Recent research on data assimilation at Météo-France

ALADIN / HIRLAM

21th Workshop / All-Staff Meeting 2011

Ludovic Auger and many contributors :

Pierre Brousseau, Thibaut Montmerle, Loïk Berre, Gerald Desroziers,…

METEO FRANCE

Toujours un temps d'avance

Outline

1. Some interesting experiments with 3dvar minimization.
2. How to use more observations inside AROME assimilation system.
3. The use of heterogeneous B matrices.
4. Refinement of global statistics based on ensembles.

Adaptative 3dvar minimization

- The 3dVar algorithm summarizes as the minimization of the following cost function :

$$J(\delta X) = \delta X^t B^{-1} \delta X + (I_0 - H_0 \delta X)^t R^{-1} (I_0 - H_0 \delta X)$$

- Suppose we want to add a second loop the new minimization summarizes :

$$J^{new}(\delta X) = (\delta X_0 + \delta X)^t B^{-1} (\delta X_0 + \delta X) + (I_1 - H_1 \delta X)^t R^{-1} (I_1 - H_1 \delta X) \quad (1)$$

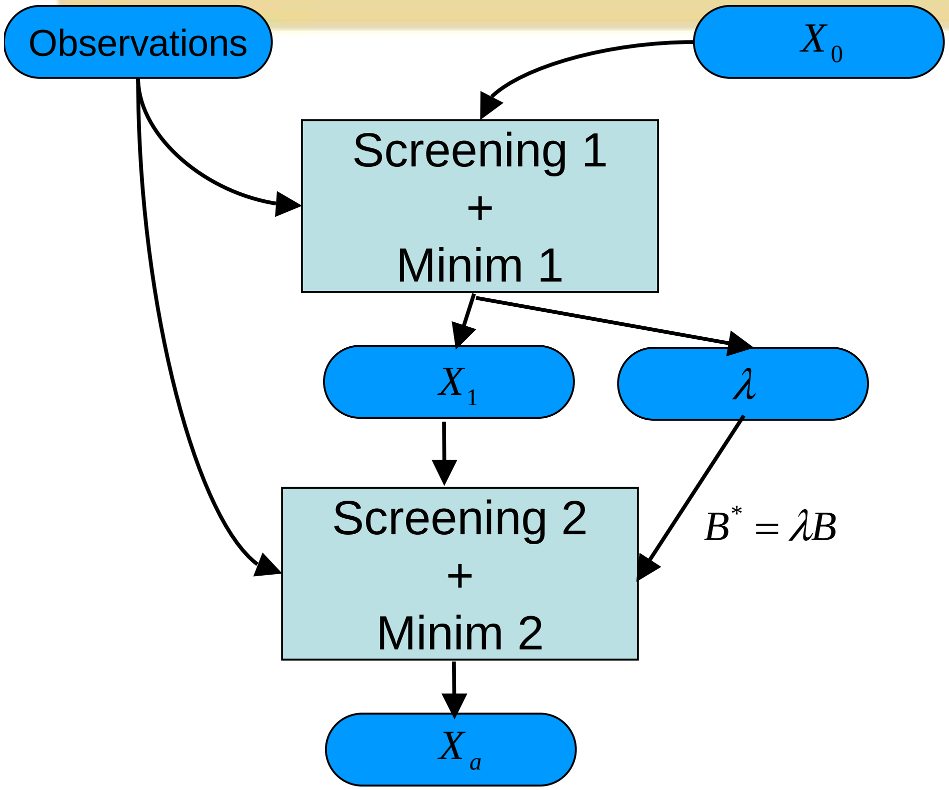
- This can be solved by setting a second outer loop with NUPTRA=1 option and providing an increment to the second minimization.

- Another way to solve this equation is to assume this is equivalent to the following one :

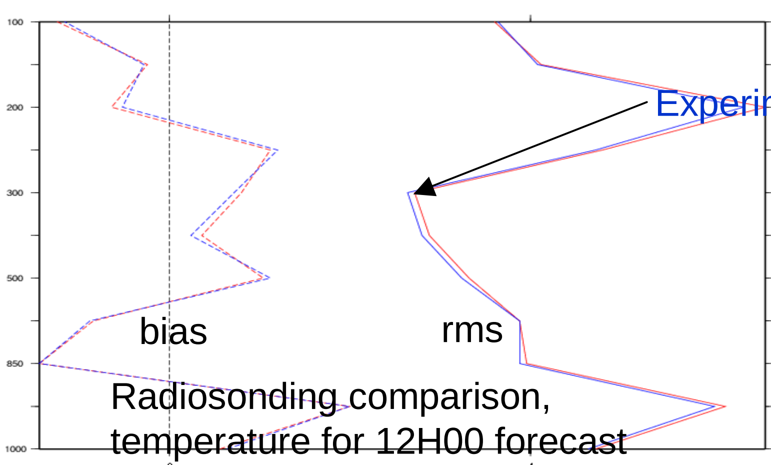
$$J^{new}(\delta X) = (\delta X)^t B*^{-1} (\delta X) + (I_1 - H_1 \delta X)^t R^{-1} (I_1 - H_1 \delta X)$$

- Of course one has to have an expression for this B* matrix, somehow it is to say that we do a first minimization, than we redo a minimization with another background error statistics, but this seems to be a much more complicated work than simply solving eq (1), however this can bring some advantages…
- B* is obtained through the expression $B^* = \lambda B$, where λ depends on diagnostics obtained from the first minimization.

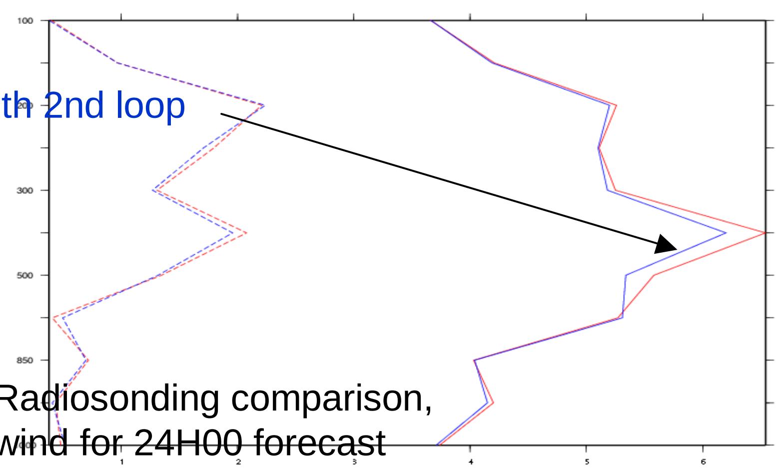
A new 3dvar algorithm organization



- This allows flow-dependent background statistics through the λ factor.
- The second outer-loop allows relinearization of the observation operators.
- The second screening enables to use certain observations that had been rejected by the first screening (might be useful in extreme weather situations)
- Objective results : Show some improvement on some parameters, but needs to be still tested as improvements are not satisfactory as regards the supplementary cost (second screening).



Radiosonding comparison, temperature for 12H00 forecast



Radiosonding comparison, wind for 24H00 forecast

1. Some interesting experiments with 3dvar minimization.
2. How to use more observations inside AROME assimilation system.
3. On the use of heterogeneous B matrices.
4. Refinement of global statistics based on ensembles.

