CS547 Final Project

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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 behavior on large scales, their assumptions can limit the amount of useful information available to fire managers. Other models capture more complexities of a fire environment, but at increased computational costs. In this paper, I seek to find a middle ground between landscape level fire behavior predictions and prohibitive computational costs by employing a machine learning approach to predict fire perimeters from the previous day's fire perimeter and other covariates. I employ a U-Net model and test three sets of hyperparameters. The model fails to find a compelling relationship between observed and predicted fire perimeters. The results were either skewed towards under-predicting unburned pixels, or towards over-predicting burned pixels at random. While the results of this study were unsuccessful, there are a number of methods available to improve model performance.

1 Introduction

Wildfires are an increasingly visible natural phenomenon across the globe. In the United States, 43,371 structures were lost due to wildfires from 2016-2019 [11]. The Wildland Urban Interface (WUI), the area where houses and vegetation intersect, was the fastest growing land use type in the United States from 1990-2015 [12]. Despite the threat to homes in the WUI, wildfires have historically been an integral part of North American forest, woodland, shrubland, and grassland 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 [2]. In addition to a more complicated landscape from an expanded WUI and altered fire regimes from fuel loading, fire managers also have to account for the affects of a warming climate on fire conditions. Thus, the number of areas with the potential to be adversely affected by wildfires has increased in the 21st century. Tools for mitigating the threat of wildfire to fire sensitive areas have traditionally included a combination of thinning projects and prescribed burns [2]. Unfortunately, the tools developed to evaluate the efficacy of such projects on a local scale rely on limiting assumptions, cannot be generalized across landscapes, and do not account for rapidly changing fire regimes due to climate change [6].

Numerous fire models fitting different niches of operational usage, predictive capabilities, computational cost, and size already exist for making predictions about fire behavior [18, 17, 19]. Sullivan divides the group of existing fire models into six sets, but consider two sets categorized by the following description. One class of fire models is based on empirically derived formulas for fire spread, operates on large landscape level domains, is computationally efficient to run, and has broad operational support. The other group of fire models, deemed physical models, use physical principles to determine fire spread, operate on stand or individual fuel species levels, are computationally expensive, and are limited to research use only. Both sets of models offers various benefits and costs, and there is a lively debate to their relative merits [5, 10, 4].

Machine learning offers an alternative approach to fire modeling with the potential for the fast computation times associated with empirical models and the complexities of fire behavior associated with physical models [9]. Several papers have attempted to predict future fire perimeters based on a collection of data consisting of previous fire behavior and other covariates. (Hodgens et. al 2020) Applies a Convolutional Neural to a multiband raster in order to predict maps of fire probability [8]. While their results are largely successful, they use synthetic data in the form of FARSITE model output in order to generate training data. Another paper by (Radke et. al 2019) uses historic fire perimeters from the GeoMAC database to train a CNN with successful results [13]. While this approach is successful, the number of fire perimeters are limited compared to other historic fire perimeter databases.

2 Methods

2.1 Data Collection

The Fire Behavior Triangle consists of three legs: fuels, topography, and weather [1]. Thus, fire behavior on a landscape is a function of those three things. With the goal of training a machine learning model to predict fire behavior, I decided to chose additional data sources according to this framework. Thus, all additional covariates fit into the categories of topograhpy, fuels, and weather.

Historic Fire Perimeters

In this paper, I propose to expand on the approach taken by (Radke et. al 2019) by exploring a larger set of historic fire perimeters through the Moderate Resolution Imaging Spectroradiometer (MODIS) burned-area product [3]. The MODIS burned area product provides raster images at a 500 meter spatial resolution and daily temporal resolution. Burned area estimates are reasonably accurate across spatial and temporal comparisons. While the author is not aware of a direct comparison between the MODIS burned area product, and the geoMAC database of fire perimeters collected from IR flights, the MODIS approach offers a unique advantage in the sheer number of detected fires.

