A RANDOM FOREST MODEL FOR THE PROBABILITY OF LARGE WILDFIRES IN CALIFORNIA

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ABSTRACT

Large wildfires in the western US are becoming more frequent and intense, but predicting their occurrence and intensity remains a challenge due to their spatio-temporal complexity and inter-dependence on coupled climatic and human factors. Remote-sensing data products for fire recognition are increasing in volume and resolution and there is an opportunity to leverage these products to develop data-driven wildfire models. However a data-driven approach first requires comprehensive validation to demonstrate model accuracy and ability to generalize, particularly if they are to be used for decision making. In this work we develop a random forest model for the occurrence of large wildfires given antecedent meteorological and vegetation parameters, using data from the recently-developed Global Fire Atlas of Andela et al. (2019), and compare the model against historical fires and existing wildfire risk models. We show that the model predictions are consistent with historical large fire occurrences, outperforming existing statistical measures. These results suggest that our model has the early-warning capability to help provide important decision making information.

1 INTRODUCTION

Climate change has made wildfires more extreme. Jolly & Bowman (2015) found that since 1979, global burnable area has doubled and fire season is 25% longer. This will only get worse, with a projected 100% increase in extreme wet/dry periods in California through the 21st century (Swain et al., 2018). Predicting fire risk is difficult due the inherent stochasticity of ignition, the spatiotemporal complexity of fire spread physics and the interdependence of climatic and human factors such as changing atmospheric temperature and moisture and the encroachment of urban landscape on forested regions. Existing models date back as far as the USDA development of the National Fire Danger Rating System (NFDRS) in the 1960s (Deeming & Cohen, 1978). The FDRS system accounts for a number of weather and environmental variables vegetation fuel moisture (calculated from daily temperature, humidity, solar radiation and precipitation), wind speed and direction. The interplay of these variables is reduced to two summary risk components, the Energy Release Component (ERC) and Burn Index (BI).

Preisler et al. (2004) developed a probabilistic framework for predicting large fires, which bypasses the complexity of modeling ignition and instead predicts the conditional probability of a fire started at time t and spatial location (x, y) growing over a certain size (40.5 hectares). We use a similar conditional probability framework in developing our model, described in section 2. Finney et al. (2011) developed a model called FSIM, which uses ERC to simulate the probabilistic generation and spread of thousands of fires. More recently Jolly et al. (2019) developed a quantile-based model that uses ERC and BI to assess historical fire occurrence and acres burned. We will compare our results against this model and the prevalent fire model used in Australia, the McArthur index Dowdy et al. (2009). Other models which used statistical approaches include Joseph et al. (2018); Finney et al. (2011); Parks et al. (2018).

Gray et al. (2018) proposed a machine learning method to predict weekly fire risk using a random forest model, as it can automatically detect patterns in large swathes of data and use them more effectively than other approaches. Although machine learning can do well at this task, only a few works in the literature address it (Ganapathi Subramanian & Crowley, 2018; Gray et al., 2018; Radke et al., 2019). One reason is the perceived lack of reliability. In this paper, we take the first step towards more comprehensive validation methods for machine learning based fire risk models by showing a case analysis methodology for validation of random forest-based wildfire risk models. Results show that a random forest beats more traditional approaches.

2 APPROACH

2.1 MODEL

We use a random forest (RF) classifier (Breiman, 2001) to model the conditional probability of large fire occurrence. On a raster map, this probability is defined as the probability that given an individual pixel is marked as burning, it spreads into a large fire. Following Gray et al. (2018), wildfires with fire size larger than $4\,\mathrm{km}^2$ are considered large fires.

The model's output is a binary classification: 0 for a small fire and 1 for a large fire. Small fires are defined as wildfires with a fire size smaller than $0.3\,\mathrm{km}^2$, given that the resolution of the historical fire data is $500\,\mathrm{m}$. We adopted a similar sampling method as described in Gray et al. (2018).

