Intensified burn severity in California’s northern coastal mountains by drier climatic condition

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Abstract

The severity of wildfire burns in interior lands of western US ecosystems has been increasing. However, less is known about its coastal mountain ecosystems, especially under extreme weather conditions, raising concerns about the vulnerability of these populated areas to catastrophic fires. Here we examine the fine-scale association between burn severity and a suite of environmental drivers including explicit fuel information, weather, climate, and topography, for diverse ecosystems in California’s northern coastal mountains. Burn severity was quantified using Relative difference Normalized Burn Ratio from Landsat multispectral imagery during 1984–2017. We found a significant increasing trend in burned areas and severity. During low-precipitation years, areas that burned had much lower fuel moisture and higher climatic water deficit than in wetter years, and the percentage of high-severity areas doubled, especially during the most recent 2012–2016 drought. The random forest (RF) machine learning model achieved overall accuracy of 79% in classifying categories of burn severity. Aspect, slope, fuel type and availability, and temperature were the most important drivers, based on both classification and regression RF models. We further examined the importance of drivers under four climatic conditions: dry vs. wet years, and during two extended drought periods (the 2012–2016 warmer drought vs. the 1987–1992 drought). During warm and dry years, the spatial variability of burn severity was a mixed effect of slope, long-term minimum temperature, fuel amount, and fuel moisture. In contrast, climatic water deficit and short-term weather became dominant factors for fires during wetter years. These results suggest that relative importance of drivers for burn severity in the broader domain of California’s northern coastal mountains varied with weather scenarios, especially when exacerbated by warm and extended drought. Our findings highlight the importance of targeting areas with high burn severity risk for fire adaptation and mitigation strategies in a changing climate and intensifying extremes.

1. Introduction

Intensifying wildfire conditions under changing climate pose risks to biodiversity conservation and to society (Schoenagel et al 2017). Large wildfires have been increasing in frequency and size in the western United States (US) (Miller and Safford 2012, Dennison et al 2014, Faiivre et al 2016), a trend projected to continue over the coming decades (Williams and Abatzoglou 2001). In interior mountain ecoregions and California’s Sierra Nevada, there is an increasing trend in the severity of burns over the most recent three decades (Miller and Safford 2012, Dennison et al 2014, Keyser and Westerling 2019), and wildfires have also moved upwards in elevation, into forest types that are less-adapted to burns (Schwartz et al 2015). Historical wildfire suppression and extreme weather conditions in California have increased the portion of high-severity areas burned (Keyser and Westerling 2019, Goss et al 2020) and contributed to high inter- and intra- heterogeneity in forested regions (Fried et al 2004, Steel et al 2018). These high-severity
fires increase carbon emissions and biomass consumption, and degrade water quality through erosion (Meigs et al 2009; Fowler 2003). They also modulate vegetation distribution and long-term carbon storage, by altering the post-fire trajectory of vegetation recovery (Meng et al 2015, Liang et al 2017).

Understanding the drivers of burn severity is critical for anticipating future changes in wildfire behavior. Disentangling and quantifying the relative importance of various environmental factors is of particular importance in informing fire and land management for complex landscapes. Burn severity represents fire damage on vegetation and soil organic matter (Keeley 2009). The spatial heterogeneity of burn severity is affected by environmental conditions, local topographical features, and ecosystem responses (Lentile et al 2007). For example, short-term fire weather directly exacerbates severity by altering fuel conditions, while long-term climate change and variation can indirectly influence burn severity through cumulative effects on fuel amount (Miller et al 2009, Parks et al 2014b, Kane et al 2015). Chronologies of wildfire occurrence and severity show that extensive and severe fires have been preceded by anomalously dry and warm weather while frequent low-severity fires in grassland-forest ecotones are positively related to wet conditions (Harvey et al 2017, Keyser and Westerling 2017). Some previous studies have examined the impact of fuels separately, but have focused on severity at the fire-event scale (Dillon et al 2011, Keyser and Westerling 2017). The heterogeneous spatial patterns within individual fires, on the other hand, have not been systematically studied across multiple fires, limiting our understanding of drivers for the burn severity at the management relevant scale.

Burn severity prediction based on fuel and climate controls at the landscape scale has been investigated in some ecoregions of California, such as the Sierra Nevada Mountains (Collins et al 2009), but much less is known about its coastal ranges due to its complex topography, climate gradients, diverse plant communities, and expanding human settlements (Stuart and Stephens 2006). Wildfire in northern California is characterized by a mixed severity fire regime with complex patterns, including a significant increase in stand density which shaped the threats of subsequent severe wildfires (Perry et al 2011). For example, this region experienced a series of devastating fires in October 2017, causing nearly 9000 buildings destroyed and more than $10 billion of economic loss (Nauslar et al 2018). Despite this dramatic increase in fire activity (Sugihara et al 2006), we lack a comprehensive and systematic examination of environmental components controlling spatial and temporal patterns of burn severity across the complex landscape of California’s northern coastal mountains, where a large population and housing structures are exposed to fire risk and destructive fires have been spreading into the rapidly growing wildland-urban interface (Jin et al 2015, Radeloff 2018). In the adjacent northern California Klamath mountains, a case study on landscape-level burn severity examined topographic and historical fire factors under moderate burning conditions in 2006, but found that fires under different weather and climatic conditions, especially effects from extreme weather and fuel characteristics, still remained to be understood, and localized variants were needed (Estes et al 2017).

In semi-arid regions such as California’s northern coastal mountains, fuel, weather, and local topographic variants have interacting impacts on burn severity and the diverse plant communities further complicated our understanding of driving factors for burn severity. For example, in Southern California, wet conditions might suppress burn severity while continuous wet winters were found to promote fine fuels and thus enhance wildfires (Jin et al 2014). On the other hand, the projected dry conditions may directly increase burn severity via fuel drying while at the same time reduce herbaceous fuel amount and may lead to less severe fires (Pausas and Fernández-Muñoz 2012, Jin et al 2015). Quantifying the relative differences in multiple environmental conditions is particularly important to fill the knowledge gaps about the uncertainties of fuel or weather effects shaping fire regimes in Mediterranean coastal mountains across the globe.

