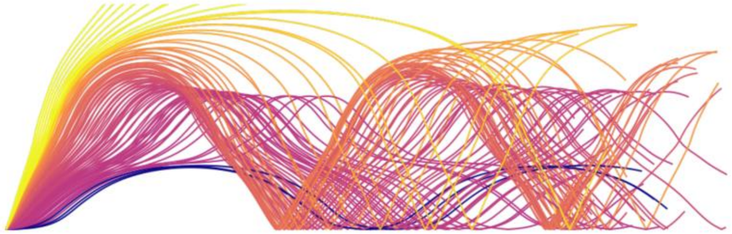


Waves & geosciences: Infrasound and beyond

Inverse problems for atmospheric dispersion

Lionel SOULHAC

INSA Lyon / Fluid Mechanics and Acoustics Laboratory

01/04/2022

Outline

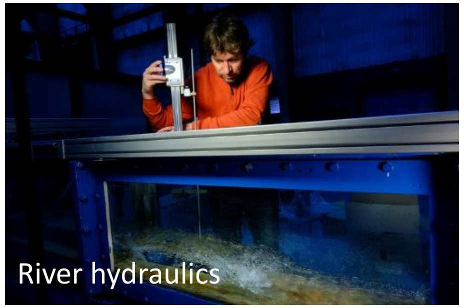
1. Introduction
2. Phenomenology and modelling of atmospheric dispersion
3. Inverse modelling : problems & approaches
4. Some applicated examples

1 – Introduction

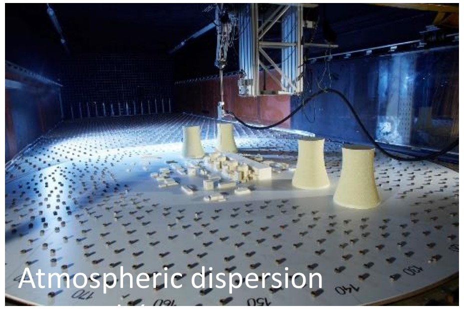
LMFA activity

Laboratoire de Mécanique des Fluides et d'Acoustique

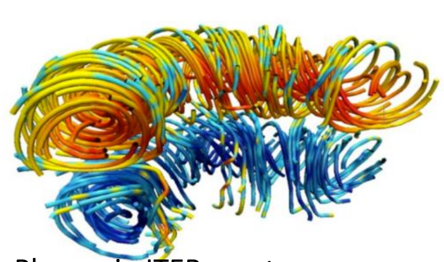
- Environment
- Transports
- Energy & process engineering
- Health


River hydraulics


Geophysical flows, mixing and stratification

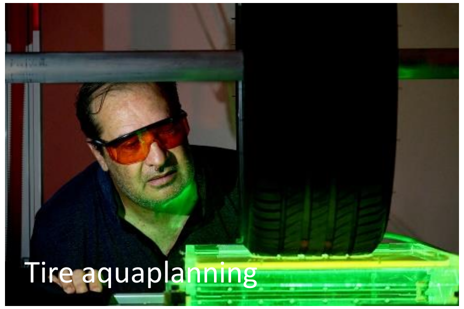

Atmospheric dispersion


Flow in aorta artery


Plasma in ITER reactor

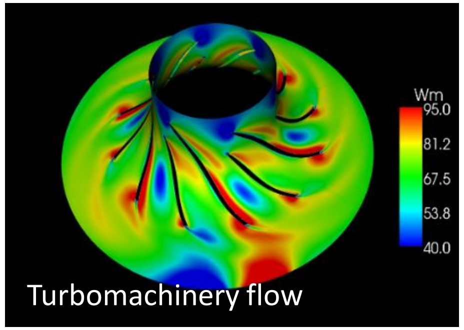

Multiphase mixing


Anechoic chamber


Tire aquaplanning


Aircraft engine


Equipex PHARE

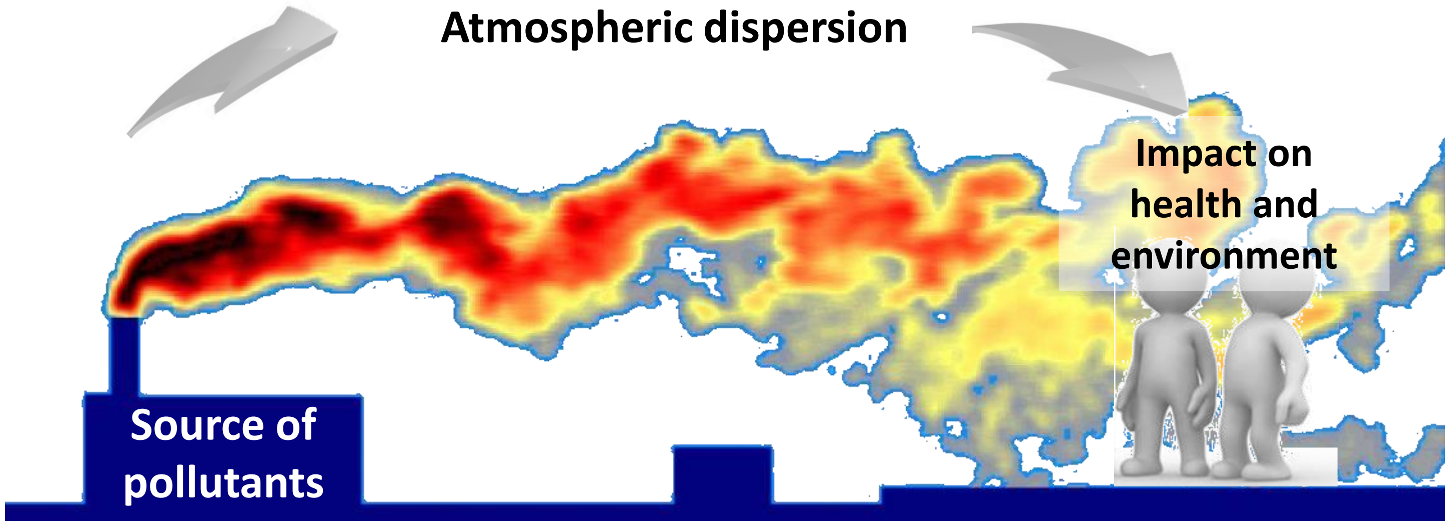


Turbomachinery flow

1 – Introduction

Atmospheric flows research

- Flow and dispersion in the atmospheric boundary layer



1 – Introduction

Atmospheric flows research

- A societal concern

LE PROGRÈS

Auvergne Rhône-Alpes

Cette pollution de l'air qui tue

Dans un rap
l'air dans la
qui s'amélic
000 au dio

Par Jean-Philippe
min

| Vu 485

LE PROGRÈS

Santé/Environnement

Pourquoi les enfants pauvres sont plus touchés p la pollution de l'air

Un rapport du Réseau Action Climat et de l'Unicef alerte sur le fait que les enfar issus de classes populaires sont plus touchés par la pollution atmosphérique qu des classes aisées. Et donc plus vulnérables, également, aux maladies liées à l'exposition aux particules fines.

Par Juliette MITOYEN - 14 oct. 2021 à 09:00 | mis à jour le 14 oct. 2021 à 09:11 - Temps de lecture : 5 r

6 | Vu 2297 fois

LE PROGRÈS

Rhône

Climat à Lyon en 2050 : des prévisions plus qu'inquiétantes

Quel climat fera-t-il à Lyon dans une trentaine d'années ? Grâce aux prévisions de
Mé
op
2,3

Par

Vu

LE PROGRÈS

Réchauffement climatique à Lyon : «Il faut planter plus et mieux»

Damien Lemoine, titulaire d'un doctorat en biologie forestière et maître de conférences à l'université Lyon-1, nous dit tout sur la manière dont un brin d'herbe ou un arbre géant piègent le carbone dans l'air. Mais encore faut-il opter pour le bon végétal.

Par Propos recueillis par Sophie MAJOU - 14 août 2021 à 19:00 | mis à jour le 15 août 2021 à 07:18 - Temps de lecture : 5 min

| Vu 6659 fois

LE PROGRÈS

Edition Est Lyonnais › Feyzin

Rhône

Raffinerie de Feyzin: la torchère activée a provoqué un épais dégagement de fumée

LE PROGRÈS

En images

Exercice de décontamination après un attentat au gaz sarin à Lyon

Ce mercredi à Lyon, un exercice de décontamination s'est déroulé à l'hôpital d'instruction des armées de Lyon, avec la participation d'étudiants de l'hôpital Edouard-Herriot : il s'agissait de prendre en charge des victimes contaminées par du gaz sarin après l'explosion d'un colis piégé déposé dans une poubelle près des urgences de l'hôpital.

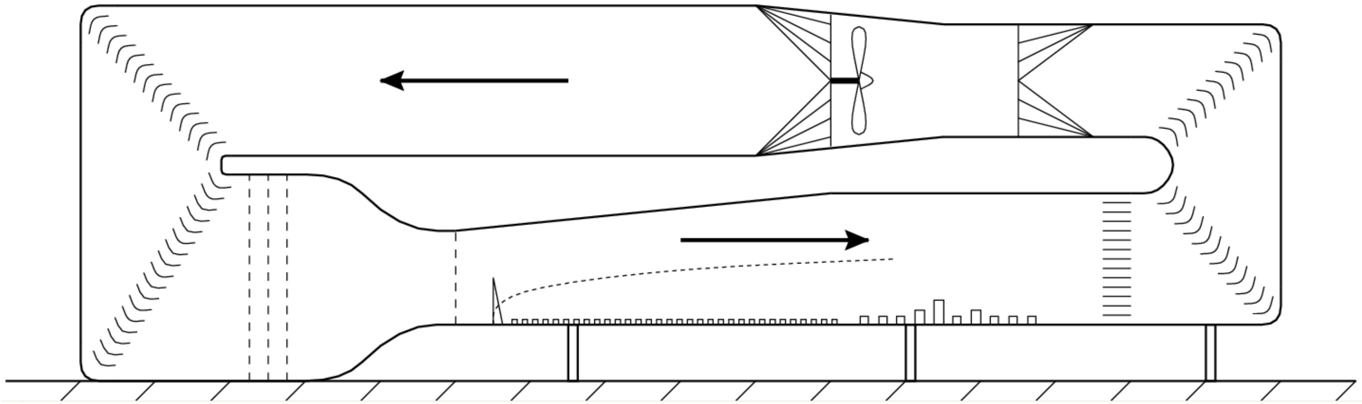
Par Le Progrès - 18 avr. 2014 à 11:03 - Temps de lecture : 1 min

