CENTRE EUROPÉEN DE RECHERCHE ET DE FORMATION AVANCÉE EN CALCUL SCIENTIFIQUE

GDR workshop

Data-driven modeling, which benefits for wildfire spread simulations?

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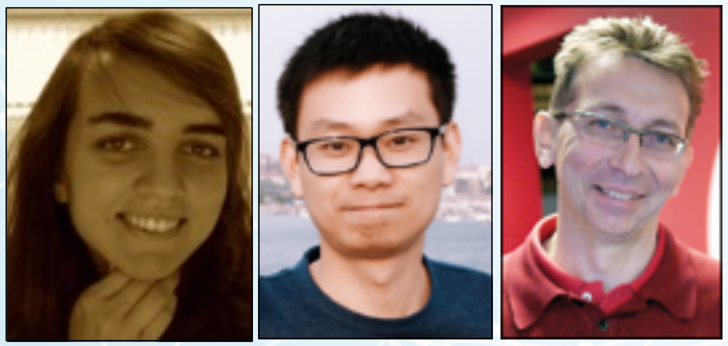


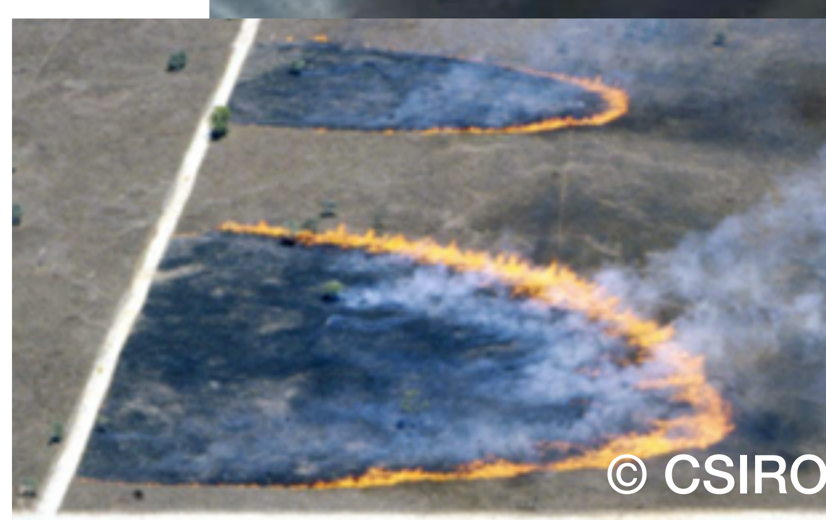
Main wildfire issues

SAFETY

Forecast wildfire behavior in real time to help fire emergency responses and strengthen firefighting actions

AIR QUALITY / CLIMATOLOGY

Evaluate emissions, their impact on micrometeorology and atmospheric chemistry



UNDERSTANDING

Analyze laboratory- and field-scale controlled burning to enhance knowledge and improve modeling

Main wildfire issues

➡ How can REMOTE SENSING help us to design on-demand high-fidelity simulations?

SAFETY
Forecast wildfire behavior in real time to help fire emergency responses and strengthen firefighting actions

AIR QUALITY / CLIMATOLOGY
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UNDERSTANDING
Analyze laboratory- and field-scale controlled burning to enhance knowledge and improve modeling

ANR FireCaster (2017-2021)

Data Sources

Aerial Imagery.
Obs satellite

Global weather forecasting model
Provide initial and boundary conditions

Daily runs

High resolution local run + resolution cascade
High resolution regional area model with fuel supersampling

Daily products

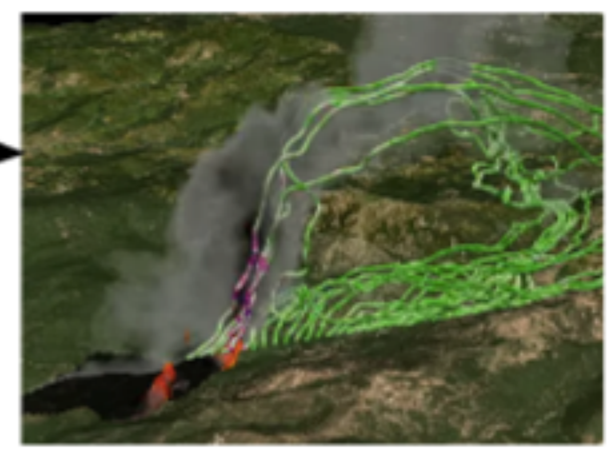
Fuel state, dx:50m
humidity & load, hourly

Ensemble based risk maps
From mass simulation h+0 to+36

Supercomputer at SPE

On demand. In case of crisis

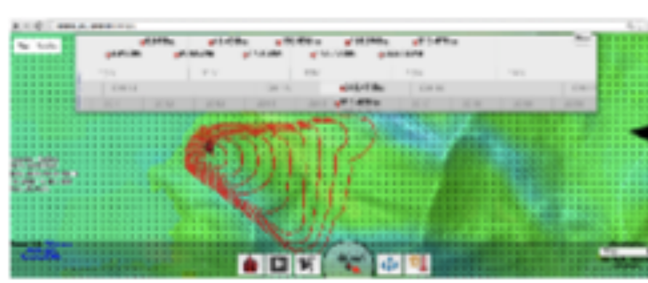
Coupled simulation with assimilation
Reference fire/weather, no fighting actions. Assimilated fire fronts from aerial/satellite imagery. Provide h+6 smoke, fire intensity and costs maps.



On-Demand products

Initial conditions wind, front

Fire fighting scenario testing platform
Perform (non coupled) interactive multiple tests to optimize fighting strategies using cost evaluation. Initialized from coupled run



EU supercomputers. Web@SPE

Modeling viewpoint

Fire front paradigm

- Interface from burnt to unburnt vegetation that self propagates in the normal direction
- Rate of spread, **ROS** ➤ parameterization of the fire front speed

Rothermel, A mathematical model for predicting fire spread in wildland fuels, Technical report, US Forest Service (1972)

$$\boxed{ROS_{1D} = f([M_v, \delta_v, m_v'', \rho_v, \Sigma_v], \vec{n}_{slope}, \vec{u}_{wind}) = ROS_0\,(1 + \Phi_w + \Phi_{sl})}$$

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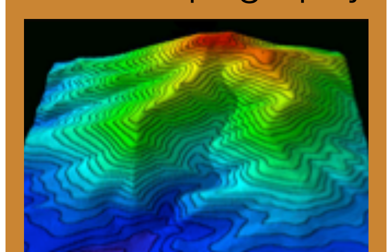
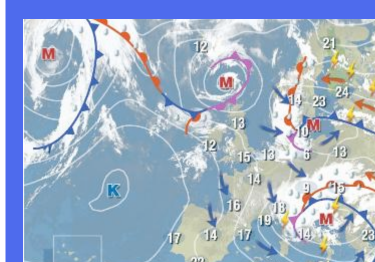
Fire initial location → **Front-tracking simulator**: Rate of spread (ROS) model; Front propagation solver (Lagrangian, Level-Set) → **Simulated time-evolving fire front location**

Environmental conditions → **Front-tracking simulator**

Terrain topography

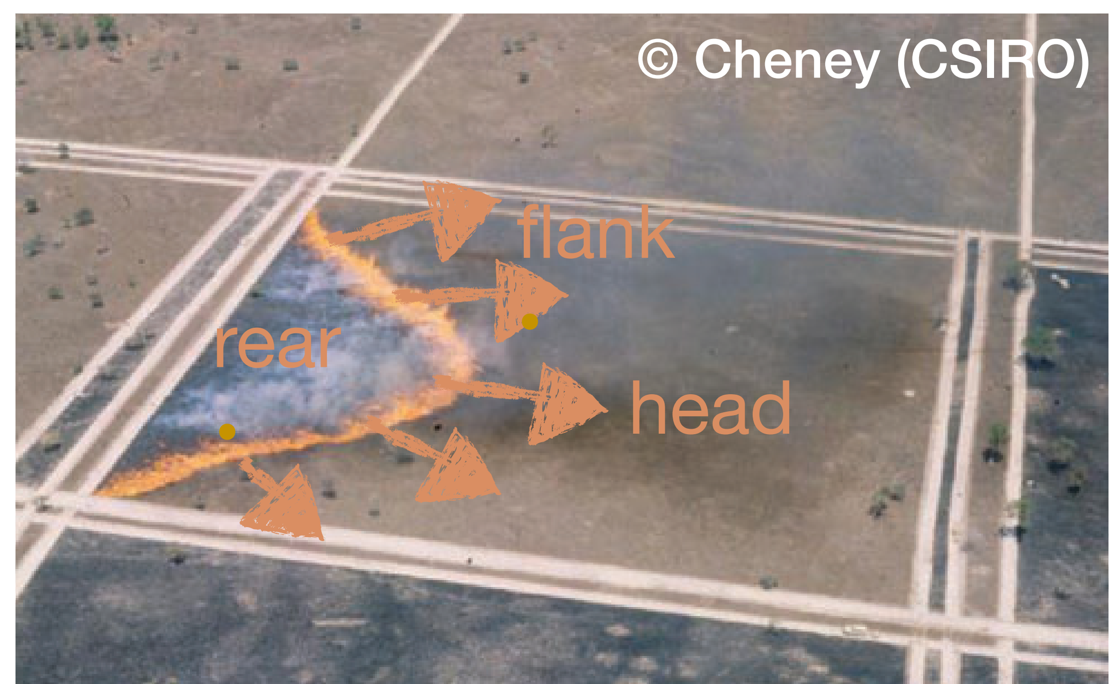


Low-level wind



Biomass fuel characteristics

Biomass moisture



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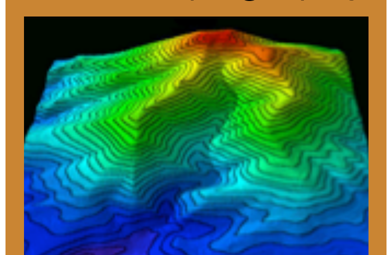

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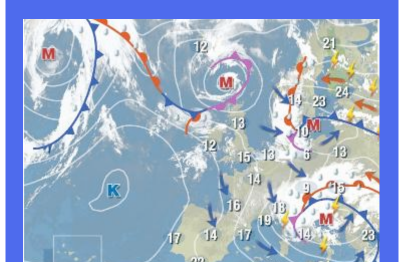

Biomass fuel characteristics

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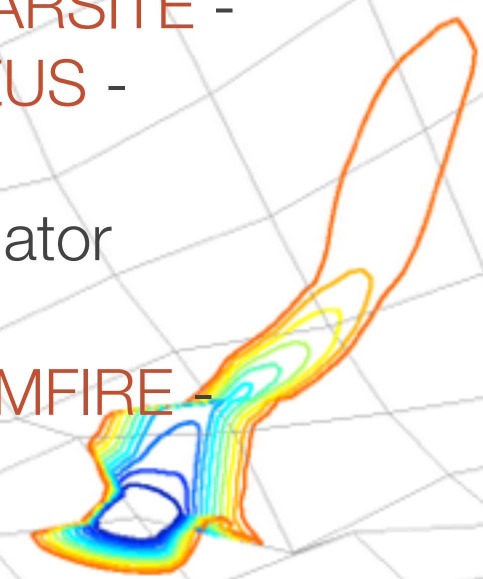
Fire growth models

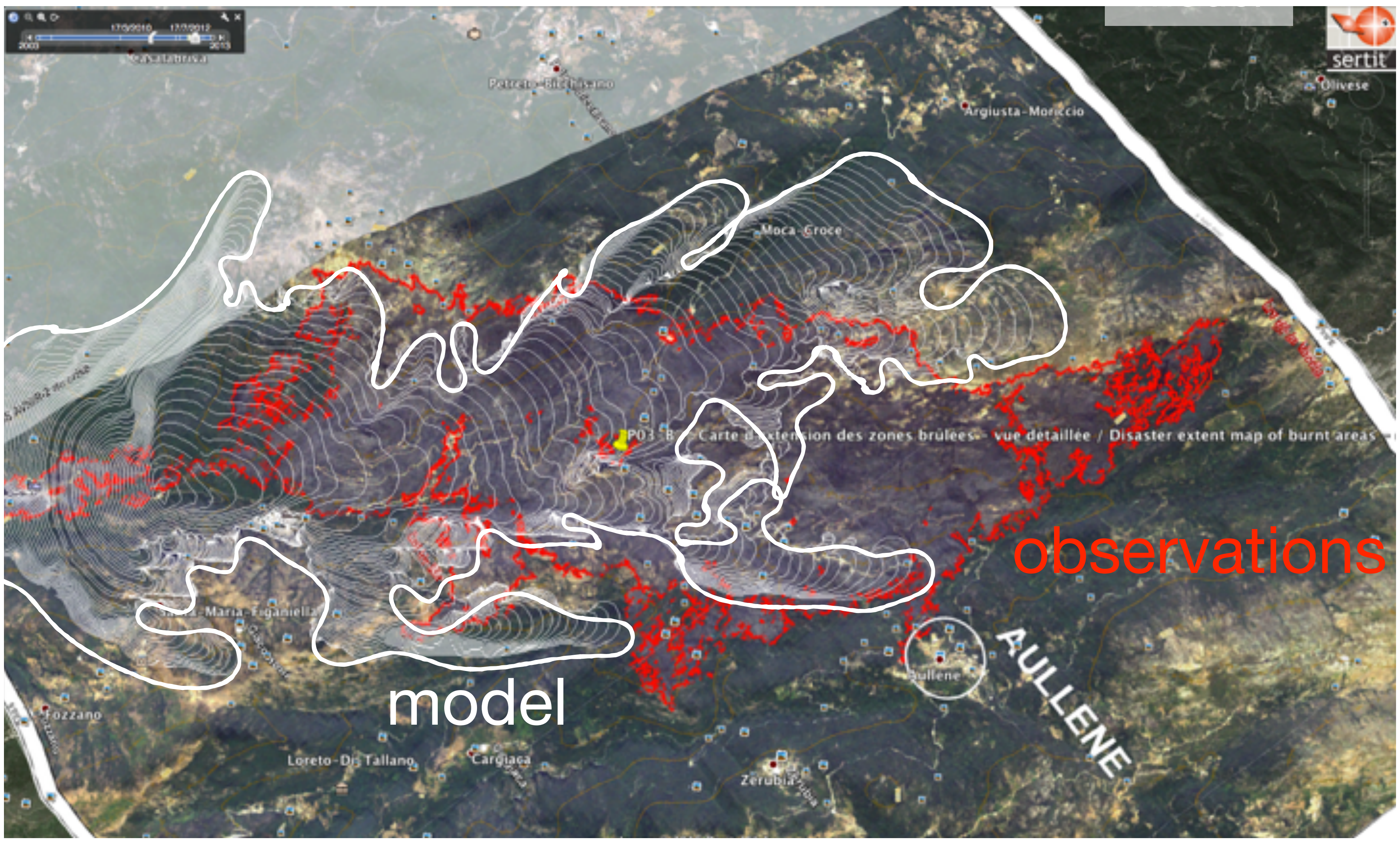
- Huygen's elliptical expansion (FARSITE - US Forest Service, PROMETHEUS - Canadian Forest Service)
- Lagrangian asynchronous simulator (FOREFIRE - Univ. Corsica)
- Level-set Eulerian simulator (ELMFIRE - Reax Engineering)



Uncertainties

Current fire growth models are far from being predictive

- Modeling challenge ➤ complex multi-physics multi-scales processes
- Data challenge ➤ input parameters that may not be known or are known with limited resolution in space and/or in time



Simulation-observation discrepancies

- shape
- size
- position

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$$ROS_{1D} = \boxed{f}\left(\boxed{[M_v, \delta_v, m_v'', \rho_v, \Sigma_v], \vec{n}_{slope}, \vec{u}_{wind}}\right)$$

Epistemic uncertainties

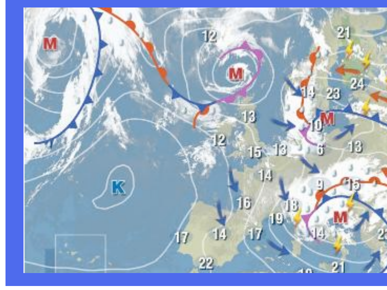
Need of deeper fundamental understanding of flame-scale processes

Epistemic/aleatory uncertainties

Need of more information on the time and space variation of the environmental and meteorological conditions

Stochastic data assimilation framework (1/2)

Surface winds

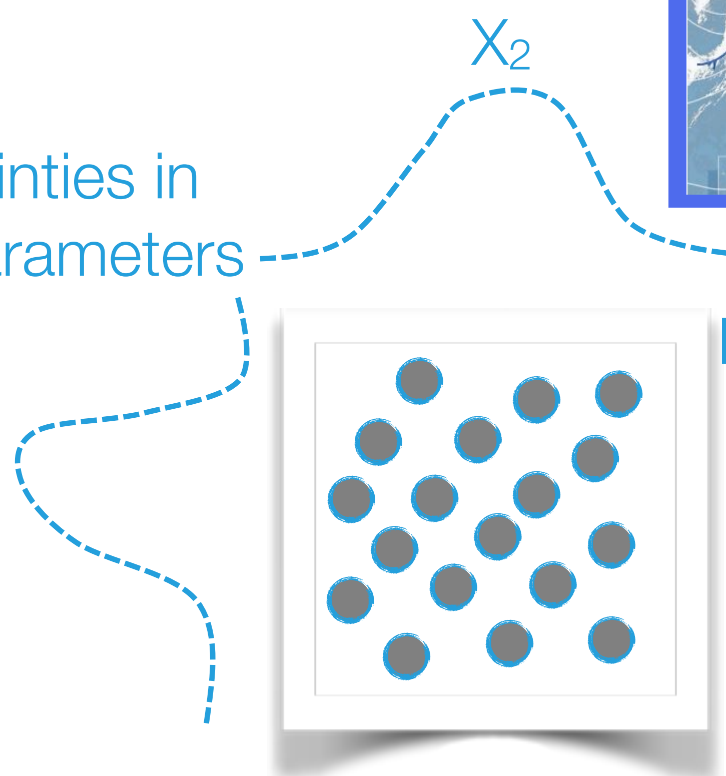


Biomass fuel properties

Biomass moisture content

Fire initial condition

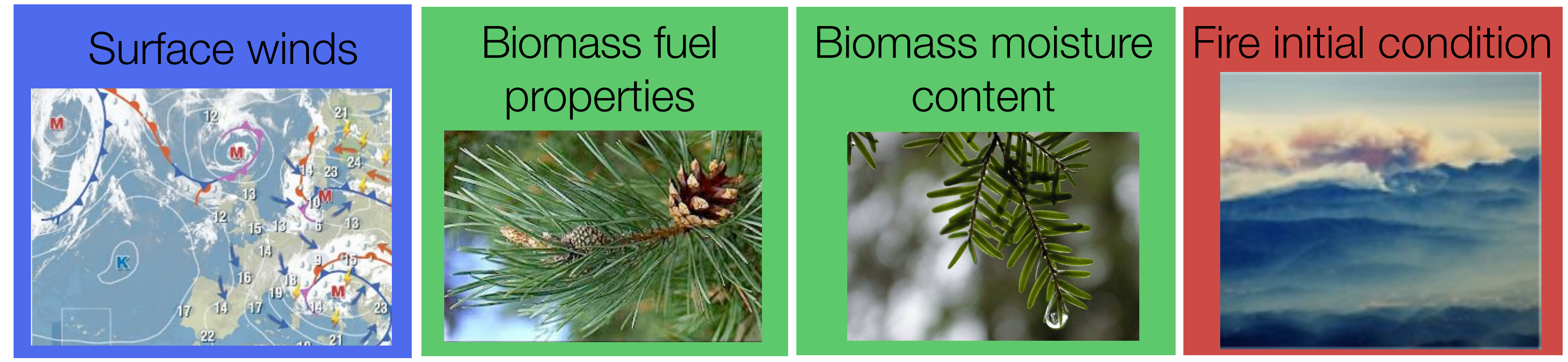
Uncertainties in input parameters

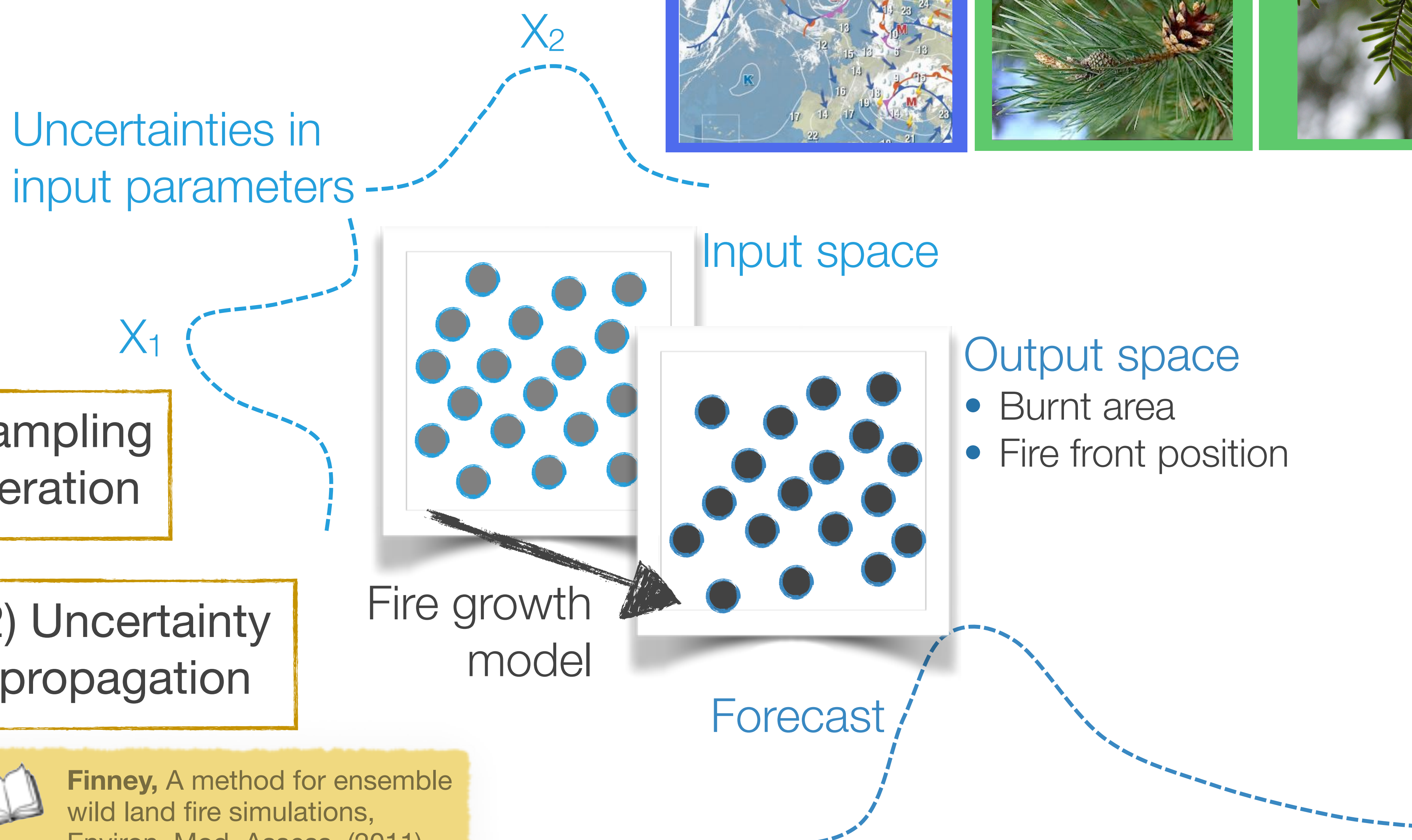


Input space

1) Sampling generation

Stochastic data assimilation framework (1/2)



