Challenges in building a system for assimilating airborne thermal infrared data to predict wildland fire behavior

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International EnKF workshop 2024

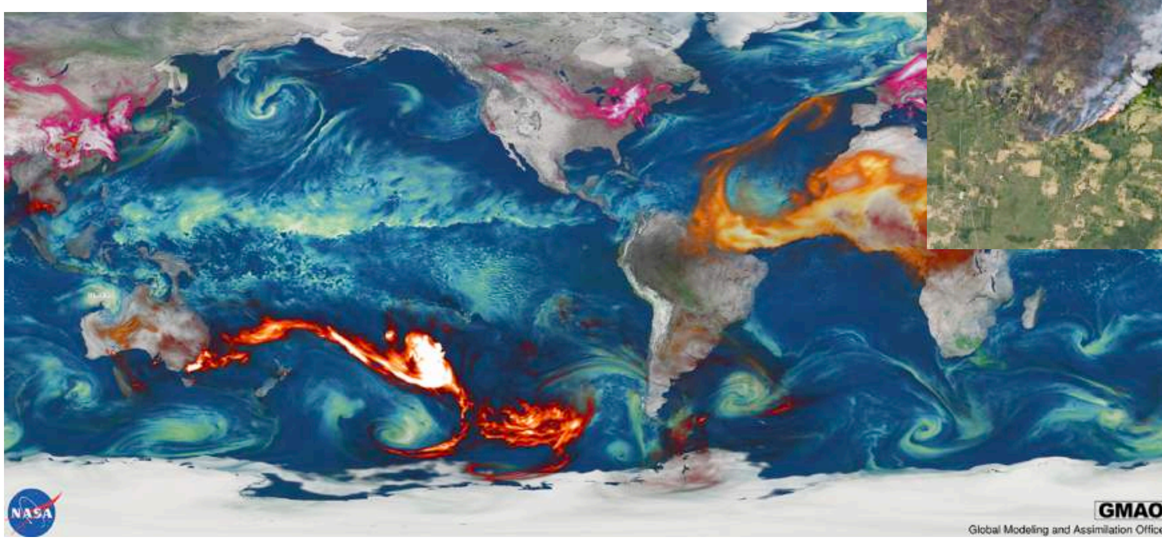
Outline of my talk

- On the importance of modelling wildfires at geographical scales
- Coupled atmosphere/fire modelling: potential and limitations
- Infrared observations: from acquisition to extraction of fire and atmospheric metrics
- Challenges of data assimilation for wildfires

Wildfires and climate change

Observation: Emergence of extreme wildfire events in many regions of the world across many ecosystems (burnt area, intensity, impacts)

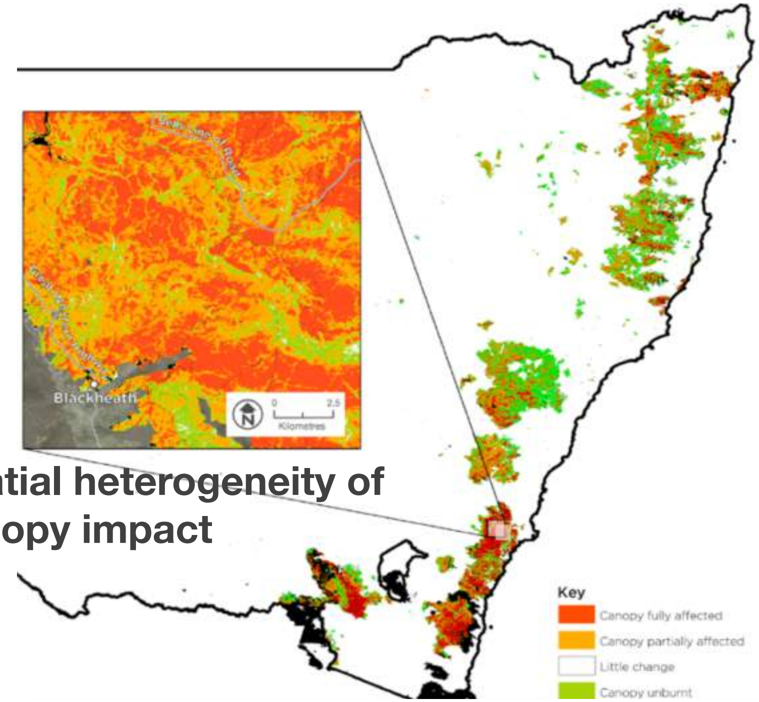
- **Key example of the Black Summer Fires in South-East Australia in 2019/2020**
  ➙ Compound fire event with no analogue in CMIP6 climate simulations, in present climate or in future projections



- **Regional and global impacts of individual fires**
  ➙ How to predict the risk of occurrence of large-scale fires?

Importance of local physical processes in wildfires

Complex wildfire behaviour: Interactions between near-surface wind, live and dead biomass fuels, and terrain topography



- **Spatial heterogeneity of canopy impact**

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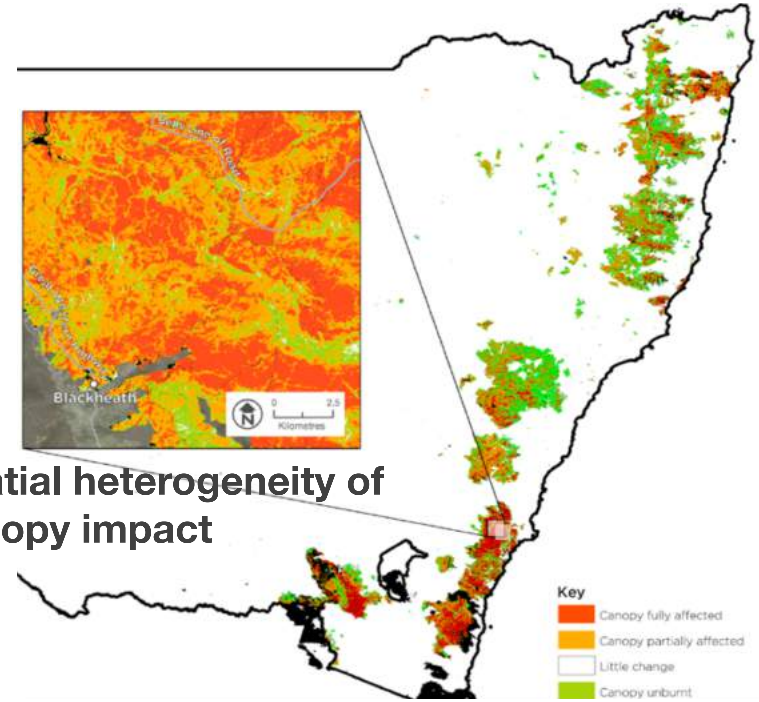

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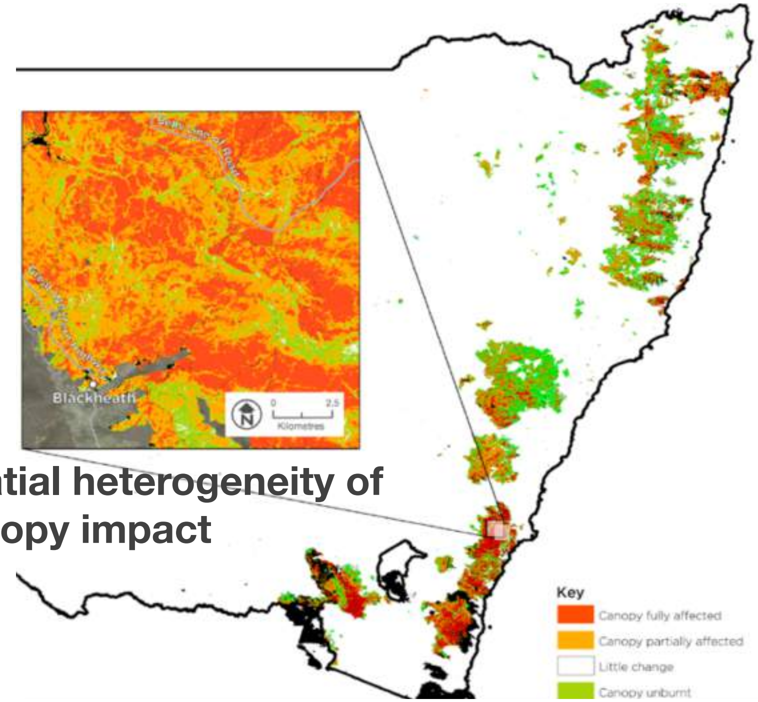

