



Comparison of the forecast background errors for nested grids in COAMPS

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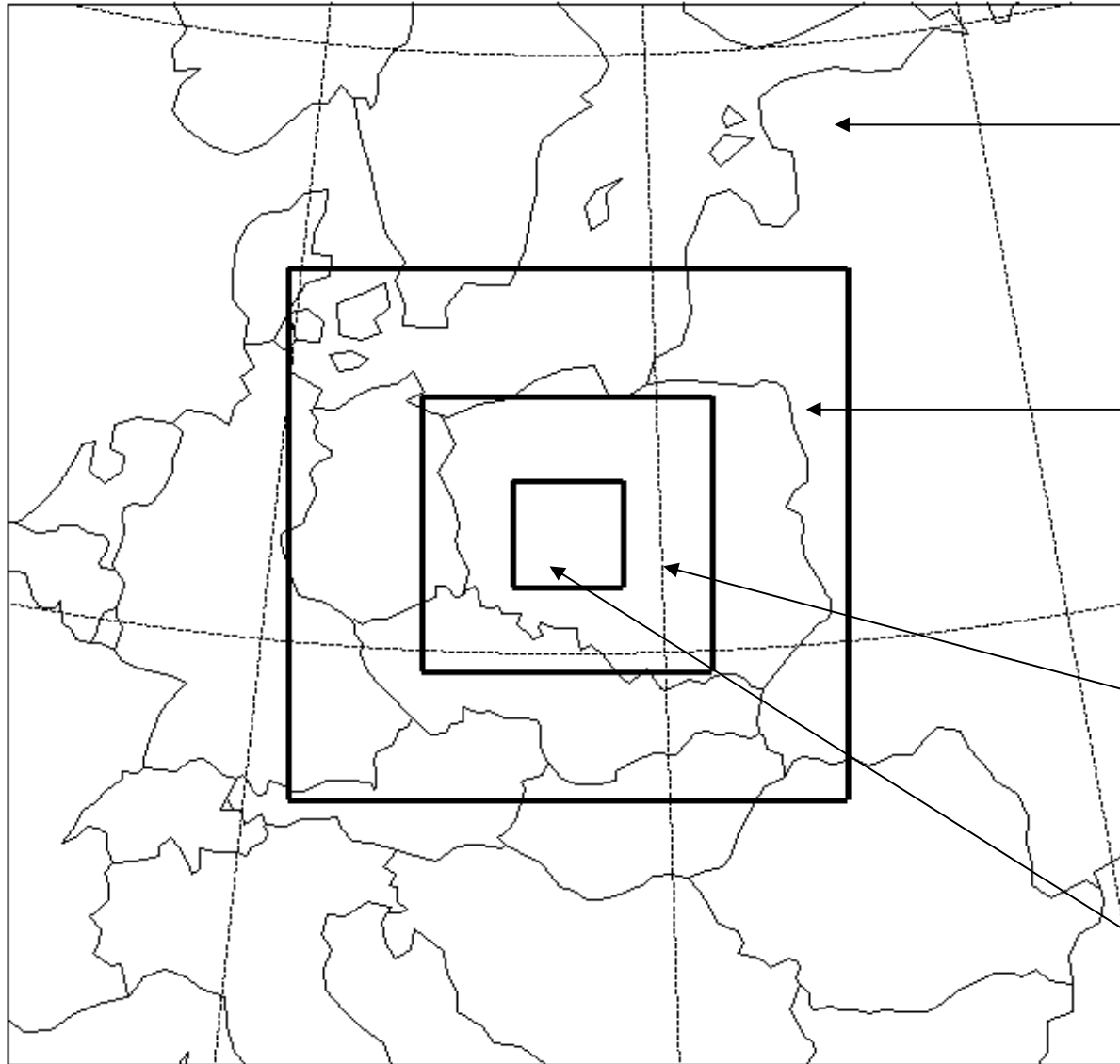
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Mesoscale Modeling

COAMPS™: **Coupled Ocean/Atmosphere Mesoscale Prediction System**
Focus: **0-3 day high-resolution forecasts**

- Complex Data Quality Control
- Analysis:
 - **Atmosphere**: MVOI analyses of u, v, and Heights; Univariate analyses of T, q
 - **Ocean**: 2D OI of SST; 3D MVOI of T, S, SSH, Sea Ice, and Currents
- Initialization:
 - **Atmosphere**: Hydrostatic Constraint on Analysis Increments, and/or Digital Filter
 - **Ocean**: Stability check
- Model:
 - **Atmosphere**:
 - Numerics: Nonhydrostatic, Scheme C, Nested Grids, Sigma-z, Flexible Lateral BCs
 - Parameterizations: PBL, Convection, Explicit Moist Physics, Radiation, Surface Layer
 - Aerosols: Surface databases, High-order Transport, Dry Deposition, Wet Removal
 - **Ocean**: Navy Coastal Ocean Model (NCOM)
 - Numerics: Hydrostatic, Scheme C, Nested Grids, Hybrid Sigma/z
 - Parameterizations: Mellor-Yamada 2.5
- Features:
 - **Globally Relocatable** (5 Map Projections)
 - **User-Defined Grid Resolutions, Dimensions, and Number of Nested/Parent Grids**
 - **Incremental Data Assimilation; Atmosphere: 6 or 12 hours; Ocean: 12 or 24 hours**
 - **Applicable for Idealized or Real-Time Applications**
 - **Single Configuration Managed System for All Applications**
- Operations (Atmospheric Components plus 2D SST Analysis):
 - **ICM**: Large European Area, grid spacing: 39 km, forecasts to 120 hours,
3 areas with grid spacing 13 km, forecasts to 72 hours,
4 km grid spacing over Poland, forecasts to 24 hours.

Nested grids for an investigation of the storm development, 29 July 2005



G1: 37x37x35, 54 km

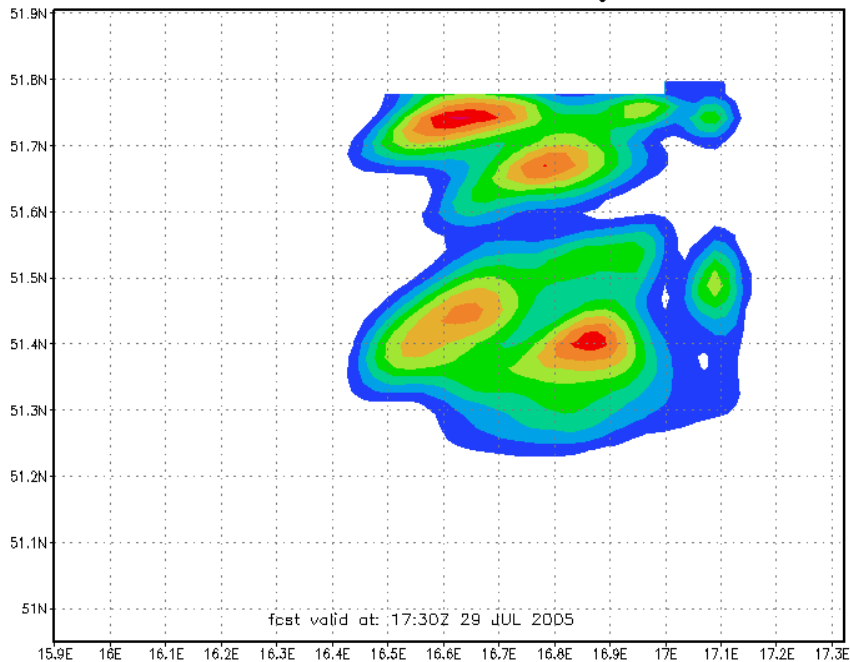
G2: 55x55x35, 18 km

G3: 85x85x35, 6 km

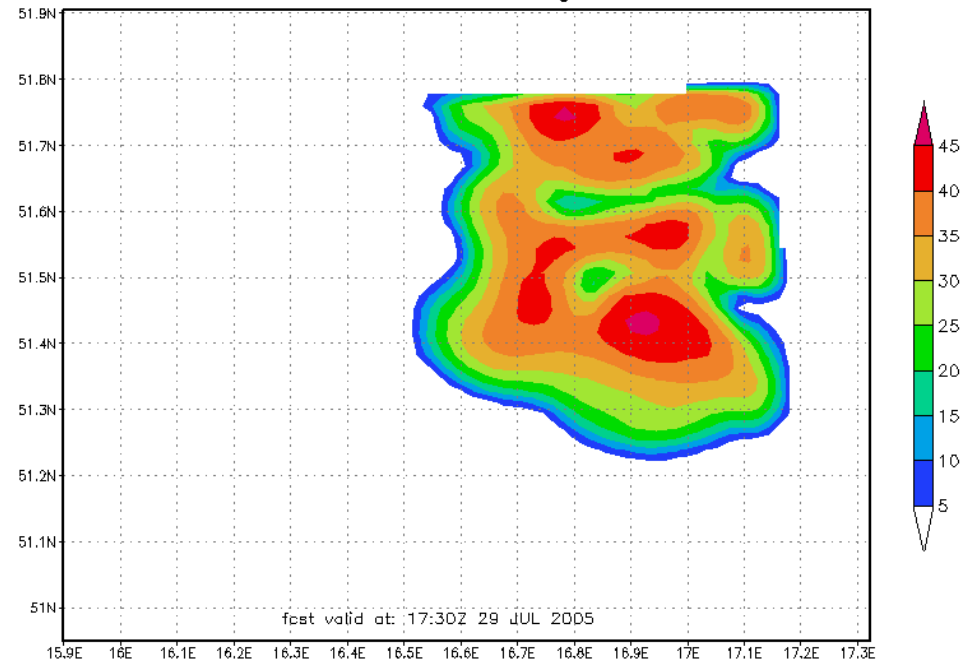
G4: 97x97x35, 2 km

2 km grid, L35, 41x41, ideal case

TOTAL PRECIPITATION, 41x41, 2km grid, ideal case



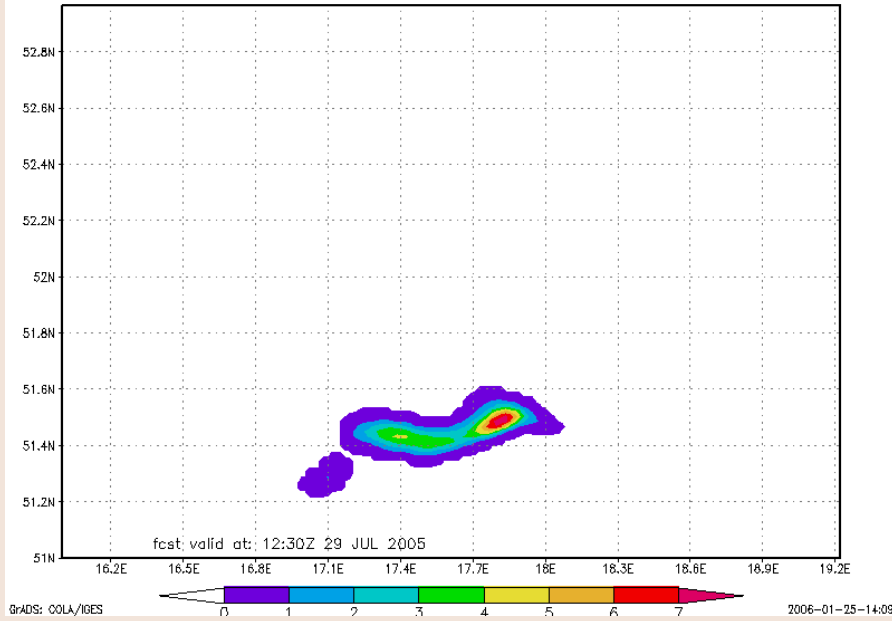
REFLECTIVITY, 41x41, 2km grid, ideal case



