CENTRE EUROPÉEN DE RECHERCHE ET DE FORMATION AVANCÉE EN CALCUL SCIENTIFIQUE

2019 Drone Garden Workshop | GIS Micro-drones

Data assimilation for wildland fire behavior

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Didier Lucor
LIMSI, CNRS, Université Paris Saclay

Talk's introduction

Data assimilation in a nutshell

Rochoux et al. (2017), Wildfire Magazine

Observations

Numerical simulations

Data assimilation in a nutshell

Rochoux et al. (2017), Wildfire Magazine

Observations

- Sparse
- Limited spatial coverage and resolution

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- Simplified physics
- Limited information on environmental and meteorological parameters

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Data assimilation

Statistical aggregation of different sources of information

- Uncertainty quantification (error model)
- Inverse modeling (estimation)
- Forecast capability (using the model to extrapolate the system dynamics beyond observation times)

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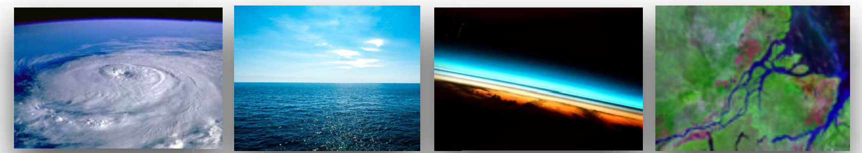

Observations

Paugam et al. (2013), IEEE transactions on geoscience and remote sensing

Paugam et al. (2019), EGU General Meeting

How to extract and assimilate information from infrared imagery?

2014 Kruger National Park

- 7-hectare savannah fire
- Operated from helicopter
- Multiple channels: MIR-LWIR-VIS
- High resolution (1 m, 1 Hz)

Datasets: controlled burn experiments

Observations

Paugam et al. (2013), IEEE transactions on geoscience and remote sensing

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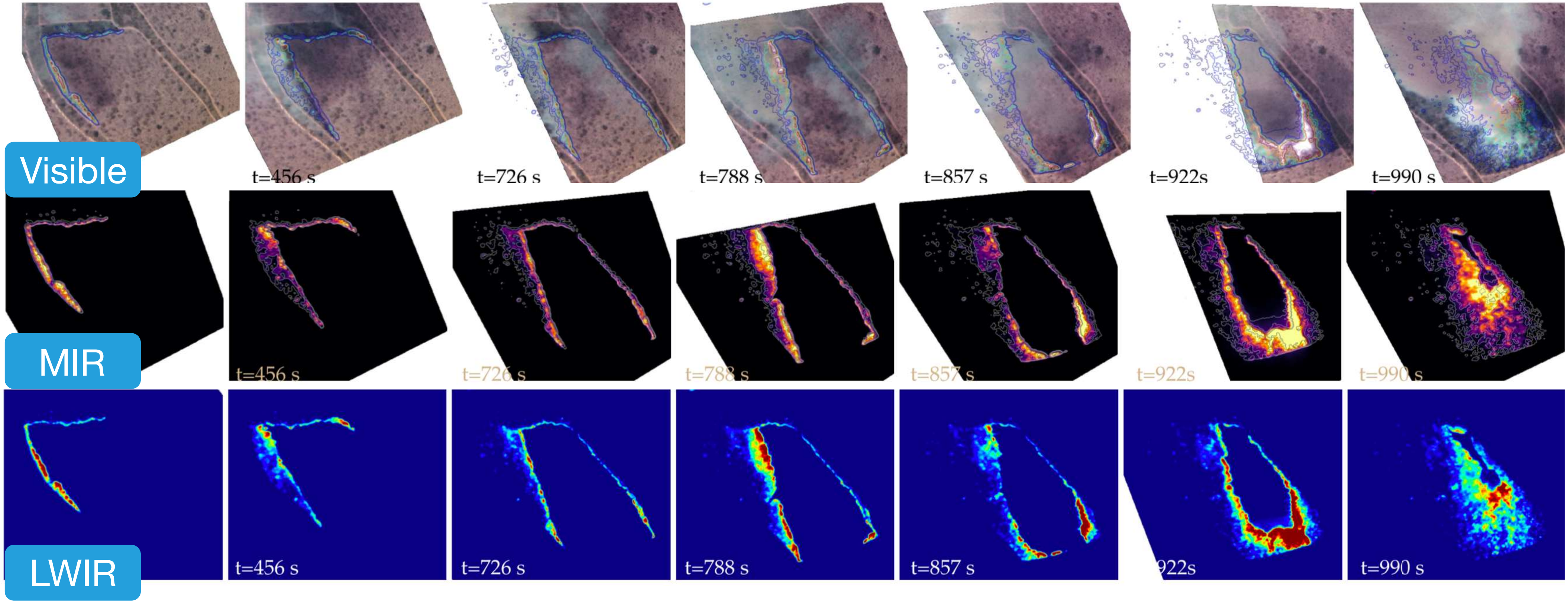

Model and uncertainties

Rochoux et al. (2017), Wildfire Magazine

Wildfire complexity

Current burnt-area models are far from being predictive

- A fire creates its own weather.
- Strong interactions between wind and terrain topography
- Limited knowledge on biomass

Current limitation: not possible to simulate infrared images

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Physical parameters

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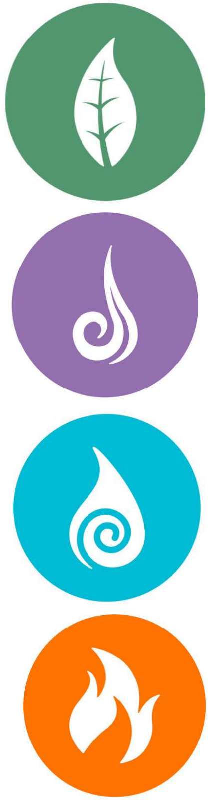

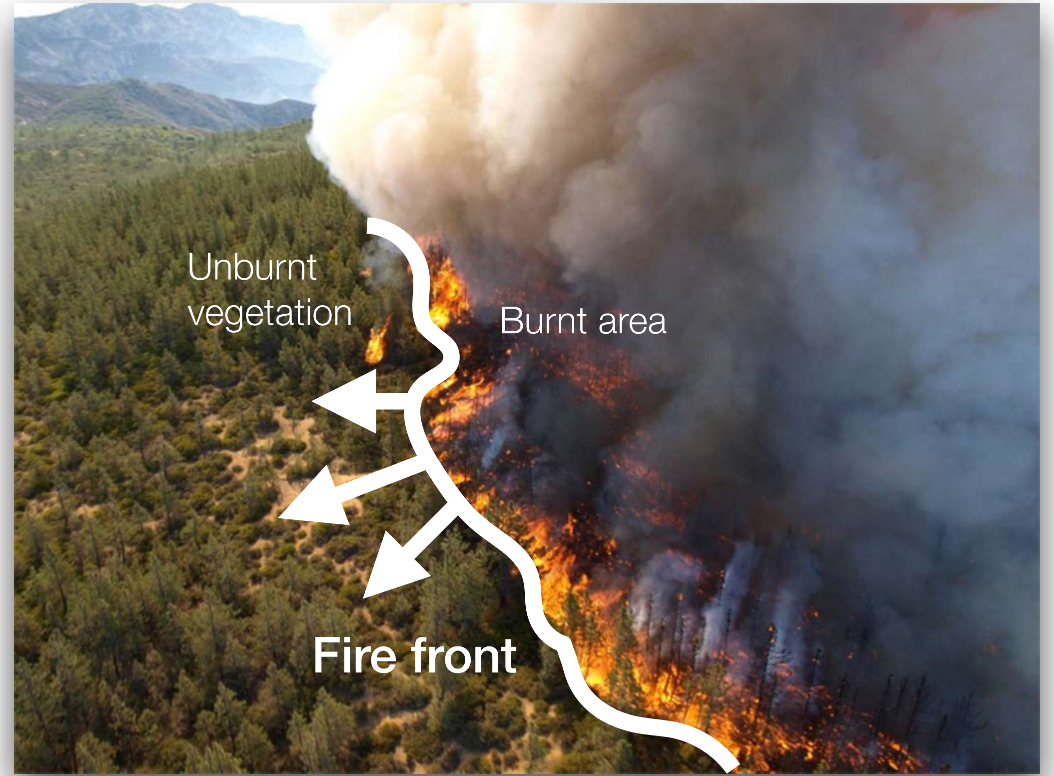

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Physical parameters → Fire spread model → Quantity of interest: fire front position

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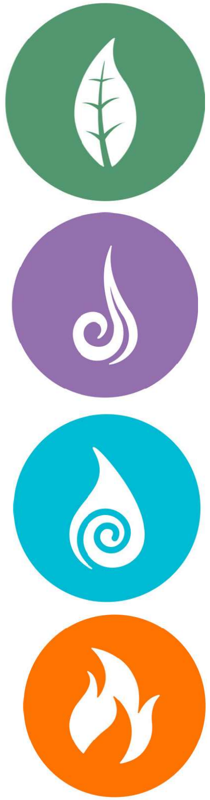

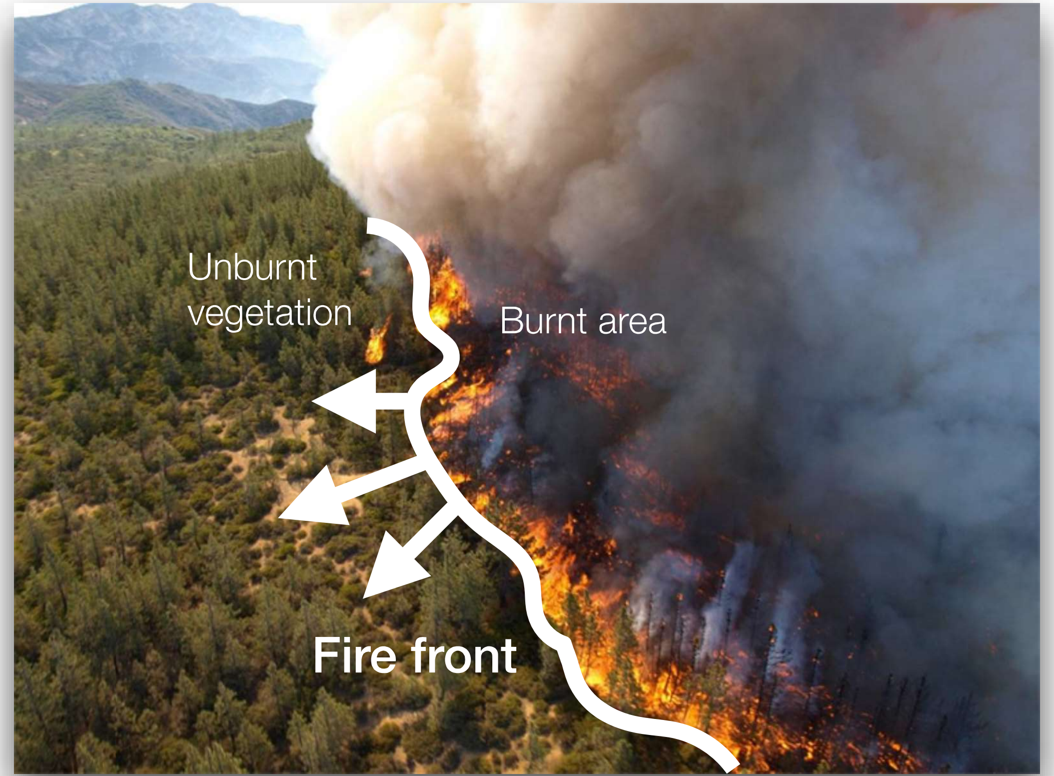

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Sources of uncertainty

Uncertainty quantification

Model and uncertainties

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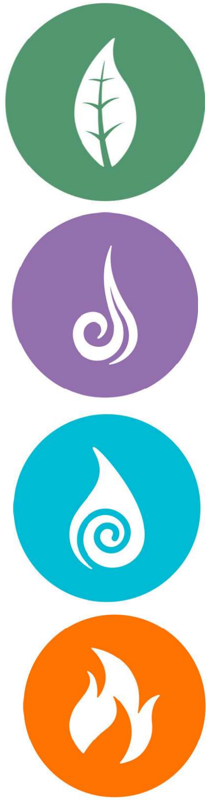

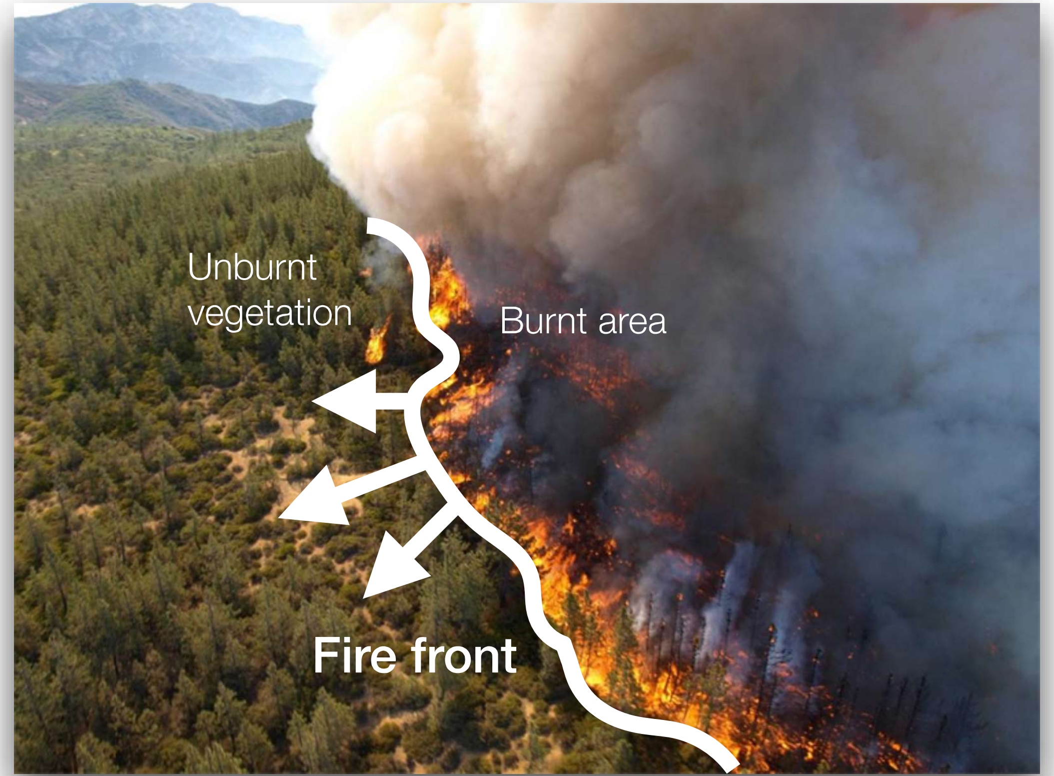

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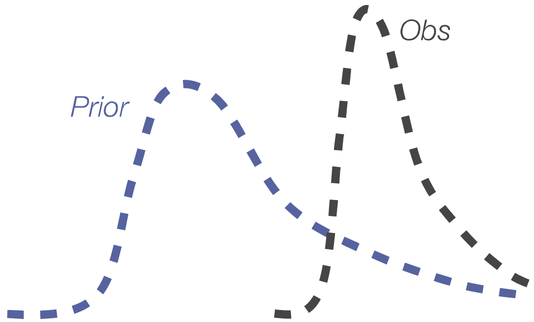

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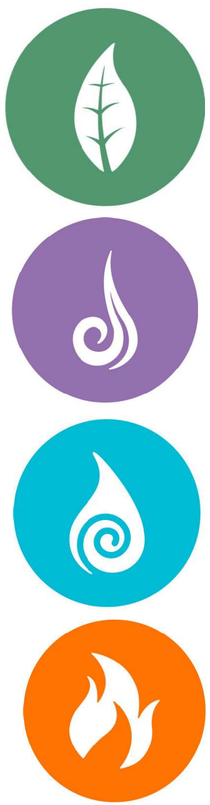

