Bayesian inference and uncertainty quantification for source reconstruction of radionuclides release

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Presentation plan

Context

Accident Ru-106

Bayesian problem

Uncertainties

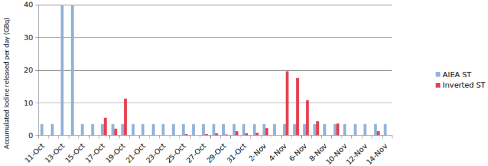
Results

Perspectives

Context

Final purpose: Evaluate release of radionuclides

- IRSN role: evaluate sanitary + environmental consequences of a release of radionuclides;
- How? Use dispersion model which take in input
  - Meteorological fields
  - *A source term*.



- The question of this PhD is: how to improve the estimation of this source term and quantify the corresponding uncertainties ?

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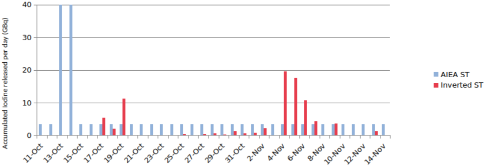

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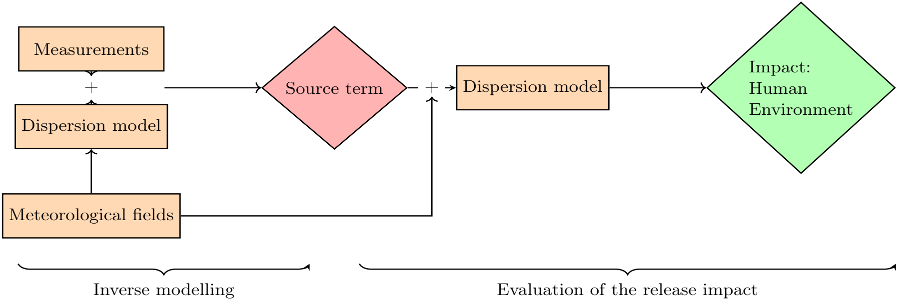
Inverse modelling in a nutshell



Detection of Ruthenium in September 2017 (Saunier et al., 2019)

- September-October 2017, concentrations of ^{106}Ru of unknown origin detected in Europe.

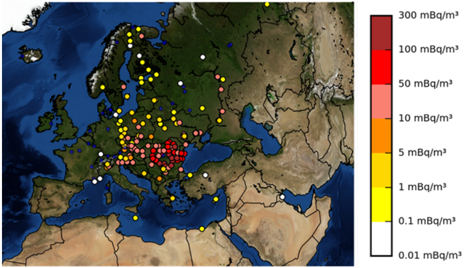


Figure: Max. concentrations of ^{106}Ru measured between the end of September 2017 and the beginning of October 2017.

Bayes and inverse modelling (Liu et al., 2017)

Bayes formula

Bayes' formula, with $\mathbf{x}$ the vector of variables characterising the source and $\mathbf{y}$ the observations:

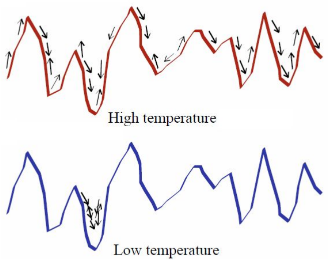
$$\overbrace{p(\mathbf{x}|\mathbf{y})}^{\text{Target}} = \frac{\overbrace{p(\mathbf{y}|\mathbf{x})}^{\text{Likelihood}}\ \overbrace{p(\mathbf{x})}^{\text{Prior}}}{p(\mathbf{y})}. \tag{1}$$

$\mathbf{x} \Rightarrow$ Longitude x_1, Latitude x_2 of the source; daily release $\mathbf{q}$; uncertainties $\mathbf{R}$.

$\mathbf{y}|\mathbf{x}$ diagnostics the difference between the dispersion model results computed with the source term $\mathbf{x}$ and the observations $\mathbf{y}$.