METEO FRANCE
Toujours un temps d'avance

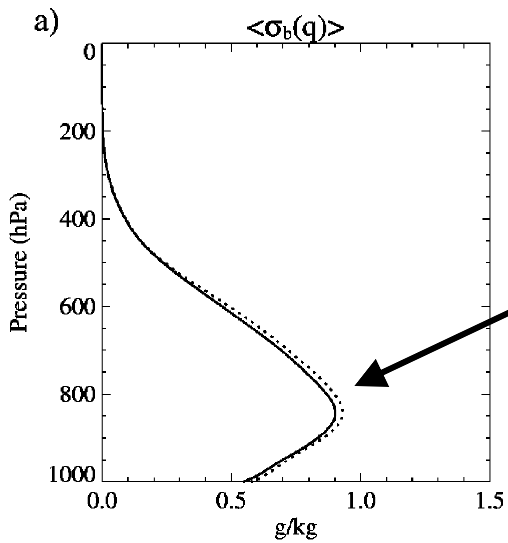
Increasing the assimilation frequency

(Brousseau, P)

- Aim :
  - Take a better advantage of the observations available at a high frequency rate, those observations are under-used currently inside AROME 3dvar, for example, radar data are available every 15 minutes, but currently we use those observations only every 3 hours !
  - It is a step towards a more frequent short term forecast for nowcasting applications.

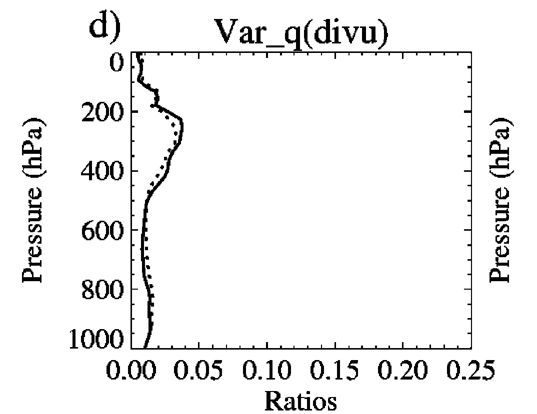
- Solutions :
  - Use of an assimilation cycle more frequent, i.e 1 hour instead of 3hours
  - Use of a 3D-FGAT : this technique with a screening at appropriate time, but innovations used at central time.
  - Use of a full 4D-Var algorithm.

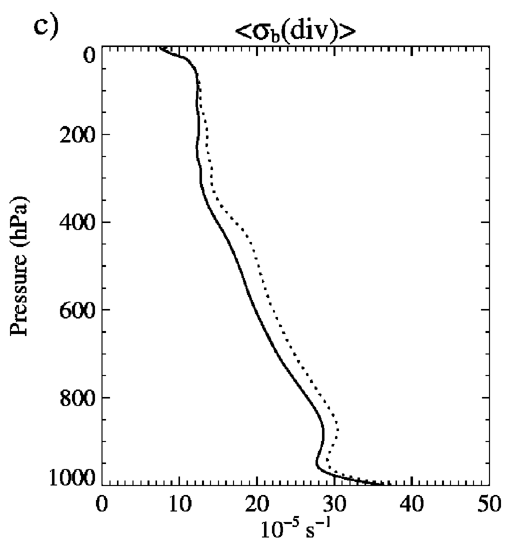
One hour cycle : background error covariances



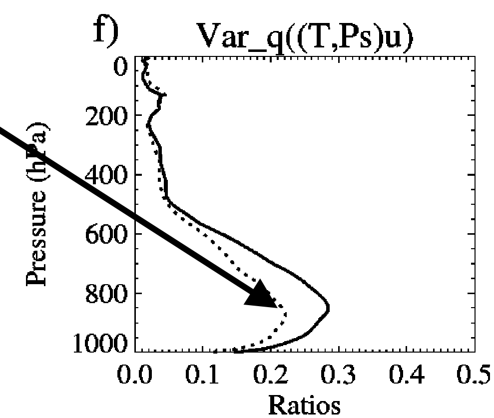
- Vertical profile of standard deviation for 3 hour and 1 hour forecast.

- Covariance between Q and (T,Ps)



