DATA ASSIMILATION AT LOCAL SCALE TO IMPROVE CFD SIMULATIONS OF DISPERSION AROUND INDUSTRIAL SITES AND URBAN NEIGHBOURHOODS

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Introduction

Methods
- Iterative ensemble Kalman smoother
- Estimation of background ensemble

Wind resource assessment
- Experimental setup
- Results of twin experiments
- Results with field observations

Dispersion in built environment (MUST)
- Experimental setup
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Conclusions and perspectives

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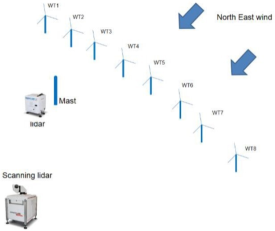
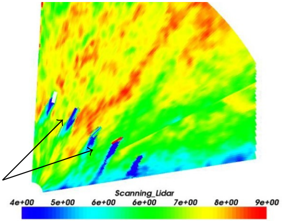
MICRO-METOROLOGICAL APPLICATIONS

- Wind resource assessment



$\leftrightarrow$

Wake effect



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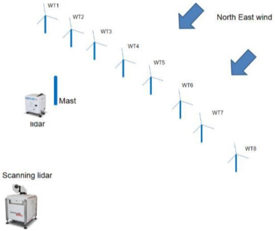

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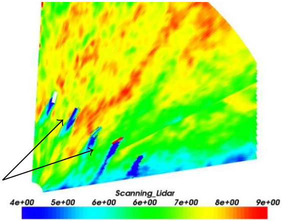
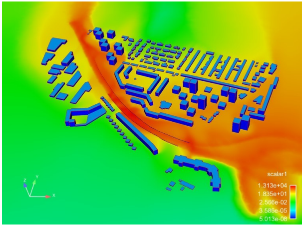
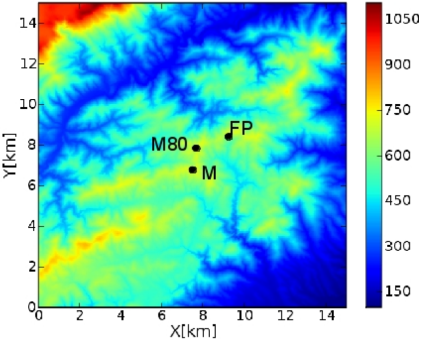


- Dispersion modelling in built environment



EXAMPLES OF IN SITU MEASUREMENTS



Candidate site for wind farm

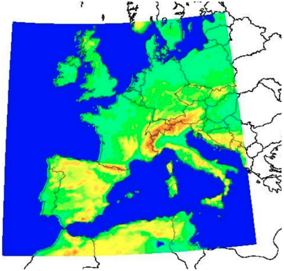
Met masts on crests

Urban area (Toulouse)

Meteo and pollutant observations

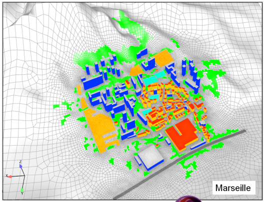
CONTEXT

Meso-scale
(ex : WRF, AROME)
$\Delta x \approx 10\mathrm{km}$, $\Delta z \approx 10\mathrm{m}$
$L \approx 3000\mathrm{km}$, $\frac{L}{U} \approx$ 7 days



$\longrightarrow$ Boundary conditions $\longrightarrow$

Local scale
(ex : *Code_Saturne*)
$\Delta x \approx 10\mathrm{m}$, $\Delta z \approx 1\mathrm{m}$
$L \approx 5\mathrm{km}$, $\frac{L}{U} \approx 17\mathrm{min}$



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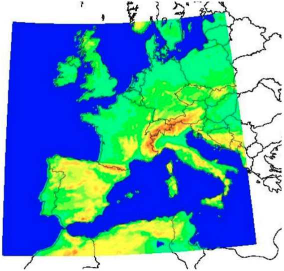

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$\uparrow$

Data assimilation

Observations

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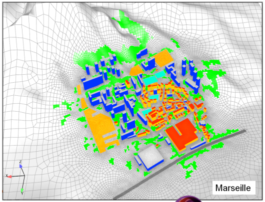

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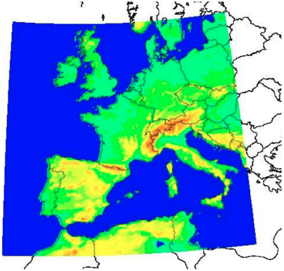