2.2 DATA

2.2.1 HISTORICAL FIRES DATABASE

We sampled data from the Global Fire Atlas dataset [1] (Andela et al., 2019), which provides information about fires between 2003 and 2016. Each fire has metadata showing its perimeters and ignition locations. We drew random samples from within these fire perimeters. We sampled equally many small and large fires across California. We drew at most one sample within each fire in order to avoid spatial auto-correlation or biasing sampling toward large fires. Data from 2003-2011 was used as training data and 2012-2016 was used for testing.

2.2.2 MODEL INPUTS: METEOROLOGY, FUEL CONDITION AND TOPOGRAPHY

Our model accepts as inputs three key aspects of the fire propagation: weather, fuel conditions, and topography; all of which have been shown to be important drivers of fire risk (Parks et al., 2018). The weather and fuel variables we use as inputs are obtained from the $4\,\mathrm{km}$ resolution gridMET dataset [2] (Abatzoglou, 2013). These include precipitation, min and max near-surface temperature, specific humidity, min and max relative humidity, mean 10-m wind speed and direction. For fuel, we use the energy release component (ERC), the Burn index (BI), 100 hour and 1000 hour dead fuel moisture (FM100 and FM1000). These variables are components of the US National Fire Danger Rating System (NFDRS) and directly reflect the fire and fuel conditions. Mean vapor pressure deficit is also used as it has been shown to affect ignition and fire size (Sedano & Randerson, 2014). For topography, we include three variables: elevation, slope and aspect, derived from the Shuttle Radar Topography Mission (SRTM) digital elevation data ($90\,\mathrm{m}$ resolution).

To put the data on the same spatial scale, all predictor variables that were not in a $1\,\mathrm{km}$ resolution were resampled using bilinear interpolation and were spatially summarized for each fire sample using a $2\,\mathrm{km} \times 2\,\mathrm{km}$ squared window. Weather and fuel variables were also temporally summarized with four different time lags: one day before the fire, one week before, one month before, and one week after the fire ends. These extra variables let us better depict the probability of a large fire over time by considering both the drivers that lead to and follow a fire at different time scales.

3 RESULTS AND VALIDATIONS

3.1 IMPORTANCE ANALYSIS: FIRE DRIVERS

Understanding which drivers most influence fire spread is a key research area and important to the interpretability of any machine learning model for fire risk. Compared to traditional methods (e.g., Joseph et al., 2018; Finney et al., 2011), random forests are particularly well-suited to exploring the

[1] `https://www.globalfiredata.org/fireatlas.html`
[2] `http://www.climatologylab.org/gridmet.html`

Table 1: The effect of time lag on predicting fire (normalized by the maximum).

TIME LAG	IMPORTANCE
One month before	1
One week before	0.86
One week before & after	0.83
One day before	0.78

interactions of the high-dimensional input variables and are easily interpretable. In this work we measure feature importance using a permutation based method (Figure 1). Permutation-based feature importance estimation is more computationally expensive than impurity-based feature importance, but it avoids the bias that the latter tends to prefer the continuous features or high cardinality categorical variables.

