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Parameter Calibration Using Data Assimilation for Simulations of Forest Fire Spread

Blaise DELMOTTE

CERFACS, September 13, 2011

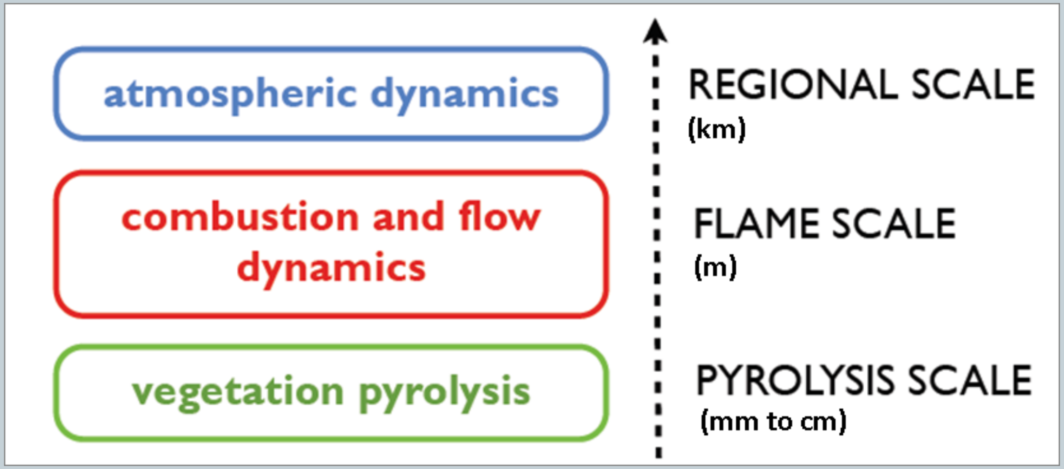
Outline

I. CONTEXT

I. Context

What is a wildfire?

- A multi-physics multi-scale phenomenon



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- Highly dependent on local conditions

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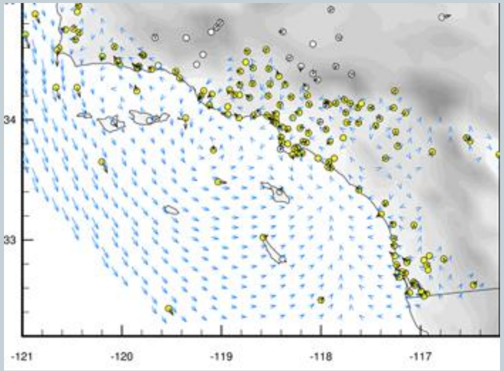
Vegetation

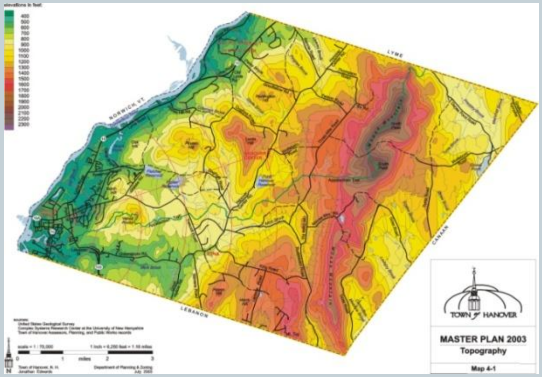
Fuel depth: δ
Moisture content: M_f
Particle size: σ

Meteorology



Wind in front direction: U

Topography



Slope: $\tan \phi$

I. Context

At a regional-scale

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How to model this front spread ?

II. WILDFIRE SPREAD MODELING

Principle

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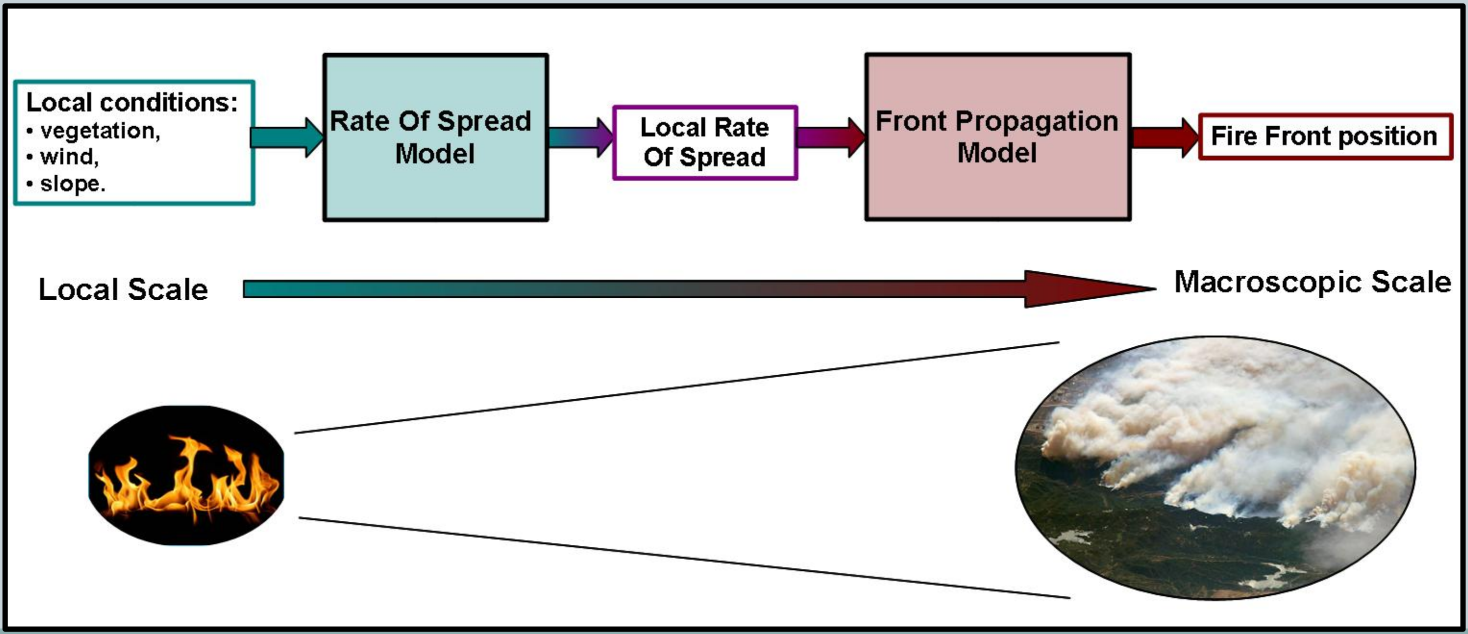

II. Wildfire spread modeling

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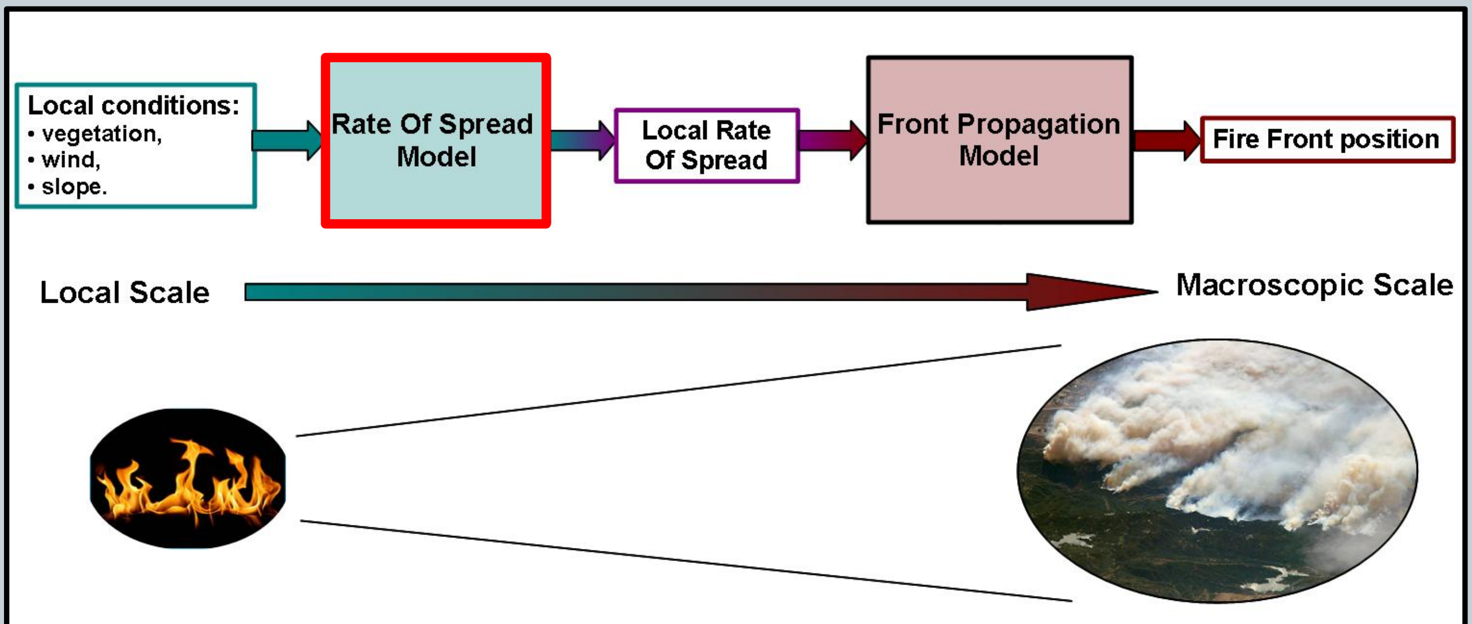

