A 3D CONVOLUTIONAL NEURAL NETWORK FOR PREDICTING WILDFIRE PROFILES

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ABSTRACT

Wildfire has become an unavoidable natural disaster that continues to threaten fire-prone communities and the frequency is expected to increase due to climate change. Therefore, predicting a wildfire spread profile is an essential tool for firefighters when planning an evacuation strategy. The current traditional, physics, and empirically based fire spread models require extensive inputs, which are often difficult to obtain. Thus, we propose a 3D Convolutional Neural Network (CNN), named WildfireNet, that can predict the profile of wildfire of the next day when given historical wildfire profiles and accessible remote-sensing data. WildfireNet utilizes 3-dimensional spaces to extract features from both the temporal and spatial dimensions to better understand the relationship between historical fires and upcoming fires. The motivation behind WildfireNet is to locate fires in a precise manner and be able to accurately predict fire profiles. Pixels that were labeled as fire but not on the previous days were extracted to calculate Intersection over Union (IoU) and recall. WildfireNet outperformed 2D CNN and logistic regression model in both IoU and recall.

1 INTRODUCTION

In recent years, the magnitude and intensity of wildfire have become challenging for the fire-prone community to withstand. Even worse, global warming and consequent fuel drying will increase the frequency of devastating wildfires (Halofsky et al., 2020). If such trend continues, upcoming wildfires will be more destructive than any fires in the past. The consequences of massive wildfires are brutal. For instance, in 2003, wildfires that occurred in San Diego County, California, burned over 376,000 acres and 3,241 households, which was estimated to be \$2.45 billion in terms of total economic costs (Diaz, 2012). Traditional, physics, and empirically based wildfire spread models have been continuously studied to mitigate losses resulting from wildfire. However, these models often require extensive inputs, which are often difficult to obtain or even impossible to get.

Convolutional Neural Networks (CNN) have been widely used with remote sensing data for various applications and showed promising results. Therefore, we implemented one of the commonly used CNN architecture, U-Net, to create WildfireNet. U-Net was developed for biomedical image segmentation that extracts global and local features to learn patterns to output a segmented image. The method has a relatively modest need for data collection and is capable of predicting a wildfire profile within a second. Thus, we present a novel deep learning method to determine dynamic wildfire profiles with the basic input data: wildfire perimeters, land cover, topography, and weather data.

2 RELATED WORKS

Modeling wildfire has been an active research topic. Works have been done towards predicting the occurrence of wildfires with spatial susceptibility (Ghorbanzadeh et al., 2019; Sayad et al., 2019). FARSITE is a two-dimensional model that utilizes a vector propagation approach to depict fire perimeter growth. The model is sophisticated to adjust different fire types and behaviors, such as surface fire, crown fire, spotting, and point source fire acceleration (Finney, 1998). The model shows a promising result in basic conditions as the prediction matches very well to the actual fire boundary. However, it is computationally expensive and requires an extensive number of inputs. Also, the model accuracy varies widely across wildfires in different regions.

In recent years, artificial intelligence has been used to solve the problem. Subramanian and Crowley presented a novel approach for utilizing Reinforcement Learning for learning forest wildfire spread dynamics directly from readily available satellite images (Subramanian & Crowley, 2018). FireCast combined Artificial Intelligence and data collection from GIS to predict which areas are at high risk in the future. It utilizes 2D CNN and is trained to predict areas that are expected to burn during the next 24 hours when given an initial fire perimeter (Radke et al., 2019) . From the studies, utilizing AI to solve the complex nature of wildfire is a promising way to predict wildfire spread and avoid complicated physical computation that many traditional methods hold. Thus, we propose a WildfireNet that can predict the profile of wildfire of the next day. To our knowledge, WildfireNet is the first 3D CNN to be used in the application of the fire spreading model.

3 WILDFIRENET ALGORITHM

3.1 TRAINING METHOD

There are two categories, fire or no fire, to classify for each pixel. Binary cross-entropy loss (BCE) is an appropriate loss function to train the model .

$$BCE = \frac{-1}{N} \sum_{i=0}^{N} y_i \cdot log(\widehat{y_i}) + (1 - y_i) \cdot log(1 - \widehat{y_i}) \tag{1}$$

As shown in the equation above, binary cross-entropy (BCE) loss is informative to our model because it tries to minimize the distance between the predicted and the ground truth probability distributions, which is the ultimate goal of our problem. For instance, if the model predicts a pixel to contain fire where it doesn't, BCE will output a high loss, penalizing the model with a large cost. From this train and error approach, the model will find the local minimum point of the loss function as its goal is to achieve a smaller loss at every training step. Thus, with BCE, the model will be optimized to maximize the likelihood of outputting the correct shape of the wildfire profile. Furthermore, Adam optimization was used and a learning rate of 1e-4 was applied to train the model.