precipitation

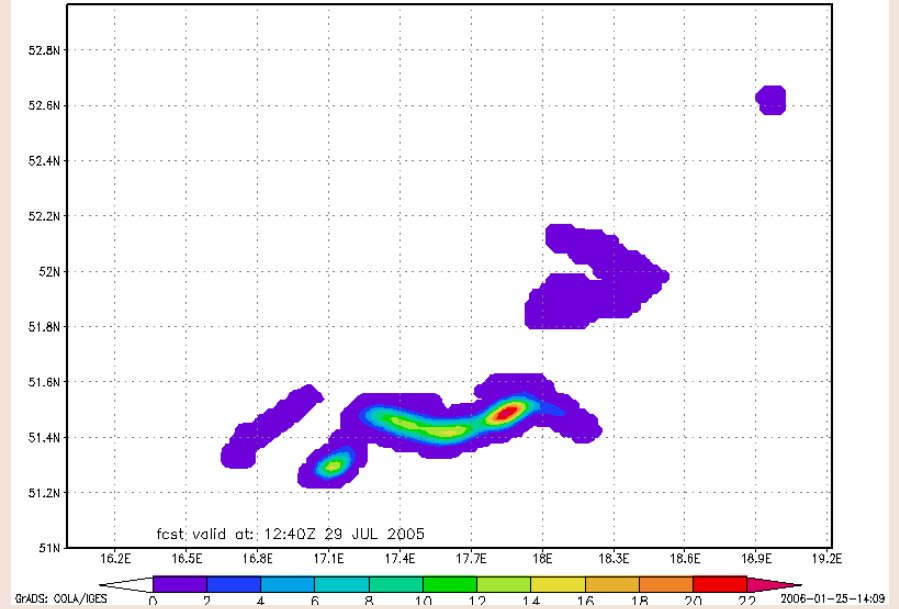
reflectivity at h=2 km

TOTAL PRECIPITATION, 97x97, 2km grid, g1_L49 case



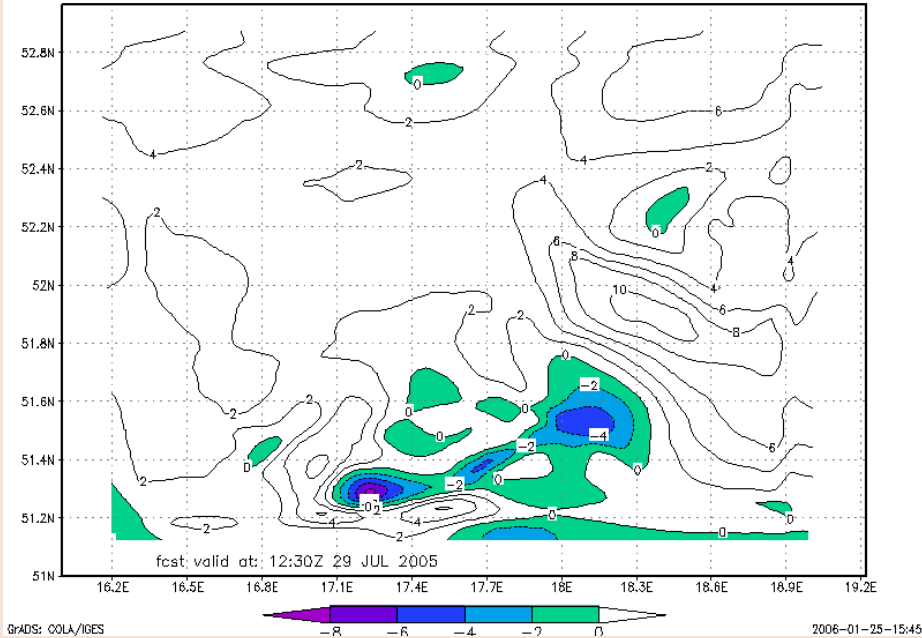
12:30 UTC

TOTAL PRECIPITATION, 97x97, 2km grid, g1_L49 case

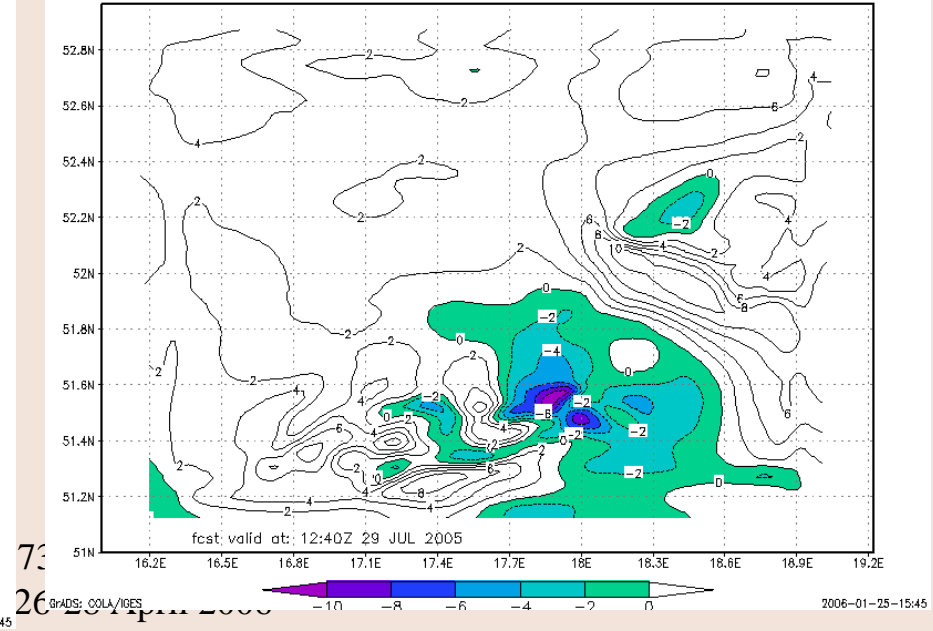


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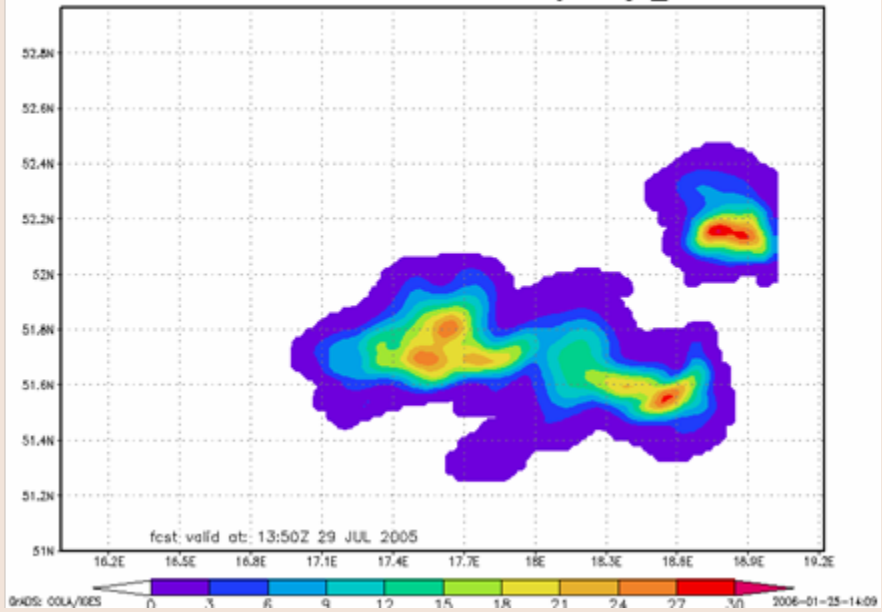
RADAR RADIAL WIND, 97x97, 2km grid, g1_L49 case



RADAR RADIAL WIND, 97x97, 2km grid, g1_L49 case

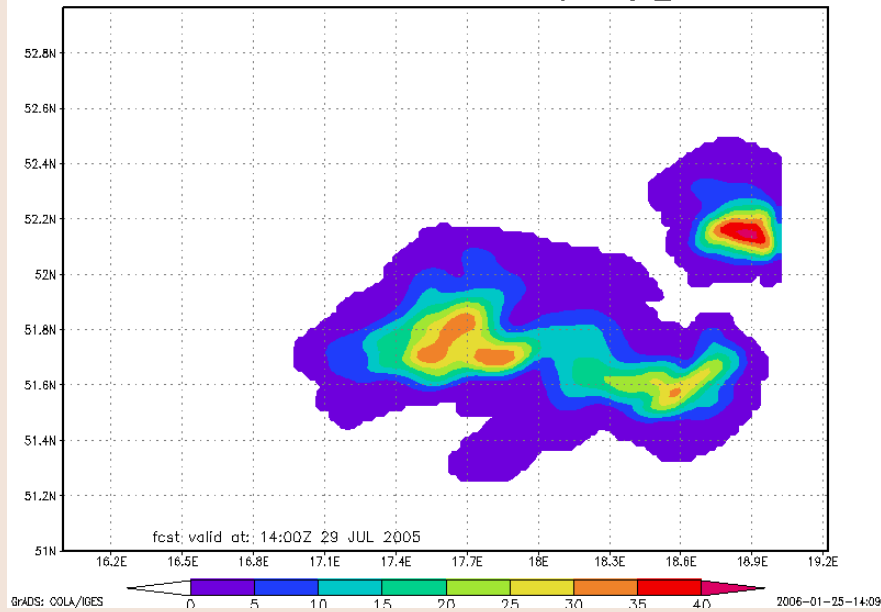


TOTAL PRECIPITATION, 97x97, 2km grid, g1_L49 case



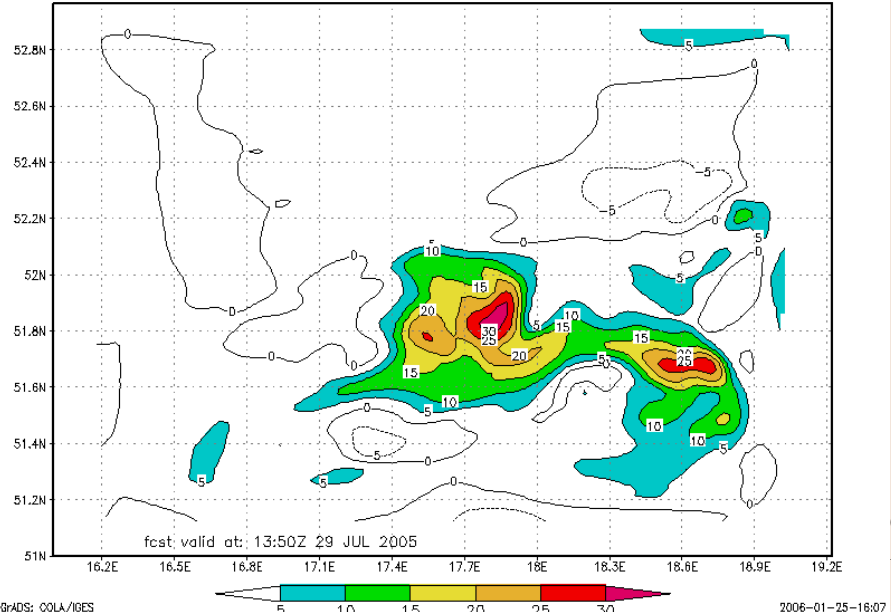
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TOTAL PRECIPITATION, 97x97, 2km grid, g1_L49 case



