



Fire Behavior Driver Classification from Geospatial Features [†]

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Abstract

Wildfire behavior can roughly be described as wind-, fuel-, or topography-driven, but these labels usually rest on expert judgment and post-fire analysis rather than on simple, reusable rules. Here, we build a small, interpretable classifier that predicts the dominant fire behavior driver: fuel-driven (plume/convection dominated), wind-driven, or topography-driven, from basic environmental information. The classifier is built using ERA5 10 m wind and relative humidity, summary elevation metrics, and fuel descriptors for a 14-event dataset of coastal Croatian wildfires. We compare the performance of multinomial logistic regression, random forest, and decision tree-based classifiers, focusing on agreement between their coefficients, feature importances, and splits rather than on formal optimization. All three models converge on a simple common rule set. Relative humidity, mean elevation, and elevation range emerge as the main axes of variation, consistent with basic fire behavior physics and published fire type schemes. Despite the small dataset, the classifier formalizes expert intuition in a transparent way and offers a template for scaling larger datasets, where it could evolve into a quick diagnostic of the dominant spread driver for ongoing fires.

Keywords: wildfire behavior; machine learning; random forest; logistic regression; decision tree

1. Introduction

Wildfire behavior can roughly be classified as topographic, wind-driven, or fuel/plume dominated, depending on whether terrain, ambient wind, or convection dominates spread and severity. These labels usually come from detailed post-fire analysis and expert judgment, not from compact, reusable rules [1–3].

Most quantitative work targets fire danger indices, spread simulations, or severity models, while these fire type schemes remain loosely tied to basic meteorological, topographic, and fuel descriptors that exist for many events [4]. This makes it hard to turn historical insight about “wind-driven” or “topographic” fires into simple decision tools that can be applied consistently.

Here, we build a small classifier that predicts the dominant fire behavior driver of a fire based on a minimal set of meteorological, topographic, and fuel indicators. The model is trained on a 14-event dataset labeled by fire behavior experts, enriched with ERA5 wind and humidity, summary elevation metrics, and fuel information as predictors. Our goal is to extract an explicit, interpretable rule set and to compare it with basic fire behavior physics and qualitative classifications of historical fires into these three categories.



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2. Data and Methods

Video footage of 14 past fire events was extracted from the OIV FireDetectAI video surveillance system [5]. Each video sequence was presented to fire behavior experts and manually labeled depending on the main driver of the fire’s behavior.

The dataset used in this research was composed of date, central coordinates, meteorology, topography, and fuel data. Meteorological inputs are 10 m wind components, derived 10 m wind speed (era5_wind_speed), and 2 m relative humidity (era5_rh), derived from 2 m dewpoint and 2 m temperature metrics [4] on the location and the date of the fire event.

Topography (mean, median, standard deviation, minimum, maximum, and range of elevation) and fuels (dominant fuel class majFuel and diversity index divFuel) were extracted for each burned area using a Web application (Figure 1) equipped with a high-resolution Croatian fuel map (FirEURisk product [6]) and the Shuttle Radar Topography Mission (SRTM GL3) Global 90 m digital elevation model accessed via OpenTopography [1,7].

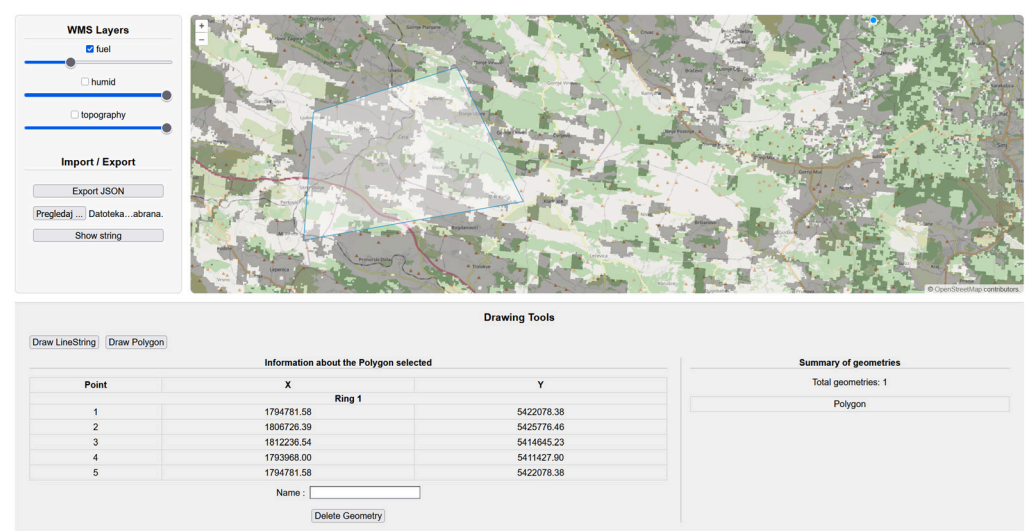


Figure 1. Fuel and topography extraction tool. Croatian “Pregledaj” translates to “Open”, while “Datoteka ...abrana” is short for “Datoteka nije izabrana” which translates to “No file chosen”. The UI features a fuel map where grayscale dots indicate fuel class for the area.

The summary in Table 1 reports mean wind speed, relative humidity, elevation range, mean elevation, and fuel diversity by driver.

Table 1. Mean values of core features separated by fire driver.

