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Vegetation, topography and daily weather influenced burn severity in central Idaho and western Montana forests

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Abstract. Burn severity as inferred from satellite-derived differenced Normalized Burn Ratio (dNBR) is useful for evaluating fire impacts on ecosystems but the environmental controls on burn severity across large forest fires are both poorly understood and likely to be different than those influencing fire extent. We related dNBR to environmental variables including vegetation, topography, fire danger indices, and daily weather for daily areas burned on 42 large forest fires in central Idaho and western Montana. The 353 fire days we analyzed burned 111,200 ha as part of large fires in 2005, 2006, 2007, and 2011. We expected that local "bottom-up" variables like topography and vegetation would influence burn severity, but that our use of daily dNBR and weather data would uncover stronger relationships between the two than previous studies have shown. We found that percent existing vegetation cover had the largest influence on burn severity, while weather variables like fine fuel moisture, relative humidity, and wind speed were also influential but somewhat less important. Our results could reflect contrasting scales of predictor variables, as many topography and vegetation variables (30-m spatial resolution) accounted for more of the variability in burn severity (also 30-m spatial resolution) than did fire danger indices and many daily weather variables (4-km spatial resolution). However, we posit that, in contrast to the strong influence of climate and weather on fire extent, "bottom-up" factors such as topography and vegetation have the most influence on burn severity. While climate and weather certainly interact with the landscape to affect burn severity, pre-fire vegetation conditions due to prior disturbance and management strongly affect vegetation response even when large areas burn quickly.

Key words: area burned; burn severity; dNBR; infrared perimeter mapping; northern US Rockies; Random Forest; wildland fire.

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Introduction

Fires are globally important disturbances that affect ecosystems (Bond et al. 2004, Bowman et al. 2009). Although large fires account for most of the area burned, garner the most media attention, have the costliest economic impacts (Butry et al. 2001), and are socially important (Lannom et al.

2014), not all land area burned in large fires is severely burned (Birch et al. 2014). Instead, many large fires cause variable ecological effects (Lentile et al. 2007), with high severity areas having long-term effects on ecosystem structure and composition (Kashian et al. 2006, Goetz et al. 2007, Romme et al. 2011). However, the environmental controls on burn severity across large forest fires are poorly understood, limiting our ability to model future burn severity.

Burn severity as inferred from remotely sensed imagery has been widely used to evaluate fire effects on ecosystems (Smith et al. 2005, 2010, French et al. 2008, Soverel et al. 2010, Morgan et al. 2014). Satellite-derived time series have been used to evaluate ecosystem recovery from fire for many science and management applications (Morgan et al. 2001, Diaz-Delgado et al. 2003, Kotliar et al. 2003). Proportion of the total fire area burned severely has been inferred from satellite imagery to evaluate whether fires have become more severe in recent decades (Miller and Safford 2012, Mallek et al. 2013), whether fires have been more severe under different land management (Miller and Urban 2000, Wells 2013), and to characterize possible changes in wildlife habitat (Hanson and Odion 2013). We define burn severity as the degree of ecosystem change due to fire (Morgan et al. 2001, Key and Benson 2006), where ecosystem change incorporates changes in overstory vegetation, understory vegetation, or soil strata (Van Wagtendonk et al. 2004, Lentile et al. 2006, French et al. 2008, Morgan et al. 2014). The differenced Normalized Burn Ratio (dNBR) spectral index of burn severity calculated from pre-fire and one year post-fire satellite imagery has been correlated with field-based assessments of burn severity (Van Wagtendonk et al. 2004, Cocke et al. 2005, De Santis and Chuvieco 2009, Jones et al. 2009), and with percent tree mortality in forested areas (Cocke et al. 2005, Hudak et al. 2007, Lentile et al. 2007, Smith et al. 2010).

Environmental conditions influence fire growth, occurrence, and extent, but the degree to which they influence burn severity is unclear. Most prior climate-fire analyses have shown significant correlations between annual burned area and summer drought in the northern US Rockies (Littell et al. 2009, Abatzoglou and Kolden 2013) with widespread fires occurring during warm, dry summers that followed warm springs (Heyerdahl et al. 2008, Morgan et al. 2008). The environmental factors influencing burn severity may be distinctly different than those influencing fire occurrence and extent (Romme and Knight 1981, Christensen et al. 1989, Heyerdahl et al. 2002, Dillon et al. 2011). Burn severity can be highly variable, even when large areas burn in a single 24-hr period (Birch et al. 2014). Jones et al. (2009) found that above average summer high temperatures and low precipitation were important in growth and severity of the largest fire on record for the North Slope of Alaska. Holden et al. (2009) found that north-facing slopes were more likely to burn severely than other aspects in New Mexico. Dillon et al. (2011) found that the probability of high burn severity was influenced by topography more than climate even in years of widespread fires when climate was more influential than in other years.

The US northern Rockies area is well-suited for examining how multiple factors interact to influence burn severity. This area provides a wide variety of forested vegetation, topographic, settings, and environmental conditions that have experienced wildfires in recent years. The northern Rocky Mountains have accounted for the majority of area burned in the western US for the last several decades (Westerling 2008) and the area is considered vulnerable to future climate-driven increases in the frequency of large fires (Westerling et al. 2006, Littell et al. 2009, Spracklen et al. 2009, Moritz et al. 2012). Burn severity is highly variable here (Dillon et al. 2011) and important to people and many ecosystem processes influenced by fire (Morgan et al. 2014).

Our objective was to understand how burn severity as indicated by dNBR varies with topography, vegetation, fire danger indices, and daily weather. We build on the study of Dillon et al. (2011) who analyzed high burn severity across six ecoregions of the western US and found that topography exerted more influence on burn severity than fire weather or climate. Their fire weather data, however, were only resolved to a 10-day summary around fire detection dates, and their climate data reflected monthly or seasonal values coincident with or antecedent to fire detection dates. Here we analyze continuous dNBR values (not just high severity) resulting from daily areas burned relative to weather and fire danger for the specific day each area burned. We expected that (1) that "bottom-up" variables such as topography and vegetation will still have a large effect on burn severity and post-fire vegetation response, (2) that using burn severity and weather data matched to the same time period will result in stronger relationships between the two and advance our understanding of how weather influences severity, and (3) topography and vegetation will influence burn severity even when we focus only on the largest daily areas burned in the largest fires even as these fires burned under extreme weather. Understanding the environmental factors influencing burn severity, especially for large fires, is critical to projecting the degree to which ecological effects of fire will change with climate.

Methods

Study area

We examined 42 forest fires in central Idaho and western Montana that burned in 2005, 2006, 2007 and 2011 (Fig. 1). (See Appendix A for full list of fires and dates of progression mapping) Our study area includes diverse forest types, topography, weather and climate and has had many fires in recent decades (Westerling et al. 2006, Morgan et al. 2008) with varying burn severity (Dillon et al. 2011).

Burn severity data

Continuous dNBR data were obtained from the Monitoring Trends in Burn Severity project (MTBS) (Eidenshink et al. 2007). The MTBS project has mapped dNBR for all large fires in the United States (>405 ha in the western US; >202 ha in the eastern US) from 1984 to present from 30-m Landsat satellite sensor data. We selected fires from the MTBS dataset that also had daily infrared (IR) fire progression maps available for at least five consecutive days. We adjusted the raw dNBR values obtained from the MTBS project by the dNBR offset value (Key 2006). The dNBR offset value represents the average difference in NBR values between relatively homogeneous unburned areas of pre- and post-fire satellite scenes. This value accounts for spectral changes that occurred from factors other than fire, such as phenological differences (Key 2006).

Infrared perimeter mapping

Aerial infrared perimeter mapping is conducted on many wildfire incidents to measure fire size and growth. Following methods established by Birch et al. (2014), we required continuous fire progression maps of five or more days per fire and buffered perimeters by 30 m in order to remove areas with inconsistent perimeters. We also removed areas of fire growth less than 0.09 ha, the area of a single Landsat pixel (30 m $\times$ 30 m), which allowed us to further stipulate the area was actual fire growth. The 30-m IR perimeter buffer resulted in a total of 136,634 ha (80% of total IR area) and 7,216 individual polygons representing daily areas burned. Loss of areas less than 0.09 ha totaled 13 ha (<0.0001% of buffered area). For the 42 fires we were able to establish 394 days of area burned.