For my analysis, I downloaded the MODIS burned area product for the months of May through October, which represent the time period of a traditional fire season in the western United States, from 2001 through 2020. I then aggregated all of the months into a single raster for each year, with each pixel's value corresponding to the first day of detected burning activity. Next, I clustered each year's fires and computed a time series of each fire's burning activity. After clustering, I created a raster image with a binary classifier denoting burned or unburned for each day of detected fire activity. In order to maintain a data balance of active burning periods, I pruned the data set to only include fires with three consecutive periods of burning. This resulted in a dataset of 6,017 fires and 95,987 days of fire growth. Thus, I had a dataset of historical fire perimeters with 95,987 observations, not including standard computer vision techniques such as rotation of transformation in order to increase sample size.

Topography

For the topography component of the fire behavior triangle, I used the LANDFIRE Digital Elevation Map product [14]. The LANDFIRE DEM provides a 30m spatial resolution raster of the continental United States. There are other topographic data products available from LANDFIRE, such as slope and aspect, which are likely important predictors of fire behavior. However, I decided to only include the DEM in this study in order to limit storage and memory requirements, and to maintain to the generalizable nature of the Machine Learning algorithm. That is, a generalized model should be capable of picking out the contribution pf topographic features like slope and aspect on fire behavior from the DEM alone.

Fuels

There are a large number of landscape level fuel products available. LANDIFRE alone offers a wide variety of fuel and vegetation products such as bulk-density, fuel loading models, fuel disturbance, and vegetation classification maps. While a combination of these products would provide the most complete summary of a complicated landscape mosaic, for the same reasons listed above I chose one 30m spatial resolution raster product, the Scott and Burgan fuels models for my analysis. The Scott and Burgan 40 fuel model classifier is a comprehensive set of generalized landscape fuel models that fit any forest or shrubland type across the United States [16].

Weather

Finally, I chose several dynamic datasets for the weather component of the Fire Behavior Triangle. The first dataset that I included is the daily Canadian Fire Weather Index from the Copernicus Emergency

Management Service. The FWI is a collection of weather observations such as fuel moisture, winds, and fire behavior measurements that produce an index from 0-100. The higher the FWI, then the higher the potential for extreme fire behavior. Copernicus provides a global reanalysis of FWI on a global scale [20]. The reanalysis product has a daily temporal resolution, and a 0.25° x 0.25° spatial resolution with data from 1979 to present.

In addition to FWI, terrain and landscape driven winds play an important role in determining fire behavior. In order to capture more specific wind information for a given landscape, I also include 10 meter u and v wind vectors and average wind gust datasets from the ERA5 global renalysis [7]. ERA5 global reanalyses provides a record of global atmospheric conditions on a 0.25° x 0.25° spatial resolution from 1979 to present. ERA5 reanalysis data is available hourly, and I chose to include wind vectors as measured at 1400. This time period generally corresponds to the period of highest fire growth.

2.2 Data Stacking

With these seven datasets: fire perimeters, DEM, SB40, FWI, u-winds, v-winds, and wind-gusts, I created 95,987 8-band rasters. Each raster corresponds to one day of fire activity for each fire, and each band corresponds to one of the seven datasets. Fire perimeter is present in two bands because I include the current fire perimeter as well as the future fire perimeter in each raster.

There were several challenges associated with aligning the gridded raster data because the datasets contained three different resolutions and projections. I decided to reproject all of the datasets to EPSG: 5070. I downsampled the 30 meter DEM and SB40 rasters to the 500 meter MODIS data using a nearest neighbors technique. Additionally, I upsampled the FWI, u, v, and gust wind components to match the 500 meter MODIS data using a cubic interpolation. Lastly, I padded all of the 8-band rasters to 64x64 pixels in order to normalize the size of each image for batch training. Figure 1 shows an example 8-band raster that I used in model training and validation. The reader can observe a large class imbalance in the 8th band associated with the binary classification of new burning pixels. This class imbalance informed three different model training configurations.