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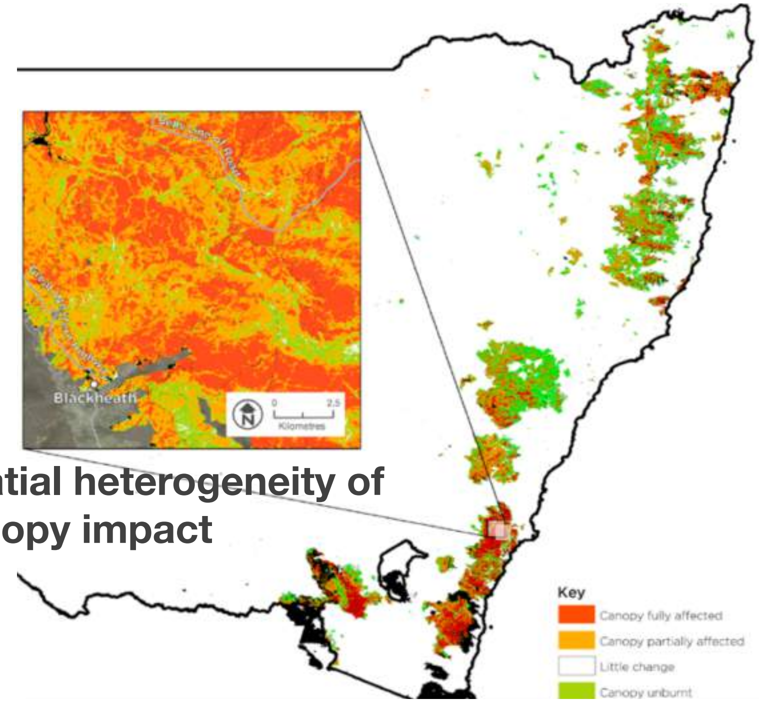
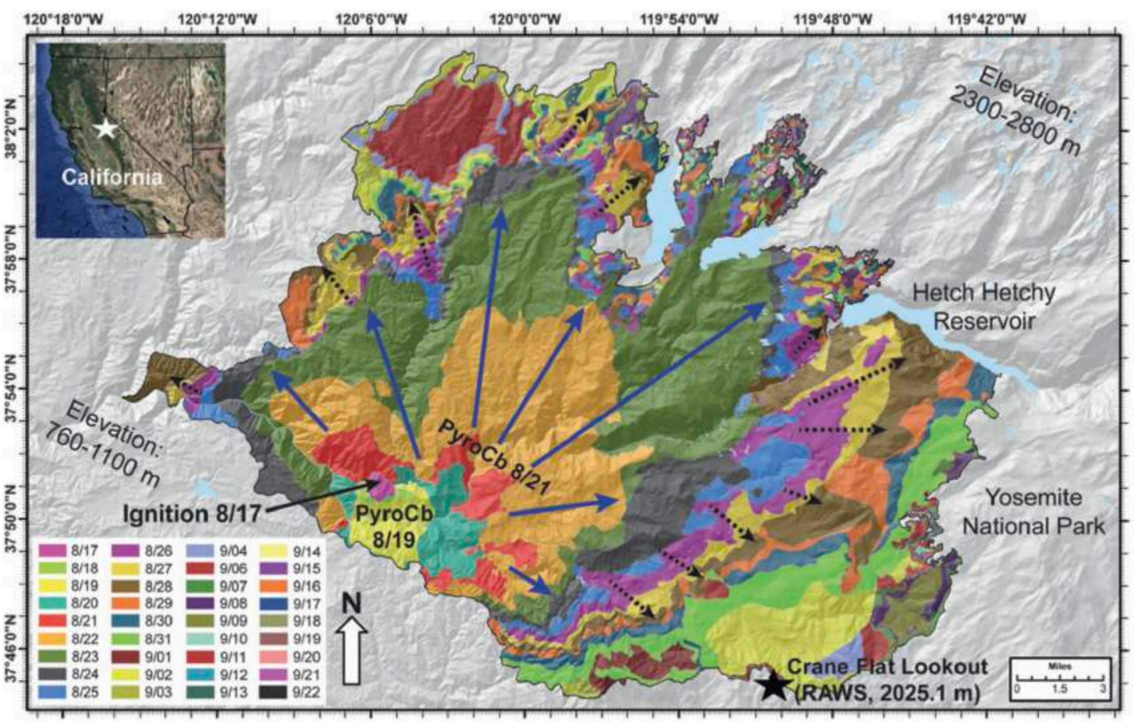


Why a coupled atmosphere/fire model?

- **Wind is a predominant factor and is modified by the fire**
  → Need to model fire/atmosphere interactions to understand what drives the development of large fires and to predict fire behavior

- **Significant variability of fire intensity during an event**
  → Need to capture the spatio-temporal variability of the key processes



→ Example of the 2013 Rim fire (California)

Fire spread modelling

Live and
dead fuels

Micro-
meteorology

Vegetation
moisture

Ignition

INPUT PARAMETERS

→ Costes et al. (2021)

**FIRE FRONT
PROPAGATION MODEL**

$$\frac{\partial \phi}{\partial t} = \mathrm{ROS}\,|\nabla \phi|$$

- Rate of spread (ROS) parameterization
- 2-D eikonal equation (level-set method)

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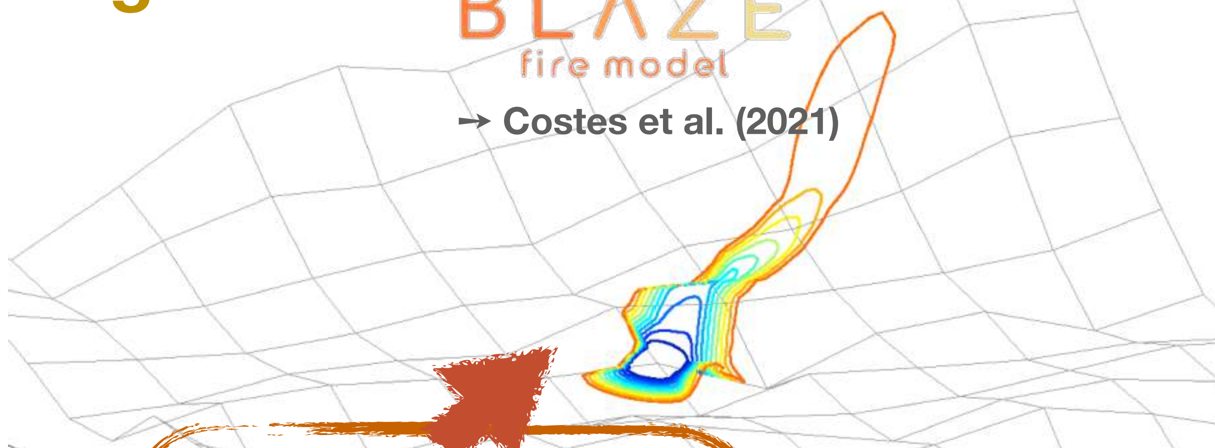

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FIRE FRONT PROPAGATION MODEL

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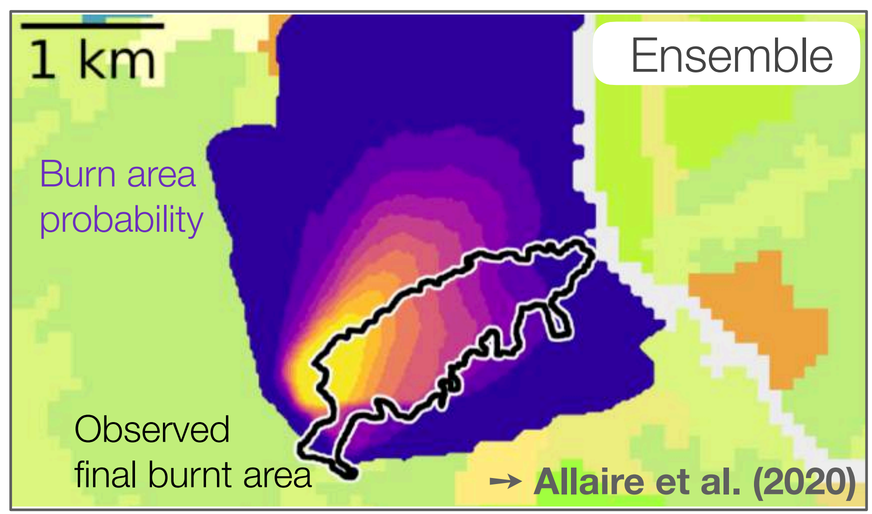
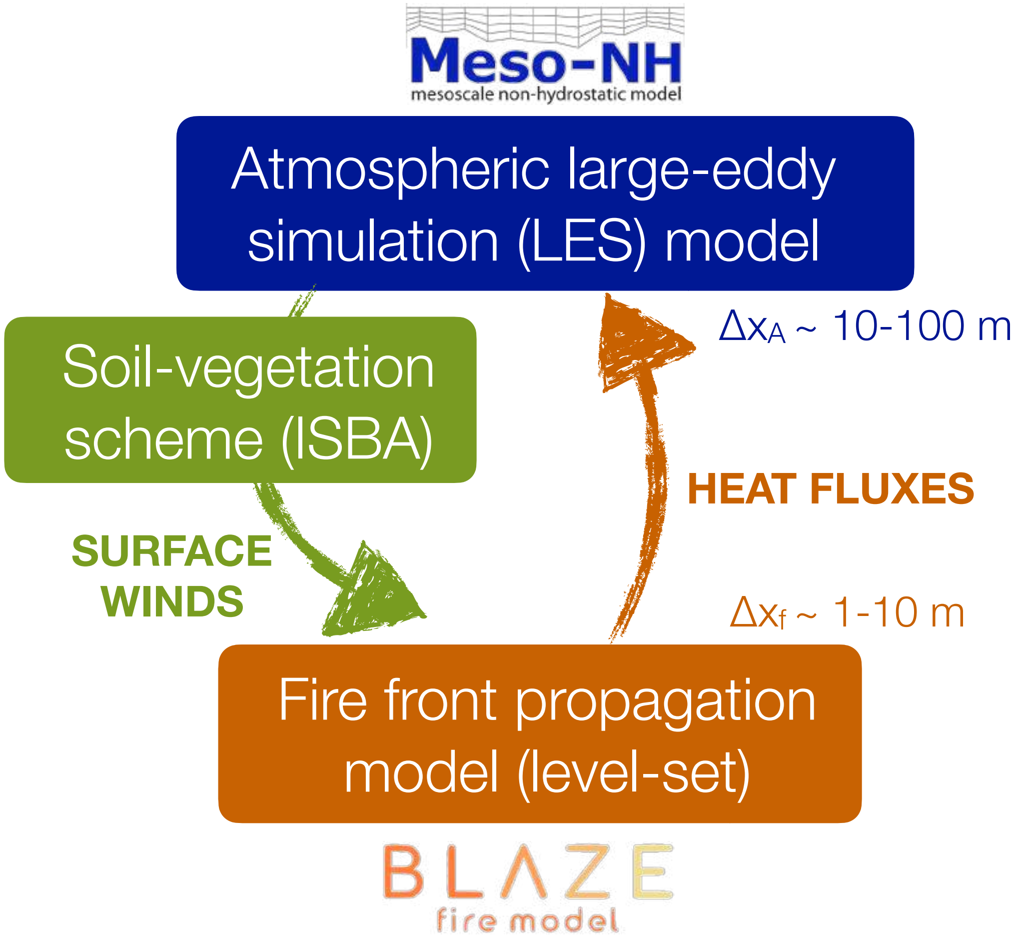
- **Need for an ensemble modelling approach** to account for uncertainties in input parameters



