

Wildland fire behaviour ensemble modelling

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Extreme wildfire events

Global issue

- ▶ Multiple ecosystems affected by wildfires (savannah, bush, forest, peat...)
- ▶ More probable and intense events under anthropogenic climate change

Composite extreme events

* Chapter 11, IPCC AR6
Climate Change 2021: The
Physical Science Basis

Drought

Heat waves

Strong winds

2019/2020 SouthEastern
Australian wildfires



How can a wildfire degenerate?

Surface fire



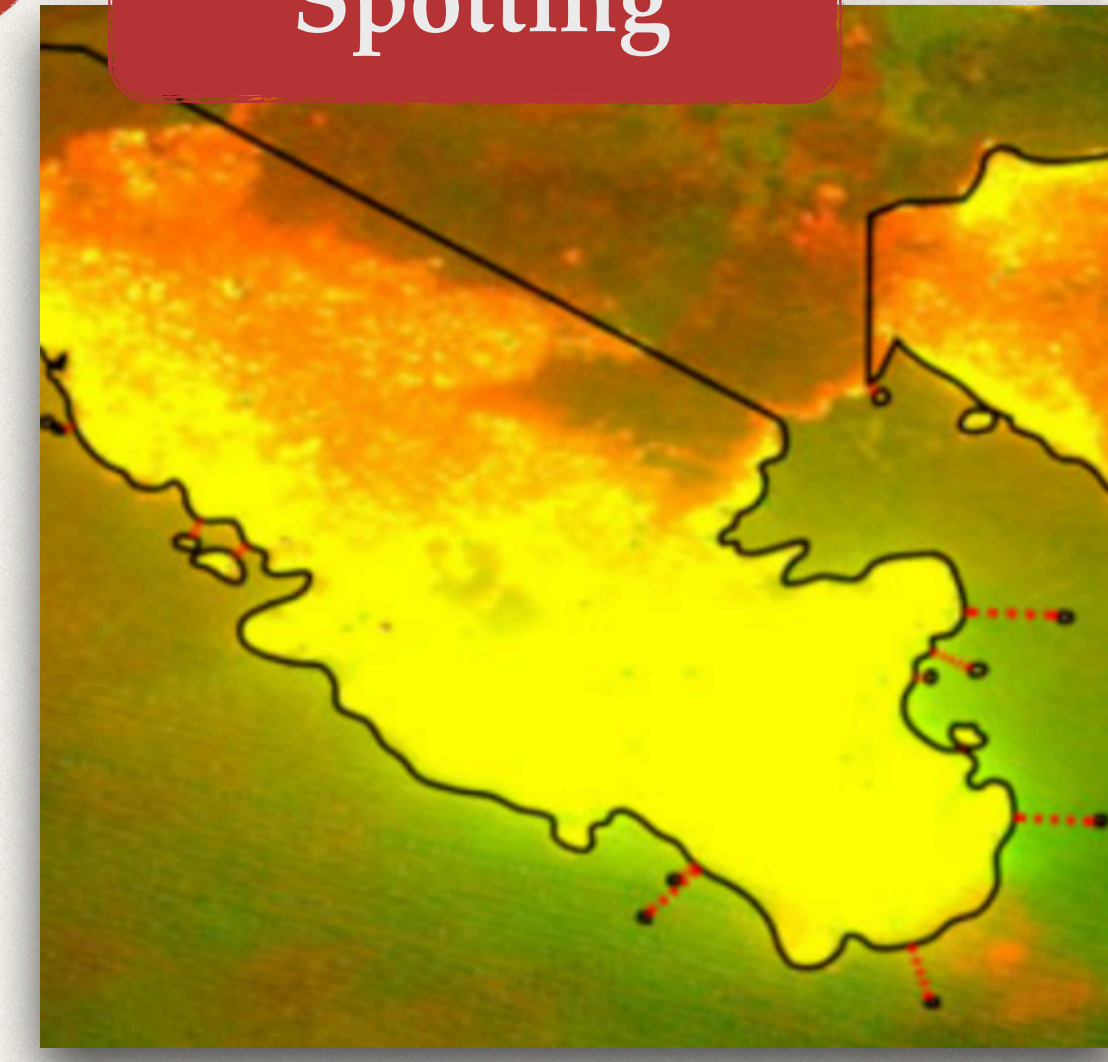
- ▶ Litter burning
- ▶ Faster surface propagation upwind and upslope

Crowning



- ▶ Possible propagation to the vertical structure of the vegetation up to the tree canopy
 - ▶ *Faster propagation and taller flames*
 - ▶ *More intense fire-induced wind*
 - ▶ *More severe fire impacts*

Spotting



- ▶ Firebrand projection at long distances
 - ▶ *New fire ignition*

How can a wildfire degenerate?

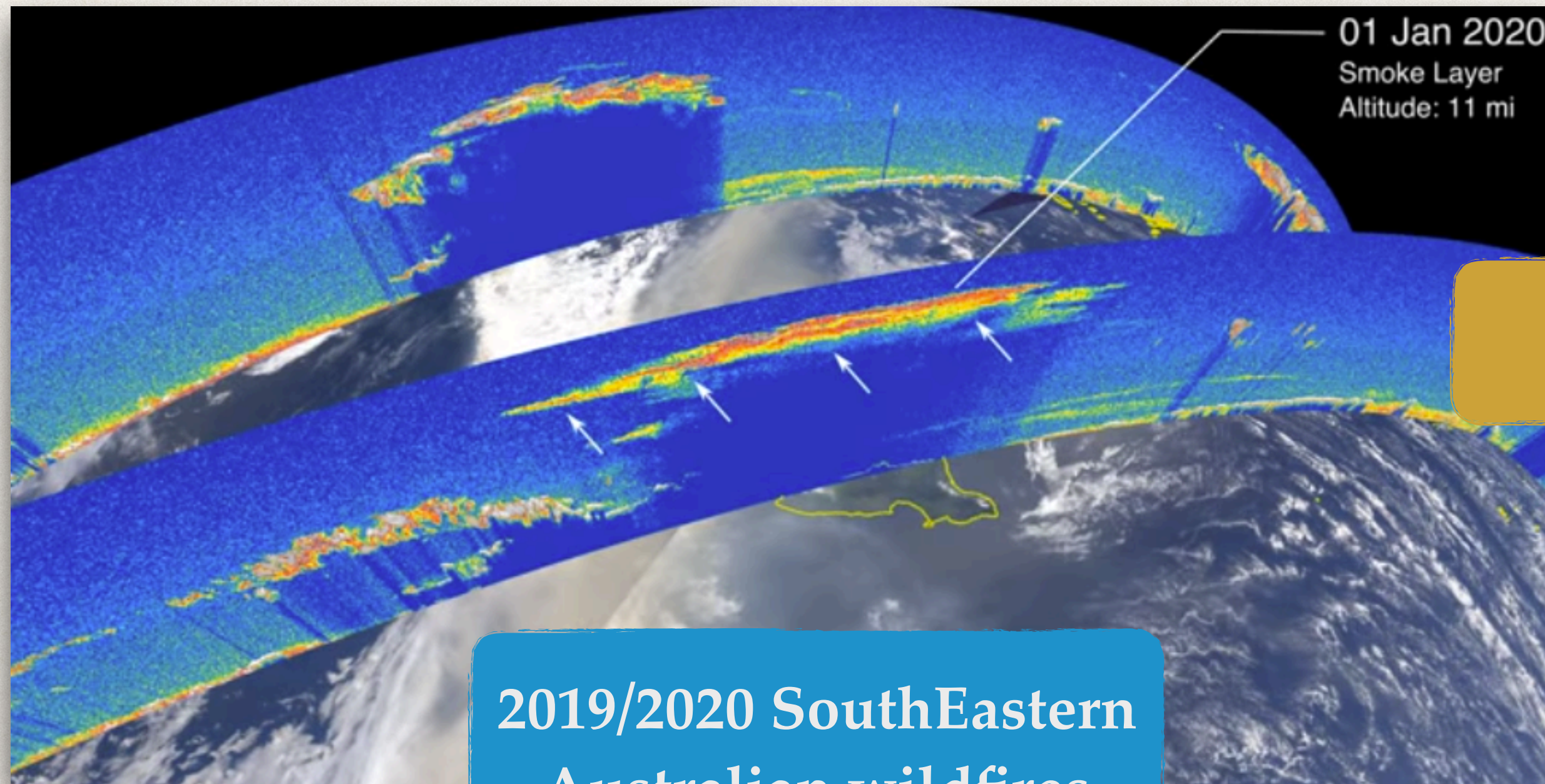
In the stratosphere

- ▶ Soot particles injection and persistence
- ▶ Similar to moderate volcano eruptions

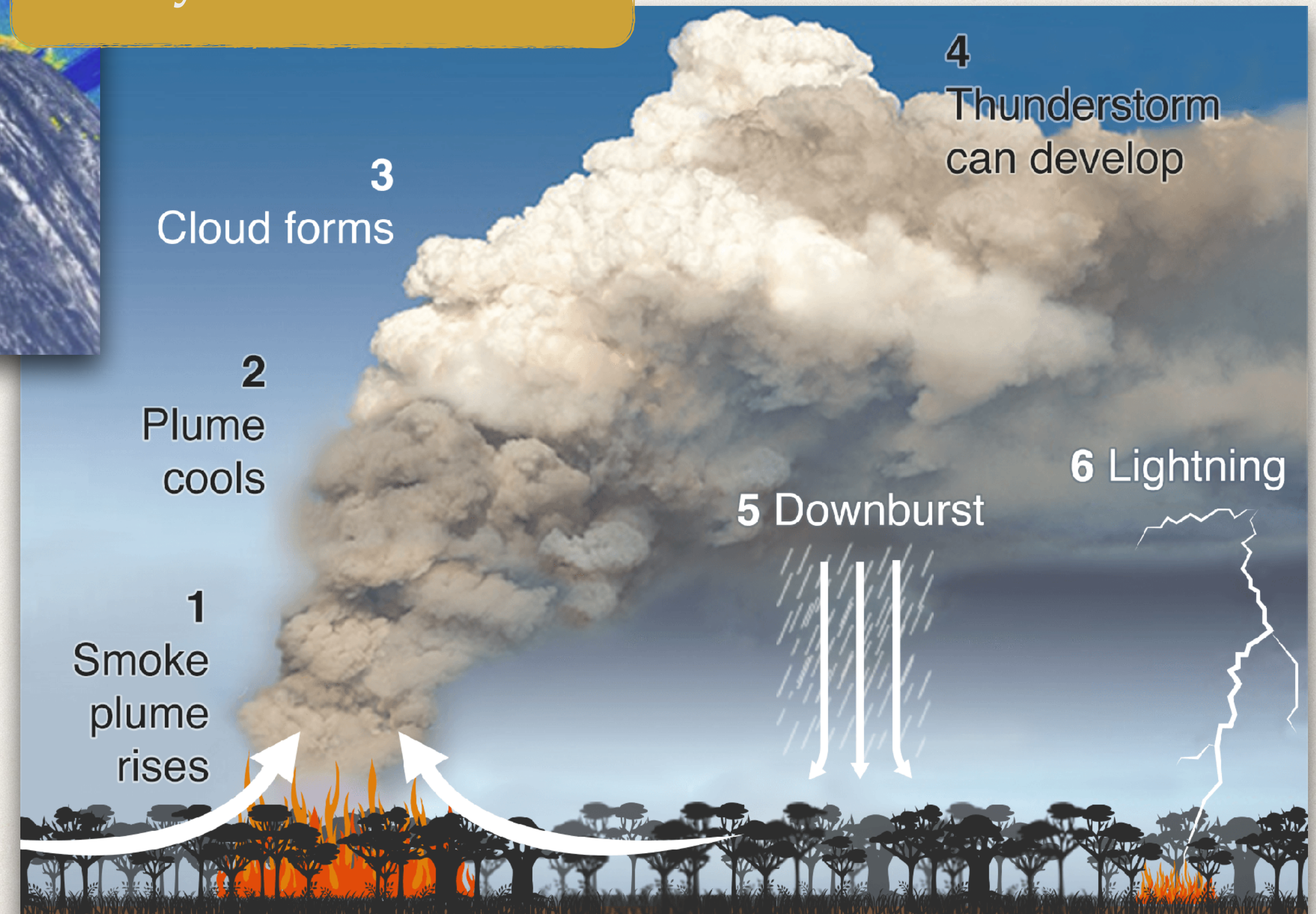
At the surface

- ▶ Strong perturbation of the surface winds
- ▶ New ignitions

Pyroconvection



2019/2020 SouthEastern Australian wildfires



Source: Australia's Bureau of Meteorology



Wildland fire behaviour ensemble modeling

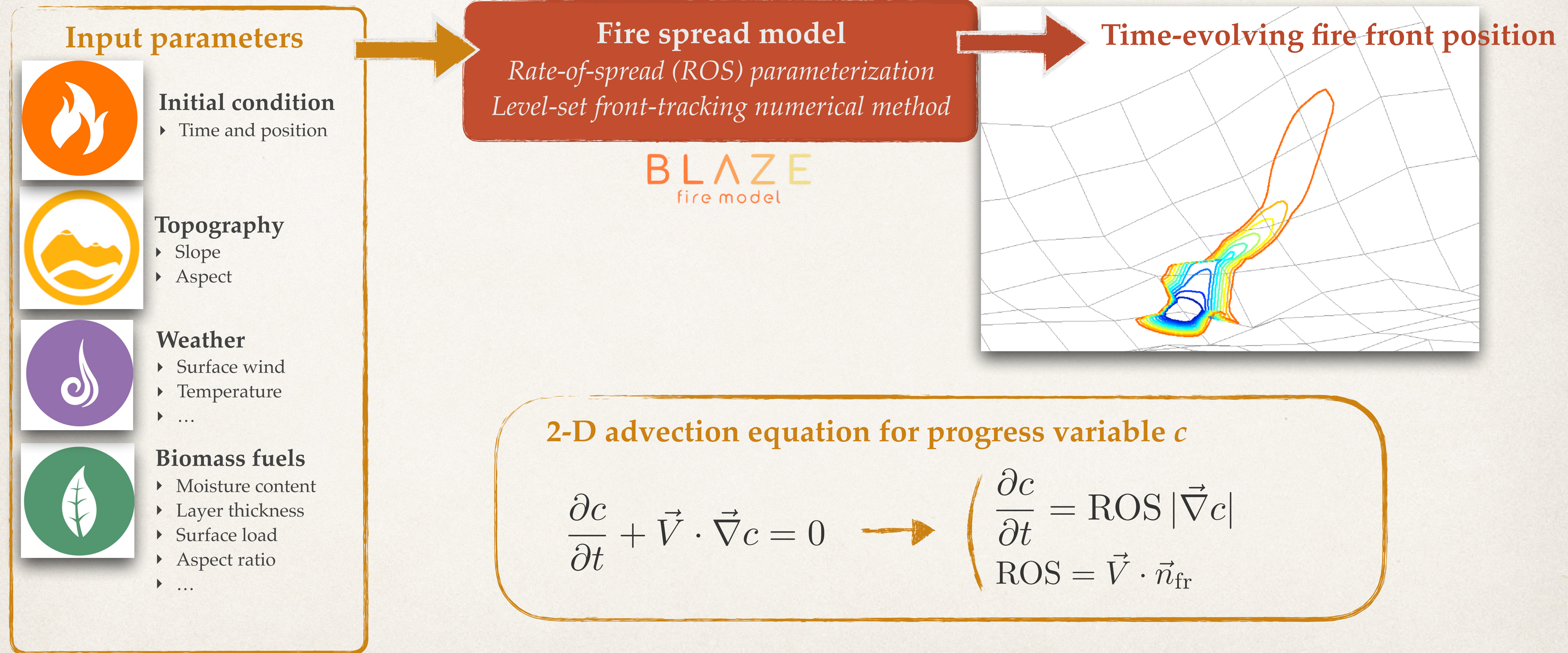
* Surface/atmosphere interactions

⇒ Landscape to meteorological scales (100 m to 100 km)

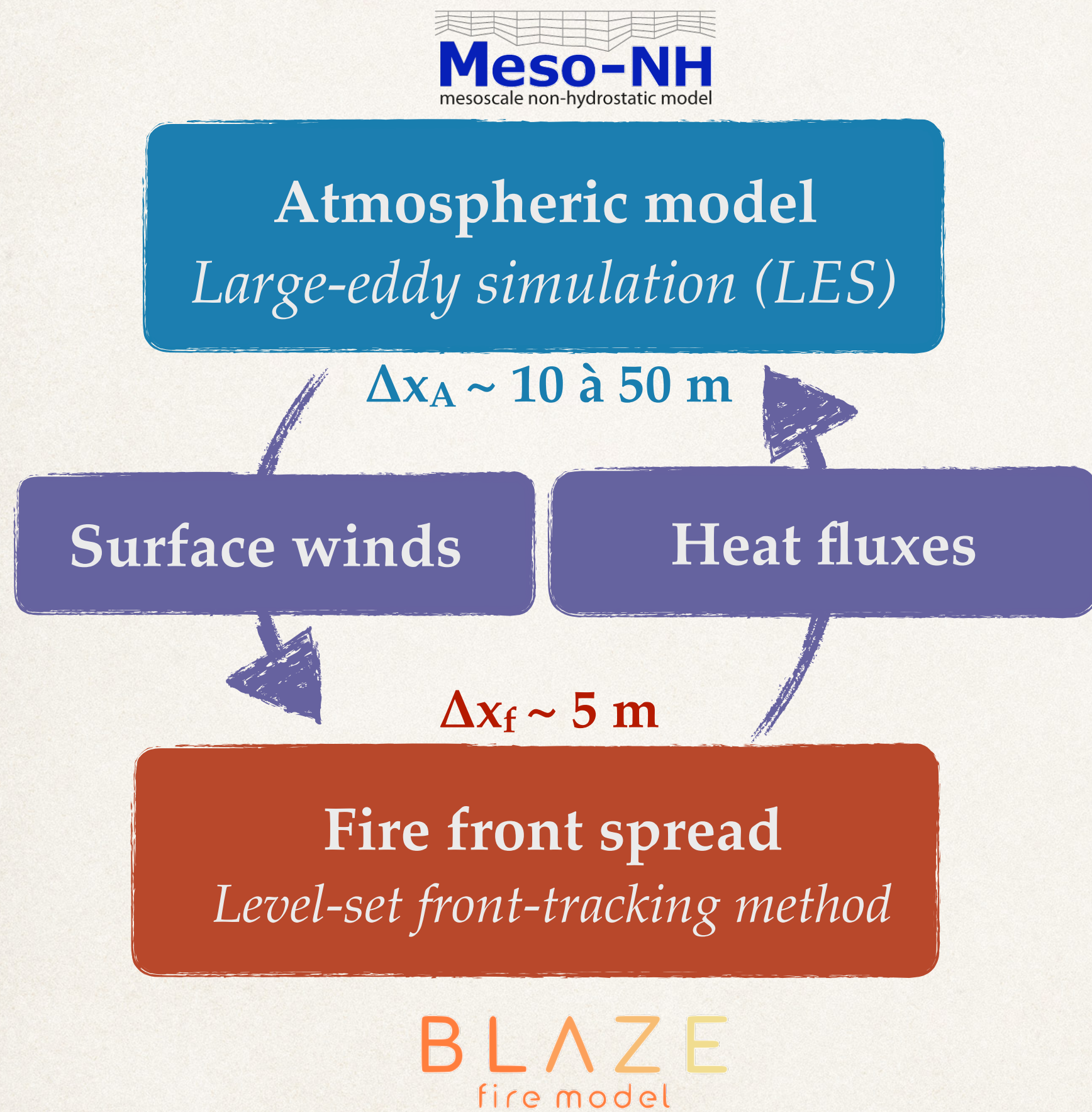
* Source characterization

⇒ Fire front scales (1 m to 100 m)