Random sample point selection

Using the IR perimeter maps from the 42 selected fires we chose random points (Fig. 2) for which we obtained daily weather and fire danger indices, topographic measurements, and vegetation characteristics. We further constrained our sampling to 111,397 ha (81% of buffered area >0.09 ha) of forests using the LANDFIRE Existing Vegetation Type geospatial layers (Rollins 2009; see Appendix B for a full list of sampled forested Existing Vegetation Types). Existing Vegetation Type represents the dominant vegetation at a specific point in time, so we used LANDFIRE Version LF2001 for all fires from 2005 to 2007, and LANDFIRE version LF2008 for 2011 fires. We randomly selected sampling points across all 42 fires with a minimum distance of 127.5 m between points. We established the minimum distance of 127.5 m as it is the rounded minimum distance required such that no two points were sampled from adjacent Landsat pixels. Moreover, setting this minimum sampling distance precluded the confounding factor of spectral mixing between pixels that are adjacent to one another, known as the adjacency effect (Otterman and Fraser 1979, Jianwen et al. 2006). Random points that fell within areas of MTBS's "Non-processed Area Masks" were removed from analysis; these areas are generally associated with Landsat 7 scan-line corrector error lines,

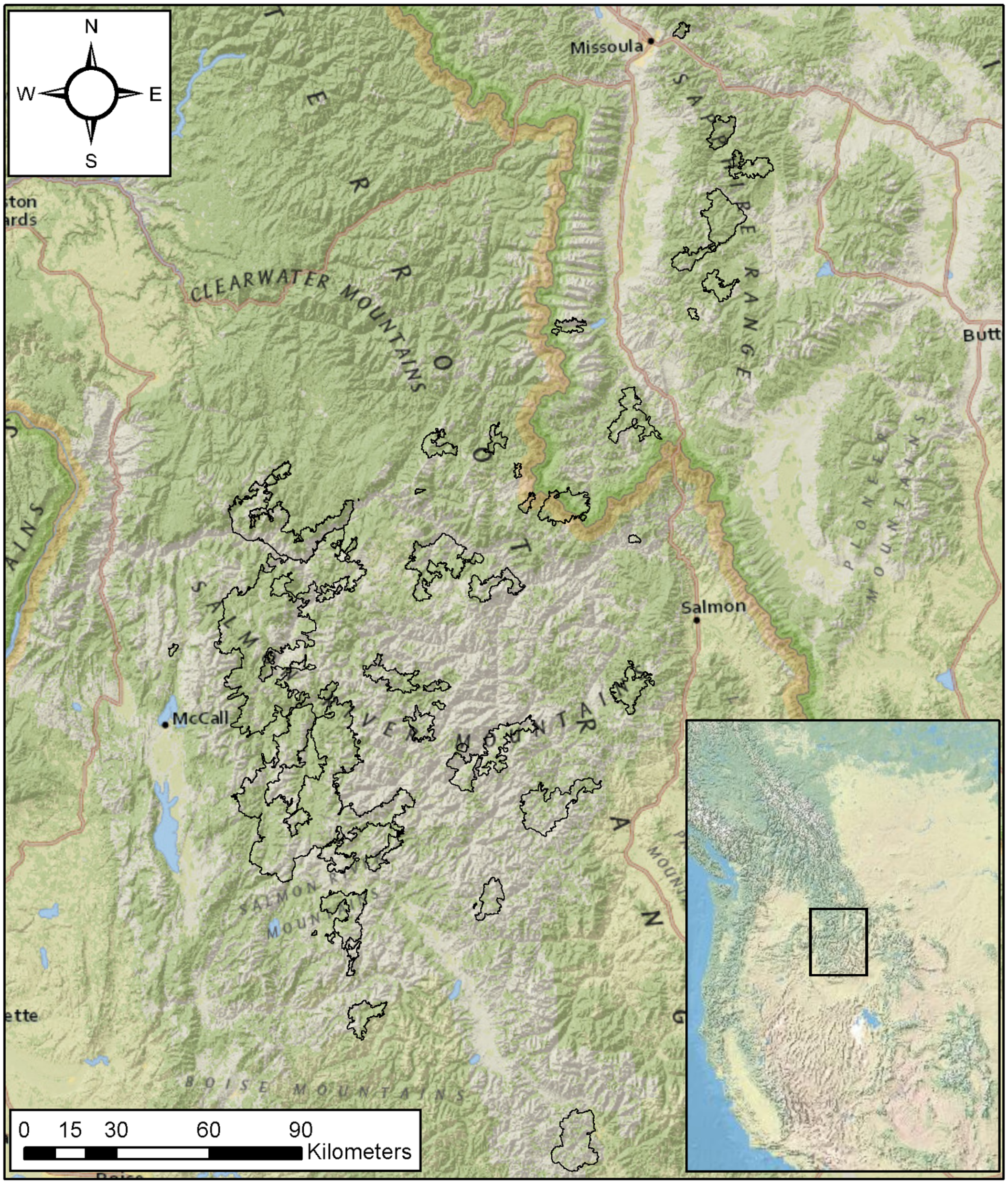

Fig. 1. Study area of central Idaho and western Montana showing the 42 fires from 2005 to 2007 and 2011 used in this study.

cloud cover, cloud shadow, and other data gaps. The minimum sample distance and Non-processed Area Masks eliminated the ability to sample from some of 394 possible IR progression days, missing 41 days and 127 ha (<0.001% of forested burned area). Of these 41 days, only five days were not sampled on another fire. Ultimately, we sampled 10,819 points in 353 fire days within a total daily forested area burned of 111,270 ha.

Topographic, vegetation, daily weather and fire danger indices

For each of the randomly located points, we obtained data for a suite of topographic, vegetation, daily weather and 30-yr percentile weather

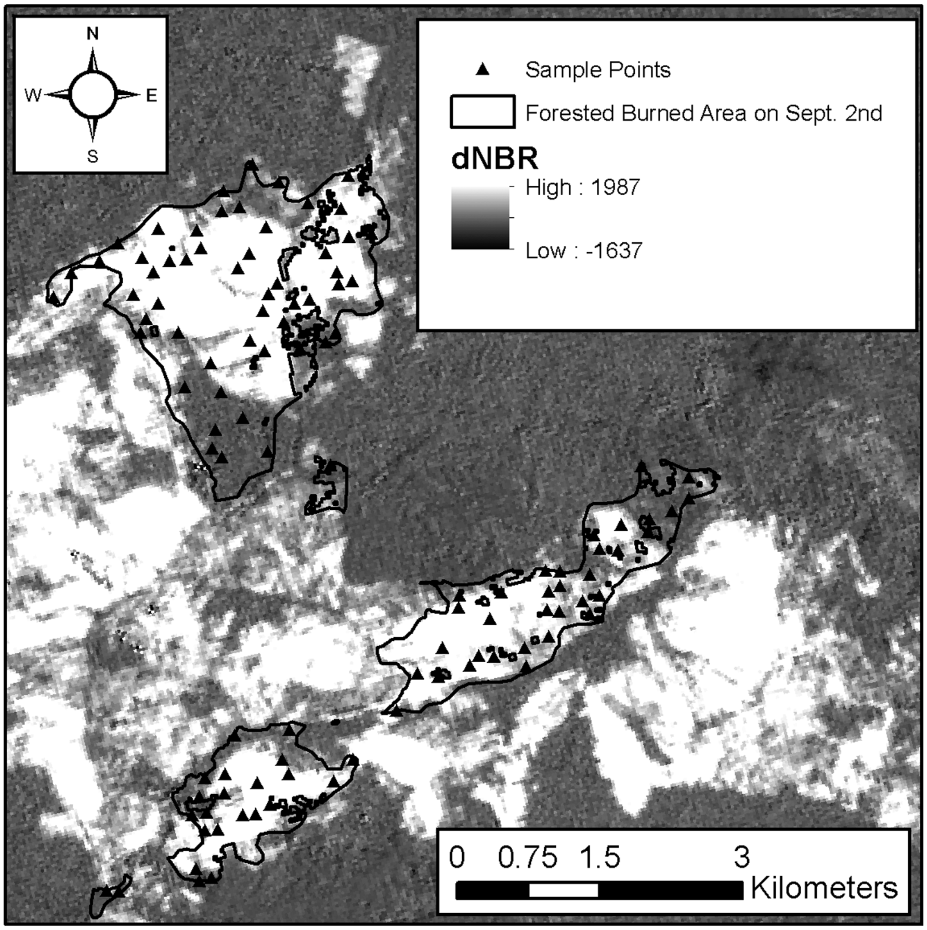

Fig. 2. Example of forested daily areas burned and randomly sampled points that occurred on the Burnt Strip Mountain Fire in central Idaho on September 2, 2005. Areas were delineated by use of daily IR perimeter maps.

