four study areas.

To quantify the influence of fuel loading, we used the normalized difference vegetation index (NDVI), an index of plant "greenness" or photosynthetic activity derived from Landsat imagery (30-m resolution; Eidenshenk et al., 2007). NDVI has been useful for tracking vegetation growth and phenology, making it a suitable proxy for fuel accumulation (Uyeda et al., 2015). Moreover this remote sensing-based imagery provided the consistent and time sensitive data needed to describe fuel conditions prior to each fire. For each fire, NDVI was derived using imagery from one year prior to fire, generally during peak growing season, where mean values across 250-m radius moving windows were assigned to each pixel (i.e., moving window averaging). We applied a moving window to account for the spectral and spatial uncertainty in mapping fire perimeters (Holden et al., 2005), and to incorporate the spatial variability of NDVI. Previous studies evaluating interactions among fires have accounted for uncertainty in fire perimeters mapped using 30-m satellite imagery by considering that fires within 200-m (Collins et al., 2009) or 375-m (Parks et al., 2015a) to have re-burn interactions. We assumed that a resolution (i.e., 250-m radius moving window) intermediate between these thresholds would adequately capture the amount and configuration of fuels and fire across each landscape.

To quantify the influence of unburnable areas (e.g., water or barren areas that can serve as natural fuel breaks), we used USGS LANDFIRE biophysical vegetation data (30-m resolution; http://www.landfire.gov) and computed the proportion of unburnable types within a 250-m radius moving window.

2.3.3. Topography

We selected five variables including: topographic position index (TPI) calculated at two spatial scales (annular neighborhoods with 300-m and 2000-m outer radii), heat load index (HLI), elevation relief ratio (ERR), and a topographic roughness index (ROUGH) (Table 2). TPI values range from negative (valley bottoms) to positive (ridge tops). Since fire boundaries tended to coincide with both valley bottoms *and* ridge tops, we transformed TPI metrics using absolute value, such that high values represent ridgetop *or* valley bottoms, and low values are flat (if slope is shallow) or mid-slope areas (if slope is substantial). This absolute value transformation aided in interpreting results.

2.4. Statistical modeling

To quantify the influence of weather, fuels, and topography in impeding fire spread, we built logistic regression models for each of these factors as follows:

$$\text{logit}(P_{edge}) = \text{Temperature} + \text{ERC} + \text{FFMC} + \text{ISI} \quad \textit{Weather Factor}$$
$$\text{logit}(P_{edge}) = \text{Burn1} + \text{Burn2} + \text{Burn3} + \text{NDVI} + \text{NonFuel} \quad \textit{Fuels Factor}$$
$$\text{logit}(P_{edge}) = \text{TPI2k} + \text{TPI300} + \text{ERR450} + \text{HLI} + \text{Rough450} \quad \textit{Topography Factor}$$

Above, *Burn* refers to the distance from edge and core samples to previous burns (by age), where Burn1 represents distance to young burns (i.e., 1–5 years), Burn2 is intermediate (6–10 years), and Burn3 is old burns (11–15 years old). The influence of each factor was measured based on the resulting R^2 from each model, where the theoretical maximum of R^2 for our models is 0.5. The R^2 is determined from the Cox model and is standard output of the 'clogit' function in the R survival package (Cox and Snell, 1989; Nagelkerke et al., 2016). We also conducted a parallel analysis using the area under the receiver operating characteristic curve (ROC) (where values above 0.5 indicate increasingly substantial explanatory power; Fielding and Bell, 1997), and present those results as supplemental material.

We next evaluated the potential for each explanatory variable to impede fire spread by building individual simple logistic regression models. As above, we used resulting R^2 values to measure a variable's influence. In addition, we built response curves to show relationships between probability of edge and certain variables that consistently ranked as influential among study areas.