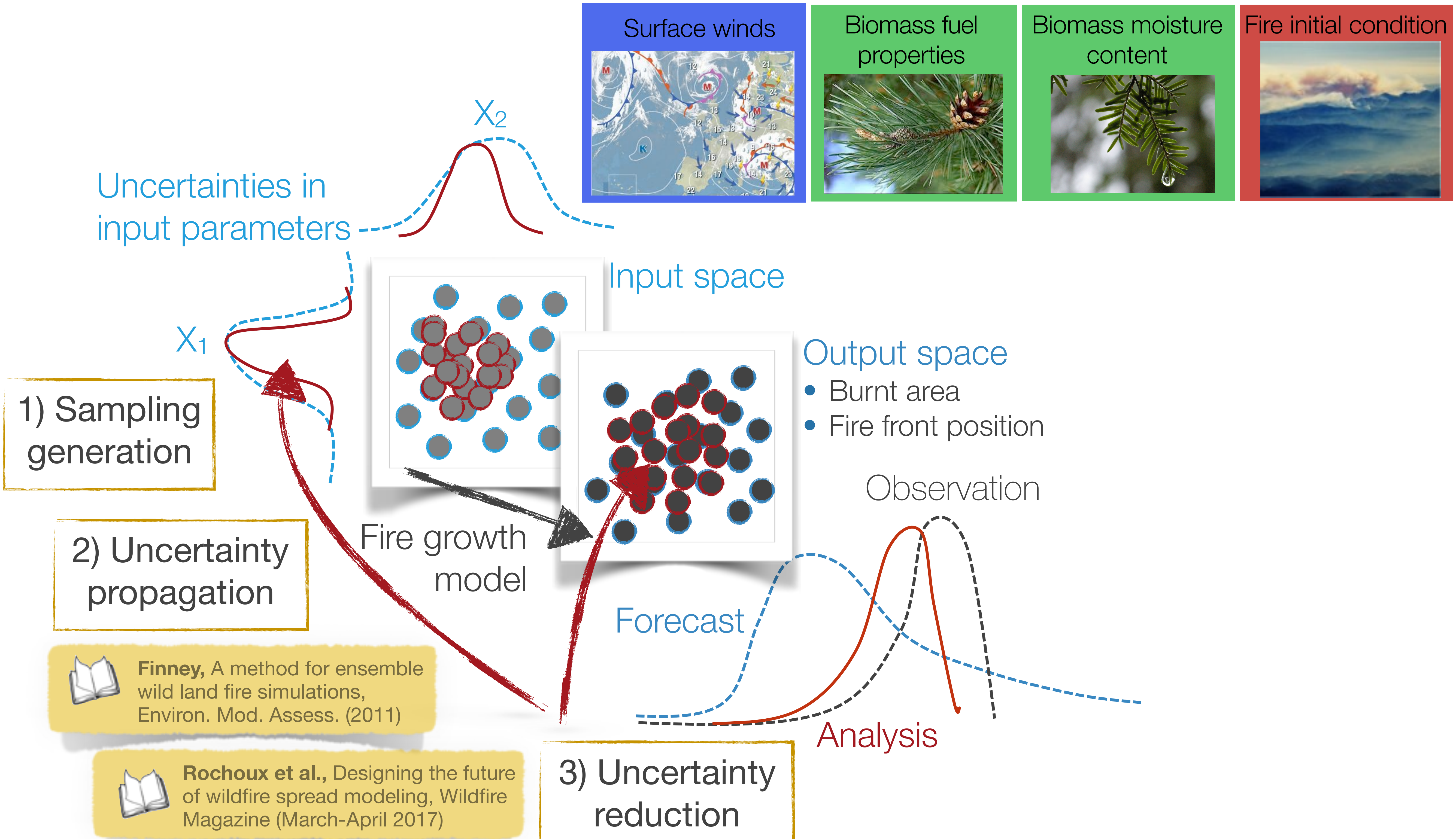


1) Sampling generation

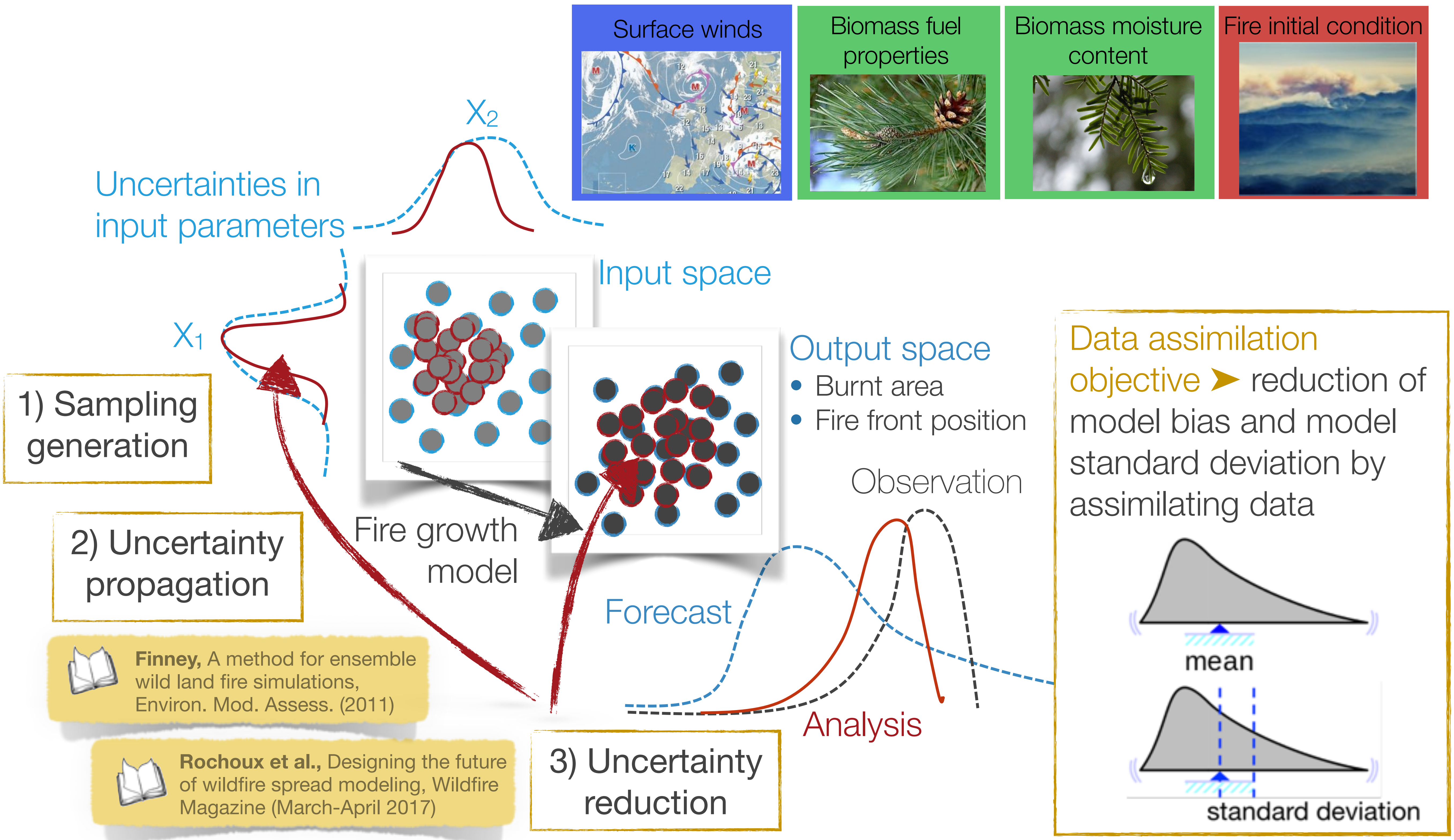
2) Uncertainty propagation

Finney, A method for ensemble wild land fire simulations, Environ. Mod. Assess. (2011)

Stochastic data assimilation framework (1/2)



Stochastic data assimilation framework (1/2)



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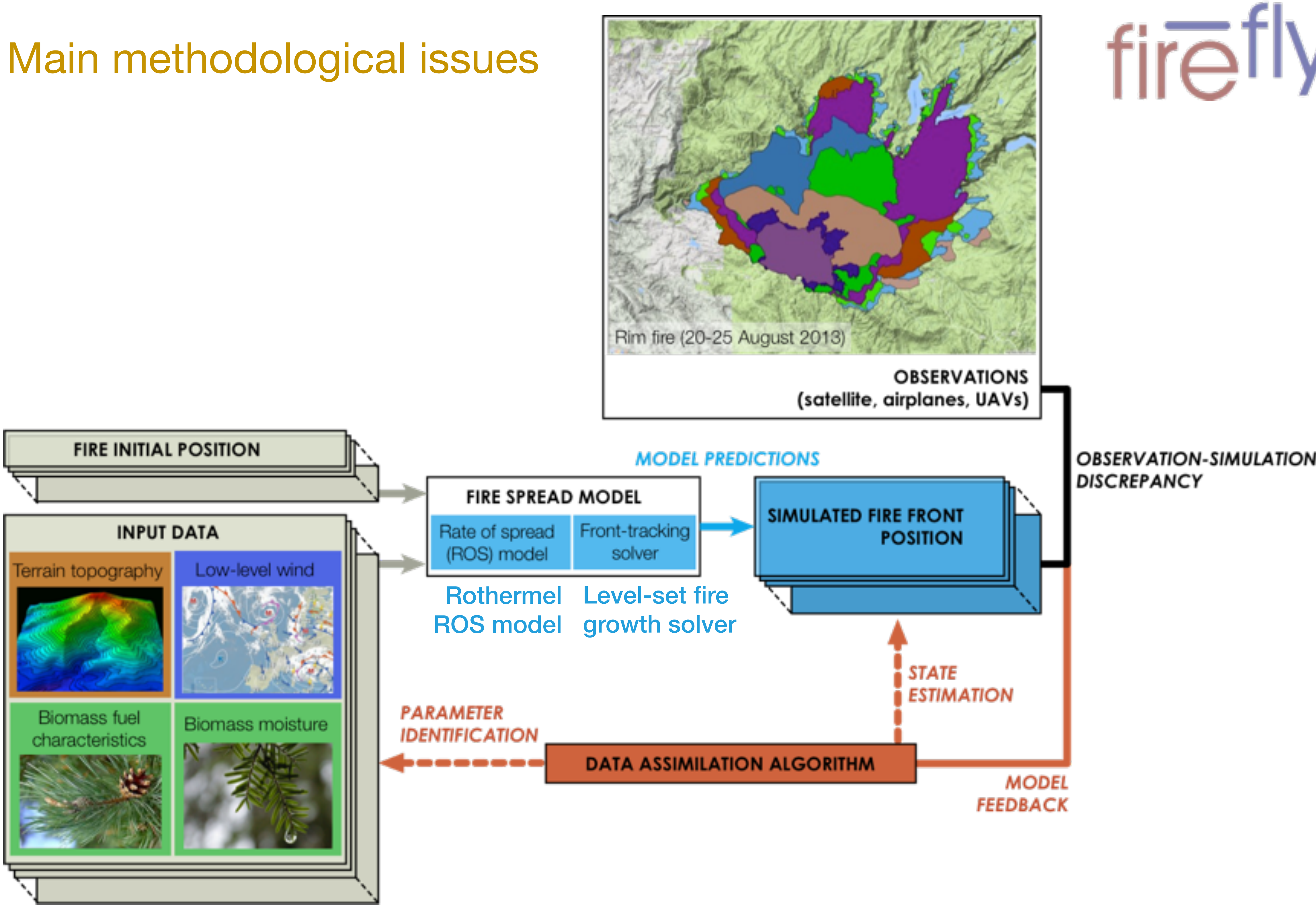
Rochoux et al., Designing the future of wildfire spread modeling, Wildfire Magazine (March-April 2017)

Stochastic data assimilation framework (2/2)

Main methodological issues



Stochastic data assimilation framework (2/2)

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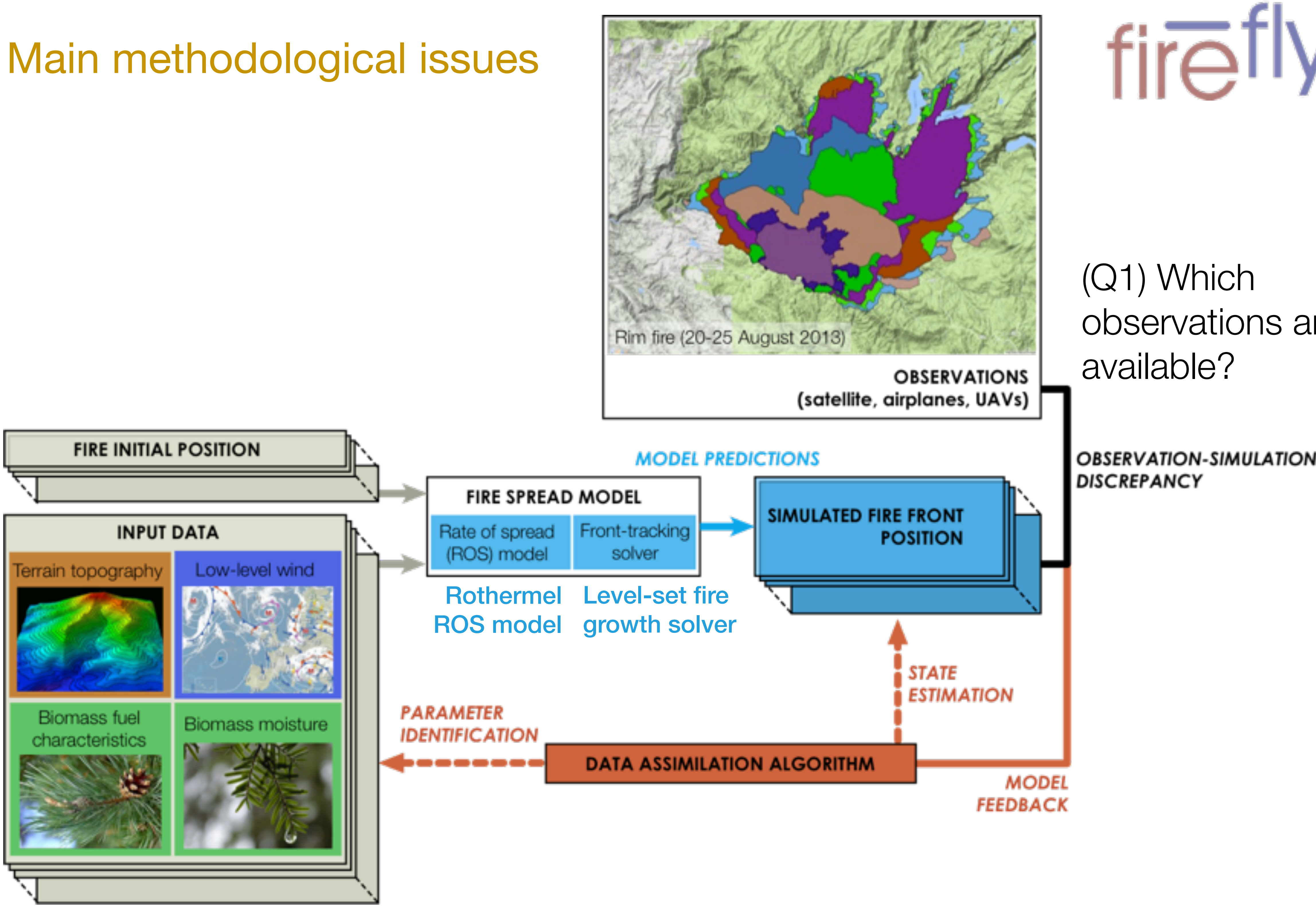
(Q1) Which observations are available?



Stochastic data assimilation framework (2/2)

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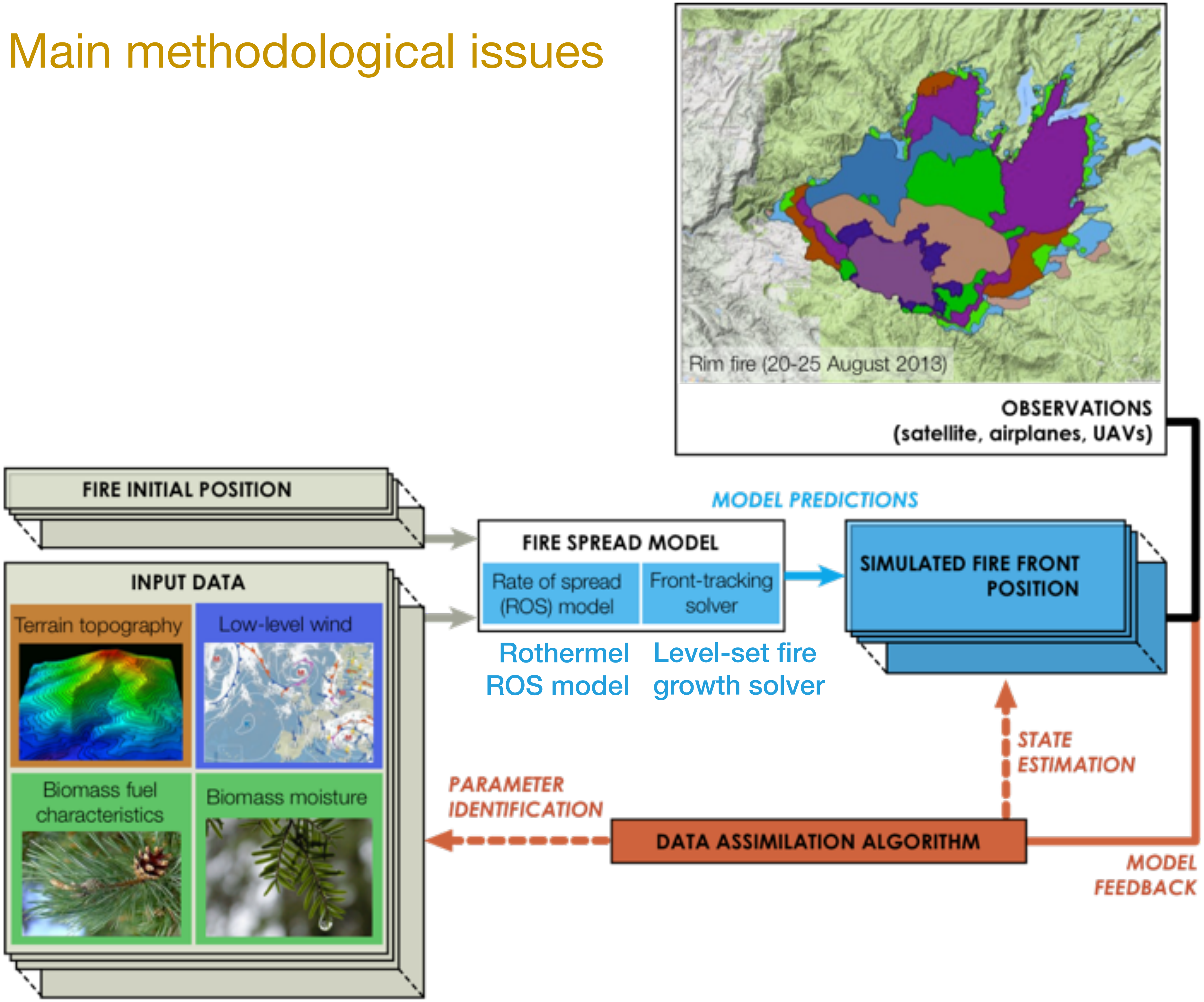

(Q1) Which observations are available?

(Q2) How to compare observations and simulations?

Stochastic data assimilation framework (2/2)

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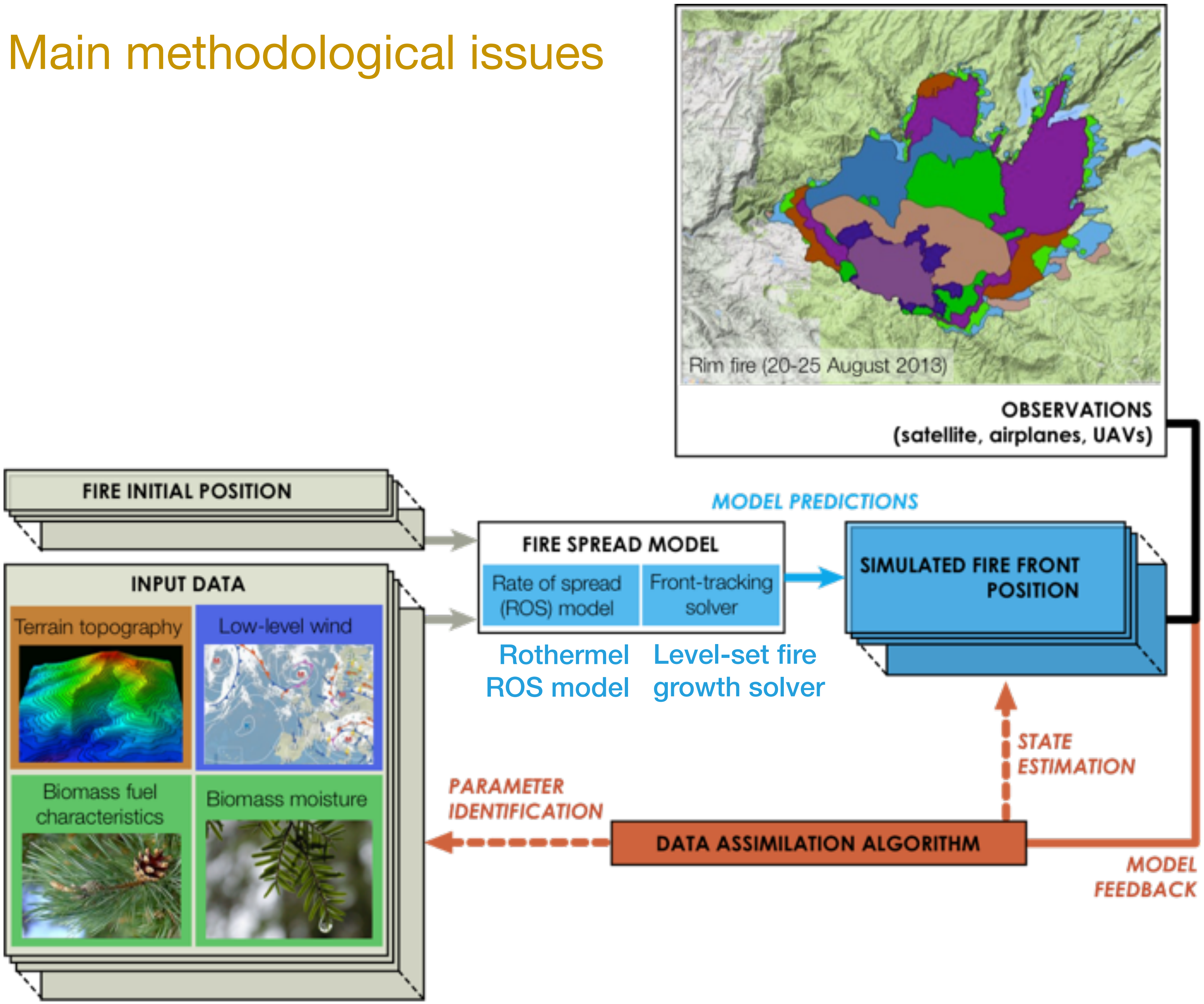

(Q1) Which observations are available?

