Preliminary test of an En3DVar for the operational AROME-France NWP system at convective scale

Thibaut Montmerle,
P. Brousseau, Y. Michel and E. Arbogast
CNRM-GAME (Météo-France/CNRS)

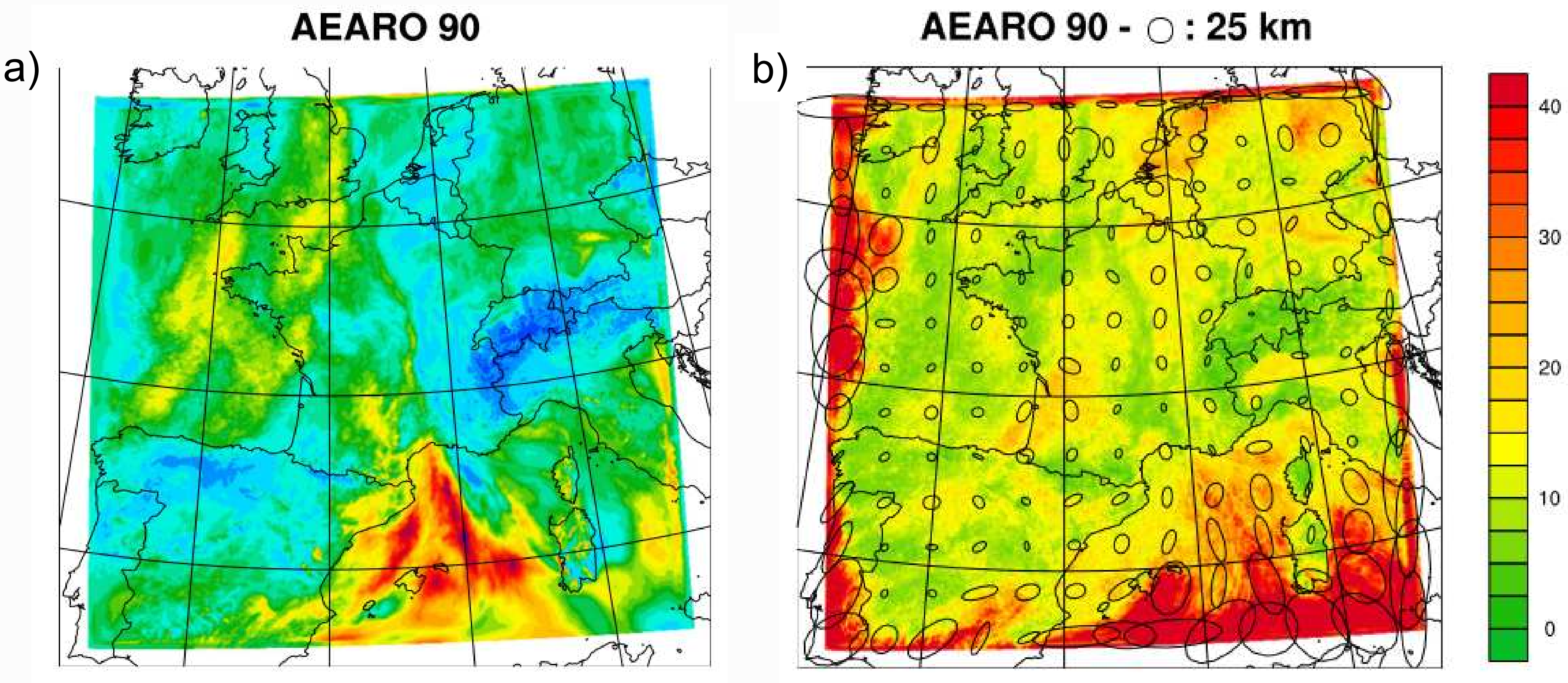
4th Int.Symposium on DA – Kobe - 2015

Outlines

- Introduction
- En3DVar for AROME
  - Perturbations
  - Localization
  - Pre-conditioning
- Impact on analyses & forecasts
- Conclusions/Perspectives

Introduction

Forecast errors at convective scale are strongly inhomogeneous and anisotropic because of the explicit convection, of diabatic processes, of the type of surface, of the coupling files…



Background error (a) variance and (b) LCH tensor for the low-level specific humidity deduced from an AROME ensemble of 90 members (Ménétrier et al. 2014)

Introduction

Forecast errors sampled from an ensemble following a Monte-Carlo approach can add flow dependency in VAR.

En-VAR methods use entirely or partially covariances deduced from an ensemble in VAR (Hamill and Snyder (2000); Lorenc (2003); Buehner (2005)) :

$$\mathbf{B}_h = \gamma^2 \mathbf{B}_c + (1-\gamma^2)\mathbf{B}_e$$

Hybrid En-VAR merges the advantages of both approaches in a flexible way (oper. at global scale at CMC (Buehner et al, 2010) and at the MO (Clayton et al, 2012), impl. for LAM (Zhang et al, 2012))

Here we will show preliminary results of a En-3DVar that has been set up for AROME in the IFS/OOPS framework.

Outlines

- Introduction
- En3DVar for AROME
  - Perturbations
  - Localization
  - Pre-conditioning
- Impact on analyses & forecasts
- Conclusions/Perspectives

