Targeting of Observations for Radionuclides Accidental Release Monitoring

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The 5th WMO International Symposium on Data Assimilation. Melbourne Australia, 5-9 October 2009.

Problem definition and objective

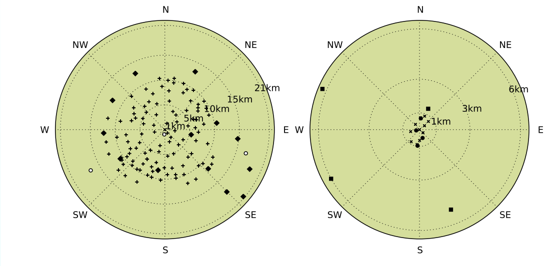
▸ Concept and formalism for the targeting of observations have been introduced in meteorology (Berliner et al. (1999)). The method is very successful but the gain is limited due to an overwhelming flux of synoptical observations.

▸ In the field of accidental dispersion monitoring, it is now possible to deploy gamma dose instruments by helicopter.

▸ How should one optimally deploy stations, with a view to improve inverse modelling of the source term or data assimilation for the plume forecast ?

Accidental release from the Bugey power plant

▸ Fictitious radionuclide accidental release studied within a radius of 50 kilometres from the nuclear power plant of Bugey, France. Current monitoring network around the plant:



Set-up of the twin experiment

▸ Fast core meltdown hypothesis without major hull breach. Dispersion of iodine-131.

▸ MM5 fields generated in two configurations: strong and weak wind fields.

▸ Transport simulated by the CTM POLAIR3D.

▸ The network is assumed to measure ^{131}I activity concentrations , although it is actually measuring gamma dose.

▸ Log-normal perturbations of synthetic observations: $\mu_i^{\text{perturb.}} \sim \exp\left(\mathcal{N}(0, 0.5)\right) \mu_i^{\text{synth}}$.

▸ 21 static observations are assimilated every two hours. 10 mobile stations are deployed on a two-hour window yielding 10 adaptive observations every two hours.

Source inverse modelling and plume data assimilation

Source-receptor relationship $\boldsymbol{\mu} = \boldsymbol{H}\boldsymbol{\sigma} + \boldsymbol{\varepsilon}$

Control variables to be determined: release rates from the plant $\boldsymbol{\sigma} \in \mathbb{R}^n$ ($\Delta t = 30$ mins)

Direct computation of the Jacobian $\boldsymbol{H} \in \mathbb{R}^{d \times n}$ (column by column)

Prior errors Gaussian relative $\boldsymbol{R} = \text{diag}(\chi_1, \chi_2, \ldots, \chi_d)$, with $\sqrt{\chi_i} \simeq 0.5\mu_i$.

Normal equations $\overline{\boldsymbol{\sigma}} = \left(\boldsymbol{H}^T\boldsymbol{R}^{-1}\boldsymbol{H}\right)^{-1}\boldsymbol{H}^T\boldsymbol{R}^{-1}\boldsymbol{\mu}$, and $\boldsymbol{P}^a_{t_n} = \left(\boldsymbol{H}^{\text{T}}\boldsymbol{R}_{t_n}\boldsymbol{H}\right)^{-1}$.

Plume data assimilation

Analysis:

▸ Activity concentration measurements in $[t_n - \Delta t_{\text{f}}, t_n]$ are collected. Vector of measurements up to t_n : $\boldsymbol{\mu}_n$.

▸ Extension of the Jacobian matrix $\boldsymbol{H}_{t_n}$, computing all elementary solutions from t_0 to t_n. The source term estimation $\overline{\boldsymbol{\sigma}}_n$ is then computed.

▸ An estimation of the error on the source $\boldsymbol{P}^{\boldsymbol{\sigma}}_{t_n^+}$ or on the plume $\boldsymbol{P}^{\boldsymbol{c}}_{t_n^+}$, can be computed.

Forecast:

▸ Forecast from t_n to t_{n+1}, thanks to a CTM.

▸ Forced by source estimation up to t_n, then by a model from t_n to t_{n+1}, generally persistence hypothesis.

▸ A source error estimation $\boldsymbol{P}^{\boldsymbol{\sigma}}_{t_{n+1}}$ or a plume error estimation $\boldsymbol{P}^{\boldsymbol{c}}_{t_{n+1}}$ can be obtained.

Targeting scheme

▸ Source analysis on $[t_0, t_1]$ using static observations $\boldsymbol{\sigma}_{t_1^+} \sim \mathcal{N}\left(\overline{\boldsymbol{\sigma}}_{t_1^+}, \boldsymbol{P}_{t_1^+}\right)$.

