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Evaluating sensitivity to input fuel resolution in popular fire behavior models

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Abstract

Fire behavior models ingest a variety of inputs such as weather, topography, and fuel maps to generate predictions of how a fire will behave. Model prediction accuracy is thus to some degree dependent on the fidelity of the input data sources. For many widely used fire models, however, the exact relationship between fuel input quality and model performance is not well understood. This paper seeks to quantify the relationship between input fuel data and output prediction accuracy in popular fire models based on the Rothermel fire spread equation. In particular, it examines how granularity of fuel classes and spatial resolution affect the accuracy of fire behavior predictions. Fuel maps used in the study are generated from remote sensing images using machine learning to map between satellite and ground conditions. Prediction accuracy is evaluated with multiple metrics including rate of spread (ROS) and fire front shape. The outcomes of this study will provide important guidance as to the benefit of producing high fidelity fuel maps when utilizing the Rothermel spread equation to predict fire behavior.

1. Introduction

Fire behavior models use several input data layers such as fuel type (defined as fuel class), moisture content, surface-to-volume ratio, heat content of fuel, bulk density of vegetation, wind velocity and topography of the terrain for predicting rate of fire spread (ROS), flame length (FL) and fire perimeter. All of the aforementioned parameters are subject to spatial and temporal changes by natural occurrences (landslides, change in weather pattern, wildfires, etc.) and human activity (prescribed burns). Therefore, the accuracy of the fire behavior model relies on the accuracy of these input layers data. It is both time-consuming and costly for land managers to keep track of the changes in the fuel type distribution and properties. The use of satellite data can quicky reciprocate the changes (in a matter of days) in fuel type and weather conditions to generate accurate input data (when coupled with machine learning algorithms) for existing fire behavior models.

In this work, an external pre-trained machine learning model will be used to label updated Sentinel-2 MSI data with coarse land cover labels, having a spatial resolution of 10 meters. These labels will be compared pixel-by-pixel, with top-level Scott & Burgan classes (Scott & Burgan, 2005) from the most recent LANDFIRE (LF) fuel product available (resampled to 10-meter resolution, Fig.1). For all pixels, if the land cover model disagrees with the LF Scott & Burgan classification that pixel will be reclassified with the updated derived classification. For example, the most recent LANDFIRE 2020 product may label a pixel as “Timber Litter 1” (TL1) while the updated land cover model – called the Lockheed Martin (LM) land cover model – labels the same pixel with current Sentinel-2 as “Shrub & Scrub” at that same point. Subsequently, this new classification will be stored with this pixel reclassification as, “Shrub 1” (SH1). The output of the LM fuel model will be a raster map of Scott & Burgan classes. This LM fuel model will be validated by predicting the rate of spread and fire perimeter of the Cameron peak fire (for which significant data points are available) which is the largest recorded wildfire in Colorado history.

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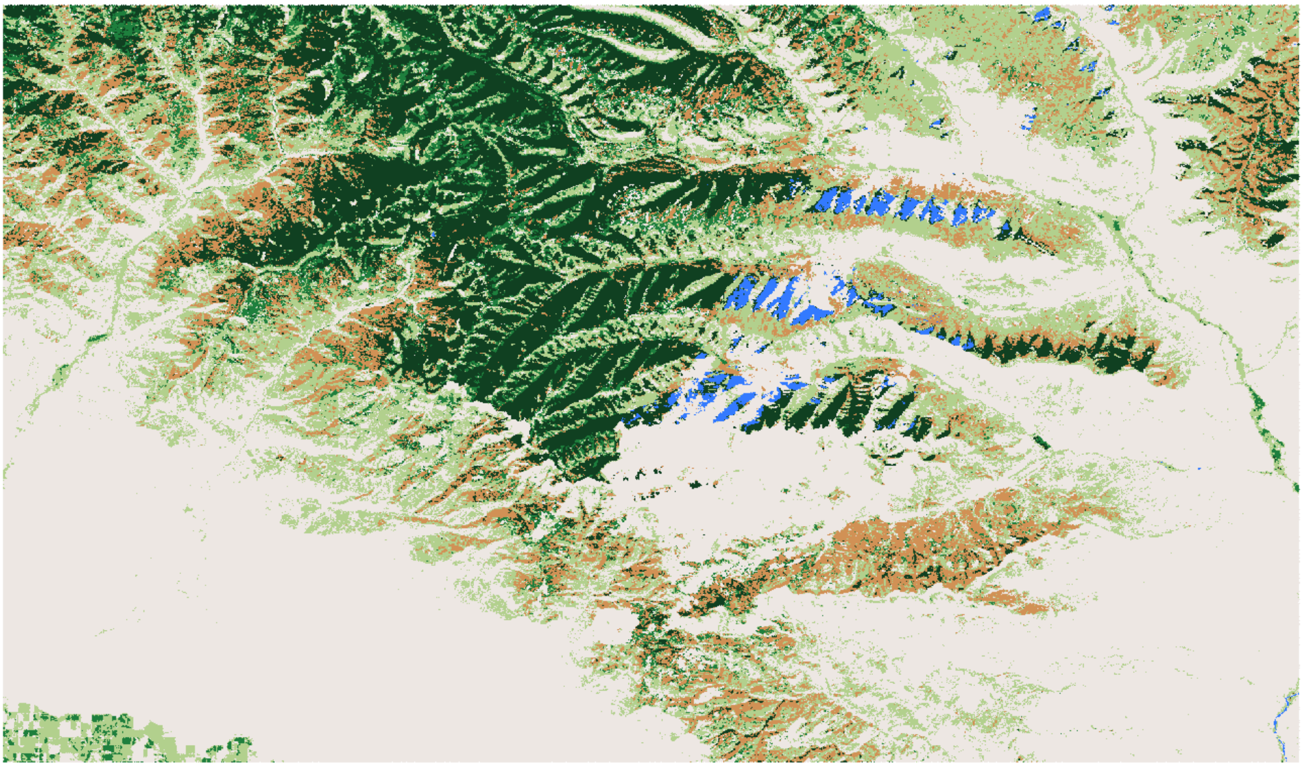

Figure 1 - Sample fuel map generated at 10m pixel resolution using Scott & Burgan fuel classes.

2. Fire Behavior Models in the Field

The most accepted fire prediction models in the United States, the Rothermel-based fire behavior model (Rothermel, 1972) will be used for predicting the rate of spread, flame length and fire perimeter for the LM fuel models.

3. Methods of Evaluation

The fire spread rate and fire perimeter at different times will be used for evaluating the LM fuel model.

4. Sensitivity to Fuel

This section will describe how various fuel map attributes were examined and observations of how each attribute affected prediction accuracy.

4.1. Granularity of Classes

Fuel class granularity will be examined through the comparison of Anderson and Scott & Burgan fuel classes (Scott & Burgan, 2005). Similar maps will be generated with the different fuel models and will be evaluated on how they influence the resulting fire shapes.

4.2. Spatial Resolution

Spatial resolution will be evaluated by generating a high-resolution fuel map and then down sampling it multiple times and comparing with prediction accuracies after each down sampling. Similar procedure will be followed for predicting the influence on fire spread through fire shapes at different times. A sensitivity analysis will also be carried out.

5. Conclusions

Based on the work reported here, recommendations will be made for generating accurate fuel maps to produce optimal prediction results with the Rothermel-based fire behavior models.

6. References

Rothermel, R.C. 1972. A mathematical model for predicting fire spread in wildland fuels. Res. Pap. INT-115. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 40 p.

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