BurnMD: A Fire Projection and Mitigation Modeling Dataset

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Abstract

Today's fire projection modeling tools struggle to keep up with the rapid rate and increasing severity of climate change, leaving disaster managers dependent on tools which are increasingly unrepresentative of complex interactions among fire behavior, environmental conditions, and various mitigation options. This has consequences for equitably minimizing wildfire risks to life, property, ecology, cultural heritage, and public health. Fortunately, decades of data exist for fuel populations, weather conditions, and outcomes of significant fires in the American West and globally. To benefit from this data, the fire management community needs data standardization and validation among many competing fire models. Likewise, the machine learning community needs curated datasets and benchmarks to develop solutions necessary to generate impact in this space. We present a novel dataset composed of 308 medium sized fires from the years 2018-2021, complete with both time series airborne based inference and ground operational estimation of fire extent, and operational mitigation data such as control line construction. As the first large wildfire dataset with mitigation information, Burn Mitigation Dataset (BurnMD) will help advance fire projection modeling, fire risk modeling, and Artificial Intelligence-generated land management policies.

1 Introduction

Wildfires are naturally occurring phenomena that are an integral part of healthy ecological systems. However, uncontrolled fires, especially those near the Wildland/Urban Interface (WUI), can pose a considerable threat to life and property and therefore must be mitigated or fully suppressed. Furthermore, there is growing concern among the scientific and firefighting communities that the effects of climate change will lead to increased intensity and severity of wildfires [1]. Due to the seriousness and complexity of the problem, updated modeling and mitigation techniques are necessary to combat it. Artificial Intelligence (AI) and Machine Learning (ML) are potential techniques that can be applied to the topics of wildland fire modeling, forecasting, and optimized mitigation planning; however, these methods require large datasets representative of historical events. These datasets currently do not exist in this domain and data sources (including aerial sensor data, weather patterns, and effects of previous wildfires) are spread across multiple agencies with incompatible formats and often non-overlapping or misaligned spatiotemporal fire spread and mitigation tracking. Fire projection, or forecasting models, are essential tools in firefighting training, fire planning, risk modeling, and real-time incident response. Wildfire behavior and spreading has long been

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modeled by the Rothermel surface fire spread model [2]. Newer models include CAWFE [3], ELMFIRE [4], and WRF-SFIRE [5]. These were developed by studying small, well-contained wildfires or physics-based simulations and were not explicitly validated against historical data. As climate change drives hotter and drier fire seasons, historical fire projection model strategies must be updated to account for emergent and novel fire behaviours. Additionally, fire disaster response is often a multi-jurisdictional and resource constrained problem which necessitates proper logistical distribution of firefighting and emergency assets that are robust to equipment failures and the realities of command. The lack of standardization among the agencies that collect wildfire data limits innovation. This work will serve as a standardized dataset that can be used in downstream efforts for modeling and predicting wildfire spread and mitigation techniques, enabling the greater wildfire community to validate and verify future modeling techniques in this domain.

1.1 Related Work

Local and foreign governments have jointly invested in improved modeling techniques for predicting the occurrence and impact of disastrous events like tsunamis, hurricanes, and floods [6, 7, 8]. Modeling these events, which include machine learning algorithms [9, 10, 11], relies on access to standardized and verified data. Wildfire models, comparatively, are not updated, standardized, or verified across historical databases [12, 13]. Researchers have curated datasets for wildfire and fire events in the past [14, 15, 16], but little attention has been paid to the role human intervention plays in the progression of a wildfire. Without this, wildfire models do not represent the behaviour seen by fire managers, leaving the general population at a larger risk for loss of life, property, and ecology. This work contributes the first wildland fire dataset that includes community mitigation efforts.

2 Data Sources

Wildfire reporting is fragmented across eight government agencies in the National Interagency Fire Center (NIFC), which adds complexity to the collection and dissemination of data. NIFC data is publicly available through their Open Data Site [17]. The datasets used in this work include: Final Fire Perimeters, Operational Mitigations, and Operational Base Camps and Water/Retardant Drop Sites. More information is in Appendix 6.1.1 and 6.1.2.

