Hirlam + ALADIN = **HARMONIE** SMHI

Flow-dependent data assimilation from a scientific perspective

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(SMHI, AEMET, KNMI, Ljubljana University, ...)

ALADIN WK/ HIRLAM ASM

16-19 April 2018
Toulouse, Météo-France

What do we have now in HARMONIE

HARMONIE AROME 4DVAR

– outer and inner loops, multi-incremental
(to resolve weak and moderate non-linearities)

HARMONIE LETKF

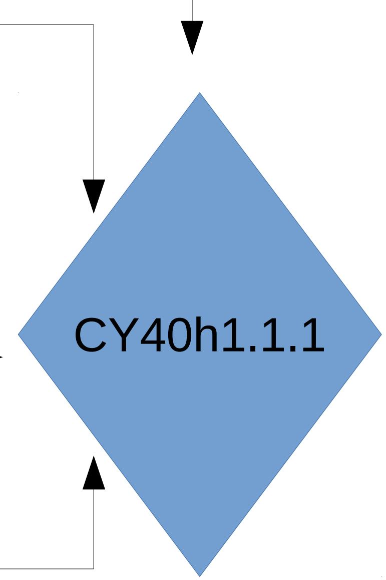
– a grid-point ensemble technique with local selection of observations and local analysis
(non-homogeneity, anisotropy,)

HARMONIE Hybrid EnVAR

– as a regularization constraint
(error-of-the-day ensemble information into variational framework with "global" selection of observation)

EPS branch

– model error uncertainty,
LBC,



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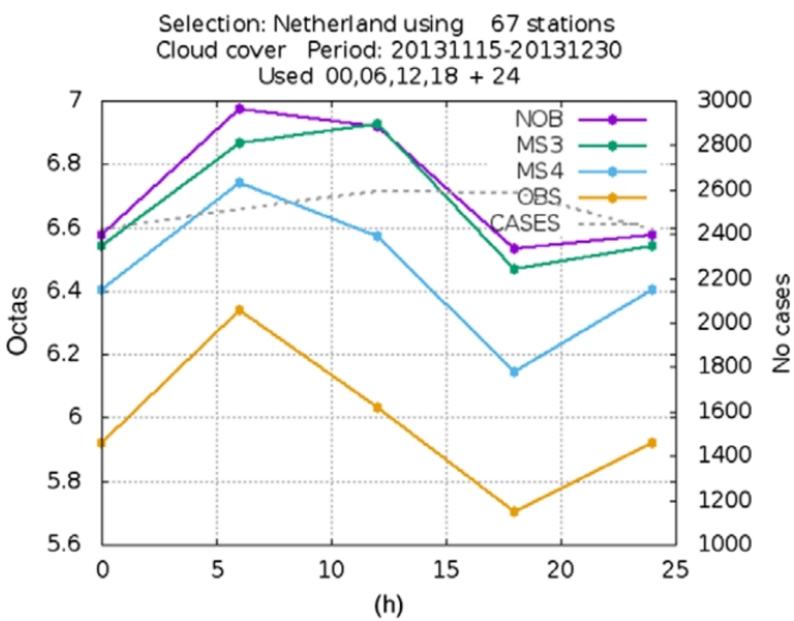
Impact of HARMONIE 4D-Var

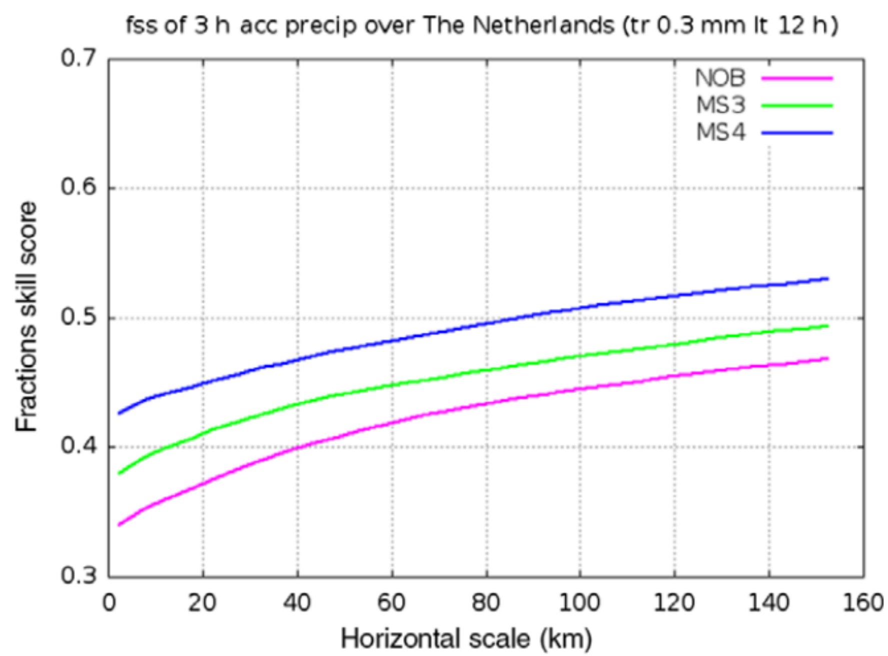
Daily cycle of Cloud cover

------------ no data assimiation
------------- 3D-Var
------------- 4D-Var
------------- observations



3 h acc. Precipitattion

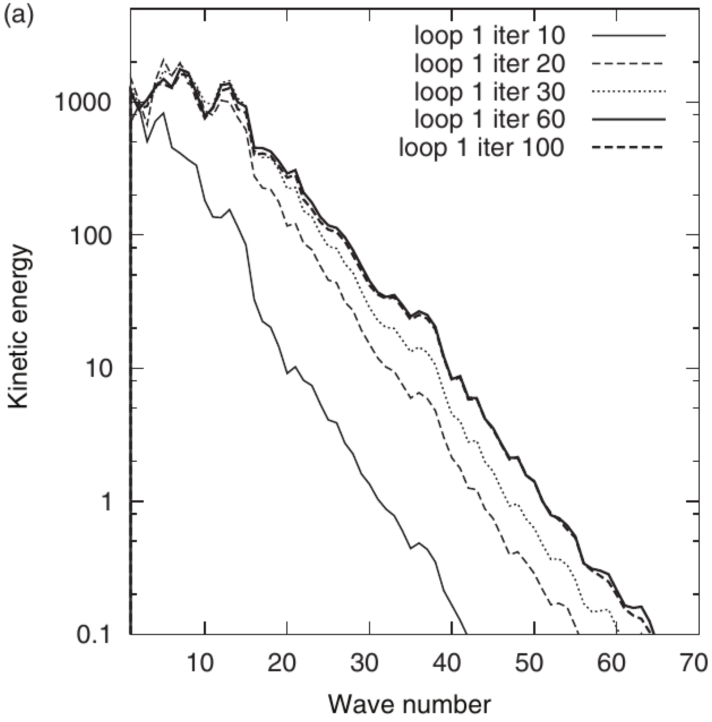
Fraction Scill Score
0.3 mm at 12h
------- no data assimilation
------- 3D-Var
------- 4D-Var



By Jan Barkmeijer

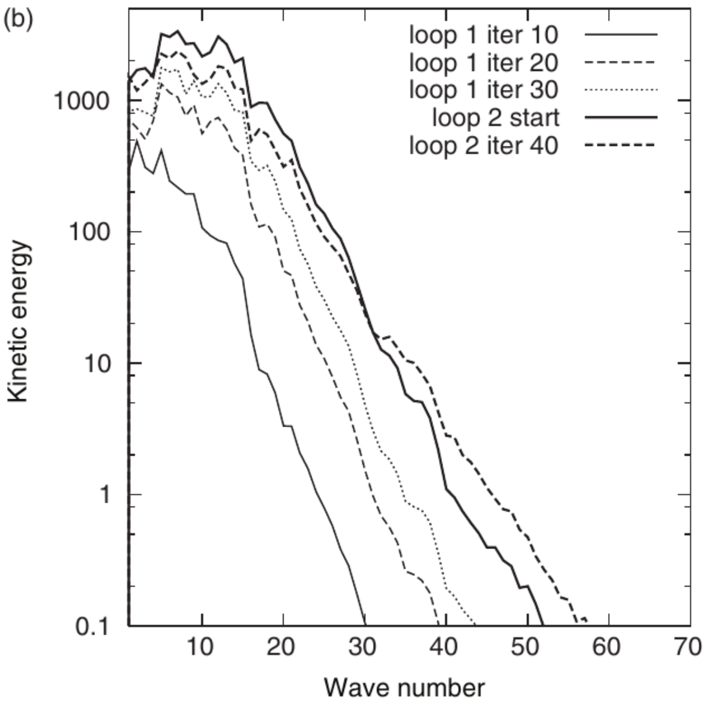
Importance of outer-loops and coarse-resolution DA