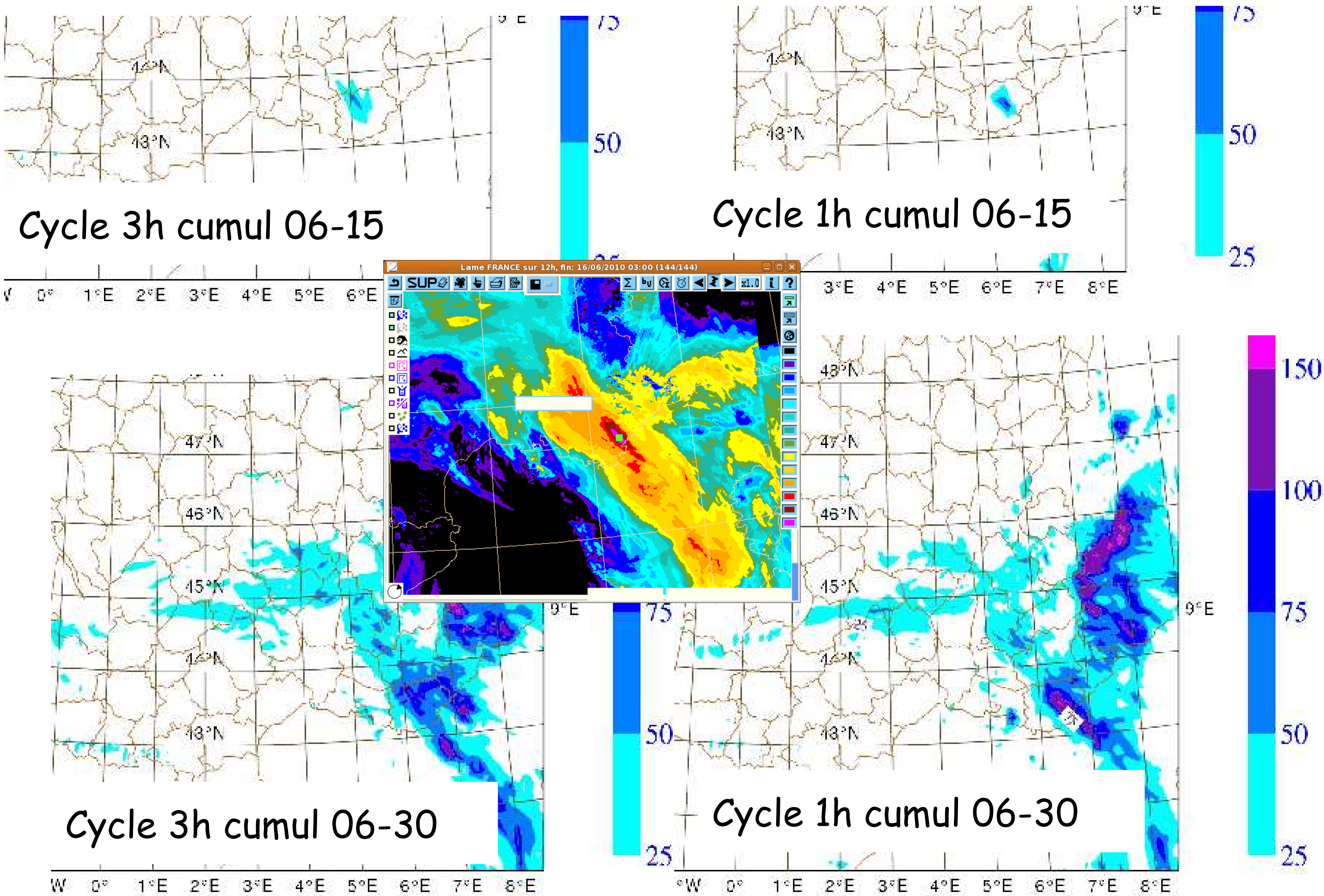


AROME 3h
AROME 1h



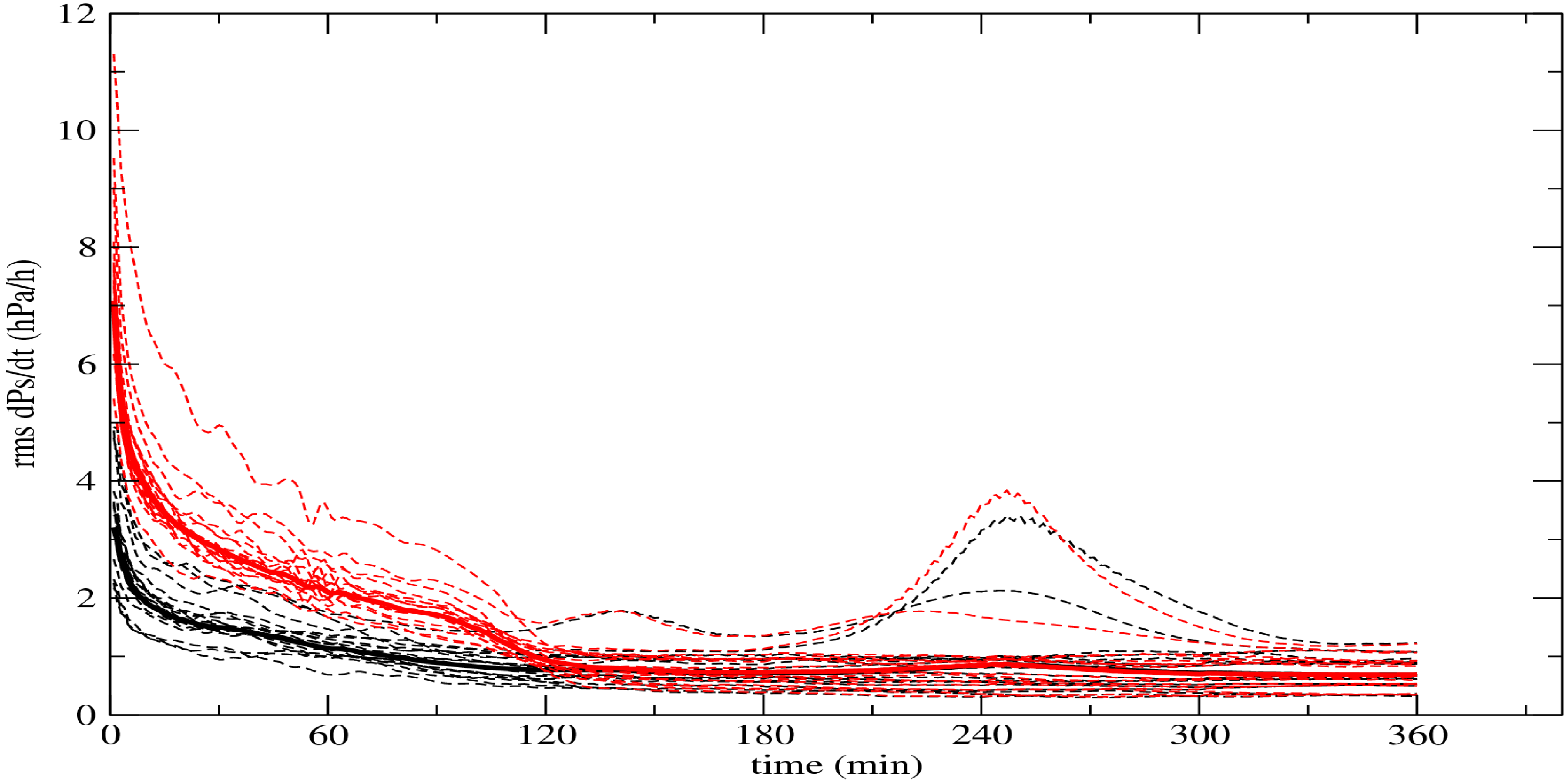
So far the results are neutral to slightly negative !

1 hour cycle : the var case 15/06/2010



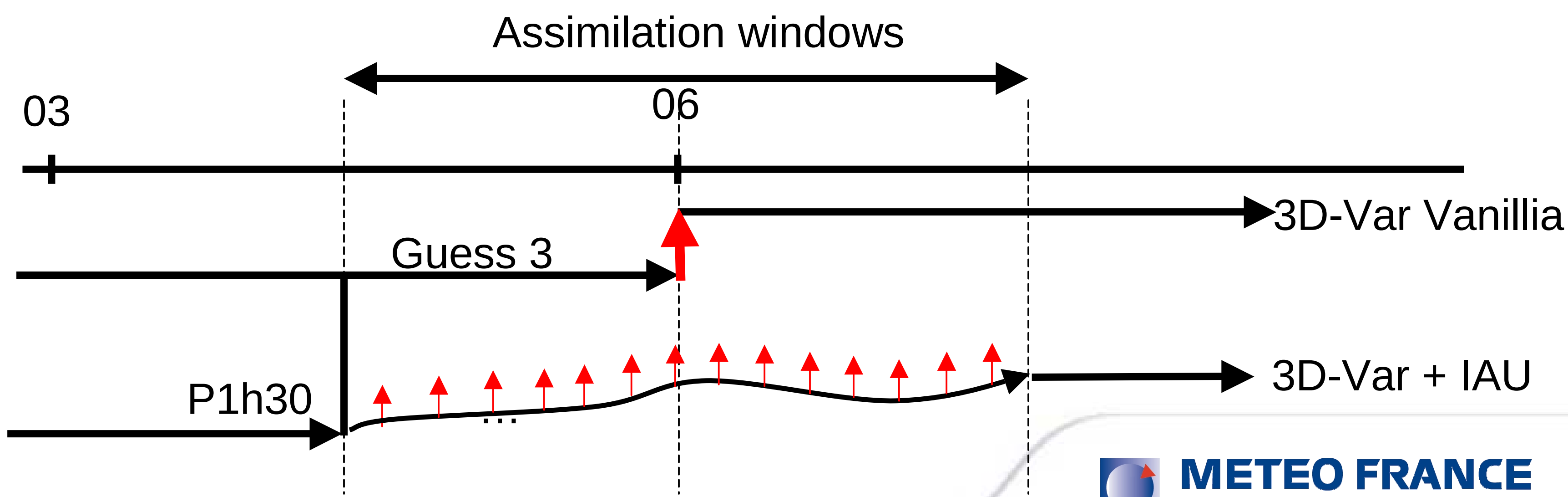
Spin-up issue

- Spurious oscillations during the beginning of the simulation, “non-physical”, mostly due to imbalance of fields generating gravity waves that do not exist in reality.
- These oscillations are particularly visible with a diagnostic on surface pressure.
- Has been reduced for example with the change of T0 coupling file from coupling file to analysis file.



