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Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006

Gregory K. Dillon,[1,†] Zachary A. Holden,[2] Penelope Morgan,[3] Michael A. Crimmins,[4] Emily K. Heyerdahl,[1] and Charles H. Luce[5]

[1]*USDA Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory, Missoula, Montana 59808 USA*
[2]*USDA Forest Service, Northern Region, Missoula, Montana 59807 USA*
[3]*Wildland Fire Program and College of Natural Resources, University of Idaho, Moscow, Idaho 83844-1133 USA*
[4]*Department of Soil, Water, and Environmental Science, The University of Arizona, Tucson, Arizona 85721 USA*
[5]*USDA Forest Service, Rocky Mountain Research Station, Boise, Idaho 83702 USA*

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Abstract. Fire is a keystone process in many ecosystems of western North America. Severe fires kill and consume large amounts of above- and belowground biomass and affect soils, resulting in long-lasting consequences for vegetation, aquatic ecosystem productivity and diversity, and other ecosystem properties. We analyzed the occurrence of, and trends in, satellite-derived burn severity across six ecoregions in the Southwest and Northwest regions of the United States from 1984 to 2006 using data from the Monitoring Trends in Burn Severity project. Using 1,024 fires from the Northwest (4,311,871 ha) and 497 fires from the Southwest (1,434,670 ha), we examined the relative influence of fine-scale topography and coarse-scale weather and climate on burn severity (the degree of change from before the fire to one year after) using the Random Forest machine learning algorithm. Together, topography, climate, and weather explained severe fire occurrence with classification accuracies ranging from 68% to 84%. Topographic variables were relatively more important predictors of severe fire occurrence than either climate or weather variables. Predictability of severe fire was consistently lower during years with widespread fires, suggesting that local control exerted by topography may be overwhelmed by regional climatic controls when fires burn in dry conditions. Annually, area burned severely was strongly correlated with area burned in all ecoregions (Pearson's correlation 0.86–0.97; $p < 0.001$), while the proportion of area burned severely was significantly correlated with area burned only in two ecoregions ($p \leq 0.037$). During our short time series, only ecoregions in the Southwest showed evidence of a significant increase ($p \leq 0.036$) in annual area burned and area burned severely, and annual proportion burned severely increased in just one of the three Southwest ecoregions. We suggest that predictive mapping of the potential for severe fire is possible, and will be improved with climate data at the scale of the topographic and Landsat-derived burn severity data. Although severity is a value-laden term implying negative ecosystem effects, we stress that severity can be objectively measured and recognize that high severity fire is an important ecological process within the historical range of variability in some ecosystems.

Key words: ecological change detection; fire ecology; Landsat TM; northwestern United States; Random Forests; relative differenced normalized burn ratio (RdNBR); remote sensing; southwestern United States; wildland fire.

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† **E-mail:** gdillon@fs.fed.us

Introduction

Fire is a keystone process in many ecosystems of western North America. High severity fires consume large amounts of above- and below-ground biomass (Keeley 2009). The resulting ecological effects have long-term consequences for vegetation structure and composition (Holden et al. 2006, Lentile et al. 2007), severity of subsequent fires (Holden et al. 2010), soil erosion and mass wasting (Istanbulluoglu et al. 2002, Cannon et al. 2010, Robichaud et al. 2010), carbon and nutrient cycling (Hurteau and Brooks 2011), and other soil properties (Certini 2005). Aquatic ecosystems are both dependent on episodic severe fire for mass wasting and log inputs and severely disrupted in the short term by the resultant temperature and sediment changes (Bisson et al. 2003), yielding a strong dependence on scaling and synchrony of severe fire occurrence within a basin (Miller et al. 2003). Recent climate-driven increases in the extent and frequency of wildland fire in the western United States have received much attention (Westerling et al. 2006, Morgan et al. 2008, Littell et al. 2009, Littell et al. 2010), but much less is known about the degree of ecological change (i.e., burn severity) caused by wildfires (Lentile et al. 2006, Lentile et al. 2007, Keane et al. 2008, Keeley 2009). Millions of dollars are spent on postfire-rehabilitation to limit erosion and weed invasion following severe fires (Parsons et al. 2010) and on fuel treatments implemented to alter the behavior and severity of subsequent fires (Wimberly et al. 2009, Hudak et al. 2011). For these reasons, it is particularly important that we increase our understanding of the landscape and climate controls of burn severity to better predict the ecological effects of wildfires.

Researchers have recently focused on characterizing the controls of spatial variation in burn severity at the fire- or landscape-scale (Broncano and Retana 2004, Chafer et al. 2004, Odion et al. 2004, Bigler et al. 2005, Lentile et al. 2006, Holden et al. 2009, Miller et al. 2009*b*, Bradstock et al. 2010). However, the severity of multiple fires at regional and sub-continental scales has not been analyzed. In the United States, wildfires, especially severe ones, retain a largely negative stigma, despite our growing awareness of their vital role in maintaining structure and function in ecosystems around the world (Bond and Keeley 2005). In many respects, it is the severity of wildland fire, rather than whether or not a location burned that has greatest effect on ecological processes.

Topography and climate are likely important drivers of burn severity

Spatial variation in burn severity reflects variation in both the intensity and duration of fire activity across the landscape. The primary factors typically thought to control fire intensity and duration are topography, weather, and fuels (Pyne et al. 1996). Many have argued that accumulation of fuels from fire suppression during the past century is influencing the occurrence of high severity fire today (Keane et al. 2002), while others have argued that weather is the primary driver of fire behavior (Bessie and Johnson 1995). Evaluating the effect of fuels on severity across regional scales is confounded by wide variation in land use and disturbance history, for which information is incomplete. However, topography and weather (and more broadly, climate) have indirect influences on the spatial variability of fuels, as well as direct influence over the biophysical conditions that may affect fire intensity and duration. The availability of spatially comprehensive data on topography (Gesch 2007) and historical climate (Mesinger et al. 2006, Rehfeldt 2006), therefore enables regional evaluation of topography and climate as drivers of burn severity.

Topography and site conditions influence vegetation distribution and productivity (Whittaker 1970, Barbour et al. 1999) across landscapes and regions, with implications for where and why fires burn severely. The effects of topography on fire behavior (ignition, spread, intensity) have been the subject of much research (Pyne et al. 1996), and some studies have focused on burn severity relative to topography (e.g., Kushla and Ripple 1997, Broncano and Retana 2004, Holden et al. 2009). Topography affects energy and water balances that control vegetation development, and therefore the accumulation of biomass that fuels fires when it is sufficiently dry. Furthermore, elevation, aspect, latitude, longitude, topographic position, and surrounding topographic context all influence microclimatic conditions (temperature, precipitation, direct solar radiation, wind exposure, etc.) that influence the moisture content of fuel. Physical properties of fires such as combustion rate, fuel consumption, total heat, and soil heating in turn cause changes to vegetation and soils that form the basis for describing or estimating burn severity (Pyne et al. 1996, Keane et al. 2010).

In the western United States during the twentieth century, climate was a strong driver of fire extent (Littell et al. 2009) and of the frequency of large fires (Westerling et al. 2006). Dendroecological studies have similarly demonstrated the strong influence of climate on pre-twentieth century fires (Kitzberger et al. 2007). There are several reasons to expect that climate influences burn severity as well. First, drier conditions generally increase the net energy released from fuel during burning. In New Mexico, for example, area burned severely was correlated with the duration of rain-free periods in the spring preceding the fire (Holden et al. 2007). Second, more fuel, including logs, duff, and tree crowns, is likely to be consumed if fuels are dry than if they are not (Pyne et al. 1996), and significant consumption of crown fuels can lead to severe fire effects. Third, Pierce and Meyer (2008) hypothesized that multidecadal climate influenced the occurrence of large, severe fires in past millennia.

In regions of complex mountainous topography, such as the western United States, topography and climate interact to create steep biophysical gradients that influence not only fire extent (Taylor and Skinner 2003), but also burn severity. With climate variations between years of widespread fire and other years, the relative influence of climate versus topography on burn severity is likely to vary as well. Bigler et al. (2005) hypothesized that the local effects of fuels and topography decline with increasingly severe fire weather, particularly across short elevation gradients. However, the importance of topographic controls on burn severity, relative to climate and weather, is largely unexplored.

Availability of west-wide burn severity data make regional-scale studies possible

Quantifying burn severity across large regions requires the acquisition and processing of large amounts of remotely-sensed imagery. While point-based measurements of severity are possible on the ground, use of satellite imagery is required to gain a landscape perspective on spatial patterns of severity (Key and Benson 2006). Fortunately, the Monitoring Trends in Burn Severity project (MTBS, *public communication*, http://www.mtbs.gov) has used Landsat satellite imagery to map burn severity for all large wildfires (>405 ha) across the western United States from 1984 to present (Eidenshink et al. 2007), covering most of the area burned during this time period. Because these data have high spatial resolution (30 m) and broad extent (the western United States), they provide a unique opportunity to study the topographic and climatic controls of burn severity at a subcontinental scale. MTBS characterizes burn severity with two closely-related indices: the differenced normalized burn ratio (dNBR; Key and Benson 2006) and the relative differenced normalized burn ratio (RdNBR; Miller and Thode 2007). Calculated from pre- and post-fire Landsat TM and ETM+ imagery, dNBR and RdNBR both use light reflected from earth in near-infrared (Landsat band 4) and mid-infrared (Landsat band 7) wavelengths to capture fire-induced changes in vegetation cover and soil characteristics. While dNBR provides a measure of absolute change, RdNBR is adjusted to account for pre-fire conditions at each pixel. As such, RdNBR provides a more consistent measure of burn severity than dNBR when evaluating severity across broad regions and diverse vegetation (Miller et al. 2009*a*, Norton et al. 2009), including sites with low preburn biomass. As an indirect measure of biomass loss, RdNBR can be used to accurately identify stand-replacing fire in forests and woodlands (Miller and Thode 2007). We define burn severity, therefore, as the degree of change one year post-fire relative to pre-fire conditions (Lentile et al. 2006) as measured by RdNBR.

Burn severity may have increased recently but this hasn't been well documented

Annual area burned by wildfires increased in the western United States during the last half of the twentieth century (Littell et al. 2009) as has the the number of large fires (Westerling et al. 2006), and the total area burned is expected to increase with climate warming (Running 2006, NWCG 2009). More area has burned in recent decades, compared to the middle 20th century, in forests in the US Northern Rockies (Morgan et al. 2008), southwestern United States (Swetnam and Betancourt 1998), and western United States as a whole (Westerling et al. 2006, Littell et al. 2009, Littell et al. 2010). When more area burns, more area burns severely (Holden et al. 2011), but it is possible that the proportion of area burned severely could be increasing as well in some areas (Miller et al. 2009*b*). Although the MTBS record of severe fires is quite short for assessing such trends, it has proven useful in detecting increases in severity for some forest types in California's Sierra Nevada mountains in recent decades (Miller et al. 2009*b*). Comparing MTBS observations across different regions with diverse vegetation, topography, climate, and land-use histories will help us understand recent trends and forecast future trends in wildfire extent and severity—both important elements of fire regimes (Morgan et al. 2001).

Objective

Our objective was to assess the influence of topography, climate, and weather on burn severity in forests and woodlands across the Northwest and Southwest regions of the United States. We also assessed whether there was an increasing trend in burn severity from 1984 to 2006. We used burn severity inferred from 1,521 remotely sensed fires (Eidenshink et al. 2007) that burned in forests and woodlands. We analyzed the influence of fine-scale topography and coarse-scale climate and weather on burn severity using the Random Forests machine learning algorithm (Breiman 2001).

Methods

Study area

Our study area encompasses two broad regions of the western United States: 63 million ha in the Northwest and 77 million ha in the Southwest (Fig. 1). The Northwest covers portions of LANDFIRE map zones 1, 2, 7, 8, 9, 10, 18, 19, and 21, while the Southwest covers all of map zones 14, 15, 16, 23, 24, 25, and 28 (*public communication*, http://landfire.cr.usgs.gov/viewer/). Rather than cover all areas in the western United States, we chose these two regions because: (1) fire plays an active role in the ecology of forests and woodlands in both regions; and (2) the Northwest and Southwest represent two centers of action in a climatic dipole characterized by out-of-phase interannual precipitation variability and demonstrated links to multicentury fire history (Kitzberger et al. 2007), potentially leading to differences in the influence of climate on burn severity. A similar analysis of burn severity trends and causes has already been conducted for California (Miller et al., *in press*), and additional work is underway to examine the potential influences of topography, climate, and vegetation on burn severity across the entire western United States (Dillon et al. 2011).

In addition to different influences on burn severity between the Northwest and Southwest regions, we also expected the relative influence of topography, climate, and weather to vary within each region. Therefore, we subdivided our analysis into six ecoregions, using groupings of existing ecological regions (CEC 2007). Our ecoregions are: (1) Pacific; (2) Inland Northwest; (3) Northern Rockies; (4) Southern Rockies; (5) Colorado Plateau; and (6) Mogollon Rim (Fig. 1).