(Q2) How to compare observations and simulations?

(Q3) How to carry out estimation at reduced computational cost compatible with operational framework?

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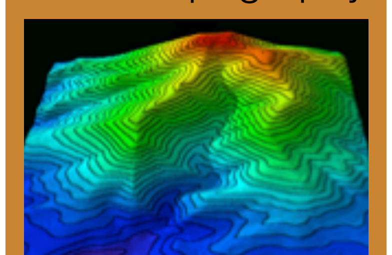


Low-level wind

Biomass fuel characteristics

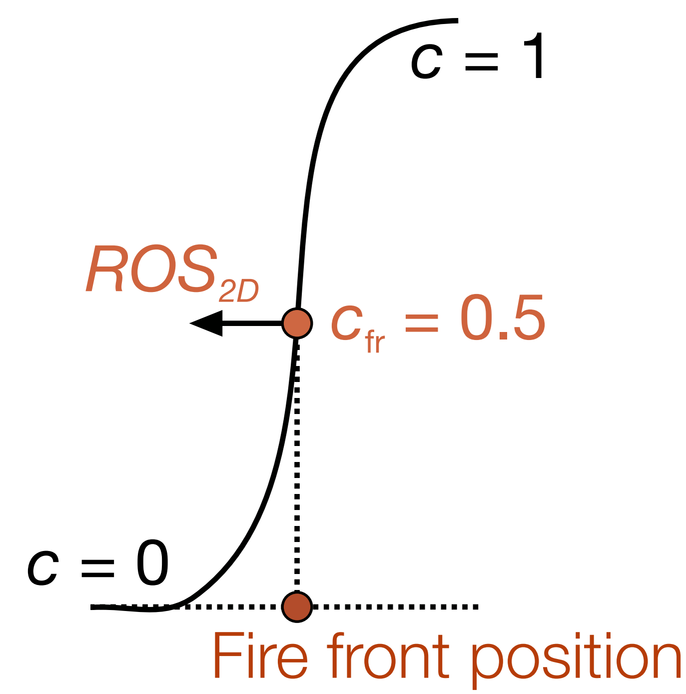
Biomass moisture

$$\frac{\partial c}{\partial t} = ROS_{2D}\,|\nabla c|$$

Eikonal partial differential equation

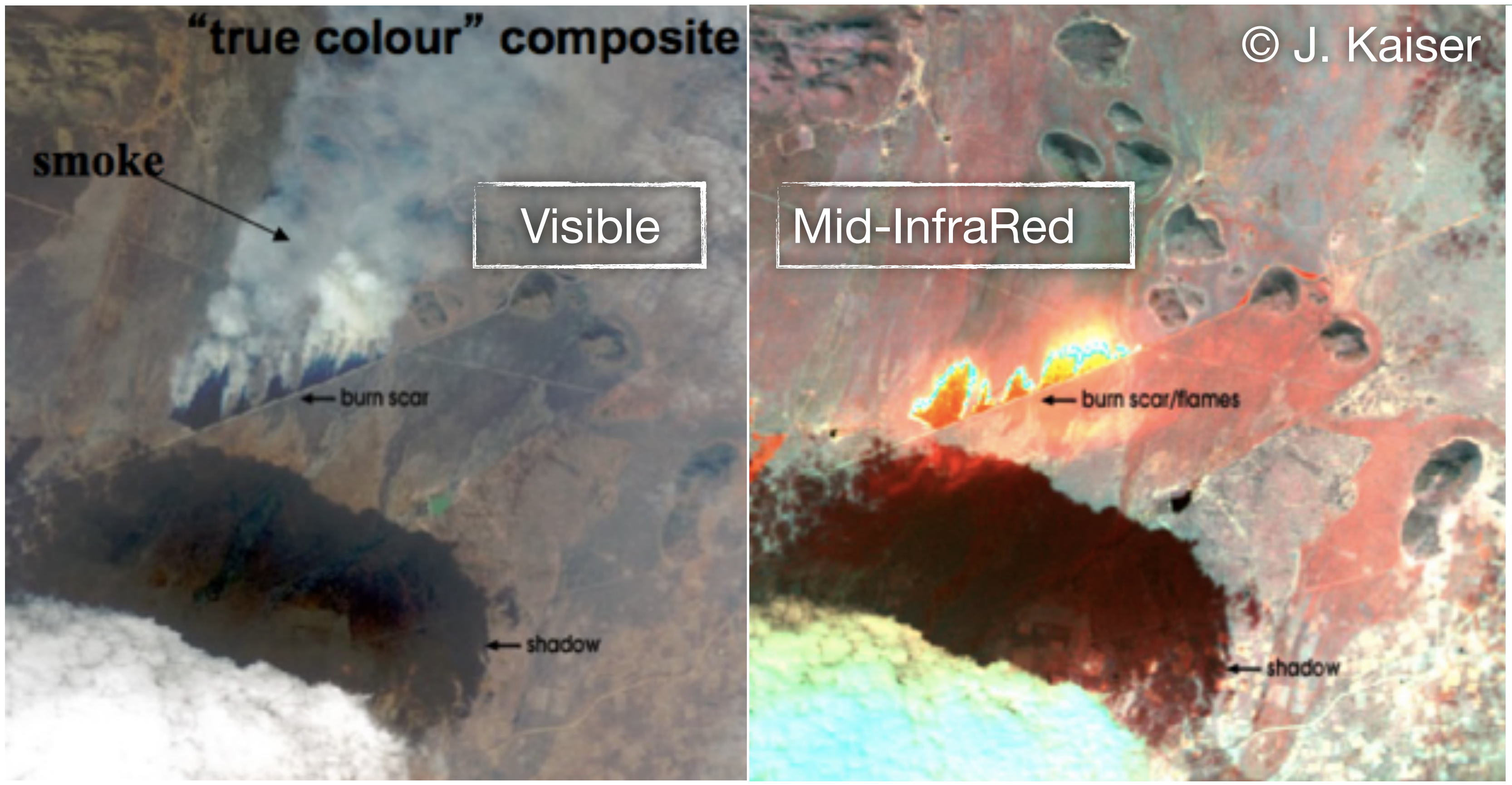
- Binary progress variable $c = c(x,t)$
- Total variation Diminishing scheme (Superbee flux limiter)

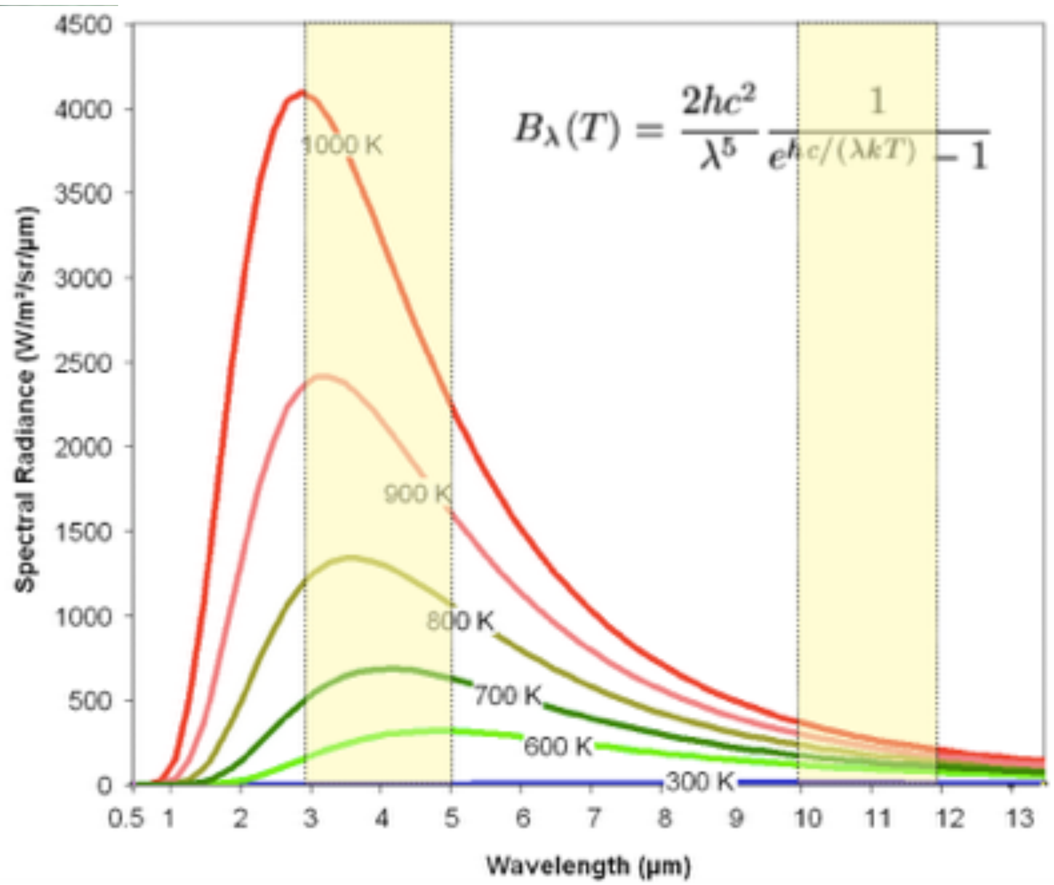
Rehm and McDermott, Fire front propagation using the level-set method, Technical report, NIST (2009)



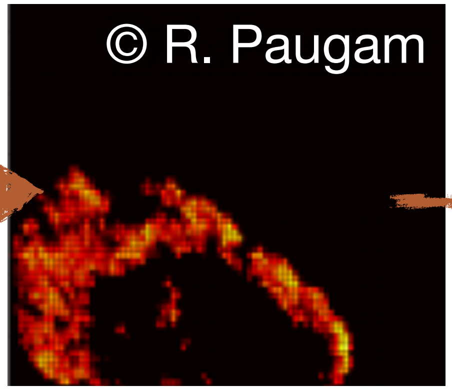
Available observation data

How to take advantage of Mid-InfraRed (MIR) imagery technology?





Instruments



Radiance temperature

?

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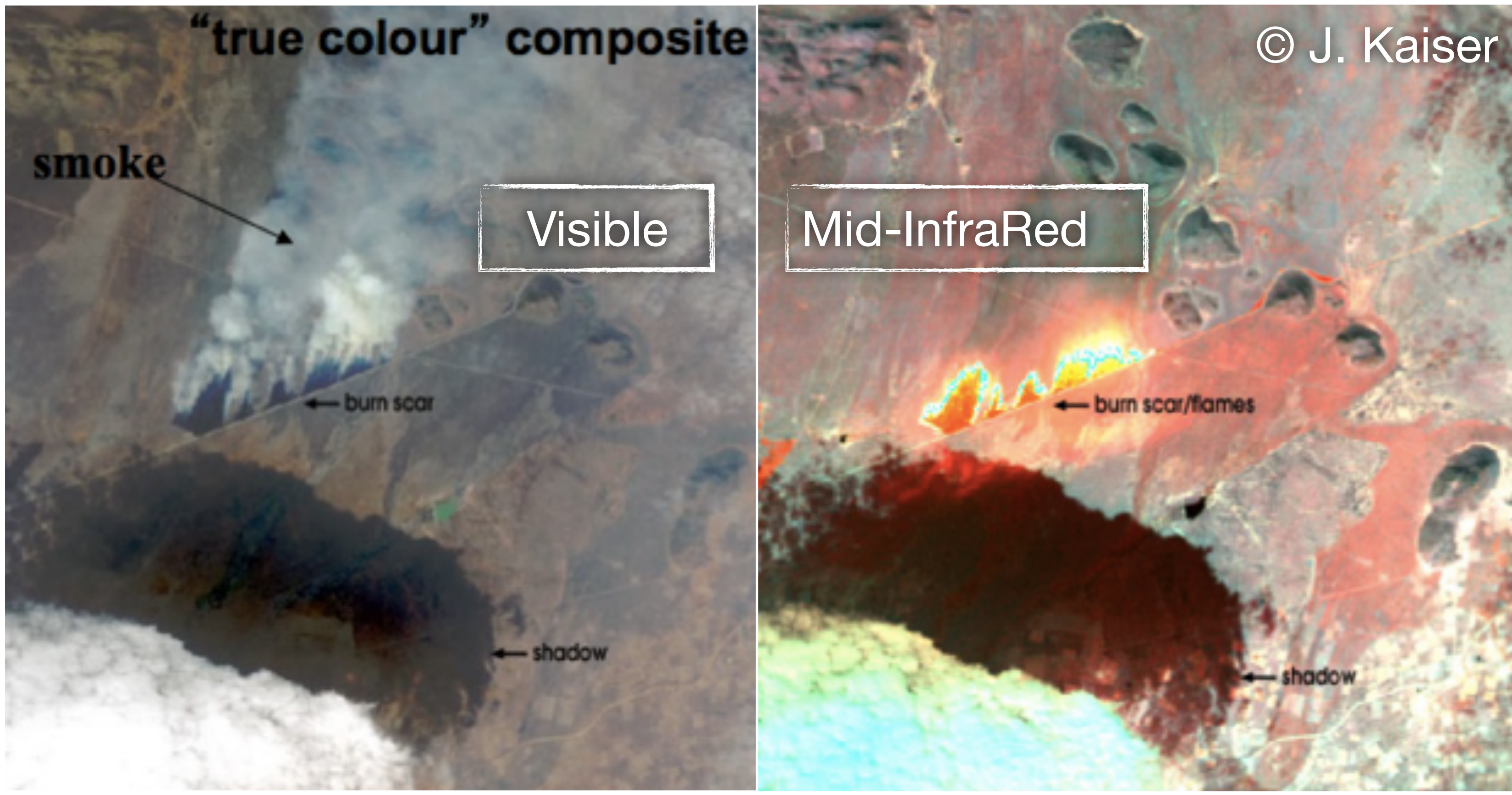

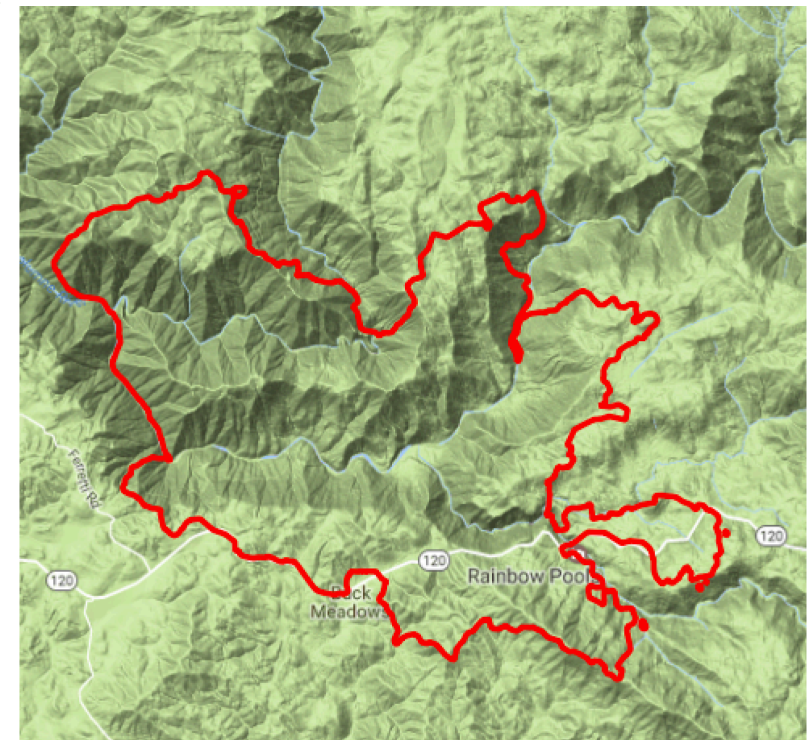

© Ellicott (UMD) - GeoMAC data for the Rim fire (2013)

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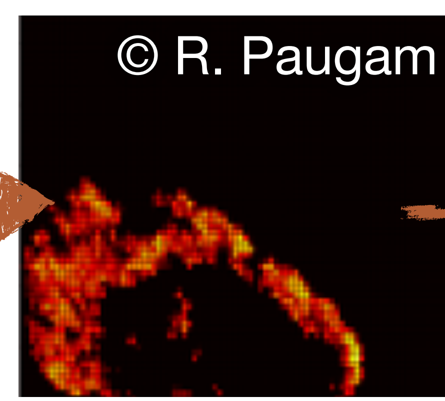

Radiance temperature

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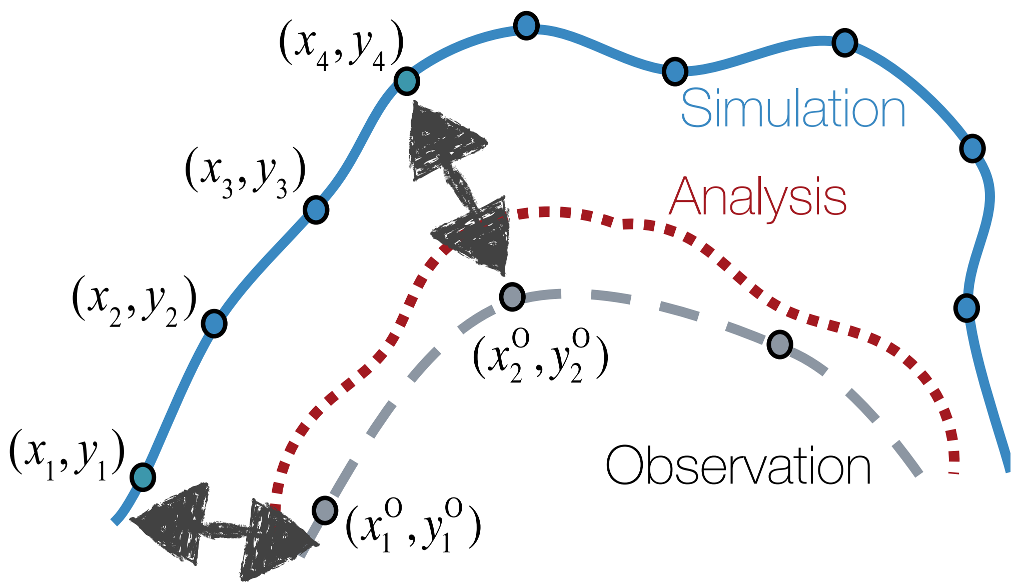
Raw image OR observation preprocessing to extract fire front position

Controlled burning application

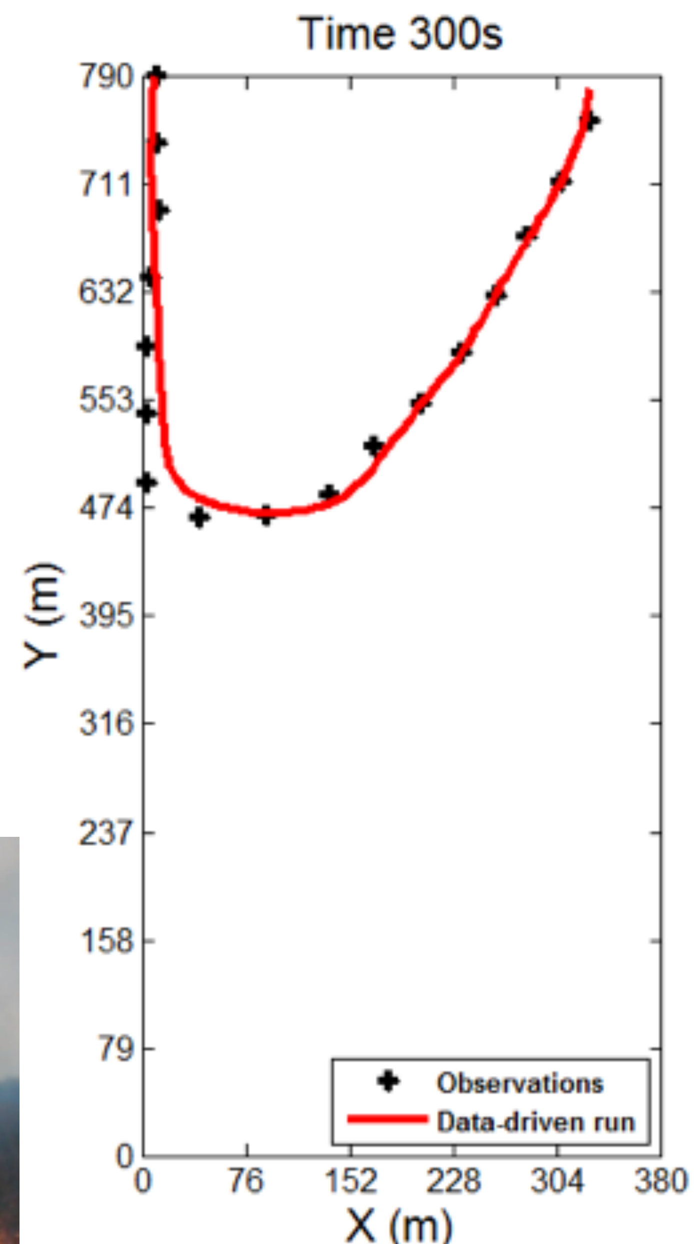
Zhang et al. (2017), Fire Safety Journal