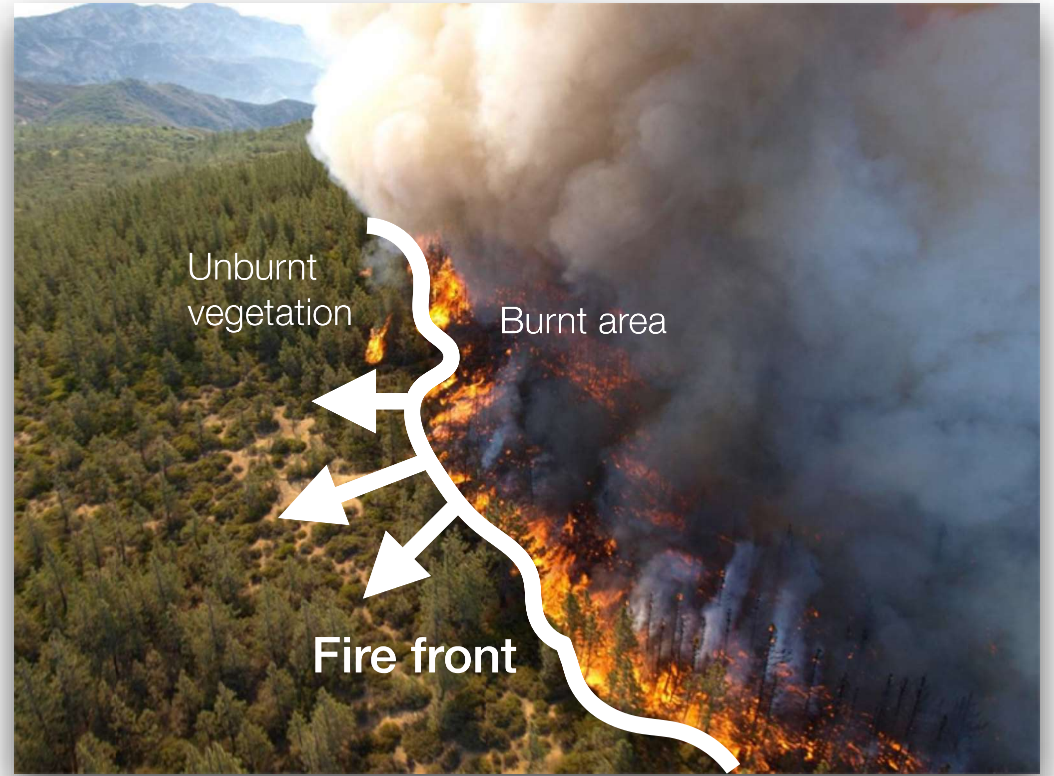

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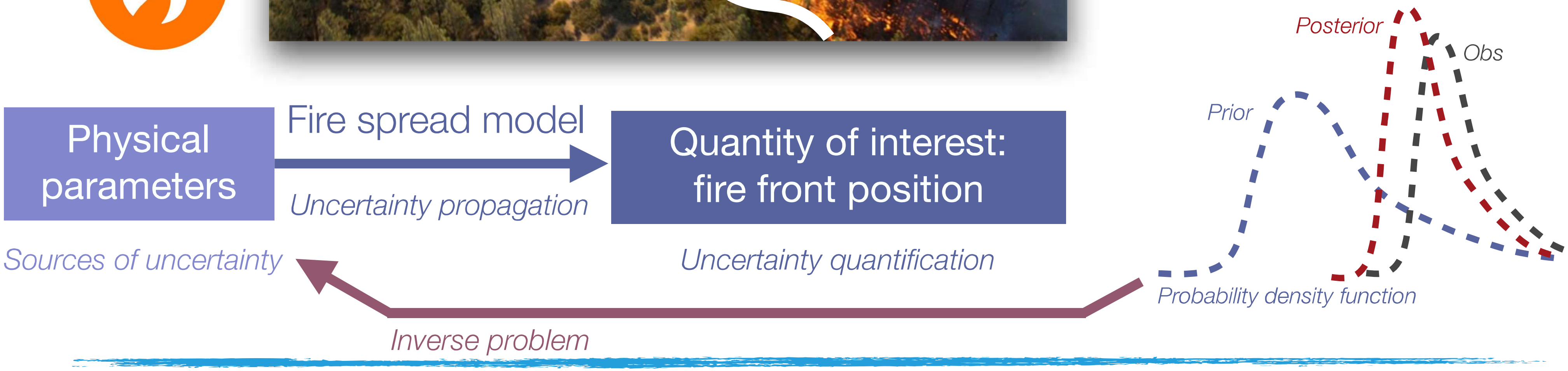
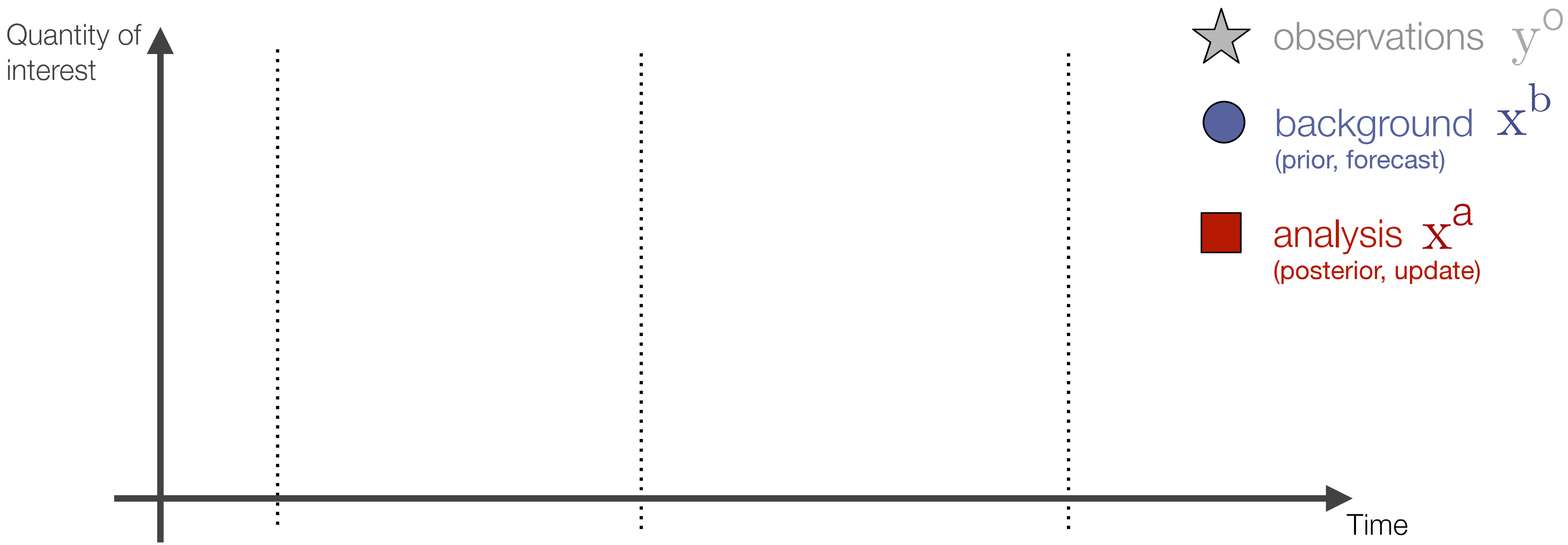


Back to data assimilation

Rochoux et al. (2017), Wildfire Magazine

Sequential data assimilation



Generalized least-squares problem

$$\mathcal{J}(x) = ||\mathcal{G}(x) - \boxed{y^o}||^2_{R^{-1}} + ||x - \boxed{x^b}||^2_{B^{-1}} \rightarrow \boxed{\mathcal{J}(x^a)} = \min \mathcal{J}(x)$$

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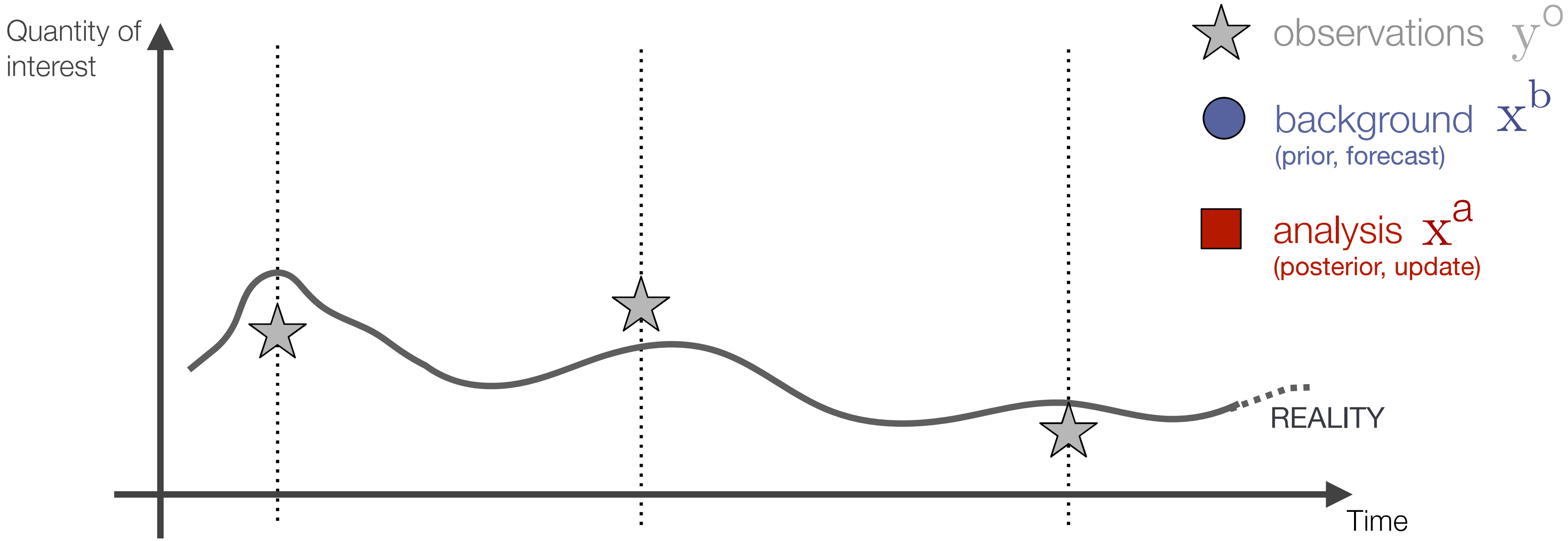

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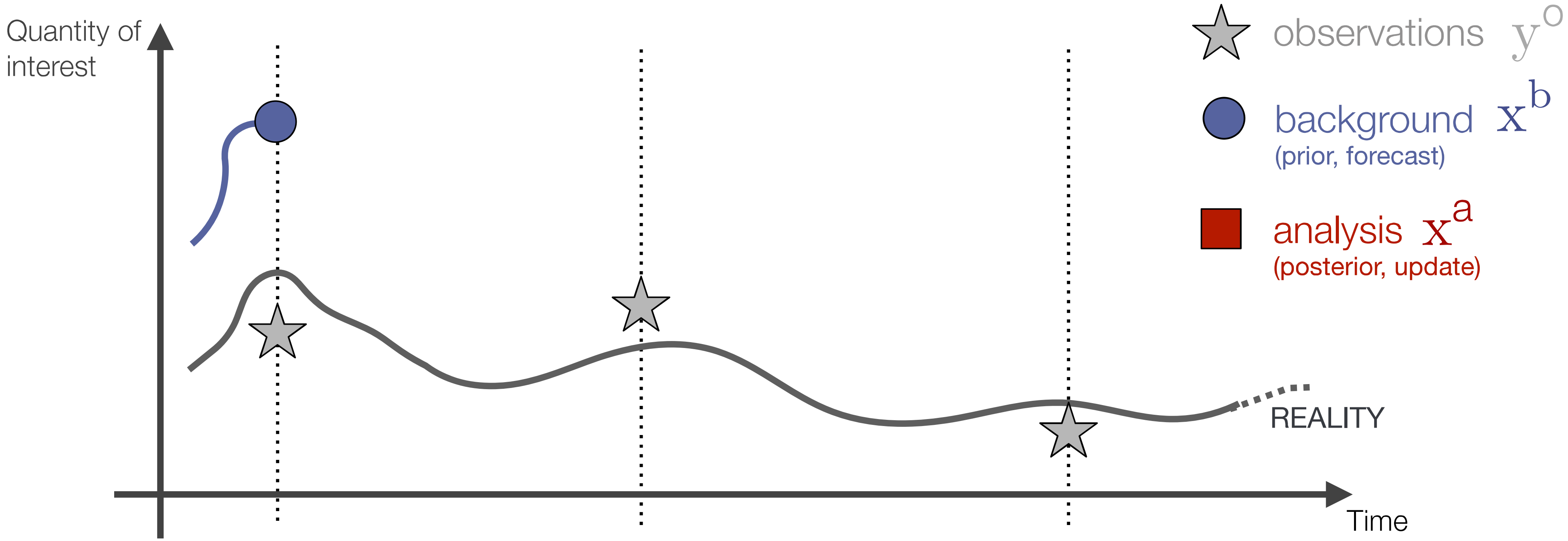

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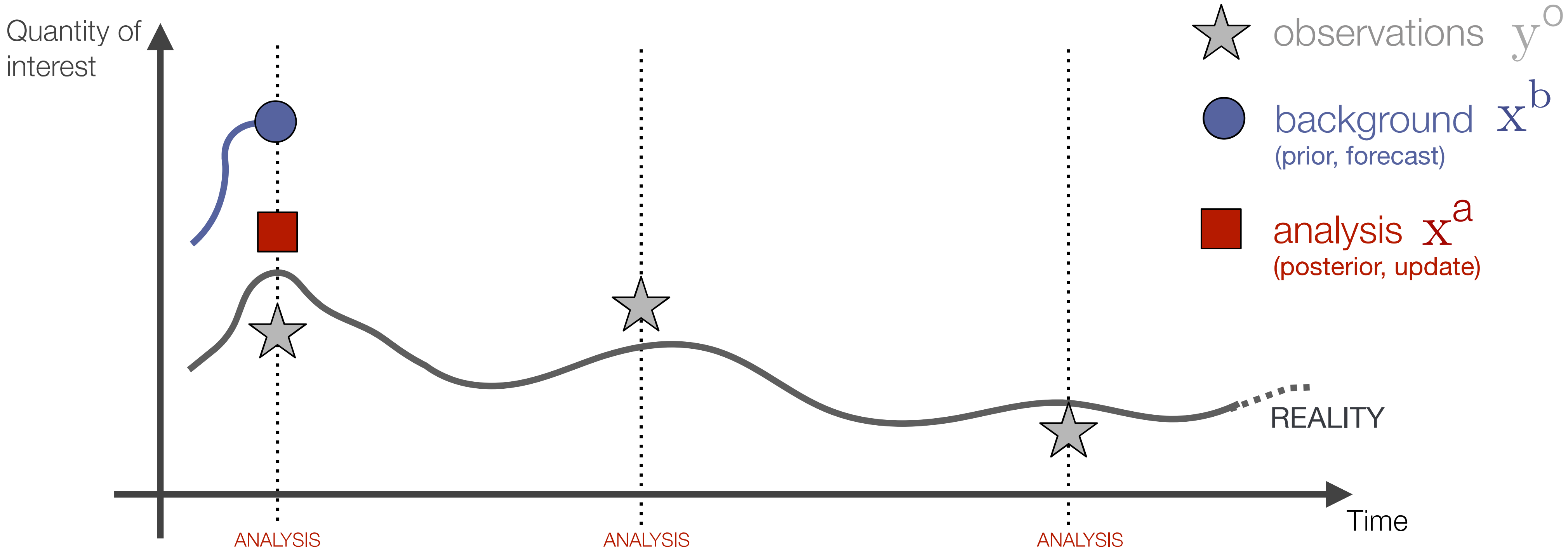