To verify dates and add missing flight times in NIFC data, this work leverages Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS), which are space-based remote sensing data sources. MODIS is onboard NASA's Terra and Aqua satellites, which covers Earth's surface every 1-2 days. MODIS provides active fire data at 1km resolution [18, 19] and burned area at 500m resolution [20]. A successor to MODIS, the VIIRS instruments are onboard two NASA/NOAA joint polar satellite systems and provide active fire data at a resolution of 375m. These products are downloadable courtesy of NASA [21].

3 Methodology

The following sections describe improvements and corrections to wildfire databases. The outcome is a dataset with corrected information and new data applicable to AI and modeling and is accessible for download at `fireline.mitre.org/burnmd`.

3.1 BurnMD Dataset

The proposed BurnMD dataset format is based on the NIFC database format of *GeoPandas* DataFrames, descibed in Table 1 and further detailed in Appendix 6.1. Table 2 shows the additions made to create the BurnMD dataset. Modifications are detailed in Section 3.2. The goals of the additions and modifications are twofold: to correct and standardize the inconsistencies that have occurred through the multi-agency reporting system, and to make spatio-temporal AI-enabled research and modeling possible. The Operational Mitigations for POINTS data detailed in Table 1 underwent schema and entry sanitizing. It is near-impossible to verify dip and drop sites for wildland fire mitigation, thus the data is used as-is in the BurnMD dataset. Additionally, some incorrectly labeled entries could not be deduced from their datetime and coordinates and therefore are currently excluded from BurnMD.

Table 1: NIFC Databases

***GeoPandas* Dataframe**	**Type**
Operational Perimeters (Completed)	POLYGONS
Operational Mitigations (Dozer Lines, Hand Lines)	LINES
Operational Mitigations (Water Drops, Fire Retardant Drops)	POINTS

Table 2: BurnMD: Example Dataset Entry Additions

Operational Perimeters: *POLYGONS*		
Fire Start Location	*geometry*(lat, long)	Approximate start location of a wildfire
Fire Start Date	*string*(Datatime)	Start datetime of the wildfire
Fire Containment Date	*string*(Datatime)	Containment datetime of the wildfire
Operational Mitigations: *LINES*		
Mitigation Start Date	*string*(Datatime)	Calculated datetime of the start of a mitigation effort
Feature Category	*string*(Feature)	Dataset only includes "*Completed*" mitigation features
Feature Timestamps	*List*(Datetime)	List of calculated timestamps to the corresponding latitude, longitude coordinate in a mitigation line

3.2 NIFC Database Inconsistencies

This section discusses solutions to missing, duplicate, and inconsistent entries in the NIFC databases. First, the timestamp entries in the *Point*, *Lines*, and *Polygon* databases were verified to be within bounds of the beginning and containment of the wildfire. Where wildfire perimeter datetimes are not specified or not entered in the *Polygon* database, we further verify through MODIS and VIIRS imaging described in Section 3.3, if no data can be recovered for a perimeter, it is removed from the BurnMD database.

Second, the *Polygon* database was analyzed for duplicate entries by referencing total burned area (in square-kilometers), timestamp entries, and perimeter coordinates. Entries with overlapping geometry, timestamps, and area were noted as duplicates. This duplication can be the result of different types of sensor measurements through reporting agencies. For example, as multiple agencies work on the same wildfire, one agency may report a fire perimeter from IR-based imaging while another agency may report the same perimeter from 'mixed methods' or GPS flights. As it is impossible to verify which agency, if any, are the true ground truth, we keep this data, but note it as a near-duplicate for a different collection method entry in the dataset. It is up to the discretion of the user to filter on these collection methods for their own use-cases.