1. Rate of Spread model

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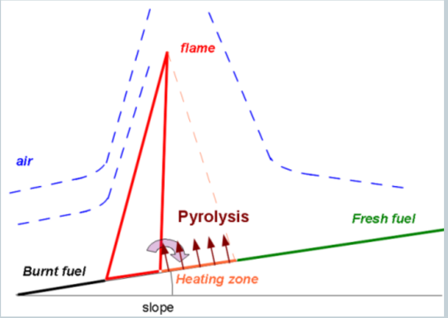
  1. CFD modeling of each phenomenon (dehydration, pyrolysis, ignition…):



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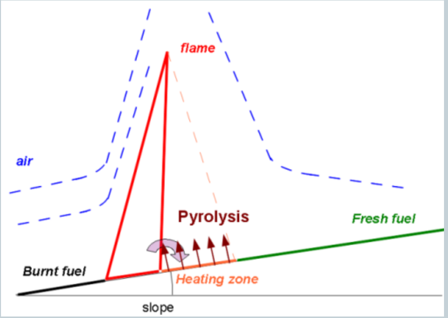

2. **Semi-empirical models based on physics and laboratory experiments:**
   - ✓ Describe some relevant aspects of the physics
   - ✓ Provide an algebraic expression of the ROS, calibrated expression
   - ✓ Easily converted from local to regional scale
   - ✓ Limited computational cost
   - • Limited domain of validity

ROS = f(vegetation, wind, slope)

1. Rate of Spread model

- **A classic semi-empirical in the forest fire community: Rothermel's model**
  - Only requires fuel makeup and environmental conditions
  - ROS depends linearly on fuel depth δ

$$R(x,y,t) = \tau(x,y,t)\delta(x,y)$$

with $\tau(x,y,t) = f\left(\beta, \sigma, M_f, U(x,y,t), \tan(\phi)\right)$ the proportionality coefficient

II. Wildfire spread modeling

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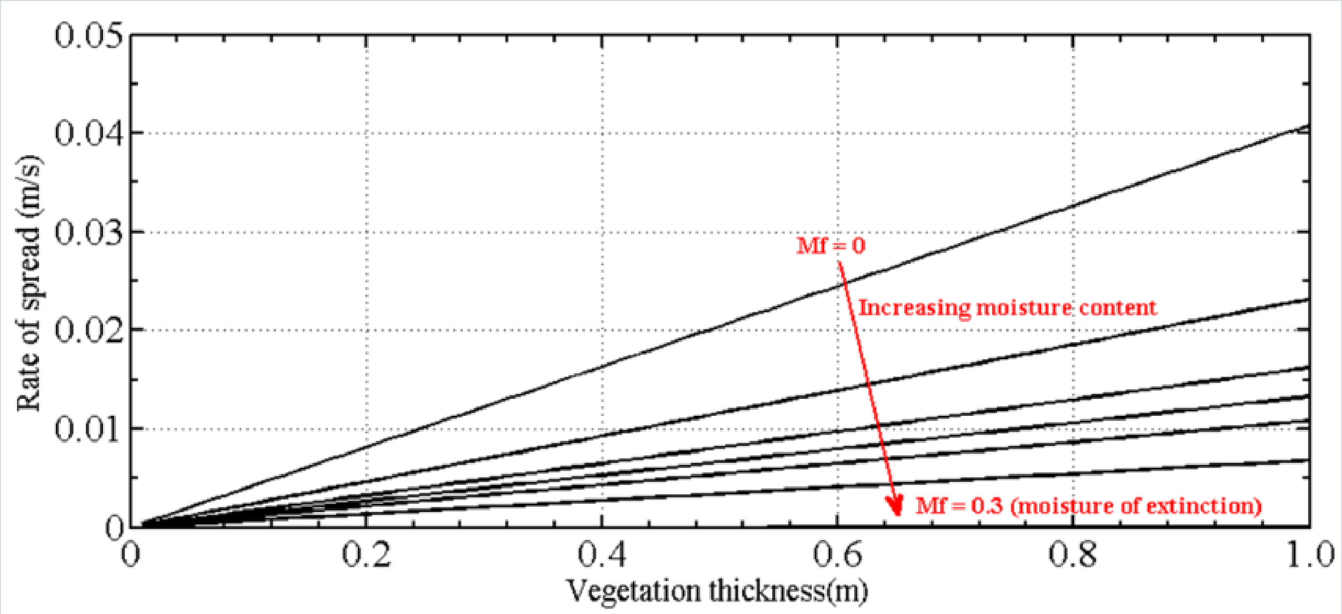

ROS = f(δ) for different moisture contents M_f

II. Wildfire spread modeling

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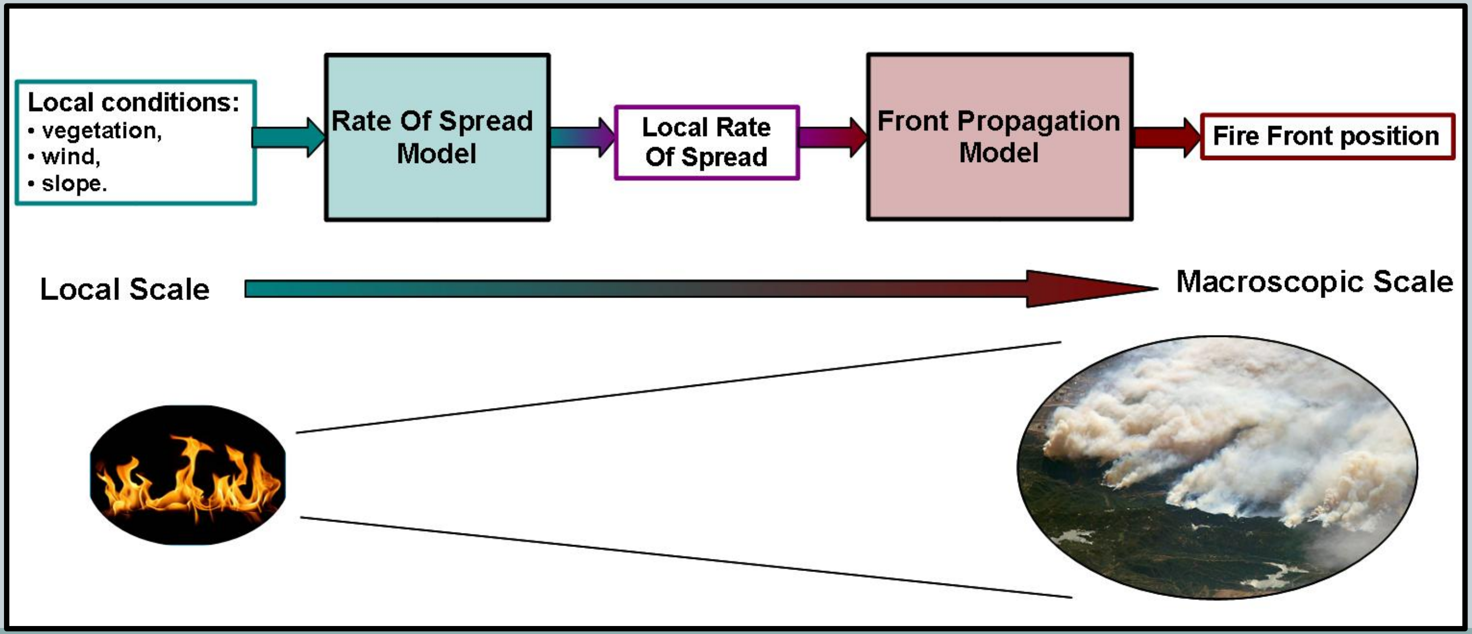

