Fuels Influence on Fire Regimes in California's Ecosystems

Sarah L. Hettema

ABSTRACT

California's ecosystems are facing longer fire seasons and warming temperatures that increase fire potential. Understanding the distribution of fuel loads and how fuel types and quantity interact to influence fire behavior could help managers devise fuel management strategies to effectively maintain ecosystem health. In this study, I aimed to determine how fuels influence fire size in different California ecoregions. I used ArcGIS Pro and Python to determine the spatial distribution of fuels in California's 13 ecoregions from 2001-2015. Next, I evaluated the trends in fuel density through time, and finally I evaluated the relationship between fuel density and fire size. The forested ecoregions contained the greatest average fuel density across the 1 hour, 10 hour, and 100 hour fuel classes and there was a statistically significant ($p < 0.001$) difference between the forested and non-forested fuel classes. Average fuel density and burn area were not correlated for any fuel classes (1 hour $R^2 = 0.002$; 10 hour, $R^2 = 0.0002$; 100 hour, $R^2 = 0.0003$). Fuel loading decreased over time and year had no impact on the relationship between fuel and fire size. Fuel loading has been suggested as a key contributor to the severity of California wildfires yet my study did not conclude a clear relationship between fuels and fire size. This can be attributed to the complexity of wildfires. Additional research on the interactions between fire regime variables is necessary to fully understand the implications of fuel distribution across the state.

KEYWORDS

California Air Resources Board (CARB), Monitoring Trends in Burn Severity (MTBS), timelag fuel classes, spatial distribution of fuels, fire size

INTRODUCTION

Global climate change is causing increased wildfire severity worldwide (Harvey 2016). Locally, California ecosystems are facing longer fire seasons and warming temperatures that increase fire potential (Liu et al. 2013). This acceleration in fire severity was demonstrated in the 2017 Tubbs Fire, the most destructive fire in California history, which killed 22 people and destroyed 5,636 structures (Herring et al. 2020). In 2018, the Camp Fire, which caused 85 deaths and destroyed 19,000 structures, surpassed the Tubbs fire and became the most deadly and destructive fire in California history (Herring et al. 2020). The 2020 fire season followed the same trend. The August Complex fire spanned seven counties, burned 1,032,648 acres, destroyed 935 structures, and resulted in one death (CAL FIRE 2021). Area burned and the length of fire seasons are projected to significantly increase by mid-century (Yue et al. 2013).

The behavior of wildfire is influenced by three key factors with different temporal properties: topography, fuels, and weather (Belongie and Minnich 2018). Topography is considered stable because it does not change over short time periods and weather is considered the most dynamic because it changes frequently and can vary greatly over landscapes (Belongie and Minnich 2018). Fuel impacts are dictated by the fire adaptations of vegetation and the spatial distributions of fuel quantity, structure, and flammability (Stephens et al. 2018). Because many variables influence fire, it is a challenge to predict the effects of climate change and human influence on California's varied fire regimes.

Fuels are a key factor that influence fires. They are the focus of current fire management strategies due to their ability to limit fires and the success of management procedures at directly altering fire regimes. Key components of fuel loads include fuel type (surface, ladder, or crown), fuel quantity, and the size of fuels (Stephens et al. 2018). Furthermore, surface fuel moisture is dictated by timelag theory, the time it takes for two-thirds of fuel to respond to atmospheric moisture (Bradshaw et al. 1984). Fuels are classified based on size because the proportion of fuel exposed to the atmosphere is related to the surface area to volume ratio (Bradshaw et al. 1984). Small fuels have a high surface area to volume ratio and dry out quickly whereas large fuels have a low surface area to volume ratio so the fuel piece dries out more slowly (Bradshaw et al. 1984). The timelag fuel classes are grouped based on how quickly they can respond to atmospheric conditions. These classes are 1 hour fuels (less than .25 inches in diameter), 10 hour fuels (between

.25 and 1 inch in diameter), and 100 hour fuels (between 1 and 3 inches in diameter) (Bradshaw et al. 1984). Ultimately, understanding the distribution of California's fuel loads and how fuel types and the quantity of fuels interact to influence fire behavior can help managers adjust fuel management strategies to more effectively maintain ecosystem health.

Fire regime variables interact throughout California's ecosystems creating a varied landscape of wildland fire. Seven attributes are proposed to classify fire regimes including seasonality, fire return interval, size, spatial complexity, fire intensity, severity, and type (Sugihara et al. 2018b). Fire size is a spatial fire regime variable that measures the unburned and burned area within a fire perimeter (Sugihara et al. 2018b). The size of a fire is determined by fuel continuity, site productivity, topography, weather, and fuel conditions (Sugihara et al. 2018b). Fire size attributes differ throughout California and are linked to the status of fuel loads. In this study, I will assess the fire regime attribute fire size. To better help California prepare for future disturbances, it is critical to understand the variables that influence fire behavior.

This study aims to determine how fuels influence fire size in different California ecoregions. I aim to answer: (1) What is the spatial distribution of surface fuel loads in each ecoregion? (2) Is fuel density changing over time?, and (3) What is the relationship between fuel density and fire size?. I expect to find that the fuel density will be significantly different across ecoregions. The ecoregions with larger burned areas will have a greater average of tons per acre of surface fuels and that fires will decrease fuel density over time.

METHODS

Study site

California is divided into diverse ecoregions and within many of these ecoregions, fire provides an important service. These regions include Cascades, Central Basin and Range, Central California Foothills and Coastal Mountains, Central California Valley, Coastal Range, Eastern Cascades Slopes and Foothills, Klamath Mountains/California High North Coast Range, Mojave Basin and Range, Northern Basin and Range, Sierra Nevada, Sonoran Basin and Range, Southern California Mountains, and Southern California/ Northern Baja Coast (Table 1) (Griffith et al. 2016). I grouped the ecoregions into three groups (forest, oak woodland/chaparral, and grassland/desert) based on their dominant vegetation types. Throughout this varied landscape, approximately 54% of the state requires fire to maintain the health of vegetation (Sugihara et al. 2018a).

Table 1. Ecoregion groups. Three ecoregion groups determined by dominant vegetation type.

Ecoregion Group	Ecoregions
Forest	1 - Coast Range (CR), 4 - Cascades (CAS), 5 - Sierra Nevada (SN), and 8 - Klamath Mountains (KM)
Oak Woodland/ Chaparral	6 - Central California Foothills and Coastal Mountains (CCFCM), 9 - Southern California Mountains (SCM), and 13 - Eastern Cascades Slopes and Foothills (ECSF)
Grassland/Desert	2 - Central Basin and Range (CBR), 3 - Mojave Basin and Range (MBR), 7 - Central California Valley (CCV), 10 - Northern Basin and Range (NBR), 11 - Sonoran Basin and Range (SBR), and 12 - Southern California/Northern Baja Coast (SCNBC)

Data selection

For this study, I used an ecoregion shapefile developed by the U.S. Geological Survey (USGS) and partner organizations (Figure 1, Griffith et al. 2016). I characterized the relationships between fuels and fire size within California's 13 ecoregions, and aggregated to the groupings in Table 1, because LANDFIRE fuels data (described below) is more accurate on a large scale (Ottmar et al. 2007).