Big problem .1. Coupled atmosphere/fire model development



Big problem .1. Coupled atmosphere/fire model development



Model evaluation



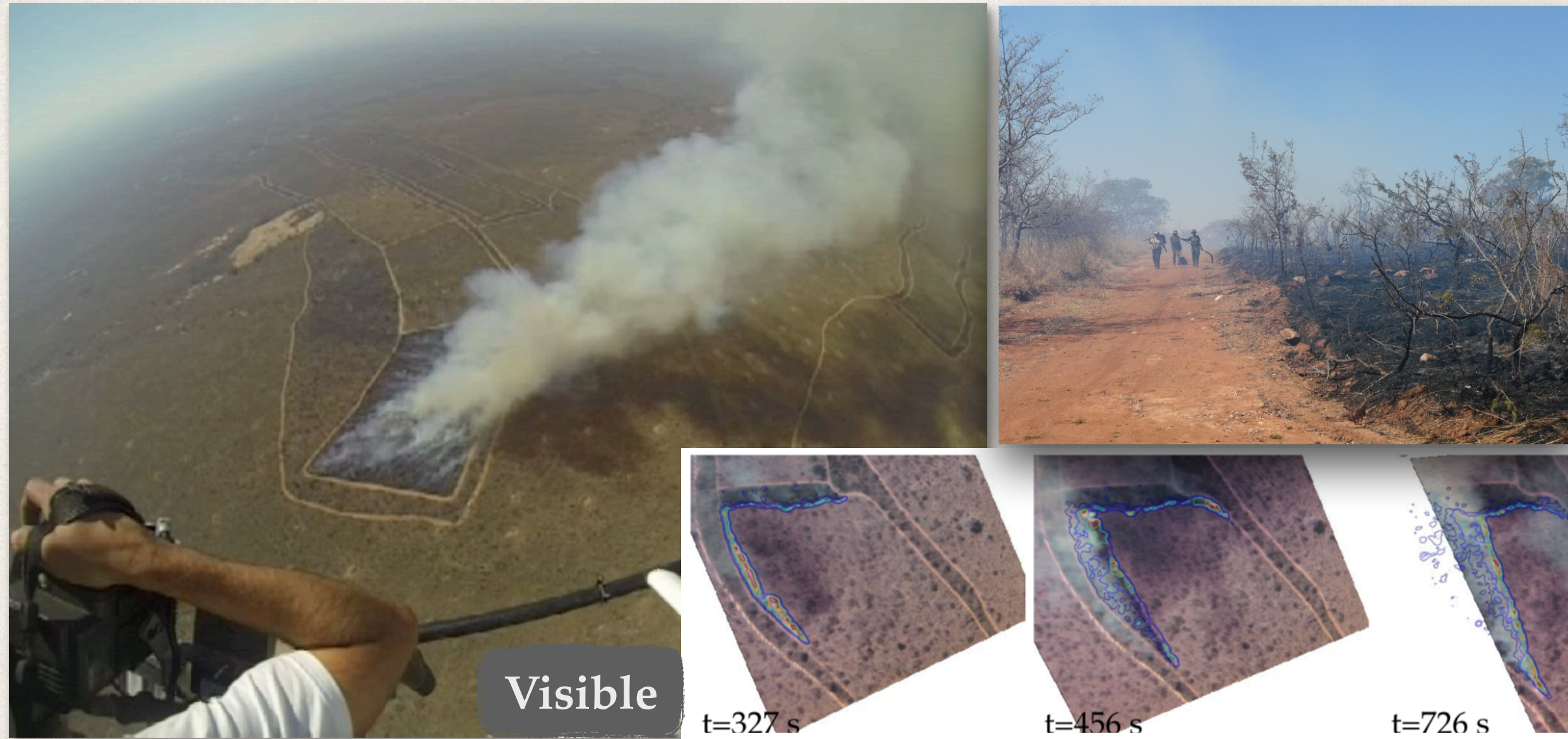
»» FireFlux I grass fire experiment (30 hectares)

»» PhD Aurélien Costes (ANR FireCaster, 2017-2021) co-supervised with Christine Lac (CNRM)

* Costes et al. (2021)

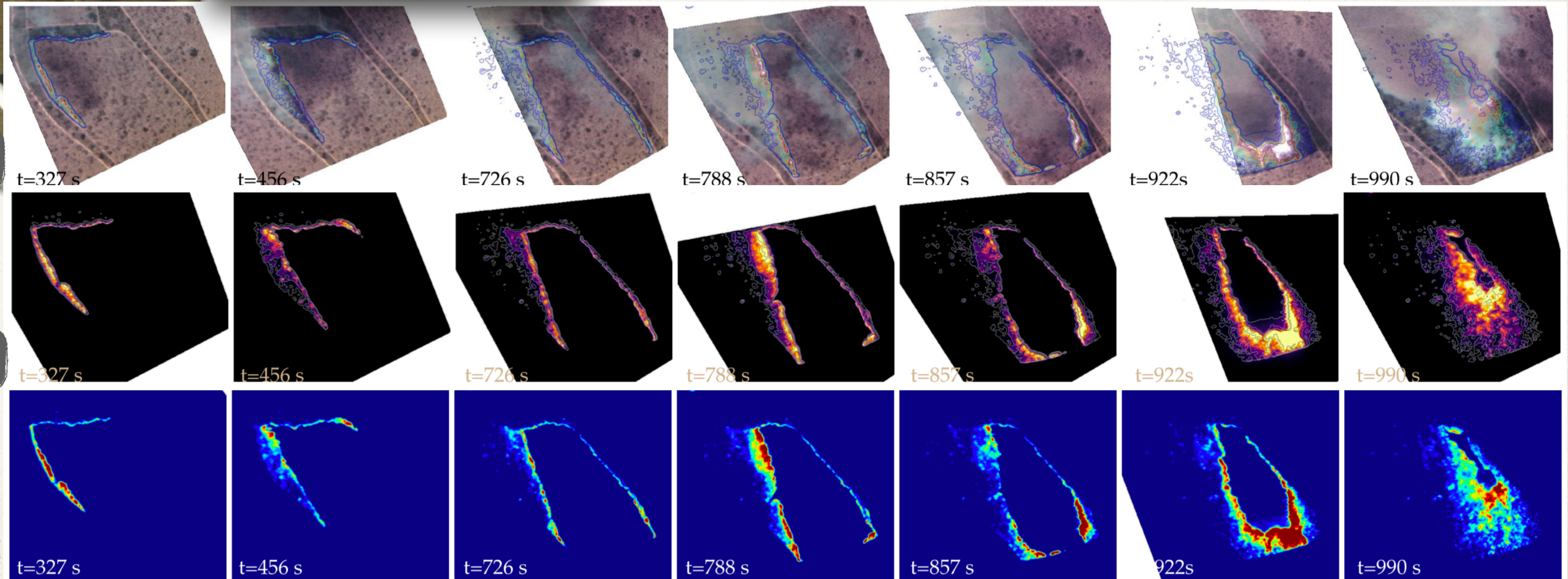


Big problem .2. Observation/model synergy



👉 **Savannah fires (3-8 hectares)**
Kruger National Park, South Africa, 2014

* *Paugam et al. (2021)*



Time

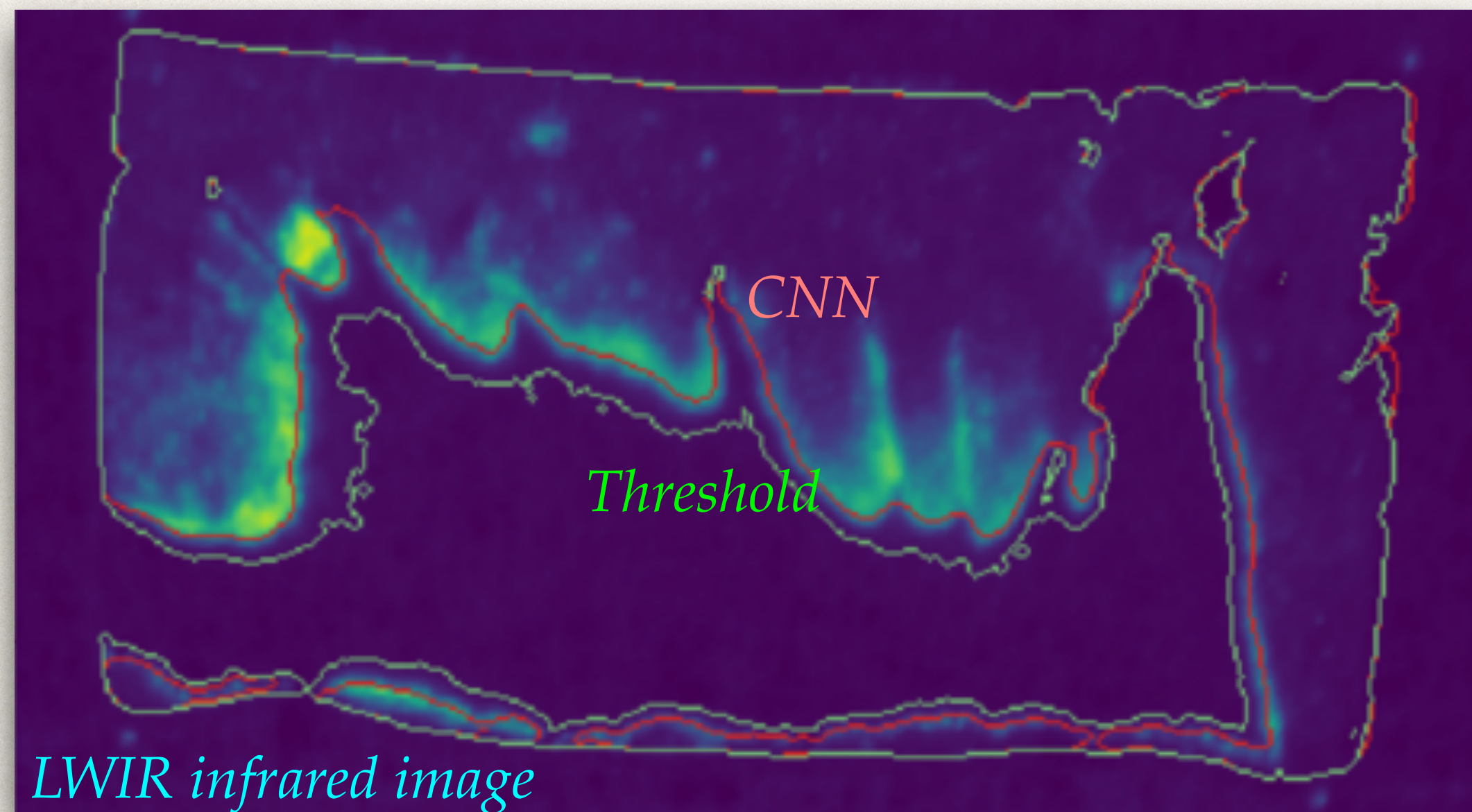
Labeling infrared images to extract observed fire front positions

Issue with radiance threshold due to the complexity of a fire scene (flame emissivity, impact of H₂O/CO₂/soot...)

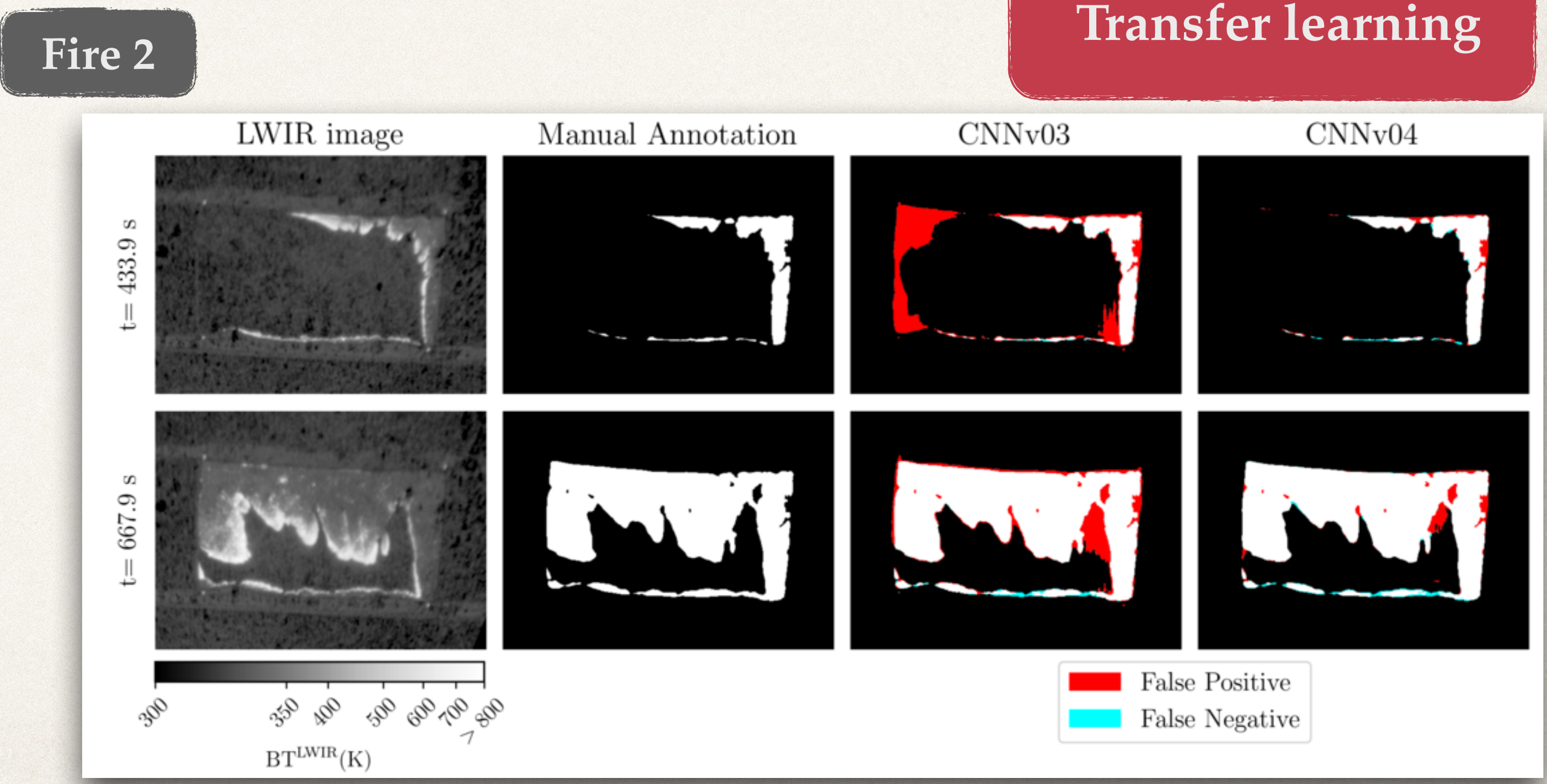
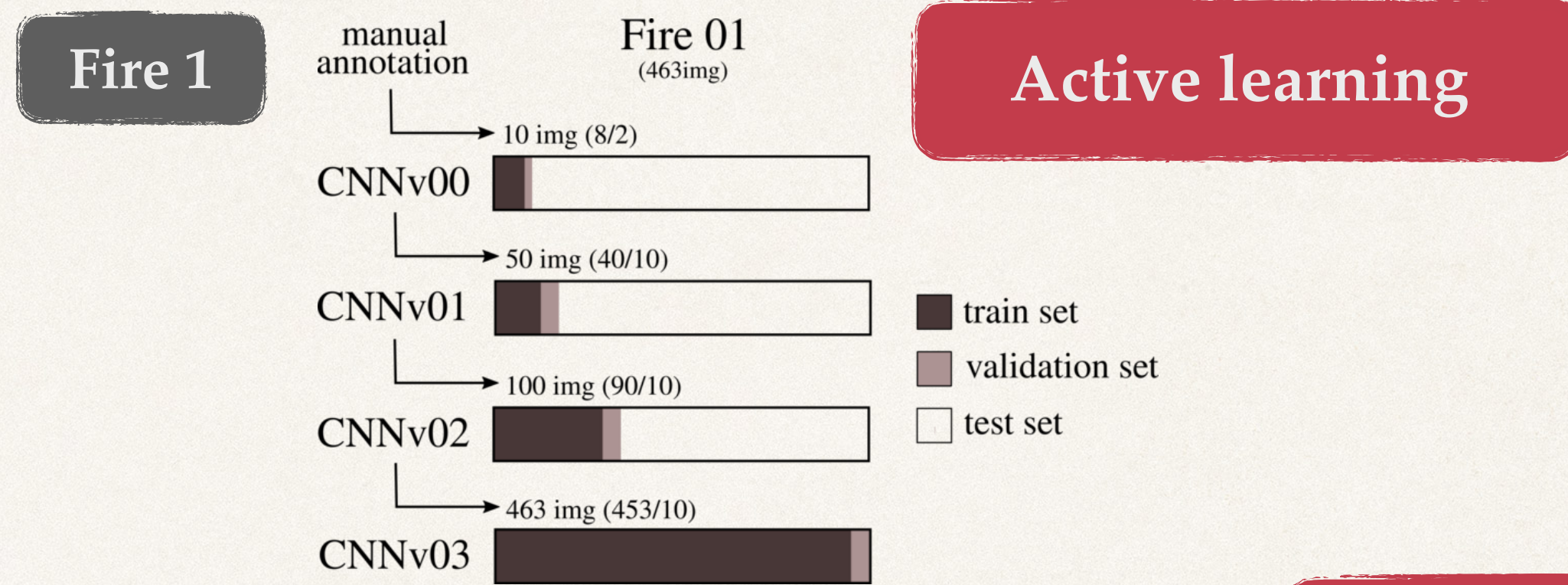


Convolutional neural networks (CNN)

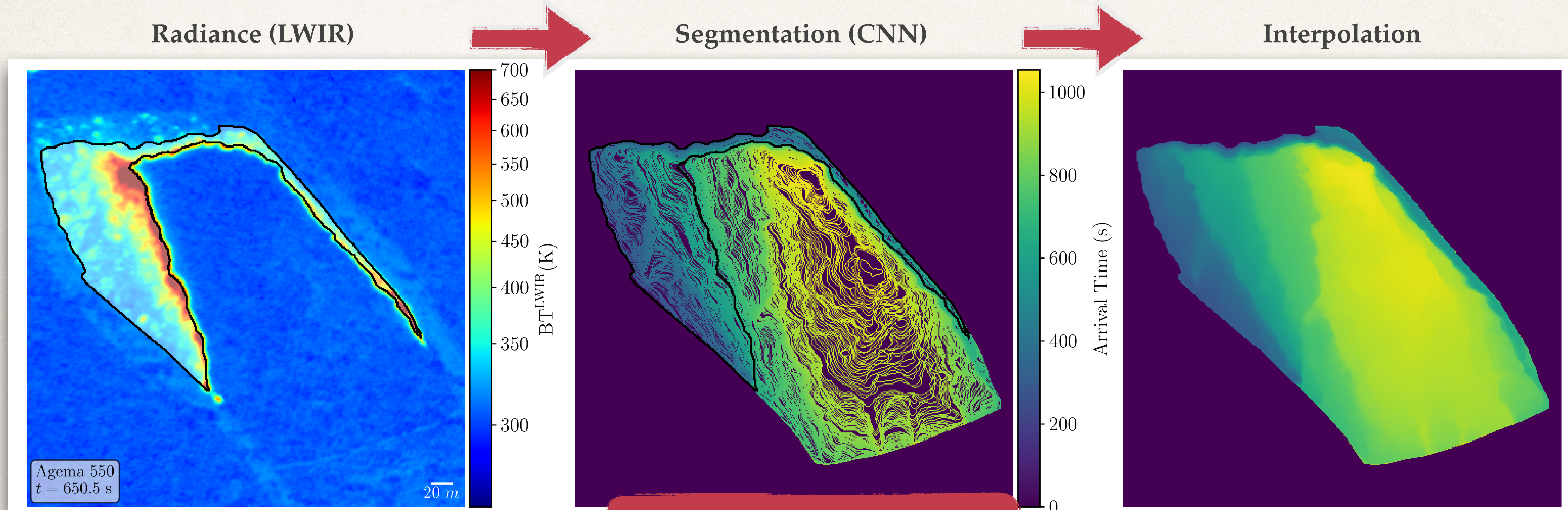
» Collaboration with Ronan Paugam (MSCA-IF 3DFIRELAB)



* Paugam et al. (under review)