To identify forests and woodlands, we used environmental site potential (ESP; Rollins 2009; *public communication*, http://www.landfire.gov/NationalProductDescriptions19.php). ESP is a potential vegetation classification that depicts the vegetation capable of being supported at a site, based on biophysical site characteristics such as climate, topography, and substrate. We combined ESP into eight broad groups but only analyzed the four groups with the potential for forest and woodland vegetation (>10% tree cover): woodland, dry forest, mesic forest, and cold forest (Appendix A).We used ESP instead of a classification of existing vegetation primarily because we wanted to capture sites that supported forest or woodland vegetation before fire. While consistent existing vegetation data exist for our study area (*public communication*, http://www.landfire.gov/NationalProductDescriptions21.php), they represent a static point in time and would in many cases depict non-forest vegetation on sites that were forest or woodland prior to disturbance. Conversely, we acknowledge that using ESP to identify forests and woodlands may have caused some fires that burned in non-forest vegetation to be included in our analysis, but we felt that this was the best approach given the lack of consistent

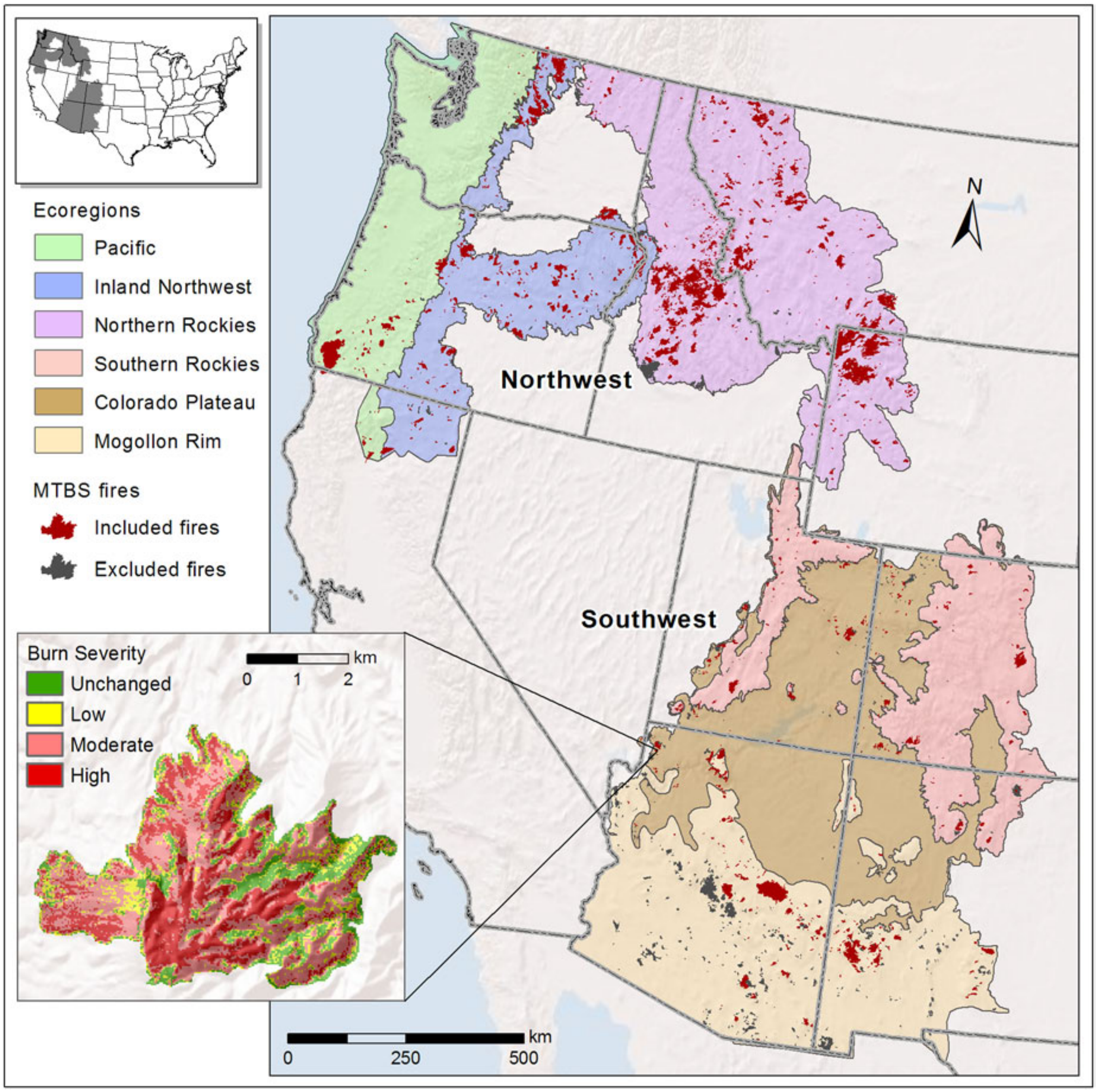

Fig. 1. Location of the study area showing the Northwest and Southwest regions, six ecoregions, and the 1,521 fires (red) included in our analysis. Fires excluded from our study (gray) were either in non-forest settings or did not meet criteria for imagery timing. A burn severity map (RdNBR) for one fire shows an example of spatial variation in severity (inset).

pre-fire vegetation data.

Burn severity data

We acquired satellite-derived severity data (RdNBR) for forest and woodland fires in our study area that burned from 1984 to 2006 (1,024 fires in the Northwest, acquired 25 February 2010; 750 fires in the Southwest, acquired 6 July 2009; *public communication* http://www.mtbs.gov). We determined a fire to be in forest and woodland if the majority of area inside the fire perimeter was mapped as one of the four forest and woodland ESP groups (Appendix A). Keeping with our definition of burn severity (degree of change from pre-fire to one year post-fire), we evaluated the timing of pre- and post-fire

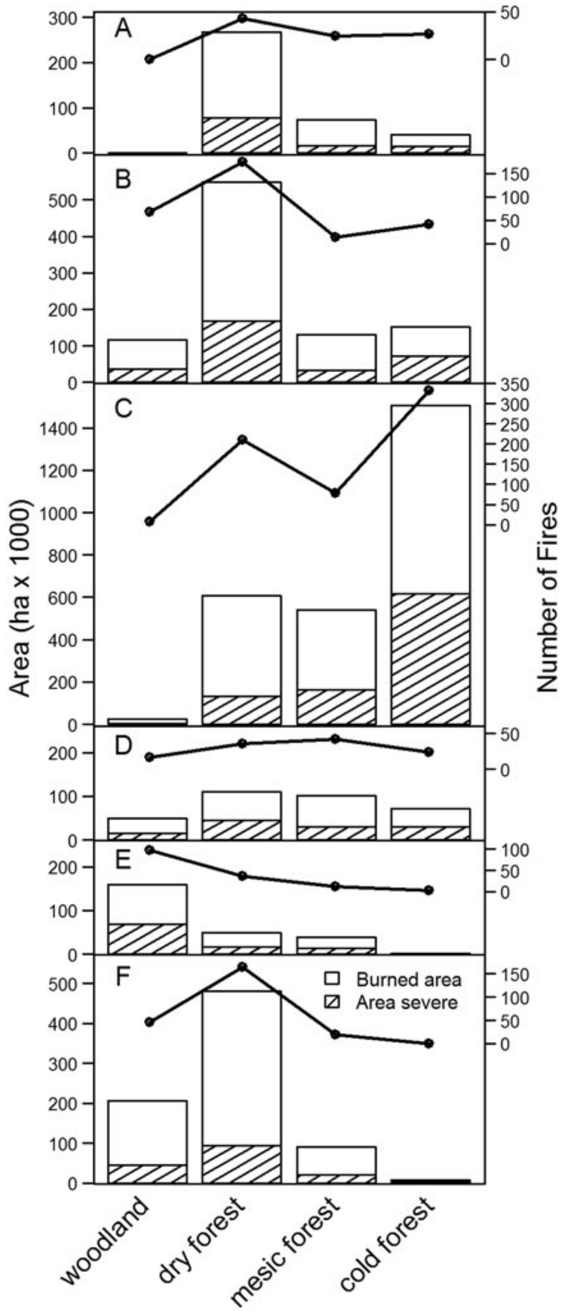

Fig. 2. Area burned (total) and burned severely within that total (hatched) by potential vegetation group, divided by ecoregion: (A) Pacific, (B) Inland Northwest, (C) Northern Rockies, (D) Southern Rockies, (E) Colorado Plateau, and (F) Mogollon Rim. Number of fires (solid line with the right side y-axis) reflects the assignment of each fire to a potential vegetation group based on majority. Small areas of non-forest (nonveg, grass, dry shrub, and

imagery for all fires to ensure that post-fire imagery was taken six to 18 months post-fire and that pre- and post-fire images were taken in the same season (±60 days). In the Northwest, relatively few fires (13%; 6% of area mapped in fires) were outside these parameters. However, in the Southwest, where 34% of fires (25% of area mapped in fires) did not meet these criteria, we eliminated 253 fires (502,093 ha) from our analyses. Of the fires that were eliminated, 93% had post-fire imagery less than six months after the fire, indicating initial assessments of severity that are typically done on non-forested sites. Further, the proportion of area burned eliminated in any one year ranged from 0% in 1984 (the smallest fire year) to 100% in 1991 (the second smallest fire year), with an average in all other years of 29% (range: 3–64%; sd = 17). In general, we felt that eliminating fires from our analysis based on image timing in the Southwest helped to refine our dataset to truly forest and woodland fires and did not bias our analysis of annual trends.

By using satellite imagery from approximately one year post-fire, we inherently included some delayed effects of fire such as plant mortality and resprouting, which can be influenced by factors other than fire (Keeley 2009). Management actions such as salvage logging, reseeding, and planting can also occur during the first year after fire, potentially influencing RdNBR values. We accepted the inclusion of these ecosystem responses and management influences as necessary to evaluate questions relating to burn severity in a consistent manner across broad geographic and temporal scales.

We analyzed 1,024 fires from the Northwest (4,311,871 ha) and 497 fires from the Southwest (1,434,670 ha; Fig. 2). Most fires (92%) were >405 ha, but they ranged from 20 ha to 228,966 ha. For areas that burned more than once from 1984 to 2006 (199,739 ha in the Northwest; 108,402 ha in the Southwest), we used only the RdNBR of the first fire because burn severity can be affected by the severity of previous fires (Holden et al. 2010, Halofsky et al. 2011).

For all fires, we classified the continuous

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mesic shrub) were included in selected fires, but account for less than 5% of total area burned.

RdNBR into discrete classes of severely burned versus not severely burned using field measurements of burn severity (composite burn index, CBI; Key and Benson 2006) from 565 plots in Grand Canyon National Park (E. Gdula, *personal communication*). Using methods similar to Miller and Thode (2007), we used a non-linear equation to regress RdNBR against CBI ($R^2 = 0.69$) and calculate a threshold for severely burned equivalent to CBI values above 2.25 (RdNBR $\geq$ 695; Fig. 3). Field-measured CBI values of 2.25 represent the midpoint between moderate and high severity for rating factors such as surface fuel consumption, soil heating, plant mortality, and alteration of foliage at different heights above the soil surface (Key and Benson 2006). Our calculated threshold of 695 between moderate and high severity was very similar to a threshold derived independently from another study using Grand Canyon field data (RdNBR = 698; Pabst 2010), and to others calculated for the Sierra Nevada (RdNBR = 641; Miller and Thode 2007), the Gila Wilderness, New Mexico (RdNBR = 677; Holden et al. 2009), and the North Cascades (RdNBR = 703; Cansler 2011).

In each ecoregion, we determined years of widespread fires ("big years") based on annual area burned. The distribution of annual area burned is positively skewed in all ecoregions, characterized by relatively low area burned in most years, punctuated by a few big years. In the Northwest, the Pacific and Northern Rockies ecoregions had particularly skewed distributions (skewness > 2), so we selected big years as those with area burned greater than the upper quartile plus 1.5 times the inter-quartile range (resulting in three big years in the Pacific and five in the Northern Rockies; Fig. 4). In the Inland Northwest, the distribution was less skewed (skewness = 1.1), so we selected big years as those with area burned greater than 0.5 standard deviation above the mean (resulting in five big years). In the Southwest, we selected the six big years in the upper quartile of annual area burned for each ecoregion. Big years accounted for over half of the total area burned from 1984 to 2006 in every ecoregion (Pacific = 82%, Inland Northwest = 57%, Northern Rockies = 81%, Southern Rockies = 85%, Colorado Plateau = 71%, Mogollon Rim = 72%). Big years are climatically distinct from other years; in all ecoregions, temperatures were above normal and precipitation was below normal during fire seasons in big years (Appendix A). In contrast, temperature and precipitation during other years were both close to long-term averages.

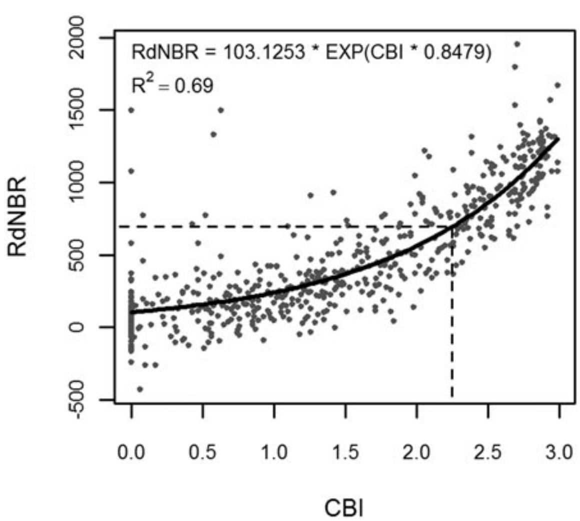

Fig. 3. Non-linear regression model of the relative differenced normalized burn ratio (RdNBR) versus 565 field-measured composite burn index (CBI) plots from Grand Canyon National Park, Arizona. Dashed lines show the threshold for high severity (CBI = 2.25; RdNBR = 695).