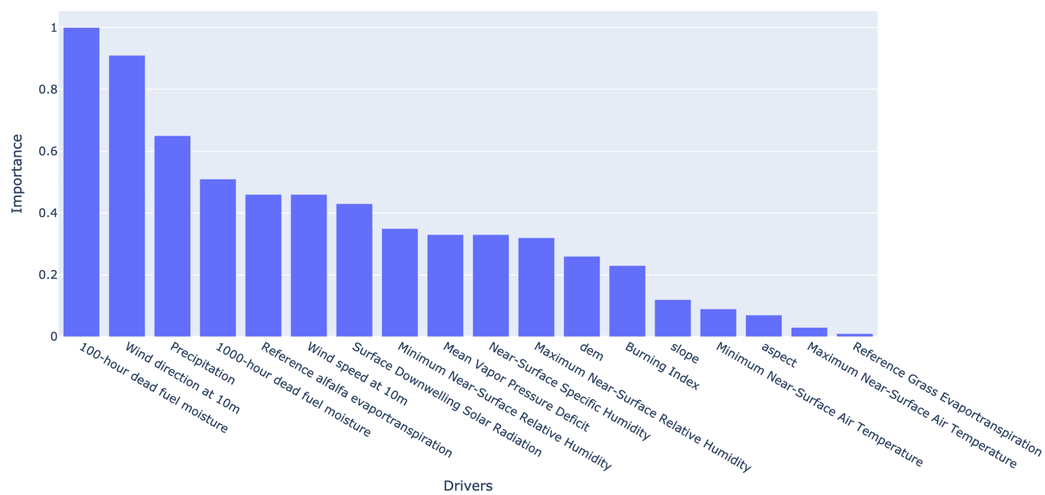


Figure 1: Describing Fire drivers vs importance (normalized to the maximum). Dead fuel moisture, precipitation and wind were found to be the significant drivers in our analysis.

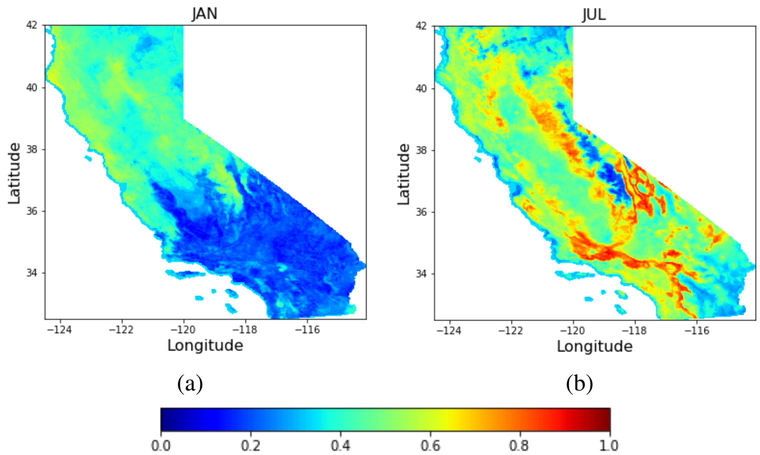
The relative driver importance (normalized by the maximum value) shown in Figure 1 is in line with the existing research (e.g., Parks et al., 2018; Dowdy et al., 2010). Dead fuel moisture, precipitation, and wind have greater influences on the fire spreading.

We predict the fire risk at every location in California over a $1\,\mathrm{km}$ resolution and generate weekly maps for the entire state. Each point on the map has a value in [0, 1], which is the probability that the classified point will become a large fire given an ignition. This value is our measurement of the Large Fire Probability (LFP), and the map is called the Large Fire Probability Map (LFPM). Weekly LFPM are averaged into monthly maps. Figure 2 is an example of LFPM in January and July 2016.

3.2 Validation on testing data

We perform validation of the LFPM in three stages. First, we evaluate our fire risk index using the test data (years 2012-2016). Second, we validate the early-warning capability of LFPM by analyzing four severe fire incidents from 2019. Third, our index is compared with a popular fire index in Australia: the McArthur Forest Fire Danger Index (FFDI) (Dowdy et al., 2009) and a fire index used officially in the US: Severe Fire Danger Index (SFDI) (Jolly et al., 2019).

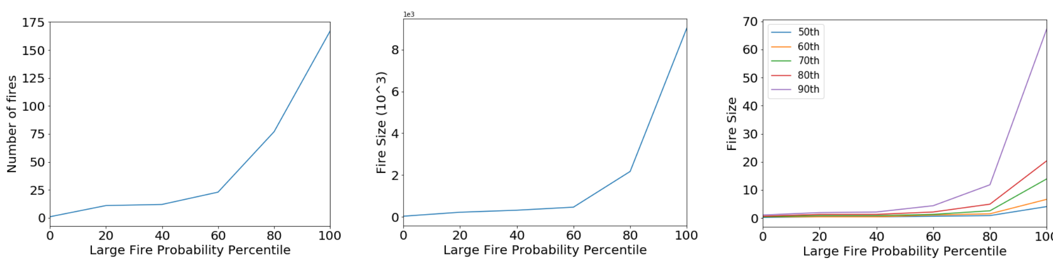
Global Fire Atlas data from 2012-2016 was used for testing. Validation of this subsection is built upon two hypotheses: (i) More large fire (fire size $> 4\,\mathrm{km}^2$) activity should be observed in higher LFP regions. (ii) Fires observed in higher LFP regions should be larger.