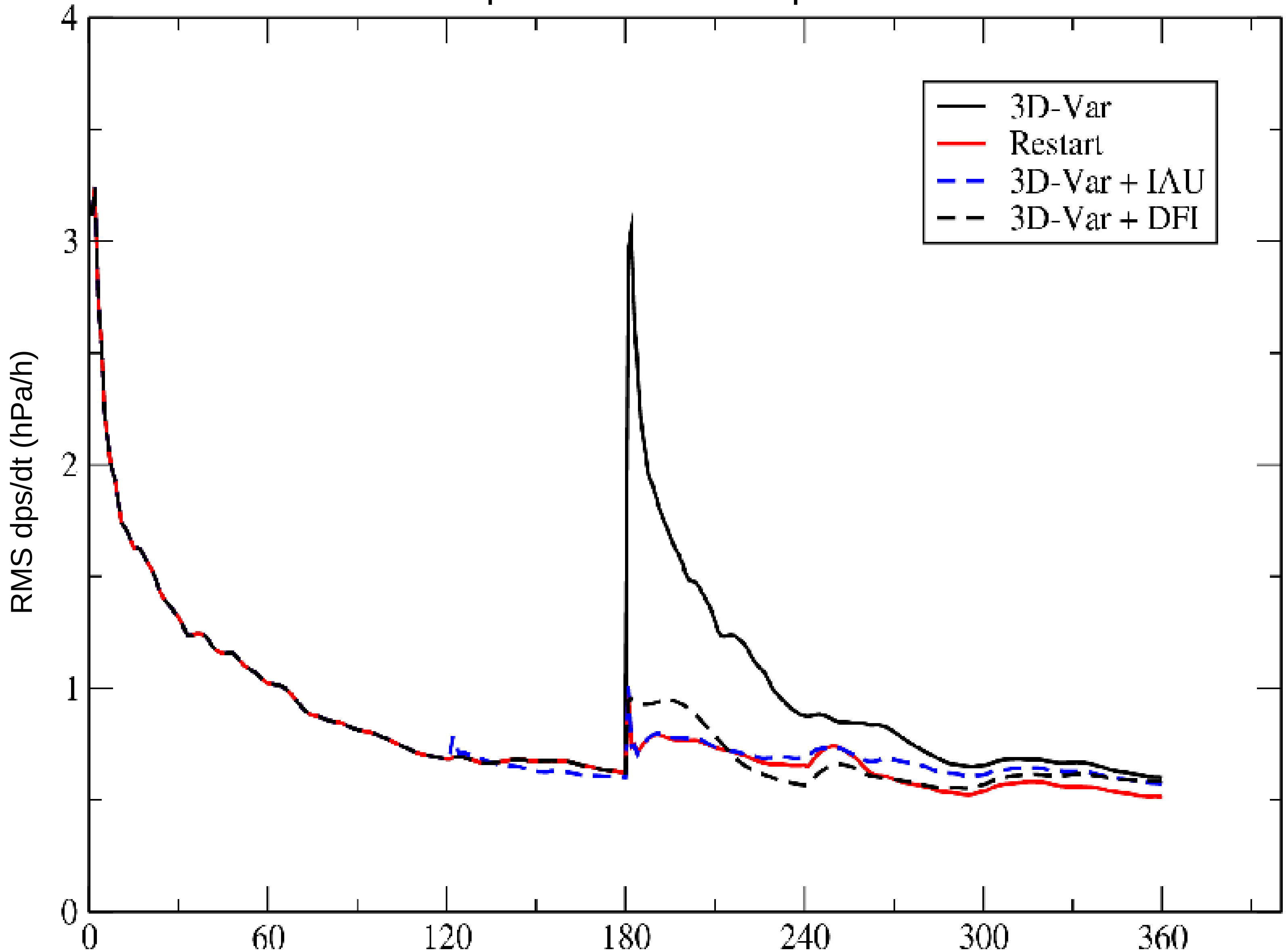
Spin-up reduction

- DFI :
  - Debugging of DFI for AROME (issue with LSPRT and grid point Q)
  - First test in cy35
  - Next we should test incremental DFI or a only-forward DFI (we are not satisfy with the backward DFI part)
- Incremental Update Analysis (Bloom et al. 1996)
  - Used in UKMO
  - Principle : the increment is added progressively during the model integration.
  - Coded in 36t1