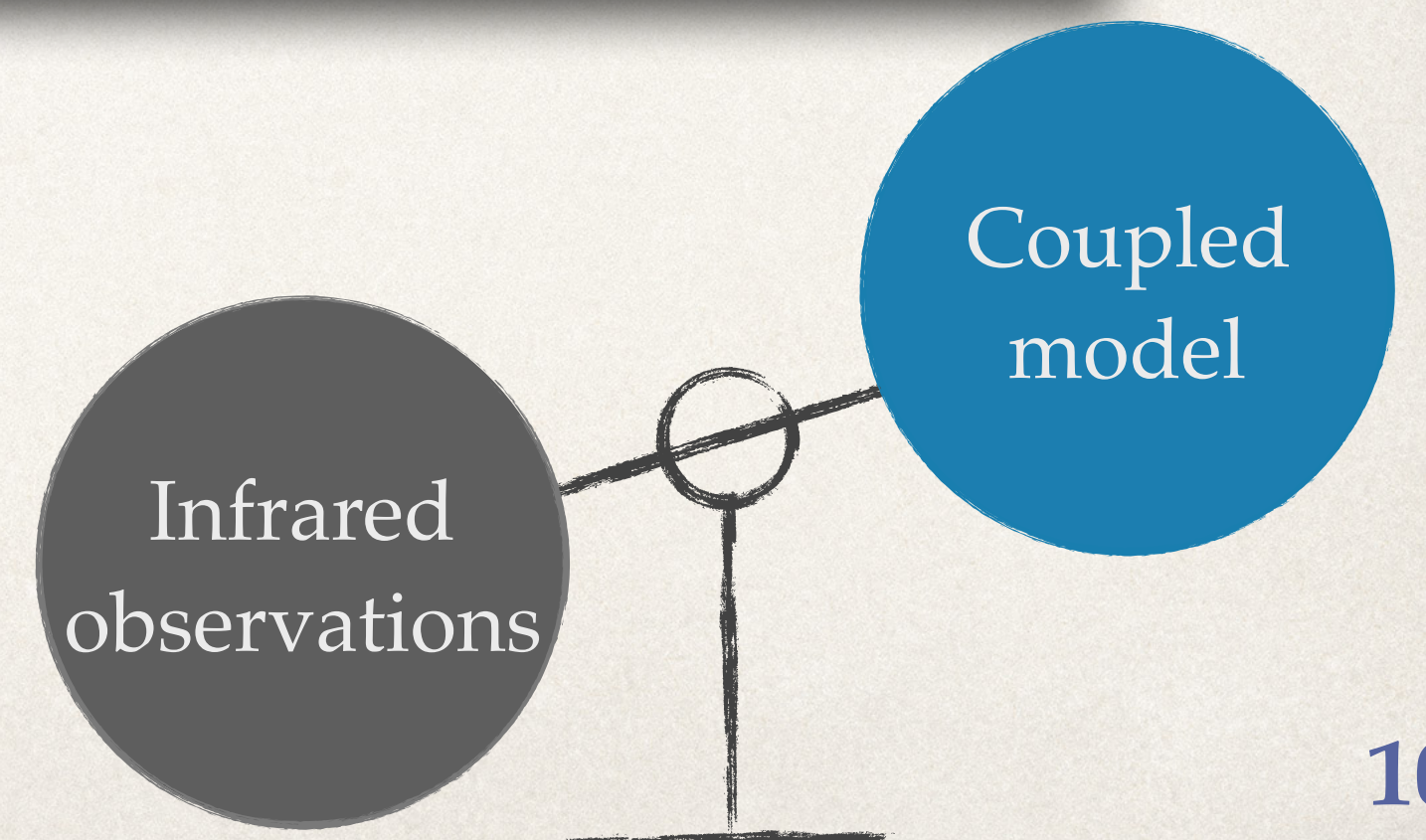


Labeling infrared images to extract observed fire front positions



Data assimilation

- ▶ Observed fire behaviour metrics (*fire front, rate of spread, intensity...*)
- ▶ Sensitivity to observation errors and frequency (*optimal sensor placement*)



Wildland fire behaviour ensemble modeling

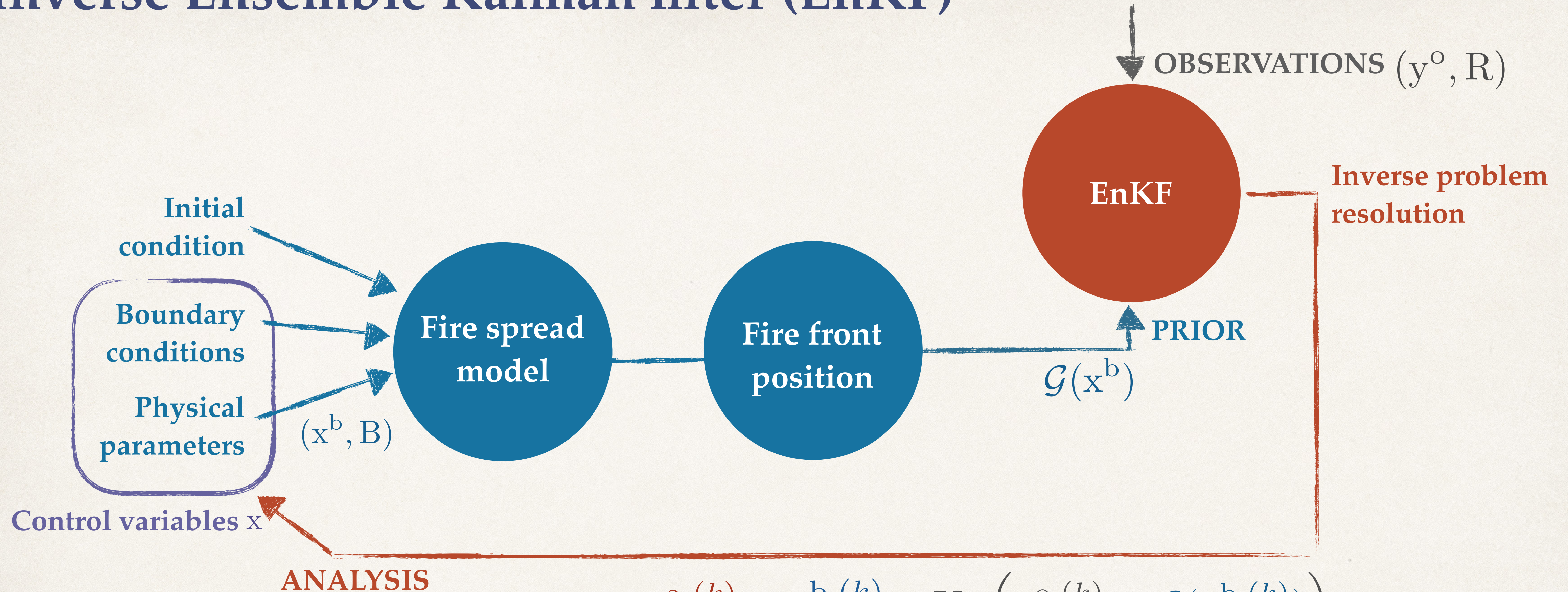
* Surface/atmosphere interactions

⇒ *Parametric reduced-order model for large-eddy simulation*

* Source characterization

⇒ *Front data assimilation with parameter estimation*

Inverse Ensemble Kalman filter (EnKF)



$$x^{a,(k)} = x^{b,(k)} + K_e \left(y^{o,(k)} - \mathcal{G}(x^{b,(k)}) \right)$$

$$K_e = \underbrace{BG^T}_{\text{1) Sensitivity parameter-observable}} \underbrace{\left(\underbrace{GBG^T}_{\text{2) Uncertainties in the observation space}} + R \right)^{-1}}$$

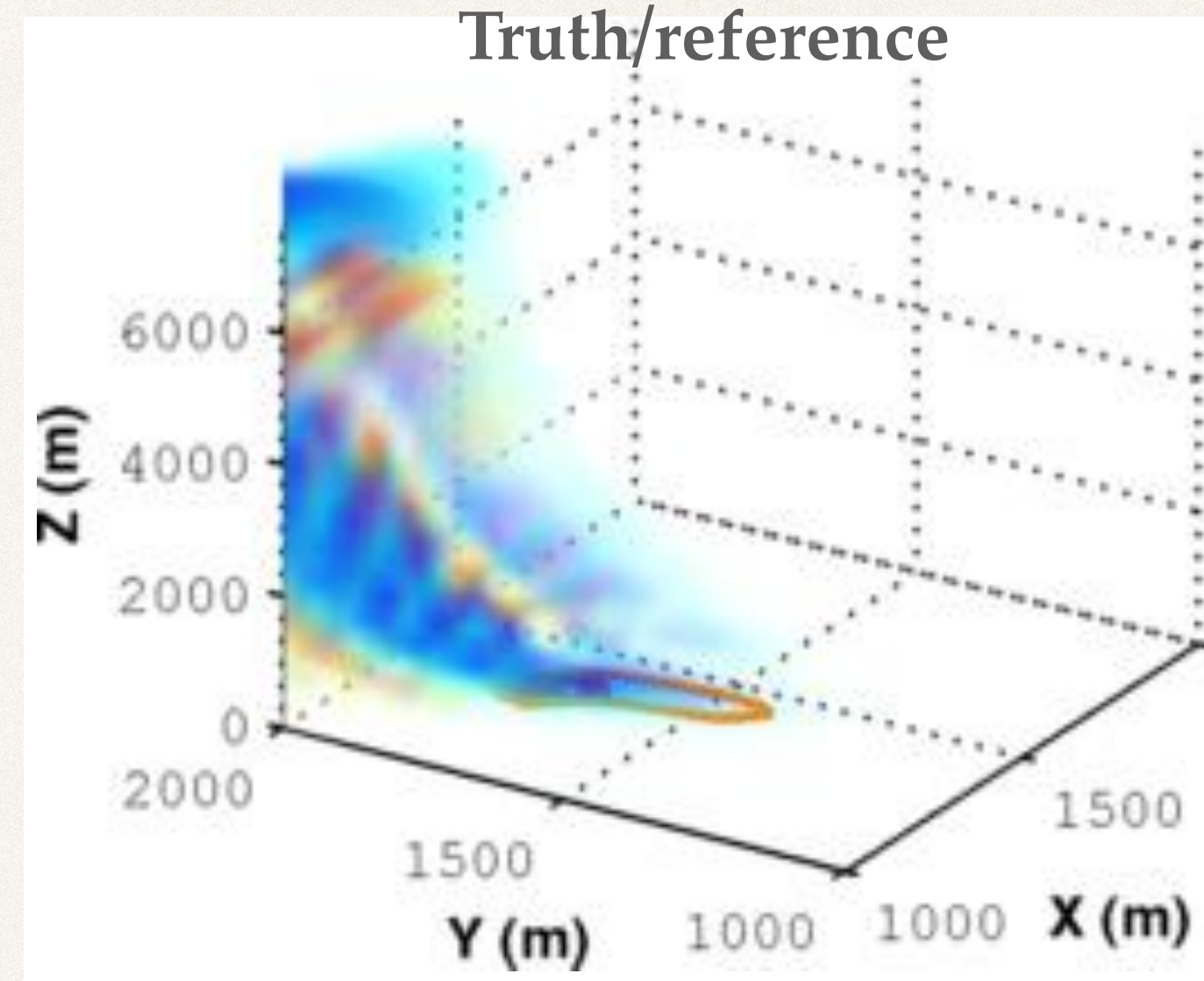
- 1) Sensitivity parameter-observable
- 2) Uncertainties in the observation space

Issue of position errors

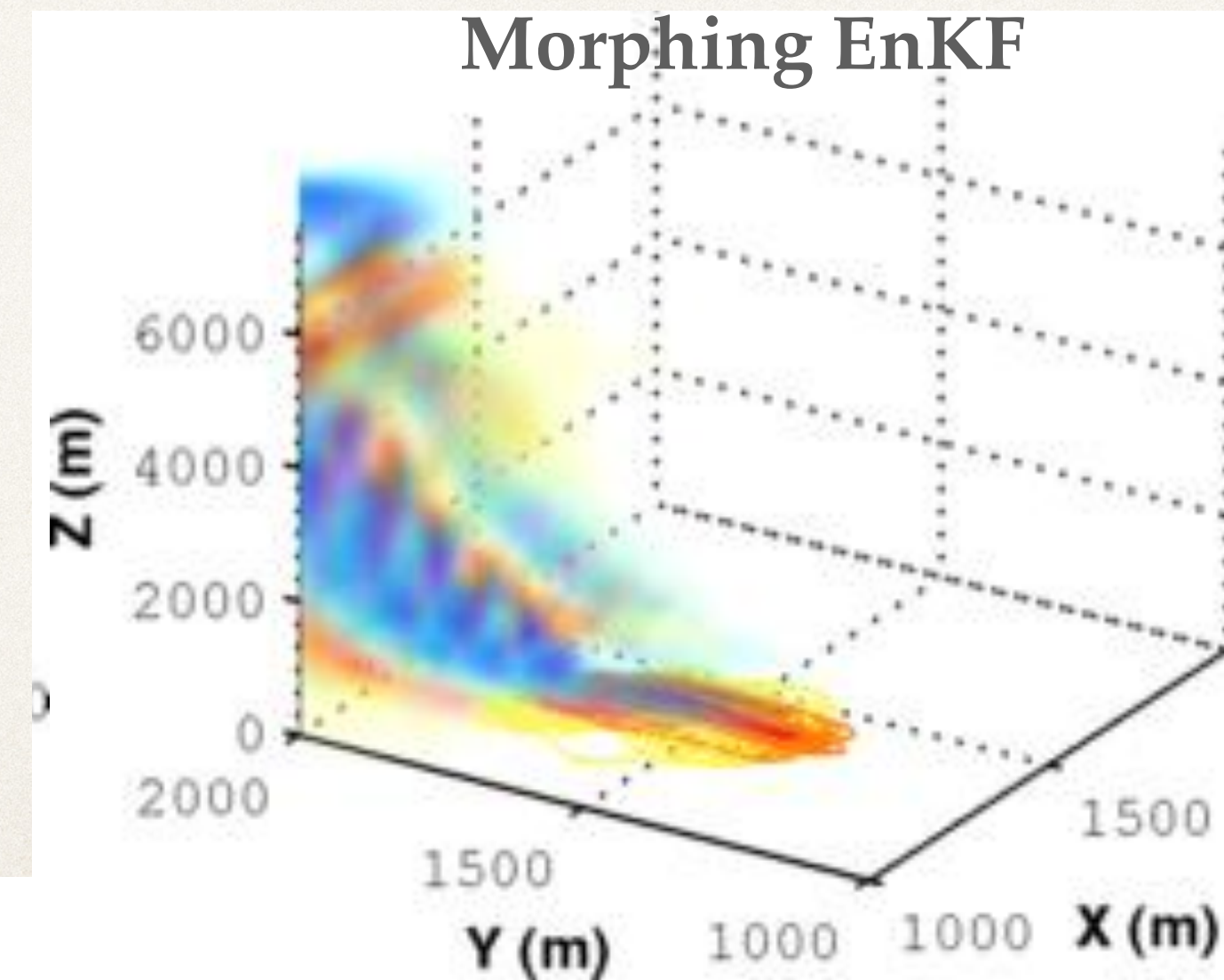
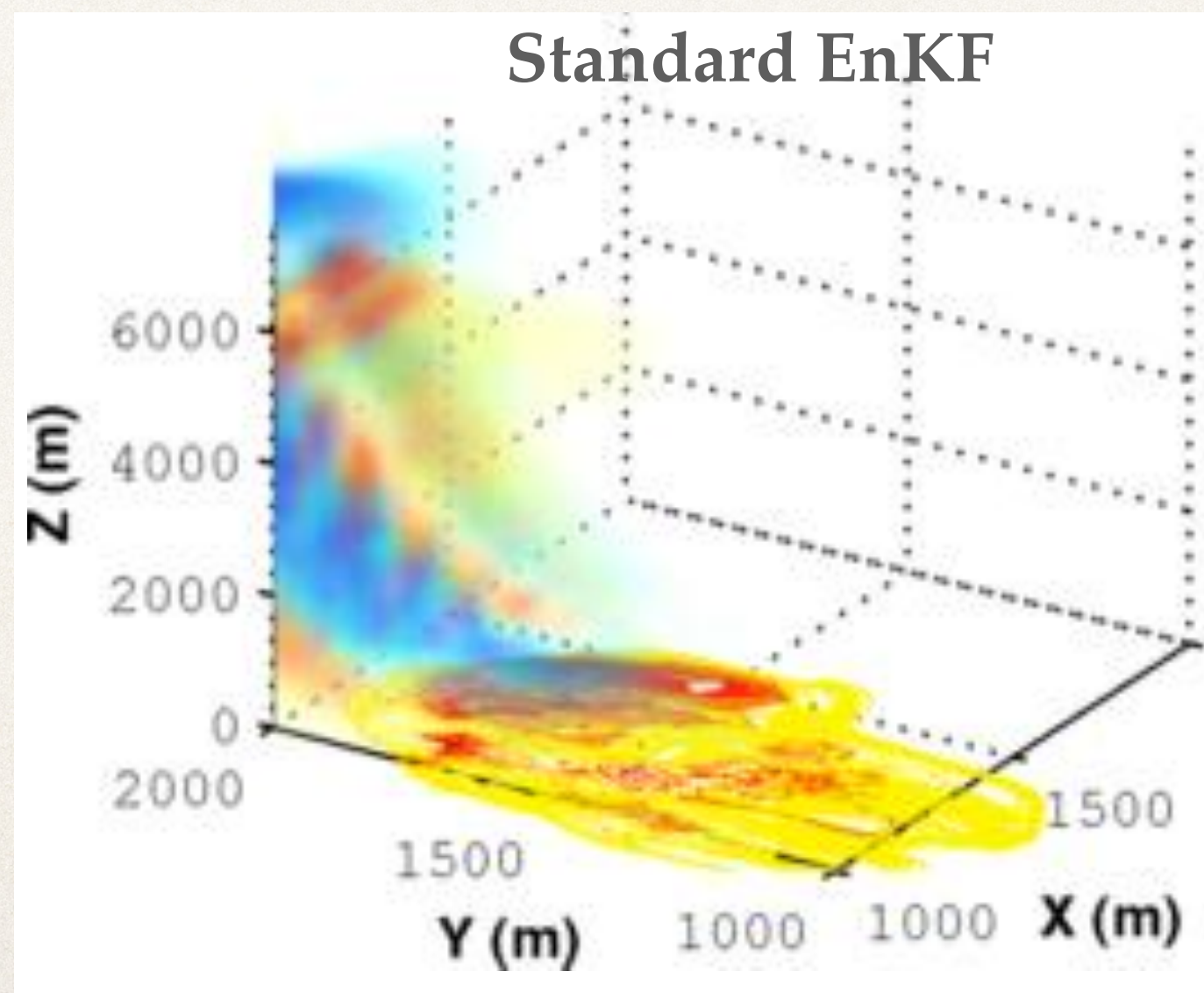
Failure of standard EnKF

»→ Generation of artificial structures during the analysis when position errors are large

- * Hurricane: Chen and Snyder (2007)
- * Wildfire: Beezley and Mandel (2008)



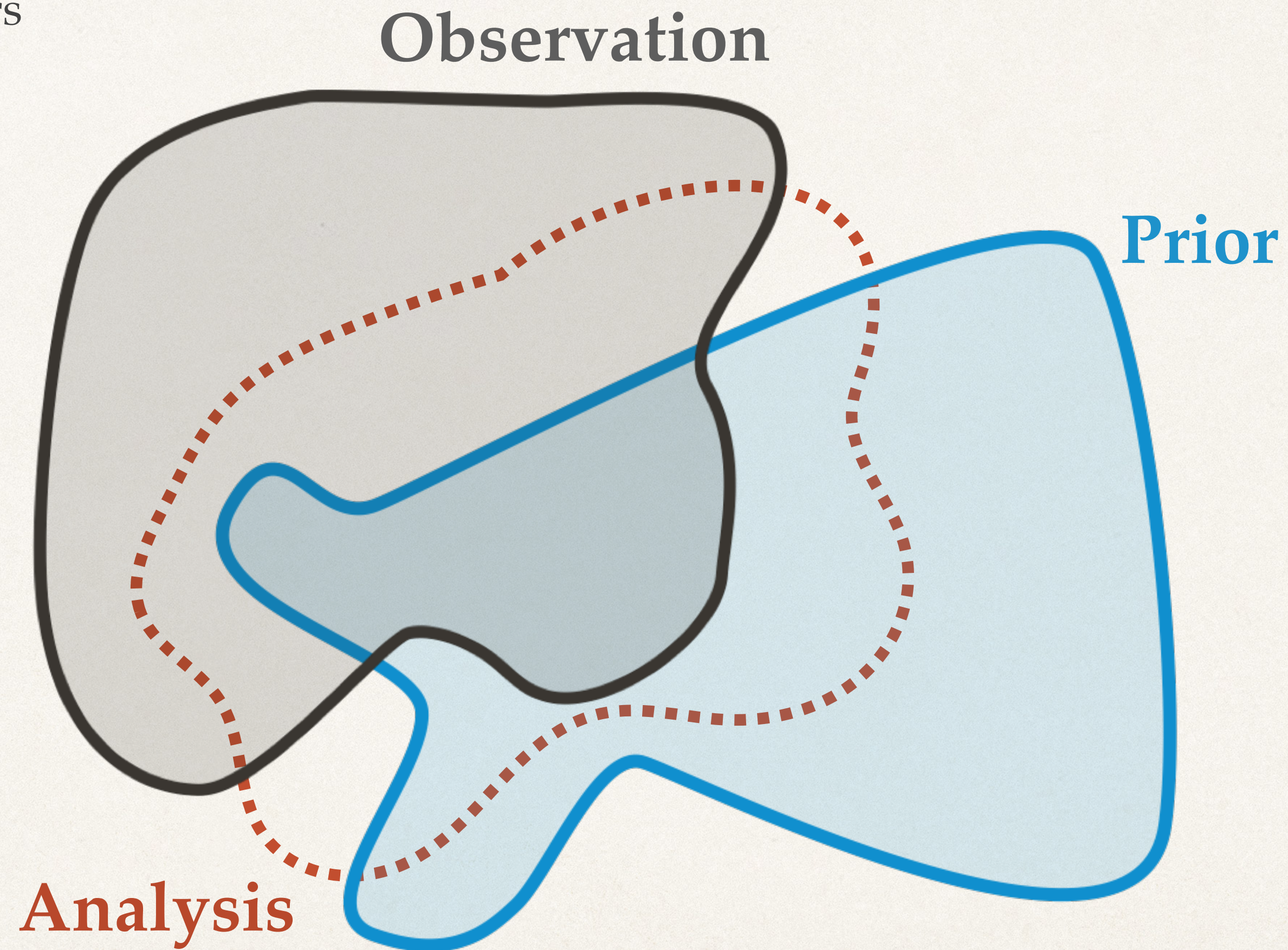
* Beezley (PhD, University of Colorado, 2009)