Warming temperatures and recent climatic extremes are altering the pre-fire environment in this region, raising questions about how burn severity will change with the increasing climatic variation and precipitation volatility (Pausas and Fernández-Muñoz 2012, Lydersen et al 2017). Extended droughts, when coupled with heat waves, are likely to have long-term and lagged effects on fuel conditions and thus amplify fire risks and burn severity (van Mantgem et al 2013, Grau-Andrés et al 2018, Goss et al 2020). This drought-fire interaction also influences post-fire regrowth and implies alteration of future carbon balance and landscape fragmentation (Bolton et al 2015, Alencar et al 2015). Several studies indicated the low predictability of burn severity during extreme years with many large fire events, probably due to irregular fire behaviors (Dillon et al 2011, Parks et al 2018). Extreme weather might be underrepresented in predicting burn severity in previous studies (e.g. Parks et al 2018). The interactions among climate, extreme weather, and fuels and their impacts on fire behavior may be further complicated by local topography (Lentile et al 2007, Dillon et al 2011). It is therefore critical to synthesize the multiple effects of environmental conditions on burn severity to provide guidance for management strategies and improve future prediction.

This study aimed to better identify the predictors for wildfire severity and to help define a potential
framework for near real-time predictions of the severity of contemporary wildfires across the diverse landscapes of California’s northern coastal mountains. In particular, we used machine-learning-based statistical models to focus on how fine-scale fuel and environmental variables control the spatial and temporal patterns of burn severity at a management relevant scale. Another objective was to quantify how the relative importance of the key drivers may change under extreme wet and dry climatic conditions. We studied the fires since 1984 when Landsat satellite data became available. We also specifically examined fires under the unusually wet and dry periods from 1984 to 2017, including two extended dry periods: the most recent 2012–2016 prolonged warm drought and a previous cool drought. Our analysis is expected to guide strategies for forest and public land agencies in California in their efforts to manage natural resources, and optimize the post-fire restoration projects.

2. Data and methods

2.1. Study area

The study focused on the coastal mountain region in northern California, mostly foothills and low mountains up to 2265 m, surrounded by low and flat Central Valley ecoregion to the east and Klamath Mountain ecoregion to the north (figure 1). The Berryessa Snow Mountain National Monument is located in the southeast of this region. Herbaceous plants (25%), shrubs (19%), and hardwood woodlands (15%) dominated the lowland of the landscape, while smaller areas of hardwood forests (16%), and conifer forests (6%) occur at higher elevations in the study area (according to FRAP 2015 vegetation type dataset, http://frap.fire.ca.gov/projects/frap_veg/classification). Located within the North America Mediterranean climate zone, the region experiences hot and dry summers and cool and wet winters, with a mean annual precipitation of 851 mm yr$^{-1}$. Precipitation varies significantly from year to year, ranging from 472 mm yr$^{-1}$ in 2014 to 1483 mm yr$^{-1}$ in 1998 (figure S1 (available online at stacks.iop.org/ERL/15/104033/mmedia)). Two extended droughts occurred since 1984; the 1987–1992 drought with a mean annual precipitation (MAP) of 618 mm and the 2012–2016 drought with a MAP of 651 mm (figure 2(a), figure S1). There were also a few years with unusually heavy precipitation such as 1998 and 1995. The long-term mean temperature during the fire season (May–November according to CALFIRE fire season summary) is 22.5 °C during 1980–2017 (figure 2(b), figure S1).

2.2. Fire perimeters and characteristics

We used fire perimeter geographic information system data compiled by the California Fire Resource and Assessment Program (FRAP)
Figure 2. Time series of (a) annual precipitation anomalies, (b) mean annual temperature anomalies, (c) wildfires including the annual total number of fires greater than 40.5 ha (100 acres) and areas burned during 1984–2017 in the study area, and (d) percentage of high severity burns. The anomalies were calculated as the departure from the 1950–2017 mean values.

(http://frap.fire.ca.gov/), which documented wildfire perimeter records back to 1950. All fires larger than 40.5 ha (100 acres) since 1984 were selected. Smaller fires were omitted because they account for less than one percent of the total areas burned in the region and the records for them are less consistent and accurate. Burn severity was derived from 30 m multispectral data from Landsat satellite with a 16 day repeat cycle. We preprocessed the whole time series of the surface reflectance products of Landsat 5, 7 and 8 on Google Earth Engine. The corresponding quality assurance layers were used to filter out cloud contaminated pixels. Due to the high percentage of herbaceous plants and shrubs in the study area, we derived burn severity map based on initial assessment, which investigate short-term loss of vegetation.
(De Santis and Chuvieco 2009, Miller and Quayle 2015), because of the rapid recovery of local plant species (Lippitt et al. 2013). Specifically, clear sky images within one month before and after fire were used to quantify pre- and post-fire normalized burn ratio (NBR), and then relative differenced NBR (RdNBR) was derived as \((\text{NBR}_{\text{pre}} - \text{NBR}_{\text{post}}) / \sqrt{\text{abs}(\text{NBR}_{\text{pre}})}\) (Miller et al. 2009). In occasions when the pre-fire NBR was equal to zero, it was replaced with 0.001, to avoid the infinity of RdNBR (Parks et al. 2014).

We further stratified areas burned into four burn severity categories (high, moderate, low, and unchanged) based on the RdNBR thresholds, as defined by Miller and Quayle classification (2015) for initial assessment (table S1). As outliers might exist in the RdNBR distributions due to those very small pre-fire NBR values, which cannot be interpreted as the fire-induced changes, we applied two unsupervised anomaly detection algorithms to remove these extreme RdNBR values (Park et al. 2014). For each fuel type and each year, the RdNBR distribution was first truncated with anomaly scores calculated by the isolation forest algorithm and then validated by one-class support vector machine to remove those ecologically meaningless observations (Li et al. 2003, Ding and Fei 2013).

Two independent variables for fire history were also explored. We created a raster layer at 30 m resolution to quantify the number of years since last fire (YSLF), for each individual year, based on the FRAP fire perimeters. Fire return interval (FRI) was from the California FRI Department database (Safford and Van de Water 2014; www.fs.usda.gov/detail/r5/landmanagement/gis/).

2.3. Vegetation information
We calculated time series of two vegetation indices, Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), from the Landsat surface reflectance as described above (Reed et al. 1994, Huete et al. 1997). For each fire year, annual maximum NDVI, maximum EVI, and average NDVI a month before each fire were calculated for each pixel within the fire perimeter (table 1). We also calculated Normalized Difference Moisture Index (NDMI) a month before each fire as an indicator of fuel moisture (Gao 1996). For land cover and fuel type, we used the FRAP vegetation type data, based on the classification scheme of California Wildlife Habitat Relationship (CWHR) system (http://frap.fire.ca.gov/projects/frap_veg/classification), as the vegetation base layer.

