Ensemble Data Assimilation at ECMWF

Massimo Bonavita

Acknowledgments:
Lars Isaksen, Elias Holm, Laure Raynaud

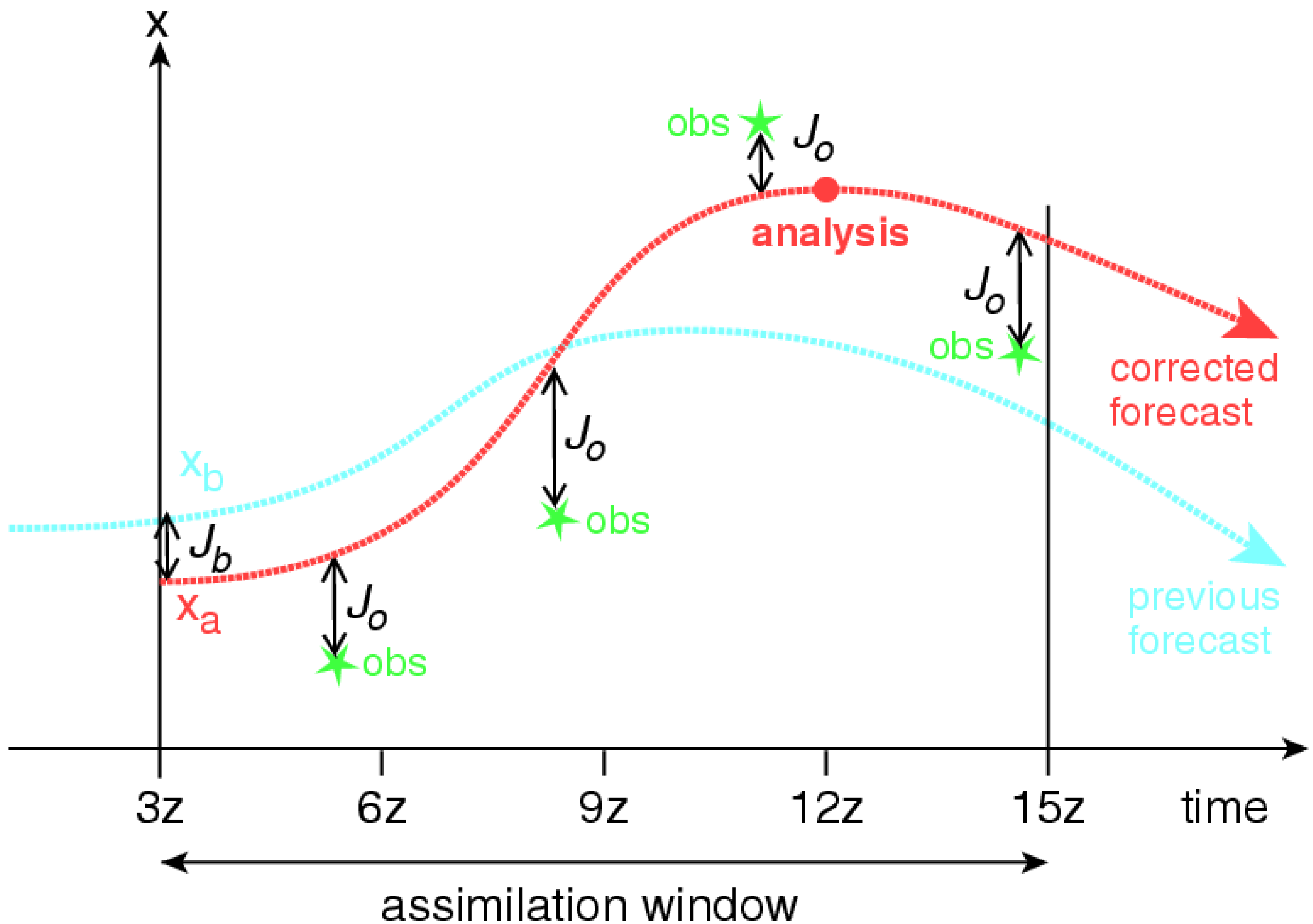
Outline

- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

Outline

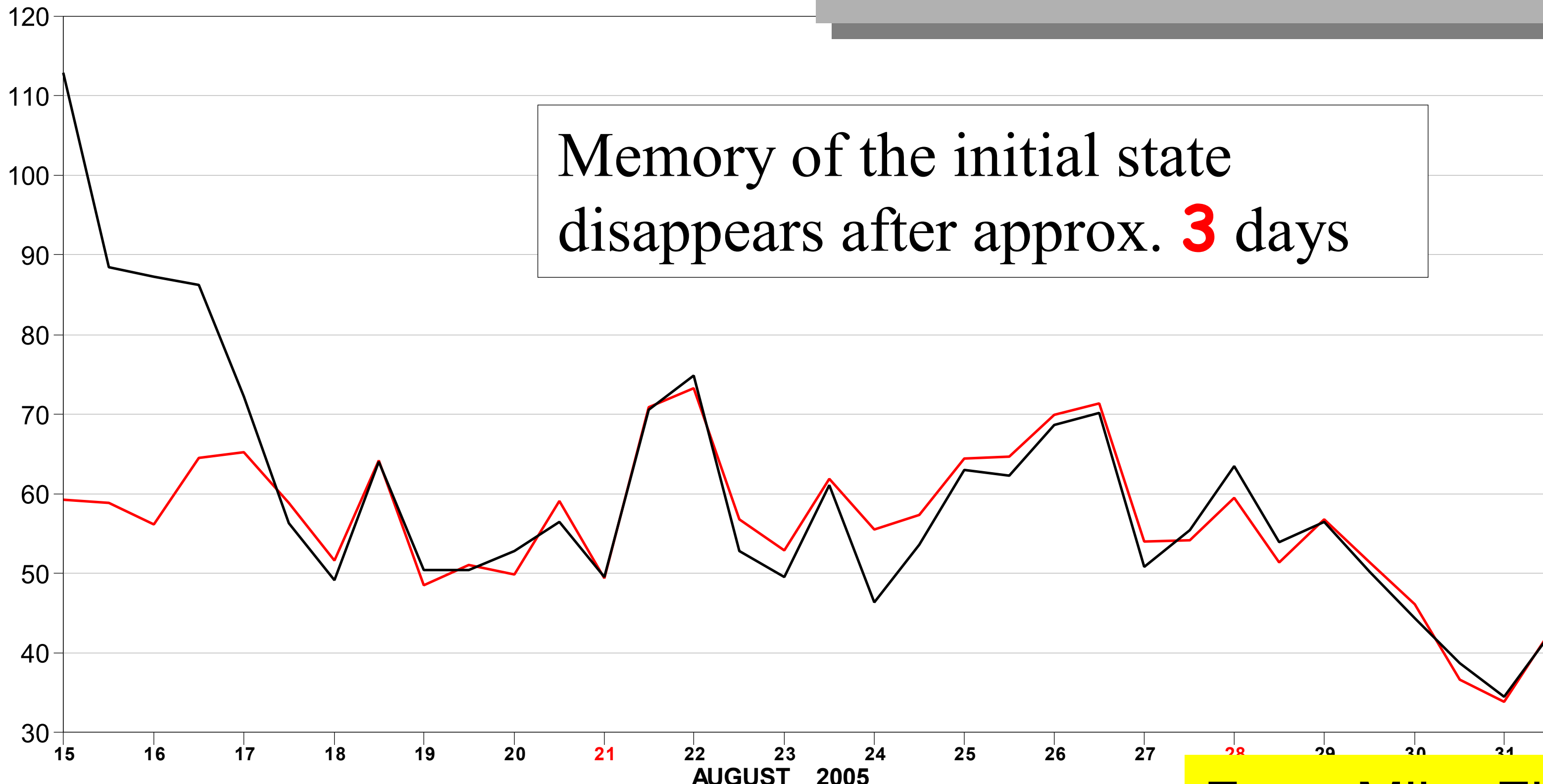
- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

Why do we need EDA in 4DVar?



Time series curves
500hPa Geopotential
Root mean square error forecast
S.hem Lat -90.0 to -20.0 Lon -180.0 to 180.0
T+120

Analysis experiment started with satellite data reintroduced on 15th August 2005



Memory of the initial state disappears after approx. **3** days

From Mike Fisher

ECMWF

Why do we need EDA in 4DVar?

- The influence of the starting point of minimization wanes after ~ 3 days
- 4DVAr does not cycle error info, only the state estimate
- From a 4DVar perspective a longer assimilation window (≥ 3days) would suppress the need to cycle (error) information

Why do we need EDA in 4DVar?

- However:
  1. An effective model error parametrization must be applied to reconcile model and measurements over a long analysis time window
  2. We would still lack an estimate of analysis errors

Why do we need EDA in 4DVar?

What if we try to cycle the errors too?

- Sequential approach (a.k.a. Kalman Filter):
  1. Assume Gaussian errors and linear error propagation
  2. Cycle state **and errors** estimates

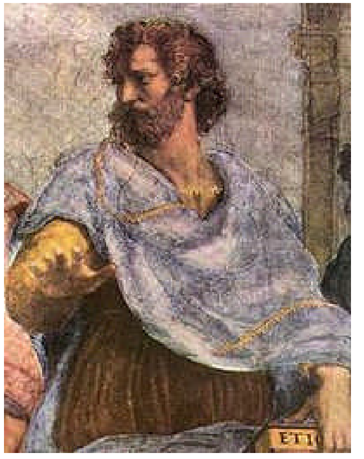
Why do we need EDA in 4DVar?

- However:

  1. Dimension of state space $O(10^7\text{-}10^8)$ makes full KF impracticable

  2. Monte Carlo approx: EnKF, i.e., run a number O(100) of equi-probable realizations and use perturbations from the mean as errors

  3. EnKF errors span the ensemble perturbations space -> rank deficiency -> localization, etc.



μεσον τε και αριστον

Aristotle, Nic. Ethics 2.6

Hybrid systems

- Use of ensemble perturbations in a 3-4DVar analysis
- Cycle error information through ensemble DA
- Retain the implicit full rank error representation of 3-4DVar

Why do we need EDA in 4DVar?