Lastly, we built a full multiple logistic regression to assess overall performance based on the area under ROC.

$$\begin{aligned}\text{logit}(P_{edge}) = {} & \text{Temperature} + \text{ERC} + \text{FFMC} + \text{ISI} + \text{Burn1} + \text{Burn2} \\ & + \text{Burn3} + \text{NDVI} + \text{NonFuel} + \text{TPI2k} + \text{TPI300} \\ & + \text{ERR450} + \text{HLI} + \text{Rough45}\end{aligned}$$

3. Results

Our single-factor multiple logistic regression models indicated that the influence of weather, fuels, and topography varied by study area (Fig. 3) with R^2 values ranging from 0.03 to 0.16. Model results indicated that weather and fuels were the most influential factors in the northern study areas of CCE, FCW, and SBW. Topography had comparatively less influence in these study areas, particularly in CCE and FCW. In contrast, fuels and topography were the most influential factors in GAL, and the influence of weather was relatively low. Results of parallel analysis using ROC were strikingly similar (Fig. S1), and reiterated the dominant influence of weather and fuel in northern study areas, and fuel and topography in GAL.

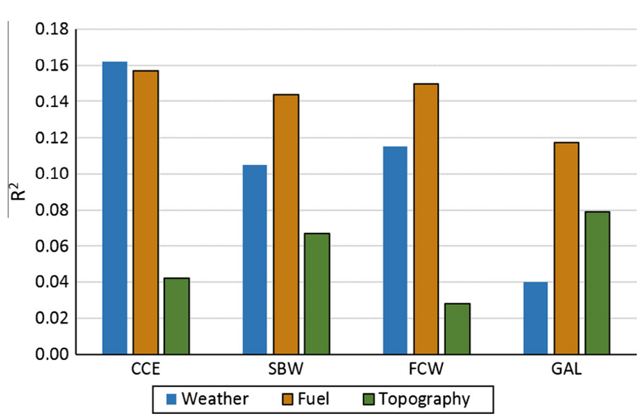

Fig. 3. R^2 from multiple regression models for weather, fuels, and topography factors on fire spread, where theoretical maximum of R^2 for any model is 0.5.

Simple logistic regression models indicated that individual variables varied in importance with R^2 values ranging from 0 to 0.12 (Fig. 4, Table S2). ROC results also corresponded similarly in the relative importance between variables (Fig. S2). Of the weather variables, temperature was the most influential in northern study areas. Lower temperatures were associated with fire edge samples, and higher temperatures were associated with core samples (Fig. 5). In contrast, in GAL, none of the weather variables were as influential as temperature was in the northern areas, although three (temperature, ERC, FFMC) were statistically significant ($p < 0.0001$). Previous burns were moderately to highly influential for younger burns (1–5 years old) across all study areas, but their influence generally decreased as burn age increased. In GAL, older burns (6–10 and 11–15 years old) not only had less influence but the direction of influence was positive (Fig. 4, Table S2). NDVI was highly influential in CCE and moderately influential in FCW; fire edges had lower NDVI compared to cores (Fig. 5). NonFuel was the most important fuel variable in CCE, but was relatively negligible in other study areas. TPI2k was the most influential topographic variable across all study areas where fire edge samples were associated with high absolute TPI2k (i.e., valley bottoms or ridge tops), and core samples with low values (flat or mid-slope areas) (Fig. 5). Topographic roughness was low to moderately influential in SBW and FCW but with opposing coefficients compared to GAL (Fig. 4, Table S2). Areas with lower roughness (e.g., shallow slopes) were associated with fire edges in SBW and FCW, whereas in GAL, higher roughness (e.g., from natural fire breaks, creeks, cool or mesic aspects) was linked with fire boundaries.

The MCC full logistic regression models performed well in describing environmental controls impeding fire spread (Table 1). Model performance was excellent in CCE (avg. ROC = 0.91) and performed well in SBW (avg. ROC = 0.89), FCW (avg. ROC = 0.89), and GAL (avg. ROC = 0.87).

4. Discussion

Weather, fuels, and topography are considered dominant factors in regulating wildland fire at the meso-scale (McKenzie et al., 2011; Moritz et al., 2011). Moritz et al. (2011) proposed that there must be mechanisms that generate "fences and corridors" on landscapes, such that some areas are less likely to burn (fences) while others are more flammable (corridors). These fences and corridors create heterogeneity across landscapes, in terms of vegetation and fire, which allows for the persistence of diverse ecosystems and landscape resilience. Over the past decade, an important body of work has emerged providing compelling evidence that fire "fences" occur at landscape scales resulting from the dominant controls of fuels, weather, and topography (Bigio et al., 2016; Heyerdahl et al., 2001; Iniguez et al., 2008; Collins et al., 2009; Parks et al., 2015a). This research has demonstrated that previous fire reduces fuels and limits the spread of future fire to varying degrees depending on ecosystem type, weather, and time since burn. In southwestern landscapes, Bigio et al., 2016 demonstrated that fire frequency varies by aspect, and steep topography reduces the influence of climate on fire frequency. Similarly Iniguez et al. (2008) found that fire frequency varied between rugged and gentle southwestern landscapes.

