
WildfireDB: An Open-Source Dataset Connecting Wildfire Spread with Relevant Determinants

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Abstract

Modeling fire spread is critical in fire risk management. Creating data-driven models to forecast spread remains challenging due to the lack of comprehensive data sources that relate fires with relevant covariates. We present the first comprehensive and open-source dataset that relates historical fire data with relevant covariates such as weather, vegetation, and topography. Our dataset, named *WildfireDB*, contains over 17 million data points that capture how fires spread in continental USA in the last decade. In this paper, we describe the algorithmic approach used to create and integrate the data, describe the dataset, and present benchmark results regarding data-driven models that can be learned to forecast the spread of wildfires.

1 Introduction

Wildfires cause loss of life, economic damage, and pose indirect environmental and health threats [Dorr and Santín, 2016]. The November 2018 Camp Fire in Northern California resulted in losses worth \$24 billion, including property destruction and firefighting costs [Bartz, 2019]. Occurrences of such extreme fire events are likely to increase [Joseph et al., 2019]. In 2021, a total of 40,945 wildfires occurred across the United States of America that burned over 4.4 million acres (as of August) [Center for Disaster Philanthropy, 2021]. The effects of wildfires are devastating; power outages, forced evacuation, destruction of housing and business, loss of life, and long-term environmental consequences make it imperative that principled and accurate methods are developed to forecast the spread of wildfires and respond to them.

Modeling the dynamics of fire spread is crucial to first responders. Responders need to allocate limited resources across large areas to combat fires and minimize the loss of life and property [Diao et al., 2020]. Traditionally, fire spread is modeled by tools that use *physics-based* modeling [Rothermel, 1972, Andrews, 1986, Finney, 1998]. While such models are widely used, prediction of fire spread can be improved by a large set of covariates. However, it is difficult to model the exact effect of each covariate on the spread of fire in closed-form. Data-driven modeling can be used to estimate the effects of a diverse set of features on wildfire susceptibility (such as geographic and climate data) [Joseph et al., 2019, Ghorbanzadeh et al., 2019] and improve response to emergency incidents in general [Mukhopadhyay et al., 2020]. However, to the best of our knowledge, there is no comprehensive and open-source data source that combines fire occurrences with geo-spatial features, fuel levels, vegetation, and weather to allow the research community to develop approaches to manage wildfires.

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Generating a comprehensive dataset about wildfires is difficult due to many reasons. **First**, data regarding fire occurrence and covariates is often collected and stored by different agencies and sources. Also, such data is usually available in different data models. For example, the locations and sizes of historical fire occurrences are usually available in a vector model, while information about vegetation, fuel, and topographic features is available in a raster model. These two data models use different storage mechanisms and computational methods that make it difficult to combine them. **Second**, fires spread through extremely large areas through which covariates can vary significantly. As an example, the number of spatial units we use to gather data about vegetation type (and other features) is over 18 billion. Mining such large-scale feature data is a massive computational bottleneck. The large size of the data sources further complicates the fusion of raster and vector data. **Third**, while weather is an important determinant of fire spread, obtaining granular weather data is challenging.

Through this paper, we make available a spatio-temporal dataset, *WildfireDB*, that can be used to model how wildfires spread as a function of relevant covariates. Our data generation, to a large extent, is based on our previous work on large-scale vector and raster analysis [Singla and Eldawy, 2020], which introduces a novel algorithmic approach to merge large scale raster and vector data. To create a comprehensive dataset regarding wildfire propagation, we use the area of continental United States, covering a total area of 8,080,464 sq. kilometers. We look at every wildfire occurrence in our area of interest from 2012-2017. Since the spread of wildfires is largely determined by determinants such as weather, topography, and fuel levels, we extract relevant information from other data streams and merge them with information about fire occurrences. Our dataset consists of a total of 17,820,835 data points.

The rest of the paper is organized as follows. We first describe the data sources used to create the dataset in section 2. Then, we describe the algorithmic approach used to generate the data in section 3. Benchmark results and intended use of the dataset is presented in section 5. We follow the framework described by Gebu et al. in “datasheet for datasets” [Gebu et al., 2018] to create a detailed documentation for the proposed dataset, which is presented in the appendix.