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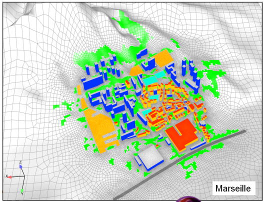
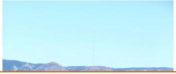


CODE SATURNE



Objective: Develop data assimilation methods adapted to local scale atmospheric simulations with CFD model

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ITERATIVE ENSEMBLE KALMAN SMOOTHER - IEnKS[1]

- Ensemble variational method appropriate for CFD simulations:
  - independent of atmospheric model
  - handle non-linear operators
  - easily parallelisable

[1] Sakov et al. (2012); Bocquet and Sakov (2014)

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- Variational method $\leftrightarrow$ minimise cost function
  $\widetilde{\mathcal{J}} = \|\text{distance to background}\|^2_{\mathbf{B}^{-1}} + \|\text{distance to observations}\|^2_{\mathbf{R}^{-1}}$

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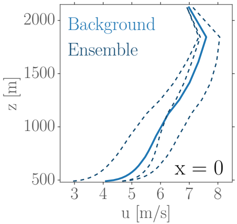
- Ensemble-based method $\leftrightarrow$ error statistics represented by an ensemble
  - Goal: Find best combination of ensemble members ($\mathbf{w}^\star$)
  - Iteratively minimise cost function, in the ensemble space

[1] Sakov et al. (2012); Bocquet and Sakov (2014)

IEnKS ALGORITHM

Ensemble = background + anomalies (BC)

Initialisation: $\mathbf{w} = \mathbf{0}$



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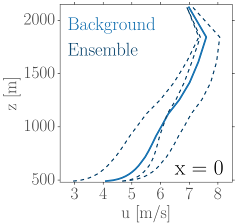
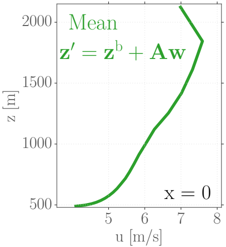


$\boxed{\mathbf{w}} \rightarrow$



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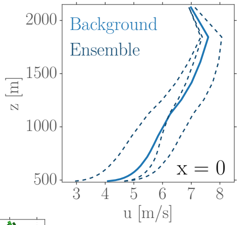

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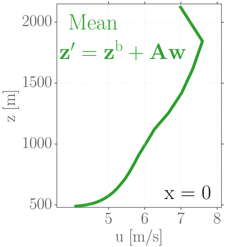

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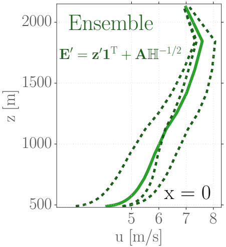

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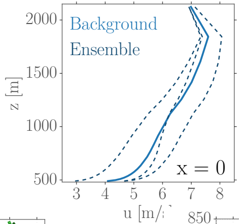
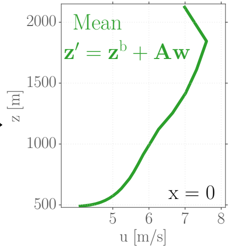


w $\rightarrow$



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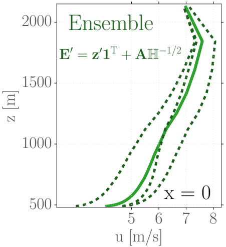
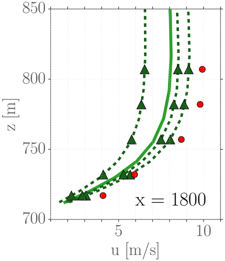


Model + Obs. op. $\longrightarrow$



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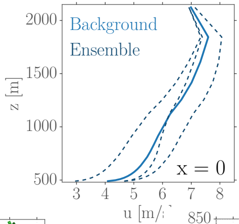