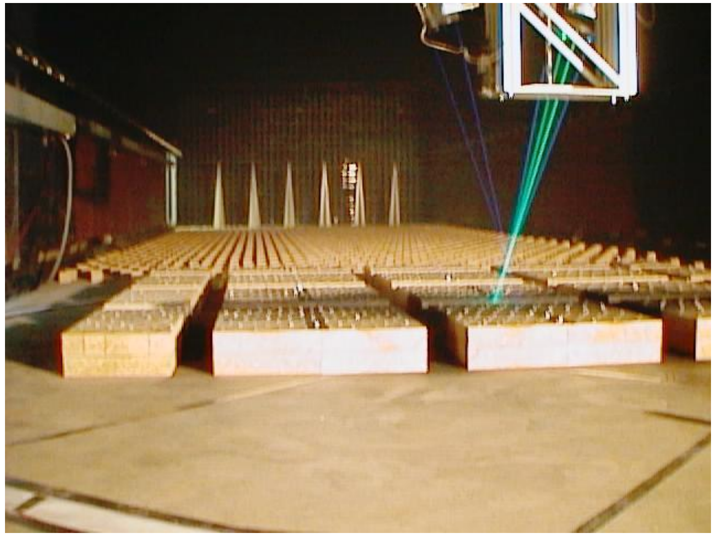
Vu 1601 fois

1 – Introduction

Atmospheric flows research

- Approaches :
  - Wind-tunnel experiments

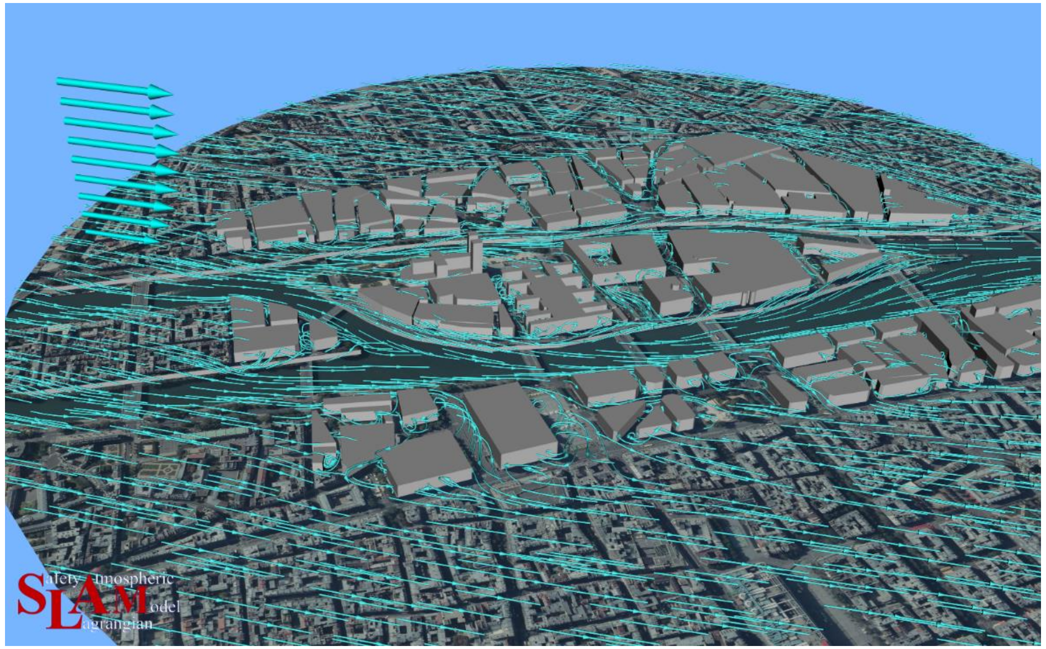


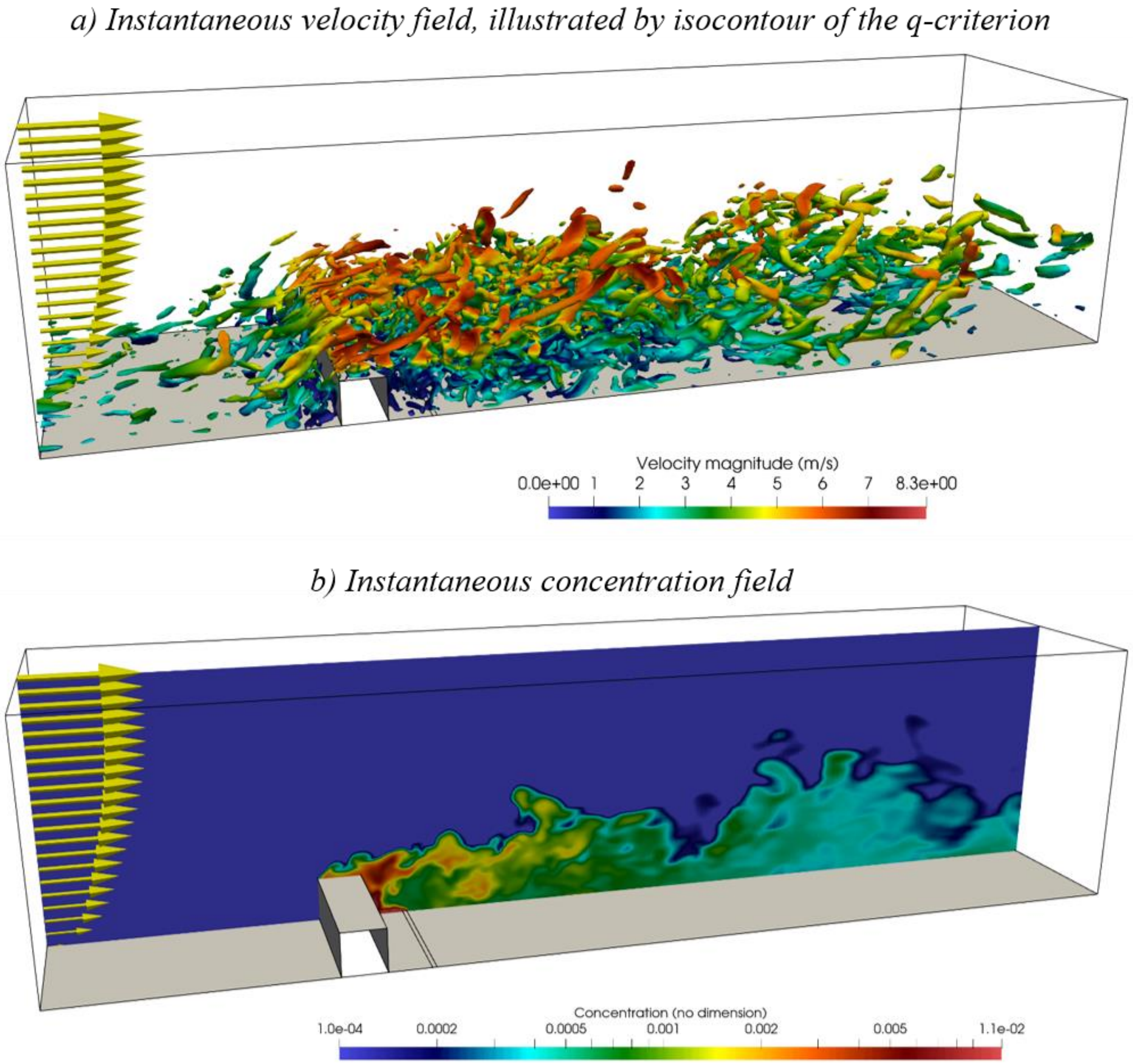


1 – Introduction

Atmospheric flows research

- Approaches :
  - Numerical simulation

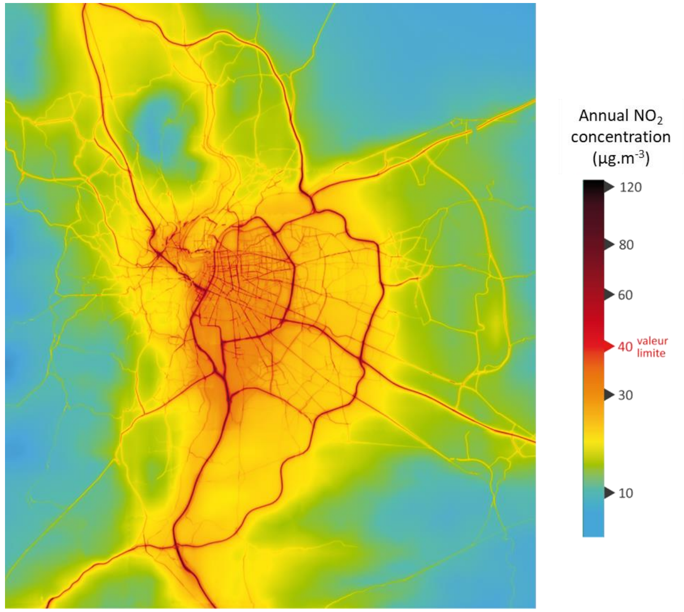




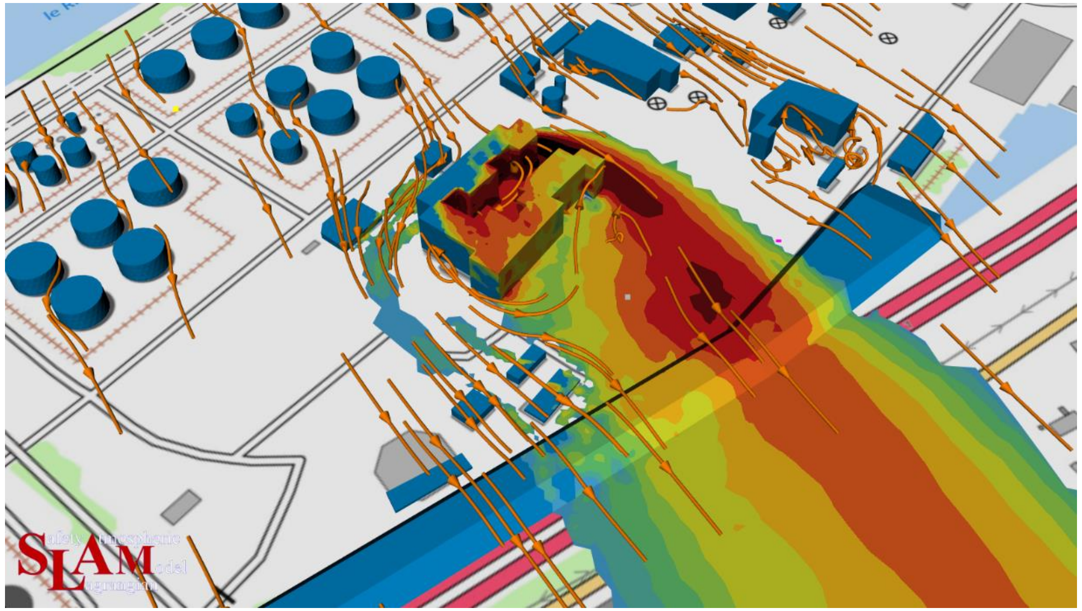
1 – Introduction

Atmospheric flows research

- Approaches :
  - Operational simplified models



SIRANE air quality model

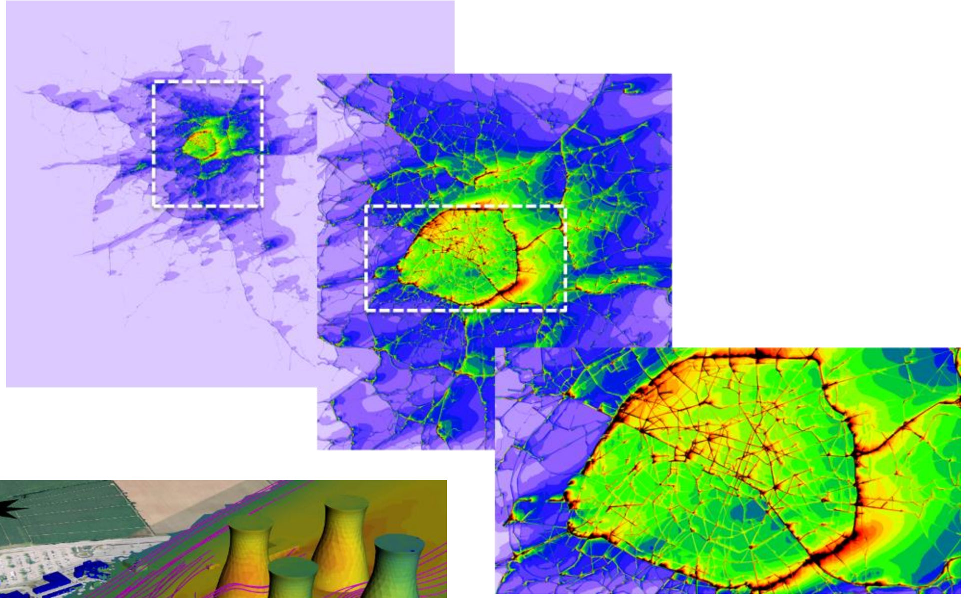


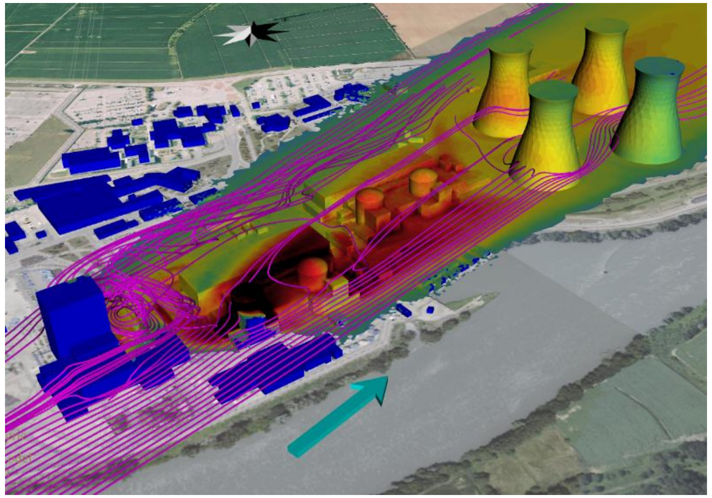
SLAM – Safety Lagrangian Atmospheric Model

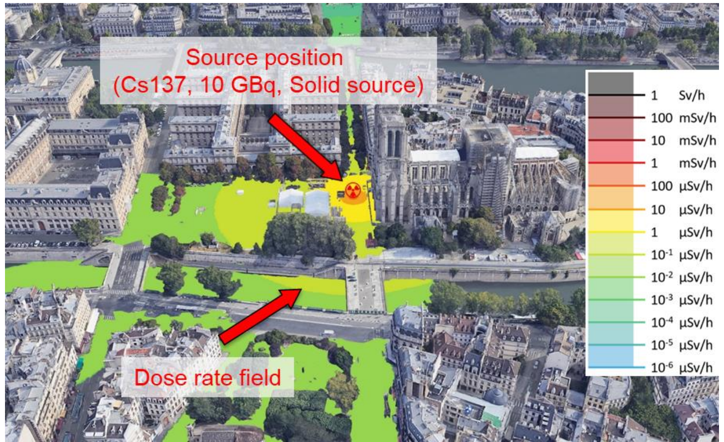
1 – Introduction

Atmospheric flows research

- Domains of application
  - Urban air quality
    - Air quality mapping
    - Population exposure and health effects
  - Industrial risk
    - Environmental impact
    - Risk assessment
    - Crisis management
  - NRBC terrorist attacks
    - Scenarios evaluation
    - Fast response modeling
  - Indoor ventilation



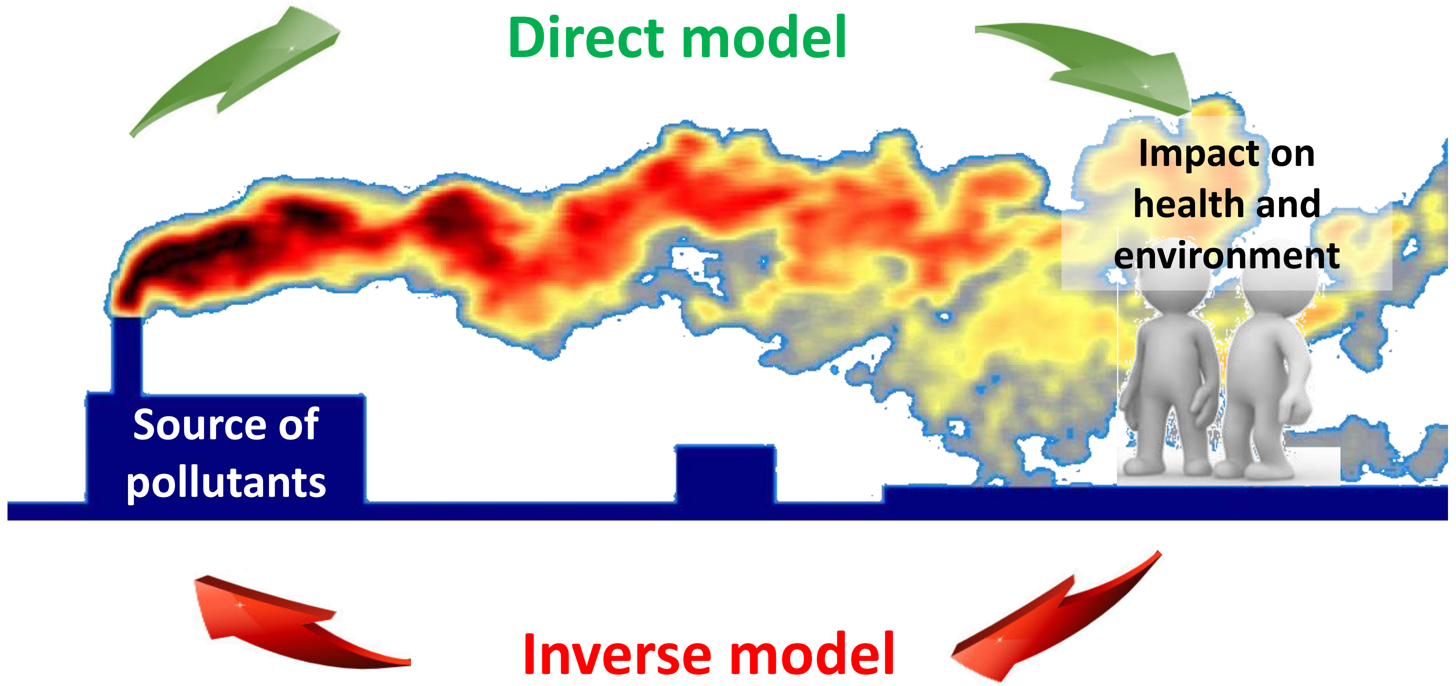




1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

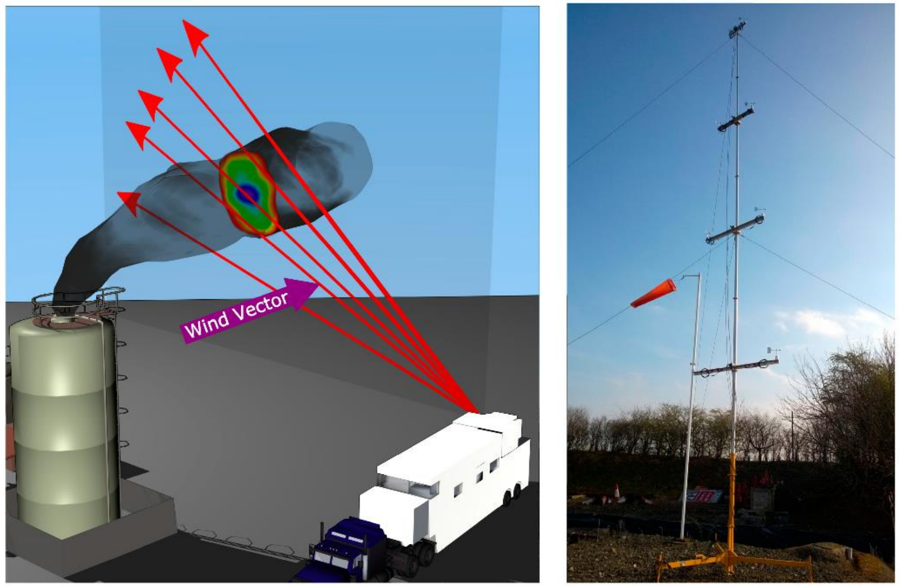
- Direct and inverse model



1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

- Characterisation of sources of atmospheric pollution
  - Quantification of emissions : third party identification, traffic, industry, etc.



(a) (b)

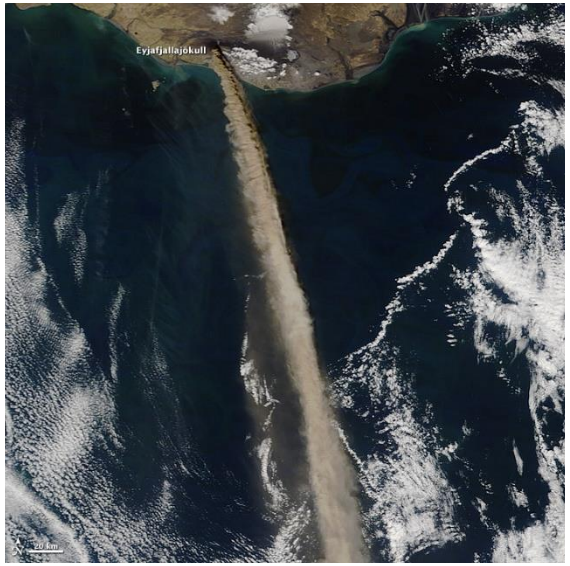
Emission estimation from LIDAR measurements

Traffic air pollution measurements

1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

- Characterisation of sources of atmospheric pollution
  - Natural emissions (volcanos, bush fires, limnic eruption, etc.)



Eyjafjallajökull volcano eruption, 2010

Australia bushfires, 2019-2020

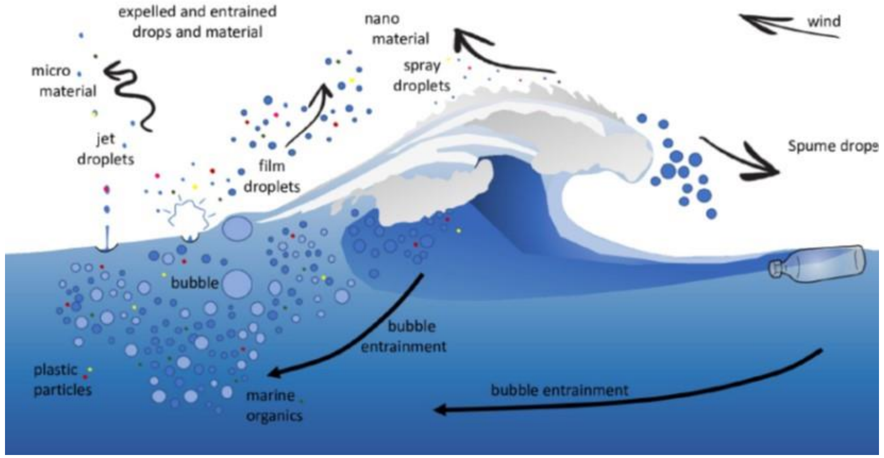
Nyos lake, 1986

1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

- Characterisation of sources of atmospheric pollution
  - Diffuse emissions (evaporation, particle entrainment, etc.)

Oil spill



Ocean-atmosphere exchange

Red dust erosion, Gardanne

1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

- Characterisation of sources of atmospheric pollution
  - Leaks, accident, fires

Leaks on an industrial site

Lubrizol, 2019

Notre-Dame, 2019

1 – Introduction

Why do we need inverse modelling of atmospheric dispersion ?

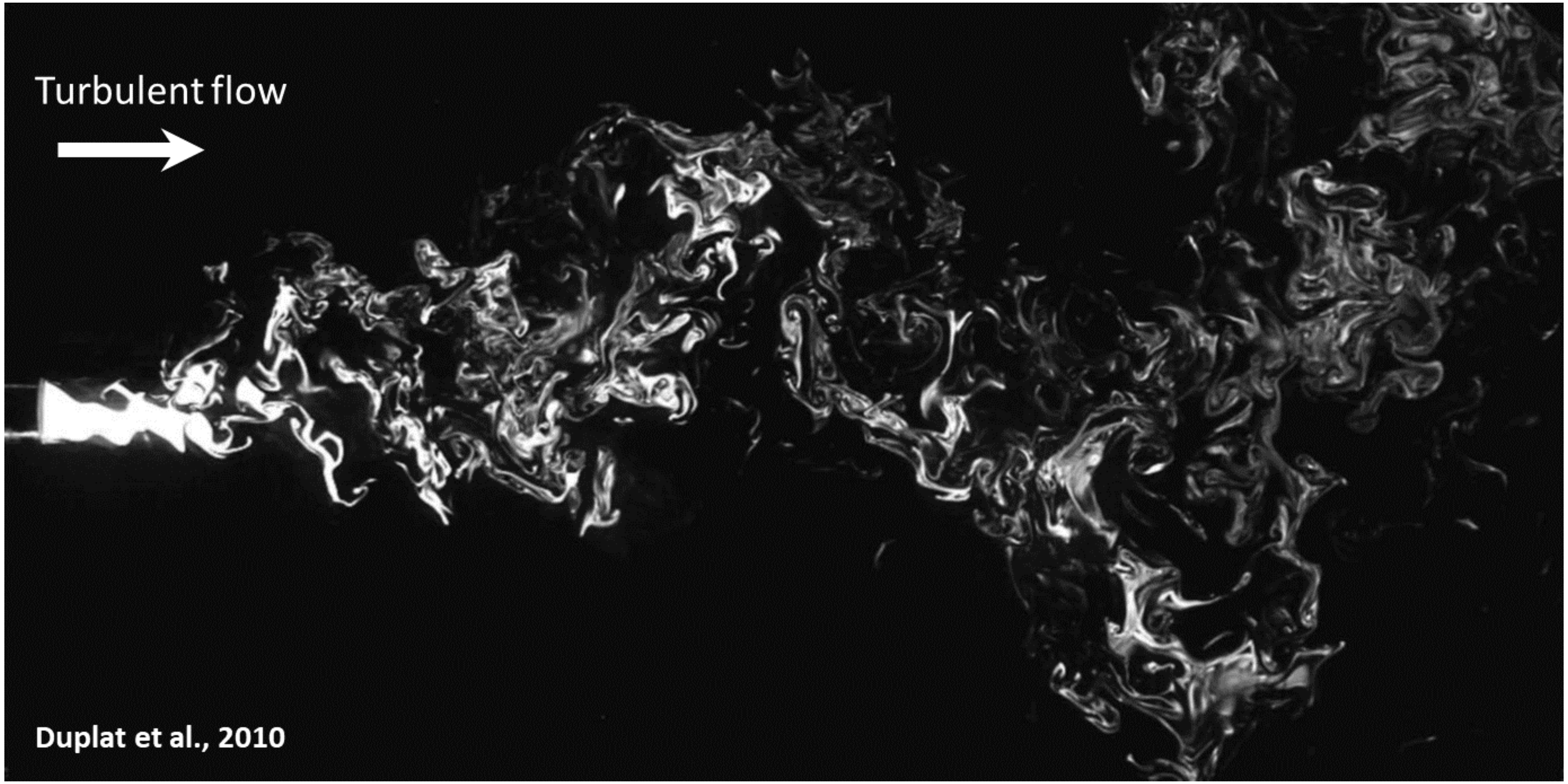
- Characterisation of sources
  - Terrorist attacks