→ Allaire et al. (2020)

Coupling with atmospheric model



Coupling with atmospheric model

Meso-NH
mesoscale non-hydrostatic model

Atmospheric large-eddy simulation (LES) model

$\Delta x_A \sim$ 10-100 m

Soil-vegetation scheme (ISBA)

HEAT FLUXES

SURFACE WINDS

$\Delta x_f \sim$ 1-10 m

Fire front propagation model (level-set)

BLAZE
fire model

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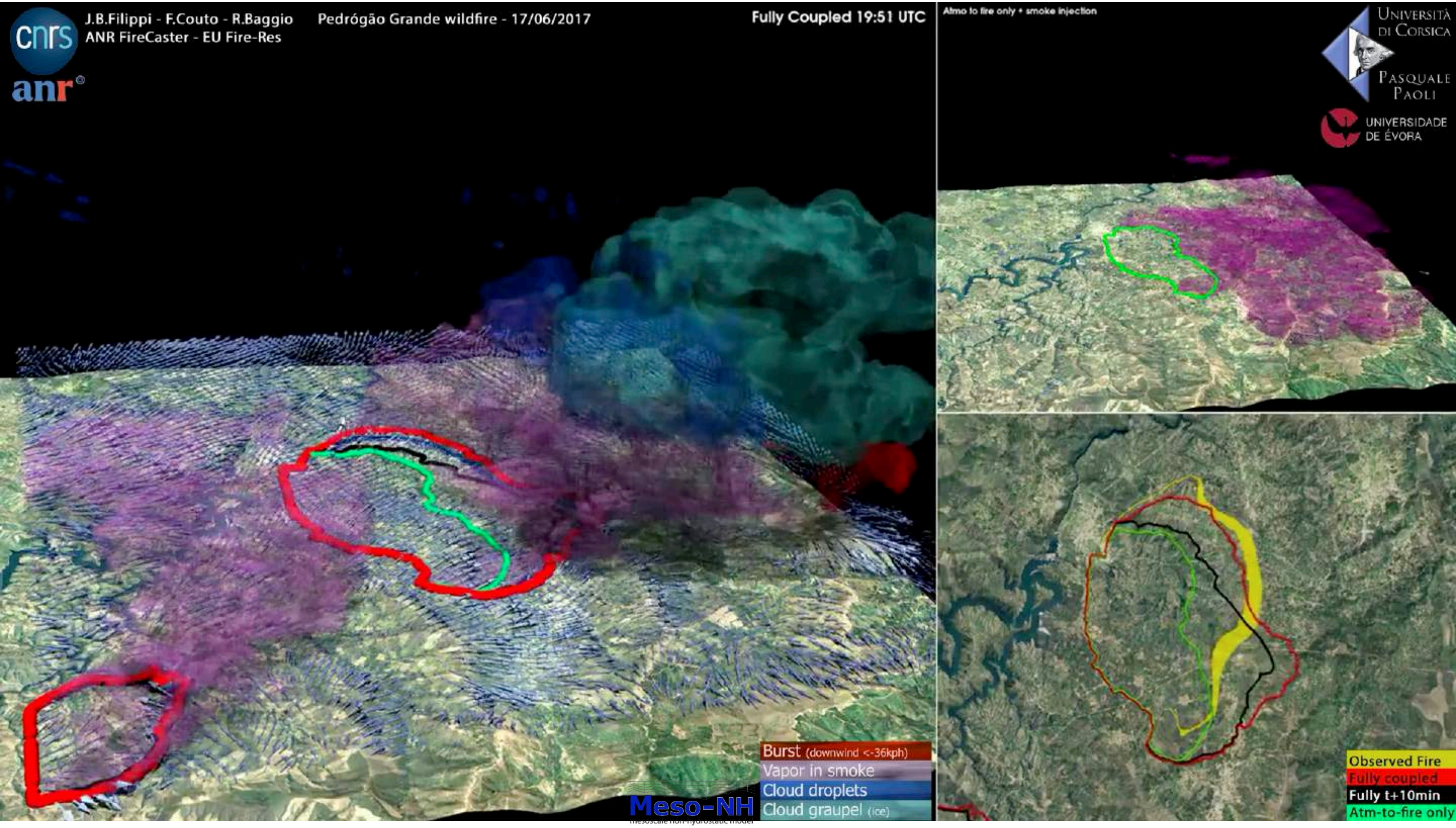
Fire front propagation model (level-set)

BLAZE
fire model

- **Need for ensemble coupled simulations** to account for internal variability
  → **Costes et al. (2021, 2022)**

Case study: Pedrogao fire (Portugal, 2017)



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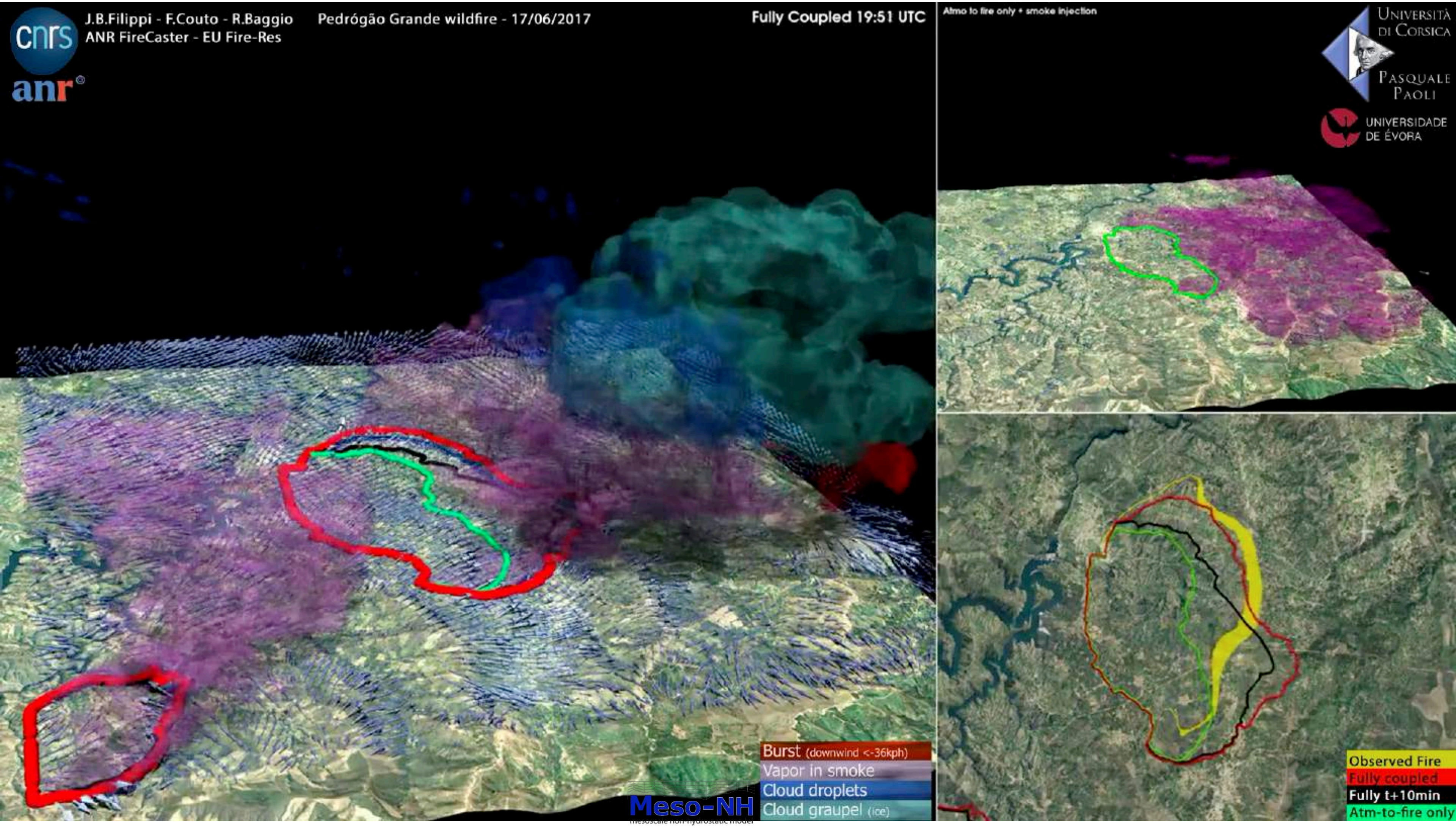


→ Couto et al. (2024)