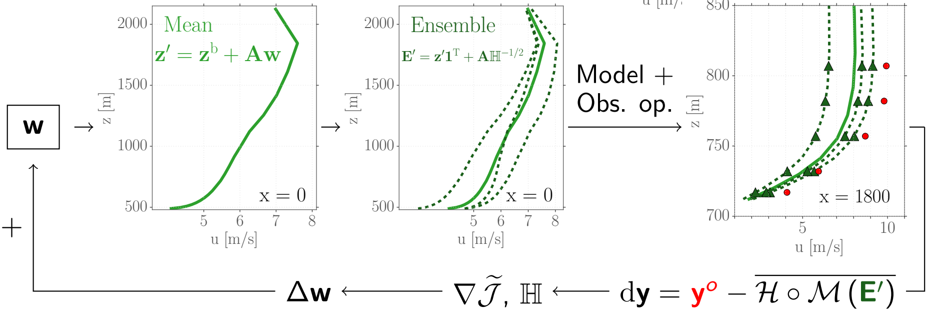

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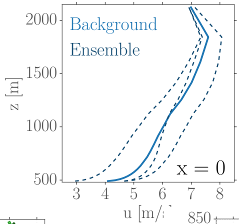

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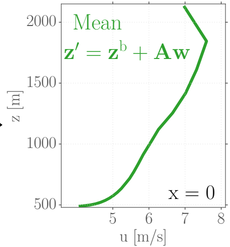

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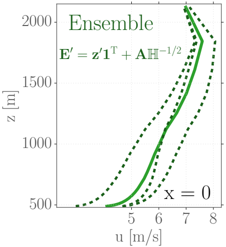

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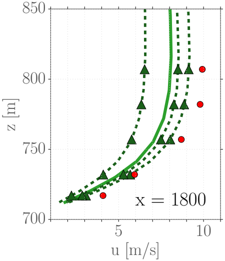
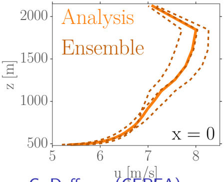


$+$

$$\Delta\mathbf{w} \longleftarrow \nabla\widetilde{\mathcal{J}},\ \mathbb{H} \longleftarrow \mathrm{d}\mathbf{y} = \mathbf{y}^o - \overline{\mathcal{H} \circ \mathcal{M}\left(\mathbf{E}'\right)}$$

until $\|\Delta\mathbf{w}\| < e$ *or* $\|\Delta\widetilde{\mathcal{J}}\| < e_J$

$\mathbf{w}^{\mathrm{a}} \ \Rightarrow$ optimal BC

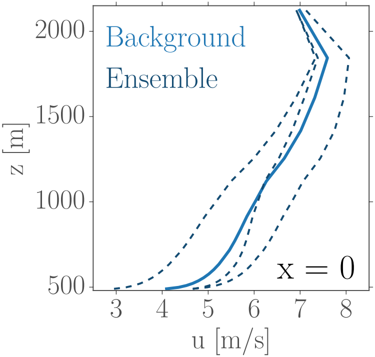


ESTIMATION OF BACKGROUND ENSEMBLE

Ensemble

$$\mathbf{E} = \mathbf{z}^{\mathrm{b}} + \mathbf{A}$$

$\mathbf{A}$ = anomalies



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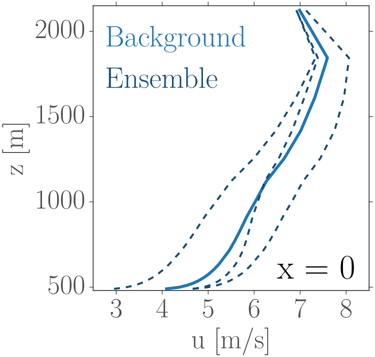
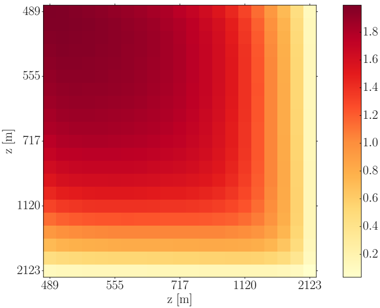


Background err. covar. mat.