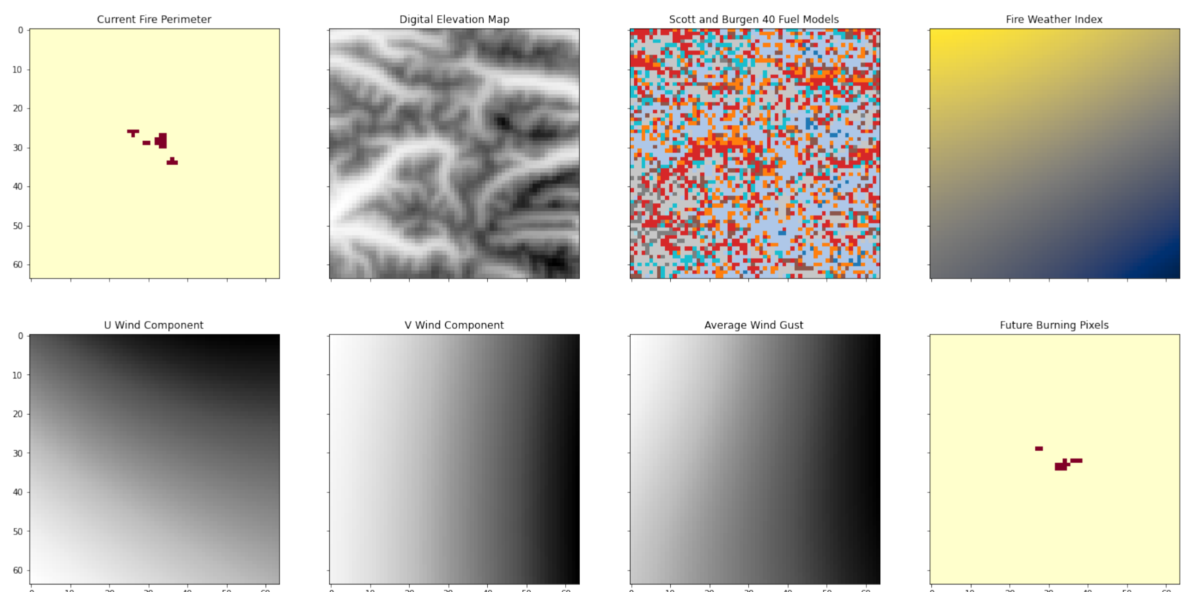

Figure 1: A 64x64 pixel plot of each band in an example 8-band raster used for model training and validation

2.3 Model Selection

I chose to use a CNN variant called a U-Net for binary classification of newly burning pixels. U-Net's have been successfully used for a number of image segmentation and classification tasks [15]. A U-Net architecture is defined by a contracting path consisting of pooling operations followed by an expansive path of up-convolutions.

2.4 Model Training

For model training I considered the fire data from 2001-2019. I split 90% of the data into training data with the rest consisting of validation data. I ran the training algorithm for 1,100 epochs and computed the cross-entropy loss over the validation data at each epoch. This process took around eight hours for training on two NVIDIA Tesla V100 GPUs.

In order to test multiple variations of model hyperparameters, I ran three model configurations that differed by their cross-entropy loss methodology. For the first model configuration, I chose a standard cross-entropy loss. For the second model configuration, I weighted the loss function for label 1 corresponding to the classification of a newly burning pixel by 500. Finally, I experimented with drawing a kernel centered at each newly burning pixel in the observed data. The kernel consisted of the newly burning pixel and it's eight nearest neighbors. Next, I aggregated all of these kernels into a label weight array. This resulted in an array whose values was 1 everywhere in the nearest neighbors window of the burning pixels, and zero otherwise. Finally, I performed element-wise multiplication between the label weight array and the non-reduced cross-entropy loss array and summed the result. This resulted in only the cross-entropy loss of pixels within the region of interest contributing to the overall cross entropy loss.

3 Results

Model Performance on 2020 Test Data		
Model Configuration	% Correctly Classified	Overfitting Ratio
Normal Cross-Entropy Loss	0.00%	0.12
Weight Cross-Entropy Loss	99.99%	323.84
Label Weight Array	9.19%	79.16

Table 1: Performance of each model configuration considering the ratio of correct newly burned pixel classifications, and false positives. Overfitting ratio is defined as $\frac{\text{\# of predicted newly burning pixels}}{\text{\# of observed newly burning pixels}}$

None of the three model configurations resulted in a satisfactory model for predicting fire perimeters. The first model attempt using a normal cross-entropy loss function resulted in 0% accuracy in predicting newly burning pixels. Furthermore, the overfitting ratio for the first model configuration was 0.12. This means that for every 100 newly burning pixels in the training data, the model only predicted 12 newly burning pixels. In light of these metrics, the first model configuration significantly under-predicts the occurrence of fire perimeter growth. While the model predicts 0% new fire growth, it's total accuracy is close to 100%. This suggests that the model found relative success by predicting nearly all pixels as label 0. Figure 2 shows an example input, target, and prediction from the first model configuration.