Principle

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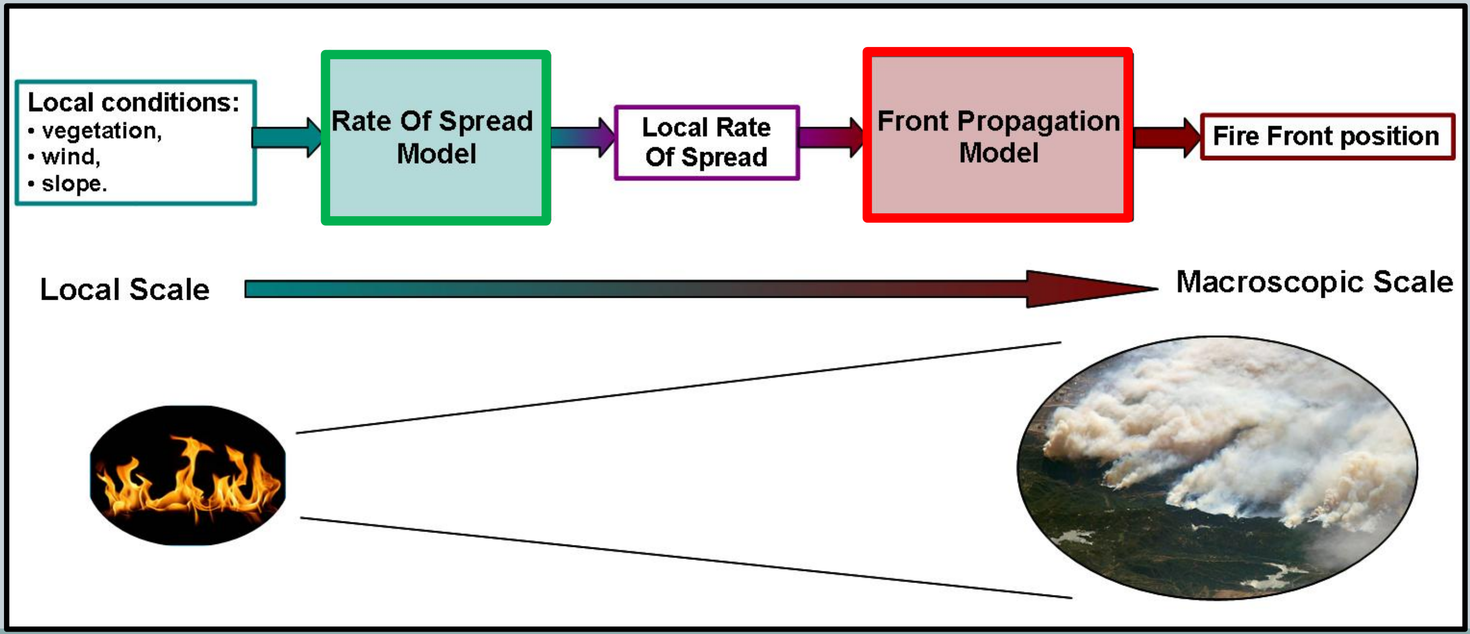
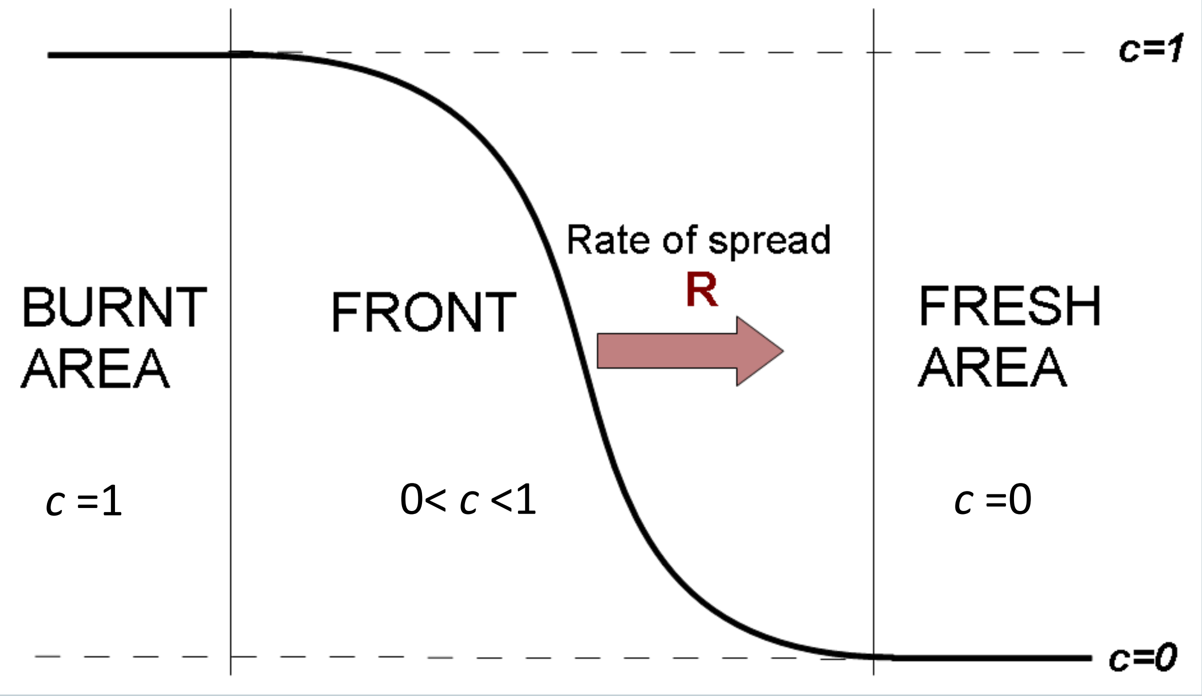


2. Propagation model

- **Front modeling**
  - Front is described with a scalar progress variable *c*



2. Propagation model

- **Propagation modeling**

  - Best model for front propagation at a given speed ***R***

The Level Set equation: front tracking method to propagate a discontinuity

$$\frac{\partial c}{\partial t} + \underbrace{\vec{R}\,.\,\vec{\nabla}\,c}_{\text{advection}} = 0$$

Requires high order numerical scheme (MUSCL + Slope limiter)

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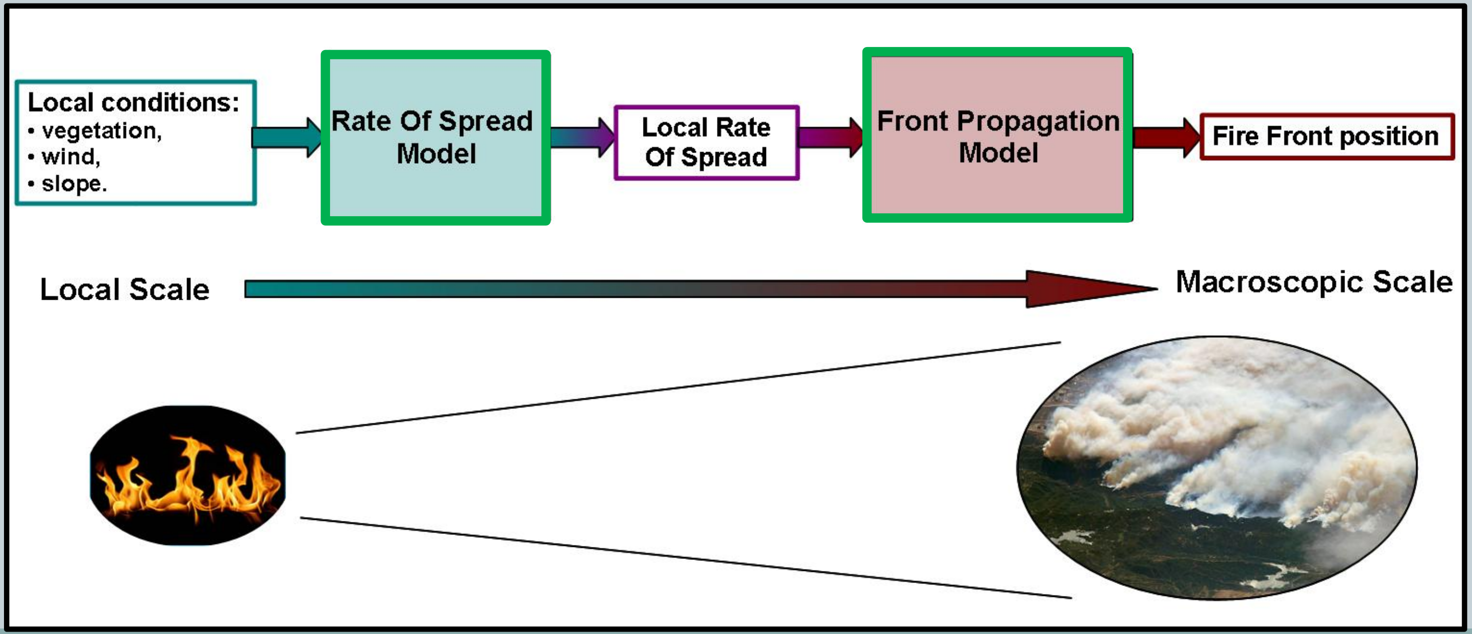
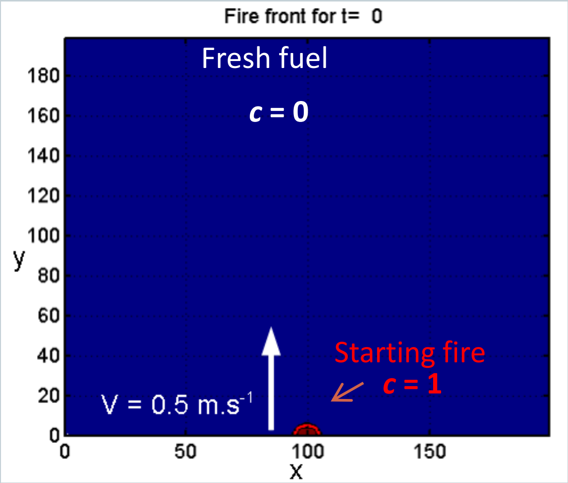