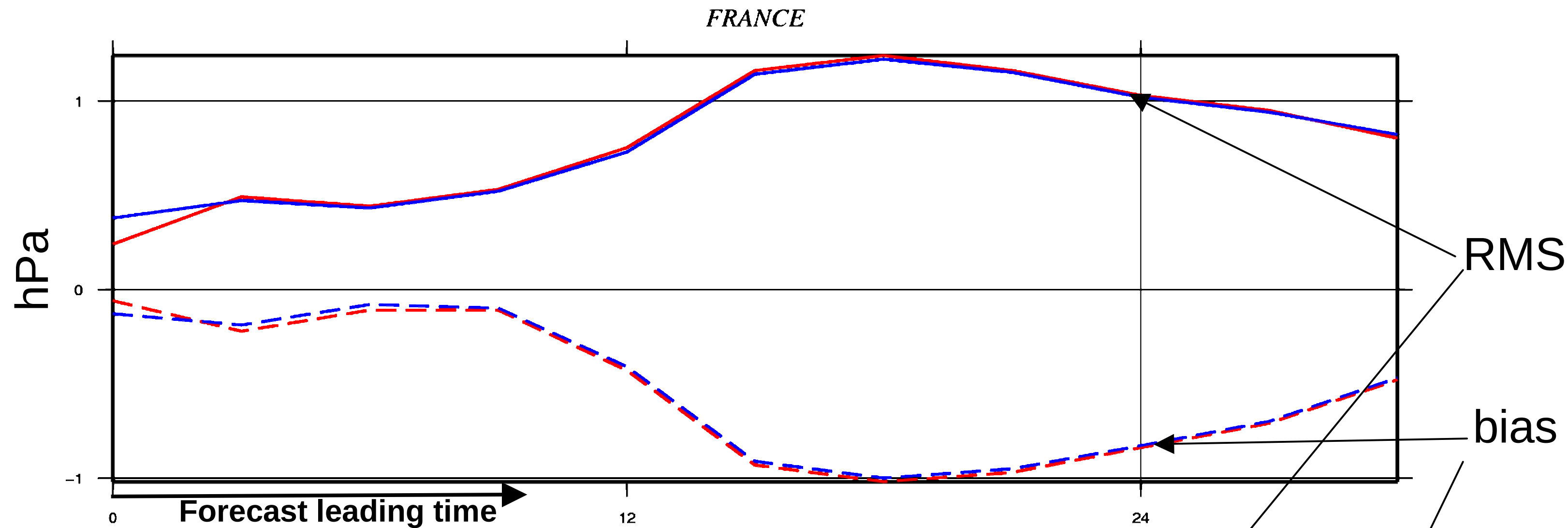
IAU

Temporal evolution of pressure derivate RMS

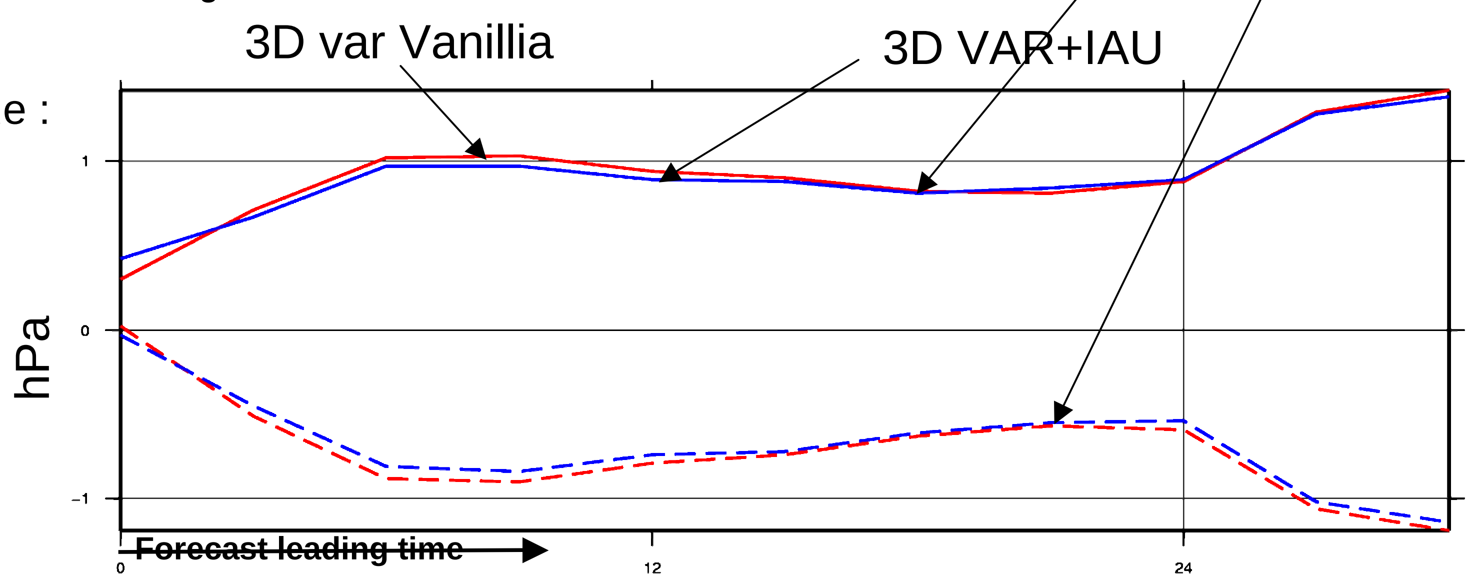


IAU

- Scores, comparaison to surface pressure observations:
  - In dynamical adaptation mode no difference on the scores



  - In 3dvar mode :



1. Some interesting experiments with 3dvar minimization.
2. How to use more observations inside AROME assimilation system.
3. On the use of heterogeneous B matrices.
4. Refinement of global statistics based on ensembles.

Use of a heterogeneous B matrix in AROME

(Montmerle, T., Menetrier, B.)

A climatological background error covariances matrix **B** is used in AROME oper. It is deduced from off-line statistics made on an ensemble of forecast differences build from an ensemble assimilation (Brousseau et al. 2011).

We know that :

• static homogeneous isotropic **B** often misbehaves in regions that are under-represented in the ensemble used for its computation, such as clouds and precipitations.

• forecast errors strongly depend on weather types and is flow-dependent

Work on progress at MF:

• set-up of an “ARPEGE-like” ensemble assimilation to produce filtered variances and filtered horizontal correlations “of the day” to modulate the static **B**

• **use of a heterogeneous formulation of background error covariances,** especially to get increments that are more adequately balanced and structured in precipitating regions where radar data (and soon cloudy radiances) are assimilated

Use of a heterogeneous B matrix in AROME

1st step: compute isotropic homogeneous **B** matrices representative of a particular phenomena (e.g convection, fog) by applying masks based on vertically integrated simulated quantities

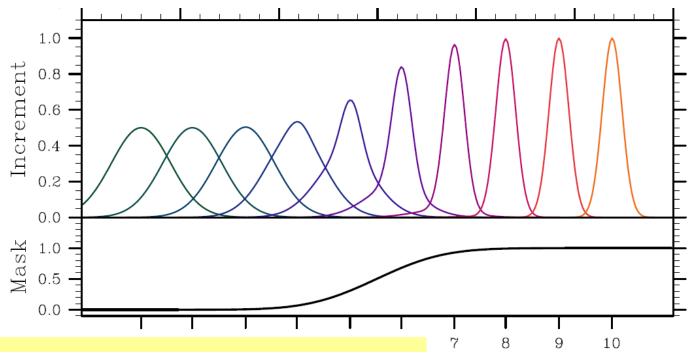
• **2nd step:** use the heterogeneous B matrix formulation allowing to decompose the increment (Montmerle and Berre, 2010):

$$\delta x = \mathbf{B}^{1/2}\chi = \mathbf{F}_1^{1/2}\mathbf{B}_1^{1/2}\chi_1 + \mathbf{F}_2^{1/2}\mathbf{B}_2^{1/2}\chi_2$$

$\mathbf{F_1}$ and $\mathbf{F_2}$ are operators defining the spatial locations where $\mathbf{B_1}$ and $\mathbf{B_2}$ are applied respectively, following:

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

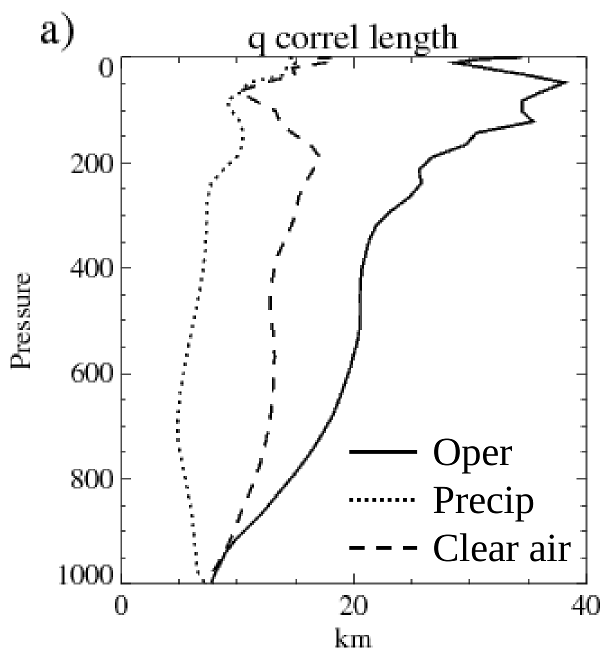
$\mathbf{S}$ and $\mathbf{S^{-1}}$ are direct and inverse Fourier transform, and $\mathbf{D}$ is a grid point mask deduced from observations, convolved with a normalized gaussian kernel to allow the spread of covariance functions across the sharp transition between 0 and 1.



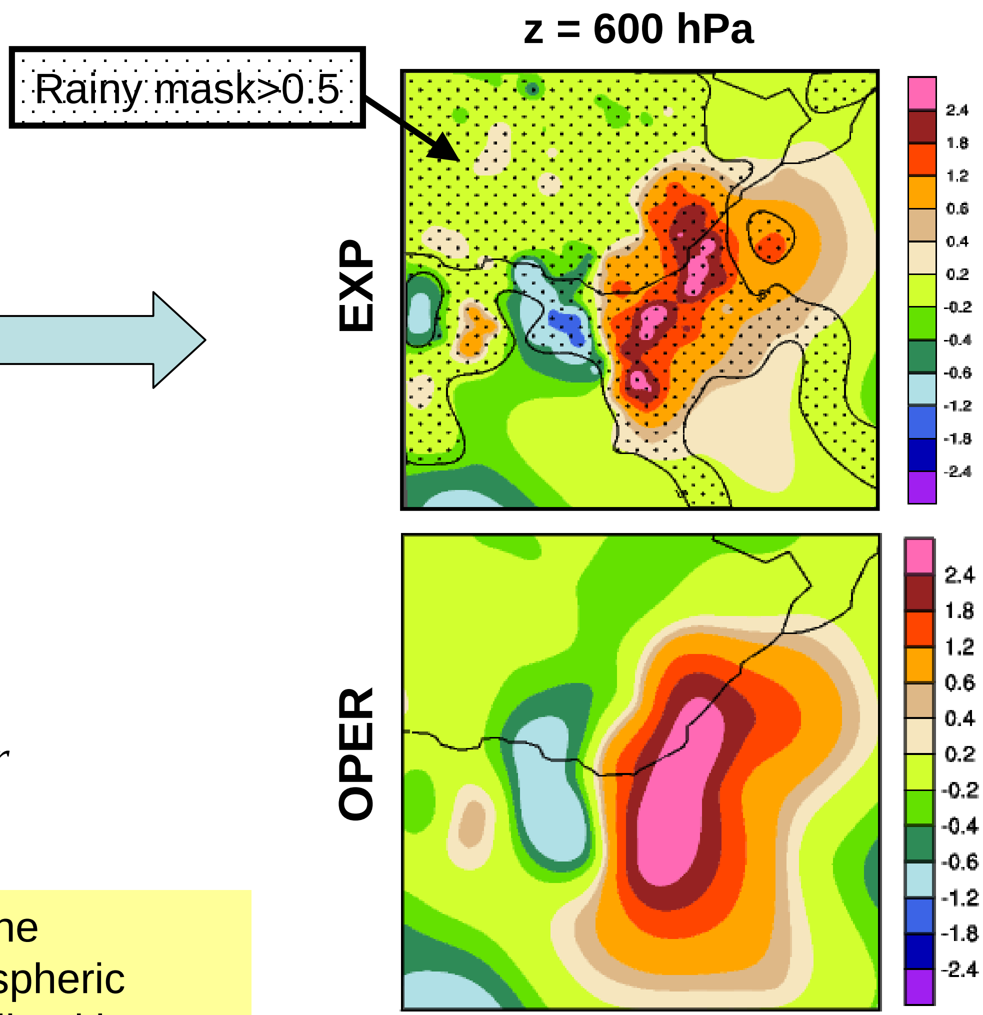
So far, preliminary tests show neutral to slightly positive conventional forecast scores and positive QPF scores for fog (Ménétrier and Montmerle 2011) and for convective rain.