Kinetic energy spectra of assimilation increment for different iteration numbers; HIRLAM 4D-Var 24 km model



1 outer loop iteration
100 iterations at 48 km

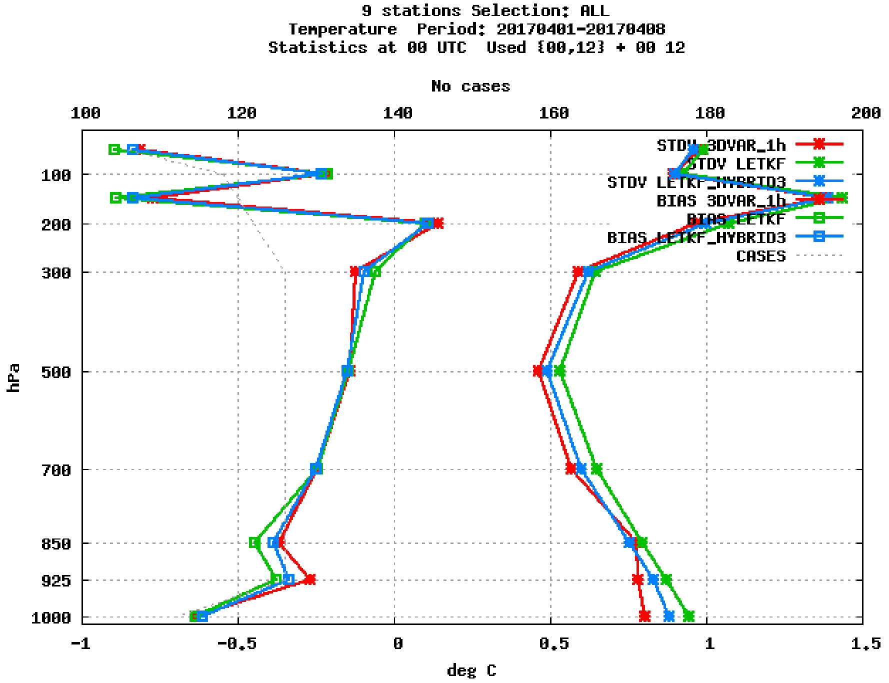
(Gustafsson et al 2012)



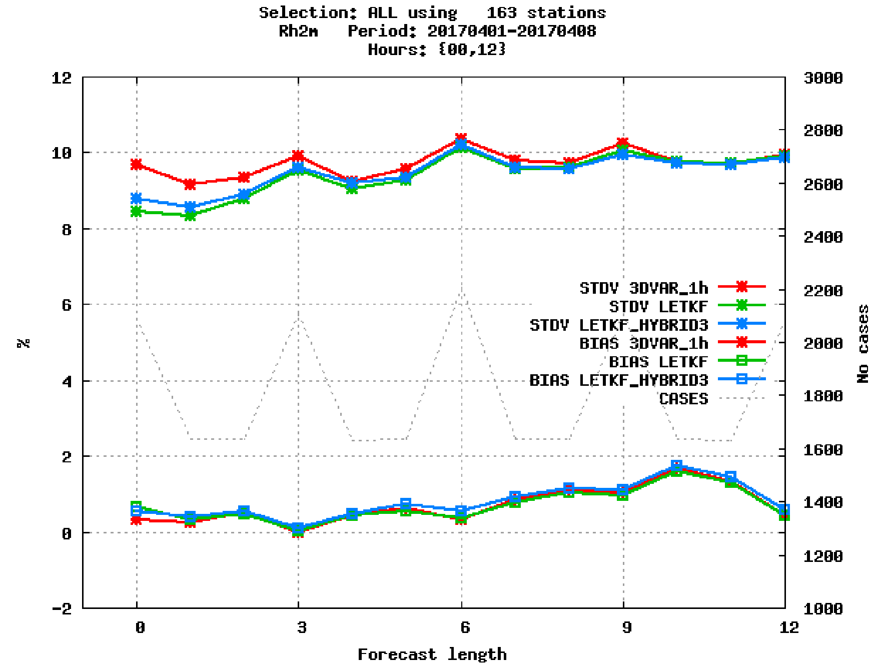
2 outer loop iterations
60 iterations at 96 km
40 iterations at 48 km

Hybrid 3DVAR/LETKF in HARMONIE

Temperature



RH2m



(By Pau Escribá)

AnHyb = K*AnLETKF + (1-K)*An3DVAR

K = O.5

HARMONIE Hybrid EnVAR finally works !

Implementation as in

A hybrid variational ensemble data assimilation for the HIgh Resolution Limited Area Model (HIRLAM)

N. Gustafsson[1], J. Bojarova[2], and O. Vignes[2]

$$J(\delta \boldsymbol{x}_{\text{var}}, \boldsymbol{\alpha}) = \beta_{\text{var}} J_{\text{var}}(\delta \boldsymbol{x}_{\text{var}}) + \beta_{\text{ens}} J_{\text{ens}}(\boldsymbol{\alpha}) + J_{\text{o}} \qquad (6)$$

$$\frac{1}{\beta_{\text{var}}} + \frac{1}{\beta_{\text{ens}}} = 1.$$

$$J_{\text{ens}} = \frac{1}{2} \boldsymbol{\alpha}^T \mathbf{A}^{-1} \boldsymbol{\alpha}$$

$$\mathbf{B}_{\text{ens}} = \mathbf{A} \circ \mathbf{B}_{\text{raw-ens}}$$

Ensemble : 20 members of BRAND perturbations
Localisation : spectrum of unbalanced surface pressure