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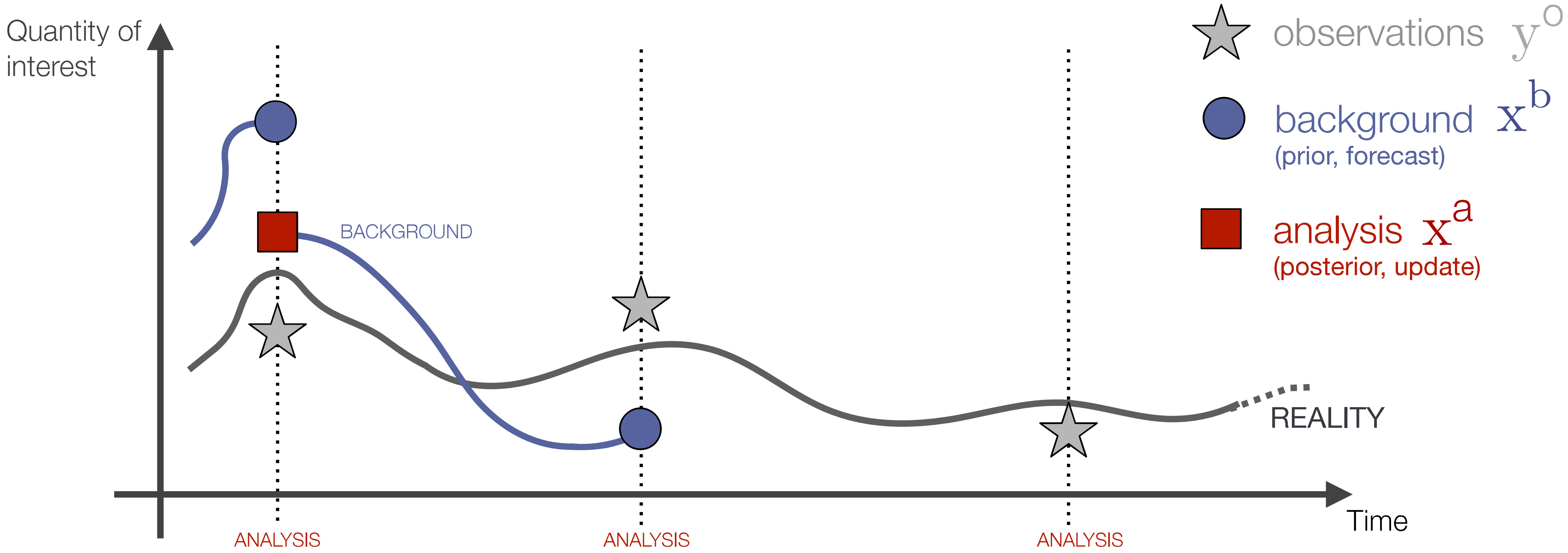

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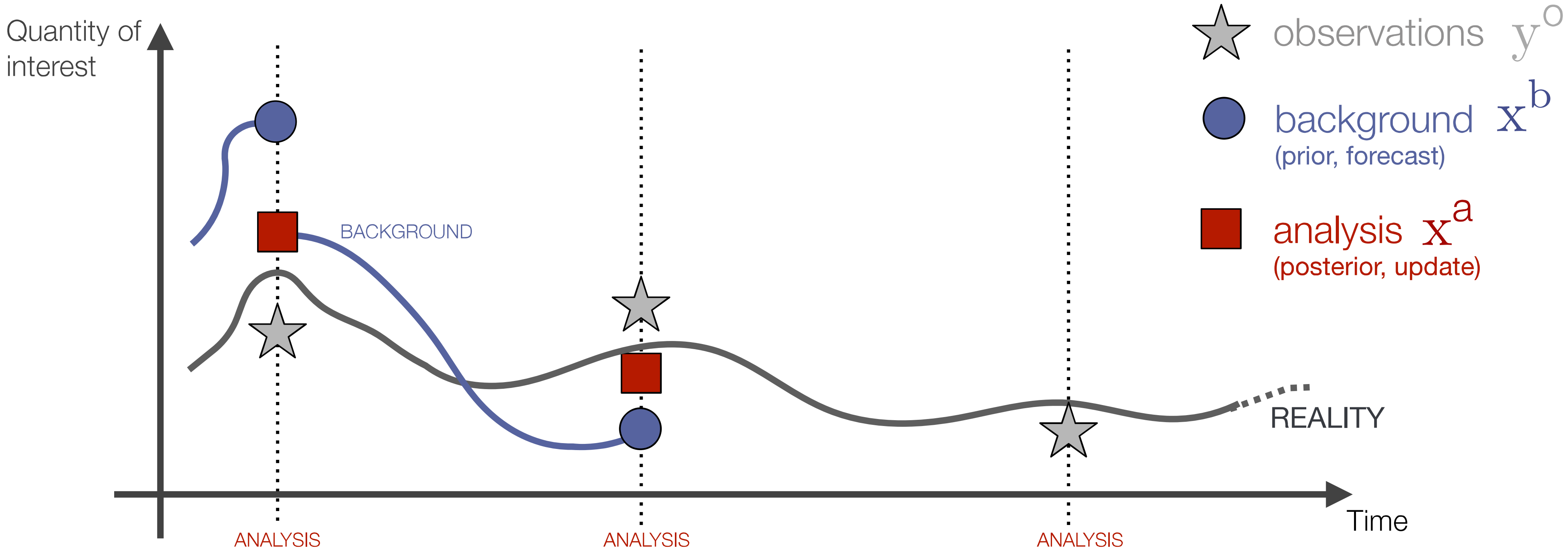

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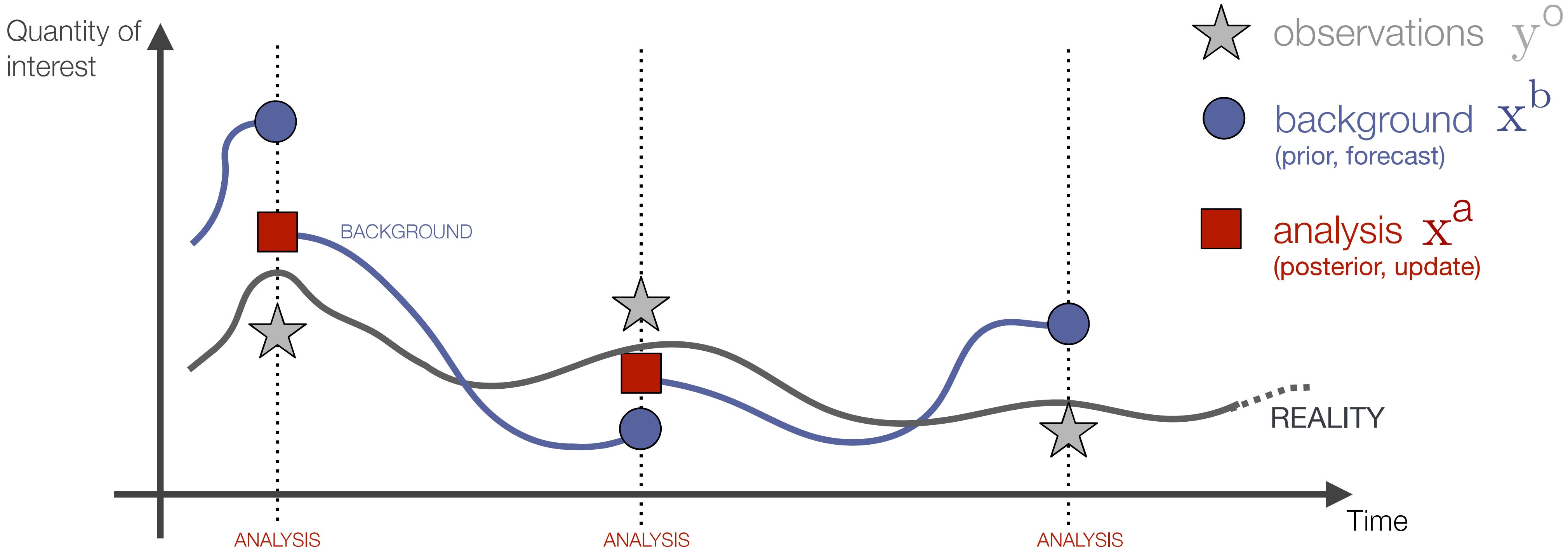

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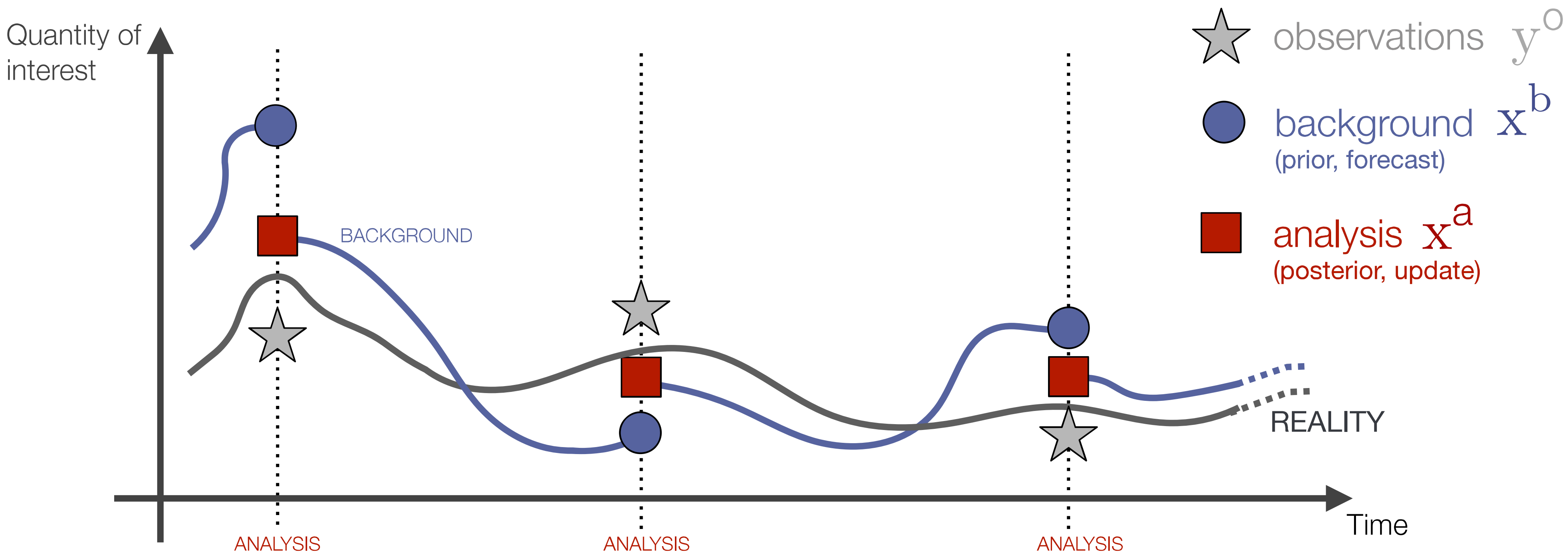

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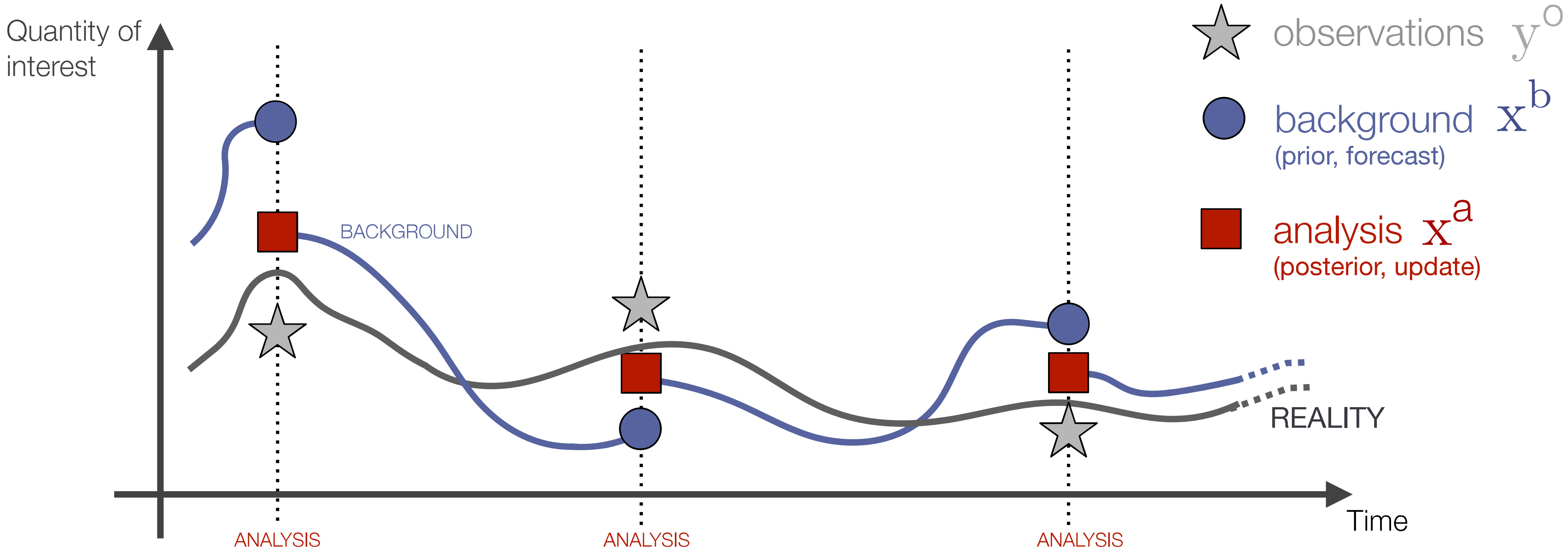


Kalman filter

$$\boxed{x^a} = \boxed{x^b} + K\left(\boxed{y^o} - \boxed{\mathcal{G}(x^b)}\right) \rightarrow K = \boxed{B}G^T\left(G\boxed{B}G^T + \boxed{R}\right)^{-1}$$

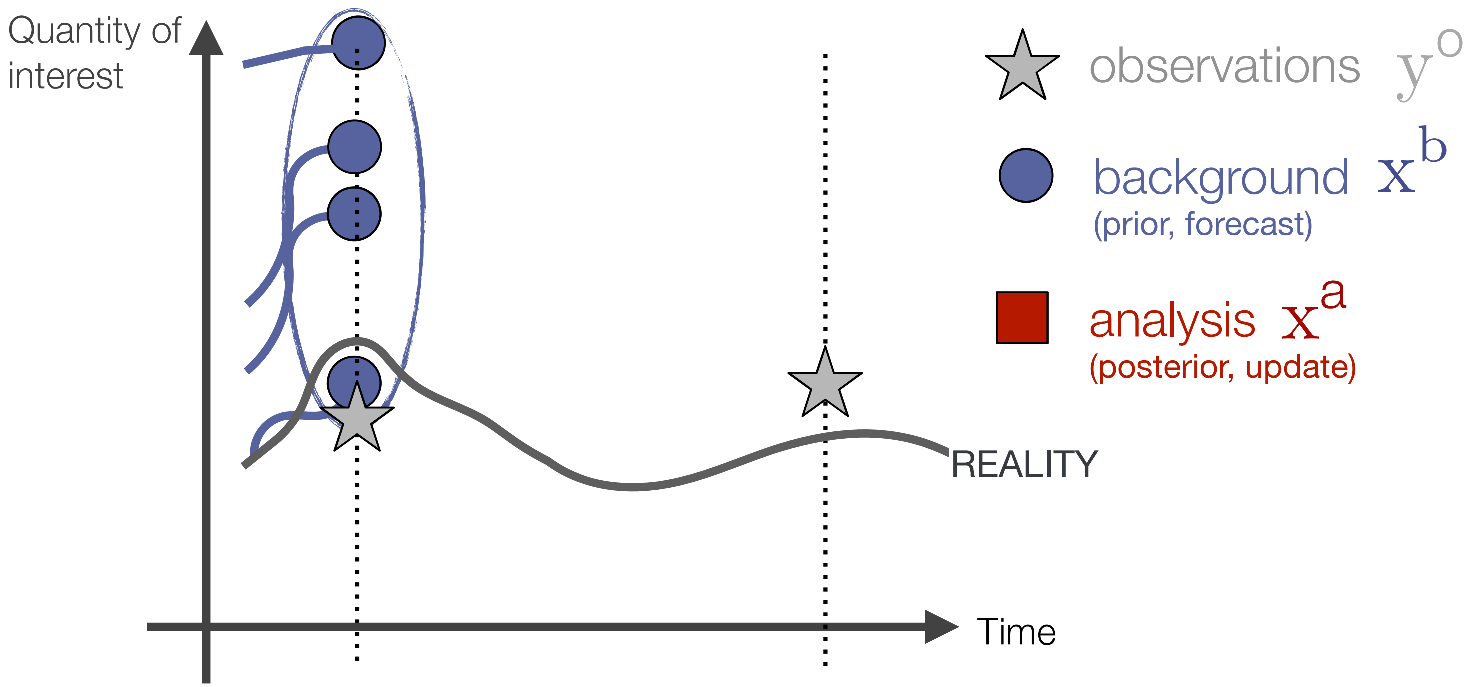
Analysis as a correction of the background