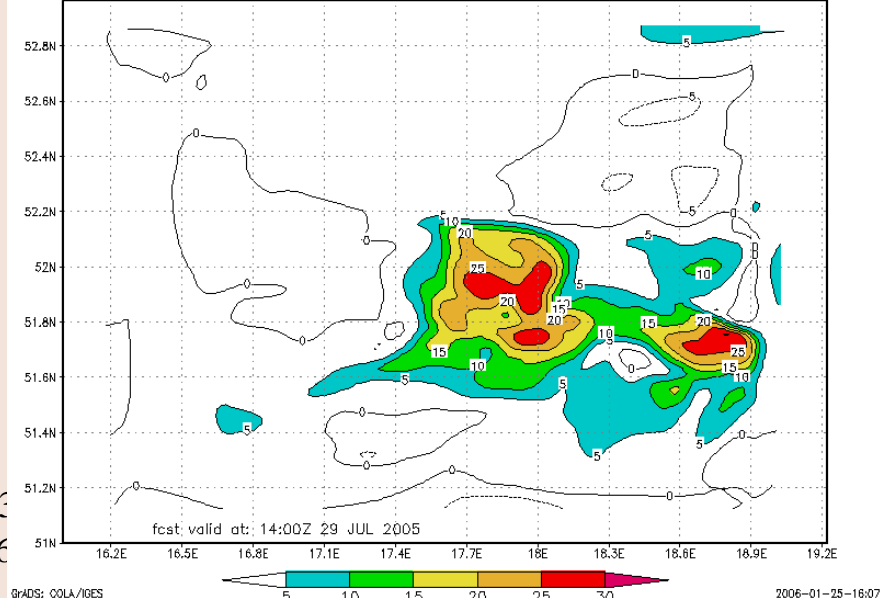
14:00 UTC

RADAR RADIAL WIND, 97x97, 2km grid, g1_L49 case



on 73
us 26

RADAR RADIAL WIND, 97x97, 2km grid, g1_L49 case



The evolution of the model state errors

- The forecast step

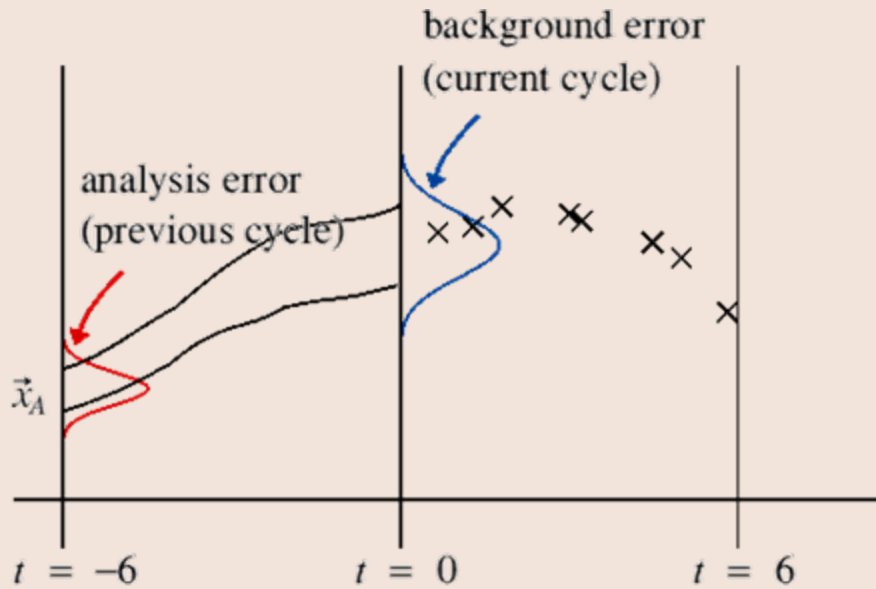
At time t_i , the analysis \mathbf{x}_i^a is an estimate of the true atmospheric state \mathbf{x}_i^* with uncertainties that correspond to the analysis error $\mathbf{e}_i^a = \mathbf{x}_i^a - \mathbf{x}_i^*$. The forecast field that is valid at time t_{i+1} is then obtained from this initial condition by integrating in time the forecast model according to $\mathbf{x}_{i+1}^b = \mathbf{M}\mathbf{x}_i^a$, where \mathbf{M} is the operator that corresponds to the evolution of the atmosphere.

- The analysis step

The forecast field \mathbf{x}_{i+1}^b will then be used as a background for the analysis at time t_{i+1} . The analysis equation transforms the background and observation vectors into the analysis vector.

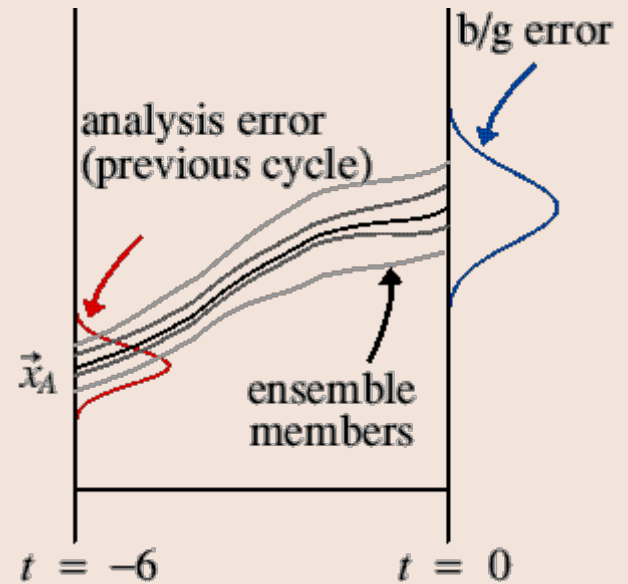
$\mathbf{x}_{i+1}^a = \mathbf{x}_{i+1}^b + \mathbf{K}(\mathbf{y}_{i+1} - \mathbf{H}\mathbf{x}_{i+1}^b)$, where \mathbf{y}_{i+1} is the observation vector at time t_{i+1} and \mathbf{K} is gain matrix $\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$. \mathbf{B} and \mathbf{R} are spatial covariance matrices.

Methods of an estimation of matrix B



„NMC” method

„Ensemble” method



The standard NMC method

The NMC method computes differences between forecasts that are valid at the same time, but for different ranges such as 12 and 24-h forecasts. Analysis innovations may be seen as an analysis perturbation, which is supposed to be an estimate of the analysis error e_i^a : $\varepsilon_i^a = \mathbf{K}(y_i - \mathbf{H}x_i^b) = \mathbf{K}(e_i^o - \mathbf{H}e_i^b)$. This allows to distinguish the respective contributions of the background and observation errors: $\varepsilon_i^a = -\mathbf{KH} e_i^b + \mathbf{K}e_i^o$. Comparison with an analysis dispersion equation $\varepsilon_i^a = (\mathbf{I}-\mathbf{KH}) \varepsilon_i^b + \mathbf{K}\varepsilon_i^o$ shows that in the NMC method the background error weight $(\mathbf{I}-\mathbf{KH})$ is approximated by $-\mathbf{KH}$. In the evolution of the NMC analysis perturbations, the representation of the analysis effect consists in adding the analysis increments to some earlier increments $\varepsilon_{i+1}^b = \mathbf{M}(x_i^a - x_i^b)$. This differs from the ensemble method, for which the representation of the analysis effect consists in applying the analysis equation to the perturbations $\varepsilon^b, \varepsilon^o$.

The ensemble simulation method

At time t_i , two different analyses are available. Their difference is equal to $\varepsilon_i^a = x_i^{a,k} - x_i^{a,l}$. Two forecast integrations are performed from these two initial states. The two different forecast fields may then be combined with two different sets of observations y_{i+1}^k, y_{i+1}^l , in order to provide two different analyses at time t_{i+1} . By calculating the difference between these two analysis equations, it appears that the analysis equation is the very same equation that transforms the background and the observation differences into the analysis differences:

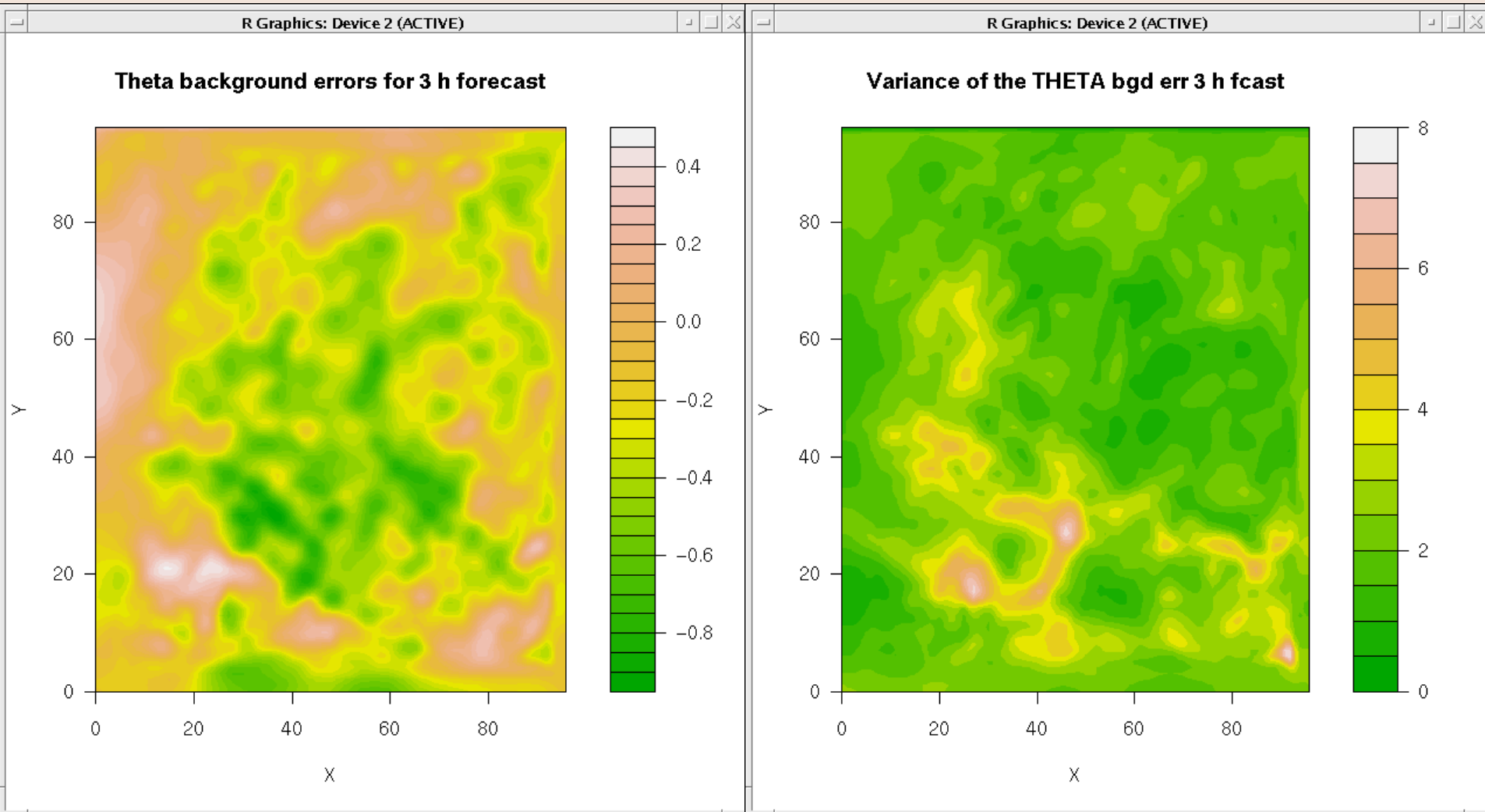
$$\varepsilon_i^a = \varepsilon_i^b + \mathbf{K}(\varepsilon_{i+1}^o - H\varepsilon_{i+1}^b).$$

The evolution processes and equations, that affect the ensemble difference fields, are the same as those of the true error fields.