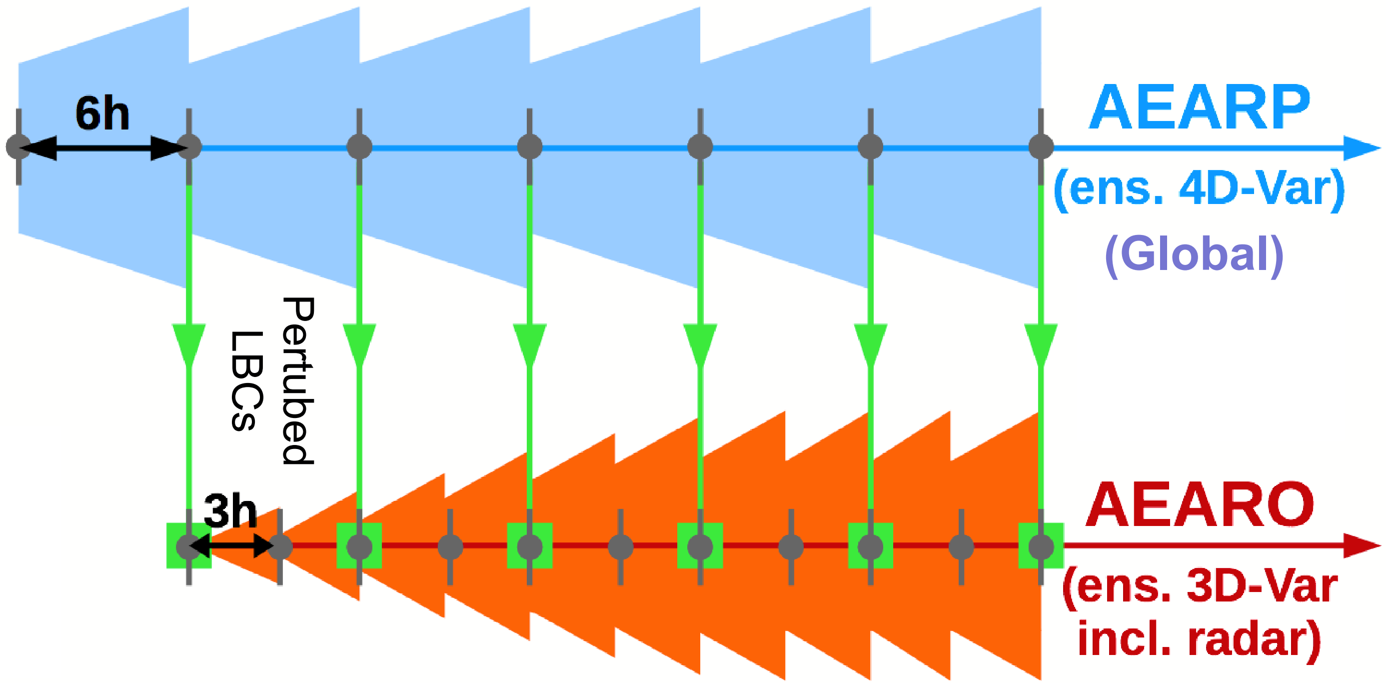
En3DVar for AROME : perturbations

Use of an EDA based on AROME at 4 km (AEARO) with *L* members to compute background perturbations :

$$\delta \widetilde{\mathbf{x}}_p^b = \frac{1}{\sqrt{L-1}}\left(\widetilde{\mathbf{x}}_p^b - \langle \widetilde{\mathbf{x}}^b \rangle\right)$$

- Explicit obs. perturb.
- Implicit Bckgd perturb.

- Explicit obs. and LBCs perturb.
- Implicit bkgd perturb.

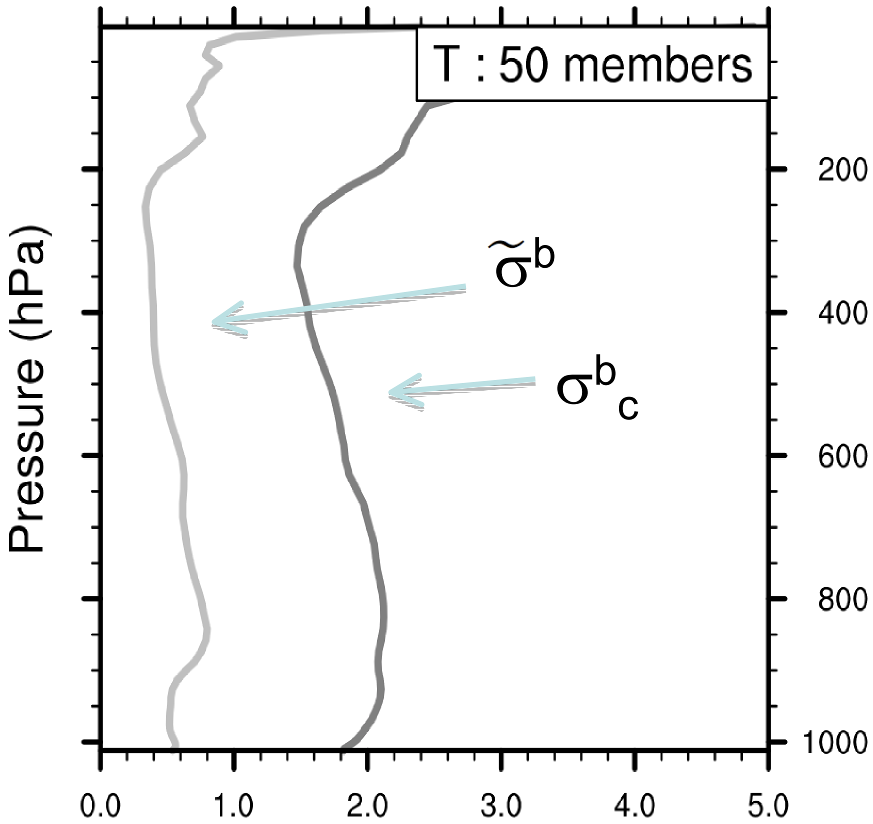


Fisher 2003 ; Kucukkaraca and Fisher (2006); Berre et al 2006

En3DVar for AROME : perturbations

Ensemble spread

$$\widetilde{\mathbf{B}} = \frac{1}{L-1}\sum_{p=1}^{L}\left(\widetilde{\mathbf{x}}_p^b - \langle\widetilde{\mathbf{x}}^b\rangle\right)\left(\widetilde{\mathbf{x}}_p^b - \langle\widetilde{\mathbf{x}}^b\rangle\right)^{\mathrm{T}}$$



Horizontally averaged background error standard deviations for Temperature

$\mathbf{B}_c$ has been calibrated using a mix of summer convective and winter cases (Brousseau et al. 2011), whereas here $\widetilde{\mathbf{B}}$ is computed for a winter case

$\Rightarrow$ Less dispersion in $\widetilde{\mathbf{B}}$

$\Rightarrow$ An inflation of 2 is applied to each perturbations

En3DVar for AROME : formulation

From these L sampled perturbations, a localized $\mathbf{B_e}$ is computed

$$\mathbf{B}_e = \widetilde{\mathbf{B}} \circ \mathbf{C} = \mathbf{X}^b \mathbf{X}^{b^T} \circ \mathbf{C}$$

with :

$$\mathbf{X}^b = \left[\delta\widetilde{\mathbf{x}}_1^b, \ldots, \delta\widetilde{\mathbf{x}}_L^b\right]$$

The localization matrix **C** aims in reducing sampling noise by damping covariances with range (*Houtekamer and Mitchell (2001)*)

Use of a simplified **C** :

$$\mathbf{C} = \begin{pmatrix} \mathbf{I}_N \\ \vdots \\ \mathbf{I}_N \end{pmatrix} \mathcal{C} \left(\mathbf{I}_N \ldots \mathbf{I}_N\right) = \mathbf{1}_N \mathcal{C} \mathbf{1}_N^T$$