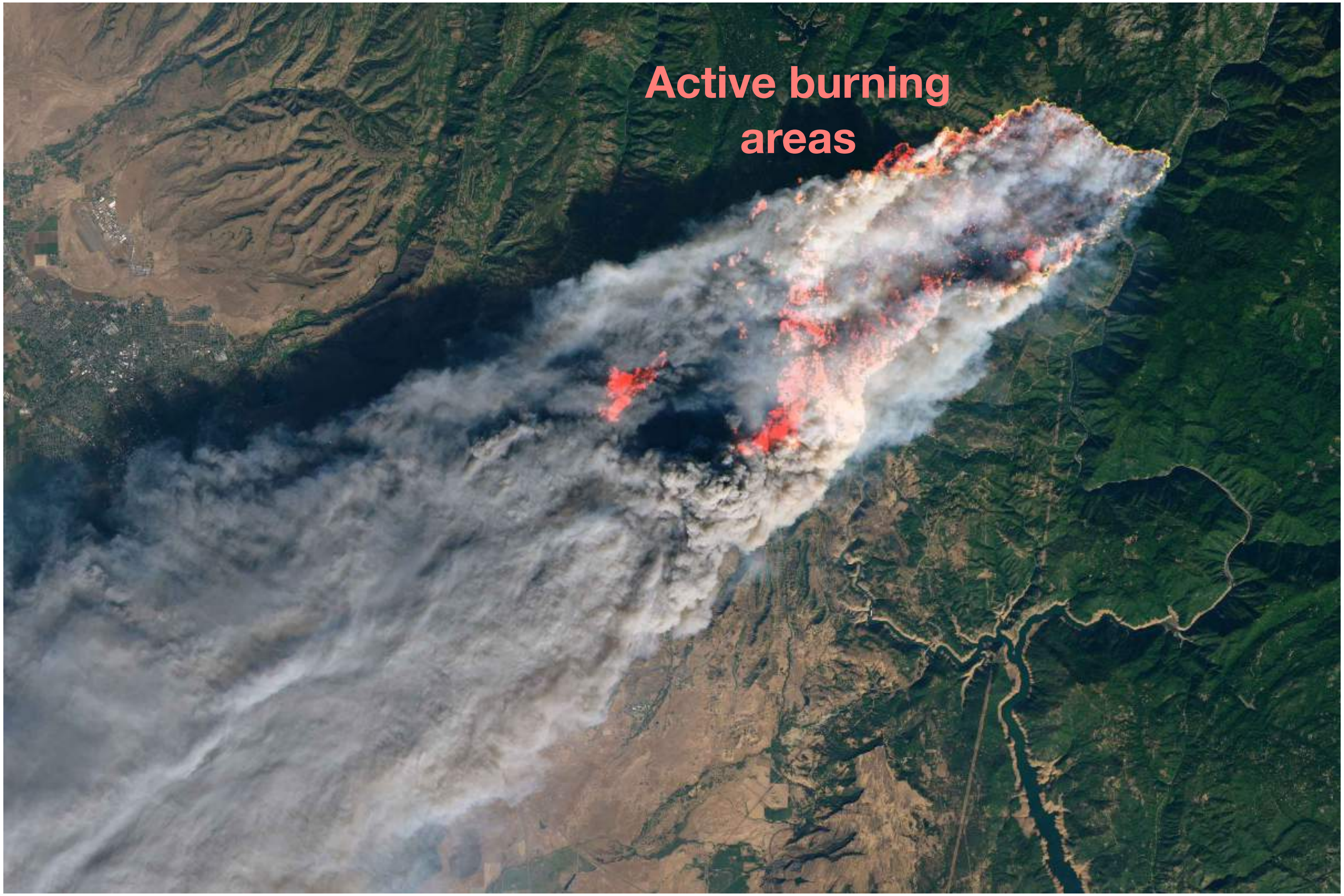
Uncertainties in coupled atmosphere/fire modelling

- **Model representativeness**
  ➙ Crowning, spotting, smoldering…

- **Input parameters (fuel and wind)**
  ➙ Improving fuel representativeness in the coupled model (PhD thesis, CNRM/Cerfacs, starting in Fall 2024)

- **Atmospheric internal variability**
  ➙ See talk by Eliott Lumet

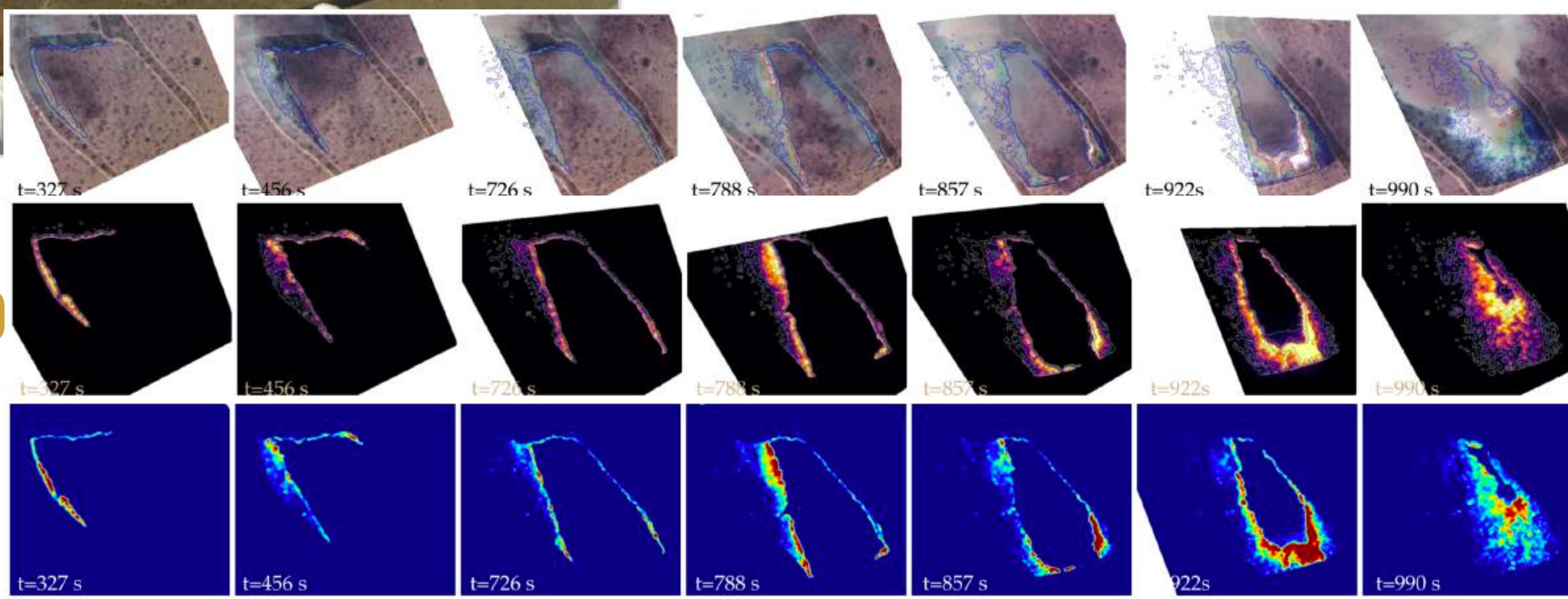
Why infrared imaging?



Compound image (visible and near-infrared) from 2018 Camp Fire (California, > 60,000 hectares) based on Landsat8 data

Segmenting infrared images

Collaboration with Ronan Paugam (UPC, Barcelona)



MIR 3.9μm

LWIR 7-13μm

→ **Paugam et al. (2021)**

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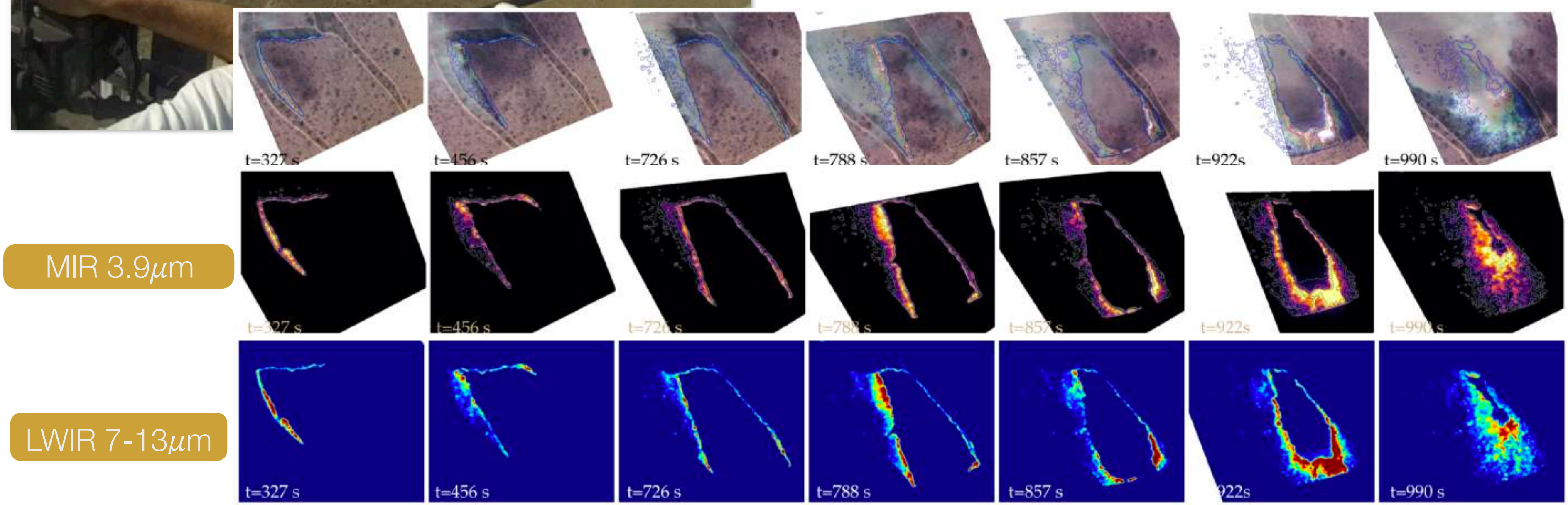

- **Need to design and evaluate a method for segmenting LWIR images**
  → example of Savannah fires of 3-8 ha, Kruger National Park, South Africa, 2014 (KCL)