Convergence of Hybrid EnVar

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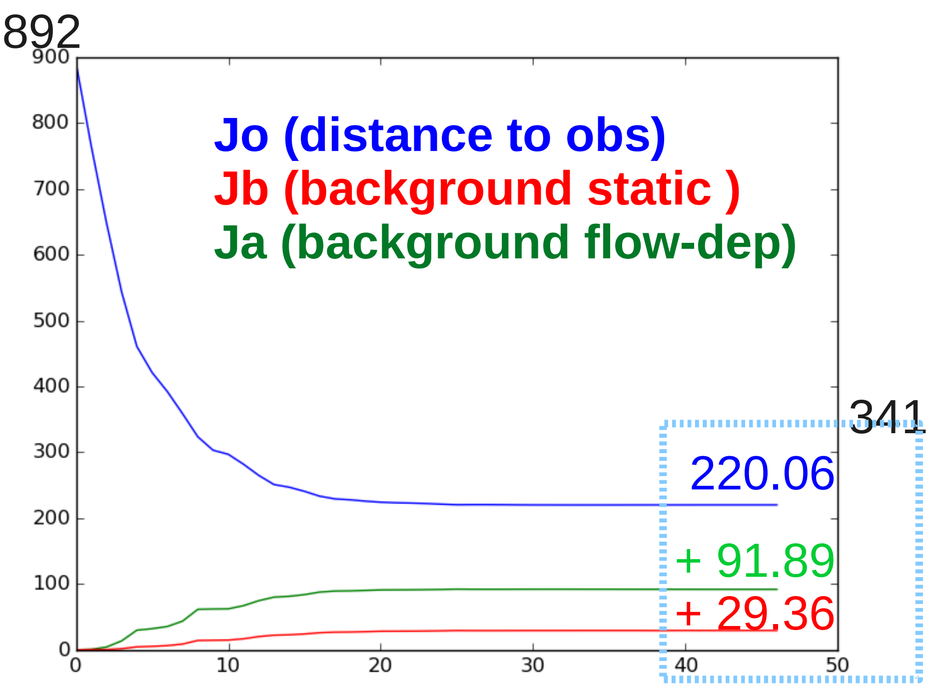
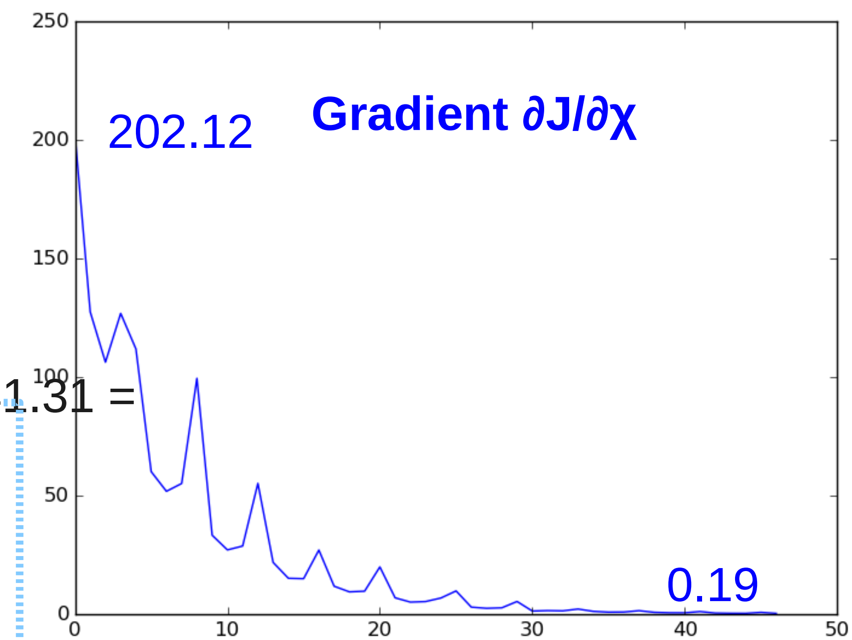
YQ%LGP=.TRUE. YQ%LSP=.FALSE.	=>	YQ%LGP=.FALSE. YQ%LSP=.TRUE.	+	Qtrans





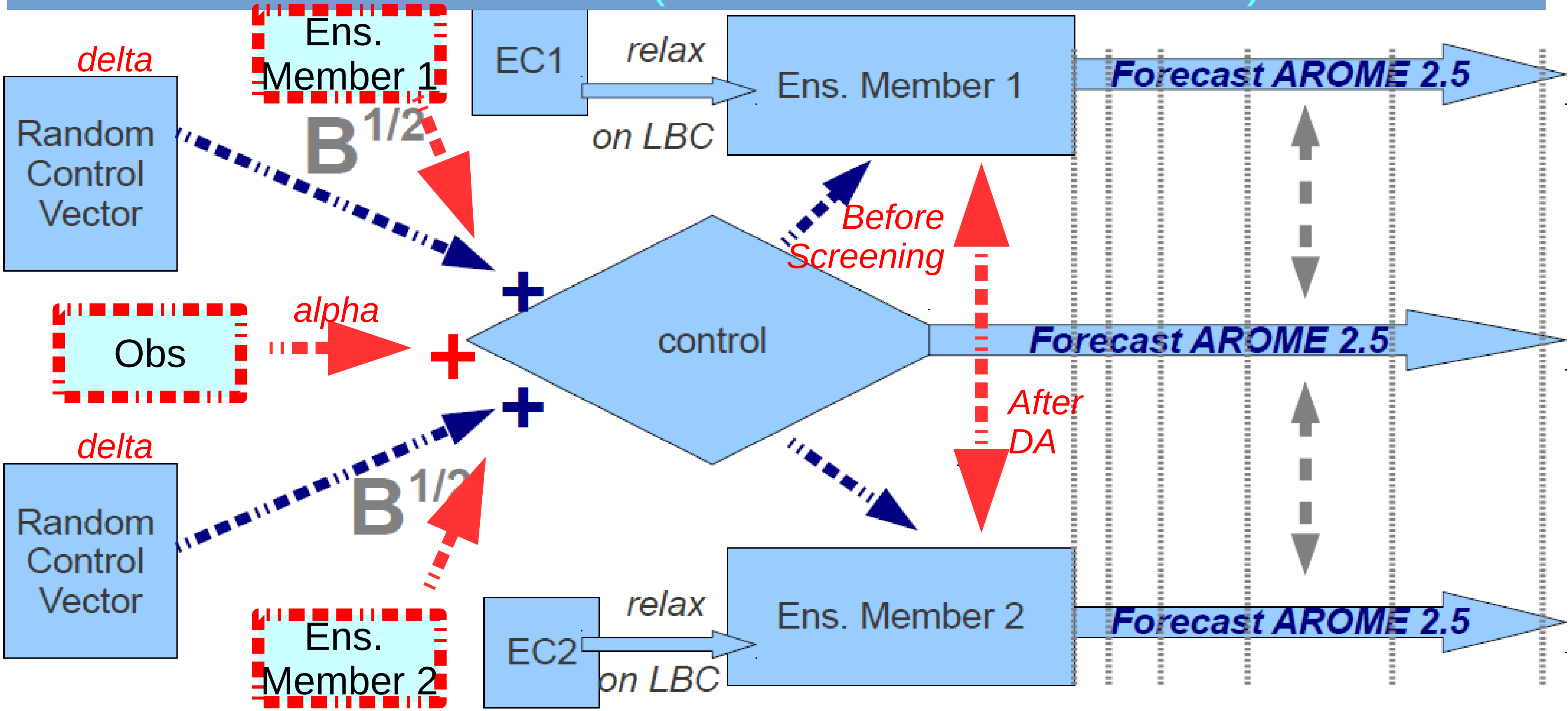
$J(\chi) = 2Jb + 2Ja + Jo$

$\min_{\chi} J(\chi) \Rightarrow$ $\boldsymbol{\partial J/\partial \chi = 0}$

Example 20120613_21 DKCOEXP (10 members)

“Brand” perturbations

10 members+control (2012061203 - 2012062718)



The Scheme: generation of perturbations with the structure of B-matrix covariance. (depends on configuration)