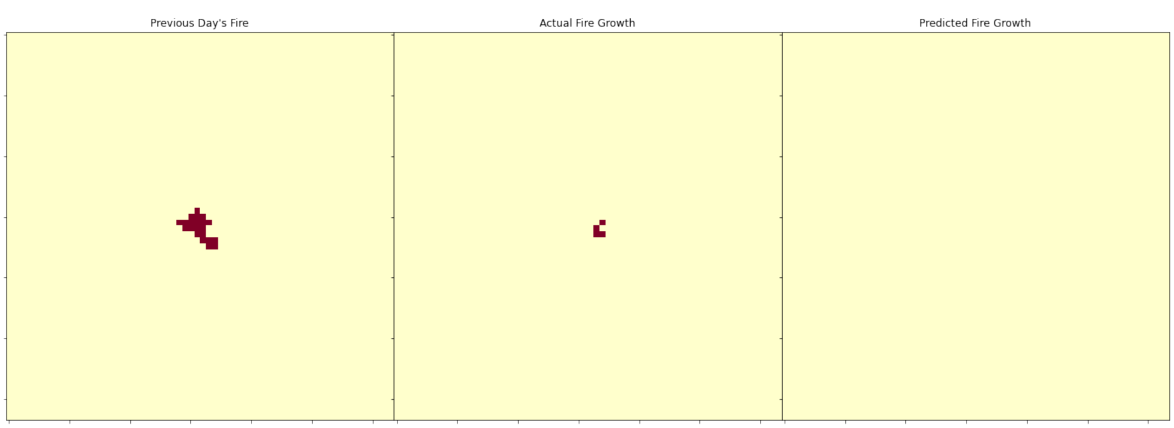

Figure 2: Model configuration one with unweighted cross-entropy loss significantly underpredicts the presence of new fire growth

In an attempt to correct for the underpredictive tendencies of the first model configuration, I created the second model configuration by weighting label weights proportional to importance. Thus, a correct label 1 classification was scaled 500 times that of a correct label 0 classification. This lead to the opposite effect in which the model over-predicted newly burning pixels. While the second model configuration achieved a classification accuracy for label 1 of 99.99%, it also had an overfitting ratio of 323.84. This means that for every observed newly burning pixel the model predicted 323.84 newly burning pixels. Thus, it is likely that the second model configuration converged by labeling all pixels as newly burning. Figure 3 shows an example input raster and model output in which the model classifies all pixels as newly burning.

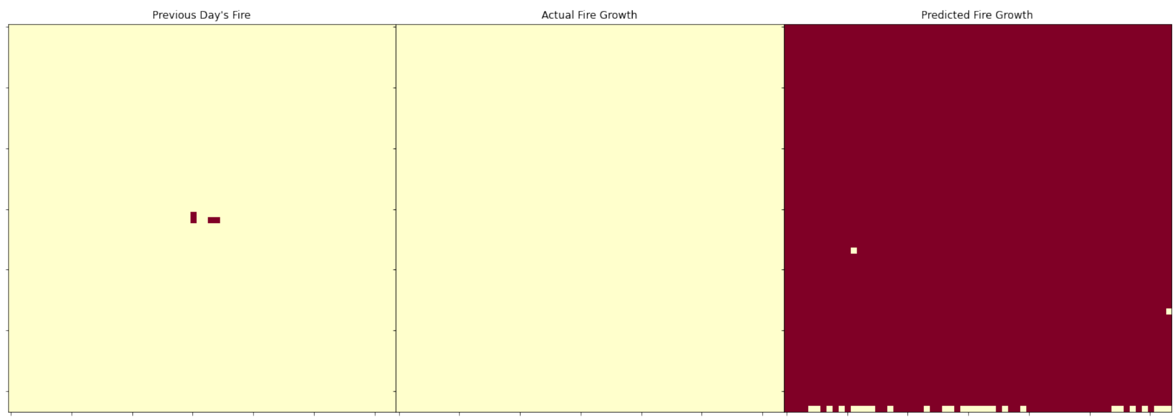

Figure 3: Model configuration two with weighted cross-entropy loss significantly over-predicts the presence of new fire growth