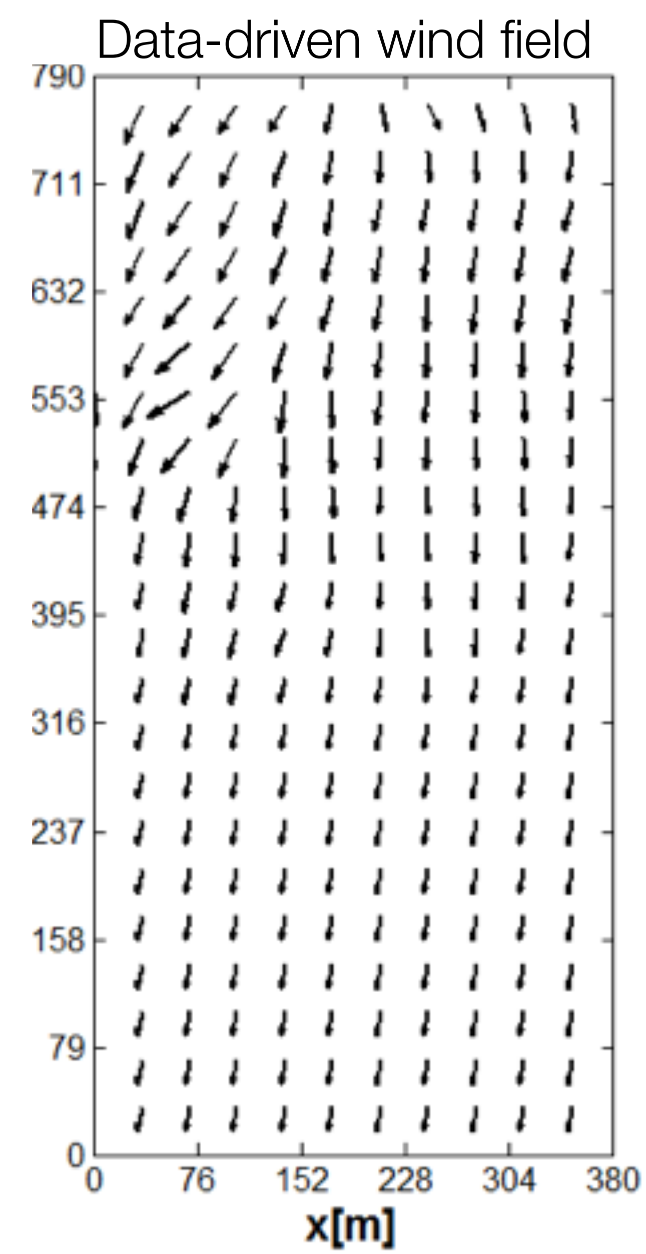
Application to the FireFlux data



FireFlux case experiment

- Average wind ~2-3 m/s, South-East
- Homogeneous tall grass (1.5 high)





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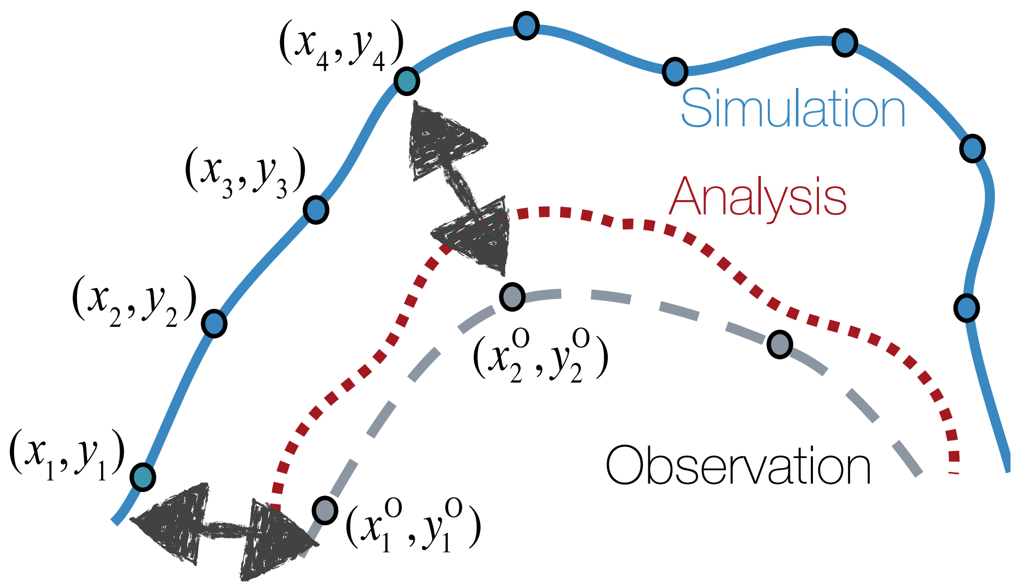

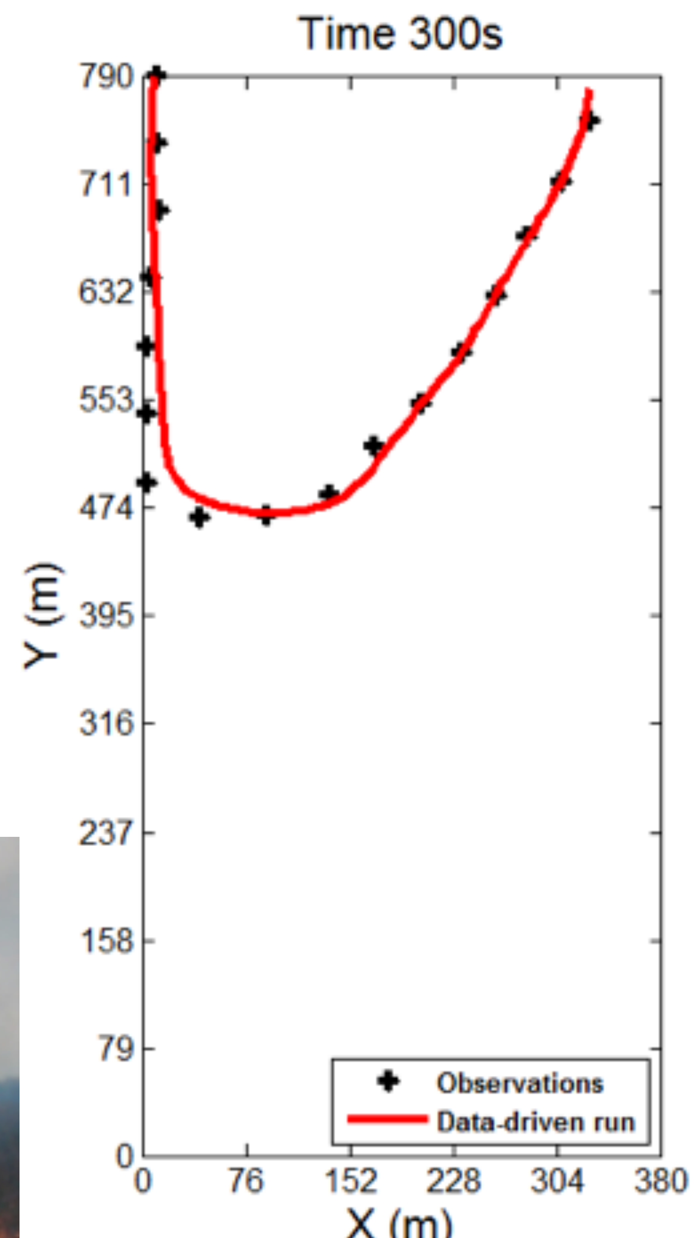

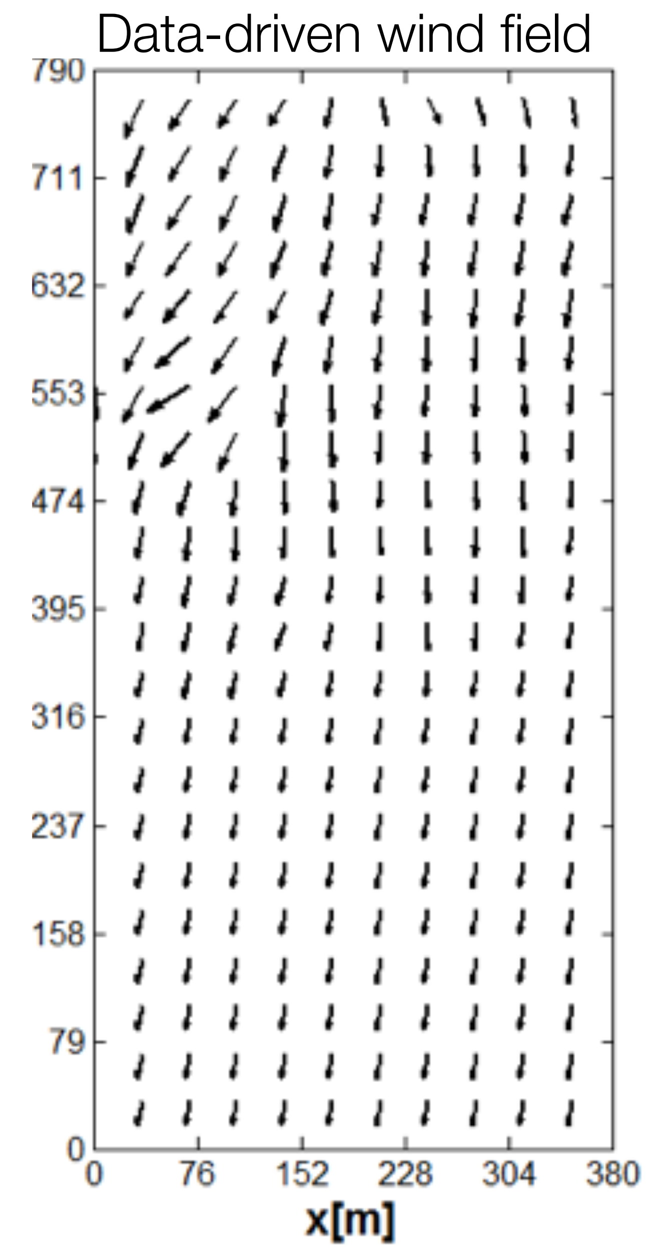

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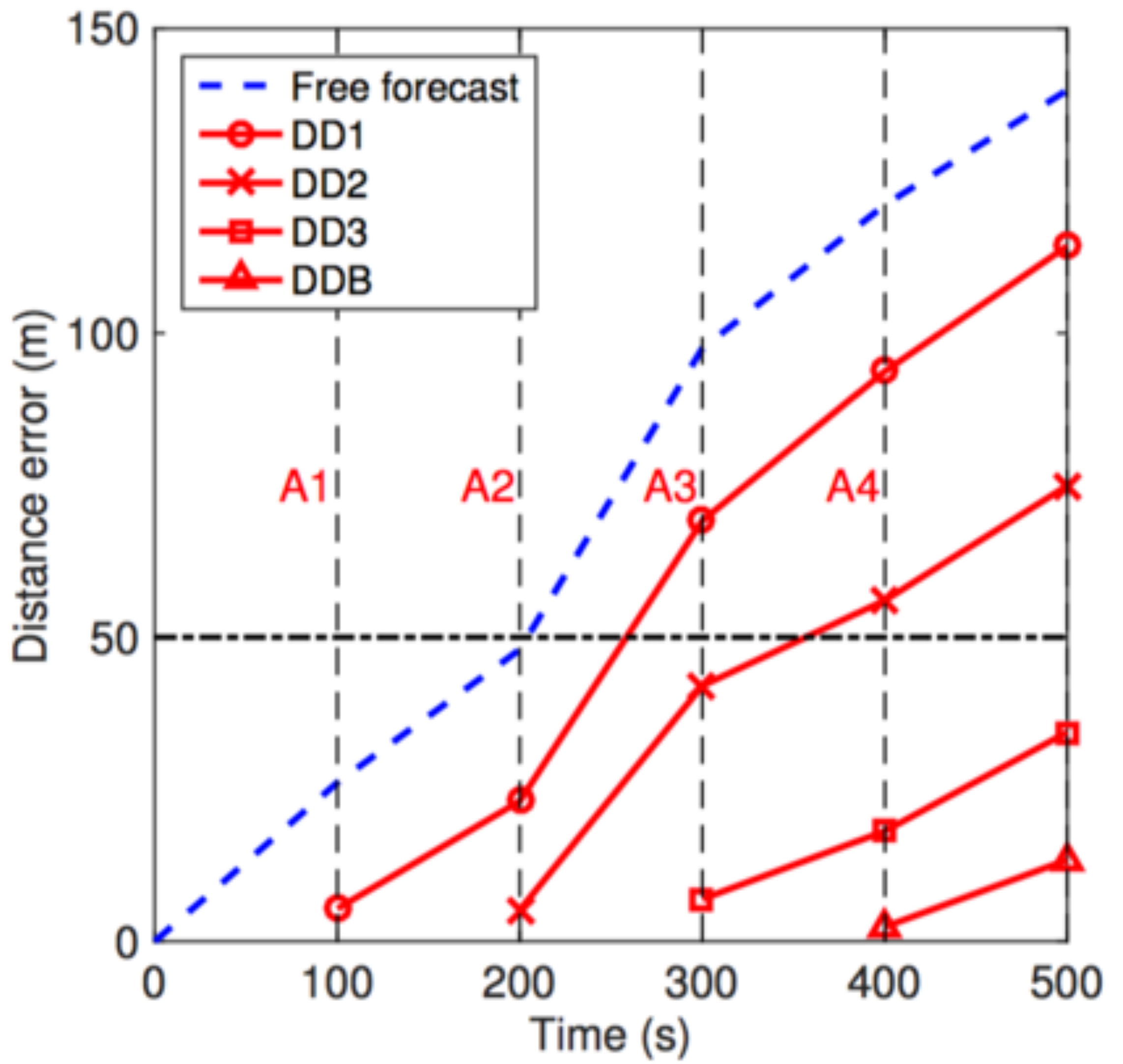
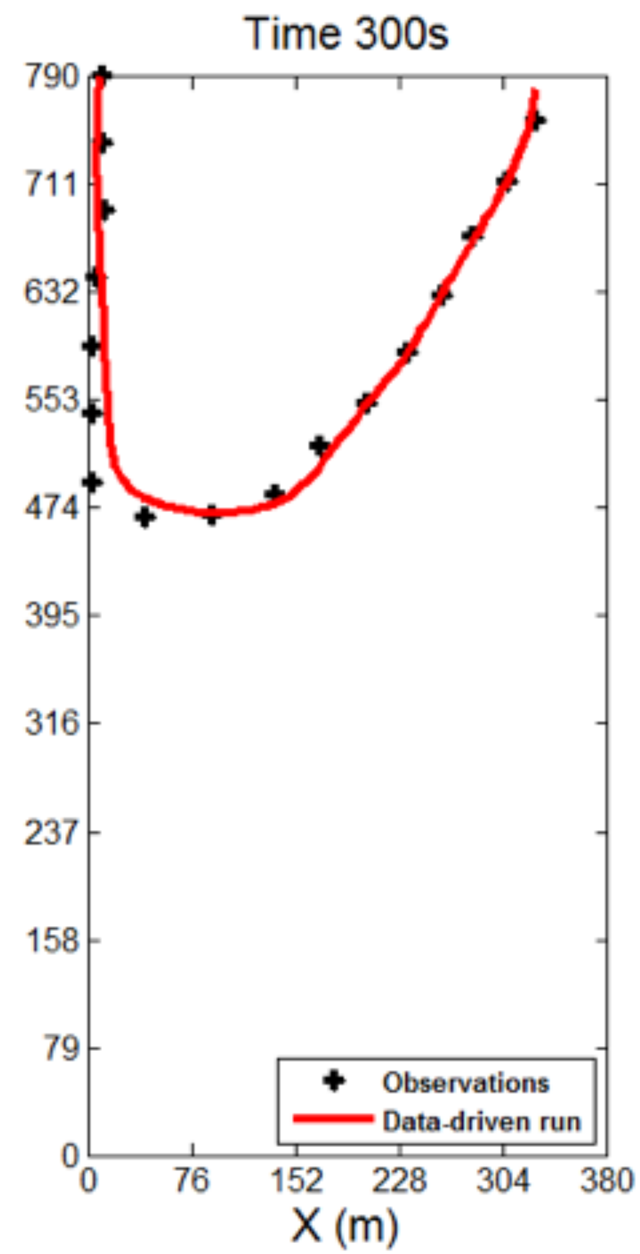
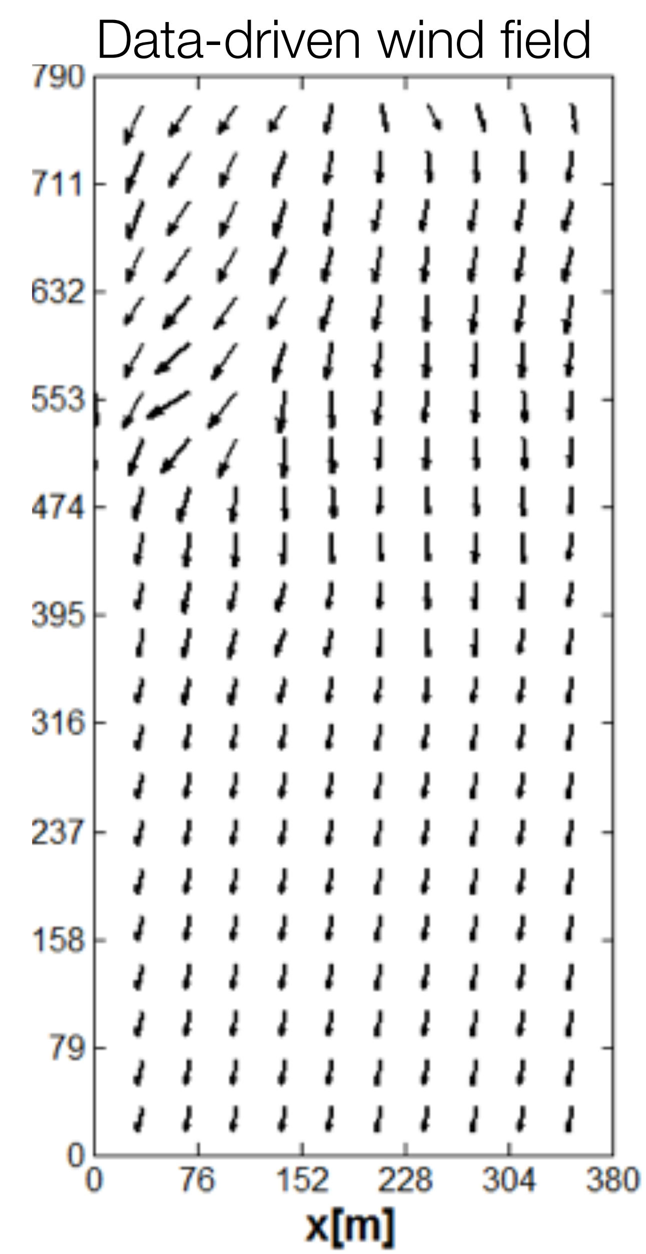






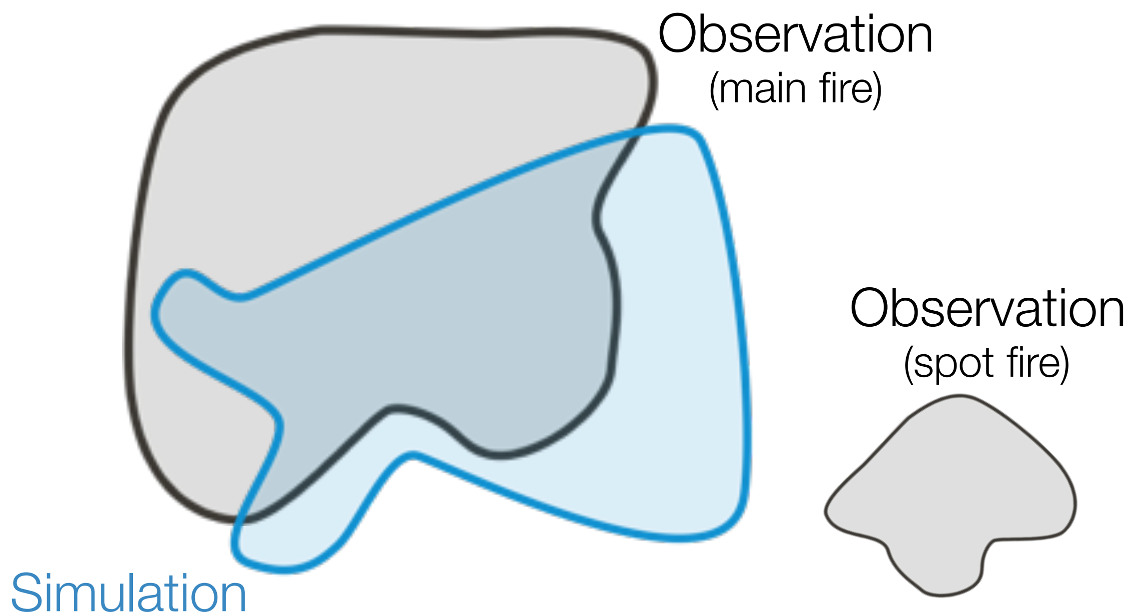
First answer to the question "How often do we need to assimilate data to control the error in the data-driven simulation?"

Requires synergy with data providers

Methodological challenge

How to properly address shape and position errors for complex fire front topology?