Hybrid systems

- Ensemble perturbations can be used in a 3-4DVar analysis in a number of different ways:

1. Use ensemble variances for observation QC
2. Use ensemble (co)variances as starting B matrix of minimization (often in linear combination with climatological B, extra control variable)
3. Use of ensemble covariances inside 4DVar minimization (En4DVAR)

Outline

- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

The ECMWF EDA system

$$\mathbf{x}_a = \left(\mathbf{I} - \mathbf{KH}\right)\mathbf{x}_f + \mathbf{Ky}$$

$$\mathbf{e}_a = \left(\mathbf{I} - \mathbf{KH}\right)\mathbf{e}_f + \mathbf{Ke}_o$$

"When simulating the error evolution of the reference system one should use the reference gain matrix K" (Berre *et al*. 2007)

The ECMWF EDA system

This is what a cycled ensemble of 4DVar analyses with random observation and SST perturbations does!

$$\boldsymbol{\varepsilon}_a = \left(\mathbf{I} - \mathbf{KH}\right)\boldsymbol{\varepsilon}_f + \mathbf{K}\boldsymbol{\varepsilon}_o$$

The ECMWF EDA system

- 10 ensemble members using 4D-Var assimilations
- **T399** outer loop, T95/T159 inner loop (reduced number of iterations)
- Observations randomly perturbed
- Cloud track wind (AMV) correlations taken into account
- SST perturbed with realistically scaled structures
- Model error represented by stochastic methods (SPPT, Leutbecher, 2009)
- All 107 conventional and satellite observations used

from: Lars Isaksen

The ECMWF EDA system

1. EDA is a 'Stochastic EnKF' with 'stochastic physics' based model error representation.

2. EDA does not use the ensemble mean and does not compute an ensemble analysis.

3. EDA is 'only' used for flow-dependent covariance evolution

4. EDA avoids the localization problems by including the (costly) 4D-Var analysis step.

from: Lars Isaksen

The ECMWF EDA system

- We start with the diagonal of the P^f matrix, i.e.:

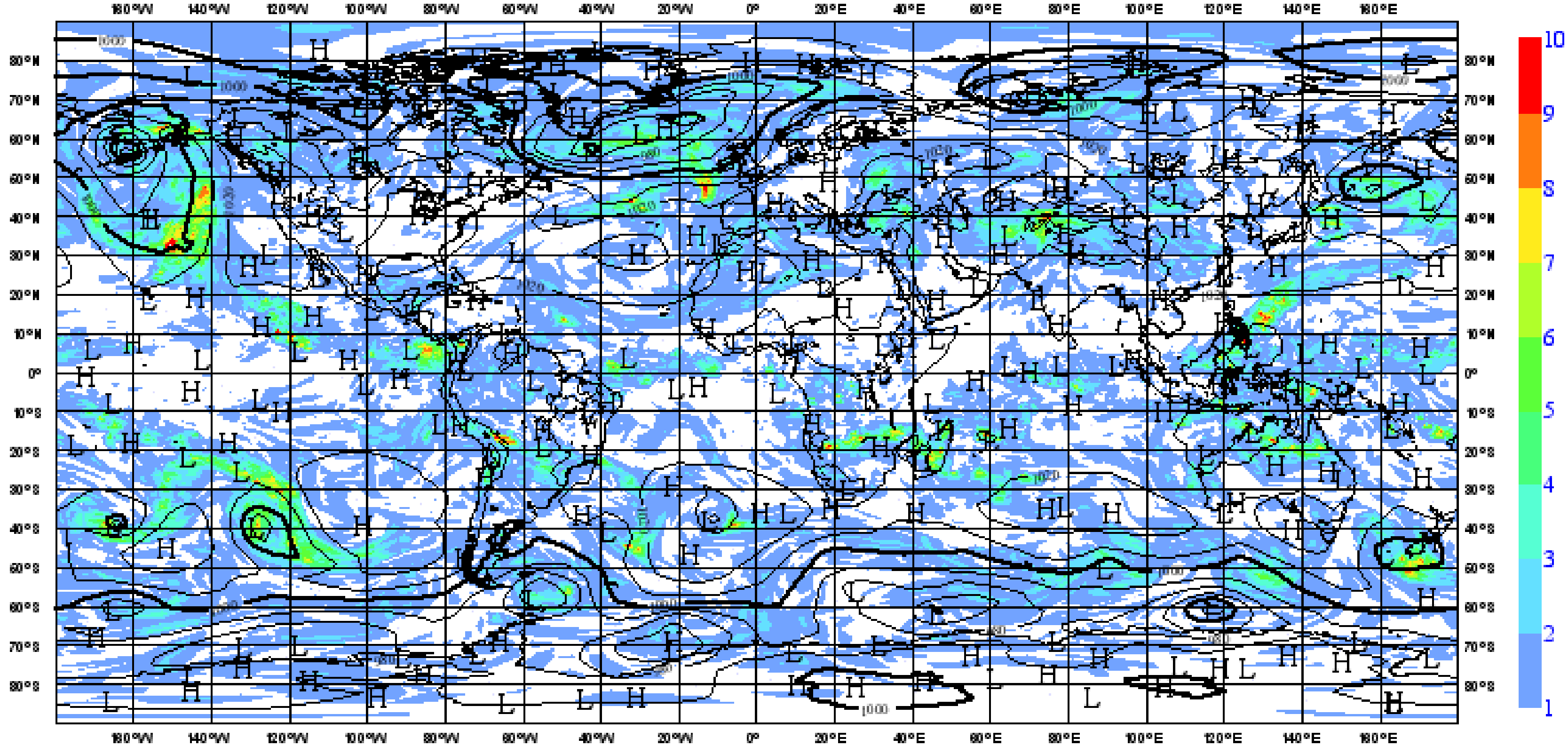
  "Estimate the first guess error variances with the StDev of the EDA short range forecasts"

- This has been tried before (Kucukkaraca and Fisher, 2006, Fisher 2007, Isaksen et al., 2007) but results have been inconclusive

The ECMWF EDA system

What raw ensemble variances look like?

Vorticity StDev, ml64 (500hPa)



The ECMWF EDA system

- Ensemble spread seems well correlated with expected error around dynamically active regions but:

Noise level of forecast ensemble is high

Outline

- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

The filtering problem

- Noise level is due to sampling errors: 10 member Ensemble
- EDA is a stochastic system: Variance errors ~ $1/N_{ens}$
- We need a system to effectively filter out noise from first guess ensemble forecast variances

The filtering problem

"**Mallat et al.**: 1998, Annals of Statistics, 26,1-47"

Define $G^e(i)$ as the random component of the sampling error in the estimated ensemble variance at gridpoint i:

$$G^e(i) \equiv \tilde{B}_{ii} - E\left[\tilde{B}_{ii}\right]$$

Then the covariance of the sampling noise can be shown to be a simple function of the ensemble error covariance:

$$E\left[G^e(i)G^e(j)\right] = \frac{2}{N-1}\left(E\left[\tilde{B}_{ij}\right]\right)^2 \qquad \textbf{(1)}$$

The filtering problem

"**Mallat et al.: 1998, Annals of Statistics, 26,1-47**"

A consequence of (1) is that:

$$L_{G^e}(i) = \frac{L_{e^b}(i)}{\sqrt{2}} \qquad (2)$$

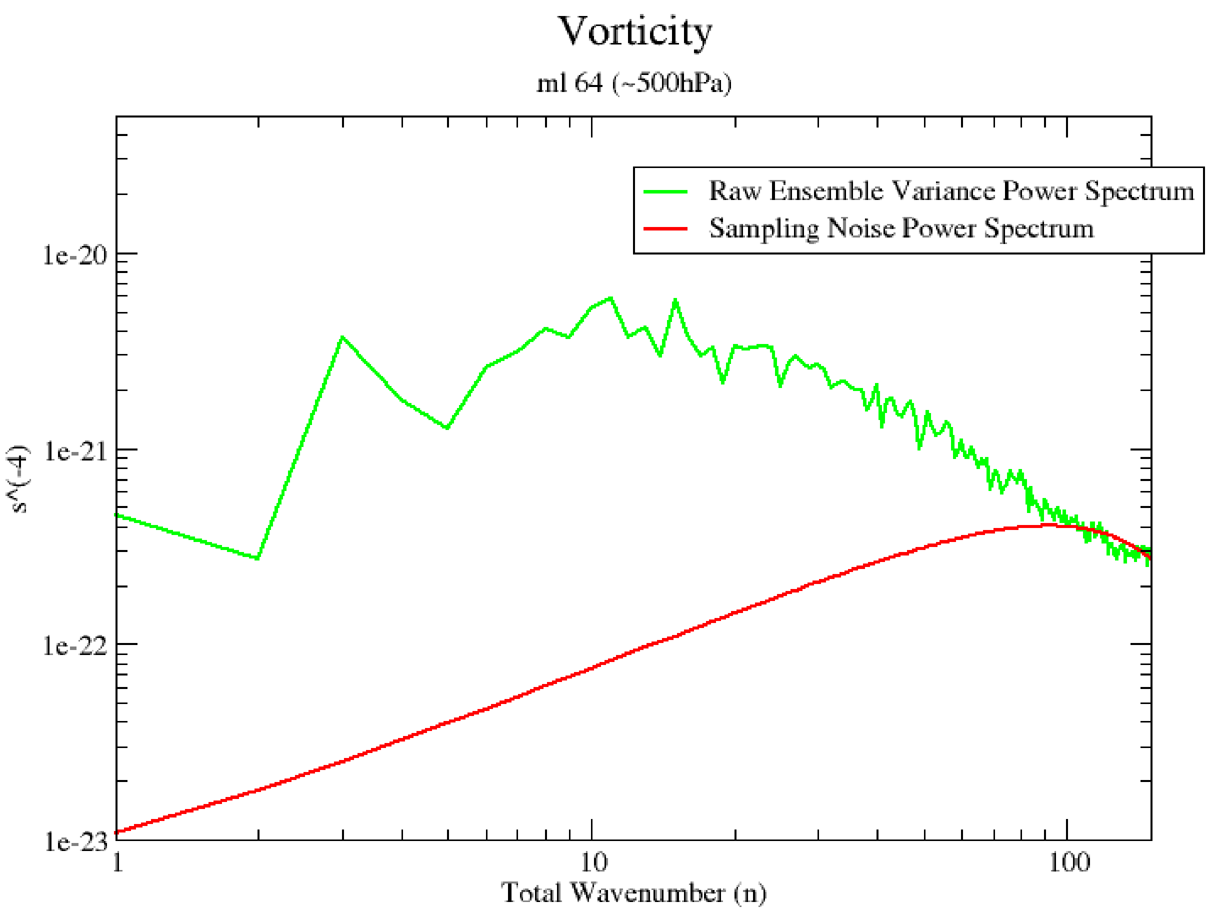
i.e., there is **scale separation** between noise error correlation and ensemble error correlation