II. Wildfire spread modeling

3. Example of fire spread simulation

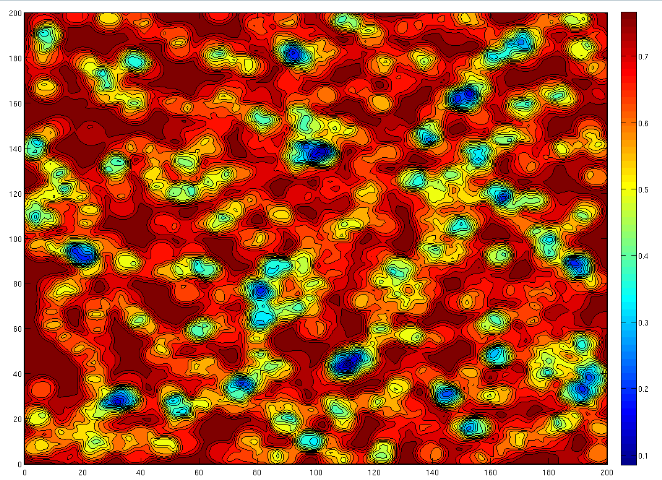
Rothermel's model + Level Set

- Heterogeneous fuel depth (e.g. surface vegetation in a forest)
- Size: 200m x 200m
- Wind in y-direction



Initial condition

+



$0.1m < \delta(x,y) < 0.8m$

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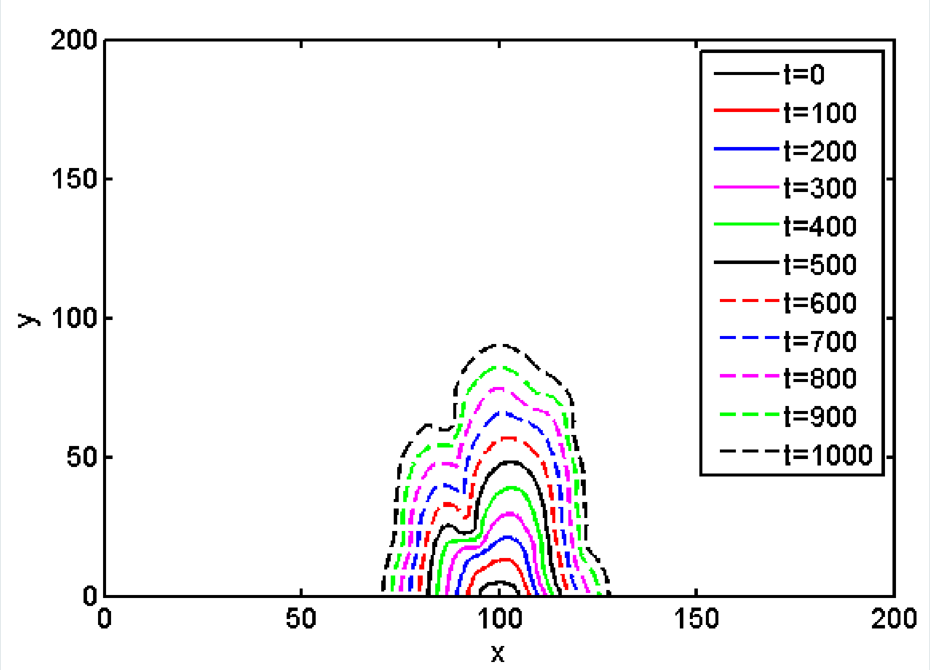

Successive front positions

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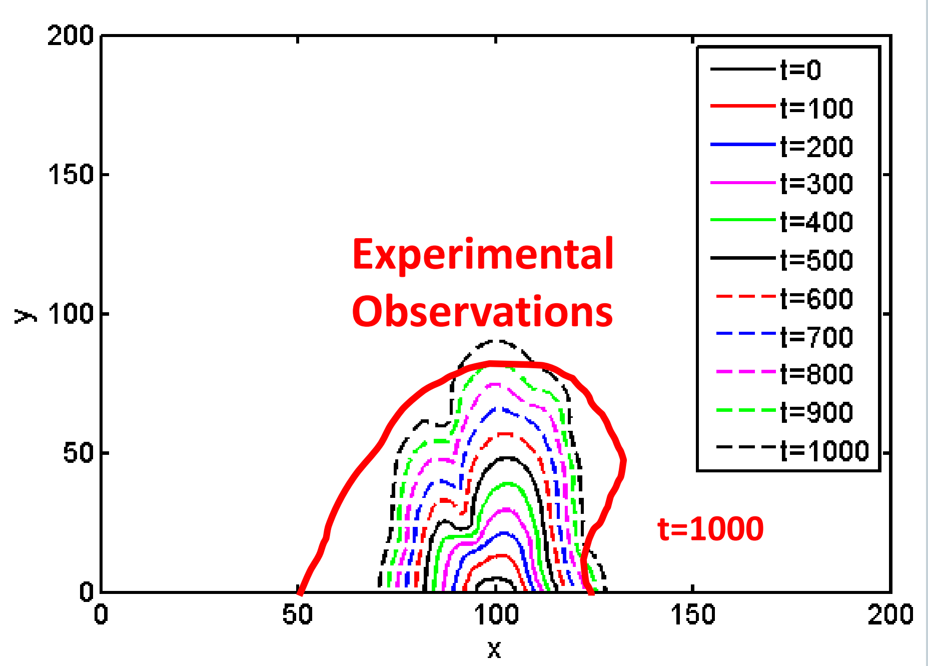

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How to make simulations more reliable ?

III. DATA ASSIMILATION FOR PARAMETER CALIBRATION

III. Parameter calibration

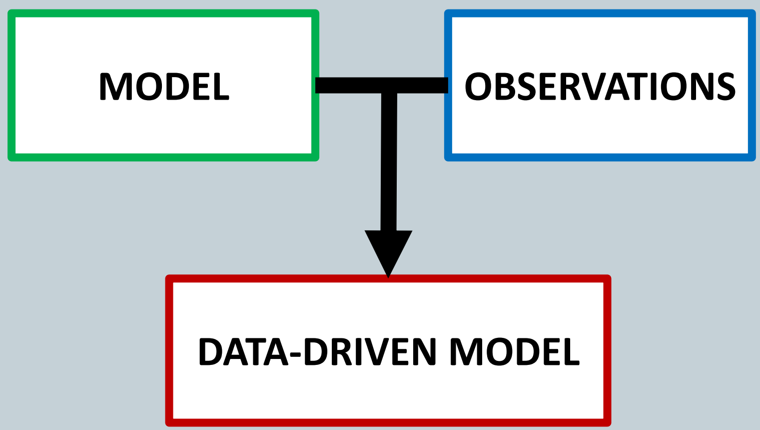
Why parameter calibration ?

- Sources of errors in the simulation:
  - Models fidelity
  - Input parameters are sources of uncertainties in the ROS determination

- Parameter correction provides
  1. a better fitness of model parameters.
  2. a better estimate of the front position;

III. Parameter calibration

Principle



III. Parameter calibration

Calibration technique

- **BLUE (Best Linear Unbiased Estimator)**
  - Correction of the most influential and/or the most uncertain model parameters $\mathbf{X}^b$.

$$\mathbf{X}^a = \mathbf{X}^b + \mathbf{K}\left(\mathbf{Y}^o - H(\mathbf{X}^b)\right)$$

Correction increment

Analysis (corrected value)

Background (*a priori* value)

Observations

Observation operator (simulation result at observation points)

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$$\mathbf{K} = \mathbf{B}\mathbf{H}^T\left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R}\right)^{-1}$$

Background errors (parameter uncertainties)

Observation errors (observation uncertainties)

  - Iterative correction if necessary.

Calibration technique

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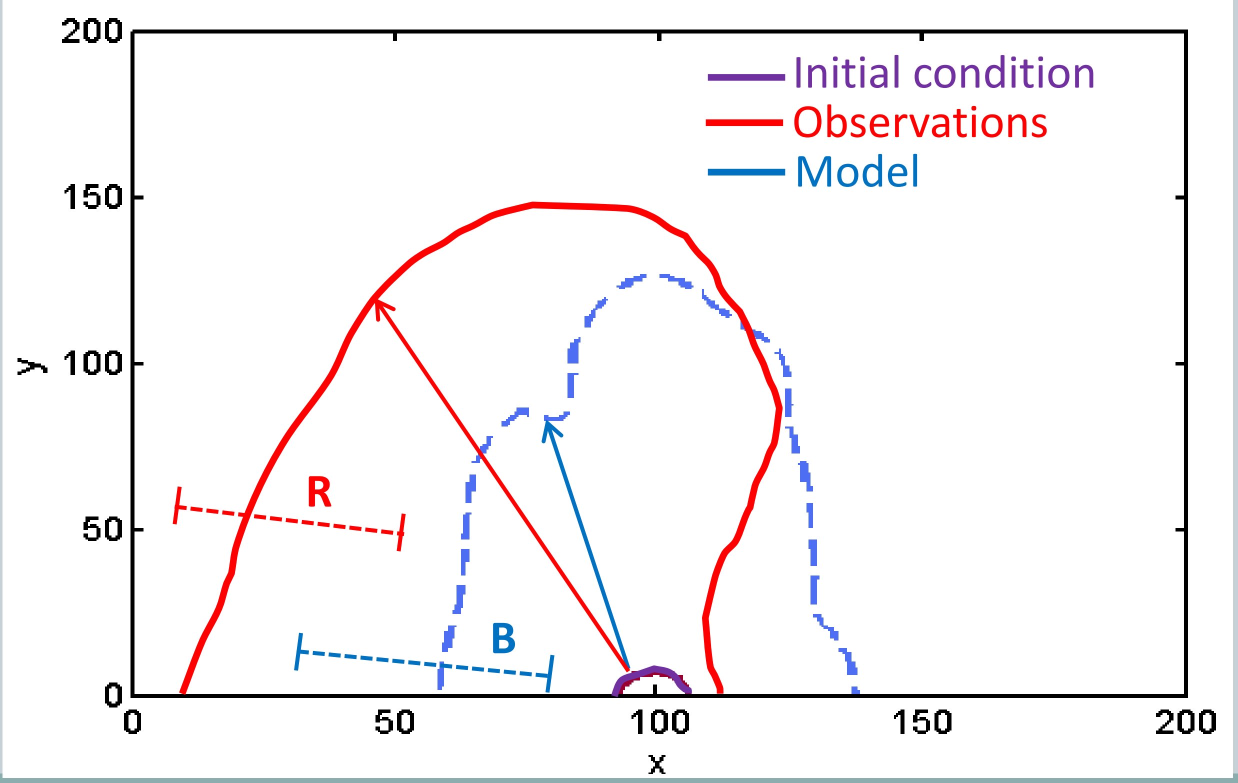