- Formulation of a non-Euclidean discrepancy operator to represent shape and topological discrepancies
- Able to assimilate image data directly



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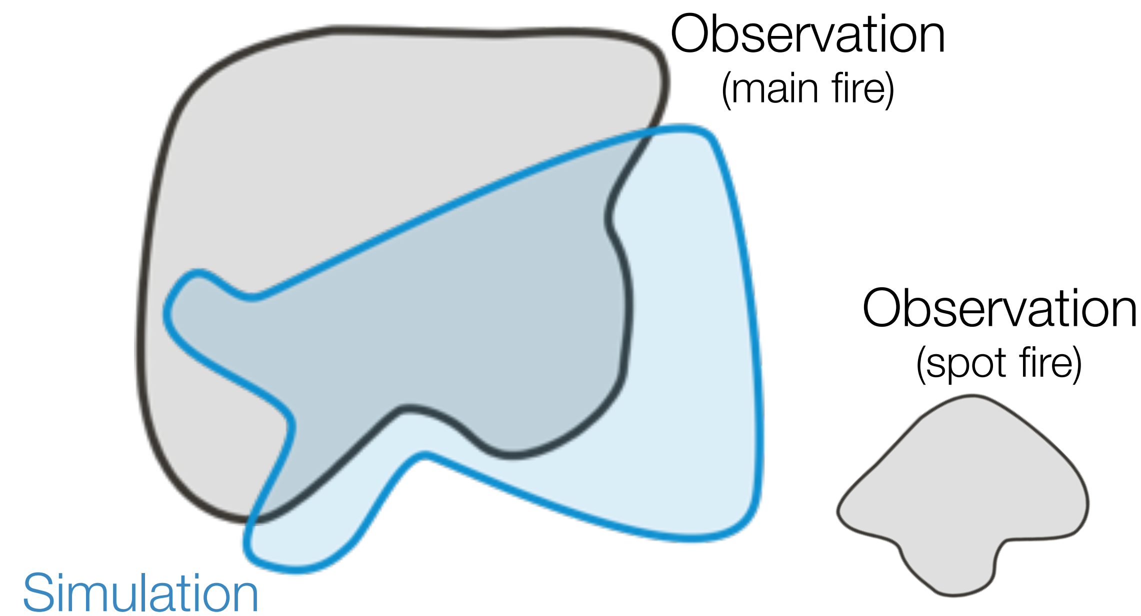

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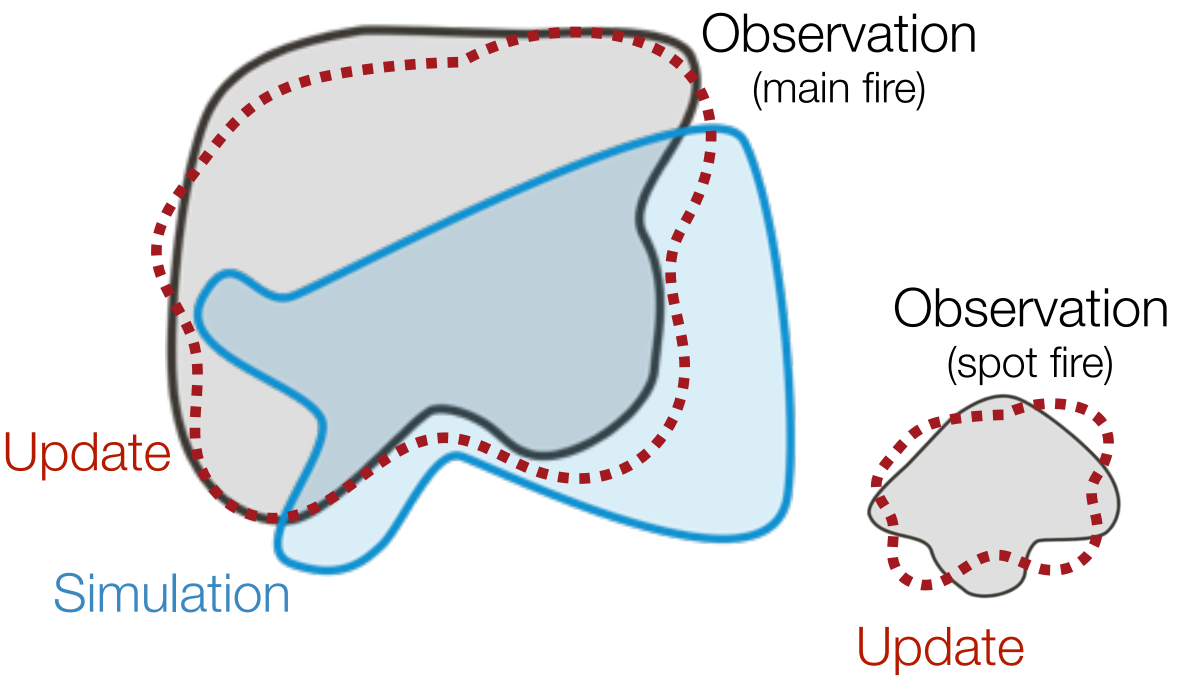

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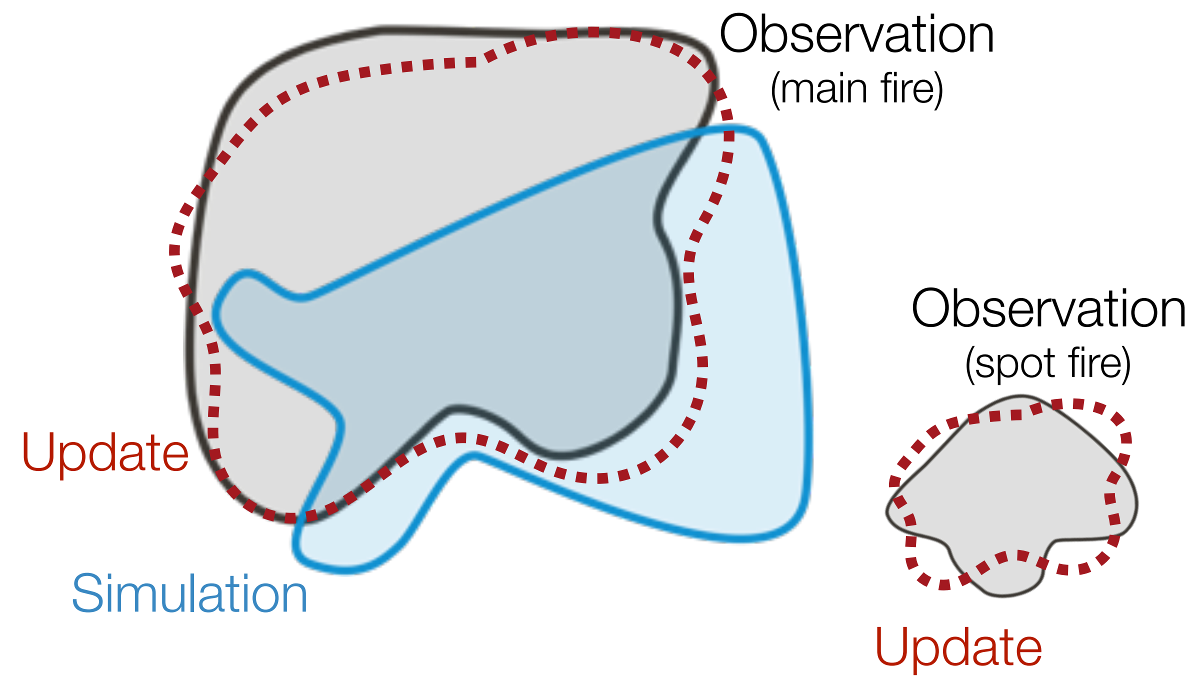

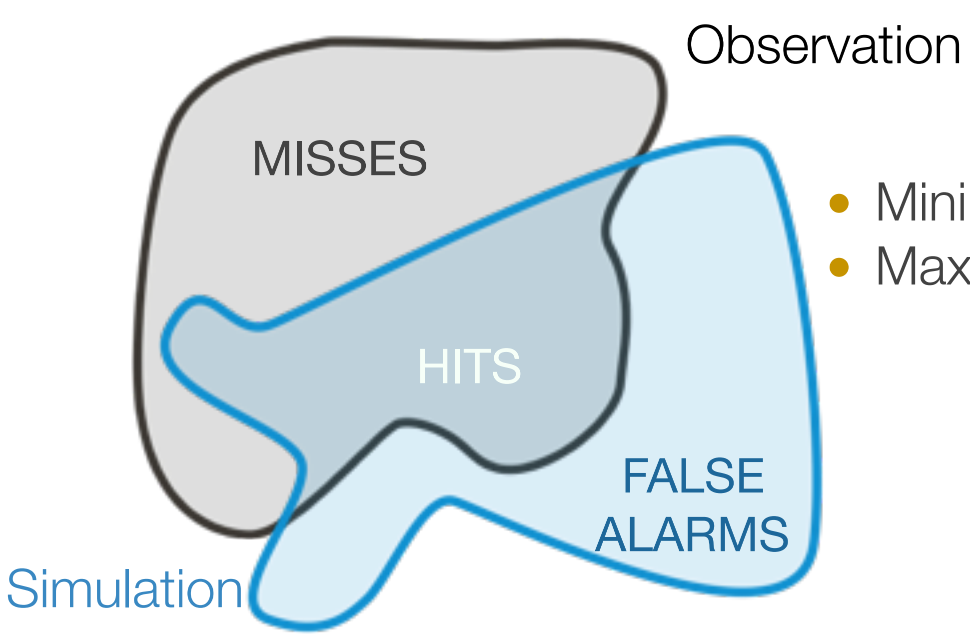

- Minimization of misses
- Maximization of hits

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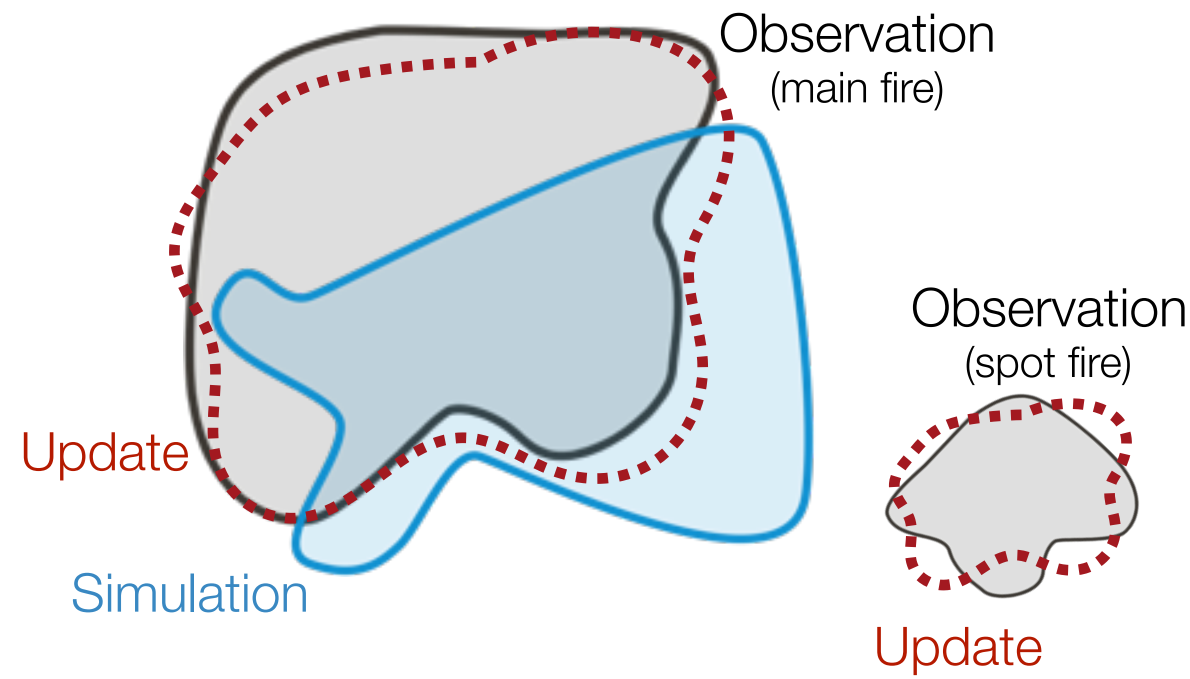

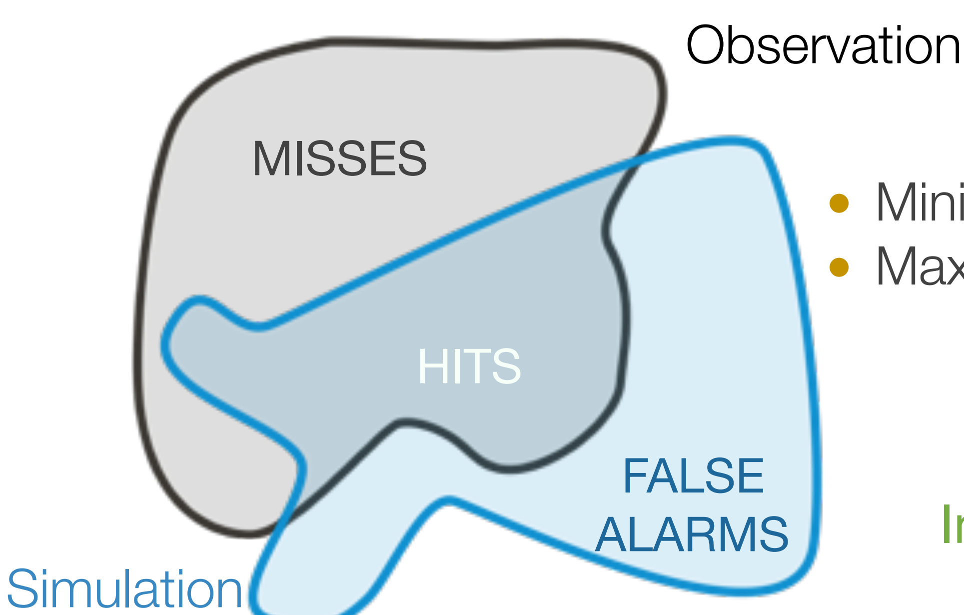

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Image segmentation theory

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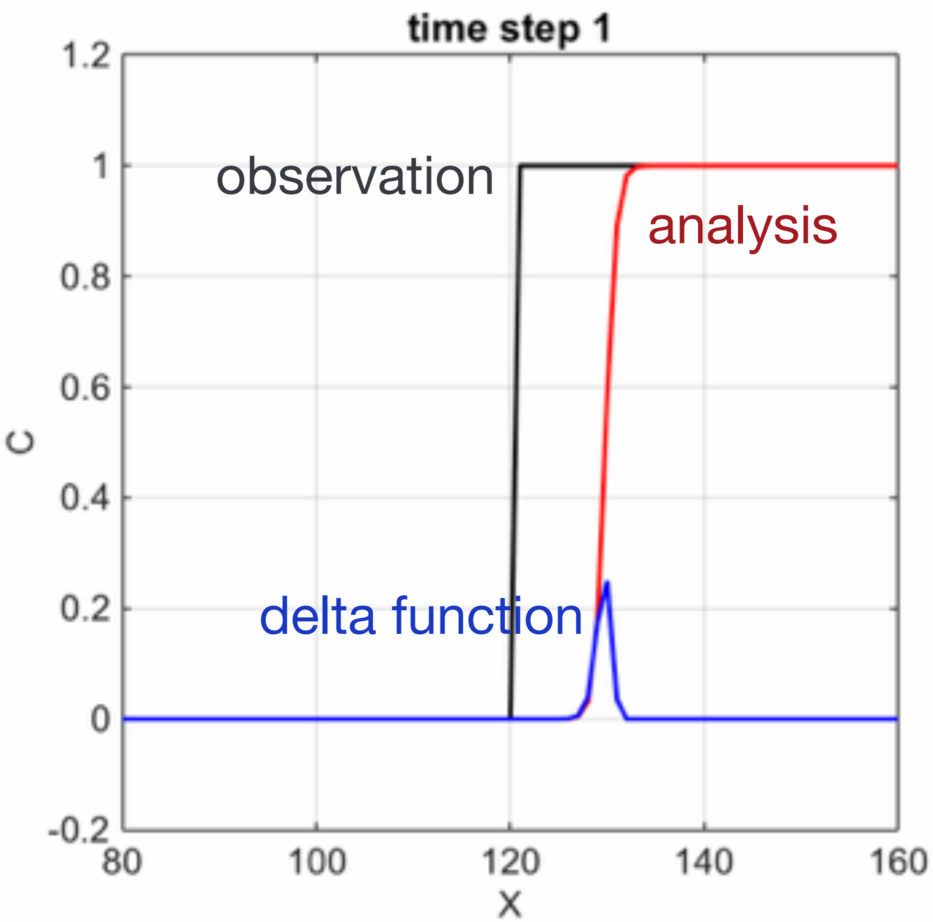
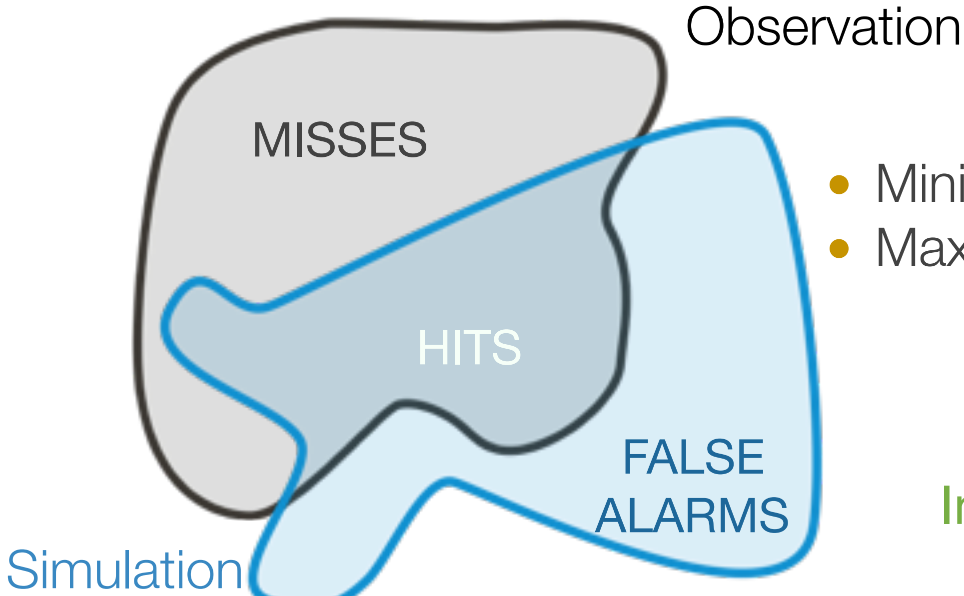


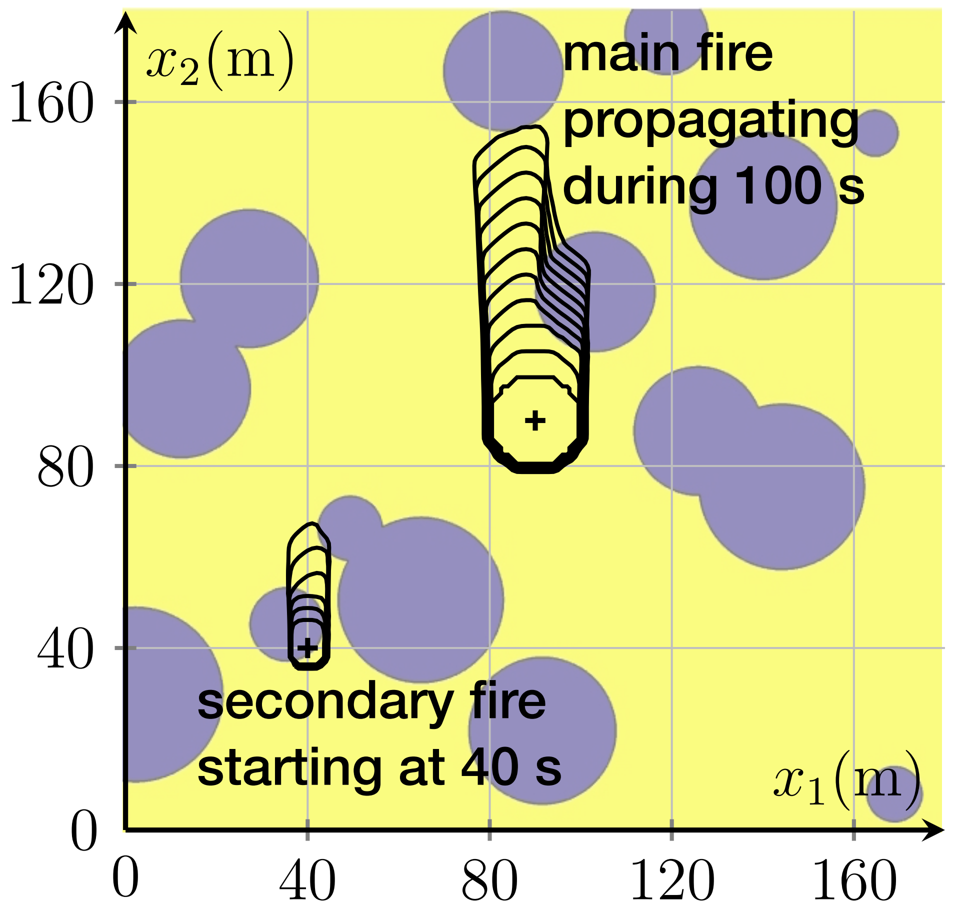


- Minimization of misses
- Maximization of hits

Image segmentation theory

Verification test case

State estimation with wrong initial condition



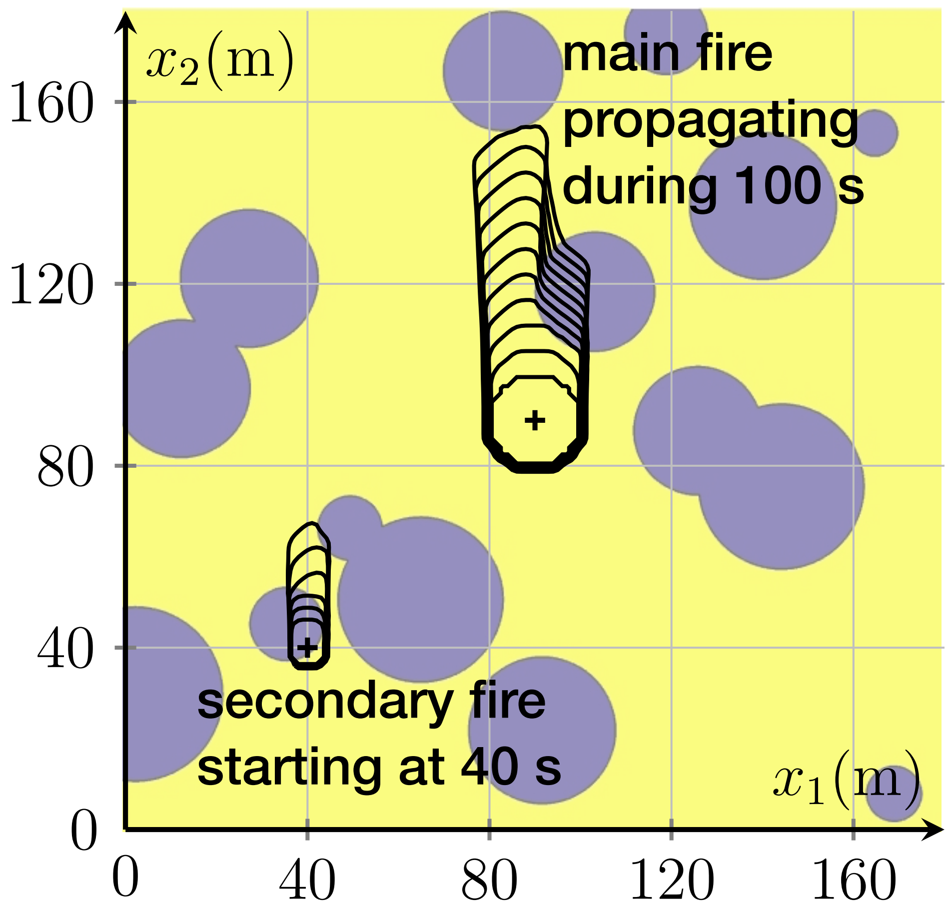
Rochoux et al. , Front shape similarity measure for front position […] data assimilation for eikonal equation, ESAIM: Proceedings and Surveys (in review).