▸ Forecasted source $\boldsymbol{\sigma}^\star_{t_2}$ on $[t_0, t_2]$: equals to $\overline{\boldsymbol{\sigma}}_{t_1^+}$ on $[t_0, t_1]$, and is defined on $[t_1, t_2]$ using the persistence assumption: $\boldsymbol{\sigma}^\star_{t_2}(t) \equiv \overline{\boldsymbol{\sigma}}_{t_1^+}(t_1)$.

▸ Plume forecast from t_1 to t_2, and computations of forecasted fixed observations in $[t_1, t_2]$.

▸ Forecasted source covariance matrix error at t_2: $\boldsymbol{P}^{\star\sigma}_{t_2} = \left(\boldsymbol{H}^T_{t_2}\left(\boldsymbol{R}^\star_{t_2}\right)^{-1}\boldsymbol{H}_{t_2}\right)^{-1}$

▸ Forecasted targeted observations follow $\boldsymbol{\mu}^\star_{t_2} = \boldsymbol{h}\boldsymbol{\sigma}^\star_{t_2} + \boldsymbol{\varepsilon}$, with $\boldsymbol{\varepsilon} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{r}^\star_{t_2})$.

▸ At decision time t_1, the forecasted update of $\boldsymbol{\sigma}$ at time t_2, follows $\boldsymbol{\sigma}^\star_{t_2^+} \sim \mathcal{N}\left(\overline{\boldsymbol{\sigma}}^\star_{t_2^+}, \boldsymbol{P}^{\star\sigma}_{t_2^+}\right)$. Standard Bayesian analysis leads to

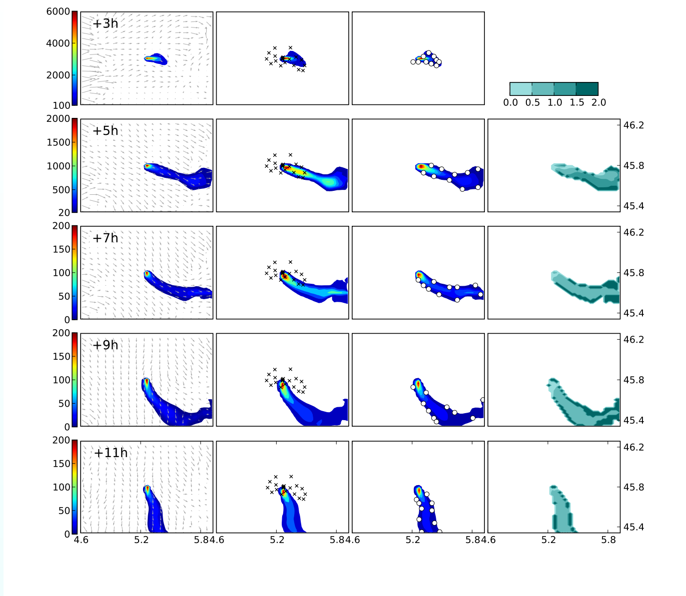
$$\boldsymbol{P}^{\star\sigma}_{t_2^+} = \left(\left(\boldsymbol{P}^{\star\sigma}_{t_2}\right)^{-1} + \boldsymbol{h}^T\left(\boldsymbol{r}^\star_{t_2}\right)^{-1}\boldsymbol{h}\right)^{-1} = \boldsymbol{P}^{\star\sigma}_{t_2} - \boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^T\left(\boldsymbol{r}^\star_{t_2} + \boldsymbol{h}\boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^T\right)^{-1}\boldsymbol{h}\boldsymbol{P}^{\star\sigma}_{t_2},$$

$$\overline{\boldsymbol{\sigma}}^\star_{t_2^+} = \overline{\boldsymbol{\sigma}}^\star_{t_2} + \boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^T\left(\boldsymbol{r}^\star_{t_2} + \boldsymbol{h}\boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^T\right)^{-1}\left(\boldsymbol{\mu}^\star_{t_2} - \boldsymbol{h}\overline{\boldsymbol{\sigma}}^\star_{t_2}\right).$$

