Forecast errors in clouds and precipitation: diagnosis and modeling for the assimilation of radar data and cloudy radiances at convective scale

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METEO FRANCE
Toujours un temps d'avance

Outlines

1. **Introduction**

1. **Modelization of B for specific meteorological phenomena**

1. **Applications:**

    - Use of a heterogeneous **B** for DA in rain and in fog

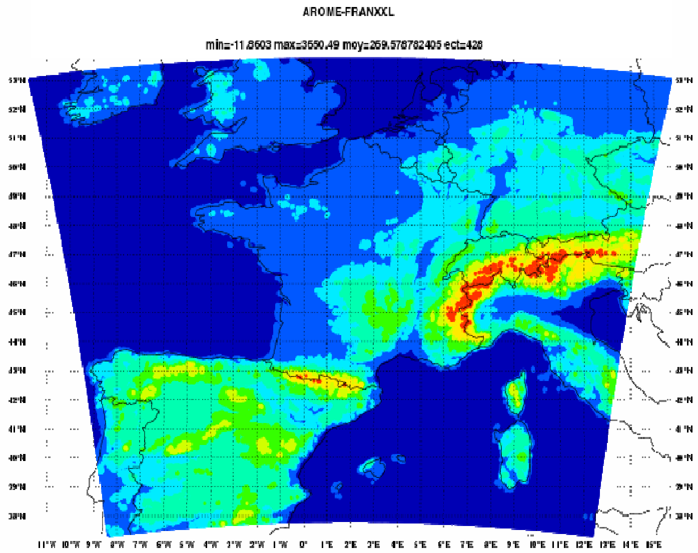
    - Assimilation of cloudy IR radiances

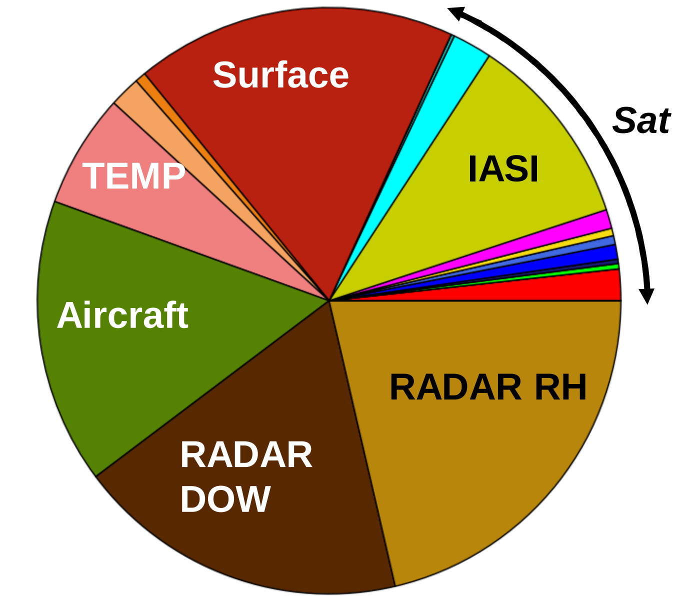
4. **Conclusions and Perspectives**

Introduction: the AROME NWP system

- Operational, covers France with dx=2.5 km
- 1.3 10^8 variables, explicit convection, realistic representations of clouds, turbulence, surface interaction…

$\Rightarrow$ DA based on « real time » ensembles unaffordable for the time being





Active obs in AROME for one rainy day

Microphysical scheme allowing to get realistic observation operators in clouds and precipitation

- DOW and reflectivities from Doppler radars are assimilated operationally
- The assimilation of cloudy radiances under study, requiring background error covariances for hydrometeors

Introduction: DA in AROME

3h cycle using an **inc3DVar** and the CVT formulation: $\delta x = \mathbf{B}^{1/2}\chi$

Following notation of Derber and Bouttier (1999) : $\mathbf{B}^{1/2} = \mathbf{K}_P \mathbf{B}_S^{1/2}$

• $\mathbf{K_p}$ **is the balance operator** allowing to output uncorrelated parameters using balance constraints.

$$\delta x = \mathbf{K}_P \tilde{\chi}$$

$$\begin{pmatrix} \delta\zeta \\ \delta\eta \\ (\delta T, \delta P_S) \\ \delta q \end{pmatrix} = \begin{pmatrix} I & 0 & 0 & 0 \\ MH & I & 0 & 0 \\ NH & P & I & 0 \\ QH & R & S & I \end{pmatrix} \begin{pmatrix} \delta\tilde{\zeta} \\ \delta\tilde{\eta}_u \\ (\delta\tilde{T}, \delta\tilde{P}_S)_u \\ \delta\tilde{q}_u \end{pmatrix}$$

analytical linear balance operator ensuring geostrophical balance

regression operators that adjust couplings with scales

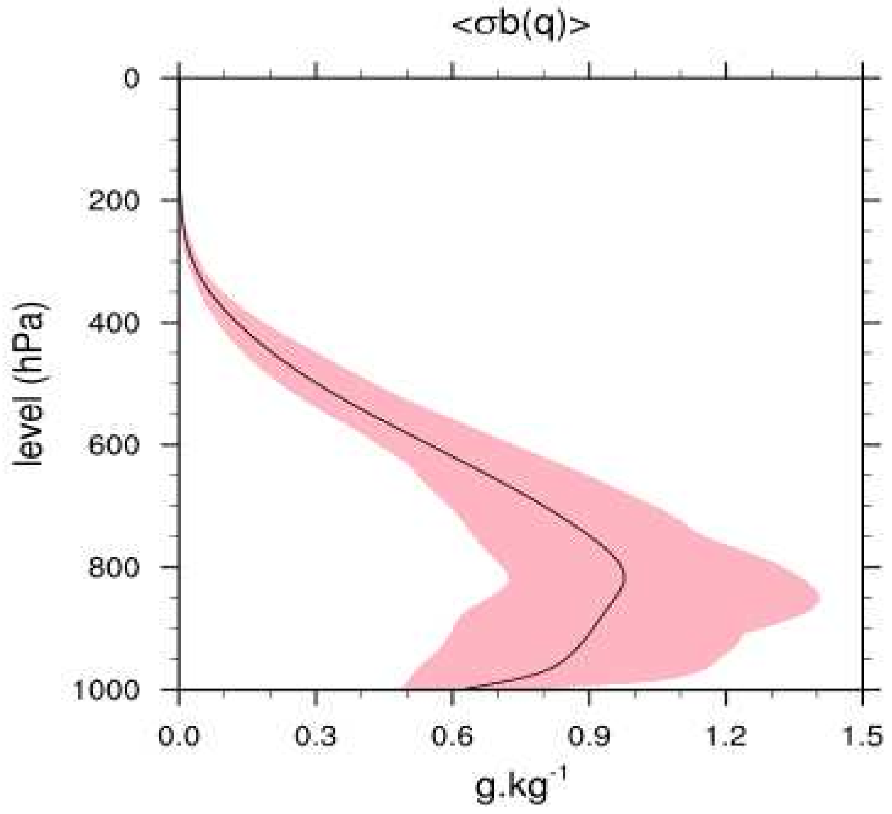
Berre (2000)

• $\mathbf{B}_\mathrm{S}$ **is the spatial transform**: $\mathbf{B_S} = \Sigma\mathbf{C}\Sigma^\mathrm{T}$