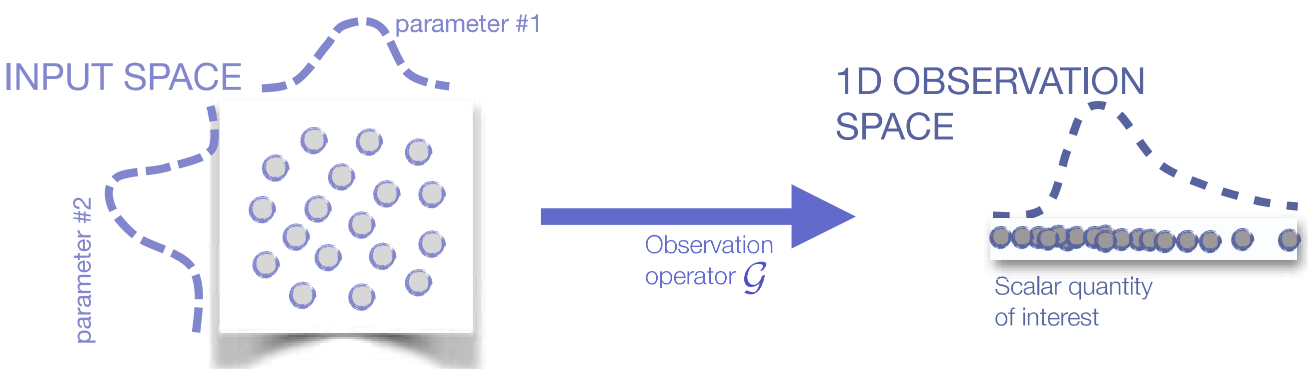
Gain matrix ➤ Weight ➤ Error model for model/observation
Gaussian error statistics (error covariance model), additive errors

Back to data assimilation

Rochoux et al. (2017), Wildfire Magazine

Stochastic viewpoint





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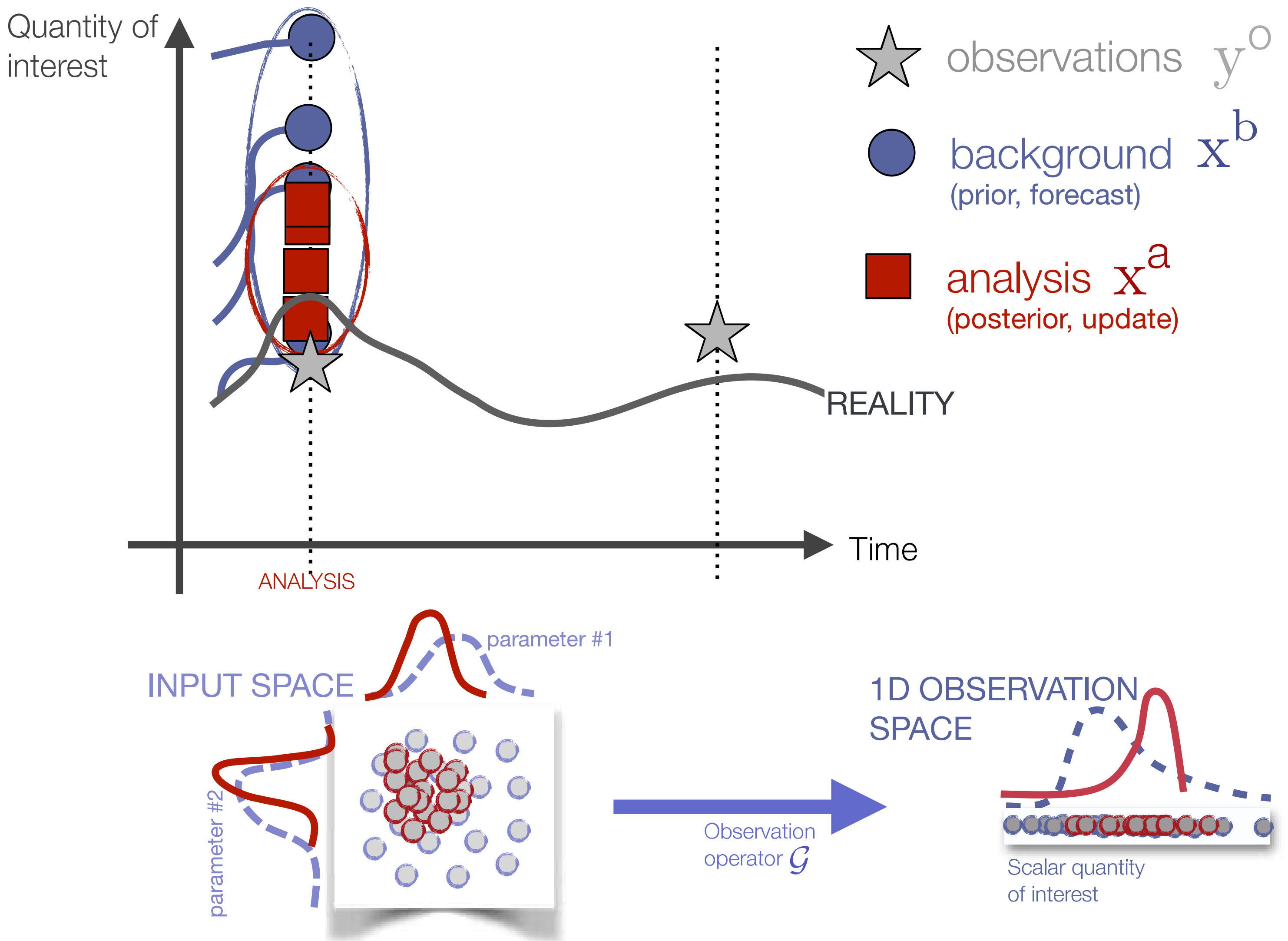

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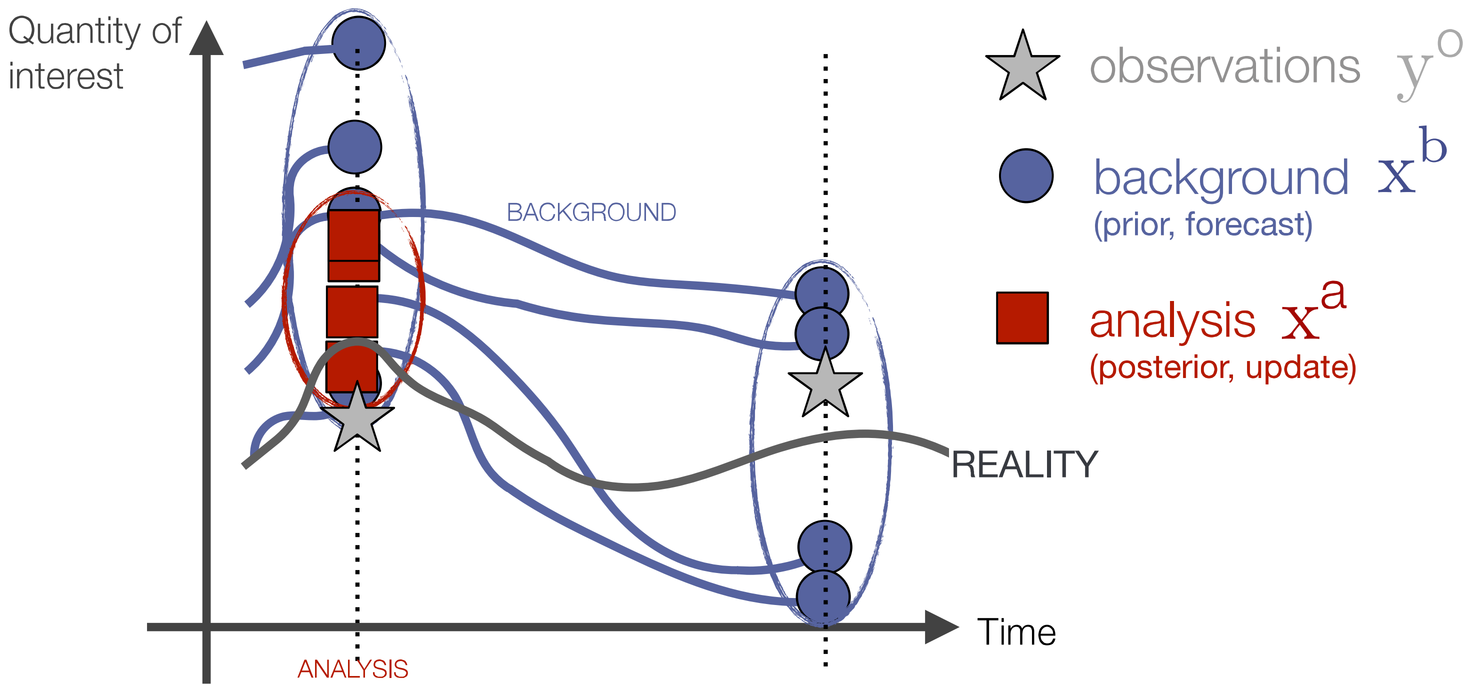

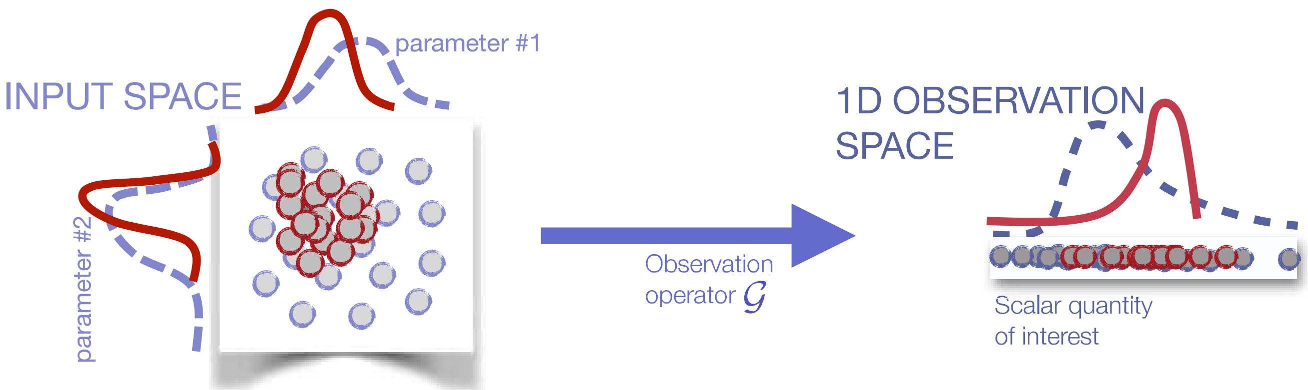

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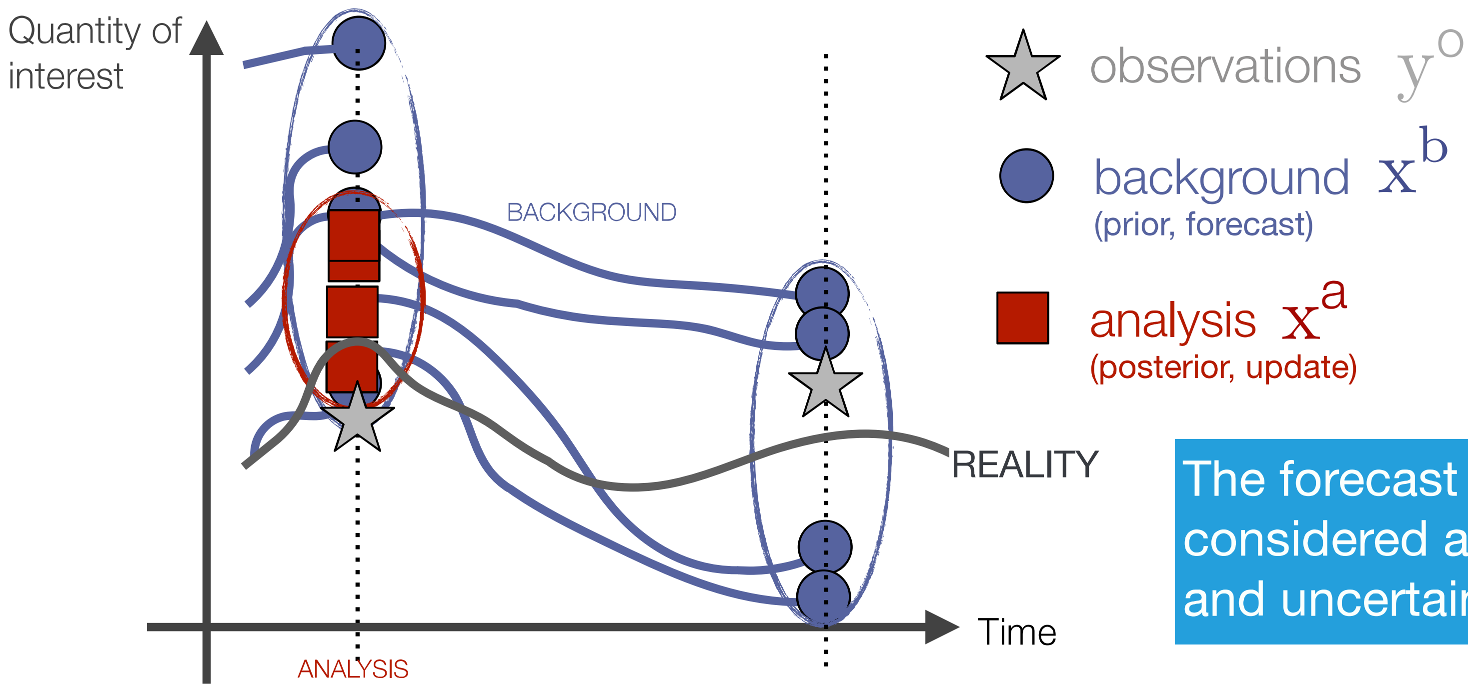
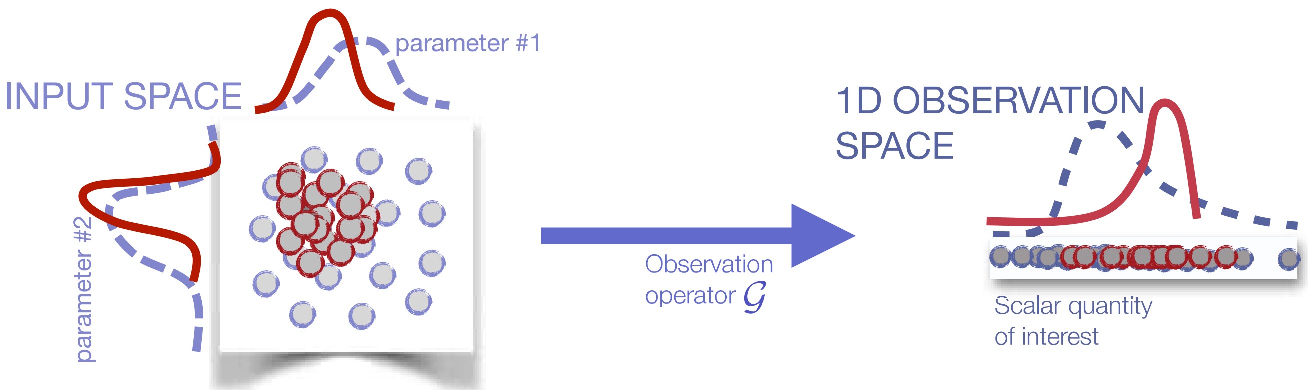


The forecast step can be considered as a sensitivity analysis and uncertainty quantification step.



