Variational & ensemble data assimilation at Météo-France

L. Berre, G. Desroziers,
H. Varella, L. Raynaud, C. Loo
Météo-France (CNRM/GAME)

Plan of the talk

- Numerical Weather Prediction and Data Assimilation
- Ensembles and Error Covariances
- Preconditioning methods

1. Numerical Weather Prediction

and Data Assimilation

The two main ingredients of weather forecasting

What will be the weather tomorrow ?

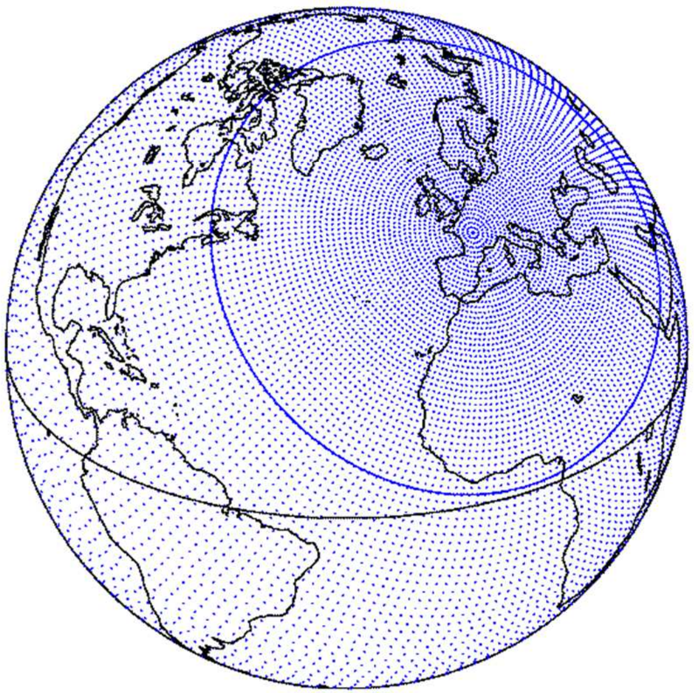
Bjerknes (1904) :

In order to do a good forecast, we need to :

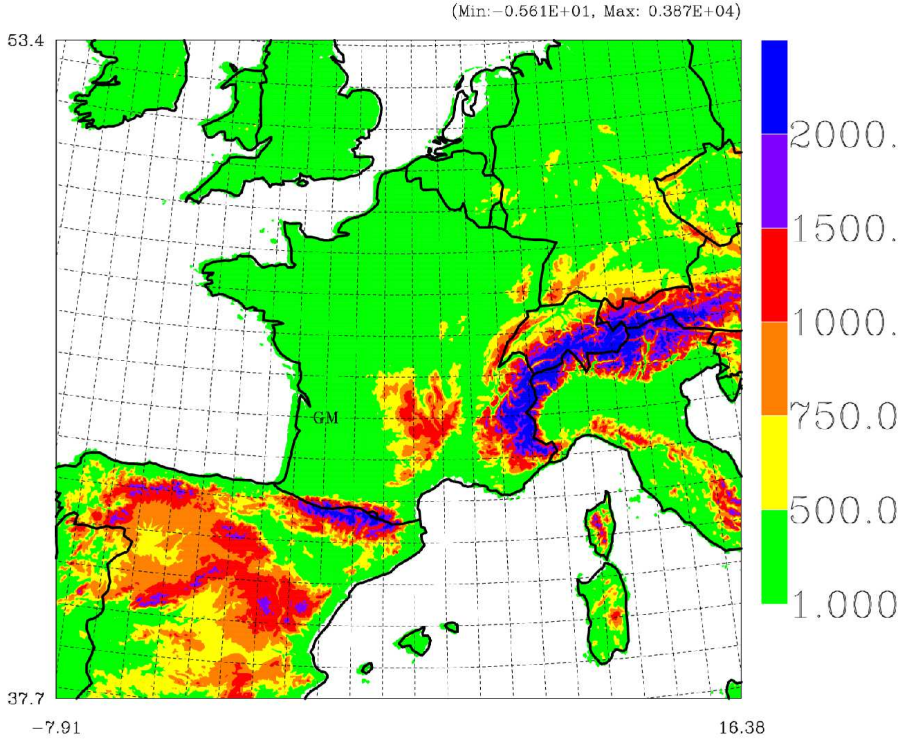
- know the atmospheric evolution laws (~ modeling) ;
- know the atmospheric state at initial time (~ data assimilation).

Numerical Weather Prediction at Météo-France
(in collaboration with e.g. ECMWF)