$\mathbf{I}_N$ is a N x N identity matrix, $\mathbf{1}_N$ is composed of M (x (K+1)) $\mathbf{I}_N$ blocks, and $\mathcal{C}$ is a N x N correlation matrix

En3DVar for AROME : Localization

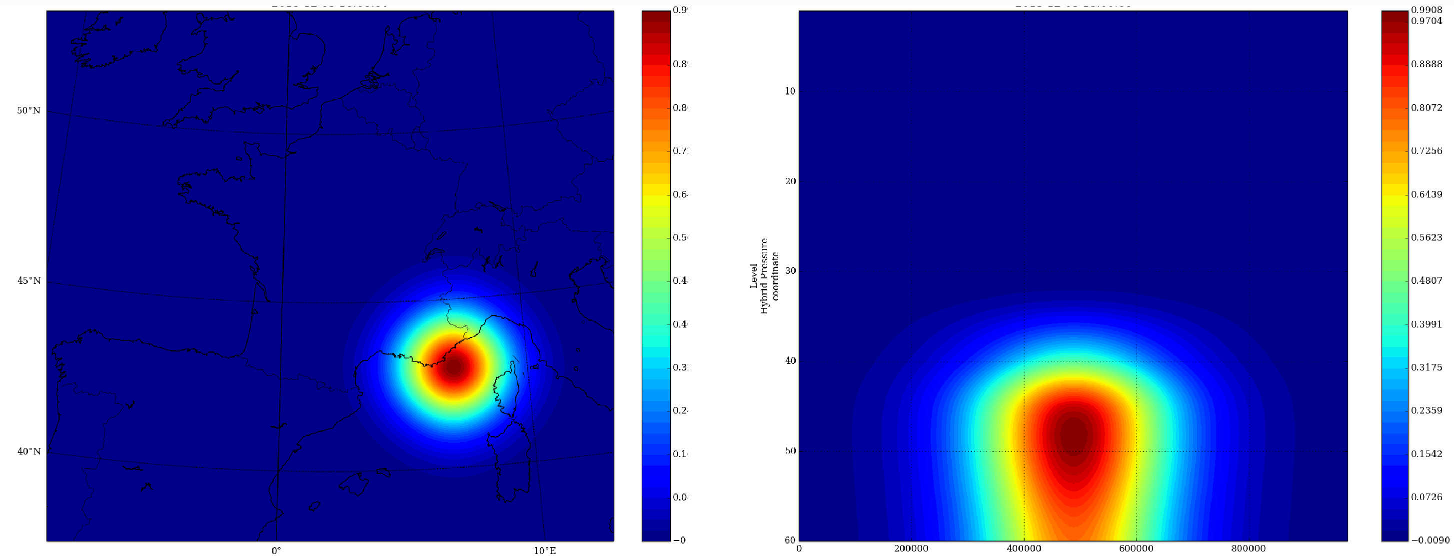
- In this formulation, applying the same vertical variations of L_h for all variables is possible
- Gaspari and Cohn (1999) compactly supported function is chosen on both directions
- Horizontally, two versions have been implemented :
  - ✓ Spectral, using bi-Fourier decomposition $\mathcal{C} = \mathbf{S}^{-1}\mathcal{C}^S\mathbf{S}^{-T}$
  - ✓ Grid-point, using recursive filters (Purser et al, 2003)
- Vertically, recursive filters with a grid deformation can also be activated, following Michel (2012)

En3DVar for AROME : Localization

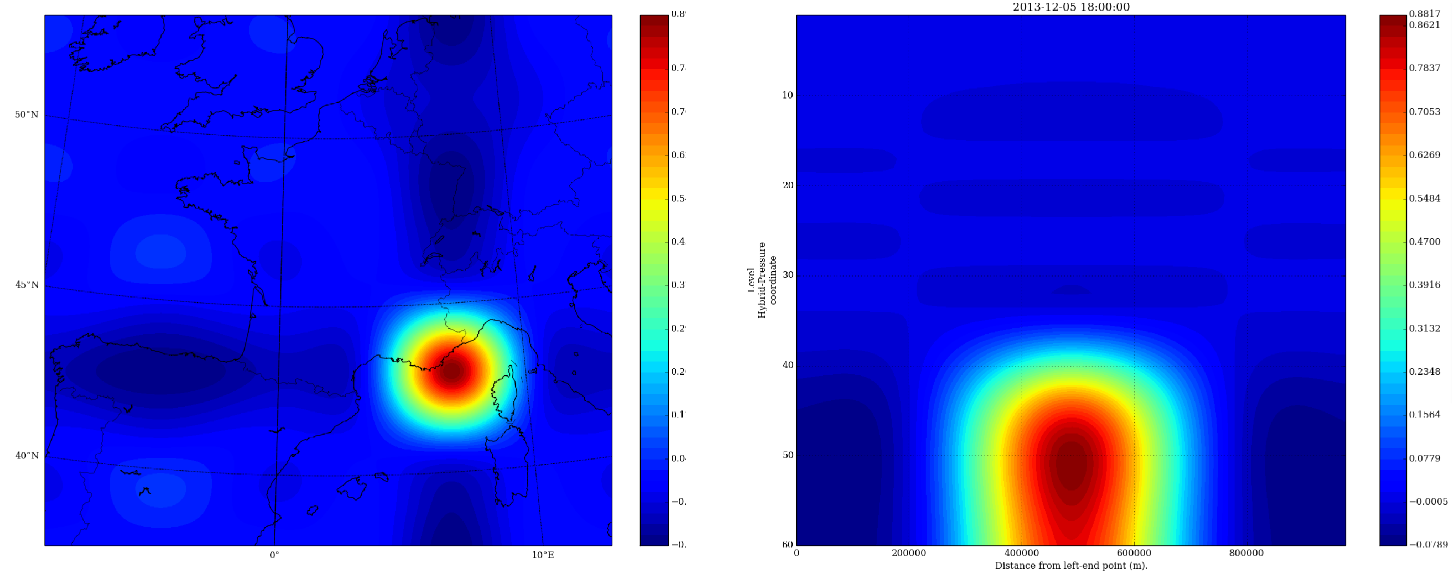
Localization functions with L_h = 250 km and L_v = 0.2 (log(P) levels) :