3.2 MODEL AND IMPLEMENTATION

U-Net was first introduced solely for the purpose of image segmentation on biomedical images. The output of U-Net is different than the typical use of CNN, which is on classification tasks that outputs a single class label to an input image. The output of U-Net is different. Instead of assigning a single label per input image, the model localizes the label for each pixel of the input image (Ronneberger et al., 2015). The model has two major paths. It first begins with contraction, which consists of convolutions and maxpool to extract features. Next, the model undergoes expansion where the size of the image resizes back to the original input to enable precise localization. The sequence of contraction and expansion yields a u-shaped architecture. The unique aspect of this model is the outputs from contraction are concatenated to the expansion output. This approach helps the model to maintain precise localization of high-resolution features at the output (Ronneberger et al., 2015).

We decided to implement the U-Net model because 1) the model has a capacity to intake a raw image and output a segmented image, 2) it works well with a small dataset, 3) and it is capable of predicting a wildfire profile within a second.

The U-Net model is adjusted so that it becomes more applicable to our study. Similar to the U-Net, WildfireNet is composed of the two major paths: contraction and expansion. The full architecture of the model is shown in Figure 1. In contrast to the U-Net, WildfireNet consists of fully connected layers at the bottom of the architecture. After the last downsampling, the 3D image is flattened into 1D array, and weather data is concatenated. The model is further trained with dense layers to learn the effect of weather variables in its prediction. Furthermore, past wildfire profiles can play a dominant role in the future shape of the wildfire. Therefore, 3D CNN was used instead of 2D. In 3D CNN, the model further extracts features from both the temporal and spatial dimensions, whereas, in 2D CNN, the model only focuses on spatial features (Tran et al., 2015). In this study, 3 previous days of wildfire profiles are combined to convert input images from 2D to 3D. This allows the model to have a better sense on how historical fires are correlated to the fire on the next day.

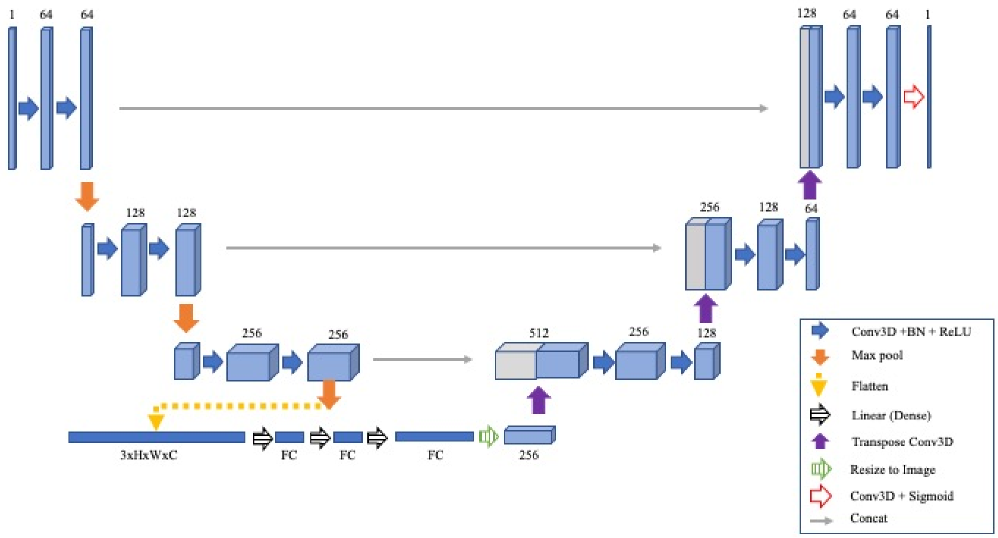


Figure 1: Architecture of WildfireNet

3.3 Input Data

Topography, weather, and available fuels are major contributor to fire growth (Estes et al., 2017). Thus, along with three days of historical fire profiles, we decided to add land cover, topography, and weather data to the model.

3.3.1 Dynamic Wildfire Perimeters

A total of 302 daily fire perimeters were retrieved. The size of the data is limited compared to other deep learning studies. However, WildfireNet, derived from U-Net, is proven to perform well with small dataset (Ronneberger et al., 2015). Wildfire perimeters were obtained from National Inter agency Fire Center FTP Server [1]. Perimeters are in the format of .kmz, which contains an array of coordinates of boundaries. In this paper, only the fires that occurred in California from 2013 to 2019 were observed.