Global model (Arpège) : DX ~ 10-60 km

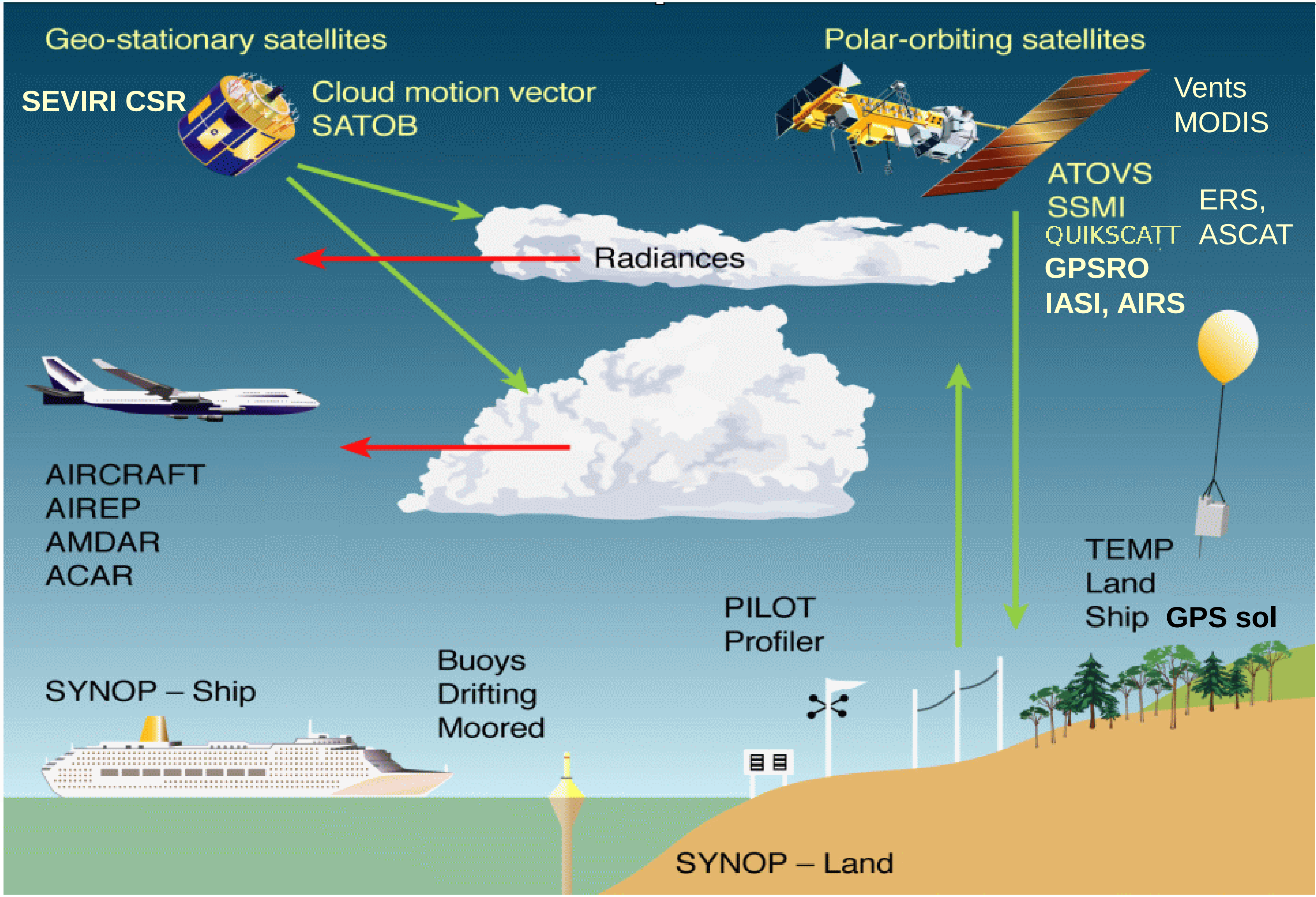


Arome : DX ~ 2.5 km

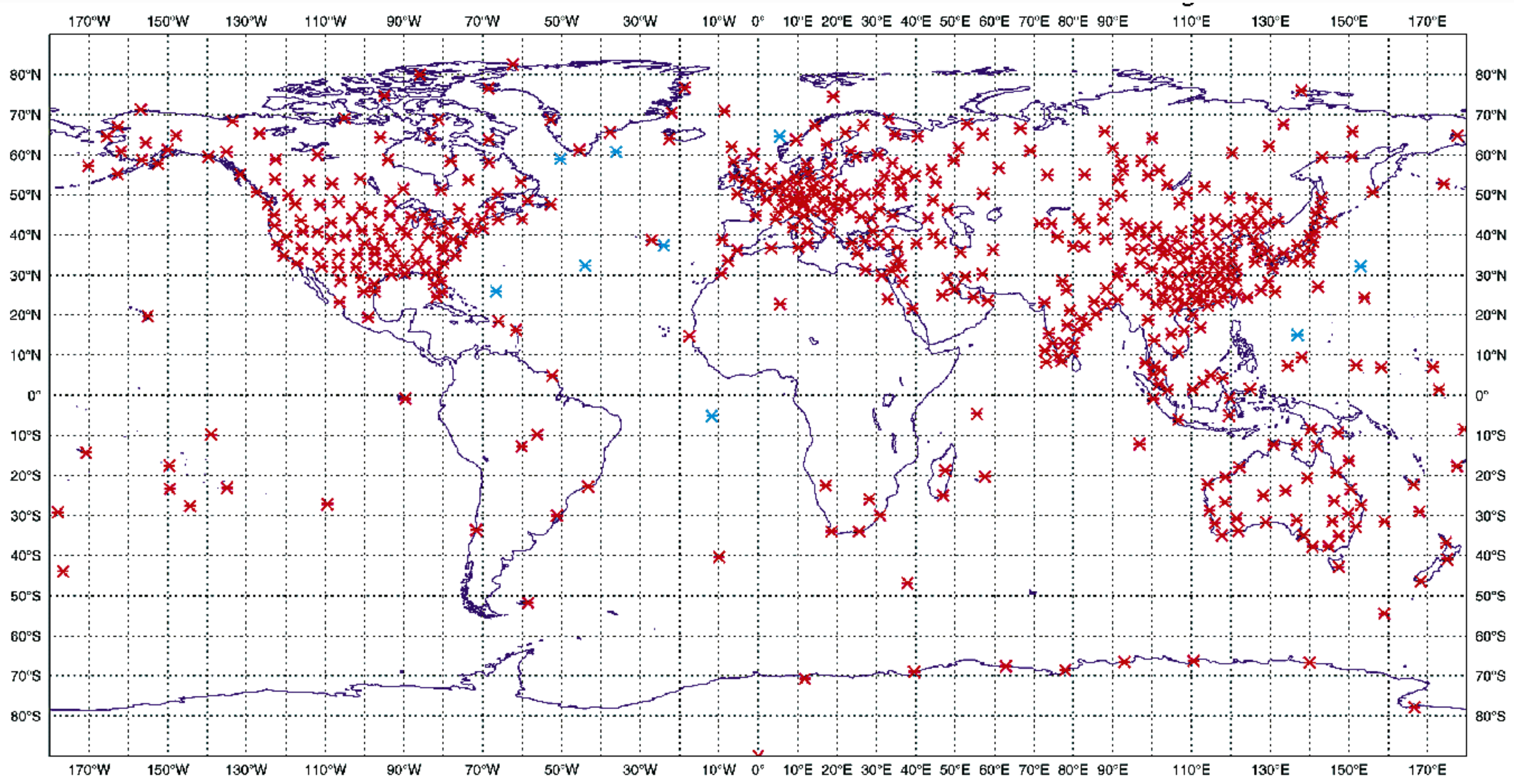


Equations of hydrodynamics and physical parametrizations (radiation, convection,…)
to predict the evolution of temperature, wind, humidity, …

Data that are assimilated in NWP models



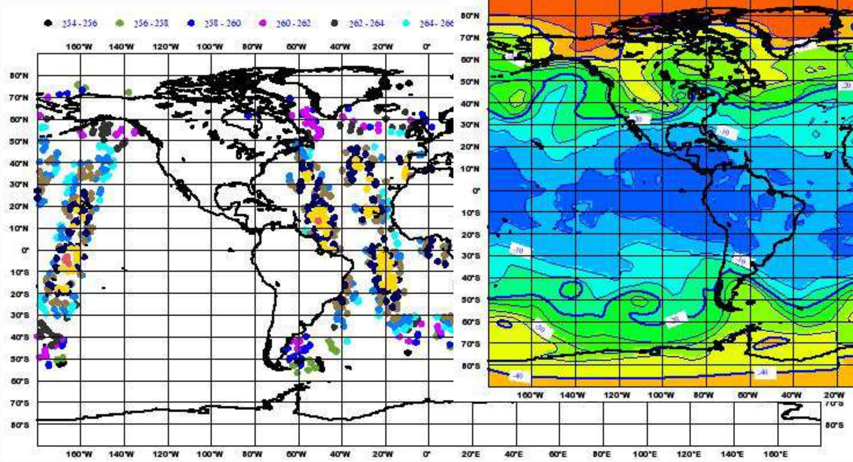
RADIOSONDE OBSERVATIONS



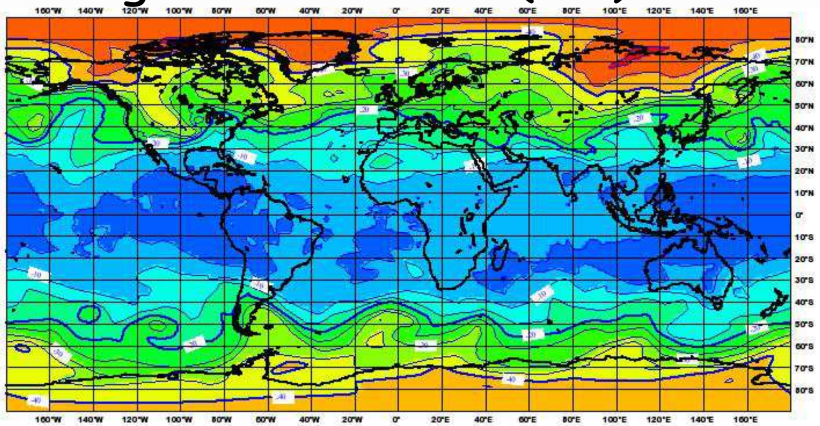
METEO FRANCE
Toujours un temps d'avance

Data assimilation for NWP : illustration

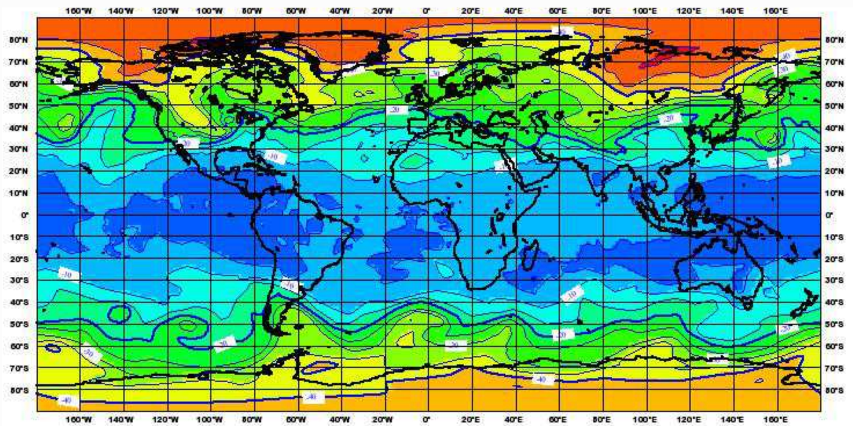
Observations $\mathbf{y}^o$



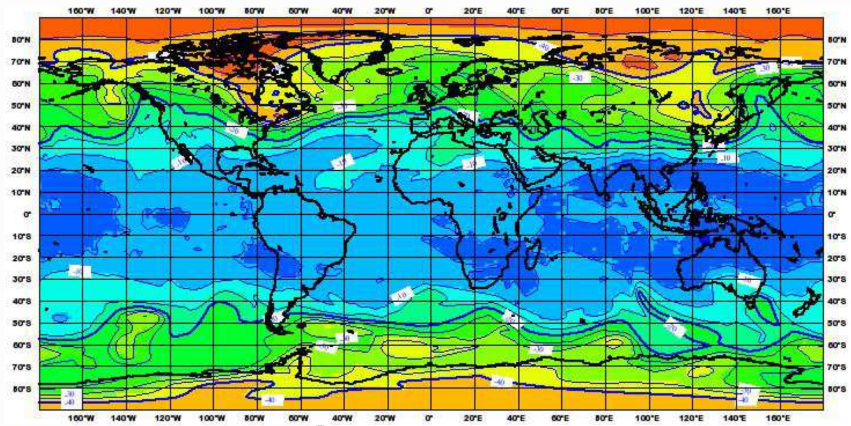
Background $\mathbf{x}^b = \boldsymbol{M}\,(\mathbf{x}^{a\,-})$