predictor variables. Percentiles help us to locally normalize variation. We initially identified 47 predictors as potentially influential to burn severity based on the literature. (See Appendix C for full list of 47 predictors.) We removed 12 predictor variables that were highly correlated (Spearman's Rho > 0.75) with another variable. Any predictor variable that was highly correlated with two or more variables was first to be removed, any weather variable that was correlated with its percentile was removed.

Using the sampled values of our 35 uncorrelated predictor variables, and dNBR as the response, we performed a preliminary Random Forest analysis (see next section) to determine an optimal set of predictor variables. We identified the optimal model (i.e., fewest predictors that could best predict changes in dNBR) by running a model selection routine that tested the performance of models with successively fewer predictors as done by Dillon et al. (2011). This resulted in an optimal set of 20 predictor variables, a summary of which follows.

Topographic.—We examined five topographic measurements from a 30-m Digital Elevation Model (DEM). We used two types of topographic information: (1) slope and aspect and (2) slope position and curvature. Indices of slope and aspect were: Percent Slope, Heat Load Index (McCune and Keon 2002), Topographic Solar Radiation Aspect Index (Roberts and Cooper 1989), and Slope-Cosine-Aspect Index (Stage 1976). The measurement of slope position and curvature was Topographic Position Index

(Weiss 2001) calculated in an annular neighborhood with a 2,000-m outer radius and 300-m inner radius. (See Appendix D for descriptions of each topographic predictor.)

Vegetation.—Three representations of pre-fire vegetation characteristics were obtained from the LANDFIRE Program (Landfire 2013): Fuel Characteristics Classification System, Environmental Site Potential, and Existing Vegetation Cover. LANDFIRE geospatial layers provide 30-m pixel representations of vegetation characteristics (Landfire 2013). Fuel Characteristics Classification System layers represent fire environment fuelbeds that contribute to fire behavior and effects (Riccardi et al. 2007). Environmental Site Potential represents the vegetation communities that would become established at late or climax stages of successional development without disturbance, based on biophysical site conditions (Landfire 2013). Existing Vegetation Cover as expressed in LANDFIRE data layers in forested areas is percent tree canopy cover from 10% to 100%, by 10% intervals. Areas with less than 10% tree canopy are not considered forested areas by LANDFIRE. (See Appendix E for descriptions of all vegetation layers obtained from LANDFIRE.)

Weather and fire danger indices.—Maximum and minimum temperature and relative humidity, precipitation, 10-meter wind velocity and downward shortwave radiation at the surface were extracted from the surface meteorological dataset of Abatzoglou (2013) (http://metdata.northwestknowledge.net) at 4-km spatial resolution. (See Appendix F for descriptions.) In addition, we calculated Duff Moisture Code and Fine Fuel Moisture Code from the Canadian Forest Fire Danger Rating System and the Energy Release Component and Burning Index from the National Fire Danger Rating System using fuel model G (dense conifer). Fire danger indices comprise timescales that integrate weather over the previous couple months and thus represent a hybrid weather-climate metric.

Data were extracted for the 4-km voxels co-located with each random point, which for many points within a fire included identical weather and fire danger indices. Due to the heterogeneity in these predictors across the study area as a function of baseline climatology, we consider these variables as observed and using a percentile based approach as both approaches have shown merit in previous studies (e.g., Abatzoglou and Kolden 2013, Parks et al. 2014). While the variables in their raw form account for geographic differences in energy and moisture, a percentile-based approach normalizes for these climatological differences and allows for comparisons to be made across locations relative to historical conditions and are often used operationally in fire suppression decisions. We calculated percentiles for each variable to contextualize environmental conditions at each site using all observations from July 1 to September 30 (92 days) over the period of record of observations (1979–2013). Percentiles were not considered separately for each day, but rather by pooling all days. (See Appendix F for descriptions of weather predictors from which climate percentiles were calculated.)

We also calculated wind-aspect alignment as the absolute value of aspect direction minus wind direction, with values of 0 and 360 having perfect up-slope wind, a value 180 having perfect down-slope wind, and values in between measuring varying degrees of cross-slope/up-slope winds (e.g., absolute value of (180 aspect direction − 359 wind direction) = 179, down-slope wind; absolute value of (225 aspect direction − 270 wind direction) = 45, cross-slope/partial up-slope wind). Slopes less than 10 percent were calculated as having a wind-aspect alignment of 0, or perfect alignment.

Analysis

We used Random Forest (Breiman 2001), a machine learning classification and regression tree analysis method, to study how our topographic, vegetation, daily weather, and 30-year percentile weather variables influenced continuous dNBR values. We implemented our analysis with the Random Forest package (Liaw and Wiener 2002) for R (R Core Team 2014), using regression tree models because of our continuous burn severity response variable. For regression tree analyses, Random Forest produces a pseudo-R^2 calculated as 1 minus the mean-square error (MSE) divided by the variance that occurs within the response variable, dNBR (i.e., $R^2 = 1 - \text{MSE}/\text{Variance (dNBR)}$). MSE is the sum of the squared residuals divided by the sample size ($n = 10{,}819$). We used the pseudo-R^2 to assess overall model performance, and used MSE in evaluating the relative importance of predictors and selecting an optimal model. We used nonparametric rank sum tests (Mann and Whitney 1947) on MSE values. We evaluated whether the variable group ranks, topographic vs. vegetation vs. daily weather vs. 30-year percentile weather, were non-random. Similarly, we compared the ranks of the "bottom-up" topography and vegetation variables relative to the "top-down" daily weather and weather percentile variables.

Similarly to Dillon et al. (2011), we first identified variable importance rankings using our full set of 35 uncorrelated predictor variables, and subsequently found the optimal model using an iterative model selection routine. Within Random Forest, the importance of each predictor variable is assessed by randomly permuting its values and determining the resultant increase in MSE; the more influence a variable has on overall model performance, the more model error will be increased by permuting its values. Using all 35 variables, we ran five replicate models, each with 1500 regression trees, and used the median importance measure (increase in MSE) across all five replicates to rank each variable. Following the methods of Dillon et al. (2011), we then formed ten groups of predictor variables based on similarity of importance values, and tested the performance of models with successively fewer predictor variables, starting with all ten groups and at each successive round eliminating the least important group. We used five replicates of five-fold cross-validation at each round of model selection, again with 1500 regression trees in each model. We selected the optimal model as the smallest set of predictor variables that resulted in overall MSE within one standard error of the model producing the lowest MSE (De'ath and Fabricius 2000).

To evaluate the relationship between individual predictor variables and burn severity, we examined partial dependence plots from our optimal Random Forest model. In a regression tree analysis, Random Forest generates these plots by calculating, at fixed values across the range of a given predictor, the average of model predictions using all combinations of observed values of other predictor variables (Cutler et al. 2007). Therefore, the partial dependence plots show how the predicted value of dNBR varies across the range of any given predictor.