(a) (b)

Figure 2: An example of LFPM in 2016. On the left is January and on the right is July. We notice a clear seasonal difference in the risk, and that areas assigned high risk match actual high risk regions.

To better quantify yearly LFP, i.e., fire danger, yearly percentiles based on monthly values of each year within 2012-2016 are calculated separately for each year. We classify LFP percentiles into 5 bins from 0 to 100. The total amount of large fire activity observed in different percentiles is summarized in each bin according to (i) The total number of fires larger than $4\,\mathrm{km}^2$. (ii) The total area burned by each fire. (iii) The (50th, 60th, 70th, 80th, 90th) percentiles of final fire sizes.



(a) Number of Large Fire incidents (b) Total Burned Area (km^2) (c) Percentiles of Fire Sizes

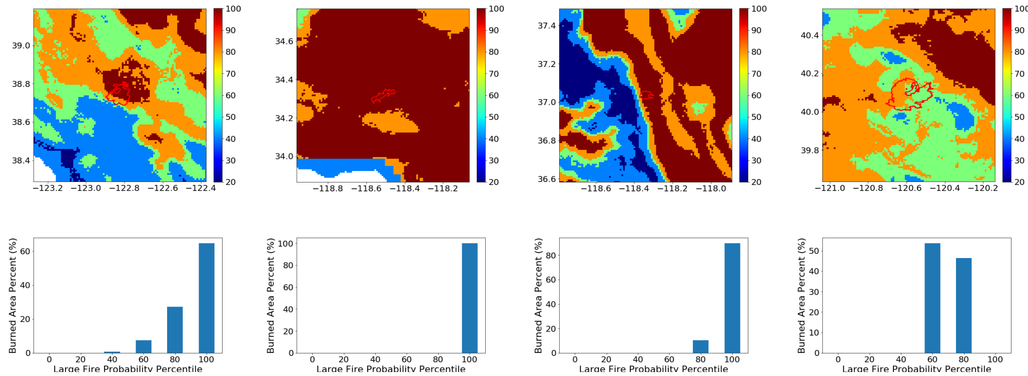
Figure 3: The relationships between LFP percentiles and historical fire activity: *(a)* counts of fire incidents with fire size larger than $4\,\mathrm{km}^2$, *(b)* cumulative burned area in each percentile bin and *(c)* percentiles of individual fire size from 2012-2016.

The plots in Figure 3 show that the number of large fire incidents and cumulative burned area increased exponentially with LFP percentiles. Figure 3(a) shows that the majority of large fires occurred when LFP was above its 80th percentile value. Figure 3(b) shows that total burned area is most highly associated with fire risk above the 80th percentile. Finally, fires which started at higher LFP ultimately achieved larger final fire sizes (figure 3(c)). These results suggest that LFP is a successful metric.

3.3 SEVERE FIRE INCIDENTS ANALYSIS IN 2019

To evaluate the early warning capabilities of LFPM, four well-known, severe fire incidents which occurred in California in 2019 were analyzed. These included the Kincade, Saddle Ridge, Walker and Taboose fires. Daily fire perimeter shape files were taken from GeoMAC[3] whenever available. The LFPM during the initial stages of the fires was selected. Forecast perfomance was evaluated by counting the number of grid cells in each LFP percentile bin that were burned during the first two days of the fire incidents. Results are shown in Figure 4.