Issue of position errors

Failure of standard EnKF

»→ Generation of artificial structures during the analysis when position errors are large



Representative and efficient ensemble generation

► Collaboration with **Didier Lucor** (LISN)

Front shape similarity measure

► Collaboration with **Annabelle Collin** and **Philippe Moireau** (Inria)

Front shape similarity measure

$$\text{Min } \mathcal{J}(\mathbf{x}) = \|\mathcal{G}(\mathbf{x}) - y^0\|^2$$



Chan-Vese data fitting functional used in image segmentation

* Chan and Vese (2001)

$$\text{Min } \mathcal{J}(\phi, y^0) = \int_{\Omega} H_v(\phi) [y^0 - C_1(y^0, \phi)]^2 + (1 - H_v(\phi)) [y^0 - C_0(y^0, \phi)]^2 dx$$

“inside” measuring HITS

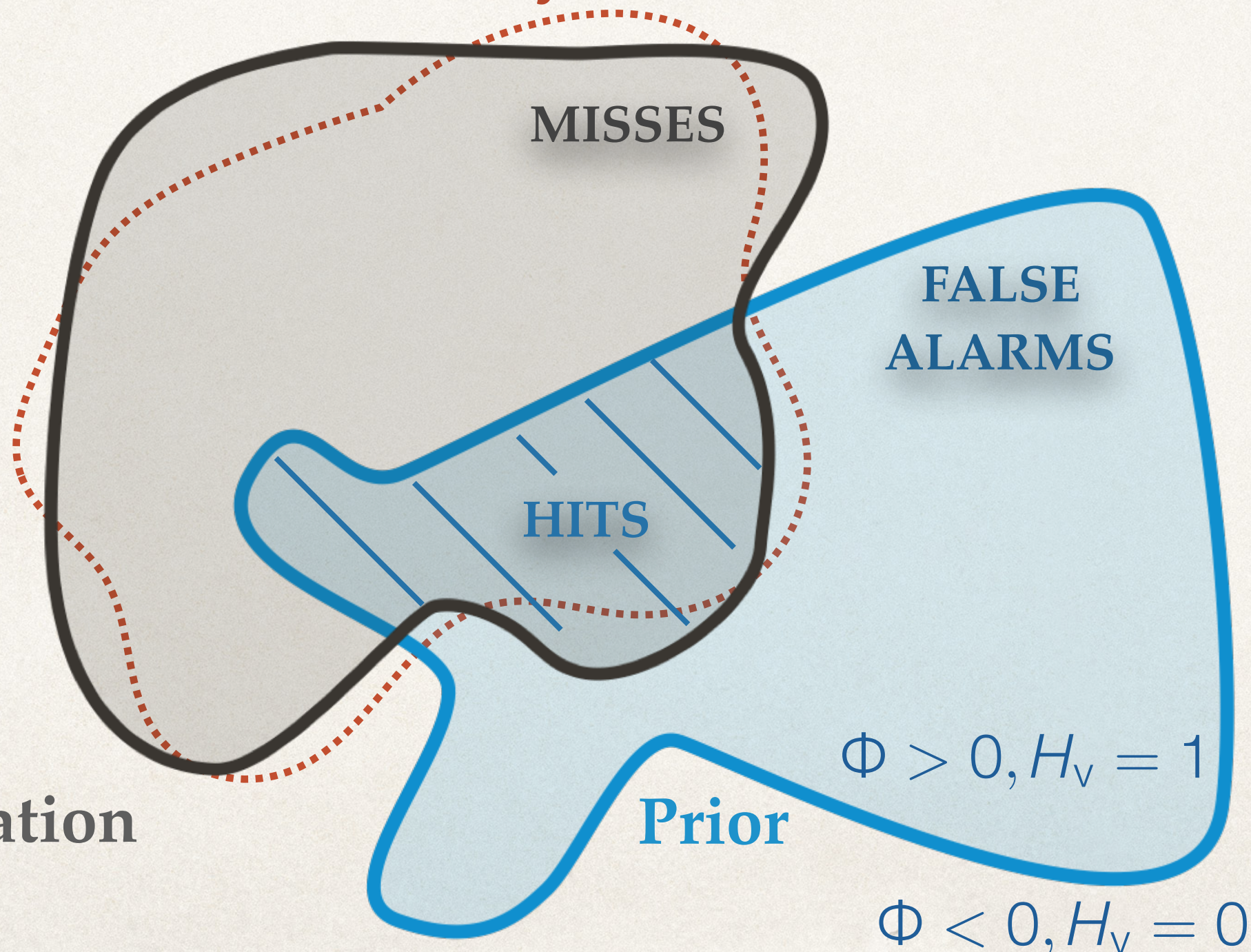
(mean of obs. in simulated burnt area)

“outside” measuring MISSES

(mean of obs. in simulated unburnt area)



Analysis



$$C_0 \approx 0, C_1 \approx 1$$

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



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

Fire front data assimilation approach

Components * Collin et al. (2015), Rochoux et al. (2018)

- ▶ New Luenberger observer for state estimation in level-set formalism

Fire spread model

Nudging term

$$\frac{\partial c}{\partial t} = \text{ROS} |\vec{\nabla} c| - \lambda \delta(c) \left\{ [y^o - C_{max}]^2 - [y^o - C_{min}]^2 \right\}$$

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

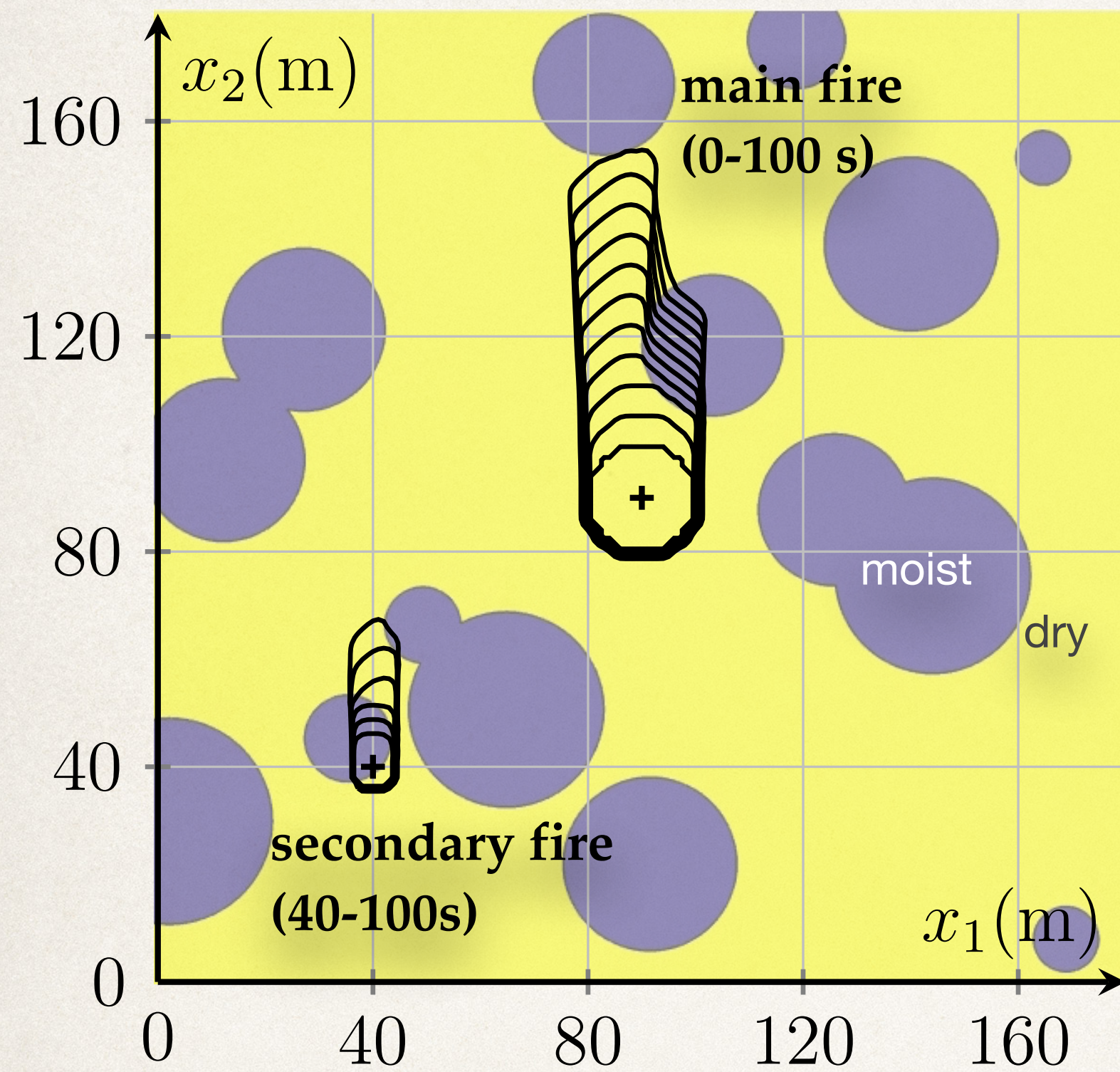
- ▶ Extended EnKF to discrepancy operator (based on the Chan-Vese functional gradient) for parameter estimation

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

Discrepancy operator

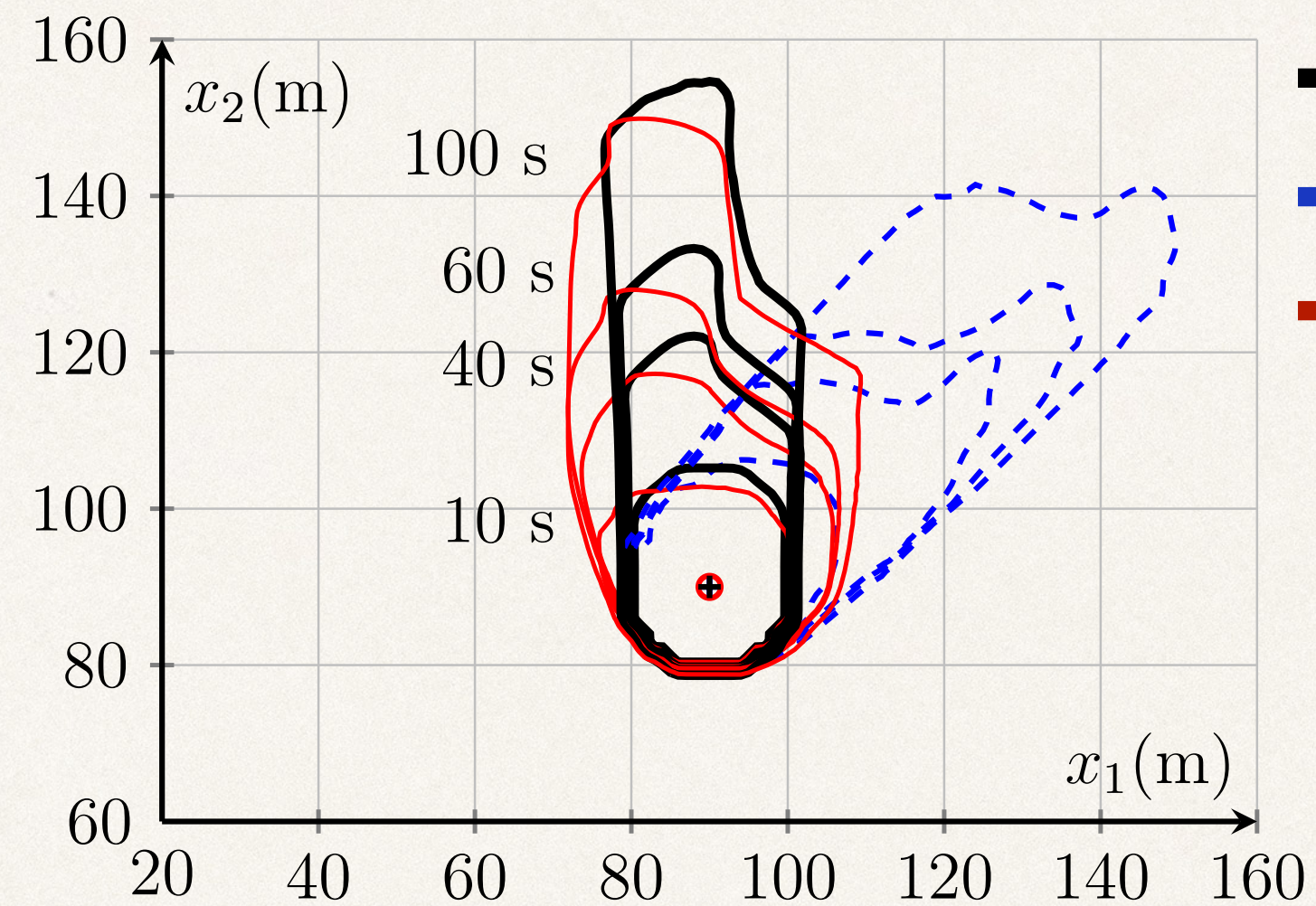
$$\begin{aligned} & (\mathcal{D}^{\epsilon,+}, \mathcal{D}^{\epsilon,-})^T \\ & \mathcal{D}^{\epsilon,-} = \left[1 - \frac{2}{\pi} \arctan\left(\frac{\phi}{\epsilon}\right) \right] \left[y^o - C_{\min}(y^o, \phi) \right] \\ & \mathcal{D}^{\epsilon,+} = \left[1 + \frac{2}{\pi} \arctan\left(\frac{\phi}{\epsilon}\right)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

Illustration on a synthetic test case



Results * Rochoux et al. (2018)

► Joint estimation with wrong wind intensity / direction



— observation
- - background mean
— analysis mean

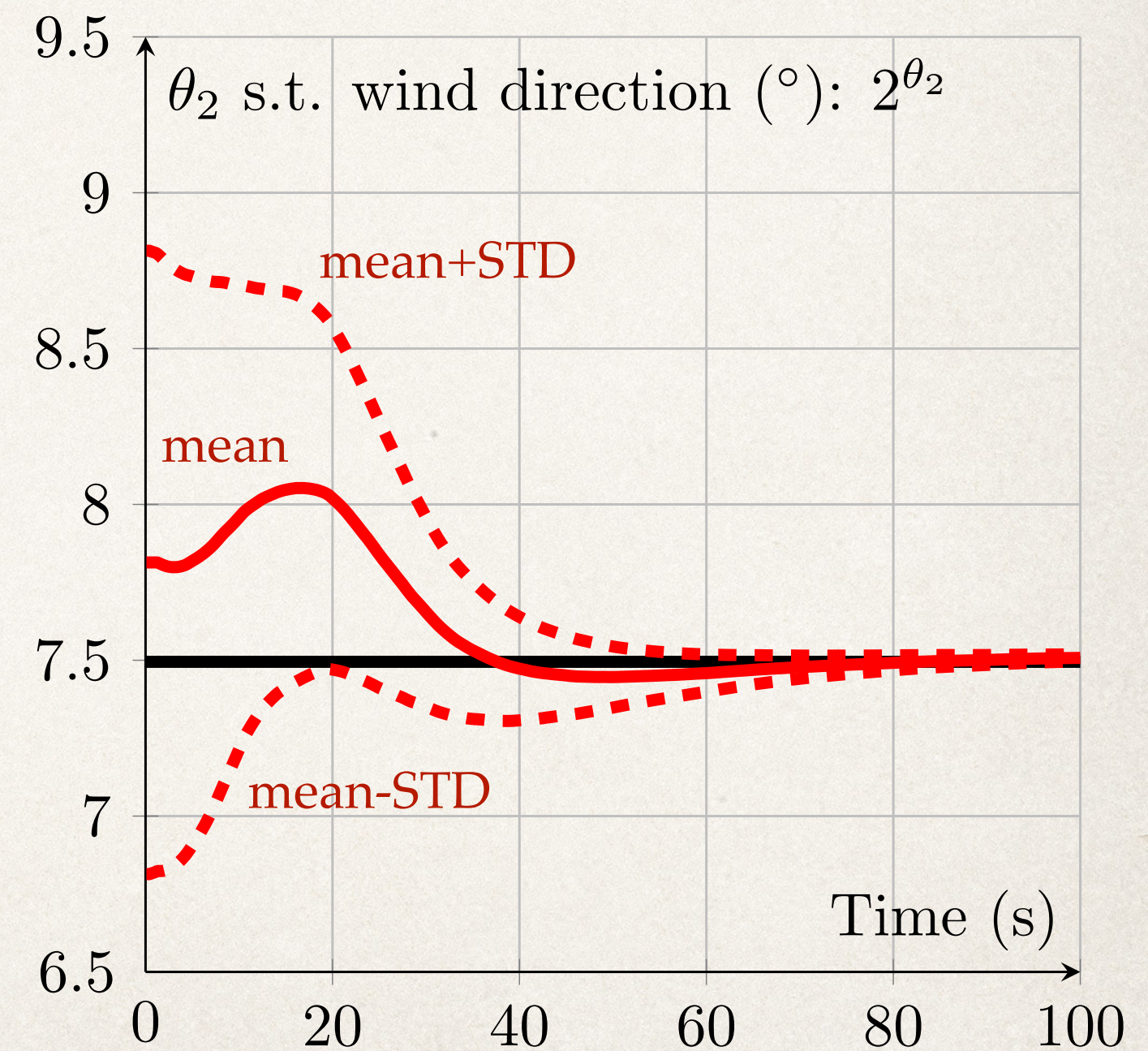
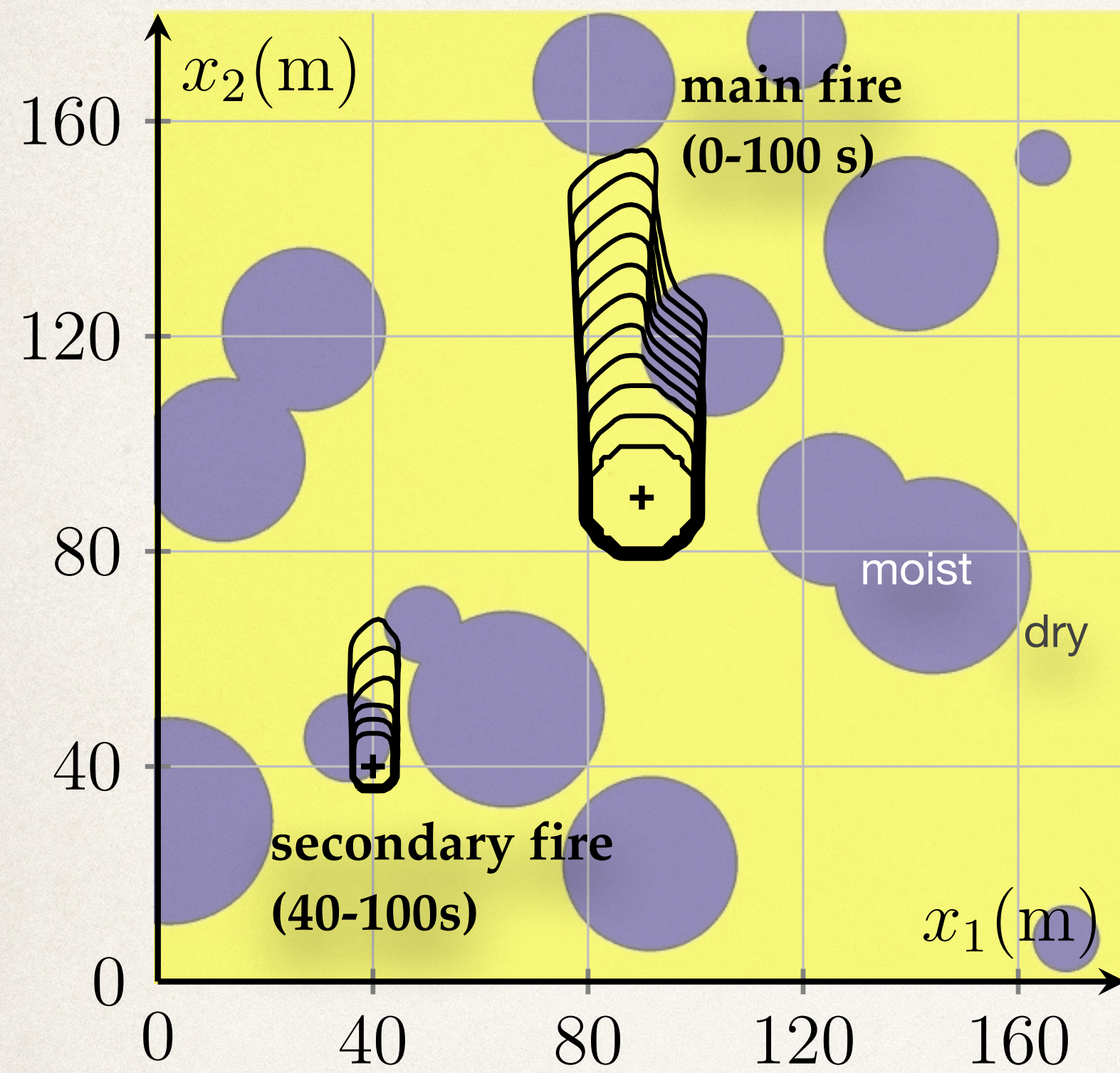
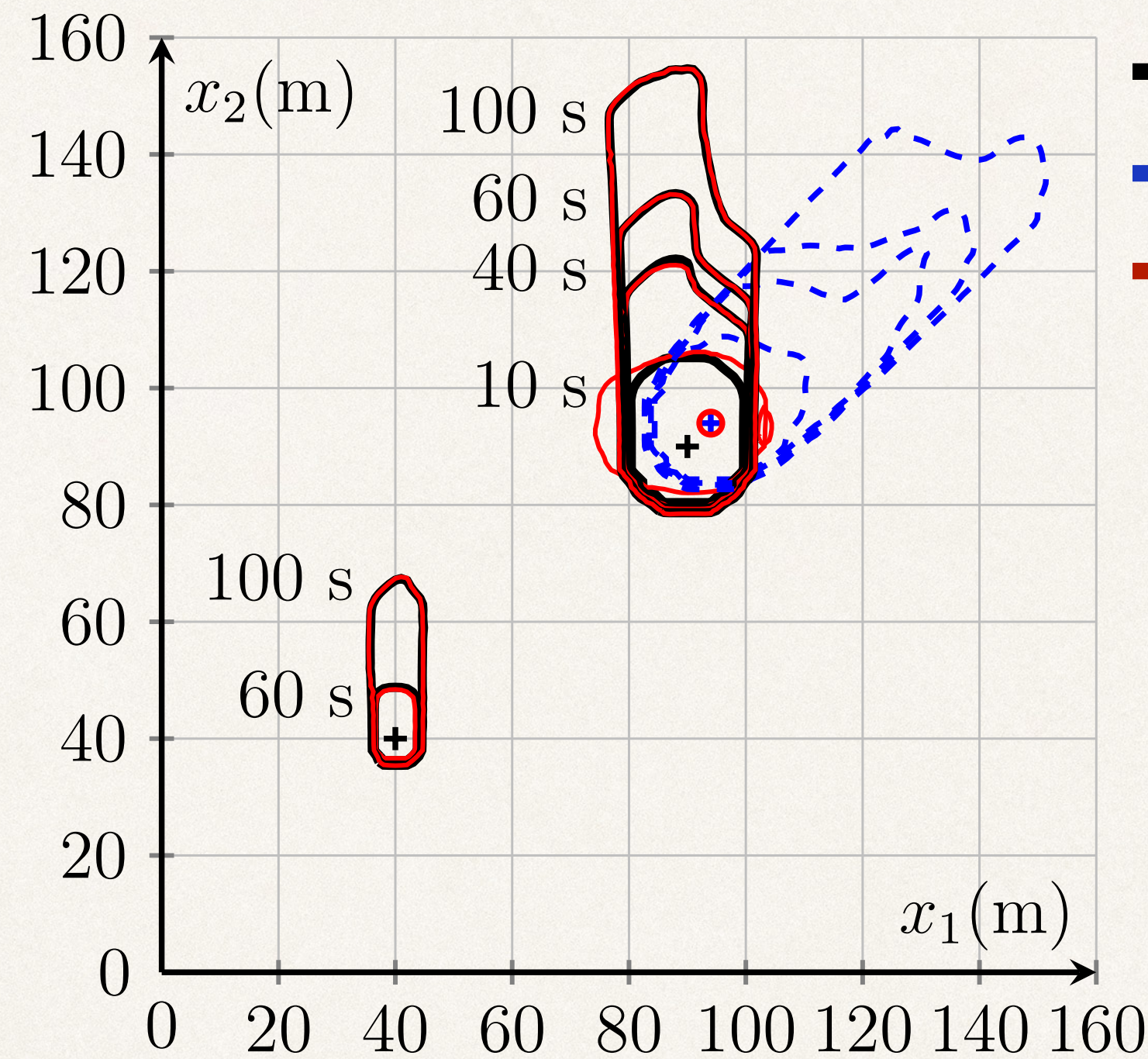


