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Environmental Influences on Large Daily Wildfire Growth in California

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ENVIRONMENTAL INFLUENCES ON LARGE DAILY WILDFIRE GROWTH IN CALIFORNIA

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ABSTRACT

ENVIRONMENTAL INFLUENCES ON LARGE DAILY WILDFIRE GROWTH IN CALIFORNIA

by Holt S. Hanley

Wildfires have become a major environmental, social, and economic problem in California. The consequences can be especially detrimental when they exhibit behavior like very large daily growth (an individual fire burning >10,000 acres over a 24-hour period). Environmental conditions influencing the risk of large daily growth include weather variables such as temperature, wind, relative humidity, and precipitation; fuel variables such as type, loading, availability, and moisture content; as well as topographic variables such as slope, aspect, elevation, and shape. However, there remains great uncertainty in the importance of these variables relative to each other and the existence of any threshold values in these variables. Our study applied random forest modeling using multivariate and high spatiotemporal data for 16,013 wildfire days in California from 2003 to 2020 to determine feature importance for the task of predicting whether a fire would burn >10,000 acres over a 24-hour period. Shapely Additive Explanations indicate that 100-hour dead fuel moisture, maximum daily air temperature, and soil moisture provide the highest predictive power for large daily growth. Additionally, our study identifies thresholds where the probability of large daily growth significantly increases. These thresholds include a 100-hour dead fuel moisture value of <10%, a maximum air temperature of >75 F, and a 0-10 cm soil moisture of <12%. Finally, we establish the number of days per year that these thresholds are being crossed has increased substantially over the last four decades.

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Finally, I'd like to express my gratitude to my parents Mark and Kelly Hanley as well as my mentor Bill Martin. Without their continued guidance throughout my life, this research would not have been done and I would not be where I am today.

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1. Introduction

The destructive nature of wildfire has become a major environmental crisis in California. Since 2000, fires in California have destroyed thousands of structures, cost billions of dollars through damages and suppression efforts, and taken hundreds of lives (National Interagency Fire Center 2021). Additionally, the crisis has been accelerating due to increases in wildfire frequency, severity, and size with nine out of ten of the largest wildfires in the Cal Fire record (dating back to 1932) occurring within the last decade (Littell *et al* 2009, Miller & Safford 2012, Dennison *et al* 2014). Although there are many contributing causes to the crisis including antecedent forest management practices and expansion into the wildland-urban interface, our study focused on better understanding key environmental factors so decision-makers and first responders can better anticipate and forecast the potential for explosive fire growth.

1.1. Wildfire factors

The three major categories influencing wildfires are illustrated in the fire behavior triangle and consist of fuel, weather, and topography (National Park Service 2021). Fuels are a crucial driver of wildfire and can be characterized by type, loading, availability, and moisture content (Parks *et al* 2014). For example, low fuel moisture promotes fire growth because more energy can go towards combustion rather than evaporation (Pyne *et al* 1996). This process can be directly linked with weather variables like temperature, humidity, wind, and precipitation, although these features play several roles in determining the rate of fire spread. Such as, wind can increase convective heat transfer, determine the direction of spread, and carry firebrands to create spot fires (National Wildfire Coordinating Group

2006). Both wind and fuel conditions can be exacerbated by the slope, aspect, elevation, and shape of topography. For example, steeper slopes can lead to faster fire growth due to the convective and radiant preheating of fuels enhanced by flame tilting and upslope winds (National Wildfire Coordinating Group 2006). While many of these relationships are well documented, comparing individual factors against acres burned leads to surprisingly small correlations (Potter and McEvoy 2021). The interactions between variables are a crucial element of wildfire, which is why machine learning has come forward as a practical approach due to its ability to capture nonlinear and interactive relationships between multiple causal factors.

1.2. Machine learning

Machine learning is a valuable tool for analyzing the critical drivers of wildfire. Techniques such as artificial neural networks, random forest models, and extreme gradient boosting algorithms have been used to predict numerous components of wildfire, including burn severity, ignition probability, and estimated acres burned (Cortez and Morais 2007, Maeda *et al* 2009, Ozbayoglu and Bozer 2011, Satir *et al* 2016, Elia *et al* 2020, Huang *et al* 2020, Wang *et al* 2021). For example, Wang *et al* (2021) built an extreme gradient boosting model incorporating meteorological, land-surface, and socioeconomic variables to predict monthly burned area over the contiguous United States with an interobserver agreement (IoA) of 0.97. Huang *et al* (2020) developed a random forest model to classify burn severity categories in California's northern coastal mountains with an accuracy of 79%. Elia *et al* (2020) estimated the probability of wildfire occurrence in the Mediterranean using an artificial neural network with a Receiver Operating Characteristic (ROC) Area Under the

Curve (AUC) value of 0.78. Our study trained a random forest model to predict large daily wildfire growth from the California/Oregon border through Los Angeles County with an AUC score of 0.831. Although machine learning models have been used to predict various wildfire components with a high degree of accuracy, a drawback is the "black-box" nature of the procedure since it is not clear how the model is interpreting the data to create its predictions. However, Shapley Additive Explanations (SHAP) discussed below, have recently come forward to ease this concern.

1.3. Shapley and LOWESS

Shapley values originated in 1953 in the field of game theory. More recently, this approach has become a useful technique that allows researchers to peek behind the curtain of machine learning models to better understand how input data is interpreted to create a prediction (Wang *et al* 2021). Shapley values can be used to rank the feature importance of the variables, identify the percentage of the model that relies on each individual factor, and explain how those factors correlate to the prediction itself.

Our study combines information from SHAPs with Locally Weighted Scatterplot Smoothing (LOWESS) to identify the key thresholds where the model tends to change its prediction from a fire-day with small growth to one with large growth. Furthermore, the number of days per year these thresholds are exceeded can be examined over time to identify trends in the conditions conducive to large fire growth.

1.4. Trends

Over the last few decades, there has been a trend toward increased fire danger in California. Warming temperatures and increased vapor pressure deficit have enhanced fuel aridity and promoted wildfire activity throughout the Southwest (Abatzoglou and Williams 2016, Williams *et al* 2019). Fuel aridity and burned area have also been enhanced due to decreased summer precipitation and earlier spring seasons (Westerling 2016, Holden *et al* 2018). Overall, the fire season in California appears to be getting hotter, drier, and longer. Since our study revealed thresholds in environmental conditions where extreme growth becomes much more likely, we investigate trends in the frequency of days crossing these thresholds.

1.5. Summary

This study utilized high-resolution fuel, weather, topography, and fire datasets along with a machine learning model to predict whether a given fire will burn greater than 10,000 acres over a 24-hour period. More specifically, we utilized a random forest model, SHAPs, and LOWESS to examine crucial wildfire factors to identify the rank order, relationship, and key thresholds crossed in the prediction of large daily growth. Once key thresholds were established, our study analyzed how many days per year these values were exceeded and any trends over the last four decades. Our analysis contributes another steppingstone in the use of machine learning for wildfire prediction and provides valuable insights that can be applied in further research and wildfire operation decisions.