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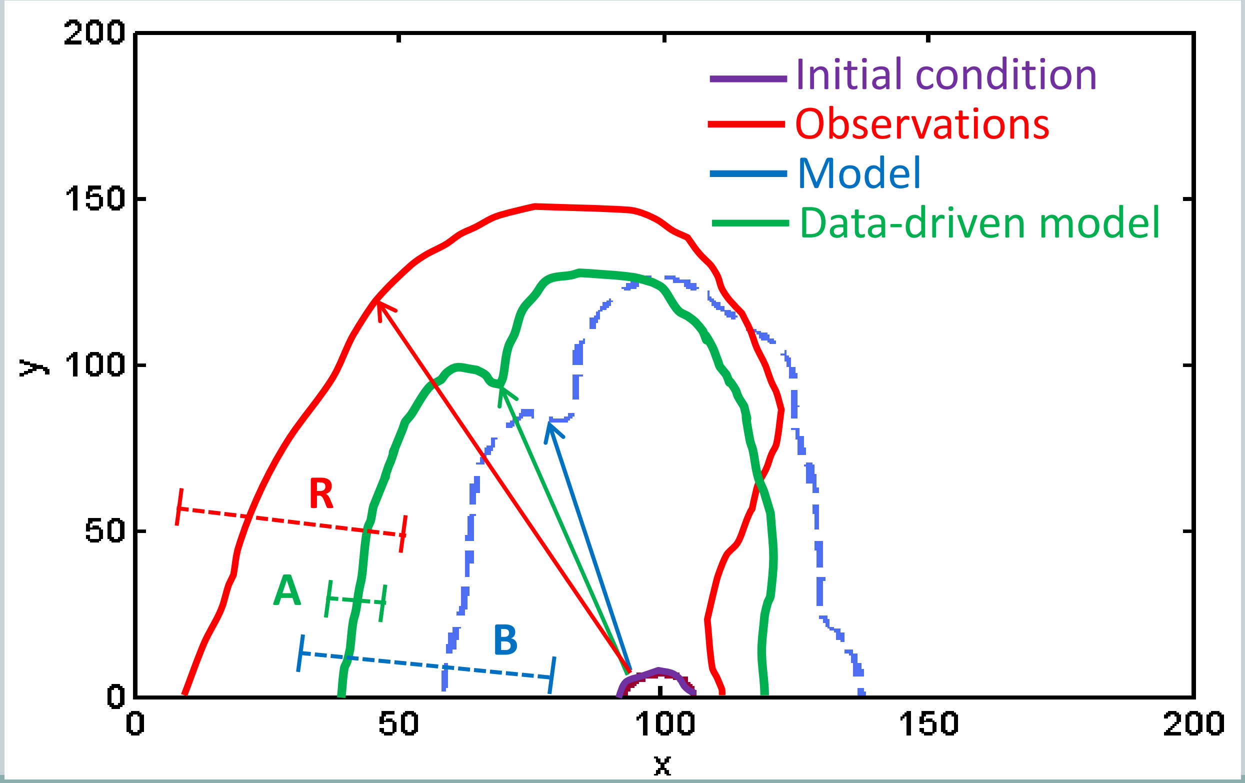

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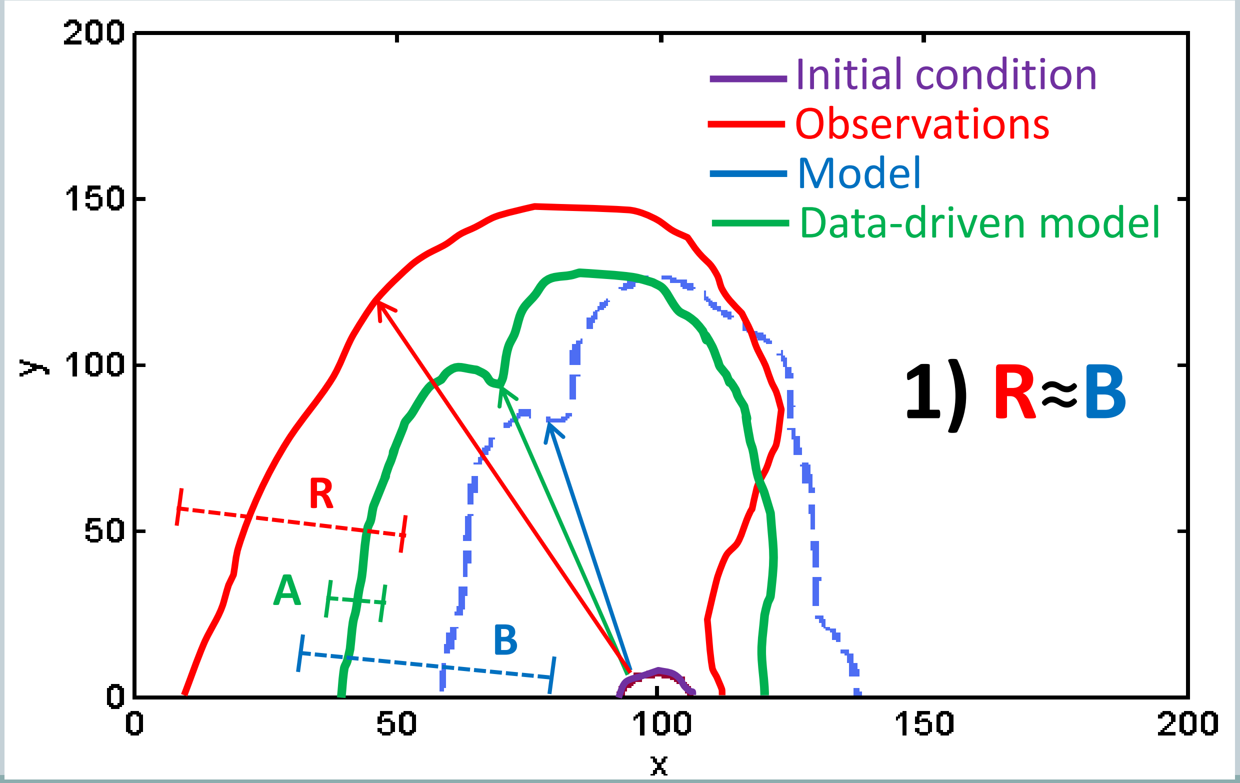

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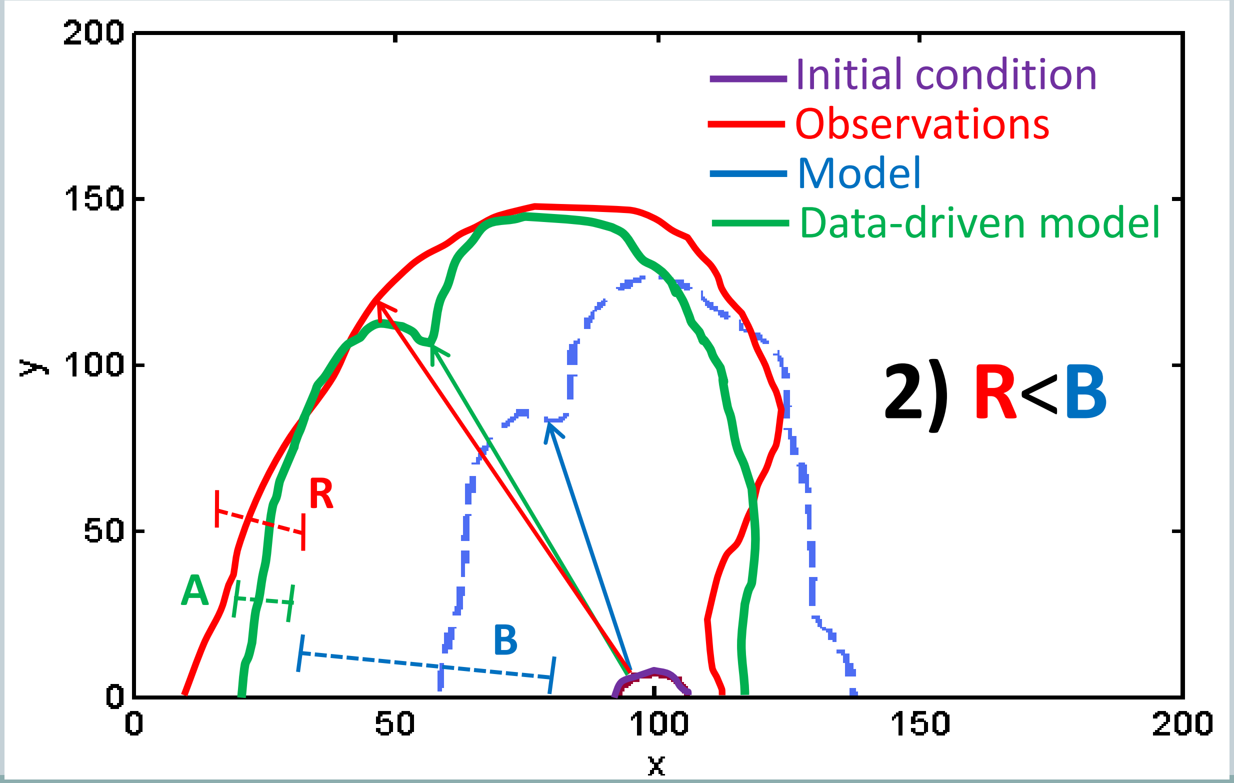