→ **Paugam et al. (2021)**

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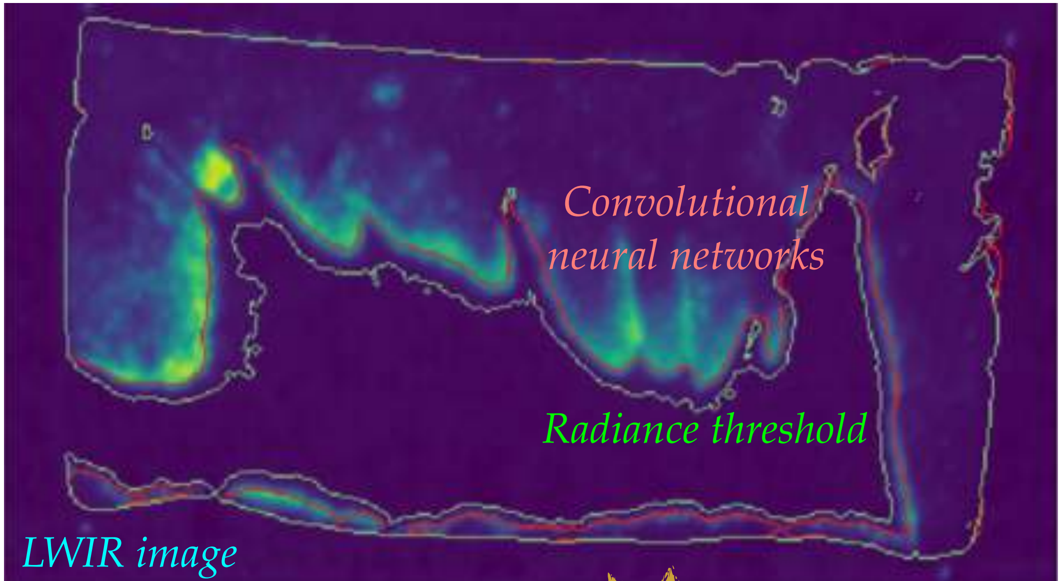
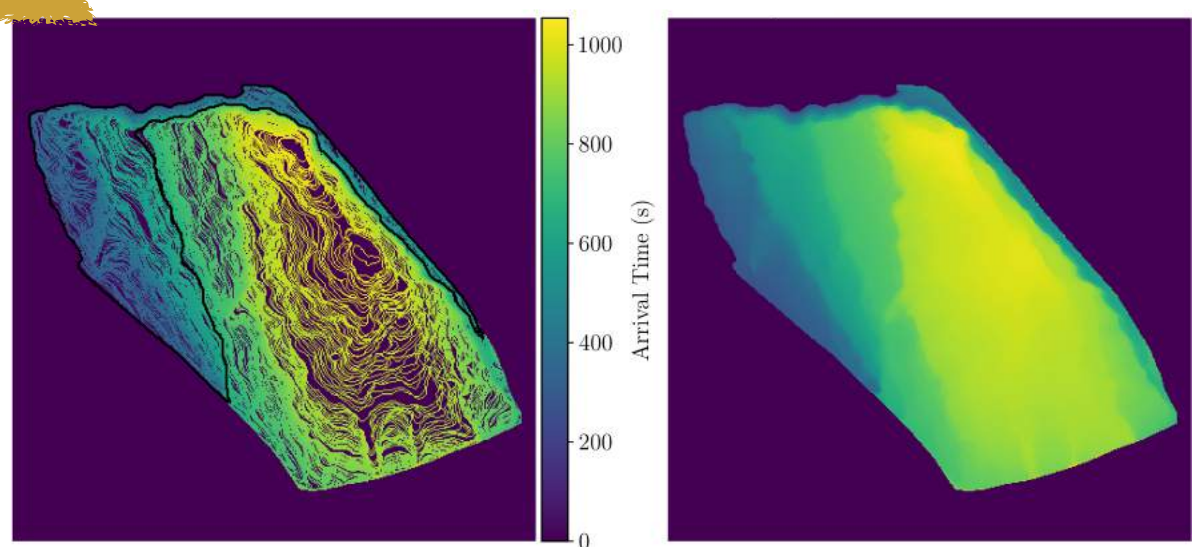


Concatenation of segmented fire fronts at 1 m, 1 s resolution



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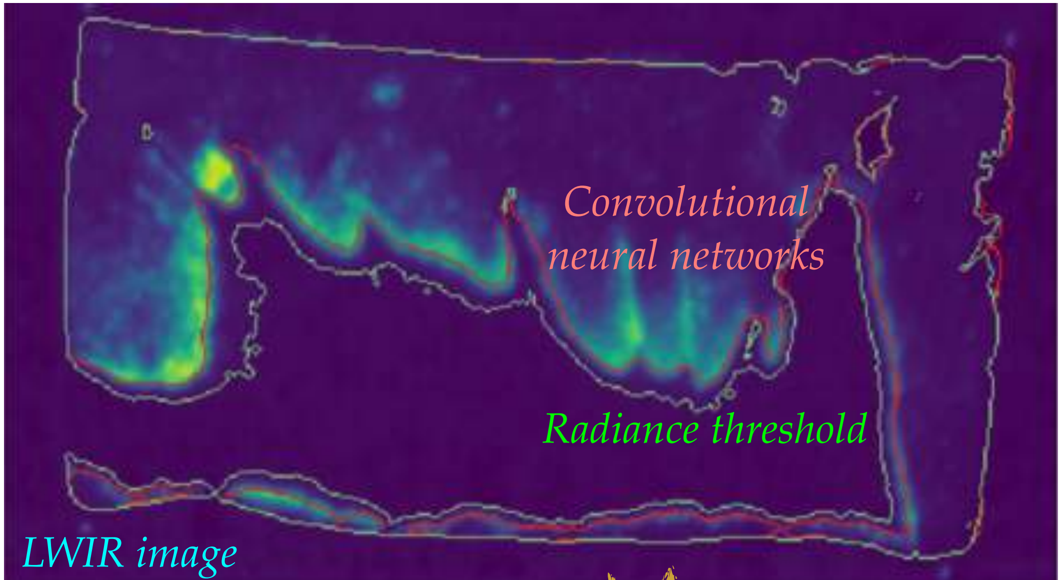

- **Complexity of a 3-D fire scene (flame, gas and soot emissivity)**
- **Series of convolutional neural networks** based on active learning and transfer learning to avoid manual data labeling and gain in generality

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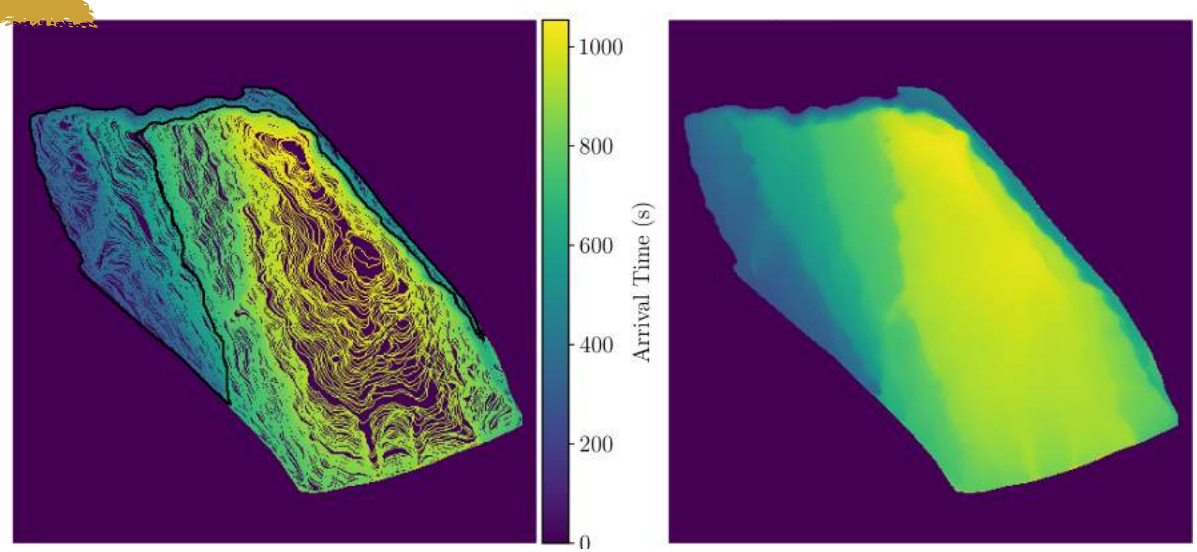
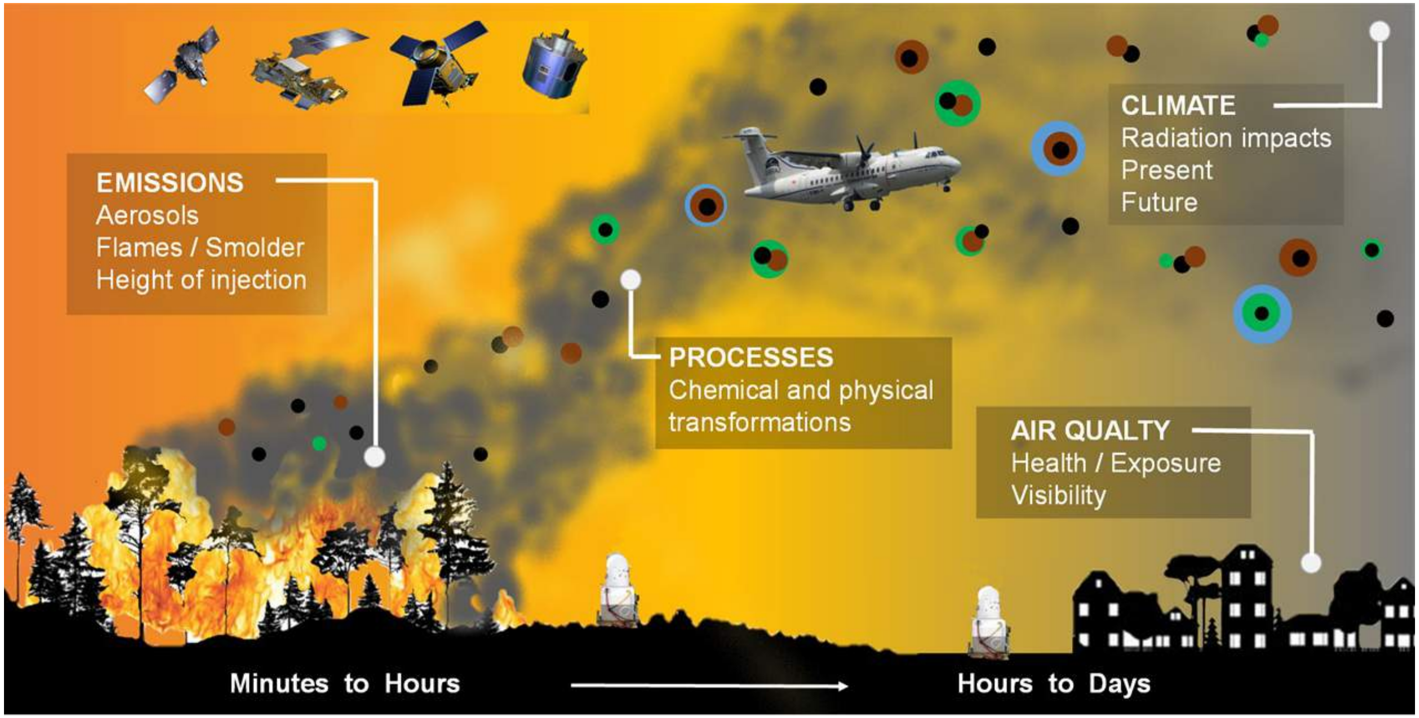
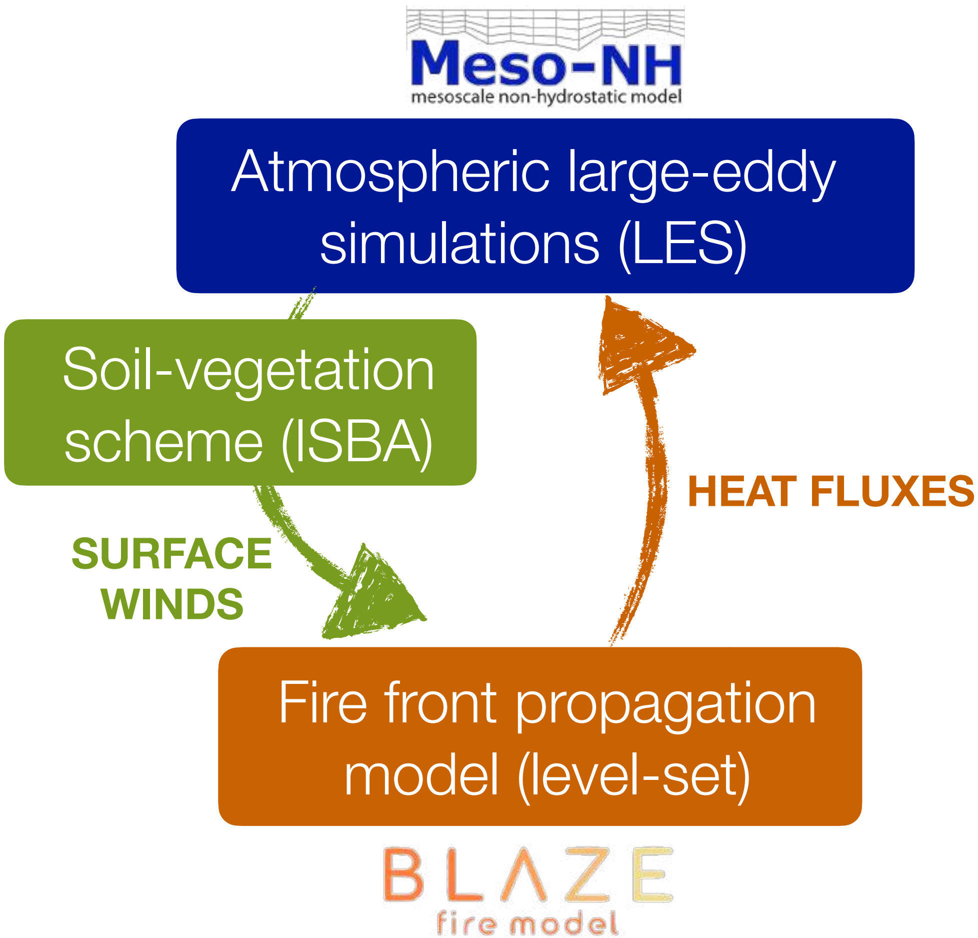