2. Data and Methods

2.1. Study area

Our study focused on the portion of California extending from the Oregon border through Los Angeles County (Figure 1A). California has a Mediterranean climate, which means most of its rainfall occurs in the winter, while summer conditions are predominantly hot and dry. This climate regime is a significant factor in California's high fire danger because warm temperatures and low relative humidity are combined with critically dry fuels. California also experiences recurring droughts. It is significant to note that the timeframe of this study (2003-2020) takes place during the driest 22-year period (2000-2021) since at least 800 (Williams *et al* 2022). Live fuels are often stressed during these exceptionally dry periods, promoting disease and pest outbreaks. Dry, weakened, or dead vegetation is an integral component of the biomass that drives wildfire in California. Forested areas mainly occur in the higher elevations, including the Coast Ranges closest to the Pacific, the Klamath Mountains in the NW portion of the state, the Cascade Range in the NE, and the Sierra Nevada in the East. Grasslands can be found in the lower elevations of the North Bay, Sacramento Valley, San Joaquin Valley, Central Coast, and Southern California.

2.2. Fire data

The fire activity dataset utilized for this study was prepared by Sonoma Technology Inc. The dataset was primarily produced using the 1-km resolution MODIS fire product combined with a fire detection algorithm and other sources, including state and national incident databases. The final fire product includes the date, time, location, daily growth, and total acreage burned for all fires detected by MODIS between 2003 and 2020. Our study utilized

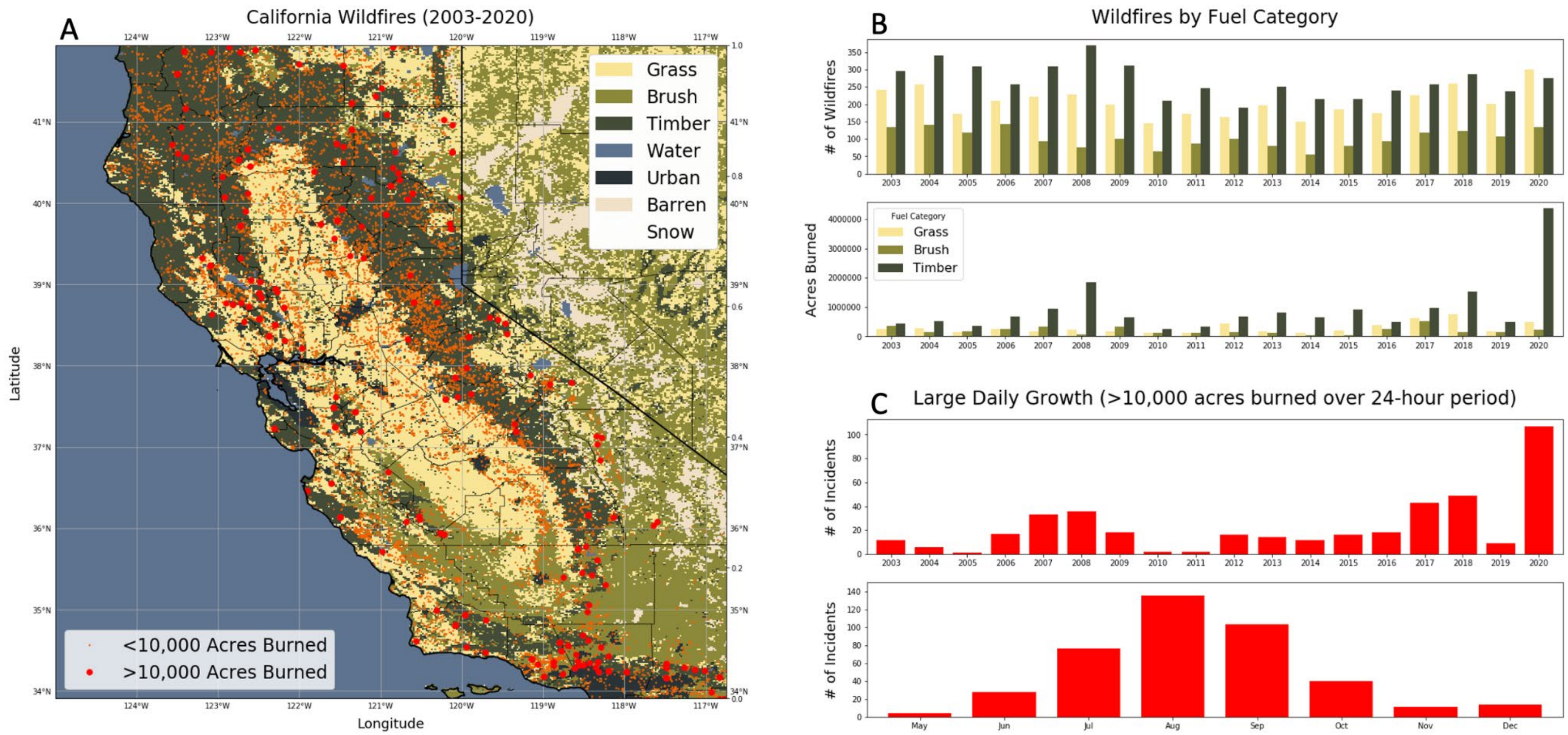

Figure 1. California wildfire data from 2003 to 2020 represented across space, time, fuel type, and large daily growth occurrence. (A) Map of study area based on land type. The small orange dots represent individual fire days with <10,000 acres burned over a 24-hour period, while the large red dots represent >10,000 acres. (B) Wildfire data is separated by the three main fuel types: grass, brush, and timber. The charts illustrate the number of wildfires and total acres burned per year for each fuel type. (C) Occurrence of large daily growth incidents (>10,000 acres burned over a 24-hour period) separated by year and month.

daily growth for all fires from 2003 to 2020, where data was available. This dataset consisted of 16,013 24-hour growth incidents derived from 10,872 individual fires. There were 70 large incidents in the grass fuel type, 62 in brush, and 266 in timber.

2.3. Fuel, weather, and topography data

We used the well-known fire behavior triangle as the foundation for selecting wildfire predictors. The three sides of the fire behavior triangle consist of fuel, weather, and topography. This study's baseline random forest model was built using three variables for each side. Soil moisture, 100-hour dead fuel moisture, and chamise live fuel moisture were used to represent the impact of fuel on wildfire. Soil moisture came from a 2-km Weather Research and Forecasting (WRF) reanalysis, where hourly values were compiled into daily averages for the grid box matching the fire's latitude and longitude at the time of ignition. The dataset containing 100-hour dead fuel moisture was developed based on the Nelson fuel model, while the live fuel moisture - chamise values were produced using a machine learning framework (Nelson 2000, Carlson *et al* 2007). Like soil moisture, the weather and topography variables were obtained from the 2-km WRF reanalysis. The variables representing weather's impact on wildfire were maximum daily air temperature (max air temperature), minimum daily relative humidity (min relative humidity), and mean daily wind speed (wind speed). These specific weather variables were selected to coincide with the conventional wisdom that fire weather is synonymous with 'hot-dry-windy' conditions. Min relative humidity and max air temperature were used instead of their daily means because they were found to have better predictive power. The topography side of the fire behavior triangle was represented by slope, elevation, and terrain ruggedness. Slope was derived using the difference in elevation between adjacent grid boxes, while the WRF variable, VAR_SSO (variance of subgrid-scale orography), was used for terrain ruggedness.