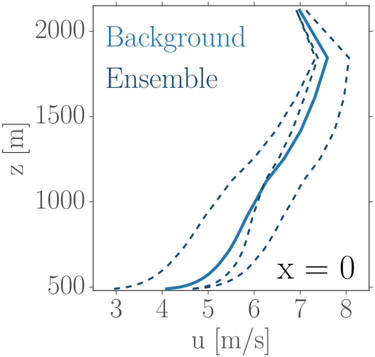
$\mathbf{B}_{i,j} = c_{i,j}\sigma_i\sigma_j$

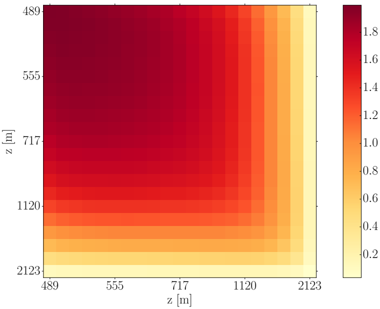
= correlation × std



ESTIMATION OF BACKGROUND ENSEMBLE

Ensemble	$\leftrightarrow$	**Background err. covar. mat.**
$\mathbf{E} = \mathbf{z}^{\mathrm{b}} + \mathbf{A}$	$\mathbf{B} = \mathbf{A}\mathbf{A}^{\mathrm{T}}$	$\mathbf{B}_{i,j} = c_{i,j}\sigma_i\sigma_j$
$\mathbf{A}$ = anomalies	$\mathbf{A} \sim$ leading modes of $\mathbf{B}$	= correlation $\times$ std





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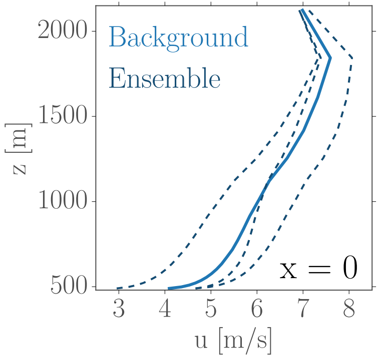

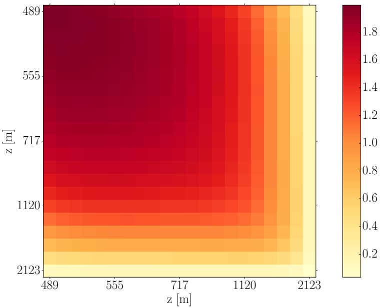

Estimate $(c_{i,j})$ and (σ_i) from statistical analysis of climatology:

- **Mesoscale simulations**: Wind resource assessment (WRF)
- **Observations**: Dispersion modelling (above the canopy for all the trials)

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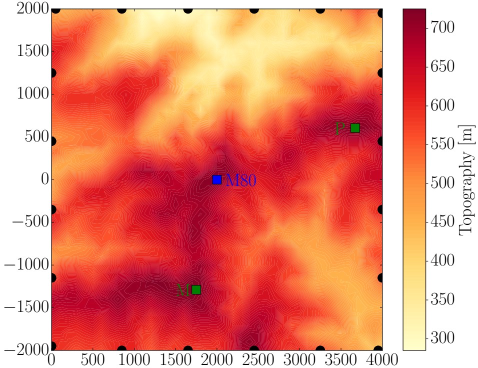
WIND RESOURCE ASSESSMENT [1]

- Site with very complex topography ($4\mathrm{km} \times 4\mathrm{km} \times 2030\mathrm{m}$)



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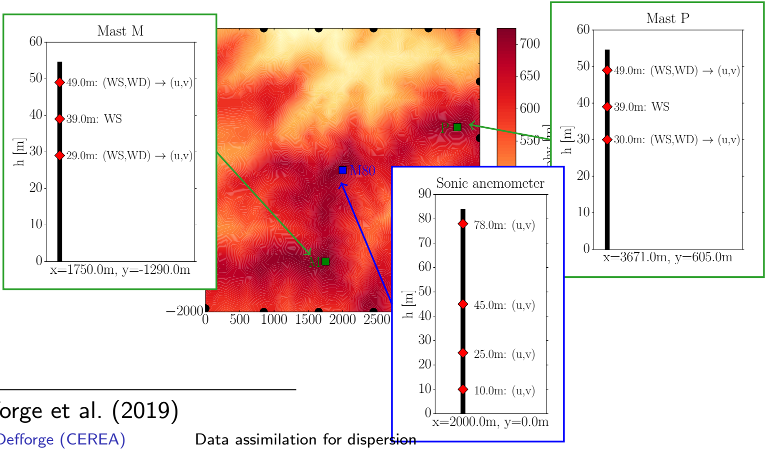
WIND RESOURCE ASSESSMENT [1]

- Site with very complex topography ($4\text{km} \times 4\text{km} \times 2030\text{m}$)
- Field campaign (August-December 2007): 3 met masts