2.4. Weather, climate, and other ancillary data
We used monthly weather and climate data at 270 m spatial resolution from the Basin Characterization Model (BCM) during 1951–2017 (Flint et al. 2013, Thorne et al. 2015). For each fire year, short-term weather information was derived for the month of a wildfire and was also averaged over the fire year of that fire, for the following variables: average daily maximum, minimum, and mean temperature, and climatic water deficit (CWD) (table 1). CWD was calculated as the difference between potential evapotranspiration and the actual evapotranspiration (Stephenson 1998). We also estimated the short-term cumulative precipitation during 1 to 3 years before the fire. To represent the spatial variation in climate, long-term mean annual values were estimated for temperature (min, mean, and max), precipitation, and CWD from 1951–1980 and 1981–2010. Detrended standard deviations of temperature and precipitation time series were also estimated by first subtracting the trend line from the original time series and then calculating the standard deviation from 1951–1980 and 1981–2010 (Flint et al. 2013). Detrended standard deviation were derived to represent long-term climatic variation. We also included mean wind speed and direction during the fire month from the GRIDMET dataset at 4 km (Abatzoglou 2013).

We used the NextMap Digital Terrain Model (DTM) at 5 m resolution (http://www.intermap.com) for elevation, and further derived other topographic variables, including aspect, slope, and hillshade. We also calculated vegetation height by subtracting DTM from the Digital Surface Model (DSM). To characterize the potential human impacts on burn severity, we obtained the wildland-urban interface (WUI) and residential density layers from WUI Fire Threat datasets (www.fire.ca.gov/). All environmental variables were then resampled to 30 m consistent with Landsat remote sensing products using a bilinear interpolation.

2.5. Burn severity modeling and assessment
We investigated the effects of a suite of environmental factors on burn severity (table 1). Univariate analysis showed only moderate to low correlations between RdNBR and environmental variables (table 1), possibly due to the complex interactions among weather, fuels, and fire behaviors. Therefore, we chose a machine learning approach, random forest (RF), due to its accuracy and performance on non-linear predictions (Lydersen et al. 2017). RF generates multiple decision trees based on randomly permuted subset variables in the out-of-bag (OOB) training samples, which can avoid the problem of multicollinearity; it can be used for both classification and regression with high accuracy and efficiency (Breiman 2001, Cutler et al. 2007).

We built five sets of RF models to examine what controlled burn severity during the whole time period, and during each of the four climatic conditions: dry years, wet years, warm drought, and cool drought, respectively. Dry and wet periods were
Table 1. Variables used for burn severity models and their correlations with RdNBR from Landsat satellite observations over all pixels burned since 1984 in the study area.

| Variables | Correlation with RdNBR |
|-----------|------------------------|
| **Dependent Variable** (source: derived from Landsat observations) | |
| Burn Severity Category (for classification models) | |
| RdNBR (for regression models) | |
| **Topography** (source: NextMap DEM) | |
| Elevation | 0.21 **** \(^a\) |
| Slope | 0.05 **** |
| Aspect | −0.02 **** |
| Hillshade | −0.12 **** |
| **Fuel** (source: FRAP vegetation maps) | |
| Fuel Type | Categorical |
| Vegetation type (Veg) | |
| Annual max NDVI (NDVI.max) | −0.14 **** |
| Annual max EVI (EVI.max) | −0.03 **** |
| Pre-fire NDVI (NDVI.pre) | 0.00 \(^b\) |
| Pre-fire NDMI (NDMI.pre) | −0.03 **** |
| Fuel height (source: NextMap DEM) | −0.16 **** |
| **Short-term Weather** (source: Basin Characterization Model (BCM) datasets) | |
| Previous 1 year precipitation (PPT.1y) | 0.18 **** |
| Previous 2 year cumulative precipitation (PPT.2y) | 0.06 **** |
| Previous 3 year cumulative precipitation (PPT.3y) | 0.02 **** |
| Average of daily max temperature in fire month (TMX) | 0.29 **** |
| Average of daily max temperature in fire year (TMX.annual) | −0.23 **** |
| Average of daily min temperature in fire month (TMN) | 0.31 **** |
| Average of daily min temperature in fire year (TMN.annual) | −0.23 **** |
| Average of daily mean temperature in fire month (TMean) | 0.26 **** |
| Average of daily mean temperature in fire year | −0.23 **** |
| Climate water deficit in fire month (CWD) | 0.34 **** |
| Climate water deficit in fire year (CWD.annual) | 0.22 **** |
| **Long-term (30 year) Mean Climate** (source: BCM datasets) | |
| Mean annual precipitation (PPT.30y) | −0.02 **** |
| Mean annual max temperature (TMX.30y) | −0.01 **** |
| Mean annual daily min temperature (TMN.30y) | −0.02 **** |
| Mean annual daily mean temperature (TMean.30y) | −0.02 **** |
| Mean annual climate water deficit (CWD.30y) | 0.11 |
| Precipitation Variation (detrended standard deviation; PPT.30y.dsd) | 0.01 **** |
| Max temperature variation (TMX.30y.dsd) | 0.31 **** |
| Min temperature variation (TMN.30y.dsd) | 0.00 \(^*\) |
| **Wind** (source: GRIDMET datasets) | |
| Average of daily wind speed in fire month (Wind.Speed) | −0.17 **** |
| Average of daily wind direction in fire month (Wind.Dir) | −0.17 **** |
| **Fire History** (source: FRAP Database & FRI Departure Database) | |
| Years since last fire (YSLF) | −0.01 **** |
| Fire return interval (Current.FRI) | −0.11 **** |
| **Socioeconomic Factor** (source: FRAP) | |
| Wildland-urban interface (WUI) | Categorical |
| Residential density (HouseDensity) | |

\(^*\)**** denotes \(p < 0.0001\),

\(^b\) for \(p < 0.05\)
selected if the precipitation was one standard deviation away from the 60-year mean and were further validated according to the California's Fourth Climate Change Assessment (Bedsworth et al 2018; figures 2(a), (b)). Dry periods since 1984 include 1985, 1987–1992, 1994, 2001, 2007–2009, and 2012–2016. Two extended drought periods were further identified, as mentioned in section 2.1. The latest 2012–2016 drought also coincided with the historical warm records, i.e. 0.63 °C higher than the 60 year average (figure 2(b)), and is often referred as ‘warm drought’. The earlier 1987–1992 drought, was only 0.28 °C higher than the long-term mean, and is therefore referred as ‘cool drought’ here (figures 2(a), (b)). Unusual wet years included 1986, 1993, 1995–1996, 1998, 2006, 2017.