2.4. Random forest model

The random forest model in this study used fuel, weather, and topography data (with the time-variant variables spanning 2003-2020) to predict whether a fire would burn >10,000 acres over a 24-hour period. The classification split of 10,000 acres was chosen to fulfill the primary goal of this research, which was to identify the key factors leading to extreme daily growth of wildfires. However, the conclusions of this study are not particularly sensitive to the specific split chosen. The hyperparameters of the model were selected using a grid search, including a “max depth” of 15, a “minimum samples leaf” of one, a “minimum samples split” of five, and a “number of estimators” of 100. Model performance was assessed using the ROC AUC test method, as this is one of the most common and reliable ways to estimate predictive power. The model used a 70/30 train-test split percentage. To prevent data leakage, the last 30 percent of the data in time was used for testing. This shows how the model would have performed operationally over the last few years.

2.5. Shapley values, LOWESS, and trend analysis

After the random forest model was trained and tested, the SHAP method and LOWESS were applied to increase model transparency. The SHAP method was used to rank the features in the order of their contribution to the model’s predictive power and show whether the variables were positively or negatively correlated with large fire growth. LOWESS was then applied to better visualize variable correlations and identify threshold values at which the model began predicting large fire growth for each individual variable. With these two methods combined, we can determine the most important features contributing to large fire growth and identify the point where that growth becomes more likely. The number of days per year this point, or threshold, is exceeded can then be analyzed to establish whether the conditions conducive to large fire growth have become more common in California over the last four decades. Long-range trends were identified using the gridMET dataset consisting of daily high-spatial-resolution (4-km) surface data from 1980 to 2020 (Climatology Lab 2022).

3. Results

3.1. Model results and feature importance

The baseline model for this study consists of three key drivers for each side of the fire behavior triangle. One way to visualize the performance of a model is a ROC curve. ROC curves plot the false positive rate on the x-axis against the true positive rate on the y-axis to illustrate the model's ability to distinguish between classes. An AUC <0.5 shows no predictive power, 0.5-0.7 is generally considered poor, 0.7-0.8 is acceptable, 0.8-0.9 is excellent, and >0.9 is outstanding (Hosmer *et al* 2013). According to these standards, our model has excellent predictive power with an AUC score of 0.831 (Figure 2A). This result indicates that the features within our model can be reliably utilized to forecast wildfire behavior.

A Shap plot is a machine learning interpretation technique that illustrates how the factors in a model influence the prediction. Figure 2B is a Shapley summary plot showing both the order of feature importance and the association between the variables and large fire growth. Each dot represents a fire-day. Higher SHAP values are associated with an increased probability of large daily growth. Where higher SHAP values are associated with higher feature values (red color), there is a positive correlation between that feature and the probability of large daily growth. For example, as the maximum daily air temperature increases, large fire growth becomes more likely. Conversely, as the values for 100-hour dead fuel moisture increase, the model generates fewer large fire growth predictions. Analyzing the list further shows correlations identified by the model are in line with a priori expectations.

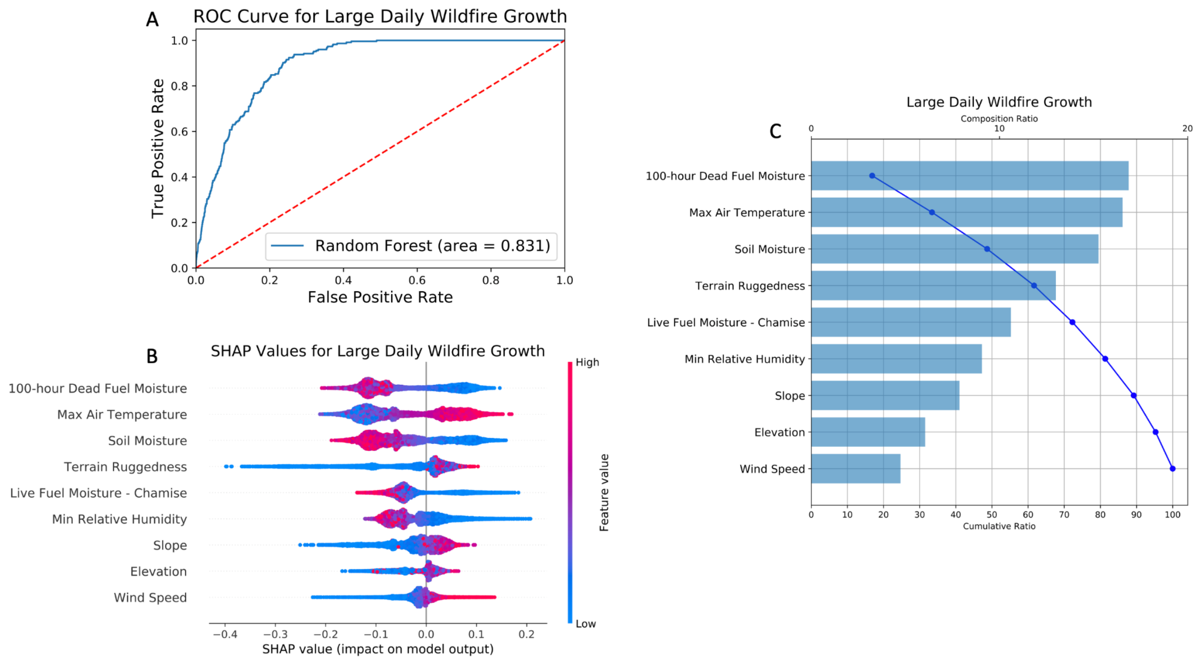

Figure 2. Results for the primary random forest model, which predicts whether a fire will burn less than or greater than 10,000 acres over a 24-hour period using three variables from each side of the fire behavior triangle. (A) ROC curve showing model performance by calculating the area under the curve. (B) Shapley summary plot illustrating feature importance and variable correlation. The red color indicates high variable correlation values; thus, gradients from blue on the left to red on the right indicate a positive correlation with large daily wildfire growth. (C) Shapley waterfall plot indicating variable importance by illustrating the composition and cumulative ratios.

A Shapley waterfall plot provides further insight into feature importance (Figure 2C). The blue bars represent the percentage of the model each variable is responsible for (composition ratio), while the blue line illustrates the cumulative model percentage. For example, 100-hour dead fuel moisture makes up ~18% of the model, while the top three features combined account for ~50%.

We are focused on daily growth, but it is important to note that features may have different relative contributions at different timescales. For example, wind speed would likely provide greater predictive power if we conducted our analysis at the hourly timescale.

3.2. Histograms for the top variable and three fire weather features

Figure 3 illustrates how feature values differ for small and large fire growth days. The figure consists of normalized histogram plots for the top variable in terms of feature importance for our model (100-hour dead fuel moisture) as well as the three weather variables. Our study chose to take a close look at the weather features for two main reasons. First, weather variables change far more rapidly than fuel or topography variables, so they have greater importance in assessing and forecasting dynamic fire behavior. Second, evaluating the histogram plots for these variables potentially explains the model's order of feature importance. The histogram plot for max air temperature (#2 feature importance) shows a significant separation between the values either above or below 10,000 acres burned (Figure 3B). Min relative humidity, which is #6 in feature importance, shows moderate separation, while wind speed, which is last in feature importance, shows a minimal discrepancy between the two curves (Figures 3C and 3D). The random forest model utilized these differences during training, partially explaining why max air temperature has higher predictive power than wind speed. The threshold line was derived from the Shapley plots below and is examined further in the subsequent section.