Missing from these lines of research has been a comprehensive approach simultaneously integrating all three dominant factors (weather, fuels, and topography) over various ecosystems. Moreover, less attention has been given to how these dominant controls

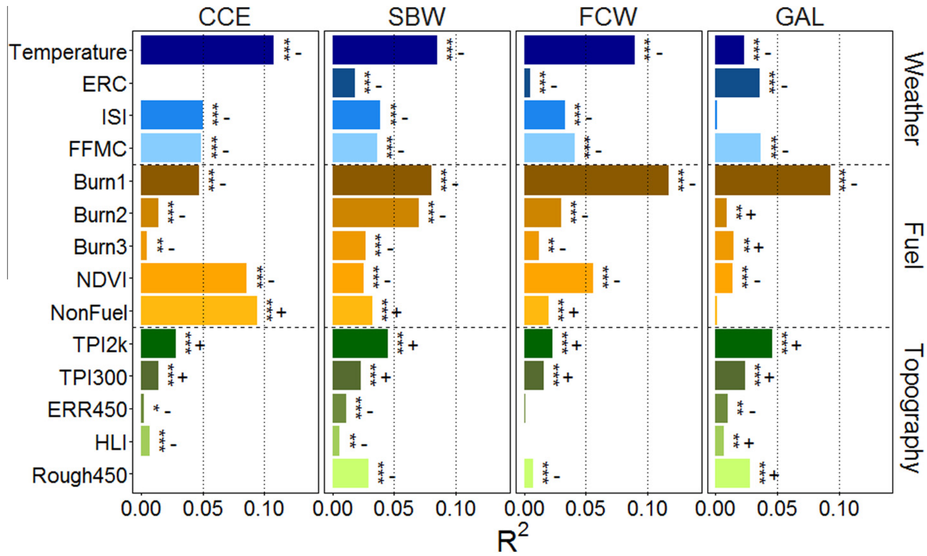

Fig. 4. R^2 from logistic regression models for individual weather, fuel, and topographic variables on fire spread, where theoretical maximum of R^2 for any model is 0.5. The influence of previous burns on subsequent fire spread is shown for three time intervals where Burn1 represents young burns (i.e., 1–5 years), Burn2 is intermediate (6–10 years), and Burn3 is old burns (11–15 years old). Significance is indicated by *** for $p \leqslant 0.001$, ** for $p \leqslant 0.01$, and * for $p \leqslant 0.05$. Negative (−) indicates that lower values impede fire spread; plus (+) indicates the opposite. TPI2k and TPI300 are based on absolute values such that (+) indicates importance of both valley bottoms and ridge tops.

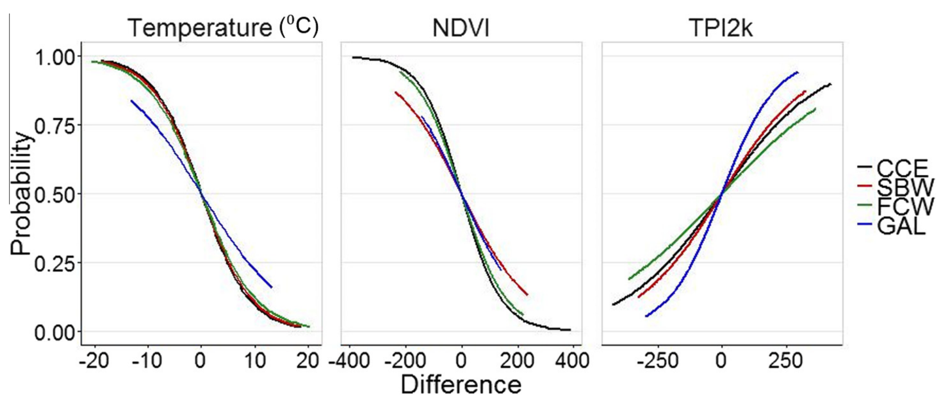

Fig. 5. Response curves from matched case-control logistic regression describing the probability of a fire boundary as a function of differences (case minus control) between fire edge and core samples for: temperature (°C), NDVI, and absolute value of TPI2k. In GAL, for example, the predicted probability of a fire boundary is ~0.75 for air temperatures that are ~10 °C cooler at the fire edge compared to a matched core sample.