For each wildfire perimeters, as shown in Figure 2, an array of coordinates was used to fill inside the perimeter to create a binary map to reflect the overall shape of the wildfire. In other words, if a given pixel is within the perimeter, the pixel is labeled as 1 to indicate fire, otherwise, if the pixel is outside the boundary, the pixel is assigned to 0 to reflect no fire. An Important assumption was made when creating a binary map. For instance, there were spots of the region within the boundary that was not on fire, but these spots were considered as a risk zone and were filled in as well. binary map consists of 256x256 pixels, covering 0.5 degrees in both latitude and longitude. It is important to maintain the same spatial scale to distinguish fires with respect to their true sizes. Overall, a preprocessed binary map is used as an input to represent the wildfire profile.

3.3.2 Land Cover and Vegetation

Normalized Difference Vegetation Index (NDVI) is a remote sensing data that combines measurement of wavelengths and intensity of visible and near-infrared light to calculate the concentrations of green leaf vegetation (Zaitunah1 et al., 2018). NDVI is useful to fire spreading models because it indicates the water content of the crop and it is more likely for fire to spread on dry vegetation than on wet crops.

[1]Wildfire perimeter source: https://ftp.nifc.gov/

(a) (b)

Figure 2: An example of preprocessing wildfire perimeter. (a) A fire perimeter is plotted. (b) Fire perimeter is shaded in to create a binary map.

Advanced Very High Resolution Radiometer (AVHRR) NDVI was collected from National Oceanic and Atmospheric Administration [2] (NOAA). The data are projected on a 0.05-degree x 0.05-degree global grid. The mean NDVI was used as an input.

3.3.3 TOPOGRAPHY

Topography has a direct effect on fire behavior (Rothermel, 1972). For example, the rate of fire spread rapidly increases on steeper slopes. Studies have shown that there is a strong correlation between topography and fire severity (Estes et al., 2017).

1/3 arc-second digital elevation model (DEM) was retrieved from the USGS national map [3] to reflect topography on locations of fires. DEM contains elevation for each pixel. This allows the model to learn fire behavior that is directly responded to topography, such as slope change. For each wildfire, four corner coordinates of the binary map were used to crop DEM to match spatial location.

3.3.4 WEATHER

Weather is an important factor that can significantly contribute to the spread of wildfires. Simplified daily weather data, including mean wind speed, mean temperature, mean relative humidity were used to represent atmospheric conditions. Weather data were retrieved from the Climatology Lab [4]. The resolution of the data is 1/24 degree x 1/24 degree.

3.4 OUTPUT

After three days of historical fire profiles and remote-sensing data are processed into WildfireNet, it outputs a probabilistic distribution of fire of the next day. A sigmoid activation is used at the last layer to ensure the values of each pixel is within the range of [0, 1], representing a probability of fire occurrence. The output is further processed to create a predicted binary map, which is evaluated with the ground truth in the loss function to train the model. To create a binary map, an optimal threshold is picked and the state of the pixel is classified as fire (1) or not (0) with the following rule:

$$\textit{State of Pixel} = \begin{cases} 1, & \text{if } p \geq threshold \\ 0, & \text{if } p < threshold \end{cases} \tag{2}$$

Various thresholds were evaluated and selected threshold yielded the highest metric scores.

[2]NDVI source: https://www.ncdc.noaa.gov/cdr/terrestrial/normalized-difference-vegetation-index

[3]Elevation data source: https://www.usgs.gov/core-science-systems/national- geospatial-program/national-map

[4]Weather data source: http://www.climatologylab.org/gridmet.html

4 Baseline Model

We decided to use the U-Net and logistic regression model as baseline models to compare and evaluate the performance of WildfireNet. Similar to WildfireNet, U-Net extracts features through downsampling and upsampling pathways, however, it does not consider historical fires since the dimension is limited to 2. U-Net will work as a baseline model to assess the temporal aspects of the WildfireNet in predicting the wildfire shape.

The logistic regression model is a commonly used baseline model due to its simplicity. However, it lacks convolution to extract features. Thus, it will provide a suitable starting point to understand the task and validate the usage of CNN in predicting wildfire spread profiles. The input for the logistic regression model includes historical binary maps, elevation data, wind speed, wind direction, and the state of the surrounding pixels. The state of the surrounding pixels is an essential aspect since the pixel has a higher probability of setting on fire if one of the neighboring pixels is on fire. Moreover, there are a total of 8 neighboring pixels that contribute to the state of the pixel, as shown in Figure 2. Baseline models were trained and tested with the same data as WildfireNet.