Forecast background error, V wind component

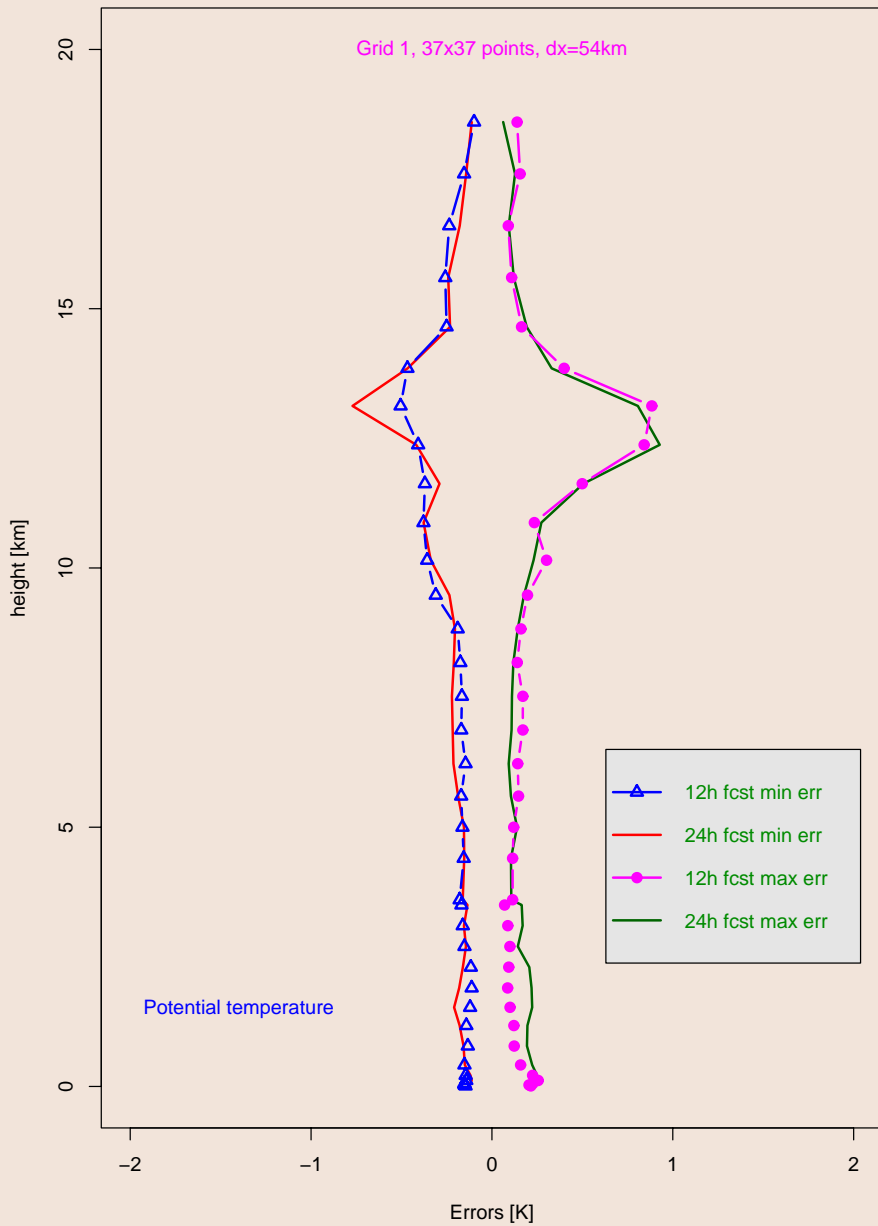
Mean error

Variance

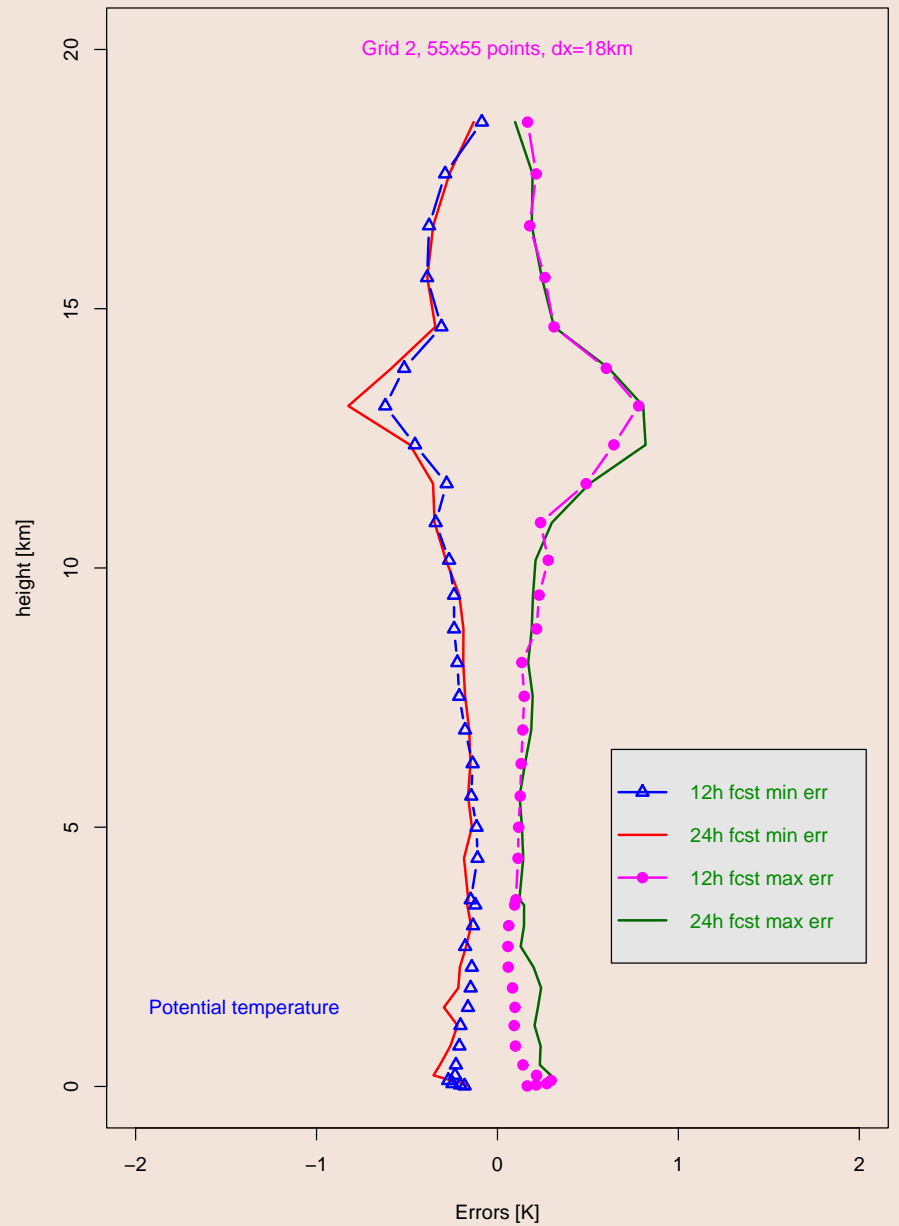


2 km grid, L35, 97x97 results for 28 model level (~1.2 km)

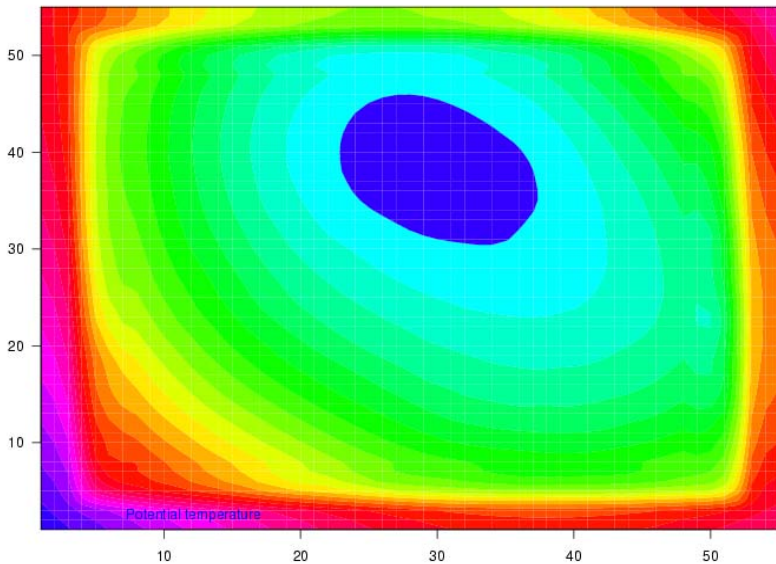
Vertical distribution of the background errors



Vertical distribution of the background errors

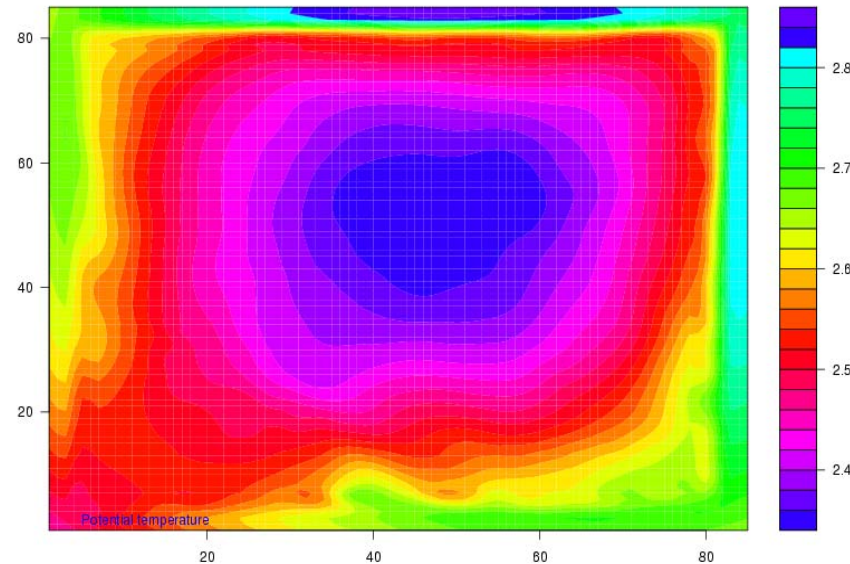


Mean error at level 1, grid 2, period of averaging 12–24h

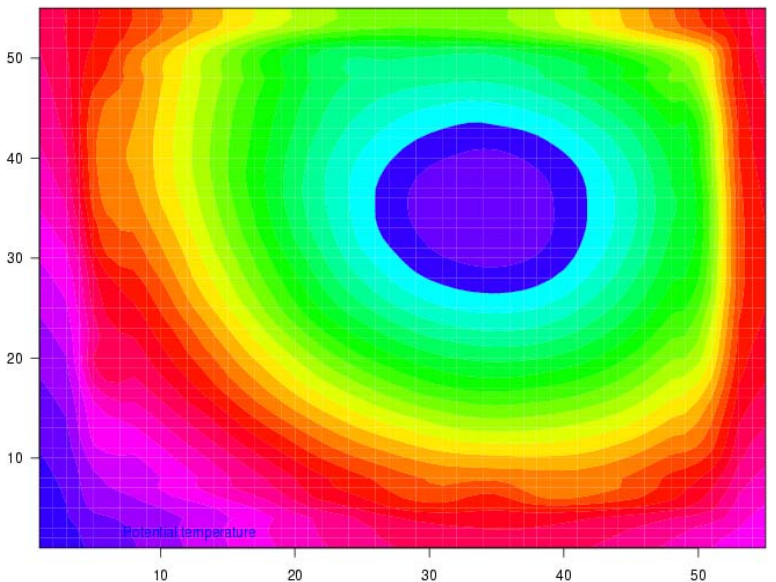


Mean error

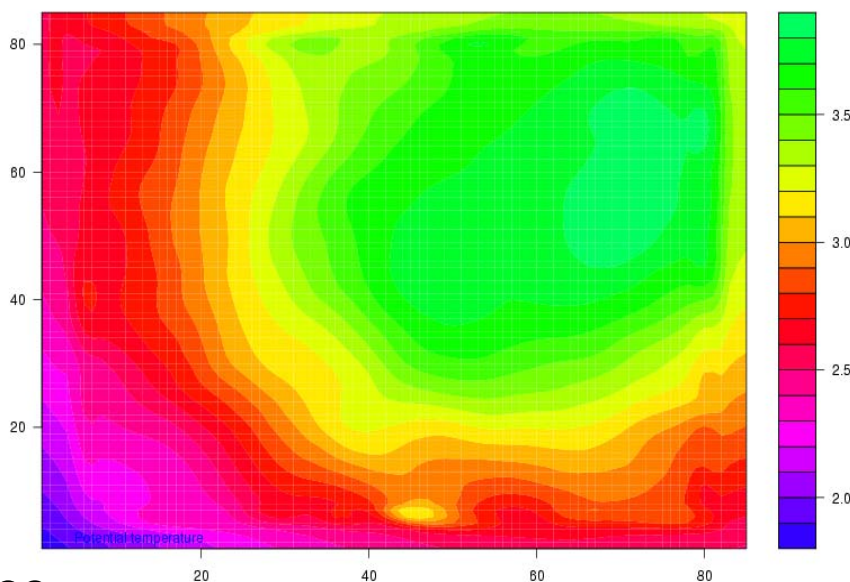
Mean error at level 1, grid 3, period of averaging 12–24h