stop fires, or how landscape "fences" impede fire spread, particularly at fine spatial and temporal scales. In this study, we extend previous work by quantifying the influence of weather, fuels, and topography in impeding fire spread in four large fire-prone study areas in the western US at fine scales. Our model results suggest that each factor has a major influence in stopping fire spread in most study areas, and the strength of each factor's influence varies among study areas. Weather and fuels were most important in northern study areas, whereas topography and fuels were dominant factors in the southwestern study area. By incorporating the effect of previous burns, we accounted for age of burn and found that the importance of fuels decreased as age of burns increased, across all study areas.

The factors controlling fire regimes are well known to vary regionally, and these differences have been attributed largely to broad-scale climate and productivity (Schoennagel et al., 2004), such that ecosystems are commonly described as weather dependent or fuel limited (e.g., Meyn et al., 2007; Krawchuk and Moritz, 2011). Our findings support this basic understanding, but we suggest more distinctions are needed, particularly for describing fire processes at finer scales. That is, dichotomizing fire regimes as either "weather-limited" or "fuel-limited" may oversimplify the mechanisms controlling fire cessation (cf. Littell et al., 2009). Our northern study areas (FCW, SBW and CCE) are often considered more weather-limited (e.g., Turner et al., 1994; Westerling et al., 2011), whereas our findings suggest that both weather *and* fuels impede fire spread. Littell et al. (2009) similarly observed that climate-fire dynamics are complicated by ecosystem vegetation, and advocated that the mechanism, particularly in northern mountainous regions, is a climatic preconditioning where large areas have low fuel moisture (due to drying of fuels and fuel production). Results from our northern areas corroborate this finding but with a proviso: the continuity of fuel across landscapes is integral as well. At the daily time scales and gridded spatial scales in this study, it was not only the effect of weather on fuel conditions that impeded fire spread but the lack of biomass (i.e., via recent burns, low productivity, or non-burnable features). This underscores the importance of heterogeneous structure in landscapes for maintaining a diversity of vegetation patterns that promotes resilience to fire events (Hessburg et al., 2015).

Findings from our Southwest study area further reinforce that factors controlling fire are more complex than depicted by the categories of weather vs. fuel-limited systems, as topography also regulates wildland fire (Rollins et al., 2002; Cansler and McKenzie, 2014; Bigio et al., 2016). In our southwestern study area (GAL), fuels *and* topography were highly associated with fire perimeters. Dry forests such as those in GAL are often considered fuel-limited (Swetnam and Baisan, 1996; Sibold and Veblen, 2006). Our findings support this view, as fuels were highly influential in impeding fire spread, in particular due to the influence from recent burns (1–5 years old). Moreover, we may have underestimated the importance of fuels in GAL. NDVI, one of the variables included in the fuels factor, quantifies the amount of *green* vegetation but does not characterize cured grasses and other dry litter (e.g., pine needles) that carry surface fires in GAL. Regardless, fuels were clearly important in GAL, and perhaps more interesting was that local-scale topographic features played a key role in stopping fire. Only a few studies have focused on topographic influences on fire in steep and rugged landscapes of the Southwest (Bigio et al., 2016; Iniguez et al., 2008), and this study provides further evidence that topography is a particularly important control in this region. In contrast, weather was of relatively little consequence in the GAL, as expected for southwestern landscapes where weather within fire seasons is not a critical driver. Rather, moist conditions in the seasons prior to the fire season are more important because they produce an abundance of fine fuels which cure and become available for fire in subsequent years (Swetnam and Betancourt, 1998). Overall, our results lend support to conceptual models that recognize a gradient between weather- and fuel-limited ecosystems (Krawchuk and Moritz, 2011), but abiotic factors such as topography should also be incorporated into such models (Parisien and Moritz, 2009).