Classification models were developed using four categories of burn severity (Table S1) as a dependent variable, i.e. high-, moderate-, and low-severity, and unchanged (Miller et al 2009). We also built the regression RF models to simulate the continuous values of RdNBR. For each climate scenario, models were trained using 70% of the randomly selected samples and tested with the remaining 30% of data. The analysis was conducted through a 5-fold cross validation. We evaluated RF classification models based on confusion matrix and quantified overall accuracy with Cohen’s Kappa, F1 score, and balanced accuracy, as shown in Table S2 (Berry and Mielke 1988). For the regression model, the predicted RdNBR was evaluated with the mean absolute error, root mean square error (RMSE), and pseudo R-squared (Table S2).

2.6. Variable importance and associations between burn severity and important drivers
We further examined the relative variable importance based on each RF classification model, using the permutation importance metric (Altmann et al 2010). For each variable, when excluded from the full model, mean decrease in prediction accuracy and percentage of increase in MSE within out-of-bag samples represents its relative importance in predicting the burn severity variation. This metric captured not only the individual impact of each predictor variable but also multivariate interactions with other predictors (Strobl et al 2007). To further clarify the decision rules for what combinations of environmental conditions were associated with each burn severity class, we built a simple representative decision tree (global surrogate for the ensemble RF trees) that had a similar structure (i.e. the number of splits and nodes) to the final random forest model (Rokach and Maimon 2005, Lakkaraju et al 2017).

For RF regression models, we further investigated the relationship between each important factor and burn severity based on the partial dependence plot (PDP). PDP is a graphical representation of the functional association between the continuous dependent variable and each independent variable, when marginalizing the derived RF regression model over mean values of all other variables (Hastie et al 2009). Specifically, the X-axis represents the range of a particular target environmental driver for burn severity, and the Y-axis shows RdNBR predictions from the model at a given value of the target variable, with all other predictors kept at their mean values. A PDP thus depicts how RdNBR partially varies with the important variables. For the PDP of each variable, we removed data points beyond the upper and lower whiskers to avoid outliers.

Finally, we tested the significance of differences in the distribution of important environmental factors under different climatic conditions using the Kruskal Wallis test, a nonparametric equivalent to the one-way analysis of variance (Kruskal and Wallis 1952).

3. Results
3.1. Fire characteristics under different climatic conditions
Wildfires have been increasing since 1984 in the study area, with the annual area burned increased by 793.4 ha per year according to a least-square linear regression (figure 2(c)). A total of 206 kha was burned by 104 fires during a total of 17 dry years (12 kha per year). During the most recent extended warm drought, much more areas were burned, 22 kha by 7.2 fires each year on average, compared to 11 kha burned by 6 fires each year during the extended cooler drought (figures 3(a), (b)). This was mostly caused by the larger fire size, 3.2 (±8) kha per fire during the warm drought vs. 1.9 (±4.9) kha during the cool drought. During the 7 wet years, 59% of the areas burned occurred in 2017 (after the extended drought), which may cause the relatively smaller difference of mean annual burned areas between wet and dry years. The mean burned area per year during wet years excluding 2017 is 9.5 kha (18 kha including 2017).

Around 36% of the total mapped burned areas of all fires during 1984–2017 had high burn severity, i.e. with RdNBR greater than 0.73 (Miller and Thode 2007, Miller and Quayle 2015). Dry years experienced much higher burn severity, with a mean RdNBR of 0.69 (±0.45), than wet years with a mean of 0.44 (±0.39) (figure 3(c)). The Kruskal Wallis test further confirmed this significant difference, with a p-value lower than 0.0001. The warm drought had the most severe fires with a mean RdNBR of 0.75 (±0.43). The mean RdNBR during the cool drought was 0.49 (±0.44), significantly lower than that during the warm drought (p-value < 0.0001). Violin plots also showed a larger proportion of high RdNBR areas during the dry periods, especially when during the warm drought (figure 3(c)).
When summarized by severity categories, we found a significant increasing trend of high-severity fires, according to the regression slope test on the annual time series of the percentage of high-severity areas burned over the study area (a slope of 0.8% per year with a p-value of 0.018, figure 2(d)). During dry years, 47% of the total burned areas were high-severity burns (figure 3(d)). In contrast, wet years had only 20% high-severity patches and the majority of the burned areas experienced moderate (38%) or low (27%) severity. The percentage of high-severity patches during the warm drought (52%) was almost twice of that during the cool drought (29%), although the proportions of moderate severity patches were similar.

We also found that the areas burned during dry years were mostly shrubs (34%) and hardwood woodland (27%), while denser vegetation, hardwood forest, was the dominant vegetation type burned (40%) during wet years (figure 3(e)). A higher
percentage of hardwood woodland burned during the extended warm drought (27%) than during the cool drought (18%). Although the herbaceous plant is the most common vegetation type in the study area, the proportion of herbaceous burned across the four climatic conditions was relatively constant, fluctuating around 10% of the total burned areas. The percent of high-severity burns increased from wet to dry periods for all vegetation types (figure 3(f)). Shrub vegetation had relatively higher burn severity than other vegetation types, e.g. 41% and 73.7% burned at high severity during the wet and dry periods (figure 3(f)). The most recent extended warm drought intensified the burn severity significantly for forests.

### 3.2. Performance of burn severity models

We built five RF classification and regression models, for the whole time period and for four individual climatic conditions, respectively, using 35 environmental factors as independent variables (table 1). The five-fold validation showed that both classification and regression RF models were able to capture the variability of burn severity categories and continuous RdNBR during the entire study period and under each climatic condition. The overall RF classification model, based on training data randomly drawn from all pixels burned by fire events since 1984, had an overall accuracy of 79% and a kappa of 0.71, when compared with the remaining testing data (table 2). Among each individual burn severity category, the models also performed well, especially for predicting the high-severity burns, with a user’s accuracy of 85% and a producer’s accuracy of 90%.

The prediction also successfully captured the spatial patterns of burn severity categories, as illustrated by the predicted burn severity maps for the 1990 Eagle fire during the cool drought, the 2015 Rocky fire during the warm drought, and a series of fires in the 2017 northern California firestorm during the wet period (figures 4(a)–(f)). For instance, for the Rocky fire, 67% of the burned areas were high-severity and the model predicted 73% of the areas as high-severity. The predictions preserved most large severity patches but still have the tendency of omitting certain small low-severity regions. Separate RF classification models for each of the four climatic conditions also achieved similar or higher accuracy (table S3).