=>

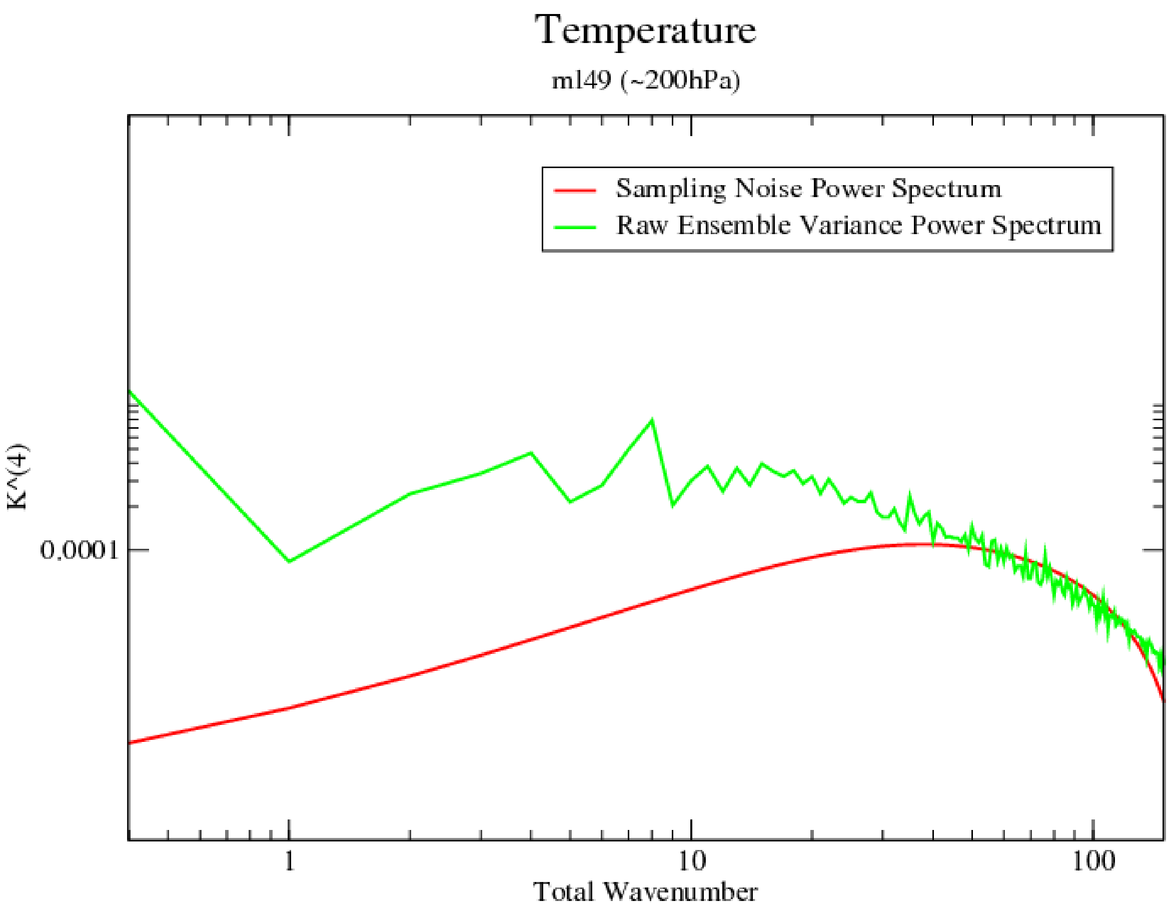
we can use a **spectral filter** to disentangle the two

Is this the case?

The filtering problem



The filtering problem

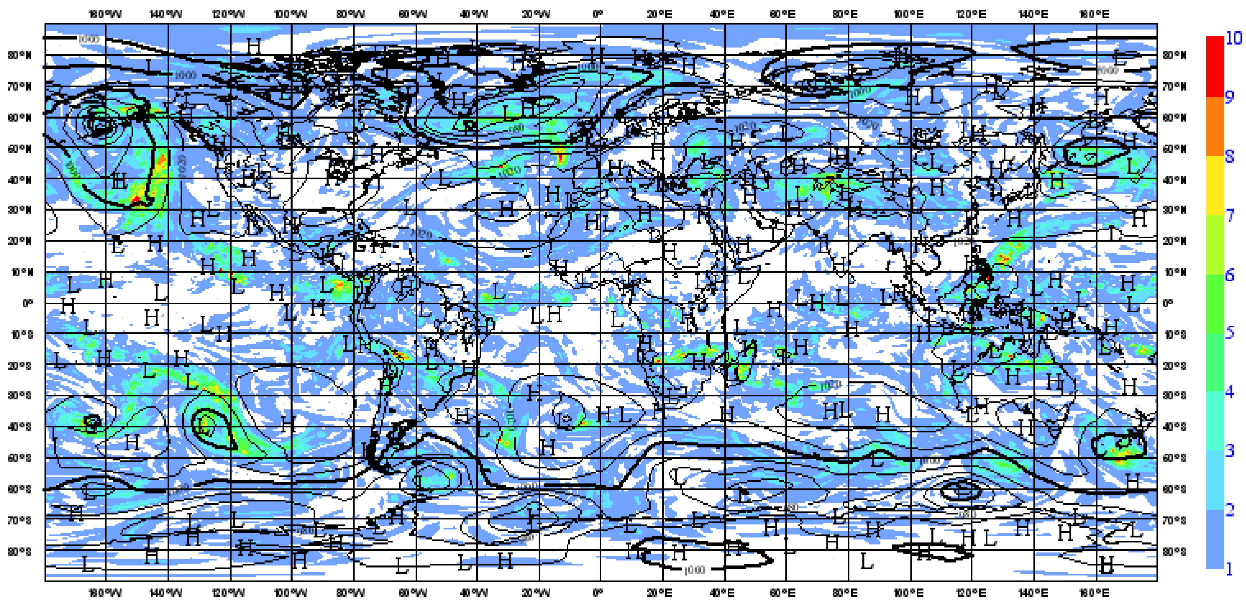


ECMWF

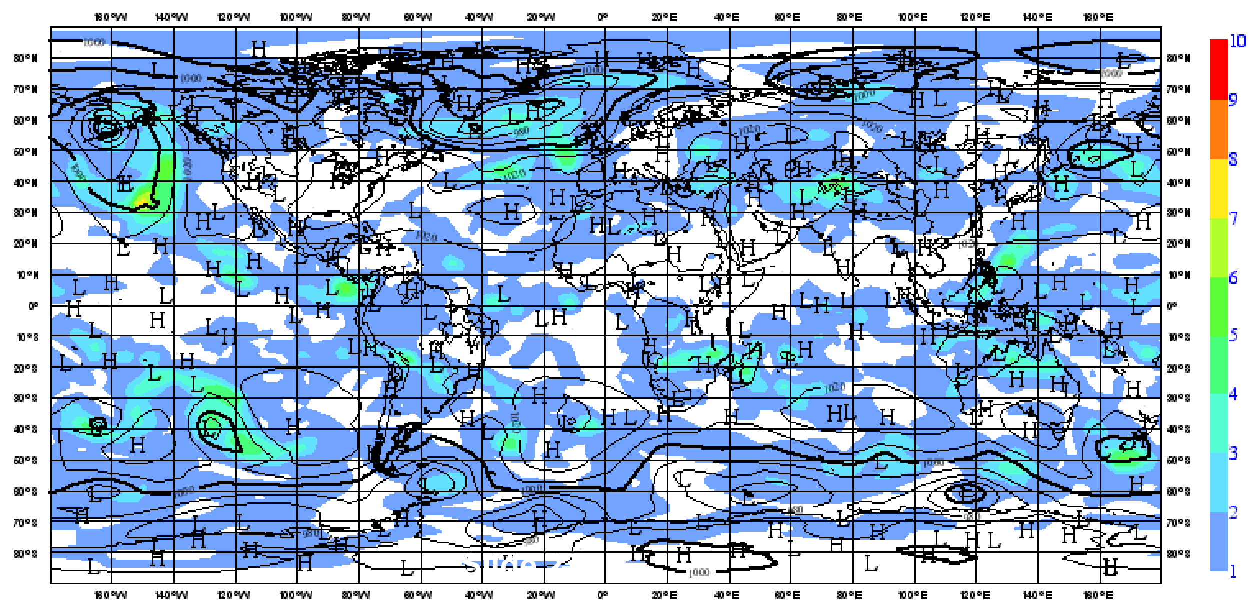
The filtering problem

- There is indeed a scale separation between signal and sampling noise!
- Truncation wavenumber is determined by **maximizing signal-to-noise** ratio of filtered variances (details in Raynaud et al., 2009, and forthcoming Tech. Memo)
- **Optimal truncation wavenumber** depends on parameter and model level

The filtering problem



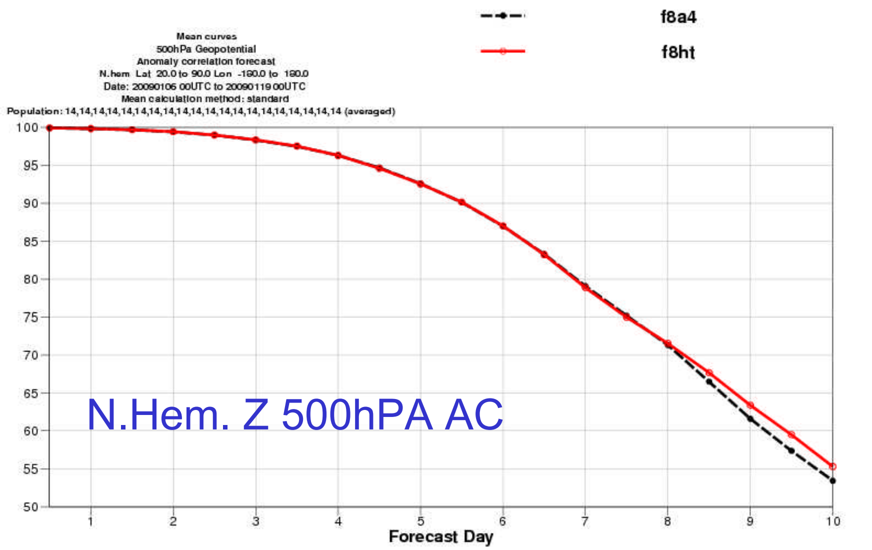
Raw Ensemble StDev
VO ml64

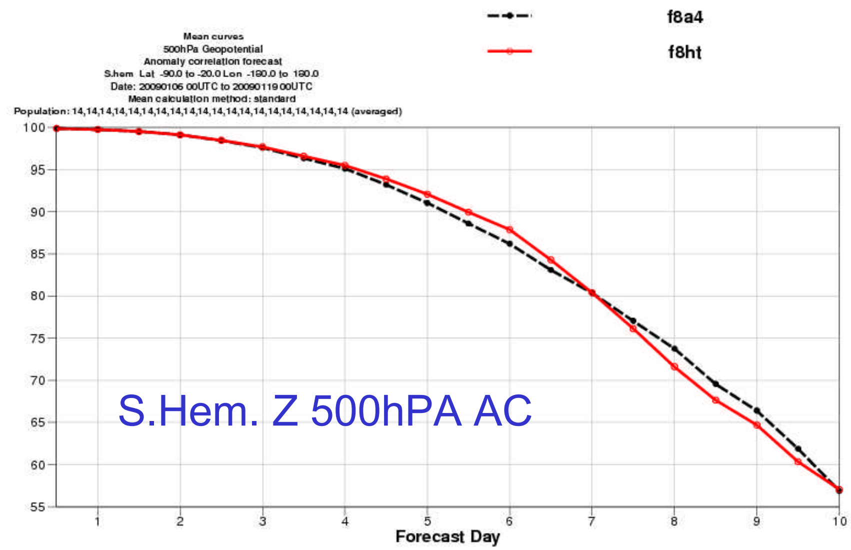


Filtered Ensemble StDev
VO ml64

The filtering problem

Is Filtering the Ensemble Variances enough to improve the analysis?