Important questions

Choice of perturbed variables
Size/variety of the ensemble
Sampling strategy
Physical model sensitivity

Scientific issues

Design of a data assimilation approach for wildfire behavior forecasting

“algorithm”

“estimation targets”

“prior information”

“front observations”

Scientific issues

Design of a data assimilation approach for wildfire behavior forecasting

(1) Design of front data assimilation method — "algorithm"

(2) Choice of control variables — "estimation targets"

(3) Improvement of physical model predictions — "prior information"

(4) Extraction of information from infrared observations — "front observations"

Scientific issues

Design of a data assimilation approach for wildfire behavior forecasting

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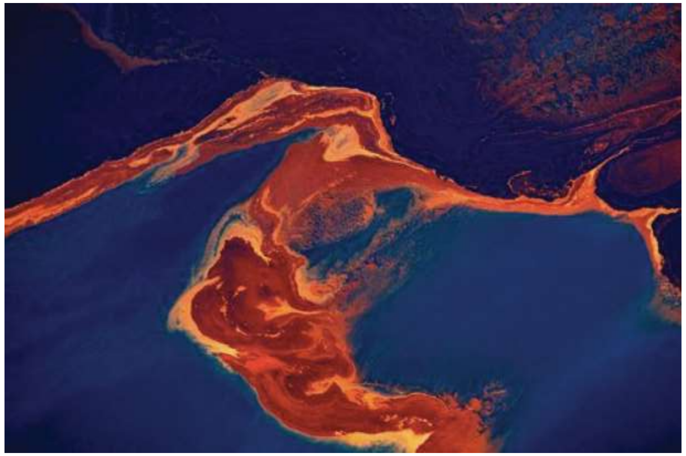
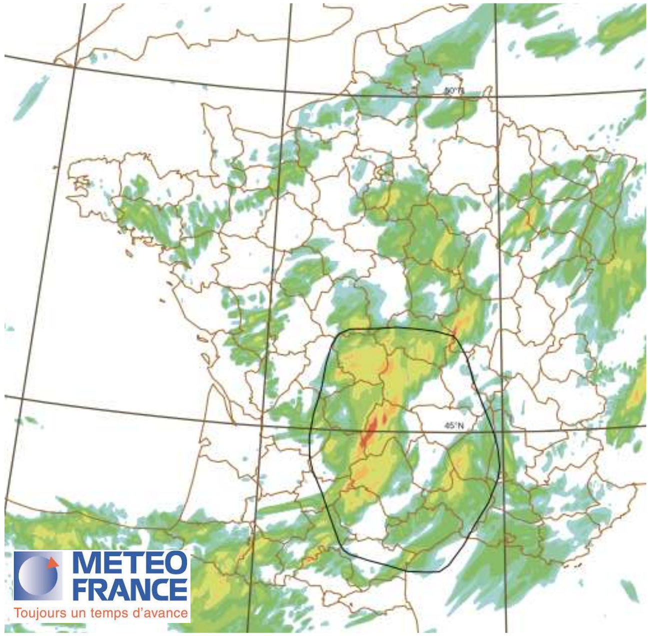
Pattern tracking

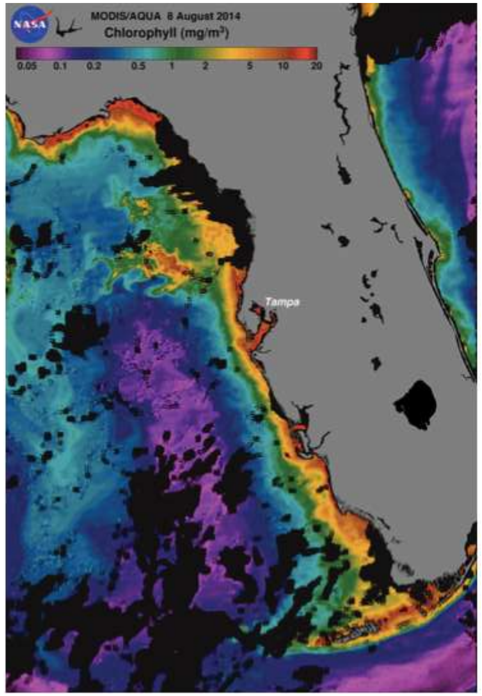
It is easy to perceive coherent structures by eye, but a full precise mathematical description is still a challenge.



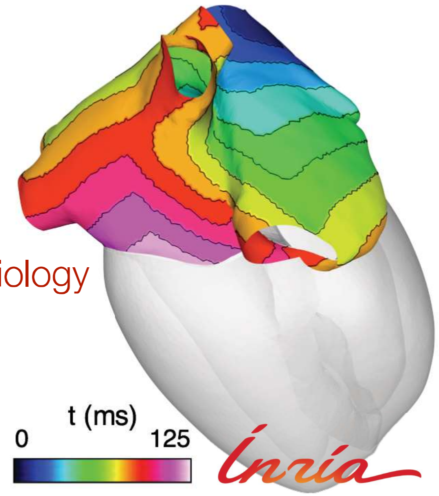
Oil spill in the ocean



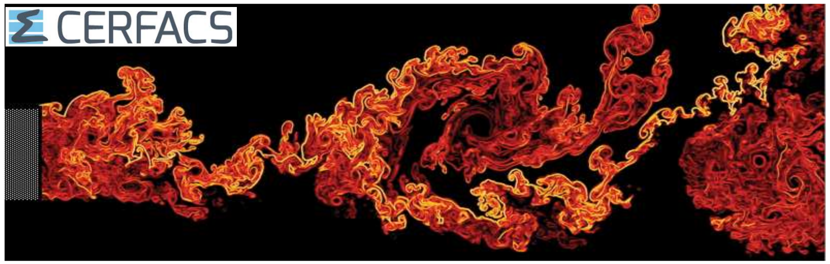
Precipitation pattern in meteorology



Chlorophylle concentration in the ocean with cloud occlusion



Cardiac electrophysiology



Flaming combustion

Data assimilation limitations

Limitation of point-wise local metrics

- Several metrics are usually required to satisfyingly compare fields
- Double penalty effect
  - A misplaced structure is predicted where it should not be and is not predicted where it should be
- Small spatial and temporal shift of the structure position
- Failure of standard data assimilation methods when position errors are large, for instance when observations are not frequent
  - Standard treatment of amplitude errors (Euclidean metrics)
  - Generation of artificial patterns

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Exemple of hurricane tracking with ensemble Kalman filter (EnKF)

Chen and Snyder (2007), Monthly Weather Review
Beezley and Mandel (2008), Tellus

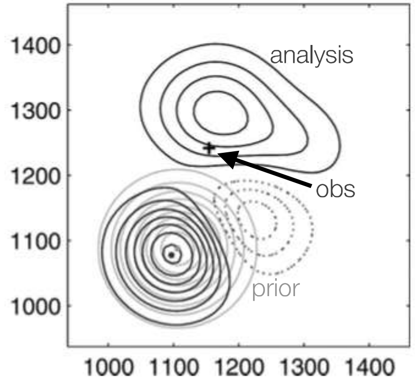


Image segmentation

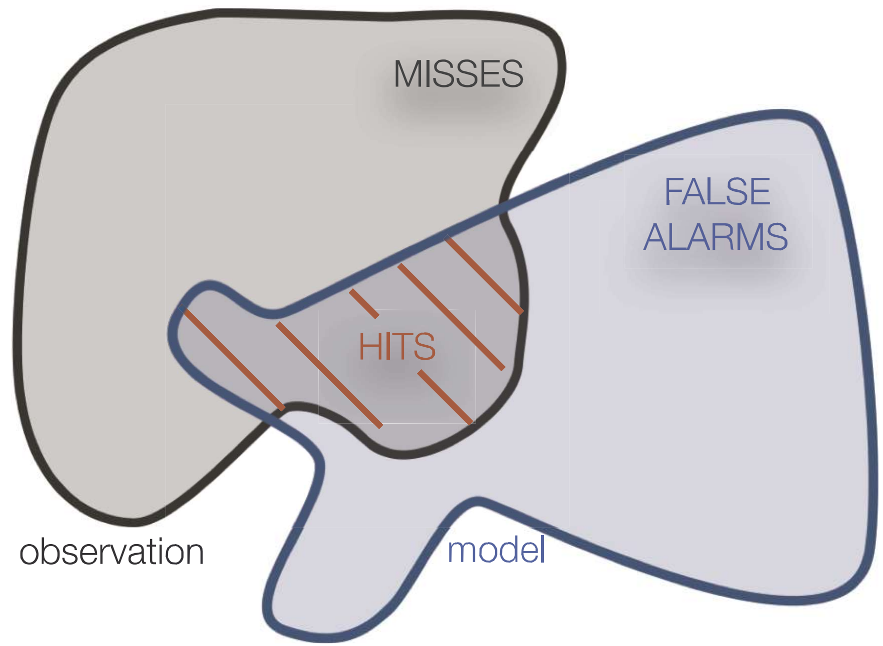
Rochoux et al. (2018), ESAIM: Proceedings and Surveys

What can we learn from image segmentation theory?

- Identification and comparison of main field features (which criteria?)
- Scale separation (ex: wavelet transform)
- Fuzzy method (ex: prior field smoothing)
- Field deformation or field displacement (ex: Wasserstein distance, Chan-Vese data-fitting functional)

Nelson Feyeux (2016), Transport optimal pour l'assimilation de données d'images, Thèse de doctorat, Communauté Université Grenoble Alpes

Collin et al. (2015), Journal of Computational Physics
Arbogast et al. (2016), Quarterly Journal of the Royal Meteorological Society



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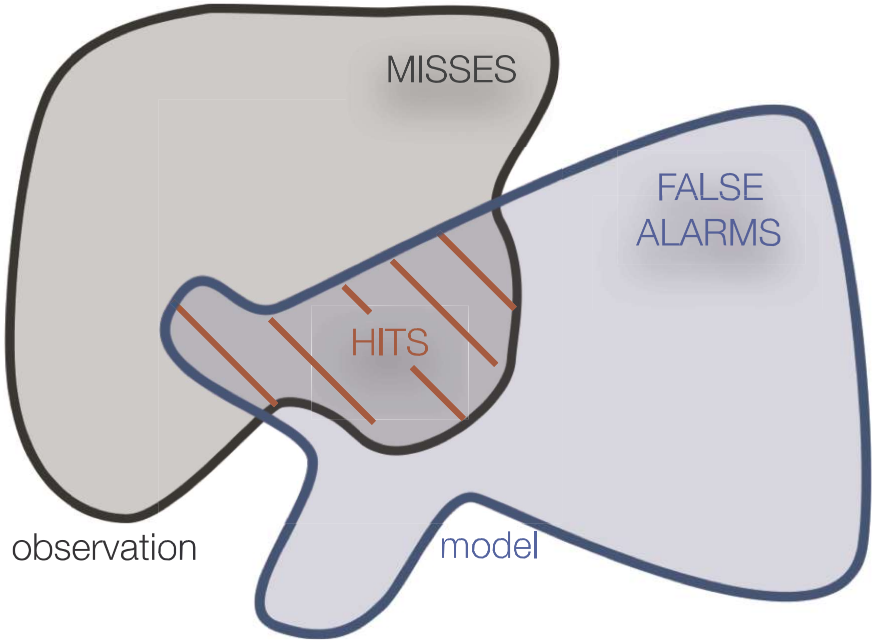
Typical image segmentation problem



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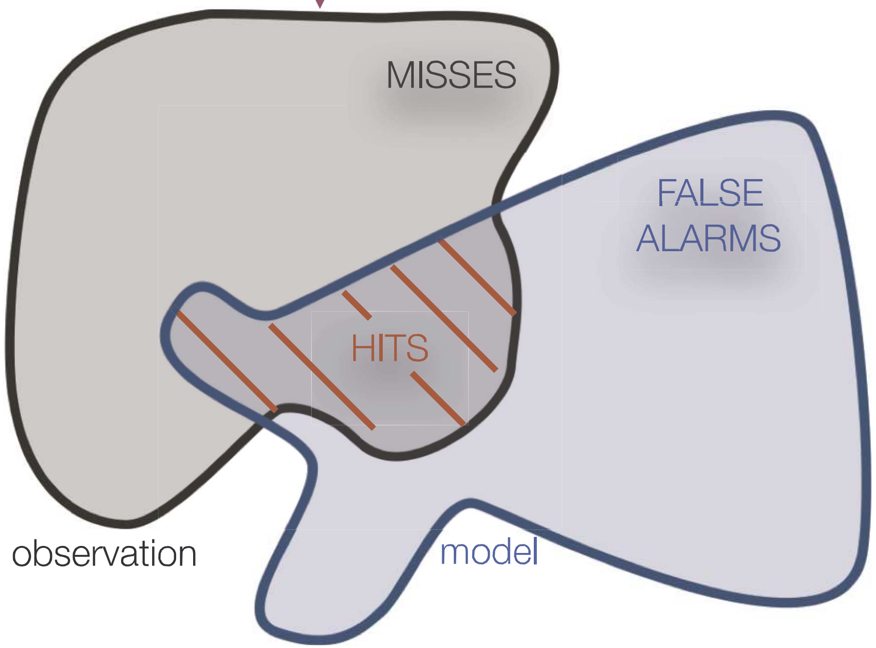
Typical image segmentation problem

Analogy with data assimilation
The "airplane object" is the observation.
The green square is the prior information.
The objective of image segmentation is to find the contour of the "airplane object".

Objectives
- maximization of hits
- minimization of misses



$$\mathcal{J}(\phi, y^o) = \int_\Omega H_v(\phi)\,[y^o - C_1(y^o,\phi)]^2 + (1 - H_v(\phi))\,[y^o - C_0(y^o,\phi)]^2\,dx$$

Functional dependency
- Level-set function (prior)
- Observation

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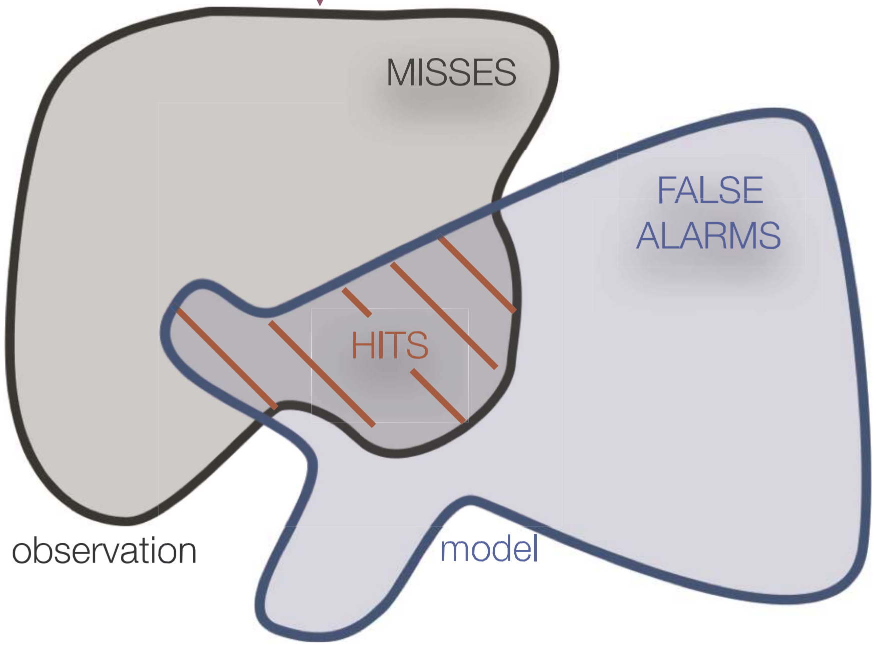

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Nelson Feyeux (2016), Transport optimal pour l'assimilation de données d'images, Thèse de doctorat, Communauté Université Grenoble Alpes

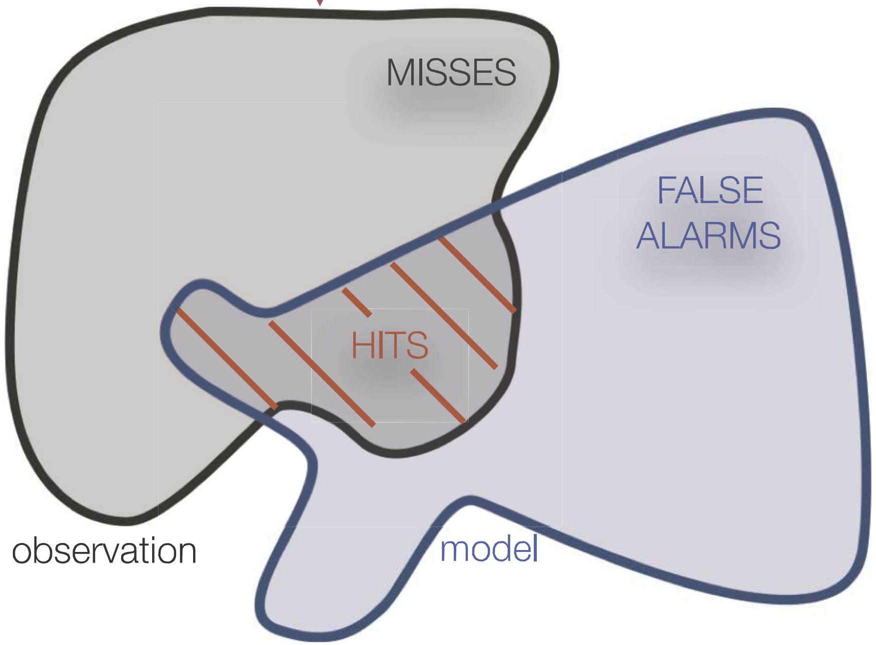
Collin et al. (2015), Journal of Computational Physics
Arbogast et al. (2016), Quarterly Journal of the Royal Meteorological Society

Chan and Vese (2001), IEEE Transactions on Image Processing

Typical image segmentation problem

Analogy with data assimilation
The "airplane object" is the observation.
The green square is the prior information.
The objective of image segmentation is to find the contour of the "airplane object".