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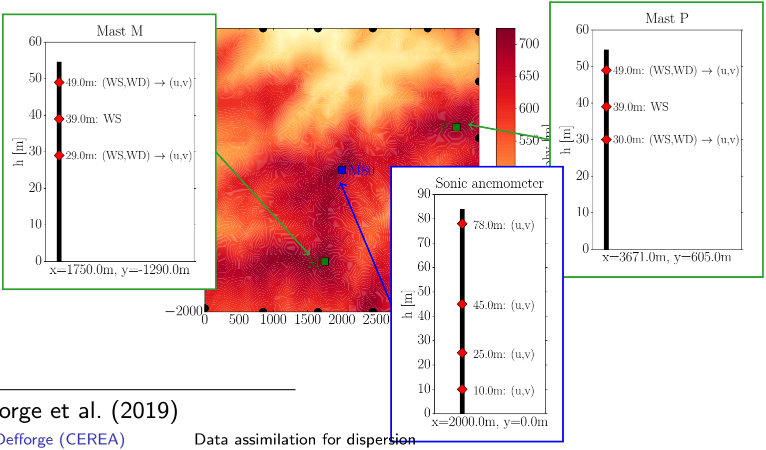
WIND RESOURCE ASSESSMENT [1]

- Site with very complex topography ($4\text{km} \times 4\text{km} \times 2030\text{m}$)
- Field campaign (August-December 2007): 3 met masts
- Hourly meso-scale simulations (WRF) over same region. Results clustered in 50 classes (WRAPP methodology)



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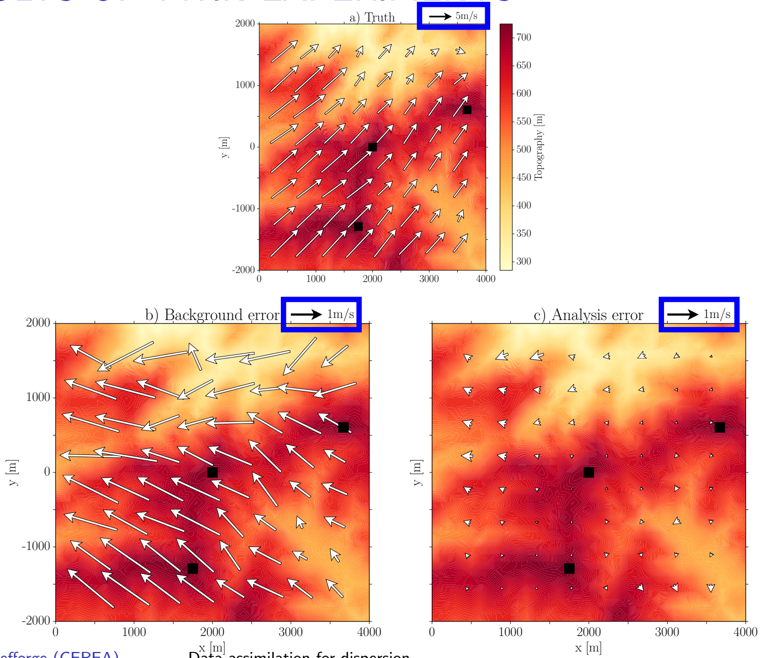
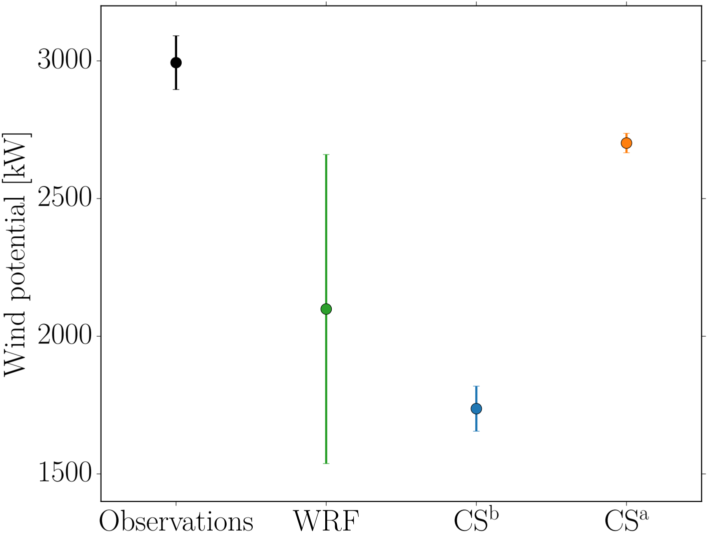
DATA ASSIMILATION EXPERIMENT