$\mathbf{K_p}$ and $\mathbf{B}_\mathrm{S}$ are static and are deduced from an ensemble assimilation (Brousseau et al. 2011a)

Introduction: limitations of the operational B

B strongly depends on weather regimes :



Spread of daily forecast error of std deviations for q

(ensemble gathering anticyclonic and perturbed situations, Brousseau et al. 2011b)

- Different methods have been published to compute a flow dependent $\mathbf{B_S}$ in a VAR context, **none for** $\mathbf{K_p}$
- Here we focus on a method allowing to diagnose and to use both different $\mathbf{B_S}$ and $\mathbf{K_p}$ in different areas

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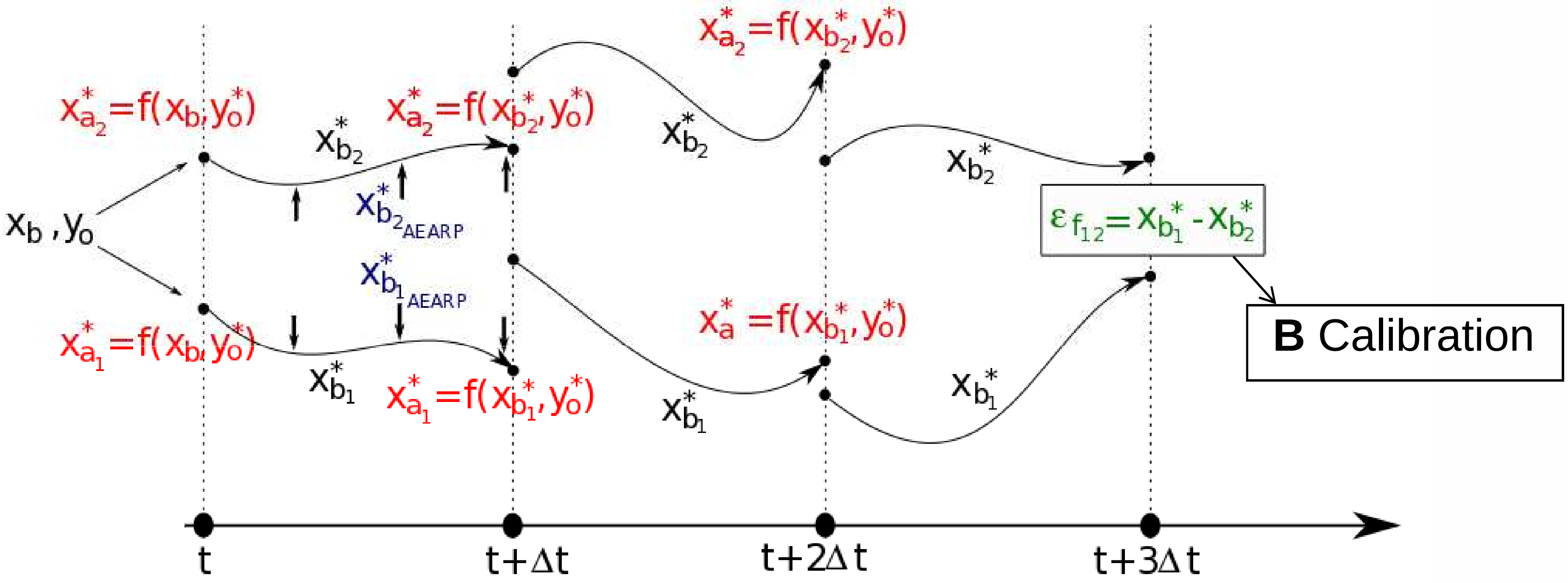
Modelization of B for specific meteorological phenomena

Use of an EDA designed for LAM (see poster P72 by P. Brousseau)



Explicit Perturbation of obs: $y^*_o = y_o + \varepsilon_o \quad (\varepsilon_o \sim N(0,\sigma_o^2))$

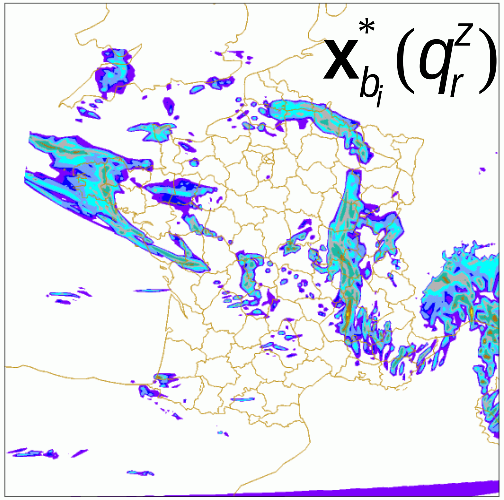
Explicit Perturbation of lateral boundary conditions coming from AEARP

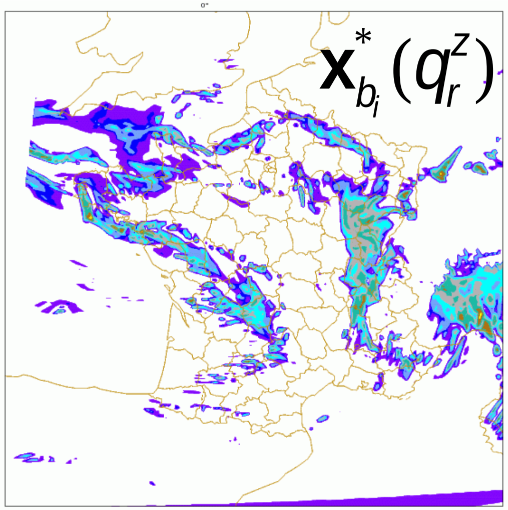
Implicit Perturbation of the background: $x^*_b = M(x^*_a) + (\varepsilon_m)$

- Few cycles needed to get the full spectra of error variances
- **High impact phenomena under-represented in the ensemble**

Modelization of B for specific meteorological phenomena
(Montmerle and Berre 2010)

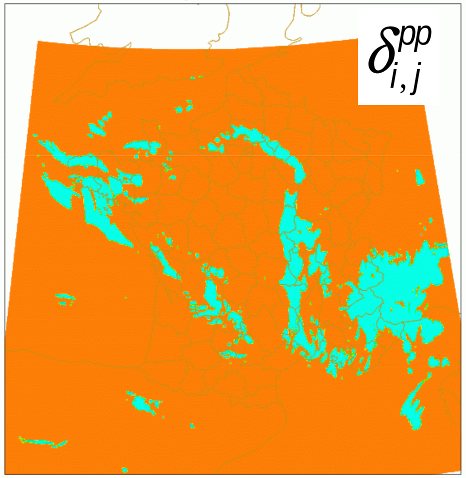
Forecast errors are decomposed using features in the background perturbations that correspond to a particular meteorological phenomena.