We repeated our Random Forest analysis, including removal of correlated predictors, ranking of variable importance, selection of an optimal model, and creation of partial dependence plots, for only observation points located within daily areas burned greater than 600 ha. We refer to this as the "large fire growth" analysis, as opposed to the "all points" analysis that used the full sample of 10,819 points. The threshold of 600 ha was selected as it corresponds to the 99.5th percentile of the size of the daily areas burned and included 4,113 observation points (38%).

Results

Values of the continuous dNBR index, indicating burn severity, ranged from −431 to 1,218 across the 10,819 sample points from 42 fires (Fig. 3). The "all points" optimal model resulted in a pseudo R^2 of 0.42. The optimal model included 20 predictors related to topography, vegetation, and weather and fire danger indices (Fig. 4). The most important predictor from this analysis was Existing Vegetation Cover by a wide margin over the next variable, Slope-Cosine-Aspect Index. Environmental Site Potential (see Table 1 for descriptions), Fine Fuel Moisture Code Percentile, and Maximum Relative Humidity followed closely as the third, fourth, and fifth most important variables. Partial dependence plots from the optimal "all points" analysis show that higher amounts of Existing Vegetation Cover and greater values of Slope-Cosine-Aspect Index (i.e., steeper slopes and/or more northern-facing aspects) were associated with higher predicted dNBR values (Fig. 5). Likewise, higher values of dNBR were predicted for cold/wet forest Environmental Site Potential classes (Table 1), 90th percentile or greater Fine Fuel Moisture Code, and Maximum Relative Humidity values below ~65% (plots not shown). Unfortunately, although the Random Forest analysis reflects all of the variables included together, the partial dependence plots are of one variable at a time, so we cannot show the interactions clearly.

For the "large fire growth" analysis, reflecting areas of daily fire growth above the 99.5th percentile in size, the optimal model had a pseudo-R^2 of 0.49. In addition to the 12 predictor

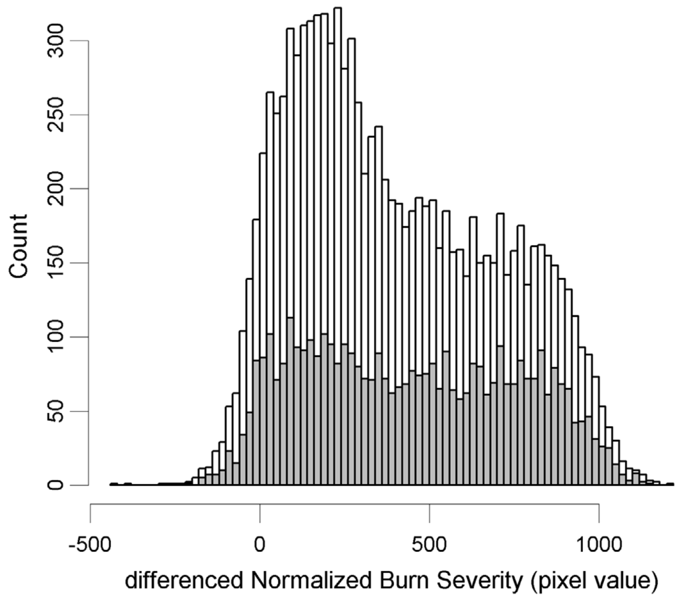

Fig. 3. Differenced Normalized Burn Ratio pixel values for all 10,819 randomly selected points (white bars) and 4,113 points within large areas of fire growth (gray bars). Bin size = 100.

variables removed from the "all points" analysis, we removed three more highly correlated variables (Spearman's Rho > 0.75) from the "large fire growth" analysis: burning index, duff moisture code (raw), and duff moisture code (percentile). (See Appendix C.) Daily areas burned greater than 600 ha still accounted for 4,113 observation points (38% of total) and 52,155 ha (47%) of daily areas burned as determined from IR perimeter mapping. Of all 7,216 daily areas burned, only 37 (0.005%) were larger than 600 ha. The Random Forest optimal model indicated just eleven predictors that could best predict dNBR (Fig. 6). Similar to the "all points" analysis, Existing Vegetation Cover provided the largest influence on dNBR, with Slope-Cosine-Aspect Index a distant second. The third and fourth predictors were different: Wind Speed Percentile and Fuels Characteristics Classification System, respectively. Thus, our findings support our expectations that "bottom-up" variables such as topography and vegetation strongly influence burn severity, even when we focus only on the largest daily areas burned in the largest fires. Since the top two predictor variables were the same for the "all points" and "large fire growth" analyses, partial dependence plots allow for comparison between the two analyses (Fig. 5). The plot for Existing Vegetation Cover shows that for any given amount of vegetation cover, our models always predict higher severity on "large fire growth" days relative to the full sample of daily areas burned. This difference is relatively small at low vegetation cover amounts, but increases slightly above about 30–40% cover. The plot for Slope-Cosine-Aspect Index shows a somewhat similar pattern, with higher severity always predicted on "large fire growth" days relative to all daily areas burned, but predicted severity becomes higher on northerly and/or steeper slopes in the "large fire growth" model.

Vegetation Group variable importance ranked significantly higher than other variables groups ($P < 0.10$). Further, the "bottom-up" factors, including vegetation and topography, ranked higher than "top-down" variables including daily weather and weather percentiles ($P = 0.067$, Mann-Whitney test on MSE values).

Discussion

The environmental controls on burn severity include interactions of vegetation, topography, and both weather and fire danger indices. Individual partial dependence plots were non-linear with thresholds for increased influence,

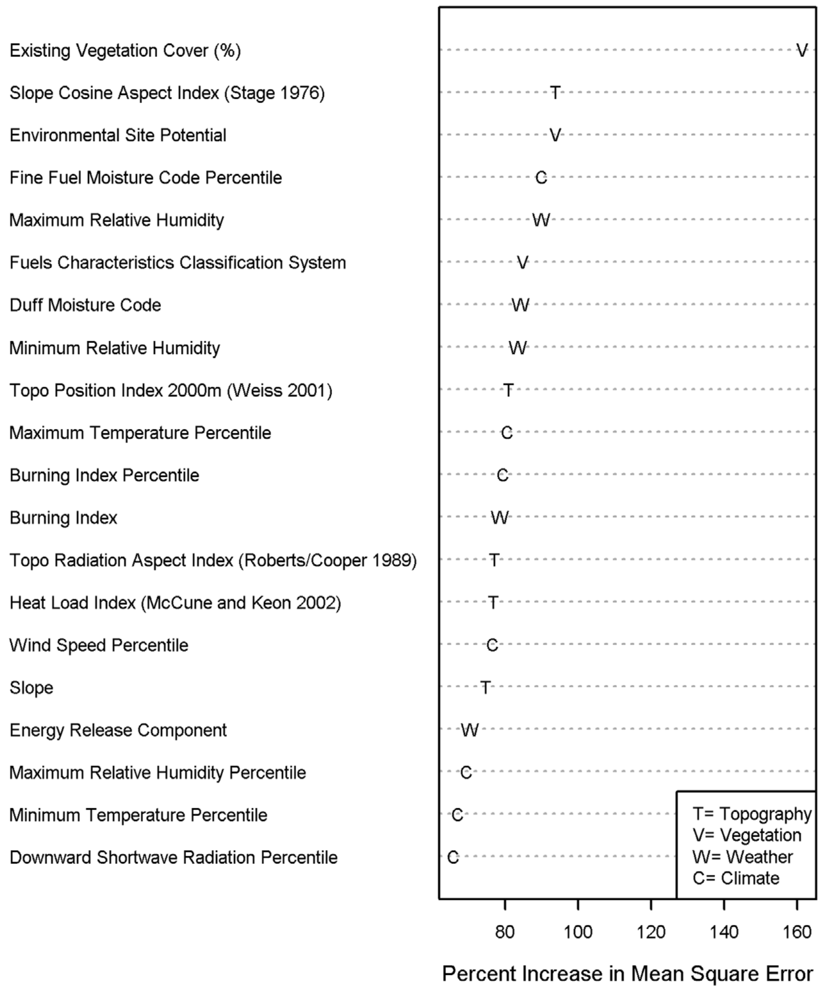

Fig. 4. Importance rankings of 20 predictors of dNBR as explained in an optimal model provided by Random Forest regression trees for 10,817 observation points. Predictor importance is measured as the percent increase of each predictor variable on the total mean square error.

indicating that many factors must reach a specific condition before having a large influence on burn severity.