Objectives
- maximization of hits
- minimization of misses



$$\mathcal{J}(\phi, y^o) = \int_\Omega \boxed{H_\mathrm{V}(\phi)} \boxed{[y^o - C_1(y^o, \phi)]^2} + \boxed{(1 - H_\mathrm{V}(\phi))} [y^o - C_0(y^o, \phi)]^2 \, \mathrm{d}x$$

Functional dependency
- Level-set function (prior)
- Observation

Inside the simulated burnt area

measuring HITS (mean of obs. in simulated burnt area)

Outside the simulated burnt area

Image segmentation

Rochoux et al. (2018), ESAIM: Proceedings and Surveys

What can we learn from image segmentation theory?

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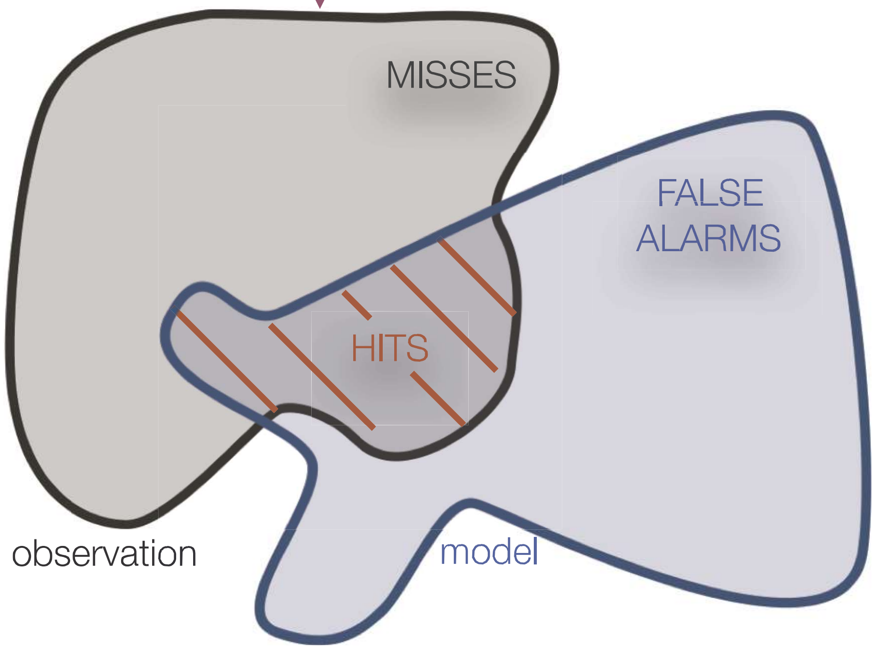

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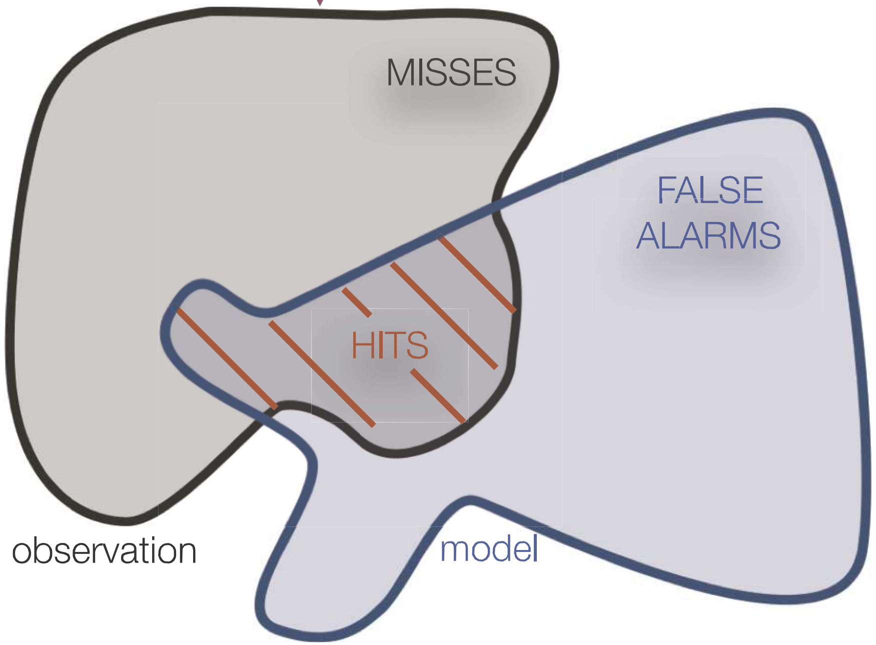

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measuring HITS (mean of obs. in simulated burnt area)

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measuring MISSES (mean of obs. outside of simulated burnt area)

Minimizing the functional acts on the contour of the simulated area to match the shape of the observed front.

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State-parameter estimation

Rochoux et al. (2014, 2015), Natural Hazards and Earth System Sciences

State of the fire spread model

- Way to address all sources of uncertainty beyond parametric uncertainties (e.g. model error)
- Better accounting for anisotropy in the fire front propagation

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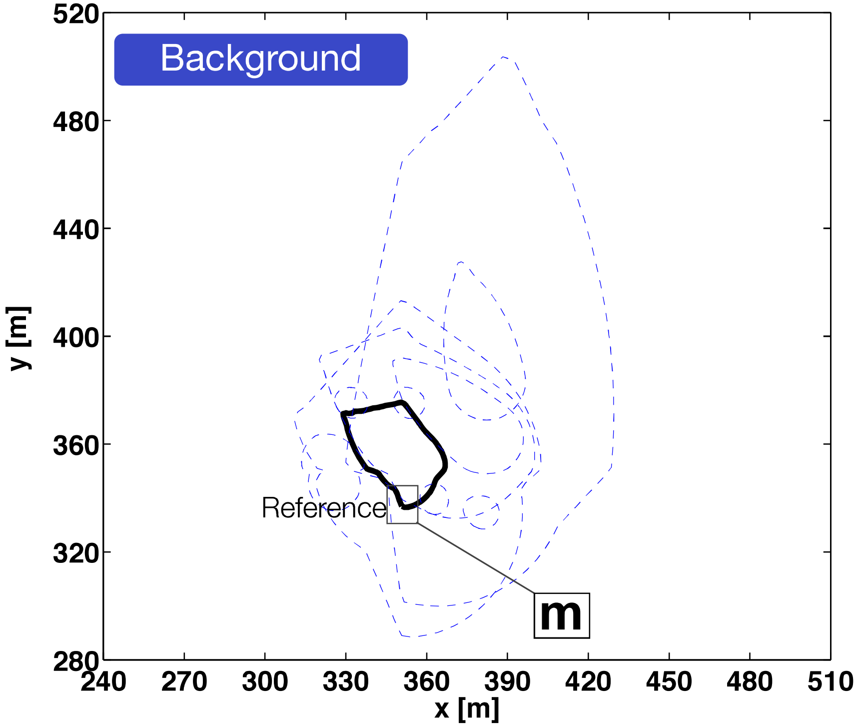
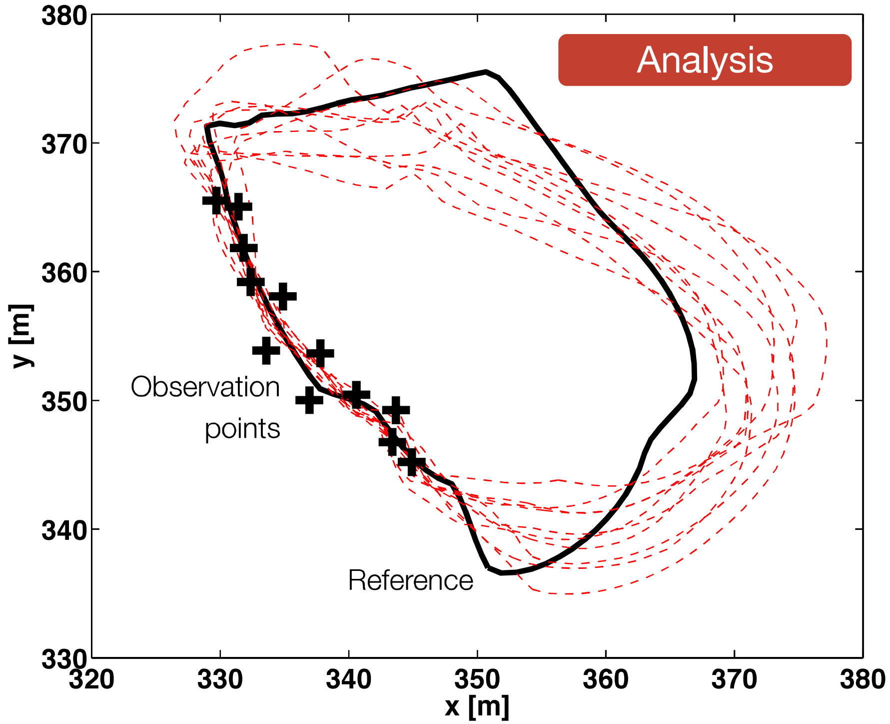
Synthetic experiments (OSSE)

Assumed sources of uncertainty

Fire initial condition, fuel properties (layer thickness, aspect ratio, moisture content), wind magnitude and direction





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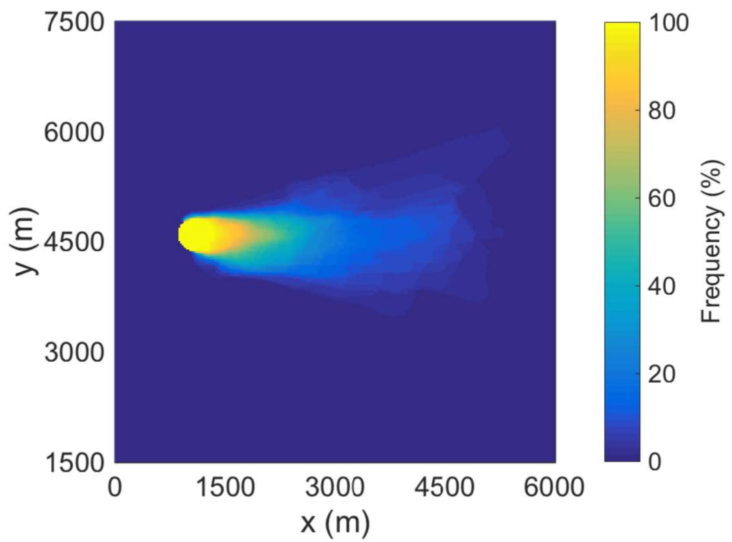
Parameters of the rate of spread model

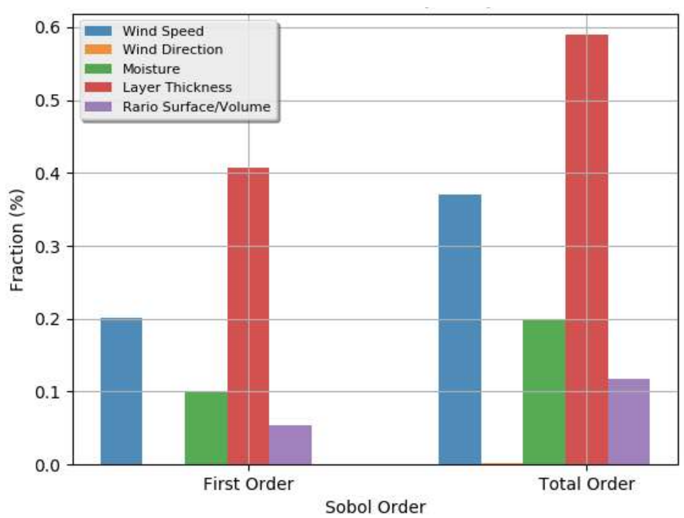
- Reduced model bias
- Improved forecast performance

Sensitivity analysis

PDF of burnt area



First-order and total-order Sobol' sensitivity indices related to the burnt area (m^2)



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Zhang et al. (2017, 2019), Fire Safety Journal

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- Note: case-dependent parameter estimation (no generic learning)

Hybrid state-parameter estimation

1/ State estimation

Correcting the observer state c through the control feedback in the advection equation

2/ Parameter estimation

Using the observer state to derive updated control parameters using ensemble Kalman filter (ETKF)

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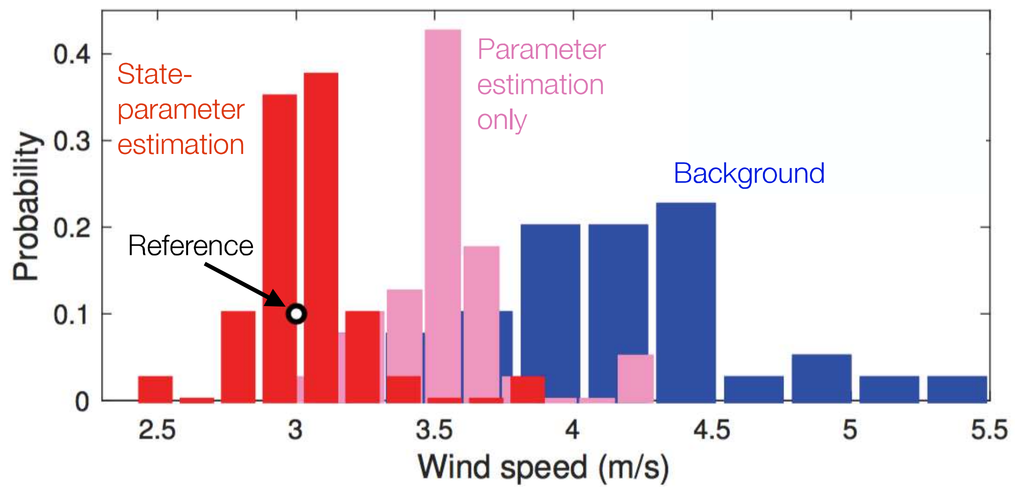
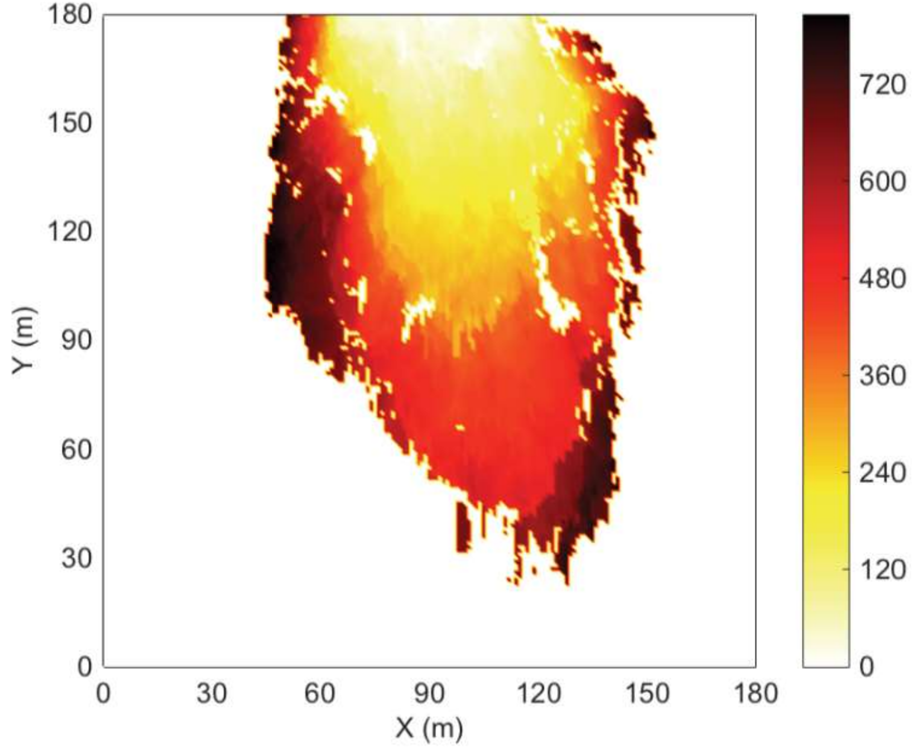
Probability distribution