Not really…

ECMWF

The calibration problem

Is the ensemble fg statistically calibrated?

A reliable ensemble satisfies:

$$\left(1-\tfrac{1}{N_{ens}}\right)^{-1}\langle \text{Ens\_Variance}\rangle=\left(1+\tfrac{1}{N_{ens}}\right)^{-1}\langle \text{Ens\_Squared\_Mean\_Error}\rangle$$

The calibration problem

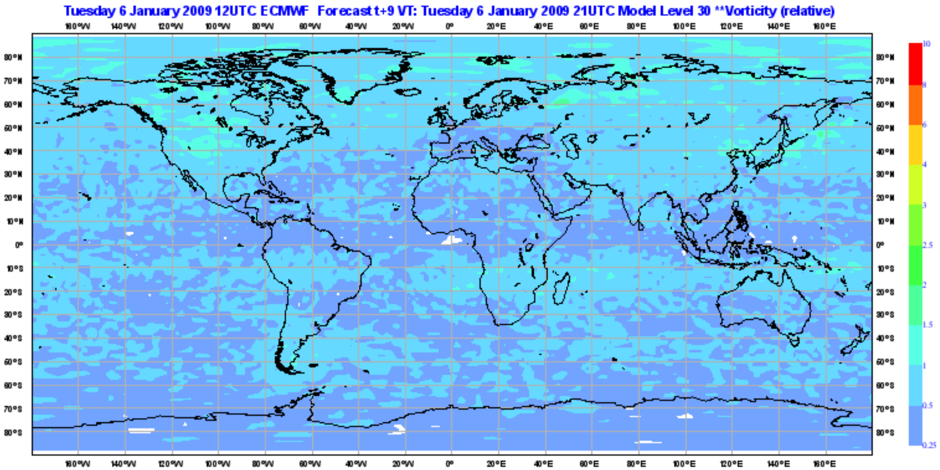
Is the ensemble fg statistically calibrated?

- Previous studies had highlighted the **under-dispersiveness** of the ensemble fg variance and tried to correct it with **one global inflation factor**
- The situation is more complicated…

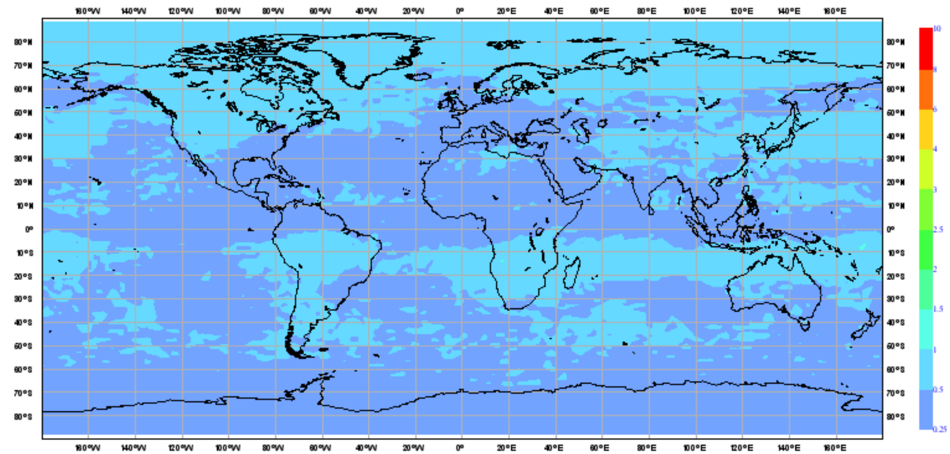
The calibration problem

Vorticity ml 30 (~50hPa)

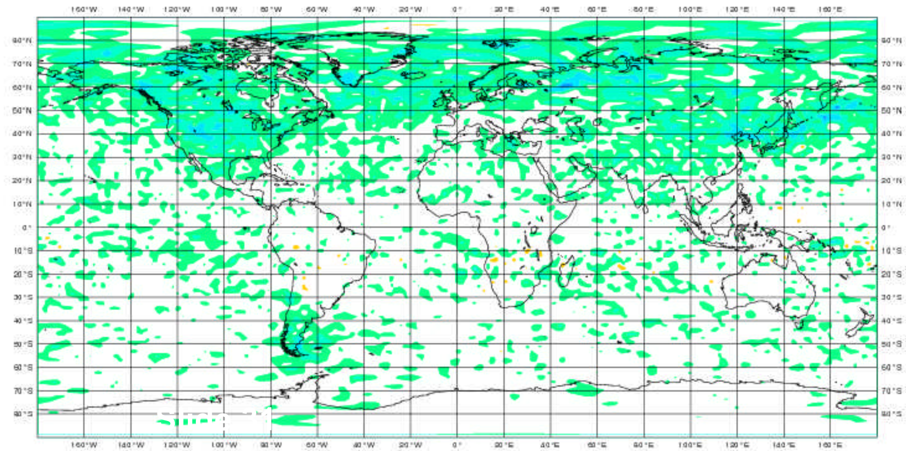
Ensemble Error



Ensemble Spread



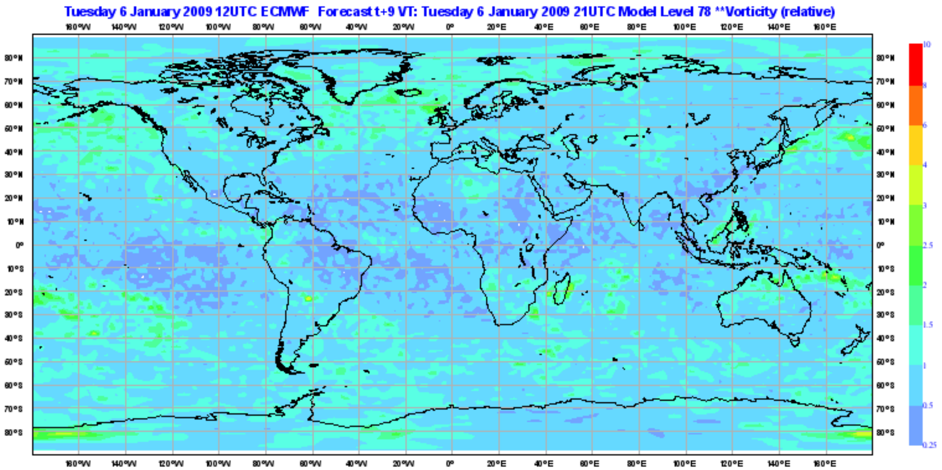
Spread - Error



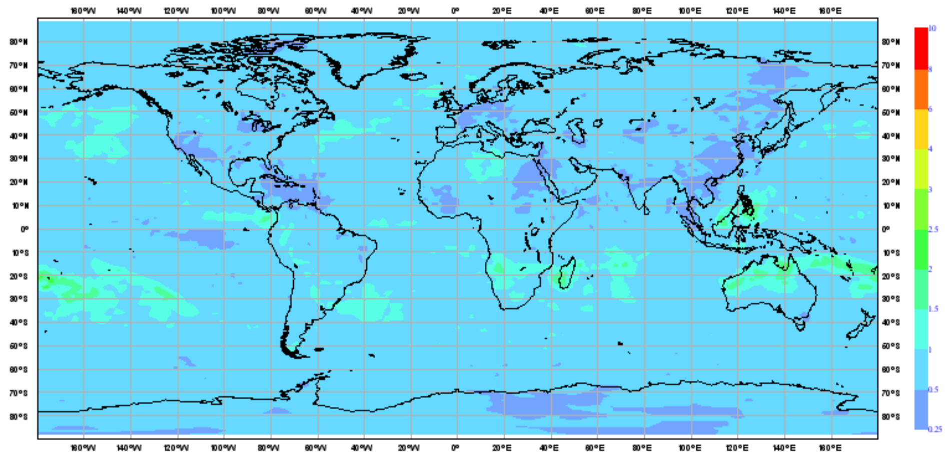
The calibration problem

Vorticity ml 78 (~850hPa)