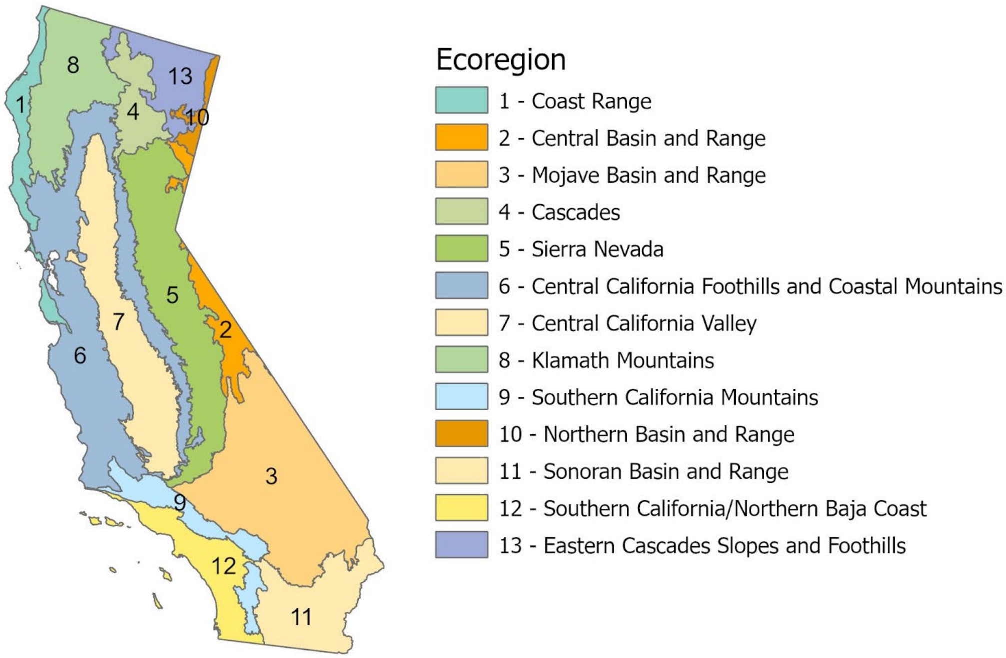


Figure 1. Ecoregion map. 13 ecoregions used in this study (Griffith et al. 2016). Forest ecoregions: 1-Coast Range (CR), 4-Cascades (CAS), 5-Sierra Nevada (SN), and 8-Klamath Mountains (KM). Oak woodland/chaparral ecoregions: 6-Central California Foothills and Coastal Mountains (CCFCM), 9-Southern California Mountains (SCM), and 13-Eastern Cascades Slopes and Foothills (ECSF). Grassland/desert ecoregions: 2-Central Basin and Range (CBR), 3-Mojave Basin and Range (MBR), 7-Central California Valley (CCV), 10-Northern Basin and Range (NBR), 11-Sonoran Basin and Range (SBR), and 12-Southern California/Northern Baja Coast (SCNBC).

In this study, I analyzed fuel and fire size data. For fuels data, I used the California Air Resource Board (CARB) (Table 2) annual fuel density rasters (Foster et al. 2019). These data are based on LANDFIRE Fuel Characteristic Classification System (FCCS) developed by the Wildland Fire Science, Earth Resources Observation and Science Center, U.S. Geological Survey (LANDFIRE 2020). FCCS includes calculations of fuelbeds, a measure of physical characteristics and potential fire behavior, and was developed by compiling published literature, fuel photo series, other fuels data sets, and expert opinion (LANDFIRE 2020). The CARB fuelbed data contains six horizontal fuel layers (canopy, shrub, non-woody vegetation, woody fuel, litter/lichen/moss, and ground fuel), taken from the LANDFIRE Existing Vegetation Type (EVT) layer, which are further classified into 1 hour, 10 hour, and 100 hour categories to represent the complexity of wildland fuels. Because the CARB data use qualitative classifications, which limits its accuracy compared to quantitative data, it is recommended for use on larger scales because it has limited accuracy for local assessments (Ottmar et al. 2007).

For fire size data, I used the Monitoring Trends in Burn Severity Project (MTBS) (Table 2) dataset, which includes the burn severity and extent of fires larger than 1000 acres (400 hectares) in the western United States from 1984 to the present (Eidenshink et al. 2007). The project was started in 2005 and is conducted by the U.S. Geological Survey Center for Earth Resources Observation and Science (EROS) and the USDA Forest Service Geospatial Technology and Applications Center (GTAC) (Eidenshink et al. 2007).

Table 2. Summary of data used for analysis.

Layer	Variables	Reference
Ecoregions of California	California ecoregion boundaries	Griffith, G. E., J. M. Omernik, D.W. Smith, T. D. Cook, E. Tallyn, K. Moseley, and C. B. Johnson. 2016. Ecoregions of California: U.S. Geological Survey. Accessed 15 November 2020 at http://ecologicalregions.info/htm/ca_eco.htm.
California Air Resources Board (CARB) - Fuel Characteristic Classification System (FCCS)	Surface fuels – 1 Hour, 10 Hour, 100 Hour fuel density (tons/acre)	Foster, D., B. Collins, and S. Stephens. 2019. Final Report for 15-AQP007:33. California Air and Resources Board. University of California, Berkeley, California, USA.
Monitoring Trends in Burn Severity project (MTBS)	Fire Size – total acres burned (acres)	Eidenshink, J., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. Howard. 2007. A Project for Monitoring Trends in Burn Severity. Fire Ecology 3:3–21.

Data analysis

To understand the spatial distribution of surface fuel loads I calculated summary statistics of fuelbeds in each ecoregion from 2001 to 2015. I downloaded the shapefile for ecoregions and TIFF files for the surface fuels data and added the raster and vector data layers to ArcGIS Pro. I then reprojected all layers to the same coordinate reference system (CRS), Albers Conic Equal Area. After confirming all layers were in the same projection, I joined the fuelbed loading table to match the corresponding raster value. Next, I split the ecoregion shapefile into 13 separate layers and clipped the fuel raster to each ecoregion. I exported the attribute tables from all 13 ecoregions for each fuel raster from 2001 to 2015.

