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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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
- $1.3 \times 10^8$ variables, explicit convection, realistic representations of clouds, turbulence, surface interaction…
  $\Rightarrow$ DA based on « real time » ensembles unaffordable for the time being

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

Following notation of Derber and Bouttier (1999): $B^{1/2} = K_p B_S^{1/2}$

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

$$\delta x = K_p \tilde{\chi}$$

$K_p$ and $B_S$ are static and are deduced from an ensemble assimilation (Brousseau et al. 2011a)

• **$B_s$ is the spatial transform:** $B_s = \Sigma C \Sigma^T$

$K_p$ and $B_s$ are static and are deduced from an ensemble assimilation (Brousseau et al. 2011a)
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 $B_S$ in a VAR context, **none for $K_p$**
- Here we focus on a method allowing to diagnose and to use both different $B_S$ and $K_p$ 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: $y_0^* = y_0 + \epsilon_0$ \ ($\epsilon_0 \sim N(0, \sigma^2_0)$)

Explicit Perturbation of lateral boundary conditions coming from AEARP

Implicit Perturbation of the background: $x_b^* = M(x_a^*) + (\epsilon_m)$

- Few cycles needed to get the full spectra of error variances
- High impact phenomena under-represented in the ensemble
Forecast errors are decomposed using features in the background perturbations that correspond to a particular meteorological phenomena.

\[ \varepsilon_{f_{ij}} = x_{b_i}^* - x_{b_j}^* \approx G \delta_{ij}^{pp} \varepsilon_{f_{ij}} + G \delta_{ij}^{cc} \varepsilon_{f_{ij}} + G \delta_{ij}^{cp} \varepsilon_{f_{ij}} \]

\((G : \text{Gaussian blur})\)
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Use of the heterogeneous formulation:
(Montmerle and Berre, 2010)

\[
\delta x = B^{1/2} \chi = \left(F_1^{1/2} B_1^{1/2} + F_2^{1/2} B_2^{1/2}\right) \begin{pmatrix} \chi_1 \\ \chi_2 \end{pmatrix}
\]

Where \(F_1\) and \(F_2\) define the geographical areas where \(B_1\) and \(B_2\) are applied:

\[
\begin{cases} 
F_1^{1/2} = SD^{1/2} S^{-1} \\
F_2^{1/2} = S(I - D)^{1/2} S^{-1}
\end{cases}
\]

⇒ This formulation allows to consider simultaneously different \(B_S\) and \(K_p\) that are representative of one particular meteorological phenomena.
Here: **EXP**: $B_1=\text{rain}$, $B_2=\text{OPER}$, $D=\text{radar mosaic}$

**Application #1: use of a « rainy » $B$ for DA of radar data**
Montmerle (MWR, 2012)

**EXP**

**OPER**

$D_{ij} > 0.5$

*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

\( \text{Cov}(\delta q, \delta \eta_u) \)

Rain

OPER

\( z = 800 \text{ hPa} \)

\( z = 400 \text{ hPa} \)

Divergence increments

- Spin-up reduction correlated with the number of grid points where \( B_1 \) 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 within the fog:

Vertical cross sections of temperature increments

$\Rightarrow$ More details in Ménétrier and Montmerle (2011)
**Problematic:** Non-Gaussian innovations due to mislocation of simulated structure and modeling deficiencies

- **Simulation of IASI radiances using profiles of \( q_I \) and \( q_i \).** 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**

![Raw innovations graph]

**Innovations after screening**

![Innovations after screening graph]
Computation of background error covariances for all hydrometeors in clouds:

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

$$
\begin{align*}
\delta T &= \delta T \\
\delta q &= T_0 \delta T + \delta q_u \\
\delta q_{i,r,s} &= T_1 \delta T + T_2 \delta q_u + \delta q_{i,r,s}
\end{align*}
$$

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

Vertical covariances between $q_i$, $q_l$ 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 $q$

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:

⇒ 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 analyze 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…


Martinet et al 2012: Towards the use of microphysical variables for the assimilation of cloud-affected infrared radiance, QJRMS in press.


Montmerle T., 2012 : Optimization of the assimilation of radar data at convective scale using specific background error covariances in precipitations. MWR, 140, 3495-3505.
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 $B_1$ is applied

⇒ 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 Skill Score), less bias, neutral on false alarm