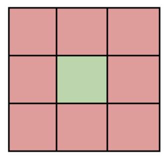


Figure 3: State of the pixel. Green pixel indicates current pixel and red pixels indicate surrounding/neighboring pixels that contribute to the state of the current pixel

5 Results

As shown in Figure 4(a,c), the output of WildfireNet shows a probabilistic distribution of fires occurring at each pixel. If the model is confident that there is a fire in a certain pixel, it will assign a low score on the pixel. The model also projects how fire will spread in the future. For example, in the Mad River Complex fire, there are two major fire bodies. WildfireNet predicts the fire will expand at the bottom of the left body and no change will occur on the right body. In fact, in the comparison between the current day to the next day, it shows that the actual fire of the next day did not expand elsewhere except at the bottom of the left body. Moreover, in the Rey fire, the model predicts the fire will enlarge on the right side of the boundary, whereas, not so much on the left side. In the comparison between the current day to the next day, it shows that the actual fire did expand to its right. These examples validate the model's capacity of predicting the growth pattern of wildfires.

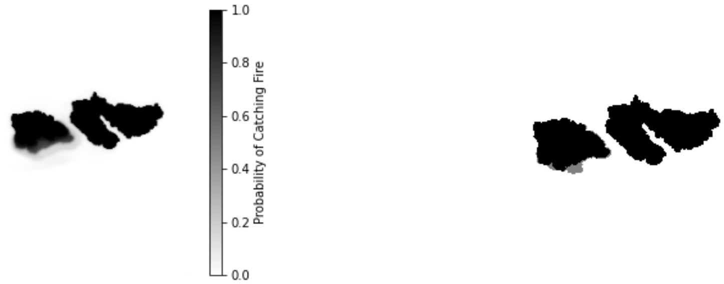
5.1 Evaluation

Intersection over Union (IoU) was calculated to evaluate the model's performance in predicting the profile of the wildfire. IoU is commonly used metric to evaluate the performance of object segmentation. IoU is defined as

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{3}$$

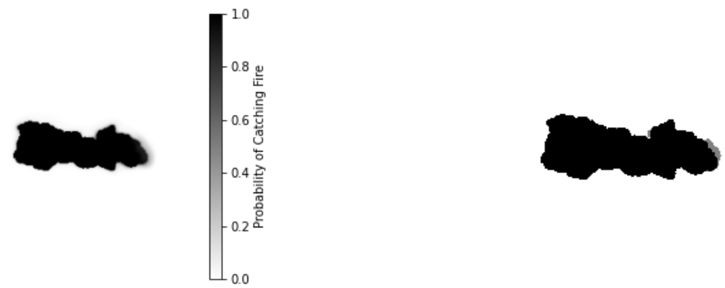
The metric is straightforward once a predicted image and a ground truth image are defined. In this study, both images are binary maps where each pixel is either 0 or 1. Then, the area of overlap is simply the number of pixels that have the same value in both images and union is the area encompassed by both images. Therefore, a predicted image that matches perfectly to the ground truth will score 1. As shown in Table 1, WildfireNet achieved an IoU score of 0.997 in the test set, while U-Net and logistic regression model scored 0.995 and 0.913, respectively. The result indicates that WildfireNet is excellent in precisely labeling each pixel with the presence of fire or not and performs better than the baseline models.

However, in the test set, only 5 percent of labels in the binary map is labeled as fire, which shows a sign of class imbalance in the data set. Therefore, IoU is not the best metric to evaluate a model's



(a) Fire probabilistic distribution of Mad River Complex fire

(b) Current and next day of Mad River Complex fire



(c) Fire probabilistic distribution of Rey fire

(d) Current and next day of Rey fire

Figure 4: WildfireNet output and comparison of real data of the current day to the next day: (a,c) WildfireNet outputs a fire probabilistic distribution of the next day, (b,d) comparison between the current day (solid black) and the next day (light gray).

performance in predicting new fires because the model can obtain a high IoU score by simply predicting every pixel to be 0. Therefore, models are evaluated on only the pixels that were labeled fire on the next day but not on the current day. We defined such pixels as changed pixels. Considering only the changed pixels will truly measure the model's performance in predicting the changes in wildfire profile. Thus, we defined expanded IoU as the area of intersection between the predicted and the truth of the changed pixels over the area of union between the predicted and the truth of the changed pixels.