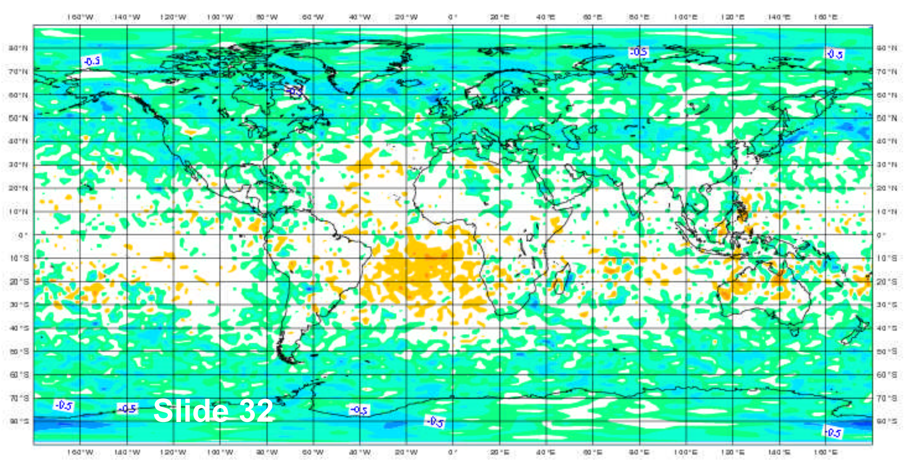
Ensemble Error



Ensemble Spread



Spread - Error

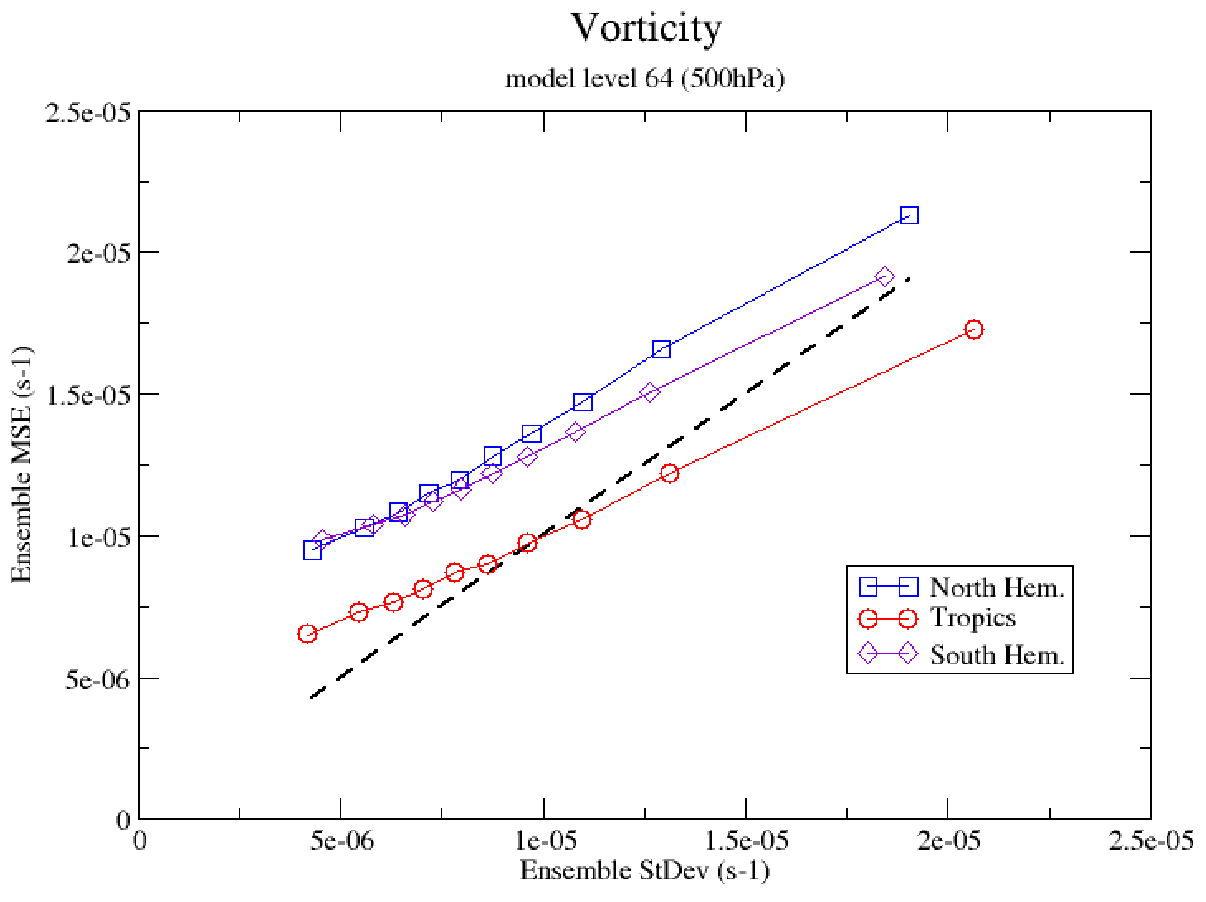


The calibration problem

Is the ensemble fg statistically calibrated?

- Calibration factors needs to be model level, latitude and parameter dependent
- Calibration factors seems also to be flow-dependent, i.e. depend on the size of the expected error

The calibration problem



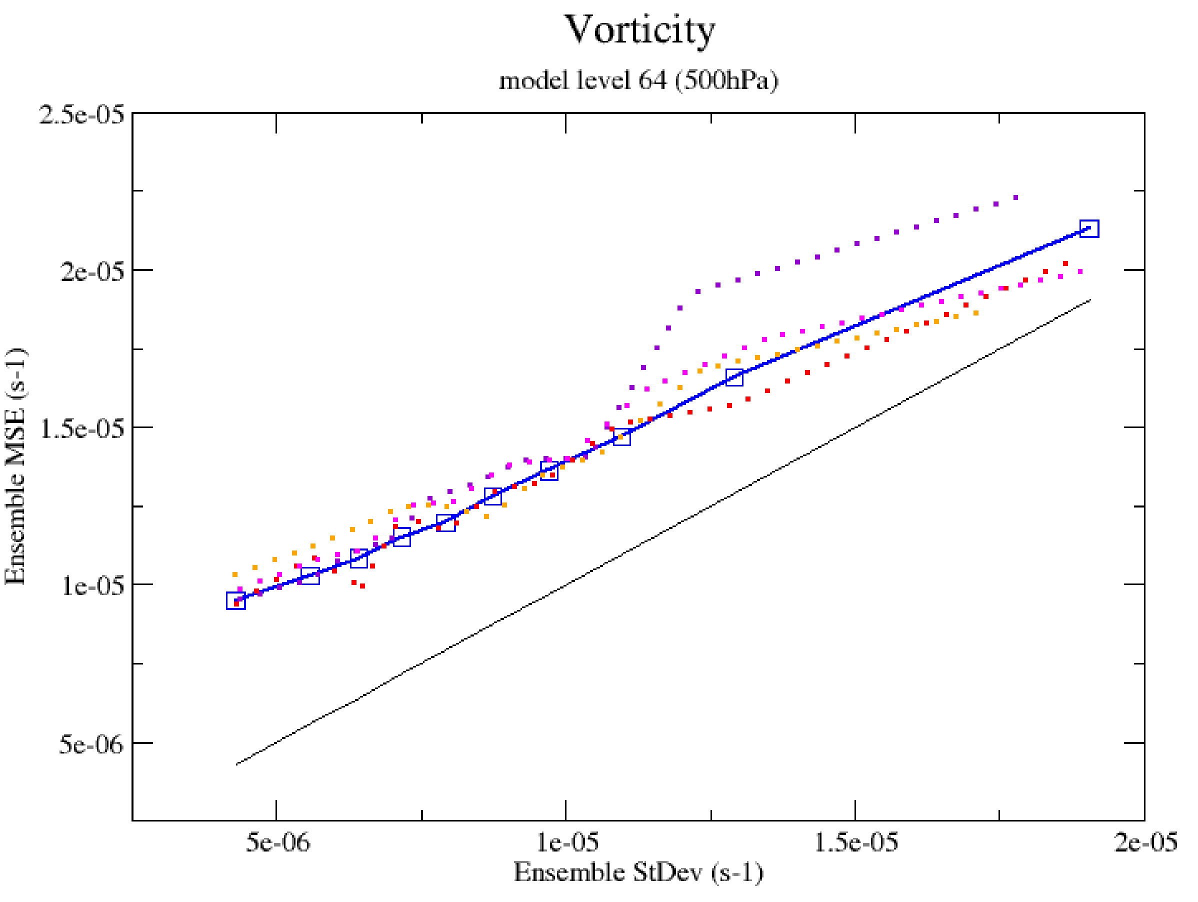
ECMWF

The calibration problem

- Calibration factors need to be **flow-dependent**, too!
- Do they also change in **time**?