- 50 representative situations
- Control vector $=$ BC for 20 vert. profiles $\times$ 21 levels $\times$ $(u,v) = 840$ var.
- 10 observations (u, v, WS) from masts M and P. $\sigma_{\mathrm{o}} = 0.1\mathrm{m}^2/\mathrm{s}^2$.
- 5 members
- Cross validation with 8 observations (u and v) from mast M80

RESULTS OF TWIN EXPERIMENTS



WIND POTENTIAL AND UNCERTAINTY



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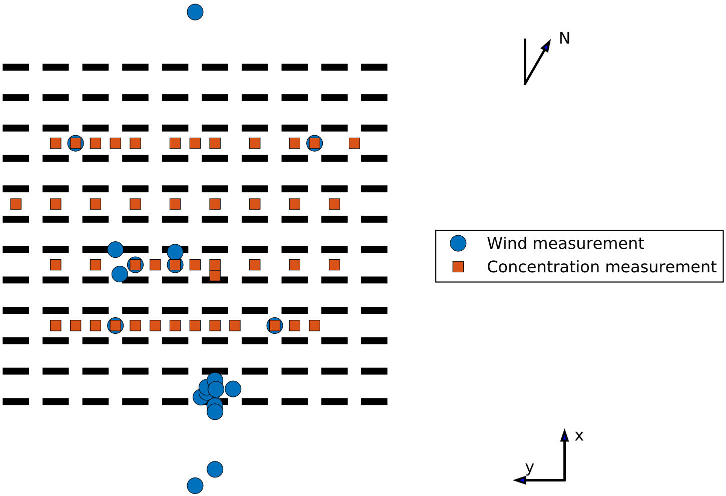
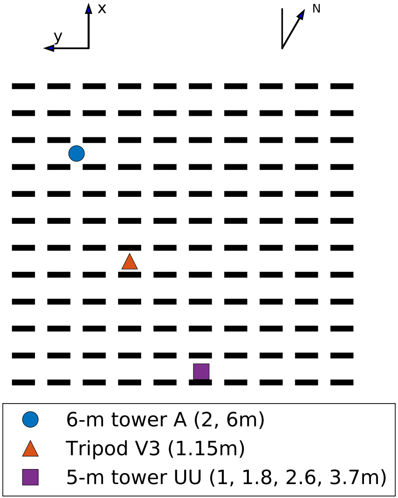
DISPERSION IN BUILT ENVIRONMENT (MUST)

- Mock Urban Setting Test (MUST) - September 2011 - Utah Desert
- Idealized city constituted with containers ($200\mathrm{m} \times 200\mathrm{m}$)
- Field campaign: wind and concentration observations

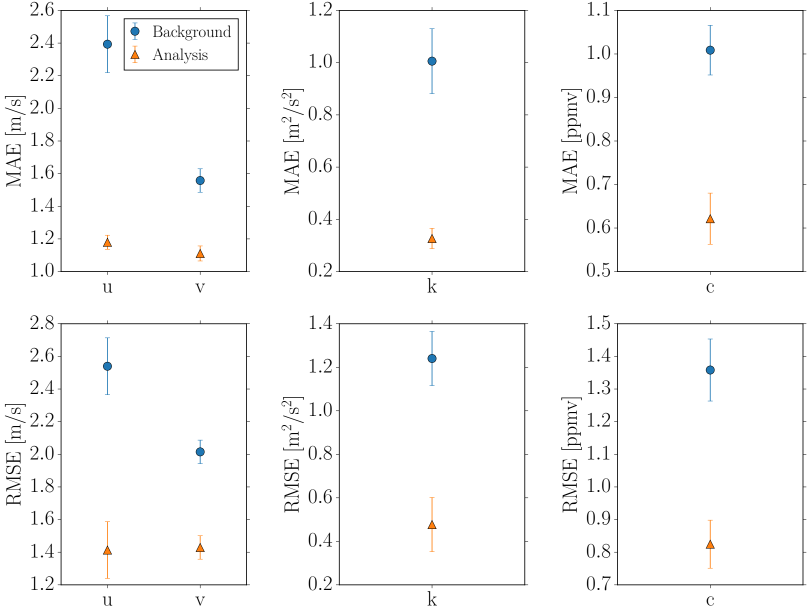


DATA ASSIMILATION EXPERIMENT

- Case 2681829: neutral stability conditions
- Control vector = 1 vert. profile (22 levels) $\times$ (u, v, k) = 66 var.
- 14 observations (u, v) from 3 locations
- 5 members
- Cross validation with observations in the canopy:
  - 12 for u,
  - 12 for v,
  - 10 for k,
  - 40 for concentration