$\delta_{i,j,k}$ **C**

Recursive filters



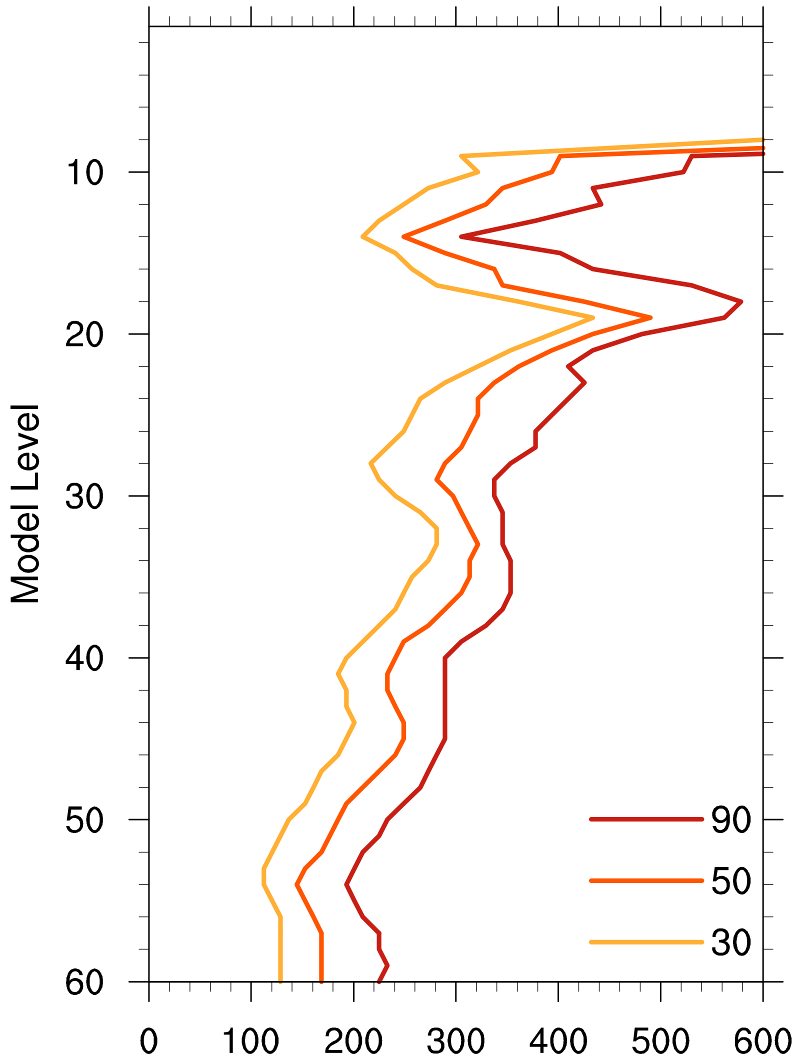
Bi-Fourier



En3DVar for AROME : Localization

Optimal L_h have also been diagnosed from the ensemble using Ménétrier et al. (2015) iterative mehod (see Y. Michel's talk tomorrow)

⇒ Variations with vertical levels, variables and ensemble size have been found



L_h in km for Temperature and for different ensemble sizes

En3DVar for AROME : Pre-conditionning

- A pre-conditionning by $\mathbf{B_e}$ is applied instead of $\mathbf{B_e}^{1/2}$.

- The DPCG algorithm (Derber and Rosati, 1989; Gürol et al, 2014) is used with $d\mathbf{x}$ as control variable (dim: M x N x (K+1))

- At each iteration, the quantity $\mathbf{h} = \mathbf{B_e}\,\mathbf{g}$ has to be computed, which is equivalent to solve for the m parameter at time k (Desroziers et al., 2014) :

$$h_{k,m} = \sum_{l=1}^{L} \sum_{k'=0}^{K} \sum_{m'=1}^{M} \delta\widetilde{\mathbf{x}}^b_{l,k,m} \circ (\mathbf{S}^{-1} \mathcal{C}^S \mathbf{S}^{-T} (\delta\widetilde{\mathbf{x}}^b_{l,k',m'} \circ g_{k',m'}))$$

⇒ No control variable change nor additional a variable

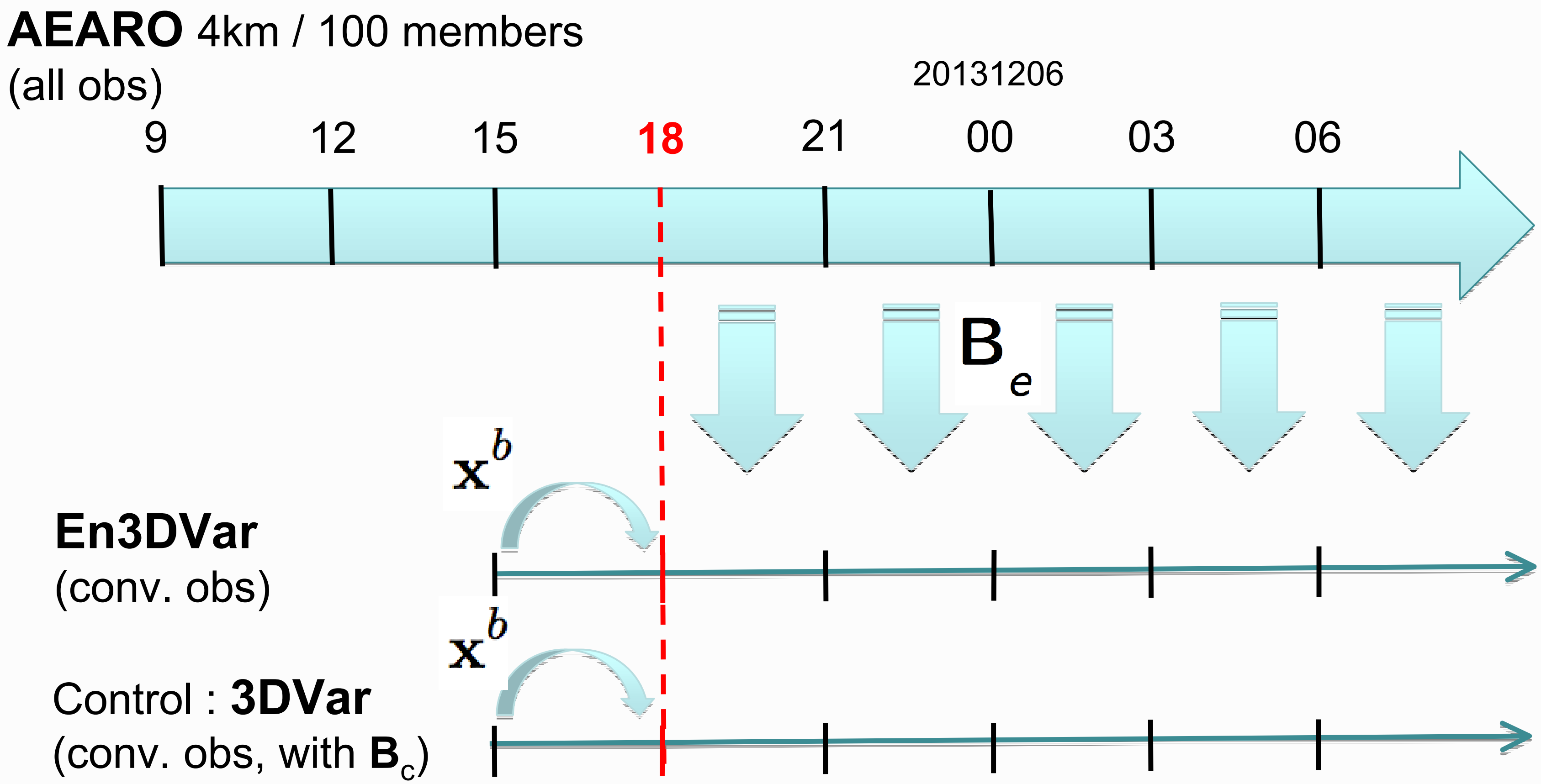
⇒ Easy implementation of hybrid versions : simply replace $\mathbf{B}_\mathrm{e}$ by $\mathbf{B}_\mathrm{h}$ in the conjugate gradient