3.3. Shapley plots for the top variable and three fire weather features

Shapley dependence plots illustrate the correlation between the variables and the model's prediction of large fire growth (Figure 4). Each blue dot represents a fire-day. Positive SHAP values (dots above the 0.00 line) indicate that that feature value (X-axis) pushed the model towards predicting large growth for that fire incident. In contrast, negative SHAP values indicate that that feature value pushed the model towards predicting small growth for that

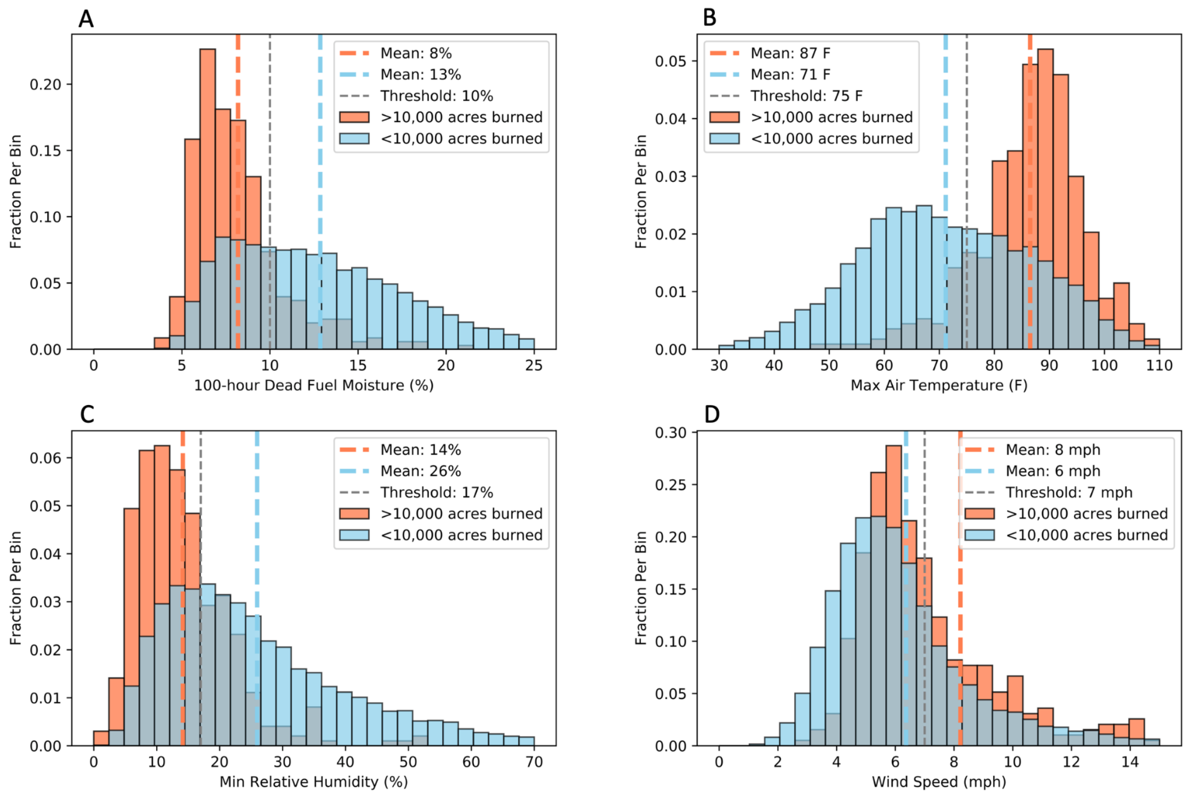

Figure 3. Histograms for the top variables in terms of feature importance ((A) 100-hour dead fuel moisture) as well as the three fire weather variables ((B) max air temperature, (C) min relative humidity, and (D) wind speed). Fire incidents within the 2-km WRF dataset are split based on whether 24-hour wildfire growth was less than or greater than 10,000 acres. Fire incidents <10,000 acres are shown in blue, while incidents >10,000 acres are shown in orange. Histograms are each normalized to have unit area (<10,000 growth occurrences were 38 times as frequent as >10,000 occurrences). Threshold values are derived from model results.

incident. The greater the SHAP value is above or below zero signifies the model's confidence in its prediction. For example, as min relative humidity gets lower, the model has higher confidence in large fire growth occurring (Figure 4C). Interestingly, the model becomes less confident of large fire growth at the extremes of the curves where 100-hour dead fuel moisture nears 5%, and max air temperature rises above 100 F (Figures 4A and 4B). One possible explanation for this unexpected result is that the model learns that

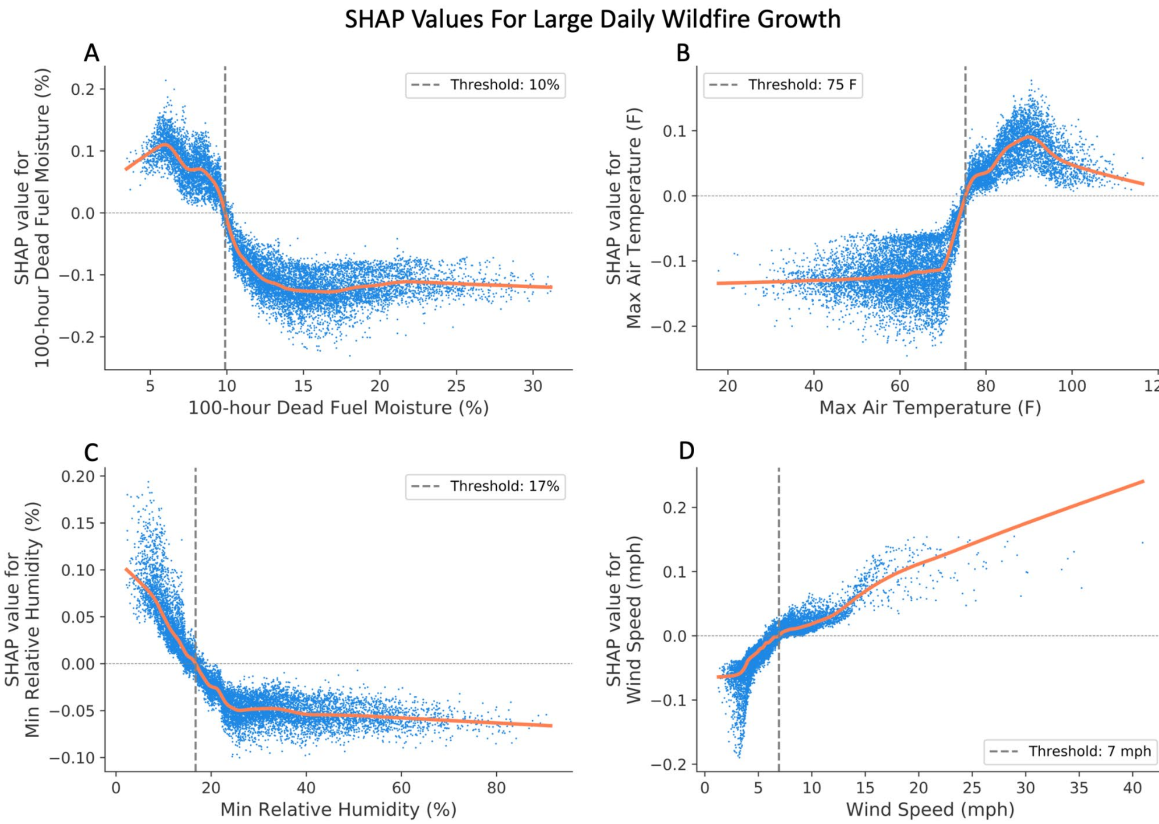

Figure 4. Shapley dependence plots illustrating the association between the variables and the model's prediction of large fire growth. Variables include the top variable in terms of feature importance ((A) 100-hour dead fuel moisture) as well as the three fire weather variables ((B) max air temperature, (C) min relative humidity, and (D) wind speed). Blue dots represent individual fire incident predictions, while the orange line is derived using Locally Weighted Scatterplot Smoothing. The threshold line indicates the point where the variable's value flips its contribution to the model prediction.

exceptionally hot and dry conditions are associated with slightly smaller probabilities for large growth because these conditions tend to occur over sparsely vegetated (desert) regions.

