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Source characterisation of large-scale urban fires by inverse modelling

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Means and objective

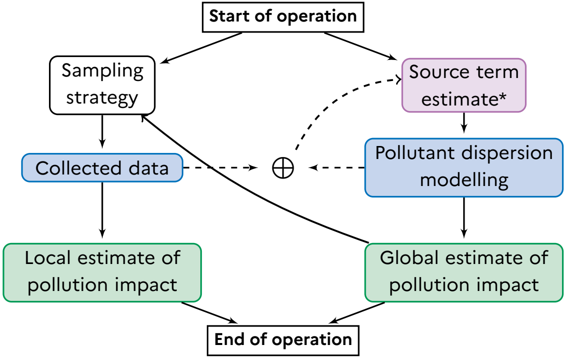


Figure: LCPP resources for assessing the health and environmental risks associated with smoke from large-scale fires.

*Use of a tracer as a first source term estimate.

Figure: Notre-Dame Cathedral fire in Paris, France (2019). Source: Internet

Objective: characterise the source term based on a release intensity (in kg/h) and an emission height (in m) for a refined global estimate of pollution impact

Atmospheric dispersion modelling

- Using **PMSS** (**P**arallel **M**icro **S**WIFT and **S**PRAY) model developed by AriaTechnologies [5]
- Meteo data real-time updated from Meteo-France – by AROME model 0.025°
- Land-use data *CORINE Land Cover* (CLC) distributed by the The National Institute of Geographic and Forest Information (IGN) – European database, resolution $25\,\mathrm{m}$
- Building database (not currently used) and topography from the IGN

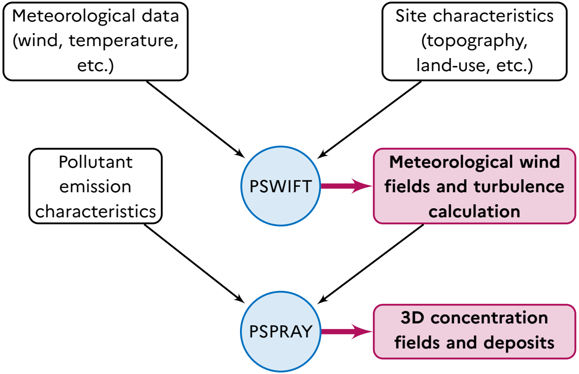


Figure: PMSS model diagram.

Inverse problem

General principle [1]

Minimise the difference between the observations $\boldsymbol{y}$ and the results of simulations $\mathbf{H}\boldsymbol{x}$ by considering a recall term towards a prior $\boldsymbol{x_b}$ to characterise the source term $\boldsymbol{x}$.

Using Bayes' formula:

$$\underbrace{p(\mathbf{x}|\mathbf{y})}_{\text{a posteriori}} = \frac{\overbrace{p(\mathbf{y}|\mathbf{x})}^{\text{likelihood}}\ \overbrace{p(\mathbf{x})}^{\text{a priori}}}{\underbrace{p(\mathbf{y})}_{\text{evidence}}},$$

- $\mathbf{x} \in \mathbb{R}^{N_{par}}$: the set of variables of interest that characterise the source
  $$N_{par} = N_{emission\ heights} \times N_{emission\ time\ intervals}$$
- $\mathbf{y} \in \mathbb{R}^{N_{obs}}$: the set of available observations
- $\mathbf{x_b} \in \mathbb{R}^{N_{par}}$: the approximation of the source
- $\mathbf{H} \in \mathbb{R}^{N_{obs} \times N_{par}}$: the transfer matrix $\sim$ linear dispersion model

