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Predicting fire severity in Montana using a random forest classification scheme

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Abstract

Fire managers often make decisions about wildfire incidents on a landscape scale. While several well developed models can predict fire behaviour at these scales, the limited data they draw upon restricts their range of validity. Other models explicitly represent the physical complexities of the fire environment, but with increased computational costs and increased sensitivity to boundary conditions. In this paper, we explore a middle ground between landscape level, data-driven fire behaviour predictions and physics-based, computationally expensive models. Machine learning is used to predict fire severity from a set of well recognized covariate features related to weather, fuel, and topography. A random forest is used for the classification task, and the model covariates are tested to determine their importance in the classification. The model demonstrates considerable skill in prediction of burn severity, with overall classification accuracy of 71%, and lower accuracy in moderate severity predictions. Our results are similar in accuracy to previous work, but distinctive in that we have made no attempts to train the model on specific ecoregions. We determine that topographic variables like elevation, slope, and aspect are the most important in this classification problem.

1. Introduction

Between 1985 and 2017, the Western United States experienced increases in both the severity and the area burned by wildfires (Center, 2017). During the same period of time, the wildland urban interface, WUI, became the fastest growing land use type in the United States (Radeloff et al., 2018), leading to increased economic consequences of wildfires (Center, 2017). Yet, wildfires have historically been an integral part of North American ecosystems, and by pursuing a policy of wildfire suppression since the early 20th century, land managers have altered fire regimes in much of North America, potentially driving some of the increases in fire frequency and intensity (Arno & Brown, 1991). In addition to a more complicated landscape from expanded WUI settlement and increased fuel loading, fire managers now have to account for a warming climate. Thus, the areas threatened by wildfires have increased, and are projected to increase still more under nearly all climate change scenarios (Flannigan et al., 2009).

Management practices aimed at mitigating the threat of wildfire have traditionally involved treatments of a landscape with a combination of thinning projects and prescribed burns (Arno & Brown, 1991). Assessment of the impact of these practices is a critical phase of planning, and involves predictive modelling of fire on the landscape being considered for treatment. Several predictive fire models exist, and have distinctive features that may be suited to requirements arising from operational use, predictive capabilities, computational cost, or model complexity (Sullivan, 2009a, 2009b, 2009c).

Sullivan (Sullivan, 2009a, 2009b, 2009c) divides existing fire models into six groups, organised by two broad classes. One class of fire models, data-driven models, are based on empirically derived formulas for fire spread, operate on large landscape level domains, are computationally efficient, and see broad operational use. The other class of fire models, called physics-based models, use physical principles to determine fire spread, operate on stand or individual fuel element levels, are computationally expensive, and are limited to research applications in fire science. Both classes of model offer various benefits and costs, and there is a lively debate to each class' relative merits (Cruz et al., 2017, 2018).

Nowadays, machine learning (ML) may offer a novel approach to fire modelling as it has the fast computation associated with data-driven models, yet may capture the complexities of fire physics. Several authors have applied ML techniques to predict fire behaviour from burn characteristics and covariates such as climate, topographic elevation and slope, and fuel descriptions (Jain et al., 2020).

In this paper we focus on predicting burn severity measured by the differenced normalised burn ratio (dNBR) (Eidenshink et al., 2007). We are not the first to apply machine learning methods to the problem of predicting burn severity. (S. A. Parks et al., 2018) predicted high severity fires using boosted regression trees using a suite of features (covariates) grouped into live fuel, topographic, climate, and fire weather. Moreover, they successfully predict high severity fires in 19 distinctive ecoregions of the American west and report that fuels descriptors have the greatest importance for prediction. S. Parks et al., 2018 predicted the probability of *low-severity* fires using a similar approach. More recently, Huang et al., 2020 carried out a similar analysis for Northern California's coastal mountains and achieved a 79% overall classification accuracy and found topographic features to have the greatest explanatory power.

Here, as in Parks et al., 2018, we set out to characterise landscapes by the severity of fire (Eidenshink et al., 2007) that would result if the landscape were to burn. Unlike Parks et al., 2018, but following Huang et al., 2020 we formulate our problem as a multi-label classification problem, using features to determine unburned, low, moderate, and high severity fires. We also include new features in our classification scheme by adding higher order products of features. Our region of interest is the state of Montana, which is broader and includes a greater variety of ecoregions than (Huang et al., 2020). In terms of data volumes, we evaluate 29 million pixels, which is 70 times the volume in (S. A. Parks et al., 2018) and more than 14 times more data than (Huang et al., 2020).