Analyzed state at t_0



Forecast state at t_0 + 48h



METEO FRANCE
Toujours un temps d'avance

Linear estimation of model state

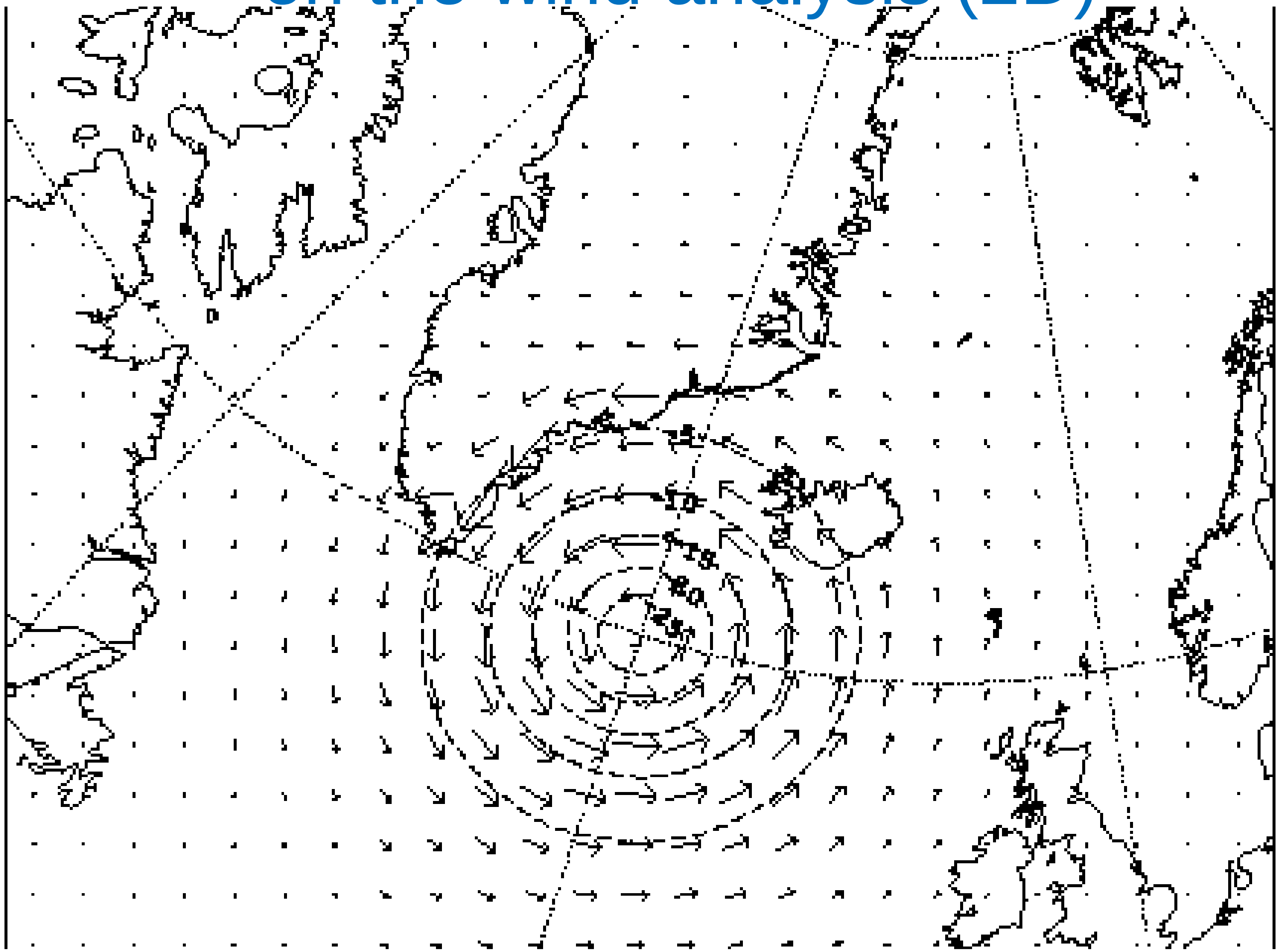
- BLUE analysis equation : $x_a = (I-KH)\, x_b + K\, y_o$
- H = observation operator = projection from model to obs space (e.g. spatial interpolation, or radiative transfer for satellite radiances).
- K = Gain matrix
  = observation weights,
  = relative amplitudes and structures of background errors (matrix B) compared to observation errors (matrix R) :

$$K = BH^T\,(\,HBH^T + R\,)^{-1}$$

$$H\,K = (\,I + R\,(HBH^T\,)^{-1}\,)^{-1}$$

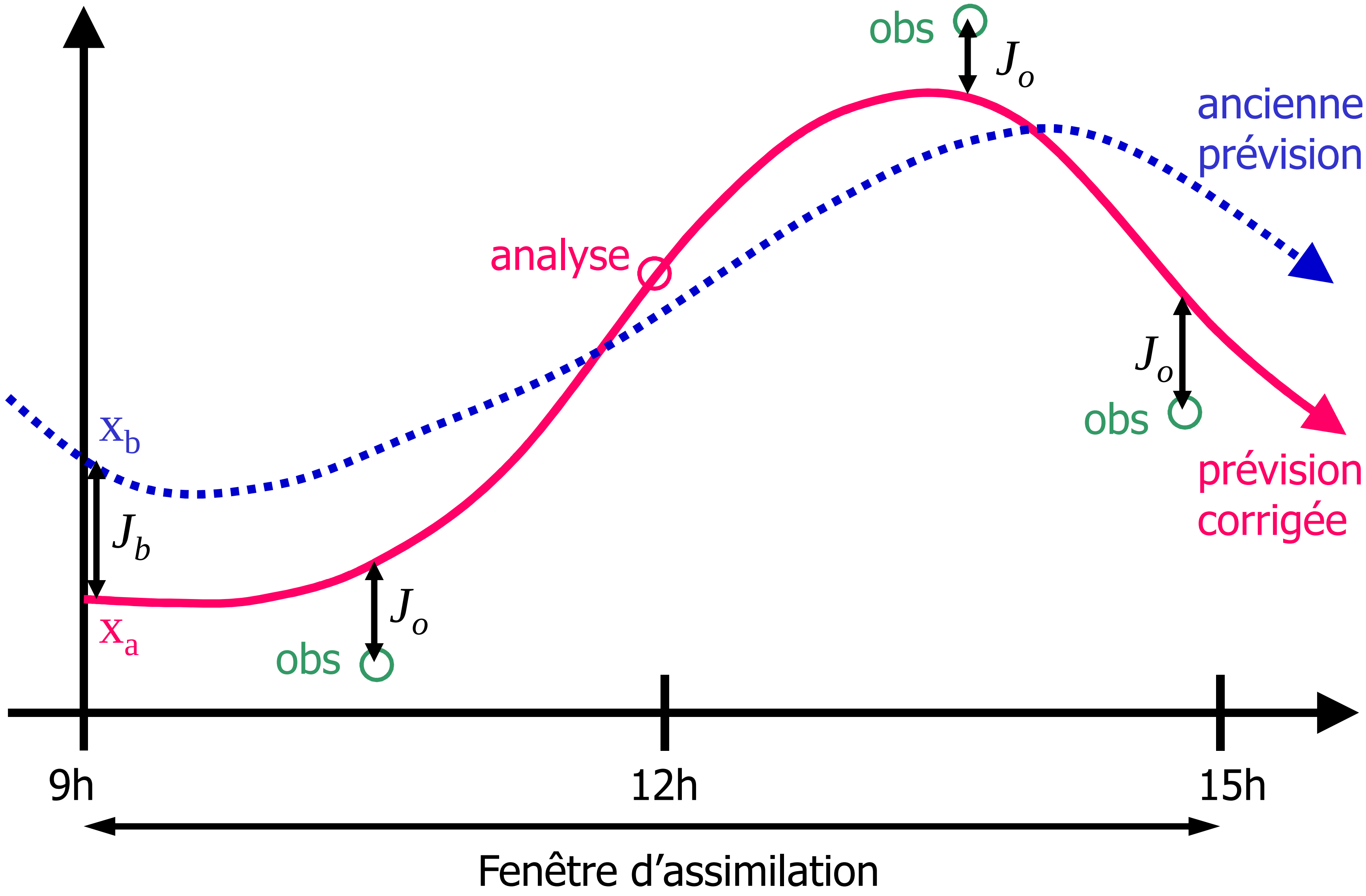
- Equivalent to minimize distance $J(x_a)$ to x_b and y_o (4D-Var).
- The covariance matrix B is huge :
  ~ square of model size ~ $(10^8)^2$ ~ 10^{16} (!),
  error covariances need to be estimated, simplified and modeled.

Impact of one surface pressure observation on the wind analysis (2D)



⇒ characteristic spatial scales and couplings (ex: pressure/wind) are included in B (e.g. Weaver and Mirouze 2013).

Principle of 4D-VAR assimilation
(e.g. Talagrand and Courtier 1987)



4D-Var : Principle

- Observation operator in 4D-Var :
- ✓ *H* includes the model integration over the assimilation window.
- ✓ takes the flow dynamics into account.

- Minimisation of J($\mathbf{x}^a$) :
- ✓ Use of an iterative algorithm.
- ✓ Uses adjoint « backwards » model integrations.
- ✓ Preconditioning issues are crucial (e.g. Tshimanga et al 2008).

METEO FRANCE
Toujours un temps d'avance

2. Ensemble Data Assimilation

How can we estimate error covariances ?

- The true atmospheric state is never exactly known.