2 Data Sources

Our goal is to present a data source that can be used to model both fire occurrences and the spread of fires. We discretize space and time to create our dataset (we discuss the unit of discretization below). Each entry in the dataset consists of a specific spatial location (we refer to such spatial units as *cells*) that is observed to be on fire at a particular time-step along with spatially-associated vegetation descriptors, fuel levels, and topography information. Each entry also consists of fire occurrence and the same set of features in a neighboring cell at the subsequent time-step.

The fire occurrence data is collected in vector form from the Visible Infrared Imaging Radiometer Suite (VIIRS) thermal anomalies/active fire database [Schroeder et al., 2014, NASA, 2020]. The database provides information from the VIIRS sensors on the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 satellites. While it is also possible to use Moderate Resolution Imaging Spectroradiometer (MODIS) fire detection, we choose VIIRS sensor data due to its improved spatial resolution and improved night-time performance. The dataset contains latitude and longitude values that correspond to the center of pixels representing 375 × 375 meter square cells. An incidence of fire is indicated by the fire radiative power (FRP) of the concerned pixel (cell) which corresponds to the pixel-integrated fire radiative power in megawatts. Due to the increased spatial and spectral resolution the data released by NASA, the fire detection algorithm is tuned in order to optimize its performance even for small fires while balancing the occurrence of false positives [NASA, 2020]. The temporal granularity of the data depends of the specific area of interest and the frequency with which satellites sweep over the area. For continental United States, we observe that the temporal frequency of fire detection varies between 1 and 8 observations per day, with about 85% of the area under consideration having 1 observation per day. As a result, we use a temporal discretization of a day. However, for spatial locations that have more than a single observation in a day, we report all observations.

The vegetation, fuel, and topography data are collected in raster form from the “LANDFIRE” project [Ryan and Opperman, 2013], which is based on satellite imagery. The raster files have a spatial resolution of 30 × 30 meter square cells. For each feature such as vegetation cover, we process approximately 15 billion raster pixels. This includes data categories such as canopy base density,

Table 1: LANDFIRE raster data categories

Name	Year(s)
Canopy Base Density	2012, 2014, 2016
Canopy Base Height	2012, 2014, 2016
Canopy Cover	2012, 2014, 2016
Canopy Height	2012, 2014, 2016
Existing Vegetation Cover	2012, 2014, 2016
Existing Vegetation Height	2012, 2014, 2016
Existing Vegetation Type	2012, 2014, 2016
Elevation	2016
Slope	2016

canopy cover, and vegetation type. We list all the data categories gathered from the Landfire project in Table 1. Further, we collect weather data from Meteostat [Meteostat, 2020], an online service which provides weather and climate statistics around the globe. For continental USA, Meteostat collects raw data from the National Oceanic and Atmospheric Administration (NOAA). We gather aggregated daily weather data for 5,787 weather stations in the continental USA. Weather parameters include average, minimum and maximum temperature, total precipitation, average atmospheric pressure, average wind speed, and average wind direction.

3 Data Generation

To reconcile the different spatial resolutions, we divide the spatial area under consideration into a grid G consisting of 375×375 meter cells (the resolution of VIIRS data), resulting in over 55 million polygons. Let an arbitrary cell be denoted by $g_i \in G$. The center of each fire pixel from the vector data can therefore overlap with exactly one cell in the grid. To compute the corresponding vegetation, fuel, and topographic information associated with each data point, we compute *zonal statistics* for the vector data using the raster data. The method of zonal statistics calculation refers to computing summary statistics using a raster dataset within zones defined by another dataset (typically in vector form). We show the process in Fig. 1.