As dNBR is a spectral index that responds primarily to vegetation change and changes in soil/char cover (Smith et al. 2005, Hudak et al. 2007), it is not surprising that percent pre-fire Existing Vegetation Cover would have the largest influence on burn severity. Likely this reflects the potential for greater change pre- to post-fire where pre fire vegetation is abundant, as identified by Miller et al. (2009). Because we used dNBR in this analysis (rather than RdNBR) this relationship is probably caused somewhat by the correlation between pre-fire NBR and the dNBR index (Miller and Thode 2007, Parks et al. 2014). We caution against equating dNBR-type indices with burn severity. The dNBR index has been shown to significantly correlate via linear relationships to post-fire live tree cover and litter weight, but no better than % char and % green vegetation estimates derived by spectral mixture analysis (SMA) of the same post-fire images as dNBR (Smith et al. 2007). Lentile et al. (2009) presents further evidence that SMA-derived fractional cover estimates may provide as good an indicator of post-fire effects as dNBR-indices, via linear relationships, but be less prone to misinterpretation as burn severity measures per se (Morgan et al. 2014).

Table 1. Environmental Site Potential (ESP) descriptions of the NatureServe terrestrial ecological systems used in this analysis (NatureServe 2011).

ESP code	Description	Forest type	Partial dependence value
1056	R Mt. Subalpine Mesic-Wet Spruce-Fir Forest	Cold	420
1055	R Mt. Subalpine Dry-Mesic Spruce-Fir Forest	Cold	412
1167	R Mt. Poor-Site Lodgepole Pine Forest	Cold	392
1046	N R Mt. Subalpine Woodland and Parkland	Cold	372
1161	N R Mt Conifer Swamp	Cold	360
1045	N R Mt Dry-Mesic Mixed Conifer Forest	Dry	362
1053	N R Mt Ponderosa Pine Woodland	Dry	341
1159	R Mt. Montane Riparian Systems	Mesic	384
1166	Middle R Mt. Montane Douglas-fir Forest	Mesic	382
1160	R Mt. Subalpine/Upper Montane Riparian	Mesic	360
1047	N R Mt Mesic Montane Mixed Conifer Forest	Mesic	335
1154	Inter-Mountain Basins Montane Riparian Systems	Mesic	333
1062	Inter-Mt. Basins Mahogany Woodland	Mesic	332
1011	R Mt. Aspen Forest and Woodland	Mesic	330
1106	N R Mt Montane-Foothill Deciduous Shrubland	Other	346
1139	N R Mt Lower Montane-Foothill-Valley Grassland	Other	344
1145	R Mt. Subalpine-Montane Mesic Meadow	Other	342
31	Barren-Rock/Sand/Clay	Other	333

Topography also influenced burn severity as indicated by dNBR. Slope-Cosine-Aspect index (Stage 1976) was the second leading predictor of dNBR as it likely reflects effective moisture and productivity of biomass available to burn, as well as probability of burning. Dillon et al. (2011) found that topography, including elevation and 2000-m topographic complexity, had the largest influence on proportion of high severity fire within large forest fires. We did not include elevation in our study. Perhaps the influence of coarse-scale topographic complexity on burn severity as found by Dillon et al. (2011) but not in our work reflects the regional scale of their analysis. All of the topographic predictor variables in our optimal model were also included in their models.

All of the polygons representing large daily areas burned within known 24-hour periods included multiple topographic facets as they burned across complex montane topography. All were part of large fires that burned for multiple days, and therefore were burning under relatively extreme conditions, which might suggest that climate and weather would be more important than topography within large areas burned. While the top two predictors, Existing Vegetation Cover and Slope-Cosine-Aspect Index, did not change in importance when we analyzed only those points in the largest daily areas burned, wind speed did become more important (third in the "large growth" analysis from 15th in the "all points" analysis).

Partial dependence plots for Slope-Cosine-Aspect Index indicate that steeper slopes and/or more northerly aspects are associated with higher values of dNBR, especially within areas of large fire growth. This may be because the vegetation on many north-facing aspects is less available to burn without the extensive drying that favors large fire growth. Within our predictor variable of Environmental Site Potential, cold/wet forest types that are often found on cooler aspects and higher on mountain slopes were also associated with higher dNBR values (Table 1). Similarly, Holden et al. (2009) found that fires on cool north-facing aspects of the Gila Wilderness of the southwestern US were more likely to burn with high severity. Barrett et al. (2010) also found that aspect influenced burn severity as indicated by the relative reduction of organic soil layers of black spruce stands in Alaskan boreal forest.

Our findings support Dillon et al.'s (2011) argument that the environmental controls on burn severity differ from those determining fire extent. In contrast to Dillon et al. (2011), we used weather data and fire danger indices at much finer spatial and temporal resolutions, providing a much closer match of temporal and spatial scales with the observations of daily area burned. We also analyzed the full range of burn severities (not just high severity) as indicated by a continuous dNBR gradient, and focused on fewer fires within a single ecoregion. As we expected,

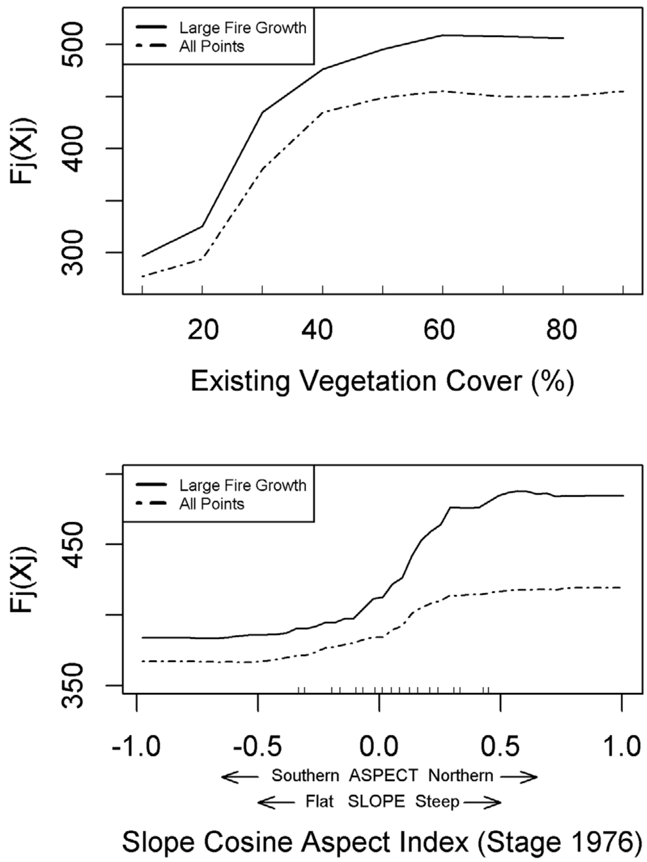

Fig. 5. Random Forest partial dependence plots of Existing Vegetation Cover and Slope-Cosine-Aspect Index for "all points" (dotted line) and points within "large fire growth" (solid line). Partial dependence plots show the dependence of the regression function (F_j (X_j)) on the predictor while holding all others at their mean. Use relative range of y-axis values to compare between "all points" and "large fire growth" lines. Existing Vegetation Cover had about the same influence on burn severity between "large fire growth" and "all points", while steeper or more northern aspects had more influence during "large fire growth".

and similar to Dillon et al. (2011), we found that while variables reflecting meteorological and climatic conditions were important, local, "bottom-up" controls reflecting topography and vegetation more strongly influenced burn severity.