With Gaussian assumptions (for now) and $\mathbf{B} = b\ \mathbf{I}_{N_{par}}$, $\mathbf{R} = r\ \mathbf{I}_{N_{obs}}$:

$$\mathbf{x} \sim \mathcal{N}(\mathbf{x_b}, \mathbf{B}) : \quad p(\mathbf{x}) = \frac{1}{|\mathbf{B}|^{1/2}\sqrt{(2\pi)^{N_{par}}}} e^{-\frac{1}{2}\left((\mathbf{x}-\mathbf{x_b})^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x_b})\right)} \tag{1a}$$

$$\mathbf{y}|\mathbf{x} \sim \mathcal{N}(\mathbf{Hx}, \mathbf{R}) : \quad p(\mathbf{y}|\mathbf{x}) = \frac{1}{|\mathbf{R}|^{1/2}\sqrt{(2\pi)^{N_{obs}}}} e^{-\frac{1}{2}\left((\mathbf{y}-\mathbf{Hx})^T\mathbf{R}^{-1}(\mathbf{y}-\mathbf{Hx})\right)} \tag{1b}$$

Maximum a posteriori (MAP)

Deterministic least squares minimisation:

$$\min_{\mathbf{x}}(\mathcal{J}(\mathbf{x})) = \min_{\mathbf{x}} \left(\underbrace{\frac{1}{2}\|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2}_{\text{residue}} + \underbrace{\lambda^2\frac{1}{2}\|\mathbf{x}-\mathbf{x_b}\|^2}_{\text{Tikhonov regularisation}} \right) \quad \text{and} \quad \mathbf{x} \geq 0$$

+ λ determined through the Generalised Cross Validation (GCV) method [2]

$$\rightarrow \quad \mathbf{x_{sol}} = \mathbf{x_b} + \underbrace{\left(\mathbf{H}^T\mathbf{H} + \lambda^2\mathbf{I}_{N_{par}}\right)^{-1}\mathbf{H}^T}_{\text{gain}}\underbrace{(\mathbf{y}-\mathbf{H}\,\mathbf{x_b})}_{\text{innovation}} \quad \text{and} \quad \mathbf{x_{sol}} \geq 0$$

$\rightarrow$ $\mathbf{x_{sol}}$ obtained by the Limited-memory Broyden–Fletcher–Goldfarb–Shanno Boundary (L BFGS B) algorithm: gradient descent

- cost function $\mathcal{J}(\mathbf{x})$
- cost function gradient $\nabla\mathcal{J}(\mathbf{x})$
- constraint bounds $[0, +\infty]$

Markov Chain Monte Carlo method (MCMC)

Objective: reconstruct the a posteriori $P_{\mathbf{y}} : \mathbf{x} \mapsto p(\mathbf{x}|\mathbf{y})$

Using **Metropolis-Hastings** [3] algorithm with:

- a transition function $g(\mathbf{x}_{old}) = \mathbf{x}_{new}$

$$\mathbf{x}_{new} \sim \mathcal{N}(\mathbf{x}_{old}, \sigma_t) \text{ folded}$$

- the detailed-balance principle

$$P_{\mathbf{y}}(\mathbf{x}_{new}|\mathbf{x}_{old})P_{\mathbf{y}}(\mathbf{x}_{old}) = P_{\mathbf{y}}(\mathbf{x}_{old}|\mathbf{x}_{new})P_{\mathbf{y}}(\mathbf{x}_{new})$$

- an acceptance rate

$$A_{\mathbf{y}}(\mathbf{x}_{new}|\mathbf{x}_{old}) = \min\left(1, \frac{g(\mathbf{x}_{old}|\mathbf{x}_{new})\ P_{\mathbf{y}}(\mathbf{x}_{new})}{g(\mathbf{x}_{new}|\mathbf{x}_{old})\ P_{\mathbf{y}}(\mathbf{x}_{old})}\right)$$

  - generate $u \sim \mathcal{U}(0,1)$
  - if $u > A_{\mathbf{y}}$: accept $\mathbf{x}_{new}$ and $\mathbf{x}_{old} \leftarrow \mathbf{x}_{new}$
  - if $u \leq A_{\mathbf{y}}$: reject $\mathbf{x}_{new}$ and $\mathbf{x}_{old} \leftarrow \mathbf{x}_{old}$