Outlines

- Introduction
- En3DVar for AROME
  - Perturbations
  - Localization
  - Pre-conditioning
- Impact on analyses & forecasts
- Conclusions/Perspectives

Impact on analyses

Experimental set-up : cycled forecast/analyses steps

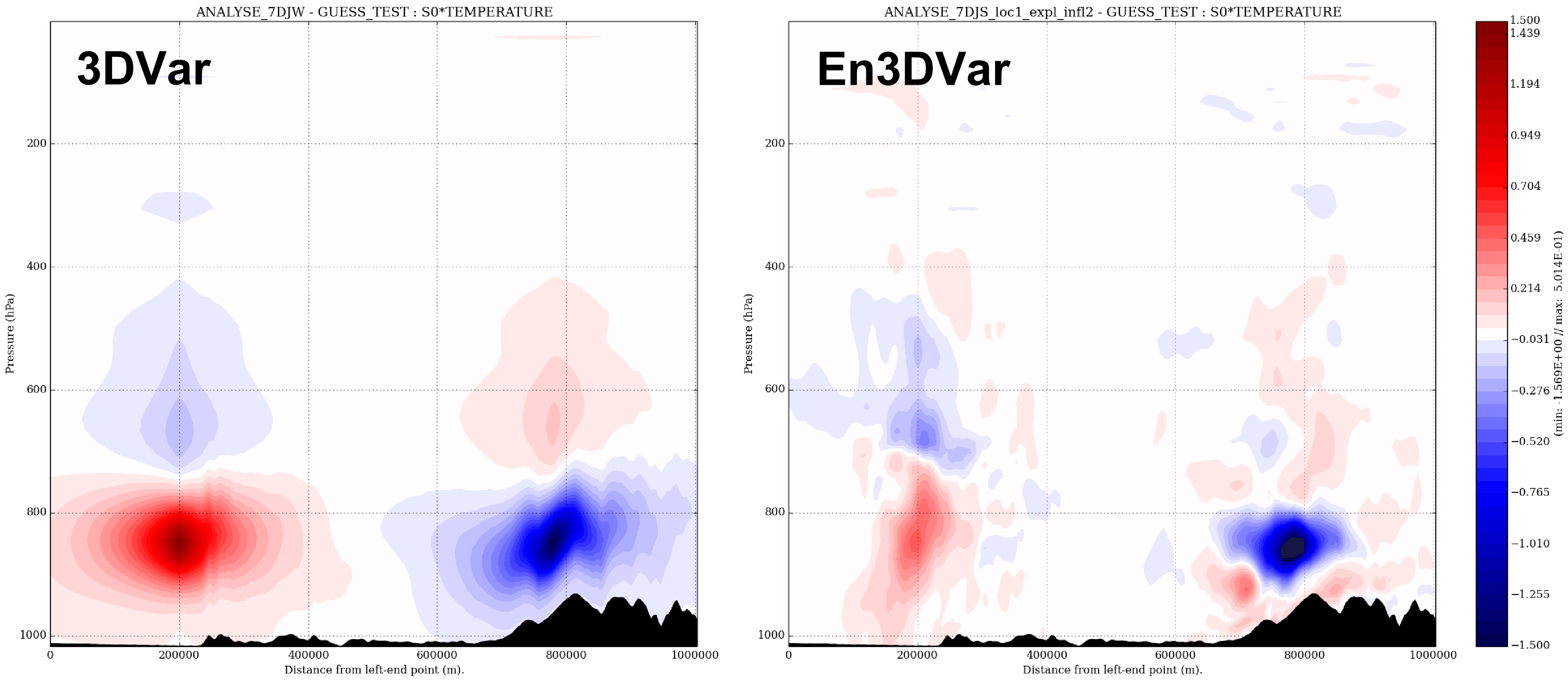


⇒ Impact on analyses at 18h, scores on 3h forecast averaged over the 5 analysis times