With respect to specific weather related variables we examined, there was surprising agreement among study areas. Temperature was highly influential in the northern study areas, as found in several other studies that evaluated fire activity on an annual (Westerling et al., 2006; Littell et al., 2009) and daily basis (Flannigan et al., 2005). The next most consistently influential variable was FFMC. FFMC reflects effects from rapid changes in temperature, wind speed, relative humidity, and precipitation on fine fuels – where fires usually start and spread. As such, FFMC has been useful for tracking ignition probability and sustainability of surface fire spread (Beverly and Wotton, 2007). Here, it also has proven informative for detecting conditions conducive to stopping fire.

Of the topographic variables we examined, topographic position index (TPI2k; a measure of valley bottom vs. ridge top) was most influential across all study areas, as fire boundaries tended to coincide with valley bottoms and ridge tops (see Figs. 4 and 5). Although this specific variable has not yet received much quantitative attention in relation to fire spread, several studies conducted at a variety of spatial scales have demonstrated the importance of topography (Taylor and Skinner, 2003; Beaty and Taylor, 2008; Cansler and McKenzie, 2014). This particular result suggests that fire simulation models (Parisien et al., 2005; Finney et al., 2011) could benefit by incorporating indices of topographic position into fire growth algorithms. For the most part, slope and aspect are the main topographic variables included in such models (Rothermel, 1972; Tymstra et al., 2010); our exploratory analysis found that slope and aspect were not consistently influential as topographic drivers impeding fire spread (see Methods). In addition, topographic position index measured with a smaller radius (300-m vs. 2000-m) had a weaker association with fire boundaries, suggesting that major ridge tops and valley bottoms are more effective fuel breaks. Another interesting result related to topography was that complexity (represented by roughness) impeded fire spread in the GAL but facilitated spread in SBW and FCW. Highly complex topography can be associated with discontinuous fuels (creeks, rocky outcrops) and edaphic conditions that can impede fire spread (Guyette et al., 2002; Yang et al., 2008) while at the same time, complex topography can be associated with steep slopes that promote fire spread because flames are closer to the ground and heat convection within fires intensifies wind (Dickson et al., 2006; DeBano et al., 1998).

In terms of the influence of specific variables related to fuels, recent fire (1–5 years old) was the most highly influential variable in all study areas except in the most northern (CCE), where unburnable features and NDVI were more important. The comparatively low influence of previous fire in CCE could be due to its comparatively longer fire return intervals (Rollins, 2009) and lower rates of burning over the last few decades (30% has burned from 1972 to 2012 compared to 54% to >100% in the other study areas). In other words, wildland fire in CCE has had less opportunity to interact with previous burns compared to the other study areas. This result is in contrast to Parks et al. (2015a), who found, for the same study area, that previous fire was highly influential at young fire ages. The discrepancy is likely due to methodological differences; Parks et al. (2015a) evaluated fire at an annual resolution (compared to five-year in this study) and only evaluated portions of fire perimeters that interacted with previous burns (this study evaluated all portions).

Previous burns limit subsequent fire spread by altering and reducing fuel availability (Taylor and Skinner, 2003; Scholl and Taylor, 2010), but vegetation regenerates and fuels re-accumulate after fire (Mack et al., 2008). In an attempt to capture this dynamic, we included information on previous burns and accounted for different age classes of burns in building regression models. Not surprisingly, model results indicate a diminishing influence of previous burns with age (cf. Collins et al., 2009; Parks et al., 2015a), supporting the concept that feedbacks associated with wildland fire regulate many aspects of subsequent fire (McKenzie et al., 2011). However, even though previous burns (particularly recent) were clearly associated with fire cessation, weather and topography were on par, if not more important, depending on the study area. Consequently, thoughtful attention should be given to all factors regulating fire spread (weather, fuels, and topography) when managing wildland fire for resource benefit (van Wagtendonk, 2007), designing and implementing fuel treatments to increase landscape resilience (Hessburg et al., 2015), and staging fire suppression resources (Thompson et al., 2016).