background mean

analysis mean

Verification test case

State estimation with wrong initial condition



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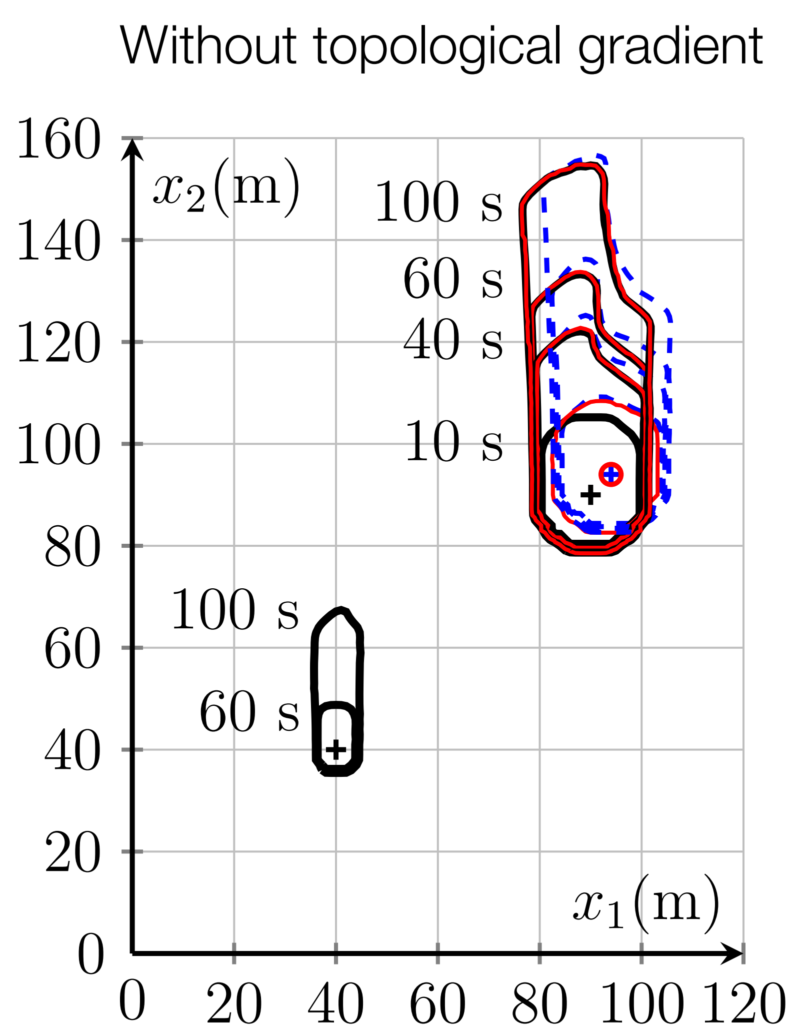
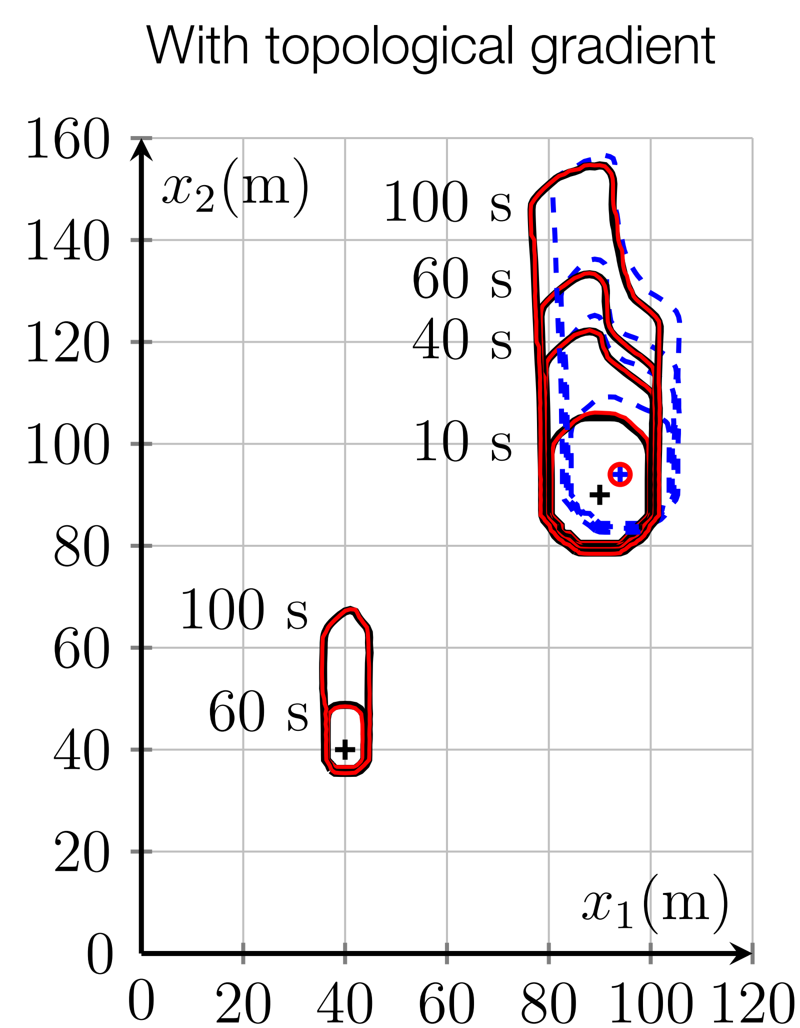


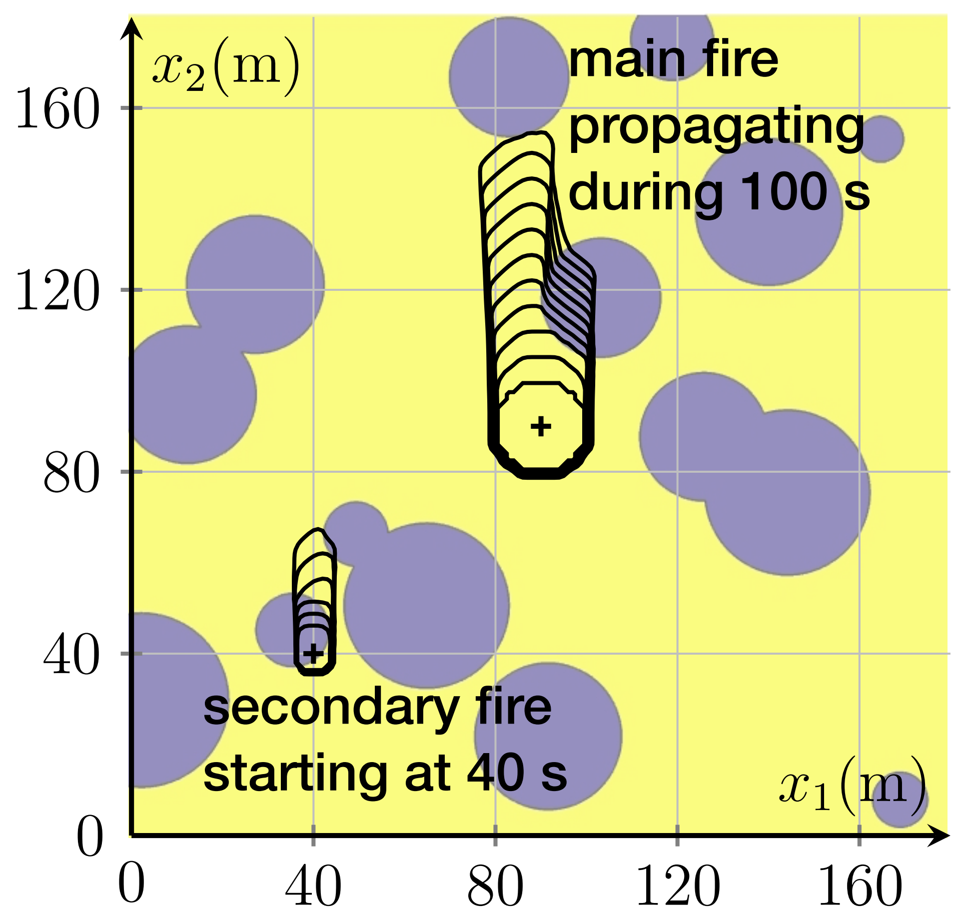


background mean

analysis mean

Verification test case

State estimation with wrong initial condition and wrong wind parameters



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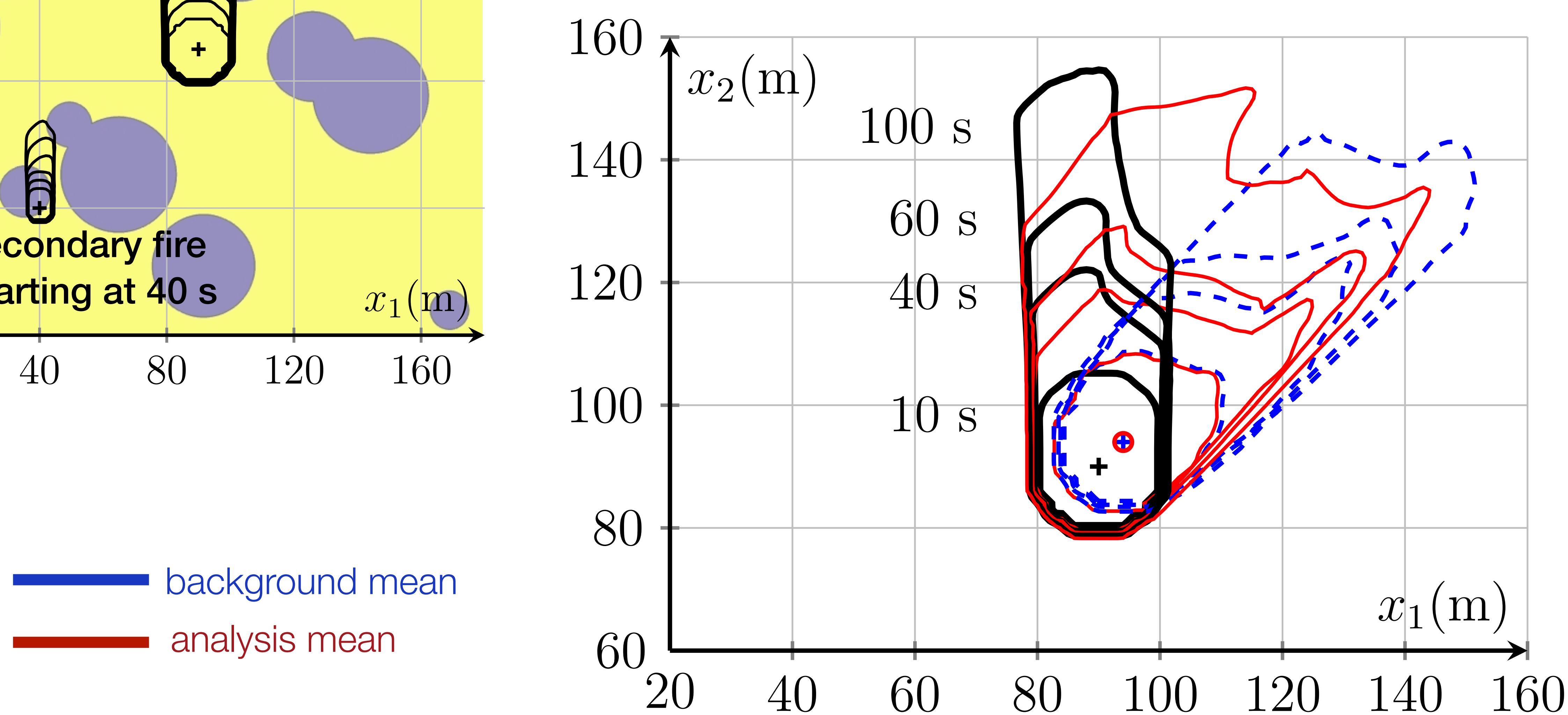
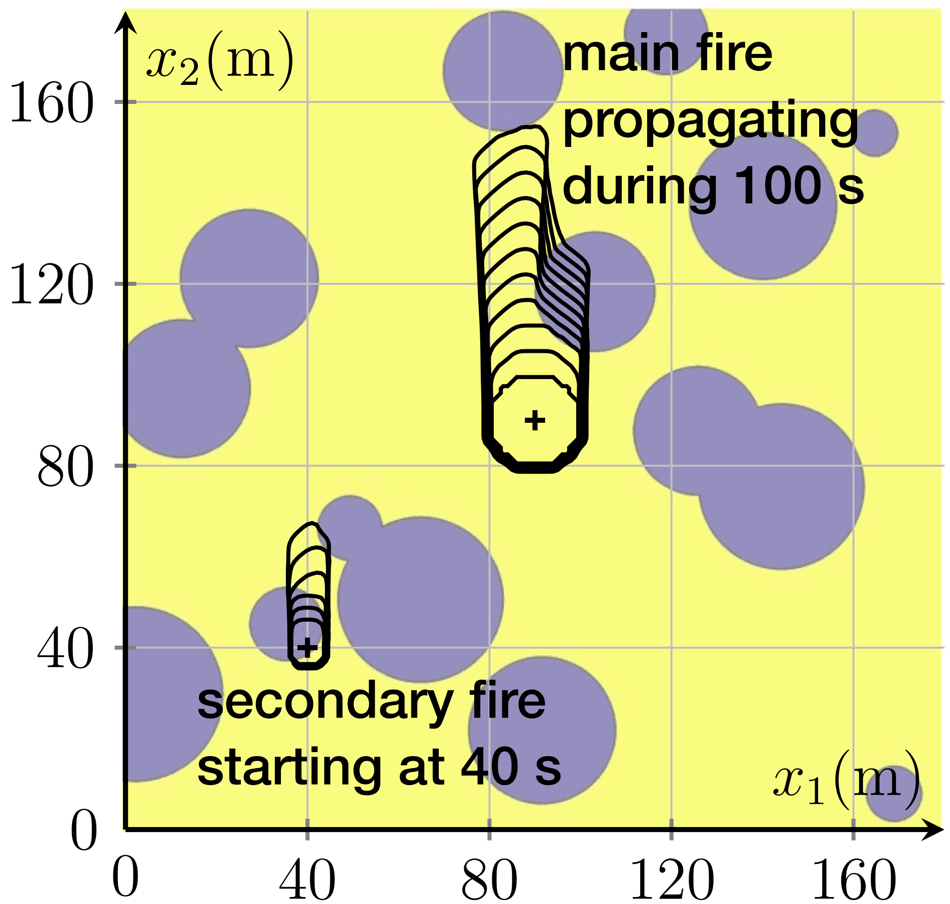


Verification test case

Parameter estimation with wrong wind conditions



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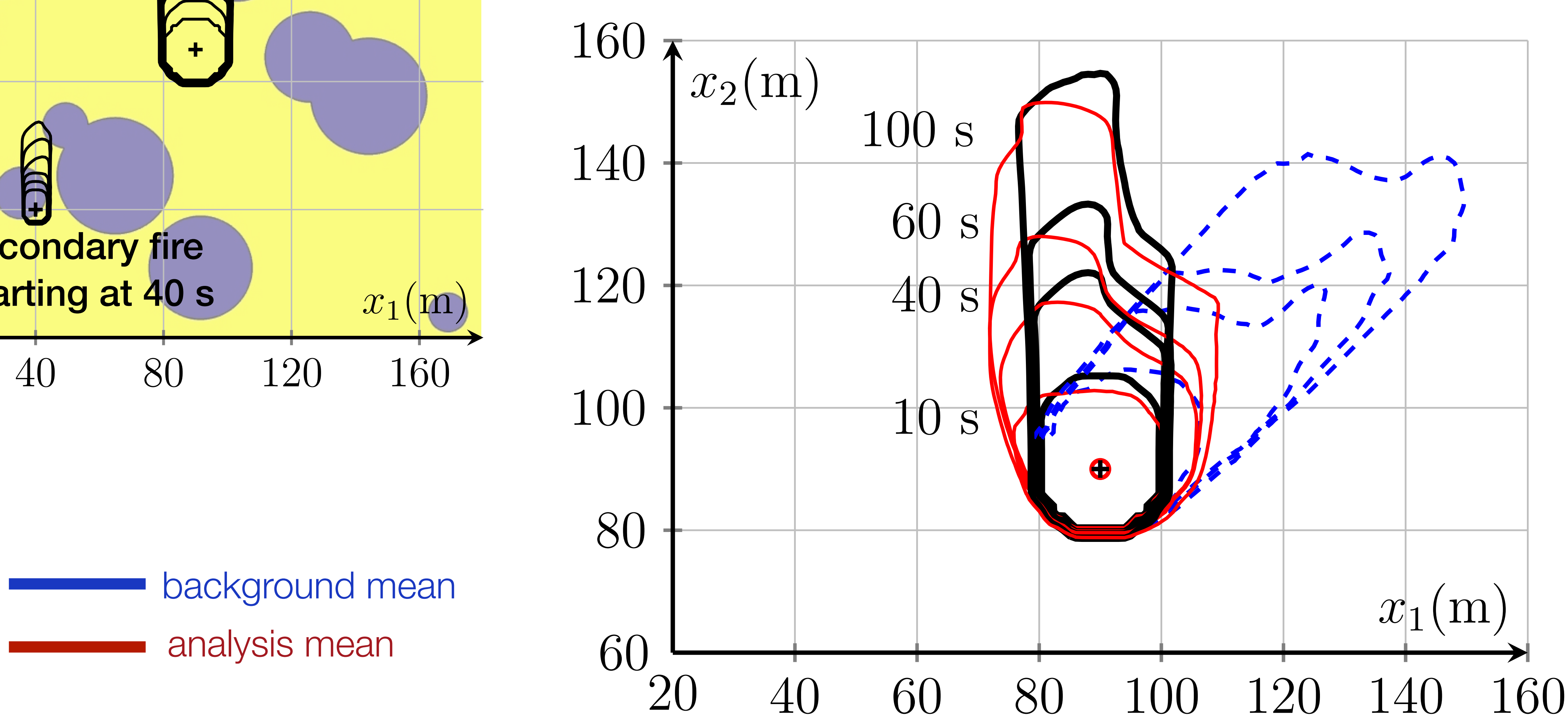

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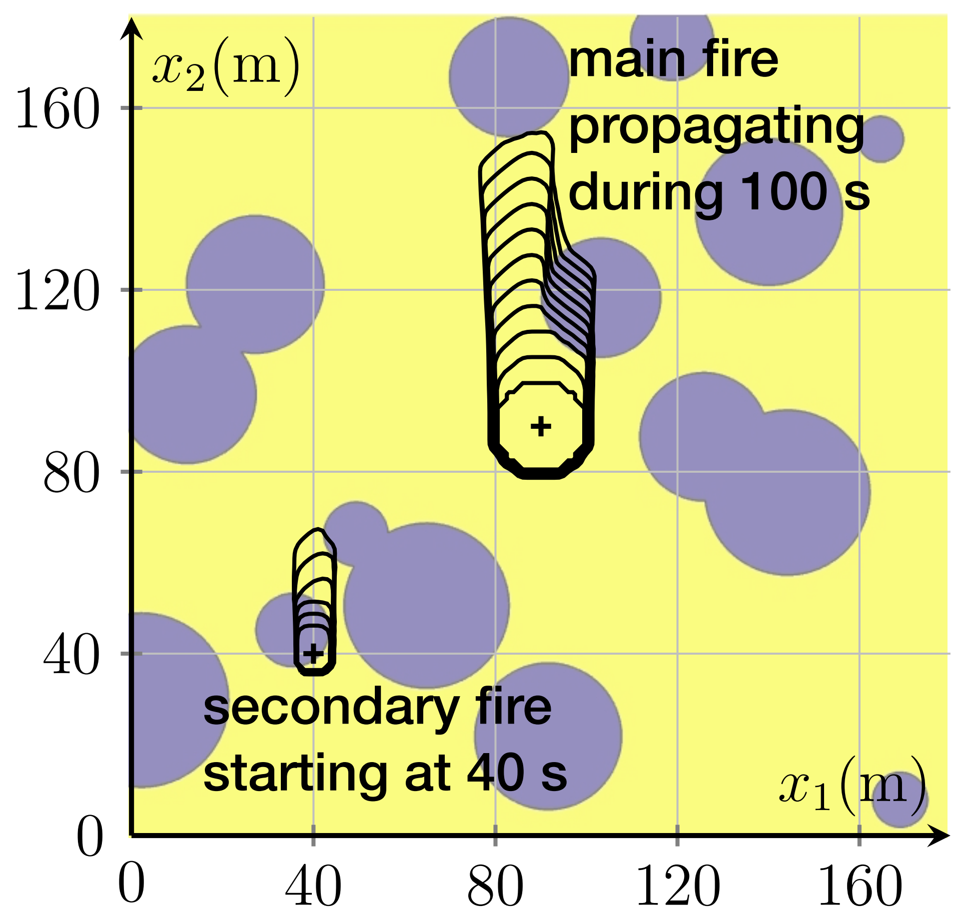

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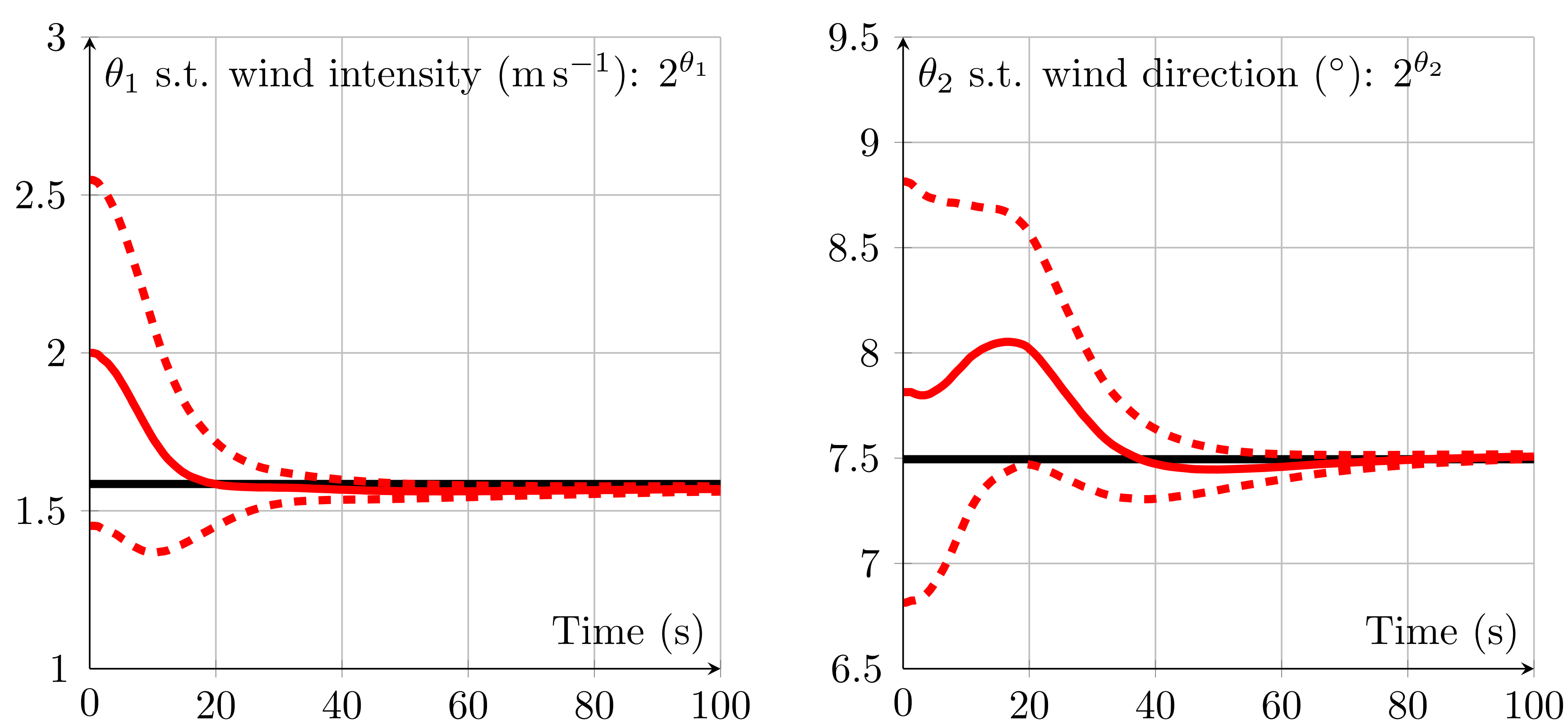