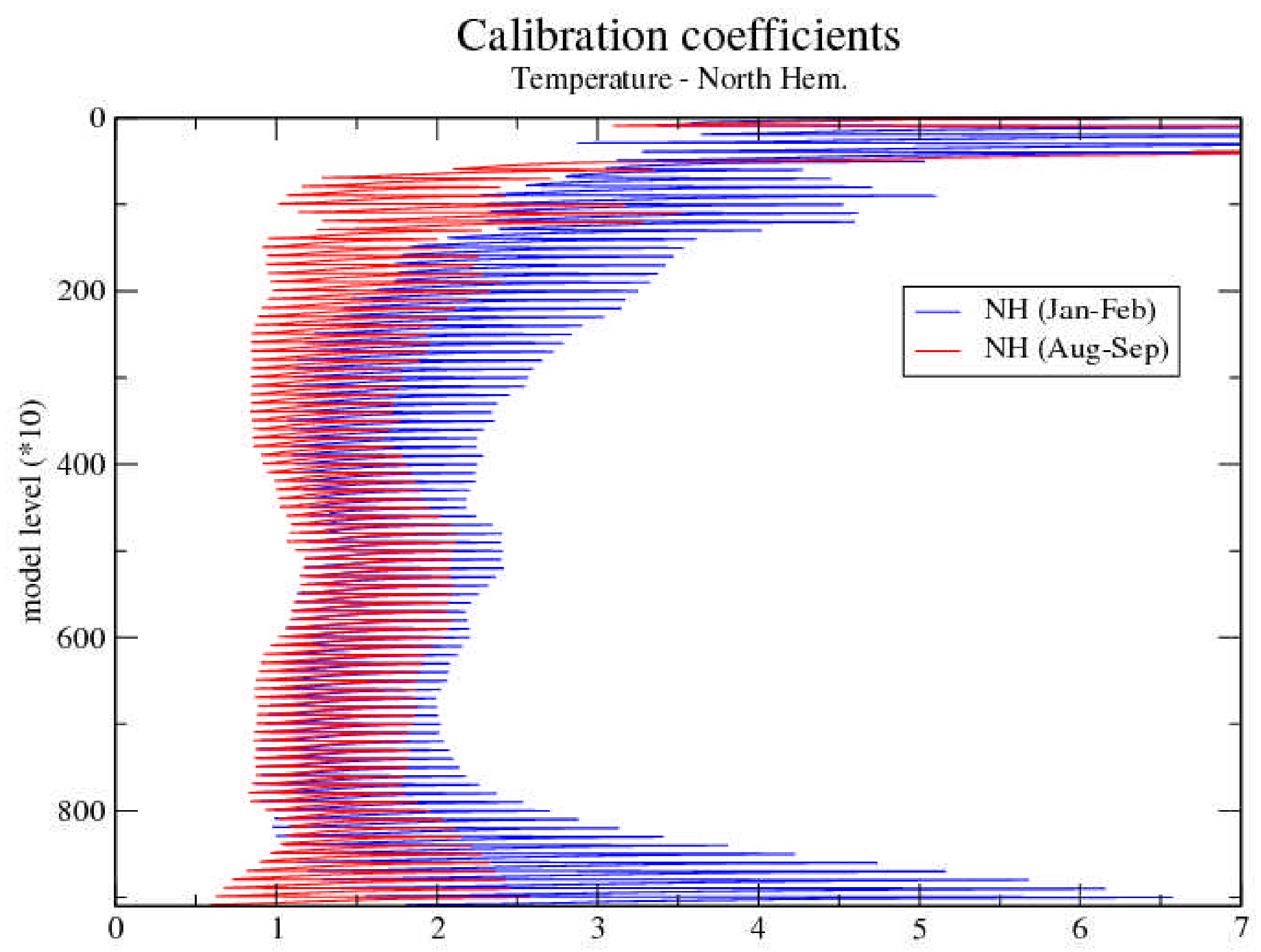
ECMWF

The calibration problem



ECMWF

The calibration problem

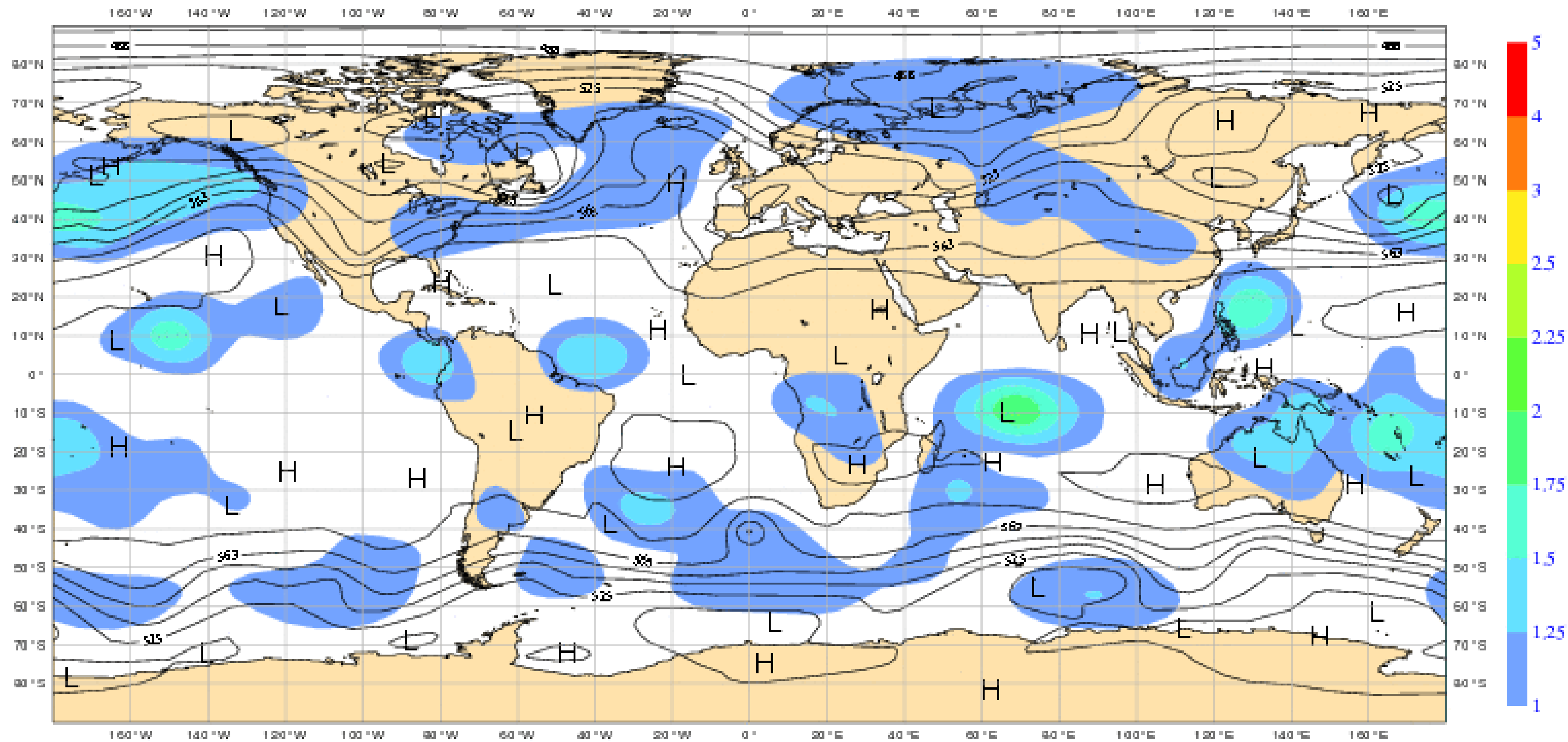


The calibration problem

- There is not a large **day-to-day** variability but **seasonal variability** is important
- General solution: **slowly varying adaptive** calibration

ECMWF Analysis VT:Tuesday 6 January 2009 18UTC Model Level 64 Vorticity (relative)

Tuesday 6 January 2009 12UTC ECMWF Forecast t+9 VT: Tuesday 6 January 2009 21UTC 500hPa Geopotential



Outline

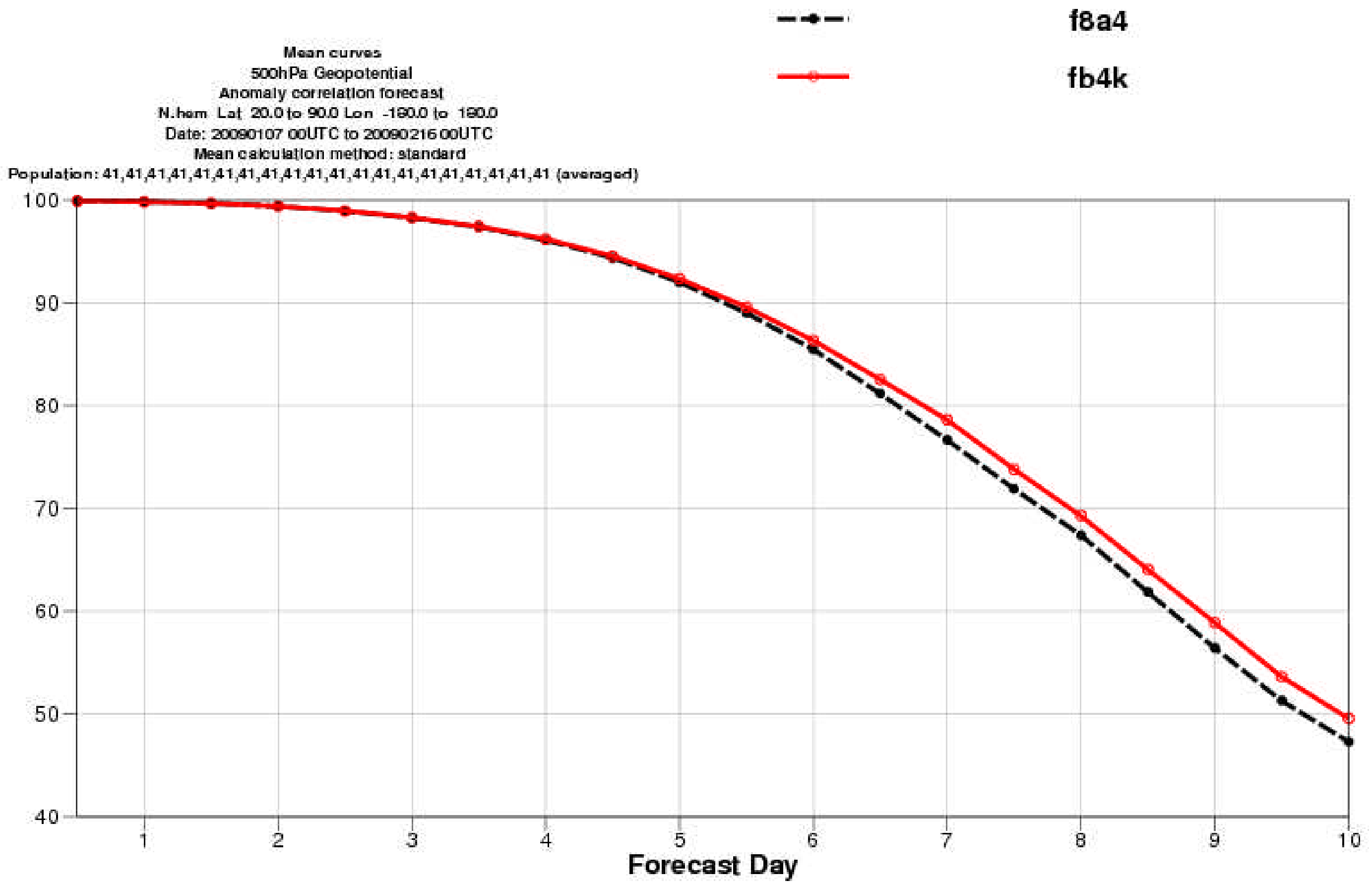
- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

4DVar assimilation with EDA variances

Deterministic DA experiments with EDA variances

1. CY35r3_esuite, T799L91, 7/01 – 16/02 2009
2. Control f8a4
3. Experiment fb4k with ensemble DA variances:
   a) **Calibration** step: adaptive, flow-dependent, regionally varying, for each parameter and model level
   b) Filtering step: **"Optimal" spectral filtering**
   c) EDA variances are used both in **observation QC** and start of **4DVar minimization** (preconditioning)

