SPATIOTEMPORALLY OPTIMIZING PRESCRIBED BURNS WITH MACHINE LEARNING

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ABSTRACT

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***K*eywords** Machine learning · Wildfire management · Prescribed Burns · Geospatial Data

1 Introduction

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2 Related Work

In this study, we train and optimize various machine learning algorithms to spatiotemporally determine optimal prescribed burns in wildfire prevention. This section provides and related work of these techniques.

*Use footnote for providing further information about author (webpage, alternative address)—*not* for acknowledging funding agencies.

2.1 Datasets

We will first discuss previously aggregated datasets and sources utilized in computational studies for wildfire prevention.

2.1.1 Remote Sensing Data

Significant progress in wildfire-related data collection has been achieved through satellite imaging. Remote sensing data collected from various satellites including the Terra and Aqua satellites have proved useful in past studies such as [12]. [12] aggregates remote-sensing data in the form of images to develop and train computer vision models for early wildfire detection. Even more specific and comprehensive approaches such as those found in [15] have integrated remote-sensing data derived from moderate resolution imaging spectroradiometer (MODIS) thermal anomalies and global position system (GPS) coordinates to compose useful wildfire data inventories. Polygons collected from the GPS systems can be correlated with MODIS products in specified study areas under designated time frames to train parameter-based models ranging from logistic regression to neural networks.

2.1.2 Other Sources

Other related studies including [1] and [13] have aggregated data from the United States Geological Survey (USGS), evaluating historical fire perimeters from the internal GeoMAC database to train and test against cases ranging from early prediction to post-wildfire debris flow. [13] provides comprehensive overview on the retrieval and cleaning of data from USGS to utilize in computational approaches, offering significant algorithm fitting towards such relevant data.

Imaging not acquired from satellite sourced images arise in studies involving controlled burn measures like [5]. [5] presents UAV-aided imaging for evaluating burn efficacies in preventing wildfires through computer detection and environmental impacts.

2.2 Computational Approaches

In this section we will discuss previous computational approaches towards wildfire prevention-related efforts. Existent studies have relied on parameter-trained prediction models to forecast and understand burn areas, potential wildfire environments, and wildfire effects on wildlife environments. Computational approaches trained on quantitative datasets attempt to create objective analysis of typically-qualitative scientific observation of wildfire-prone environments.

2.2.1 Machine Learning

Extensive work had been conducted on using both linear and non-linear models in early prediction and modeling of wildfires. [3] describes an XGBoost founded attempt using parameters including temperature, RH, 10 m wind speed, boundary layer depth, Lavdas Atmospheric Dispersion Index, daily total precipitation, and the climatological probability of fire towards discovering ideal conditions for prescribed burns, optimizing for the climatological-specific factors of this study's objective of spatiotemporally optimizing prescribed burns.

Various additional works including [6], [10], [16], and [15] implement random forest classification within a workflow, for inference testing, wildfire mapping, and susceptibility prediction/mapping, respectively. Other non-linear methods including Boosting Regression Trees (BRT), Support Vector Machines (SVM) and more traditional methods like Logistic Regression are also tested in studies to map and model wildfires. Logistic regression as used by [8] develop prediction models for geolocational fire control taking into account fuel types, topographic features and natural and anthropogenic barriers with respectively accurate implementations of boosted logistic regression. Predictive modeling in [13] is conducted with a variety of probabilistic methods including naïve Bayes, mixture discriminant analysis, and other more classical methods like classification trees, and logistic regression. Two studies both involving Ghorbanzadeh et al, [16] and [15], test a variety of methods outside of those previously discussed, including dmine regression, DM neural, least angle regression, multi-layer perceptron, radial basis function, self-organizing maps, and decision tree for correlation of satellite imaging and GPS field survey polygons in a self-created wildfire inventory database.

2.2.2 Deep Learning

Work involving deep learning's more expansive algorithmic complexity has mirrored its depth and creativity. Preliminary studies such as [1] illustrate the usage of simple neural networks, specifically a 2D convolutional neural network in efforts to parameterize and evaluate USGS datasets. Artificial neural networks as used in continued studies by Ghorbanzadeh et al appear to be outperformed by more standard non-linear approaches.