The threshold line indicates the point where the model switches between small and large daily wildfire growth predictions. Knowing the exact point at which extreme fire behavior becomes more likely is useful for wildfire operations and forecasting. These points include fuel thresholds of <10% 100-hr dead fuel moisture, <70% live fuel moisture - chamise, and <12% soil moisture; weather thresholds of >75 F max air temperature, <17% min relative humidity, and >7 mph wind speed; and topographic thresholds of >883 terrain ruggedness, 3°< slope <11°, and 453 m< elevation <1,889 m. To our knowledge, most of these thresholds are being identified for the first time, although previous research corroborates the threshold found for live fuel moisture - chamise. Dennison *et al* (2008) arrived at the conclusion that most large fires occurred below 71%, while a study dating back to 1967 suggested that fire behavior transitions at a chamise live fuel moisture value of 70% (Pirsko and Green 1967).

3.4. Trend maps for the top variable and three fire weather features

Given that the threshold value represents the point at which large fire growth becomes more likely, it is important to analyze trends in the occurrence of these conditions. If max air temperature above 75 F leads to a higher probability of >10,000 acres burned over a 24-hour period, it is valuable to know how many days per year that threshold has been met and exceeded. Furthermore, by examining the trends in the occurrence of these thresholds, we can provide further understanding as to why wildfire activity has increased in California over recent decades. Evidence for this explanation can be seen in the trend maps for 100-hour dead fuel moisture and min relative humidity, where almost all of California has seen an increase in the number of days per year where the threshold for low moisture has been met (Figures 5A and 5C). While the trends for max air temperature and wind speed are not as large, conditions are getting warmer and windier in critical fire danger areas such as Napa County, Butte County, the Sierra, and the Santa Ana area in Southern California (Figures 5B and 5D).

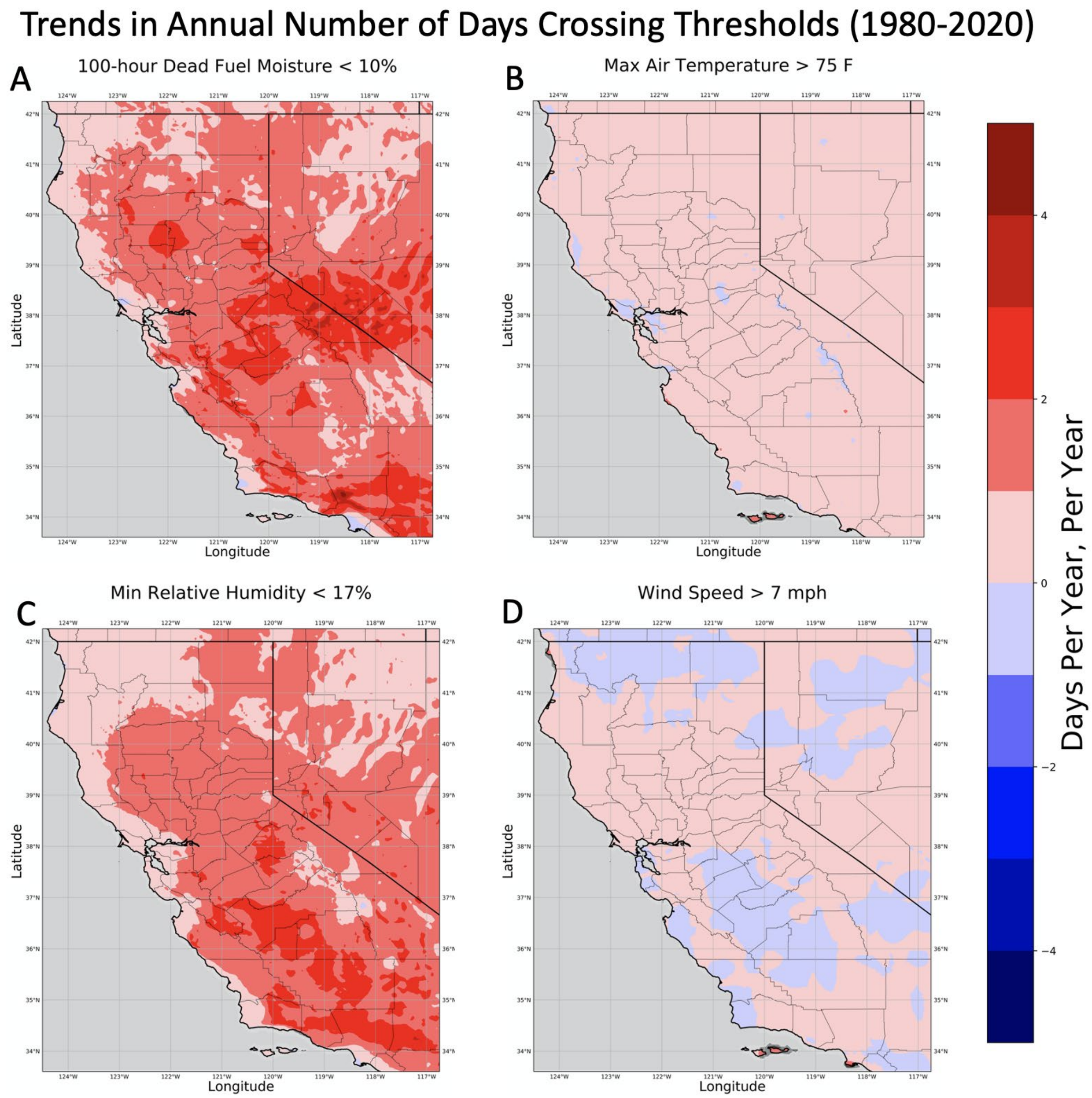

Figure 5. Maps illustrating the trends in the annual number of days crossing thresholds for (A) 100-hour dead fuel moisture, (B) max air temperature, (C) min relative humidity, and (D) wind speed. The red color indicates an increase in the number of days crossing thresholds per year, while the blue represents a decrease. Trends were identified using the 4-km gridMET dataset from 1980 to 2020 (Climatology Lab 2022). Threshold values are derived from model results.