The data generation process as depicted in Figure 2 includes the following steps: **1.** Compute zonal statistics for each spatial cell (in the form of a polygon in the vector data) using the LANDFIRE raster data. **2.** Find the spatial neighbors for each cell. We define spatial neighborhood of a cell as the set of all adjacent cells in the grid. **3.** For each fire observed in the VIIRS dataset, find its corresponding cell in the grid. **4.** Let an arbitrary fire observed be denoted by (g_i, t) where $g_i \in G$ and t denote the location of the fire and its observed time of occurrence respectively. For each such point, we generate the tuple $(f_{g_i, t}, f_i, x_{it}, g_n, t + 1, f_n, x_{nt+1})$, where g_i and g_n are neighbors, g_i is observed to be on fire at time-step t , and g_n may or may not be burning at time-step $t + 1$. The feature vectors for the cells g_i and g_n are denoted by f_i and f_n respectively. Similarly, x_{it} and x_{nt+1} denote the FRP value of cell g_i (at time t) and cell g_n (at time $t + 1$) respectively. We describe each step below.

1. Compute Zonal Statistics: For each spatial cell in the $375\text{m} \times 375\text{m}$ grid placed over continental USA and for each raster dataset mentioned in Table 1, we want to compute aggregated feature vectors. To compute zonal statistics, we employ the fully distributed system proposed in Singla and Eldawy [2020] on an Amazon AWS EMR cluster with one head node and 19 worker nodes of type m4.2xlarge with 2.4 GHz Intel Xeon E5 – 2676 v3 processor, 32 GB of RAM, up to 100 GB of SSD, and 2 – 8-core processors. We work with data in their native formats by computing an intermediate data structure called *intersection file* that maps raster to vector data. The creation of *intersection file* also facilitates the use of distributed computing to compute zonal statistics, thereby enabling the processing of massive vector and raster data. This process outputs a collection of tuples $(g_i, \text{Geometry}_i, f_i)$ where Geometry_i and f_i refer to the actual spatial geometry and the set of feature values calculated for cell g_i respectively.

2. Find neighbors: The neighbors for each cell in the spatial grid are computed by doing a spatial self-join using the predicate *touches* on the *Geometry* values of the tuples generated in the previous step. The predicate *touches* returns true, if and only if the boundaries of the cells intersect. We

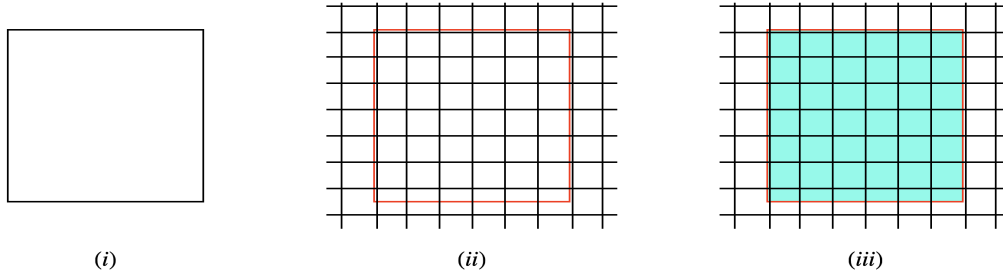


Figure 1: Calculating zonal statistics. (i) An example cell $g_j \in G$ from VIIRS fire occurrence data with a spatial resolution of 375m x 375m. (ii) Multiple LANDFIRE pixels (available in the form of raster data) overlap with g_j . (iii) The process of calculating zonal statistics computes the set of raster pixels that overlap with g_j (shown in blue) and then calculates summary statistics using the set

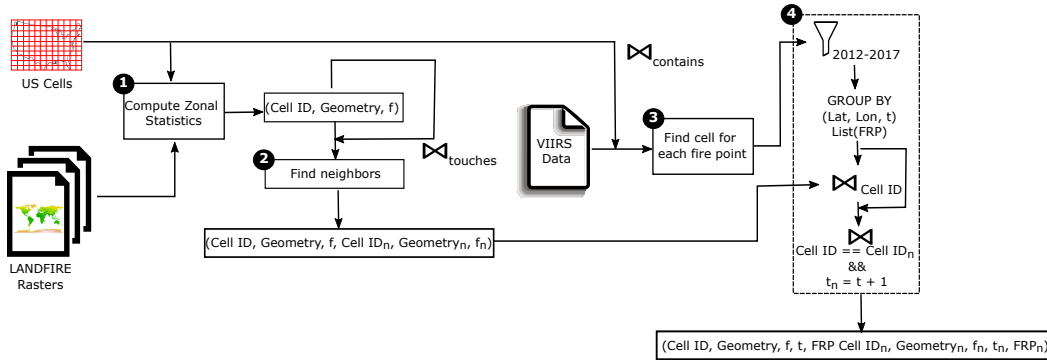


Figure 2: Data Generation Process

implement the spatial join using SpatialHadoop [Eldawy and Mokbel, 2015]. It outputs a collection of tuples $(g_j, Geometry_j, f_j, g_n, Geometry_n, f_n)$ where each tuple in the previous step is appended by the tuples of one of its neighbors (recall that we use subscript n to denote variables that refer to the neighbors of the cell in consideration).