Illustration on a synthetic test case

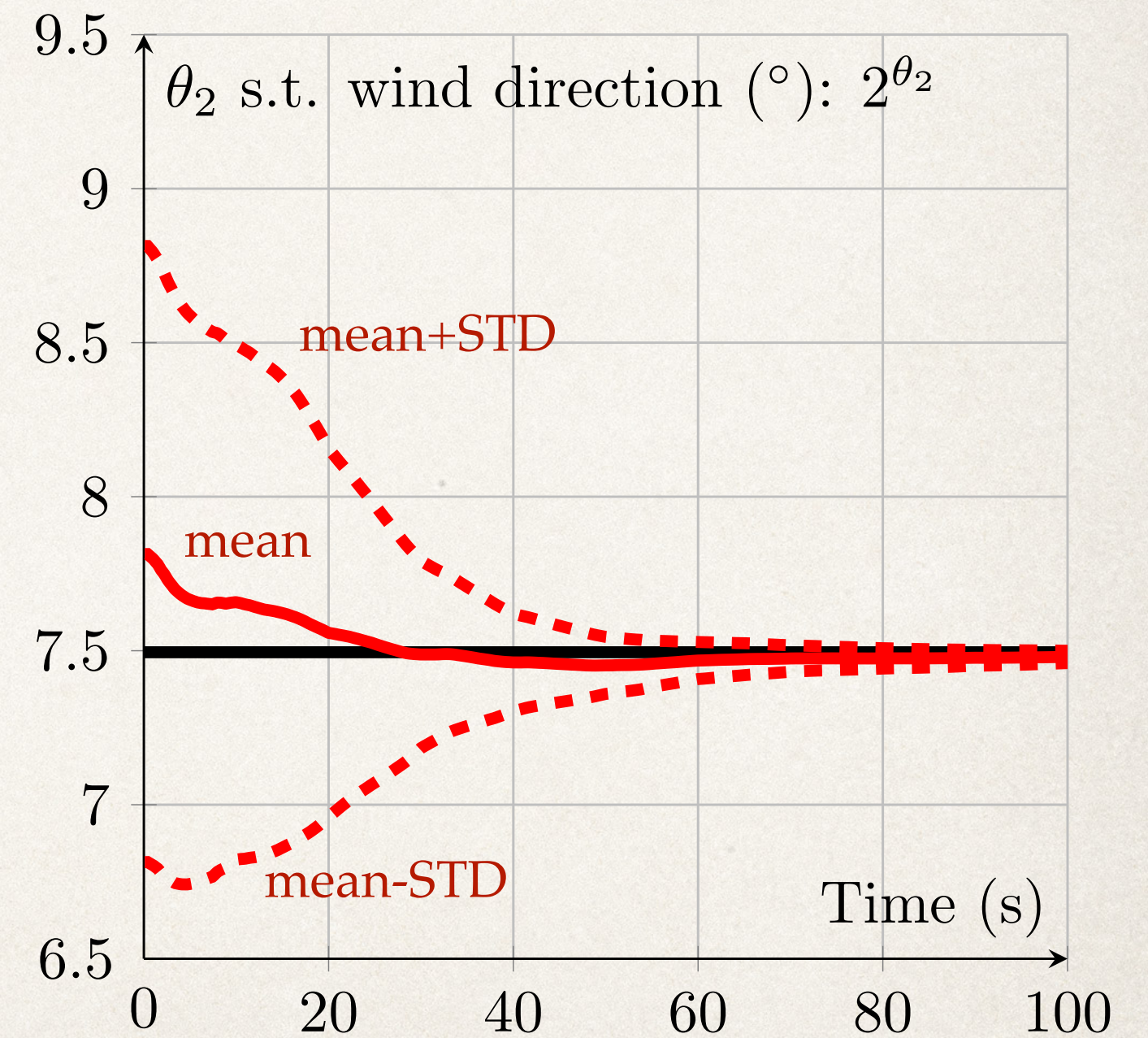


Results * Rochoux et al. (2018)

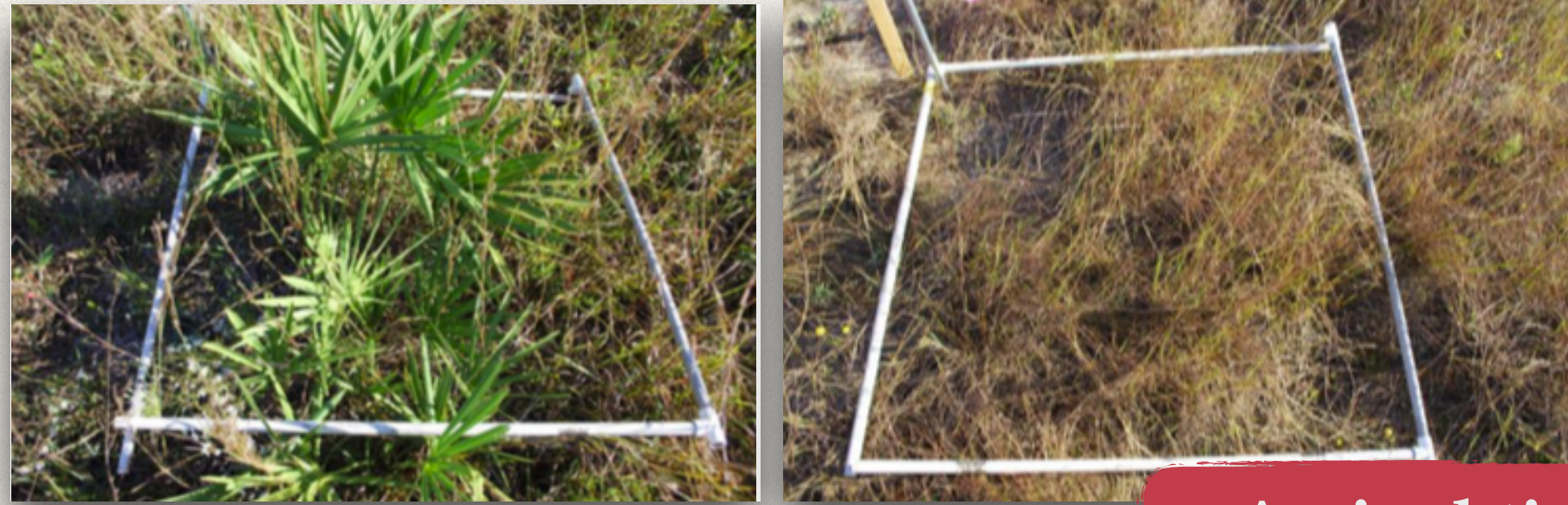
► Joint estimation with wrong wind intensity / direction and wrong ignitions



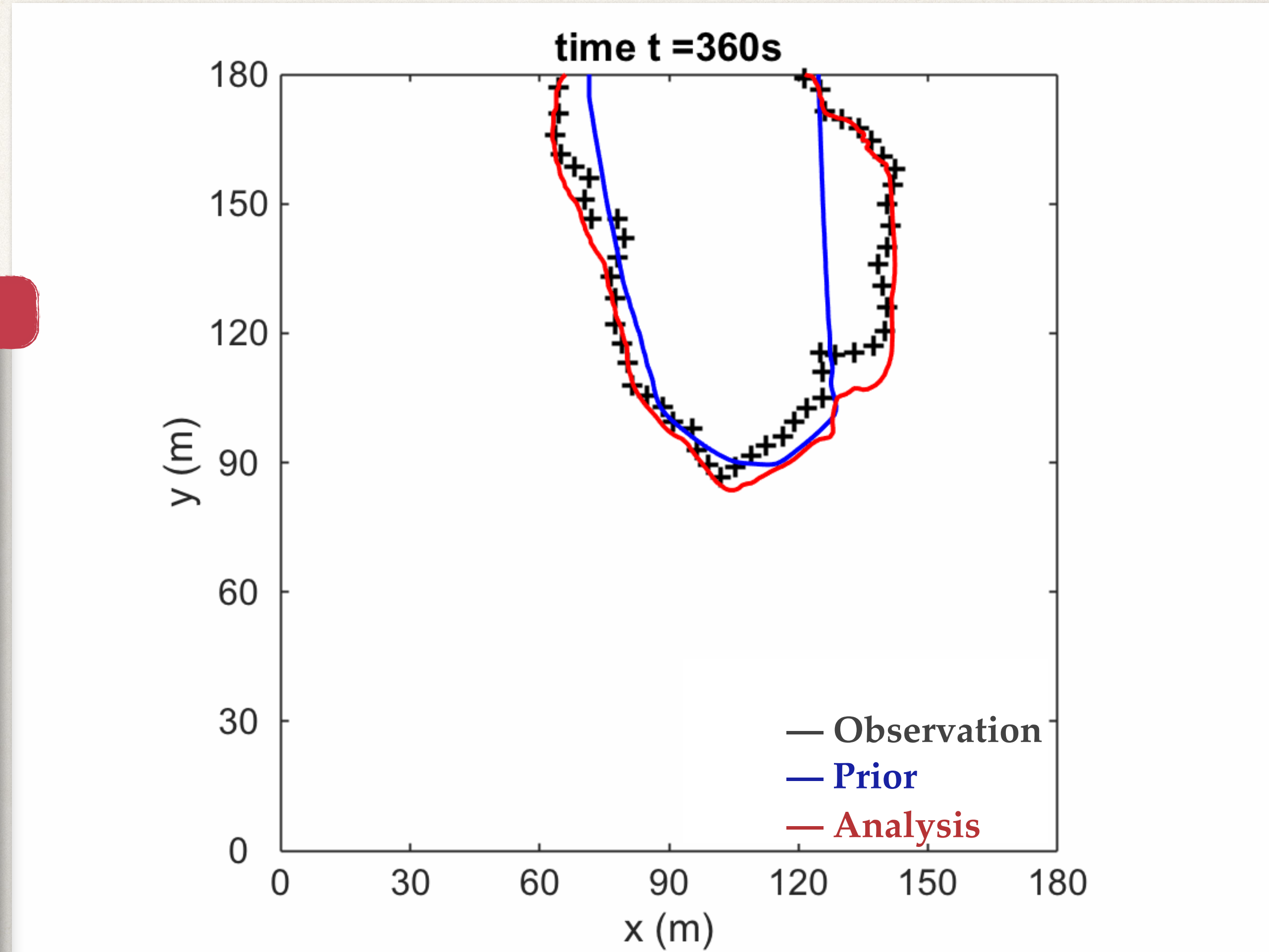
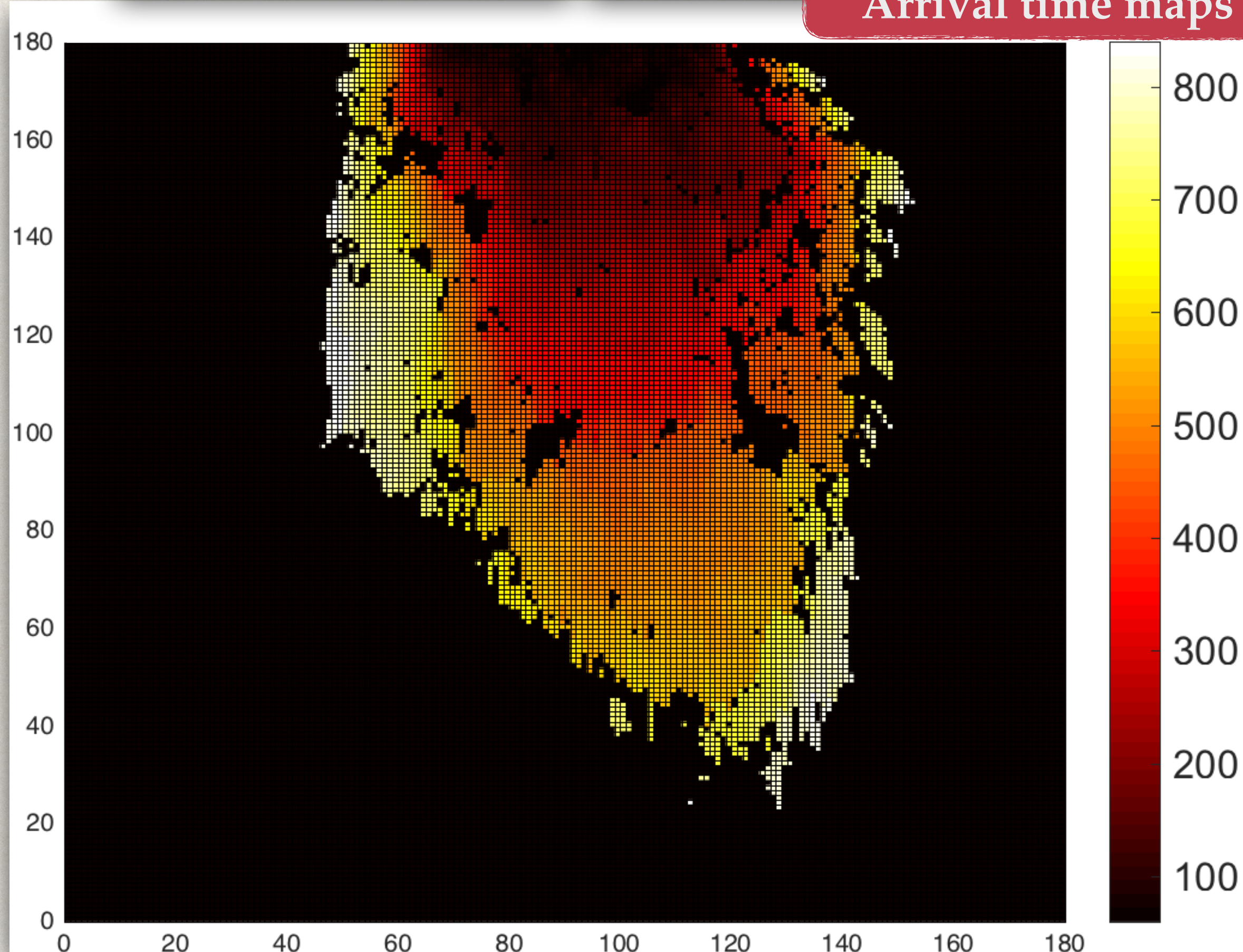
— observation
 - - background mean
 — analysis mean