$$Expanded\ IoU = \frac{Area\ of\ Overlap\ of\ Changed\ Pixels}{Area\ of\ Union\ of\ Changed\ Pixels} \tag{4}$$

Moreover, expanded recall was formulated as true positives of the changed pixels over the total positive of changed pixels.

$$Expanded\ Recall = \frac{True\ Positive\ of\ Changed\ Pixels}{Total\ Positive\ of\ Changed\ Pixels} \tag{5}$$

On the test set, WildfireNet performed better than the baseline models in both expanded IoU and recall. All models scored the lowest in expanded IoU because the metric further penalizes when predicted fires are not present in the actual fire. WildfireNet achieved 0.541 on recall while the U-Net and baseline model scored 0.458 and 0.154, respectively. This implies that WildfireNet predicts correctly more than half of the time on how fires are growing in the actual fire expansion, while the logistic regression model is only correct about 15% of the time. From this result, WildfireNet is superior to baseline models.

Table 1: Statistical analysis of models performance. Metrics used to evaluate the performance of the models. IoU, expanded IoU, and expanded recall were used.

Model	IoU	Expanded IoU	Expanded Recall
WildfireNet	0.998	0.229	0.541
U-Net	0.995	0.165	0.498
Logistic Regression	0.914	0.108	0.154

Wildfires are further categorized into three classes based on the percentage of fire growth from the previous day. Fire is defined as rapid if the fire body expands more than 7% than the previous day, moderate if the growth is between 3% and 7%, and subtle if the growth is under 3%.

Table 2 shows that all models having the highest score in the following order: subtle, moderate, and rapid. It is reasonable for models to perform poorly as fire changes rapidly from one day to another. Wildfire is affected by various dynamic factors including but not limited to the inputs that were used to train the model. For instance, unstable weather conditions are often the major contributor to the rapid fire growth. However, daily weather data is not detailed enough to reflect the volatile nature of the weather. The abrupt changes in the weather, such as gust usually occurs for less than 20 seconds. Daily weather data, having a time interval of 24 hours, is not finite enough to inform the model about the sudden changes. In addition, human-induced fire growth can be a huge factor in contributing fire growth, but simply ignoring the effect can hinder the model's prediction. Therefore, it is reasonable for models to fail in keeping up with the rapid change. In figure 5, WildfireNet outputs a reasonable prediction on the moderate fire. Prediction nearly matches the overall shape of the truth and it predicts the most bottom of the fire body to enlarge, which is the actual case in the real fire. However, in figure 6, WildfireNet cannot keep with a large change of the rapid fire. The model predicts the fire to increase only at the bottom. But in the actual fire, it increases in every direction.

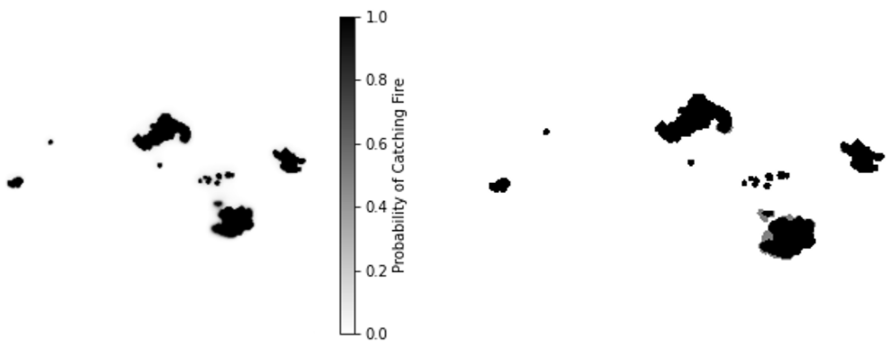


Figure 5: Moderate fire.

Table 2: Recall of different wildfire categories.

Model	Subtle	Moderate	Rapid
WildfireNet	0.653	0.597	0.534
U-Net	0.553	0.401	0.409
Logistic Regression	0.393	0.225	0.209

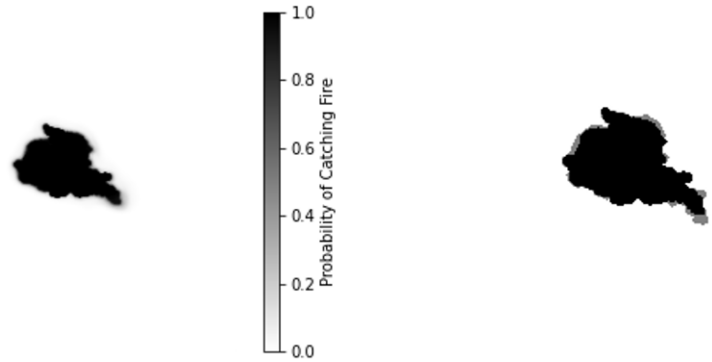


Figure 6: Rapid fire.