Fine-scale topography data

We considered elevation (acquired from LANDFIRE, *public communication*, http://landfire.cr.usgs.gov/viewer/) and a suite of topographic indices derived from elevation, all at 30-m^2 spatial resolution (Appendix A). We calculated indices covering three broad categories of topographic information: slope and aspect, slope position and curvature, and topographic complexity. Our indices of slope and aspect were percent slope, heat load index (McCune and Keon 2002, Eq. 3), solar radiation aspect index (Roberts and Cooper 1989), and an index combining slope and cosine-transformed aspect (Stage 1976). Indices of slope position and curvature were hierarchical slope position (Murphy et al. 2010), compound topographic index (Moore et al. 1993), and a topographic position index (Weiss 2001) that we calculated at three spatial scales (annular neighborhoods with 150 m, 300 m, and 2,000 m outer radii). Indices of

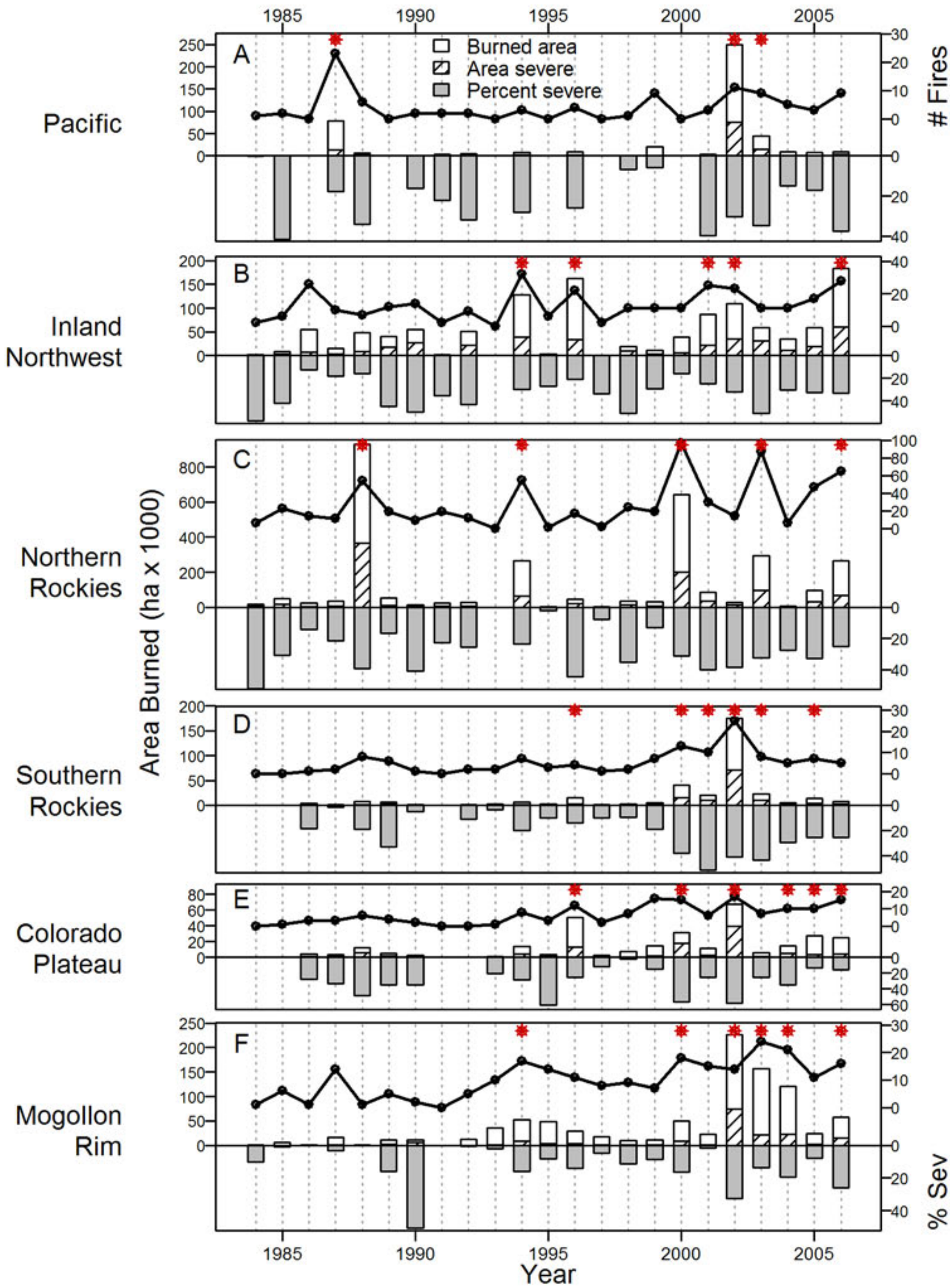

Fig. 4. Selected annual fire metrics from our data set of 1,521 MTBS fires, divided by ecoregion: (A) Pacific, (B) Inland Northwest, (C) Northern Rockies, (D) Southern Rockies, (E) Colorado Plateau, and (F) Mogollon Rim. In each pane, the bars above the zero line display annual area burned (total) and the area burned severely within that total (hatched). Number of fires is shown as a line with the right side y axis. Annual percent of area mapped as high severity is shown as inverted gray bars below the zero line. Years identified as widespread (big) fire years are marked with red asterisks (*) along the top of each pane.

topographic complexity, also calculated at three spatial scales (circular neighborhoods with 90 m, 450 m, and 810 m radii), were Martonne's modified dissection coefficient (Evans 1972) and elevation relief ratio (Pike and Wilson 1971). Prior to modeling, we eliminated variables that were highly correlated with others (Spearman's rho > 0.75). From our 16 candidate topographic predictor variables, we retained between 12 and 14 variables in each ecoregion (Appendix A).

Coarse-scale climate and weather data

We considered three categories of climate and weather variables, computed for each fire: normalized monthly temperature and precipitation, soil moisture, and fire weather (Appendix A). We used Rehfeldt's (2006) thin plate spline model and 56-year climate record (1950–2006) to interpolate monthly minimum, maximum, and average temperature, and monthly precipitation for the approximate central latitude and longitude and mean elevation of each of the 1,521 fires. To capture the departure from average conditions at each fire location, we took the monthly values for the year of fire and the previous year, and normalized them by subtracting the 56-year mean for that month and location and dividing by the standard deviation. From normalized temperature and precipitation, we selected variables that capture both climate departures in the month of fire ignition and the previous month, and antecedent seasonal conditions. In the Northwest, we defined antecedent seasons as: spring (March through May), winter (December through February), fall (September through November; previous year) and summer (June through August; previous year). In the Southwest, we shifted seasons later by one month (spring = April through June, winter = January through March, fall = October through December, summer = July through September) due to earlier warming and shifts in seasonal precipitation due the North American Monsoon (Sheppard et al. 2002).

We derived soil moisture from a modeled time series produced by the surface water monitor (SWM; Wood 2008), a real-time hydrologic simulation system that incorporates the variable infiltration capacity (VIC) hydrologic model (Liang et al. 1994). For each fire, we identified the VIC half-degree (latitude and longitude) grid cell containing the approximate center of the fire, and extracted daily soil moisture values at three depths (0–10 cm, 10–40 cm, 40–100 cm). At each of these depths, for the 10-day period starting with the detection date for each fire, we calculated both 30-year percentiles (with respect to 1960–1999) and 30-day seasonal percentiles (with respect to the previous 30 days).

We acquired fire weather variables for each fire from the 32-km^2 North American Regional Reanalysis (NARR) dataset (Mesinger et al. 2006; Appendix A). For the 10-day period starting on the detection date of each fire, we determined the maximum and mean values of the Fosberg fire weather index (FFWI; Fosberg 1978) and wind speed, and the number of days with FFWI above the 90th percentile and wind speed above 20 miles per hour.

Prior to modeling, we eliminated variables that were highly correlated with others (Spearman's rho > 0.75). From the 36 candidate climate and weather variables, we retained between 22 and 26 in each ecoregion (Appendix A).

Influence of topography, climate, and weather on burn severity: statistical analysis

We used Random Forests (Breiman 2001), an extension of classification and regression trees, to investigate the influence of topographic, climatic, and fire weather variables on burn severity, using the Random Forest package (Liaw and Wiener 2002) for R (R Development Core Team 2010). As a data-mining algorithm, Random Forest has several advantages over other statistical methods. It has been increasingly advocated in recent years for ecological questions that require non-parametric techniques and involve complex interactions between many variables (e.g., Prasad et al. 2006, Cutler et al. 2007, Holden et al. 2009). Random Forest excels at uncovering inherent relationships and structure in data that may have hierarchical or non-additive variables (Prasad et al. 2006), and is specifically designed to produce accurate predictions that do not overfit the data (Breiman 2001). Using a binary response variable (RdNBR classified as high severity versus not), we tested our ability to explain whether or not individual pixels burned as high severity. For all combinations of our six ecoregions and our three categories of fire year (all, big, other), we constructed one set of models using just topographic predictors and another set with topographic, climatic, and weather predictors. This enabled us to measure whether the addition of coarse-scale climate and weather data could improve our ability to predict the spatial occurrence of severe fire from topography alone.

Our independent observations were a random subset of 2 million pixels (1 million each from the Northwest and Southwest), from which we drew stratified random samples for each ecoregion. Our target was 24,000 pixels per ecoregion: 3,000 pixels in each of eight strata (four potential vegetation (ESP) groups by two burn severity classes, all resolved to the pixel level). The actual number of pixels ranged from 18,163 to 24,000 because some ecoregions include only small areas of certain ESP groups (Fig. 2). For each sample pixel, we extracted fine-scale topographic data (derived in or surrounding that pixel) and coarse-scale climate and weather data (one value for each weather and climate variable across an entire fire), as described above.

To assess the relative influence of individual predictors on burn severity, we examined variable importance rankings from Random Forest models. Within each model, Random Forest calculates variable importance by randomly permuting the values of each variable, one at a time, and calculating the change in overall model performance (mean decrease in accuracy for binary models) as a result. In each of our modeling scenarios (i.e., given combination of ecoregion, fire years, and predictors) we produced stable rankings of predictor variables by running 10 replicate Random Forest models with all predictors (each with 2,000 classification trees). We used the median of Random Forest's permutation variable importance measure across all 10 replicate models to: (1) assign a final importance ranking to each variable; and (2) place variables into 10 importance groups (1 = most important variables; 10 = least important variables), using k-means clustering based upon importance values.

In each modeling scenario, we identified the optimal model (i.e., fewest predictors that could best predict the occurrence of severe fire) by running a model selection routine that tested the performance of models with successively fewer predictor variables, starting with all 10 groups (from k-means clustering) and at each successive round eliminating the least important group. We used five replications of five-fold cross-validation at each round of model selection to avoid problems of overfitting that can occur from using Random Forest's out-of-bag error to compare models in this type of iterative performance assessment (Svetnik et al. 2004). In all cases, we used 2,000 classification trees per model. We then identified the optimal model as the one with the smallest set of predictors that resulted in model error within one standard error of the minimum (Breiman et al. 1984, De'ath and Fabricius 2000). Our approach to model selection is similar to other efforts (Diaz-Uriarte and Alvarez de Andres 2006, Murphy et al. 2010), but unique in using cross-validation and variable groupings derived from k-means clustering.

To assess the relative performance of our model results, we used three measures of accuracy, averaged across the cross-validated replicates of the optimal models: overall percentage correctly classified (PCC), kappa, and area under the receiver operating characteristic curve (AUC). Given that our models have a binary response with relatively balanced samples in each response category (high severity versus not), we expected PCC and AUC values to range from 0.5 (50% accuracy expected at random) to 1.0 (perfect accuracy). We assumed that AUC values of >0.7, 0.8, and 0.9 indicate fair, good, or excellent accuracy, respectively (Swets 1988). We used kappa values to indicate the degree to which correct classifications are due to chance alone, with 0.0 being pure chance and 1.0 being a perfect classification (Cohen 1960).

To evaluate the influence of specific variables on burn severity, we generated partial dependence plots from our optimal Random Forest models. These plots display the relationship between individual predictors and the likelihood of high severity fire, showing how different values of each predictor affect the response while holding other variables constant at their average (Cutler et al. 2007).

Did fire extent and severity increase from 1984 to 2006?

Given recent increases reported in wildfire area burned (Littell et al. 2009) and burn severity (Miller et al. 2009*b*), we tested our MTBS dataset for trends in area burned, area burned severely, and proportion of area burned severely. We log-transformed area burned and area burned severely to satisfy the normality assumptions of our statistical tests. We first assessed whether two annual measures of severity, area burned severely and proportion of area burned severely, were significantly correlated with area burned in years that had fire (Pearson's correlation, $\alpha = 0.05$). We then tested for significant trends ($\alpha = 0.05$) in all three measures over the period of record (1984 to 2006) using the p-value of the slope estimate from a simple linear regression of each measure against year. In cases where residuals from simple linear models were autocorrelated (Durbin-Watson test, $\alpha = 0.05$), we used generalized least squares regression instead, with a first-order autoregressive moving average correlation structure.