I completed my analysis in Python by reading in each table and compiling the data into one data frame using pandas (McKinney 2010). To normalize the size of the ecoregions, I created an average fuel density metric by dividing the fuel amount by the area of each ecoregion. I used an independent t-test to determine if there was a significant difference between forested and non-forested ecoregions. For the t-test my null hypothesis was there is no difference in the mean fuel density between forested and non-forested ecoregions and the alternative hypothesis was there is a difference in the mean fuel density between forested and non-forested ecoregions. I used the scipy.stats package to determine the t-statistic and p-value for the t-test (Virtanen et al. 2020). I plotted the fuel density data using plotnine, a python graphing package based on ggplot2 (Kibirige 2021).

To determine the relationship between fuel density and fire size, I used the spatial distribution of fuel density and fire size data to better understand fire size over the landscape. I added the MTBS shapefile to ArcGIS Pro and reprojected the CRS to Albers Conic Equal Area. I then used the Clip Raster by Polygon tool to clip the MTBS layer to the extent of California and created a new layer that included only the fires from 2001-2015. I then used the Spatial Join tool to add the ecoregion location to each fire. For each year, I further subset the fires to include fires that started in the same year.

Next, I clipped the fuel raster to the subset fire layer. Because the fuel data account for the disturbances that occurred in the same year, the fuel raster was offset by one year from the fire size data (ie. for 2002, I used 2001 fuel data and 2002 fire perimeters). I computed the mean fuel loading for the three fuel classes within each fire using the zonal statistics tool and joined the mean fuel load of each fire to the fire perimeter tables. Finally, I exported the combined fire and fuel data to Python and compiled all attribute tables into a comprehensive data frame. I excluded fires with a burn area of above 50,000 acres in my analysis. I visualized the relationship between fuel and fire size by creating scatter plots. I also ran a regression analysis computing the least-squares regression equation and R^2 to determine the linear relationship between the variables using the sklearn.linear_model package (Pedregosa et al. 2011).

RESULTS

What is the spatial distribution of surface fuel loads in each ecoregion?

The forested ecoregions (Table 1) had the highest fuel densities (Figure 2, Table 3). The CR (1) ecoregion contained the greatest average density of 100 hour fuels (1.951 tons/acre) over the 2001-2015 period followed by the CAS (4) (1.603 tons/acre), KM (8) (1.428 tons/acre), and SN (5) (1.395 tons/acre, Figure 2). The CAS (4) had the greatest density of 10 hour fuel (1.748 tons/acre), followed by the CR (1) (1.455 tons/acre), KM (8) (1.417 tons/acre), and the SN (5) (1.365 tons/acre). The oak woodland/ chaparral dominated ecoregions contained the next highest average 10 and 100 hour fuel densities (Figure 2, Table 3). The CCFCM (6) contained 0.352 tons/acre 10 hour fuels and 0.418 tons/acre 100 hour fuels, SCM (9) contained 0.476 tons/acre 10 hour fuels and 0.619 tons/acre 100 hour fuels, and ECSF (13) contained 0.352 tons/acre 10 hour fuels and 0.418 tons/acre 100 hour fuels. The grassland/desert dominated ecoregions contained the lowest fuel densities across the three fuel classes (Figure 2, Table 3). These ecoregions include CBR (2), MBR (3), CCV (7), NBR (10), SBR (11), and SCNBC (12). There was a statistically significant difference between the forested and non-forested ecoregions for all three fuel classes (1 hour, $p < 0.001$, t-stat = 6.791; 10 hour, $p < 0.001$, t-stat = 13.887; 100 hour, $p < 0.001$, t-stat = 9.648).

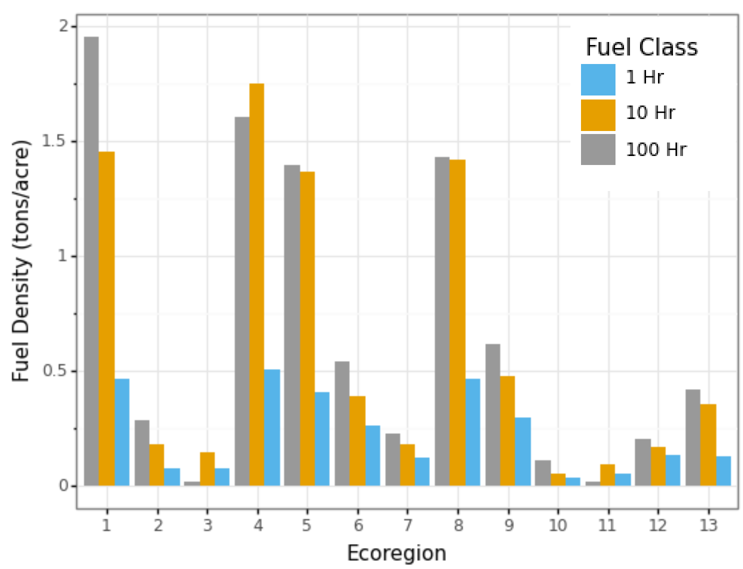


Figure 2. Average fuel density by fuel class for California's 13 ecoregions. 1 hour fuel (blue), 10 hour fuel (yellow), 100 hour fuel (grey). Forest ecoregions: 1-Coast Range (CR), 4-Cascades (CAS), 5-Sierra Nevada (SN), and 8-Klamath Mountains (KM). Oak woodland/chaparral ecoregions: 6-Central California Foothills and Coastal Mountains (CCFCM), 9-Southern California Mountains (SCM), and 13-Eastern Cascades Slopes and Foothills (ECSF). Grassland/desert ecoregions: 2-Central Basin and Range (CBR), 3-Mojave Basin and Range (MBR), 7-Central California Valley (CCV), 10-Northern Basin and Range (NBR), 11-Sonoran Basin and Range (SBR), and 12-Southern California/Northern Baja Coast (SCNBC).

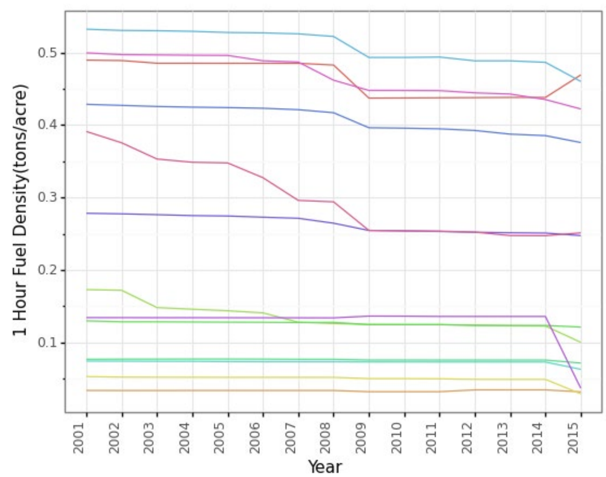
Table 3. Average fuel density for 1, 10, and 100 hour fuels in 13 ecoregions. Averages computed for the 2001-2015 period.