When trained with randomly-sampled RdNBR observations from areas burned from 1984 to 2017, the overall RF regression model explained 70% and 67% of the variance in the training and testing data across burned pixels from all fires, respectively. The predicted RdNBR values agreed reasonably well with the observations in the testing data set, as shown by the 2D density scatter plot (figure 5), and had a similar distribution with a similar mean value of 0.58 as observations, according to the paired statistical test.

### 3.3. Drivers for burn severity

Topography, long-term climate, and fuels were among the top predictors for burn severity levels (high, moderate, low, and unchanged), as shown by variable importance from the RF classification models (figure 6(a)). Slope and aspect were the two most influential factors in determining burn severity categories across all fires since 1984. The OOB accuracy would decrease by more than 200% if they were randomly permuted from the full model. Similar relative importance was found for several long-term temperature metrics including minimum, mean, and maximum daily temperature (figure 6(a)). Fuel characteristics, as represented by NDVI and EVI values, both right before fire and the annual maximum, and pre-fire NDMI, also played an important role, as well as vegetation type. Removing any of these variables from the full model would result in more than 150% decrease in OOB accuracy. Hillshade, variations in the mean long-term daily minimum temperature, and the long-term mean CWD were also found significant, followed by annual CWD during fire year, elevation, housing density, and long-term mean annual precipitation (figure 6(a)). Wind and socioeconomic factors were among the least important factors.

The surrogate classification tree, built on the 16 most important variables, showed how environmental conditions shaped burn severity categories (figure 7). For the training sets for the overall RF classification model, the node first split shrubs vs other vegetation types (figure 7(a)). For shrubs, high severity patches occurred over areas with fire year max NDVI lower than 0.75 or when both NDVI and fire-year NDMI were also found significant, followed by annual CWD during fire year, elevation, housing density, and long-term mean annual precipitation (figure 6(a)). Wind and socioeconomic factors were among the least important factors.

For hardwood woodland, burn severity was relatively low within areas with lower CWD during the fire year, especially when there was high preceding NDMI over areas with long-term mean precipitation between 540 mm yr\(^{-1}\) and 947 mm yr\(^{-1}\), while the moderate burns occurred with lower preceding fuel moisture (figure 7(b)). In contrast, all high-severity burns of hardwood woodland occurred with higher fire year CWD, and the majority were associated with higher long-term mean daily minimum temperature and pre-fire NDVI (figure 7(b)). Hardwood forests were more likely to experience fire with higher severity burns at an elevation higher than 352 m (figure 7(c)). Furthermore, over warmer but wetter areas, i.e. the long-term max temperature higher than 21.1 °C and long-term mean precipitation greater than 949 mm yr\(^{-1}\), high severity hardwood forest burns occurred.
when annual CWD was higher than 70 mm yr\(^{-1}\); while over the climatologically cooler areas, higher elevation (>770 m) but with higher long-term CWD were more vulnerable to high fire severity (figure 7(c)).

Across the whole landscape, results from the regression model validated the importance of fuel characteristics and climate (figure S4). The partial dependence analysis further revealed that higher NDVI right before fire was found to increase burn severity (figure 8(a)). A consistent negative relationship was also found between burn severity and fuel moisture, i.e. RdNBR dropped rapidly when pre-fire NDMI was higher than 0.2 (figure 8(b)). Higher CWD during the fire year was found to be associated with higher RdNBR (figure 8(c)). Interestingly, long-term mean temperature showed bimodal effects on burn severity, i.e. RdNBR increased with 30-year minimum temperature, but started to decrease when the temperature reached around 6.5 °C, and then peaked around 8.5 °C (figure 8(d)). As for topographic factors, both slope and elevation were positively related to RdNBR (figures 8(e) and (f)). RdNBR increased significantly with slope until 15° and then plateaued at approximately 24°, when other variables were held at the mean effects (figure 8(e)).

### 3.4. Differences in environmental variables among different climatic conditions

The Kruskal Wallis test further confirmed the significant differences of important environmental factors, as identified from the previous section, over areas burned under the four climate conditions (figure 9). Areas burned during dry years had much lower fuel amount, as represented by prefire NDVI of the year, than fires during wet years, with a mean of 0.49 ± 0.14 vs. 0.63 ± 0.18 (figure 9(a)). However, fuels were much drier, e.g. as shown by much lower pre-fire NDMI of 0.09 ± 0.15 over those burned during dry years as compared to 0.19 ± 0.19 in wet years (figure 9(b)); The mean fire-year CWD over dry year fires was 48 mm higher than those during wet years (figure 9(c)). Compared to those in wet years, fires during droughts tended to occur at areas with a slightly lower long-term minimum temperature (8.13 ± 0.84 °C vs. 8.23 ± 1.08 °C) but higher temperature during fire month (22.6 ± 2.38 °C vs. 21.7 ± 1.02 °C) and higher mean annual temperature during fire year (16.23 ± 0.96 °C vs. 15.13 ± 0.63 °C) than during wet years (figures 9(d)–(f)). The differences of environmental variables between warm and cool droughts were significant, but much smaller. These evidences suggest that the burn severity was intensified during dry years mostly by the drought conditions.

### 3.5. Differences in variable importance among different climatic conditions

The RF classification model during dry years identified a set of similar top ten important drivers for categorical burn severity, with an accuracy decrease of more than 150% if removing any one of those variables (figure 6(b)). Burn severity was mainly shaped by a mixed effect of aspect, long-term temperature and CWD, NDVI, and variations in long-term temperature during dry years (figure 6(b)). In contrast, during the wet years, besides topographic effects (slope and elevation), both long term mean and fire-year CWD were found dominating burn severity, with a decrease in OOB accuracy ranging from 200%–300 % (figure 6(c)); additionally, long-term minimum temperature and annual maximum NDVI also had relatively strong impacts on burn severity. As for the differences between the warm and the cool drought (figure S3), severity of warm drought fires was shaped by the mixed effects of aspect, long-term temperature, and fuel availability, while cool drought burn severity was mainly driven by slope, followed by fuel type, CWD, and temperature.