- Use observation-minus-forecast departures :

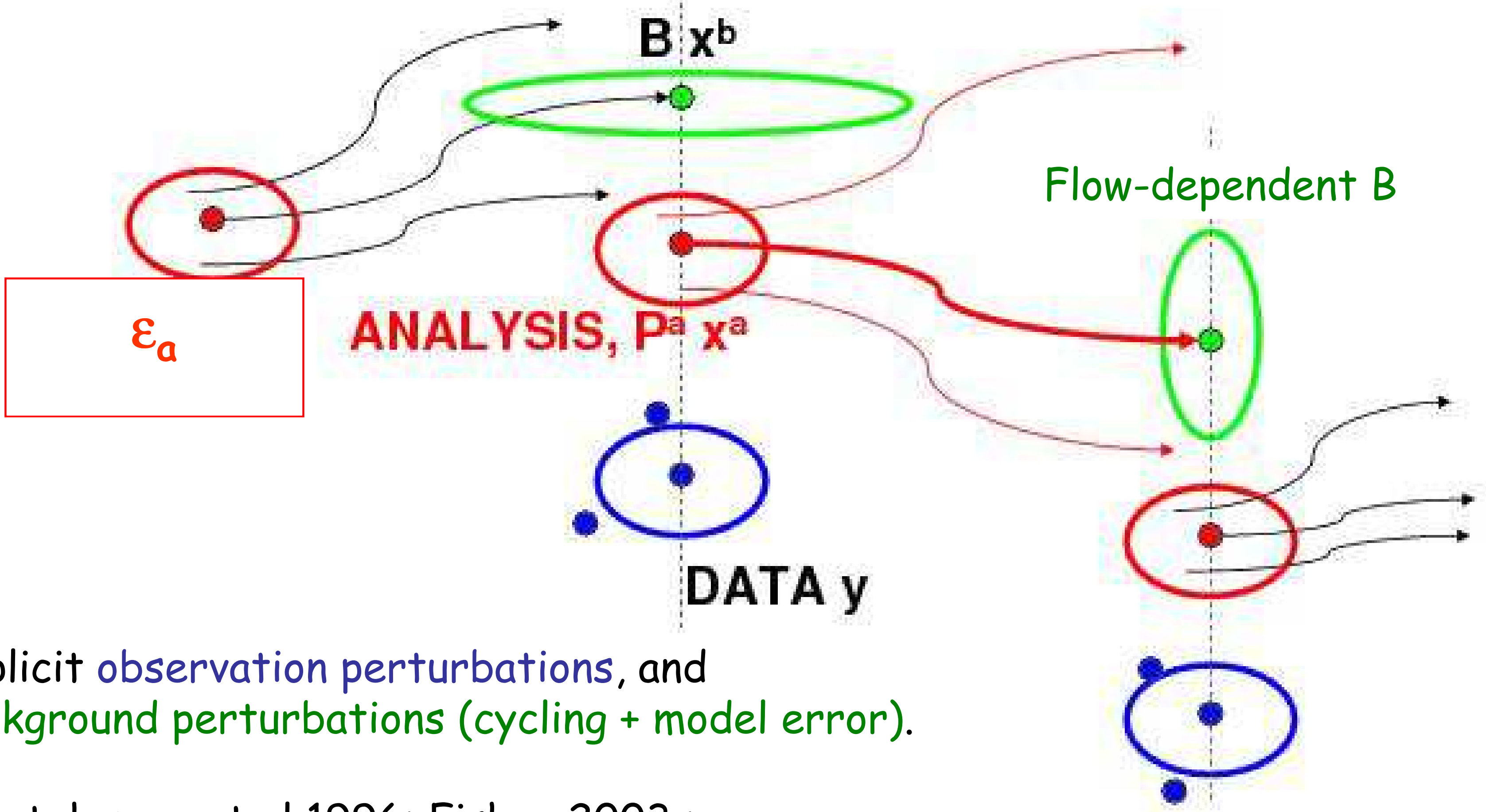
$$y_o - H\,x_b \;\sim\; e_o - H\,e_b$$

to estimate some error parameters (e.g. variances, correlations), using assumptions on spatial structures of errors.

- Use ensemble to simulate the error evolution and to estimate complex forecast error structures.

Ensemble assimilation (EnDA = EnVar, EnKF, …) : simulation of the error evolution

$$\varepsilon_f = \mathbf{M}\,\varepsilon_a + \varepsilon_m$$



Explicit observation perturbations, and background perturbations (cycling + model error).

(Houtekamer et al 1996; Fisher 2003 ; Ehrendorfer 2006 ; Berre et al 2006)

Analysis error equation

- Analysis state (BLUE, K = 4D-Var gain matrix) :

$$x_a = (I-KH)\, x_b + K\, y_o$$

- True state :

$$x_t = (I-KH)\, x_t + K\, Hx_t$$

- Analysis error :

$$e_a = x_a - x_t$$

i.e.

$$e_a = (I-KH)\, e_b + K\, e_o$$

Analysis perturbation equation

- Perturbed analysis :

$$x'_a = (I-KH)\, x'_b + K\, y'_o$$

- Unperturbed analysis :

$$x_a = (I-KH)\, x_b + K\, y_o$$

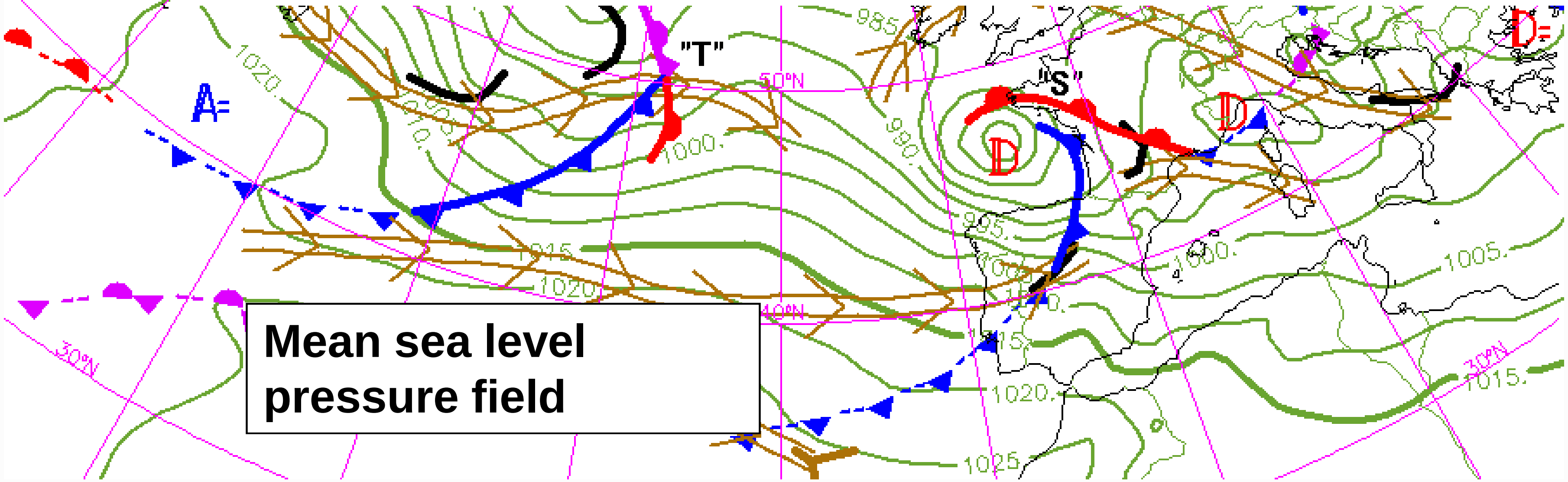
- Analysis perturbation :