Ecoregion	1 hour fuel density(tons/acre)	10 hour fuel density(tons/acre)	100 hour fuel density(tons/acre)
1 - Coast Range (CR)	0.466928	1.455890	1.951268
2 - Central Basin and Range (CBR)	0.076147	0.179660	0.284453
3 - Mojave Basin and Range (MBR)	0.074289	0.146259	0.016720
4 - Cascades (CAS)	0.507037	1.748633	1.603653
5 - Sierra Nevada (SN)	0.409609	1.365144	1.395988
6 - Central California Foothills and Coastal Mountains (CCFCM)	0.264256	0.389429	0.543982
7 - Central California Valley (CCV)	0.124403	0.178433	0.228040
8 - Klamath Mountains (KM)	0.465428	1.417144	1.428170
9 - Southern California Mountains (SCM)	0.296906	0.476442	0.619096
10 - Northern Basin and Range (NBR)	0.033467	0.054452	0.110589
11 - Sonoran Basin and Range (SBR)	0.051305	0.094968	0.016934
12 - Southern California/Northern Baja Coast (SCNBC)	0.136168	0.172185	0.207318
13 - Eastern Cascades Slopes and Foothills (ECSF)	0.126383	0.352863	0.418274

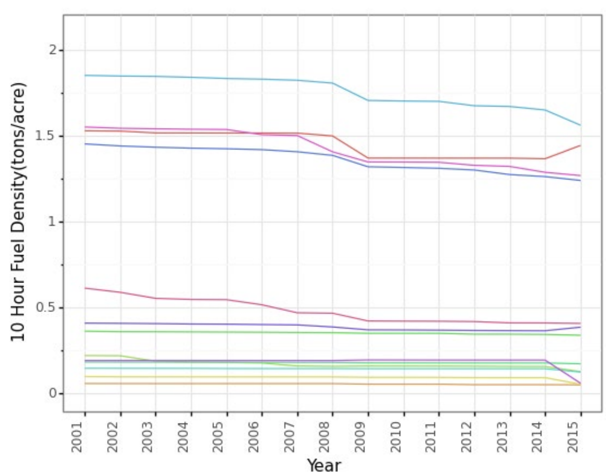
Is fuel density changing over time?

The forested ecoregions (CR (1), CAS (4), SN (5), and KM (8)) contained the highest fuel density for the three fuel classes in all years during 2001-2015 period (Table 3, Figure 3). This was followed by the oak woodland/chaparral ecoregions (CCFCM (6), SCM (9), and ECSF (13)). The grassland/desert dominated ecoregions contained the least amount of fuel over the time period. There was a downward linear trend over all ecoregions from 2001-2008. In 2009, the KM (8) experienced a slight increase in 100 hour fuels (2008, 1.360 tons/acre to 2009, 1.431 tons/acre). From 2008-2014, the downward trend continues but in 2015 the CR (1) (2014, 0.438 tons/acre to 2015, 0.469 tons/acre) and SCM (9) (2014, 0.247 tons/acre to 2015, 0.251 tons/acre) experienced an increase in 1 hour fuels, CR (1) (2014, 1.366 tons/acre to 2015, 1.444 tons/acre) and CCFCM

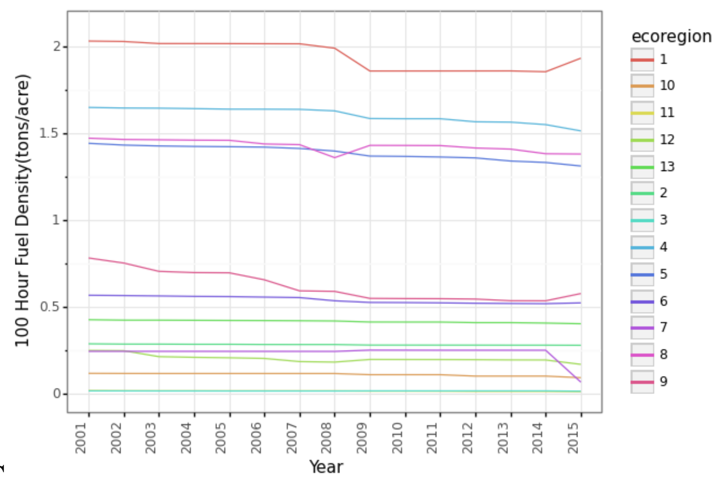
(6) (2014, 0.364 tons/acre to 2015, 0.385 tons/acre) experienced an increase in 10 hour fuels, and CR (1) (2014, 1.855 tons/acre to 2015, 1.933 tons/acre) and SCM (9) (2014, 0.535 tons/acre to 2015, 0.577 tons/acre) experienced an increase in 100 hour fuels.



A



B



C

Figure 3. Fuel density for three fuel classes from 2001-2015. (A) 1 hour fuel density, range (y-axis) from 0 tons/acre to 0.6 tons/acre. (B) 10 hour fuel density. (C) 100 hour fuel density.

What is the relationship between fuel density and fire size?

I found that average fuel density and burn area are not correlated in any fuel classes (1 hour, $R^2 = 0.002$; 10 hour, $R^2 = 0.0002$; 100 hour, $R^2 = 0.0003$ (Figure 4). There is not sufficient evidence of a relationship between fuel and fire size when looking at fires by ecoregion (Figure 4), nor by year (Figure 5). The Sierra Nevada (5) ecoregion demonstrates this lack of relationship (Figure 6). In the Sierra Nevada (5), average fuel density and burn area are not correlated in any fuel classifications (1 hour, $R^2 = 0.0006$; 10 hour, $R^2 = 0.0042$; 100 hour, $R^2 = 0.0046$) (Figure 6).