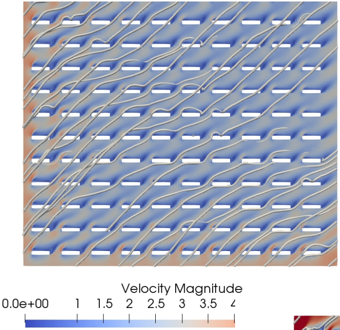


MAE AND RMSE FOR U, V, K, AND CONCENTRATION

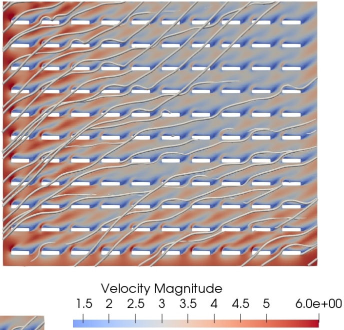


COMPARISON WITH REFERENCE[1]: Wind speed at 1m

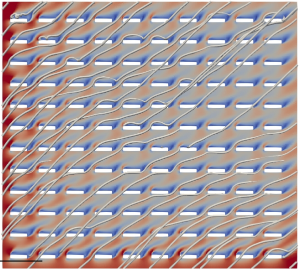
Background



Analysis



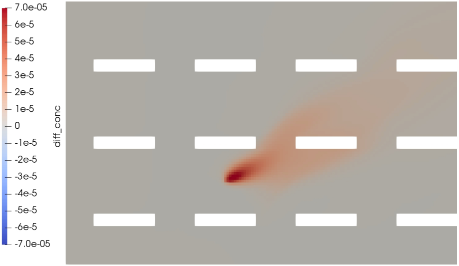
Reference



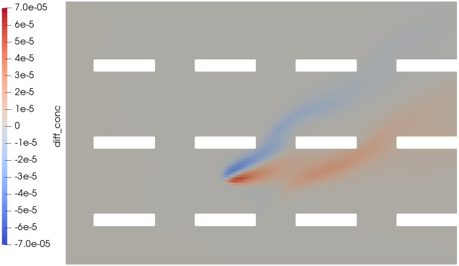
[1] Milliez and Carissimo (2007)

COMPARISON WITH REFERENCE: Concentration at 1m

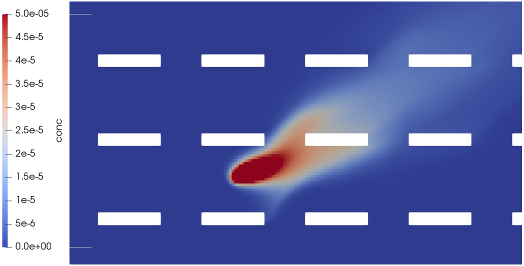
Background (departure from ref)



Analysis (departure from ref)



Reference



Introduction

Methods
- Iterative ensemble Kalman smoother
- Estimation of background ensemble

Wind resource assessment
- Experimental setup
- Results of twin experiments
- Results with field observations

Dispersion in built environment (MUST)
- Experimental setup
- Results with field observations

Conclusions and perspectives

CONCLUSIONS & PERSPECTIVES

- The IEnKS can be applied to local scale atmospheric simulations
- Application to 2 micro-meteorological applications: wind resource assessment + dispersion modelling
- The IEnKS has double action: improve exactitude (mean) + improve accuracy (variance) of BC and thus simulated values (wind, turbulence, concentration) within the domain.
- Control variables (BC) highly correlated $\Rightarrow$ method efficient with small ensemble ($N = 5$)
- The IEnKS is easily adaptable to different models or study cases

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- The IEnKS is easily adaptable to different models or study cases
- Perspectives :
  - MUST: assimilate observations of concentration

THANKS FOR YOUR ATTENTION

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