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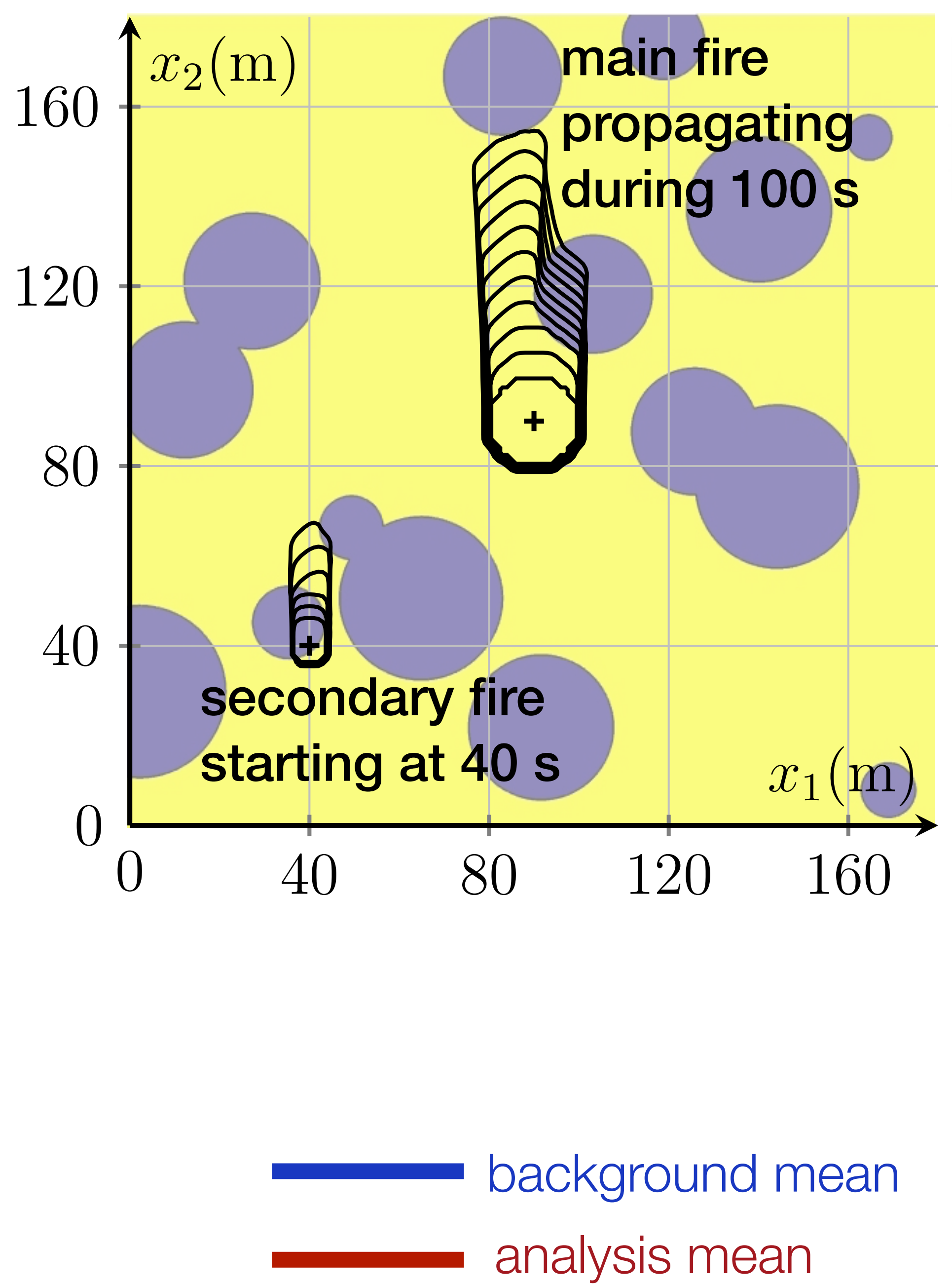

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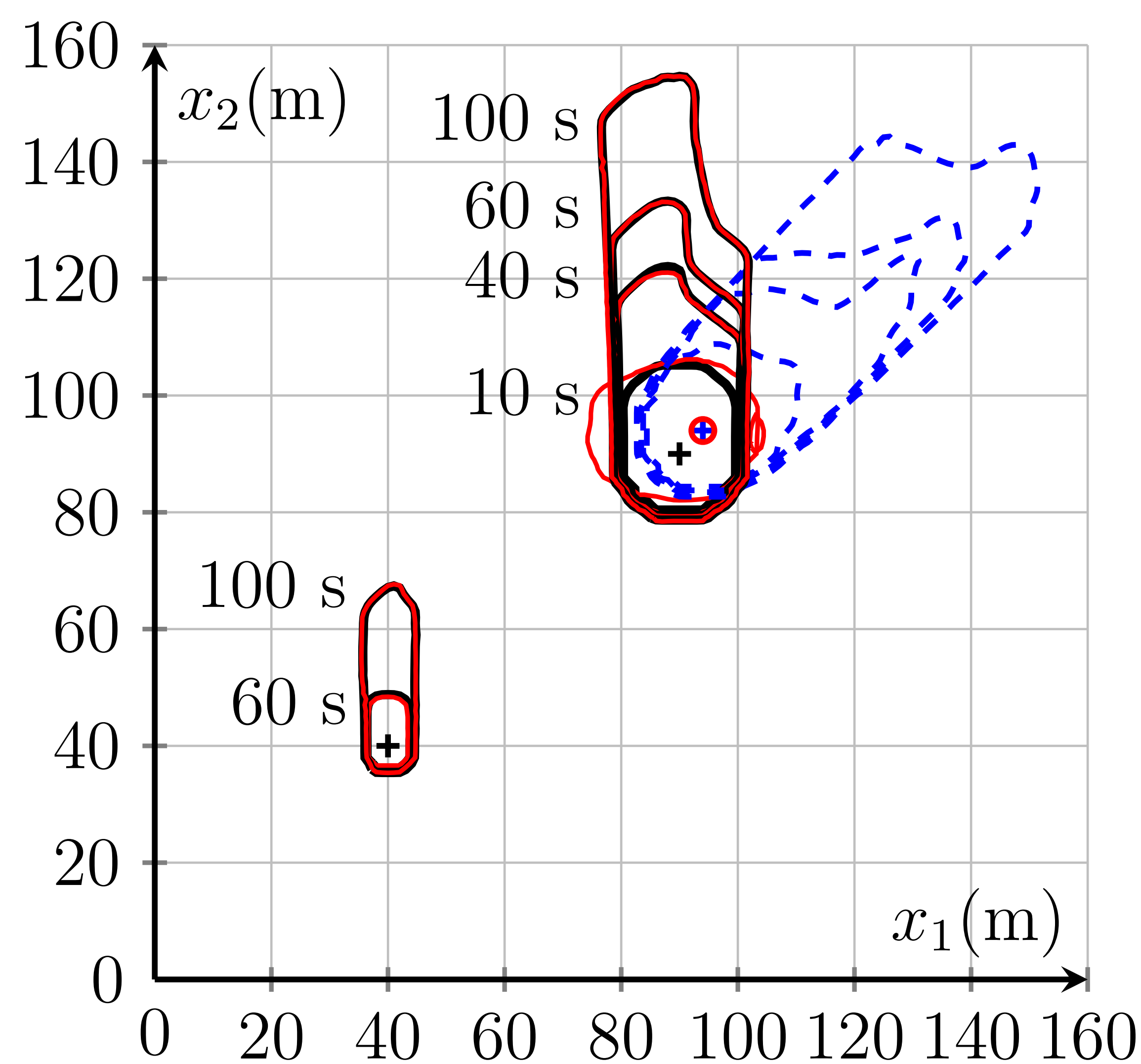

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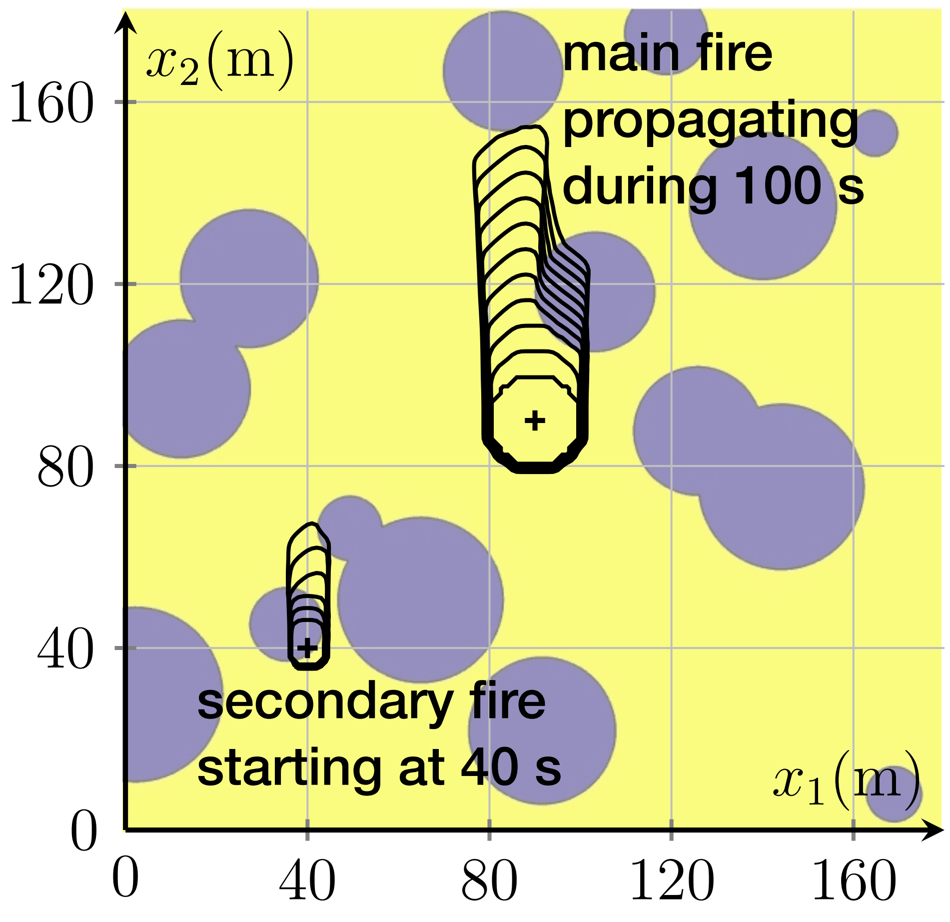

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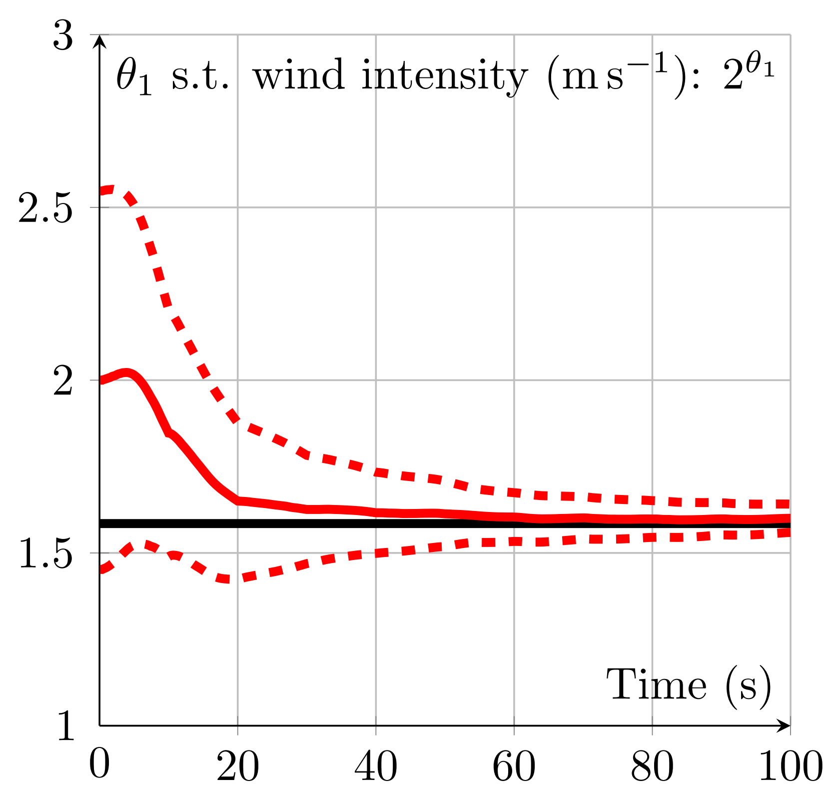

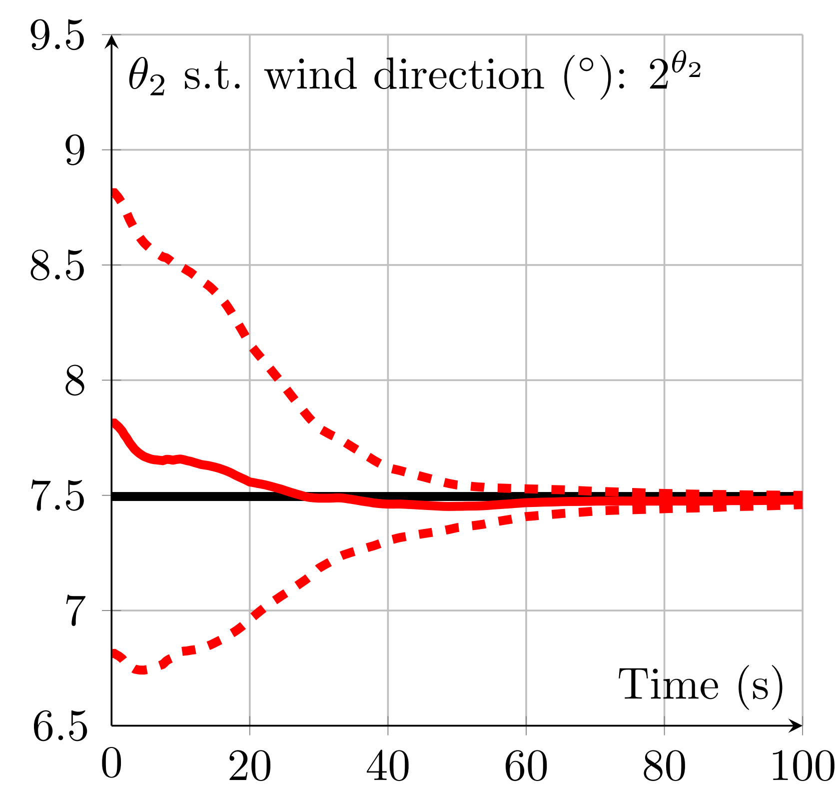

background mean
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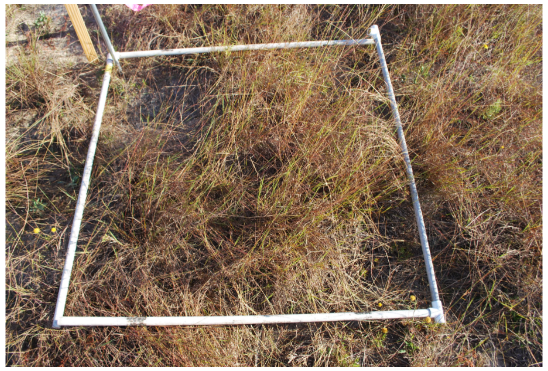
Validation

2012 RxCADRE S5 fire

- 15-min controlled burn (ROS ~20cm/s)
- flat terrain ~180 m x 180 m
- average wind speed ~2.5 m/s
- grass with light shrub ~20 cm high
- observation time period ~60 s



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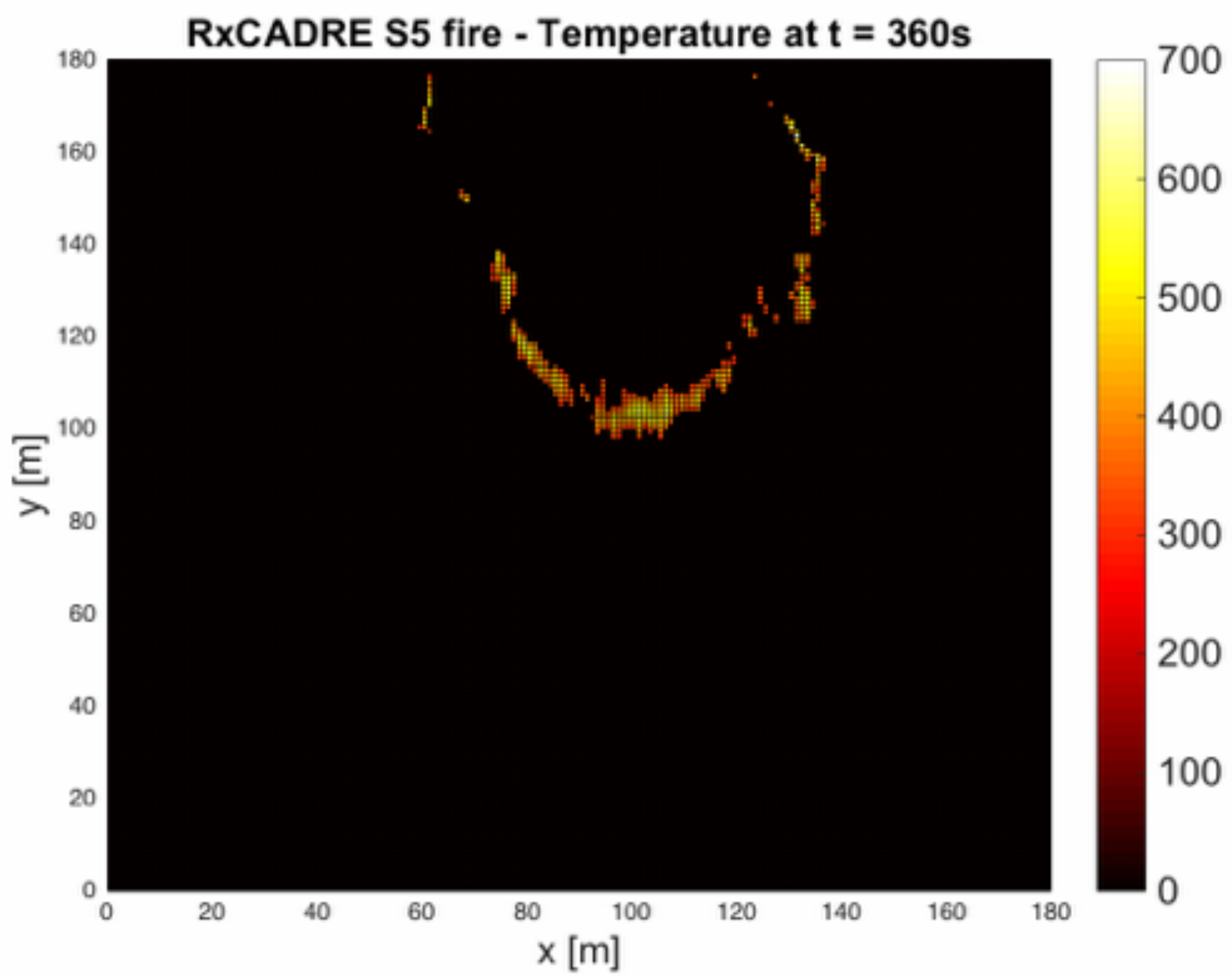

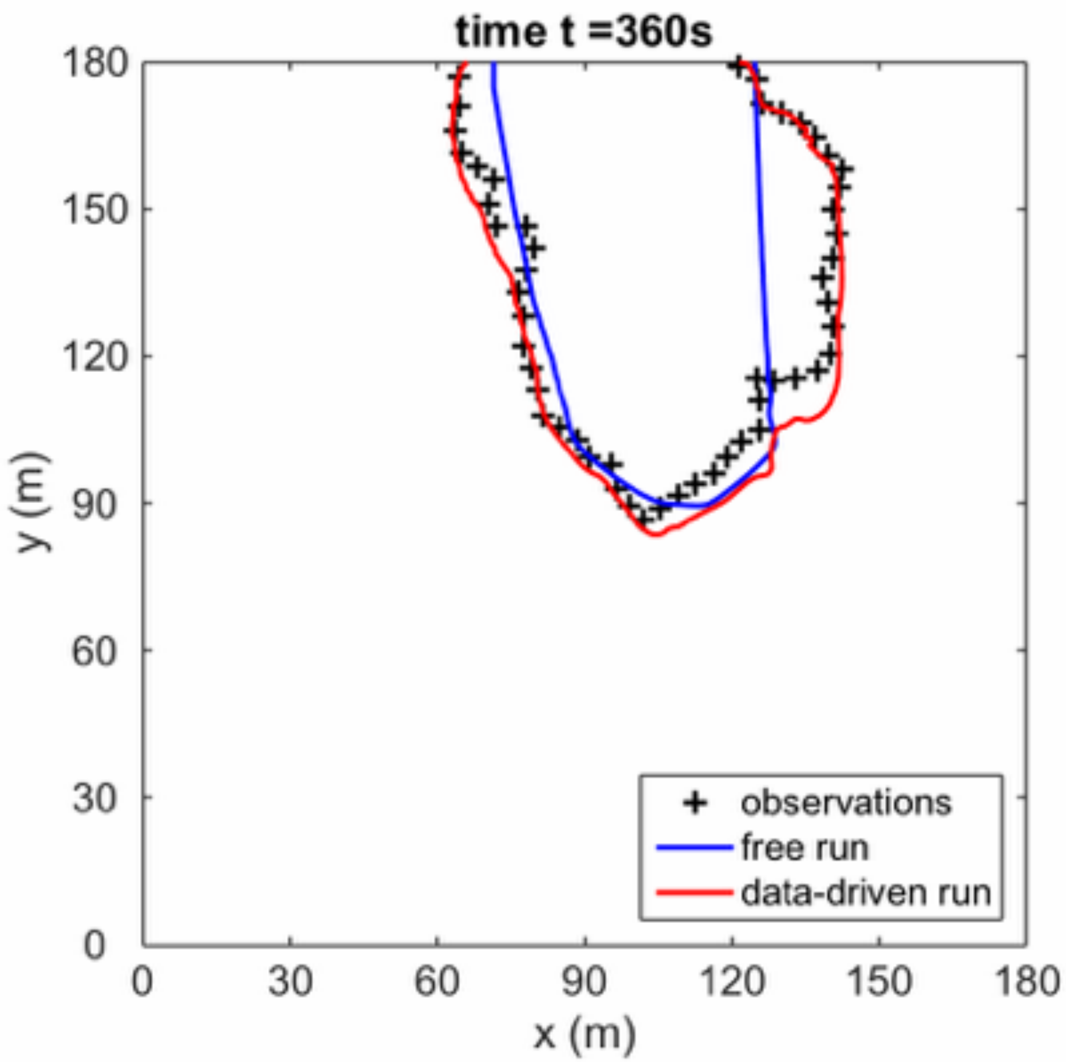

Validation

2013 Rim fire (California)

- large scale fire (illegal campfire)
- complex terrain ~70 km x 50 km
- grass and forest wild land fuels
- 11 observations over 20-25 August
- GeoMAC data (Evan Ellicott, UMD)