Hybrid EnVar EPS

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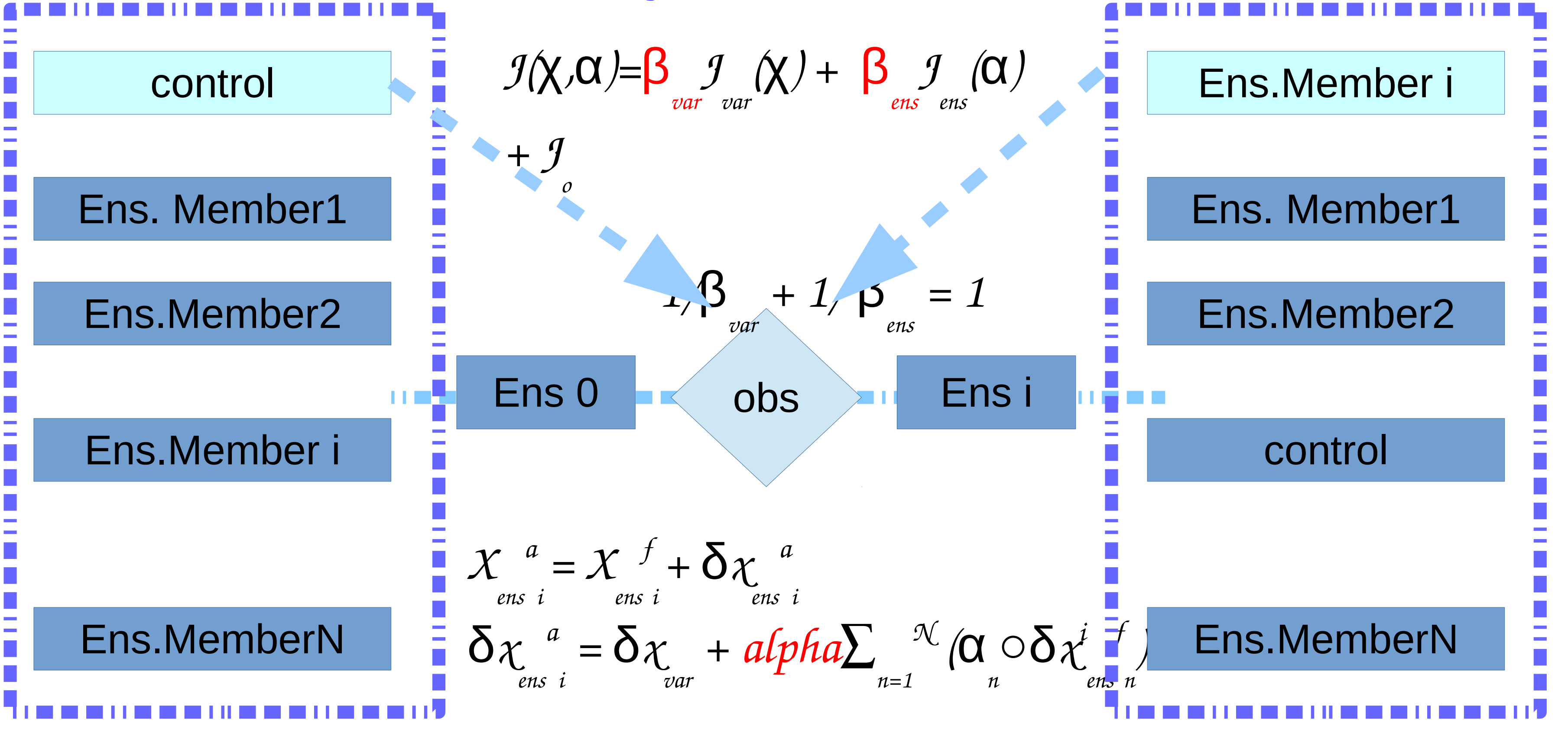
N+1 Hybrid EnVAR runs

$$\mathcal{J}(\chi,\alpha)=\beta_{var}\mathcal{J}_{var}(\chi)+\beta_{ens}\mathcal{J}_{ens}(\alpha)+\mathcal{J}_{o}$$

$$1/\beta_{var}+1/\beta_{ens}=1$$



$$x^{a}_{ens\ i}=x^{f}_{ens\ i}+\delta x^{a}_{ens\ i}$$

$$\delta x^{a}_{ens\ i}=\delta x_{var}+alpha\sum_{n=1}^{\mathcal{N}}(\alpha_{n}\circ\delta x^{i\ f}_{ens\ n})$$

$X^{0,f}_{ens}$

values of tunable parameters might be different for control and ensemble members

$X^{i,f}_{ens}$

Genealogical Tree of DA Algorithms

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3D-Var: single time, clim. forecast error stat.

4D-Var: time window

LETKF / **3DEnVar**

3D ens. forecast error stat.

single time

local obs. sel / global obs. sel

ens. space form. / var form.

Hybrid 4D-Var:
time window
3D forecast error stat.

4D LETKF / **4DEnVAR**

4D ens. forecast error stat.

Hybrids: Mixed clim. and ens. forecast error statistics

Different perturbation generation techniques

Samples forecast model error space : **BRAND**

$$\delta x_i = B^{1/2}\,\delta\xi_i \,,\ \xi_i \sim \mathcal{N}(0,1) \qquad i = 1,\ldots,N^{ens}$$

Mimics analysis error behaviour : **EDA**

$$H(x^f+\delta x_i) + HBH^T(HBH^T+R)^{-1}(y+\varepsilon_i - Hx^f - H\delta x_i)$$

$$-Hx^f \qquad -HBH^T(HBH^T+R)^{-1}(y- \quad Hx^f) \ \Rightarrow$$

$$\delta x^a_i = \delta x_i + BH^T(HBH^T+R)^{-1}(\varepsilon_i - H\delta x_i)\ ,\ \ \varepsilon_i \sim \mathcal{N}(0,1)$$

Quantifies analysis error uncertainty : **ETKF**

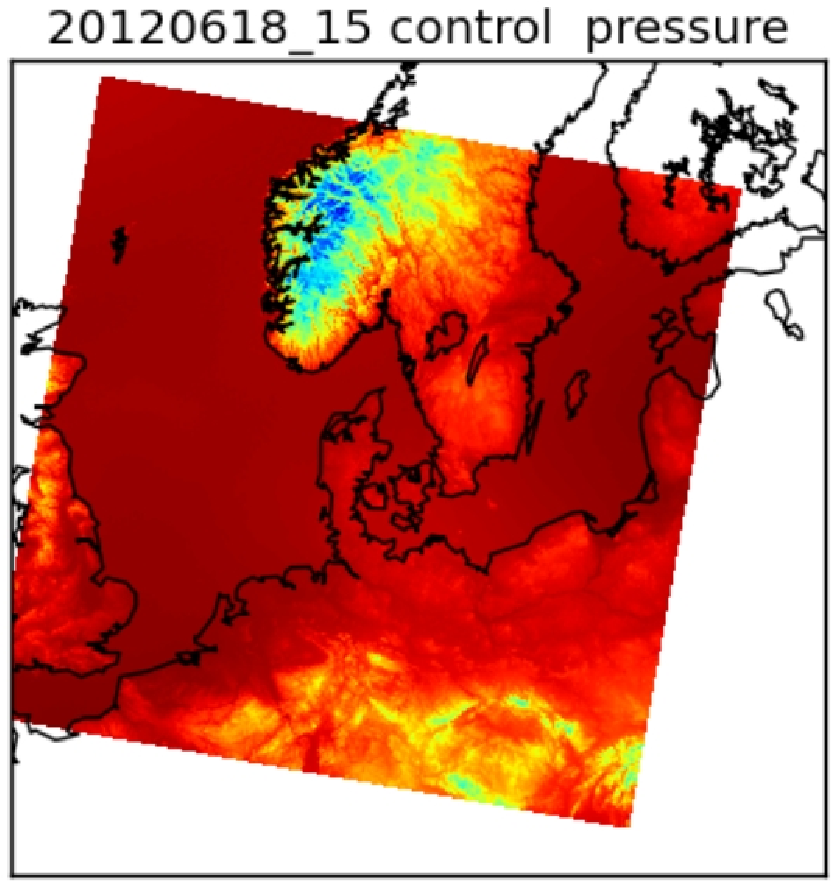
$$B^a = B - BH^T(HBH^T+R)^{-1}HB;\ U = (\delta x_1, \ldots, \delta x_i, \ldots, \delta x_{N_{ens}})$$

$$B = UU^T,\ B^a = U^a(U^a)^T,\ U^a = UV\ ;\ \ U_{mxN_{ens}}\ ,\ V_{N_{ens}xN_{ens}} \ \Rightarrow$$

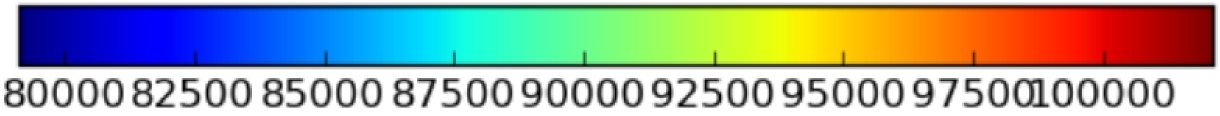
LETKF

$$H \rightarrow H(z)_{loc}\ ,\ \ V \rightarrow V(z)_{loc}\ ,\ U^a(z)_{loc} = U\,V(z)_{loc}$$