Results

Influence of topography, climate, and weather on burn severity

Across all ecoregions, topography had the most influence on the probability of a location having high burn severity, but climate before and during the fire also contributed significantly (Fig. 5A; Appendix B). Models including only topography had kappas $\leq$0.37 (PCC $\leq$ 0.69, AUC less than fair to fair) whereas models that also included climate and weather performed better, with kappa $\geq$ 0.39 (PCC $\geq$ 0.70, AUC fair to good). While these results were consistent across our study area, our ability to accurately predict the occurrence of severe fire varied somewhat among ecoregions. Topography and climate less accurately captured the occurrence of severe fires in the Northwest than in the Southwest (kappa $\leq$ 0.43 versus $\geq$ 0.44; PCC $\leq$ 0.72 versus $\geq$ 0.72 and AUC fair versus good; respectively).

With few exceptions, topographic variables had more predictive power than climate and weather variables (Table 1; Appendix B). The full set of topographic variables was almost always included in the best models and almost all of them ranked higher than the climate and weather variables (Table 1). For all models, the top five topographic variables always included elevation in the first or second rank followed by the macro-scale topographic position index (2000 m), often in second rank. These variables underscore the

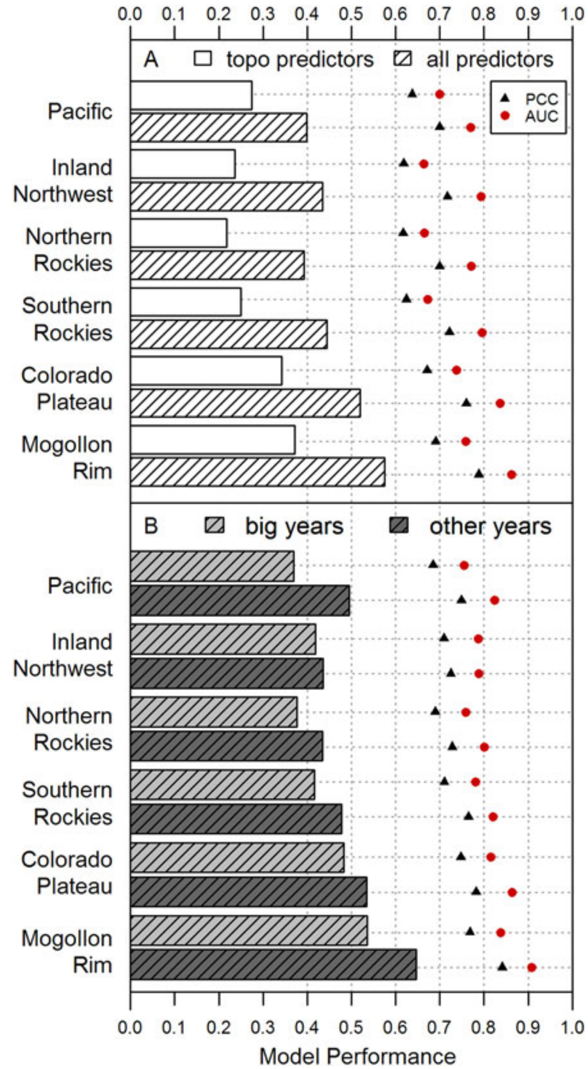

Fig. 5. Overall performance of Random Forest models. (A) Models with just topographic variables versus models with topography, climate, and weather variables for all years. (B) Models with topography, climate, and weather variables for big years versus other years. Model performance metrics are kappa (bars), percent correctly classified (PCC; black triangles), and area under the receiver operating characteristic curve (AUC; red circles).

importance of broad-scale topographic setting (i.e., a point's location relative to its surroundings on a scale of kilometers) for burn severity among fires at the scale of our ecoregions. Likewise, macro-scale (810 m), but not finer, topographic complexity indices (dissection and elevation

Table 1. Relative importance of predictors for Random Forest models relating topography, climate, and weather to burn severity, grouped by categories of fire year (all, big, other) and ecoregion.

	All						Big						Other					
Variable	p	in	nr	sr	cp	mr	p	in	nr	sr	cp	mr	p	in	nr	sr	cp	mr
Conditions during fire																		
Temperature	...	L	...	L	L	...	...	...	...	L	...	...	L	...	...	L	L	...
Precipitation	...	L	vl	...	...	L	...	...	...	...	L	L	...	L	...	...	...	...
Soil moisture	L	L	L	L	...	...	...	...	L	L	L	L	...	L	...	...	L	L
FFWI	...	L	...	...	...	...	...	L	...	...	...	...	...	...	M	...	...	...
Wind speed	...	L	—	...	...	...	...	...	—	...	...	...	...	...	—	...	...	...
Antecedent conditions																		
Temperature	L	L	L	L	L	L	L	L	L	...	L	L	L	L	M	M	L	...
Precipitation	L	L	L	L	L	L	L	L	L	L	L	L	L	L	**H**	L	L	L
Topography																		
Elevation	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**
Slope/aspect	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**
Position	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	M	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**H**
Complexity	**H**	M	M	**H**	**H**	**H**	**H**	M	M	**H**	**H**	**H**	**H**	M	M	**H**	**H**	**H**

Notes: Values reflect the highest importance ranking in each category of variables. **H** = high importance (rank of 1–5), M = moderate importance (6–10), L = low importance (11–20), vl = very low importance (included, but rank > 20), ellipsis (...) = variables not selected, dash (—) = variables not included in a particular ecoregion due to high correlations with other variables. Ecoregions are: p = Pacific, in = Inland Northwest, nr = Northern Rockies, sr = Southern Rockies, cp = Colorado Plateau, mr = Mogollon Rim.

relief ratio) were among the top five variables in all but the models from the Inland Northwest and the Northern Rockies. Pixel-scale slope and aspect variables were also included in the top five variables in all models, indicating an important influence of finer-scale topography as well. Climate variables were included in all of the best models, and always included conditions both before and during fires. However, two fire weather variables (wind speed and FFWI) were rarely important, and were included only in models for the Inland Northwest and Northern Rockies. Antecedent temperature and precipitation variables were included in the best models for all ecoregions. The models for every ecoregion also included event-proximal climate variables, but the specific variables selected varied among regions.

We were better able to predict burn severity during years other than big years across all ecoregions (Fig. 5B). Models using topography, climate, and weather variables had kappas $\geq$0.44 (PCC $\geq$ 0.72, AUC generally good to excellent) for other years, compared to kappas $\geq$0.37 (PCC $\geq$ 0.68, AUC fair to good) for big years. However, this difference was greater in some ecoregions (Pacific and Mogollon Rim), consistent with the large difference in area burned during other versus big years in these ecoregions compared to the other ecoregions (Fig. 4). Overall, the importance of individual variables was similar among models constructed for big, other, and all years, with topographic variables consistently more important than climate or weather variables (Table 1; Appendix B).

The specific influence of individual topographic variables on burn severity was fairly consistent among ecoregions but varied between big years versus other years (Fig. 6). With the exception of the Inland Northwest ecoregion, the probability of severe fire is generally higher across the full range of topographic variables in big years than in other years. In most ecoregions, the highest probability of severe fire in other years is often constrained to upper elevations, but shifts toward lower elevations (and covers a broader elevation range) in big years. This shift in elevation is strongest in the Mogollon Rim and Southern Rockies ecoregions, is most subtle in the Pacific ecoregion, and is reversed in the Inland Northwest. Regardless of year, severe fire is generally more likely at sites with low to moderate heat load (generally northwest through southeast aspects). The influence of heat load, however, is reversed for other years in the Pacific ecoregion, where the probability of high severity is greatest on the warmest southwest aspects.

Among ecoregions, the role of climate variables is inconsistent in other years, but we did observe some consistent patterns in big years

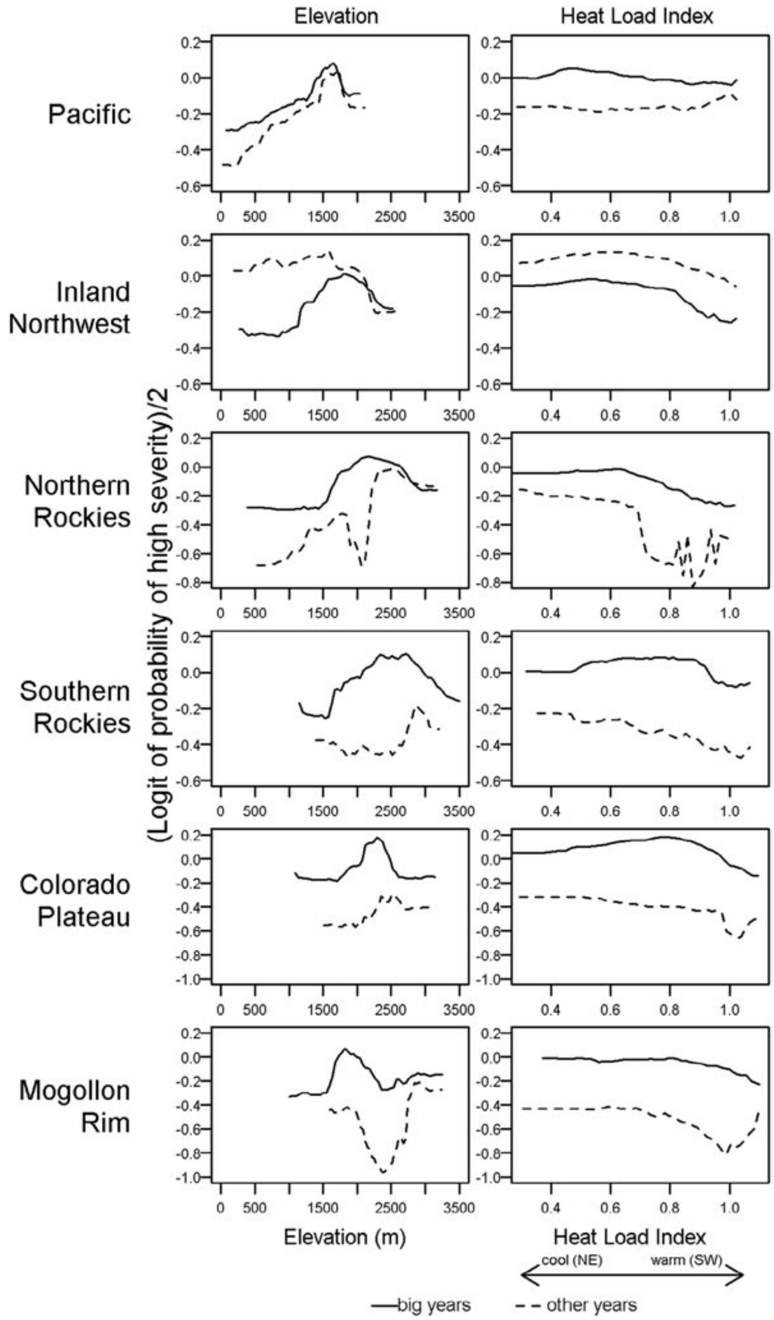

Fig. 6. Random Forest partial dependence plots for selected topographic variables. Plots indicate the dependence of the probability of severe fire on one predictor after holding all other predictors in the model at their average. Solid lines represent models for widespread (big) fire years, and dotted lines represent models for other years. See Cutler et al. 2007 for an explanation of the y-axis metric.