However, more unique approaches including [5]'s probabilistic neural network design works to simulate real-world testing of UAV imaging on wildfires leverage more specifically-oriented designs for exact problems. Investigations such as [4] implement significantly more complex algorithmic approaches, specifically reinforcement learning (RL) based approaches towards wildfires as spatially spreading processes (SSPs). [4] connects computer vision and image processing of satellite-derived wildfire images with agent policy in a RL-developed "game system", extensively implementing and evaluating five RL algorithms: value iteration, policy iteration, Q-learning, Monte Carlo Tree Search, and Asynchronous Advantage Actor-Critic (A3C), to correctly gauge early detection.

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3.1 Headings: second level

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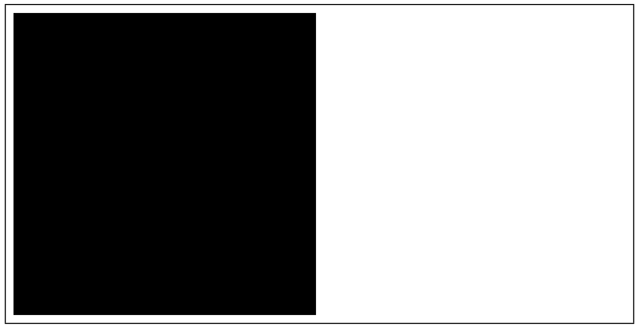

Figure 1: Sample figure caption.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

Hasselmo, et al. (1995) investigated...

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4.1 Figures

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4.2 Tables

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4.3 Lists

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[2] Sample of the first footnote.

5 Reference Annotations

[1, Contains extensive information on the intersection of geographic information systems and using AI to process those formats of data; implements a 2D convolutional neural network with simple parameters; evaluates historical fire perimeters from GeoMAC, a United States Geological Survey (USGS) database, for each of the training and testing fires; fairly preliminary work, limited by data amount and quality]

[2, Very novel and interesting approach towards a problem typically viewed in a geospatial or at least spatiotemporal sense; uses tweets with geolocation and natural language processing for the early detection of fires; extensive Twitter mining and sentiment analysis work done to correlate with wildfires; offers a creative approach to locate and estimate fires with high precision compared to standard reporting]

[3, Highly relevant to my original ideas–dicusses finding optimal conditions for prescribed burns; quantifies a machine learning approach in XGBoost for temperature, RH, 10 m wind speed, boundary layer depth, Lavdas Atmospheric Dispersion Index, daily total precipitation, and the climatological probability of fire; works towards probability-based prediction for wildfires to be aided by prescribed burns]

[4, Discusses spatially spreading processes (SSPs) in depth, and machine learning applications to model and account for these intricacies; this source adopts a more complex reinforcement learning approach to "game" the model, with an agent policy rewarded by the correct identification of cells with/without fire as validated by satellite images; very extensive implementations and validation through five RL algorithms: value iteration, policy iteration, Q-learning, Monte Carlo Tree Search, and Asynchronous Advantage Actor-Critic (A3C).]

[5, Similar but not entirely the same for my research; uses computer vision techniques implemented on UAVs to judge and measure effiacy of controlled burns–could be useful to open source in the situation of actually testing and evaluating methods in real-time; adopts probabilistic neural networks (slightly non-industry standard); to measure factors like vegetation, soil burn severity etc.; appears to be moderately effective at identifying relevant conclusions on burn severity]

[6, Focuses on the quality and availability for machine learning applications in forest fire optimizations; examines sample sizes, imbalances, transferability, and need for classifiers; employs random forest models to test inferences for each parameter of datasets; discovers a discrepancy in wildfire prediction vs. optimizing prescribed burns with similar data, likely due to the poorer classification performance for low fire severity classes, the dominant severity classes in prescribed burns; classification is mostly accurate]

[7, Focuses on Alaska, but not a huge deal because of cross-trainaiblity; this paper uses decision trees (solid, simpler method) to investigate final fire sizes at time of ignition; accuracy is not signficant at around 50%, but these investigations can provide valuable insight once analyzed about resource allocation and the intricacies of quantification on fire sizes and their relevance to fire intensity]

[8, Leverages slightly varying conditions like topography and fuels to quantify the effects of topography, fuel characteristics, road networks and fire suppression effort on the perimeter locations of large fires; they develop a prediction model for geolocational fire control taking into account fuel types, topographic features and natural and anthropogenic barriers; uses boosted logistic regression to a decently accurate margin in spatiotemporal terms; highly relevant, may look to open source from authors to build off of or test another model for]