3.5. Mean trends for the top variable and three fire weather features

Similar conclusions can be drawn when we look at the trend in the domain average annual number of days where the variable thresholds for large fire growth have been met and exceeded from 1980 to 2020 (Figure 6). There appears to be a slight trend toward warmer and windier conditions, with the number of days the threshold has been met for wind speed increasing by ~5 days and for max air temperature by ~10 (Figures 6B and 6D). A much clearer trend can be seen in our moisture values, with min relative humidity increasing by ~40 days in the last 40 years and 100-hour dead fuel moisture increasing by ~50 days (Figures 6C and 6A).

In summary, the most crucial variable for predicting large fire growth is 100-hour dead fuel moisture. Machine learning tells us that the threshold at which 100-hour dead fuel moisture leads to an increased probability of >10,000 acres being burned over a 24-hour period is around 10%. Throughout almost all of California, the number of days this threshold has been met has increased, growing from an average of ~125 days/year in 1980 to ~175 days/year in 2020. This partially explains why large fire growth has become more common in California over recent decades.

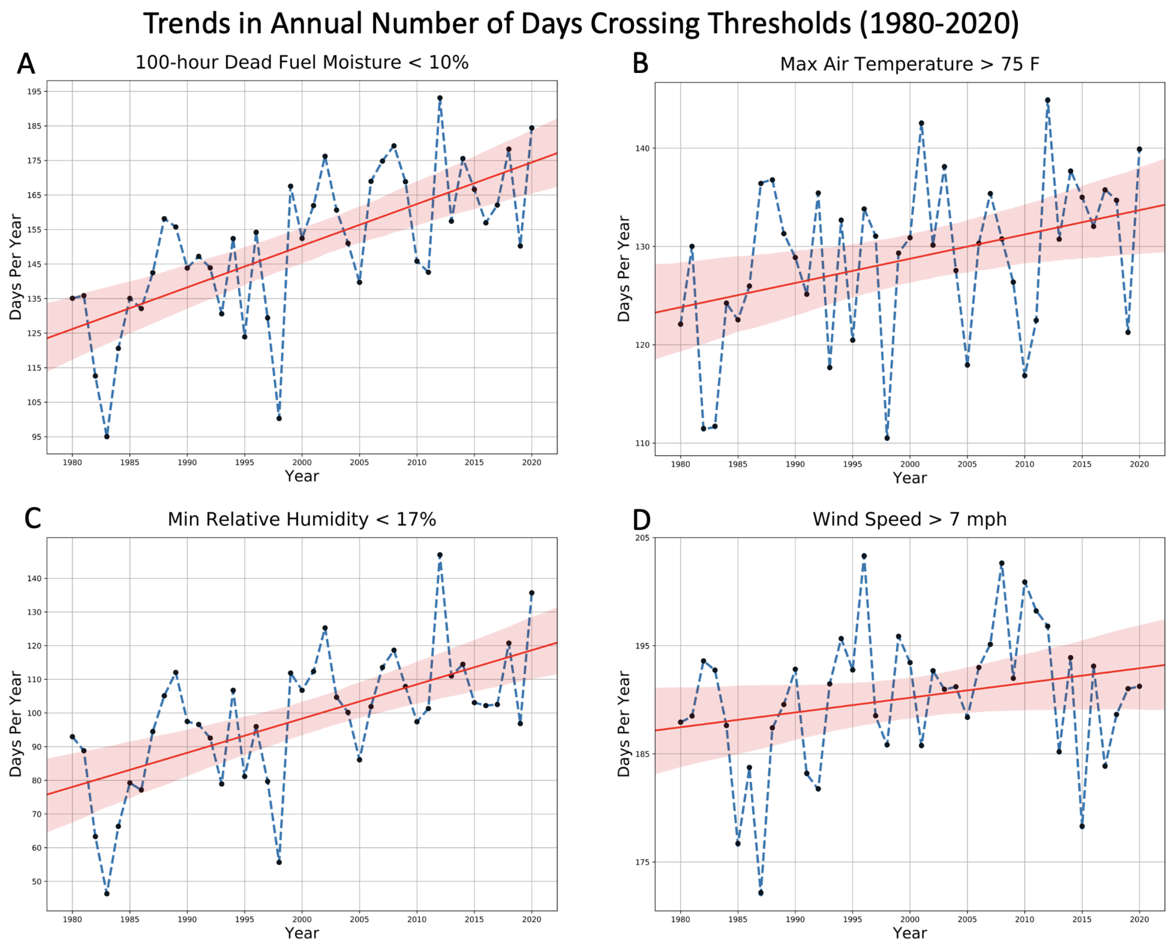

Figure 6. Plots illustrating the trends in the annual number of days crossing thresholds for (A) 100-hour dead fuel moisture, (B) max air temperature, (C) min relative humidity, and (D) wind speed. Trends were identified using the 4-km gridMET dataset from 1980 to 2020 (Climatology Lab 2022). Threshold values are derived from model results.

4. Additional Experiments

4.1. Experiment 1 – Random forest vs. logistic regression

Having a model with predictive power allows us to run experiments that provide further insight into the environmental influences on large daily wildfire growth. For the first experiment, our study compared the baseline random forest model against a logistic regression model using the same features (Figure 7). This was done to test how allowing components to interact nonlinearly affects predictive power. The results show that although the logistic regression model had a fair AUC of 0.759, the random forest model had more skill in predicting large fire growth with an excellent AUC of 0.831. This result indicates the importance of using an approach that can capture nonlinear and interactive relationships when predicting wildfire behavior.

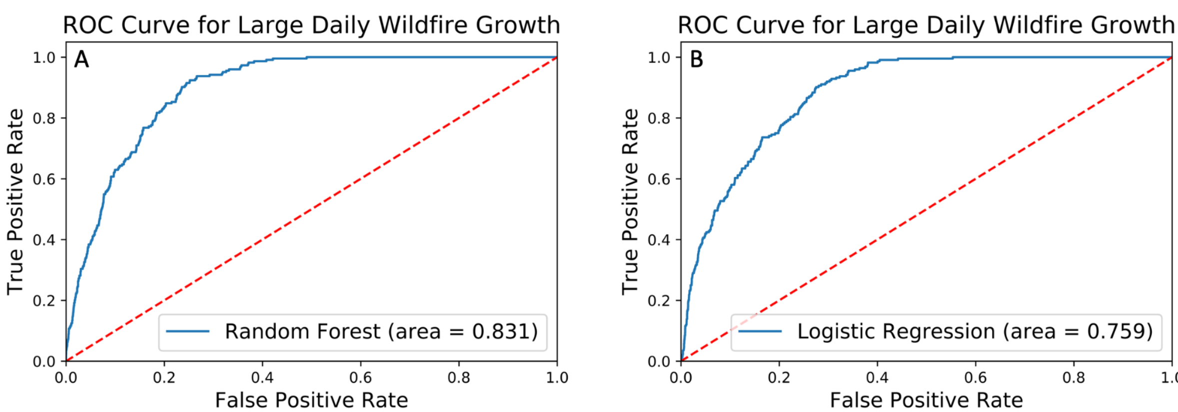

Figure 7. ROC curves comparing the primary random forest model to logistic regression. (A) This is the ROC curve for the primary random forest model previously discussed throughout this paper. (B) This curve utilizes the same nine variables as the primary model, but with a logistic regression algorithm as opposed to a random forest.

