The HIRLAM hybrid variational ensemble data assimilation

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Motivation

- To introduce flow-dependent covariances of background errors – flow-dependency becomes more important at mesoscale
- To stay within the framework of variational assimilation
- To preserve the full rank covariance
- To pave the path for structure assimilation

Basic formulation

Following Lorenc (2003), we consider the assimilation increment δx to include two parts, one part δx_{3D-Var} corresponding to the constraint given by the static part of the background error covariance, and another part that is a linear combination of the ensemble perturbations, i.e. the deviations between the ensemble members and the ensemble mean:

$$\delta x = \delta x_{3D-Var} + \sum_{k=1}^{K} (\alpha_k \circ \delta x_k^{ens})$$

where K is the number of ensemble members, α_k is the weight given to ensemble member k in the linear combination of ensemble perturbations and

$$\delta x_k^{ens} = x_k^{ens} - \frac{1}{K} \sum_{l=1}^{K} x_l^{ens}$$

is the ensemble perturbation, i.e. the deviation of the k'th background ensemble member from the ensemble mean. The weights given to the ensemble background perturbations may be functions of horizontal and vertical position and these weights are determined by adding an ensemble constraint $J_{ens}(\alpha)$, being a function of the vector α of all the weights for the different ensemble members, to the cost function to be minimized. Thus, in the case of a hybrid 3D-Var ensemble data assimilation we will have for the total cost function

$$J(\delta x_{3D-Var}, \alpha) = \beta_{3D-Var} J_{3D-Var}(\delta x_{3D-Var}) + \beta_{ens} J_{ens}(\alpha) + J_o$$

where $J_{3D-Var}(\delta x_{3D-Var})$ denotes the original 3D-Var background error constraint, based on a static background error covariance, and J_o the original 3D-Var observation constraint.

In order to preserve total background error variance, the weights for the two parts of the background error cost-function terms need to fulfill

$$\frac{1}{\beta_{3D}} + \frac{1}{\beta_{ens}} = 1$$

The ensemble background error cost function can be formulated in the following way

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

where the covariance matrix $\mathbf{A}$ can be interpreted as a covariance for localized ensemble member weights described by, for example, a variance and a spatial scale of the localized ensemble weights. In the expressions above $\alpha_k \circ \delta x_k^{ens}$ means element-by-element multiplication with a similar localization effect as the Schur product in the covariance localization.

HIRLAM implementation of the hybrid

- The ensemble perturbation weights α are dependent on horizontal position only and are controlled in spectral space (assuming homogeneity with respect to correlations).
- The horizontal scale of the ensemble perturbation weights (of the order of 500-1000 km) is given via a horizontal autocorrelation function (equivalent to the covariance localization in EnsKF).
- In order to reduce the effects of the localization on balances, ensemble perturbations are represented by vorticity, divergence, surface pressure, temperature and specific humudity.
- The hybrid scheme can be applied with 3D-Var as well as 4D-Var

ETKF re-scaling in HIRLAM

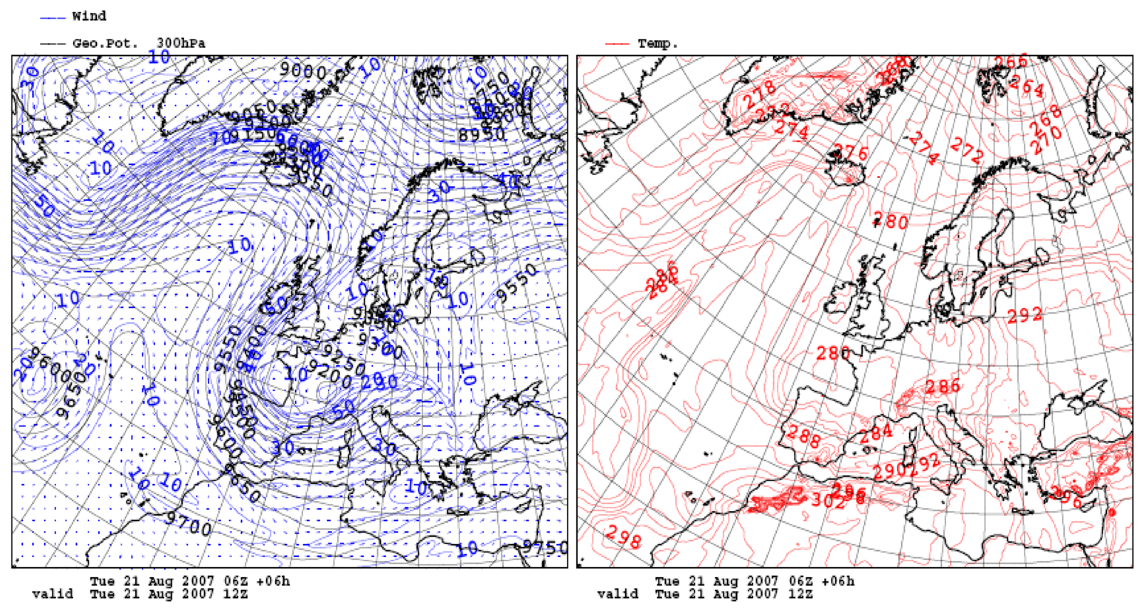
Analysis ensemble perturbations are derived from forecast ensemble perturbations through an Ensemble Transform Kalman Filter (ETKF, Bishop et a1. 2001):

- Application of the real observation distributions (conventional data so far)
- Multiplicative inflation by comparing ensemble variance with innovations.
- Additative inflation by adding random perturbations based on the 3D-Var background error covariance
- Lateral boundary conditions from ECMWF TEPS
- Adjustment toward ECMWF TEPS also in the stratosphere

Perspective:

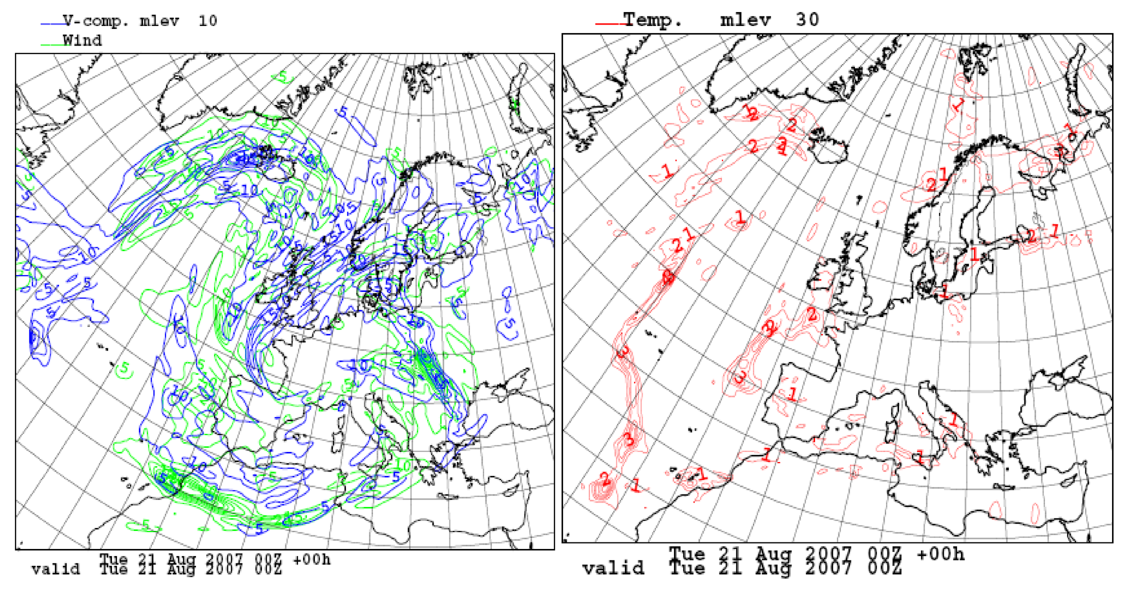
- The hybrid assimilation will be tested together with 3D-Var as well as with 4D-Var (3D-Var so far)
- First results with HIRLAM 3D-Var are very encouraging
- First further tests with HIRLAM at synoptic scales (10-20 km grid resolution), later at mesoscale with the HARMONIE forecasting system
- By assigning different (local) variances for the ensemble perturbation weights α_i of different ensemble members, it will be possible to put preference to a certain member that fits, for example, satellite images better in a particular sub-domain. This will be used in trial to correct forecast phase errors ("structure assimilation")

Single simulated observation experiments



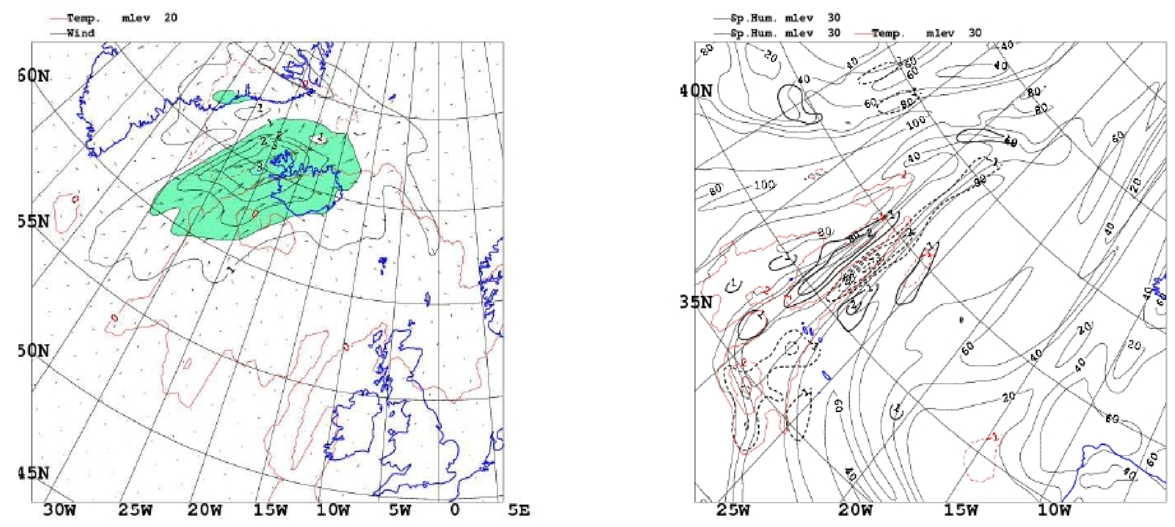
300 hPa wind and geopotential   850 hPa temperature

Background states (control)



Model level 10 winds   Model level 30 temperature

Ensemble background error variances



300 hPa wind observation
Model level 10 wind increments
Model level 20 temperature increments

850 hPa temperature observation
Model level 30 temperature and specific humidity increments

Single simulated observation assimilation increments

First comparison between 3D-Var and hybrid assimilation with real observation data assimilation experiments

We have done experiments in three different settings

- (**Config1**) with full weight to the 3D-Var background error constraint (leaving out the ensemble background error constraint),
- (**Config2**) with equal weights to the two background error constraints ($\beta_{3D-Var} = \beta_{ens} = 2.0$) and
- (**Config3**) with a strong penalty on the static background error constraint ($\beta_{3D-Var} = 11.0$).

**Verification of temperature, wind speed and relative humidity forecast profiles against radiosonde data
16-22 August 2007 (7 days only)
Average over +12h, +24h, +36h and +48h forecast length:**