Collaboration modellers-experimenters for future field campaigns

- **Need to acquire informative observational data for model validation and for algorithm development**
  - ➙ UAV data (collaboration with LAAS and ENAC)
  - ➙ plume and aerosols (collaboration with CNRM, program EUBURN)



Challenges for data assimilation



- **Emulation of the coupled model for ensemble generation (postdoc)**
  ➙ Component-by-component emulation?
  ➙ Need for joint state-parameter estimation for the fire spread model component
- **Assimilation of observed fire front positions (PhD Cong Zhang, 2018)**
  ➙ How to compare fronts and formulate the innovation term? How to account for shape and topological errors?
  ➙ How to estimate front statistics? How to integrate these statistics in the EnKF algorithm?

1) The front challenge

Observation: Failure of standard data assimilation methods when substantial position errors (Chen and Snyder 2007)

- **Limitation of point-wise local metrics**
  ➙ Small spatial shift can induce large errors in the metrics
  ➙ Several metrics required to compare fields
  ➙ Double penalty effect: a misplaced object is predicted where it should not be, and it is not predicted where it should be

- **Generation of artificial structures in the analysis**
  ➙ Morphing (Beezley and Mandel 2008)

- **Introduction of a new way to measure front discrepancies for the innovation term**
  ➙ Derived from Chan-Vase functional (Collin et al. 2014, Rochoux et al. 2018)

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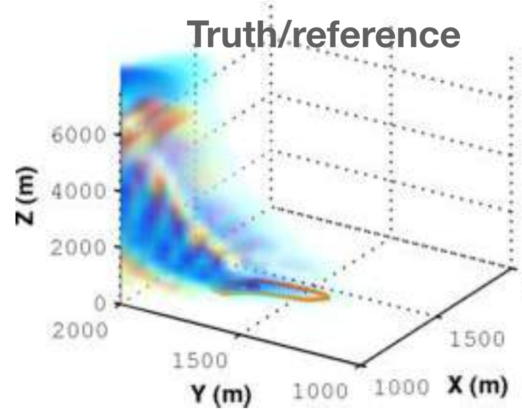

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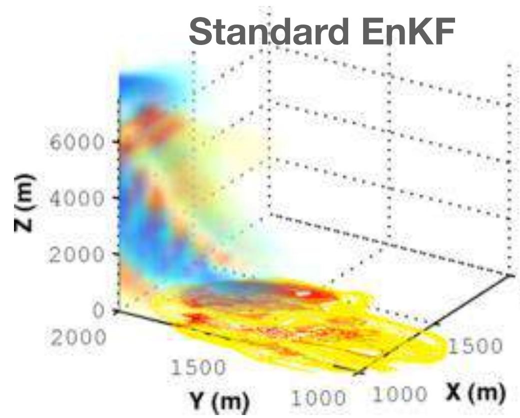

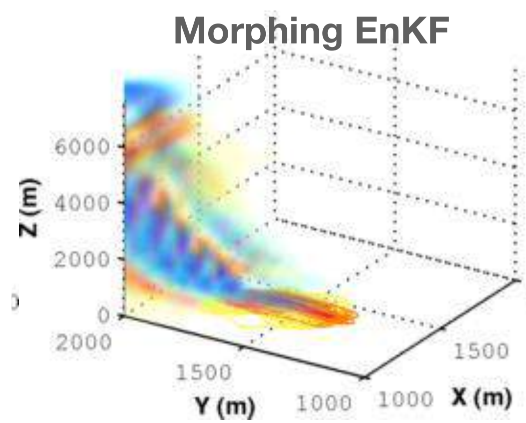

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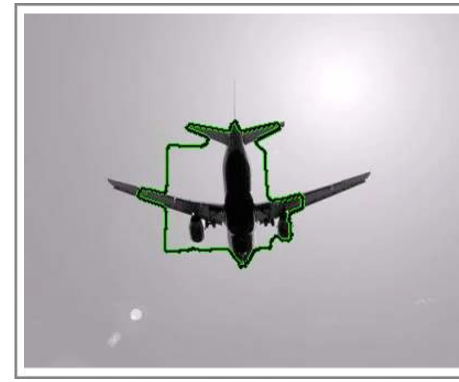


$$\cancel{\mathcal{J}(\mathrm{x}) = ||\mathcal{G}(\mathrm{x})} - \mathrm{y^o}||^2$$

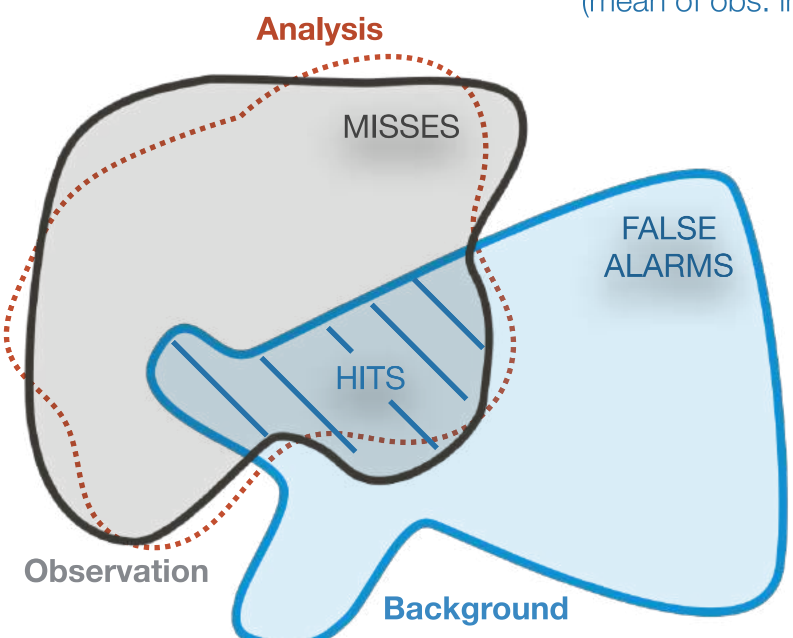
Level-set formalism

Chan and Vese (2001)