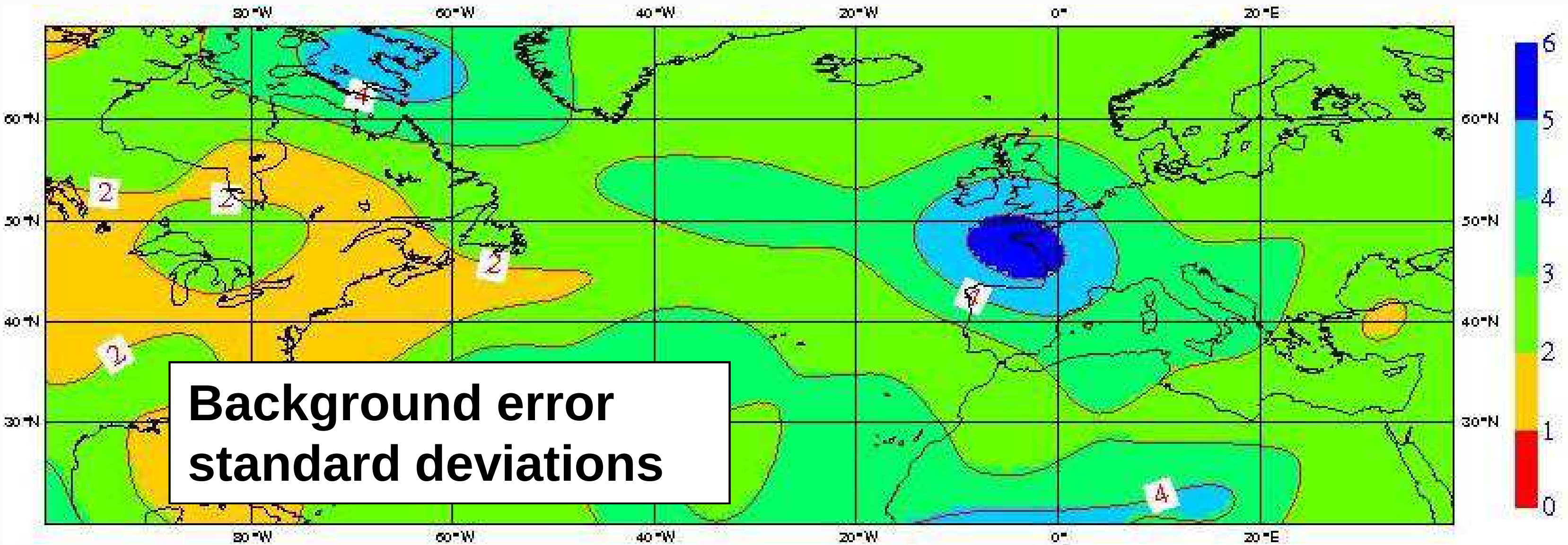
$$\varepsilon_a = x'_a - x_a$$

i.e.

$$\varepsilon_a = (I-KH)\, \varepsilon_b + K\, \varepsilon_o$$

Connexion between large errors and intense weather
(Klaus storm, 24/01/2009, 00/03 UTC)

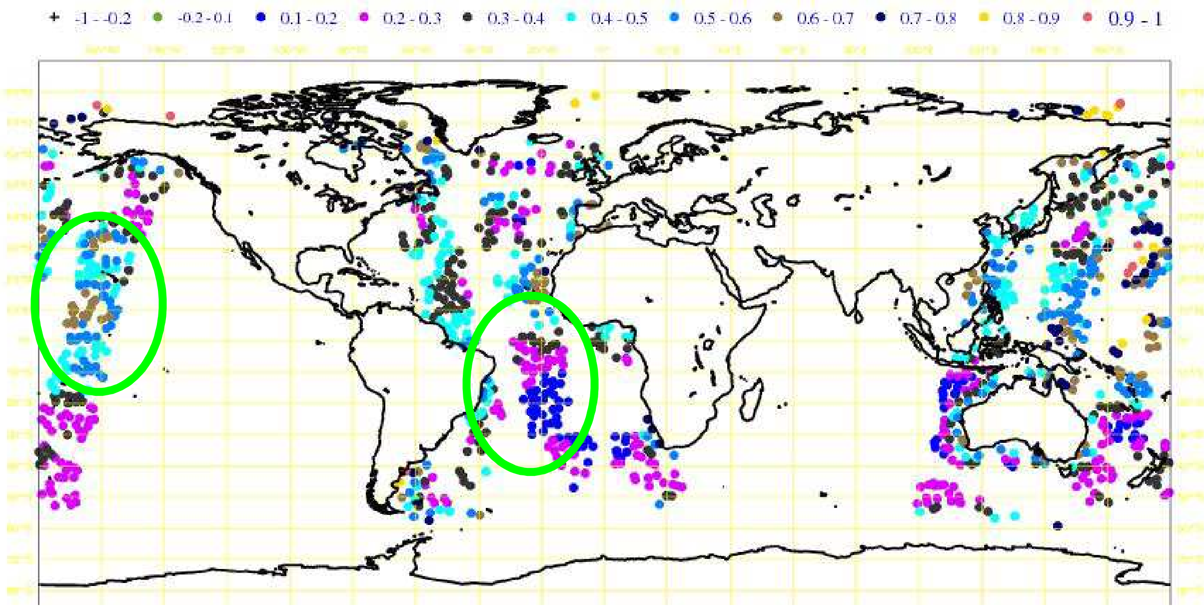




Validation of flow-dependent estimates of errors in HIRS 7 space (28/08/2006 00h) (Berre et al 2007, 2010)

Ensemble estimate

of error std-devs

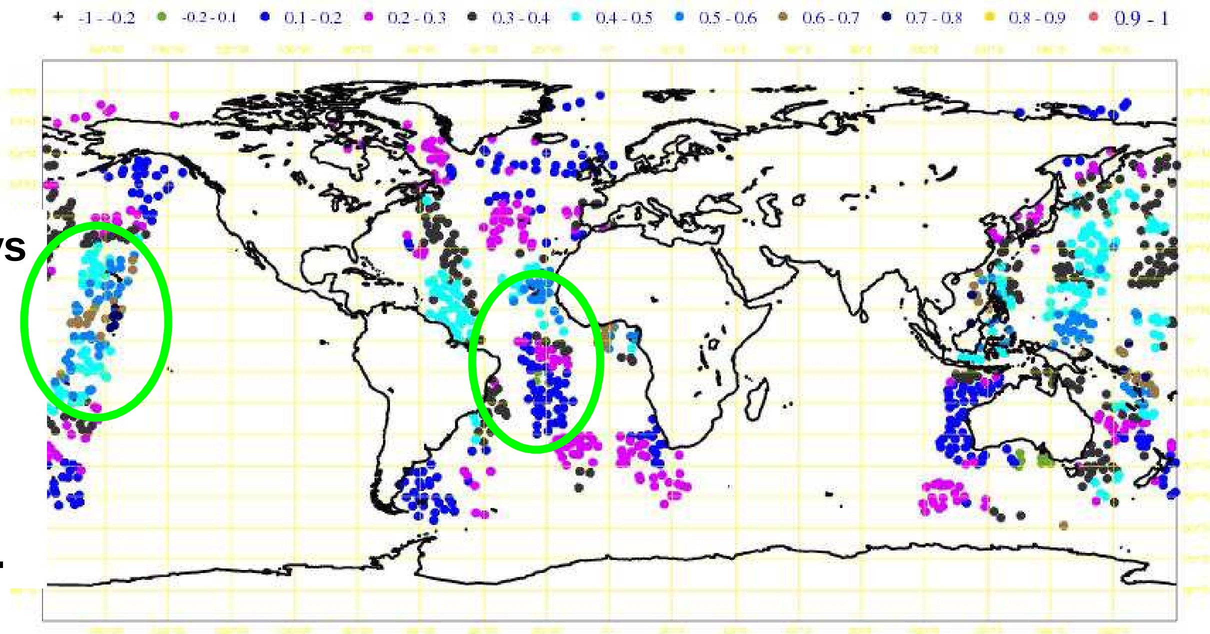


« Observed » error std-devs

cov(H dx , dy) ~ H B H^T

(Desroziers et al 2005)

=> model error estimation.



Use of innovations to estimate model error covariances $Q=cov(e_m)$

- Forecast error equation :

$$e_f = M\, e_a + e_m$$

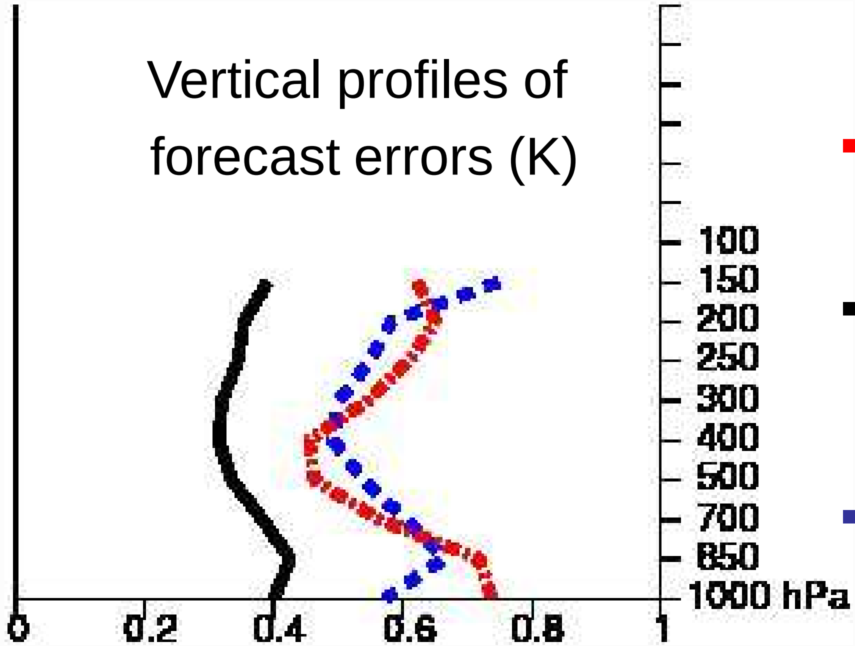
- Use ensemble assimilation (before adding model perturbations) to estimate evolved analysis error covariances (MAM^T).

- Use innovation diagnostics to estimate « B » (or at least HBH^T) (forecast error covariances).

- Estimate Q by comparing B and MAM^T (e.g. Daley 1992).

- Represent model error by inflating forecast perturbations in accordance with Q estimate.