[3]`https://rmgsc.cr.usgs.gov/outgoing/GeoMAC/`



(a) Kincade, $314.7\,\mathrm{km}^2$ (b) Saddle Ridge, $35.6\,\mathrm{km}^2$ (c) Taboose, $41.7\,\mathrm{km}^2$ (d) Walker, $221\,\mathrm{km}^2$

Figure 4: Four severe fire incidents in 2019 (a-d) Kincade, Saddle Ridge, Taboose and Walker. Top: LFP percentile maps overlaid with the perimeter of the fire incident in the first two days. Bottom: summaries of burned pixels percentage of each percentile bin

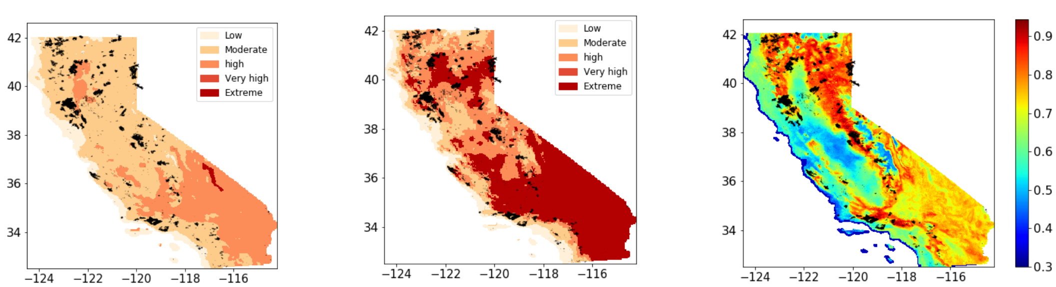
In our analysis, over 80% of the area that burned during the first two days was classified into very dangerous by weekly LFPM. Over 90% had very high LFP and 100% was over the 50th percentile. These results demonstrate the ability of LFPM to provide advanced fire danger information to help with decision making.

3.4 Comparing LFPM to FFDI and SFDI from 2012-2018

We compare our metric (LFPM) with FFDI and SFDI, spatially and temporally, to evaluate its accuracy. FFDI is the primary fire danger estimation in Australia (Sanabria et al., 2013). It is based on a combination of temperature, humidity, wind speed and drought factor (Dowdy et al., 2010), and has also been used as the US fire danger indicator (e.g., Abatzoglou & Williams, 2016). SFDI is a severe fire index recently proposed in Jolly et al. (2019). It is an index based on the product of the percentiles of two main components of the NFDRS, ERC and BI. It is used in the US to help provide critical decision support information and also serves as an early-warning system.

3.4.1 Spatial comparison

To compare the LFPM with FFDI and SFDI spatially to understand a broad-scale relationship, 95th percentiles of these three indices were used. Different from LFP percentiles, these 95th percentiles were calculated separately for each grid point throughout California during the years 2012-2018, as shown in Figure 5.



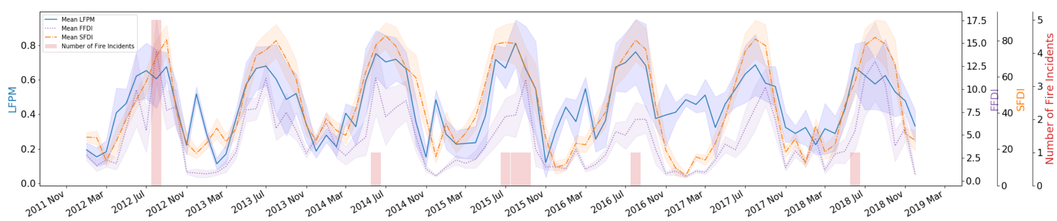
(a) FFDI (b) SFDI (c) LFPM

Figure 5: The 95th percentiles of each metric based on weekly values of the indices during 2012 - 2018 overlaid with historical fires (black contours) in the same years. FFDI and SFDI are all shown as the fire danger rating classes (see Appendix table 2 and table 3). LFPM is well correlated with the incidence of historical wildfires, in contrast with the poorly-performing FFDI and SFDI