Variance at level 1, grid 2, period of averaging 12–24h



Variance at level 1, grid 3, period of averaging 12–24h

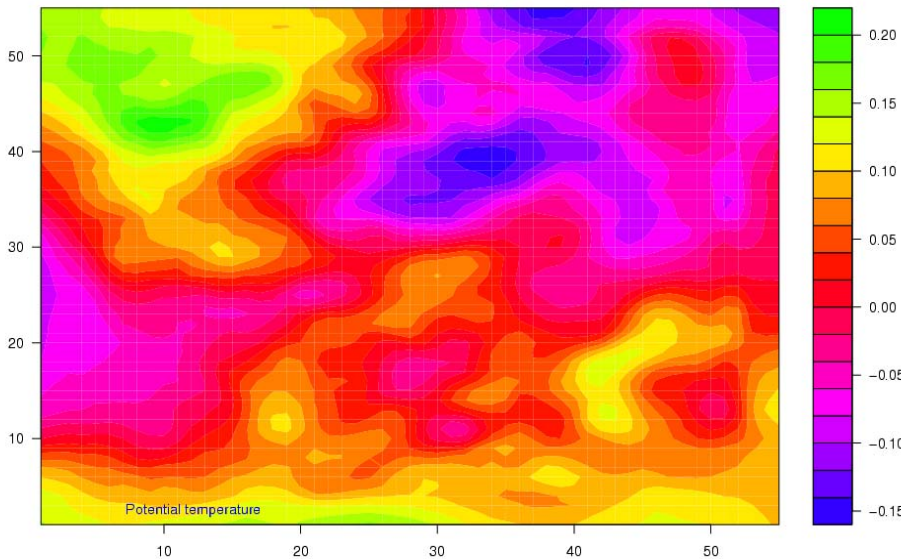


Variance

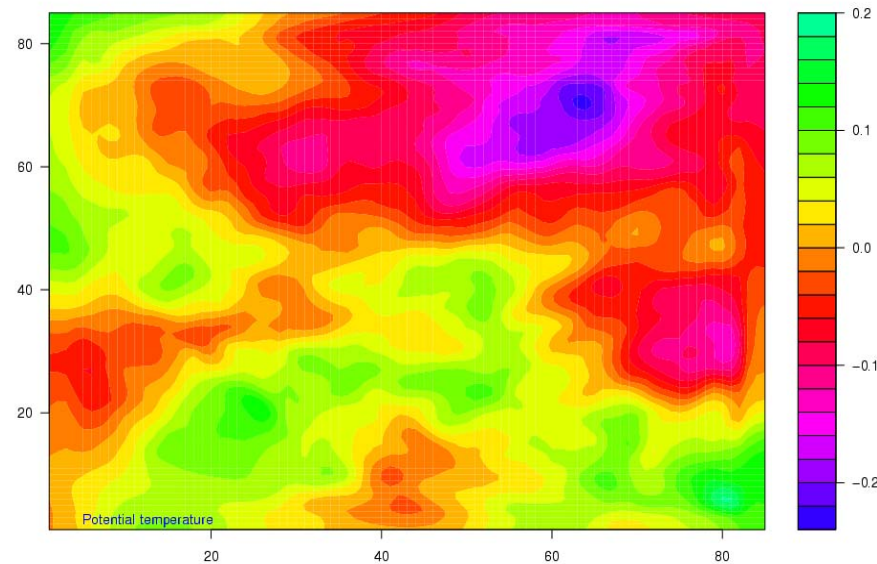
18 km grid

6 km grid

Mean error at level 17, grid 2, period of averaging 24–36h



Mean error at level 17, grid 3, period of averaging 24–36h

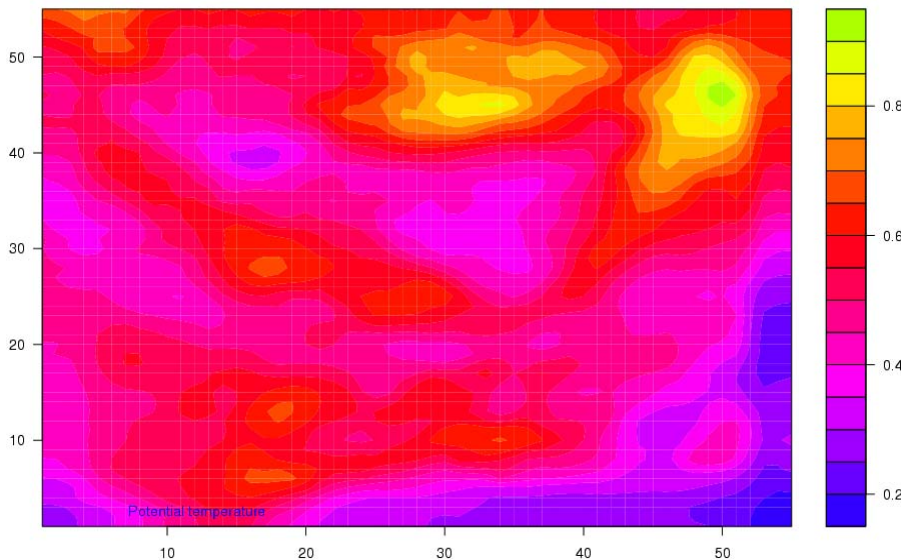


18 km grid

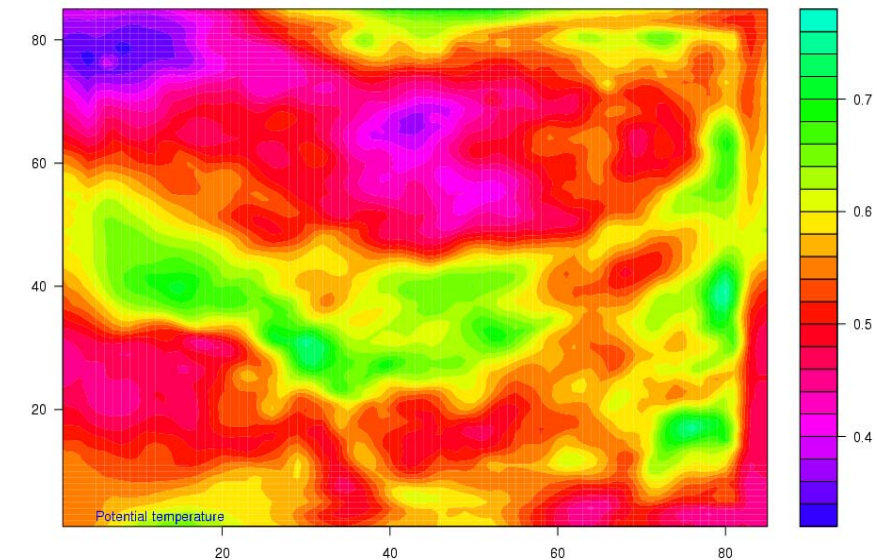
Level 17, 5 km

6 km grid

Variance at level 17, grid 2, period of averaging 24–36h



Variance at level 17, grid 3, period of averaging 24–36h



Ensemble initiation methodology

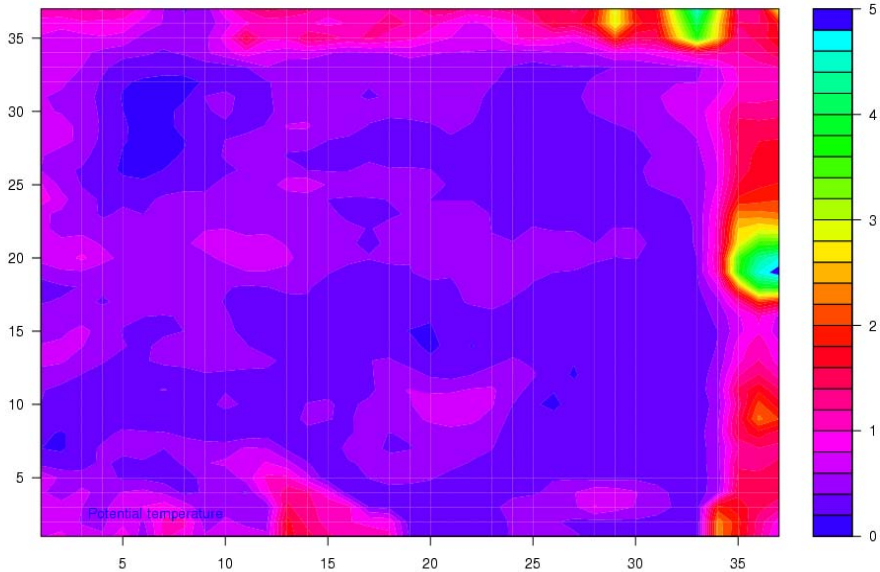
- The uncorrelated-random method

A standard uncorrelated normal random variable with zero mean and unit variance is created first (by Box-Muller method). Using a prescribed standard deviation σ_z , one can create an uncorrelated random variable $Z \sim N(0, \sigma_z)$. Then, using the linear transformation $\mathbf{F}=\mathbf{I}$, the actual initial perturbation used is $P=Z$. This is followed by an ensemble integration from $t_0-\tau$ to t_0 .

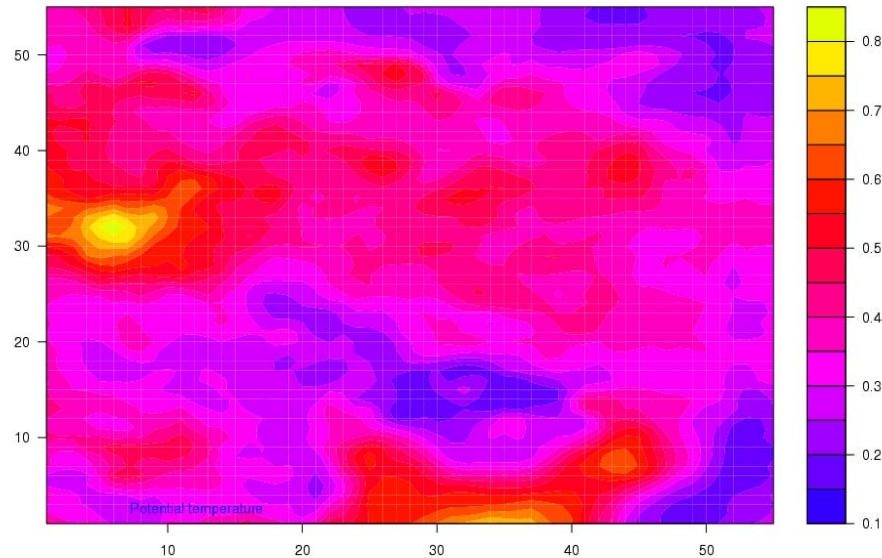
- the correlated random method

In order to improve the forecast error covariance at time t_0 , a change of variable $P=\mathbf{F}Z$ is introduced at time $t_0-\tau$, which creates correlated random perturbations. The matrix \mathbf{F} is a block-diagonal Toeplitz matrix, with the elements calculated using the space-limited compactly support function. Each block corresponds to a particular model variable.