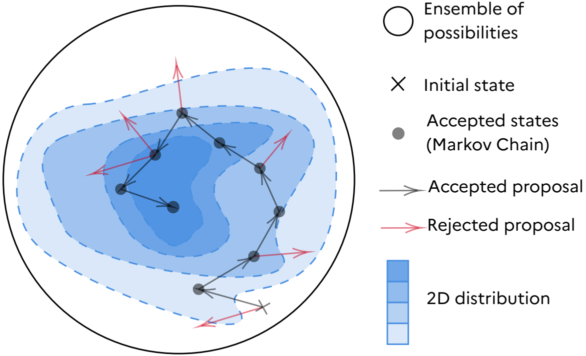


Figure: MCMC principle.

Validation of implementation

Figure: Notre-Dame de Paris cathedral fire. Source: Internet.

- Type of accident: Notre-Dame de Paris cathedral fire
- Beginning of fire: 2019/04/15 16:50 UTC
- Fully developed fire phase: between 17:00 UTC and 20:00 UTC

A synthetic case:

- using meteorological forecast

  + a source term based on National Institute of Risks (INERIS) Report [4]

  $\rightarrow$ to generate fictive observations
- using meteorological forecast

  $\rightarrow$ to build the transfer matrix

- for the validation of implementation of both methods
- with a current procedure:
  - For MAP application: λ obtained by the GCV method
  - For MCMC application: $b = 30$ and $r = \lambda^2 \times b$

Application to a real large scale fire

Figure: Tool warehouse fire near Paris. Source: Internet.

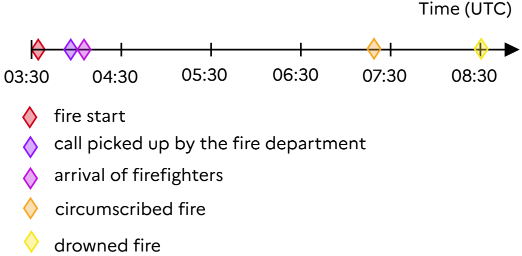


Figure: Steps of Aubervilliers's fire.

- Type of accident: tool warehouse fire of 4000 m^2 in Aubervilliers (near Paris)
- Date of the fire: 2021/04/16

- $N_{emission\ heights}$ = 5 heights (100 m, 200 m, 300 m, 400 m, 500 m)
- $N_{emission\ time\ intervals}$ = 5 hours
- pollutant: PM10 tracer

Application to a real large scale fire

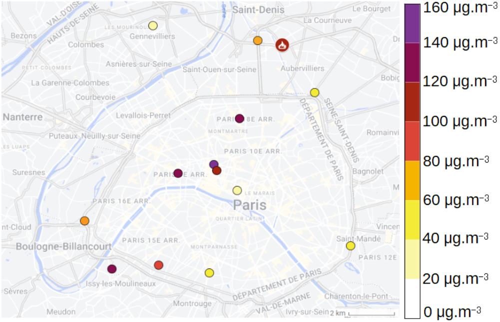


Figure: Concentration peak value of observations on Aubervilliers's fire between 3:30 UTC and 8:30 UTC.