3. Find cell for each fire point: For specific points (latitude-longitude pairs) in VIIRS data and the cells in our spatial grid, a spatial join using the predicate *contains* is performed to find the cell that each fire point is contained in. The predicate *contains* returns true, if and only if the fire point lies in the interior of the cell. This step is implemented using SpatialHadoop [Eldawy and Mokbel, 2015].

4. Generate tuples: To generate the final tuples for *WildfireDB*, we start by filtering the tuples in the VIIRS data for the years 2012 to 2017. The VIIRS dataset may contain multiple tuples for the same fire point having the same time-step yet different FRP values. We group all such tuples by the fire point and time-step and create a list for the FRP values to generate a single tuple. The resulting VIIRS tuples are then joined with tuples from Step 2. Finally, we filter information about each neighbor of the cell under consideration at the next time step. This results in tuples of the form $(g_j, Geometry_j, f_j, t, x_{jt}, g_n, Geometry_n, f_n, t + 1, x_{nt+1})$. If the condition on the neighbor's time-step is not satisfied, the value of x_{nt+1} is set to zero, i.e. no fire.

5. Weather: To incorporate weather, for each tuple generated in step 4, we find all weather stations within 160 km and sort the stations by distance to the centroid of the cell's geometry. For each weather parameter we find the weather reading from the nearest weather station for which a valid reading was available. If there is no valid weather reading for a given parameter from a station within 160 km of the centroid of a cell on a given day, a null value is recorded for that parameter. Recall that each data point in our dataset consists of information about two spatial cells: a reference cell observed to be on fire at a time-step and a neighboring cell that may or may not be on fire in the subsequent time-step. Since we want to capture how fire spreads spatially, we incorporate how wind blows relative to the reference and the neighboring cell. Consider an arbitrary tuple with reference

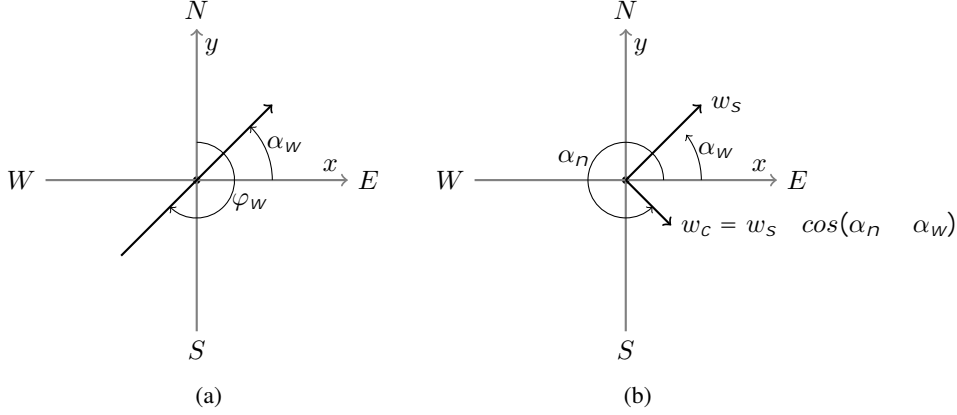


Figure 3: (a) A SW wind (southwesterly) with meteorological wind direction $\varphi_W = 225^\circ$, which corresponds to a polar wind direction of $\alpha_W = 45^\circ$. (b) Calculating the wind component (w_c) of a southwesterly wind with $\alpha_W = 45^\circ$ and magnitude of w_s on a neighboring cell directly southeast ($\alpha_n = 315^\circ$).