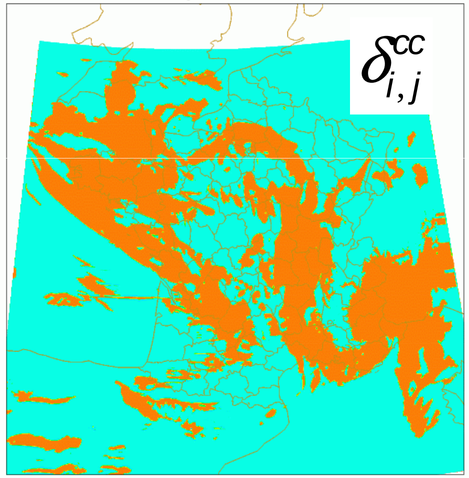




Example for precipitation

Binary masks: 1 0





rain/rain *non rainy/non rainy*

$$\varepsilon_{f_{ij}} = \mathbf{x}^*_{b_i} - \mathbf{x}^*_{b_j} \approx \left[G\delta^{pp}_{ij}\right]\varepsilon_{f_{ij}} + \left[G\delta^{cc}_{ij}\right]\varepsilon_{f_{ij}} + \left[G\delta^{cp}_{ij}\right]\varepsilon_{f_{ij}}$$

(G : Gaussian blur)

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Application #1: use of a « rainy » B for DA of radar data

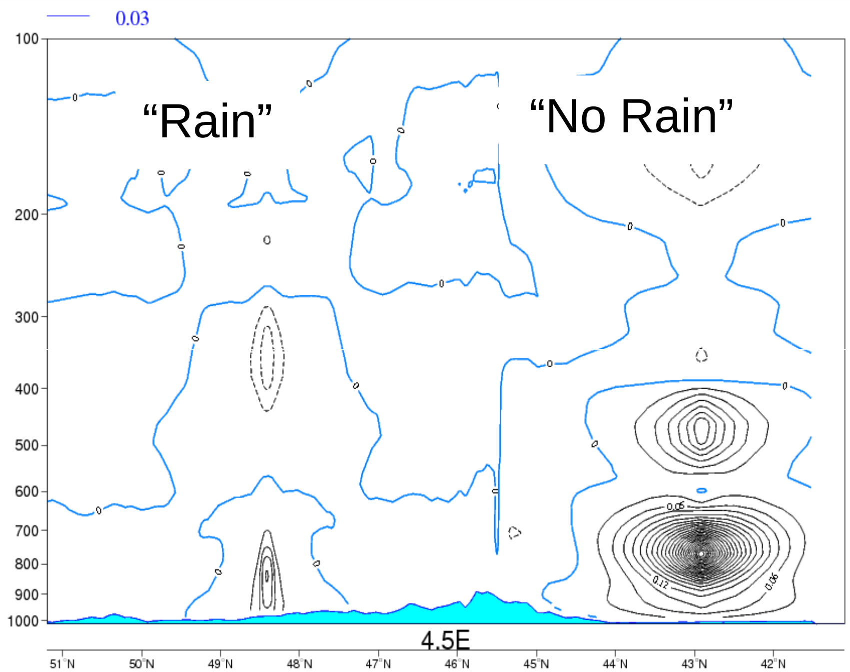
Use of the heterogeneous formulation:
(Montmerle and Berre, 2010)

$$\delta x = \mathbf{B}^{1/2}\chi = \begin{pmatrix} \mathbf{F}_1^{1/2}\mathbf{B}_1^{1/2} & \mathbf{F}_2^{1/2}\mathbf{B}_2^{1/2} \end{pmatrix} \begin{pmatrix} \chi_1 \\ \chi_2 \end{pmatrix}$$

Where $\mathbf{F_1}$ and $\mathbf{F_2}$ define the geographical areas where $\mathbf{B_1}$ and $\mathbf{B_2}$ are applied:

$$\begin{cases} \mathbf{F}_1^{1/2} = \mathbf{S}\mathbf{D}^{1/2}\mathbf{S}^{-1} \\ \mathbf{F}_2^{1/2} = \mathbf{S}(\mathbf{I}-\mathbf{D})^{1/2}\mathbf{S}^{-1} \end{cases}$$

$\Rightarrow$ This formulation allows to consider simultaneously different $\mathbf{B_S}$ and $\mathbf{K_p}$ that are representative of one particular meteorological phenomena

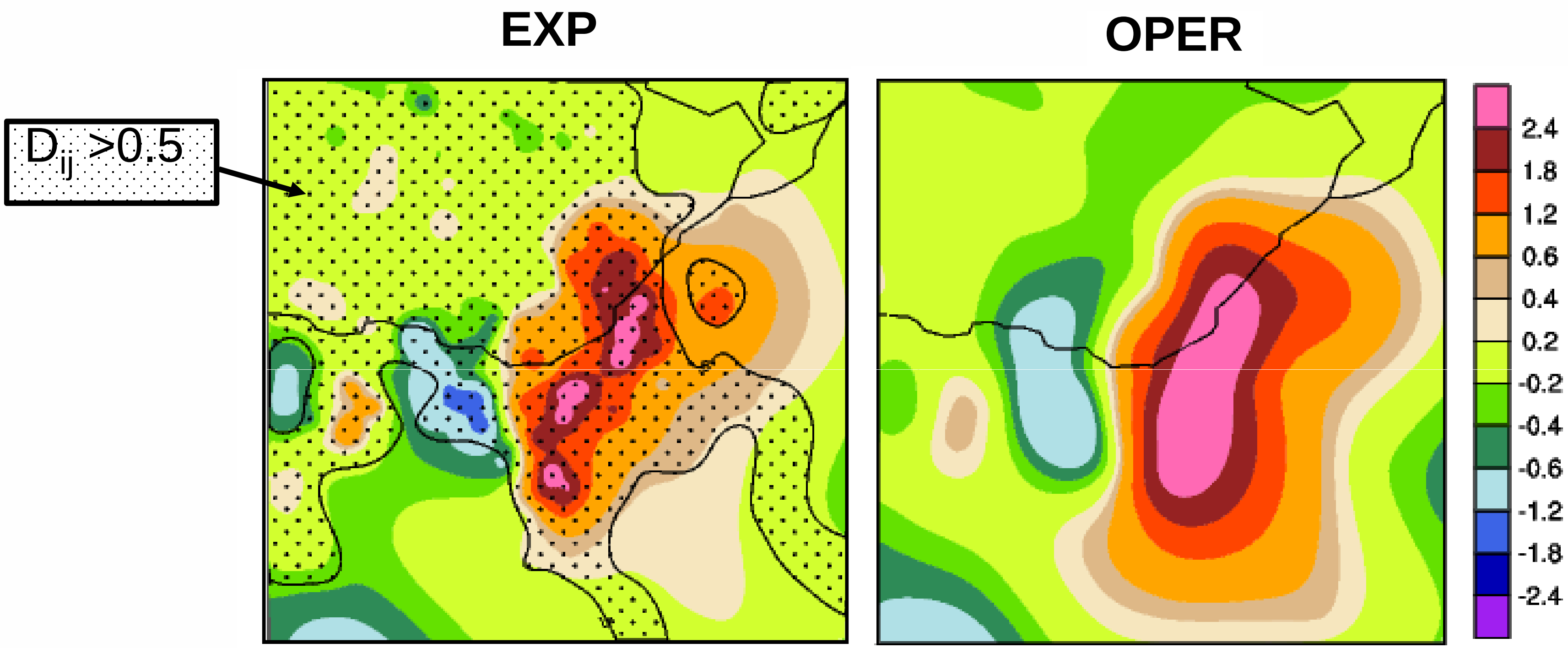


Vertical Cross section of q increments
4 obs exp: Innovations of – 30% RH
At 800 and 500 hPa