4.2. Experiment 2 – Logistic regression with fire weather indices

In the second experiment, three logistic regression models were built using three of the most commonly used fire weather indices: Sharples Fire Weather Index (FWI), Fosberg FWI, and Hot-Dry-Windy. This test was done to see if large fire growth is better predicted using the traditional fire weather indices where fire danger is represented using a mathematical formula, or using a random forest model where the variables are individually inputted and machine learning is used to derive the relationships leading to extreme fire behavior. Surprisingly, the fire weather indices had poor performance, with a maximum AUC of only 0.608 for the Hot-Dry-Windy model (Figure 8B). Considering these indices are widely used for wildfire management, it is necessary to compare these results against the excellent predictive power of the random forest model. Our model's AUC of 0.831 not only supports the idea that machine learning has great potential in the future of wildfire forecasting but also makes the case that it is the approach we should already be utilizing today.

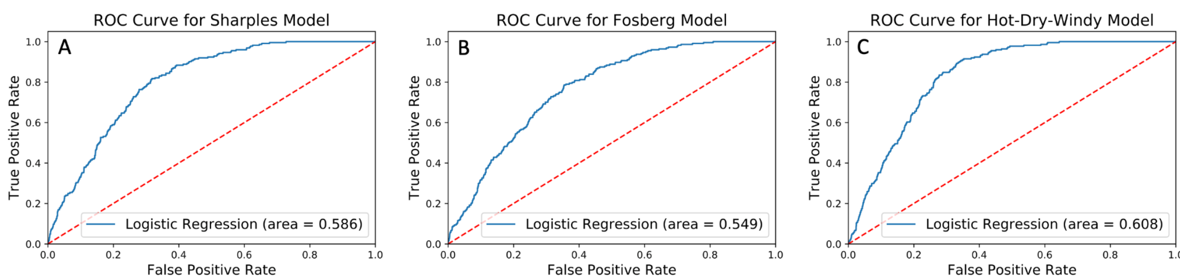

Figure 8. ROC curves for three logistic regression models built using the (A) Sharples Fire Weather Index, (B) Fosberg Fire Weather Index, and (C) Hot-Dry-Windy. The three fire weather indices were derived using the 2-km WRF dataset and the corresponding formulas.

4.3. Experiment 3 – Index substitution for weather and fuel features

For the third experiment, our study substituted the weather and fuel features with some of the leading fire weather and fuel indices. This was done to test whether the model performed better using the established representations of the weather and fuel components or the individual features themselves. The indices were derived using the 2-km WRF dataset and the corresponding formulas, while the 4-km gridMET dataset (Climatology Lab 2022) was used for Energy Release Component. In the first test, the weather and fuel features were removed from the primary model and replaced with the Sharples FWI and the Sharples Fuel Moisture Index (Figure 9A). Although this received a fair AUC of 0.788, this is decreased performance compared to the baseline model. A similar result was seen in the second test, where the fuel features were replaced by Energy Release Component, and Hot-Dry-Windy replaced the weather features (Figure 9B). Although this model failed to outperform the baseline, it proved to be the top-performing index model with an AUC of 0.809. Energy Release Component was used again in the third test, but with the Fosberg FWI in place for the weather features (Figure 9C). This model had an acceptable AUC of 0.792. Interestingly, Energy Release Component was the most useful feature in this model by a significant amount, accounting for over 50% of the model's performance. These results provide further evidence that allowing a machine learning model to uncover the relationships between individual variables provides greater predictive power than an index approach.

4.4. Experiment 4 - Grass, brush, and timber models

In the fourth experiment, the model was separated into the three major fuel categories: grass, brush, and timber, as it is well known that fire behavior can be fundamentally different among these different fuels. Fuel categories were derived from the 2-km WRF reanalysis using the land-use variable, LU_INDEX. As expected, the order of feature importance varies among the various fuel types. To maximize model comparability, 100-hr dead fuel moisture was included in the grass model as a general representation of antecedent aridity. 100-hour dead fuel moisture ended up being the top feature for the grass model, followed by terrain

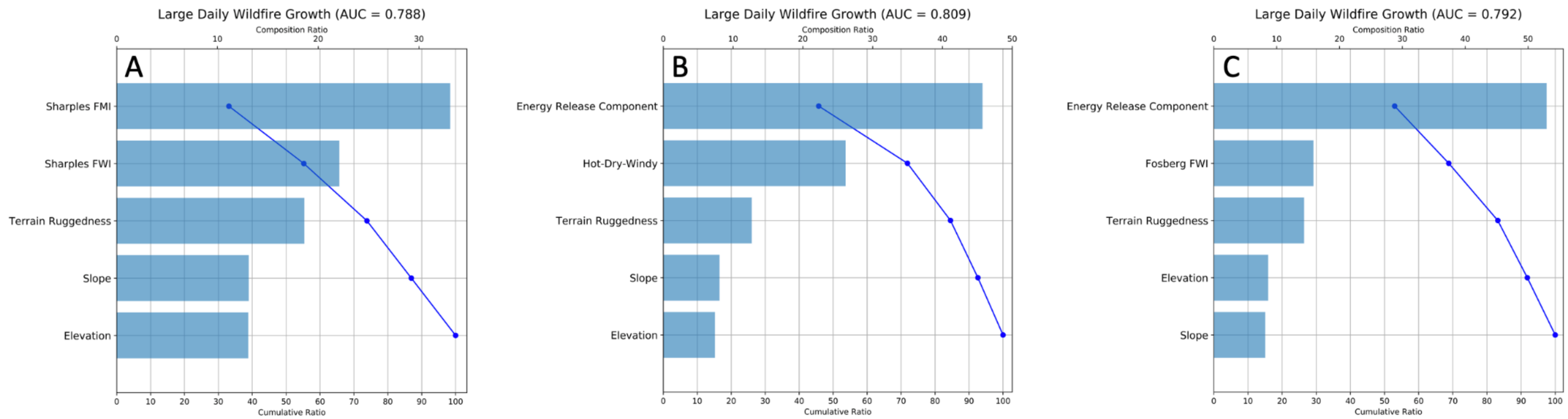

Figure 9. Shapley waterfall plots for three experiments substituting various indices for the weather and fuel features within the primary random forest model. (A) Weather features are substituted by the Sharples Fire Weather Index (FWI), while fuel features are represented by the Sharples Fuel Moisture Index. (B) Weather features are substituted by Hot-Dry-Windy, while fuel features are represented by Energy Release Component. (C) Weather features are substituted by the Fosberg FWI, while fuel features are represented by Energy Release Component. Energy Release Component was pulled from the 4-km gridMet dataset (Climatology Lab 2022).

ruggedness, min relative humidity, and elevation (Figure 10A). Topography also provided a large amount of predictive power for the brush model, with slope and terrain ruggedness accounting for ~45% of the model's performance (Figure 10B). Conversely, the topography variables were last on the list of feature importance for the timber model, collectively adding only ~8% to the model's predictive power (Figure 10C). The most surprising results were the AUC values achieved for each model. As a reminder, the fire incidents used in all models undergo a 70/30 train-test split percentage. The baseline model was trained and tested on 16,013 fire incidents and achieved an AUC score of 0.831. Given that machine learning models are highly dependent on the amount of data utilized in the model's training, it was assumed that separating the model into three separate fuel categories would reduce model performance. On the contrary, the grass model, trained and tested on 4,439 fire incidents, had an AUC score of 0.857. The brush model, based on only 2,213 incidents, achieved an excellent AUC score of 0.850. Finally, the timber model, trained and tested on 8,806 incidents, saw an AUC score of 0.824. This tells us that the differences in fire behavior between various fuel types outweigh the value of utilizing more training data in our dataset.