Application to RxCADRE experimental grass fire

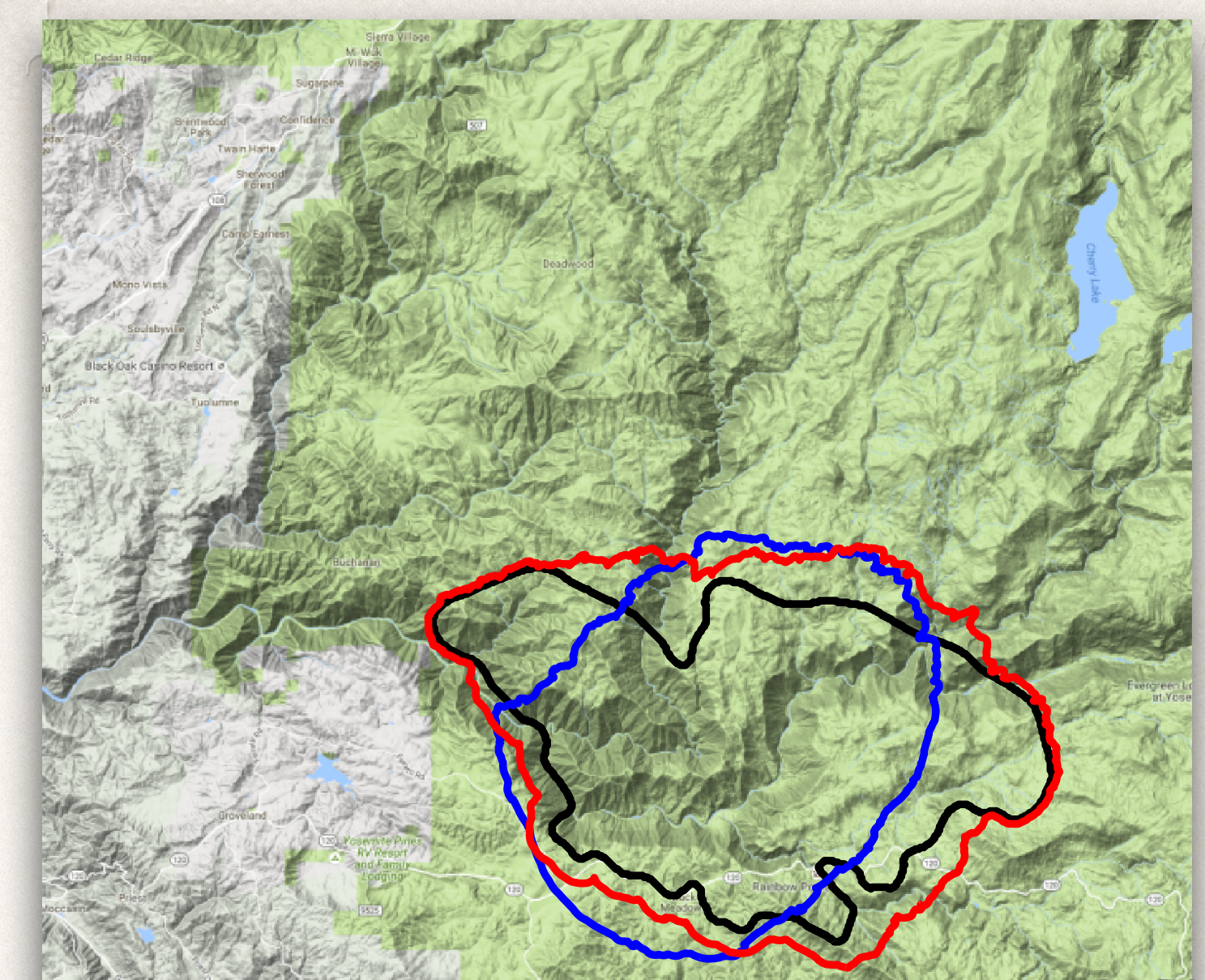
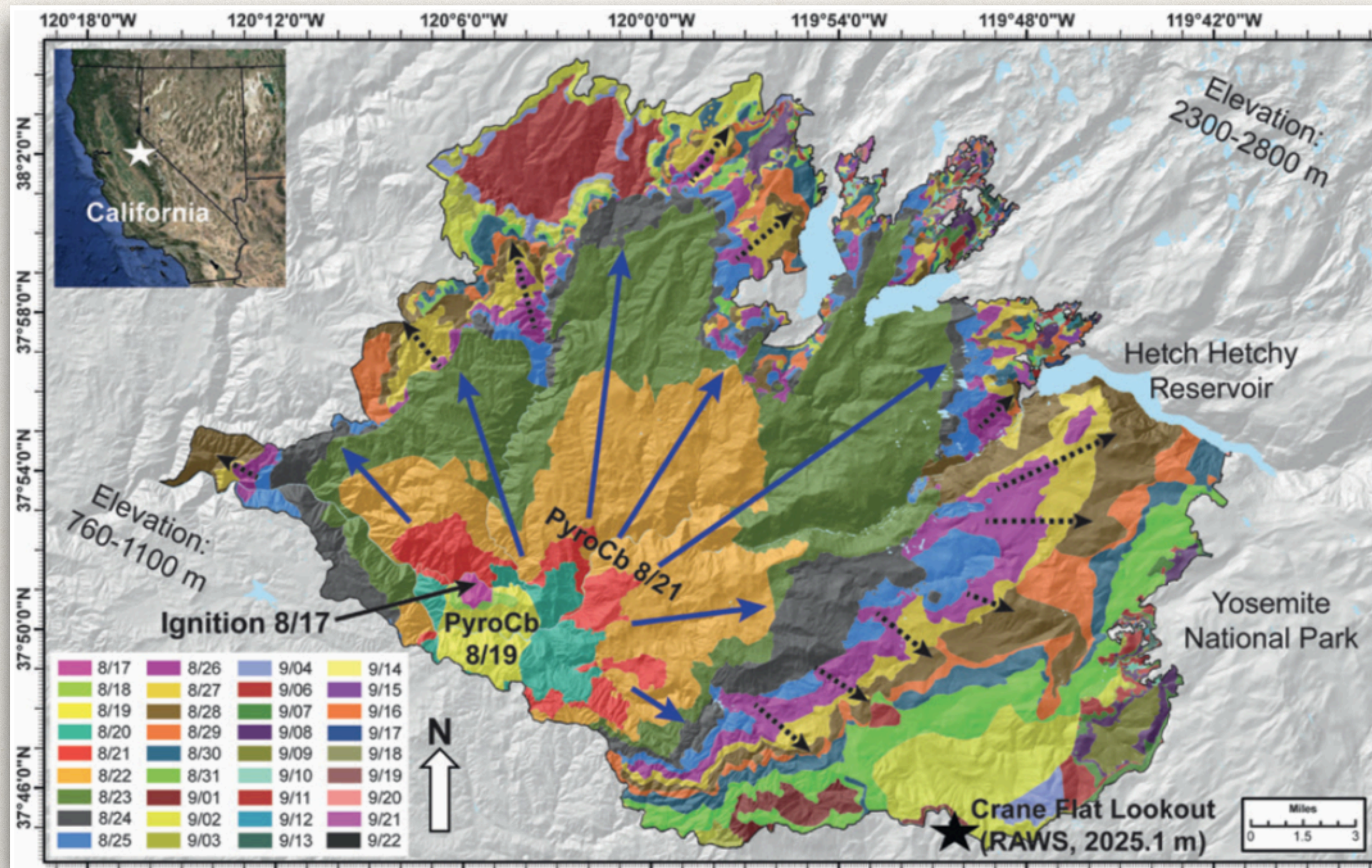


Arrival time maps

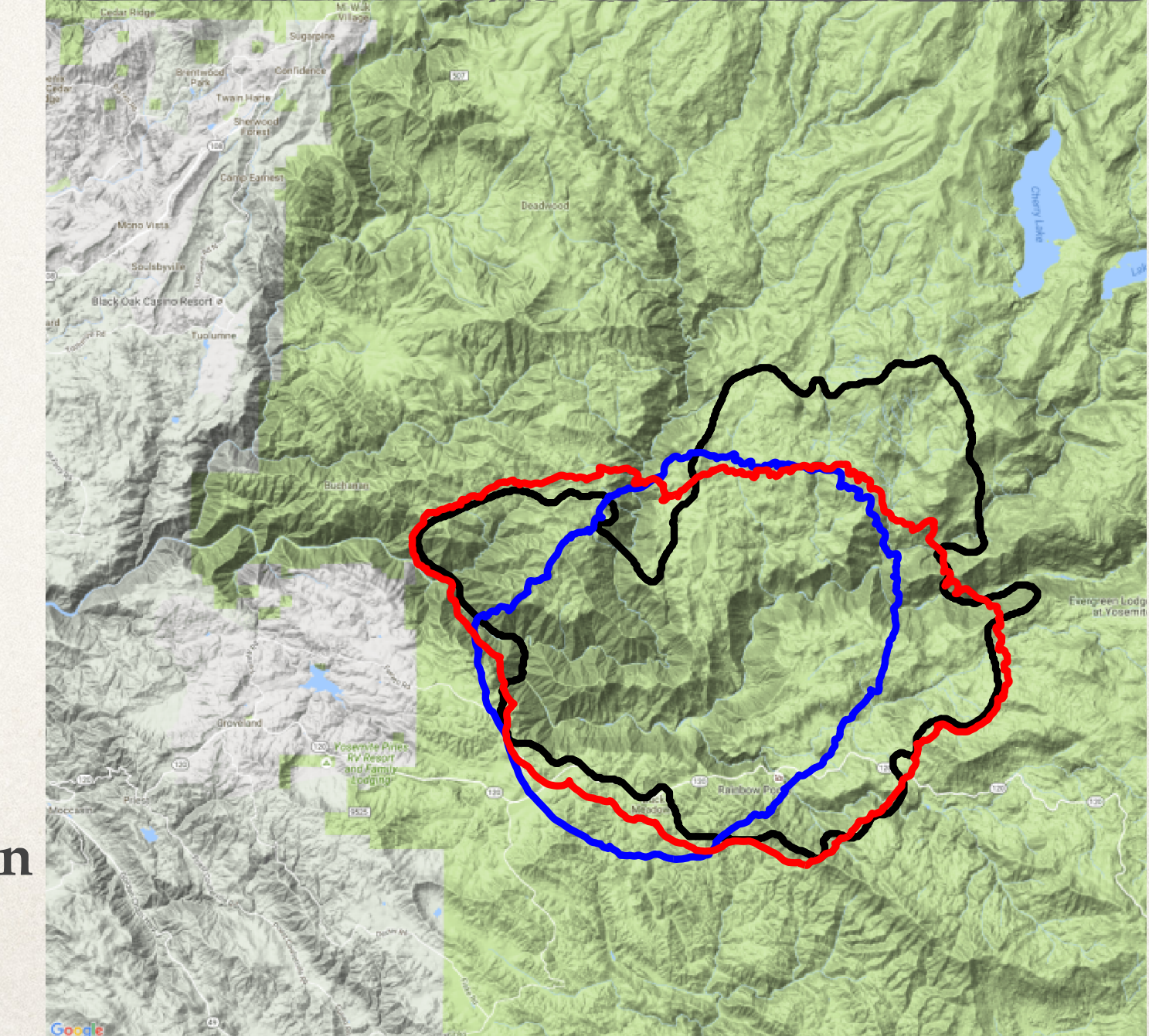


* Zhang et al. (FISJ, 2019)

Towards application to actual wildfires



Rim fire (grass/forest, California, August 2013)



Time

Conclusion

- ▶ Parameter estimation is essential for the wildfire application.
- ▶ Need to improve prior information (biomass fuels, atmosphere / fire interactions)
- ▶ Submitted ANR JCJC to continue this work...

— Observation
 — Prior
 — Analysis

Wildland fire behaviour ensemble modeling

* Surface/atmosphere interactions

» *Parametric reduced-order model
for large-eddy simulation*

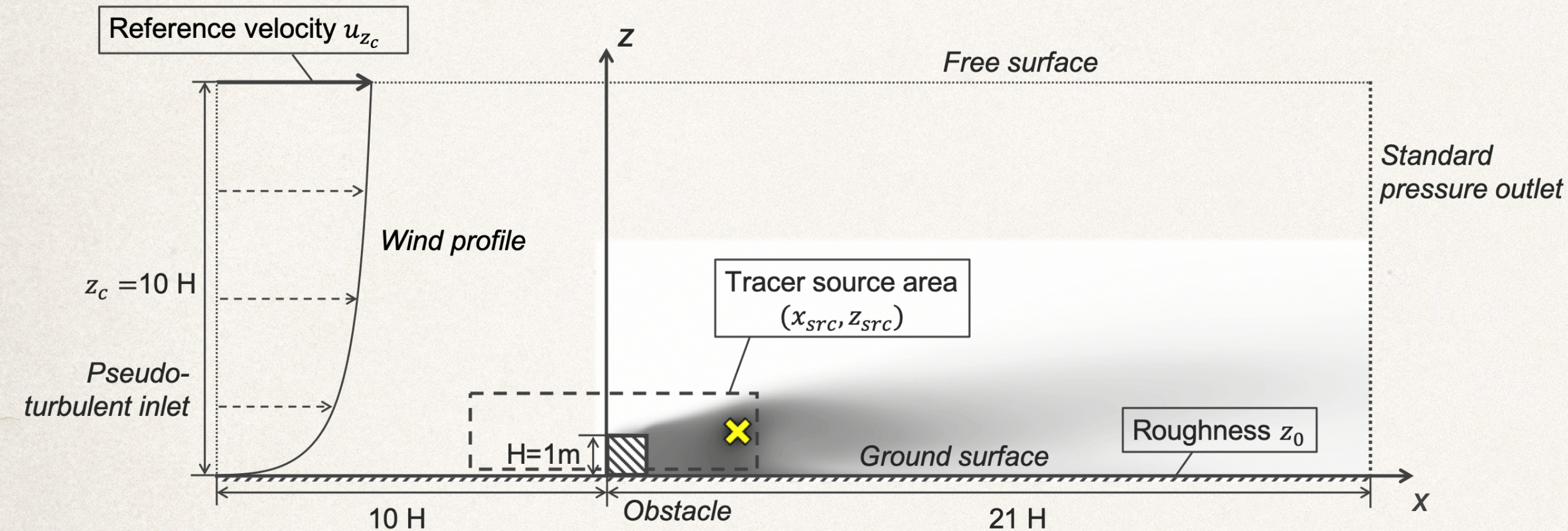
* Source characterization

» *Front data assimilation with parameter estimation*

Statistical emulation of atmospheric boundary-layer flows

➔ Passive tracer dispersion in complex geometry (idealized urban environment)

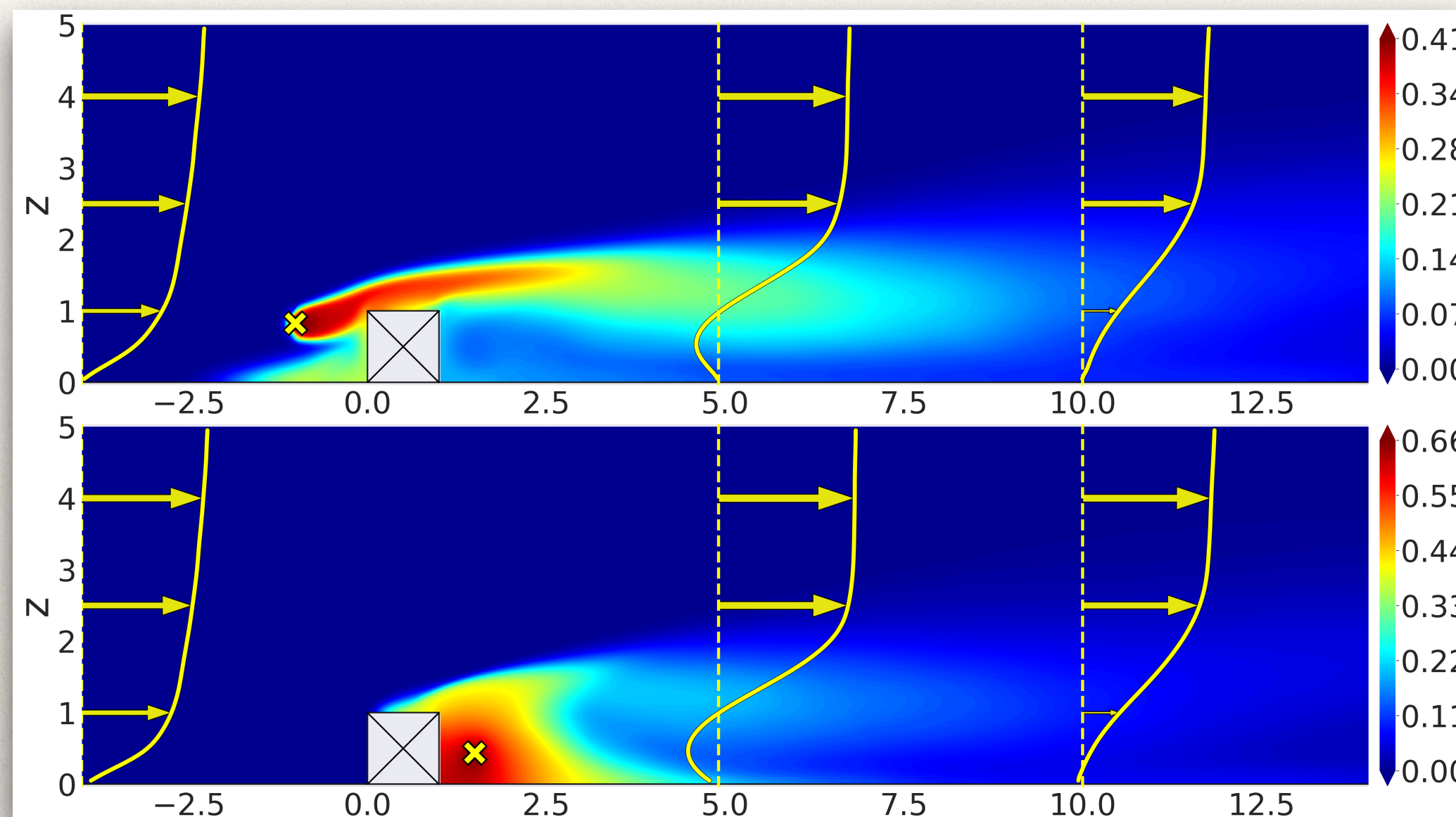
* PhD Bastien Nony (Cerfacs/LISN)



4 uncertain atmosphere/source parameters

- ▶ Wind magnitude
- ▶ Surface roughness
- ▶ Source position and height

Tracer concentration mean (time-averaged) fields

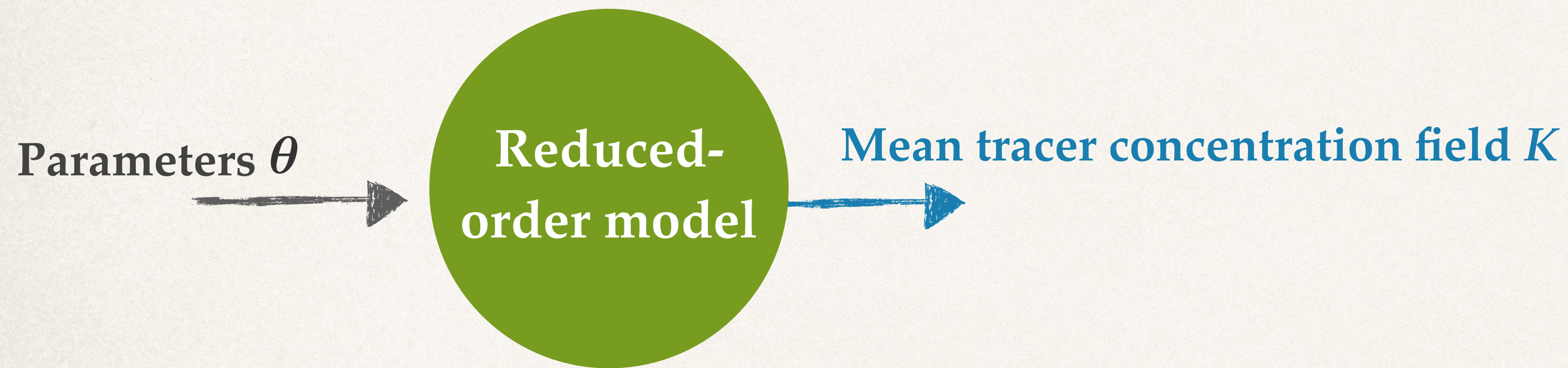


- ▶ « Large » LES database: 750 AVBP simulations
- ▶ 700 hCPU per run (525 000 hCPU in total)
- ▶ 70% training / 30% validation

Statistical emulation of atmospheric boundary-layer flows

➔ Passive tracer dispersion in complex geometry (idealized urban environment)