Domain and orographic conditions



Surface pressure



The weather situation

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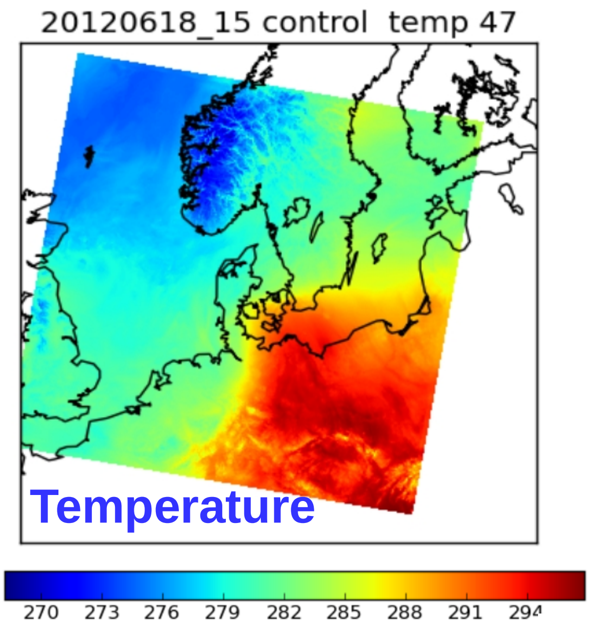
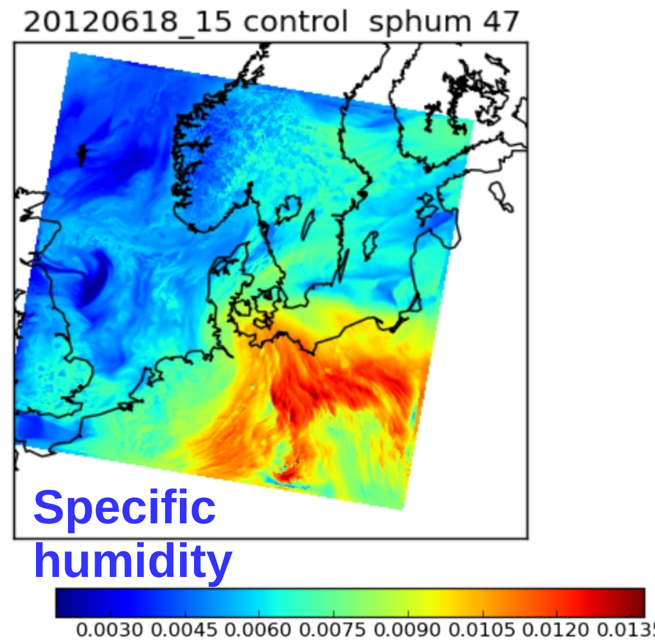


Strong front (around 850hPa):
warm and wet air meets cold and dry air.