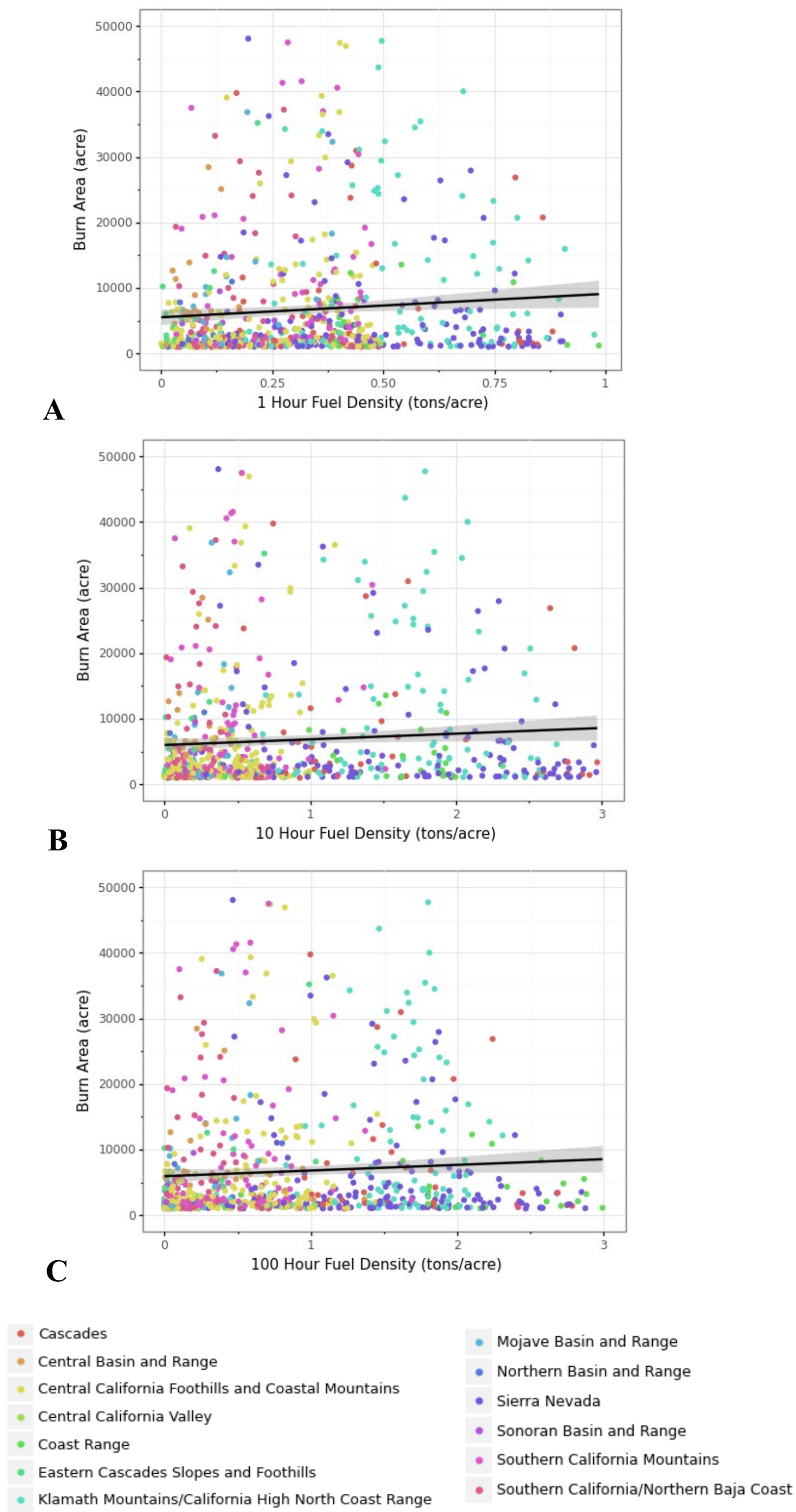


Figure 4. Fuel density and burn area by ecoregion for three fuel classes. (A) Regression equation for 1 hour fuel density vs burn area y = 6856.601x + 10245.580, $R^2 = 0.0020$. 1 hour fuel density range (x-axis) from 0 tons/acre to 1 tons/acre. (B) Regression equation for 10 hour fuel density vs burn area y = 544.308x + 12061.64, $R^2 = 0.0001$. (C) Regression equation for 100 hour fuel density vs burn area y = 847.764x + 11768.524, $R^2 = 0.0003$.

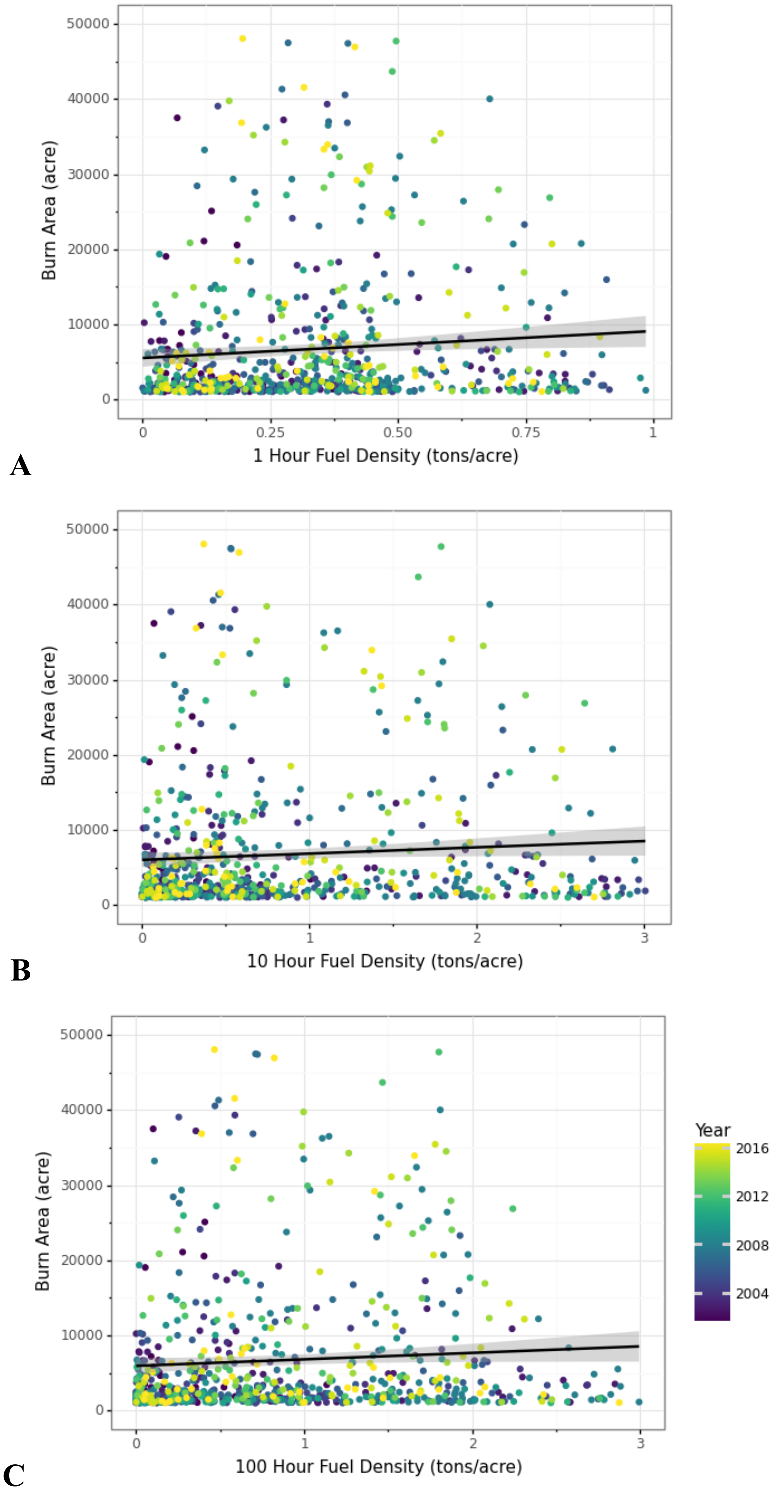
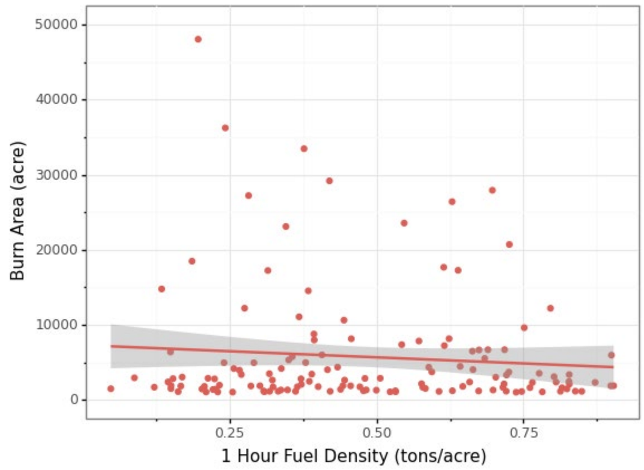
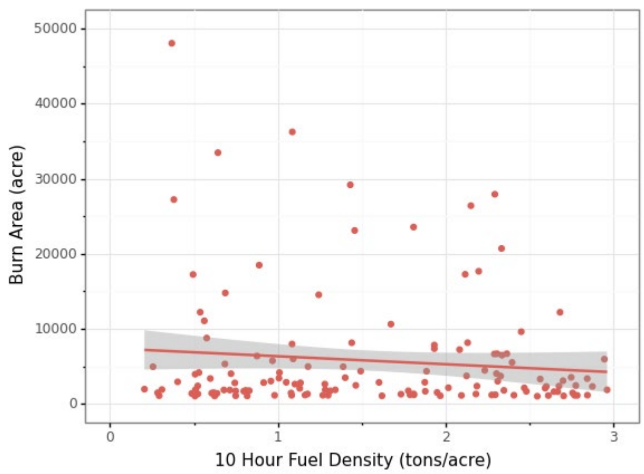