Monte Carlo Markov chain (MCMC)

- Sampling to reconstruct the range of the possible sources;
- Use of the Parallel Tempering algorithm (to escape local minima) (Baragatti, 2011)



Where are the uncertainties

Coordinates of the release

Likelihood definition

Dispersion model

$$p(\mathbf{x}|\mathbf{y}) \propto p(\mathbf{x})p(\mathbf{y}|\mathbf{H}_{\mathbf{x}_1,\mathbf{x}_2}(\mathbf{m})\mathbf{q}, r)$$

Error variance

Prior definition

Measurements

Discrete function of the release

Meteorology

Adding meteorological and air dispersion modelling uncertainties?

$\mathbf{H}$ = resolvent of the atmospheric dispersion model or observation operator

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \epsilon = \mathbf{y}_S + \epsilon. \tag{2}$$

Idea: using a mixture of different $\mathbf{H}$ computed with different fields and different dispersion parameters:

- meteorological uncertainty: using an ensemble weather forecast (a set of forecasts that represents potential weather outcomes);
- dispersion uncertainty: perturbed parameters (dry and wet deposit, Kz, release height).

Sampling over the weights of the members (Dumont Le Brazidec et al., 2020b), preparation.

Sampling of a range of $\mathbf{H}_1, ..., \mathbf{H}_{30}$ (30 members)
Calculation of the predictions is then done with

$$\mathbf{H} = \sum_{i=1}^{\mathrm{N_{meteo}}} w_i \mathbf{H}(m_i). \tag{3}$$

This adds 30 new variables to retrieve in the model:
$\left(x_1, x_2, \mathbf{q}_1, ..., \mathbf{q}_{\mathrm{N_{imp}}}, r\right) \rightarrow \left(x_1, x_2, \mathbf{q}_1, ..., \mathbf{q}_{\mathrm{N_{imp}}}, r, w_1, ..., w_{30}\right)$.

What is a good likelihood?

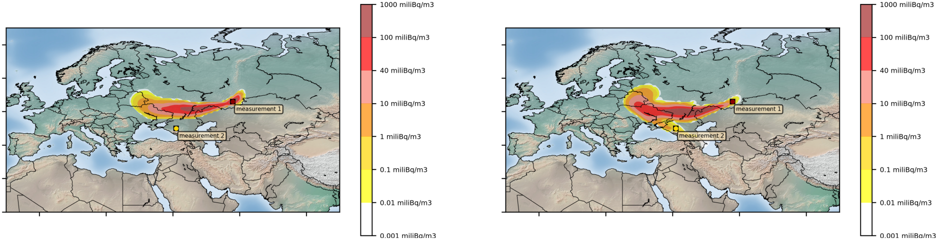
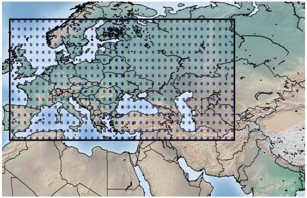


Figure: Two plumes and two observations. Each plume is best suited to a specific measurement. How to choose the most suited plume ?

Application to the Ru-106 accident (Dumont Le Brazidec et al., 2020a)

Modelling

- $>$ 1500 air concentration measurements used ;
- Domain of research:
  - location: from west Europe to Russia;
  - time: between the 22$^{\text{th}}$ of September and the 28$^{\text{th}}$ of September;
- ECMWF Era5 meteorological data are used
  HRES: $\Delta_x = 0.28125$, $\Delta_t = 1$h; enhanced EDA: $\Delta_x = 0.5625$, $\Delta_t = 3$h
- Modelling is performed using ldX Eulerian transport model;
- **H** computed over a spatial grid with a resolution of 1 degrees.