Variance at level 35, grid 1, period of averaging 12-24h



Variance at level 35, grid 2, period of averaging 12-24h

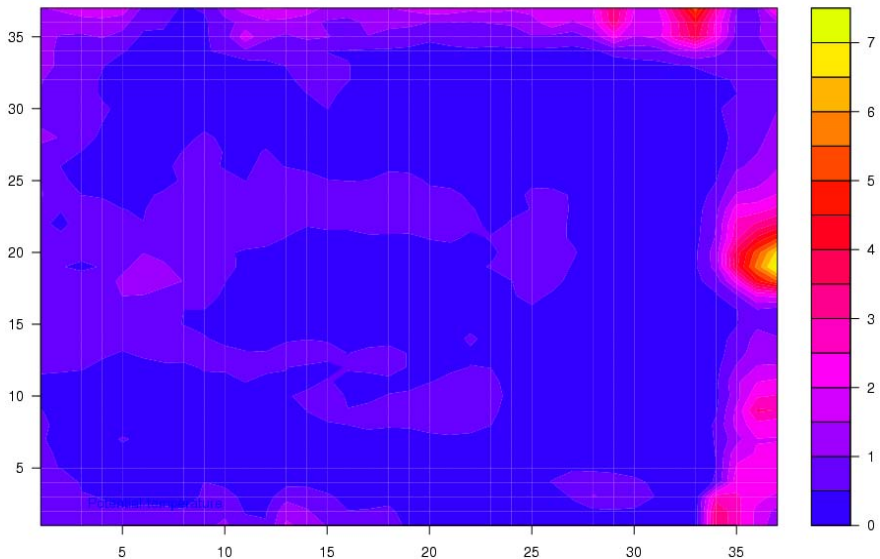


54 km grid

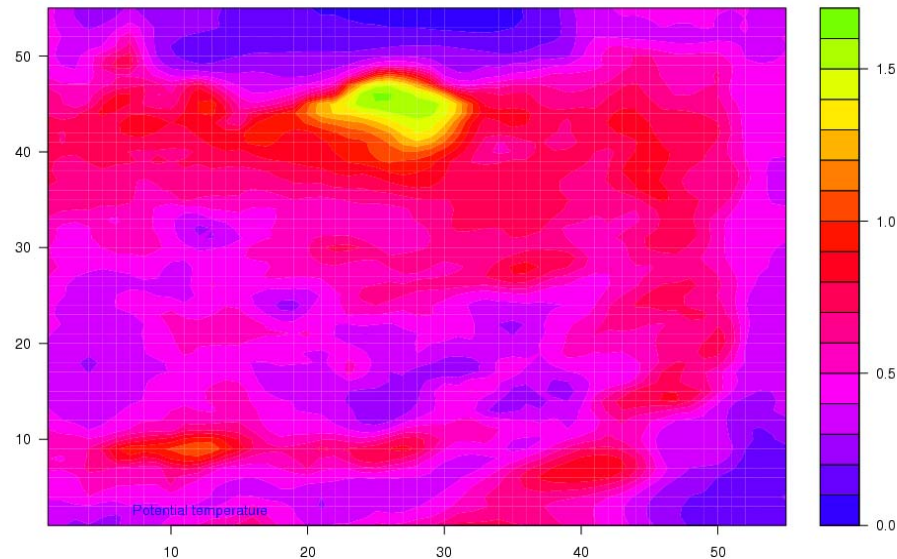
Level 35, 0.01m

18 km grid

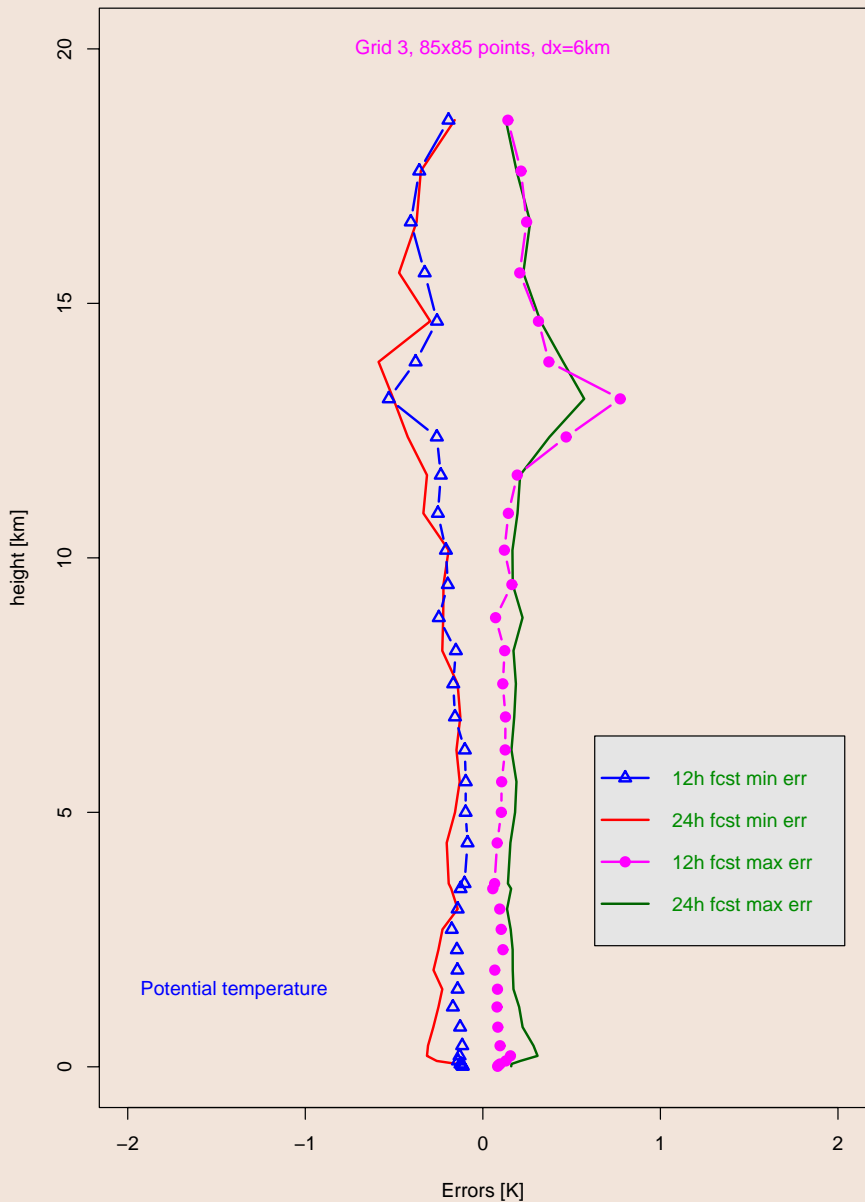
Variance at level 35, grid 1, period of averaging 24-36h



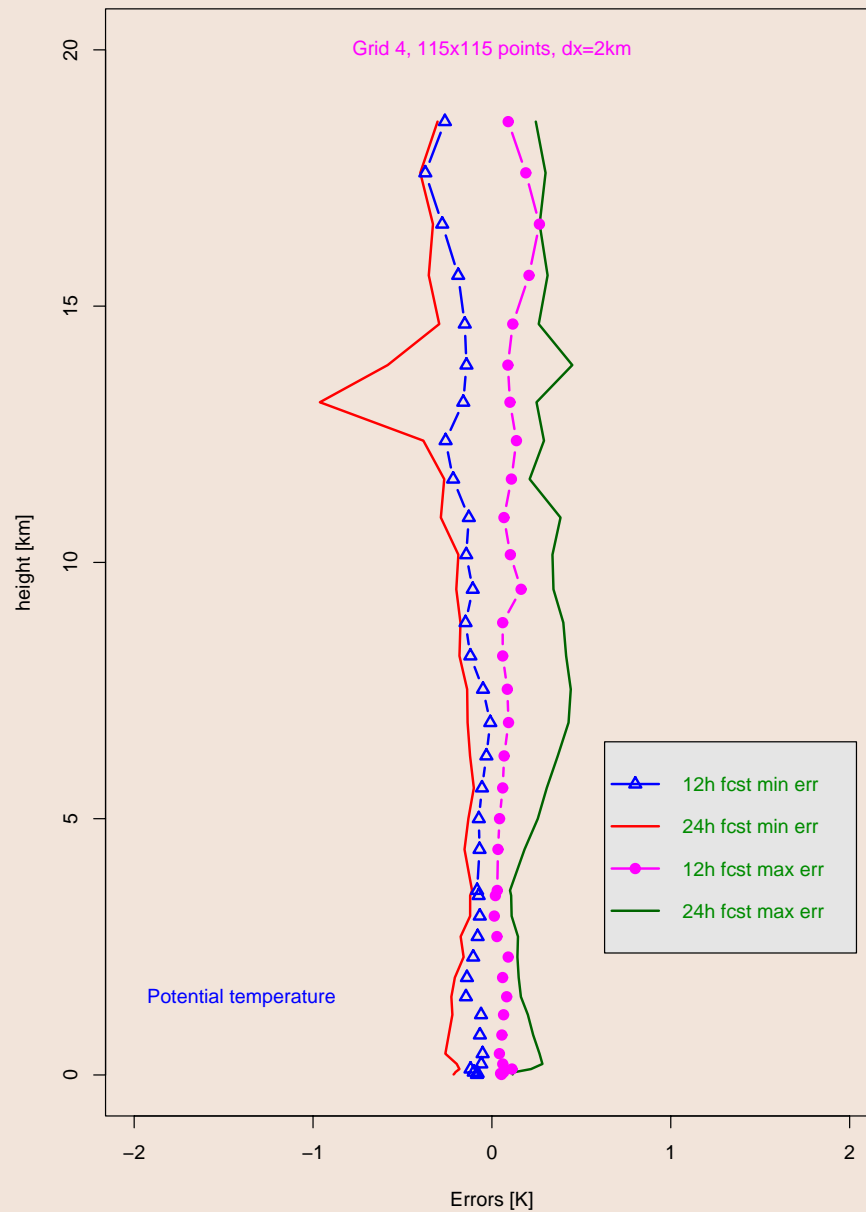
Variance at level 35, grid 2, period of averaging 24-36h



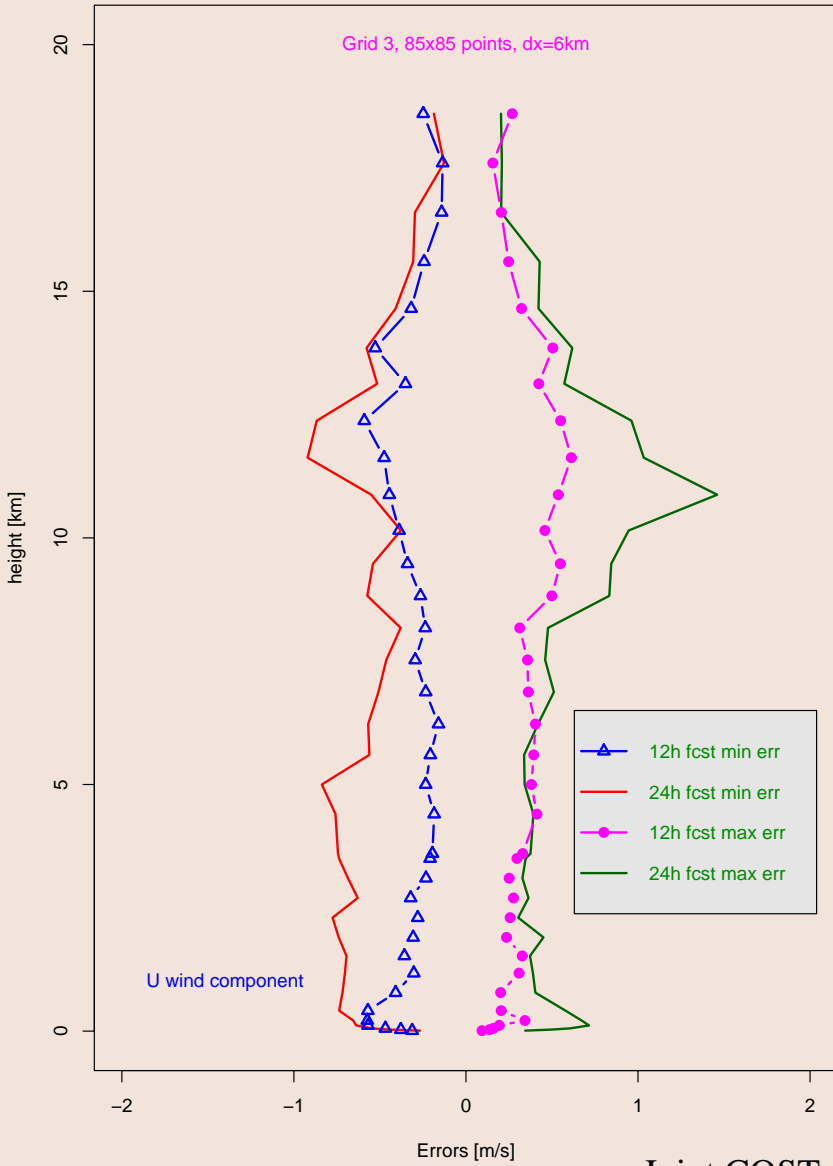
Vertical distribution of the background errors



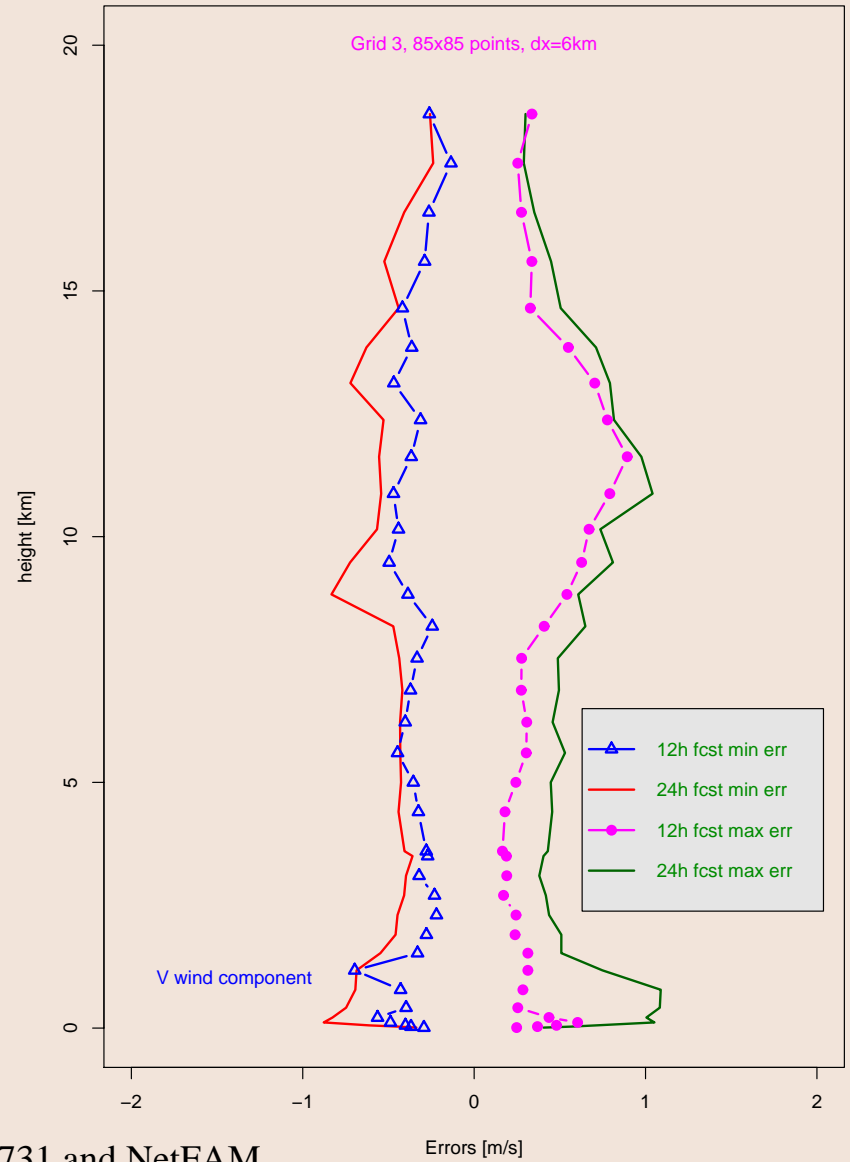
Vertical distribution of the background errors