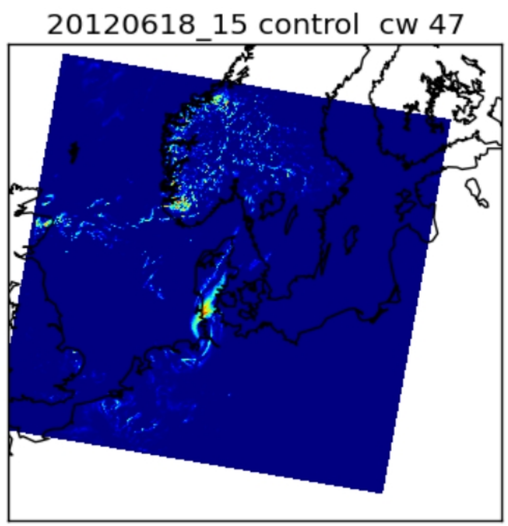
Valid time 20120618 18UTC

Forecast +03h



We impose perturbations

Temperature, humidity, u- ans v- winds components, surface pressure

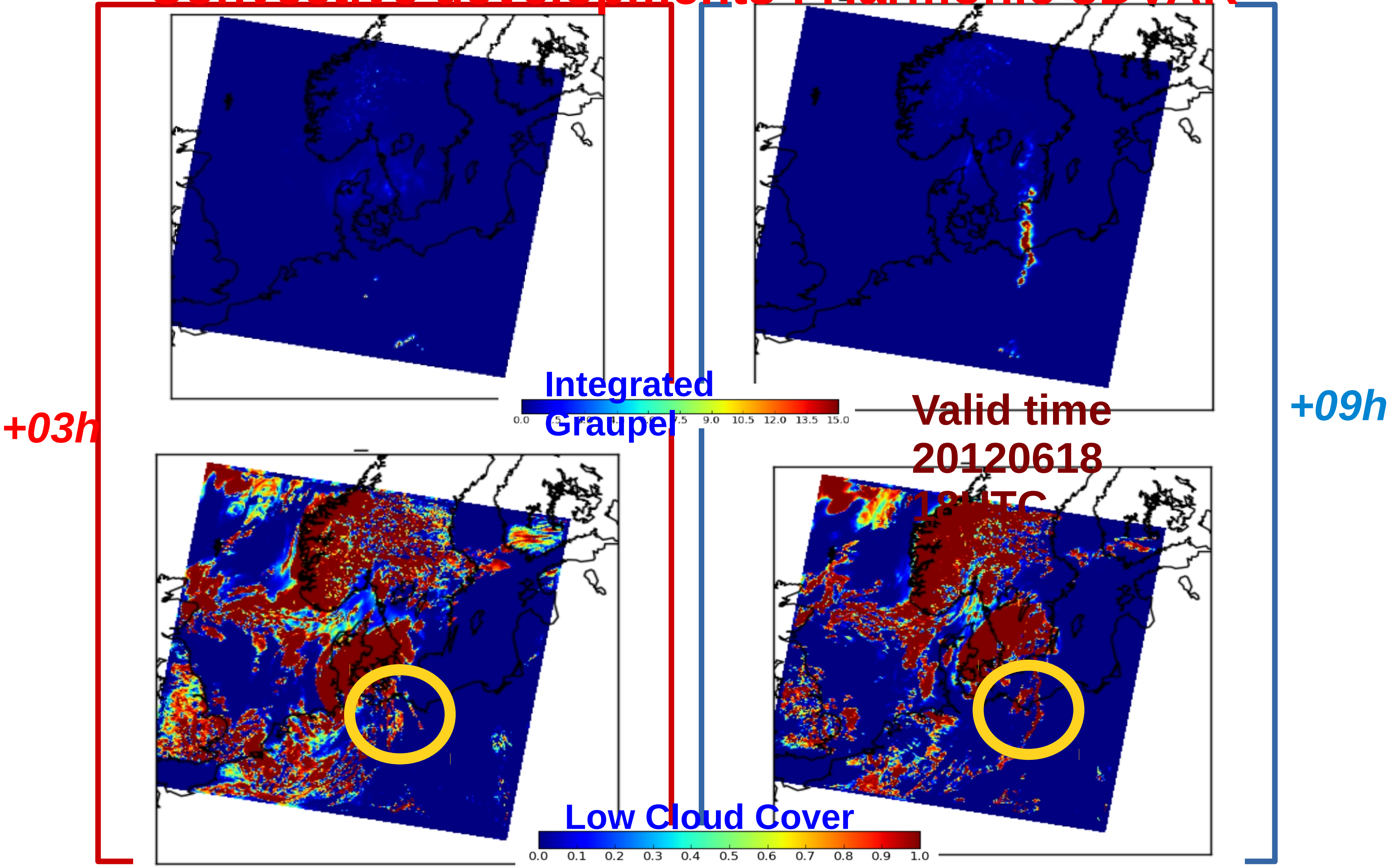


We obtaine response

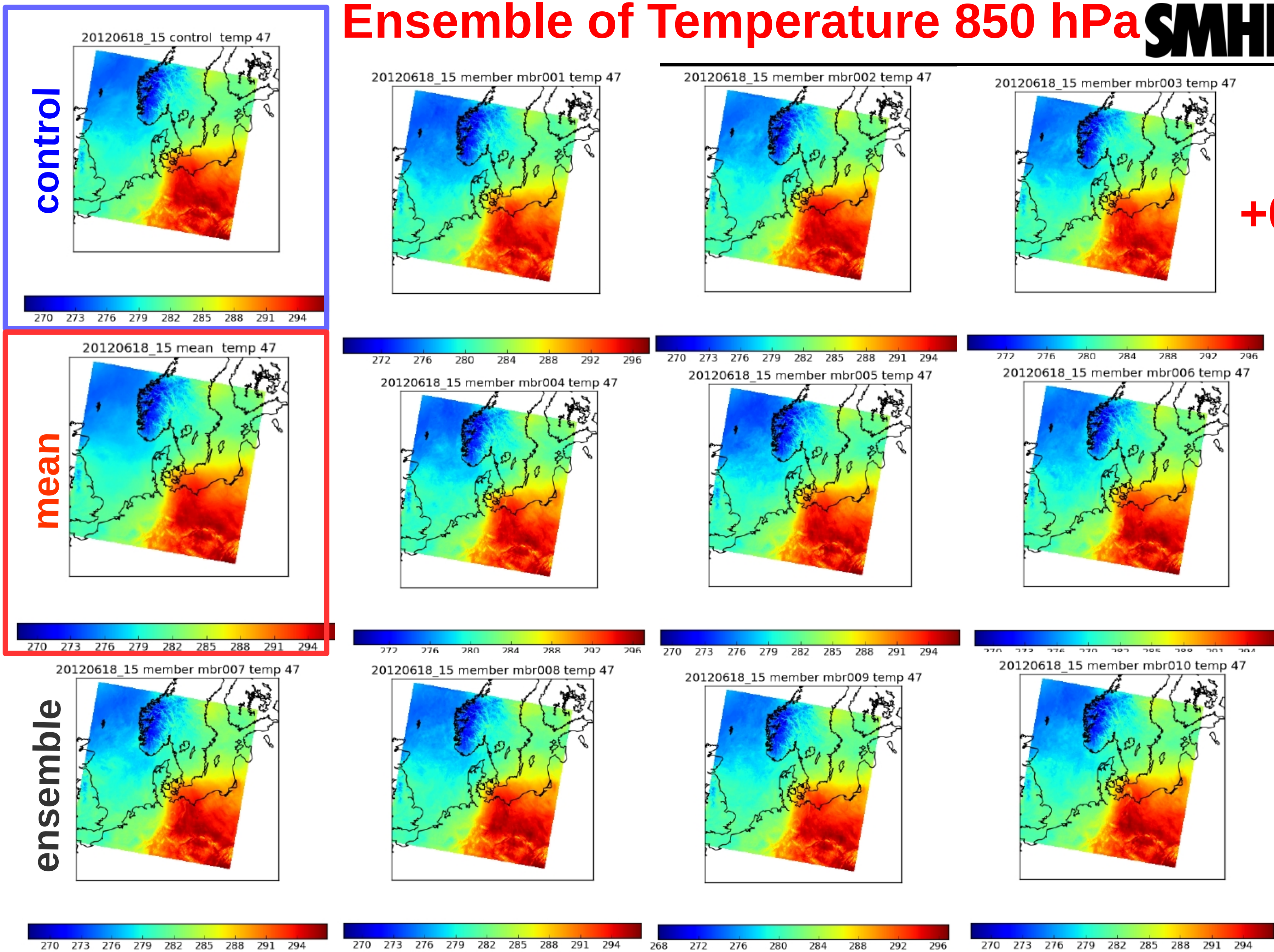
Cloud Water around 850hPa

Cloud water is a small scale field that depends on spatial derivatives of temperature and humidity

Convective developments : Harmonie 3DVAR



Ensemble of Temperature 850 hPa



+03h

Ensemble of Specific Humidity 850 hPa +3h

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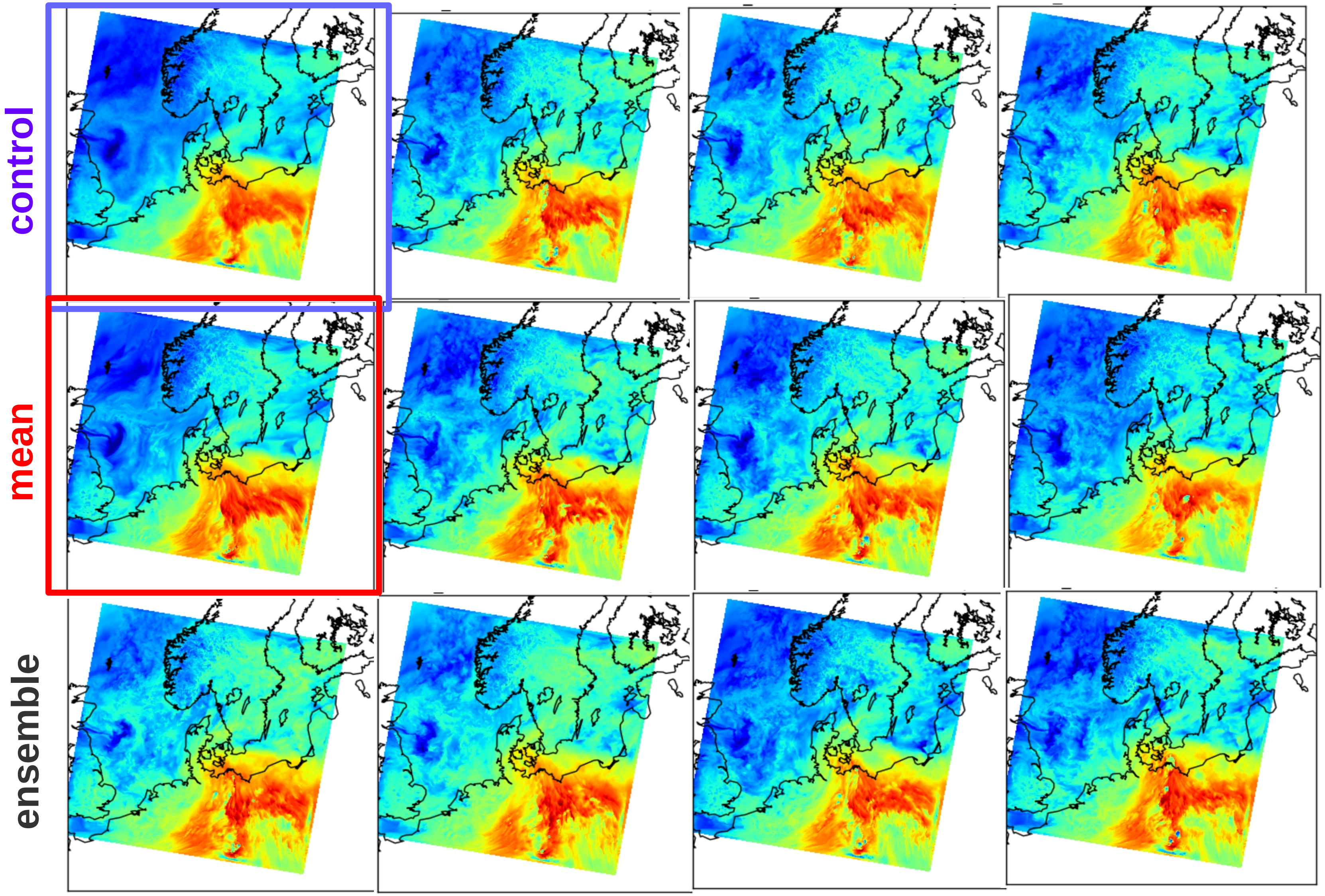