4DVar assimilation with EDA variances

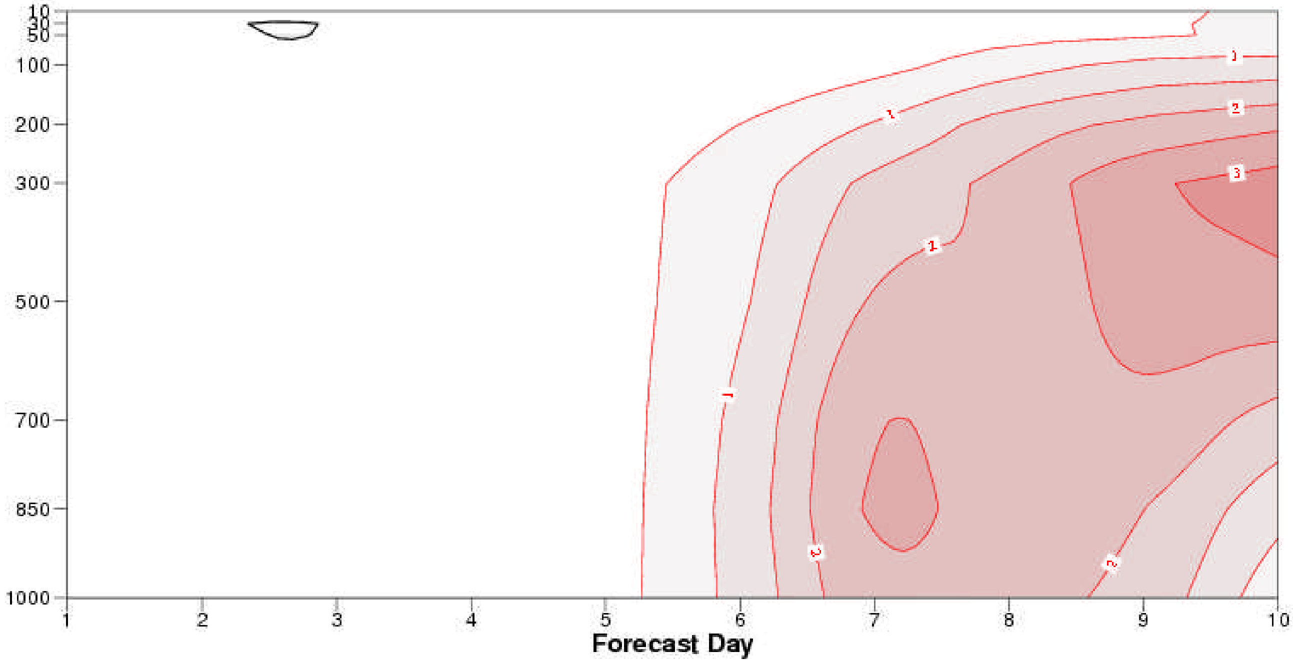


ECMWF

4DVar assimilation with EDA variances

N.HEM Z ac
Jan-Feb

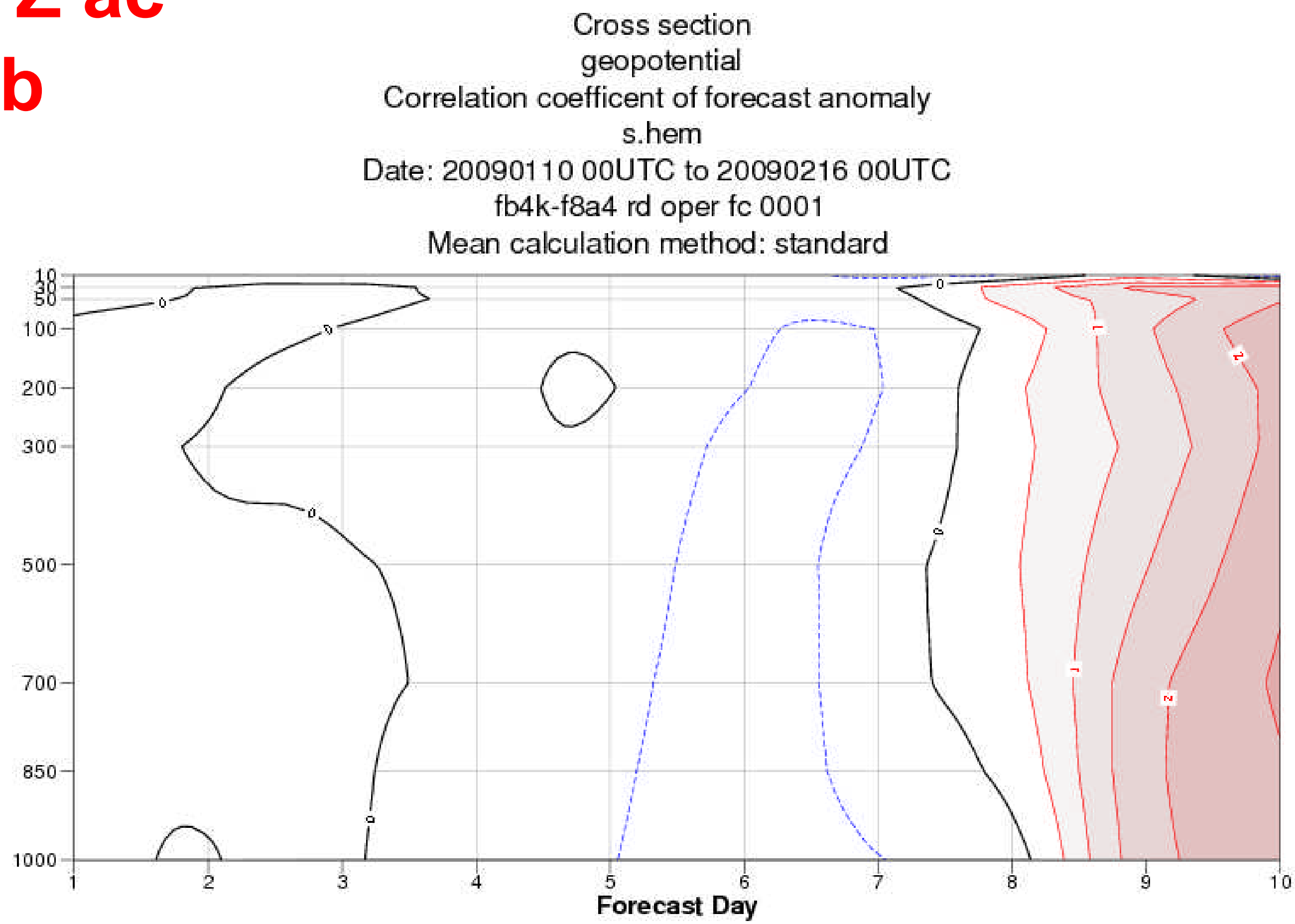
Cross section
geopotential
Correlation coefficent of forecast anomaly
n.hem
Date: 20090110 00UTC to 20090216 00UTC
fb4k-f8a4 rd oper fc 0001
Mean calculation method: standard