Application #1: use of a « rainy » B for DA of radar data

Montmerle (MWR, 2012)

Here: EXP: B_1=rain, B_2=OPER , D=radar mosaic



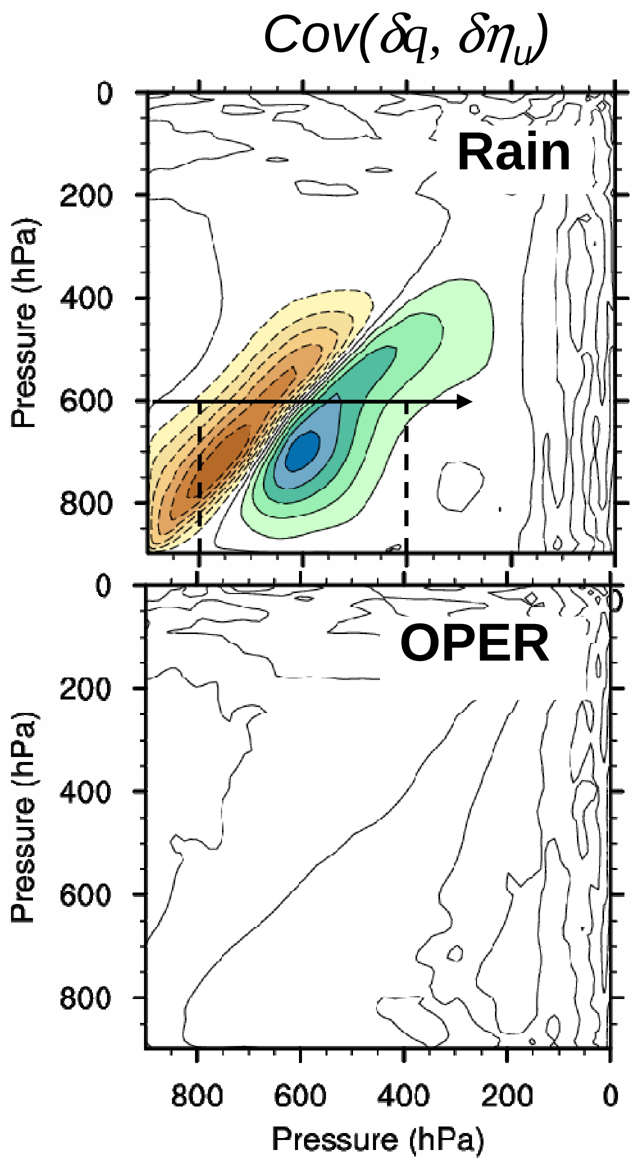
Humidity increment at 600 hPa ($g.kg^{-1}$)
(zoom over SE France)

B_1 has shorter correlation lengths:

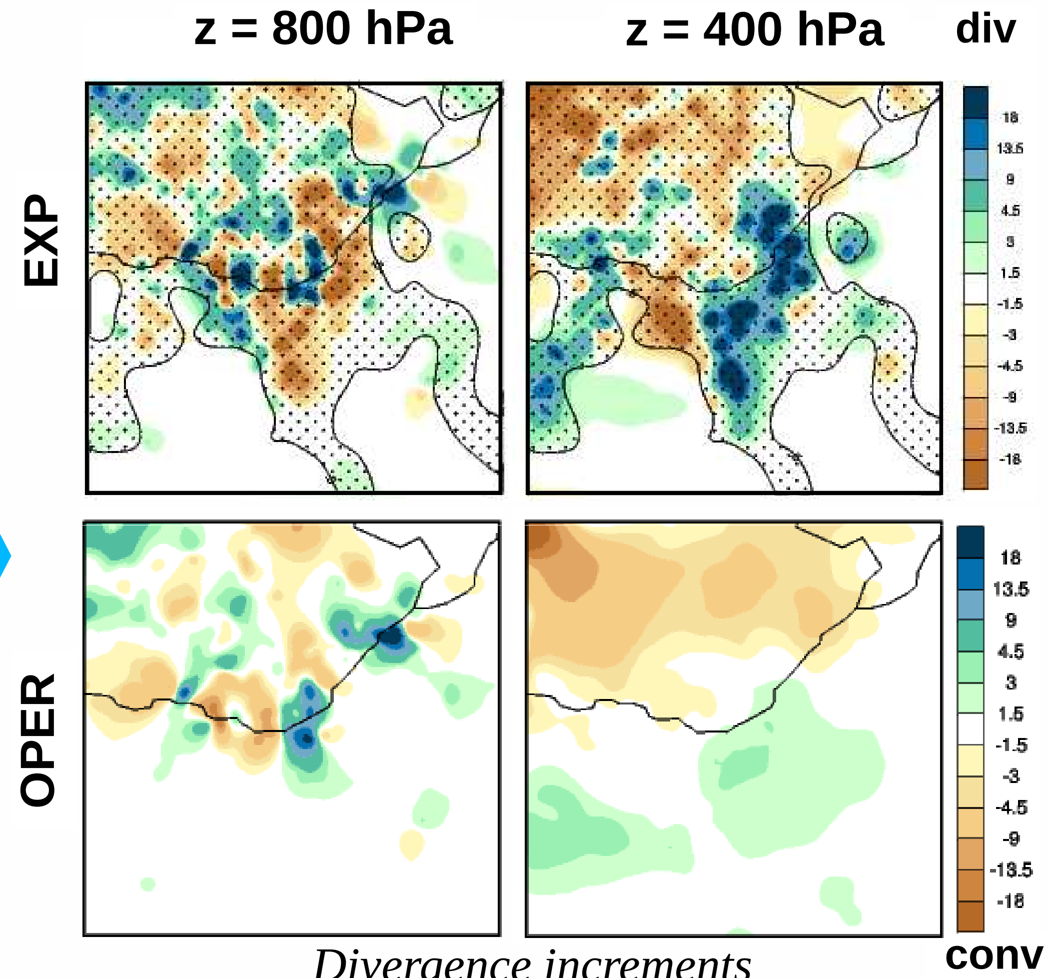
⇒ increments have higher spatial resolutions in precipitation