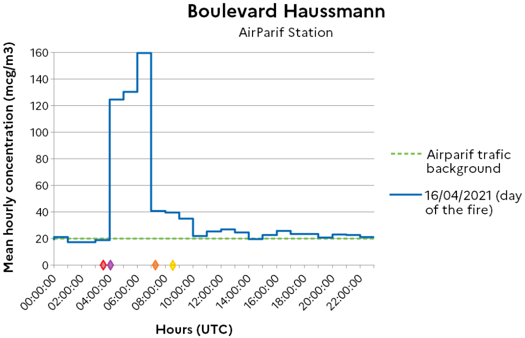
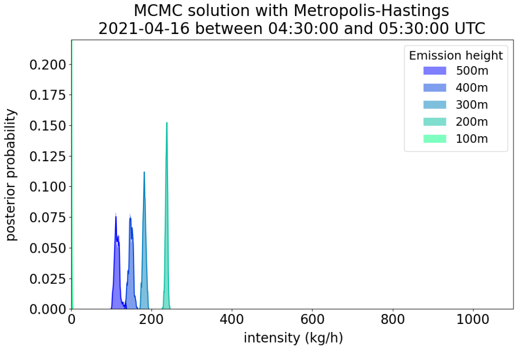


Figure: Most affected observation on Aubervilliers's fire.

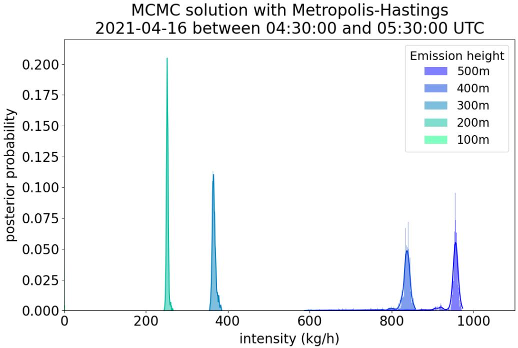
- Ten Airparif stations and one LCPP measurement are taken into account (6 observations with an abnormal PM10 concentration peak) without background

Results

- MCMC parameters: $r = 1.45$, $b = 30$, $x_{init} = 150$, $\sigma_t = 0.1$, $N_{iter} = 500000$, $N_{burn} = 30000$



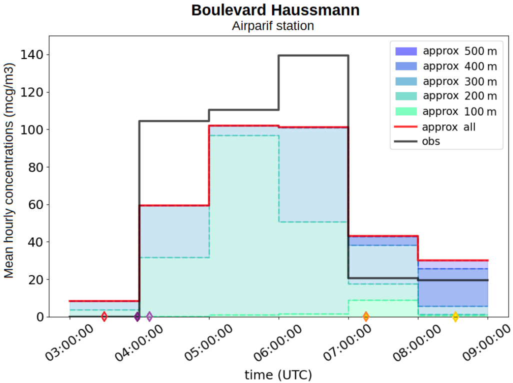
(a) MCMC results assuming a 100 kg/h uniform emission rate for the a priori ($\alpha = 0.7$).



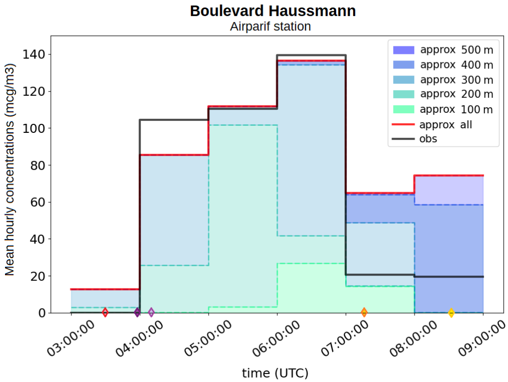
(b) MCMC results assuming a 1000 kg/h uniform emission rate for the a priori ($\alpha = 0.4$).

LCPP – CEREA

Results



(a) Cumulative concentration estimate by height, without background, and assuming a 100 kg/h uniform emission rate for the a priori.



(b) Cumulative concentration estimate by height, without background, and assuming a 1000 kg/h uniform emission rate for the a priori.

Conclusion and perspectives

Conclusions:

- implementation of both inverse methods validated with a synthetic case
- discrimination of several potential emission heights using the mcmc principle
- inverse response that seems to coincide with the observed reality

Perspectives:

- pass **R** as hyper-parameter of MCMC method
- use other probability distributions for prior and likelihood
- define a new prior distribution more restrictive on the heights
- background inversion

References

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