New York, Sept. 11, 2001

Crisis management exercise

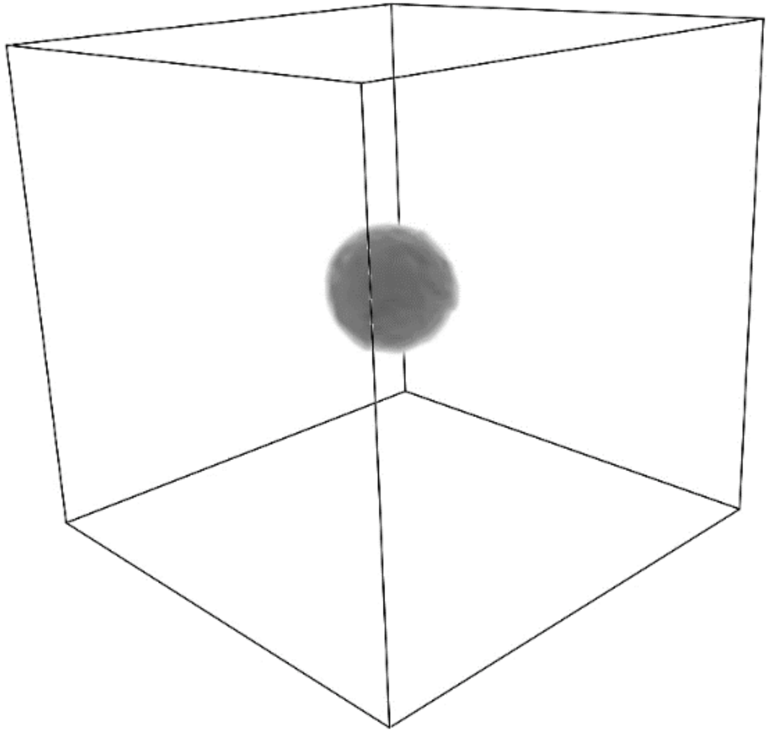
2 – Phenomenology and modelling of atmospheric dispersion

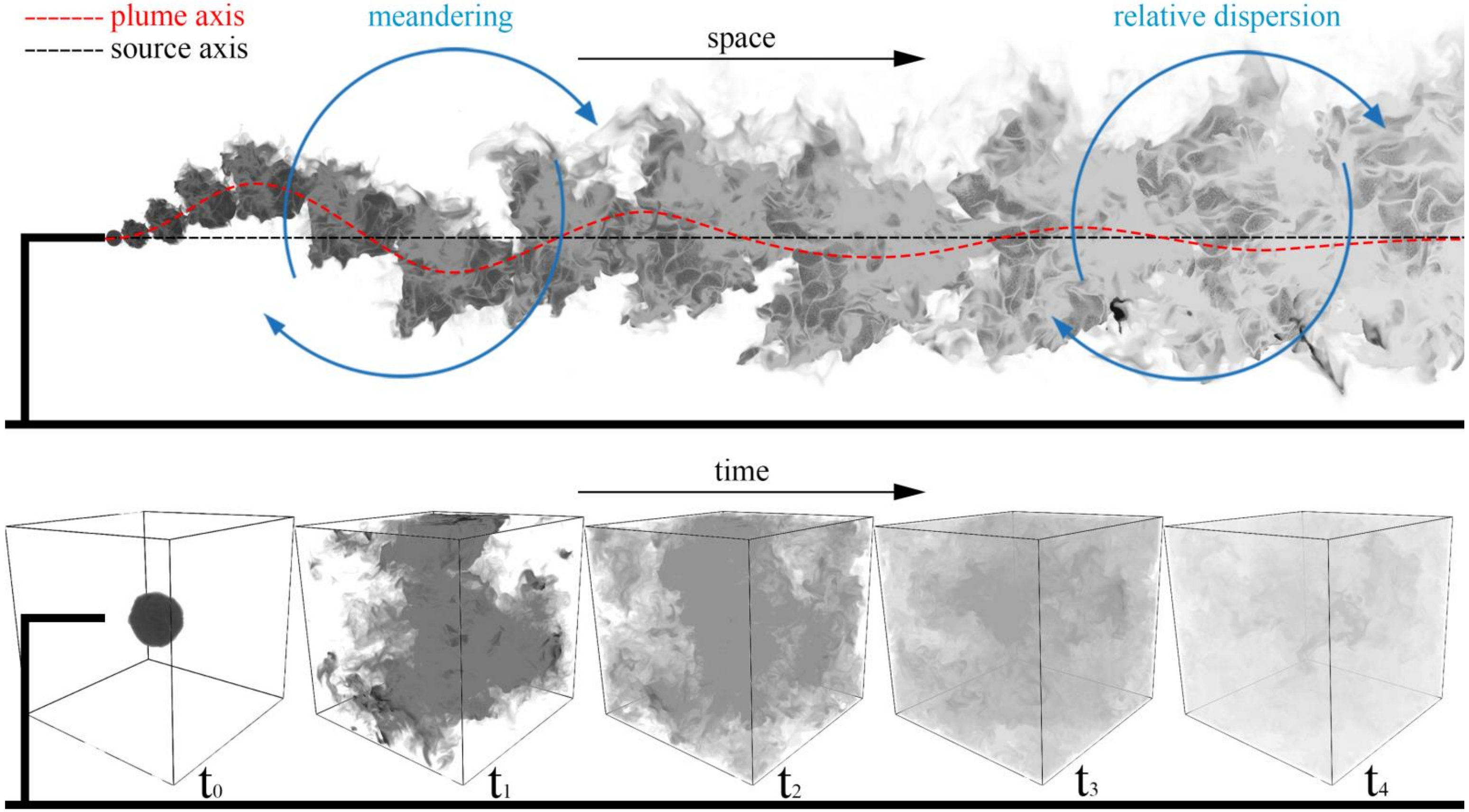
Turbulent dispersion



2 – Phenomenology and modelling of atmospheric dispersion

Turbulent dispersion



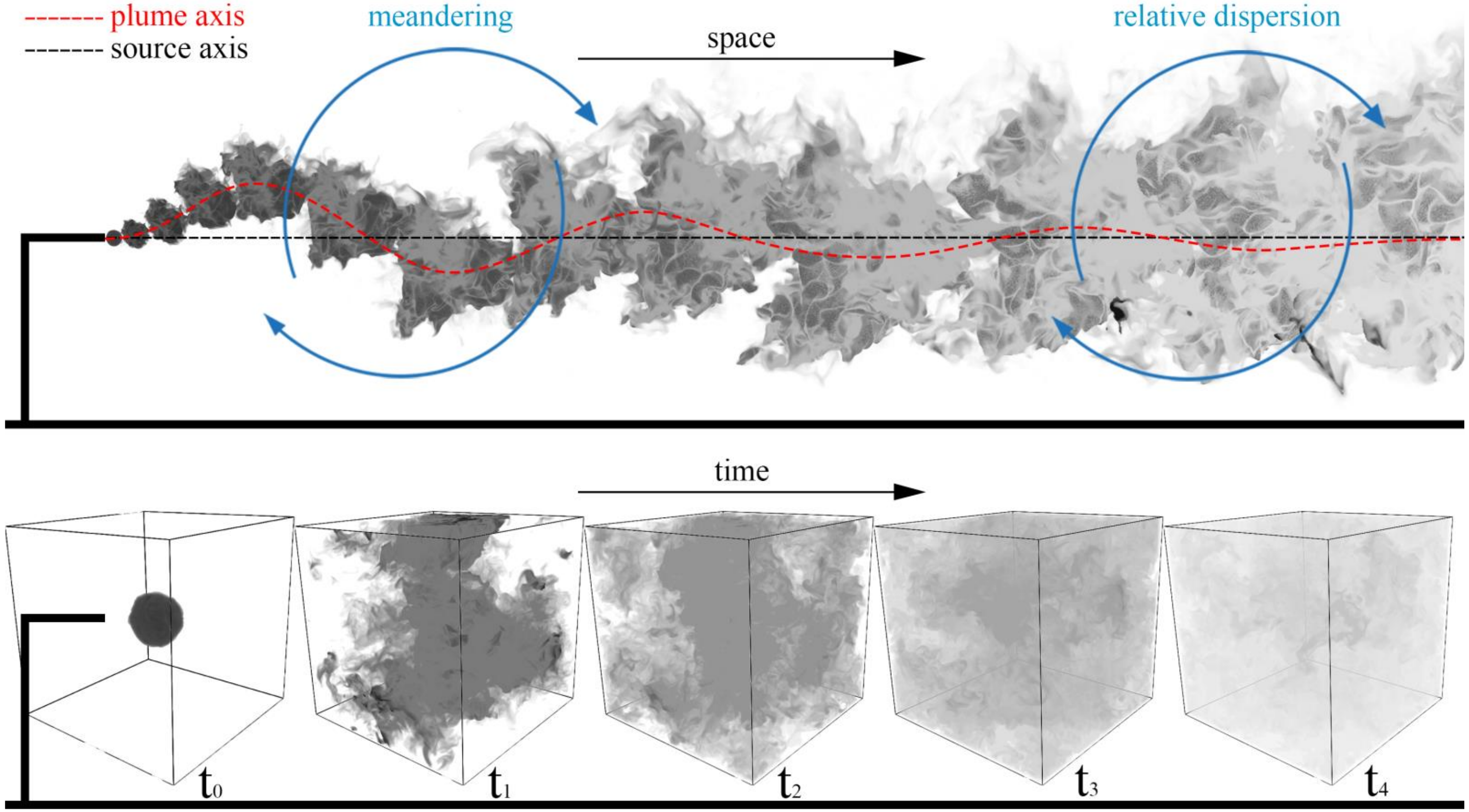


Orsi et al. (2021)

2 – Phenomenology and modelling of atmospheric dispersion

Turbulent dispersion

Raffinerie de Feyzin (source France Inter)

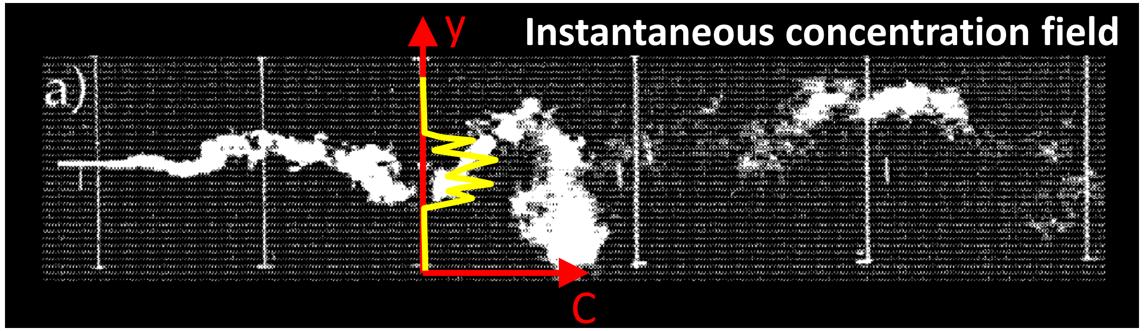


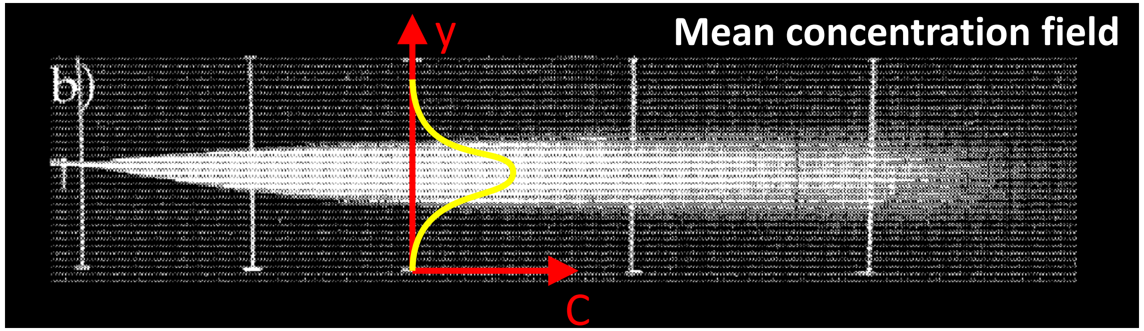
Orsi et al. (2021)

2 – Phenomenology and modelling of atmospheric dispersion

Turbulent dispersion

- Instantaneous vs mean concentration field





Gaussian model for the mean concentration

Analytical solution of the advection-diffusion equation

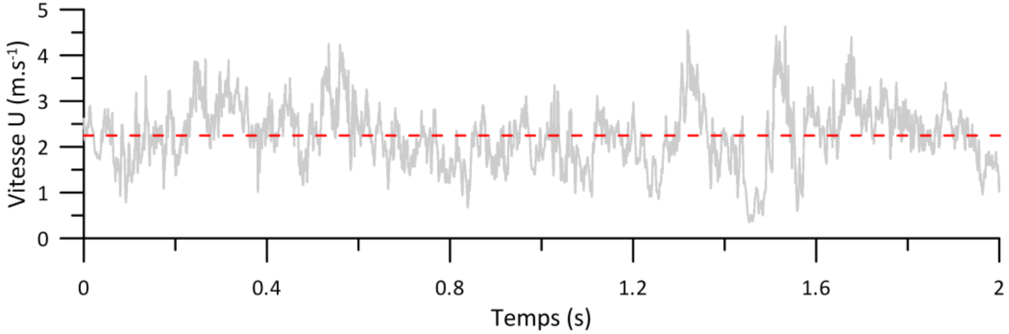
$$\overline{c}(x,y,z,t)=\frac{Q}{2\pi U\sigma_y\sigma_z}\exp\left[-\frac{1}{2}\left(\frac{(y-y_0)^2}{\sigma_y^2}+\frac{(z-z_0)^2}{\sigma_z^2}\right)\right]$$

2 – Phenomenology and modelling of atmospheric dispersion

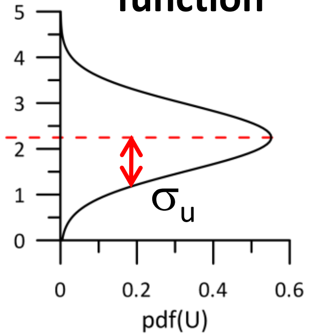
Turbulent dispersion

- Influence of turbulence on dispersion

Time evolution of the fluctuating velocity



Probability density function

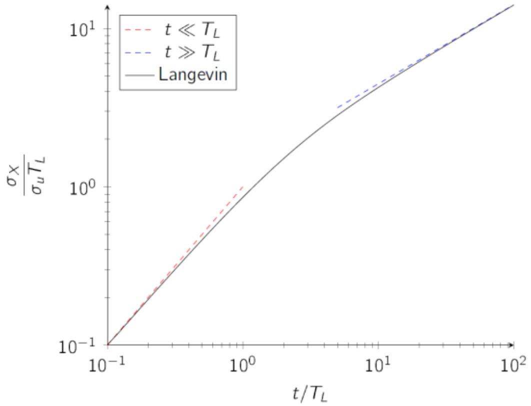


Taylor theory (1921)

$$\sigma_{X_i}^2 = 2\sigma_{U_i}^2 T_{L,i}\left\{t - T_{L,i}\left[1 - \exp\left(-\frac{t}{T_{L,i}}\right)\right]\right\}$$

Asymptotic behaviours

$$\begin{cases} \sigma_{X_i}(t) \simeq \sigma_{U_i} t & \text{for} \quad t \ll T_{L,i} \\ \sigma_{X_i}(t) \simeq \sqrt{2\sigma_{U_i}^2 T_{L,i} t} & \text{for} \quad t \gg T_{L,i} \end{cases}$$