Third, in many cases, perimeter entries were inputted with incorrect datetimes. The reported datetimes often referenced the time when an "infrared interpreter" added a polygon into the database, rather than the time the data was collected. Similarly to missing datetimes entered in the database, these entries can also be verified through MODIS and VIIRS sensor imaging.

3.2.1 Database Additions

This section discusses solutions to the original NIFC databases that enable the use of historical wildfires for validation and verification of current and future fire projection modeling, fire risk modeling, and AI-generated land management policies. To accomplish this, multiple additions to these databases needed to be made to resolve the fragmented data spread across multiple agencies. As described in Table 2, the wildfire perimeter database was further expanded through the addition of wildfire start location, start datetime, and containment datetime. This data was collected through cross-referencing data with documentation from reporting agencies and final wildfire statistics. A wildfire's containment is when it has been 100% contained and no agency is actively fighting it. These datetimes are critical for both verification and in downstream modeling of weather and fuel at the start of a wildfire.

Further described in Table 2, the Operational Mitigations database can be significantly improved by adding datetimes for individual mitigation lines. As such, BurnMD database includes datetimes for individual latitude and longitude coordinates along a mitigation line that was "Completed", i.e, hand lines and dozer lines. This information is necessary for AI and other modeling and simulation tools, where fire spread and trajectory can be impacted by mitigation efforts at specific times.

To recover datetimes of a line, this work uses the final timestamp of a mitigation line, the rate of production for mitigations lines descibed in [22], and the relative fuel and topography provided by[23] of a given coordinate along a line to calculate each corresponding coordinate's timestamp.

To perform this calculation, we first leveraged documentation provided by the National Wildfire Coordinating Group (NWCG) [22] to determine hand crews and bulldozer production rates of completed production lines. The BurnMD dataset assumes a 20-person hand crew places hand lines and the most-common type of Dozer, a D6C, places the dozer lines. We also assume the standard rate of chains per hour in which a production, or mitigation, line is implemented is chains per 3-feet per hour for hand lines and chains per 30-feet per hour for dozer lines. Documentation is not provided for the width of a chain, which is approximately 66-feet in length.

Production rates change with respect to the relative fuel and topography of the latitude and longitude coordinate and the directness of an approaching wildfire edge. So, next we collected fuel and topography data from LandFire at 30 meter resolution [23]. We use the 13-Anderson Fuel Models to calculate the rate of production, and currently assume a Type I Indirect approach as described in [22].

Last, we identify the hand line approach since it impacts the duration and subsequent datetime between any set of latitude and longitude coordinates. We assume the hand crew is spaced closely together and works across the line to avoid holes in the line which could allow for fingering of the fire.

The following equation estimates this calculation. Given a completed production line timestamp, t_P, and each point, $P_{\mathit{(latitude,\ longitude)}}$ along a line, we can calculate each timestamp, $t_{p(i)}$, using the rate of production, $R_{\mathit{(fuel,\ topography,\ incident\ type)}}$:

$$t_{p(i)} = t_{p(i+1)} - (\Delta P * R)$$

where ΔP is the calculated length between the previous point, $p_(i+1)$, and the current point, p_i.

3.3 Verification

MODIS and VIIRS are leveraged for verification of the NIFC daily fire perimeter data. As noted in Section 3.2, daily fire perimeter entries into the database may have missing or incorrect datetimes, while still maintaining the polygon, or perimeter data. To overcome these inconsistent values, we can use this IR data to approximate datetimes, and further verify the extent of a wildfire.