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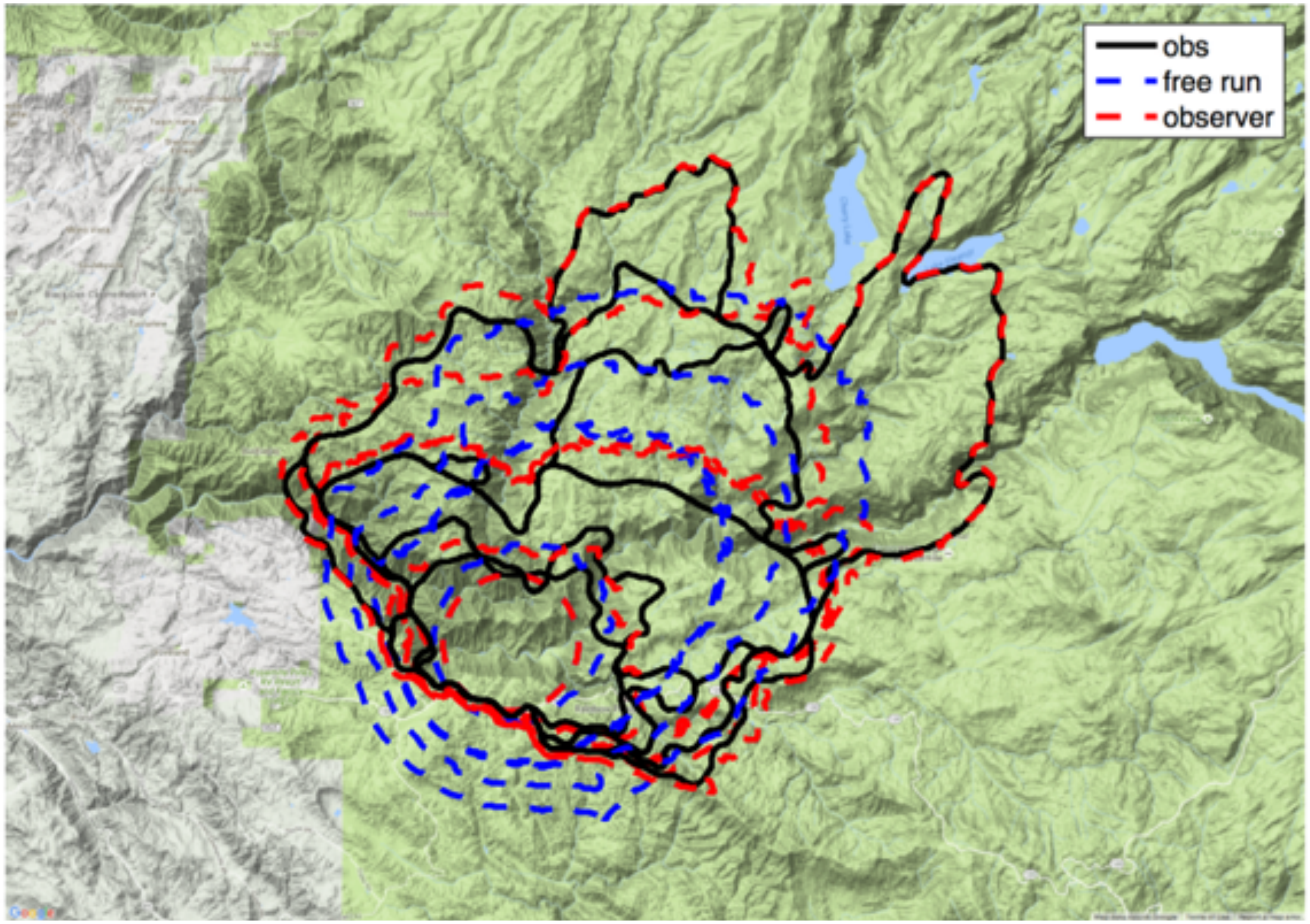

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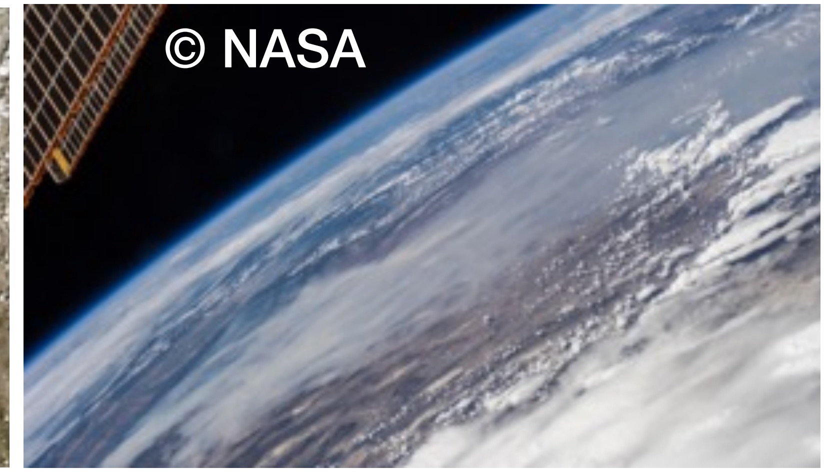
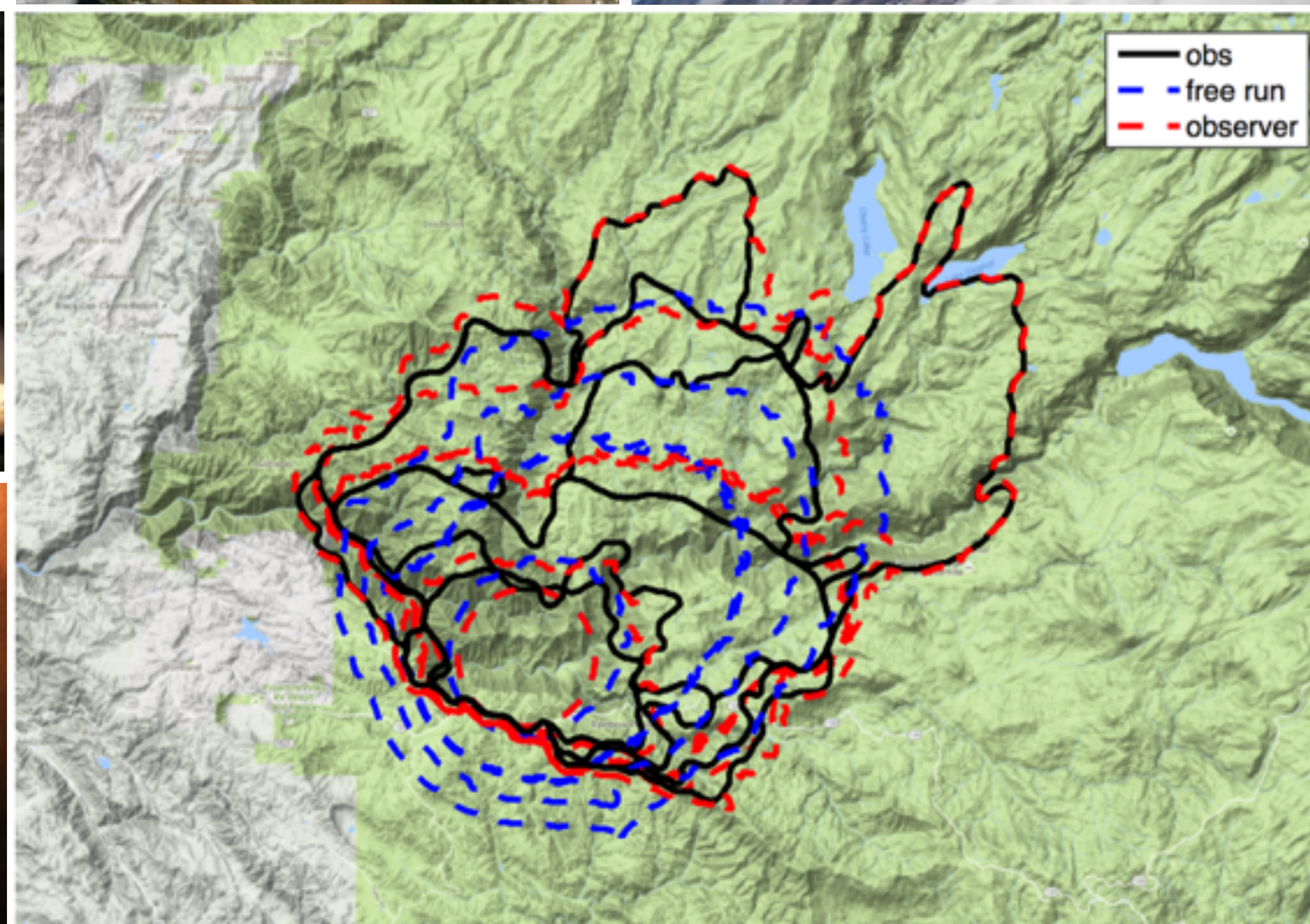




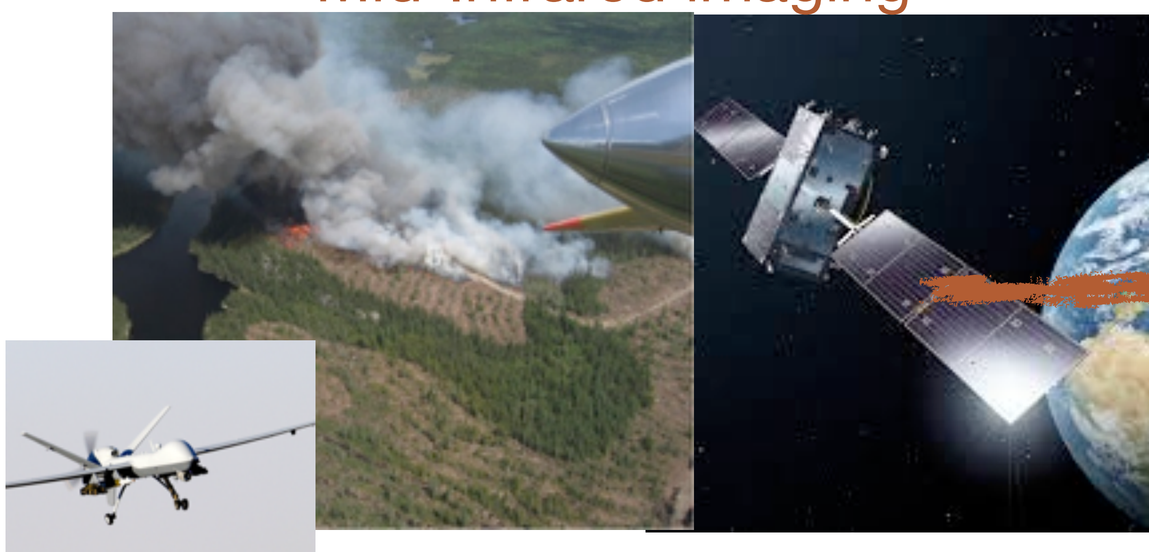
Computational cost for the integration of the fire growth model

- spatial resolution ~70 m
- Time step ~60 s
- Simulation time ~100 hr ↔ CPU time ~20 min

Data assimilation, the science of compromises

Fire growth prediction

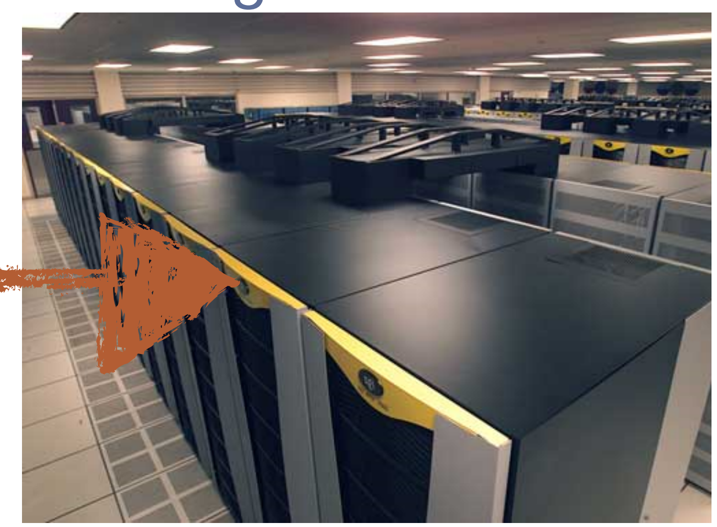
Mid-Infrared imaging



- detection of active burning areas
- opacity of the smoke plume
- sparse measurements

➡ measurement and representativeness errors

Fire growth model

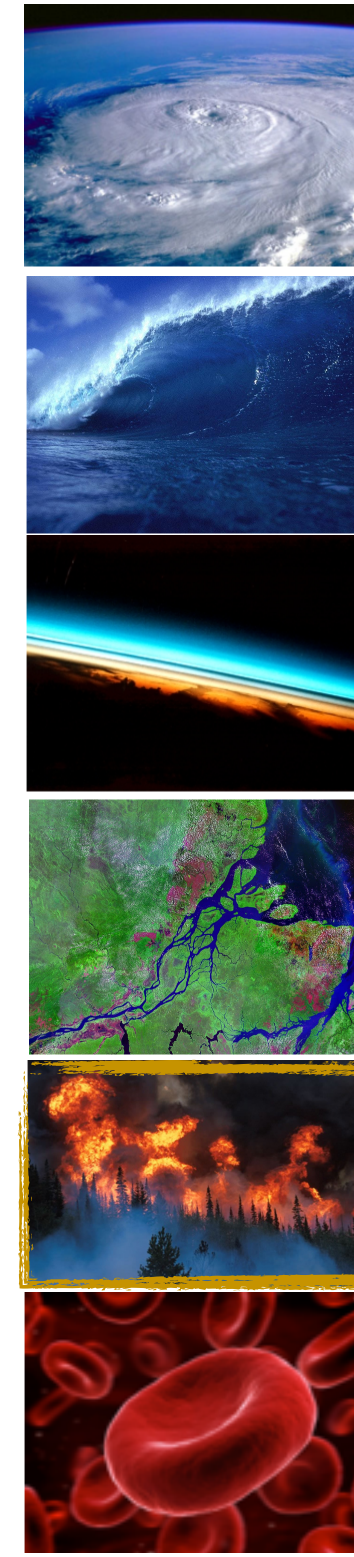


- burnt or unburnt state
- many inputs: physical parameters to the ROS model, initial condition

➡ uncertainties in inputs and model assumptions

➡ Find more optimal values of the estimation targets by minimizing the misfit error with respect to the observations

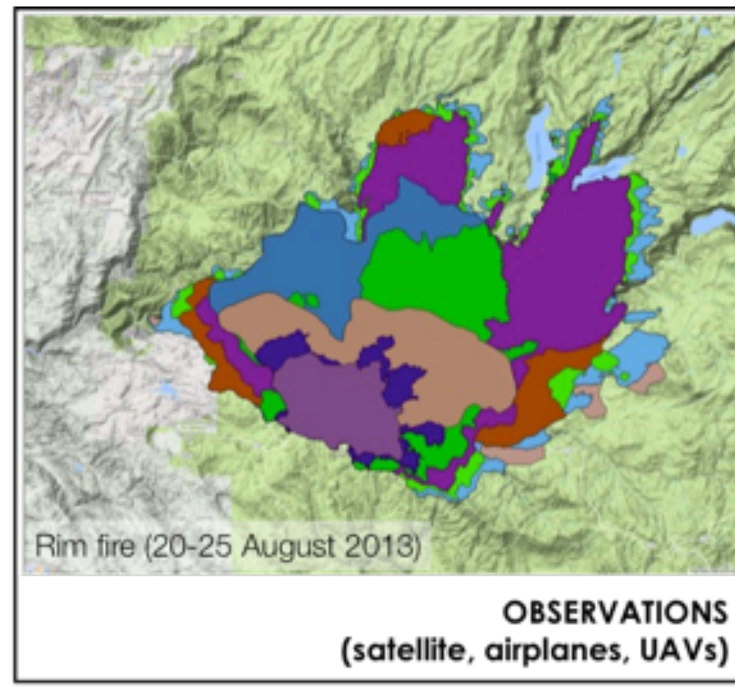
➡ Improved representation of the simulation-observation discrepancies using the front shape similarity measure

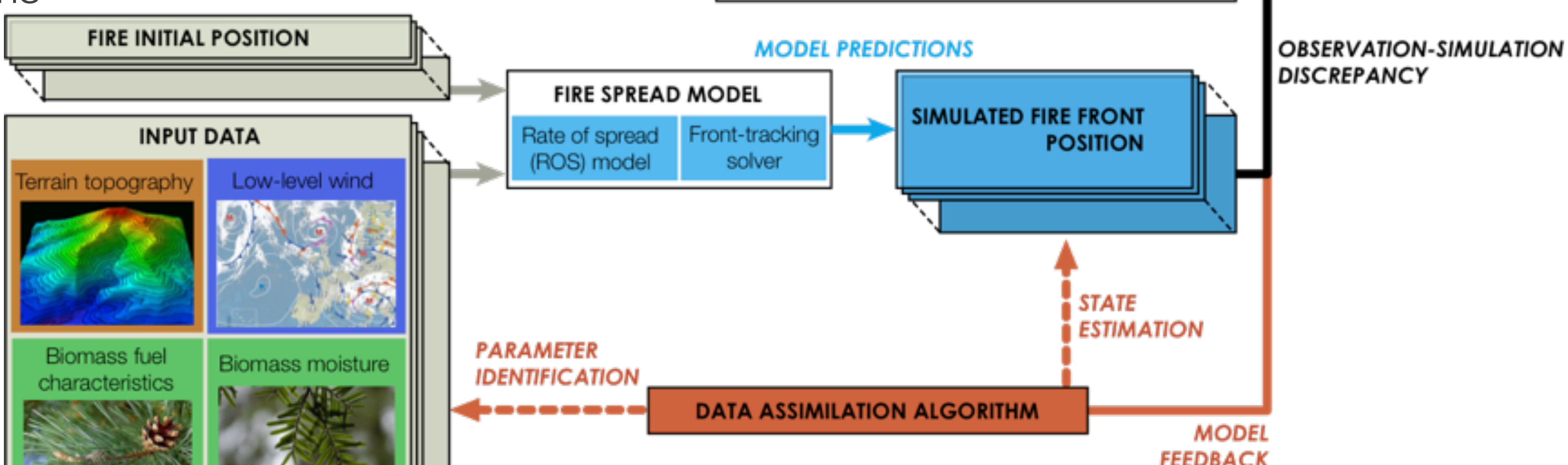


Wide variety of applications

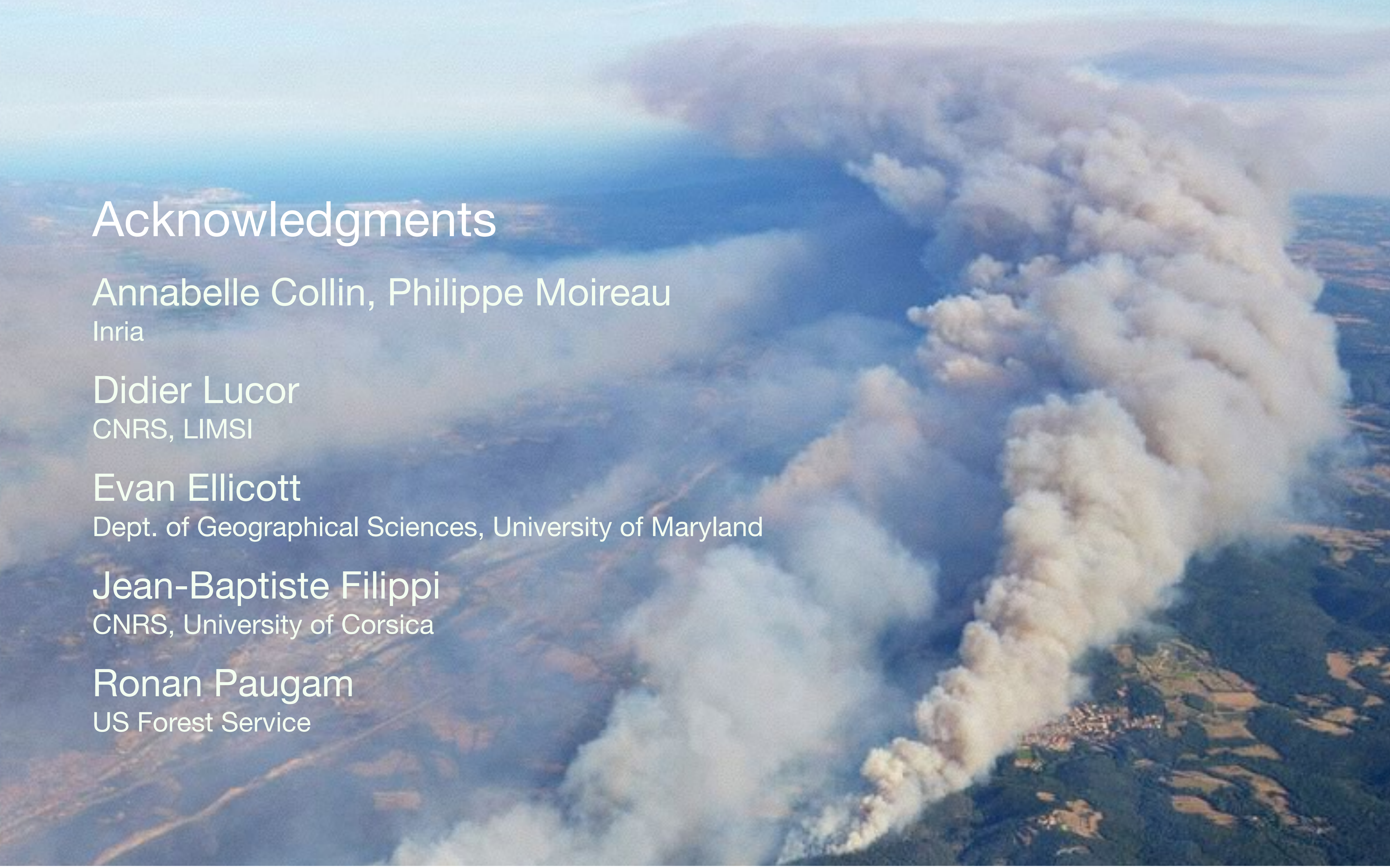
Perspectives

- ➡ Develop a unique framework for Eulerian and Lagrangian fire growth models
- ➡ Test joint state-parameter estimation on multiple datasets (2013 Rim fire, 2011 Greece fire…) in reanalysis mode
- ➡ Apply to coupled fire-atmosphere models (ex: FOREFIRE-MesoNH)
- ➡ Help to design adapted observation systems





Paving the way towards application to regional-scale wildfire spread in forecast mode



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CNRS, University of Corsica

Ronan Paugam
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Thank you for your attention.
Any question?

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