Wildfire Visualization Interface

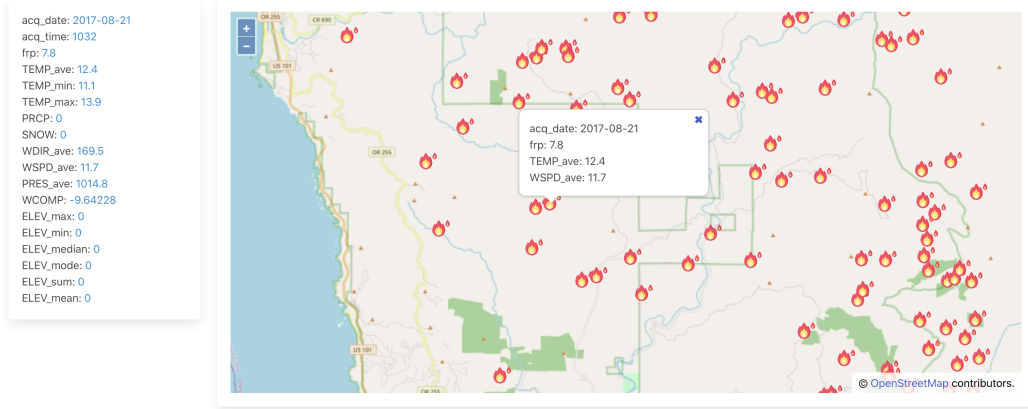


Figure 4: WildfireDB Visualization Interface

cell $g_i \in G$ and neighboring cell $g_j \in G$. Let the time under consideration be denoted by t . Let the average wind speed be w_s and the average meteorological wind direction be φ_W at time t . We follow the convention of measuring meteorological wind direction with respect to the north-south line in a clockwise manner (see Fig. 3). Let the component of w_s that lies on the line connecting g_i and g_j be denoted by w_c . The component w_c can be calculated as $w_s \cos(\alpha_n - \alpha_W)$, where $\alpha_n = \text{atan2}(y, x)$, where y and x are the difference in latitude and longitude between the cells respectively (see Figure 3 for details).

4 Data Availability

In order to enable practitioners and researchers access the data based on their needs, we have created an online interface where users can visualize the WildfireDB dataset. The users can use pan and zoom functions to explore the data. Users can also download data based on a specific area of interest or by using a specific zoom level (or download the entire data at once). Information pertaining to individual fires can also be seen by hovering or clicking. We show the interface in Figure 4. The database and its description is also maintained at <https://wildfire-modeling.github.io/>.

5 Benchmark Results

While our goal is to release an open-source dataset that links fire occurrence with relevant determinants, we also present some results using standard learning approaches to show how *WildfireDB* can be used to forecast the spread of wildfires. The results are presented using data instances that did not have any missing values; we do not perform (or suggest) any data imputation to preserve the original data that was collected. Practitioners and users can choose to replace missing values based on the context and domain expertise. The total number of data points we use for learning is 9,210,537. We use 80% of the data for training and 20% for testing, resulting in 7,368,430 data points in the train set and 1,842,107 in the test dataset.

We present results using three regression models, namely linear regression, random forests, and artificial neural network (ANN) [Murphy, 2012, Goodfellow et al., 2016]. The results of the regression models are provided in Table 2. The random forest model consists of a maximum depth of 30, maximum samples per iteration of 5,000, and trees are varied between 50, 100, and 500. We find that the random forest model was insensitive to the number of trees. The neural network regression model consists of four hidden layers of 500, 400, 128, and 64 units respectively with ReLU activation and a single neuron in the output layer with linear activation. We use the Adam optimizer [Kingma and Ba, 2014] with learning rate of 0.001 to train the network. We find that all the regression models have similar performance.

Forecasting fire intensity can also be presented as a classification problem. In this case, a forecast is labeled as a true positive when both the predicted fire intensity and the recorded fire intensity are greater than a pre-specified threshold (ϵ , say). We investigate three threshold values (0.5, 1.0, and 5.0). The results of the classification models (random forest, logistic regression, and neural network) are provided in Table 3. We observe that both regression and classification models perform poorly when trained using *WildfireDB*. We hypothesize that this results is largely due to the extremely high sparsity in the dataset. We point out that our goal in this paper is solely to create, document, and explain the data source and not focus on modeling fire spread. As a result, we only provide benchmark results using standard approaches and do not seek to create models that can outperform such baselines.

