

Recovering fire arrival time from satellite data by machine learning



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1. INTRODUCTION

3. SUPPORT VECTOR MACHINE (SVM)

WRF-SFIRE is a coupled **atmosphere-fire model** which can be assimilated using different data sources. [1]



Satellite data can **start fire simulations** from an ignition point or from an assumed fire perimeter. By estimating the fire arrival time (time that the fire arrives at each location), one can spin up the weather model, and proceed with the assimilated coupled simulation in a consistent fire-atmosphere state.

2. OBJECTIVES

Estimation of fire arrival time as a function on a 2D domain on Earth surface going through some constraints or bounds.

- Upper bounds: information that a certain location at a certain time space is burning.
- Lower bounds: information that a location is not burning.

Find the best separation between soft bounds (errors and inconsistency of the data).



SVM is a machine learning technique which finds the best separation between two groups of data maximizing the margin between both representatives of each group or support vectors. [2]

Allow bends by using a separating surface defined by a Gaussian radial basis kernel decision function, and use soft bounds by including a penalization term.



5. RESULTS



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6. CONCLUSIONS

The SVM approach offers improvements over other methods, which tend to be harder numerically or develop artifacts. These methods include:

· Penalize the difference of the posterior fire arrival time surface from the prior assuring that point constraints are visible (using Sobolev norms $H^{1+\varepsilon}$, $\varepsilon > 0$ or $W^{1,p}, p > 1$). [3]

wx + b = 0

wx + b = -1

Pole Creek Fire, Utah, 2018

Visualization in Google Earth of

of the fire arrival times.

satellite fire detections compared

with the evolution of the perimeters

- · Penalize by a norm of the residual of the eikonal equation $\|\nabla u\| = \frac{1}{p}$, where the rate of spread R = R(x, y, u) depends on the fuel in the first approximation, and really on the history of the fire through the fire winds. [4]
- Use the prior assumption that in the absence of other information, the fire propagation does not change: $\nabla u = \text{constant}$. Thus, minimize $\|\nabla^2 u\|_{L^p}$ subject to the upper and lower bounds, with penalizations for soft bounds. [5]

Next step would be to assimilate other data inputs:

- Infrared fire perimeters can be interpreted as mesh points inside the perimeter on fire, providing upper bounds, and points outside of the perimeter not on fire, providing lower bounds.
- Forecast fire arrival time (Bayesian prior) becomes both an upper bound and a lower bound at every mesh point. The softer the bound, the less weight the data assimilation puts on the prior.

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