Lagrangian auto-correlation coefficient of turbulence

$$R_{uu}(\tau) = \frac{\int u'(t)u'(t+\tau)dt}{\int u'(t)u'(t)dt}$$

Lagrangian time scale

$$T_{L,x} = \int_0^{+\infty} R_{uu}(\tau)d\tau$$

2 – Phenomenology and modelling of atmospheric dispersion

Turbulent dispersion

- Influence of stratification on turbulence and on dispersion

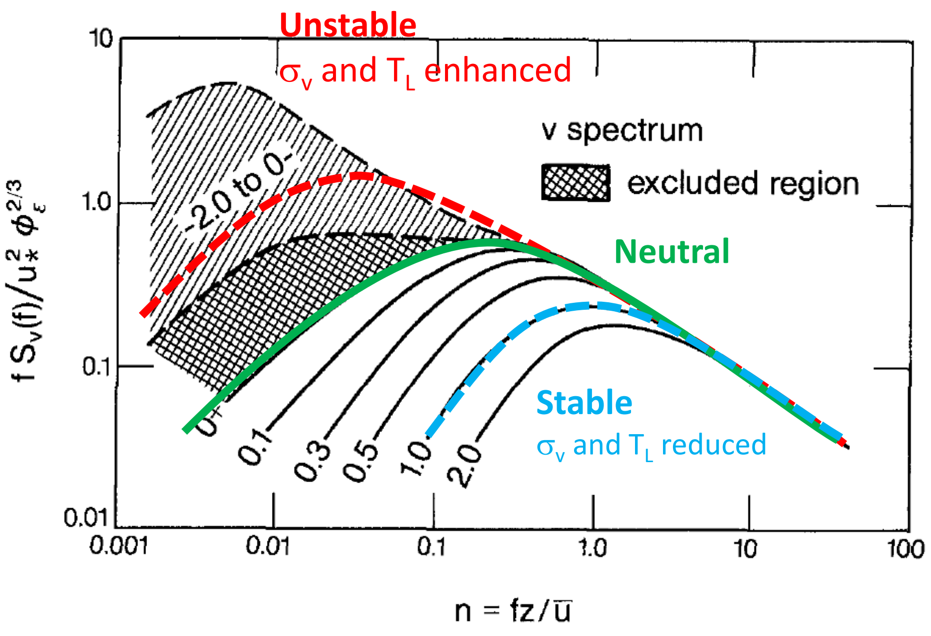


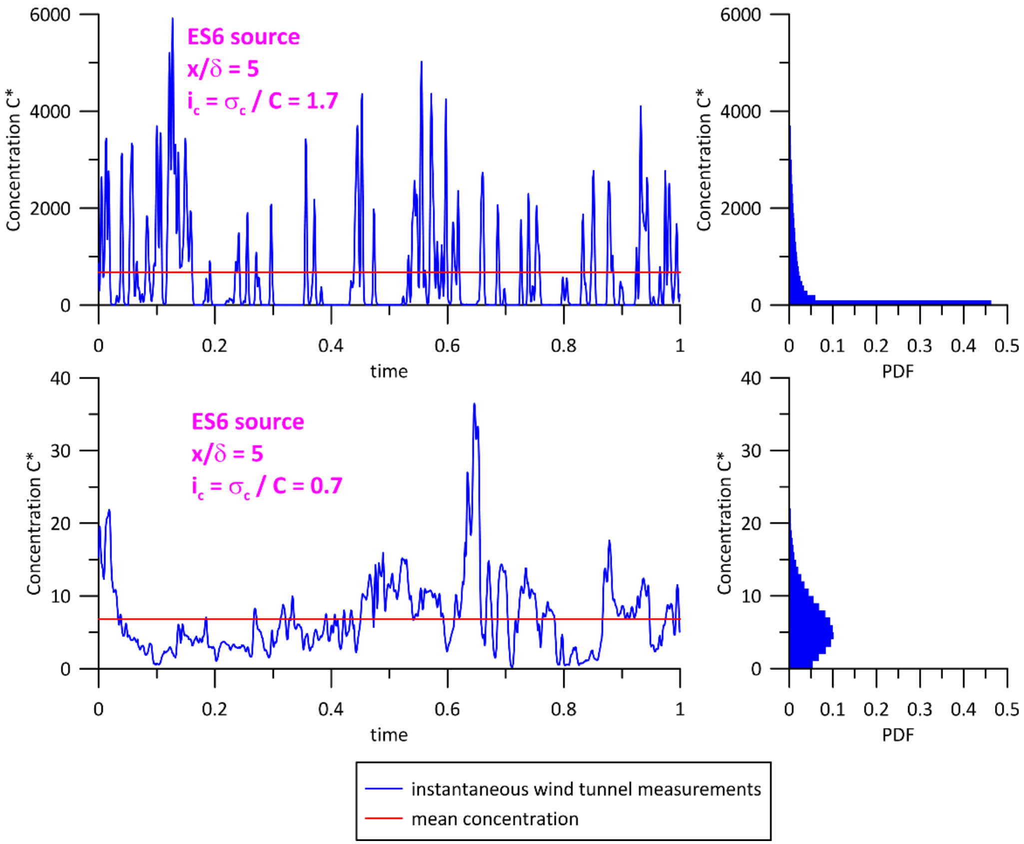
FIG. 2.6. Normalized surface layer v spectrum shown varying with z/L.

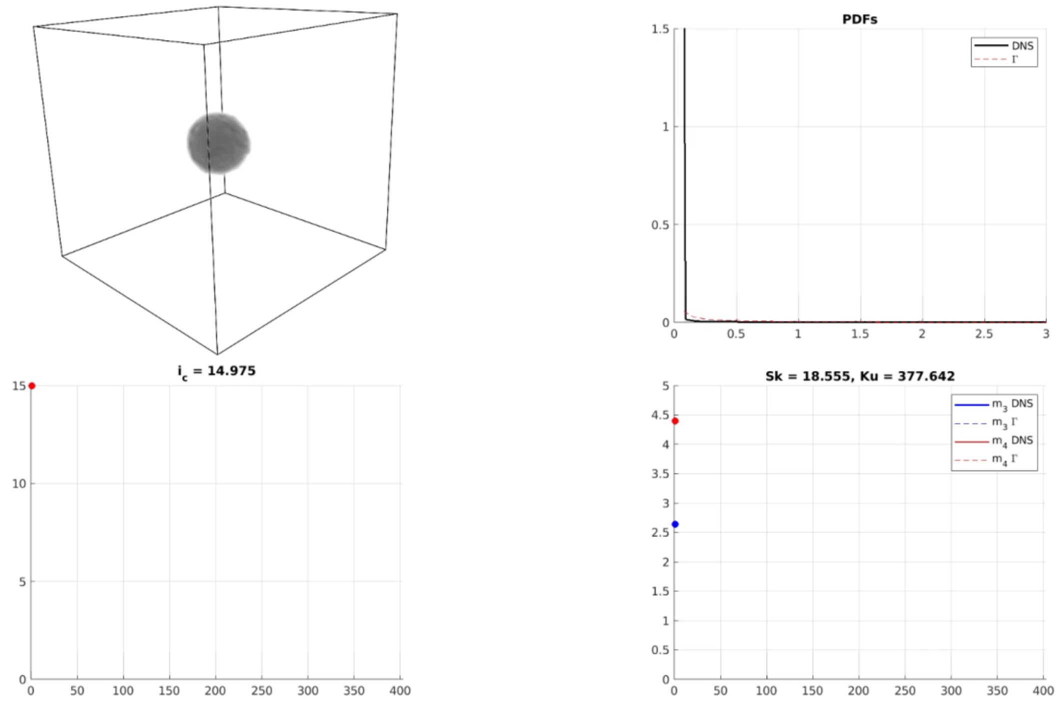
Kaimal and Finnigan (1994)

2 – Phenomenology and modelling of atmospheric dispersion

Turbulent dispersion

- Turbulent variability of the concentration

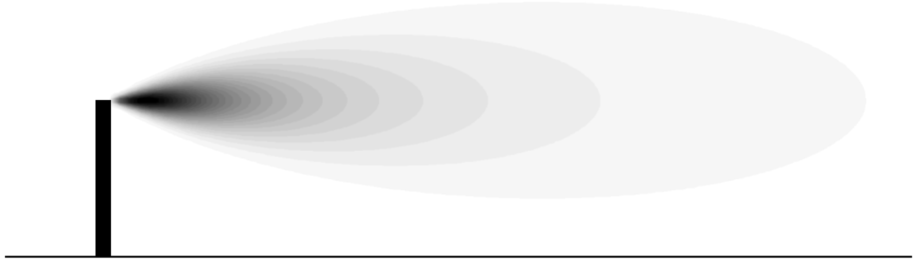




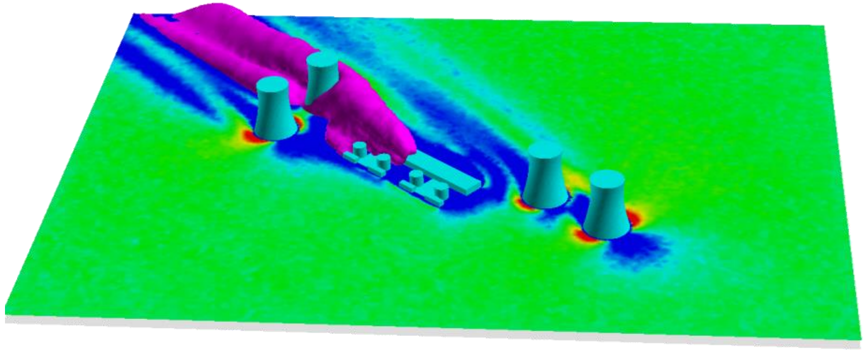
2 – Phenomenology and modelling of atmospheric dispersion

Modelling approaches

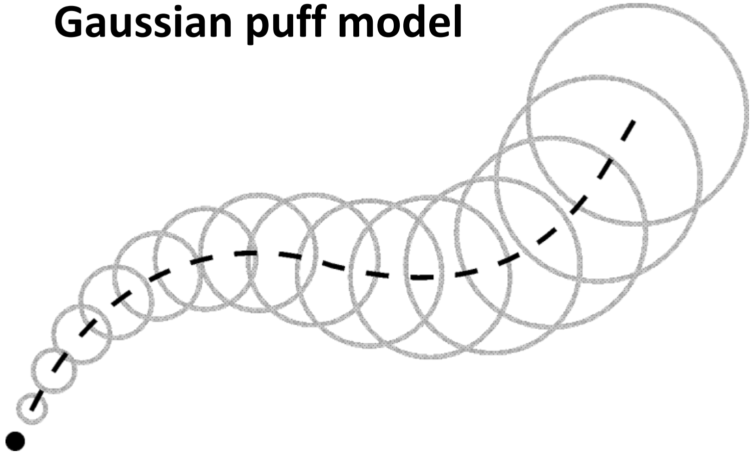
Gaussian plume model



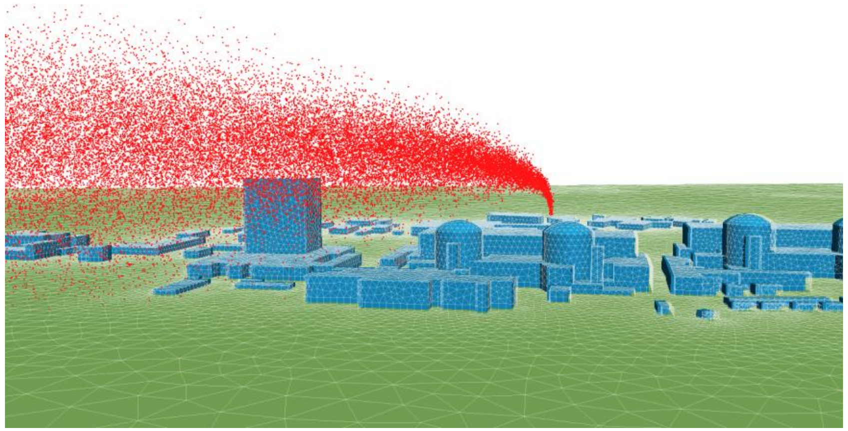
Eulerian CFD model



Gaussian puff model



Lagrangian stochastic model

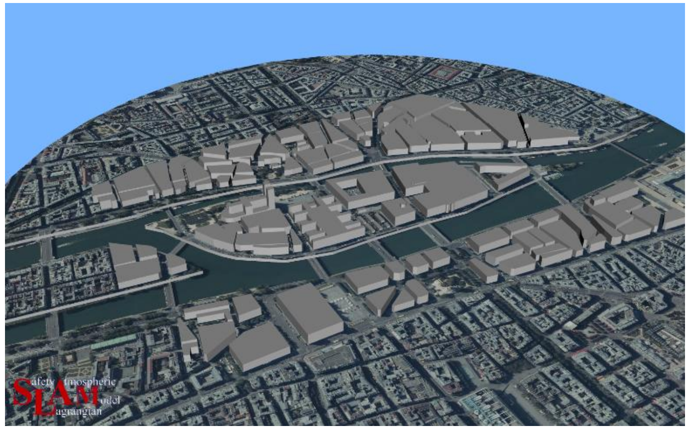


2 – Phenomenology and modelling of atmospheric dispersion

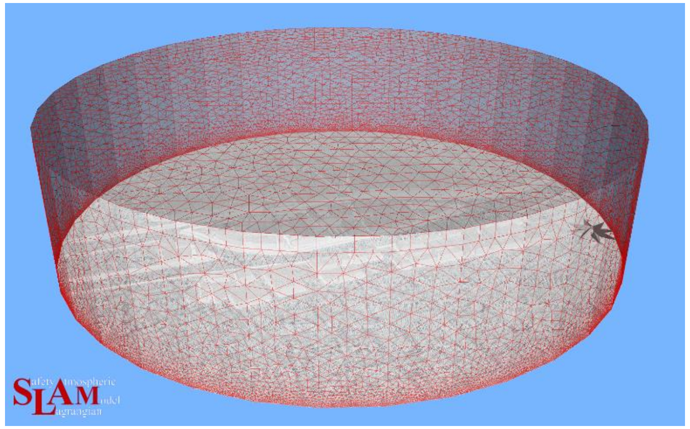
Modelling approaches

- Modelling process

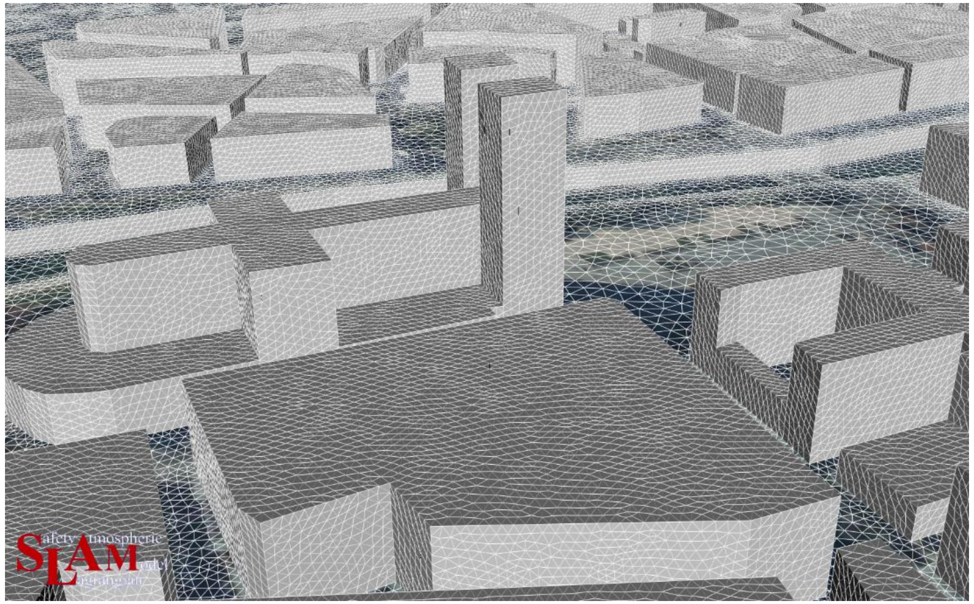
3D digital model



Simulation domain



Mesh of cells

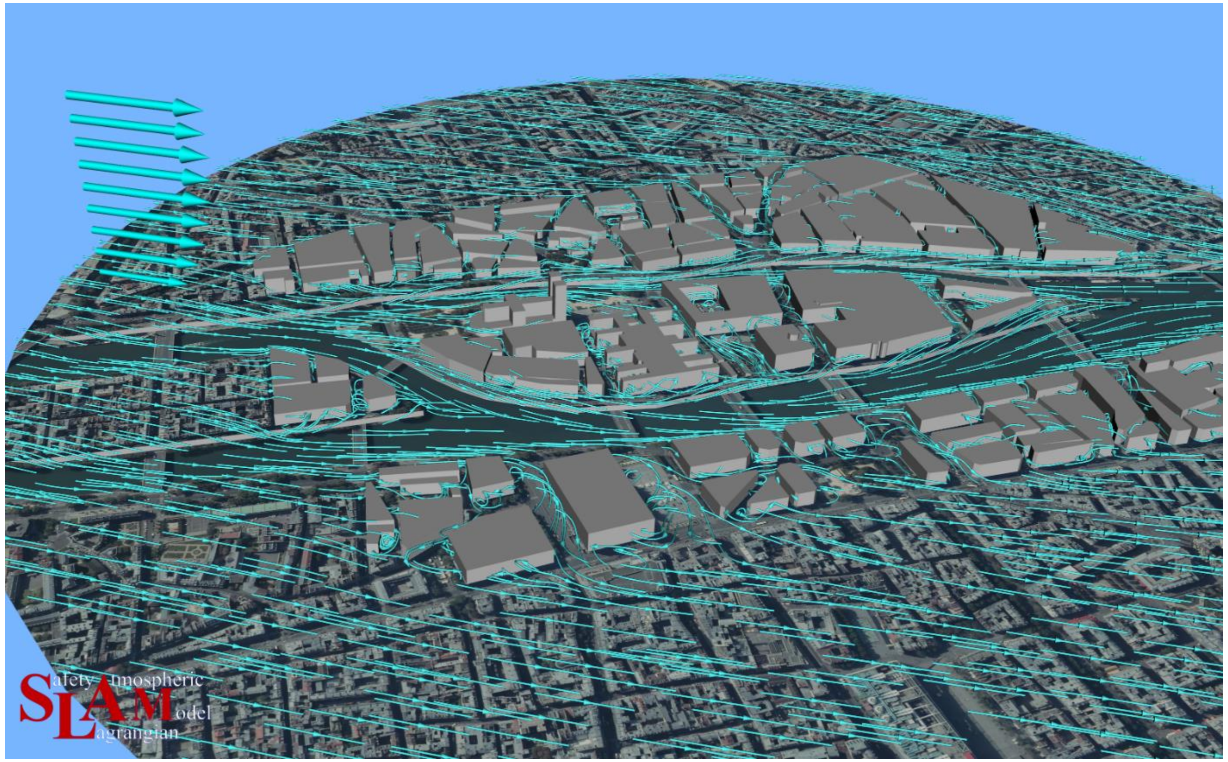


2 – Phenomenology and modelling of atmospheric dispersion

Modelling approaches

- Modelling process

Numerical simulation of the wind in each city street

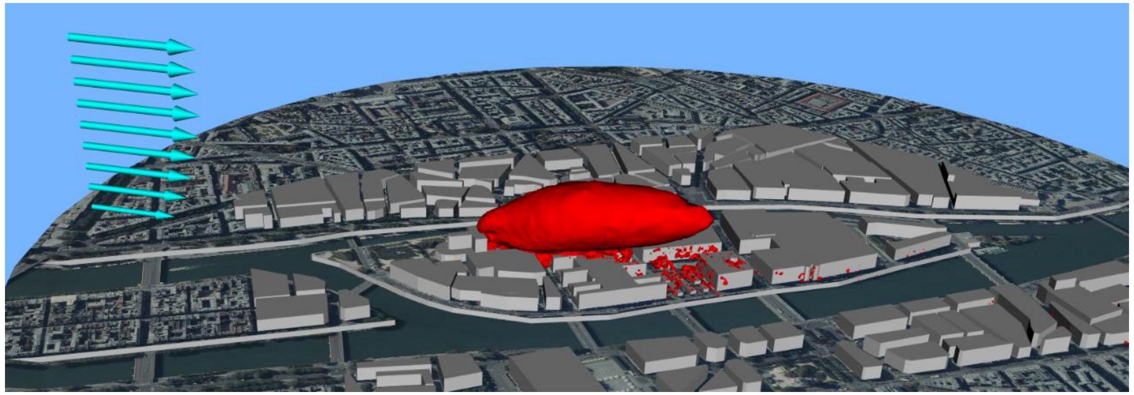


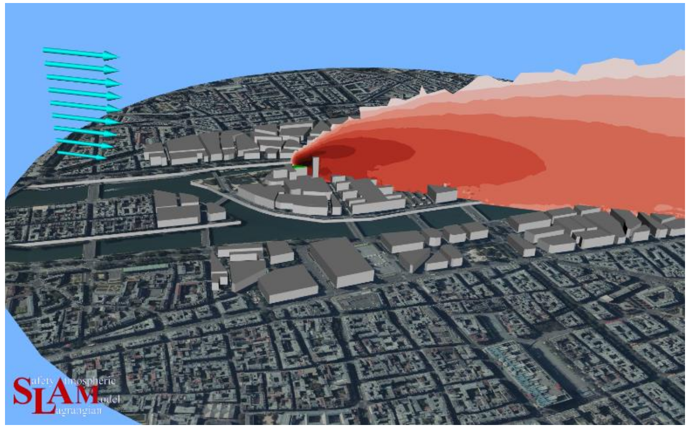
2 – Phenomenology and modelling of atmospheric dispersion