Ensemble of Integrated Graupel +3h

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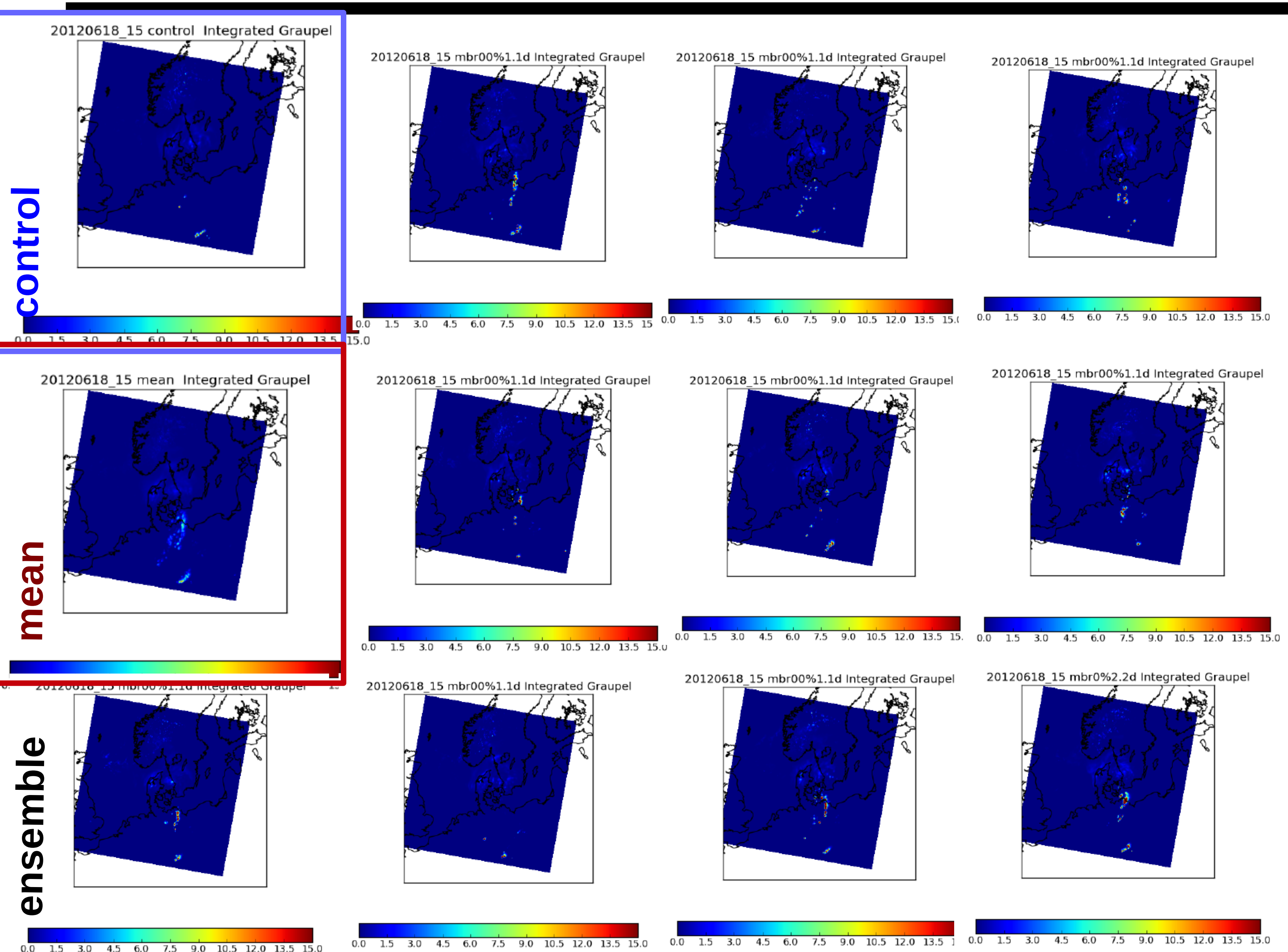

Model for the background error covariance

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Climatological

$$X = \mathbf{B}^{1/2}\xi$$

$$\mathbf{B}^{-1/2} = VD^{-1}F$$

where

$\boldsymbol{B}^{-1/2}$ is the inverse of square-root of the background error covariance,

$\boldsymbol{F}$ is horizontal 2-dimensional Fourier transform from physical grid-point space to spectral space,

$\boldsymbol{D}^{-1}$ is a de-correlation operator,

$\boldsymbol{V}$ is a vertical transform utilizing the eigenvectors of vertical covariance matrices.

Ensemble estimate

$$\mathbf{B}_{\text{ens}} = \mathbf{A} \circ \mathbf{B}_{\text{raw-ens}}$$

Balance operator and assumptions

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(Powerful diagnostic tool)

It is assumed that background error statistics are homogeneous => the spectral component for different wave-numbers are statistically uncorrelated
It is assumed that background error statistics are isotropic in horizontal=> the horizontal correlations can be represented via 1D spectra for control variables

The balance operator D is derived in spectral space through step-wise multivariate statistical regression technique for each wave number component separately

Inertia-Gravity waves (IGW)

$$
\begin{aligned}
\zeta &= \zeta \\
\eta &= MH\zeta + \eta_u \\
(T, P_s) &= NH\zeta + P\eta_u + (T, P_s)_u \\
q &= QH\zeta + R\eta_u + S(T, P_s)_u + q_u
\end{aligned}
$$

Rossby waves

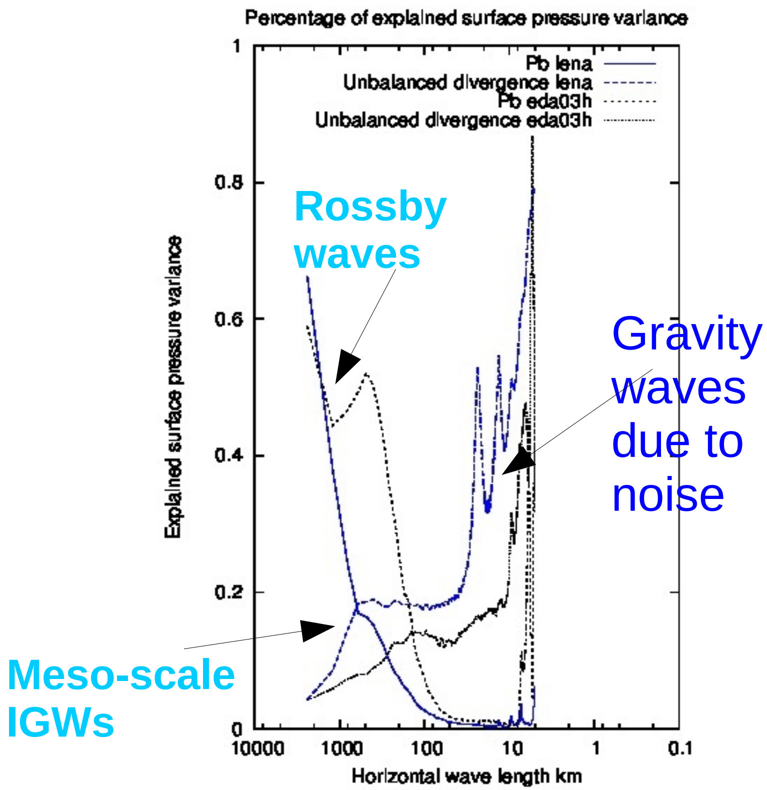
Structure functions derived from different ensembles

EDA with perturbed observations

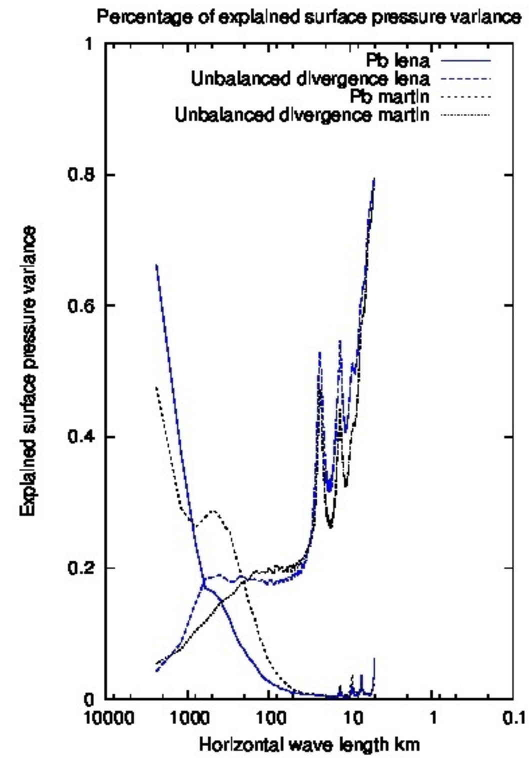
BRAND: additative inflation to control BG

Surface pressure variance explained by
- vorticity (solid line)
- unbalanced divergence (dashed line)

EDA conv (6 hour DA cycle)



EDA MetCoOp (3 hour DA cycle)



(thanks to Nils Gustafsson and Martin Ridal)

What is the origin of mesoscale inertia-gravity waves?