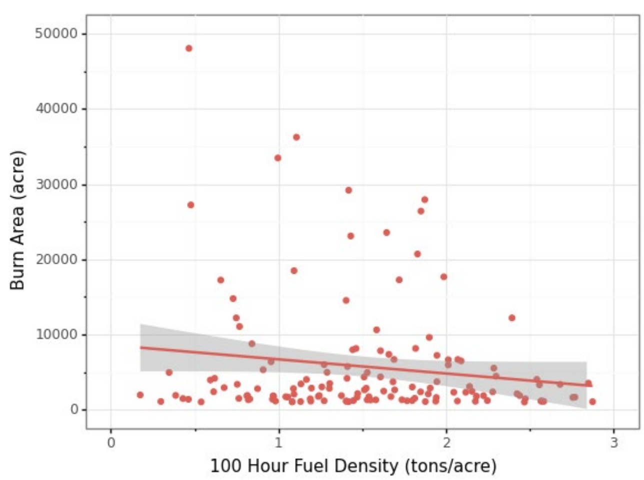
Figure 5. Fuel density and burn area by year for three fuel classes. (A) Regression equation for 1 hour fuel density vs burn area $y = 6856.601x + 10245.580$, $R^2 = 0.0020$. 1 hour fuel density range (x-axis) from 0 tons/acre to 1 tons/acre. (B) Regression equation for 10 hour fuel density vs burn area $y = 544.308x + 12061.64$, $R^2 = 0.0001$. (C) Regression equation for 100 hour fuel density vs burn area $y = 847.764x + 11768.524$, $R^2 = 0.0003$.



A



B



C

Figure 6. Sierra Nevada fuel density and burn area for three fuel classes. (A) Regression equation for 1 hour fuel density vs burn area y = -3416.806x + 12921.793, R^2 = 0.0006. 1 hour fuel density range (x-axis) from 0 tons/acre to 1 tons/acre. (B) Regression equation for 10 hour fuel density vs burn area y = -2408.768x + 15023.006, R^2 = 0.0042. (C) Regression equation for 100 hour fuel density vs burn area y = -3308.870x + 16278.223, R^2 = 0.0046.

DISCUSSION

I found that forested ecoregions contain the greatest fuel density across the three fuel classes followed by chaparral/oak woodland ecoregions, and the desert/grassland ecoregions contained the least amount of fuel. From 2001-2015 there was an average downward trend in fuel density across all 13 ecoregions. Even with this decrease, fuel density and fire size do not have a statistically significant relationship. This lack of relationship between fuel density and fire size over 2002-2016 suggests that other variables are impacting fire size. Wildfire is a complex system with many variables and studying these variables in isolation does not result in clear relationships.

What is the spatial distribution of surface fuel loads in each ecoregion?

Fuel is an important driver of high severity fire in forested regions (Park et al. 2018) and the larger fuel classes have the potential to contribute to larger more damaging fires (Bradshaw et al. 1984). The forested ecoregions had the greatest quantity of 1 hour, 10 hour, and 100 hour surface fuels. The higher level of 10 and 100 hour fuels can be attributed to trees as the dominant vegetation type (Omernik and Griffith 2014). The difference in average fuel density between the forest and non-forested ecoregions was significant. The forested ecoregions contain a greater density of fuels indicating there should be a focus on managing the fuelbeds in higher density ecoregions (Keeley and Syphard 2019).

Is fuel density changing over time?

Over the 2001-2015 period, on average the fuel density decreased over time. Again the forested ecoregions contained the greatest fuel density for the three fuel classes followed by the chaparral/oak woodland ecoregions, and grassland/desert ecoregions. This is indicative of the fuel consumed in a fire over the time period. In other studies, a significant linear relationship between fuel loading and consumption of dead and downed woody material has been observed across a range of fire intensities (Reid et al. 2012, Clark et al. 2015, Ottmar et al. 2016). Further research on how surface fuels are consumed in a fire can help plan prescribed burns and improve understanding of fire behavior (Clark et al. 2020).

I did not analyze fuel density and fire area relationships in 2016, which included an increase in all fuel class densities across all ecoregions. This increase was likely due to mass tree mortality during the California drought (Fettig et al. 2019); however, because I did not include drought metrics in my study I am not able to draw this conclusion. Determining the relationship between fire regimes and ecoregions is extremely useful for land managers so they can better prepare California for wildfires (Bailey 2010).

What is the relationship between fuel density and fire size?