In extrapolating our findings to non-wilderness settings where fire suppression is both more prevalent and effective, we posit that suppression efforts may interact with the biophysical factors that we studied and actually increase their ability to impede fire spread. For example, the finding by Narayanaraj and Wimberly (2011) that fire boundaries were more likely to be near roads may be due to an interactive effect between topography and fire suppression because roads provide access for fire suppression resources and are often located along valley bottoms and ridge tops. Similarly, the ability of fuel treatments or previously burned areas to impede fire spread may be enhanced when coupled with suppression efforts (Moghaddas and Craggs, 2008; Thompson et al., 2016).

Our findings implicate the major factors and specific variables responsible for extinguishing fire across several fire-prone ecosystems in the western US; however, the analysis is not without limitations. For example, we aggregated data by study area and evaluated each study area as an individual unit thereby not accounting for intra-study area variation. Thus, care should be taken in making inference to individual forest types or other landscapes that might have different environmental drivers. Furthermore, a longer fire history and weather dataset would allow us to investigate a broader range in weather, including more moderate and extreme events, and provide a more comprehensive evaluation of factors controlling fire spread. Also, our weather measurements were temporally fine (i.e., daily) but spatially coarse, such that the possible influence from microclimates created by local-scale topographic variation (Hemstrom and Franklin, 1982; Heyerdahl et al., 2001) was not directly included. In addition, we evaluated ecosystems located in the northern and southern portions of the western US providing evidence for varying constraints on fire cessation, but lacking data for the diversity of ecosystems between the two geographic regions, we did not implement a more hypothesis-driven examination, such as across ecological gradients (e.g., Meyn et al., 2007; Krawchuk and Moritz, 2011). Further research and synthesis at spatially and temporally fine-scales across the West (especially in wilderness areas minimally affected by anthropogenic influences) would allow for explicit testing of constraints on fire spread across spatial gradients (e.g., net primary productivity, potential evapotranspiration). Finally, due to the broad geographic scope of this study, we did not examine the assortment of complex interactions between fuels, topography, and weather that may also act to extinguish fire spread (*sensu* Cavard et al., 2015; Taylor and Skinner, 2003). Future investigations of these interactions could provide further valuable insights about the mechanisms controlling fire, such as determining tipping points where intensifying fire weather outweighs the combined influence of fuels and topography, thereby improving prediction accuracies in modeling fire behavior.

5. Conclusion

This study improves our understanding of the environmental drivers that impede fire spread and complements and expands upon previous work conducted in smaller landscapes or on individual fires (e.g., Collins et al., 2009; Narayanaraj and Wimberly, 2011). We provide evidence from western US landscapes that weather, fuels, and topography all impede the spread of fire, but the influence of these factors varies among ecosystems. For example, weather (mostly driven by daily temperature) and fuels were the most influential factors in the cooler and wetter study areas in the northern Rocky Mountains, whereas fuels and topography were most influential in the warmer and drier study area in the southwestern US.

Wildland fire, as an agent of landscape pattern, is a well-recognized source of ecological heterogeneity that is crucial for ecological resilience in fire-prone forests (McKenzie et al., 2011; Stephens et al., 2014). A mosaic of vegetation patterns resulting from fire disturbance provides habitat and diversity to which native flora and fauna are adapted (Hessburg et al., 2015), which are critically important to conservation in a changing world (Millar et al., 2007). Understanding the process of fire cessation is as fundamental to explaining fire-created patterns as the process of fire spread. By identifying the dominant mechanisms behind fire cessation in varied ecosystems, this study gets us one step closer towards understanding how landscapes self-regulate, a fundamental property of fire as an ecosystem process (McKenzie et al., 2011). Here we find that weather, fuels, and topography are each integral to creating fire-derived landscape patterns where, depending on the ecosystem, fires are more likely to stop spreading under cooler, moisture weather conditions, in the presence of fuel breaks (caused by previous fire, lower productivity, or unburnable features), or ridgetops and valley bottoms. This more comprehensive understanding is crucial today as we see—and manage—more fires of large extent and long duration on our landscapes (Westerling et al., 2006). If we tailor management of wildland fire (whether for resource benefit or suppression) and fuel treatments according to the dominant controls unique to each ecosystem, we can take advantage of features that may act as fire barriers, and we can promote fire dynamics that create the natural fuel breaks and vegetation mosaics which restore self-regulation and resiliency to landscapes.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2016.08.035.

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