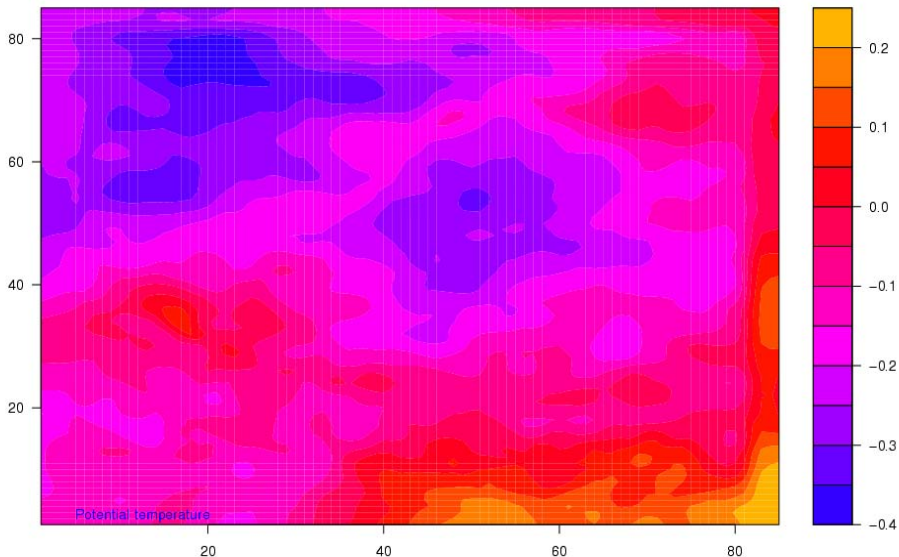
Vertical distribution of the background errors



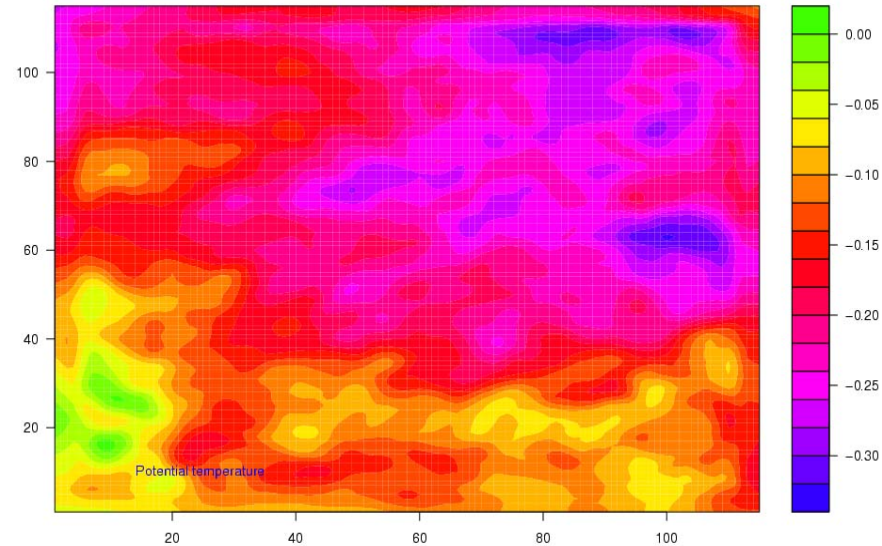
Vertical distribution of the background errors



Mean error at level 35, grid 3, period of averaging 12–24h



Mean error at level 35, grid 4, period of averaging 12–24h

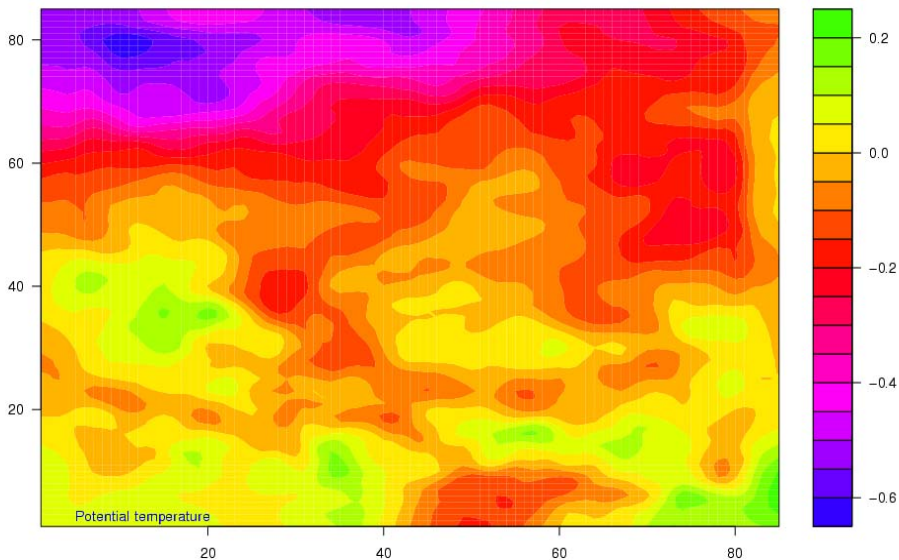


6 km grid

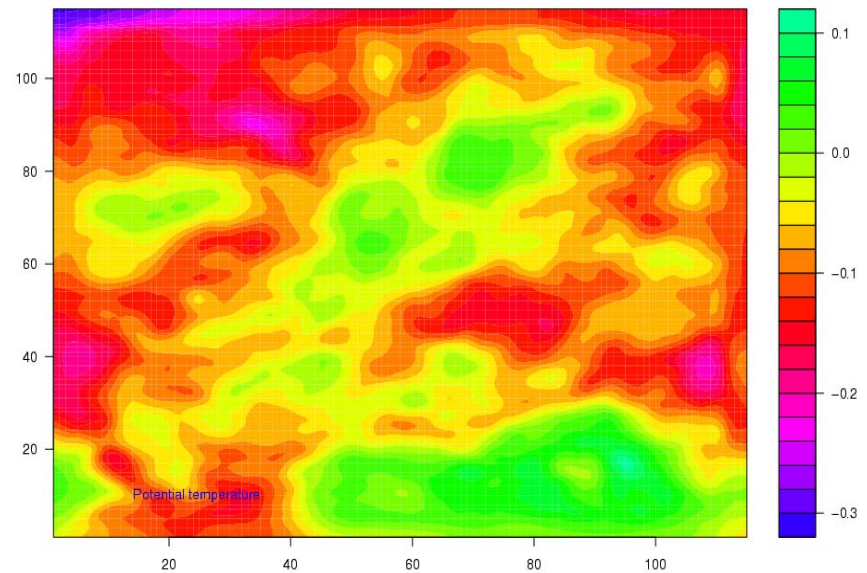
Mean error, level 35

2 km grid

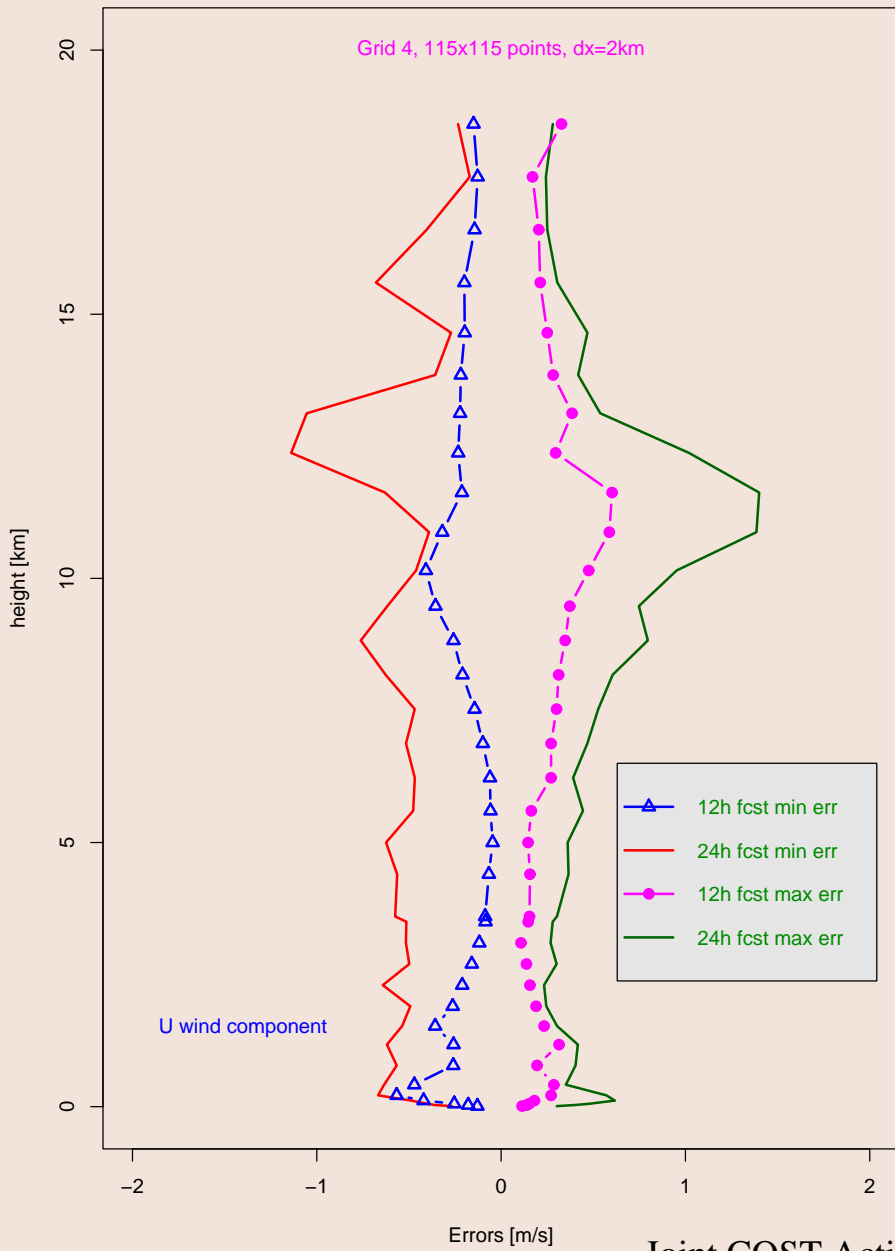
Mean error at level 35, grid 3, period of averaging 24–36h