Table 2: Regression Models

Model	MSE	MAE
Linear Regression	45.88	1.08
Random Forest	46.53	1.09
Neural Network	46.73	1.08

Table 3: Classification Models

Model	FRP Threshold (ϵ)	Accuracy	Precision	Recall
Random Forest	0.5	93%	0.62	0.00
Random Forest	1.0	94%	0.61	0.00
Random Forest	5.0	98%	0.00	0.00
Logistic Regression	0.5	93%	0.31	0.02
Logistic Regression	1.0	94%	0.26	0.01
Logistic Regression	5.0	98%	0.00	0.00
Neural Network	0.5	93%	0.00	0.00
Neural Network	1.0	94%	0.00	0.00
Neural Network	5.0	98%	0.00	0.00

6 Discussion

Intended Use: As we show, the proposed dataset can be used to model the spread of wildfires as a function of relevant determinants like vegetation, altitude, canopy height, and weather. We hypothesize that the dataset can be used to achieve the following: a) simulate how fires can spread in the real-time to assist evacuation, b) inform agent-based modeling for planning emergency response,

c) simulate how fires might spread in the near future under the effects of deforestation and climate change, and d) aid planning of new infrastructure development and analyze risk from potential fires. Although the dataset is primarily designed to capture the spread of historic fires, it implicitly also contains data about fire occurrence itself. For example, it is possible to isolate spatial cells where fires originated by searching the spatial-temporal neighborhood of the fires. Using such an analysis, it is then possible to model the occurrence of fires.

Limitations: We point out the following limitations and words of caution about using the data. **1)** Although the dataset captures relevant determinants of fire spread, note that we do not claim any causal link between the features and the spread of fire. For example, consider that a cell $g_i \in G$ is observed to be on fire at time-step t and a neighboring cell $g_j \in G$ is observed to be on fire at the subsequent time step $t + 1$. Although such data can be used to model the spread of fire, we do not claim (for reasons mentioned below) that the fire indeed spread to g_j from g_i . The fire could have spread to g_j from a different neighbor (which would also be captured by the data) or a new fire could have started in it. **2)** Since wildfires pose threats to human lives, infrastructure, and the environment, first responders and firefighters respond to wildfires in order to suppress their spread. Such intervention focuses typically by targeting one of the two important ingredients that help fires spread – fuel and heat. Firefighters reduce heat by using water or fire retardant either on the ground or through air through aeroplanes. Fuel is removed by clearing areas of vegetation, which can include planned fires [US Department of Interior, 2020]. Our dataset does not consist of any information about such interventions. For example, consider a cell observed to be on fire through satellite imagery. Firefighters can respond to the fire before it spreads to a neighboring cell; while the fire *not* spreading to the neighboring cell is captured by our data, the intervention by firefighters is not captured. **3)** Parts of the data we use to aggregate *WildfireDB* is generated through modeling on raw data. For example, the VIIRS fire product NASA [2020] determines the presence of fire by balancing the detection of small fires while simultaneously minimizing false positives. Any noise or inaccuracies generated through such modeling is also present in the proposed dataset.

7 Conclusion

We present an open-source dataset that captures fire occurrences in continental United States between 2012-17. We also extract information about determinants of fire spread such as topography, vegetation, and weather. Our data, presented in a discretized spatial and temporal setting, can be used to model fire spread as a function of different covariates. We also present benchmark results using well-known machine learning algorithms. Importantly, our findings reveal that it is difficult to model the spread of fire using machine learning models due to high sparsity in the data. To the best of our knowledge, *WildfireDB* is the first open-source dataset that connects occurrences of wildfires with topography, vegetation, and weather.

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A Supplementary Material

We present a detailed description of the dataset based on “datasheet for datasets” [Gebru et al., 2018]. We only explain details pertaining to *WildfireDB* (as suggested in [Gebru et al., 2018]); for example, as the dataset does not pertain to people, topics such as re-identification, criminal history, gender composition, etc. are not relevant to the dataset in consideration.

