

# Retrieving Fire Perimeters and Ignition Points of Large Wildfires from Satellite Observations

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## Abstract

We present a new statistical interpolation method to estimate fire perimeters from Active Fires detection data from satellite-based sensors, such as MODIS, VIIRS, and GOES-16. Active Fires data is available at varying temporal and spatial resolutions (375m and up several times a day, or 2km every 15 minutes), but pixels are often missing due to clouds or incomplete data. The question arises how to fill in the missing pixels, which is useful, e.g., to distinguish in an automated fashion between a single large fire visible as separate clusters of detection pixels because of cloud cover, and separate fires. We process the satellite data into information when was fire first detected at a location, and when was clear ground without fire detected at the location last. We are then looking for the most likely fire arrival time, which satisfies such constraints. Models at various levels of complexity are possible. Our base assumption in the absence of information to the contrary is that the fire keeps progressing without change, which is expressed as the assumption that the gradient of the fire arrival time is approximately constant. The method is then formulated as an optimization problem to minimize the total change in the gradient of the fire arrival time subject to the constraints given by the data. We consider probabilistic interpretations of the method as well as extensions, such as soft constraints to accommodate the uncertainty of the detection and the uncertainty where exactly the fire is within the pixel. This method is statistical in nature and it does not use fuel information or a fire propagation model. The results are demonstrated on satellite observations of large wildfires in the U.S. in summer 2018 and compared with ground and aerial data.

# Recovering Fire Perimeters and Ignition Points of Large Wildfires from Satellite Observations

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## GOAL: Estimate Fire Arrival Time from Satellite Data As a Continuous Spatial Field

- Perimeters = the fire arrival time is constant
- To spin up and assimilate in coupled atmosphere-fire models
- To fill in missing pixels for smoke estimation
- Light-weight, no physics model, statistically justified
- Use all data granules intersecting the domain and time of interest

Unfortunately in reality...

- Data are often missing (clouds, smoke, obscured by terrain,...)
- Pixels do not form a nice continuous progression in time.

## How Do the Data Look Like?



Fire Radiative Power in a time progression of sample VIIRS and MODIS granules. Pixel sizes from instrument properties and the scan angle. (2018 Camp Fire)

## No-fire Detections of Clear Ground Are Important Too!



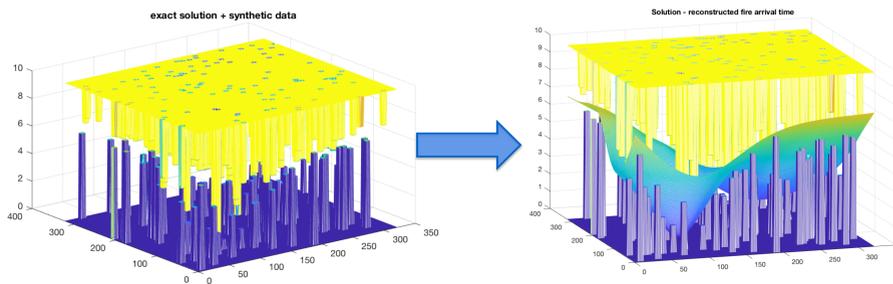
Fire detections in the domain of interest in one MODIS granule.

Green = no fire  
Red = fire  
Clear = no data

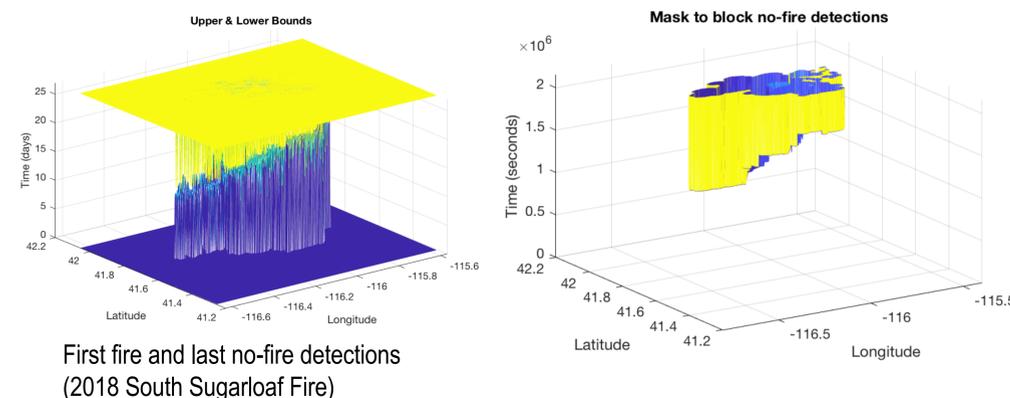
(2015 Cougar Creek Fire)