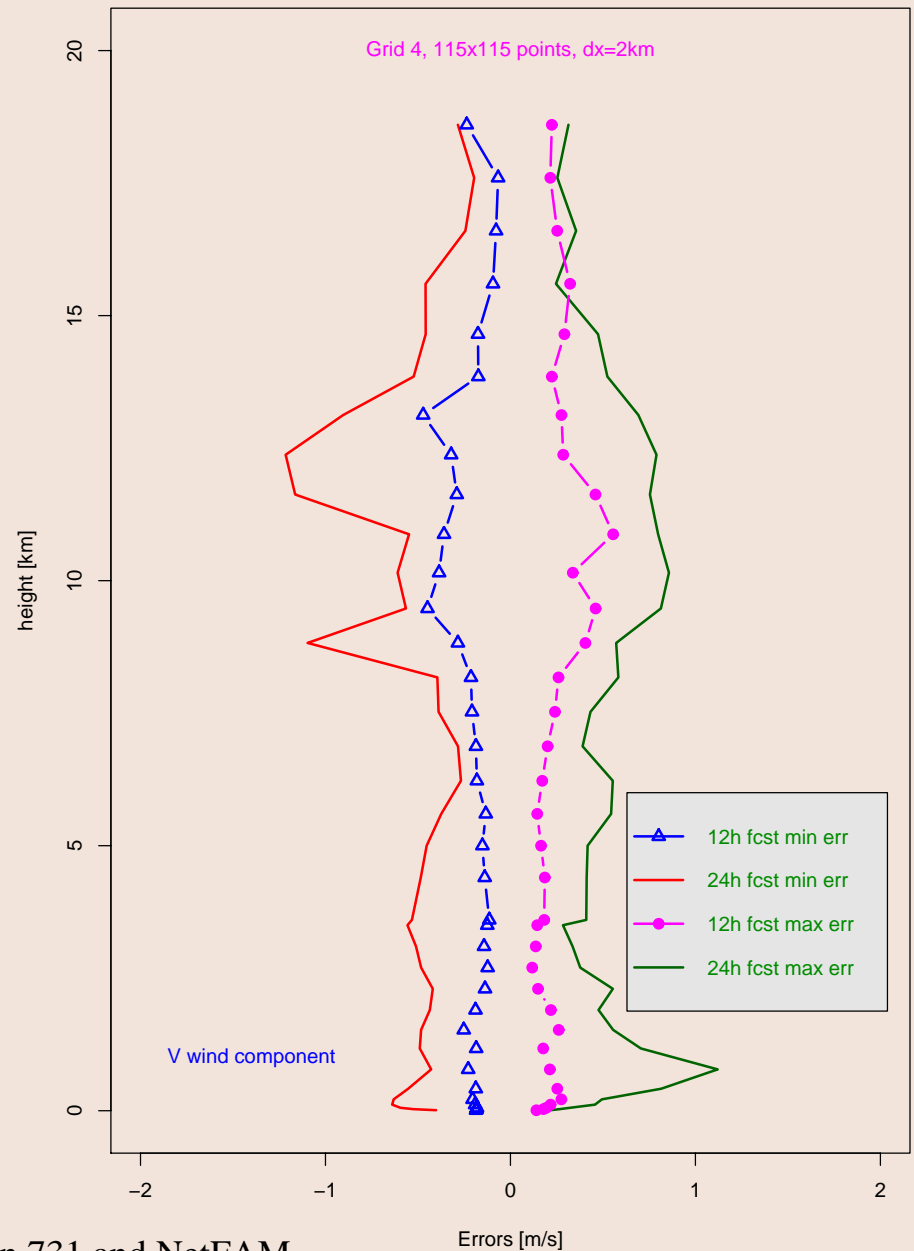
Mean error at level 35, grid 4, period of averaging 24–36h



Vertical distribution of the background errors



Vertical distribution of the background errors

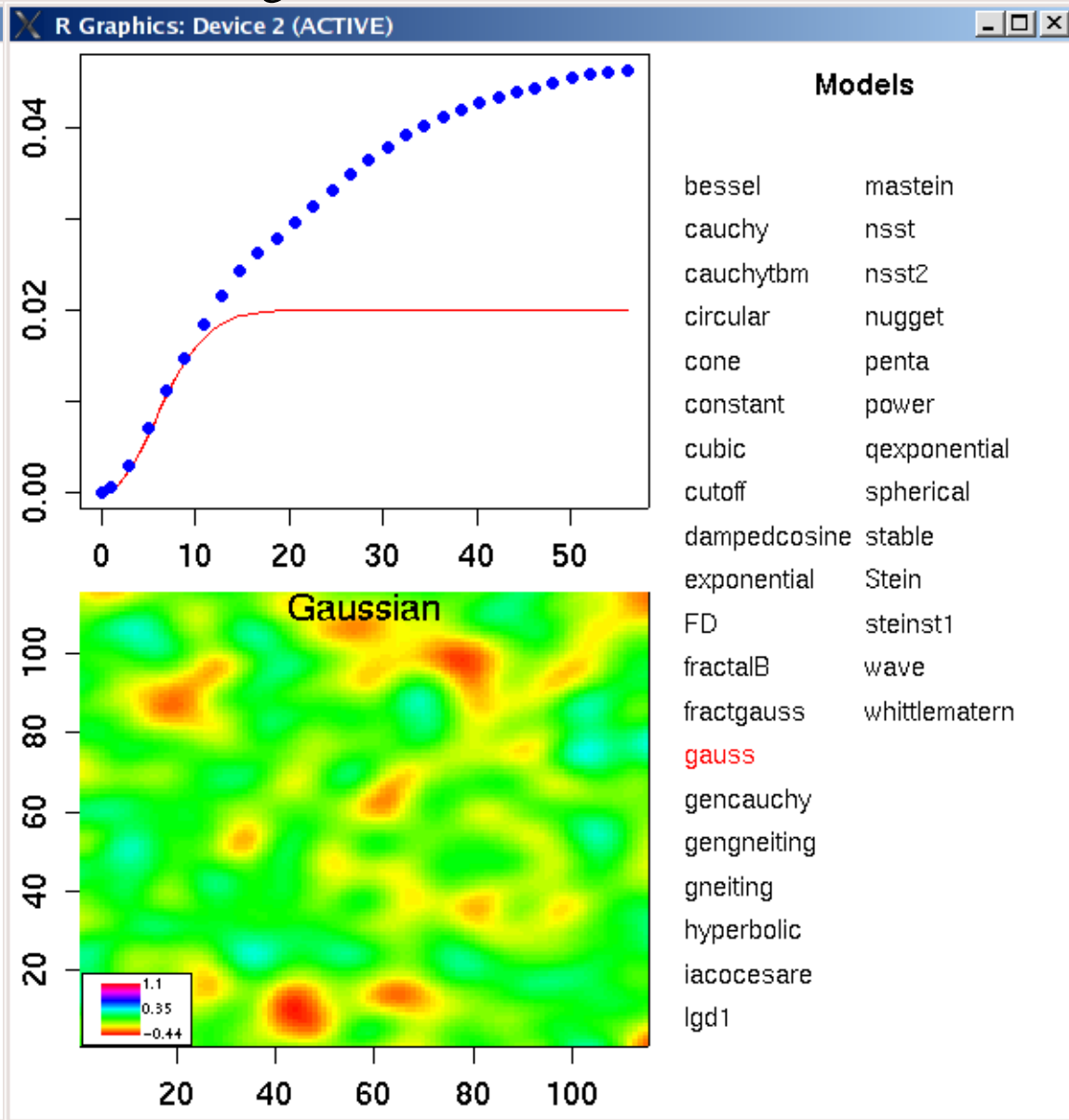
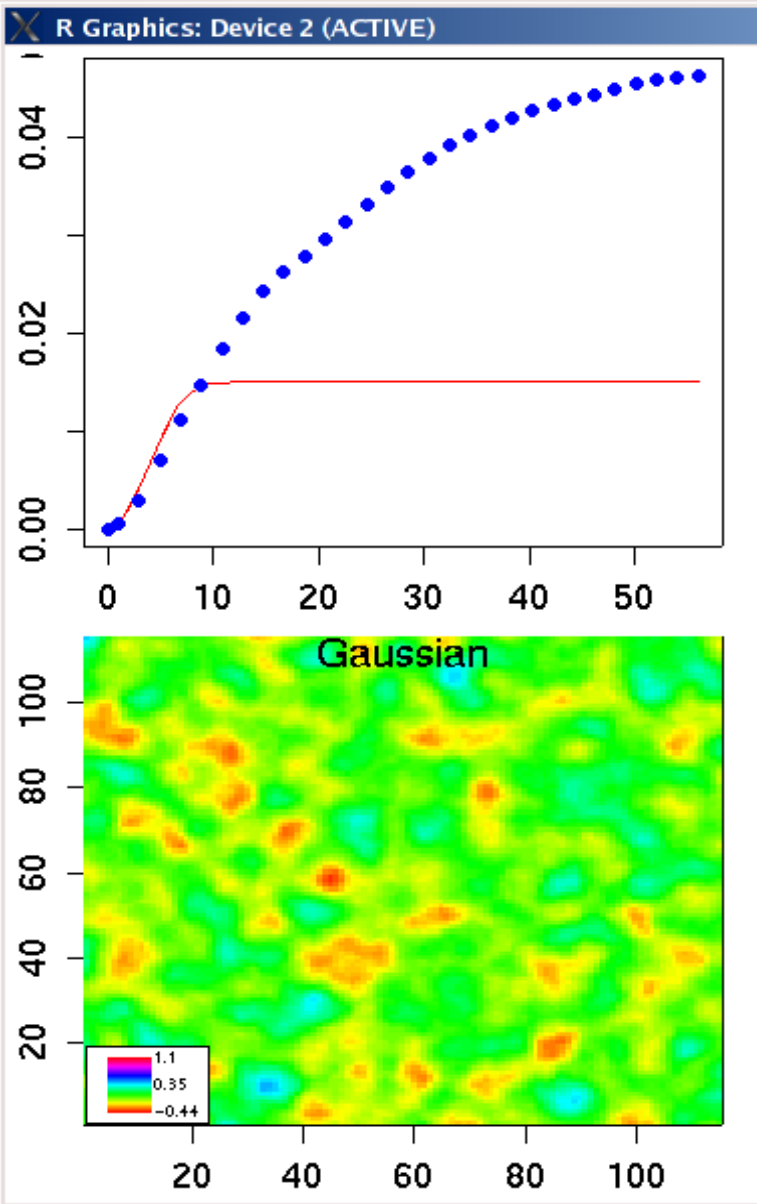


Single-sample parameter estimation

Model error parameterization imply a parameterization of the innovation covariance. Considering one arbitrary time instant at which an innovation \mathbf{v} is produced, we assume that we have a covariance model for \mathbf{v} which involves a number of unknown parameters: $E(\mathbf{v}\mathbf{v}^T) \sim \mathbf{S}(\boldsymbol{\alpha})$, where $\mathbf{S}(\boldsymbol{\alpha})$ is a family of known covariance matrices parameterized by $\boldsymbol{\alpha}$. The conditional probability density $p(\mathbf{v}|\boldsymbol{\alpha})$ of the random vector is given by the Gaussian density function $p(\mathbf{v}|\boldsymbol{\alpha})=c[\det \mathbf{S}(\boldsymbol{\alpha})]^{-1/2} \exp\{-1/2[\mathbf{v}^T\mathbf{S}^{-1}(\boldsymbol{\alpha})\mathbf{v}]\}$. Given the innovation sample \mathbf{v} , the maximum likelihood parameter estimate $\boldsymbol{\alpha}^{ML}$ of $\boldsymbol{\alpha}^*$ is obtained by finding that value of $\boldsymbol{\alpha}$ for which the probability density attains a maximum. Suppose that the innovation covariance parameterization is linear in a single parameter: $\mathbf{S}(\boldsymbol{\alpha})=\alpha \mathbf{S}_0$ with a \mathbf{S}_0 fixed covariance matrix and α an unknown scalar. In this case optimization of the maximum-likelihood function can be performed analytically.

cubic

gauss



Conclusions

- Identifying a viable strategy for specific the background error covariance remains an important problem in meteorological data assimilation
- The NMC method relies on the analysis increment equation
- In the analysis ensemble approach the analysis equation is used to transform the background and observation dispersion into the analysis dispersion
- In near future we plan to introduce on-line estimation of error covariance parameters into our OI scheme

References:

Berre L., S.E. Stefanescu and M. Belo, 2006: The representation of the analysis effect in three simulation techniques. *Tellus*, 58A, 196-209.

Dee D.P., 1995: On-line estimation of error covariance parameters for atmospheric data assimilation. *Mon. Wea. Rev.*, 123, 1128-1145.

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Acknowledgments



L. Herman-Izycki, O. Kapala, R. Brojewski



R. Hodur, C. Bishop, A. Zhao

Joint COST Action 731 and NetFAM
workshop, Vilnius 26-28 April 2006