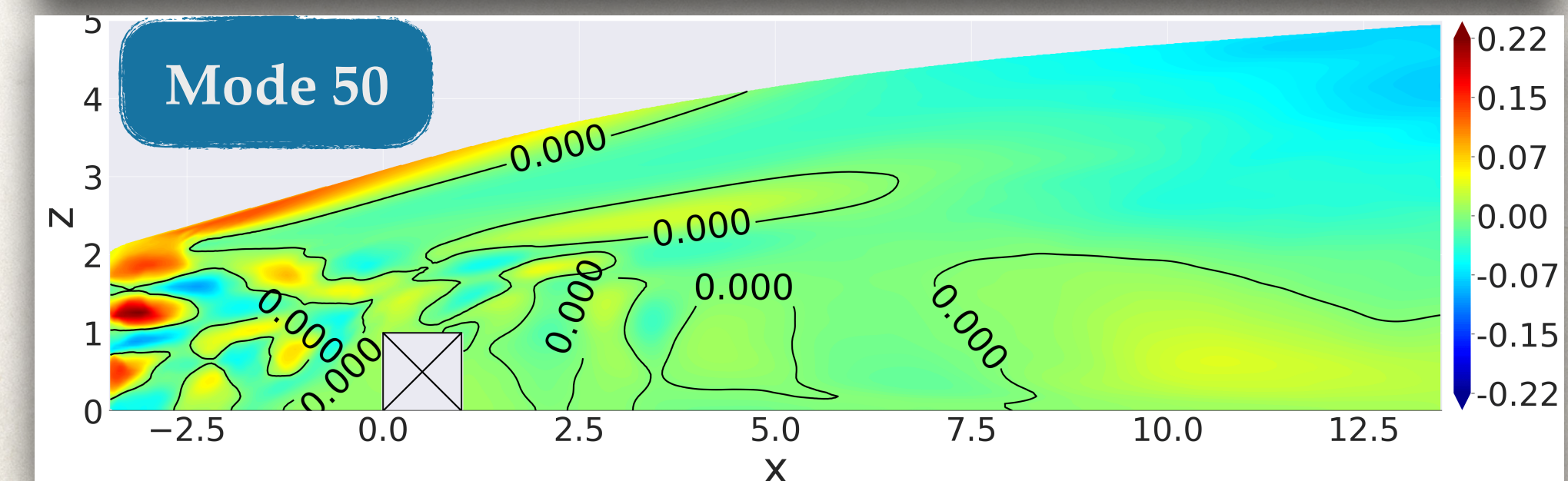
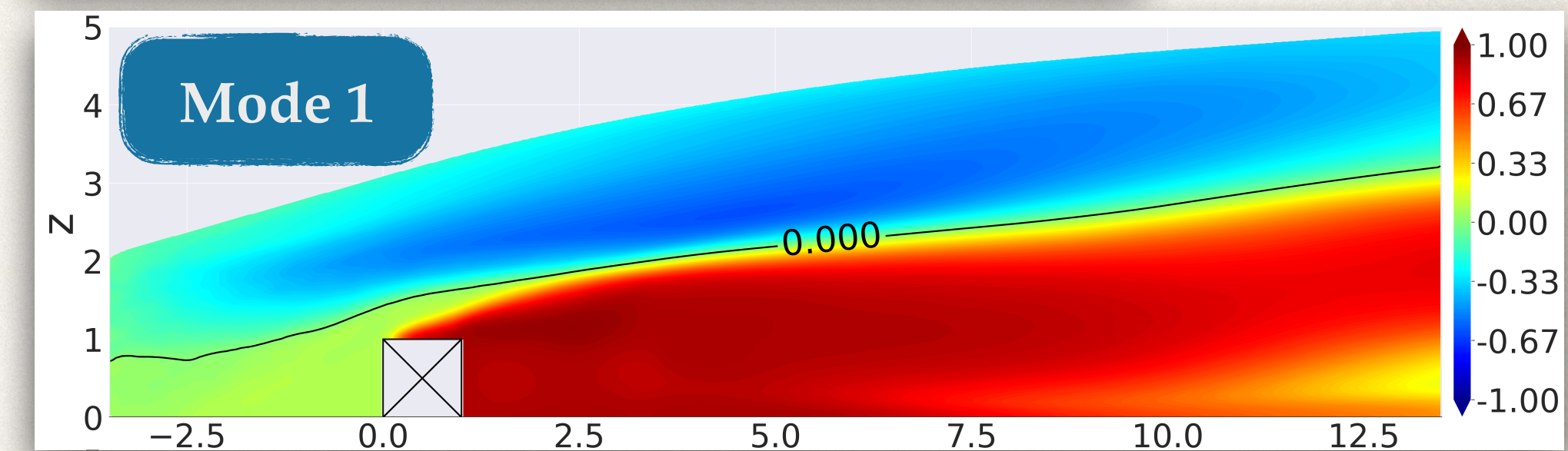
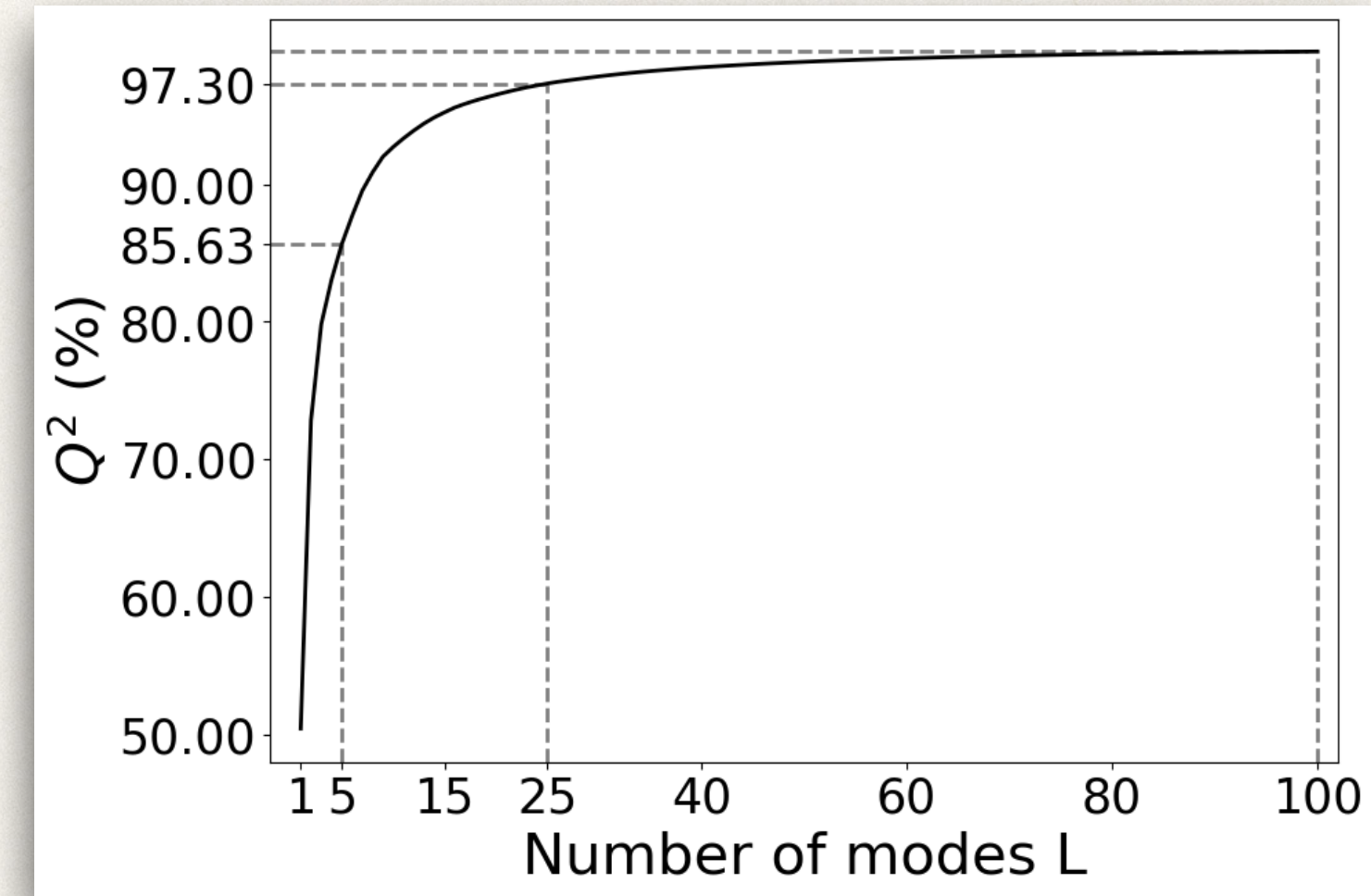
* PhD Bastien Nony (Cerfacs/LISN)



$$K \equiv K(x, y, \theta) = \sum_{m=1}^{N_{\text{modes}}} p_m(\theta) \psi_m(x, y)$$

Proper Orthogonal Decomposition (POD) for dimension reduction

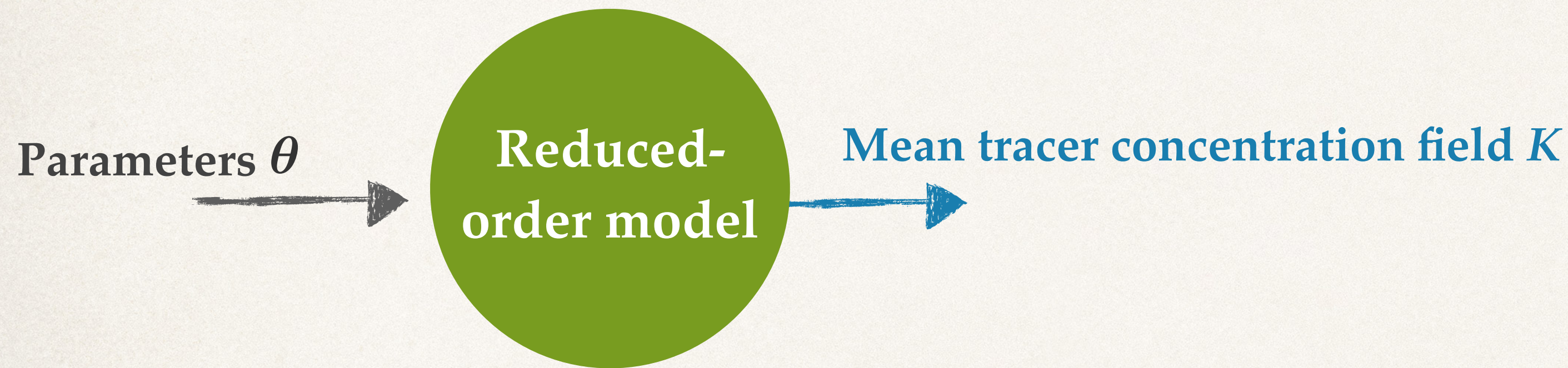
- ▶ High-order modes correspond to localized structures in the concentration fields but are not only noise



Statistical emulation of atmospheric boundary-layer flows

➔ Passive tracer dispersion in complex geometry (idealized urban environment)

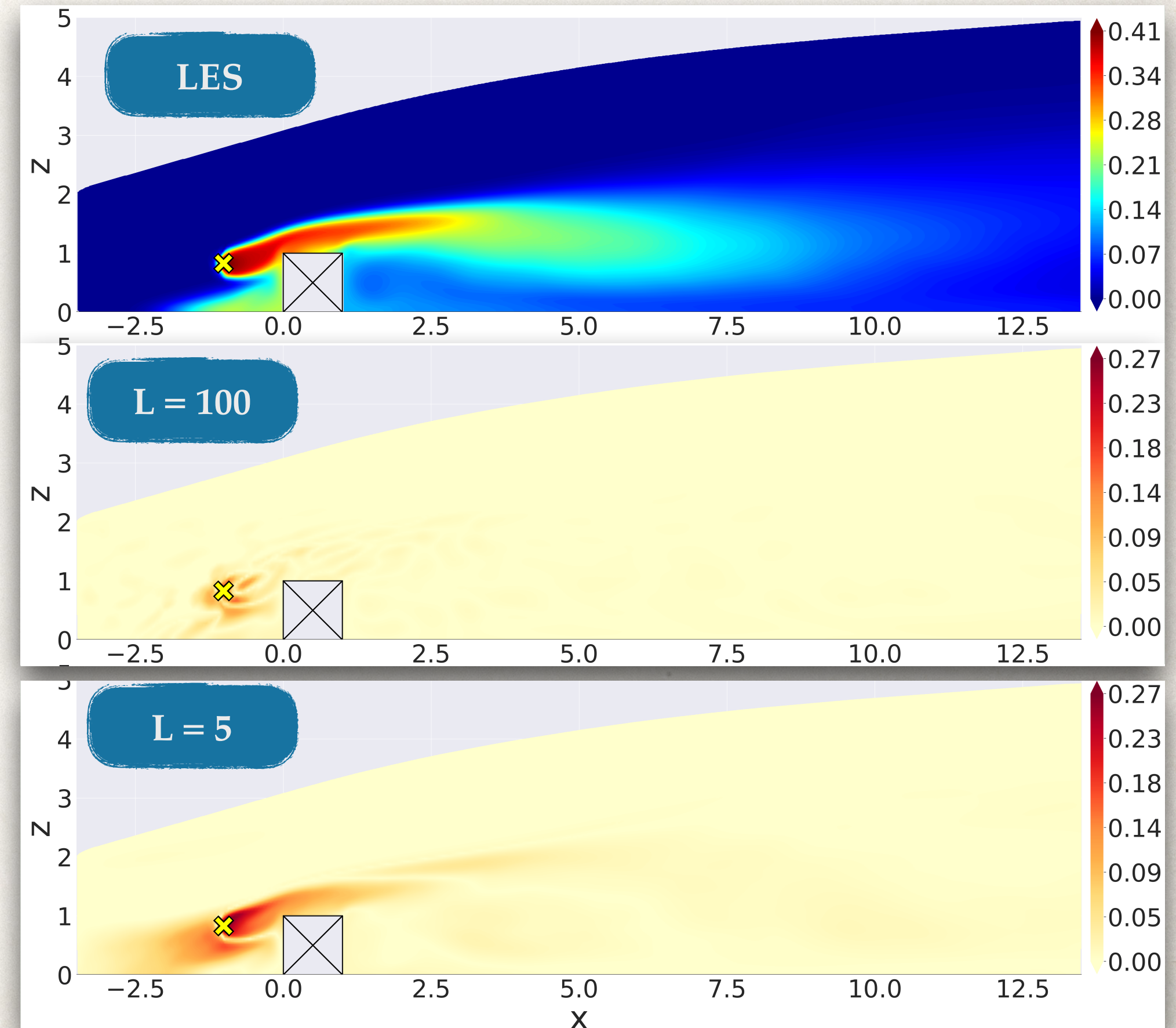
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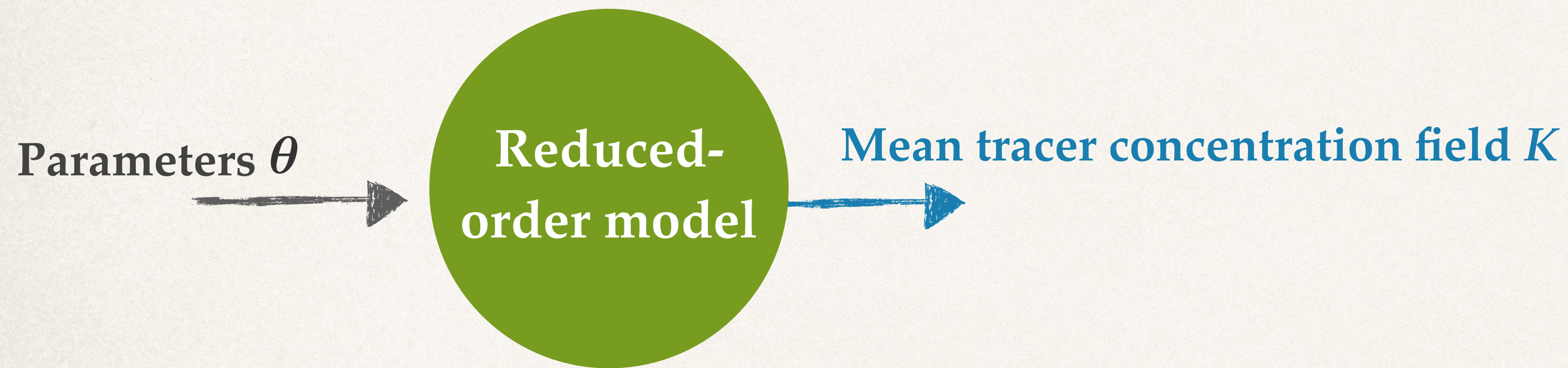
- ▶ High-order modes correspond to localized structures in the concentration fields but are not only noise
- ▶ Need to retain a large number of modes ($L = 100$) to reconstruct the near-source dispersion



Statistical emulation of atmospheric boundary-layer flows

➔ Passive tracer dispersion in complex geometry (idealized urban environment)

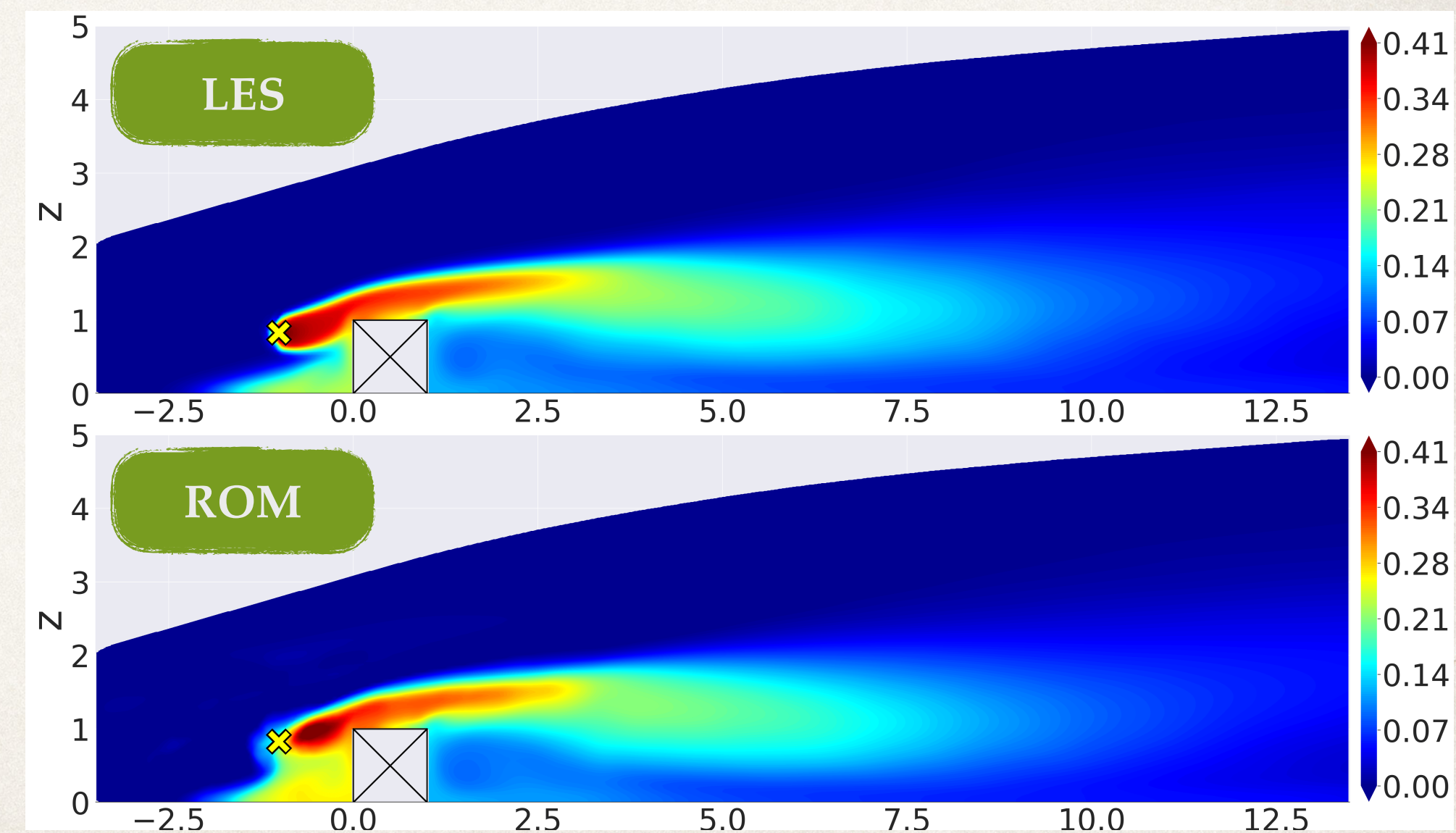
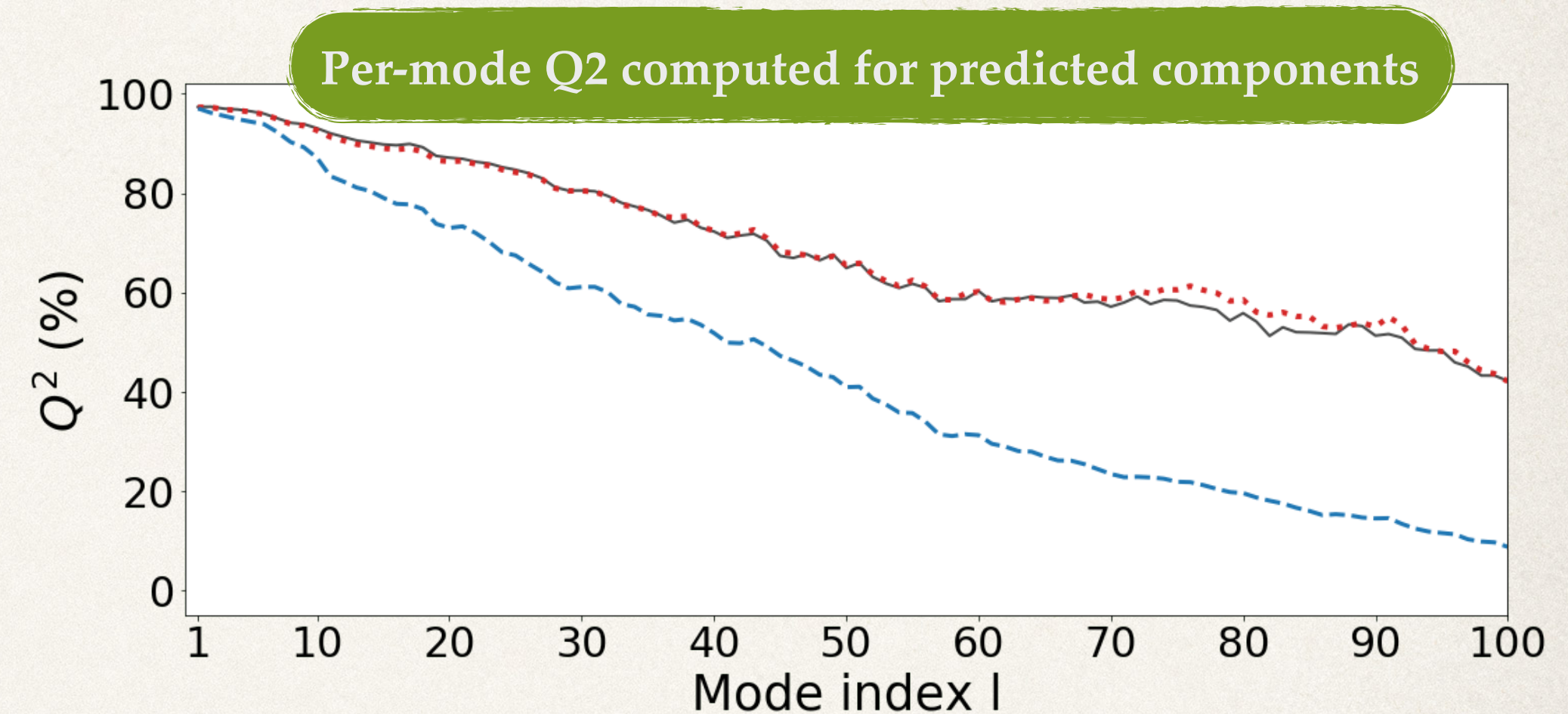
* PhD Bastien Nony (Cerfacs/LISN)



$$K \equiv K(x, y, \theta) = \sum_{m=1}^{N_{\text{modes}}} p_m(\theta) \psi_m(x, y)$$