2. Methods

2.1. Collection of the Features and Training Data

Covariates considered in this work fit into three broad categories; topography, weather, and fuels. In Table 1 we detail the features, resolutions, and sources used in this analysis. To improve the classification, these 9 fields were multiplied by themselves and each other in order to create a total of 54 features (9 features plus 45 squares or products of features). The Monitoring Trends in Burn Severity (MTBS)(Eidenshink et al., 2007), provides fire perimeters and burn severity during the 35 year period from 1985-2020, totaling to 825 unique wildfires.

Table 1: The data used in the analysis, the resolution, and the source.

	Feature	**Resolution**	**Source**
Topography	Elevation	30 m, Constant	EDNA (Layers, 2005)
	Slope	30 m, Constant	EDNA (Layers, 2005)
	Aspect	30 m, Constant	EDNA (Layers, 2005)
Weather	Solar Radiation	4 km, weekly average	gridMET (Abatzoglou, 2013)
	Min Relative Humidity	4 km, weekly average	gridMET (Abatzoglou, 2013)
	Max Temperature	4 km, weekly average	gridMET (Abatzoglou, 2013)
	Precipitation	4 km, annual average	gridMET (Abatzoglou, 2013)
Fuels	Landfire Vegetation Type	30 m, 2014 Update	LANDFIRE (Rollins, 2009)
	Landfire Fuels Model 40	30 m, 2014 Update	LANDFIRE (Rollins, 2009)

2.2. Model Selection

The statistical modelling is done with Scikit-learn's RandomForestClassifier [17]. This method employs randomly created ensembles of classification trees. Through averaging of trees the variance of model output is reduced without a commensurate increase in model bias. This approach is well-suited to the large number of samples in the training dataset and the underlying physics of the classification problem, which is not overly dependent on spatial or temporal gradients in the feature set. The lack of gradient dependence justifies the decision to avoid convolutional neural networks (CNNs). It is also true that compared to deep CNNs, the RandomForestClassifier is easier to train and interpret, especially with regard to feature importance.

2.3. Model Training

For model training we split 75% of the pixel level feature vectors into training data with the remaining 25% reserved for testing. The test and training data were randomly sampled from the complete data set of 29,379,900 feature vectors. To avoid a class imbalance the training data are sampled in proportion to the number of records in each of the severity classes. Gini impurity was used for the loss function, and 100 trees were grown.

3. Results

To measure performance, we report the confusion matrix (Table 2), precision, recall and F1 scores for each category (Table 3), and a pair of summary statistics. Our classes are relatively well balanced and the summary statistics are a reasonable means of expressing our overall success. Tables 1 and 2 reveal the detailed structure of classifications.

The first summary statistic is the accuracy score for the classification, which was 0.711. The second summary statistic is the area under the receiver operating characteristics (AUROC) and was found to be 0.872.

An impurity method was used to evaluate the importance of the features. The results for the ten most important features appear in Table 4. We also map predicted and observed fire severities in Figures 1-3. These provide a means of visually inspecting fires to determine where predictions are failing. In considering these figures, it is important to note that the extent of the fire is determined by the outline provided in the MTBS data, our prediction method does not determine fire perimeters.

Table 2: A confusion matrix documents the performance of our classification algorithm. Diagonal elements represent instances of successful classification. Off-diagonal values indicate the number of times misclassification took place in each class.

	Low Severity	**Moderate Severity**	**High Severity**
Low Severity	**2,853,697**	**544,457**	**134,909**
Moderate Severity	**725,985**	**1,165,844**	**210,226**
High Severity	**120,313**	**285,448**	**1,204,096**

Table 3: A classification report summarises the values of various metrics for each class. Precision is true positives divided by the sum of true and false positives. Recall is true positives divided by the sum of true positives and false negatives. F1 is twice the ratio of precision times recall divided by the sum of precision and recall. Support refers to the number of labels in each class.

Category	**Precision**	**Recall**	**F1**	**Support**
Low Severity	**0.77**	**0.81**	**0.79**	**3,533,063**
Moderate Severity	**0.58**	**0.53**	**0.56**	**2,202,055**
High Severity	**0.73**	**0.75**	**0.74**	**1,609,857**
Accuracy			**0.71**	**7,344,975**
Weighted Average	**0.71**	**0.71**	**0.71**	**7,344,975**

Table 4: The fractional importance of the 10 most relevant features in the model.