Illustration of the method for precipitation

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

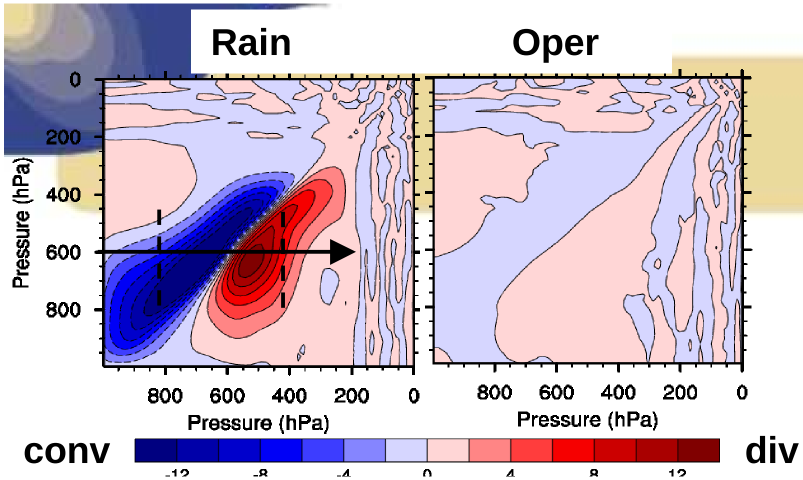


Horizontal correlation lengths
of the specific humidity q forecast error

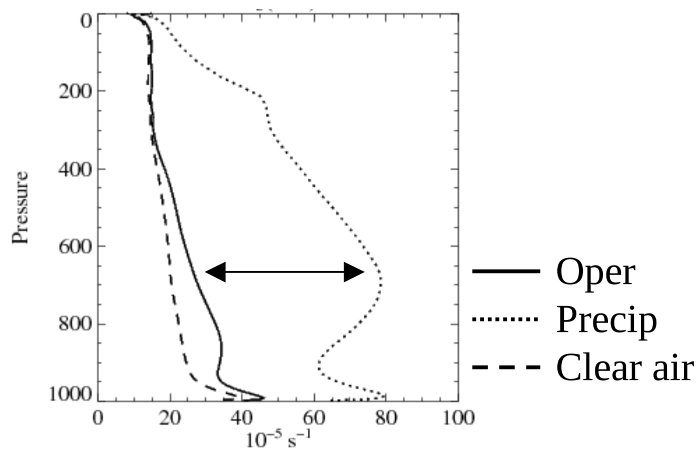


Zoom in SE France of
q increments ($g.kg^{-1}$)

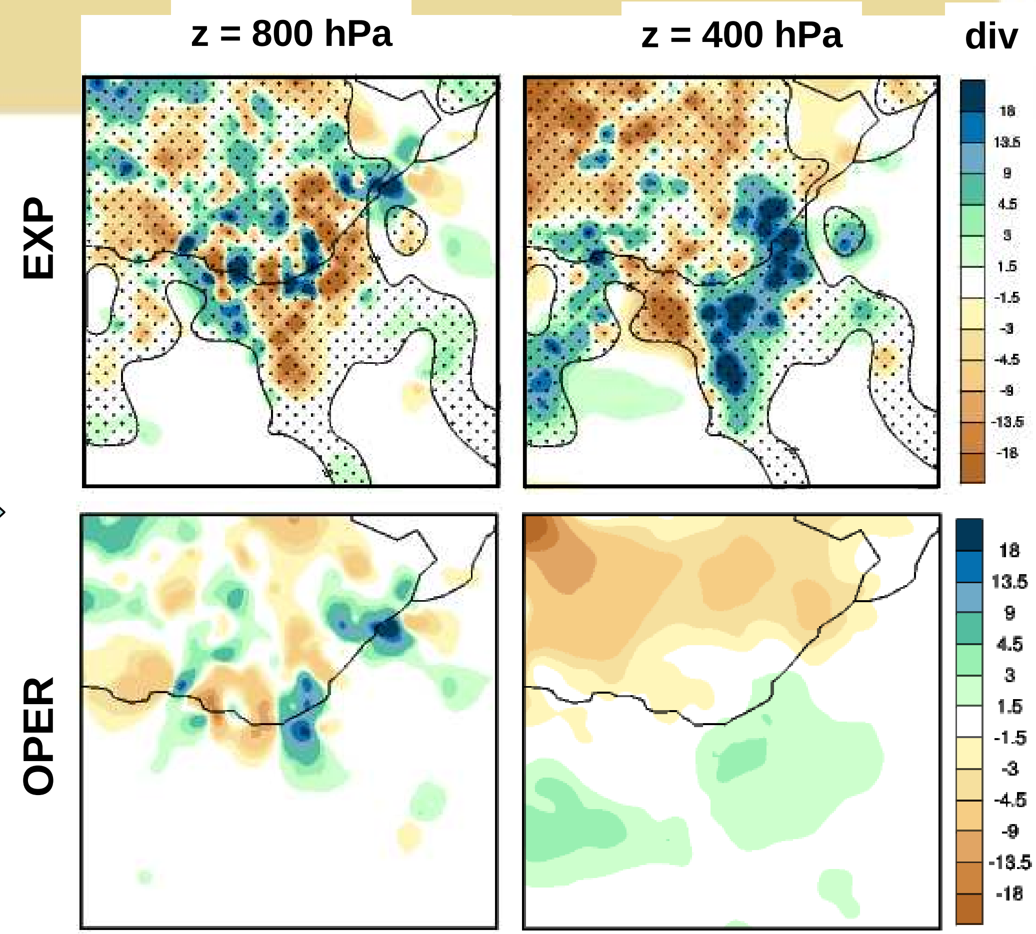
Increments of *q* (and *T*), mainly due to the assimilation of reflectivities in mid-tropospheric precipitating areas, are much more localized in rainy areas for EXP.