⇒ Potential increase of the spatial resolution of assimilated radar data

Application #1: use of a « rainy » B for DA of radar data



Vertical cross covariances



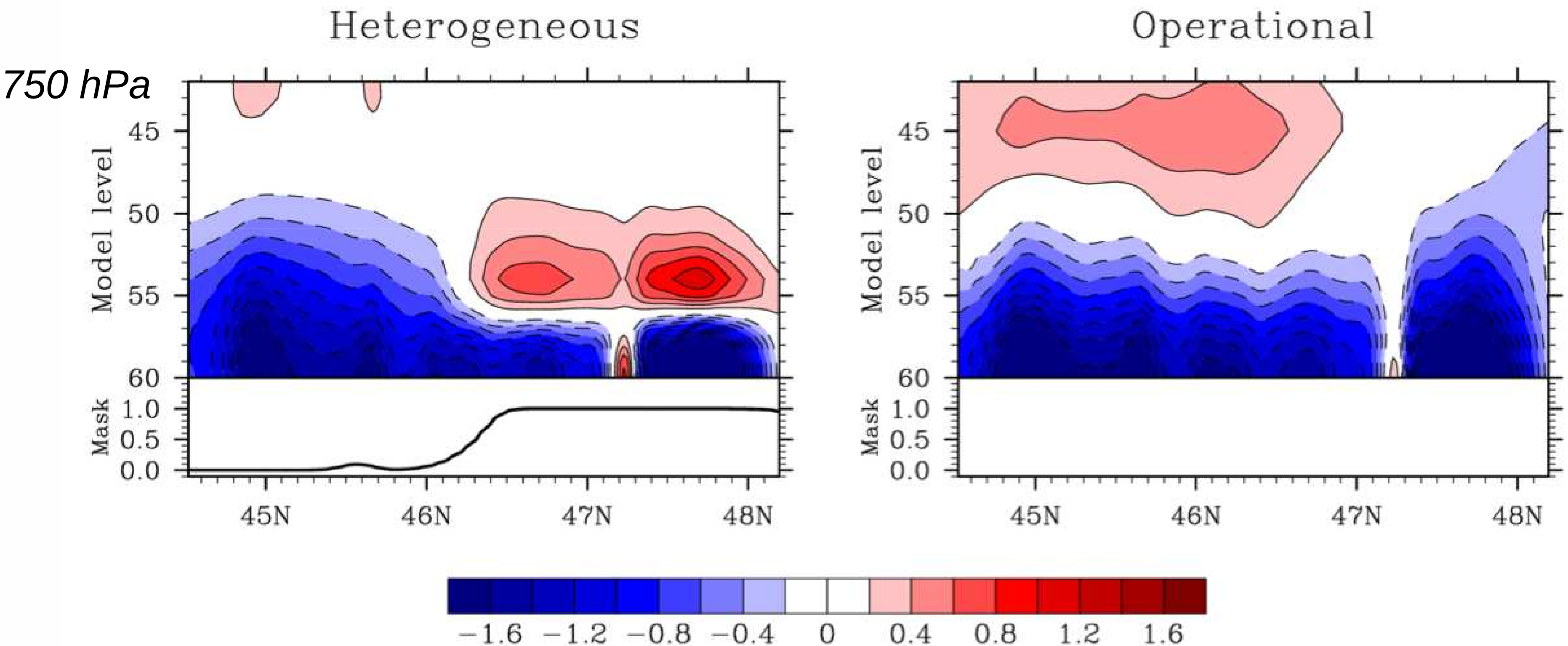
Divergence increments

- Spin-up reduction correlated with the number of grid points where $\mathbf{B_1}$ is applied
- Positive forecasts scores up to 24h for precipitation and for T and q in the mid and lower troposphere

Application #2: heterogeneous 3DVar for fog forecast

In fog, T and q are strongly coupled and their background errors below the inversion are strongly decorrelated with higher levels.

$\Rightarrow$ Increments due to ground measurements are confined whithin the fog:



Vertical cross sections of temperature increments

$\Rightarrow$ More details in Ménétrier and Montmerle (2011)

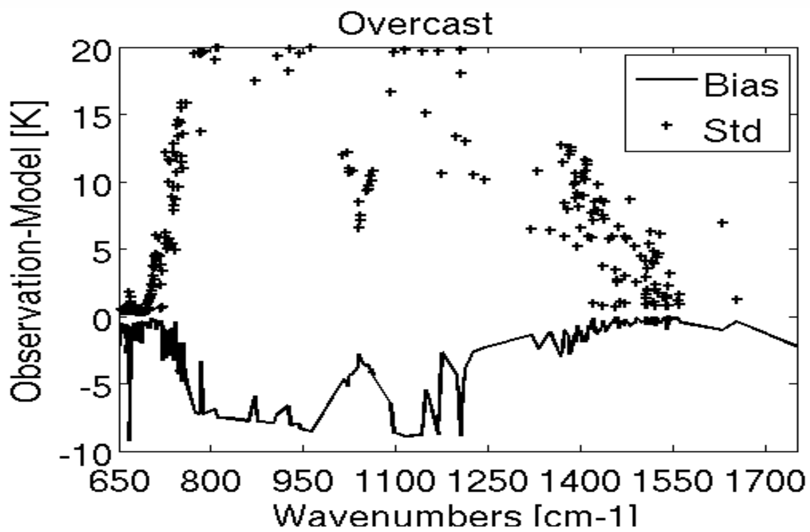
Application #3: Assimilation of cloudy radiances in a 1DVar
Martinet et al. (2012)

Problematic: Non-Gaussian innovations due to mislocation of simulated structure and modeling defficiencies

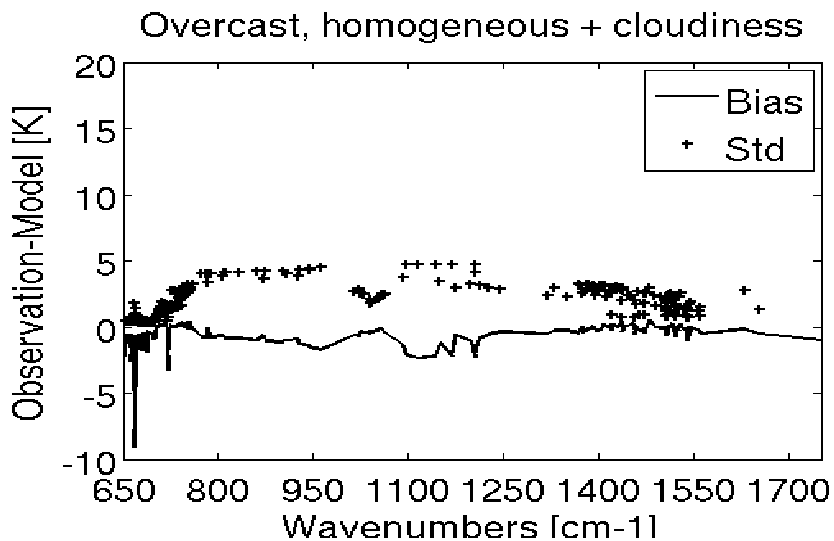
⇒ **Simulation of IASI radiances using profiles of ql and qi**. Modelling of multi-layer clouds and cloud scattering with RTTOV-CLD.

⇒ **Selection of homogeneous overcast scenes** from a database of profiles extracted from AROME forecasts by comparing simulated and observed AVHRR radiances co-located with the IASI field of view