(Fig. 7). In the Mogollon Rim and Southern Rockies, severe fire is much more likely under hot and dry conditions, with below normal precipitation before the fire (previous month or spring) and higher than normal temperatures just before or during the fire. We also found higher

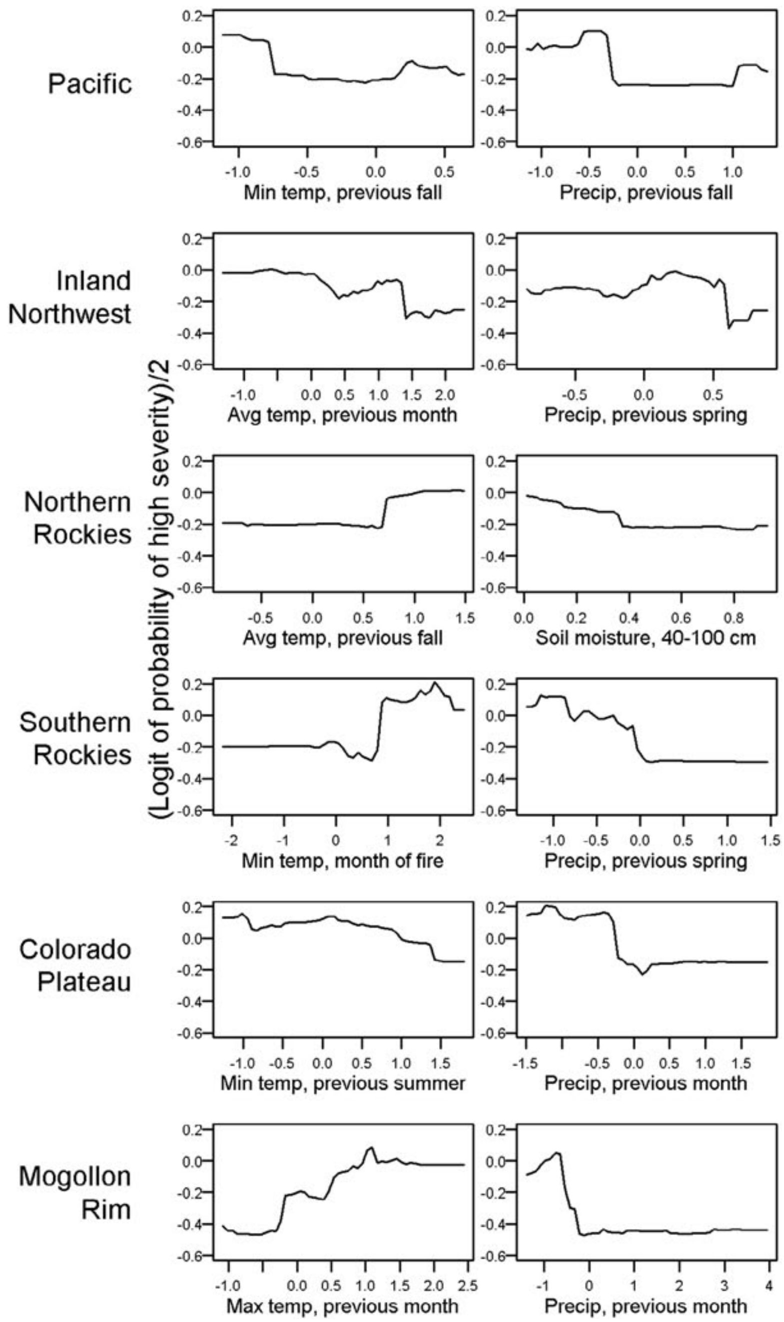

Fig. 7. Random Forest partial dependence plots for selected climate variables in big fire years. Plots indicate the dependence of the probability of severe fire on one predictor after holding all other predictors in the model at their average. Temperature and precipitation variables represent departure from 1950 to 2006 averages (units are standard deviations). Soil moisture is a percentile, calculated for the 10 days starting with the fire detection date, relative to 1960 to 1999 values for the same dates. See Cutler et al. 2007 for an explanation of the y-axis metric.

Table 2. Results from the analysis of temporal trends in annual fire metrics from selected MTBS fires by ecoregion, 1984–2006.

Parameter	Linear trend		Correlation with area burned	
	Slope	p	r	p
Pacific				
Area burned	0.17	0.206	—	—
Area high severity	0.19	0.110	0.91	**<0.001**
Proportion high severity	0.42	0.390	0.28	0.280
Inland Northwest				
Area burned	0.11	0.209	—	—
Area high severity	0.11	0.166	0.97	**<0.001**
Proportion high severity	−0.05	0.906	−0.24	0.278
Northern Rockies				
Area burned	0.05	0.566	—	—
Area high severity	0.05	0.582	0.97	**<0.001**
Proportion high severity	0.04	0.923	0.45	**0.037**
Southern Rockies				
Area burned	0.30	**0.002**	—	—
Area high severity	0.31	**<0.001**	0.96	**<0.001**
Proportion high severity†	1.14	**0.011**	0.81	**<0.001**
Colorado Plateau				
Area burned†	0.30	**0.036**	—	—
Area high severity†	0.28	**0.036**	0.86	**<0.001**
Proportion high severity	0.47	0.444	0.34	0.141
Mogollon Rim				
Area burned	0.21	**0.006**	—	—
Area high severity	0.31	**<0.001**	0.90	**<0.001**
Proportion high severity	0.53	0.174	0.39	0.071

Notes: Evidence for linear trend is suggested by the p-value of the slope estimate from linear regressions against year. We used Pearson's correlations to test for correlation with annual area burned in years that experienced fire. For the two area metrics, we performed a log transformation prior to statistical tests. Bold typeface indicates significant results at $\alpha = 0.05$.

† These series displayed autocorrelation in the residuals from a simple linear regression ($p < 0.05$ in Durbin-Watson test), and we used a generalized least squares regression instead, with a first-order autoregressive moving average correlation structure.

probabilities of severe fire related to dry conditions in the Colorado Plateau and Northern Rockies, indicated by below normal precipitation in the previous month and deep soil moisture deficits at the time of fire, respectively. In other cases, antecedent climate may be contributing to growth of fine and herbaceous fuels. For example, in the Inland Northwest we found increased probability of severe fire with cooler temperatures in the previous month and slightly above average precipitation in the previous spring. For all variables (topography and climate), relationships between individual predictors and burn severity are generally non-linear and indicate possible thresholds.

Did fire extent and severity increase from 1984 to 2006?

Annual area burned severely is closely related to area burned (Fig. 4, top half of panels), while the proportion of area burned severely is generally more independent of area burned (Fig. 4, bottom half of panels). Annual area burned and area burned severely were significantly correlated in all ecoregions, with Pearson's correlation ranging from 0.86 to 0.97 ($p < 0.001$; Table 2). However, we found significant correlations between area burned and the proportion of area burned severely only in the Northern Rockies ($r = 0.45$, $p = 0.037$) and Southern Rockies ($r = 0.81$, $p < 0.001$).

Generally, only ecoregions in the Southwest showed evidence of an increase in annual area burned and area burned severely, and fires trended toward higher severity (i.e., higher proportion burned severely) in just one of the three Southwest ecoregions. From 1984 to 2006, the increasing trend in annual area burned and area burned severely was only significant in the Southern Rockies, Mogollon Rim, and Colorado Plateau ecoregions ($p \leq 0.036$; Table 2). The increasing trend in proportion burned severely was only significant in the Southern Rockies ($p = 0.011$). We found no significant temporal trends in area burned or area burned severely for the three Northwest ecoregions during this period

(Table 2). We found very similar results when we repeated these analyses using more conservative non-parametric methods (Kendall's tau for correlations; Mann-Kendall test for trends; results not shown).

Discussion

Both topography and climate were drivers of burn severity

Topographic variables were consistently important in modeling where fires burned severely from 1984 to 2006 in the Northwest and Southwest United States, despite the great diversity in vegetation and land use across these large regions. Topography affects the spatial distribution of fuels at the fine spatial scale at which fire interacts with the landscape, and also affects local wind and weather patterns which are poorly represented in our temporally and spatially coarse weather and climate variables. Climate associated with individual fires, while somewhat less important than topography, increased the predictive ability of our models in all cases. While our results varied considerably among ecoregions, it is remarkable that together, topography and climate variables alone predicted the occurrence of high severity fire with overall accuracies ranging from 68% in the Pacific to 84% in the Mogollon Rim, despite the lack of data on fine-scale weather, fuels, and vegetation. Our findings are consistent with Holden et al. (2009), who predicted the occurrence of high severity fire with 65–74% accuracy on the Gila National Forest in New Mexico, using only topographic indices. While these accuracies are marginal for predictive modeling with a binary response, they suggest that with better integration of topography, climate, weather, and fuels, there is strong potential for the development of predictive burn severity models.

Across ecoregions, the influence of topography on burn severity seen in our models was generally consistent with our expectations, with some exceptions. For example, in average years in most ecoregions, sites at higher elevations that support cold and mesic forest species have a high probability of burning severely (Fig. 6), consistent with findings from the Southwest United States (Holden et al. 2009), the Rocky Mountains (Bigler et al. 2005), and the Pacific Northwest United States (Pickford et al. 1980, Kushla and Ripple 1997). Likewise, previous studies have found high burn severity more on north-facing slopes than south-facing slopes in Southwest and Rocky Mountain ecosystems (Bigler et al. 2005, Holden et al. 2009: Fig. 3), and we generally found the highest probability of severe fire on sites with cooler aspects as well. The relatively cool and wet environment of upper elevations and northerly aspects can result in more total biomass available to burn than in more open forests and woodlands at lower elevations and warmer aspects. Although the cooler and wetter sites burn less often, when they do burn they are more likely to experience crown fires, resulting in a higher degree of change. However, there are exceptions. For example, extreme weather conditions found in widespread fire years can increase the probability of high severity fire at lower elevations in most ecoregions (Fig. 6). Also, in the Pacific ecoregion the probability of severe fire is sometimes highest on the warmest aspects, consistent with a fire history from the Klamath Mountains of California that also found that south- and west-facing slopes historically experienced more severe fires than other aspects (Taylor and Skinner 1998). In relatively mesic environments, such as the Pacific ecoregion and Northern California, productivity can be high on all aspects and fuel is not a limiting factor. Therefore, when all slope aspects are available to burn during the summer droughts characteristic of the Mediterranean climate there, it is likely that the drier conditions found on warmer aspects can lead to an increased probability of severe fire on those sites.

Our models indicate that weather and climate at the time of fire, as well as antecedent temperature and precipitation, exert some influence on burn severity. Likely, the type of coarse-scale weather and climate variables we analyzed condition fuels and make them available for burning (i.e., relatively wet conditions that lead to an abundance of fine fuels or relatively warm and dry conditions that decrease fuel moistures). This idea is supported by partial dependence plots, which isolate the influence of individual climate variables and indicate non-linear shifts in the probability of severe fire with weather and climate (Fig. 7). A good example is the Southern Rockies ecoregion, where the probability for severe fire is relatively low until the minimum temperature in the month of fire approaches one standard deviation above normal. At that point, fuels have presumably become dry enough to carry fire, and the probability of severe fire increases and stays high as temperatures increase. Similarly, the probability of high severity increases sharply in all Southwest ecoregions when precipitation during the previous month or spring drops below average, consistent with the suggestion from Holden et al. (2007) that the likelihood of high severity in the Gila Wilderness, New Mexico increases with longer rain-free periods. In our three Northwest ecoregions, where the maritime influence on climate changes from west to east, the direct effects of weather and climate on severity are more variable and difficult to interpret. Some variables, such as deep soil moisture in the Northern Rockies indicate higher probability for severe fire during periods of drought, while variables in the Inland Northwest suggest an association between increased severity and relatively cool, moist conditions in the months prior to fire, and variables in the Pacific ecoregion suggest that climatic conditions during to the previous fall may influence severity.

The non-linear relationships of topography and climate to burn severity observed in our analysis may be due to tipping points. For topographic variables, non-linear relationships observed in partial dependence plots may simply reflect that relatively small changes in topography can result in sharp transitions between ecosystems. Alternatively, the non-linear relationships may be due to the multi-modal distribution of some topographic variables. For climate variables, our observation of thresholds is consistent with the notion that critical shifts in fuel moisture conditions can directly influence fire occurrence and behavior (Holden et al. 2007), evident in climatologically-based fire danger rating indices used in predicting the probability of fire occurrence (Andrews et al. 2003).

Some of the topographic variables in our analysis may act as indirect proxies for more direct, physically-based variables that would better capture interactions among topography, climate, and weather and their effects on fire behavior and burn severity. For example, the topographic dissection indices used here have been related to the location of snow drifts, as well as patterns of nocturnal air temperatures (e.g., cold air drainage) and relative humidity in the northern Rockies (Holden et al. 2011). Many fine-scale topoclimatic and biophysical variables (e.g., snowmelt timing, snow drifts, nocturnal air temperatures, and wind fields) influence fuel moistures, fire behavior, and fire intensity at fine spatial scales in mountainous terrain, but data on these are not currently available at the resolution needed to compare directly with 30-m burn severity data across broad regions. We attempted to account for the complex interactions among terrain, climate and burn severity by combining climate and weather variables with topographic complexity and position indices in a machine learning environment. Although specific interpretations about mechanistic processes are difficult from this modeling approach, it has some utility in fingerprinting the conditions or situations that yield high severity fire in a given location. Future analyses and development of predictive models of burn severity will benefit from having physically-based variables related to soil and fuel moisture prior to and during the fire (Keane et al. 2010). In regions of complex topography, additional data and models will be needed to capture topographic variation in temperature, humidity and snowmelt timing at the scale of terrain (Holden and Jolly 2011). Additionally, vegetation type and structure clearly influence burn severity (Bigler et al. 2005, Thompson and Spies 2010). Although reconstruction of pre-fire vegetation and fuel conditions is currently difficult over the large spatial and temporal domains assessed here, these could be inferred using remote sensing indices such as the normalized differenced vegetation index (Rouse et al. 1973). Our ability to forecast the severity of future fires will likely improve when our analyses include climate and weather data of much higher spatial resolution, along with variables describing pre-fire vegetation conditions (e.g., local fuels, vegetation type, and prior disturbances).

Severe fire is more likely, and spatial occurrence is less predictable, in widespread fire years

Our ability to predict whether a pixel burned severely was consistently lower during years of widespread fire, or framed another way, fire burned more indiscriminately in big years. Consistent with that finding, the probability of severe fire occurrence in all ecoregions is higher across a range of topographic conditions during those years (Fig. 6). The probability of a location burning or burning severely, in reality, is conditional on many factors including ignition, antecedent climate, and weather, interacting with topography, fuels, and vegetation. Decisions about fire management and availability of suppression resources also play an important role. Based on our results, we speculate that in dry years, landscape and topographic controls on fire spread and intensity are diminished, with regional-scale climatic variation overwhelming local-scale biophysical and topographic constraints, as has been reconstructed for the extent of past fires elsewhere (Taylor and Skinner 2003). In relatively cool, wet fire seasons for example, north-facing slopes at high elevation are unlikely to burn due to delayed snowmelt timing, low solar insolation, low vapor pressure deficit, and low surface air temperatures (Holden and Jolly 2011). Thus, until climatic and moisture conditions become conducive to fire spread on a large enough portion of the landscape, as occurs in big years, terrain can impose spatial constraints on fire spread and intensity, limiting the influence of short term weather and climate factors.