[9, Broad, encompassing overview on the research done on machine learning methods for wildfire-based problems; very recent research; categorizes six approximate domains for fire-related machine learning problems: 1) fuels characterization, fire detection, and mapping; 2) fire weather and climate change; 3) fire occurrence, susceptibility, and risk; 4) fire behavior prediction; 5) fire effects; and 6) fire management; analyzes data size, computational requirements, generalizability, and interpretability, potential advances in of wildfires management within machine learning applications; reviews over 300 papers in this issue; this will likely be my most useful source]

6 Reference Annotations 2

[10, Study offers foundation for basic machine learning techniques in mapping human-initiated wildfires. Implements Random Forest (RF), Boosting Regression Trees (BRT), and Support Vector Machines (SVM) in comparison with traditional methods like Logistic Regression to achieve more accurate results. Decent AUC reaching .7s with random forest and boosting regression trees. Works in the specific region of Spain but should be widely applicable to other regions as well]

[11, Focuses moreso on the effects of wildfires–could be an interesting extension or modification of direction. Paper discusses the analysis for the fine particulate matter (PM) released from wildfires that can be potentially dangerous to environments. Conducts this analysis with a generalized boosting model applied to chemical transport models and satellite retrievals, with a RMSE of around .8. Offers fair commentary on the most important predictors and factors in predicting PM emissions]

[12, Presents a wealth of satellite images that could be useful in developing and training models for image recognition surrounding wildfires. Covers large areas of land to maximize predictor and factor detection–from the Remote Sensing Data source of crops, weather conditions, thermal anomalies, etc. Acquired from the Moderate Resolution Imaging Spectroradiometer aboard the Terra and Aqua satellites. Paper claims significant accuracy of 98%. Assessed with validation against other early-warning systems.]

[13, Extensive machine learning workflow involving predictive modeling for wildfires: including data retrieval and cleaning from the United States Geological Survey, in-depth and mass model algorithm design and training, along with comprehensive cross-validation. Applied linear, nonlinear, and rule-based predictive models not limited to naïve Bayes, mixture discriminant analysis, classification trees, and logistic regression models, achieving double the success rate of typical linear models in current literature. Presents state-of-the-art improvement. Significant paper with quality workflow and dataset.]

[14, Similar to an above paper to estimate and model air quality effects after wildfire incidents. Offers opportunity to either expand current aims or provide small add-ons. Study focuses on Northern California ground-level ozone levels during wildfires with ten different algorithms. Evaluation was conducted with leave-one-location-out cross-validation (LOLO CV) to avoid typical biases of k-fold cross validation when applied to coarser spatial resolutions. Paper presents very good performance of several models, i.e. RMSE of .228 and $r\hat{2}$ of .677 with gradient boosting; however, multiple validation techniques demonstrate that the performed spatiotemporal evaluations were not suited to sufficient accuracy. Concludes with non-achievement.]

[15, Comprehensive machine learning workflow consisting of complete data aggregation and cleaning, neural network and standard machine learning algorithm fits, and cross-validations. Presents a wildfire data inventory created by "integrating global positioning system (GPS) polygons with data collected from the moderate resolution imaging spectroradiometer (MODIS) thermal anomalies product between 2012 and 2017 for Amol County, northern Iran." 16 different evaluation metrics were used to determine an optimal machine learning approach–approaches included an artificial neural network, support vector machines, and random forest. 75/25 split for cross validation leading to admirable accuracies of 74%, 79% and 88% for the ANN, SVM and RF, respectively.]

[16, Continued project/paper from previous author. Also implements workflow and data analysis from remote-sensing data types. Presents the same wildfire inventory data "created by integrating the polygons collected through field surveys using global positioning systems (GPS) and the data collected from the moderate resolution imaging spectrometer (MODIS) thermal anomalies product between 2012 and 2017 for the study area." This time, 16 predictors are assesed with a multitude of machine learning and deep learning techniques including artificial neural networks, dmine regression, DM neural, least angle regression, multi-layer perceptron, random forest, radial basis function, self-organizing maps, support vector machine, and decision tree, along with logistic regression. 3-fold cateogrization yielded random forest to have a respectable 88% accuracy.]

[17, Focuses on the region of Liguria in Italy–analyzes susceptability to wildfire based off five factors over a lengthy 21-year time period. Compares various models with spatial-cross validation to offer ML-derived susceptability maps. Provides visual source and region-specific work on assessing problem zones correlated to specific predictors visualized on maps.]

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