Wind did not highly influence dNBR-indicated burn severity in the "all points" analysis, though it was important for burn severity in the very largest daily areas burned, likely reflecting the importance of wind in influencing fire spread and size. This surprised us because sustained crown fires that can result in tree mortality are usually associated with wind (Van Wagner 1977). Wind is a common factor in both fire extent and fire behavior (Beer 1991, Bessie and Johnson 1995) especially in dry fuels (Cruz and Alexander 2010). Neither wind direction nor speed contributed highly to burn severity in our "all points" analysis (see Appendix G for analysis using 30-m scale wind data using WindNinja) even though both increase fire intensity (Rothermel 1972). For the 99.5th percentile of daily areas burned, wind was third in order of variable importance, consistent with the very high intensity of wind-driven fires. The lack of wind as a significant contributing factor to burn severity in our "all points" analysis is consistent with what Dillon et al. (2011) found, but it is possible that the spatial and temporal resolution of our wind data, though better matched, is still too coarse or inaccurate, as we don't know the concurrent

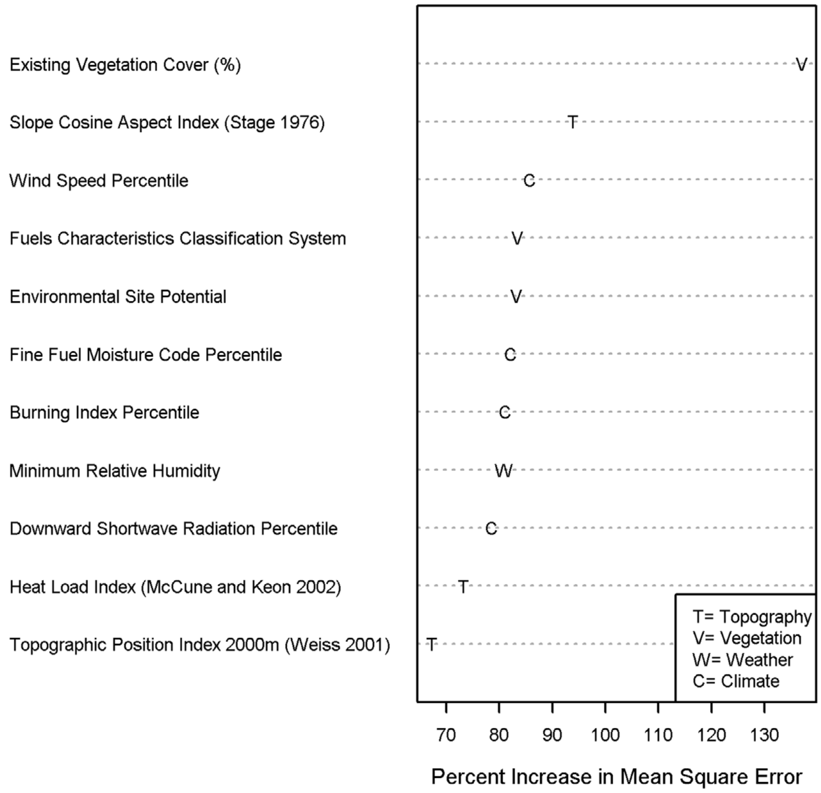

Fig. 6. Predictor importance of 11 factors of dNBR, for 4,113 observations in daily areas burned larger than 600 ha, as explained in an optimal model provided by Random Forest regression trees. "Percentile" predictors are considered climate and calculated as the percentile from the 34 year mean for day of observation for summer fire months: July, August, and September.

wind conditions at the time when a particular point burned. Further, our data on prevailing wind do not consistently reflect the interaction between fire and wind. The lack of a relationship between wind attributes and both RdNBR (Dillon et al. 2011) and dNBR (this study) could also be due to the selection of dNBR-type burn severity metrics; given its applicability is limited to the spatial scale of the Landsat imagery (i.e., 30 $\times$ 30 m pixels) and to only capturing broad spectral changes in vegetation and soil cover. Potentially, non-remote sensing measures of burn severity (e.g., field based measures of the height of bole char and crown scorch on individual trees) could lead to improved connections with wind direction and speed.

Parks et al. (2014) found that burn severity-inferred dNBR increased with greater fuel amount and fuel moisture. Thus, we expected duff and 1000-hr fuel moisture to influence burn severity, for they reflect long-term drying which could result in large areas with a majority of biomass dry enough to be consumed in fires (Meyn et al. 2007, Krawchuk and Moritz 2011). Four of our top eight predictor variables are a measure of moisture content, whether air (RH) or vegetation (Duff or Fine Fuel Code). These many different forms of moisture content may account for changes in burn severity. Higher moisture content, especially Maximum RH, which we interpret as night-time RH recovery, may limit smoldering combustion (Ferguson et al. 2002) which influences burn severity (Wade 1993, Sackett et al. 1996).

Understanding the relative importance of the drivers of burn severity will require further research. Environmental variables, especially wind, interact to influence fire behavior (Bessie and Johnson 1995). Within our analysis there were a large number of predictors and many potential interactions. Perhaps the lack of dominance by a single group of predictors (topography, vegetation, climate, or weather) in influencing burn severity reflects the different potential causes of burn severity among the many different types of vegetation that the fires burned across and the number of IR progression days that we were able to use for weather and climate observations. While dNBR is more often correlated with overstory tree mortality (Cocke et al. 2005, Hudak et al. 2007), it also reflects soil effects (Lewis et al. 2006). Possibly, these different aspects of burn severity are influenced by different environmental characteristics and thus may explain why we see the intermixing of predictor variable types. Soil burn severity (Parson et al. 2010) may be more influenced by duff consumption and soil heating (Ice et al. 2004) while overstory tree scorch and crown consumption might be tied more to flame length and intensity (Rothermel 1972). In a recent review, Morgan et al. (2014) recommend defining different burn severity indices depending on purpose; this may help to sort out the influence of environmental factors on burn severity.

Burn severity may also be controlled by pre-fire and post-fire conditions such as winter snow fall and conditions of the next growing season, which may have greater influence on severity then do conditions that occurred on the day the area was burned. Drying and warming trends days before an area burned also likely influence burn severity and are reflected in the fire danger indices. Hudak et al. (2011) found that weather up to 5 days before was significant in predicting daily area burned. Further, our fires were all larger than 405 ha and had escaped initial fire suppression actions or were managed with limited suppression. Fires that were contained or areas of fires that were initially suppressed may have different factors that contributed to burn severity. Previous fires that occurred but were not accounted for in changes in vegetation data layers may also have a moderating effect on burn severity (Parks et al. 2013), and prior disturbances including bark beetles and logging were not considered. We also did not account for the effects of fire suppression tactics such as burnouts or large backfires. These could significantly alter patterns and intensities of fire activity (Backer et al. 2004), but detailed data on locations of tactics applied is difficult to obtain. While these tactics are used for public and firefighter safety and to limit future fire growth, they may influence both burn severity and direction of fire spread.

Limitations

We constrained our sampling to forested areas within the northern Rockies. Areas of non-forest and those forested areas outside the northern Rockies may likely have different interactions between the factors contributing to burn severity that would be specific to that area, due to weather or climate, and for that type of ecosystem, due to vegetation characteristics. Our data were sampled at both 30-m and 4-km spatial scales which could have influenced our findings. The coarse scale of our weather and fire danger predictor variables (4 km) does not represent the microclimate gradients that might drive burn severity. Namely, many of the random points we selected occurred within common voxels thereby limiting the explanatory power of weather and fire danger indices to explain heterogeneity in burn severity. The LANDFIRE (Landfire 2013) data also contain errors, and we did not have field data to verify vegetation classification and cover percentage. At the scale of individual 30-m pixels, LANDFIRE existing vegetation data may only be approximately 60% accurate (Swetnam and Brown 2010), and cannot capture finer-scale vegetation heterogeneity (<30 m) that may also drive burn severity. The vegetation data, however, is at the same spatial resolution as our topographic predictors and dNBR.

Our topographic predictor variables match the spatial scale of dNBR (30 m) observations which may account for them being placed higher in importance rankings. Random Forest analyses are more selective of predictors with more categories and continuous data (Strobl et al. 2007, 2009). Our dataset contains both types of data, with our analysis showing intermixing of predictor data types within the importance rankings.

