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**Wildfire Burn Area Modeling in Colorado Using Multi-Layer Perceptron Classification**

**Introduction**

Fire frequency in the US Mountain West appears to be increasing, so understanding variables that contribute to ignition, intensity and area is critical for preserving human life, conservation planning, and emergency management (Oliveira & Sá 2021). Fire risk modeling is a technique used to predict the likelihood and potential impact of wildfire events in a given area. Fire modeling is particularly important in areas like Colorado, where wildfires are a regular occurrence and can have serious consequences for both human populations and natural environments. Regular wildfire maintains ecosystem services and has naturally occurred in the Western US for millennia, but these fires can have devastating impacts on communities- destroying homes, businesses, and natural habitats when uncontrolled. In order to better understand and manage this risk, it is important to develop fire risk models for Colorado. In this study, we will use TerrSet, a geospatial software platform, to create a fire risk model for the state of Colorado that generates binary burn area predictions.

**Study Area**

The study area for this analysis is the state of Colorado. Located in the western United States, Colorado covers an area of 104,094 square miles. The state is bordered by Wyoming to the north, Nebraska to the northeast, Kansas to the east, Oklahoma to the southeast, New Mexico to the south, Utah to the west, and Arizona to the southwest. Colorado’s dry climate and vegetation types like shrub and grassland makes it particularly susceptible to drought and wildfires. In recent years, the state has been hit by a series of large wildfires that have caused significant damage, like Waldo Canyon Fire in 2012 and Black Forest Fire in 2013, among many others. Colorado also has large exurban communities surrounding denser suburbs and cities; these interface and intermingle with wilderness and grasslands, increasing wildfire’s potential destruction of lives and livelihoods. Using the National Centers for Environmental Information “Climate at a Glance Statewide Rankings” page of Colorado precipitation averages, we selected two study years to assess if there is a difference in model performance between wet and dry years; 2015 was selected as the wet year with 21.57 inches, and 2021 for dry with 16.2 inches (NOAA, 2022).

**Objectives**

1. Identify relevant variables for categorizing wildfire risk in Colorado.
2. Combine these into a classification model using TerrSet and ArcGIS Pro.
3. Test models, variables, and variable cross-correlation using TerrSet’s Multi-Layer Perceptron neural network image classifier.
4. Summarize variables with the strongest predictive power, identify model shortfalls and regional considerations, and characterize model performance with total operating characteristic (TOC) curves.

The objective of this study is to use neural network fire risk modeling to identify areas of the state of Colorado that are most at risk for wildfire. This will involve the use of TerrSet, a software program designed for land use and land cover change modeling, to simulate the extent of wildfire for different years. The results of this study will be used to inform fire management decisions and to develop effective strategies for reducing the risk of wildfire in Colorado.

**Methodology**

1. Obtain and pre-process relevant data on the study area, including topographic data, climate data, and land use data.
2. Use TerrSet to create a fire risk model for the study area, incorporating the data obtained.
3. Use the fire risk model to identify areas of high fire risk.
4. Analyze the results and provide recommendations for model testing and improvement.

First, we decided to use the artificial neural network Multi-Layer Perceptron (MLP) tool to generate an empirical fire model. MLP uses the ubiquitous back-propagation algorithm, which is well-suited for fire susceptibility use cases (Jain et al., 2020). The bulk of our time was spent processing data into continuous variables for MLP inputs for each study year. Aspect and slope were generated using Google Earth Engine then imported into TerrSet and clipped to the study area. Existing vegetation types were downloaded from LANDFIRE then processed in ArcGIS Pro for TerrSet import; once imported each type was reclassed as an evidence likelihood, the percent of burn area contained within the type. The historic fire record 1950-2021 was acquired from Idaho State University’s database. Watersheds (HU12 level) were acquired from USGS, and using the Summarize Within tool in ArcGIS Pro, were assigned a density ratio of total historical burn area (pre-study year) within each watershed, then exported to TerrSet (Burkholder et al., 2022). Finally, Wilderness-Urban-Interface (WUI) layers were acquired and transformed into a distance surface using TerrSet’s DISTANCE module. The USGS-standard Albers Equal Area Conic NAD83 projection was used for all layers.

Once processed, the model was tested and trained with a burned / unburned area boolean image for each study year, masked to the study area. MLP parameters were adjusted according to the TerrSet Help System entry to optimize model accuracy and skill. After several exploratory MLP runs, we removed the aspect variable due to low influence, and chose to use 800 training and testing pixels, a learning rate of 0.05 and momentum factor of 0.6. Model performance was then assessed with the MLP report and TOC Curves. See presentation slides 4-13 for methodology flowchart, variable images, and MLP model outputs.

**Data**

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| **Product** | **Source** | **Purpose** |
| NASA SRTM 30m DEM | Google Earth Engine | Aspect and Slope images |
| Colorado State Boundary | Esri Living Atlas | Study Area mask image |
| Existing Vegetation Type | LANDFIRE | Vegetation type Evidence Likelihood image |
| Historic Fires Database | Idaho State University GISTReC | Fire Booleans, densities, likelihoods images |
| Wilderness-Urban Interface | U-Wisconsin SILVA Lab | WUI distance surface images |
| WHD HU 12 Watersheds | USGS WHD Datasets | Fire density by watershed |

**Results**

Using TerrSet’s MLP tool, we generated two boolean classification images of predicted burn areas for 2015 and 2021. Visually, the risk is particularly high in the state’s central Front Range and northwest quadrant. The accuracy rates for the 2015 and 2021 models were 81% and 77% respectively; the 2021 model generally fared worse, especially in early models. Fire density by watershed was consistently the most influential driver in 2015, interface and intermix WUI influenced the 2021 model most strongly, and EVT Evidence Likelihood was frequently low influence both years (Slide 13). TOC Curve analysis shows the 2021 model has a much higher hit intensity than 2015 despite a lower accuracy; this is because more hits are predicted and thus available, with a much higher number of false alarms than 2015 as well.

**Discussion and conclusion**

Our models performed well enough for interesting results but could be improved in many ways. First, there was notable overprediction of fire for both study years. For this use case this is acceptable, because a false alarm is better than a miss; in other words, unnecessarily cautious evacuation or fire planning is better than the destructive of missed burn areas. Second, our EVT Evidence Likelihood method was flawed; we should have generated the likelihoods with additive yearly burn area to capture recurrent burned vegetation types instead of a 1950-2014 and 1950-2020 overlay of burn area. Our method caused strong shift between vegetation types burned, although it also highlighted the possibility that susceptibility of different vegetation types to fire is changing with climate change. Finally, the model would likely be greatly improved with non-static atmospheric variables; our accuracy levels were surprising given all variables were static. Drought and moisture indicators like Evaporative Stress Index or the Normalized Difference Moisture Index could yield higher accuracy.

One of the most interesting findings was how strong WUI layers drove the 2021 model, suggesting more human ignition or hidden drivers of burn area. WUI areas have been rapidly expanding and are known to elevate fire danger, but the latest data is from 2010, and more recent data would be fascinating to examine (Radeloff et al., 2018). This modeling project has revealed so many different possible interactions, variables, and questions to be answered about fire modeling it was overwhelming to narrow our focus to a select few questions. In conclusion, fire risk modeling is a valuable tool for understanding and predicting the potential impact of wildfires, and as climate change continues to exacerbate extreme hazard events like wildfire, spatial data scientists must continue refining neural network applications to mitigate future hazards.

**References**

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