Driver	Era5_Wind_Speed [m/s]	Era5_rh [%]	rangeTopo [m]	divFuel
fuel	4.73	55.73	79.5	5.50
topography	3.76	54.40	298.0	6.25
wind	3.67	45.77	228.13	6.87

To limit model complexity, we use six predictors: era5_wind_speed, era5_rh, mean-Topo, rangeTopo, majFuel, and divFuel. majFuel is encoded as a categorical index and divFuel is kept as a continuous measure of within-event fuel heterogeneity.

Preprocessing is minimal: continuous predictors are standardized for logistic regression, tree-based models use raw values, and no further feature selection is applied. We train three classifiers—multinomial logistic regression [8], random forest [9], and decision tree [10], and read them mainly through their coefficients, feature importances, and splits. The depth-3 decision tree provides an explicit if–else rule set that splits mainly on mean

elevation, elevation range, and wind speed. The small size of the dataset limits the possibility of applying cross-validation and heavy tuning and instead checks whether the implied rules agree with basic fire-behavior expectations and existing topographic/wind-driven/fuel-driven schemes; the classifier is a compact formalization of expert judgment rather than a fully validated predictive tool.

3. Results and Discussion

Our results show that a small set of environmental indicators can efficiently separate fires into three spread drivers. The scatterplot of ERA5 wind speed versus mean elevation (Figure 2) shows limited but manageable separation of data items. The shallow decision tree finds that mean elevation, elevation range, and wind speed are enough for efficient fire behavior main driver prediction and achieves an accuracy of 0.86 (macro precision 0.93, recall 0.83, F1 0.85).

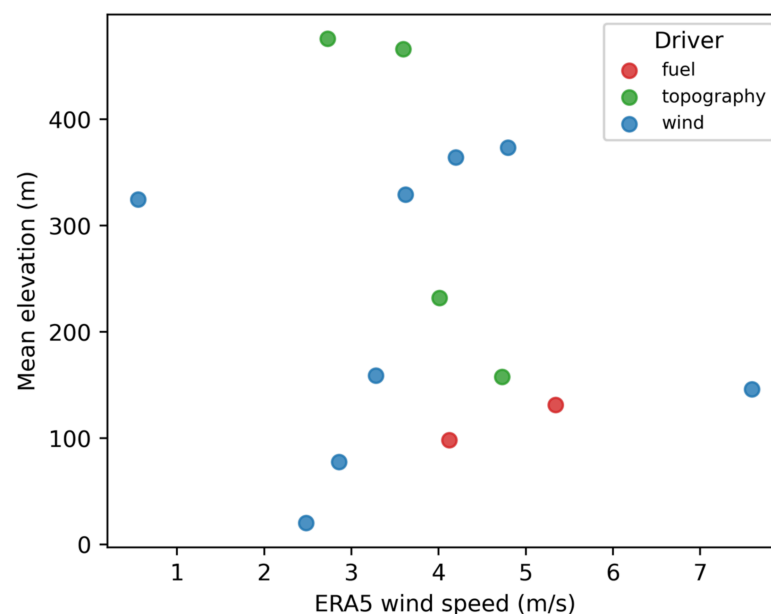


Figure 2. Scatterplot of mean elevation and ERA5 wind speed by driver.

Multinomial logistic regression performs slightly worse (accuracy 0.71, macro precision/recall/F1 all 0.75), whereas a random forest achieves an accuracy of 0.93, macro precision 0.96, recall 0.83, and F1 0.87. Logistic regression coefficients and random forest importances point in the same direction and match published schemes that distinguish topographic, wind-driven, and fuel-driven fires [1–3]. Feature importance analysis shows that in this dataset, relative humidity, mean elevation, and elevation range form the main axes of variation, with wind speed and fuel metrics as secondary influences. These metrics are computed on the training set only and therefore reflect in-sample fit rather than out-of-sample predictive skill.

The classifier has clear limits: only 14 labeled fires, the majority of which are wind-driven fires, which is a major behavior for the study area, subjective labels, and coarse ERA5 meteorology relative to local fire-scale conditions. Even so, it captures a simple, interpretable structure and turns a handful of environmental variables into an explicit rule set that could be scaled to larger datasets and used as a quick diagnostic of whether an event is mainly wind-, fuel-, or topography-driven.

4. Conclusions

We built a small, interpretable classifier that predicts the main wildfire behavior driver—fuel, wind, and topography—using ERA5 wind and humidity, simple topographic summaries, and fuel descriptors. The predictor is trained on a dataset of 14 events. The resulting rules, based on mean elevation, elevation range, and wind speed, align with established views that steep terrain favors topographic control, strong winds and dry air favor wind and fuel dominance, and intermediate conditions mix both influences. Logistic regression, a small random forest, and a shallow decision tree were chosen mainly to expose transparent rules on such a small sample.

In future work, we plan to extend the labeled dataset beyond coastal Croatia and include more precise meteorology data and test operative capabilities of the classifier. A larger dataset will make it possible to test more structured yet interpretable models. In practice, a classifier of this type could act as a quick diagnostic, indicating the main driver of an ongoing fire and which environmental variables deserve closer attention during operations.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ERA5	ECMWF Reanalysis v5
OIV	Odašiljači i Veze (eng. Transmitters and Communications Ltd.)
SRTM GL3	Shuttle Radar Topography Mission Global 3 arc-second

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