Implications

In contrast to the strong influence of fire danger indices, weather, and climate on fire extent (Littell et al. 2009, Abatzoglou and Kolden 2013), "bottom-up" factors such as topography and vegetation have the most influence on burn severity, even on the largest daily areas burned on the largest fires. While climate and weather certainly interact with the landscape to affect burn severity, pre-fire vegetation conditions due to prior disturbance and management strongly affect vegetation response even when large areas burn quickly. Over a third of the predictors that influenced forest burn severity are weather and fire danger indices. This suggests that burn severity may be somewhat sensitive to projected changes in climate (IPCC 2013), and to the degree that climate does change, burn severity may change as well (Miller et al. 2009). The effects of a warming climate on burn severity may even be indirect as suggested by van Mantgem et al. (2013), if trees become stressed by warmer temperatures and thus more susceptible to being killed by fire. However, while fire extent is strongly influenced by climate and weather, our findings and those of Dillon et al. (2011) indicate that the ecological effects of fire are relatively less sensitive to climate and influenced by vegetation cover and topography. Over the last century, fire suppression actions have increased amounts of both dead and living vegetation throughout the western United States (Barrett et al. 1991, Arno et al. 1997) and changed forest composition (Arno et al. 1995, 1997, Keane et al. 1996). Such changes in vegetation conditions can lead to uncharacteristic burn severity (Quigley et al. 1996, Barbouletos et al. 1998), but they can sometimes be reversed through fire and fuels management that reduces fuels available to future fires. Information about thresholds of burn severity like we see for vegetation cover and topographic setting (Fig. 5) can inform fuels management across landscapes. Based on our results, we would expect that strategically managing fuels for lower vegetation cover would lead to less severe fire effects when fire does occur, especially on the lower and warmer landscape facets and in dry forests that experienced frequent fire historically. On other landscape facets, such as north-facing slopes, perhaps we can accept severe fires as there may be operational and ecological (Hutto 2008) reasons why we cannot or should not limit severity on these sites. Even when large fires burn large areas in a single day, burn severity varies (Birch et al. 2014), creating a mosaic that can provide ecosystem services valued by society.

Conclusion

Vegetation and topography were more important influences on burn severity than weather and fire danger indices for 353 daily areas burned across 42 large forest fires. Thus our findings support those of Dillon et al. (2011), though ours were at daily temporal resolution. While this could still reflect a mismatch in temporal and spatial scales between burn severity and topography data versus weather data and fire danger indices, our findings clearly suggest that local vegetation conditions and topography influence the ecological effects of fires, even for large forest fires and for days on which large areas burn in a short time. If so, as the climatic, vegetation, and fuels conditions in Northern Rockies forests change, the implications for burn severity may be quite different than the implications for fire extent, with concomitant implications on the fire and fuels management strategies that could most effectively foster the ecosystem processes and ecosystem services valued by society.

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Supplemental Material

Appendix A

Table A1. We analyzed 42 forest fires in a six-year period (total fire days: 353; total area: 111,270 ha). Fires were selected based on availability of both dNBR burn severity indexes obtained from the Monitoring Trend in Burn Severity Project and infrared perimeter data.

Fire	Year	Progression dates analyzed	Forested area analyzed (ha)
Beaverjack	2005	9/2–9/4; 9/6; 9/8	732
Burnt Strip Mountain	2005	8/26–9/4	2451
Center	2005	8/26; 8/31; 9/2–9/3	63
Reynolds Lake	2005	9/2–9/3; 9/7–9/8	235
Rockin	2005	9/2–9/3	95
Signal Rock	2005	9/1–9/8	1372
Boundary	2006	9/2–9/5	190
Meadow	2006	9/2–9/5	246
North Elk	2006	9/2–9/5	185
Potato	2006	7/30–7/31; 8/2	908
Red Mountain	2006	8/31–9/4	1099
Cascade Complex†	2007	9/7–9/15	4329
Castle Rock	2007	8/20–8/31	8568
Cottonwood	2007	8/24–8/30	1244
Fisher Point	2007	8/11–8/18; 8/25–8/27; 8/29–9/3	2591
Goat	2007	8/10–8/12; 8/25–8/30; 9/7–9/12	2702
Lolo	2007	8/11–8/18; 8/24–8/26; 8/29–8/31; 9/3	1358
LoonZena	2007	8/22–8/30	1610
Monumental	2007	7/27–7/31; 8/3–8/7	2829
Monumental-North Fork‡	2007	8/26–8/30	2829
Monumental-Yellow§	2007	8/9–8/14	12985
North Fork	2007	8/11–8/15,	6133
Papoose	2007	8/28–9/3	287
Raines	2007	8/25–8/30	1579
Rattlesnake	2007	7/18–7/22; 8/9–8/15	8999
Red Bluff	2007	8/23–8/30	3317
Riordan	2007	7/26–7/31; 8/3–8/5; 8/7; 8/26–8/30	5395
Rombo Mountain	2007	8/25–8/30	1194
Sandy	2007	7/28–7/31; 8/3–8/4; 8/6	3342
Shower Bath	2007	8/25–8/30	150
Tag	2007	8/7–8/12; 8/28–8/29; 8/31–9/3; 9/7–9/14	5240
Trapper Ridge	2007	7/27–7/28; 730–7/31	405
Wyman #2	2007	8/11–8/18; 8/22; 8/25–8/31; 9/2–9/3	4956
Yellow	2007	8/3–8/7	993
Castro	2011	9/1–9/11	456
Coyote Meadows	2011	9/7; 9/11–9/12	98
Hells Half	2011	9/7–9/8; 9/10–9/14	224
Indian	2011	7/24–7/27	57
Saddle	2011	8/22–8/27; 8/30; 9/1–9/8; 9/10–9/14	9519
Salt	2011	8/27–9/8	5220
Up Top	2011	9/4–9/14	2145
West River Side	2011	8/24–8/29	495

† Cascade Complex includes North Fork, Monumental, Yellow, Sandy, and Riordan fires after they were mapped as one IR perimeter.

‡Monumental North Fork includes the Monumental and North Fork fires after they were mapped as one IR perimeter.

§ Monumental Yellow includes Monumental, North Fork, Sandy, and Yellow fires after they were mapped as one IR perimeter.

Appendix B

Table B1. Forested vegetation types within study area.

EVT Code	EVT Description
2011	Rocky Mountain Aspen Forest and Woodland
2045	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest
2046	Northern Rocky Mountain Subalpine Woodland and Parkland
2047	Northern Rocky Mountain Mesic Montane Mixed Conifer Forest
2050	Rocky Mountain Lodgepole Pine Forest
2053	Northern Rocky Mountain Ponderosa Pine Woodland and Savanna
2055	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland
2056	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland
2061	Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland
2062	Inter-Mountain Basins Curl-leaf Mountain Mahogany Woodland and Shrubland
2159	Rocky Mountain Montane Riparian Systems
2160	Rocky Mountain Subalpine/Upper Montane Riparian Systems
2161	Northern Rocky Mountain Conifer Swamp
2166	Middle Rocky Mountain Montane Douglas-fir Forest and Woodland
2167	Rocky Mountain Poor-Site Lodgepole Pine Forest
2227	*Pseudotsuga menziesii* Forest Alliance
2228	*Larix occidentalis* Forest Alliance

Notes: Forested Existing Vegetation Type (EVT) groups used in selecting areas within progression days. The LANDFIRE Existing Vegetation Type layer represents the species composition at a given site.

Appendix C

Table C1. Importance ranking of predictor variables used in Random Forest regression relating topography, vegetation, and both daily weather and fire danger indices in both raw and percentile values to differenced Normalized Burn Ratio for "all points" and points within areas of "large fire growth" (> 600 ha). Climate predictors were calculated as the percentile from 34 year mean for day of observation for summer fire months: July, August, and September.