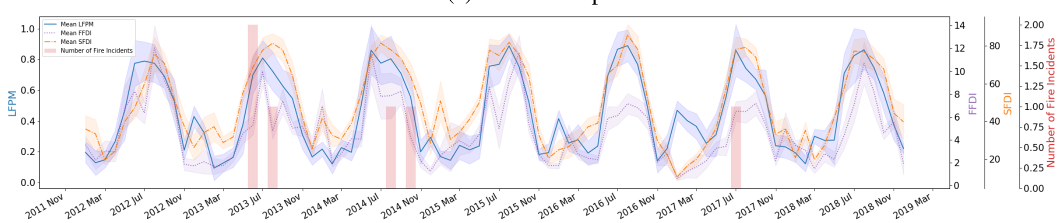
Figure 5 shows that LFPM has a good spatial alignment with the historical fires, while, although SFDI shows better results compared to FFDI, they both failed to predict the fire danger over the sand area. Unexpected high index values shown in the black square in Figure 5(a) is the death valley, where should have relative low fire risk. The LFPM reflects this spatial variability (Figure 5(c)). This shows that LFPM can handle different land types and has better spatial prediction capability than FFDI and SFDI.

3.4.2 Temporal comparison

Several locations were selected to analyze the temporal relationship among the indices. Figure 6 is an example of time series plots at two locations. These two locations are both high fire risk regions. A seasonal pattern is observed among the indices, which indicates they all have the ability to predict the occurrence of the fire seasons. LFPM and SFDI are highly correlated, and both have clear temporal patterns that match the fire occurrence well. FFDI doesn't successfully capture fire trends in 2016 and 2017. Moreover, FFDI consistently under estimated the fire risk (Table 2 in Appendix).



(a) Sonoma/Napa



(b) Yosemite

Figure 6: Time series plots of the averaged indices over a 25 km circular buffer. The axes represent LFPM, SFDI, LFPM and the number of the fire incidents, respectively. The bar chart shows the number of the fire occurrences in each month. All of the indices predicted the temporal up and down trend of the historical fire events reasonably. SFDI and LFPM show very similar patterns, while FFDI consistently indicates medium and low risk values, whereas the proposed index indicates high risk.

4 Conclusion and Future work

This work is meant as a first step towards using machine learning for fire risk prediction. We defined a validation framework and metric (LPFM) that shows reasonable predictive ability of large fire occurrence and has the ability to provide an early-warning of large fires.

There are several ways in which the work could be advanced. First is that the wind variables we use, obtained from gridMET are interpolated from NARR reanalysis at 32km and averaged daily. Using wind inputs at higher temporal and spatial resolutions will likely better capture the dynamic down-slope mountain winds which are particularly important in driving California fires (the Diablo winds in Northern California and the Santa Anas in Southern California) (Rolinski et al., 2016; Mass & Ovens, 2019). Additional improvements could also be made by (i) Adding more predictor variables such as the vegetation indices NDVI, NDWI, long period climate variables, etc. and (ii) Applying a regression model for fire size prediction rather than a binary classifier.

REFERENCES

John T Abatzoglou. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, 33(1):121–131, 2013.

John T Abatzoglou and A Park Williams. Impact of anthropogenic climate change on wildfire across western us forests. *Proceedings of the National Academy of Sciences*, 113(42):11770–11775, 2016.

Niels Andela, Douglas C Morton, Louis Giglio, Ronan Paugam, Yang Chen, Stijn Hantson, Guido R Werf, and James T Randerson. The global fire atlas of individual fire size, duration, speed and direction. *Earth System Science Data*, 11(2):529–552, 2019.

Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

R. E.; Deeming, J. E.; Burgan and J. D. Cohen. The national fire-danger rating system. *USDA Forest Service, Intermountain Forest and Range Experiment Station*, 1978.

Andrew J Dowdy, Graham A Mills, Klara Finkele, and William de Groot. Australian fire weather as represented by the mcarthur forest fire danger index and the canadian forest fire weather index. *Centre for Australian Weather and Climate Research, Melbourne, Australia, Tech. Rep*, 2009.

Andrew J Dowdy, Graham A Mills, Klara Finkele, and William de Groot. Index sensitivity analysis applied to the canadian forest fire weather index and the mcarthur forest fire danger index. *Meteorological Applications*, 17(3):298–312, 2010.