While somewhat intuitive, our finding that topography exerts strong control on burn severity under moderate climatic conditions has profound implications for how we manage wildfires in the future. Under current fire management practices, suppression tactics are employed on most fires. As a consequence, most wildfire area burned occurs during extreme climatic conditions, likely with higher probability of severe fire occurrence. While extensive, severe fires are within the range of historical variability in cold forest ecosystems, they would have occurred less frequently in woodlands and mesic forests with mixed-severity fire regimes, and were rare in dry forest ecosystems (Schoennagel et al. 2004, Keane et al. 2008). Our results suggest that if more fires ignited under moderate conditions in ecosystems that historically did not sustain extensive, severe fires are allowed to burn within topographic constraints, those fires would have greater potential for serving beneficial ecological roles and potentially reduce the severity of subsequent fires that could burn under more extreme conditions (Holden et al. 2010, Halofsky et al. 2011, Hurteau and Brooks 2011). In years that are not widespread fire years, climatic conditions will be closer to long term averages (Appendix A), and fires that are allowed to burn during those years will likely behave in a way consistent with expectations based on local vegetation and fire regimes and within the historical range of variation. In contrast, in years of widespread fire, climatic conditions will likely be further from normal and fire behavior and effects will likely be more uncharacteristic relative to historical regimes in low-mid elevation forests and woodlands that did not historically sustain extensive, severe fires (Fig. 6).

These results also have important implications for resilience of terrestrial and aquatic ecosystems. If during the big years, during which most area is burned, severely burned areas are not regulated by fine-scale topographic features, disturbance patches may be more continuous and homogeneous than they were historically. Uncharacteristically large severe patches can more effectively disrupt both terrestrial (Turner et al. 1997) and aquatic systems (Dunham et al. 2003) for longer periods of time. If the future brings more big fire years, the proportion of area severely burned may not increase, but how it is arranged on the landscape may become a critical ecological issue.

Has the extent of severe fire increased in recent decades, and are fires becoming more severe?

We found statistically significant increases in the annual extent of severe fire from 1984 to 2006 in only the three Southwest ecoregions, and none in the Northwest. By definition, more area burned in the big fire years than in the other years, and we observed a corresponding rise in area burned severely during big years (Pearson's correlation 0.86–0.97). In the Southwest ecoregions, big years were concentrated in the later portion of our time series, with five out of six big years in each ecoregion occurring from 2000 to 2006 (Fig. 4). As a result, we see increases in annual area burned severely during our time period for these ecoregions. In the Northwest, where some big fire years occurred earlier in the time series, we do not see significant trends. It is important to note that these results are specific to our relatively short time series and could be different if data for a longer time period were available.

Only in the Southern Rockies ecoregion did we find evidence that fires are becoming more severe. The majority of area burned in this ecoregion was in the dry and mesic forest ESP groups (Fig. 2) that would have generally experienced low-severity and mixed-severity fire regimes historically. Increased fuel loads in some portions of these landscapes due to fire suppression and land use during the 20th century (Keane et al. 2002, Schoennagel et al. 2004, Keane et al. 2008), combined with a shift toward drier climatic conditions that began in 1998 (Hoerling and Kumar 2003) could account for increased burn severity in the Southern Rockies.

Based on the analyses from this study, we can only speculate on the possible mechanisms behind our observed trends. The shift toward generally increased fire activity since approximately 2000 in the Southwest ecoregions (Fig. 4) appears tied to low-frequency climatological changes (decades to years) related to the El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO; Crimmins 2010). Time series of ENSO and PDO indices indicate a shift from positive to negative PDO in 1998, coinciding with a shift from roughly two decades dominated by higher frequency of El Niño events to a period with stronger and more frequent La Niñas (Hoerling and Kumar 2003, Crimmins 2010: Fig. 4). Consequently, the entire Southwest region generally experienced much drier conditions after about 1999, which could have contributed to the trends we observed for the Southwest ecoregions. Conversely in the Northwest, active fire years have historically been associated with a positive PDO phase, sometimes aligned with El Niño conditions (i.e., years when the Northwest-Southwest precipitation dipole is strongest, with warm dry conditions in the Northwest and wet conditions in the Southwest; Heyerdahl et al. 2008, Morgan et al. 2008). Although these historical fire-climate relationships are somewhat weaker in the Northwest than the Southwest, particularly during the 20th century in some places (Hessl et al. 2004), they provide some explanation for the lack of trends we observed in the Northwest.

It is difficult to determine whether the annual extent or proportion of severe fire is within the historical range of variability for any of our ecoregions. Our data span only 23 years. From this short time series alone, we cannot say whether the increases in extent and severity that we observed in the Southwest exceed historical patterns. In the context of longer-term reconstructive studies, however, it appears that our results are consistent with others that have shown increases in annual area burned in the Southwest in recent decades that are unprecedented in the last century (Swetnam and Betancourt 1998). Likewise, in open ponderosa pine forests in the Southern Rockies, where severe fire was historically limited by fuel availability, the increase we observed in proportion of severe fire likely represents a departure from historical fire regimes (Schoennagel et al. 2004). In forests with a historically mixed-severity fire regime (e.g., Douglas-fir), however, the occurrence of high severity fire may be within the historical range of variability, but the extent of high severity patches may not be (Schoennagel et al. 2004, Schoennagel et al. 2011). In the Northwest, the fact that we found no apparent increases in extent or proportion of severe fire corroborates previous work demonstrating that fire dynamics from recent decades are within historical ranges there (Keane et al. 2008, Morgan et al. 2008).

Scope and limitations

Inferring burn severity from remotely sensed data is appealing because we can compare many fires over multiple vegetation types and regions, each with a range of land use and history. However, there are some important limitations to our study. First, there is great variation in the timing of the satellite imagery from which burn severity was estimated. We imposed somewhat broad constraints on timing of imagery to ensure that pre- and post-fire images were compared that were one year apart (6–18 months) and when vegetation was in the same phenological condition pre- and post-fire (±60 days). These constraints resulted in the elimination of 253 fires (502,095 ha) from our analysis. We could have used tighter constraints, but this would have resulted in still fewer fires to analyze. Second, in some ecoregions, most of the area burned in just a few individual fires that may have exerted a strong influence on our results. For example, the 2002 Biscuit fire in Oregon accounted for ~147,000 ha, or 38% of burned area in the Pacific ecoregion. Likewise, the greater Yellowstone fires of 1988 burned ~660,000 ha (25% of area burned in the Northern Rockies), the 2002 Rodeo-Chedeski fire in Arizona burned ~172,500 ha (21% of area burned in the Mogollon Rim), and the 2002 Hayman Fire in Colorado burned ~53,500 ha (16% of area burned in the Southern Rockies). Excluding these large single fire events would have greatly decreased the pixels available for our analysis. Third, we do not know the accuracy of the burn severity classification across all events. The thresholds we used for defining severe fires are based on geographically limited field data. Further field testing and assessment of the value of RdNBR as an indicator of ecological change is needed. Hudak et al. (2007) found that dNBR and post-fire NBR were reasonable metrics of burn severity when using data on vegetation and soil effects immediately and one year post-fire in eight different large fires from Montana, California, and Alaska. More such studies are needed for longer-term assessment of fire effects. Keeley et al. (2008) found that RdNBR accuracy is limited in shrublands where resprouting occurs, but RdNBR has been tested successfully in forests, woodlands, and sagebrush shrublands in California (Miller and Thode 2007, Miller et al. 2009*a*) and sagebrush steppe in Idaho (Norton et al. 2009). Fourth, it is possible that the consistently higher performance of topographic variables in the Random Forest models is an artifact of the difference in spatial scale. Topographic variables were at the same spatial resolution (30-m) as the fire data, while the climatic variables were coarser. Also, by not including maps of actual vegetation type, structure, and fuels we ignore many landscape factors (e.g., previous fires, thinning, timber harvest, and insect-induced tree mortality) that would likely influence satellite-inferred burn severity. Not accounting for these variables likely contributed additional noise to our data. It is possible that some areas burned severely in part because they have experienced few fires in recent decades, or because prior and existing land uses affect the likelihood that they burn, somewhat obscuring the influence of the particular topographic and climate conditions under which those fires burned. Finally, many of these fires represent those that escaped initial suppression efforts. Thousands more were successfully stopped before reaching mapable size. We may never know how spatial burn severity patterns of those fires, potentially burning under more moderate climatic conditions would have differed from those fires that did burn.

Implications for future research

We expected and found that the influences of climate and topography on burn severity differed from their influences on fire occurrence and extent. This is consistent with our hypothesis that while climate strongly influences area burned, topography, vegetation, land use, and other local conditions are relatively more important than climate in determining how fires burn.

The effects of warming climate and lengthening fire seasons are likely to increase the number of large fires (Westerling et al. 2006). Consequently, the area burned severely could increase, with potentially great but not well understood ecological consequences for severity of subsequent fires, vegetation structure and composition, carbon, acquatic ecosystems, and other ecosystem services. Until we develop an understanding of the relative influence of topography, climate, vegetation, fuels and land use on fire extent and burn severity, our response to these large fires will be driven by the perception of fires as largely detrimental. Understanding the role of topography will be particularly important. To the extent that topography directly influences burn severity, burn severity will be relatively stable even as climate changes. In so far as topography is acting indirectly by shaping fuels and vegetation productivity, our management actions will have potential to alter the way fires burn across the landscape (Wimberly et al. 2009, Hudak et al. 2011), perhaps moreso in some environments than others (Schoennagel et al. 2004).

Our study is one of many recent efforts using satellite-derived data to address questions about burn severity (e.g., Holden et al. 2009, Wimberly et al. 2009; Miller et al., *in press*). Although fire occurrence, synchrony, and extent have been related to climate at regional and sub-continental scales (Kitzberger et al. 2007, Littell et al. 2009, Littell et al. 2010), relatively few studies have focused on burn severity at these scales (but see Miller et al. 2009*a*). Moving forward, studies such as ours that include information on pre-fire fuels and vegetation, as well as finer-scale climate and weather, will be important. Analyses for particular vegetation types and/or elevation ranges may also be useful, as both recent trends and drivers of burn severity may differ among ecosystems (Miller et al. 2009*b*), just as drivers of fire occurrence differ with vegetation type (Littell et al. 2009). Further, future investigations of burn severity across broad spatial and temporal scales may be improved by evaluating shifts in the statistical distribution of continuous RdNBR and dNBR values, rather than assessing severity as a binary or ordinal phenomenon (Holden et al. 2010, Lutz et al. 2011). Comparative studies among regions are needed, as are local case studies that help advance understanding of the ways that climate, topography, land use, vegetation and prior disturbance interact to influence ecological effects of fire.

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Supplemental Material

Appendix A

Details Regarding Inputs to the Analysis

The four potential vegetation (ESP) groups we used to identify forest and woodland sites for this study include numerous LANDFIRE ESP map units. A complete listing of the specific ESP units within each group, and their total area within burned areas, is provided for the Northwest (Table A1) and Southwest (Table A2).

For Random Forest modeling, we considered a total of 16 topographic variables and 36 climate and weather variables as predictors. Prior to running Random Forest models, we evaluated the correlation between individual variables in each ecoregion, to eliminate redundancy. We provide complete lists of all candidate topographic variables (Table A3), and climate and weather variables (Table A4), with details about which ones were retained for modeling in each ecoregion and source information for specific datasets.

In designating years as widespread (big) fire years, we evaluated monthly normalized temperature and precipitation data. Within each category of years, we averaged the monthly normalized values of minimum temperature, maximum temperature, and precipitation for the year of fire and the preceding year (Fig. A1).

Fire weather variables including daily maximum windspeed, minimum relative humidity (RH) and the maximum temperature were extracted from the North American Regional Reanalysis (NARR) data. The NARR is long-term, internally consistent data produced through the assimilation of observational and modeled climate data to a gridded domain (32-km^2 grid resolution) at three hourly timesteps (Mesinger et al. 2006). Hall and Brown (2007) compared NARR data to observations collected by Remote Automated Weather Stations (RAWS) across the western United States and found that most meteorological variables were well correlated, suggesting that NARR data could be useful in wildfire research and management applications.

We used NARR data to evaluate wildfire event weather conditions by extracting time series from the grid cell that matched the initial location and start date for each fire as specified in the MTBS data. Fire weather conditions were evaluated within a 10-day window from the initial fire discovery date consistent with our assumpution that extreme conditions were occuring at some point during this period. Westerling et al. (2006) reported that the average time between the discovery and control of large wildfire events across the western United States was 37.1 days during the period of 1987 to 2003. It is likely that most of the fires we included in our analysis were

Table A1. LANDFIRE environmental site potential (ESP) map units within each grouping used in this analysis for the Northwest.