Results with a HRES meteorology

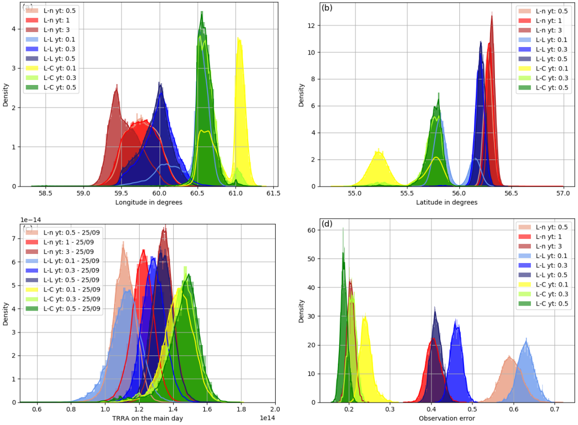


Figure: Distribution of the variables describing the Ruthenium source using several likelihoods and the parallel tempering algorithm. L-L= log-Laplace, L-n=log-normal, L-C= log-Cauchy and y_t= likelihood threshold.

Results with a EDA meteorology and the meteorology weight sampling strategy

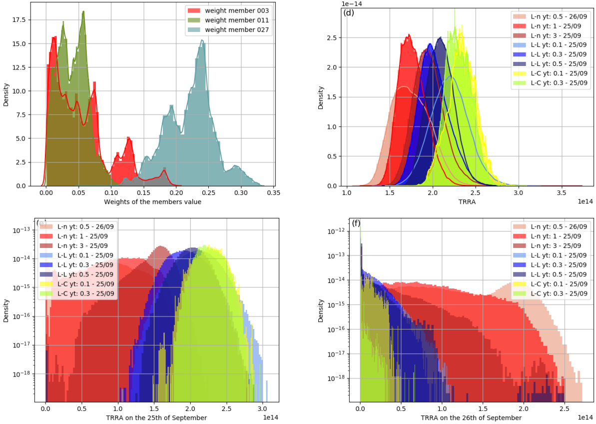


Figure: Distribution of the variables using several likelihoods and with interpolation on weight members (parallel tempering). L-L= log-Laplace, L-n=log-normal, L-C= log-Cauchy and y_t= likelihood threshold.

Discussions

- Magnitude of the release ranges between 100 and 350 TBq. Both 25$^{\text{th}}$ and 26$^{\text{th}}$ are considered as possible days of release.
- Assessment of the uncertainty on the location of the source enhanced by the use of various likelihoods.
- Evaluation of the uncertainty on the magnitude and the day of the release greatly improved by the use of an ensemble instead of a HRES meteorology.

Perspectives

- Reconstruction of the Chernobyl fires radionuclide (April 2020) source term;
- Reconstruction of the source term with quantification of the uncertainties on a more complex case study: the Fukushima accident;
- Mixing air concentration measurements with deposit measurements.

Conclusion

Thanks for your attention !

Baragatti, M., 2011: Sélection bayésienne de variables et méthodes de type Parallel Tempering avec et sans vraisemblance. thesis, Aix-Marseille 2.

Dumont Le Brazidec, J., M. Bocquet, O. Saunier, and Y. Roustan, 2020a: MCMC methods applied to the reconstruction of the autumn 2017 Ruthenium 106 atmospheric contamination source. *Atmospheric Environment X*.

Dumont Le Brazidec, J., M. Bocquet, O. Saunier, and Y. Roustan, 2020b: Uncertainties quantification in CBRN source assessment and application to the reconstruction of the autumn 2017 Ruthenium 106 atmospheric contamination source.

Liu, Y., J.-M. Haussaire, M. Bocquet, Y. Roustan, O. Saunier, and A. Mathieu, 2017: Uncertainty quantification of pollutant source retrieval: comparison of Bayesian methods with application to the Chernobyl and Fukushima Daiichi accidental releases of radionuclides. *Quarterly Journal of the Royal Meteorological Society*, **143 (708)**, 2886–2901, doi:10.1002/qj.3138.

Saunier, O., D. Didier, A. Mathieu, O. Masson, and J. Dumont Le Brazidec, 2019: Atmospheric modeling and source reconstruction of radioactive ruthenium from an undeclared major release in 2017. *Proceedings of the National Academy of Sciences*, **116 (50)**, 24 991, doi:10.1073/pnas.1907823116.