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

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

"outside" measuring MISSES
(mean of obs. in simulated unburnt area)



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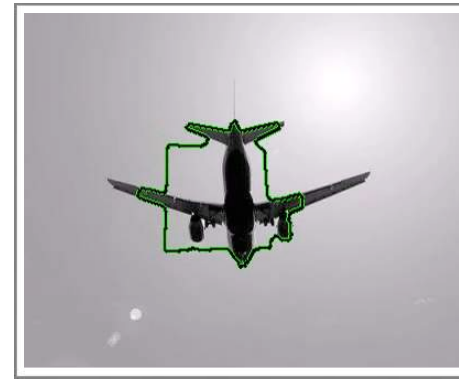

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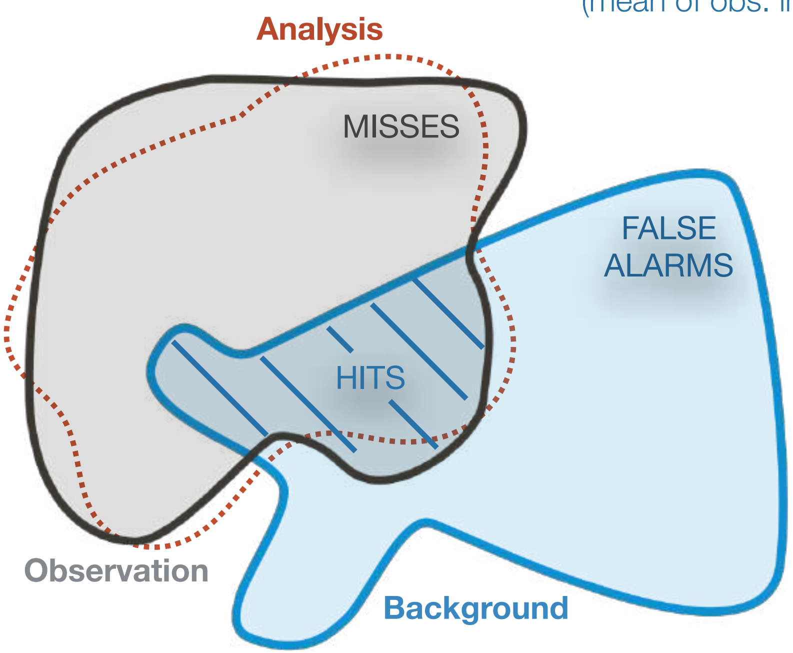

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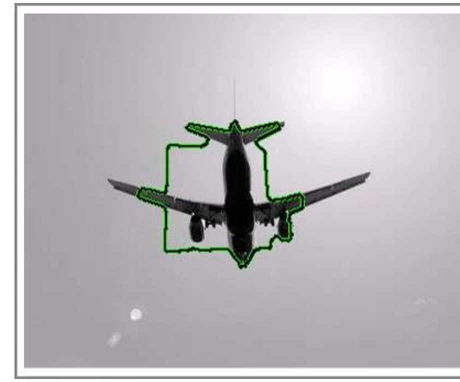

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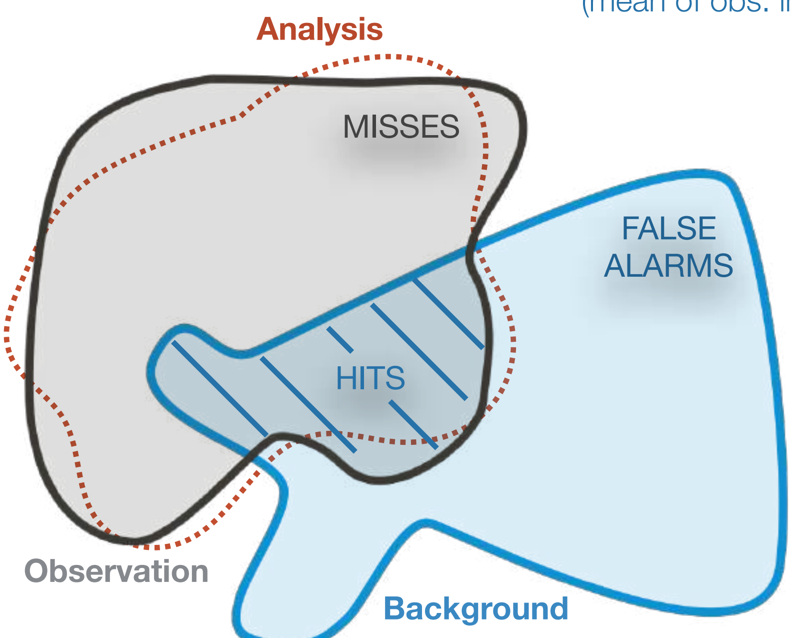


Minimizing the function acts on the contour of the simulated front to match the shape of the observed front

$C_0 \approx 0$, $C_1 \approx 1$ — **Case 1:** Perfect match

$0 < C_1 < 1$, $C_0 \approx 0$ — **Case 2:** Only false alarms

$0 < C_0 < 1$, $0 < C_1 < 1$ — **Case 3:** False alarms and hits

1) The front challenge

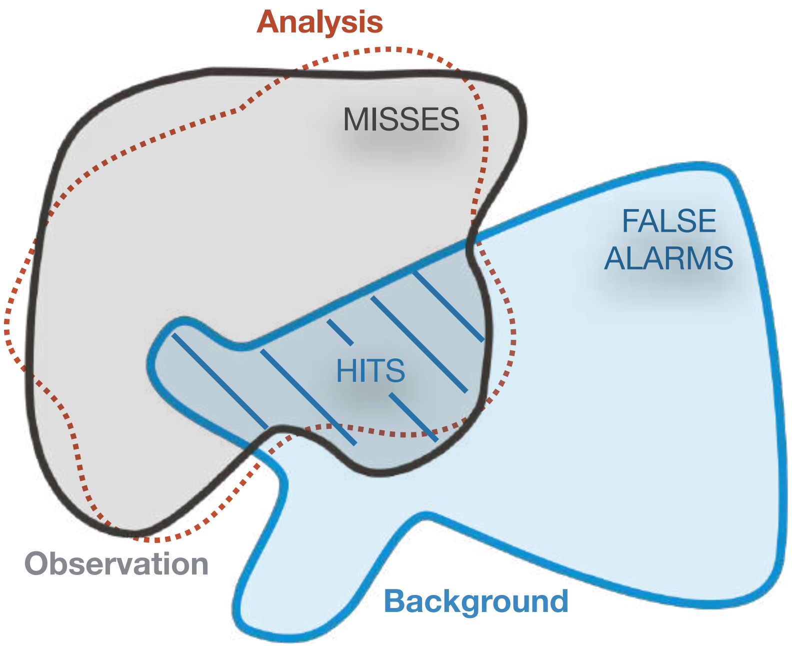
New nudging term for state estimation applied to front propagation equation

- Level-set formalism
- Can be extended to Lagrangian propagation model (Zhang et al. 2019)

$$\boxed{\frac{\partial \phi}{\partial t} = ROS\,|\nabla \phi|} + \boxed{\lambda\,\delta(\phi)\left[(\mathrm{y}^o - C_{\max})^2 - (\mathrm{y}^o - C_{\min})^2\right]}$$

Propagation equation

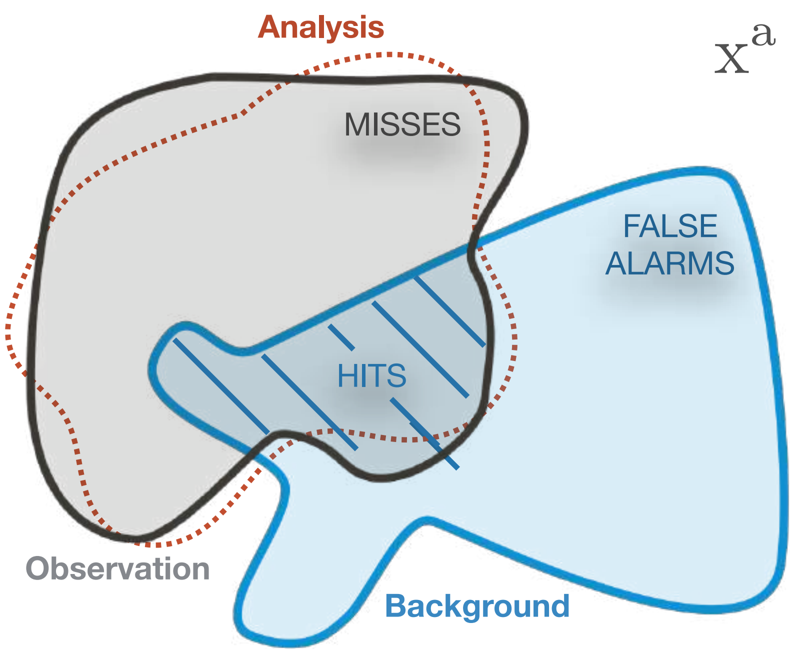
Nudging term ‣ Dirac δ function localizing the data assimilation feedback on the simulated fire front



1) The front challenge

Parameter estimation using EnKF with discrepancy operator

- Level-set formalism (Rochoux et al. 2018, Zhang et al. 2019)
- To reduce model bias



Discrepancy operator

- Based on the gradient of the Chan-Vese functional
- Analysis still formulated as a correction of the background

$$\mathrm{x^a} = \mathrm{x^b} + \mathrm{K}_e \left[\mathcal{D} \left(\mathrm{y^o}, \mathcal{G}(\mathrm{x^b}) \right) \right]$$

$$(\mathcal{D}^{\epsilon,+}, \mathcal{D}^{\epsilon,-})^T$$

$$\mathcal{D}^{\epsilon,-} = \left[1 - \frac{2}{\pi} \arctan\left(\frac{\phi}{\epsilon} \right) \right] \left[\mathrm{y}^o - C_{\mathrm{min}}(\mathrm{y}^o, \phi) \right]$$

$$\mathcal{D}^{\epsilon,+} = \left[1 + \frac{2}{\pi} \arctan\left(\frac{\phi}{\epsilon} \right) \right] \left[\mathrm{y}^o - C_{\mathrm{max}}(\mathrm{y}^o, \phi) \right]$$