ESP	ESP code	Area (ha)	FRG†	Elev
Low-dry woodlands ("woodland")				
Columbia Plateau western juniper woodland and savanna	1017	119,709	3	broad
Rocky Mt foothill limber pine-juniper woodland	1049	26,014	3	low
Great Basin pinyon-juniper woodland	1019	424	3	low
Inter-Mt Basins juniper savanna	1115	41	3	low
Mid-dry forest and woodland ("dry forest")				
N Rocky Mt dry mesic montane mixed conifer forest	1045	949,327	1	mid
N Rocky Mt ponderosa pine woodland and savanna	1053	157,935	1	mid
Med Calif mixed evergreen forest	1043	151,300	1	low-mid
Med Calif dry mesic mixed conifer forest and woodland	1027	66,411	1	mid
Med Calif mesic mixed conifer forest and woodland	1028	64,628	1	mid
Klamath-Siskiyou upper montane serpentine mixed conifer woodland	1022	16,274	1	mid
Med Calif lower montane black oak-conifer forest and woodland	1030	6,432	1	low-mid
Klamath-Siskiyou lower montane serpentine mixed conifer woodland	1021	5,936	1	mid
Calif montane Jeffrey pine(-ponderosa pine) woodland	1031	5,868	1	mid
N Rocky Mt foothill conifer wooded steppe	1165	4,286	1	low-mid
Med Calif mixed oak woodland	1029	2,606	1	low-mid
N Pacific oak woodland	1008	1,862	1	low-mid
East Cascades oak-ponderosa pine forest and woodland	1060	1,387	1	low-mid
Sierran-Intermontane Desert western white pine-white fir woodland	1172	680	1	mid-high
S Rocky Mtn dry mesic montane mixed conifer forest and woodland	1051	0	1	mid
Mesic forest and woodland ("mesic forest")				
Middle Rocky Mt montane Douglas-fir forest and woodland	1166	344,960	3	mid
Rocky Mt montane riparian systems	1159	93,968	3	broad
N Rocky Mt mesic montane mixed conifer forest	1047	81,009	3	low-mid
Rocky Mt subalpine/upper montane riparian systems	1160	69,787	3	upper
N Pacific Maritime dry mesic Douglas-fir-western hemlock forest	1037	50,111	3	low-mid
East Cascades mesic montane mixed conifer forest and woodland	1018	48,477	3	low-mid
Inter-Mt Basins montane riparian systems	1154	14,437	3	broad
Rocky Mt aspen forest and woodland	1011	13,930	4	broad
N Pacific dry mesic silver fir-western hemlock-Douglas-fir forest	1174	10,435	3	mid
Inter-Mt Basin curl-leaf mountain mahogany woodland and shrubland	1062	6,157	3	mid
Calif montane riparian systems	1152	5,103	3	mid
Inter-Mt Basins aspen-mixed conifer forest and woodland	1061	2,277	3	broad
Med Calif red fir forest	1032	2,133	3	high
N Pacific dry Douglas-fir(-madrone) forest and woodland	1035	1,196	3	low
Sierra Nevada subalpine lodgepole pine forest and woodland	1058	123	3	mid-high
Northwestern Great Plains aspen forest and parkland	1009	5	4	low
Rocky Mt Bigtooth maple ravine woodland	1012	2	3	mid
Cold/wet forest and woodland ("cold forest")				
Rocky Mt subalpine dry mesic spruce-fir forest and woodland	1055	903,137	4	high
Rocky Mt subalpine mesic wet spruce-fir forest and woodland	1056	648,406	5	high
N Rocky Mt subalpine woodland and parkland	1046	39,043	3	high
N Rocky Mt conifer swamp	1161	32,358	5	broad
Rocky Mt poor-site lodgepole pine forest	1167	29,653	4	mid-high
N Pacific mountain hemlock forest	1041	20,933	5	high
N Pacific maritime mesic wet Douglas-fir-western hemlock forest	1039	9,269	5	low-mid
N Pacific mesic western hemlock-silver fir forest	1042	5,957	5	mid
N Pacific montane riparian woodland and shrubland	1158	5,683	5	mid
N Pacific swamp systems	1157	2,172	5	broad
N Pacific lowland riparian forest and shrubland	1156	1,359	5	low
N Pacific wooded volcanic flowage	1173	934	5	broad
N Pacific hypermaritime western red cedar-western hemlock forest	1178	632	5	low
N Pacific maritime mesic subalpine parkland	1038	449	5	high
Med Calif subalpine woodland	1033	330	3	high
N Pacific broadleaf landslide forest and shrubland	1063	32	5	broad
N Pacific hypermaritime sitka spruce forest	1036	1	5	low

Notes: Areas reported are just from burned areas included in our study. Total areas for ESP groups shown are: woodland = 146,187 ha; dry forest = 1,434,931 ha; mesic forest = 744,112 ha; cold forest = 1,700,347 ha. Other ESP groups appearing within burned areas included in our study include: dry shrub (83,855 ha), grassland (81,783 ha), nonveg/alpine (73,881 ha), mesic shrub (77,861 ha). Abbreviations are: Mt = Mountain; Med = Mediterranean; Calif = California; N = north, northern; S = southern.

†FRG is historical natural fire regime group (1 = 0–35 year frequency, low severity; 3 = 35–200 year frequency, mixed severity; 4 = 35–200 year frequency, stand-replacement severity; 5 = 200+ year frequency, stand-replacement severity). Source: LANDFIRE vegetation dynamics models (http://www.landfire.gov).

Table A2. LANDFIRE environmental site potential (ESP) map units within each grouping used in this analysis for the Southwest.

ESP	ESP code	Area (ha)	FRG†	Elev
Low-dry woodlands ("woodland")				
Colorado Plateau pinyon-juniper woodland	1016	212,536	3	low
Madrean pinyon-juniper woodland	1025	151,490	3	low
Great Basin pinyon-juniper woodland	1019	31,366	3	low
S Rocky Mt pinyon-juniper woodland	1059	10,005	3	low
Colorado Plateau pinyon-juniper shrubland	1102	7,717	3	low
Madrean juniper savanna	1116	1,135	3	low
Inter-Mt Basins juniper savanna	1115	712	3	low
Rocky Mt Foothill limber pine-juniper woodland	1049	49	3	low
S Rocky Mt juniper woodland and savanna	1119	0	3	low
Mid-dry forest and woodland ("dry forest")				
S Rocky Mt ponderosa pine woodland	1054	323,990	1	mid
S Rocky Mtn dry-mesic montane mixed conifer forest and woodland	1051	161,148	1	mid
Madrean lower montane pine-oak forest and woodland	1024	108,675	1	mid
S Rocky Mt ponderosa pine savanna	1117	30,747	1	mid
Madrean encinal	1023	14,085	1	mid
Madrean upper montane conifer-oak forest and woodland	1026	2,023	1	mid
Mesic forest and woodland ("mesic forest")				
S Rocky Mt mesic montane mixed conifer forest and woodland	1052	107,945	3	mid
Rocky Mt montane riparian systems	1159	45,449	3	low-mid
Rocky Mt gGambel oak-mixed montane shrubland	1107	24,910	3	mid
Inter-Mt Basins aspen-mixed conifer forest and woodland	1061	13,346	3	low-high
Rocky Mt aspen forest and woodland	1011	12,852	4	low-high
Inter-Mt Basin curl-leaf mountain mahogany woodland and shrubland	1062	10,944	3	mid
Rocky Mt bigtooth maple ravine woodland	1012	8,337	3	mid
Rocky Mt subalpine/upper montane riparian systems	1160	7,491	3	mid-high
Inter-Mt Basins montane riparian systems	1154	89	3	low-mid
Cold/wet forest and woodland ("cold forest")				
Rocky Mt subalpine dry-mesic spruce-fir forest and woodland	1055	75,593	4	high
Rocky Mt lodgepole pine forest	1050	3,840	4	high
Rocky Mt subalpine mesic-wet spruce-fir forest and woodland	1056	528	5	high
Rocky Mt subalpine-montane limber-bristlecone pine woodland	1057	433	3	high

Notes: Areas reported are just from burned areas included in our study. Total areas for ESP groups shown are: woodland = 415,010 ha; dry forest = 640,669 ha; mesic forest = 231,362 ha; cold forest = 80,394 ha. Other ESP groups appearing within burned areas included in our study include: dry shrub (53,887 ha), grassland (5,439 ha), nonveg/alpine (4,909 ha), mesic shrub (4,032 ha). Abbreviations are: Mt = Mountain; Med = Mediterranean; Calif = California; N = north, northern; S = southern.

†FRG is historical natural Fire Regime Group (1 = 0–35 year frequency, low severity; 3 = 35–200 year frequency, mixed severity; 4 = 35–200 year frequency, stand-replacement severity; 5 = 200+ year frequency, stand-replacement severity). Source: LANDFIRE vegetation dynamics models (http://www.landfire.gov).

actively burning and potentially influenced by fire weather conditions during our 10-day evaluation window. Fire weather variables examined included daily maximum temperature, maximum wind speed, and minimum relative humidity. The combined impact of these variables were also examined through the calculation of a daily maximum Fosberg Fire Weather Index (FFWI) value. The FFWI acts as a non-linear filter of meteorological variables that support rapid wildfire growth and can be used to discern extreme fire weather conditions in a meteorological time series (Fosberg 1978, Goodrick 2002, Crimmins 2006). It is very similar in structure to the National Fire Danger Rating System spread component with higher values representing higher potential rates of spread under more extreme fire weather conditions.

Table A3. Candidate topographic predictor variables for all Random Forest models.

Variable	Pacific	Inland Northwest	Northern Rockies	Southern Rockies	Colorado Plateau	Mogollon Rim
Elevation †	X	X	X	X	X	X
Slope and aspect indices						
Slope	X	X	X	X	X	X
Heat load index	X	X	X	X	X	X
Solar radiation aspect index	X	X	X	X	X	X
Slope cosine aspect index	X	X	X	X	X	X
Slope position indices						
Hierarchical slope position	X	X	X	X	X	X
Compound topographic index	X	X	X	X	X	X
Topographic position index						
150 m	X	X	X	X	X	X
300 m	...	...	...	...	...	...
2000 m	X	X	X	X	X	X
Topographic complexity indices						
Dissection						
90 m	X	X	X	...	...	...
450m	...	...	...	...	...	...
810 m	X	X	X	X	X	X
Elevation relief ratio						
90 m	X	X	X	X	X	X
450 m	X	X	X	...	...	...
810 m	X	X	X	X	X	X

Note: For each ecoregion, an X indicates that the variable was used in Random Forest models, and an ellipsis (...) indicates that the variable was eliminated prior to modeling due to high correlation (Spearman's rho $>$ 0.75) with other candidate variables.

† 30 m^2 digital elevation models acquired from LANDFIRE (http://landfire.cr.usgs.gov/viewer/), originally produced by the USGS Elevation Data for National Applications program (http://edna.usgs.gov/).

Table A4. Candidate climate and weather predictor variables for all Random Forest models.

Variable	Pacific	Inland Northwest	Northern Rockies	Southern Rockies	Colorado Plateau	Mogollon Rim
Climate†						
Minimum temperature						
Month of fire	...	...	...	X	X	X
Previous month	...	...	...	X	X	X
Spring, year of fire	...	...	...	X	X	X
Winter, year of fire	...	...	...	X	X	X
Fall, previous year	X	...	X	X	X	X
Summer, previous year	...	...	X	X	X	X
Maximum temperature						
Month of fire	...	...	...	X	X	X
Previous month	...	...	...	X	X	X
Spring, year of fire	...	...	...	X	X	X
Winter, year of fire	...	...	...	X	X	X
Fall, previous year	...	...	...	X	X	X
Summer, previous year	...	...	...	X	X	X
Average temperature						
Month of fire	X	X	X	...	...	...
Previous month	X	X	X	...	...	...
Spring, year of fire	X	X	X	...	...	...
Winter, year of fire	X	X	X	...	...	...
Fall, previous year	X	X	X	...	...	...
Summer, previous year	X	X	X	...	...	...
Total precipitation						
Month of fire	X	X	X	X	X	X
Previous month	X	X	X	X	X	X
Spring, year of fire	X	X	X	X	X	X
Winter, year of fire	X	X	X	X	X	X
Fall, previous year	X	X	X	X	X	X
Summer, previous year	X	X	X	X	X	X
Soil moisture‡§						
0–10 cm						
30-year percentile	X	X	X	X	X	X
30-day percentile	X	X	X	X	X	X
10–40 cm						
30-year percentile	X	X	X	X	X	X
30-day percentile	X	X	X	X	X	X
40–100 cm						
30-year percentile	X	X	X	X	X	X
30-day percentile	X	X	X	X	X	X
Fire weather¶§						
Fosberg Fire Weather Index						
10-day mean	...	...	...	...	...	...
10-day max	X	X	X	...	...	...
Days > 90th percentile	X	X	X	X	X	X
Wind speed						
10-day mean	X	X	...	...	...	...
10-day max	X	...	...	...	...	...
Days > 20 mph	X	X	X	X	X	X

Note: For each ecoregion, an X indicates that the variable was used in Random Forest models, and an ellipsis (...) indicates that the variable was eliminated prior to modeling due to high correlation (Spearman's rho > 0.75) with other candidate variables.