Between 2002 and 2016 fire size was not limited by fuels. These results were contrary to my prediction that as fuel density increased burn area would increase. Recent studies show that extreme weather conditions can dominate the behavior of fires and heavy fuel loads do not determine the ultimate size of fires (Keeley and Syphard 2019). In lower elevation ecoregions with foehn winds, fuels are not the dominant driver of fire behavior whereas in higher elevation forested ecoregions fuel treatments can be an effective management strategy (Keeley and Syphard 2019). However, in forested ecoregions fuel treatments have yet to be deployed at an effective scale (Keeley and Syphard 2019). An additional study found no trends in the burned area over time but found an increase in the mean size of high severity burn area within fires (Rivera-Huerta et al. 2016).

I found that fuel and fire size do not have a significant relationship but this does not mean that these variables are unrelated. Fire is a complex system with many variables influencing fire behavior (Keeley and Syphard 2016). Studying two variables in isolation is not a holistic representation of a wildfire's effect. Additional variables impact fuel including quantity, structure, and flammability (Stephens et al. 2018) and fire suppression has strongly impacted the quantity and structure of fuelbeds. Fire suppression policies started in 1904, inhibiting indigenous fire stewardship and leaving California ecosystems without the necessary ecosystem service of fire (Taylor et al. 2016). Suppression allowed for the accumulation of fuels, increased continuity of fuels, reduced fuel patch heterogeneity, and diminished the self-limiting effect of burns (Taylor et al. 2016). The diversity of California's ecoregions brings a range of dynamics affecting the overall impact of fire variables across the landscape.

Limitations

In this study, I used pre-collected data for my analysis. Because these datasets were produced for general fire research, they contribute to the limitations of this study. I used ecoregion borders as an approximation for fire regimes. Because of climate change and the diversity of the California ecosystems it may be necessary to create ecoregion borders that account for expected changes in vegetation that drive fire regime changes (Syphard and Keeley 2020). Having a fire ecoregion map that incorporates projected vegetation and other fire regime variables could lead to a better understanding of fuel and fire dynamics (Syphard and Keeley 2020).

The fuel data also have limitations due to fuel classification inaccuracies (Keane et al. 2013). Because it is difficult to scale the classification scheme across large spatial domains the classification struggles to differentiate fuel bed components within the fuel classes (Keane et al. 2013). There are few projects that gather comprehensive fuel loading data despite fuel's importance in determining fire behavior effects (Keane et al. 2013). The 2020 LANDFIRE remap has been revised with disturbances between 2010 and 2016 and is able to estimate expected 2020 vegetation conditions (Picotte et al. 2019). The CARB project processed the FCCS data to include the effects of wildfire, timber harvest, and fuel treatments for 2001, 2008, and 2014 (Foster et al. 2019). An effort to apply the CARB methods to the remapped FCCS data may yield informative fuel loading results. Furthermore, the fire size data only maps fires above 400 hectares and because of this my analysis had an artificial lower limit for the fuel and fire size analysis (Whittier and Gray 2016).

Climate change and ecosystems changes are continually altering fire regime borders. Additionally, geospatial fuel data lacks high quality training and validation data (Keane et al. 2013). This combination of factors highlights the fundamental flaws of using top down geospatial analysis to model the effects of fire. My study could be improved by addressing the limitations of currently available fire data and better incorporating the known variables that influence fire.

Future Directions

Further research into fire regime variables and ecoregions is needed to better understand the interactions between variables. The first step in understanding these dynamics would be to redo my analysis with other databases. The 2020 FCCS remap data would provide a 2016 base map and with additional processing, one could compare the fuel loading from this study. Additionally, the CAL FIRE Fire and Resource Assessment Program (FRAP) contains fires from 1950-2001 including sizes of 10 acres and greater from the US Forest Service, 300 acres and greater from CAL FIRE, and starting in 2002 fires 10 acres and greater from the Bureau of Land Management and the National Park Service (CAL FIRE 2017). The FRAP fire perimeters would allow for an analysis of smaller fires. Finally, creating a fire regime-based ecoregion shapefile that maps vegetation changes would add additional depth to this study by accounting for the ecosystem changes that have occurred in the past century. Incorporating the amount of each fuel class consumed in each fire could further understanding of the spatial distribution of fuels over time.

Broader Implications

California fuel management is focused on prescribed burns and mechanical fuel treatments to decrease fuel loading because they have been found to reduce fire severity, crown scorch, and tree mortality (Kalies and Yocom Kent 2016). An ecosystem-based approach to current fuel management is essential because it would decrease tree density, increase mean canopy base height, and reduce surface fuels (Winford et al. 2015). Treatments that target surface fuels and tree density have been shown to have a positive effect on forest resilience to disturbances and stress (Winford et al. 2015). Fuel loading is a key contributor to the severity of California wildfires yet my study did not conclude a clear relationship between fuels and fire size. This indicates fire are not currently fuel-limited and there is substantial opportunity for large scale fuels treatments. Additional research on the interactions between fuels and fire regime variables is necessary to fully understand the implications of fuel distribution across the state.

ACKNOWLEDGMENTS

Thank you to Polly Buotte and Lara Kueppers for their help framing my research questions, data selection, and analysis. Their mentorship was vital to the completion of my project. I thank the ESPM 175 teaching team and my peer work group for their guidance. I specifically thank Patina Mendez and Natalie Coy for their support in developing my project and continuous feedback on my paper. Thank you to the UC Berkeley Geospatial Innovative Facility for assistance in geospatial analysis. This project would not have been possible without fuel data produced by the California Air Resources Board. Finally, I thank my family and friends for their love and support throughout this process.

REFERENCES

Bailey, R. G. 2010. Fire Regimes and Ecoregions. USDA Forest service RMRS GTR-231.

Belongie, B. L., and R. A. Minnich. 2018. Fire Weather Principles. Pages 27–38 Fire in California's Ecosystems.

Bradshaw, L. S., J. E. Deeming, R. E. Burgan, and J. D. Cohen. 1984. The 1978 National Fire-Danger Rating System: technical documentation. Pages 1-169. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT.

CAL FIRE [California Department of Forestry and Fire Protection]. 2017. California Interagency Fire Perimeter Database. http://frap.fire.ca.gov/data/frapgisdata-sw-fireperimeters_download

CAL FIRE [California Department of Forestry and Fire Protection]. 2021. Top 20 Largest California Wildfires. CAL FIRE, Sacramento, California, USA.

Clark, K. L., N. Skowronski, and M. Gallagher. 2015. Fire Management and Carbon Sequestration in Pine Barren Forests. Journal of Sustainable Forestry 34:125–146.

Clark, K. L., W. E. Heilman, N. S. Skowronski, M. R. Gallagher, E. Mueller, R. M. Hadden, and A. Simeoni. 2020. Fire Behavior, Fuel Consumption, and Turbulence and Energy Exchange during Prescribed Fires in Pitch Pine Forests. Atmosphere 11:242.