### 4. Conclusions and discussion

We used a comprehensive set of spatial data sets to investigate the drivers of burn severity in California’s northern coastal mountains. The RF machine learning models developed were robust in capturing
Figure 4. Spatial maps of satellite-observed and predicted burn severity categories for three example fires: (a), (b) the 1990 Eagle fire during the cool drought, (c), (d) the 2015 Rocky fire during the warm drought, and (e), (f) the 2017 Northern California firestorm. The Rocky fire burned 28 100.64 ha at the end of July 2015. The Eagle fire occurred in August 1990 and burned 777.81 ha. The 2017 October firestorm burned 82 057.54 ha.

variations of burn severity at 30 m under and across different climate conditions, with models for all climatic scenarios achieving accuracy higher than 79%. We quantified the relative importance of short-term weather, fuels, long-term climate, and local environmental conditions in determining burn severity over the region’s diverse ecosystems and topography. Overall, topography (e.g. slope and aspect) and long-term temperature largely determined burn severity variation and lower fuel moisture, as indicated by lower pre-fire NDMI and higher CWD during the fire year, increased the burn severity. More shrubs and hardwood woodlands in the study area were burned during dry periods and higher severity occurred within shrubs. We also found the relative importance of variables varied under various climate conditions. Fire activity was more intense under warm and dry conditions, in terms of burned area, fire size, and burn severity. During dry years, severity of fires was affected almost equally
Figure 5. 2D density plot of the observed vs. predicted RdNBR for all burned pixels. The random forest regression model was based on all fire events. The red line represents 1:1 line. Density level was calculated via a multivariate kernel density estimation.

Figure 6. Variable importance of the RF classification models, (a) during all fire events, (b) during the dry conditions, and (c) during the wet conditions, respectively; Mean decrease accuracy for the classification models was based on the out-of-bag (OOB) samples, representing the amount of decrease in accuracy when removing the variable from a particular model. Variables were ranked according to the relative importance from the model based on all fire events.

by aspect, slope, long-term min temperature variations, fuel availability, and fuel moisture. However, for fires that burned during relatively wet years, current CWD, long-term CWD, and long-term temperature were dominant besides slope and elevation.

We also tested some other more sophisticated machine learning models, such as the light gradient boosting machine (Ke et al. 2017) and extreme gradient boosting machine (Chen and Guestrin 2016), for modeling the four categories of burn severity. These models only achieved slightly higher overall accuracy by less than 3% for the model including all fires across the years. For models under the four climatic conditions (namely dry, wet, the warm drought, and the cool drought), the RF model had achieved even higher accuracy and Kappa than these gradient boosting machines (Table S4).
Future improvement of the model accuracy may take advantages of some other advanced machine learning approaches such as deep neural networks.

### 4.1. Topographic impacts

Topographic factors, such as slope and aspect, strongly controlled burn severity across the landscape.

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**Figure 7.** The surrogate classification trees for (a) all burned pixels during 1984–2017, and for (b) hardwood woodland and (c) hardwood forest, based on top 16 important variables from the random forest classification model. The final nodes were labeled by the dominant category. The percentage under each node shows the corresponding proportion of samples belonging to that node.
of California’s northern coastal Mountains. This is similar with the findings in Sierra Nevada and Klamath mountains of northern California by Kane et al (2015) and Estes et al (2017). In several ecosystems of the western US, however, previous studies indicated more marginal effects of topography on severity (Thompson and Spies 2010, Parks et al 2018). The differences in the relative importance of variables may depend on the study area and the associated topographic variability. For example, Thompson & Spies only examined the 2002 Biscuit fire in southwestern Oregon, which had relatively low variability in elevation. Across the western US, topography was found with negligible influence on burn severity (Parks et al 2018), but for California ecoregions their high-severity probability model based on nine environmental features still showed significant local effects of topography on burn severity.

4.2. Influences of climate and weather
Climatic and weather extremes have long been argued driving the increase in the intensity of wildfire size
and severity (Bessie and Johnson 1995, Thompson and Spies 2010). A study in the western US showed that high temperature and precipitation extremes intensified droughts and accumulated CWD, which further increased burn severity (Crockett and Westerling 2018). Our results showed that both long-term minimum temperature and long-term CWD were key factors affecting the variation of burn severity across all fires since 1984, followed by annual CWD during the fire year, especially over areas burned during the wet periods. Under most climatic scenarios, weather conditions, such as temperature and precipitation, during the fire year/month were not among the top important variables, except during the wet years. This might be because the indirect impacts of other preceding weather have been represented by their influence on fuel characteristics variables such as NDMI in our study, consistent with findings from previous studies (Lutz et al 2010, Parks et al 2018).

Wind speed and direction at 4 km resolution had low predictive ability according to our model results for the whole time periods and warm droughts, probably due to the spatial resolution of wind datasets. The spatial variations of wind patterns within fire perimeters could not be captured by the coarse resolution GRIDMET wind data (Abatzoglou 2013). When compared among the four climatic conditions, however, wind speed had relatively the highest importance for burn severity during wet years (figure 6). This is consistent with some previous studies showing an increasing wind effects on recent extreme fire events, such as the wet year 2017 with extreme fires (Nauslar et al 2018, Mass and Ovens 2019). Further studies are needed when high-resolution wind data becomes available, to separate fires into fuel- and wind- dominant types for a better quantification of the impacts of wind on burn severity (Keeley and Syphard 2019).

In addition, although we considered the potential lag effect of precipitation, e.g. previous 1- to 3-year cumulative rainfall, the potential compounding effects of the transition from a prolonged multi-year drought to a wet year are worth a comprehensive study. For example, the catastrophic 2017 fire storms in the wine counties coincided with strong Diablo wind events, a relatively wet winter, and preceding four-year drought (Nauslar et al 2018). In California, the increasing frequency of a rapid transition from extreme dry-to-wet precipitation events has been observed in the past 2 decades (Berg and Hall 2015, Swain et al 2018). This climate whiplash is projected to continue to increase through mid-to-late of the century, on top of extreme temperature, further worsening future severe fire risk in the region (Swain et al 2018).

4.3. Influences of fuels
Fuel characteristics, such as fuel loading and moisture, were key variables in determining burn severity across all fires, according to both classification and regression models. This is consistent with previous findings that pre-fire stand conditions affect burn severity significantly both within individual fires and across fires in western US (Bigler et al 2005, Thompson and Spies 2010, Birch et al 2015, Estes et al 2017, Safford and Stevens 2017, Parks et al 2018). Our results showed that fuel levels played an important role in burn severity across the landscape, as indicated by NDMI and annual maximum EVI. Interactions may exist among NDMI, fuel type, and vegetation height. Across the four climatic scenarios, fuel amount was found to have stronger impacts on burn severity when under warm and dry conditions. A possible explanation is that fuels desiccate faster during droughts (Bigler et al 2005). Accumulations of dry fuels might thus increase burn severity during droughts.