Impact on analyses

2 obs experiments, +/- 2K Temperature innovations

Vertical cross-sections of T increments



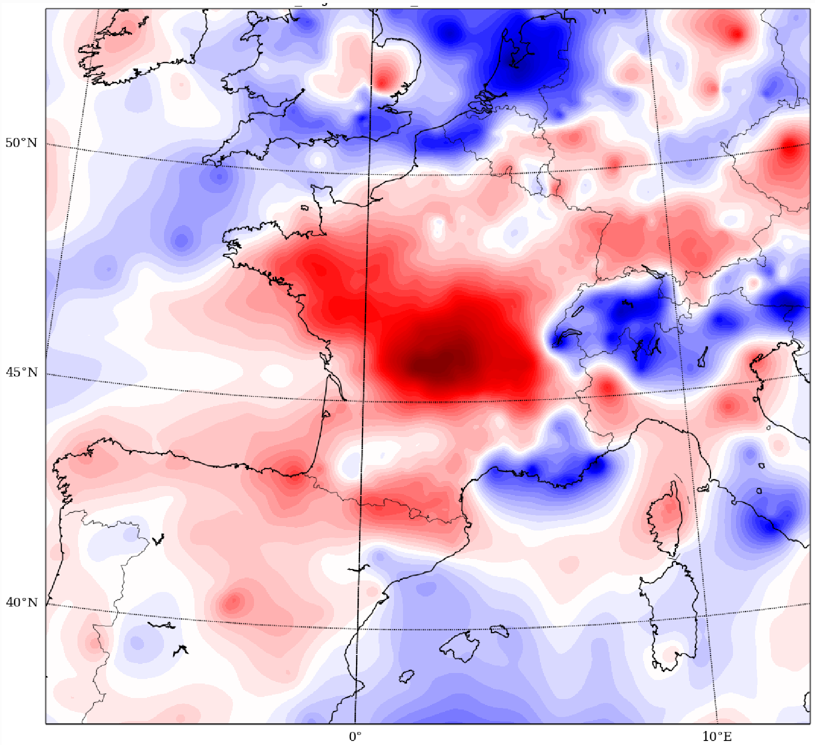
⇒ More localized but more noisy increments

⇒ Information spread coherent with covariances of $\mathbf{B}_c$

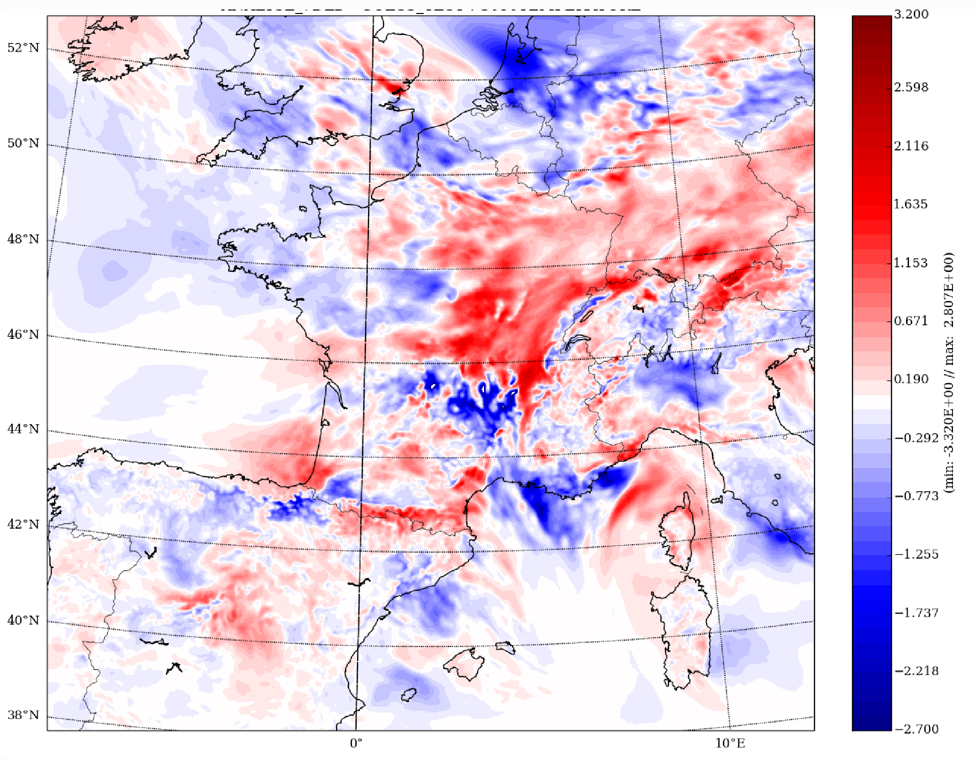
Impact on analyses

With conventional observations

3DVar



En3DVar



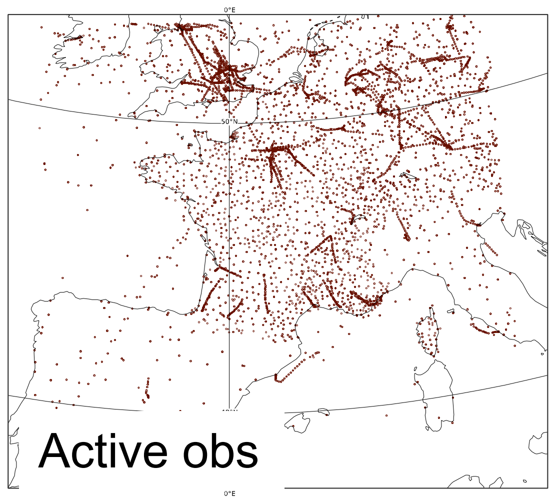
Horizontal cross-sections of T increments at 850 hPa