Model error in M.F. ensemble 4D-Var
(Raynaud et al 2012, QJRMS)



Observation-based estimate

Ensemble-based estimate, model error neglected

Ensemble-based estimate, model error accounted for

METEO FRANCE
Toujours un temps d'avance

- Spectral block-diagonal approach :
  homogeneous correlations from EnDA.

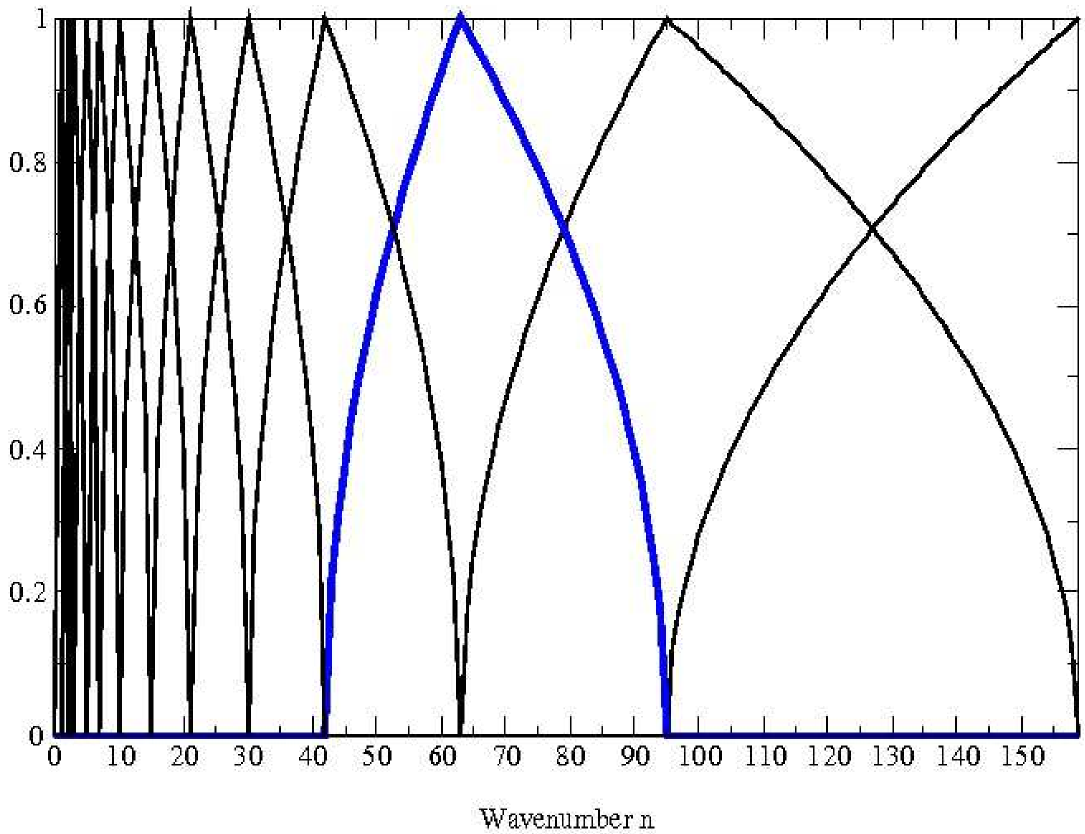
- Wavelet block-diagonal approach :

  heterogeneous correlations from EnDA.

⇒ Ecmwf : static heterogeneous correlations (Fisher 2003),
Météo-France : flow-dependent correlations (Varella et al 2011, 2013).

⇒ Implicit use of local spatial averages :
spatial filtering of sampling noise (Berre and Desroziers 2010).

Wavelet expansion of background error e_b using spectral bands ψ_j (Fisher 2003)



$$e_b(j) = \psi_j \otimes e_b$$

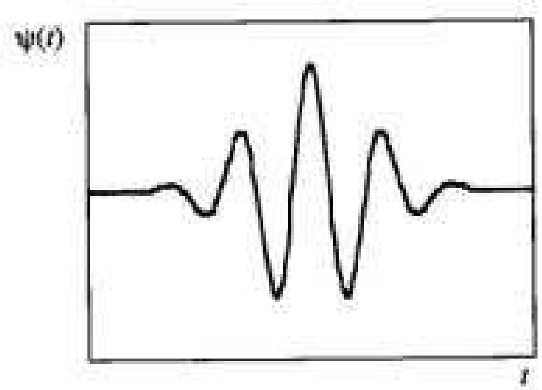
= local convolution in gridpoint space (at different scales).

$\Rightarrow$ infos about local spatial structures of e_b

Heterogeneous correlations using wavelets

- Wavelet expansion of background error field e_b :

$$e_b = \sum_j \psi_j \otimes e_b(j)$$

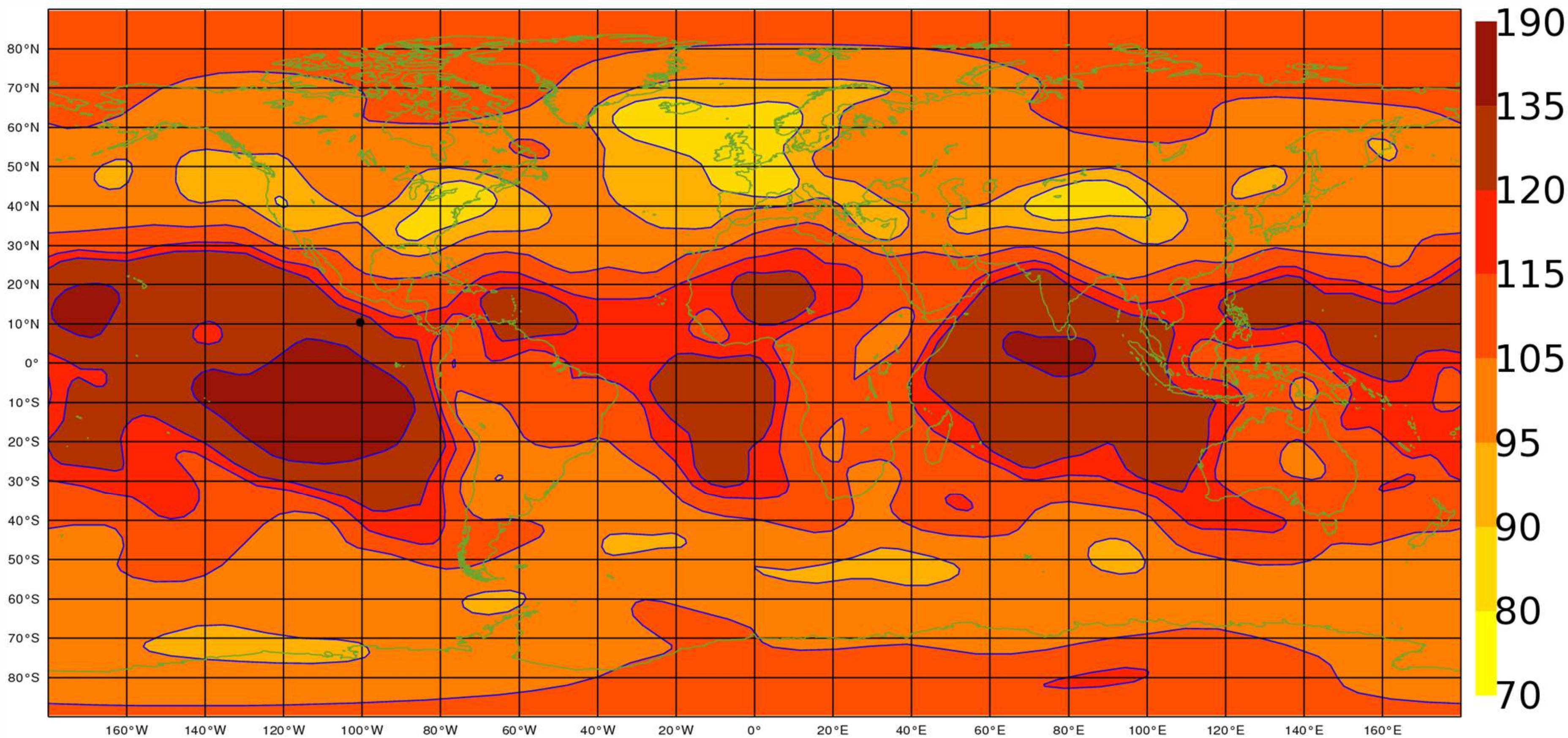


- Wavelet expansion of error covariances (using a (block-)diagonal assumption) :

$$\mathbf{B} = \sum_j \psi^2_j \otimes C_j(x,y)$$

$\Rightarrow$ Correlations vary as function of scale (j) and position (x,y).

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 2013)

METEO FRANCE
Toujours un temps d'avance

3. Preconditioning issues

and conclusions

Lanczos algorithm and preconditioning

$Ax = b$, where $A = B^{-1} + H^T R^{-1} H = J''$ is the Hessian matrix of J.