State-parameter estimation

Zhang et al. (2017, 2019), Fire Safety Journal

RxCADRE controlled burn experiments



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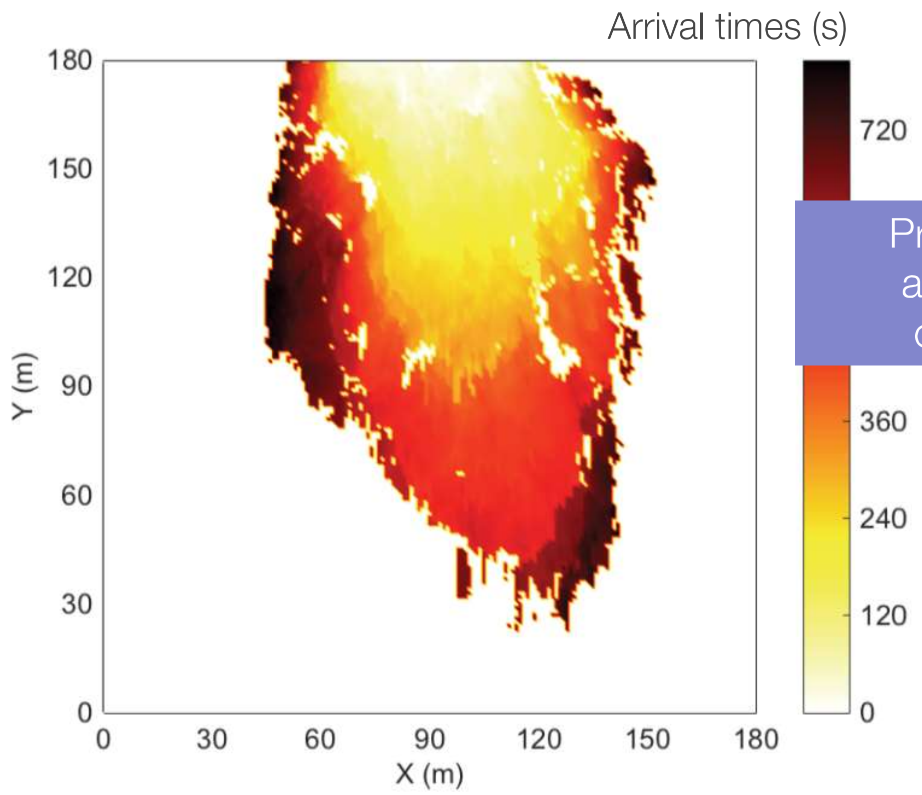
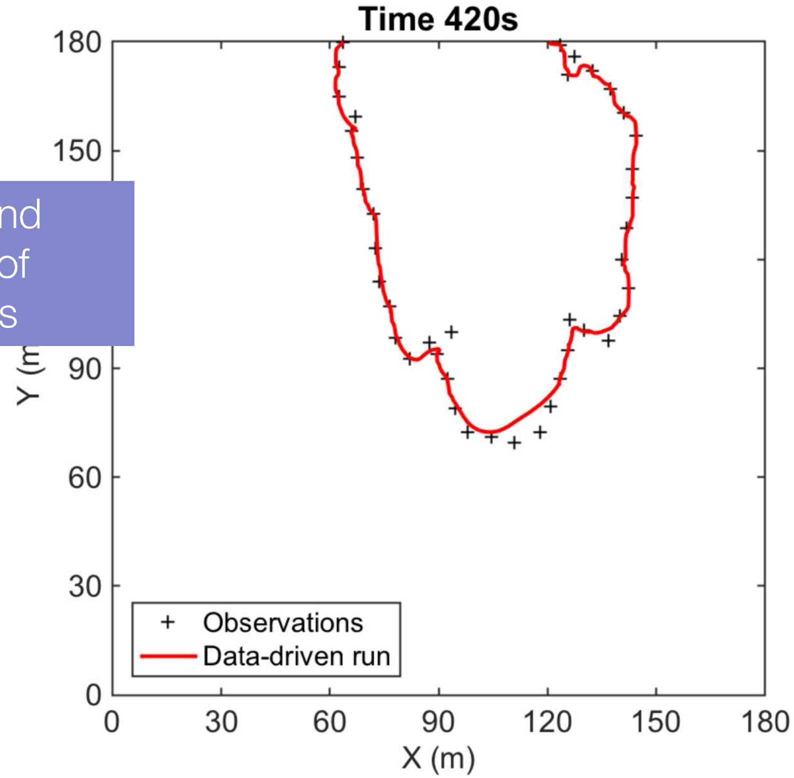


Processing and assimilation of observations



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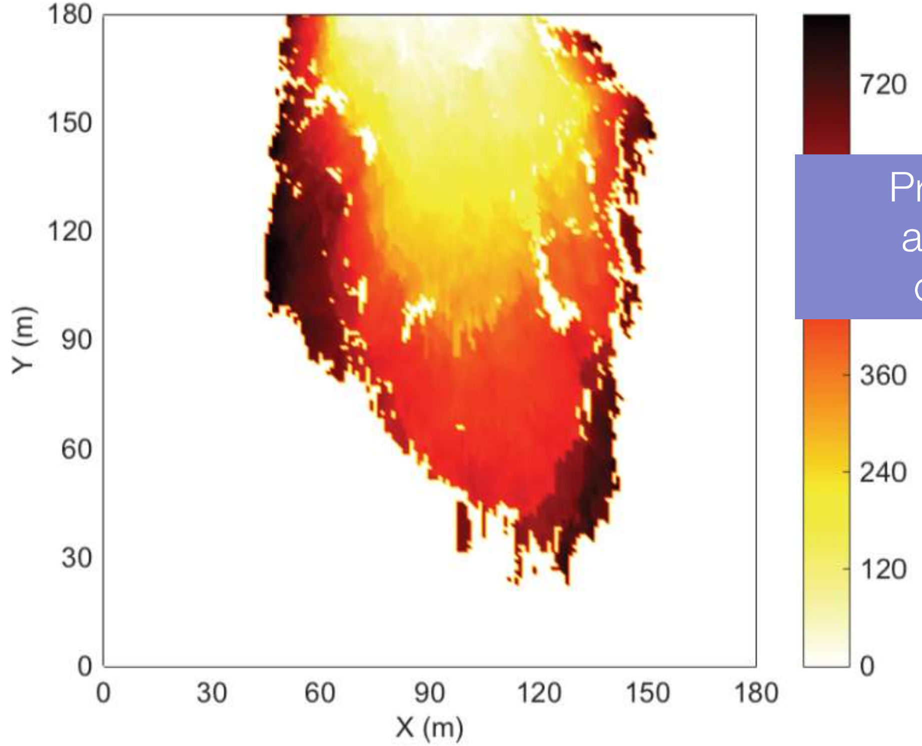

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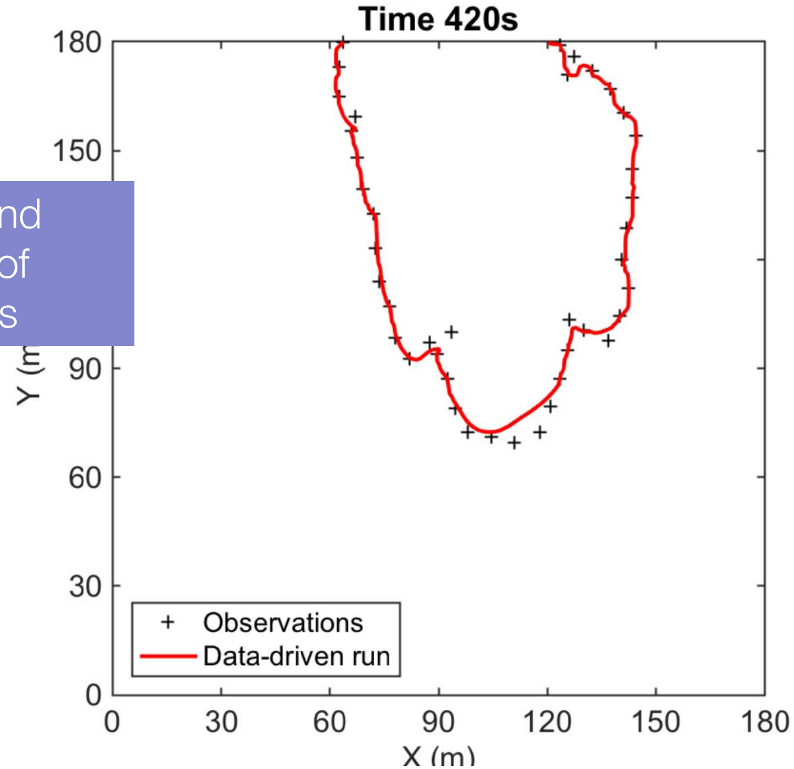
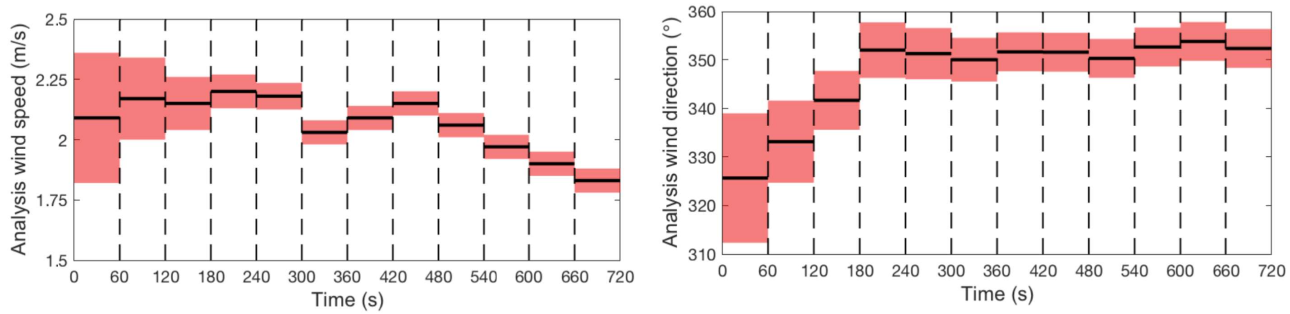


Near-surface wind parameters (magnitude, direction) sequential estimation



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Fire-atmosphere simulation

Costes et al. (2018), International Conf on Forest Fire Research

Filippi et al. (2018), Atmosphere

Fireline position

FOREFIRE (SPE/Univ. de Corse)
- Fire spread model
- Rate-of-spread parameterization
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Wind surface

Surface fluxes

Atmospheric dynamics

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(IGN BD TOPO/BD ALTI, ONF dead fuel classification)

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(Interaction Soil-Biosphere-Atmosphere parameterization)

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- Parameters: fixed nominal values, burning duration

Wind interpolation

from the first grid level along the vertical direction

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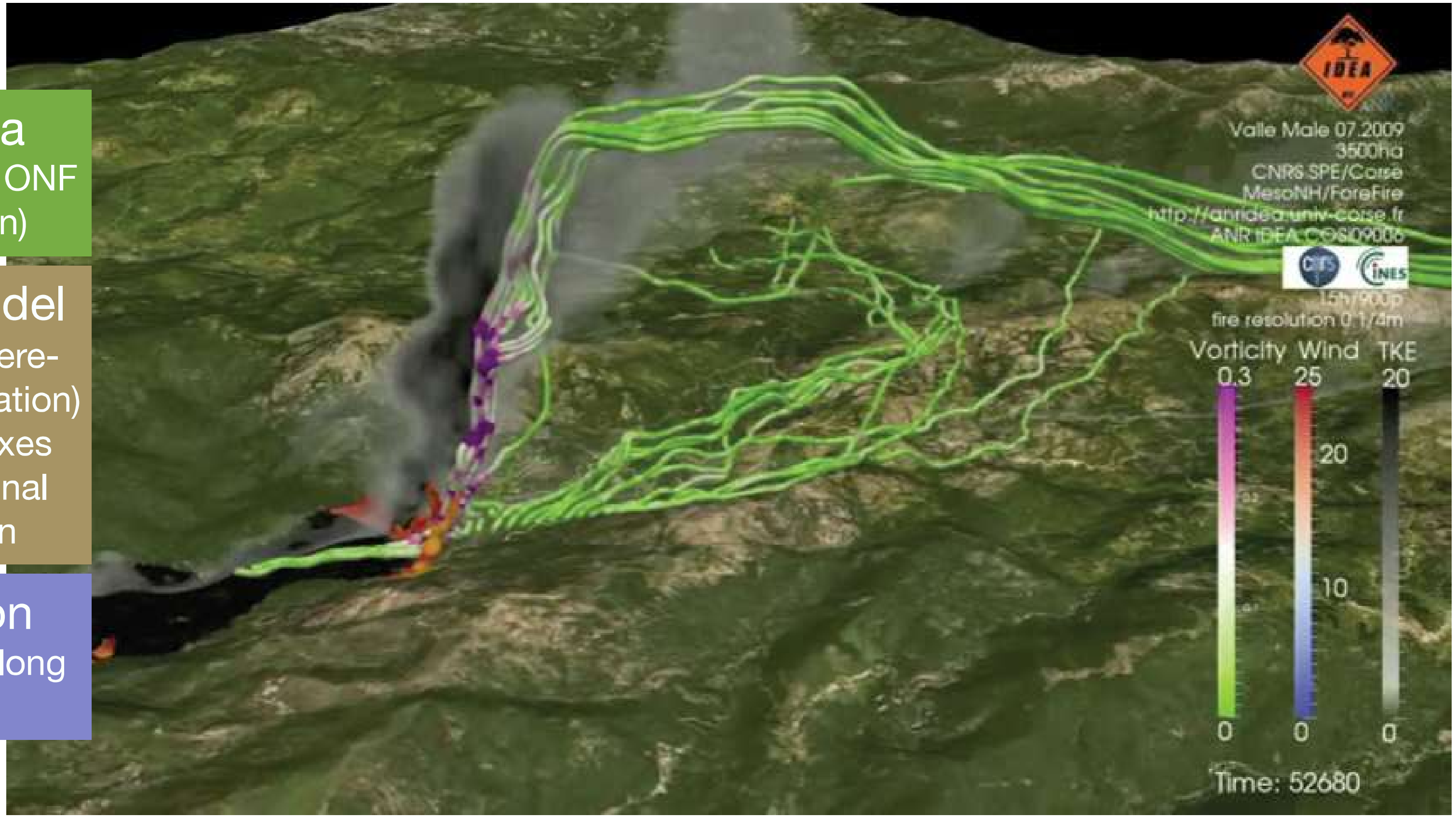