Predictor	Importance ranking	
Topography (15)	All points	> 600 ha
Martonne's Modified Dissection Coefficient (Evans 1972)		
90 m	*	*
450 m	*	*
810 m	*	*
Elevation Relief Ratio (Pike and Wilson 1971)		
90 m	+	+
450 m	*	*
810 m	+	+
Topographic Position Index (Weiss 1972)		
150 m	+	+
300 m	*	*
2000 m	9	11
Topographic Solar Radiation Aspect Index (Roberts and Cooper 1989)	13	+
Compound Topographic Index (Moore et al. 1993)	+	+
Heat Load Index (McCune and Keon 2002)	14	10
Slope Cosine Aspect Index (Stage 1976)	2	2
Slope (Percent)	16	+
Aspect (Degrees)	+	+
Vegetation (9)		
Environmental Site Potential	3	5
Fuel Loading Models	+	+
Existing Vegetation Cover	1	1
Canopy Bulk Density	*	*
Canopy Base Height	+	+
Existing Vegetation Height	+	+
Existing Vegetation Type	+	

Table C1. Continued.

Predictor	Importance ranking	
Fuel Characteristic Classification Fuelbeds	6	4
Fire Behavior Fuel Models, Scott and Burgan 40	+	+
Daily Weather and Fire Danger Indices (12)		
Maximum Temperature (Degrees Kelvin)	*	*
Minimum Temperature (Degrees Kelvin)	*	*
Maximum Relative Humidity (Percent)	5	8
Minimum Relative Humidity (Percent)	8	+
Precipitation (mm)	+	+
Downward Solar Radiation (W m^{-2})	*	*
Wind Speed (m/s)	*	*
Wind Direction (Degrees from North)	+	+
Energy Release Component	17	+
Burning Index	12	*
Duff Moisture Code	7	*
Fine Fuel Moisture Code	*	*
Daily Weather Percentiles (10)		
Maximum Temperature (Degrees Kelvin)	10	+
Minimum Temperature (Degrees Kelvin)	19	+
Maximum Relative Humidity (Percent)	18	*
Minimum Relative Humidity (Percent)	*	*
Downward Solar Radiation (W m^{-2})	20	9
Wind Speed (m/s)	15	3
Energy Release Component	+	+
Burning Index	11	7
Duff Moisture Code	+	*
Fine Fuel Moisture Code	4	6
Other		
Wind-Aspect Alignment	+	+

Notes: An asterisk indicates a predictor removed due to high correlation with other predictors. A plus sign indicates a predictor removed for optimal model.

Appendix D

Table D1. Descriptions of topography predictors. All values and indices were calculated from a 30-m digital elevation model.

Predictor	Description
Aspect	The direction in degrees from north in which the exposure faces.
Slope	The percent change of elevation over a specific area.
Slope Cosine Aspect Index	Calculation indicating combinations of slope and aspect, higher values are those areas that are steeper slopes or more northern aspects (Stage 1976).
Topographic Radiation Aspect Index	Assigns values to a circular aspect variable. Values of 0 indicate north-northeast aspects, and a value of 1 to south-south-westerly aspects (Roberts and Cooper 1989).
Heat Load Index	Calculates solar radiation so that the highest values are southwest and the lowest values are northeast and also accounts for steepness of the slope (McCune and Keon 2002).
Compound Topographic Index	Calculates topographic convergence, were higher values represent drainages and lower values represent ridges or rises (Moore et al. 1993).
Topographic Position Index	Calculates slope position by subtracting a central mean from the surrounding elevation by use of annular ring sizes. Higher values indicate ridges, with negative values indicating valleys, and 0 indicating flat areas (Weiss 1972). Calculated at 1–150, 150–300, and 300–2000 m annular rings.
Elevation Relief Ratio	Describes how ridged the surface. Small values indicate areas of features standing above surrounding level surfaces, with high values indicating level surfaces with depressions. (Pike and Wilson 1971). Calculated at 90, 450, and 810 m radius circles.
Martonne's Modified Dissection Coefficient	Describes terrain dissection within an area. Higher values indicate large changes in elevation, with lower values indicating small changes in elevation (Evans 1972). Calculated at 90, 450, and 810 m radius circles.

Appendix E

Table E1. Description of vegetation predictors from LANDFIRE. All vegetation characteristics are represented at a 30-m spatial resolution obtained from LANDFIRE (www.Landfire.gov).

Predictor	Description
Environmental Site Potential	The vegetation that could be at a given location; based on NatureServe's Ecological Systems classification (NatureServe 2011); represents the natural plant communities that would become established at late or climax stages of successional development in the absence of disturbance.
Existing Vegetation Type	The species characteristics at a given site at the time of classification; derived from NatureServe's Ecological Systems classification.
Fuel Loading Models	Characterizes wildland surface fuel.
Existing Vegetation Cover	Depicts percent canopy. All vegetation cover was expressed as percent of ground covered.
Existing Vegetation Height	The average height of the vegetation. All vegetation height was expressed as tree height.
Canopy Bulk Density	The density (kg m^{-3}) of available canopy fuel in a stand; generated using Landsat imagery and biophysical gradients to model bulk density.
Canopy Base Height	The height from the ground to a forest stand's canopy bottom, measured in meters and only within forested areas.
Fuels Characteristics Classification System	Characterizes fuel bed as it might contribute to fire behavior and effects (Ottmar et al. 2007).
Fire Behavior Fuel Models	Represent fuel loadings of size classes and fuel types within dead and live fuels.

Appendix F

Table F1. Description of daily weather and fire danger predictors. We obtained weather data from a gridded (4-km spatial resolution) modeled dataset of surface meteorological data (Abatzoglou 2013, http://metdata.northwestknowledge.net). The spatially gridded data is a combination of temporal attributes of regional-scale reanalysis and daily gauge-based measurements.

Predictor	Description
Minimum and Maximum Temperature	Minimum and maximum temperature measured in degrees Celsius.
Minimum and Maximum Relative Humidity	Minimum and maximum relative humidity expressed as a percentage.
Precipitation	Daily accumulated precipitation as measured in millimeters.
Wind Speed	Mean wind velocity expressed as meters per second.
Wind Direction	Average wind direction expressed as degrees from North.
Duff Moisture Code	A rating of the average moisture content of loosely compacted duff layers. This code is calculated using the Canadian Forest Fire Danger Rating System (Van Wagner 1987).
Fine Fuel Moisture Code	A rating of the moisture content of litter and other cured fine fuels. The code is an indicator of the ease of ignition and the flammability of fine fuels. The code is calculated using the Canadian Forest Fire Danger Rating System (Van Wagner 1987).
Downward Shortwave Radiation Flux	The mean daily shortwave radiation at the surface not accounting for any topographic factors (W m^{-2}).
Energy Release Component (ERC)	Combines the daily temperature, precipitation and humidity that may represent the amount of energy released at the flaming front of a fireline (Deeming et al. 1977).
Burning Index (BI)	A value related to the contribution of fire behavior to the effort of containing a fire (Deeming et al. 1977). The value may be divided by 10 to estimate flame length.

Appendix G

Fine-scale wind analysis

WindNinja calculations were obtained from Zack Holden of the US Forest Service in Missoula for the 2007 Rattlesnake Fire to test if fine-scale (30 m) wind direction and speed observations provided a greater contributing influence to variations in dNBR. WindNinja is used to calculate fine-scale, terrain-influenced winds (Forthofer et al. 2003) for input to wildland fire behavior models such as FARSITE and FlamMap. IR perimeter maps for the Rattlesnake Fire from central Idaho covered 12 days of fire weather. Using the 127.5 m minimum spacing between observation points we obtained 1053 wind speed and direction values. This fire was used as a small test case to test if adding fine-scale wind data provided additional explanation for variation in burn severity. As with the analysis of all 42 fires, the 30 m analysis and identical 4 km analysis included removal of highly correlated predictor variable. Wind-Aspect Alignment measurements were calculated based on wind direction from both datasets. With no large change in Mean Square Error values for wind specific predicator variables (i.e., wind variables didn't increase in importance) between 30 m and 4 km analyses we didn't conduct optimal Random Forest runs. Using WindNinja data for wind on the 2007 Rattlesnake fire did not increase the explained variation in dNBR. A pseudo R-squared of 0.43 was achieved using WindNinja 30 m data compared to 0.41 for the 4 km data form this single fire. With the large time investment requirement to calculate WindNinja data for the remaining 9,766 randomly located points, we decided not to include WindNinja data for our final analysis across all 42 fires.