Across the landscape, the moisture of fuels was affected by long term climate such as 30 year mean CWD and further regulated by short term weather, e.g. both lack of precipitation and higher temperature drying out fuels. NDMI is a proxy of leaf water content from Landsat remote sensing observations and indicates fuel moisture. It has been found to serve as a robust driver of severity (Estes et al 2017; Parks et al 2014b). In our study, lower NDMI before fire was found significantly associated with higher severity of burns.

4.4. Management implications
Wildfire adaptation, mitigation strategies, and management practices are needed for local communities, to reduce future burn severity, in response to increased warming and drying and associated increasing wildfire activity (Hessburg et al 2015). The predictive capability of our RF models is expected to help us anticipate the probability of high severity burns, based on near real-time fuel information from satellite observations and weather, in addition to the baseline climate. For example, the predictions showed a very heterogeneous pattern of high burn severity across the whole study area and also suggested an increased high severity probability during the dry years than wet years, especially in the northwest and southern part of the region (figure S7). Our model, however, used the explicit near real-time information from Landsat satellite observations, which limits the potential for projecting burn severity under the future climate change scenarios. Future studies are needed to incorporate the dynamic vegetation and fuel models for a more realistic projection. Overall, the RF classification model has the capability to predict the probability of each burn severity category in near real time or forecast the short-term burn severity at a 30 m scale in the study region if a fire would occur, driven by current and preceding fuel information and the corresponding weather data.
Although factors like long-term temperature or temperature variations are externalities to local management, this study can help us to identify areas subject to high fire severity, to design corresponding adaptation strategies to mitigate the impacts of future extreme weather events for both ecological and human systems. Our study highlighted that the topographic and long-term climate conditions are associated with severe burns along with fuels. For example, more mitigation efforts could be beneficially focused on steep slopes and areas with higher long-term minimum temperature and CWD, or areas where the projected increase in minimum temperature and CWD is more pronounced.

Our study also suggested that the degree to which one could manage the landscape varies with climate conditions. For example, fuel reduction and management may be helpful in reducing future risks of high severity burns, especially under dry and warm conditions, but it may be less effective during wet years. Our approaches can also be applied to other Mediterranean coastal mountain ranges, e.g. western Australia or the Mediterranean Basin, which are typically subject to high fire risk and have extensive wildland-urban interface (Rundel 1998, Fernandes 2013).

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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References