Eidenshink, J., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. Howard. 2007. A Project for Monitoring Trends in Burn Severity. Fire Ecology 3:3–21.

Fettig, C. J., L. A. Mortenson, B. M. Bulaon, and P. B. Foulk. 2019. Tree mortality following drought in the central and southern Sierra Nevada, California, U.S. Forest Ecology and Management 432:164–178.

Foster, D., B. Collins, and S. Stephens. 2019. Final Report for 15-AQP007:33. California Air and Resources Board. University of California, Berkeley, California, USA.

Griffith, G. E., J. M. Omernik, D.W. Smith, T. D. Cook, E. Tallyn, K. Moseley, and C. B.

Johnson. 2016. Ecoregions of California: U.S. Geological Survey. Accessed 15 November 2020 at http://ecologicalregions.info/htm/ca_eco.htm

Harvey, B. J. 2016, October 18. Human-caused climate change is now a key driver of forest fire activity in the western United States. National Academy of Sciences.

Herring, S. C., N. Christidis, A. Hoell, M. P. Hoerling, and P. A. Stott. 2020. Explaining Extreme Events of 2018 from a Climate Perspective. Bulletin of the American Meteorological Society 101:S1–S140.

Kalies, E. L., and L. L. Yocom Kent. 2016. Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. Forest Ecology and Management 375:84–95.

Keane, R. E., J. M. Herynk, C. Toney, S. P. Urbanski, D. C. Lutes, and R. D. Ottmar. 2013. Evaluating the performance and mapping of three fuel classification systems using Forest Inventory and Analysis surface fuel measurements. Forest Ecology and Management 305.

Keeley, J. E., and A. D. Syphard. 2016. Climate Change and Future Fire Regimes: Examples from California. Geosciences 6:37.

Keeley, J. E., and A. D. Syphard. 2019. Twenty-first century California, USA, wildfires: fuel-dominated vs. wind-dominated fires. Fire Ecology 15:24, s42408-019-0041–0.

Kibirige H. 2021. plotnine 0.8.0. https://plotnine.readthedocs.io/en/stable/about-plotnine.html

LANDFIRE, 2020, Fuel Characteristic Classification System Fuelbeds, LANDFIRE 2.0.0, U.S. Department of the Interior, Geological Survey. Accessed 15 November 2020 at https://www.landfire.gov/version_comparison.php.

Liu, Y., S. L. Goodrick, and J. A. Stanturf. 2013. Future U.S. wildfire potential trends projected using a dynamically downscaled climate change scenario. Forest Ecology and Management 294:120–135.

McKinney W. 2010. Data Structures for Statistical Computing in Python, Proceedings of the 9th Python in Science Conference, 51-56.

Omernik, J. M., and G. E. Griffith. 2014. Ecoregions of the Conterminous United States: Evolution of a Hierarchical Spatial Framework. Environmental Management 54:1249–1266.

Ottmar, R. D., D. V. Sandberg, C. L. Riccardi, and S. J. Prichard. 2007. An overview of the Fuel Characteristic Classification System — Quantifying, classifying, and creating fuelbeds for resource planning. Canadian Journal of Forest Research 37:2383–2393.

Ottmar, R. D., A. T. Hudak, S. J. Prichard, C. S. Wright, J. C. Restaino, M. C. Kennedy, and R. E. Vihnanek. 2016. Pre-fire and post-fire surface fuel and cover measurements collected in the south-eastern United States for model evaluation and development – RxCADRE 2008, 2011 and 2012. International Journal of Wildland Fire 25:10.

Parks, S. A., L. M. Holsinger, M. H. Panunto, W. M. Jolly, S. Z. Dobrowski, and G. K. Dillon. 2018. High-severity fire: Evaluating its key drivers and mapping its probability across western US forests. Environmental Research Letters 13.

Pedregosa, F. and G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research pp. 2825-2830.

Picotte, J. J., D. Dockter, J. Long, B. Tolk, A. Davidson, and B. Peterson. 2019. LANDFIRE Remap Prototype Mapping Effort: Developing a New Framework for Mapping Vegetation Classification, Change, and Structure. Fire 2:35.

Reid, A. M., K. M. Robertson, and T. L. Hmielowski. 2012. Predicting litter and live herb fuel consumption during prescribed fires in native and old-field upland pine communities of the southeastern United States. Canadian Journal of Forest Research.

Rivera-Huerta, H., H. D. Safford, and J. D. Miller. 2016. Patterns and Trends in Burned Area and Fire Severity from 1984 to 2010 in the Sierra de San Pedro Mártir, Baja California, Mexico. Fire Ecology 12:52–72.

Stephens, S. L., S. J. Husari, H. T. Nichols, N. G. Sugihara, and B. M. Collins. 2018. Fire and Fuel Management. Pages 411–428 Fire in California's Ecosystems.

Sugihara, N. G., T. Keeler-Wolf, and M. G. Barbour. 2018a. Introduction: Fire and California Vegetation. Pages 1–8 *Fire in California's Ecosystems*.

Sugihara, N. G., J. W. Van Wagtendonk, and J. A. Fites-Kaufman. 2018b. Fire as an Ecological Process. Pages 57–70 Fire in California's Ecosystems.

Syphard, A. D., and J. E. Keeley. 2020. Mapping fire regime ecoregions in California. International Journal of Wildland Fire 29.

Taylor, A. H., V. Trouet, C. N. Skinner, and S. Stephens. 2016. Socioecological transitions trigger fire regime shifts and modulate fire–climate interactions in the Sierra Nevada, USA, 1600–2015 CE. Proceedings of the National Academy of Sciences 113:13684–13689.

Virtanen P., R. Gommers, T. E. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, S. J. van der Walt, M. Brett, J. Wilson, K. J. Millman, N. Mayorov, A. R. J. Nelson, E. Jones, R. Kern, E. Larson, C. J. Carey, İ. Polat,

Y. Feng, E. W. Moore, J. VanderPlas, D. Laxalde, J. Perktold, R. Cimrman, I. Henriksen, E. A. Quintero, C. R. Harris, A. M. Archibald, A. H. Ribeiro, F. Pedregosa, P. van Mulbregt, and SciPy 1.0 Contributors. 2020. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. Nature Methods, 17(3), 261-272.

Whittier, T. R., and A. N. Gray. 2016. Tree mortality based fire severity classification for forest inventories: A Pacific Northwest national forests example. Forest Ecology and Management 359.

Winford, E. M., J. T. Stevens, and H. D. Safford. 2015. Effects of fuel treatments on California mixed-conifer forests. California Agriculture 69:150–156.

Yue, X., L. J. Mickley, J. A. Logan, and J. O. Kaplan. 2013. Ensemble projections of wildfire activity and carbonaceous aerosol concentrations over the western United States in the mid-21st century. Atmospheric Environment 77:767–780.