Modelling approaches

- Modelling process

Numerical simulation of atmospheric dispersion





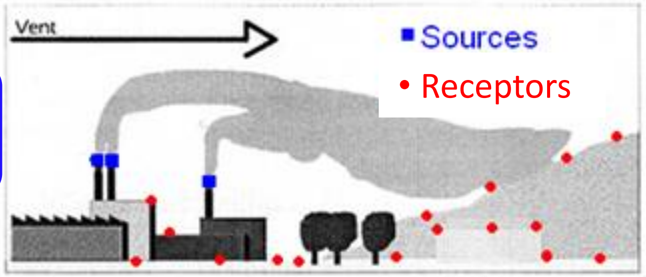
3 – Inverse modelling : problems & approaches

Concept of inverse modelling

- Direct problem & inverse problem

Direct model

Sources
other parameters



Concentrations

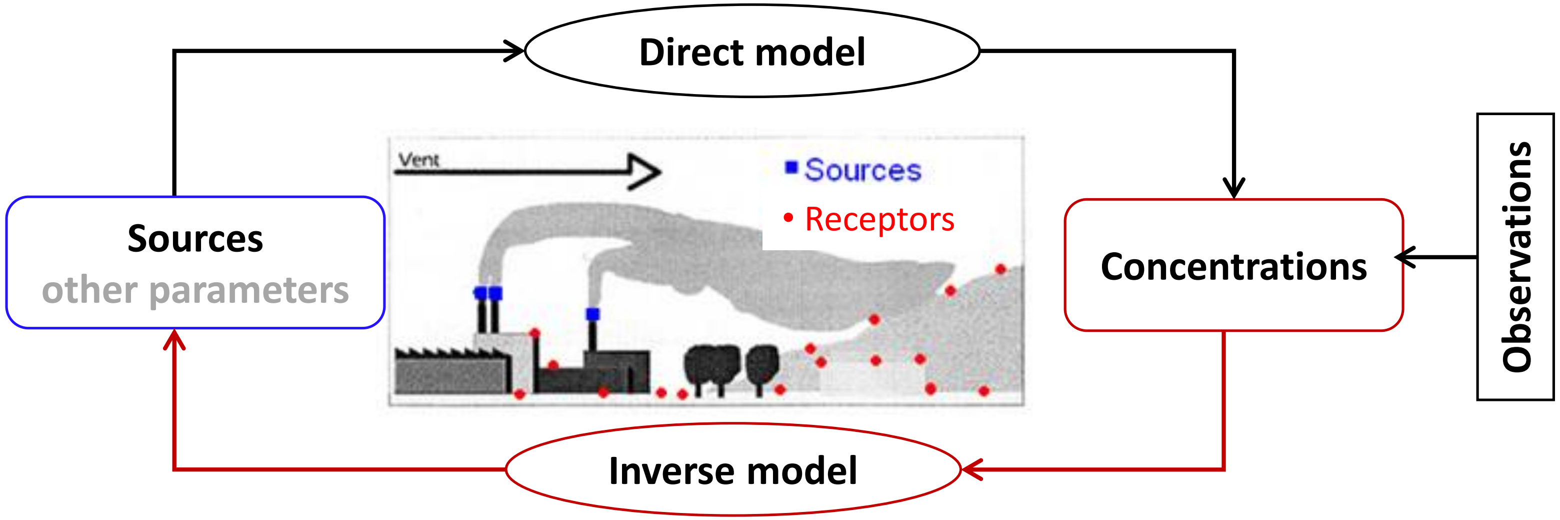
Direct problem

Finding consequences from causes

3 – Inverse modelling : problems & approaches

Concept of inverse modelling

- Direct problem & inverse problem



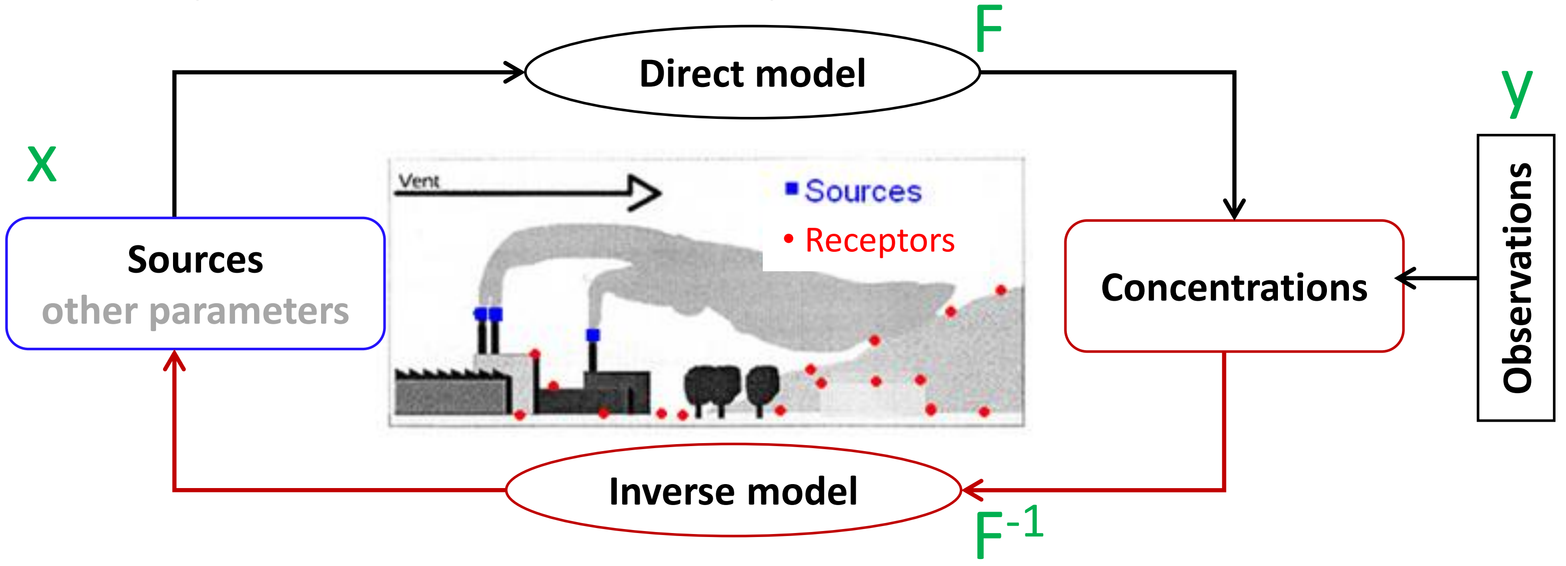
Inverse problem

Finding causes from consequences

3 – Inverse modelling : problems & approaches

Concept of inverse modelling

- Direct problem & inverse problem



Direct problem

$$F(x) = y$$

Inverse problem

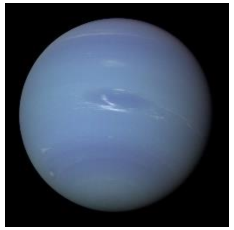
$$x = F^{-1}(y)$$

- Analogy with 1D equation solving

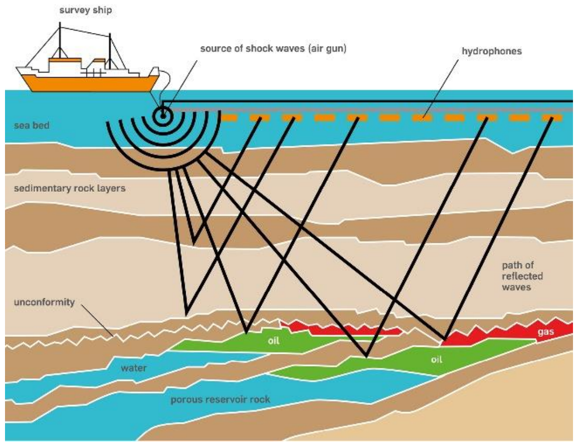
3 – Inverse modelling : problems & approaches

Concept of inverse modelling

- Inverse modelling is used in many domains
  - Astronomy
  - Geology
  - Acoustics propagation
  - Medicine
  - Image processing
  - Etc.

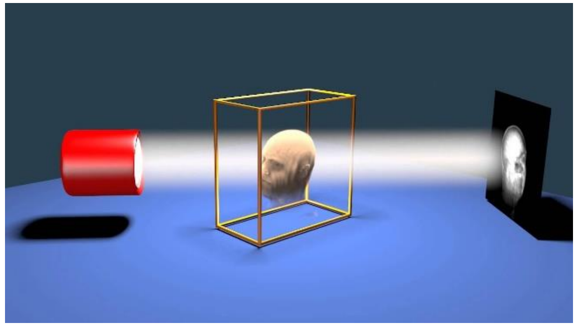


Discovery of Neptune from the effect on Saturne trajectory (Adams, Le Verrier, 1846)



Oil fields exploration

Acoustic sniper detection

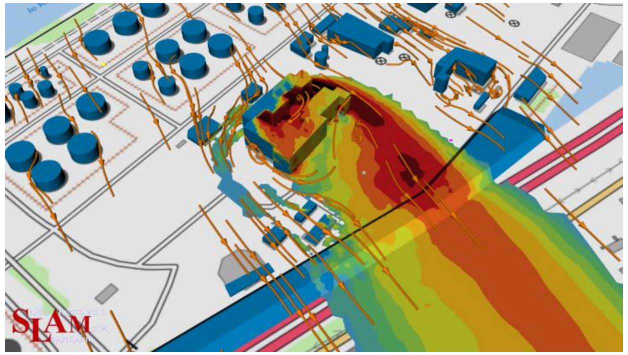


Computed tomography

Image deblurring

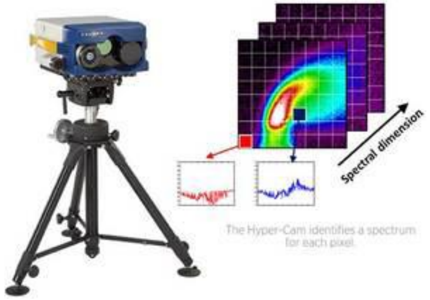
3 – Inverse modelling : problems & approaches

Concept of inverse modelling



- Inverse modelling requires
  - A direct model
    - which have uncertainties
  - Measurements
    - which have uncertainties

Monitoring station



Hyperspectral camera

µ-sensors

  - An inversion algorithm
    - which has its own limitations

3 – Inverse modelling : problems & approaches

Inverse problems of atmospheric dispersion

- 1 source
  - Point / distributed source (line, area, volume)
  - Continuous / instantaneous / time evolving
  - Fixed / moving
- N sources
  - Point / distributed source (line, area, volume)
  - Continuous / instantaneous / time evolving
  - Fixed / moving

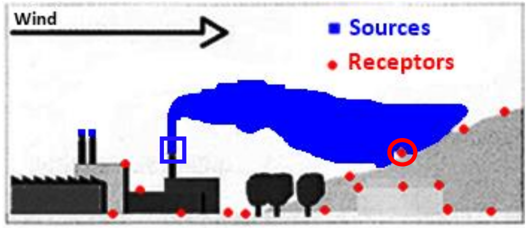
Unknowns of the inverse problem

Emission rate	Release conditions	Released species	Meteorol. conditions

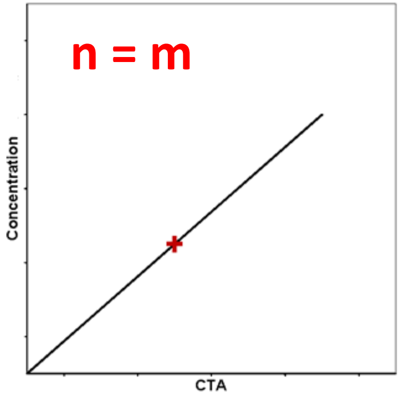
➔ n unknowns vs m measurements

3 – Inverse modelling : problems & approaches

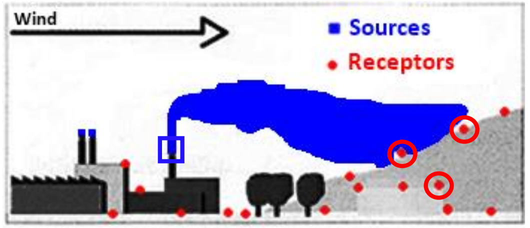
Inverse problems of atmospheric dispersion



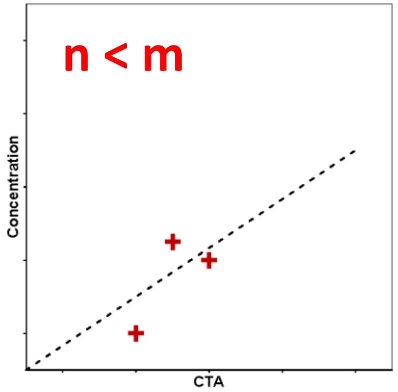
$$C_1^{Obs} = CTA_{1\to1} * Q_1$$



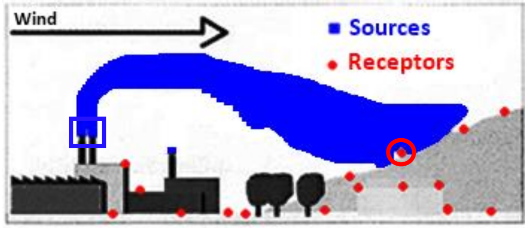
Unique solution



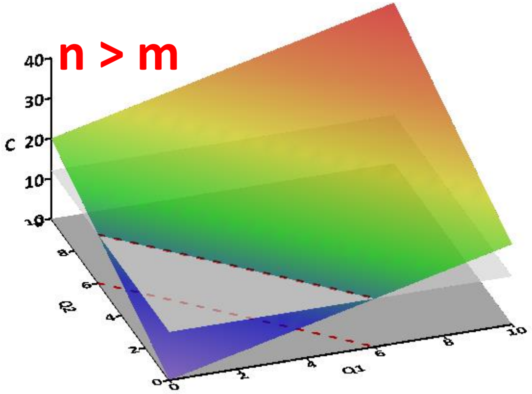
$$\begin{cases} C_1^{Obs} = CTA_{1\to1} * Q_1 \\ C_2^{Obs} = CTA_{1\to2} * Q_1 \\ C_3^{Obs} = CTA_{1\to3} * Q_1 \end{cases}$$



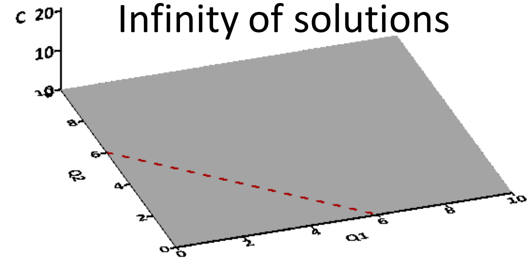
No exact solution



$$C_1^{Obs} = CTA_{1\to1} * Q_1 + CTA_{2\to1} * Q_2$$



Infinity of solutions

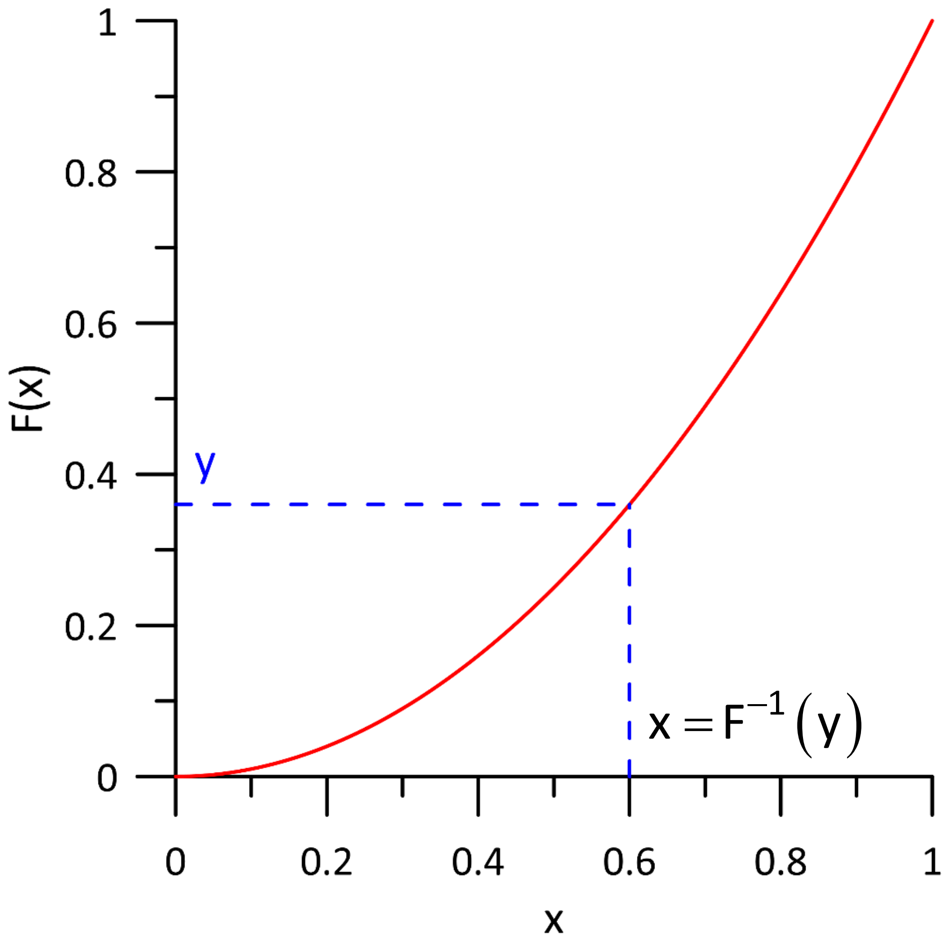


3 – Inverse modelling : problems & approaches

Intuitive introduction to inverse modelling

Minimisation/optimization of a criterion

- Methods for non linear equation solving
  1. Guess an initial value of x
  2. Calculate F(x) with the model F
  3. Compare F(x) with the measurement y
     - Need of a cost function
     - e.g. L1 or L2 norm of the difference F(x) vs y
  4. Adjust x
     - Systematic testing (brute force method)
     - Random testing (Monte Carlo method)
     - Dichotomy method
     - Newton-Raphson method
       - requires the inverse of F'(x) = adjoint model of F