➤ Joint state-parameter estimation

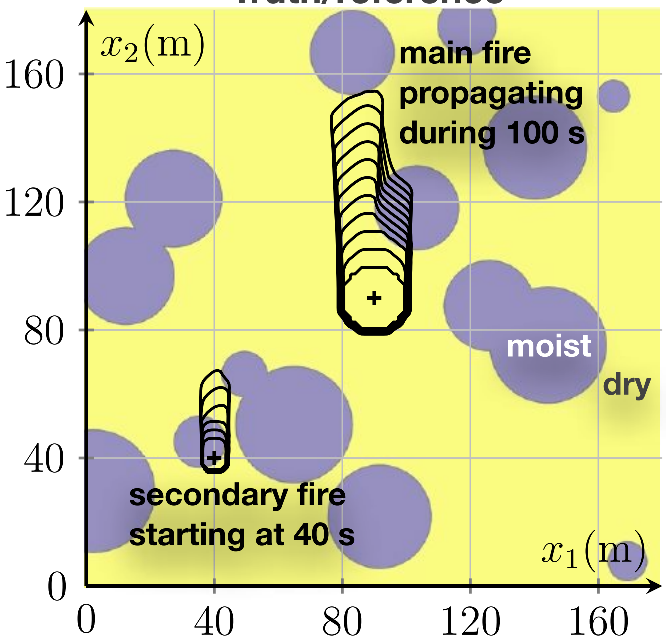
- Luenberger observer for state estimation
- Object-oriented EnKF for parameter estimation

1) The front challenge

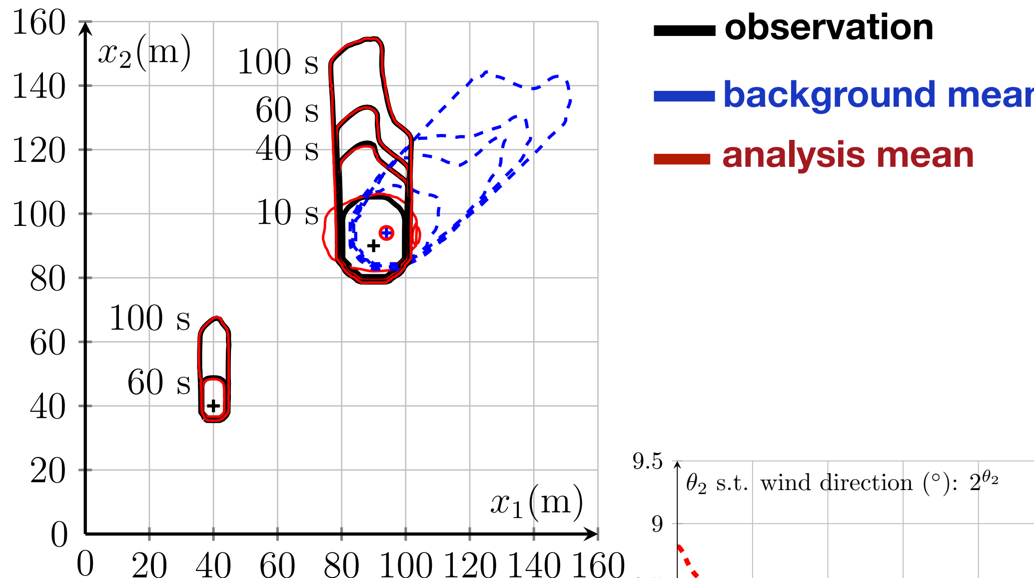
Example of joint estimation with wrong wind and initial condition (Rochoux et al. 2018)

- OSSE for the joint state-parameter estimation approach
- Additional topological gradient in the state estimation to account for topological errors

Truth/reference

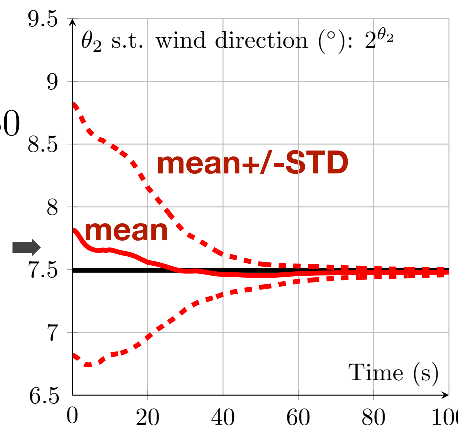


Data assimilation results



⬆ **Fire front positions**

Wind direction ➡



- **Consistent behavior of the data assimilation approach**
  → Next: Introduction of more robust front shape statistics (Charpiat PhD 2006)

2) The emulation challenge

Fire front component emulation
- Fire front propagation
- Surface heat fluxes (integration of texture, Cremers et al. 2007)

➙ Preliminary work: polynomial chaos expansion (Rochoux et al. 2012, 2014)

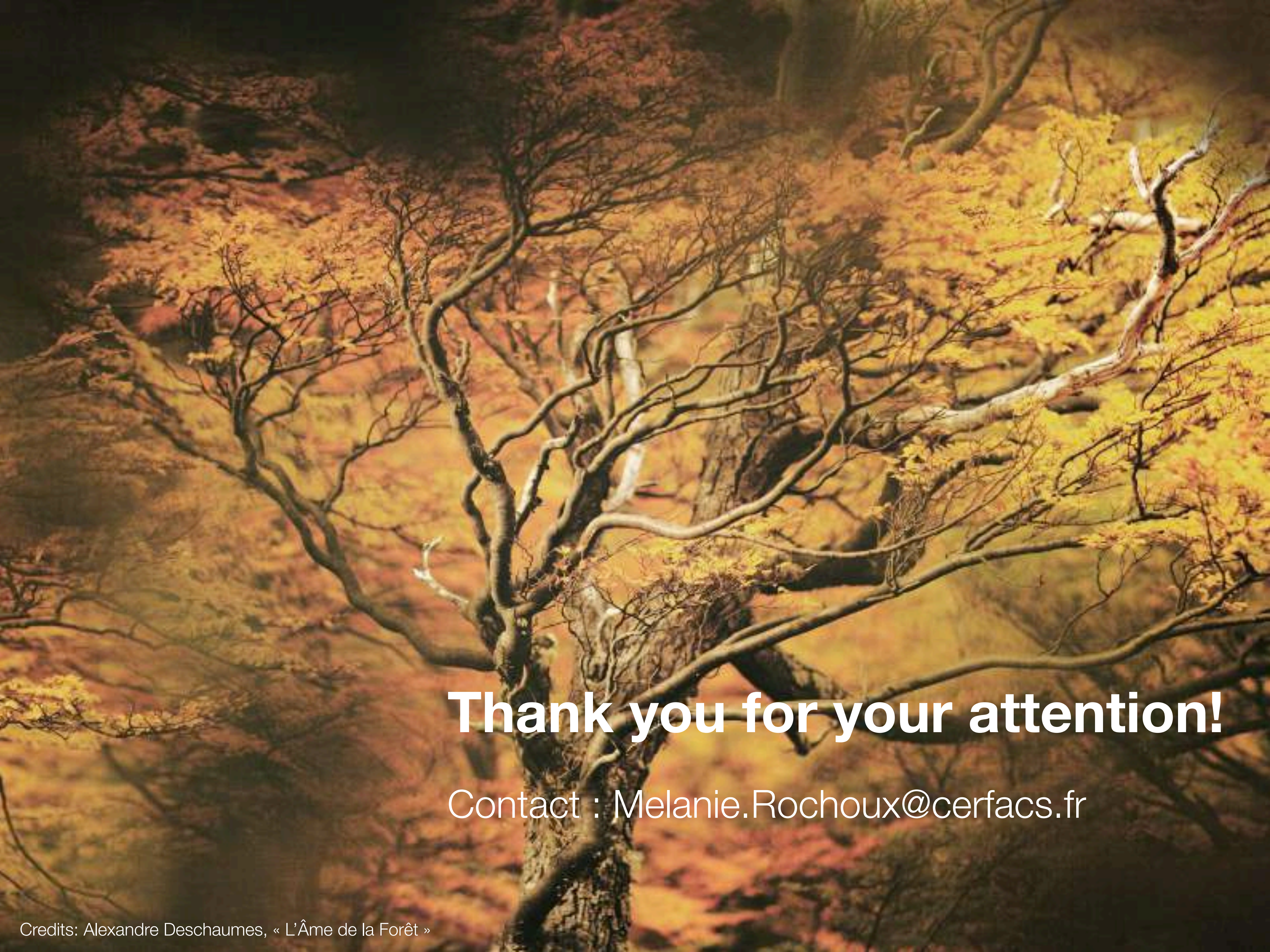
Atmospheric component emulation
- Surface wind
- Accounting for internal variability (Costes et al. 2021, Lumet et al. 2024)

➙ Preliminary work: POD combined with Gaussian process regression for fixed, cold source (Lumet et al. to be submitted)

➙ Extension to hot, mobile source

Concluding remarks

- Goal #1 Build a reference model for simulating wildland fires at geographical scales (in collaboration with CNRM)
- Goal #2 Emulate the coupled atmosphere/fire model, while accounting for uncertainties
  - Prediction (fire module to plug in to AROME?)
  - Fire parameterization (Earth system modelling?)
- Goal #3 Build a prediction capability of wildland fire behavior
  - Assimilating infrared data from airborne platforms
  - Integrating emulator within the data assimilation workflow
  - Prediction (services to « Sécurité Civile »?)



Thank you for your attention!

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Credits: Alexandre Deschaumes, « L’Âme de la Forêt »