6 LIMITATIONS

Compared to many other deep learning applications, WildfireNet is trained with a small dataset. The lack of variability in training data could limit the model to predict accurately when new weather conditions, land cover, and fire profile are introduced. Furthermore, neglecting human-induced fire spread could stall the performance of the model. Furthermore, wildfire is highly influenced by interdependence on coupled climatic and human factors, but several factors were not considered, such as human-induced fire growth. Moreover, a key assumption was made when fire perimeters were preprocessed to create binary maps, which was to consider spots within the boundary that was not on fire to be labeled as fire. Due to such modification, the binary map couldn't have reflected the actual shape of the fire. In addition, fire perimeters were recorded daily, but there is uncertainty whether fire perimeters were obtained at the same time. If time interval varies between days, the fire growth does not reflect changes in the 24-hour time window.

Remote sensing data had different resolutions (wind speed: 1/24 degree, elevation: 1/512 degree, NDVI: 1/200 degree) and contained missing values. Thus, interpolations were put in place to properly complete the data, but it could lead to an error when there is a large amount of missing data.

7 CONCLUSION AND FUTURE WORK

WildfireNet is built and experimented to establish a footprint of using 3D CNN to predict wildfire spread profile. Unlike current traditional, physics, and empirically based fire spreading models, WildfireNet does not require extensive inputs and complex computations and with fire profiles and accessible remote sensing data, it can output an upcoming fire profile within a second. Statistical analysis shows WildfireNet is capable of learning patterns from historical fire spread along with land cover, topography, and weather. The model shows a promising result by obtaining higher scores in IoU, expanded IoU, and recall than the baseline models.

Future work includes obtaining more fire incidents and remote sensing data. Currently, WildfireNet is trained solely on the fires that existed in California and we believe the model can be flexible to predict any types of fire once it has been trained with various types and conditions of wildfires.

REFERENCES

John M. Diaz. Economic impacts of wildfire. *Southern Fire exchange*, 2012.

Becky L. Estes, Eric E. Knapp, Carl N. Skinner, Jay D. Miller, and Haiganoush K. Preisler. Factors influencing fire severity under moderate burning conditions in the klamath mountains, northern california, usa. *Ecosphere*, 8(5), 2017.

Mark A. Finney. Farsite: Fire area simulator-model development and evaluation. *Research Paper, RMRS-RP-4, Revised 2004, Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station*, 1998.

Omid Ghorbanzadeh, Khalil Valizadeh Kamran, Thomas Blaschke, Jagannath Aryal, Amin Naboureh, Jamshid Einali, and Jinhu Bian. Spatial prediction of wildfire susceptibility using field survey gps data and machine learning approaches. *Fire*, 2(3):43, 2019.

Jessica E. Halofsky, David L. Peterson, and Brian J. Harvey. Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the pacific northwest, usa. *Fire Ecology*, 16(1), 2020.

David Radke, Anna Hessler, and Dan Ellsworth. Firecast: Leveraging deep learning to predict wildfire spread. *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, 2019.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. *Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, pp. 234–241, 2015.

Richard C. Rothermel. A mathematical model for predicting fire spread in wildland fuels. *Research Paper, Ogden, UT: U.S. Department of Agriculture, Intermountain Forest and Range Experiment Station*, pp. 40, 1972.

Younes Oulad Sayad, Hajar Mousannif, and Hassan Al Moatassime. Predictive modeling of wildfires: A new dataset and machine learning approach. *Fire Safety Journal*, 104:130 – 146, 2019.

Sriram Ganapathi Subramanian and Mark Crowley. Using spatial reinforcement learning to build forest wildfire dynamics models from satellite images. *Frontiers in ICT*, 5, 2018.

Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. *2015 IEEE International Conference on Computer Vision (ICCV)*, 2015.

A Zaitunah1, Samsuri1, A G Ahmad1, and R A Safitri2. Normalized difference vegetation index (ndvi) analysis for land cover types using landsat 8 oli in besitang watershed, indonesia. *IOP Conference Series: Earth and Environmental Science*, 2018.