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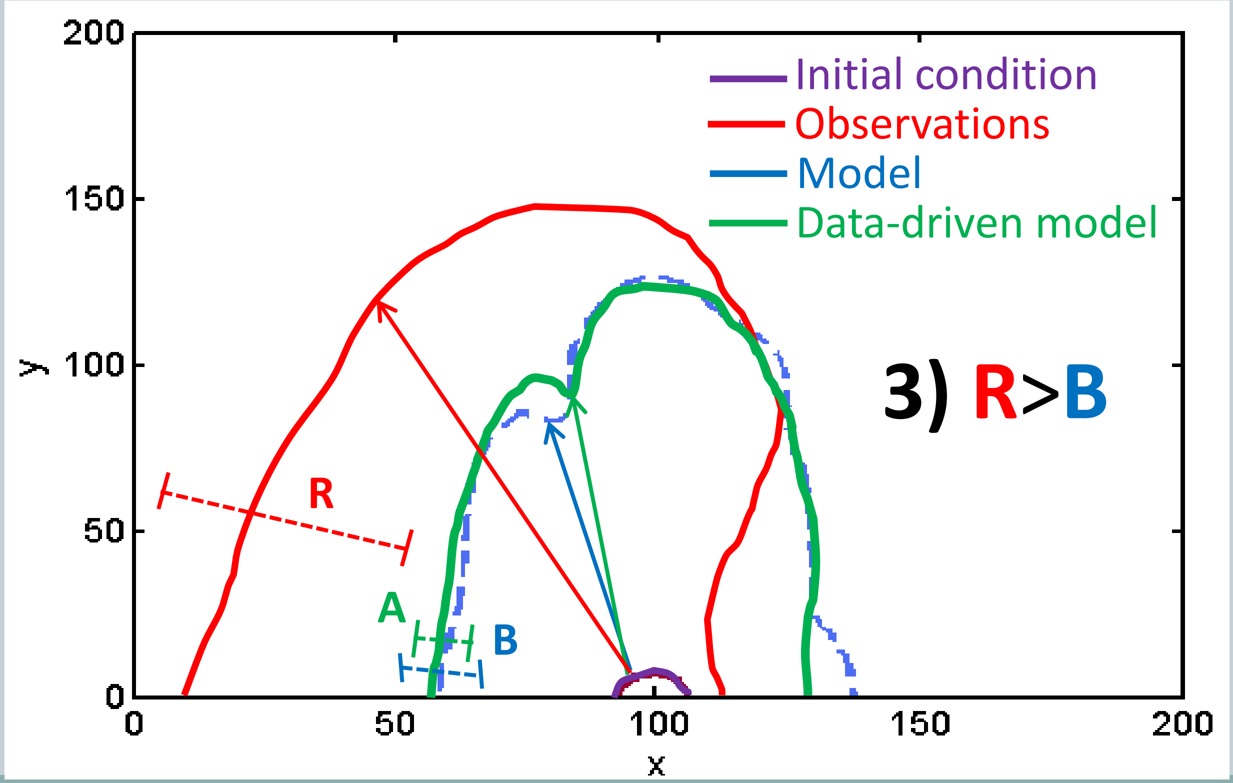

Validation framework

- **Validation framework :**

  - Observations synthetically-generated using the fire spread model;
  - Background (model parameters) and observation errors ***B*** and ***R*** perfectly controlled;
  - Quantification of the quality of the calibration algorithm (BLUE).

Validation framework

- **2 types of observations:**
  - Field observations
  - Front observations

III. Parameter calibration

What type of observations $\mathbf{Y}^o$?

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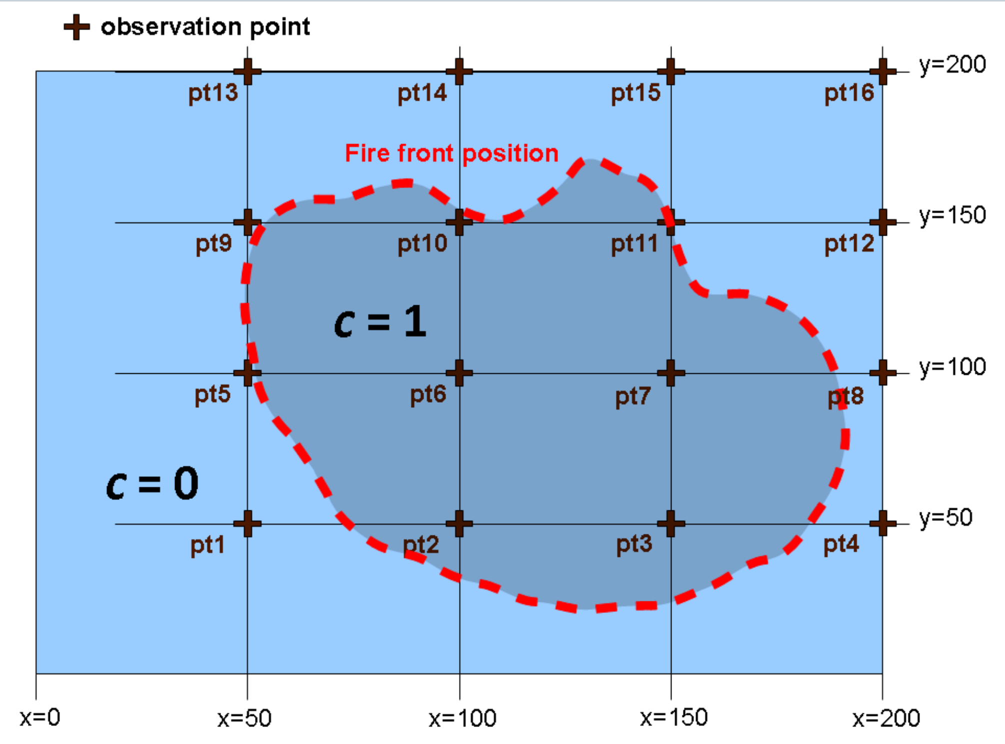

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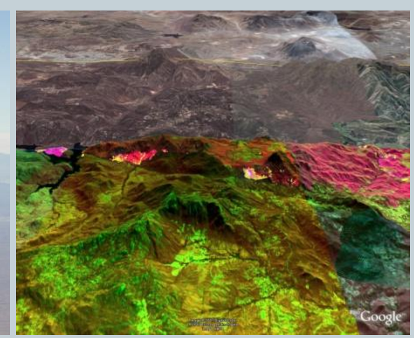
- **Front observations (e.g. airborne observations)**
  - Following time-evolving locations of fire front:
    - Visible or infrared imagery.
    - Reconstruction of fire front positions.





