SPATIO-TEMPORAL WILDFIRE SPREAD TRACKING

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ABSTRACT

While the increasing frequency of wildfires has been attributed to anthropogenic climate change, predicting the behavior of fires remains a grand challenge. Machine learning algorithms have advanced tremendously over the recent years but are yet to be fully utilized in this domain. The current state-of-art methods rely on physics-based models that are computationally expensive to run. In this work, we propose to use spatio-temporal networks along with Earth science data from remote sensing, and Geographic Information System (GIS) as a prior to predict near-future wildfire spread based on historical fire data. Here we develop a vision to use physical and environmental parameters along with machine learning techniques to improve results in the climate science domain.

1 INTRODUCTION

Wildfires are known to destroy billions of dollars worth of property every year. Changing climate and associated warming has been associated with an increase in the length and severity of the wildfire season. It gets worse when wildfires lead to further damage to climate by affecting not just infrastructure, flora, and fauna but also the air quality thus leading to a vicious circle of climate degradation.

Therefore predicting the behavior of wildfires and increasing the efficiency of wildfire management is pressing and extremely important. Traditionally, most conventional approaches have been built upon human expertise based on scientific intuition and related physics variables Finney (1998). We propose to tackle this problem by considering it a specific case of spatially spreading process (SSP) where we also take climate and geographical features into consideration. Note that this is different from conventional visual tracking of a single object since there can be multiple SSP units (objects) active at multiple locations in an image.

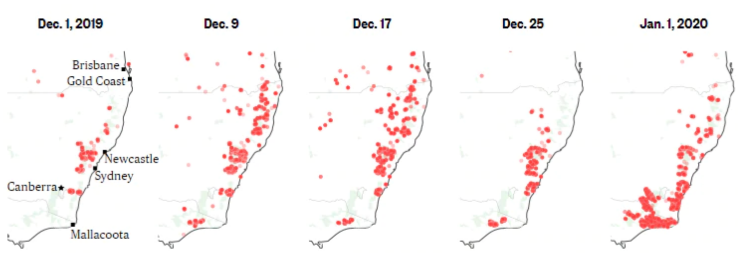

Figure 1: Spread of a wildfire in Australia over a period of 30 days (Source:NASA)

An ideal model needs to effectively infer patterns from fire-spread over past few days (or the chosen unit of time) while also taking the climate parameters into account and capture their influence on the ground truth. Fig. 1 represents the fire spread in Australia over 30 days. In this work, we propose a model that uses data from Geographic Information System (GIS) as a prior to the spread tracking technique. Given the representation of the initial burn area, the model will predict the occurrence of fire in the surrounding area in a given time interval.

This work can have applications in forest wildfire management and also other extreme climate event tracking techniques. More importantly, this can help save a significant amount of flora and fauna along with saving human lives.

2 RELATED WORKS

Conventional forest fire detection and management methods rely on numerical simulation-based methods or require constant data collection through drones to determine and model the behavior of fire in a region (Finney (1998), Lin et al. (2018)). These hand-crafted models' simulations have high accuracy but are expensive to create and update and computationally expensive to use. They use location-based variables, such as manually generated landscape files, weather, fuel, fuel moisture, spread rate adjustments, etc as inputs that are difficult and often require human surveyors on the ground to obtain precise information for every location.

Recently, researchers have started to leverage machine learning and deep-learning techniques. In Castelli et al. (2015), the authors make use of genetic programming for fire modeling and conclude that their techniques are better. Sitanggang & Ismail (2011) use decision trees and a set of if-then rules to develop a model to predict the occurrence of fires in Indonesia. Saranya & Hemalatha (2012) use spatial data mining to obtain useful information from the data set and subsequently apply ANN and Sequential Minimal Optimization(SMO) to quantify ignition risk and hence fire occurrence. The works by Alkhatib (2014) and Zhang et al. (2011) explain the advantage of satellite-based methods for fire prediction but also highlight the hindrances due to temporal resolution. Subramanian & Crowley (2017) use agent-based prediction model called MCTS-A3C with fire as the agent given the task of spreading across the surrounding areas.

Our work finds similarities with the work by Radke et al. (2019) in terms of considering Geo-spatial features, they, however, do not address the effect of time in their approach.

3 IDEA

We propose a framework to train a model that can learn spatio-temporal patterns to make robust predictions over a heterogeneous set of locations around the world. To formulate the problem mathematically, given a climate video $\mathbf{X}$ of length T with the each frame $\mathbf{X}_i$ representing a 2D image with pixels representing burned areas ($\mathbf{y}_i^{j,k} \epsilon \{0,1\}$) along with geographical and atmospheric data for i ranging from 0 to $T-1$, the goal is to predict the areas surrounding the current fire that are expected to burn (change in the value of pixels $\mathbf{\hat{y}_i^{j,k}}$) in the subsequent n frames for $i = T$, ... $T+n-1$

The ground truth $\mathbf{y}_i$ is a 2-D matrix for i^{th} time interval with each cell $\mathbf{\hat{y}_i^{j,k}}$ representing a pixel at j^{th} row and k^{th} column with value $\{1,0\}$ representing burn.

Within this framework, we propose the use of historical fire perimeters provided by GeoMAC[1], a United States Geological Survey (USGS) database as input. For geographical features such as Normalized Difference Vegetation Index (NDVI), elevation, etc, we will use Landsat 8[2] and SAR-equipped satellite (e.g. Sentinel 1)[3] data. Other features, like wind speed, atmospheric pressure, temperature, etc, related to weather and climate can be obtained using National Oceanic and Atmospheric Administration (NOAA)[4] data.

Models trained to detect fire spread in the past have overlooked the temporal features that influence the result. We propose to train a spatio-temporal network(e.g. ST-LSTM) to observe past t frames and predict the fire-spread of next n frames along with a confidence score. The results will be compared with various existing and proposed baselines in terms of efficiency based on both, time taken and prediction accuracy.

Through our experiments, we seek to find the affect of utilizing geospatial information for the predictions while also studying the affect of time-series inputs by answering the following few questions:

1. Given the fire spread perimeters along with Geo-spatial parameters of each day over the past, say 6 days, can a model be trained to efficiently predict the perimeters for the 7^{th} day? What is the difference in results without geospatial features?

[1]https://rmgsc.cr.usgs.gov/outgoing/GeoMAC
[2]https://www.usgs.gov/land-resources/nli/landsat/landsat-8
[3]https://sentinel.esa.int/web/sentinel/user-guides/sentinel-1-sar
[4]https://www.ncdc.noaa.gov/

2. How are the results in (1) different from those obtained when only the perimeter for the previous day was used to train the model?

We expect that both spatial and temporal information will have a positive affect on the prediction accuracy.

Considering how fast fire spreads in real-life scenarios, number of input frames (t) need to be small while being able to predict fire spread for a large n. We find that the following questions need to be answered for the same:

1. Assuming we only want predictions for the next time interval (i.e., n=1), what is the minimum value of t for which we can get highly accurate predictions.
2. What is the maximum value of n for which highly accurate predictions can be made? How does it depend on the number of input frames(t)?

4 Discussion

In this paper, we propose using geospatial features along with fire perimeters as input to train a spatio-temporal model to predict the likelihood of fire spread in the future.

We will also investigate the effect of geospatial parameters on the results. Lastly, we will also explore the relationship between the number of input frames and the number of subsequent output frames that can be predicted with high accuracy. We believe that this approach can be used to track other spatially spreading processes, e.g. oil spills, etc., as well.

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