Raw innovations



Innovations after screening

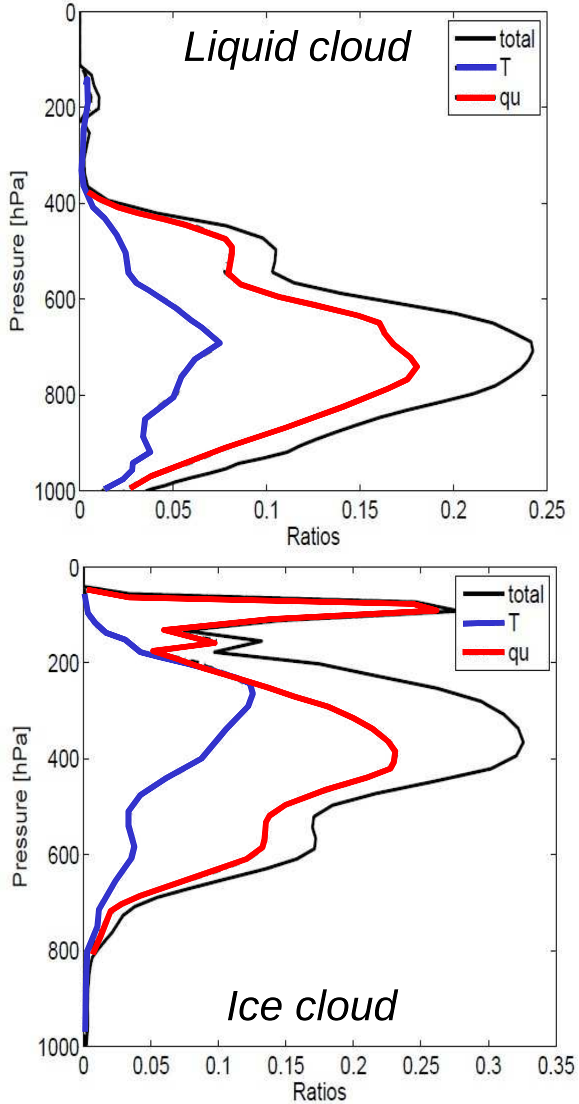


Application #3: Assimilation of cloudy radiances in a 1DVar

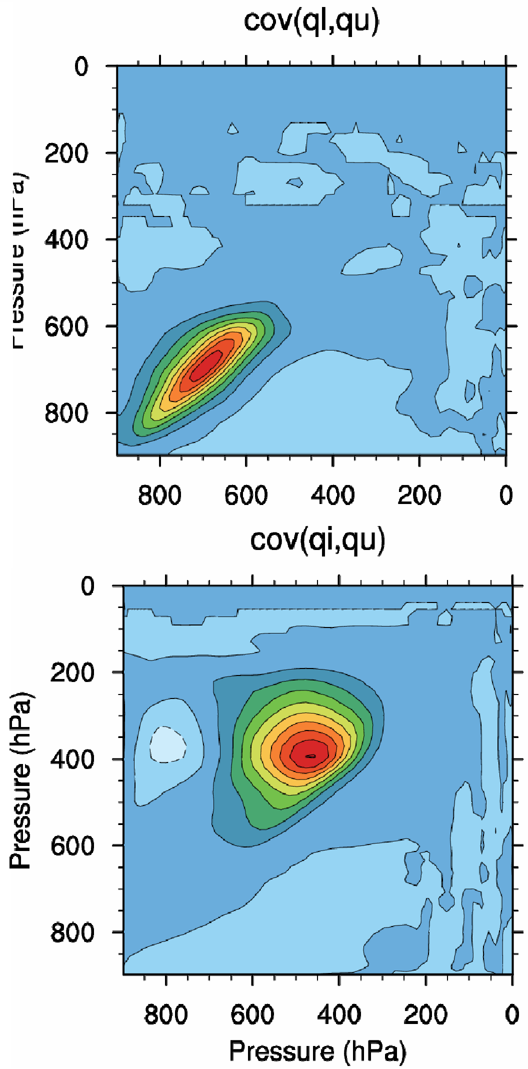
Computation of background error covariances for all hydrometeors in clouds:

Analogously to Michel et al. (2011), the mask-based method and an extension of $\mathbf{K_p}$ have been used:

$$\begin{cases} \delta T = \delta T \\ \delta q = T_0 \delta T + \delta q_u \\ \delta q^{l,i,r,s} = T_1 \delta T + T_2 \delta q_u + \delta q_u^{l,i,r,s} \end{cases}$$



% of explained error variances for q_l (top) and q_i (bottom)



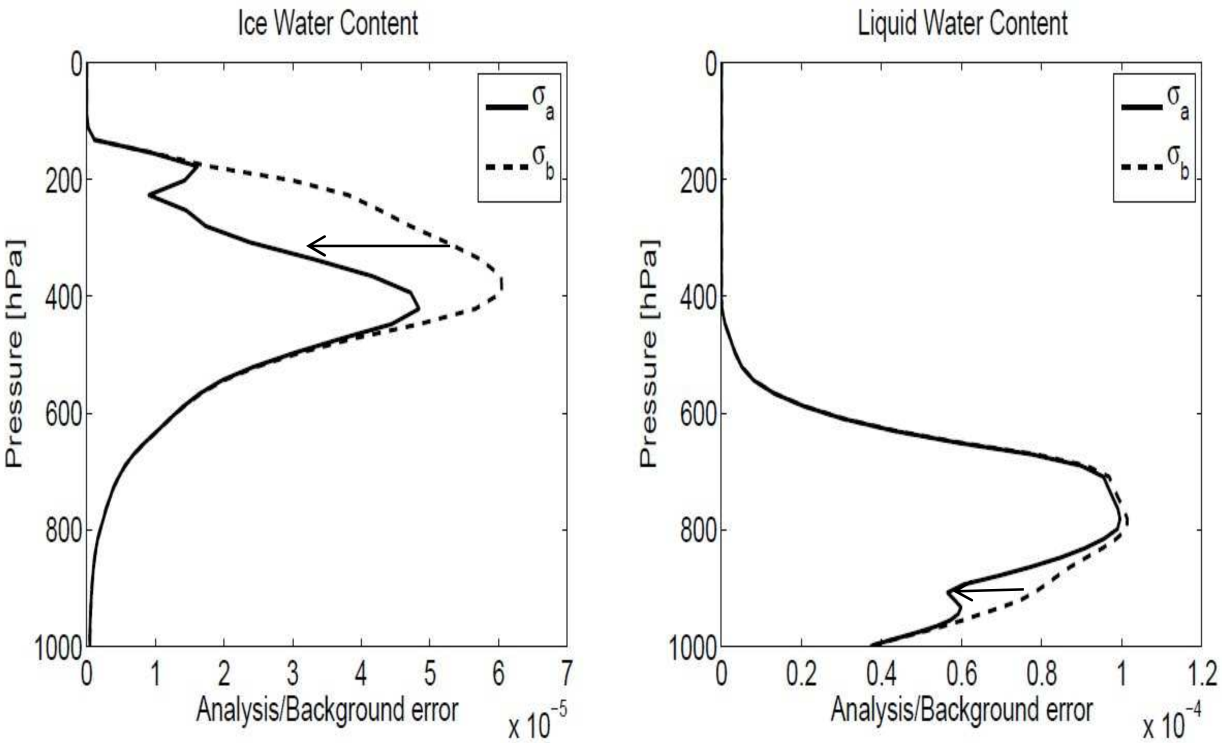
Vertical covariances between qi , ql and the unbalanced humidity q_u

Application #3: Assimilation of cloudy radiances in a 1DVar

Assimilation of IASI cloudy radiances

q_l and q_i have been added to the state vector of a1DVar, along with T and q

Reduction of background error variances for selections of high opaque cloud (left) and low liquid cloud (right)