⇓

$KAx = Kb$ where K = preconditioning matrix written as $K = PP^T$

SPECTRAL	RITZ
$P^S = I - \Sigma_{j=1,k} [(1-\lambda_j^{-1/2}) u_j u_j^T]$	$P^R = I - \Sigma_{j=1,k} [(1-\theta_j^{-1/2}) z_j z_j^T + \omega_j z_j q_{k+1}^T]$
(λ_j, u_j) eigen values+vectors of A	(θ_j, z_j) Ritz pairs of A q_{k+1} last Lanczos vector of A $\omega_j = f$(primitive Ritz pairs of A)
⇓	⇓
in ARPEGE *(Fisher 1998)*	in NEMOVAR *(Tshimanga et al 2008)*

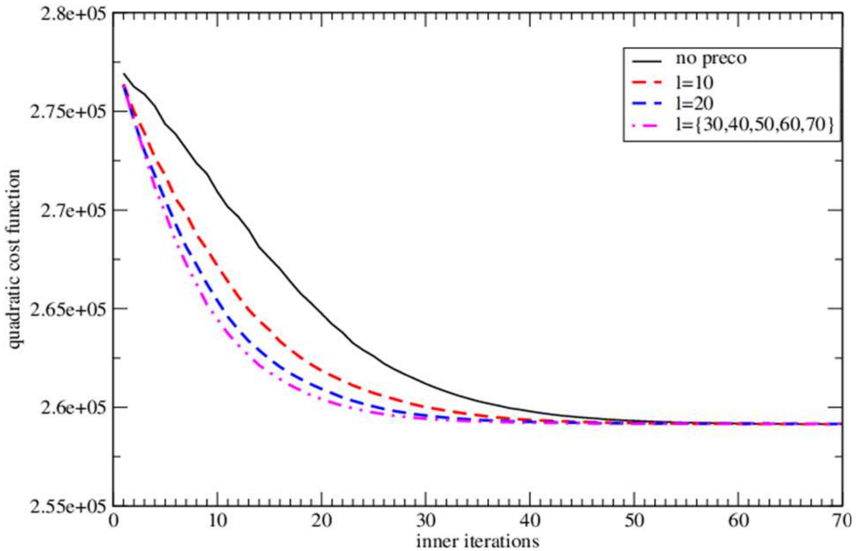
Limited Memory Preconditioners

Ritz / spectral comparison

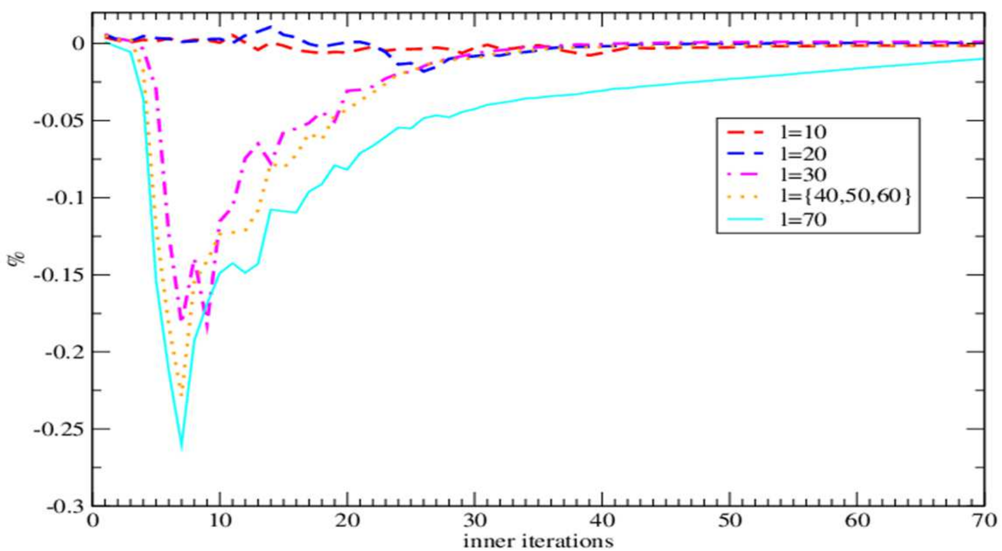
1st minim 70 iter ⇨ 70 pairs are available
2nd minim 70 iter / preconditioning by Ritz or spectral / from l=10 to l=70 pairs to be used.

Decrease of J during 2nd minim

Ritz (spectral)



Ritz - spectral



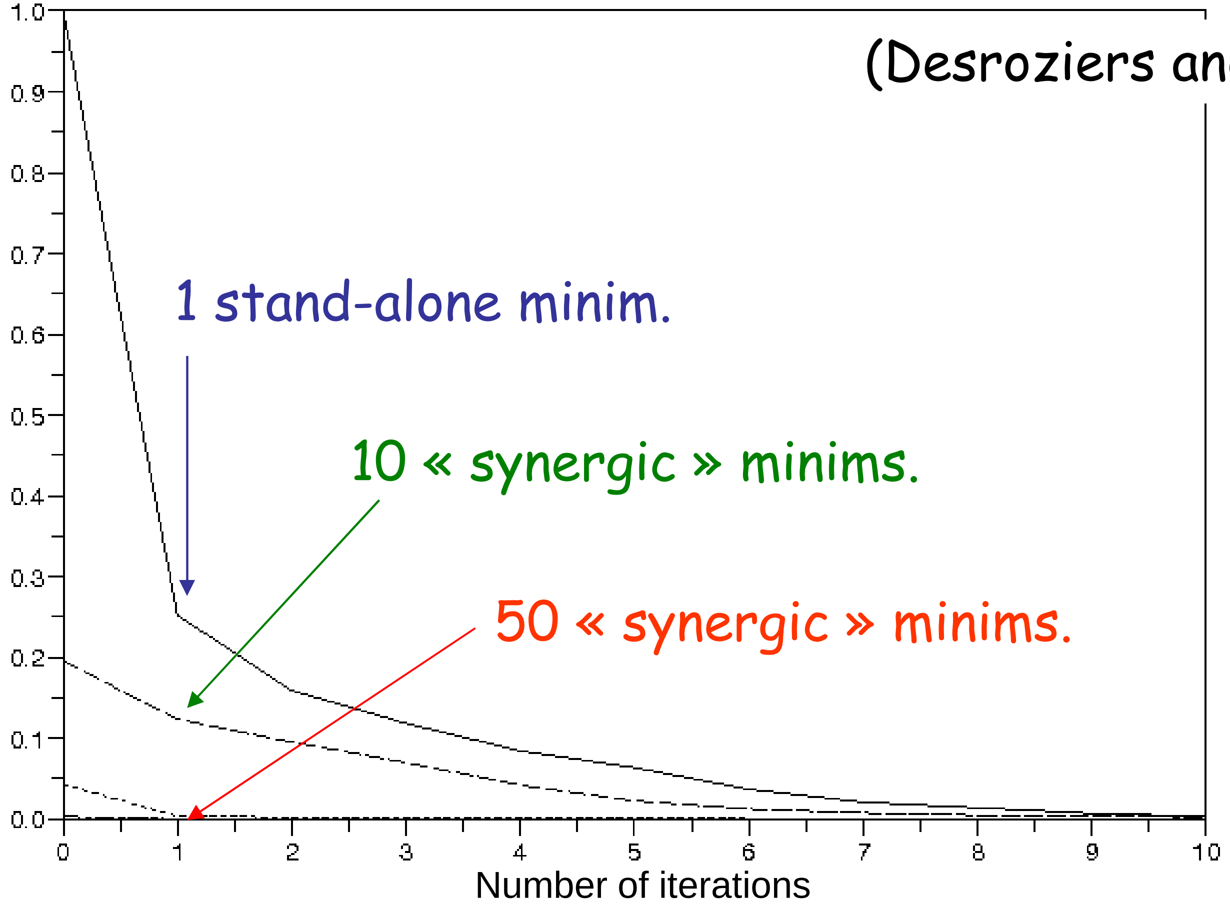
- LMPs improve decrease of J
- Improvement is larger when number of pairs increases up to ~ l=30
- Improvement is maximum for 10/15 iter in 2nd minim

- Ritz better than spectral for l ≥ 30 with max improvement for 8/10 iter in 2nd minim

METEO FRANCE
Toujours un temps d'avance

Accelerating and parallelizing Ensemble/Deterministic Var minimizations (proof of concept in 1D toy)

(Desroziers and Berre 2012)



Decrease of cost function (for a given member)
when using shared Lanczos vectors
for starting point and preconditioning

METEO FRANCE
Toujours un temps d'avance

Conclusions

- Data assimilation is vital for weather forecasting (NWP).
- Many issues and methods are transversal in geosciences (see e.g. A. Weaver's presentation).
- Variational techniques for 4D aspects and flexibility, including preconditioning issues (e.g. Gürol 2013).
- Ensemble methods for error simulation and covariance estimation.
- Observations for validation of error covariances, and for estimation of model errors.