ECMWF

4DVar assimilation with EDA variances

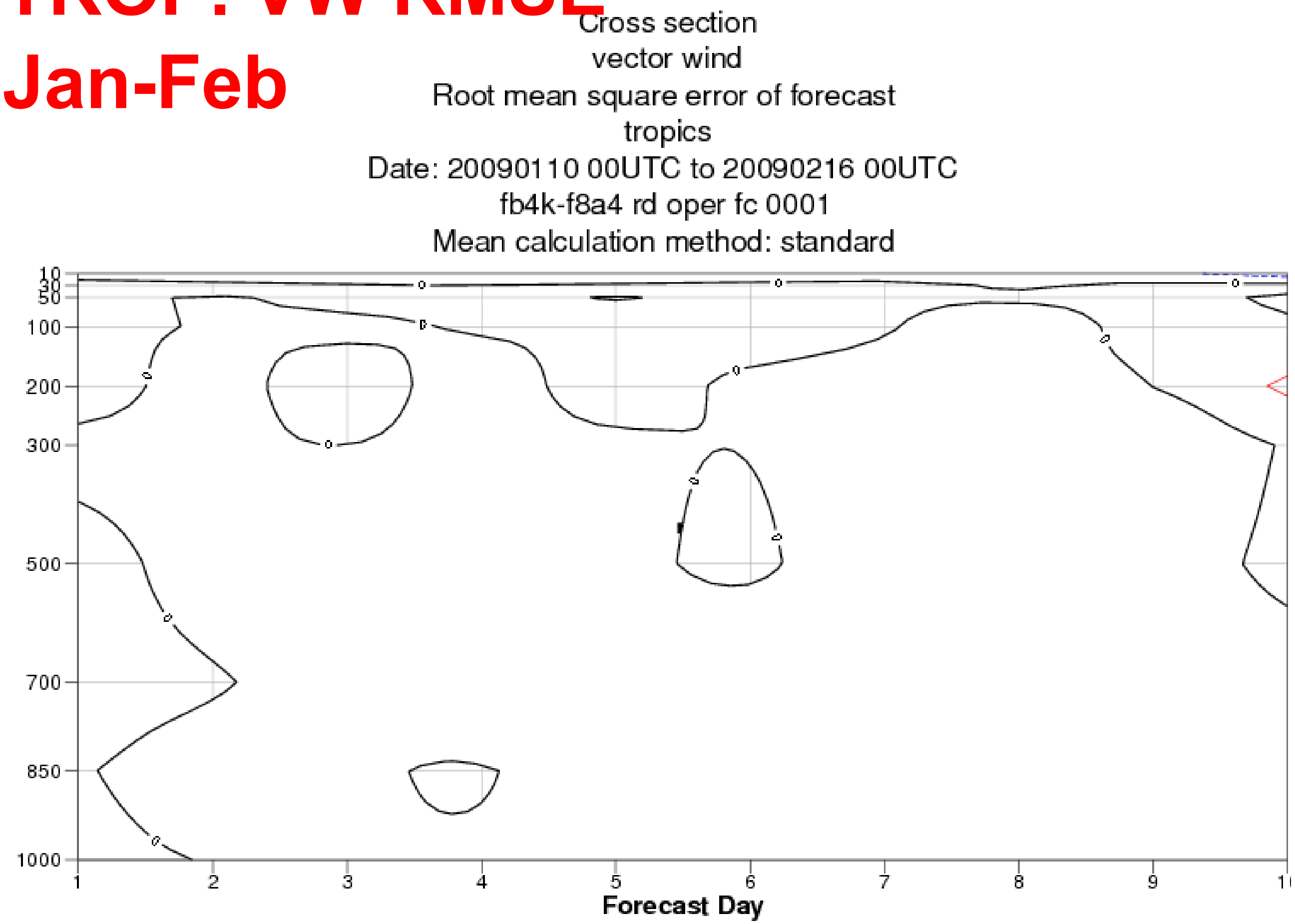
S.HEM Z ac
Jan-Feb

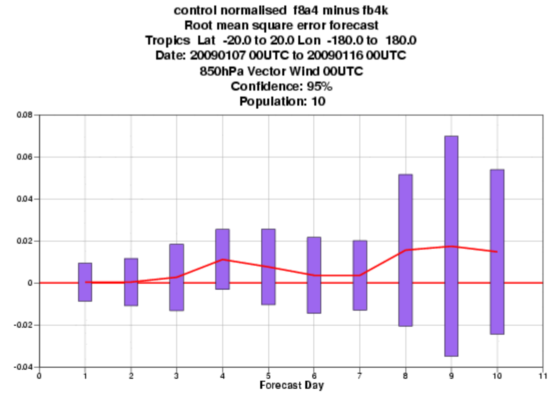


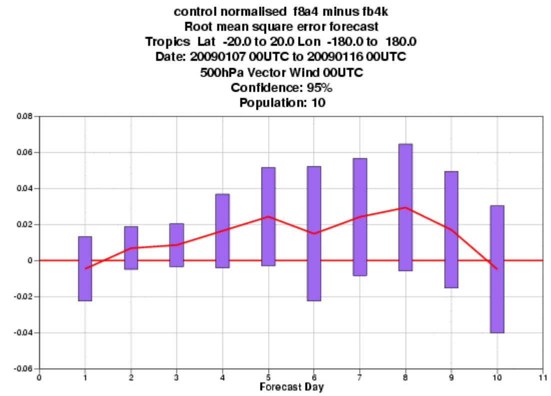
ECMWF

4DVar assimilation with EDA variances

TROP. VW RMSE
Jan-Feb

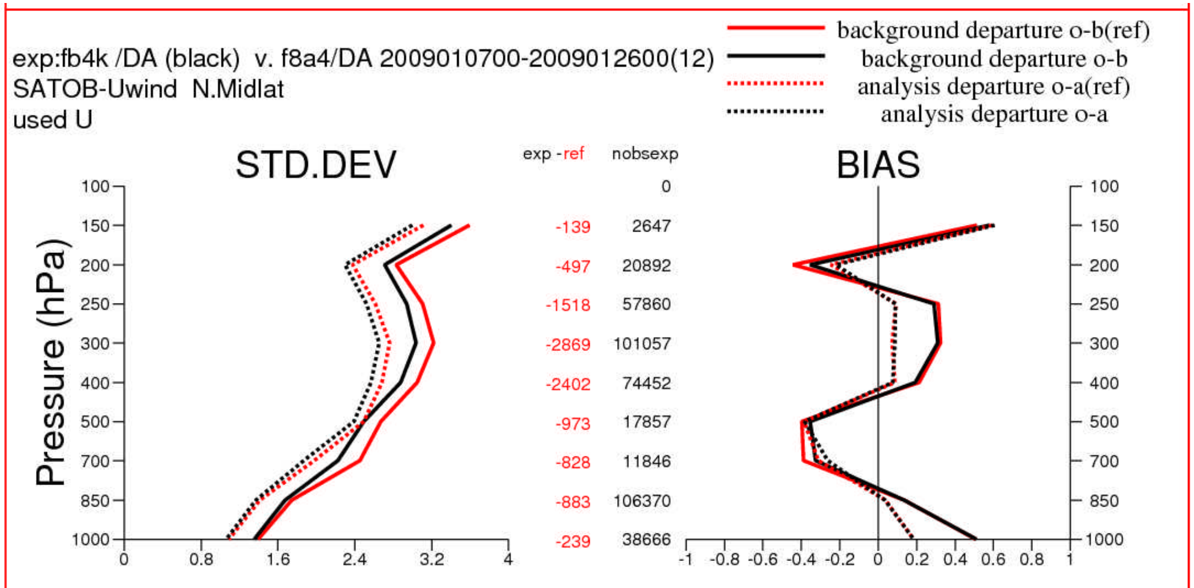




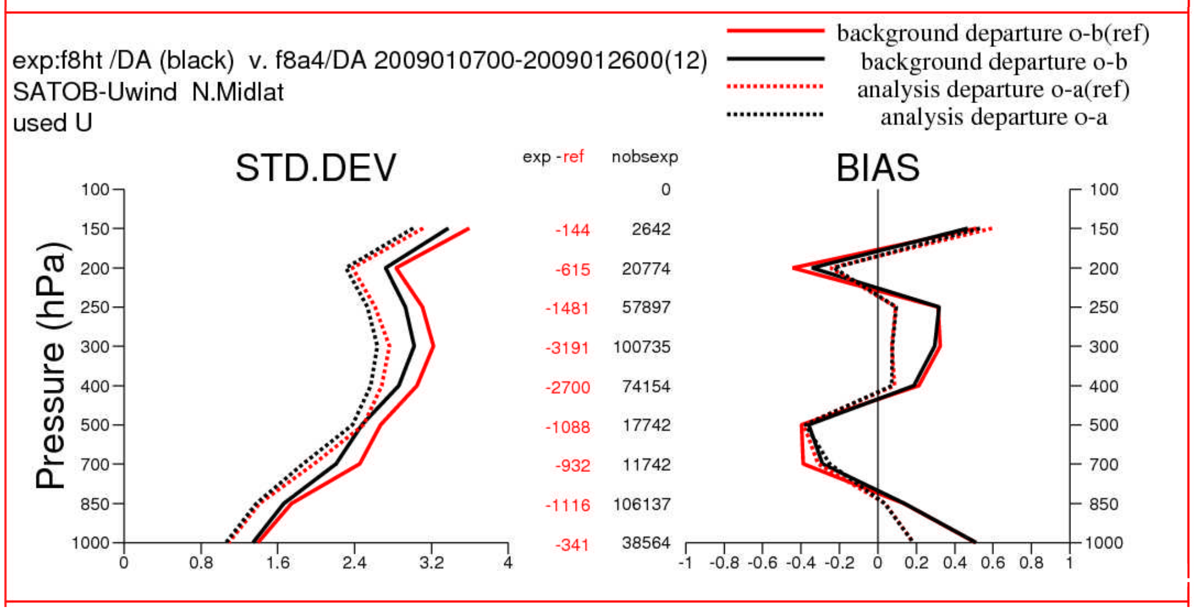


ECMWF

4DVar assimilation with EDA variances



Filtered + Calibrated EDA



Filtered EDA

Preliminary Conclusions

- Use of flow dependent EDA variances does improve the deterministic scores!

- A careful post-processing step of the raw ensemble first guess forecast is necessary to:

  a) Filter sampling noise

  b) Adaptively calibrate the ensemble

Preliminary Conclusions

- Improvement possibly linked to better OBS QC decisions, given 4DVar relative insensitivity to initial BG variances (Fisher, 2003)
- Further improvements in model error parameterizations will directly benefit the system
- Increase in ensemble size will benefit the system

Preliminary Conclusions

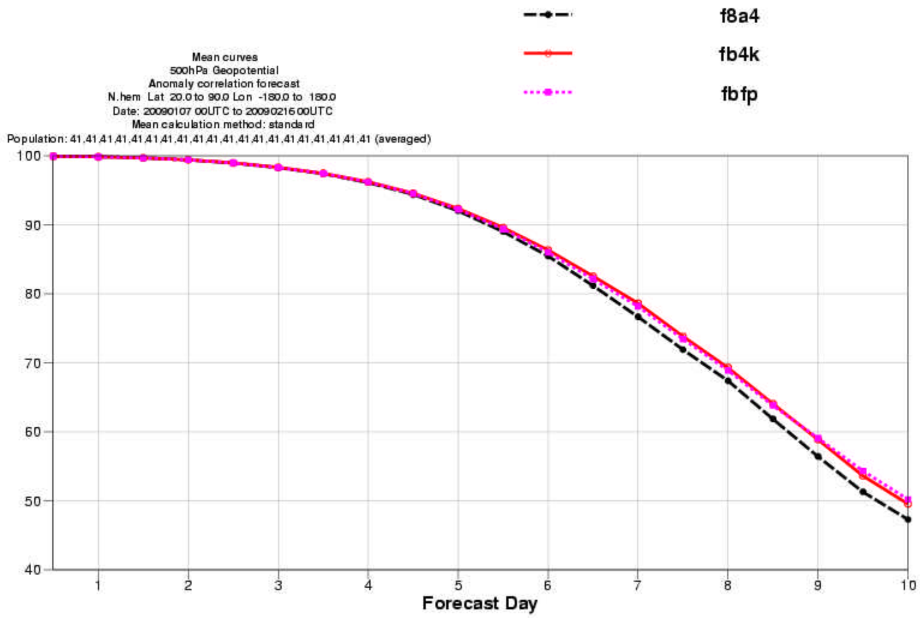
WHERE NEXT

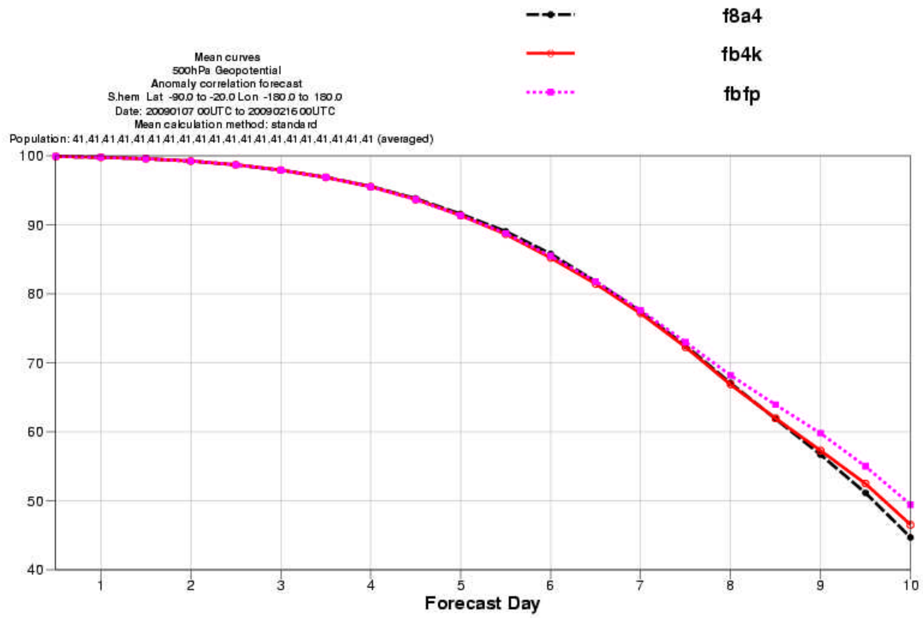
- Operational implementation and testing
- Further tuning of system at full operational resolution (T1279L91)
- Generalize the use of EDA variances to unbalanced components of control vector

Preliminary Conclusions

WHERE NEXT

- Investigate the impact of EDA size increases on deterministic analysis





ECMWF

Preliminary Conclusions

Medium term:

- Refine the representation of initial uncertainties (correlated perturbations, surface fields uncertainties) in stochastic EDA
- Evaluate EnKF covariances
- Further develop the hybridization of 4DVar with EDA (investigate the use of EDA covariances)

Outline

- Why do we need EDA information in 4DVar?
- The ECMWF EDA system
- Optimal filtering and calibration
- 4DVar assimilation with EDA variances
- The ECMWF EnKF project: motivations and goals

ECMWF ENKF

People: Mats Hamrud, 

Massimo Bonavita,

David Tan, 

+ Jeff Whitaker (consultant)

ECMWF ENKF

Motivation:

1. EnKF is currently the only viable alternative to 4DVar for operational NWP. EnKF applications (Canada, Japan) have almost reached similar quality to 4DVar

2. Computational scalability of 4DVar is limited, of EnKF almost perfect

ECMWF ENKF

Motivation:

3. Test the benefit of a hybrid EnKF/4DVar assimilation system (vs Ensemble of 4DVar DA/4DVar)

4. Interest in EnKF method for ERA CLIM project of early 20th century reanalysis using surface observations only

ECMWF ENKF

Plans:

1. Implement a square root type EnKF (EnSRF and LETKF)
2. Implementation to take advantage of future massively parallel architectures: minimize communication ("High latency implementation", Anderson and Collins, 2007)

ECMWF ENKF

High latency implementation, Anderson and Collins, 2007

1. Advance the model ensemble to analysis time;
2. Compute all the observation priors (Hx) ;
3. Assign to each processor a number of spatially contiguous grid points (for load balancing purposes the number of grid points assigned per processor should be inversely proportional to the local observation density);
4. Each processor is sent the complete ensemble state of its grid points plus all the observations and observation priors inside the „influence region";
5. Analysis can be computed independently on each processor grid point by grid point
6. The updated ensemble states are collected from each processor.

ECMWF ENKF

Status:

1. Project started in late January 2010, is under active (part time!) development

Thanks for your attention!

I welcome your questions/comments...