4 Results

BurnMD is hosted at `fireline.mitre.org/burnmd`. As an example of BurnMD data, Figure 1 shows the Mineral Fire from California's 2020 fire season, which burned approximately

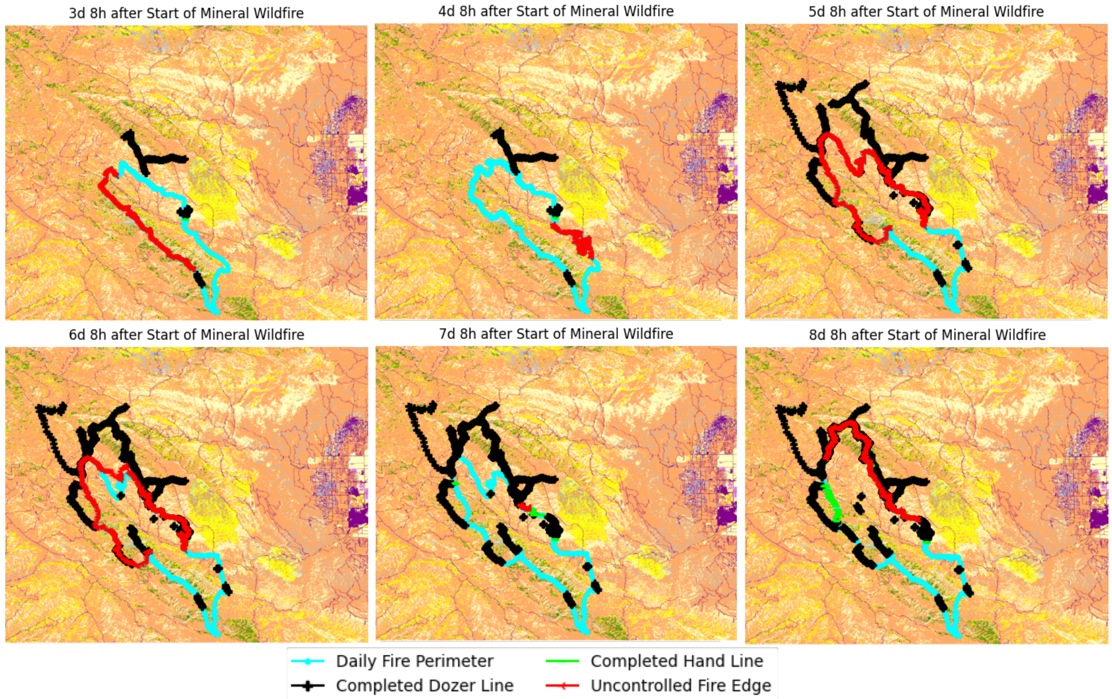

Figure 1: Sample case from the BurnMD dataset of the 2020 Mineral Fire in California over multiple days showing fire propagation extent and mitigation actions over time. Lines are dilated for visibility.

29,667 acres in 13 days. This example shows mitigation lines and fire perimeters as a function of time, which is critical for modeling and simulation of the event. This information is available for a total of 308 medium sized fires from the years 2018-2021 that occurred in the western United States. We define a medium-sized fire as a fire with a final perimeter between 6,400-64,000 acres (10-100 square miles). Tables 6 and 7 in Appendix 6.2 show the number of fires per state per year, and an example of metadata for the California 2020 fires included in BurnMD, respectively.

5 Discussion

This paper describes a database that includes time series of wildfire perimeters and mitigations for 308 medium-sized fires in the western United States from the years 2018-2021. Data was primarily obtained from NIFC and was corrected and modified for internal consistency and ease of use. These additions and modifications allow consistent time resolution, which is essential for the use of time-series based ML algorithms in fire mitigation.

Future database features will include land cover layers, road and other structure layers, as well as weather information for each fire. The database can also expand to small fires. This work focused on medium to large fires, since these fires have escaped containment and thus are a priority for fire managers. To improve accuracy and reliability, the database can leverage data from positioning and tracking devices recorded at the time of a wildfire's occurrence. This is currently infeasible since some agencies lack these devices or the data is proprietary.

BurnMD's historical wildfire and mitigation data will accelerate the AI community in developing algorithms that simulate wildland fire behavior, improve fire management strategy and planning, extract insights from effective land management strategies, and validate and verify existing wildland fire models.