Summary w.r.t. ADTAO

- Flow-dependent error correlations in wavelet space (Varella et al 2012, Fisher 2003).
- Estimation of model error covariances (Raynaud et al 2012, Daget et al 2009).
- Preconditioning of 4D-Var (Tshimanga et al 2008, Desroziers and Berre 2012).
- ADTAO project is a very good framework for transversal research collaborations (e.g. CERFACS).
- The combination of variational and ensemble methods is a crucial research axis (4DEnVar, AVENUE project).

References

Berre, L. and G. Desroziers, 2010:
Filtering of Background Error Variances and Correlations
by Local Spatial Averaging: A Review.
Mon. Wea. Rev., 138, 3693-3720.

Desroziers, G. and Berre, L., 2012 :
Accelerating and parallelizing minimizations in ensemble and deterministic
variational assimilations. QJRMS., 138, 1599–1610.

Varella, H., Berre, L., and Desroziers, G., 2011 :
Diagnostic and impact studies of a wavelet formulation of background error correlations
in a global model. QJRMS, 137, 1369-1379.

Raynaud, L., L. Berre, and G. Desroziers, 2012 :
Accounting for model error in the Meteo-France ensemble
data assimilation system. QJRMS, 138, 249-262.

Thank you

for your attention

Applications of EnDA at M.F.

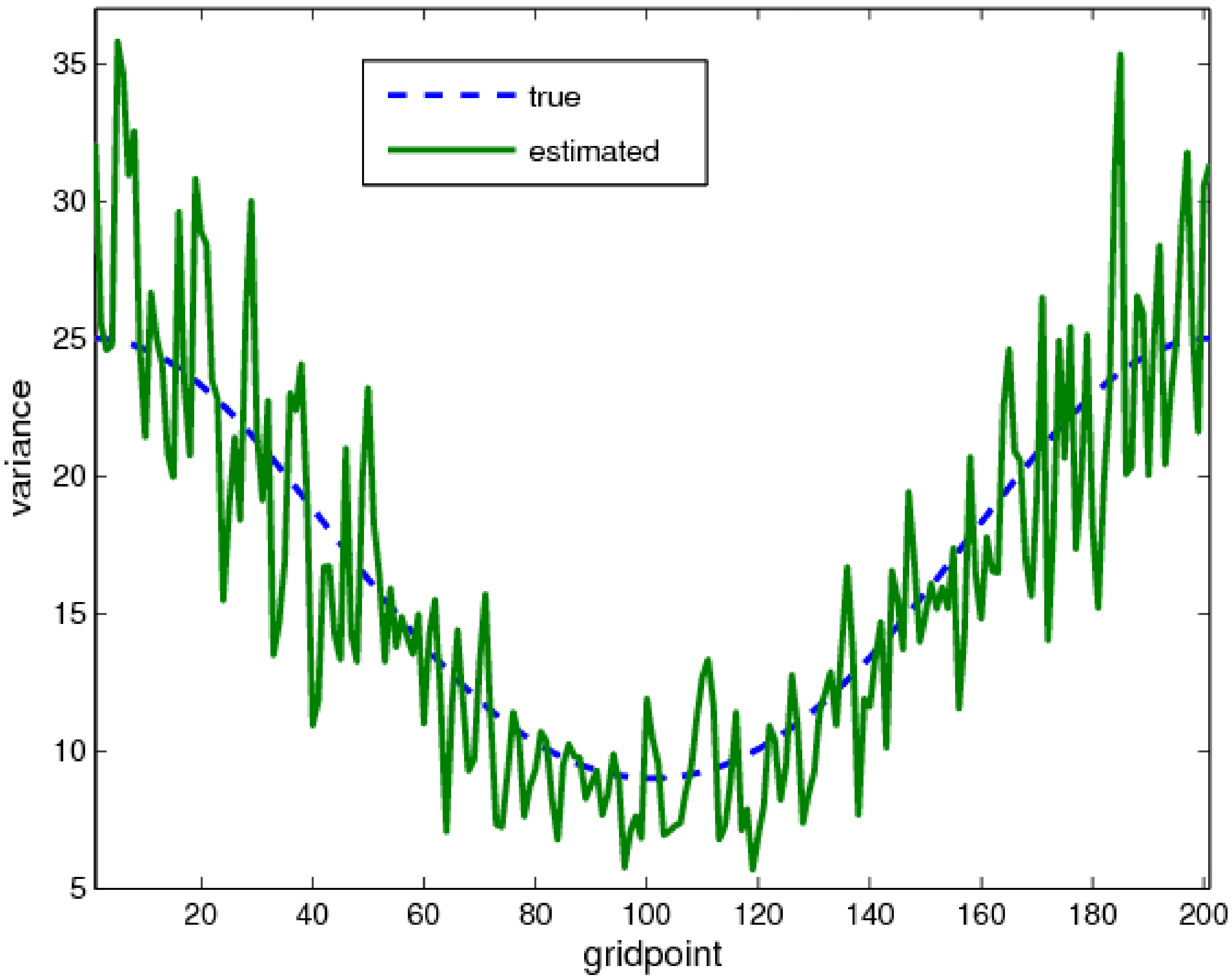
- Flow-dependent background error variances (oper 2008) (for all variables including humidity and unbalanced variables)

⇒ for **obs. quality control** and for **analysis (minimization).**

- Flow-dependent background error correlations experimented using wavelet filtering properties (Varella et al 2011, 2012).

- Initialisation of M.F. ensemble prediction (PEARP) by EnDA (2009) : EnDA is now a major component of PEARP.

Spatial structure of sampling noise for variances (Raynaud et al 2008a)



N = 50

L(ε_b) = 200 km

$\Rightarrow$ While the signal of interest is large scale,
the sampling noise is small scale.

Spatial structure of sampling noise for variances (Raynaud et al 2009)

Spatial covariance of sampling noise $V^e = V(N) - V^*$:

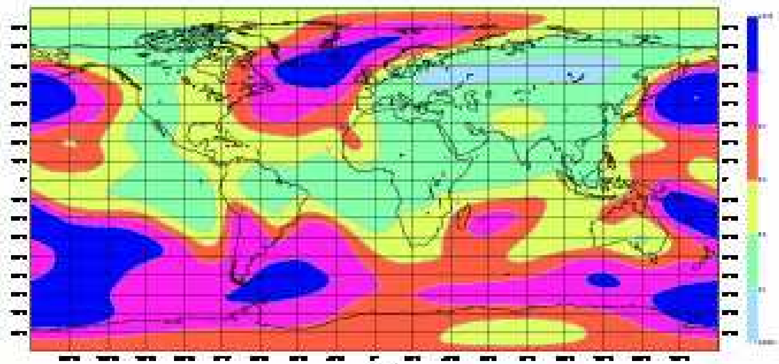
$$\overline{V^e (V^e)^T} = 2/(N-1) \; B^* \circ B^*$$

$B^* \circ B^*$ = Hadamard auto-product of $B^* = \overline{\varepsilon_b (\varepsilon_b)^T}$.

$\Rightarrow$ Structure of sampling noise V^e is closely connected to structure of background errors ε_b.

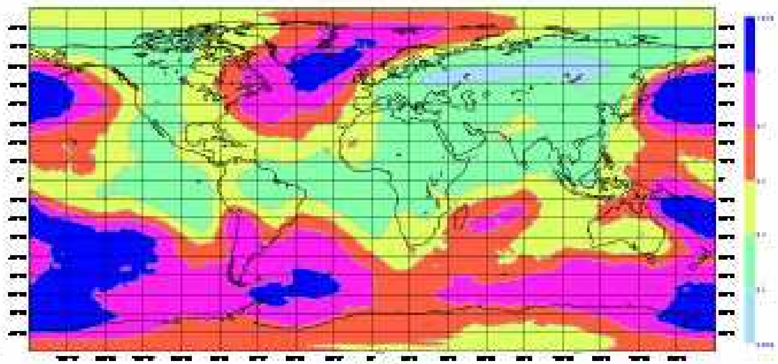
"OPTIMIZED" SPATIAL FILTERING
OF THE VARIANCE FIELD

« TRUE » VARIANCES

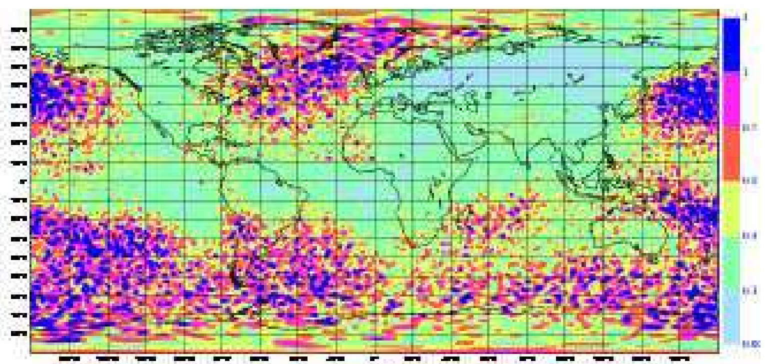


(a)

FILTERED VARIANCES (N = 6)



(b)



(c)

RAW VARIANCES (N = 6)

$$V_b^* \sim \rho \, V_b$$

where ρ = signal/(signal+noise)

(Berre et al 2007,2010, Raynaud et al 2008,2009,2011)