Lastly, the third model configuration uses a nearest-neighbors region of interest to scale the training loss. This model also over-predicts the presence of burning pixels. It achieves a label 1 classification accuracy of 9.19%, much lower than model configuration two, but continues to over-predict newly burning pixels as evidenced by an overfitting ratio of 79.16. Figure 4 shows an example input raster with model prediction from the third model configuration.

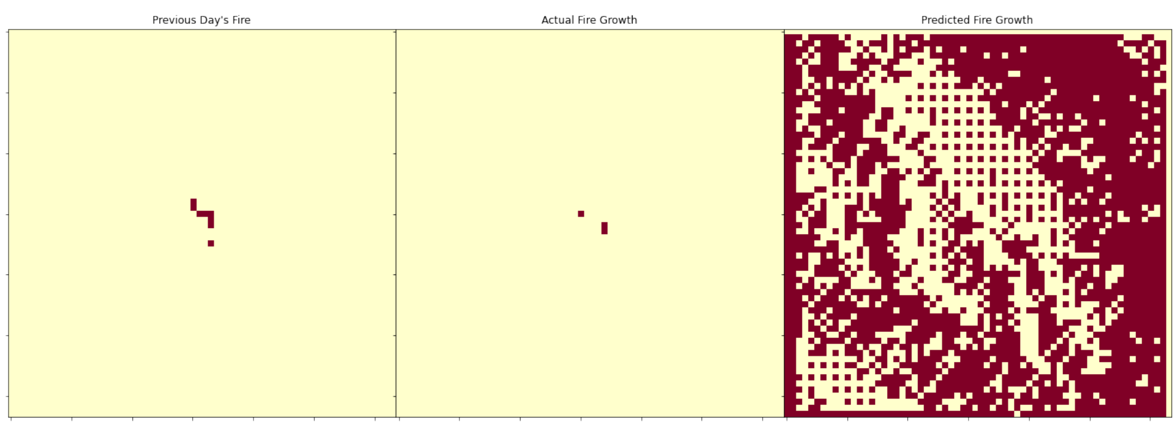

Figure 4: Model configuration three with a windowed cross-entropy loss also over-predicts the presence of new fire growth

4 Results

While the results of all three model configurations suggest that this approach is invalid, there are a number of improvements with potential to improve model outcomes. Firstly, it is likely that important topographic and fuel information was lost in the down-sampling procedure from 30 meter to 500 meter gridded raster data. An alternative model infrastructure such as a J-Net, would allow high resolution gridded data inputs. This model could then capture the nuances of high resolution data while allowing for covariates, and the variable of interest, at a lower spatial resolution.

Additionally, there are a large number of additional datasets that I could explore with the potential to provide additional fire behavior information through the context of the fire behavior triangle. For example, there are raster data for a wide variety of fuel parameters, vegetation densities, and forest disturbance trends. Weather, which is likely the most important predictor of fire behavior, also has many potential options for further inclusion. Products such as Wind Ninja can produce local terrain driven winds from DEM maps and large scale wind information like ERA5. Additionally, FWI is a strong indicator for daily fire danger, but it does not capture warming and drying trends. It may help to include time series data on FWI in order to capture the important impact of trends.

Finally, my model makes the assumption that all fires burned in a natural, untrammeled, landscape. This is clearly a false assumption. Humans regularly take a wide variety of actions to influence the spread of fires on the landscape. This intervention can occur before or during the period of fire growth. Thus, it is difficult to fully describe the scope of management action with regards to an individual fire. Some potential solutions are to switch from MODIS data to geoMAC fire perimeters which would allow for linking a fire to suppression activity, or to account for management action by including including the presence of arial firefighting resources.

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