***Cross covariances** between errors of humidity (y-axis) and the unbalanced divergence (x-axis)*



*background error **standard deviations** σ_b for divergence*



***Increments of divergence** ($10^{-5}\ s^{-1}$)*

Increments of divergence are more controlled by observations in EXP, and a positive increment of humidity at 600 hPa will enhance convergence below and divergence above in precipitating areas.

1. Some interesting experiments with 3dvar minimization.
2. How to use more observations inside AROME assimilation system.
3. On the use of heterogeneous B matrices.
4. Refinement of global statistics based on ensembles.

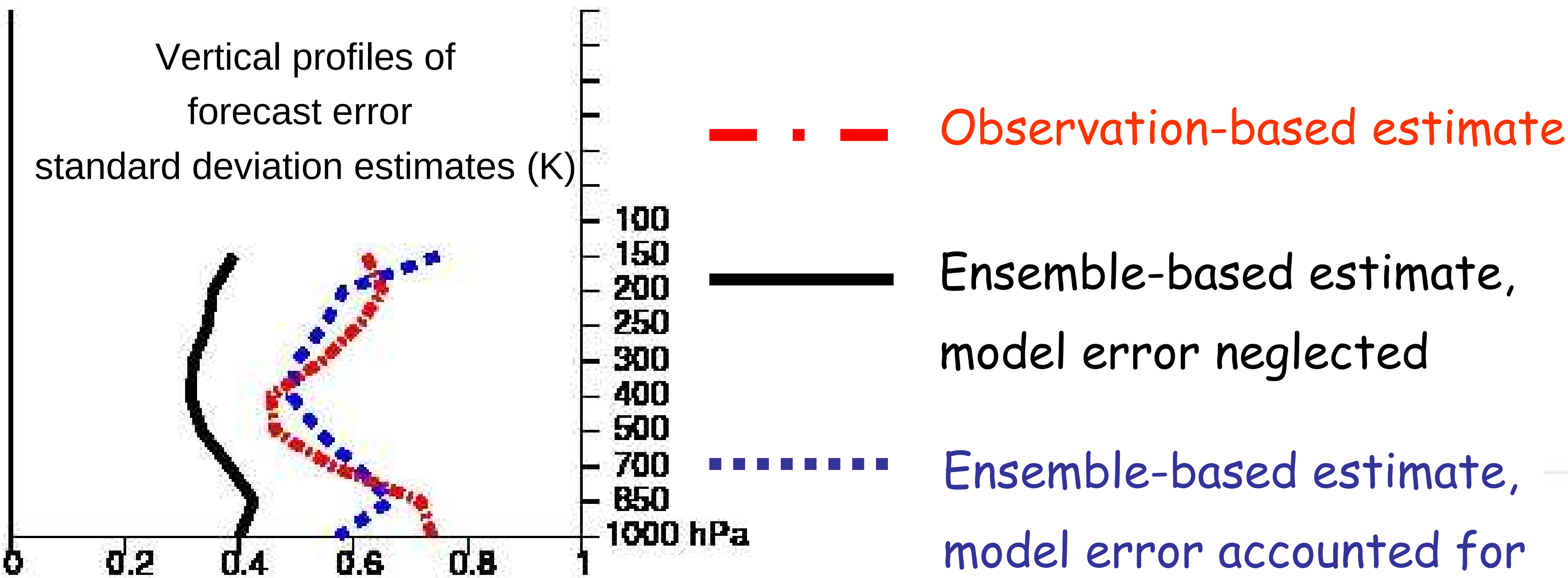
Model error estimation and representation in M.F. ensemble 4D-Var *(Raynaud,L., Berre, L., Desroziers, G.)*

Methodology (with positive impacts on deterministic and ensemble forecasts) :

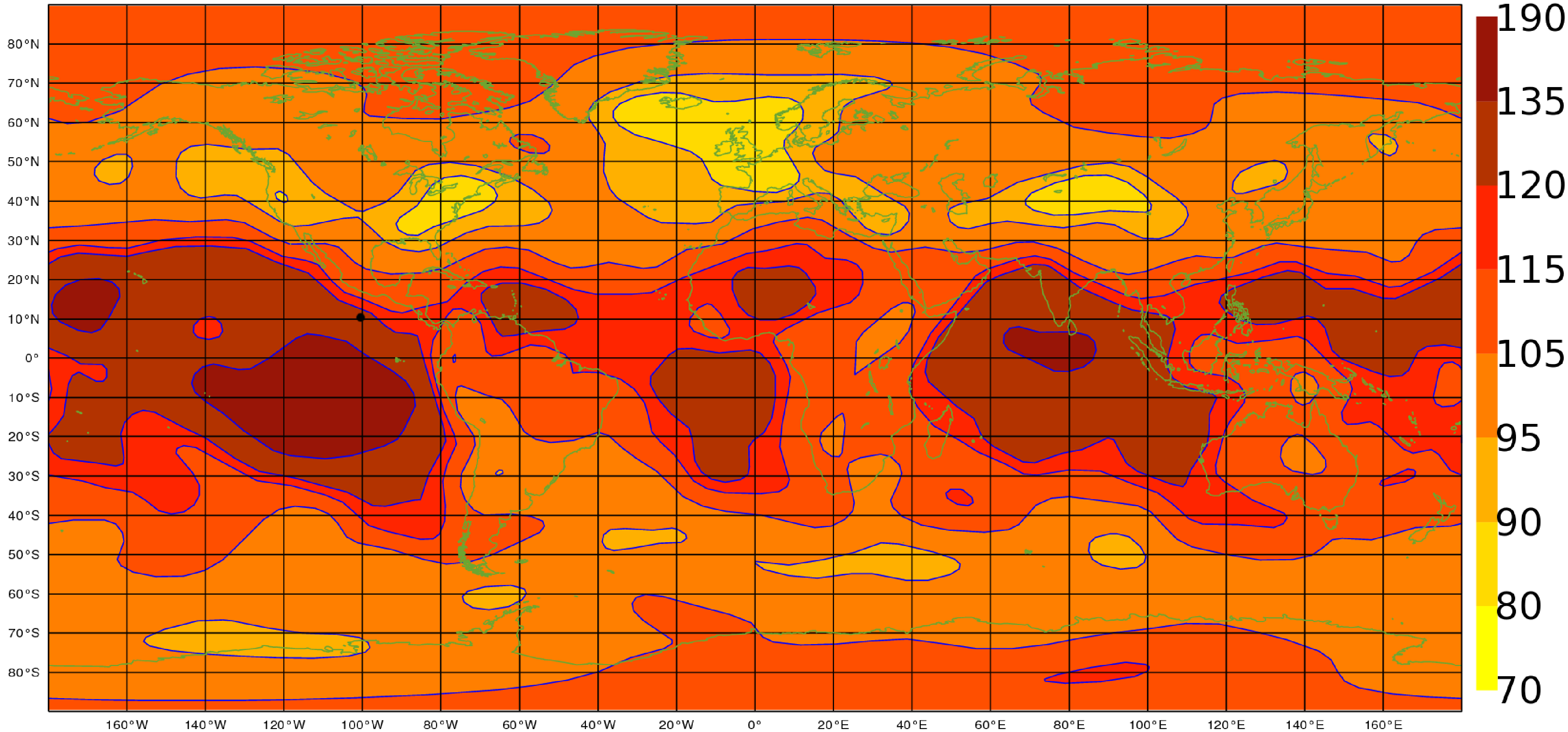
1. Estimation of « total » forecast error variances V[M e^a + e^m] using observation-based diagnostics (Jb_min).