3 – Inverse modelling : problems & approaches

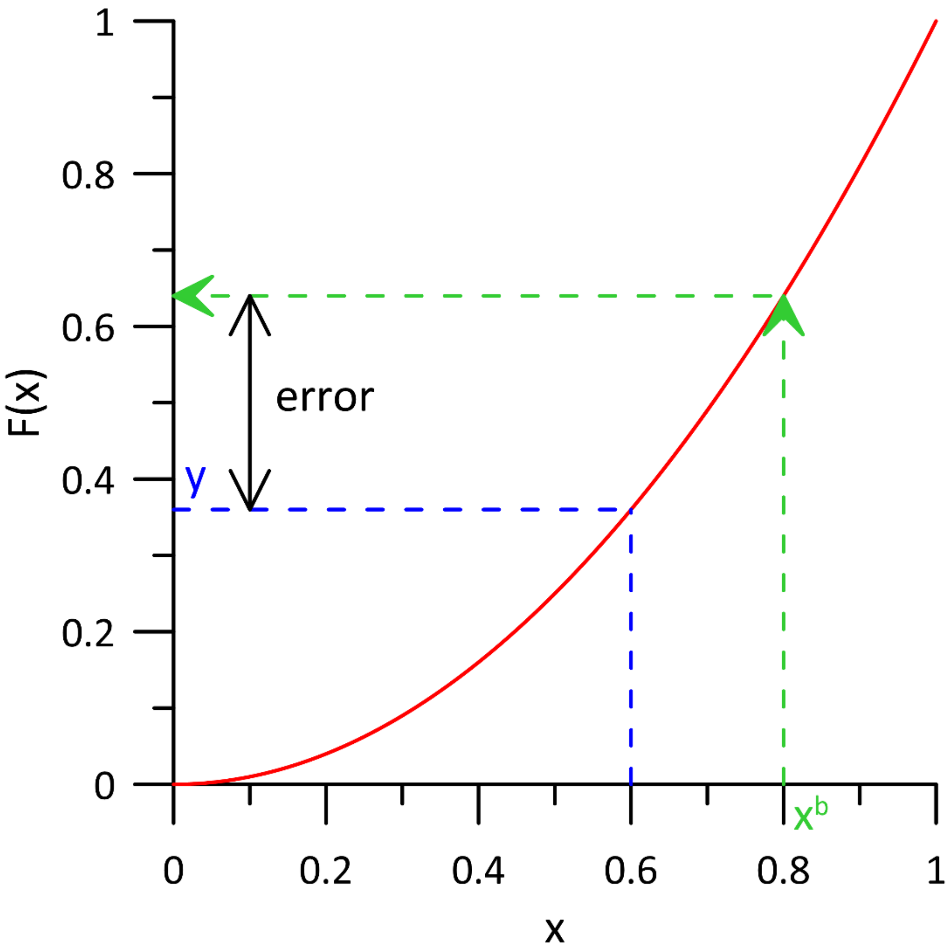
Intuitive introduction to inverse modelling

Minimisation/optimization of a criterion

- Variational approach
  1. Guess an initial value of x
  2. Calculate F(x) with the model F
  3. Compare F(x) with the measurement y
     - Evaluate of a cost function (error)

$$J(x)=\frac{1}{2}(x-x^b)^T B^{-1}(x-x^b)+\frac{1}{2}\sum_{i=0}^{m}(y_i-H_iF(x))^T R^{-1}(y_i-H_iF(x))$$

  4. Adjust x
     - Systematic testing (brute force method)
     - Optimized Random iterative testing
       - e.g. Markov Chain Monte Carlo (MCMC)



3 – Inverse modelling : problems & approaches

Intuitive introduction to inverse modelling

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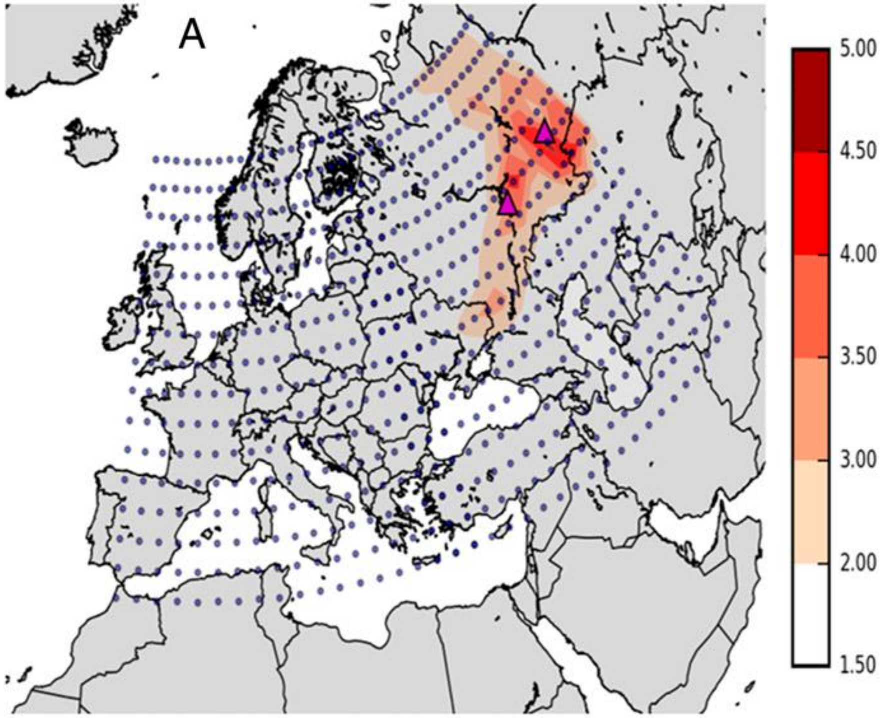


Mayak event of Ruthenium release, 2017
Saunier et al., IRSN (2019)

3 – Inverse modelling : problems & approaches

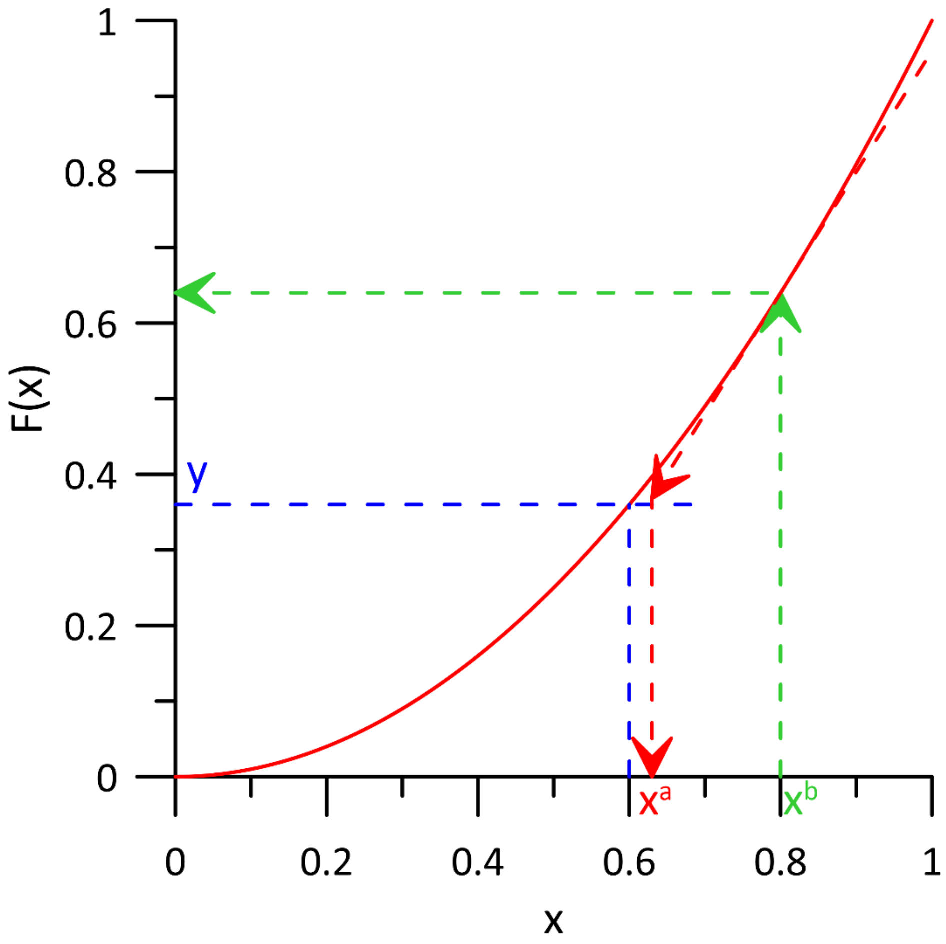
Intuitive introduction to inverse modelling

Minimisation/optimization of a criterion

- Variational approach with adjoint model
  1. Guess an initial value of x
  2. Calculate F(x) with the model F
  3. Compare F(x) with the measurement y
     - Evaluate of a cost function (error)

$$J(x)=\frac{1}{2}(x-x^b)^T B^{-1}(x-x^b)+\frac{1}{2}\sum_{i=0}^{m}(y_i-H_iF(x))^T R^{-1}(y_i-H_iF(x))$$

  4. Adjust x
     - Systematic testing (brute force method)
     - Optimized Random iterative testing
       - e.g. Markov Chain Monte Carlo (MCMC)
     - Gradient method
       - requires the inverse of F'(x) = adjoint model of F



3 – Inverse modelling : problems & approaches

Intuitive introduction to inverse modelling

Minimisation/optimization of a criterion

- Variational approach with adjoint model
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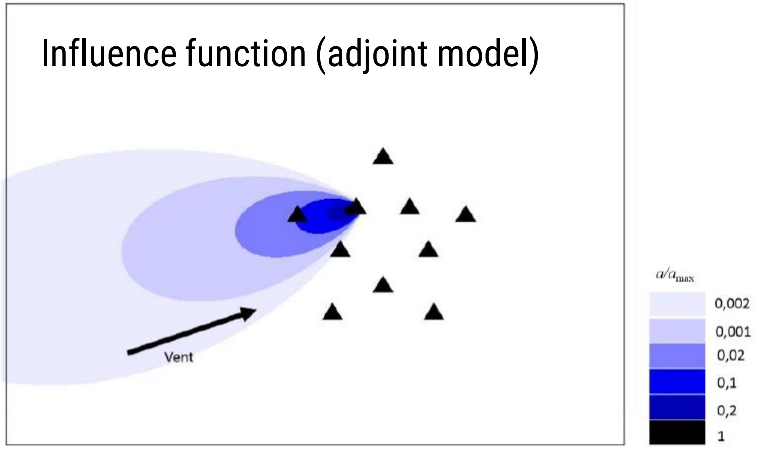
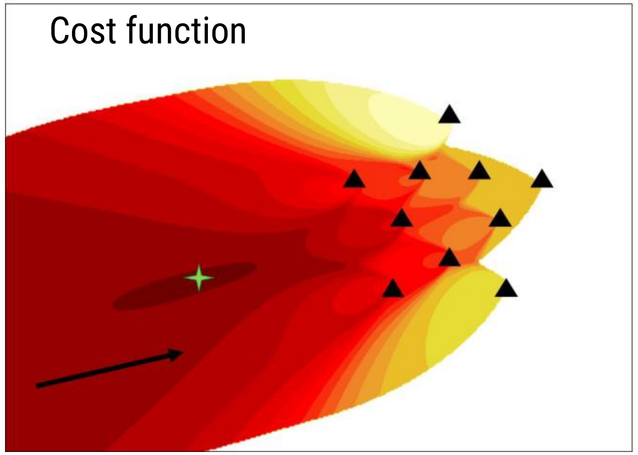


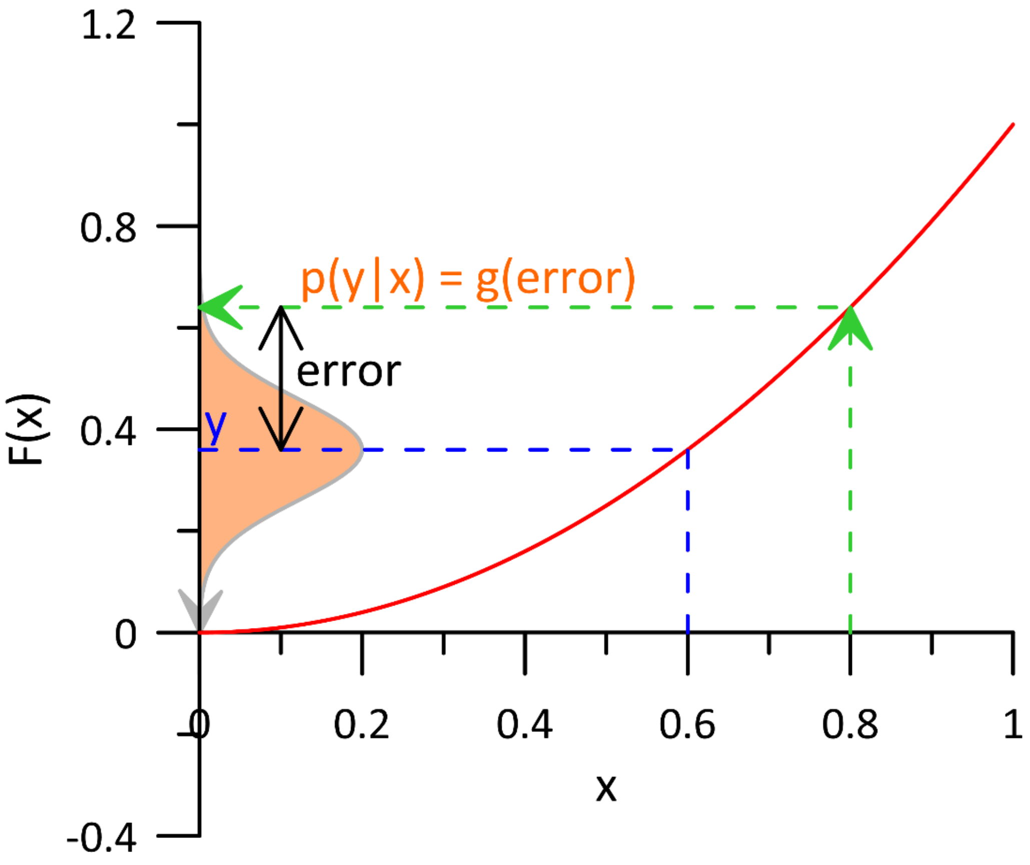


Turbelin (2019)

3 – Inverse modelling : problems & approaches

Intuitive introduction to inverse modelling

- Bayesian approach
  1. Guess some initial values of x
  2. Calculate F(x) with the model F
  3. Compare F(x) with the measurement y
     - Evaluate of a likelihood function from the error which give the probability p(y|x)



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  1. Guess some initial values of x
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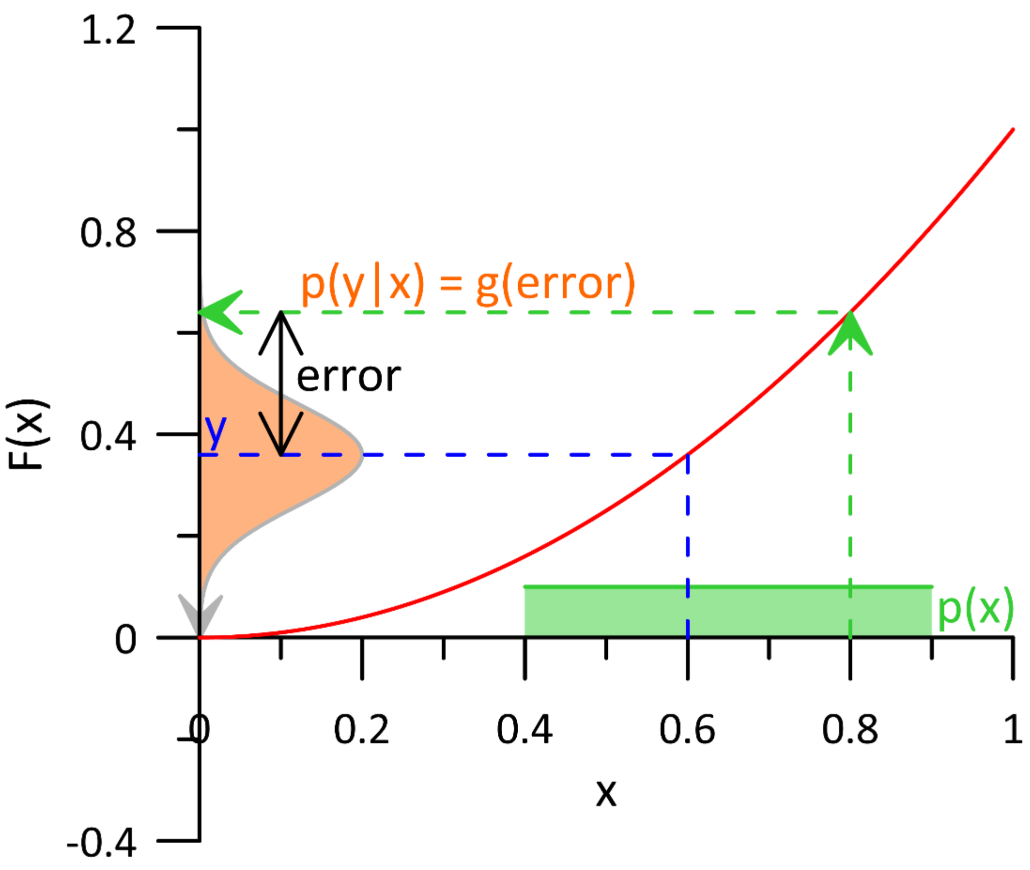
  4. Assume a prior distribution of x
     - p(x) is the prior information about x