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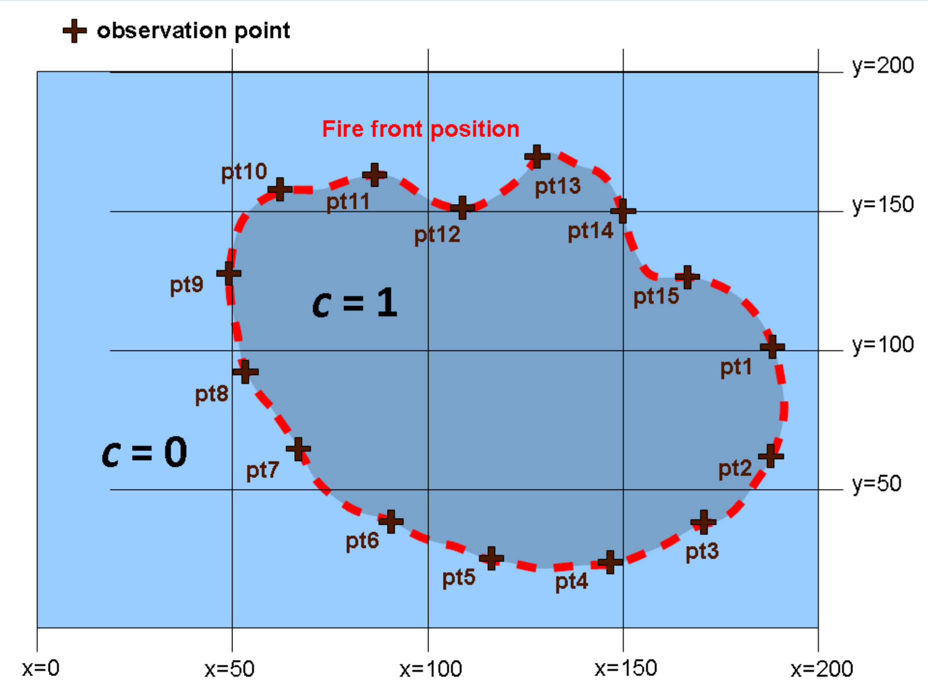

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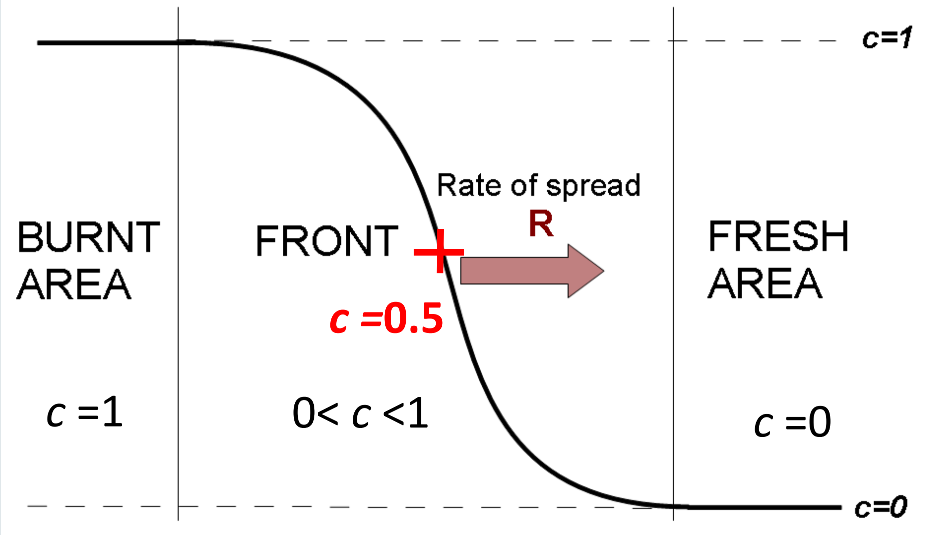

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Parameter correction based on the distance between obs. $\mathbf{Y}^o$ and simulations $H(\mathbf{X})$

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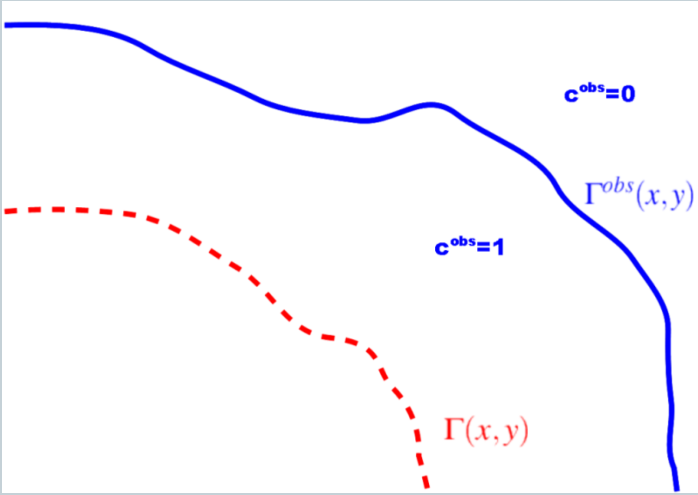
How to calculate the distance between observed and simulated isocontours ?

1. Discretization of the modeled isocontour $\Gamma(x,y,t)$ with N_p points:

$$H(\mathbf{X}) = D\left(\Gamma(x,y,t)\right)$$



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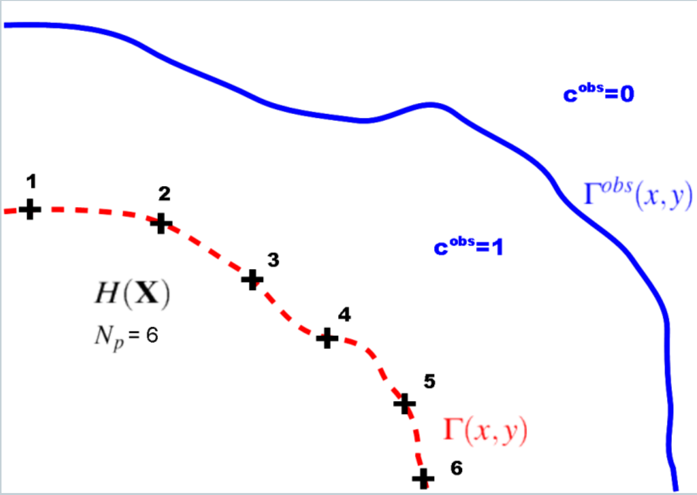

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2. Projection of the discretized points on the observed isocontour $\Gamma^{obs}(x,y,t)$:

$$\mathbf{Y}^o = P(H(\mathbf{X}))$$

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How to calculate the distance between observed and simulated isocontours ?

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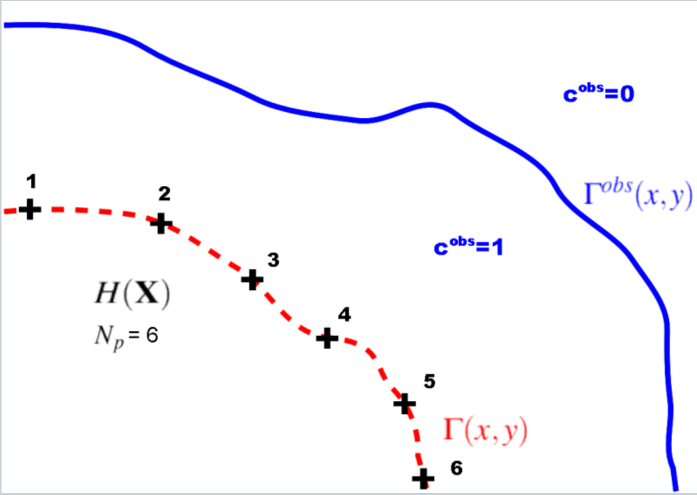

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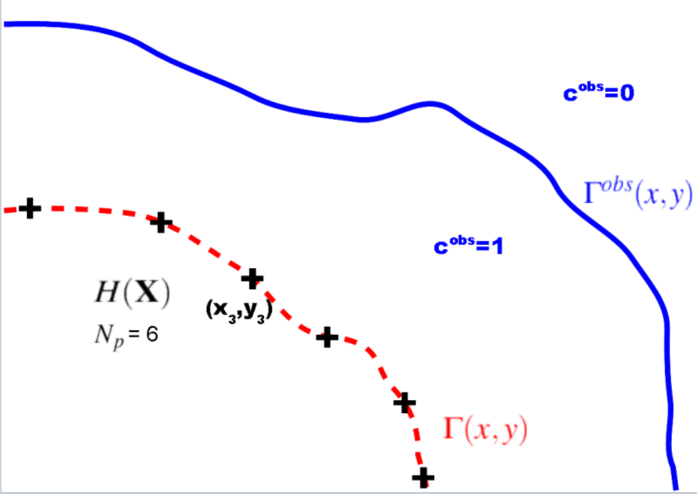

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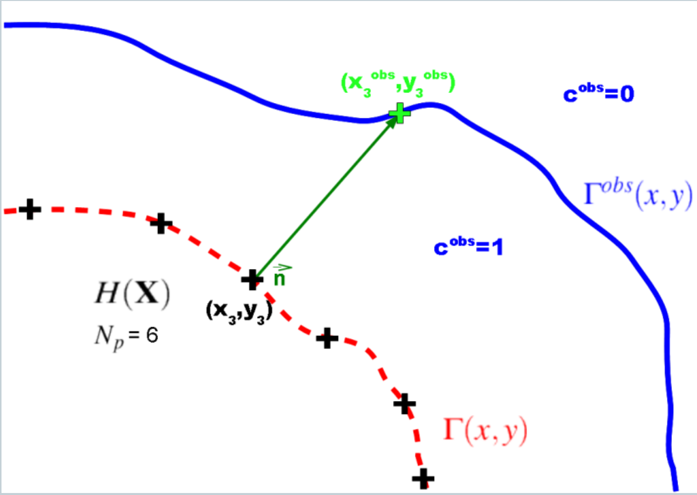