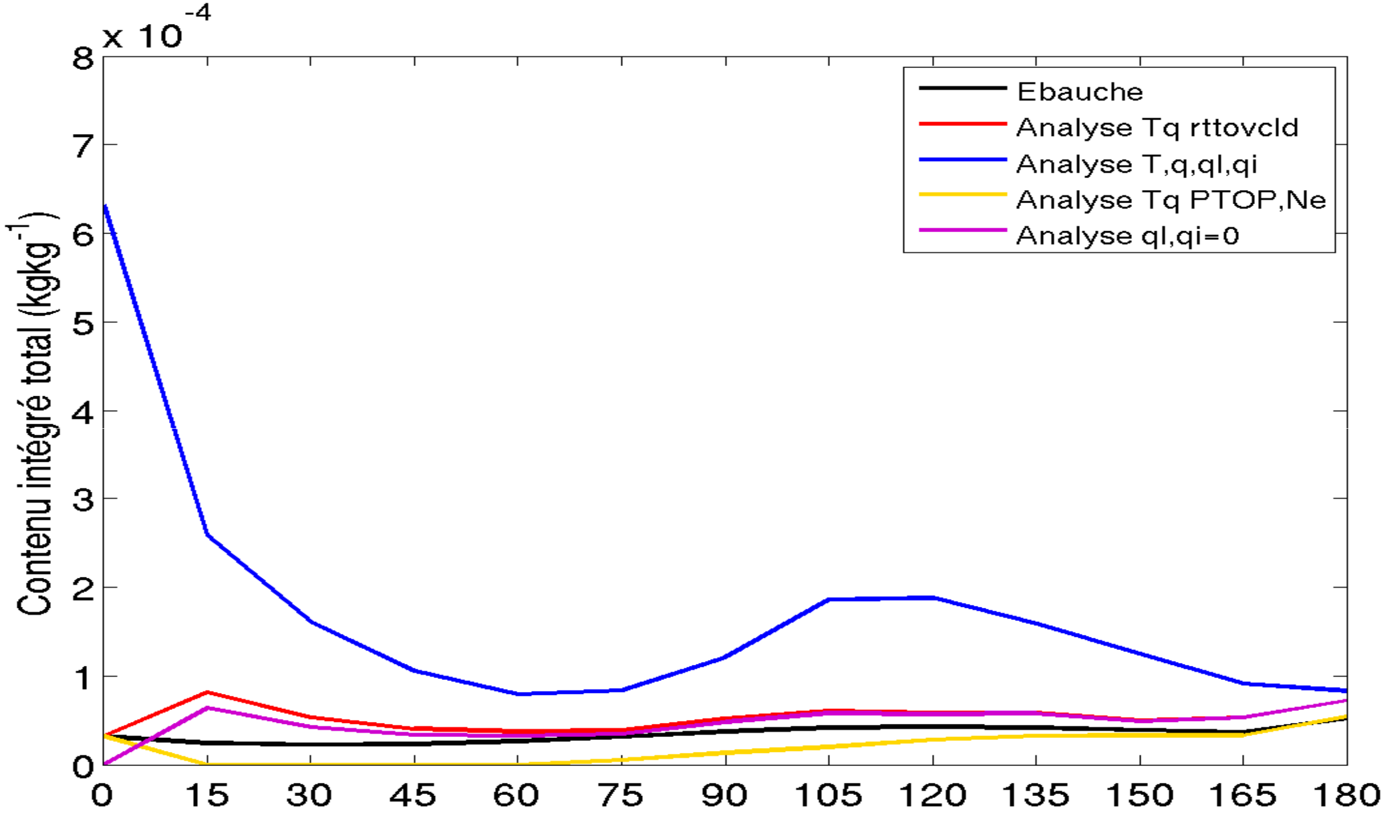
⇒ Background errors are reduced for q_l and q_i (as well as for T and q (not shown)), increments are coherently balanced for all variables.

Martinet et al. (2012)

Application #3: Assimilation of cloudy radiances in a 1DVar

Evolution of analyzed profiles using AROME 1D

Example for low semi-transparent ice clouds:



Time evolution of integrated ice cloud contents (min)

⇒ Thanks to the multivariate relationships and despite the spin-down, integrated contents keep values greater than those forecasted by the background and by other assimilation methods up to 3h

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Conclusions & perspectives

- High impact weather phenomena (e.g convective precipitations, fog…) are under-represented in ensembles that are used to compute climatological **B** : DA of observations is clearly sub-optimal in these areas
- By using geographical masks based on features in background perturbations in EDA, specific **B** matrices can be computed
- These **B** matrices, characterized by different spatial transforms and by different balance operators, can be used simultaneously in the VAR framework using the heterogeneous formulation
- So far, positive impacts while combining radar data and “rainy” **B** : spin-up reduction, positive scores
- The formulation of the balance operator has been extended for all hydrometeors that are represented in AROME in order to compute their multivariate background error covariances using cloudy mask.
- The latter are currently exploited to analyzed cloud contents from DA of cloudy radiances in a 1D framework.

Conclusions & perspectives

- As spatial covariances, balance relationships also depend on the meteorological flow, especially in cloud and precipitation (e.g freezing level, LFC…).

⇒Tests are ongoing using ensembles “of the day”

- An EDA at convective scale AEARO is currently under test, mimicking at first what is done in the AEARP at global scale (see presentation of Loïk Berre)

- In parallel, studies about the filtering of variances and horizontal correlations computed from such an ensemble are ongoing: So far, very different structures have been obtained compared to global scale and inhomogeneous filters are likely to be used (see P74 B. Ménétrier’s poster)

Thank you for your attention…

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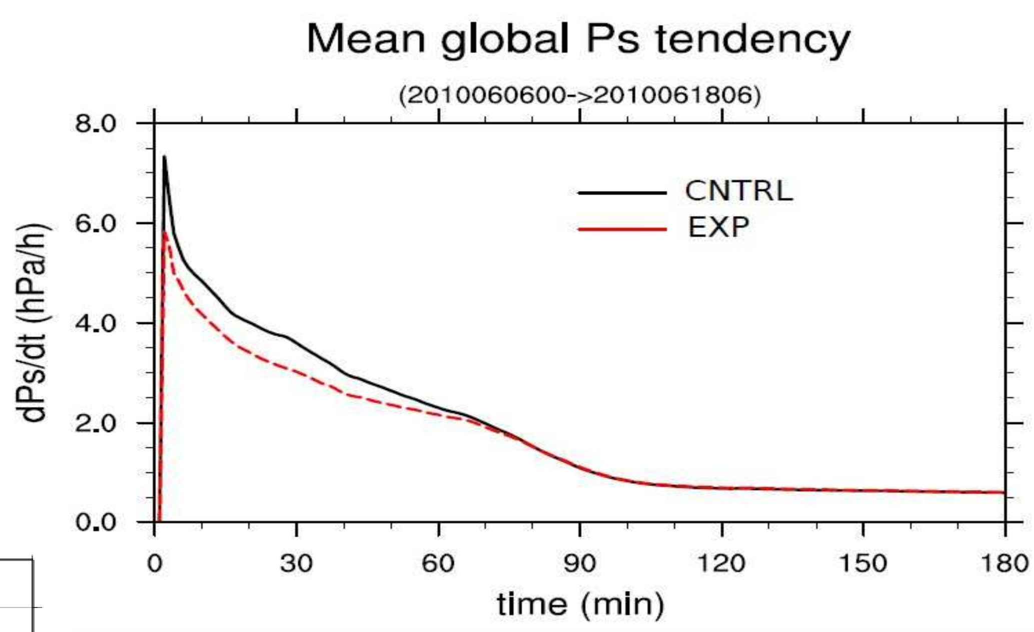
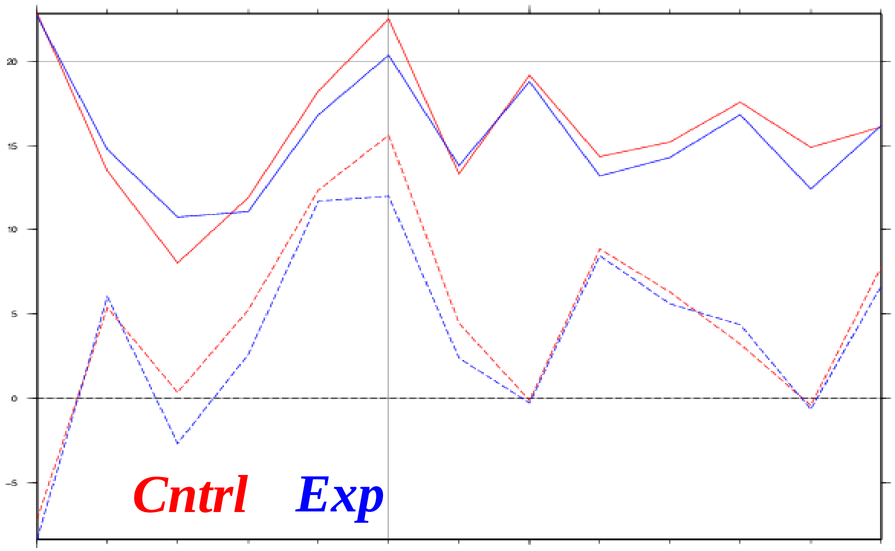
Application #1: use of a « rainy » B for DA of radar data