Feature	**Importance**
Elevation × Annual Precipitation	**3.96%**
Elevation × Solar Radiation	**3.67%**
Elevation × Vegetation Type	**3.16%**
Elevation^2	**3.14%**
Elevation × Fuel Type	**3.05%**
Elevation	**3.00%**
Elevation × Minimum Daily Humidity	**2.83%**
Slope × Annual Precipitation	**2.59%**
Elevation × Aspect	**2.58%**
Elevation × Slope	**2.51%**

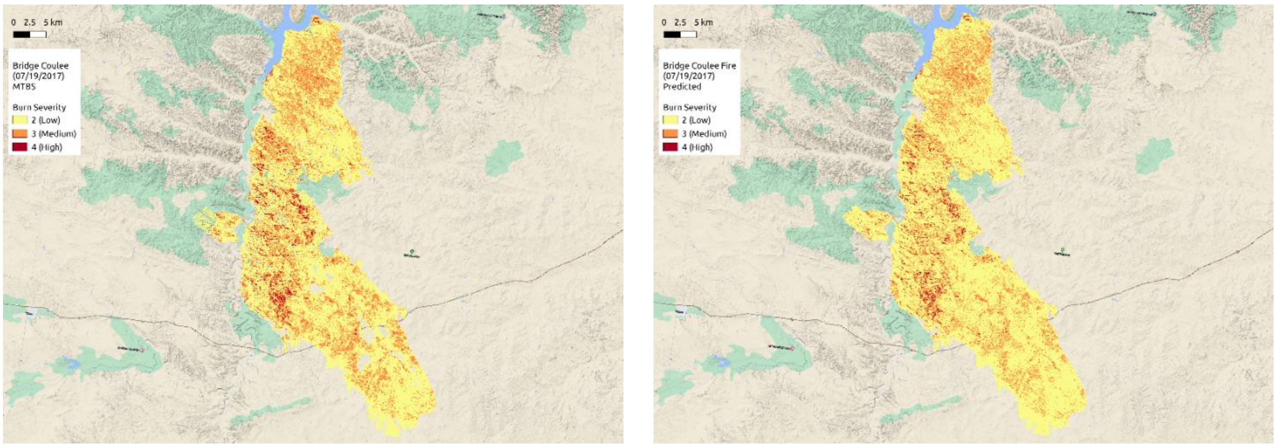

Figure 1: The Bridge Coulee fire, 7/19/2017. Left panel shows the fire severity determined by MTBS (Eidenshink et al., 2007). Right panel shows the fire severity predicted by our random forest classifier.

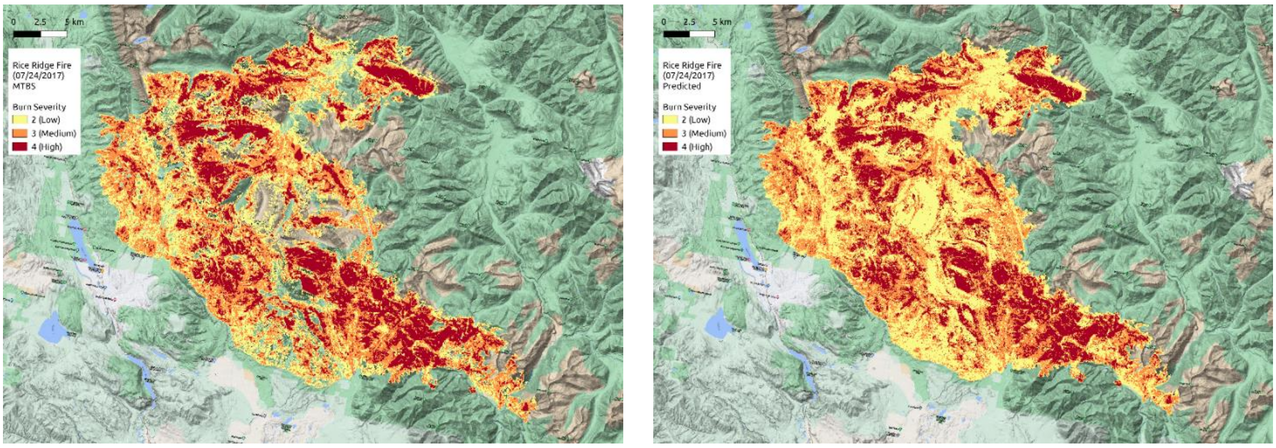

Figure 2: The Rice Ridge fire, 07/24/2017. Left panel shows the fire severity determined by MTBS (Eidenshink et al., 2007). Right panel shows the fire severity predicted by our random forest classifier.