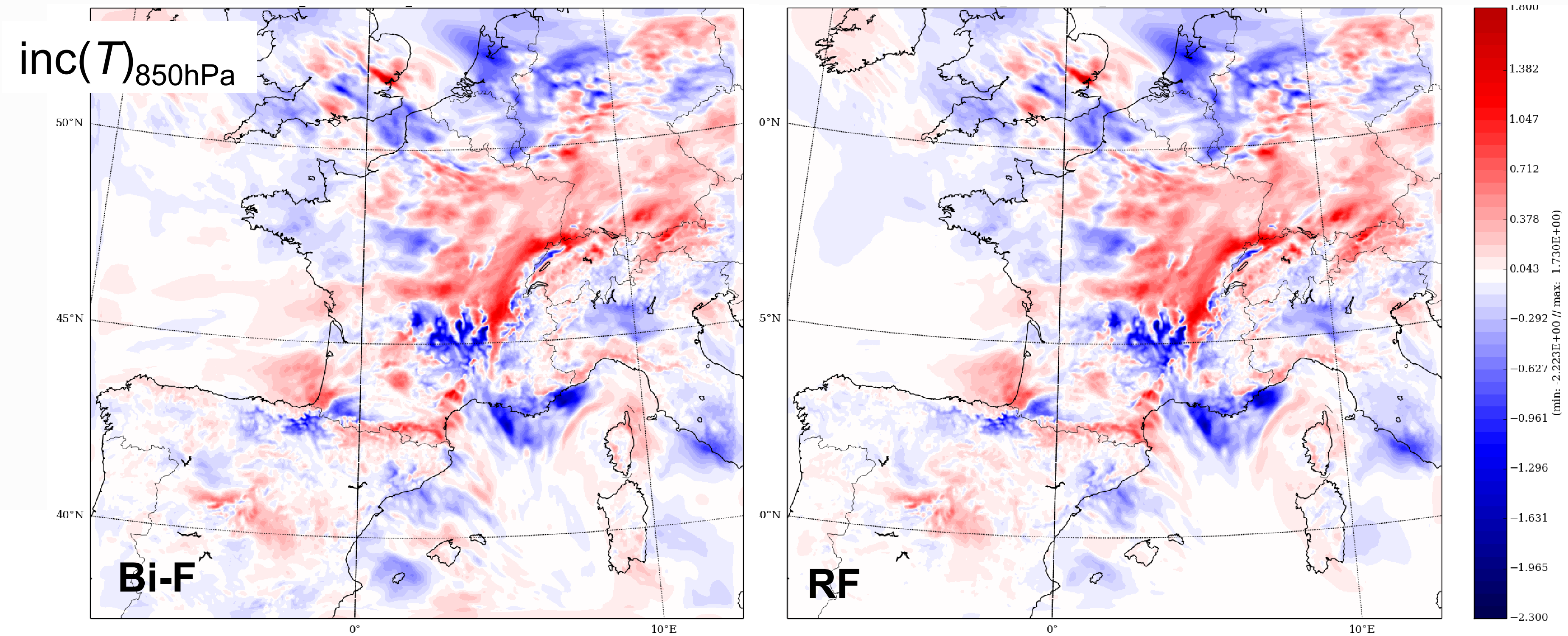
Impact on analyses

Bi-Fourier vs. recursive filters horizontal localizations

⇒No spurious increments in observation-void areas with RF

⇒Very close results elsewhere

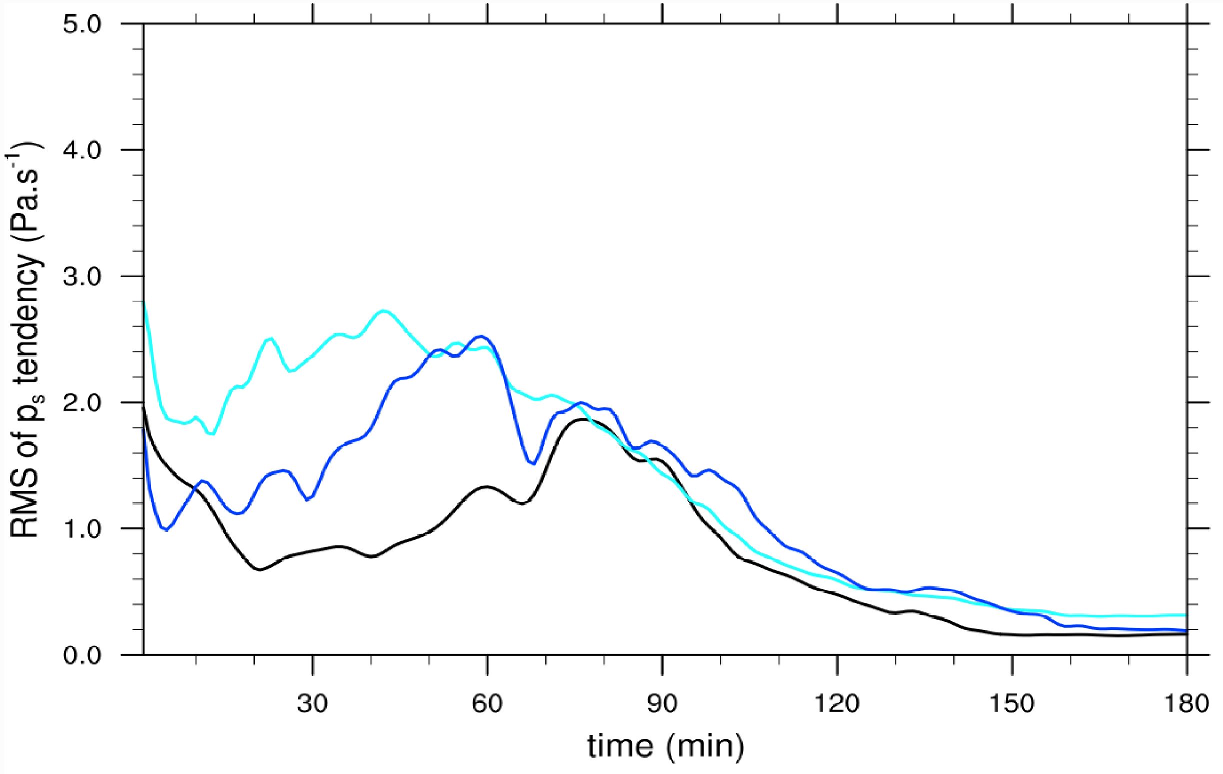




Impact on forecast

Impact on spin-up

$$\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\frac{dP_s^j}{dt}-\left\langle\frac{dP_s}{dt}\right\rangle\right)^2}$$