Mark A Finney, Charles W McHugh, Isaac C Grenfell, Karin L Riley, and Karen C Short. A simulation of probabilistic wildfire risk components for the continental united states. *Stochastic Environmental Research and Risk Assessment*, 25(7):973–1000, 2011.

Sriram Ganapathi Subramanian and Mark Crowley. Using spatial reinforcement learning to build forest wildfire dynamics models from satellite images. *Frontiers in ICT*, 5:6, 2018.

Miranda E Gray, Luke J Zachmann, and Brett G Dickson. A weekly, continually updated dataset of the probability of large wildfires across western us forests and woodlands. *Earth System Science Data*, 10(3):1715–1727, 2018.

Cochrane M. A. Freeborn P. H. Holden Z. A. Brown T. J. Williamson G. J. Jolly, W. M. and D. M. J. S. Bowman. Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat. Commun.*, 6:1527–1554, 2015. doi: https://doi.org/10.1038/ncomms8537.

W Matt Jolly, Patrick H Freeborn, Wesley G Page, and Bret W Butler. Severe fire danger index: A forecastable metric to inform firefighter and community wildfire risk management. *Fire*, 2(3):47, 2019.

Maxwell Joseph, Matthew Rossi, Nathan Mietkiewicz, Adam Mahood, Megan Cattau, Lise St Denis, Chelsea Nagy, Virginia Iglesias, John Abatzoglou, and Jennifer Balch. Understanding and predicting extreme wildfires in the contiguous united states. 08 2018. doi: 10.1101/384115.

Clifford F. Mass and David Ovens. The northern california wildfires of 8-9 october 2017: The role of a major downslope wind event. *Bulletin of the American Meteorological Society*, 100(2): 235–256, 2019. doi: 10.1175/BAMS-D-18-0037.1.

Sean A Parks, Lisa M Holsinger, Matthew H Panunto, W Matt Jolly, Solomon Z Dobrowski, and Gregory K Dillon. High-severity fire: evaluating its key drivers and mapping its probability across western us forests. *Environmental research letters*, 13(4):044037, 2018.

Haiganoush Preisler, D. R. Brillinger, R. E. Burgan, and John Benoit. Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire*, 13(2):133–142, 2004. doi: https://doi.org/10.1071/WF02061.

David Radke, Anna Hessler, and Dan Ellsworth. Firecast: leveraging deep learning to predict wildfire spread. In *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, pp. 4575–4581. AAAI Press, 2019.

Tom Rolinski, Scott B. Capps, Robert G. Fovell, Yang Cao, Brian J. DÄôAgostino, and Steve Vanderburg. The santa ana wildfire threat index: Methodology and operational implementation. *Weather and Forecasting*, 31(6):1881–1897, 2016. doi: 10.1175/WAF-D-15-0141.1.

LA Sanabria, X Qin, J Li, RP Cechet, and C Lucas. Spatial interpolation of mcarthur's forest fire danger index across australia: observational study. *Environmental modelling & software*, 50: 37–50, 2013.

F Sedano and JT Randerson. Multi-scale influence of vapor pressure deficit on fire ignition and spread in boreal forest ecosystems. *Biogeosciences*, 11(14):3739–3755, 2014.

Daniel L. Swain, Baird Langenbrunner, J. David Neelin, and Alex Hall. Increasing precipitation volatility in twenty-first-century california. *Nature Climate Change*, 8(5):427–433, 2018. doi: 10.1038/s41558-018-0140-y.

A Appendix

A.1 FFDI fire danger rating class

Table 2: FFDI values for each fire danger rating class (Dowdy et al., 2010)

Fire danger rating	FFDI range
Low	0-5
Moderate	5-12
High	12-24
Very High	24-50
Extreme	50+

A.2 SFDI fire danger rating class

Table 3: SFDI classification thresdholds (Jolly et al., 2019)

Fire danger rating	SFDI range
Low	0-60
Moderate	60-80
High	80-90
Very High	90-97
Severe	97-100