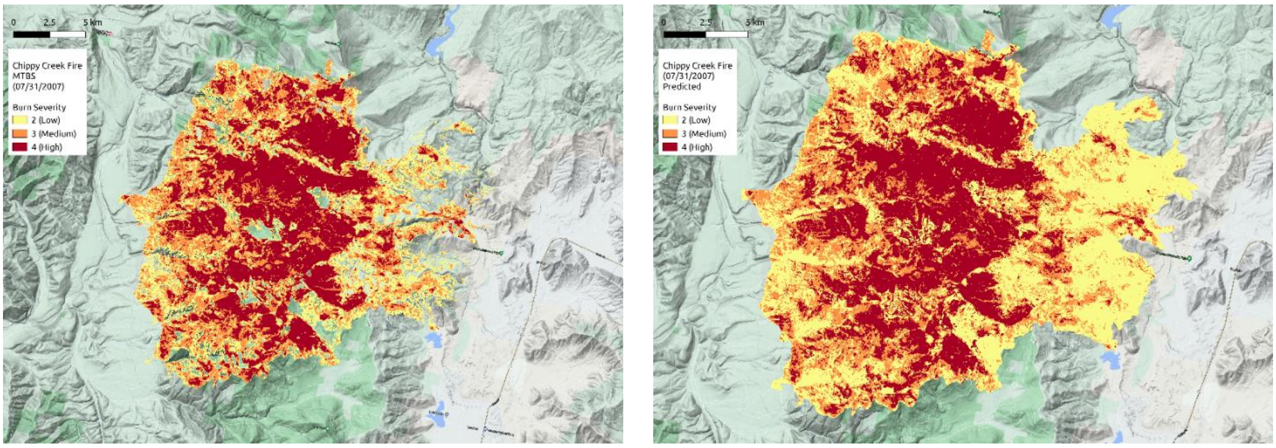

Figure 3: The Chippy Creek fire, 07/31/2007. Left panel shows the fire severity determined by MTBS (Eidenshink et al., 2007). Right panel shows the fire severity predicted by our random forest classifier.

4. Discussion and Conclusions

A number of favourable outcomes were achieved in this work. First, we achieve nearly the accuracy reported in (Huang et al., 2020), which reported 79%. Our reported accuracies do not take into consideration the ecoregions used in both (Huang et al., 2020; S. A. Parks et al., 2018). We attribute our relative success within the inhomogeneous state of Montana to the large volumes of data we used in training; nearly 29 million feature vectors for our work, compared to 462 thousand in (Huang et al., 2020) and 100 thousand per ecoregion in (S. A. Parks et al., 2018). (S. A. Parks et al., 2018) do not report accuracy, and have a boolean classification variable. This makes direct comparison difficult, however our AUC of 0.87 compares favourably to their value of 0.72.

We tested a large number of features and dropped ones determined to be less significant. So far as we know, we are the first investigators to use products of features in our analysis. The results show that some of these products have considerable explanatory power. The ability to account for some curvature in subdividing feature vectors appears to improve classification.

The lower scores for classification of moderate burn severity are noteworthy. We know burn severity suffers from classification errors due to the thresholding of its classification(Kolden et al., 2015), and expect those inherent difficulties to become prominent when classifying across inhomogeneous terrain, where the differences in severity might reflect changes in fuel composition and climate more than genuine thresholds in the classification.

We only classified low, moderate, and high because it is difficult to interpret land that burned but undisturbed. Nevertheless, we carried out analyses that included the unburned category and found overall classification accuracy fell to 65%. This is important to consider when comparing our results to (Huang et al., 2020).

Our software framework for carrying out these analyses is robust and highly scalable. We expect that the addition of more features such as primary productivity derived variables and climate data will improve our accuracy rates. It would also be a straightforward matter to begin identifying ecoregions and training a unique random forest within each of those. Our most significant advance may be to demonstrate that classification of burn severity can achieve near to cutting-edge results by simply increasing the volumes of data used in the analysis.

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