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6 Appendix

6.1 Wildfire Database Sources

6.1.1 NIFC: Final Fire Perimeters

The NIFC provides final fire perimeters for all known historical fires in the "Interagency Fire Perimeter History" database. These perimeters have been derived from a variety of methods ranging from carbon dating for very old fires, to hand-walked GPS and aerial reconnaissance for more modern fires. The database includes the fire year (defined as the year in which the fire started), incident name, calculated perimeter size, information about the agency reporting the perimeter, and other relevant data. The Interagency Fire Perimeter History[24] database can be downloaded as a CSV file, KML file, GIS shapefile, or a GeoJSON file. For more details on the contents of the database, please refer to the NIFC database schema [25].

6.1.2 NIFC: Operational Database

NIFC also provides operational datasets which are yearly collections available from 2018-2021 that include *Point*, *Lines*, and *Polygon* databases that describe all of the firefighting operations from participating agencies. *Point* data described in Table 3 includes base camp locations and water dipping sites. *Line* data described in Table 4 includes mitigation lines created by dozers or hand crews, roads that were used as firelines, the uncontrolled fire edge, and any planned hand or dozer lines that have not been started or are incomplete. This database does not include the size of the hand crew nor the type/class and number of dozers used to implement mitigation lines, however this data does exist spread across other reports. Future iterations of our work will attempt to include this data.

Table 3: NIFC Operational Database: Points

Incident Name	*string*	Name of the wildland fire incident
Complex ID	*Number*	The IRWIN ID of the incident's parent Complex Record
Incident ID	*Number*	Unique identifier assigned to each incident record in IRWIN
Feature Category	*string*	Database entry type i.e Dip Site
Label	*string*	Describes the feature, i.e Staging Dip
Map Method	*string*	Defines how the source polygon was derived
Point Date	*string*(Datetime)	Timestamp of source point feature creation
Date Current	*string*(Datetime)	Timestamp of source point feature database entry
Point Date	*string*(Datetime)	Timestamp of source point feature collection
geometry	*GeoSeries* POINT	latitude, longitude of the feature or action

Contents of the NIFC Operational Database for Point data containing operational mitigations [25].

Polygon data shown in Table 5 consist of the fire perimeters after an indiscriminate amount of time. This differs from the other datasets, since the agencies typically update this data well after the fire was contained. The final recorded perimeter in this data is occasionally the same as the one found in Section 6.1.1 data. Thus, we compared fire perimeters to active fire locations from space-based observations for several cases.

Table 4: NIFC Operational Database: Lines

Incident Name	*string*	Name of the wildland fire incident
Complex ID	*Number*	The IRWIN ID of the incident's parent Complex Record
Incident ID	*Number*	Unique identifier assigned to each incident record in IRWIN
Feature Category	*string*	Database entry type i.e Uncontrolled Fire Edge
Map Method	*string*	Defines how the source polygon was derived
Create Date	*string*(Datetime)	Timestamp for the source feature creation
Date Current	*string*(Datetime)	Timestamp of feature database entry
Line Date	*string*(Datetime)	Timestamp of source feature collection
Length Feet	*Number*	Calculated length (feet) of line *geometry*
geometry	*GeoSeries* LINE	latitude, longitude points that define the line

Contents of the NIFC Operational Database for Line data containing operational mitigations [25].

Table 5: NIFC Operational Database: Polygons

Incident Name	*string*	Name of the wildland fire incident
Complex ID	*Number*	The IRWIN ID of the incident's parent Complex Record
Incident ID	*Number*	Unique identifier assigned to each incident record in IRWIN
Feature Category	*string*	Database entry type i.e Wildfire Daily Fire Perimeter
Map Method	*string*	Defines how the source polygon was derived
GIS Acres	*Number*	Automated calculation of the source polygon acreage
Create Date	*string*(Datetime)	Timestamp for the source polygon feature creation
Date Current	*string*(Datetime)	Timestamp of a particular database entry
Polygon Date	*string*(Datetime)	Timestamp of source polygon feature collection
Shape Area	*Number*	Calculated area (meters) of polygon *geometry*
geometry	*GeoSeries* POLYGON	latitude, longitude points that define the polygon shape

Contents of the NIFC Operational Database for Wildland Fire Perimeters [25].