▸ A-design criterion $\text{Tr}\left(\boldsymbol{P}^{\star\sigma}_{t_2^+}\right) = \text{Tr}\left(\boldsymbol{P}^{\star\sigma}_{t_2}\right) - \text{Tr}\left(\left(\boldsymbol{r}^\star_{t_2} + \boldsymbol{h}\boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^{\text{T}}\right)^{-1}\boldsymbol{h}\left(\boldsymbol{P}^{\star\sigma}_{t_2}\right)^2\boldsymbol{h}^{\text{T}}\right)$, leads to the targeting criterion $J(\boldsymbol{h}) = \text{Tr}\left(\left(\boldsymbol{r}^\star_{t_2} + \boldsymbol{h}\boldsymbol{P}^{\star\sigma}_{t_2}\boldsymbol{h}^{\text{T}}\right)^{-1}\boldsymbol{h}\left(\boldsymbol{P}^{\star\sigma}_{t_2}\right)^2\boldsymbol{h}^{\text{T}}\right)$.

▸ Optimisation of $J(\boldsymbol{h})$ relies on simulated annealing.

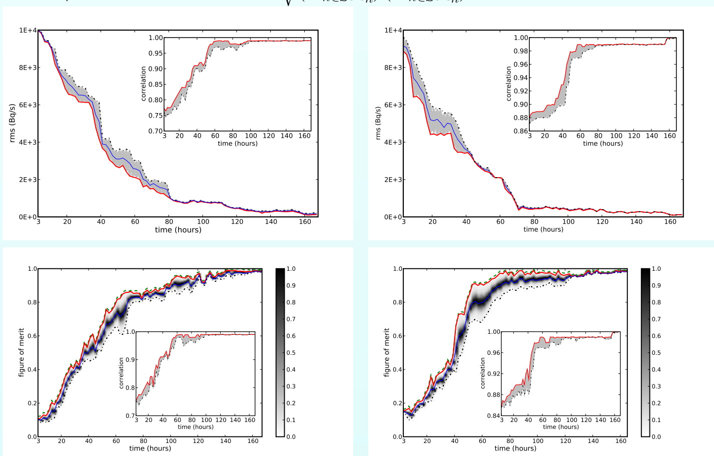
Twin experiment



First column: reference simulation (truth) knowing the true source. Second column: forecast of plume using data assimilation of fixed observations. Third column: forecast of plume using data assimilation of fixed and adaptive observations. Fourth column: contrast factor between the second and third column.

Statistical indicators

$$\text{rmse} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left([\boldsymbol{\sigma}]_i - [\overline{\boldsymbol{\sigma}}]_i\right)^2}, \quad \rho = \sum_{h \in S}\frac{[\overline{\boldsymbol{c}}]_h[\boldsymbol{c}]_h}{\sqrt{\left(\sum_{h\in\mathbf{S}}[\overline{\boldsymbol{c}}]_h^2\right)\left(\sum_{h\in\mathbf{S}}[\boldsymbol{c}]_h^2\right)}}, \quad \text{fm} = \frac{\sum_{h\in S}\min\left([\overline{\boldsymbol{c}}]_h, [\boldsymbol{c}]_h\right)}{\sum_{h\in S}\max\left([\overline{\boldsymbol{c}}]_h, [\boldsymbol{c}]_h\right)}$$

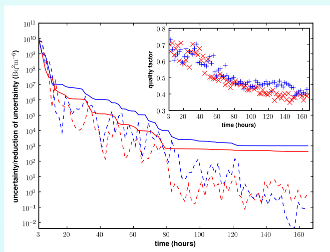


Information gain from adaptive observations versus static observations

▸ Gain indicator:

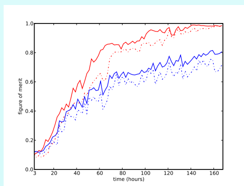
$$\text{QF} = \frac{\text{Tr}\left(\boldsymbol{P}^{\star c}_{t_{n+1}}\right) - \text{Tr}\left(\boldsymbol{P}^{\star c}_{t^+_{n+1}}\right)}{\text{Tr}\left(\boldsymbol{P}^{c}_{t_n}\right) - \text{Tr}\left(\boldsymbol{P}^{c}_{t^+_{n+1}}\right)}.$$

▸ Targeting is very beneficial in this context, in particular in strong wind conditions.



Meteorological model error test

The meteorological fields are shifted by 15 minutes, which simulates some kind of model error. Is targeting still beneficial to data assimilation ? Yes !



References

Abida, R. and and Bocquet, M. (2009). Targeting of observations for accidental atmospheric release monitoring, *Atmos. Env.*, in press.

Berliner, L.M., Lu, Z.Q. and Snyder, C. (1999). Statistical design for Adaptive Weather Observations. *J. Atmos Sci.*, **56**, 2536–2552.