Gaussian process regression

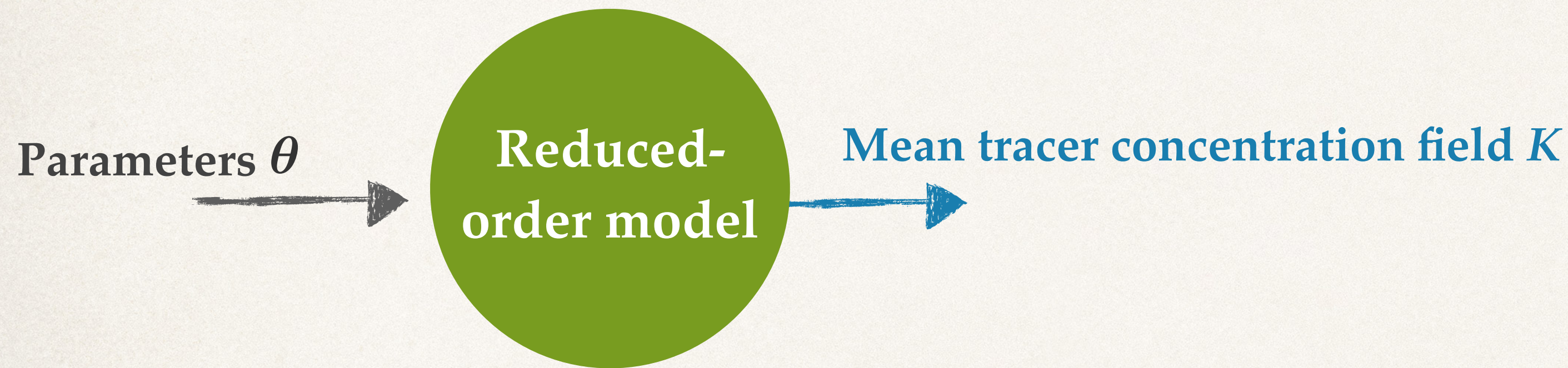
- ▶ Anisotropic Matern kernel
- ▶ Gaussian process noise
- ▶ Hyperparameter optimisation based on prior information (POD) and maximum a posteriori estimation (MAP, GPyTorch)



Statistical emulation of atmospheric boundary-layer flows

➔ Passive tracer dispersion in complex geometry (idealized urban environment)

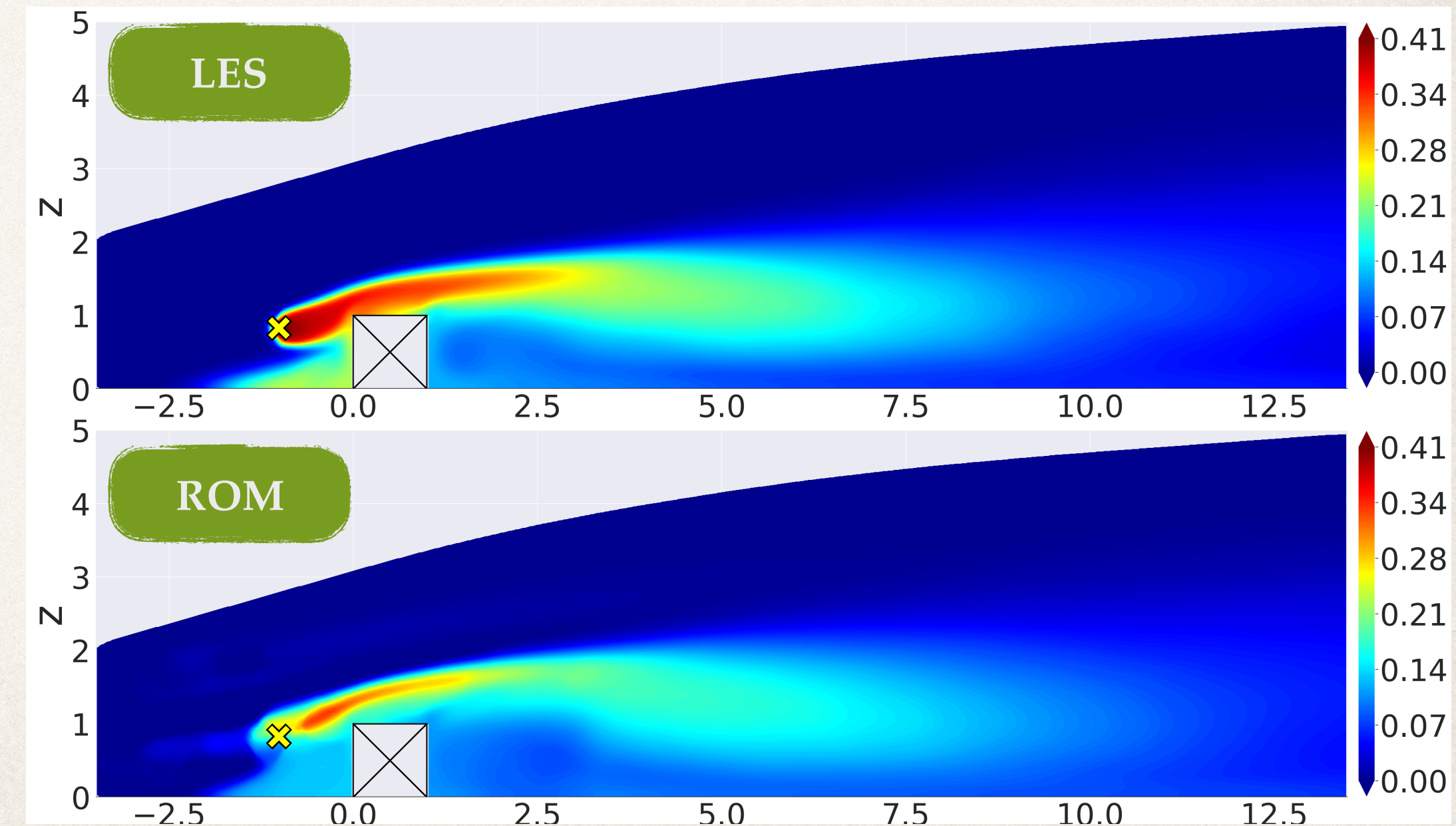
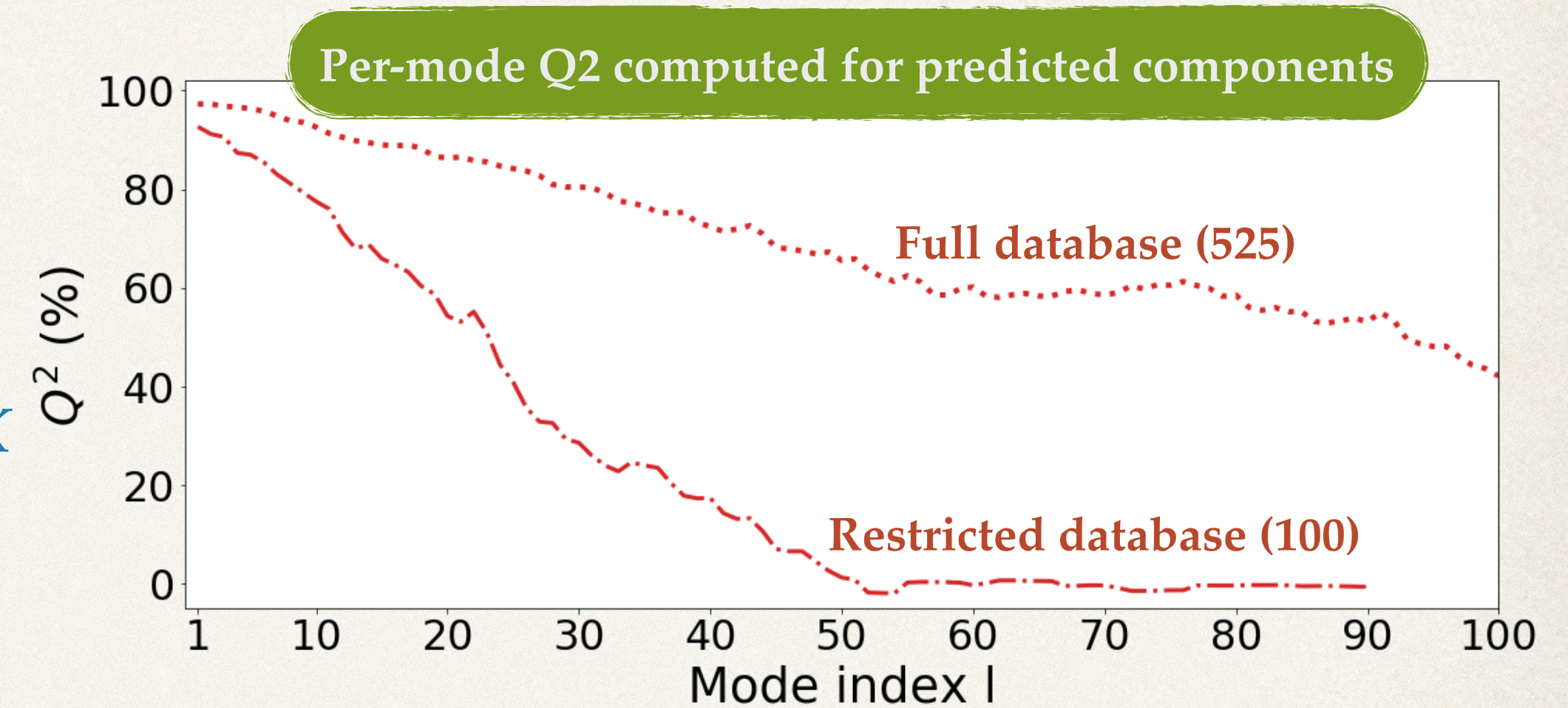
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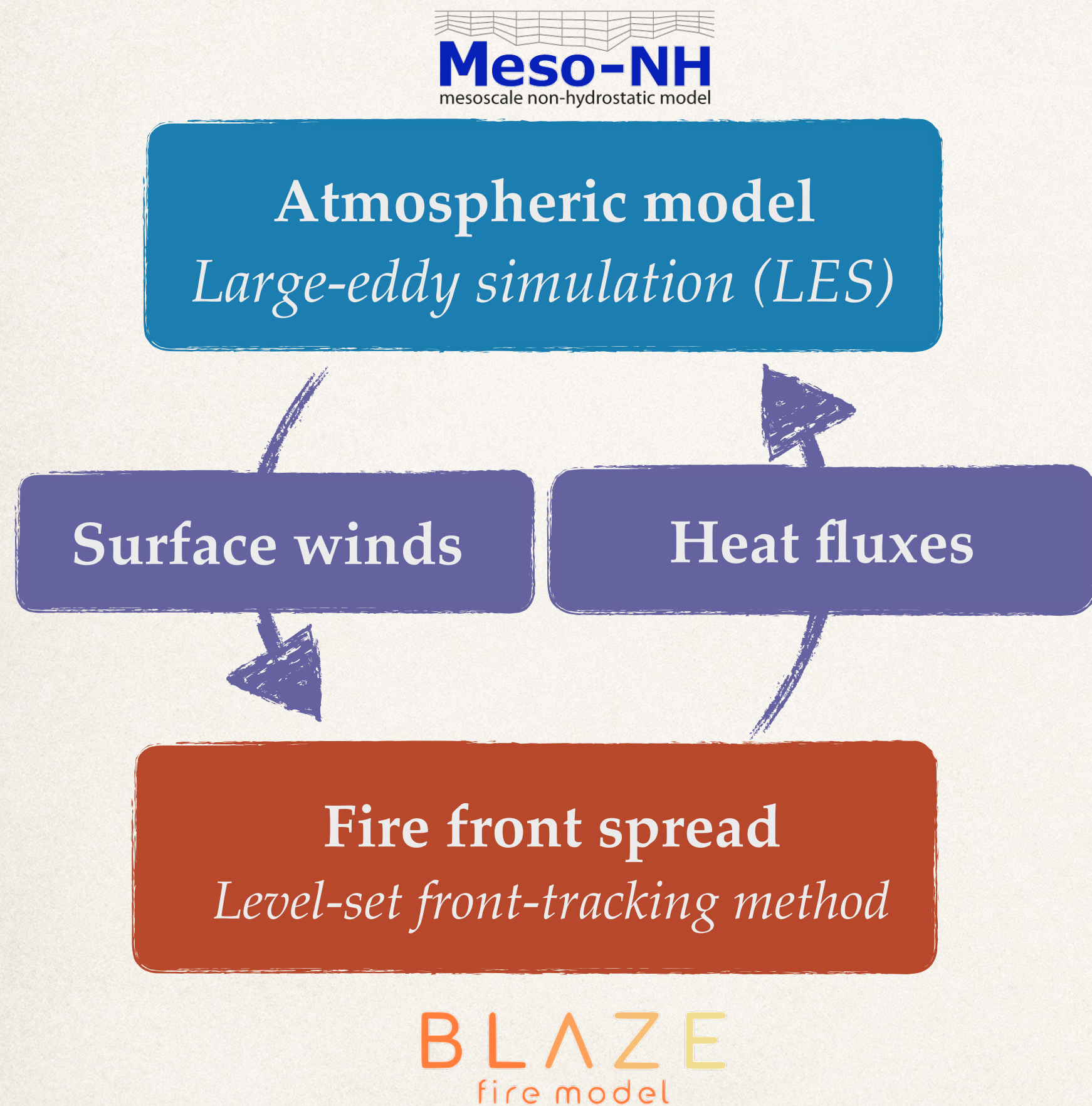
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Gaussian process regression

- ▶ Anisotropic Matern kernel
- ▶ Gaussian process noise
- ▶ Hyperparameter optimisation based on prior information (POD) and maximum a posteriori estimation (MAP, GPyTorch)



Next steps



1 Data assimilation for coupled model

- ▶ GSA/ Selection of most influential biomass fuel parameters
- ▶ UQ/ Reduced-order modeling approach for mobile source and
- ▶ Observation-model comparison/ Front shape similarity measure

Submitted ANR JCJC project

2 Measurements

- ▶ Instruments/ Infrared imaging and lidar/ radar
- ▶ Optimal sensor placement

PhD Elliott Lumet (Cerfacs/LAAS)

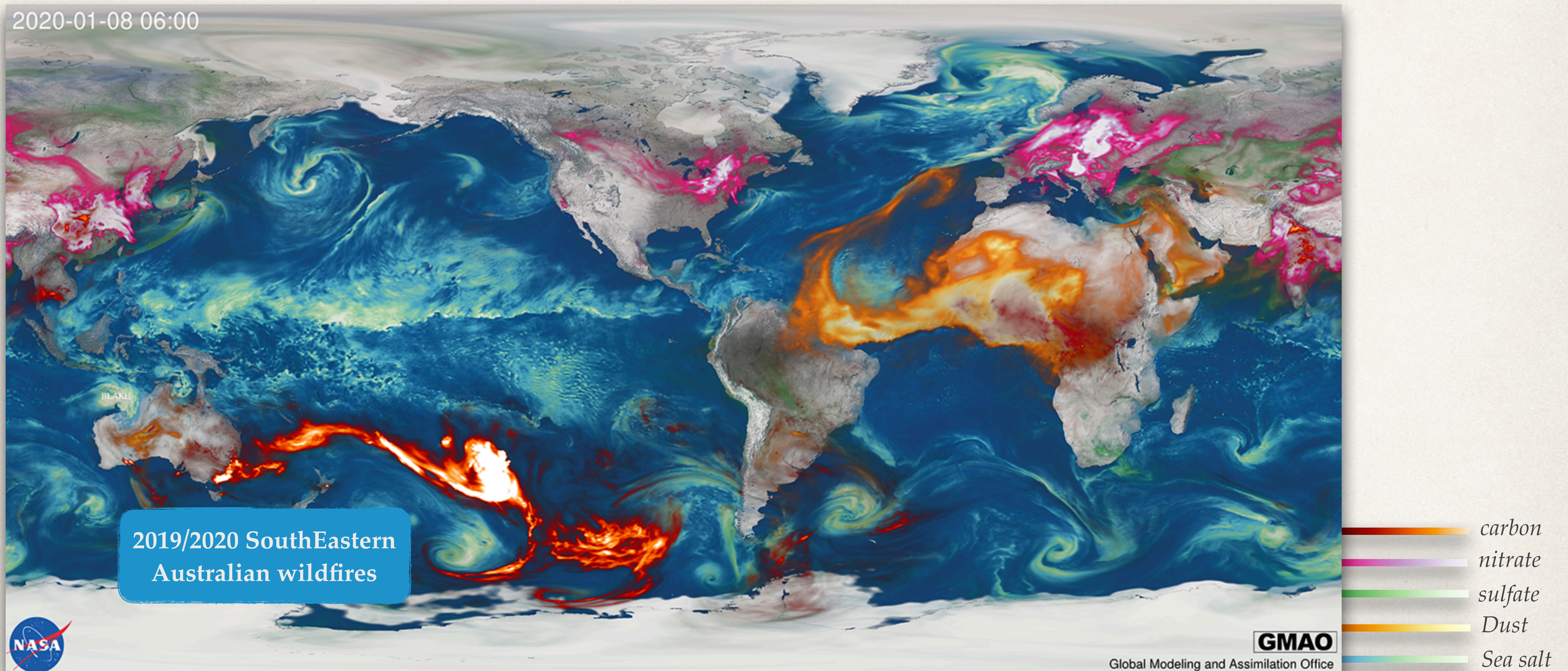
3 Coupled atmosphere/fire modeling

- ▶ Validation against experimental fires in different ecosystems
- ▶ Capacity to represent extreme fire behavior?

PhD William Antolin (Cerfacs/CNRM)

Long-term question:

How to use high-fidelity simulations to inform large-scale models?



One-year atmospheric chemistry reanalysis for different aerosols



Thank you for your attention!

Contact

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