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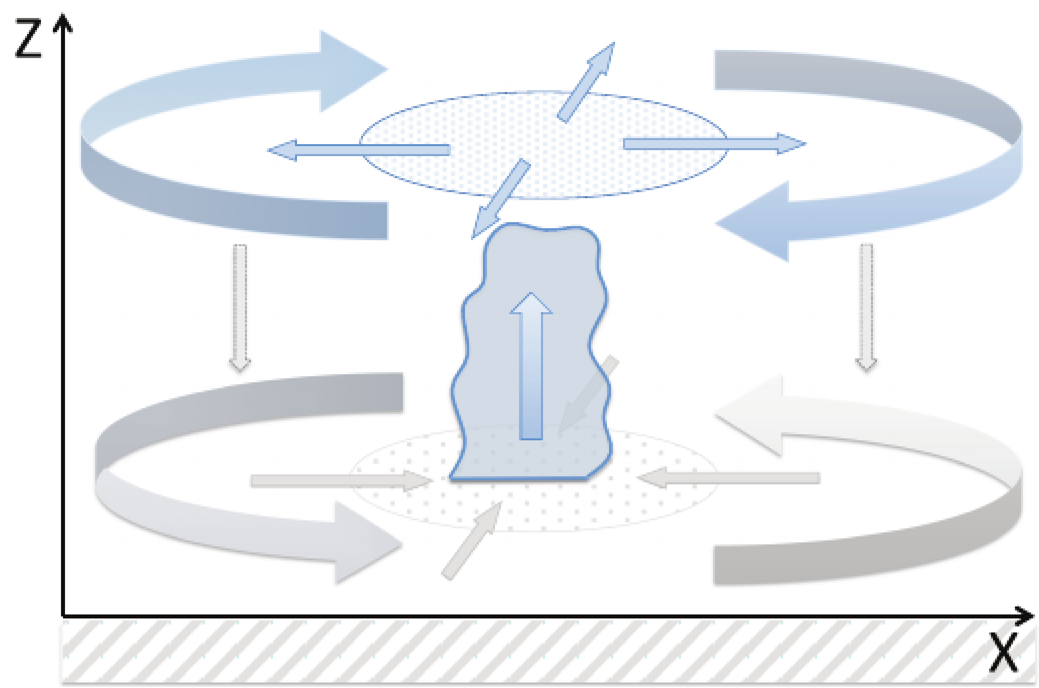
One example of a source: Schematic illustration of the geostrophic adjustment process governing upscale growth of errors from the convective scales:



From **Bierdel, Selz and Craig, 2017**, Theoretical aspects of upscale error growth through the mesoscales: an analytical model

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Jean-Francois Geleyn, 2006, during joint HIRLAM-ALADIN planning of mesoscale data assimilation:

"How to project on a good estimate of the moist attractor before it anyhow moves away?"

Very different time scales of convective processes and inertia-gravity waves => learn from turbulence and sub-grid variability

Are variational techniques still appropriate? Should we put more efforts in altewrnative data assimilation schemes (particle filters)?

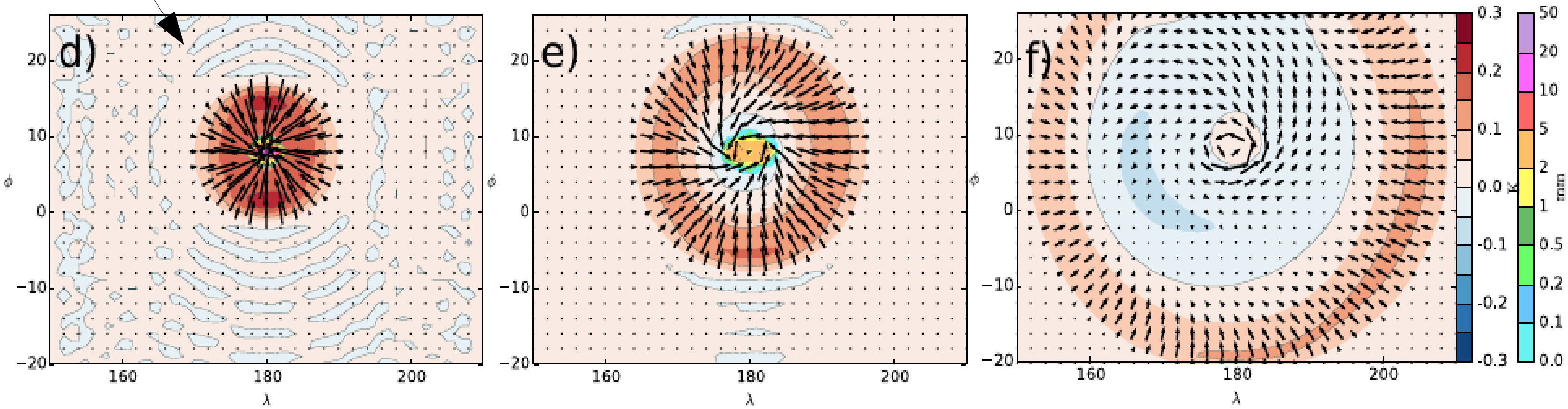
Could 4DEnVAR help (“a simple exercise”)?

Equatorial domain shallow water model; moisture and condensation added.

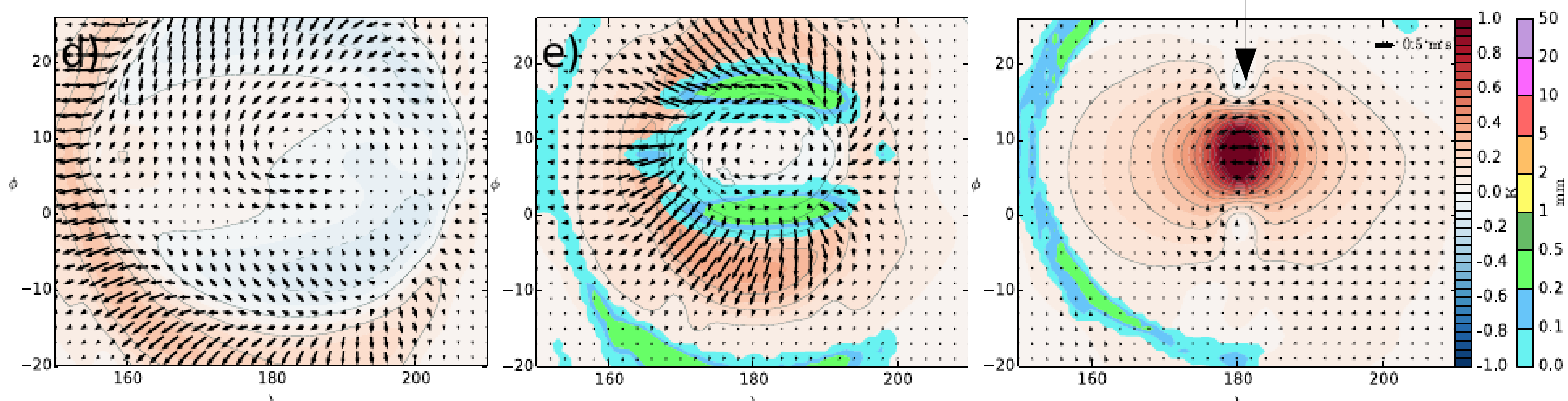
By Ziga Zaplotnik et al 2018

Forward non-linear model sensitivity experiment from a temperature perturbation at +0h

+3 h **+6 h** **+12 h**



4D-Var data assimilation experiment with a temperature observation at +12h



+0 h **+6 h** **+12 h**