2. Comparison with ensemble-based variances V[M e^a] and estimation of the inflation factor α.

3. Inflation of forecast perturbations (by a factor $\alpha > 1$).



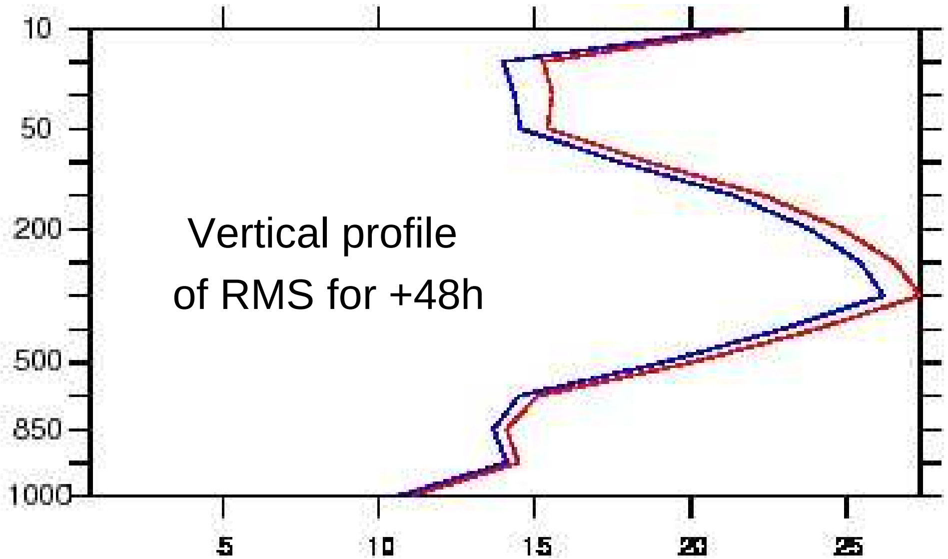
Flow-dependent background error correlations using EnDA and wavelets

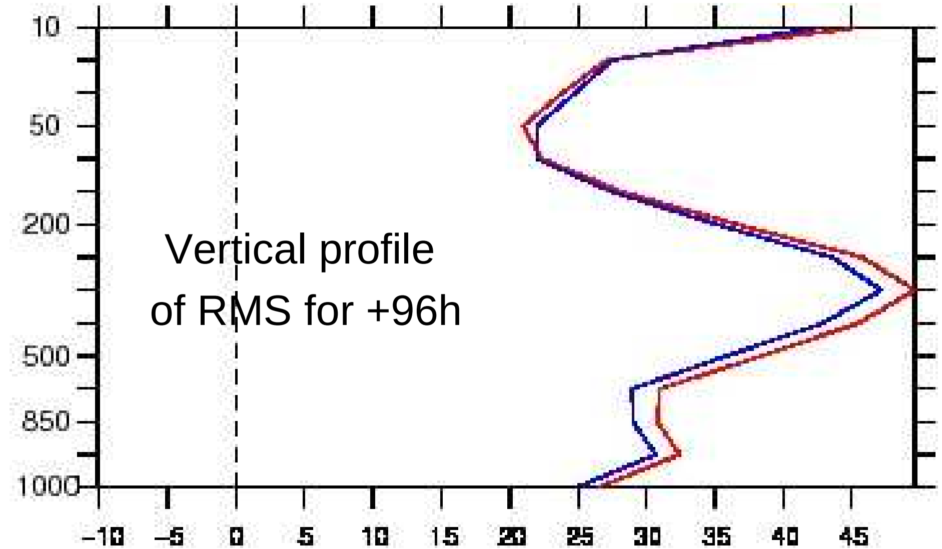


Wavelet-implied horizontal length-scales (in km),
for wind near 500 hPa, averaged over a 4-day period.

(Varella et al 2011b, following « static applications » in Fisher 2003, Deckmyn and Berre 2005, Pannekoucke et al 2007)

Impact of wavelet flow-dependent correlations against spectral static correlations *(Varella, H., Berre, L., Desroziers, G.)*



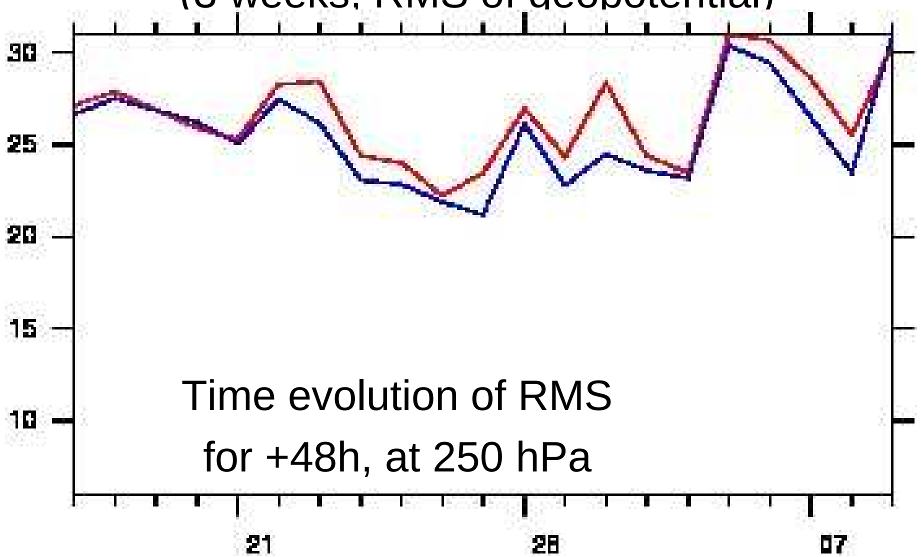


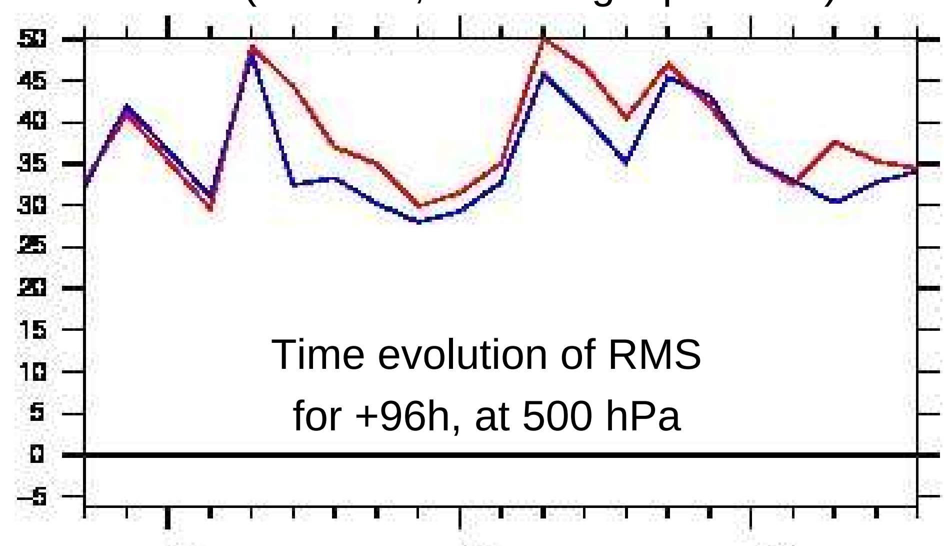
SOUTHERN HEMISPHERE

(3 weeks, RMS of geopotential)

EUROPE AND N. ATLANTIC

(3 weeks, RMS of geopotential)





Conclusion

2 main research axes :

- *Increase the number of observations, for example by increasing the assimilation frequency in AROME.*
- *Having more sophisticated background covariances statistics, more and more depending on the flow.*

It seems we have difficulties to have a net positive impact on classical scores, the 3dvar algorithm is a quite robust system !