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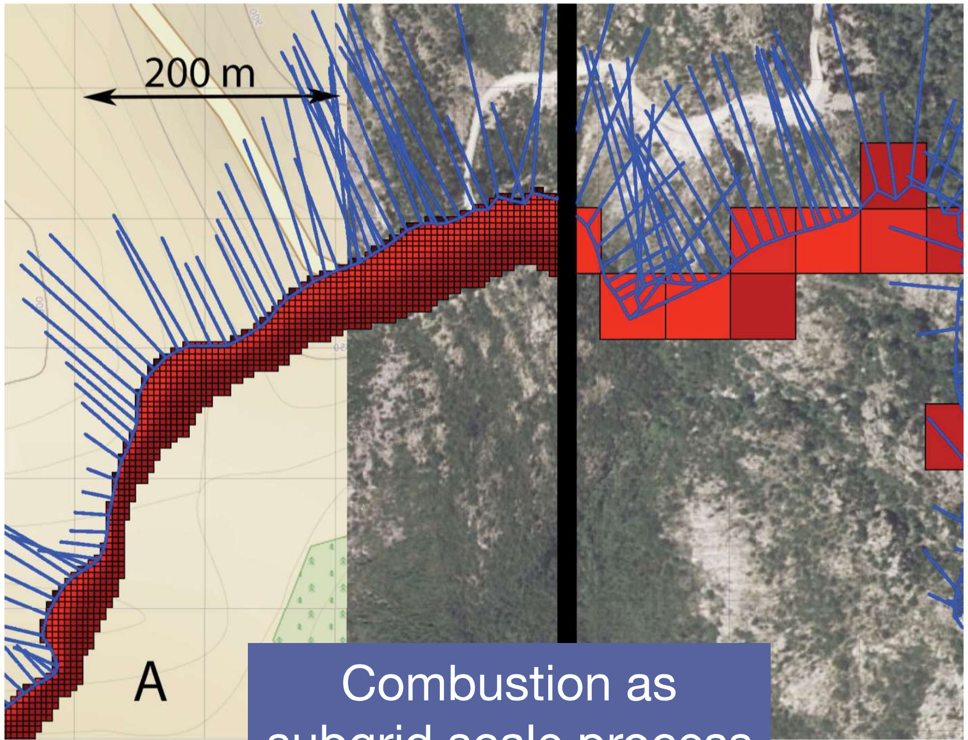
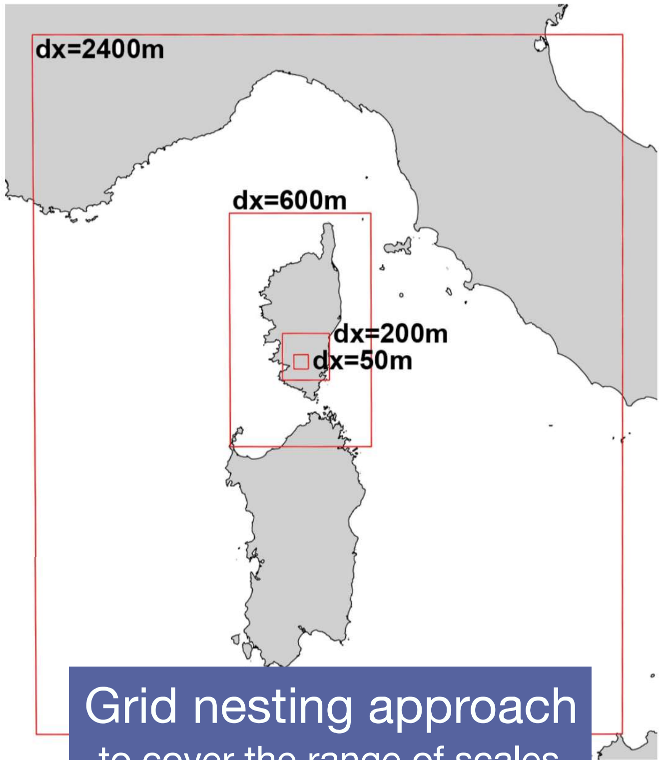


Combustion as subgrid scale process



Grid nesting approach
to cover the range of scales

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Infrared images

Paugam et al. (2013), IEEE transactions on geoscience and remote sensing

Paugam et al. (2019), EGU General Meeting

Image segmentation

1- Automated orthorectification

2- Segmentation

- Objective: Extracting the fire front location out of the orthorectified radiance field
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  - Starting from a small number of manually annotated images (11)
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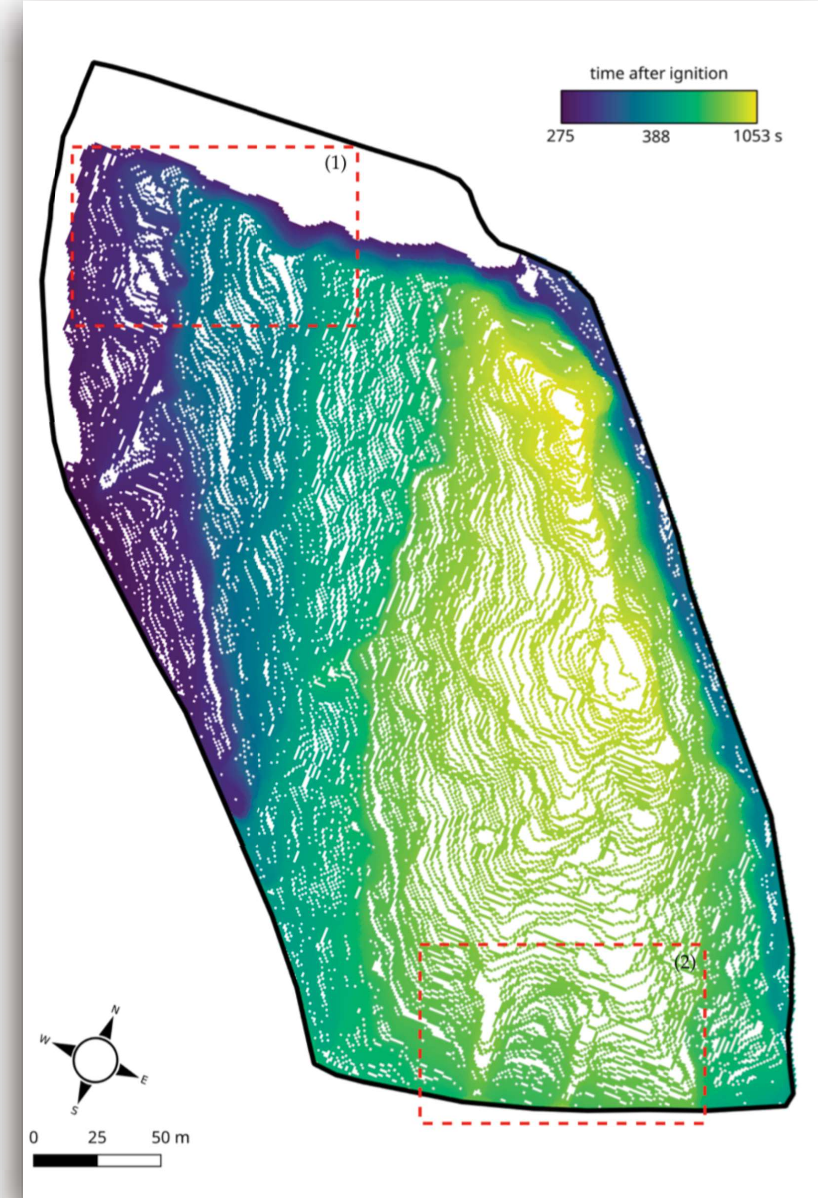
3- Fire behavior metrics

Rate of spread, fire radiative power, fireline intensity, flame depth



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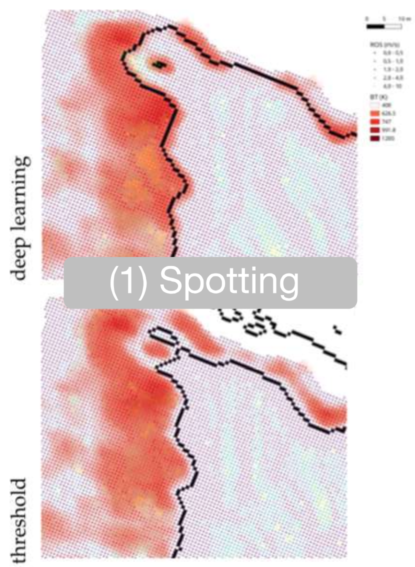

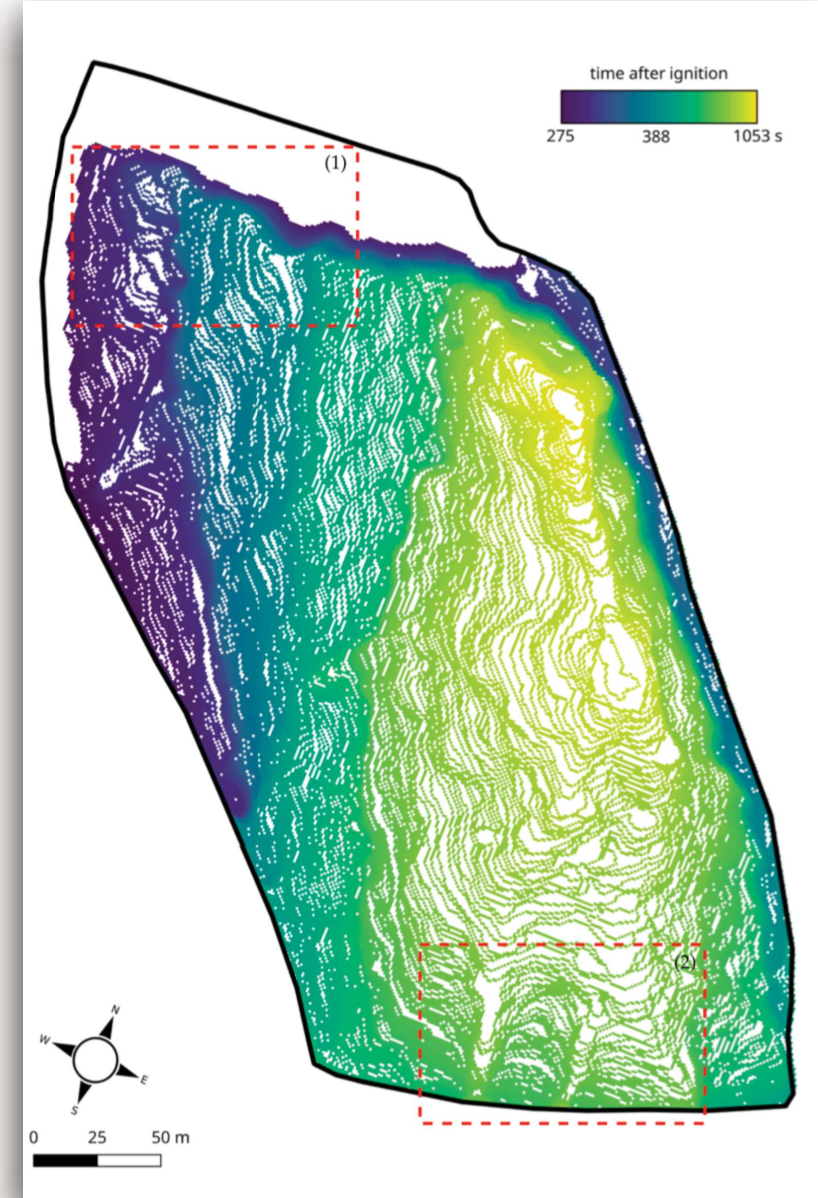

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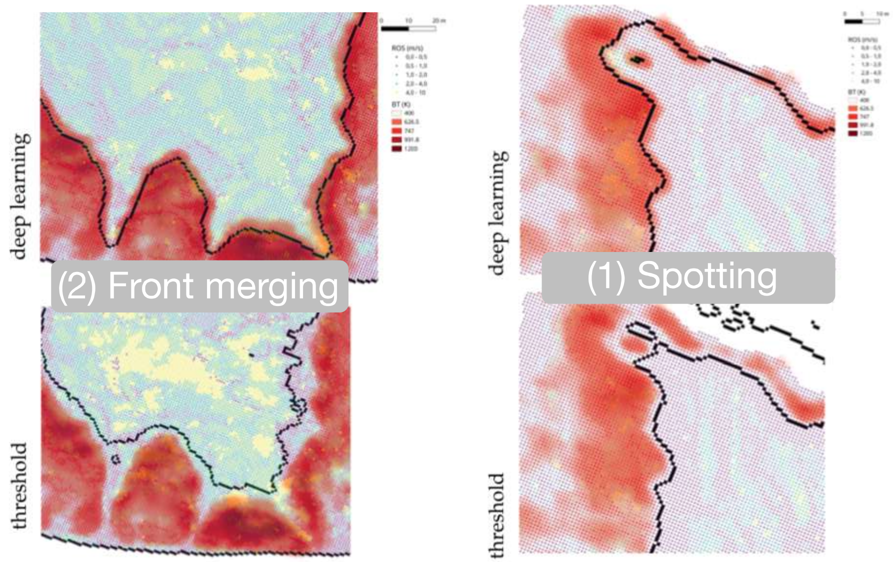

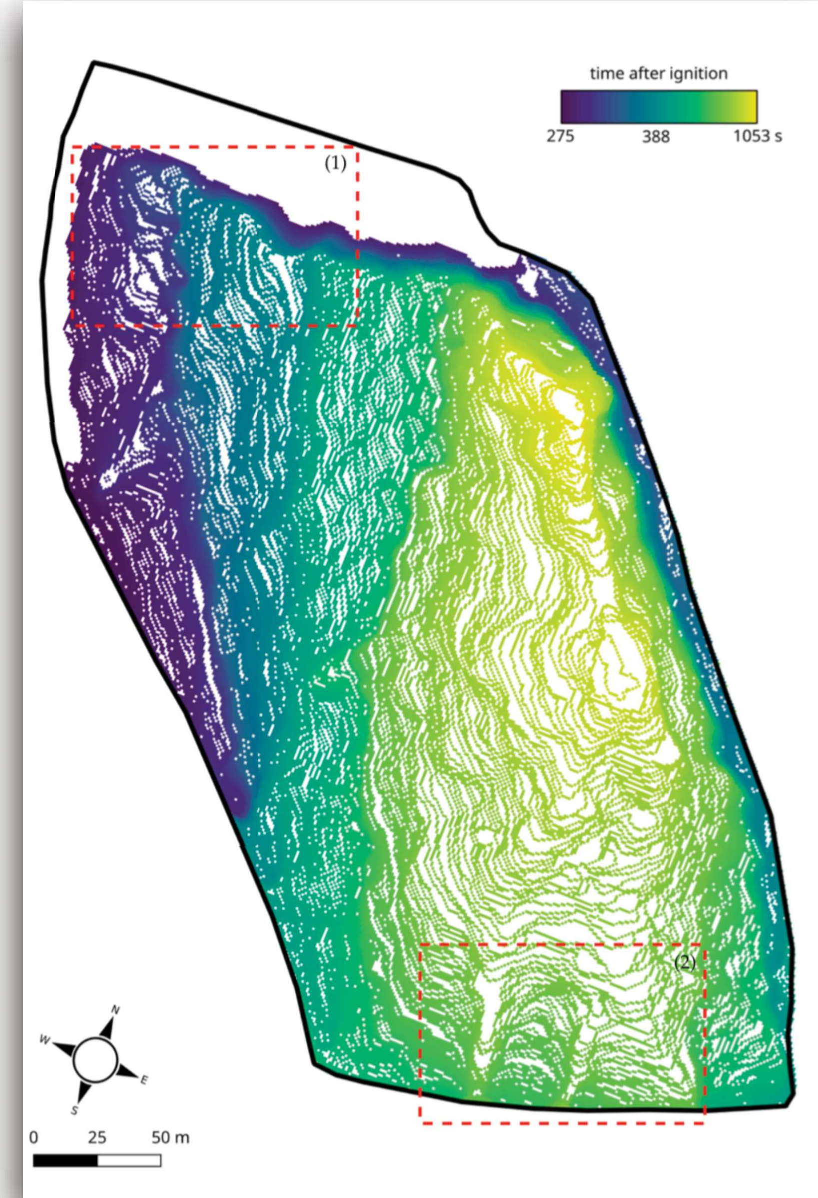

Data assimilation for wildland fire behavior

Strategy: Aggregate information from observed and simulated fire fronts

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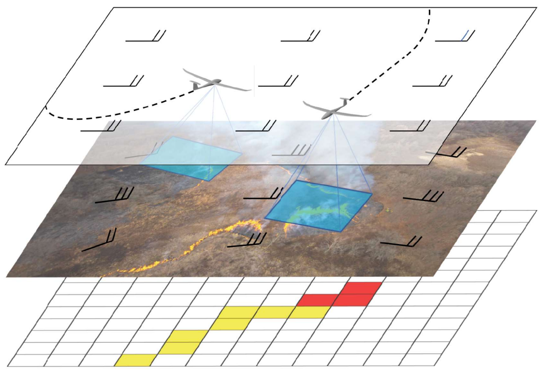
Prospective: Assimilating UAV data?



- Ideas/questions
  - Idea: adjustment of drone flight plan according to data-driven simulations
  - Feasibility? Flight altitude? Turbulent conditions near the fire
  - Data resolution/quality?

Data assimilation can be used to design an observation network using “synthetic” experiments.


Thank you for your attention.
Any question?
Contact
Melanie.Rochoux@cerfacs.fr
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