## Basic Method – Ideal Case

- To fill missing data, assume the fire propagates with the same rate of spread and direction
- Background state: **constant spatial gradient of the fire arrival time  $T$**
- Solve  $\text{grad grad } T=0$  approximately by least squares
- **First fire detection** at a location  $\Rightarrow$  upper bound on the fire arrival time
- **Last detection of ground with no fire**  $\Rightarrow$  lower bound on the fire arrival time
- This is the same as the bending of an elastic plate between an upper and a lower obstacle



## Real Data Are More Tricky



First fire and last no-fire detections (2018 South Sugarloaf Fire)

- Many false negative and some false positive detections  $\Rightarrow$  make the obstacles **soft**, with the lower obstacle even softer.
- After a while, a location with fire detected will give no-fire detections again  $\Rightarrow$  **mask** no-fire detections in future around every fire detection.

## The Math

- Variational inequality for the 4<sup>th</sup> order plate bending partial differential equation:  $\int_{\Omega} \|\text{grad grad } T\|^2 dx_1 dx_2 \rightarrow \min_{L \leq T \leq U}$
- The unknown fire arrival time is represented by the Adini element on a rectangular mesh as piecewise cubic functions. The degrees of freedom are the values and the partial derivatives at the mesh nodes:
- The discrete penalized problem, solved by a multigrid method:

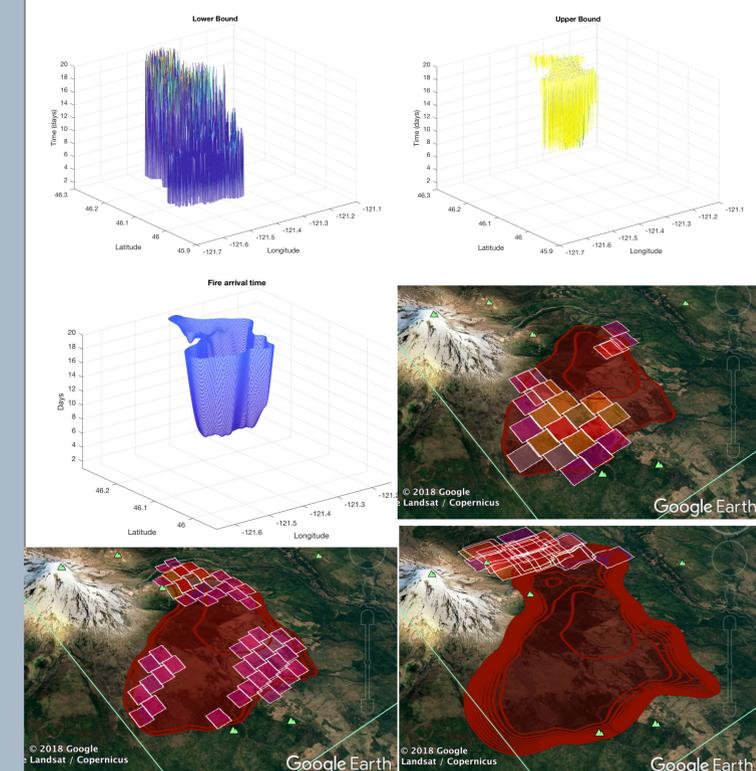
$$\underbrace{\sum_{i=1}^n \sum_{j=1}^n T_i^T C_{ij} T_j}_{\text{bending energy}} + \underbrace{\sum_{i=1}^n a_i^2 \min \{T_{i,1} - L_i, 0\}^2}_{\text{lower penalty = soft constraint}} + \underbrace{\sum_{i=1}^n b_i^2 \max \{T_{i,1} - U_i, 0\}^2}_{\text{upper penalty = soft constraint}} \rightarrow \min_T$$

- Statistical interpretation: maximum a-posteriori probability Bayesian estimate.
  - Gaussian prior log density equals minus the bending energy, with maximum probability when  $\text{grad}T$  is constant.
  - The log data likelihood equals minus the sum of the penalty terms.

## Results



Retrieved perimeters of 2018 Camp Fire estimated from VIIRS and MODIS data



Lower bound, upper bound, fire arrival time, and retrieved perimeters with satellite detections at select time points. (2015 Cougar Creek Fire)

## Acknowledgements

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