4.5. Experiment 5 – Eliminating sides of the fire behavior triangle

4.5.1. Experiment 5.a. We retrained the baseline model in the fifth experiment, but with individual sides of the fire behavior triangle removed from the list of features. This process identifies the relative importance of fuel, weather, and topography by analyzing the loss in the model's predictive power when individual sides of the triangle are eliminated. The AUC

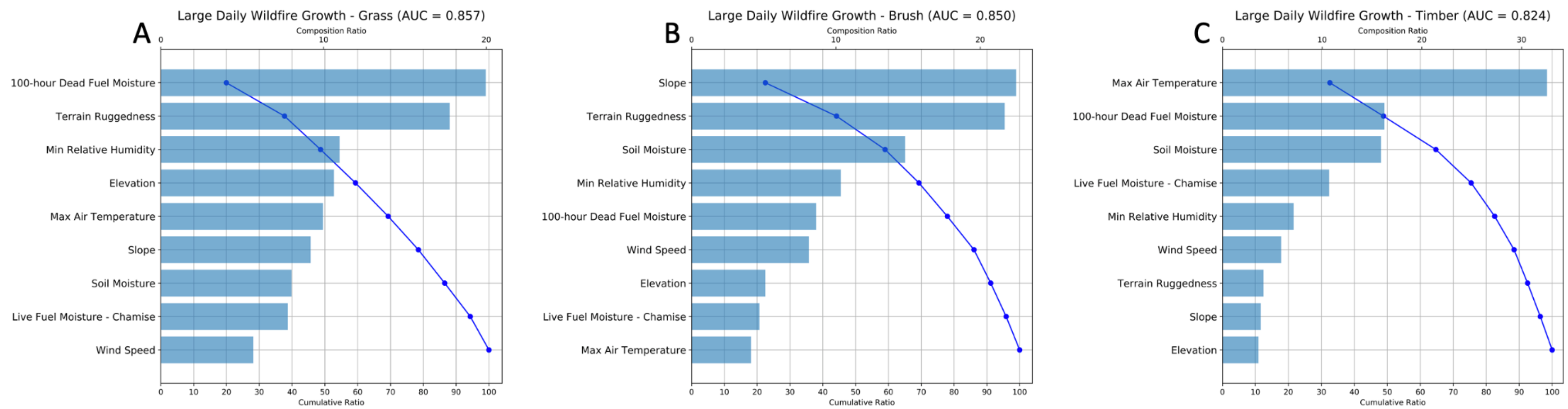

Figure 10. Shapley waterfall plots for three experiments separating the primary random forest model into the three main fuel types: (A) grass, (B) brush, and (C) timber. Data and variables utilized are consistent with the primary random forest model.

dropped to 0.790 when the weather variables were removed, 0.819 when the fuel variables were removed, and 0.793 when the topography variables were removed (Figure 11). This indicates that the weather variables we used provide the greatest predictive power.

4.5.2. Experiment 5.b. A second way of testing if weather provides the largest amount of predictive power is to retrain the model, but with only one side of the fire behavior triangle included at a time. When fuels were the only variables utilized, the AUC dropped to 0.736, and when only topography variables were inputted, the AUC decreased to 0.676. Amazingly, when max air temperature, min relative humidity, and wind speed were the only features used to predict fire growth >10,000 acres over a 24-hour period, the model achieved a nearly excellent AUC score of 0.791. Overall, weather variables are the most important features for predicting large fire growth, but the highest predictive power is produced by representing the interconnected characteristics of the fire behavior triangle.

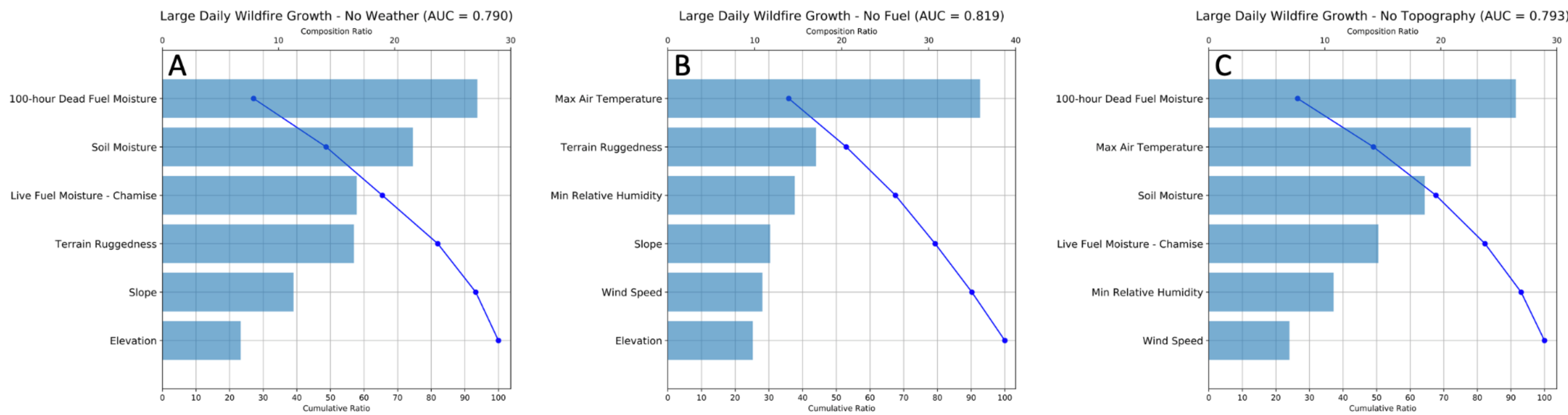

Figure 11. Shapley waterfall plots for three experiments eliminating the (A) weather variables, (B) fuel variables, and (C) topography variables from the primary random forest model. Data and variables not eliminated are consistent with the primary random forest model.

5. Conclusion

This study utilized high-resolution fuel, weather, topography, and wildfire datasets to train a random forest model to predict whether an incident will burn greater than 10,000 acres over a 24-hour period. SHAPs and LOWESS were used to analyze model results. We found that 100-hour dead fuel moisture provides the greatest power for predicting large fire growth, followed by max air temperature and soil moisture. Our study also identified the exact points at which contributors to wildfire begin to promote large daily growth. These thresholds include a 100-hour dead fuel moisture <10%, max air temperature >75 F, min relative humidity <17%, and daily mean wind speed >7 mph. The number of days per year these thresholds are being crossed has increased for all four variables. On average, the annual threshold exceeding days for 100-hour dead fuel moisture, identified as the most significant contributor to large fire growth, has increased by ~50 days in the last 40 years.

In summary, our study determined the most important features contributing to large fire growth, identified the thresholds where that growth becomes more likely, and uncovered trends in the occurrence of threshold exceeding days. Additionally, our experimental findings provide evidence for the advantages of machine learning compared to traditional approaches, the significance of fuel type in predicting fire behavior, and the idea that weather variables are the most critical component of wildfire forecasting. Although these results can already be utilized in fields such as wildfire operations and management, more research is needed to further understand the complex relationships between environmental influences and large daily wildfire growth.

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