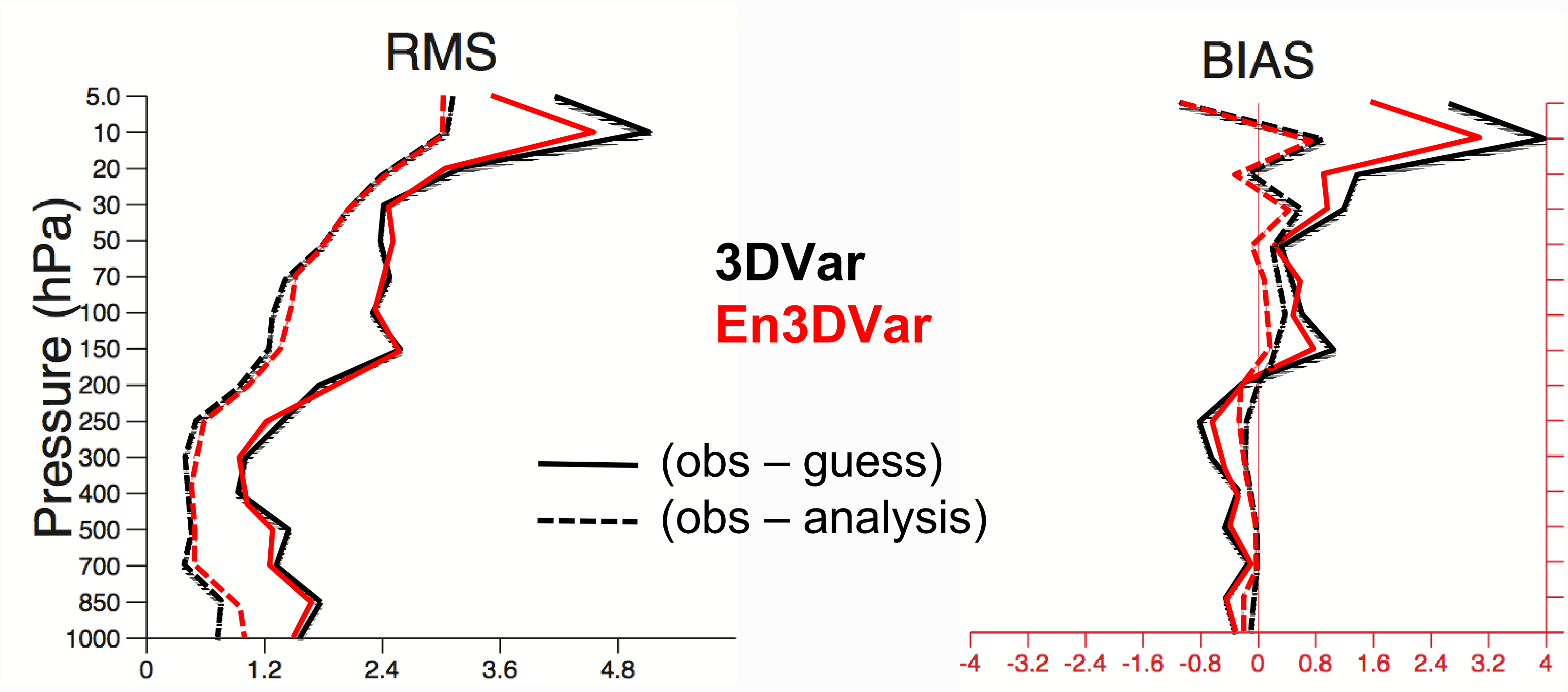


3DVar
En3DVar
En3DVar infl 2

Same order of imbalances between the different configurations

Impact on forecast

Scores against rawinsondes averaged over 5 assimilation times for Temperature



⇒ For T, improvements of (o-g) RMS values for almost all levels, reduction of the 3-h forecast bias above the tropopause

⇒ Overall, scores are neutral to slightly positive for 3h forecasts

Conclusions/Perpectives

An experimental En-3DVar has been set up for the AROME - France and successfully tested with conv. obs. It uses :

•perturbations from an EDA at convective scale

•SP or GP localization methods, with variation on the vertical

•DPCG algorithm with a **B** pre-conditionning

Perspectives :

•Implement operational satellite and radar observation operators

•En-4DVar, Hybrid versions

•Work on alternative ensemble design

•Validation and tuning (inflation) using innovation-based diagnostics

Thank you for your attention !

References

Berre L, Stefanescu SE, Belo-Pereira M. 2006. The representation of a the analysis effect in three error simulation techniques. Tellus 58A: 196–209.

Brousseau, P., L. Berre, F. Bouttier, and G. Desroziers, 2011: Background-error covariances for a convective scale data assimilation system: AROME-France 3DVar. Quart. J. Roy. Meteor. Soc., 137, 409-422.

Buehner, M., 2005: Ensemble-derived stationary and flow-dependent background-error covariances: Evaluation in a quasi-operational NWP setting. Quart. J. Roy. Meteor. Soc., 131, 1013–1043.

Buehner M, Houtekamer P, Charette C, Mitchell H, He B. 2010. Intercomparison of variational data assimilation and the ensemble Kalman filter for global deterministic NWP. Part I: Description and single- observation experiments. *Mon. Wea. Rev.* **138**: 1550– 1566.

Clayton, A. C. Lorenc and D. M. Barker, 2012: Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. QJRMS.

Desroziers et al, 2014:4DEnVar: link with 4D state formulation of variational asimilation and possible different implementation. QJRMS, in press.

Fisher M. 2003. Background error covariance modelling. In: *Proceedings of the ECMWF Workshop on Recent Developments in Data Assimilation for Atmosphere and Ocean*. Reading, pp. 97–123. 8-12 September.

Gaspari, G., and S. E. Cohn, 1999: Construction of correlation functions in two and three dimensions. Quart. J. Roy. Meteor. Soc., 125, 723–757.

Gu¨rol S, Weaver A, Moore A, Piacentini A, Arango H, Gratton S. 2014. B-Preconditioned minimization algorithms for variational data assimilation with the dual formulation. *Q. J. R. Meteor. Soc.* 10.1002/qj2150..

Hamill T, Snyder C. 2000. A hybrid ensemble Kalman filter- 3D variational analysis scheme. *Mon. Wea. Rev.* **128**: 2905–2919.

Houtekamer P, Mitchell H. 2001. A sequential ensemble Kalman filter for atmospheric data assimilation. *Mon. Wea. Rev.* **129**: 123–137.

Kucukkaraca E, Fisher M. 2006. Use of analysis ensembles in estimating flow-dependent background error variances. Technical Report 492, ECMWF.

Lorenc AC. 2003. The potential of the ensemble Kalman filter for NWP - a comparison with 4D-Var. Q. J. R. Meteorol. Soc. 129: 3183–3203.

Ménétrier B, Montmerle T., Berre L. and Michel Y., 2014: Estimation and diagnosis of heterogeneous flow-dependent background error covariances at convective scale using either large or small ensembles. QJRMS10.1002/qj2267.

Ménétrier, B., Montmerle, T., Michel, Y. and Berre, L. (2014) Linear Filtering of Sample Covariances for Ensemble-Based Data Assimilation. Part I: optimality Criteria and Application to Variances Filtering and Covariances Localization. Monthly Weather Review, in press.

Michel Y. 2012. Estimating deformations of random processes for correlation modelling: methodology and the one-dimensional case. Quarterly Journal of the Royal Meteorological Society 139: 771–783.

Montmerle T. and L. Berre, 2010: Diagnosis and formulation of heterogeneous background error covariances at mesoscale. Quart. J. Roy. Meteor. Soc., 136, 1408–1420.

Purser RJ, WuWS, Parrish DF, Roberts NM. 2003. Numerical aspects of the application of recursive filters to variational analysis. Part I: Spatially homogeneous and isotropic Gaussian covariances. Mon. Weather Rev. 131: 1524–1535.

Zhang et. al, 2013: E3DVar: coupling an ensemble KF with a 3DVar DA in a limited area weather prediction model and comparson to E4DVar. MWR, 141, 900, 917.