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Intuitive introduction to inverse modelling

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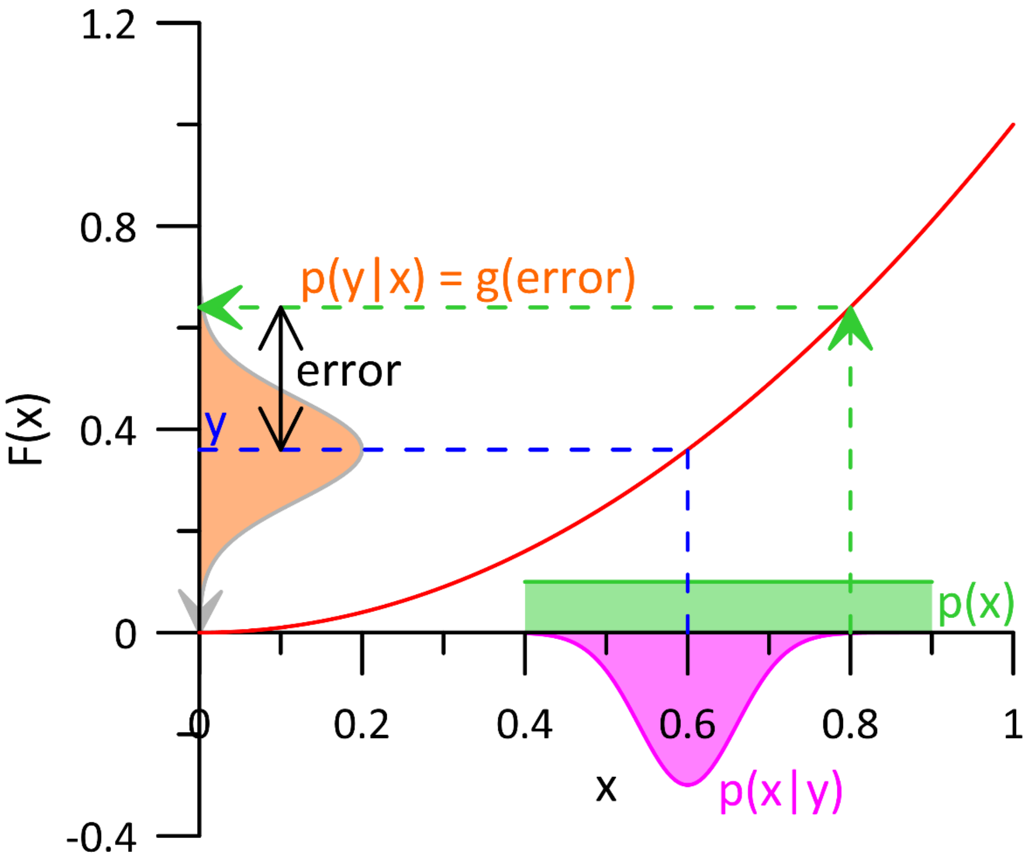
  5. Bayes formula
     - Posterior probability $p(x|y) = \dfrac{p(y|x)p(x)}{p(y)}$
     - Marginal probability p(y) = normalisation function



3 – Inverse modelling : problems & approaches

Intuitive introduction to inverse modelling

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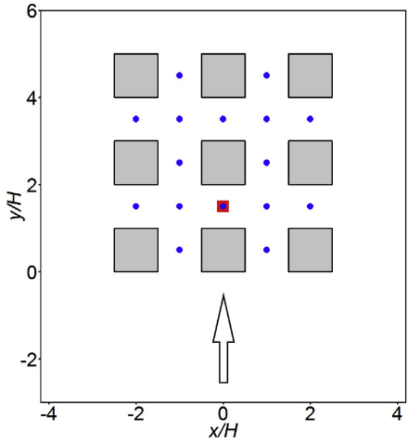
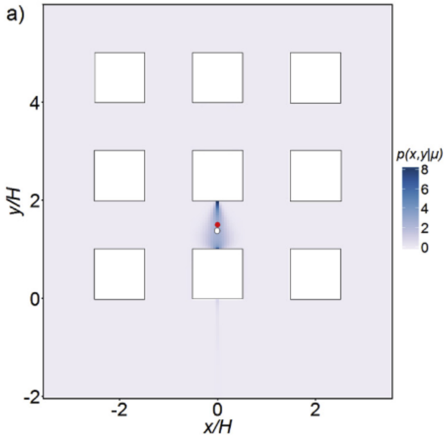
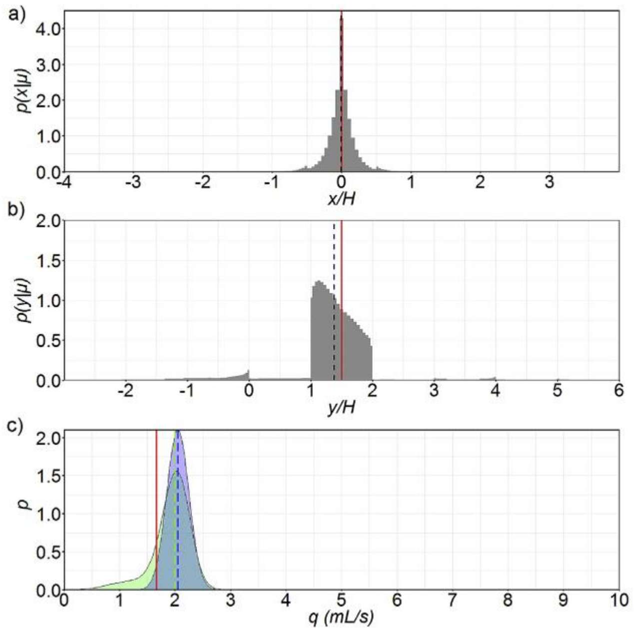


a) Case 1



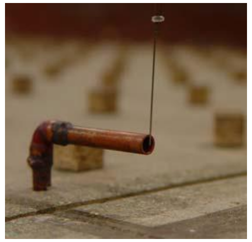


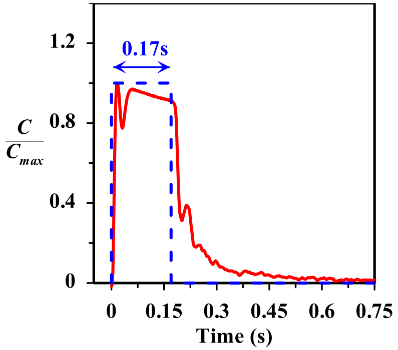
Xue et al. (2017)

5 – Some applicated examples

Estimating accidental pollutant releases inbuilt environment from turbulent concentration signals (Ben Salem et al., 2017)

- Wind tunnel experiments of instantaneous releases in a district





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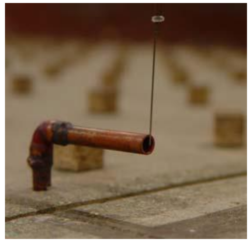

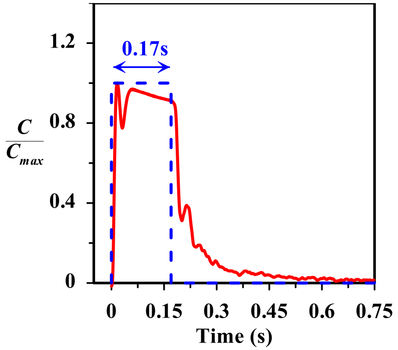

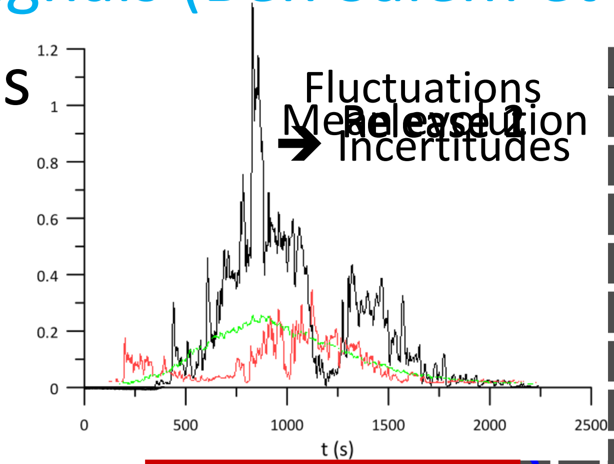

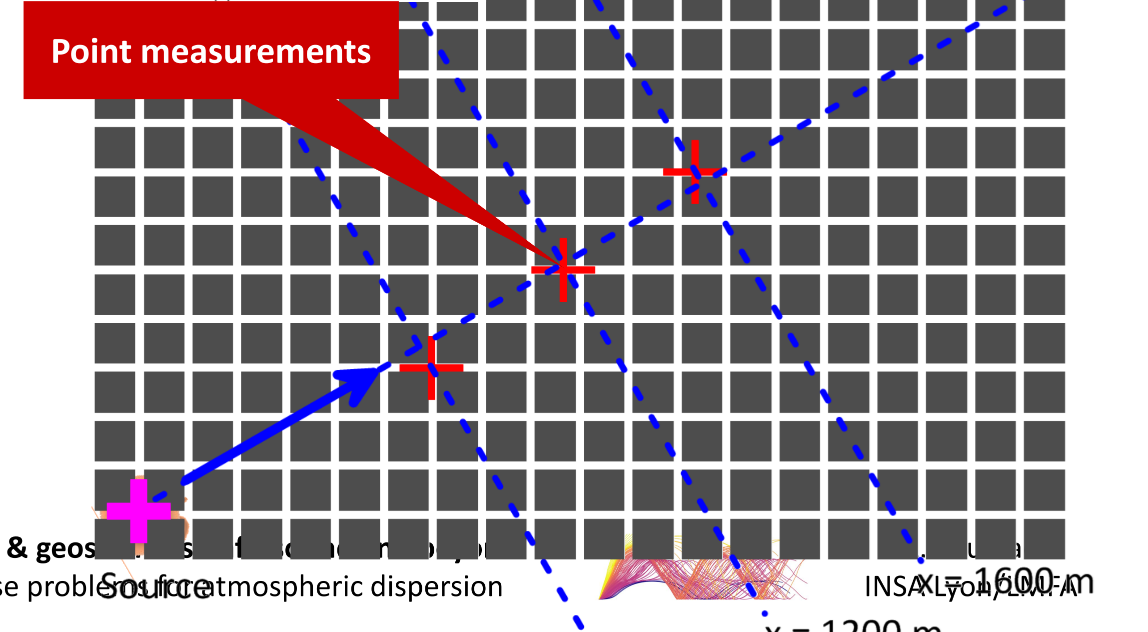

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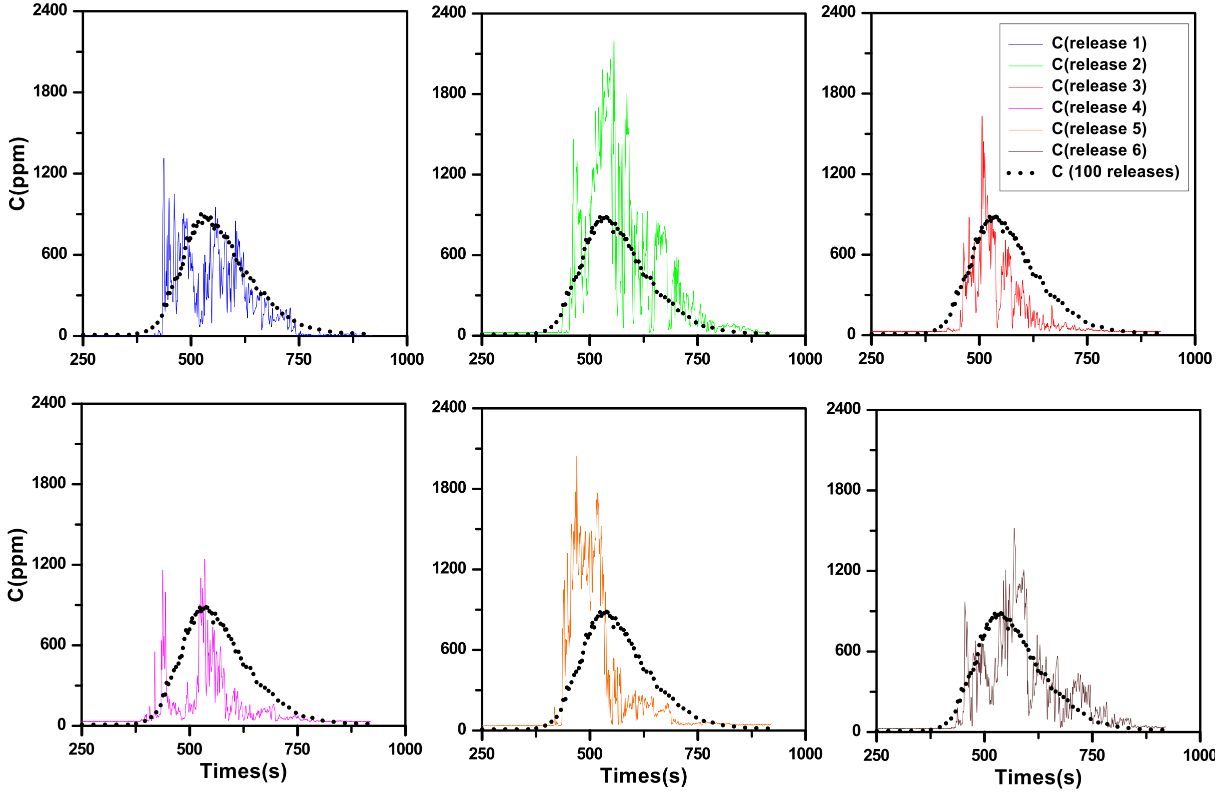
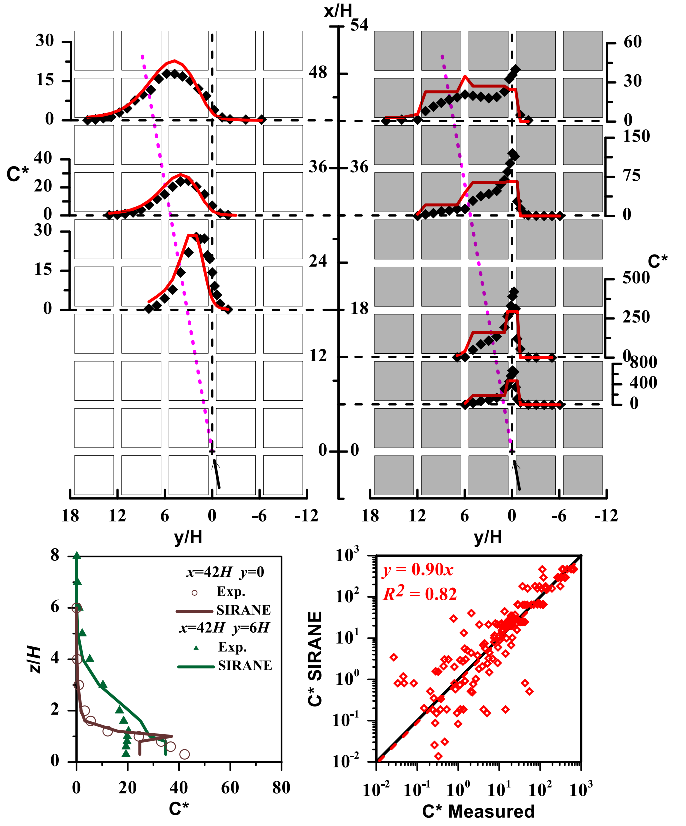




Comparison of the direct model for the mean concentration

5 – Some applicated examples

Estimating accidental pollutant releases inbuilt environment from turbulent concentration signals (Ben Salem et al., 2017)

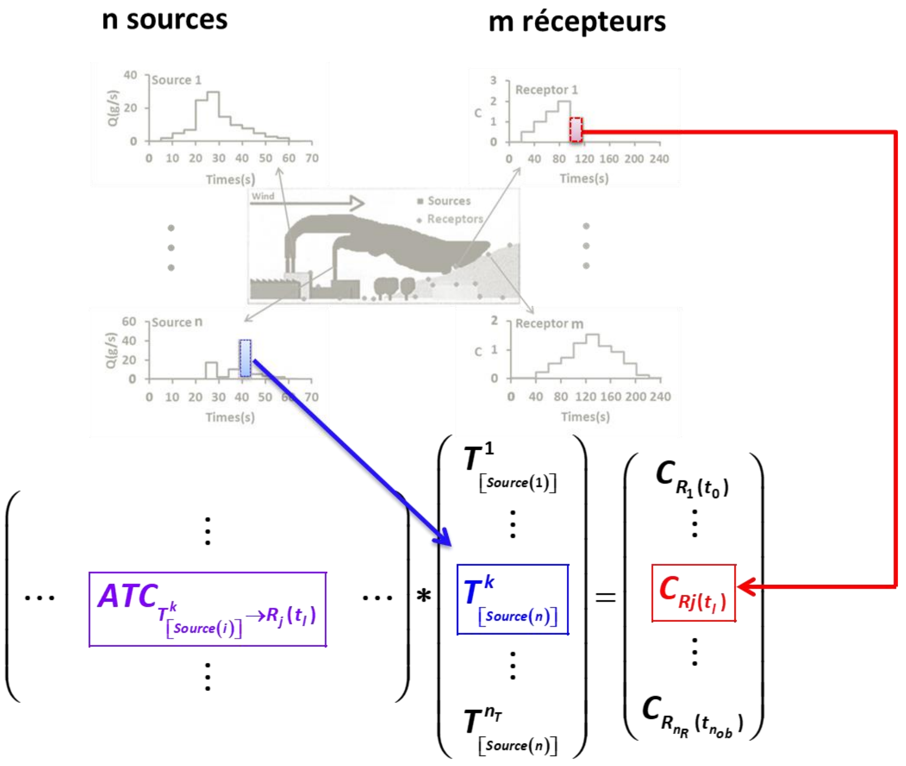
- Variational approach for inverse modelling
  - The position of the source is known
  - We assume a linear relation between
    - Concentration C
    - Release rate Q

$$C^{obs}(m) = ATC(m,n) \times Q(n)$$

  - We use a cost function with a Thikonov regularisation term

$$J = \left\| C^{obs} - CTA \times Q \right\|^2_{\mathbb{R}^{n_C}} + \varepsilon^2 \Gamma(Q)$$