2 weeks of cycled experiments

Spin-up reduction:
⇒ Analyzed fields better balanced
⇒ Spin up reduction correlated with the number of grid points where $\mathbf{B_1}$ is applied





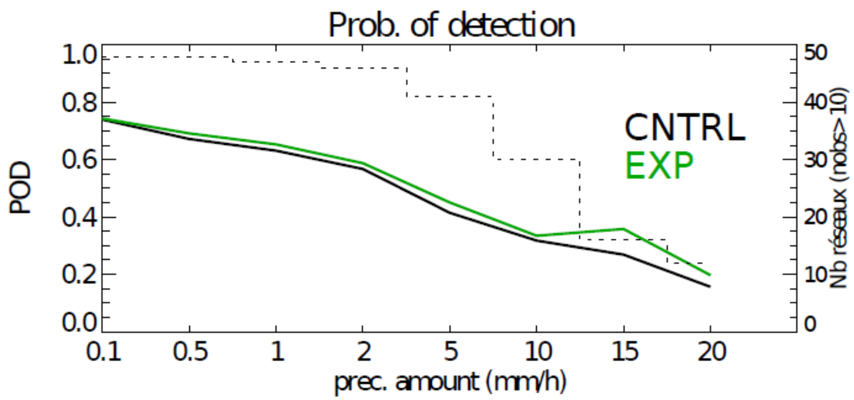
time serie of bias and std dev for 12h forecast of q_{850hPa} against RS

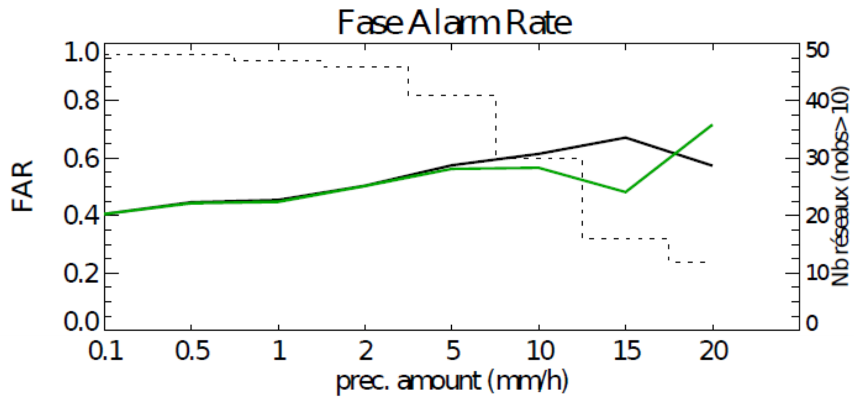
⇒ Positive scores up to 24h against soundings (and ECMWF analyses) in the mid and lower troposphere for T and q, neutral otherwise
⇒ Scores on rainrates: better detection, less bias, neutral on false alarm

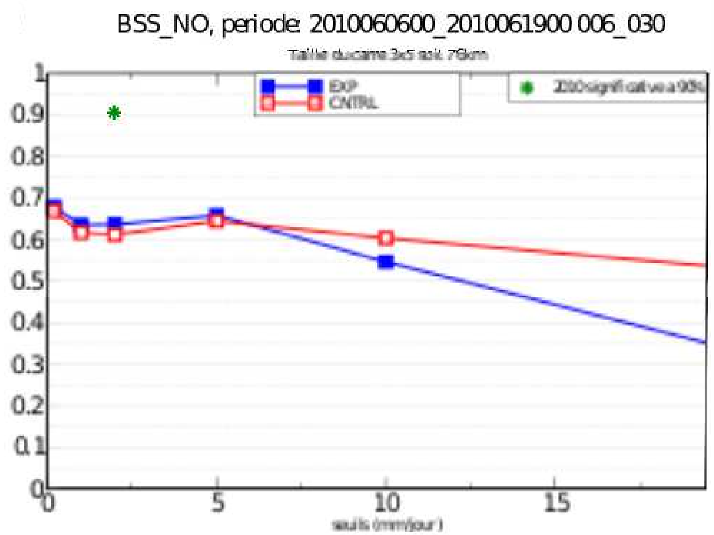
Impact on forecasts

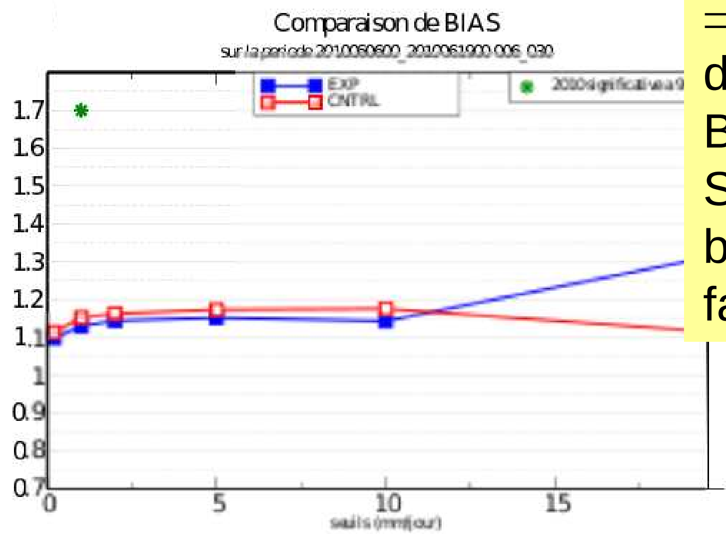
Cycled experiment 6 -> 19 June 2010

Scores against raingauges for 3h (top) and 24h (bottom) cumulated rainfall









⇒ Better detection (POD, Brier Skil Score), less bias, neutral on false alarm