A.1 Motivation

WildfireDB is created to enable data-driven forecasting of wildfires which in turn can aid emergency response. Traditional models that forecast the spread of fires are *physics-based*, that model the effect of each covariate on the spread of fire in closed-form. Data-driven models can accommodate a diverse set of covariates and capture complex non-linear combinations of such features to predict the dynamics of how fires propagate in the real world. The lack of a comprehensive dataset in this regard was the primary motivator behind the creation of *WildfireDB*.

The dataset was created by a collaboration between Vanderbilt University, Stanford University, and University of California, Riverside. The dataset was initially curated for studying how principled decision making under partially observable state spaces can aid response to wildfires. Multiple agencies have helped fund the creation of the dataset (see the following author initials and funding sources). Author SS was funded by Agriculture and Food Research Initiative Competitive Grants no. 2019-67022-29696 and 2020-69012-31914 from the USDA National Institute of Food and Agriculture, AM was funded by the Center of Automotive Research at Stanford (CARS) and National Science Foundation Award Number IIS181495, MW was funded by National Science Foundation Award Number IIS181495, and TD was funded by the Department of Management Science and Engineering at Stanford University.

A.2 Composition

Each instance in the dataset consists of information (vegetation type, canopy height, etc.) of a specific discretized spatial area (referred to as the reference cell) observed to be on fire at a given point in time. It also consists of information about one adjacent spatial area (referred to as a neighboring cell) and whether the neighboring cell was on fire at the subsequent time step or not. Each instance also consists of the local weather conditions (precipitation, humidity, etc.) and the relative strength of wind from the reference cell to the neighboring cell. The spatial and temporal granularity of the data are based on the maximum resolution at which fire occurrence data is available; each discrete spatial area is 375m x 375m and the time resolution is that of a day. The “label” of each instance is the FRP (fire radioactive power) of the neighboring cell. We envision that the data can be used to predict the spatial-temporal spread of fire. However, it is entirely possible to use the data to visualize historical fire occurrences, vegetation types, and weather; in such cases, the presence of a label is not required. The total number of data points is 17,820,835.

The data consists of all spatial areas detected to be on fire in continental United States between the years 2012-2017 through VIIRS sensors on the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 satellites. We point out that the direction of wind is missing for about 40% of the data. However, the magnitude of the wind is present for all data points.

A.3 Collection Process and Author Contributions

Each data source is listed in section 2 of the main paper. The data was collected by authors TD, SS, MW, and AM. TD and AM evaluated multiple sources pertaining to wildfire data and finalized the chosen data source (VIIRS). The data was collected by TD directly from Earth Data, an open source data portal managed by NASA. SS merged the vector and raster data (see section 3). MW collected the weather data from Meteostat [Meteostat, 2020] and matched each instance of observed fire with relevant weather information. MW generated the benchmark results. The visualization platform was created by VG. The manuscript was written by AM and SS. Feedback about the manuscript was provided by MK, AD, AE, and RS. The overall process was supervised by AM. All authors were compensated through their salaries/research stipend at their respective universities.

A.4 Preprocessing

Preprocessing steps are mentioned in the main body of the paper.

A.5 Uses

The primary purpose of the dataset is to forecast the spread of fires as a function of relevant covariates. The dataset has already been used to optimize response to wildfires [Diao et al., 2020]. We also

tested the use of the data in Vanderbilt University’s graduate level course on Big Data (Topics of Big Data, CS:4266/5266). The dataset can also be used for visualizing the spread of historical fires and studying the occurrence of wildfires themselves.

A.6 Distribution

We have released the data as open-source, which means that the data can be distributed freely. We require that the paper accompanying this release be cited when the dataset is used. The location of the data is mentioned in the main body of the paper.

A.7 Maintenance

The dataset is currently being maintained by the authors SS, MW, and AM. The contact information of the authors are provided in the dataset webpage and on the main body of the paper. Any issues and/or inconsistencies found with the data should be reported to SS, MW, and AM. We welcome other contributors who want to augment the data and request them to contact author AM. An older version of the dataset was released at the Neurips AI for Earth Sciences Workshop 2020. We will currently continue to maintain the earlier release although the current version subsumes the earlier data.