  - The idea is to avoid that the model “follows” each fluctuation of the instantaneous measurements
  - The optimum solution is given by $Q = \left(CTA^t \times CTA + \varepsilon^2 I \right)^{-1} \times CTA^t \times C^{obs}$



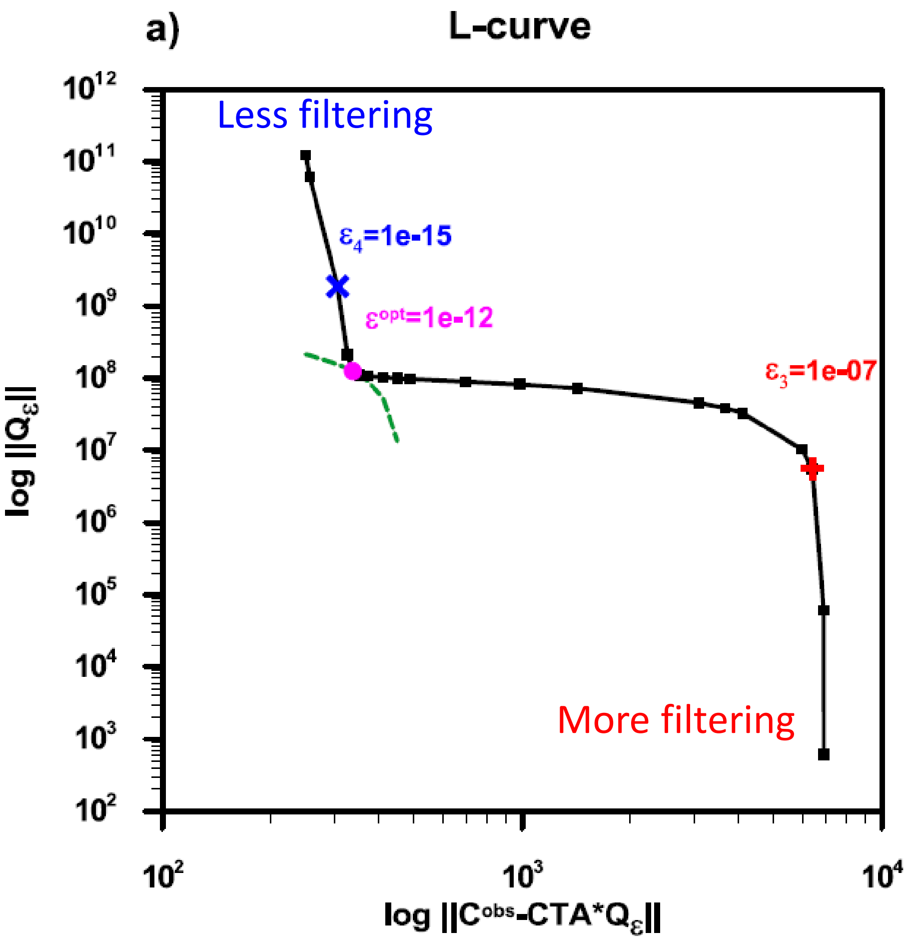
5 – Some applicated examples

Estimating accidental pollutant releases inbuilt environment from turbulent concentration signals (Ben Salem et al., 2017)

- Regularisation parameter ε

$$J = \left\| C^{obs} - CTA \times Q \right\|^2_{\mathbb{R}^{n_C}} + \varepsilon^2 \Gamma(Q)$$

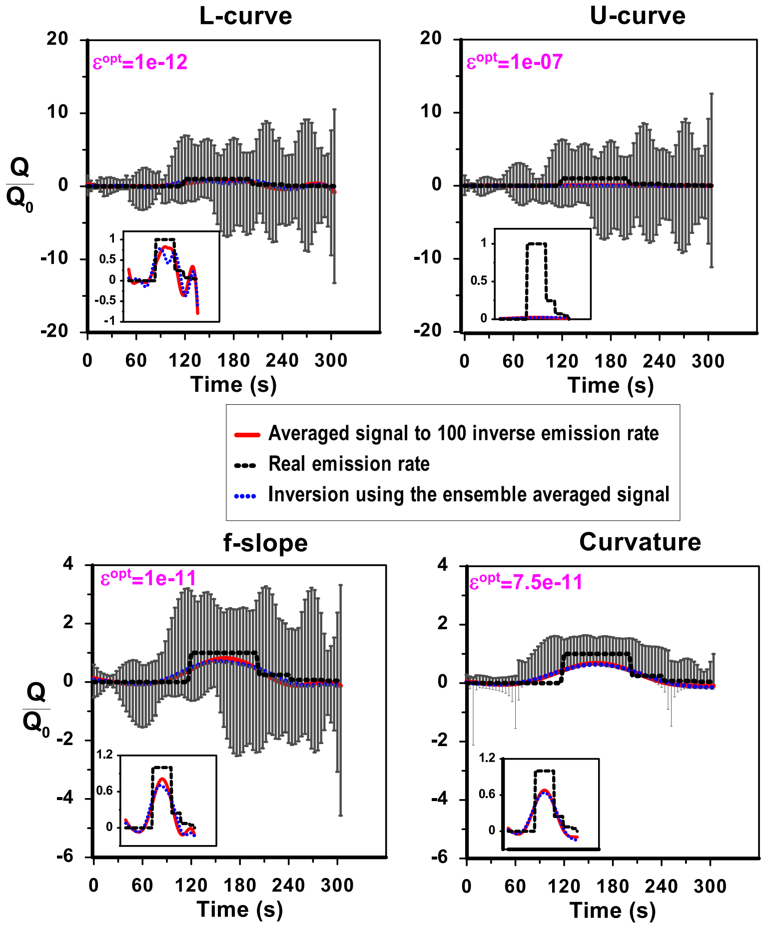
  - ε has to be optimized with specific method
  - Example of the L-curve method



5 – Some applicated examples

Estimating accidental pollutant releases inbuilt environment from turbulent concentration signals (Ben Salem et al., 2017)

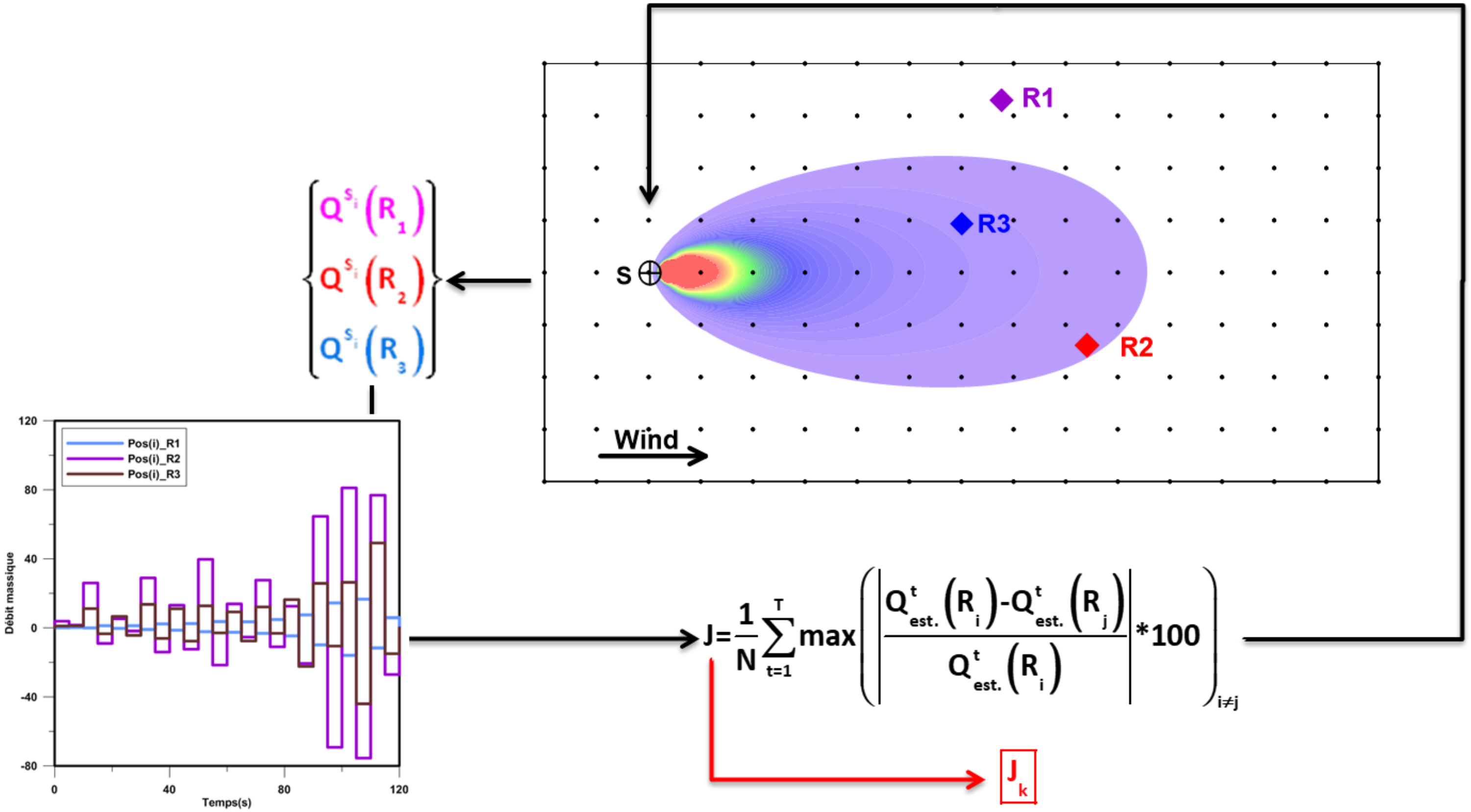
- Results for the time evolution of the emission rate
  - It has to be optimized
  - f-slope approach provides the better results for the inversion from the mean concentration
  - Maximum of curvature method provides the better results for inversion from instantaneous measurements



5 – Some applicated examples

Localization of a source in a district (Ben Salem, 2015)

- Brute force approach to characterize the field of the cost function



5 – Some applicated examples

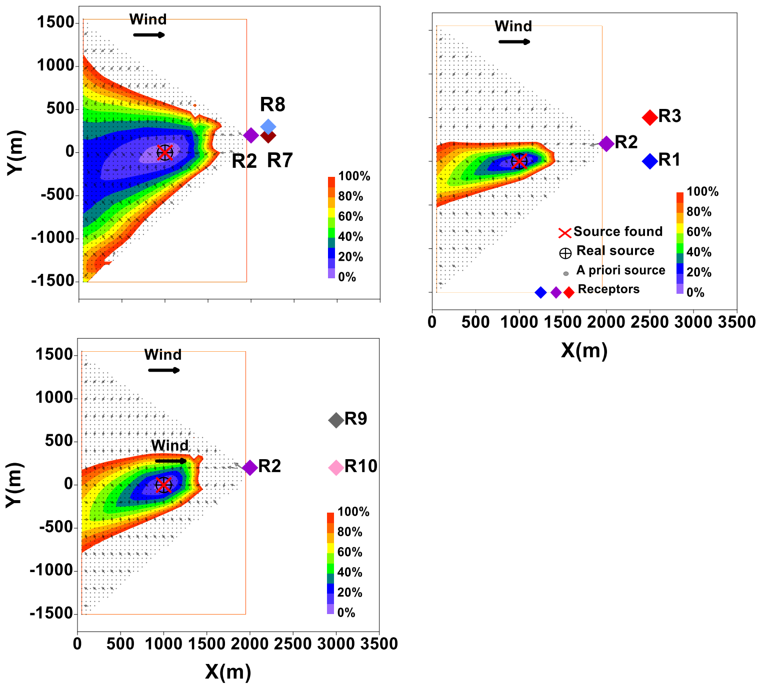
Localization of a source in a district (Ben Salem, 2015)

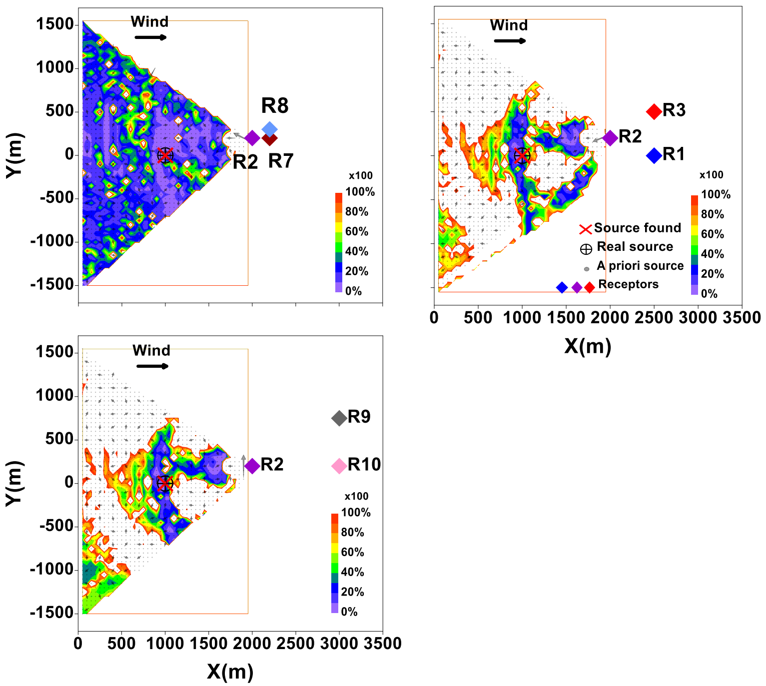
- Brute force approach to characterize the field of the cost function

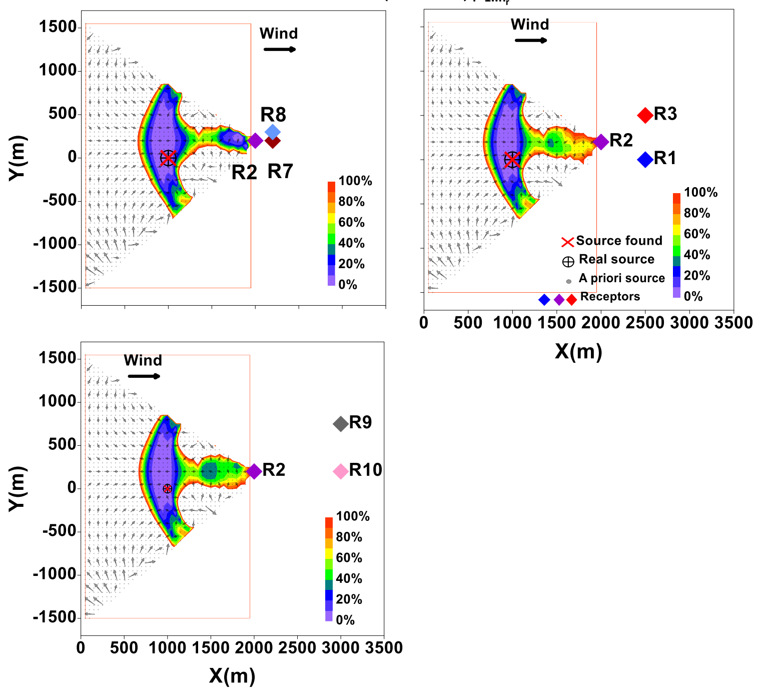
$$CR1(\%) = \max\left(\left|\frac{Qtt(R_i) - Qtt(R_j)}{Qtt(R_i)}\right| * 100\right)_{i \neq j}$$

$$CR2 = \frac{1}{N}\sum_{k=1}^{N} \max\left(\frac{Q^k_{inv}(R_i) - Q^k_{inv}(R_j)}{Q^k_{inv}(R_i)} * 100\right)_{i \neq j}$$

$$CR3 = \frac{\left(\frac{1}{N}\sum_{t=1}^{t_f}\left(\max\left(\left|Q^t_{inv}(R_i) - Q^t_{inv}(R_j)\right|_{i \neq j}\right) * \Delta t\right)\right)}{\min\left(Qtt(R_i)\right)_{i=1..n_r}} * 100$$







5 – Some applicated examples

Crisis management tool for CBRN events (H2020 TERRIFFIC project, https://www.terriffic.eu/ & Nguyen et al, 2021)

- Methodology
  - Inverse modelling of an atmospheric flow/dispersion/radiation simulation system
  - Coupling with real time mobile measurements
  - Minimization of a cost function and optimization of the source position and intensity
- Results
  - Field test case using
    - real radioactive sources
    - drones and robots
    - sensors and cameras
  - Use of wind field database and optimized operational dispersion model to get real time inversion results

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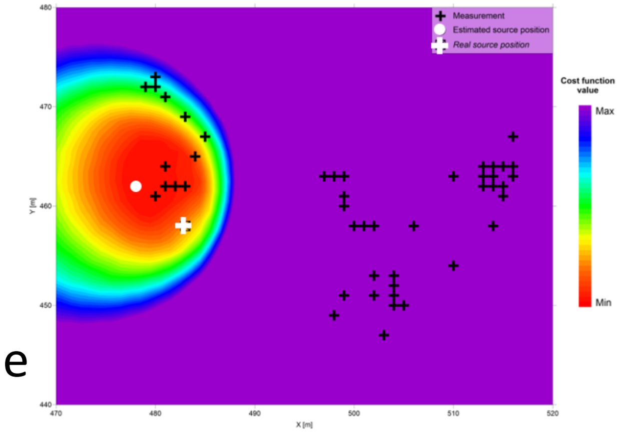
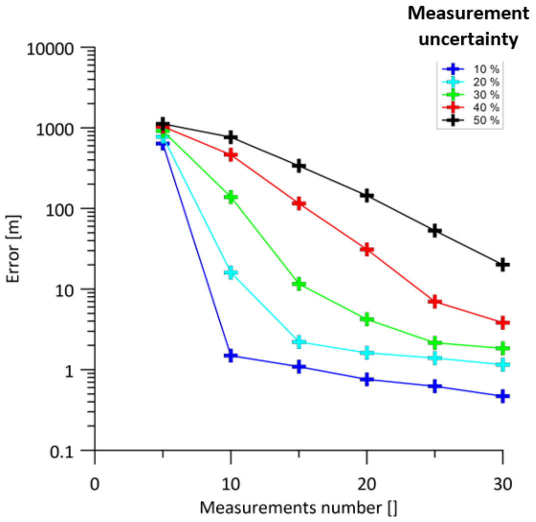
Drone view with gamma camera

Ground robot view with gamma camera



Cost function field and source position estimated



Thank you !