6.2 Wildfire Metadata Examples

Table 6 provides an overview of the number of fires in each western State for the years 2018-2021 that have a final perimeter between 6,400 and 64,000 acres (10-100 sq. miles). Table 7 is an example of available metadata for the fires in California in the year 2020.

Table 6: BurnMD wildfires with final perimeters between 6,400-64,000 Acres

State	**2018**	**2019**	**2020**	**2021**	**Total**
Arizona	4	9	17	9	39
California	13	10	25	8	56
Colorado	9	1	4	2	16
Idaho	17	6	4	10	37
Montana	5	1	4	15	25
Nevada	7	5	11	2	25
New Mexico	3	3	4	1	11
Oregon	12	3	6	12	33
Utah	5	3	5	4	17
Washington	6	5	9	14	34
Wyoming	8	2	4	1	15
Total	87	48	93	78	**308**

Table 7: BurnMD 2020 California wildfires with final perimeters between 6,400-64,000 acres

Incident Name	**Incident ID**	**Start Date/Time (UTC)**	**Days Active***	**Start Location (Lat, Lon)**	**Acres**
Apple	CA-RRU-096640	08/01/20 01:08	13	33.991, -116.962	33,235
Blue Ridge	CA-ORC-0121612	10/26/20 21:32	7	33.877,-117.675	13,695
Blue Jay	CA-YNP-000054	07/25/20 01:00	118	37.812,-119.646	6,922
Bond	CA-ORC-136890	12/03/20 01:14	9	33.744,-117.675	6,680
Carmel	CA-BEU-004081	08/18/20 21:24	11	36.444,-121.682	6,995
Devil	CA-KNF-007084	09/09/20 unk	67	41.766, -123.375	8,870
Dome	CA-MNP-012356	08/15/20 22:22	7	35.301, -115.598	44,219
El Dorado	CA-BDF-013409	09/05/20 12:51	71	34.080, -116.986	22,745
Gold	CA-LMU-003917	07/20/20 14:12	23	41.110, -120.923	22,650
Hog	CA-LMU-003874	07/18/20 17:28	30	40.420, -120.863	9,565
Lake	CA-ANF-003289	8/12/2020 22:38	19	34.671, -118.518	31,000
Loyalton	CA-TNF-001600	08/12/20 17:13	46	34.679, -118.452	46,765
Mineral	CA-FKU-010219	07/13/20 16:40	13	36.095, -120.522	29,665
Mountain View	CA-OVD-030860	11/17/20 19:15	13	38.515, -119.465	20,380
Nadeau	CA-CDD-011339	07/30/20 unk	6	36.020, -117.476	9,150
North	NV-CCD-030547	08/02/20 unk	7	39.849, -119.991	6,882
Rattlesnake	CA-KNP-000080	08/16/20 17:35	15	37.736, -119.783	8,420
River	CA-BEU-004024	08/16/20 10:04	19	39.088, -121.014	50,215
Sheep	CA-PNF-001299	08/22/20 22:02	17	40.274, -120.757	29,540
Silverado	CA-ORC-0121364	10/26/20 07:54	11	33.736, -117.657	12,470
Slink	NV-HTF-030684	08/30/20 01:00	16	38.568, -119.568	26,765
Stagecoach	CA-CND-002309	08/03/20 17:33	15	35.430, -118.533	7,750
Valley	CA-CNF-002833	09/05/20 16:02	18	32.765, -116.692	16,390
Walbridge**	CA-LNU-013407	08/17/20 06:40	46	38.481, -122.148	55,210
Zogg	CA-SHU-009978	09/27/20 16:03	16	40.539, -122.566	56,340

**Days with records in NIFC Final Reports, otherwise determined through MODIS/VIIRS verification; **Part of the LNU Lightning Complex; unk = unknown*