Abatzoglou J T Development of gridded surface meteorological data for ecological applications and modelling Int. J. Climatol. 33 121–31
Alencar A A, Brando P M, Asner G P and Putz F E 2015 Landscape fragmentation, severe drought, and the new Amazon forest fire regime Ecol. Appl. 25 1493–505
Altmann A, Tesoli L, Sander O and Lengauer T 2010 Permutation importance: a corrected feature importance measure Bioinformatics 26 1340–7
Bedsworth L, Cayan D, Franco G, Fisher L and Ziaja S 2018 Statewide Summary Report, California’s Fourth Climate Change Assessment. Publication number: SUMCCCCA4-2018-013
Berg N and Hall A 2015 Increased interannual precipitation extremes over California under climate change J. Clim. 28 6524–34
Berry K J and Mielke P W Jr 1988 A generalization of Cohen’s kappa agreement measure to interval measurement and multiple raters Educ. Psychol. Mess. 48 921–33
Bessie W C and Johnson E A 1995 The relative importance of fuels and weather on fire behavior in subalpine forests Ecology 76 747–62
Bigler C, Kulakowski D and Veblen T T 2005 Multiple disturbance interactions and drought influence fire severity in Rocky Mountain subalpine forests Ecology 86 3018–29
Birch D S, Morgan P, Kolden C A, Abatzoglou J T, Dillon G K, Hadak A T and Smith A M S 2015 Vegetation, topography and daily weather influenced burn severity in central Idaho and western Montana forests Ecosphere 6 1–23
Bolton D K, Coops N C and Wulder M A 2015 Characterizing residual structure and forest recovery following high-severity fire in the western boreal of Canada using Landsat time-series and airborne lidar data Remote Sens. Environ. 163 48–60
Breiman L 2001 Random forests Mach. Learning 45 5–32
Chen T and Guestrin C 2016 Xgboost: a scalable tree boosting system Proc.22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining pp 785–94
Collins B M, Miller J D, Thode A E, Kelly M, van Wagendorp J W and Stephens S L 2009 Interactions among wildfire fires in a long-established Sierra Nevada natural fire area Ecosystems 12 114–23
Crockett J L and Westerling A L 2018 Greater temperature and precipitation extremes intensify Western US droughts, wildfire severity, and Sierra Nevada tree mortality J. Clim. 31 341–54
Cutler D R, Edwards Jr T C, Beard K H, Cutler A, Hess K T, Gibson J and Lawler J J 2007 Random forests for classification in ecolog. Ecology 88 2783–92
De Santis A and Chuvieco E 2009 GeoCBI: A modified version of the Composite Burn Index for the initial assessment of the short-term burn severity from remotely sensed data Remote Sens. Environ. 113 554–62
Dennison P E, Brewer S C, Arnold J D and Moritz M A 2014 Large wildfire trends in the western United States, 1984–2011 Geophys. Res. Lett. 41 2928–33
Dillon G K, Holder Z A, Morgan P, Crimmins M A, Heyerdahl E K and Lucre C H 2011 Topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006 Ecosphere 2 1–33
Ding Z and Fei M 2013 An anomaly detection approach based on isolation forest algorithm for streaming data using sliding window IFAC Proc. 46 12–17
Estes B L, Knapp E E, Skinner C N, Miller J D and Preisler H K 2017 Factors influencing fire severity under moderate burning conditions in the Klamath Mountains, northern California, USA Ecosphere 8 e01794
Fairen N R, Jin Y, Goulden M L and Randerson J T 2016 Spatial patterns and controls on burned area for two contrasting fire regimes in Southern California Ecosphere 7 e01210
Fernandes P M 2013 Fire-smart management of forest landscapes in the Mediterranean basin under global change Landsc. Urban Plan 110 175–82
Flint L E, Flint A L, Thorne J H and Boynton R 2013 Fine-scale hydrologic modeling for regional landscape applications: the California Basin characterization model development and performance Ecol. Process. 2 1–21
Fowler C T 2003 Human health impacts of forest fires in the southern United States: a literature review J. Ecol. Anthropol. 7 39–63
Fried J S, Torn M S and Mills E 2004 The impact of climate change on wildfire severity: a regional forecast for northern California Clim. Change 64 169–91
Liang S, Hurteau M D and Westerling A L 2017 Potential decline of fire-prone shrublands in California, USA Int. J. Wildland Fire 22 184–93
Lutz J A, Van Wagtendonk J W and Franklin J F 2010 Climatic water deficit, tree species ranges, and climate change in Yosemite National Park J. Biogeogr. 37 936–50
Lydersen J M, Collins B M, Brooks M L, Matchett J R, Shive K L, Povak N A, Kane V R and Smith D F 2017 Evidence of fuels management and fire weather influencing fire severity in an extreme fire event Ecol. Appl. 27 2013–30
Mass C F and Ovens D 2019 The Northern California wildfires of 8–9 October 2017: the role of a major downslope wind event Bull. Am. Meteorol. Soc. 100 235–56
Meigs G W, Donato D C, Campbell J L, Martin J G and Law B E 2009 Forest fire impacts on carbon uptake, storage, and emission: the role of burn severity in the Eastern Cascades, Oregon Ecosystems 12 1246–67
Meng R, Dennis P E, Huang C, Moritz M A and D’Antonio C 2015 Effects of fire severity and post-fire climate on short-term vegetation recovery of mixed-conifer and red fir forests in the Sierra Nevada Mountains of California Remote Sens. Environ. 171 311–25
Miller J D, Knapp E E, Key C H, Skinner C N, Isbell C J, Creasy R M and Sherlock J W 2009 Calibration and validation of the relative differenced Normalized Burn Ratio (dNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA Remote Sens. Environ. 113 645–56
Miller J D and Quayle B 2015 Calibration and validation of immediate post-fire satellite-derived data to three severity metrics Fire Ecol. 11 12–30
Miller J D and Safford H 2012 Trends in wildfire severity: 1984 to 2010 in the Sierra Nevada, Modoc Plateau, and southern Cascades, California, USA Fire Ecol. 8 41–57
Miller J D and Tohe, A E 2007 Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR) Remote Sens. Environ. 109 66–80
Nauslar N J, Abatzoglou J T and Marsh P T 2018 The 2017 North Bay and Southern California fires: a case study Fire 1 18
Parks S A, Dillon G K and Miller C 2014a A new metric for quantifying burn severity: the relativized burn ratio Remote Sens. Environ. 148 3182–44
Parks S A, Holsinger L M, Panunto M H, Jolly W M, Dobrowski S Z and Dillon G K 2018 High-severity fire: evaluating its key drivers and mapping its probability across western US forests Environ. Res. Lett. 13 044037
Parks S A, Paraisy M A, Miller C and Dobrowski S Z 2014b Fire activity and severity in the western US vary along slope gradients representing fuel amount and fuel moisture PLoS One 9 e99699
Pausas J G and Fernández-Muñoz S 2012 Fire regime changes in the Western Mediterranean Basin: from fuel-limited to drought-driven fire regime Clim. Change 110 215–26
Perry D A, Hessburg P F, Skinner C N, Spies T A, Stephens S L, Taylor A H, Franklin J F, McComb B and Riegel G 2011 The ecology of mixed severity fire regimes in Washington, Oregon, and Northern California For. Ecol. Manage. 262 70–81
Radeloff V C et al 2018 Rapid growth of the US wildland-urban interface raises wildfire risk Proc. Natl Acad. Sci. 115 3314–9
Reed B C, Brown J F, Vanderzee D, Loveland T R, Merchant J W and Olhen D O 1994 Measuring phenological variability from satellite imagery J. Veg. Sci. 5 703–14
Rokach L and Maimon O 2005 Top-down induction of decision trees—an overview Machine Learning and Cybernetics (IEEE Cat. No. 03EX693) IEEE 5 3077–81
Rundel P W 1998 Landscape disturbance in Mediterranean-type ecosystems: an overview Landscape Disturbance and Biodiversity in Mediterranean-type Ecosystems (Berlin: Springer) pp 3–22
Safford H D and Stevens J T 2017 Natural range of variation for yellow pine and mixed-conifer forests in the Sierra Nevada,
southern Cascades, and Modoc and Inyo National Forests, California, USA. Gen. Tech. Rep. PSW-GTR-256
Albany, CA: US Department of Agriculture, Forest Service, Pacific Southwest Research Station. 229 p 256
Safford H D and Van de Water K M 2014 Using fire return interval departure (FRID) analysis to map spatial and temporal changes in fire frequency on national forest lands in California. Res. Pap. PSW-RP-266. Albany, CA: US Department of Agriculture, Forest Service, Pacific Southwest Research Station. 59 p 266
Schoennagel T et al 2017 Adapt to more wildfire in western North American forests as climate changes Proc. Natl Acad. Sci. 114 4582–90
Schwartz M W, Butt N, Dolanc C R, Holguin A, Moritz M A, North M P, Safford H D, Stephenson H D, Thorne J H and van Mantgem P J 2015 Increasing elevation of fire in the Sierra Nevada and implications for forest change Ecosphere 6 1–10
Steel Z L, Koontz M J and Safford H D 2018 The changing landscape of wildfire: burn pattern trends and implications for California’s yellow pine and mixed conifer forests Landsc. Ecol. 33 1159–76
Stephenson N 1998 Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales J. Biogeogr. 25 855–70
Strobl C, Boulesteix A-L, Zeileis A and Hothorn T 2007 Bias in random forest variable importance measures: illustrations, sources and a solution BMC Bioinformatics. 8 25
Stuart J, Stephens Set al 2006 North Coast Bioregion Fire in California’s Ecosystems, ed N G Sugihara, J W Van Wagtendonk and J Fites-Kaufman (Berkeley, CA: University of California Press) pp 147–69
Sugihara N G, Van Wagtendonk J W and Fites-Kaufman J 2006 Fire as an ecological process Fire California’s Ecosyst. 1916 58–74
Swain D L, Langenbrunner B, Neelin J D and Hall A 2018 Increasing precipitation volatility in twenty-first-century California Nat. Clim. Chang. 8 427
Thompson J R and Spies T A 2010 Factors associated with crown damage following recurring mixed-severity wildfires and post-fire management in southwestern Oregon Landsc. Ecol. 25 773–89
Thorne J H, Boynton R M, Flint L E and Flint A L 2015 The magnitude and spatial patterns of historical and future hydrologic change in California’s watersheds Ecosphere 6 1–30
van Mantgem P J, Nesmith J C B, Keifer M, Knapp E E, Flint A and Flint L 2013 Climatic stress increases forest fire severity across the western United States Ecol. Lett. 16 1151–6
Williams A P and Breiman L 2001 Random forests Machine Learning 45 5–32