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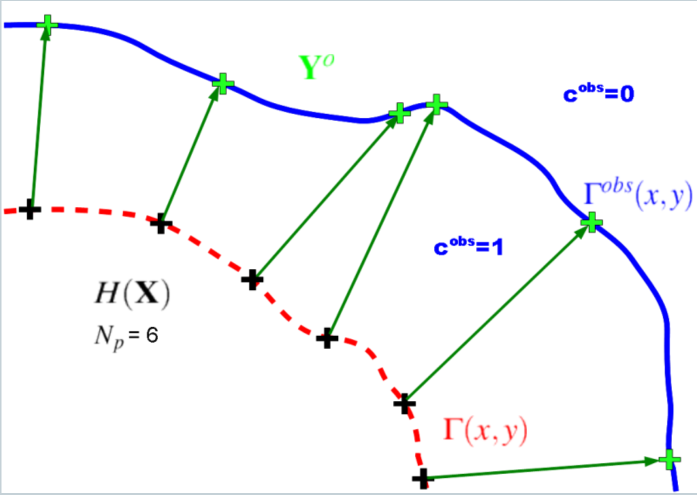

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2. Projection of the discretized points on the observed isocontour $\Gamma^{obs}(x,y,t)$.
3. Distance calculation between the equivalent points of $\Gamma(x,y,t)$ and $\Gamma^{obs}(x,y,t)$:

$$\mathbf{d} = \mathbf{Y}^o - H(\mathbf{X})$$

IV. APPLICATION TO WILDFIRE SPREAD MODEL

1 parameter calibration : τ

- Calibration of the proportionality coefficient τ

$$R(x,y,t) = \tau(x,y,t)\delta(x,y)$$

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- Calibration of the proportionality coefficient τ

$$R(x,y,t) = \tau(x,y,t)\delta(x,y)$$

- Objectives:
  - grant observations a high confidence (**R**<**B**) and check if the analysis is equal to the true value, used for observation generation:

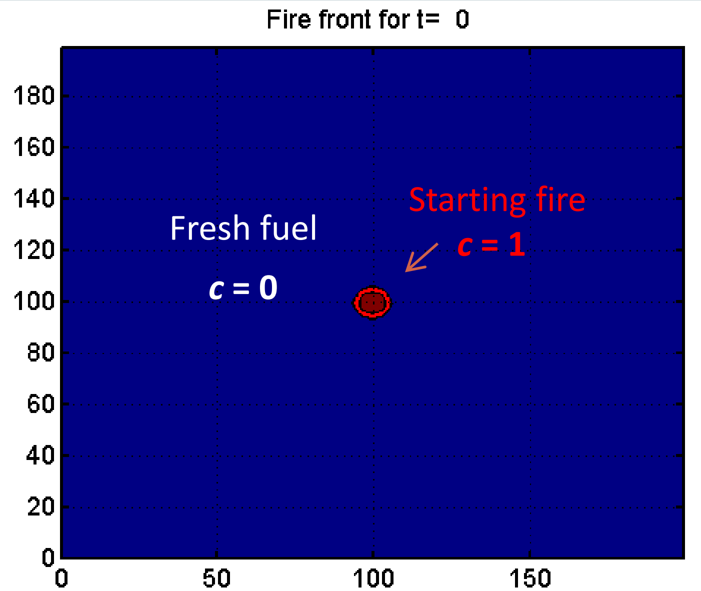
$$\tau^a = \tau^t$$

  - compare performances between field and front observations

IV. Application to wildfire

1 parameter calibration : τ

- Assimilation configuration:
  - Heterogeneous fuel distribution
  - Initial condition : centered circle



Initial condition

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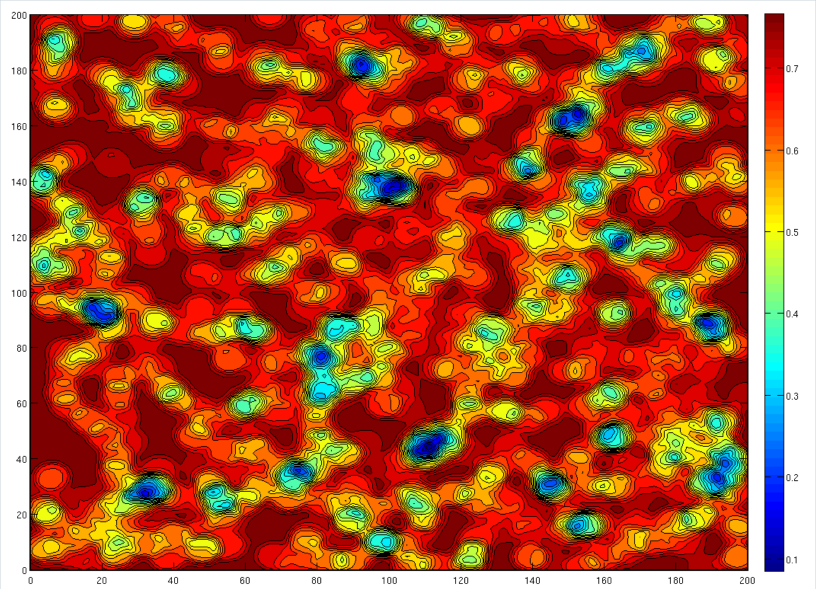

$$0.1m < \delta(x,y) < 0.8m$$

1 parameter calibration : τ

- Assimilation configuration:

  - Heterogeneous fuel distribution
  - Initial condition : centered circle

  - True value: τ^t = 0.1
    - order of magnitude given by Rothermel's model for no-wind, no-slope conditions

  - Different of values of parameter estimation (background) tested

$$0.2\tau^t < \tau^b < 1.8\tau^t$$

1 parameter calibration : τ

- Performances:
  - True value: τ^t = 0.1

Background τ^b	Type of obs.	Analysis τ^a
0.02 (-80%)	Field	0.02
	Front	0.10
0.07 (-30%)	Field	7.61
	Front	0.10

IV. Application to wildfire

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Out of range **No correction**

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Front observations > Field observations

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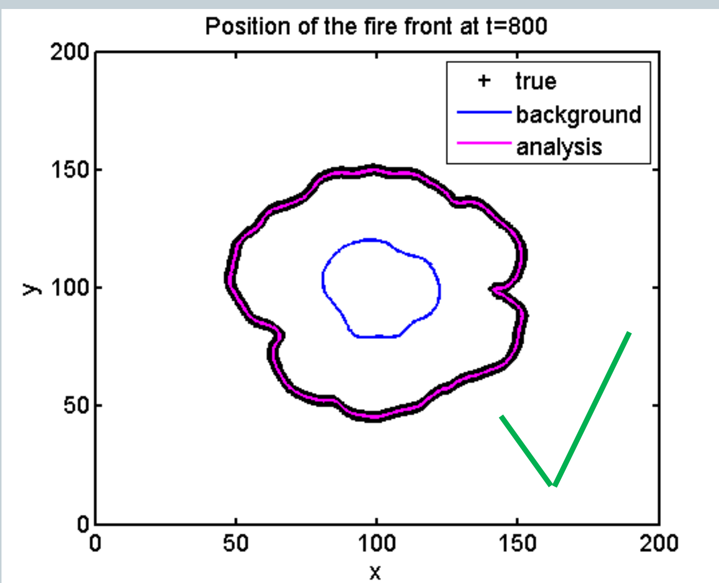
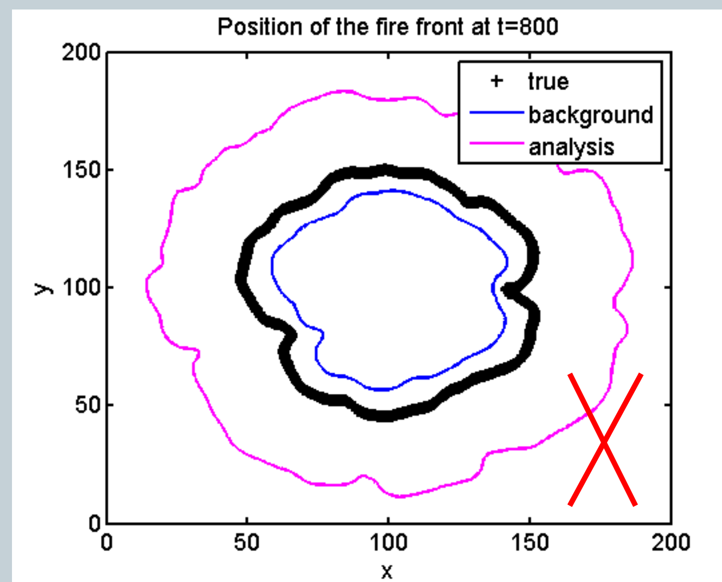
  - True value: τ^t = 0.1

Front observations > Field observations





Correction of τ^b= 0.04 (-60%) with front obs. Correction of τ^b= 0.07 (-30%) with field obs.

V. CONCLUSIONS AND PERSPECTIVES

V. Conclusions

Conclusions

- Forest fire spread is an innovative application of data assimilation
- Preliminary study by Mélanie Rochoux has been a good starting point
- New assimilation strategy for front observations is more adapted
  - Contain more information than field observations
  - Provide better assimilation results
- Several parameters has been calibrated at the same time
  - Input parameters
  - Experimentally fitted parameters from Rothermel's model
- Non-linearitiy impact overcome thanks to iterative calibration process
- The robustness of the method allows a wide study of configurations

V. Conclusions

Perspectives

- Ongoing application to real data
- Use CFD model to obtain better parametrization of the ROS
- Use other assimilation methods such as Ensemble Kalmann Filter to assimilate both front positions and model parameters
- Couple fire spread model with an atmosphere model

Thank you for your attention !

Questions ?