† Normalized monthly values, relative to 1950–2006 averages (averaged to create seasonal variables). Spatial resolution = interpolated for fire centroids (latitude, longitude, elevation) from weather station locations; temporal resolution = monthly. Source: Rehfeldt (2006) spline model.

‡ Spatial resolution = half-degree grid cells; temporal resolution = daily. Source: Surface Water Monitor hydrologic simulation system (Wood 2008).

§ Calculated from daily values for the 10 days starting with the fire detection date.

¶ Spatial resolution = 32 km^2 grid cells; temporal resolution = daily. Source: North American Regional Reanalysis (Mesinger et al. 2006).

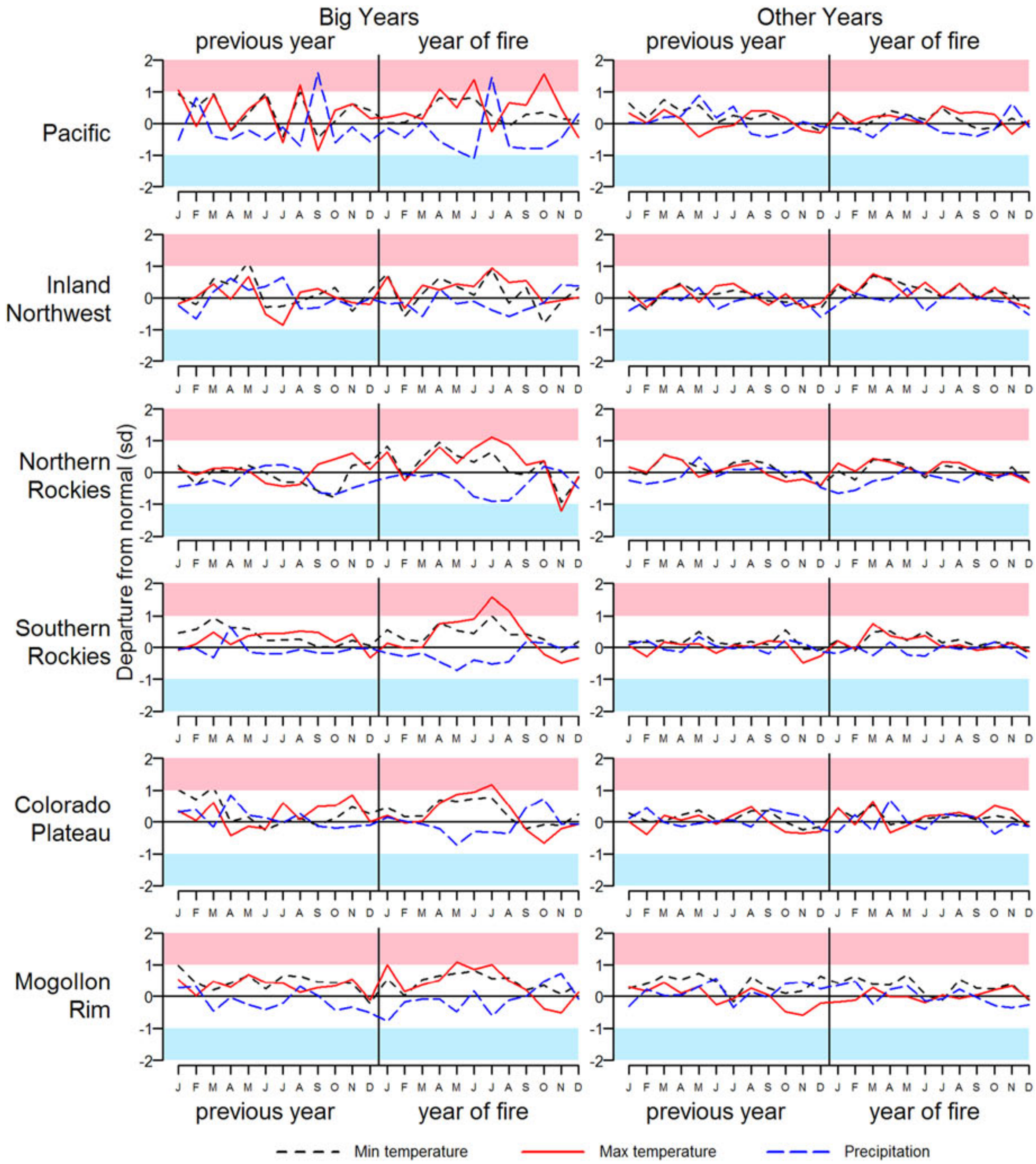

Fig. A1. Departure from normal climate conditions for each month in the year of fire and previous year. Lines in each figure represent normalized climate data (standard deviations above or below 1950 to 2006 averages) from individual fire events, averaged across all fires in a given ecoregion and year subset.

Appendix B
Detailed Random Forest Modeling Results

Table B1. Variable importance rankings for Northwest Random Forest models relating topography, climate, and weather to burn severity, grouped by ecoregion and categories of fire year (all, big, other).

Variable	Pacific			Inland Northwest			Northern Rockies		
	All	Big	Other	All	Big	Other	All	Big	Other
Conditions during fire									
Average temperature, month of fire†	...	...	16	18	...	...	...	...	...
Precipitation, month of fire†	...	...	...	11	...	17	23	...	...
Soil moisture									
0–10 cm (30yr%)‡	...	...	...	20	...	...	21	20	...
10–40 cm (30yr%)‡	16	...	...	19	...	16	...	...	...
40–100 cm (30yr%)‡	...	...	...	21	...	...	18	13	...
Maximum Fosberg Fire Weather Index‡	...	...	...	16	12	...	...	...	9
Average wind speed‡	...	...	...	17	...	...	—	—	—
Antecedent conditions									
Minimum temperature									
Previous fall (SON)†	15	14	17	—	—	—	22	...	8
Previous summer (JJA)†	—	—	—	—	—	—	15	18	10
Average temperature									
Previous month†	...	...	19	13	11	10	17	17	...
Previous spring (MAM)†	...	...	...	24	...	...	20	22	...
Previous winter (DJF)†	...	...	...	...	...	...	...	21	...
Previous fall (SON)†	...	...	18	12	15	13	14	11	...
Previous summer (JJA)†	...	...	...	...	...	...	16	19	...
Precipitation									
Previous spring (MAM)†	...	...	14	23	13	...	12	14	6
Previous winter (DJF)†	...	...	13	14	14	...	...	...	...
Previous fall (SON)†	14	16	11	22	...	15	19	15	...
Previous summer (JJA)†	...	15	15	...	...	14	11	16	5
Topography									
Elevation	1	1	1	3	1	1	1	1	1
Slope	8	7	8	4	6	5	3	5	4
Heat load index	5	6	6	1	3	2	2	2	3
Solar radiation aspect index	11	11	10	6	5	7	6	4	...
Slope cosine aspect index	4	5	4	5	4	4	4	3	11
Hierarchical slope position	7	4	9	9	10	9	9	8	...
Compound topographic index	17	17	...	...	...	...	...	...	...
Topographic position index									
150 m	9	9	12	15	...	12	13	12	...
2000 m	2	2	2	2	2	3	5	6	2
Dissection									
90 m	13	13	...	...	...	...	...	...	...
810 m	3	3	3	7	8	6	7	7	...
Elevation relief ratio									
90 m	12	10	...	...	...	...	...	...	...
450 m	10	12	7	10	9	11	10	10	...
810 m	6	8	5	8	7	8	8	9	7

Notes: Values reflect each variable's ranking (1 = most important) based on its contribution to overall model accuracy in the optimal Random Forest model. Columns are separate models for all years, big years, and other years in each ecoregion. Variables not selected by a particular model are indicated with an ellipsis (...), and variables not selected in any models are omitted from this table. Dashes indicate variables that were not used in a particular ecoregion due to high correlation with other variables.

† Normalized monthly values, relative to 1950–2006 averages (averaged to create seasonal variables).

‡ Calculated from daily values for the 10 days starting with the fire detection date.

Table B2. Variable importance rankings for Southwest Random Forest models relating topography, climate, and weather to burn severity, grouped by ecoregion and categories of fire year (all, big, other).

	Mogollon Rim			Colorado Plateau			Southern Rockies		
Variable	All	Big	Other	All	Big	Other	All	Big	Other
Conditions during fire									
Minimum temperature, month of fire†	...	...	...	17	...	11	11	11	16
Maximum temperature, month of fire†	...	...	...	...	...	...	...	...	15
Precipitation, month of fire†	15	15	...	...	13	...	...	...	...
Soil moisture									
0–10 cm (30yr%)‡	...	...	12	...	...	...	16	15	...
0–10 cm (30day%)‡	...	16	...	...	...	...	...	...	...
10–40 cm (30yr%)‡	...	...	13	...	19	15	...	...	...
Antecedent conditions									
Minimum temperature									
Previous month†	...	...	...	16	...	...	14	...	10
Previous spring (AMJ)†	...	...	...	...	18	...	...	...	...
Previous fall (OND)†	...	...	...	15	...	...	...	...	13
Previous summer (JAS)†	17	17	...	...	15	...	...	...	...
Maximum temperature									
Previous month†	...	14	...	...	...	14	17	...	14
Previous spring (AMJ)†	...	...	...	...	16	...	18	...	...
Previous winter (JFM)†	...	...	...	...	...	...	19	...	...
Previous summer (JAS)†	...	18	...	14	20	13	...	...	...
Precipitation									
Previous month†	13	13	...	...	14	...	20	...	...
Previous spring (AMJ)†	14	...	11	...	...	...	...	14	...
Previous winter (JFM)†	...	...	...	...	...	12	...	16	12
Previous fall (OND)†	16	...	14	13	17	...	15	...	...
Topography									
Elevation	2	2	1	1	1	1	1	1	1
Slope	7	6	8	6	7	4	6	6	6
Heat load index	6	5	6	7	5	7	7	4	4
Solar radiation aspect index	9	9	7	9	9	8	8	8	8
Slope cosine aspect index	5	4	4	3	2	5	3	3	7
Hierarchical slope position	8	8	9	8	8	9	9	9	9
Compound topographic index	12	12	...	12	12	...	13	13	...
Topographic position index									
150 m	10	10	10	10	10	16	10	10	11
2000 m	1	1	2	2	3	2	2	2	2
Dissection, 810 m	3	3	5	5	4	6	4	5	5
Elevation relief ratio									
90 m	11	11	...	11	11	10	12	12	...
810 m	4	7	3	4	6	3	5	7	3

Notes: Values reflect each variable's ranking (1 = most important) based on its contribution to overall model accuracy in the optimal Random Forest model. Columns are separate models for all years, big years, and other years in each ecoregion. Variables not selected by a particular model are indicated with an ellipsis (...), and variables not selected in any models are omitted from this table.

† Normalized monthly values, relative to 1950–2006 averages (averaged to create seasonal variables).

‡ Calculated from daily values for the 10 days starting with the fire detection date.

Table B3. Results from optimal Random Forest models for the Northwest.

Metric	Pacific			Inland Northwest			Northern Rockies		
	All	Big	Other	All	Big	Other	All	Big	Other
Topographic predictors only									
PCC	0.64	0.64	0.66	0.62	0.63	0.64	0.62	0.62	0.65
Kappa	0.27	0.28	0.32	0.24	0.26	0.26	0.22	0.23	0.26
AUC	0.70	0.70	0.73	0.66	0.69	0.67	0.67	0.67	0.69
Number of pixels	18,163	13,220	4,943	24,000	14,198	9,802	21,794	16,722	5,072
Topographic, climatic and weather predictors									
PCC	0.70	0.68	0.75	0.72	0.71	0.72	0.70	0.69	0.73
Kappa	0.40	0.37	0.49	0.43	0.42	0.44	0.39	0.38	0.44
AUC	0.77	0.76	0.82	0.79	0.79	0.79	0.77	0.76	0.80
Number of pixels	17,389	13,099	4,290	23,664	14,156	9,508	21,729	16,720	5,009

Notes: Columns are separate models for all years, big years, and other years in each ecoregion. PCC is percent correctly classified. AUC is area under the receiver operating characteristic curve.

Table B4. Results from optimal Random Forest models for the Southwest.

Metric	Mogollon Rim			Colorado Plateau			Southern Rockies		
	All	Big	Other	All	Big	Other	All	Big	Other
Topographic predictors only									
PCC	0.69	0.68	0.77	0.67	0.69	0.71	0.62	0.63	0.69
Kappa	0.37	0.37	0.48	0.34	0.36	0.34	0.25	0.26	0.29
AUC	0.76	0.75	0.82	0.74	0.75	0.77	0.67	0.68	0.72
Number of pixels	21,808	15,679	6,129	19,099	13,154	5,945	24,000	19,475	4,525
Topographic, climatic, and weather predictors									
PCC	0.79	0.77	0.84	0.76	0.75	0.78	0.72	0.71	0.76
Kappa	0.58	0.54	0.65	0.52	0.48	0.53	0.44	0.42	0.48
AUC	0.86	0.84	0.91	0.84	0.82	0.86	0.80	0.78	0.82
Number of pixels	21,637	15,671	5,966	18,511	12,951	5,560	23,235	19,153	4,082

Notes: Columns are separate models for all years, big years, and other years in each ecoregion. PCC is percent correctly classified. AUC is area under the receiver operating characteristic curve.