Advancing data assimilation in global NWP: the ECMWF perspective

Massimo Bonavita and many colleagues

ECMWF

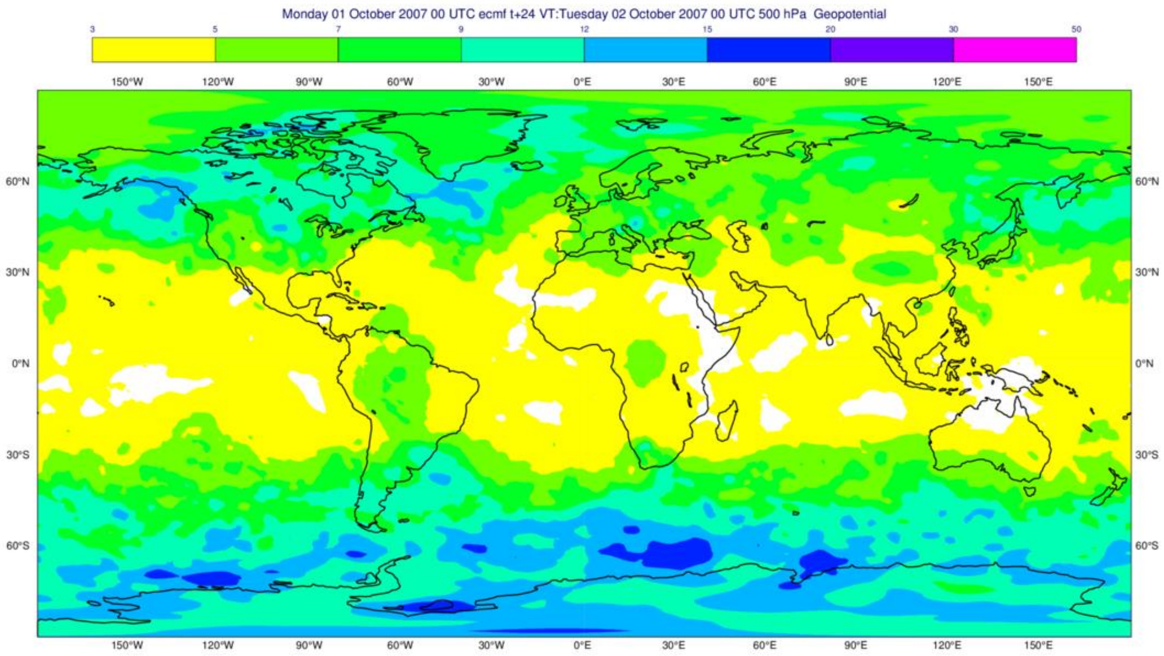
Acknowledgments.: P. Lean, E. Holm, S. Massart, S. Lang, P. Laloyaux, A. Geer, L. Isaksen, R. Radu, C. Soci, G. Biavati

Outline

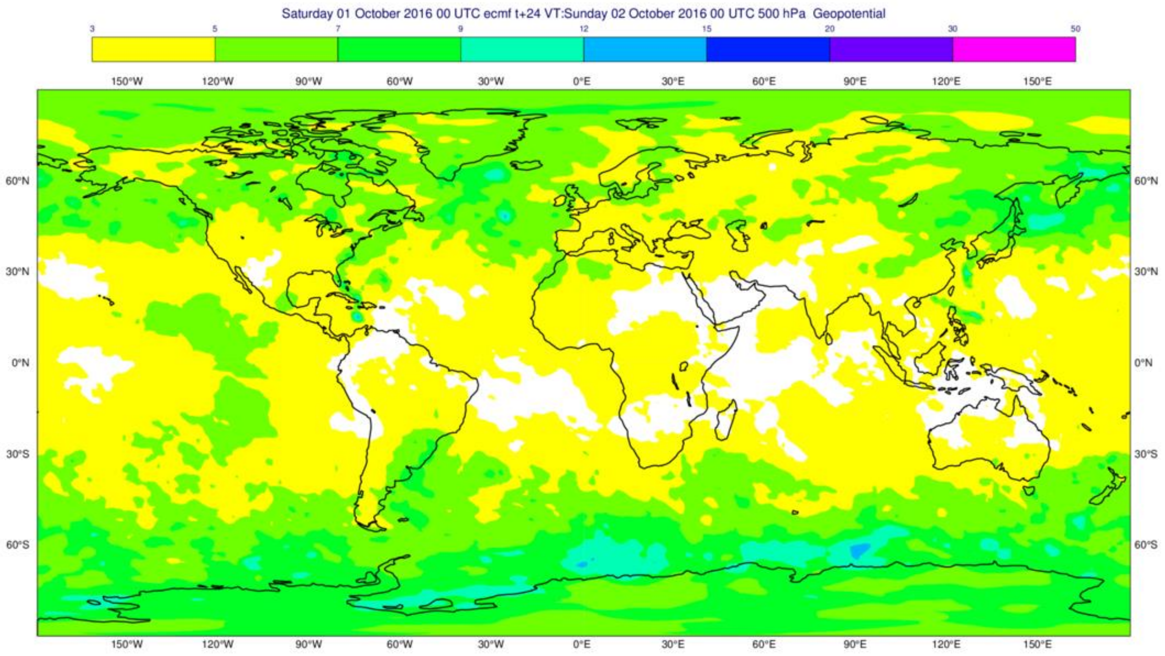
- The past 10 years: where has DA progress come from?
- The next 10 years: where will DA progress come from?

The past 10 years

RMSE of t+24h ECMWF geopot. fcst, October 2007



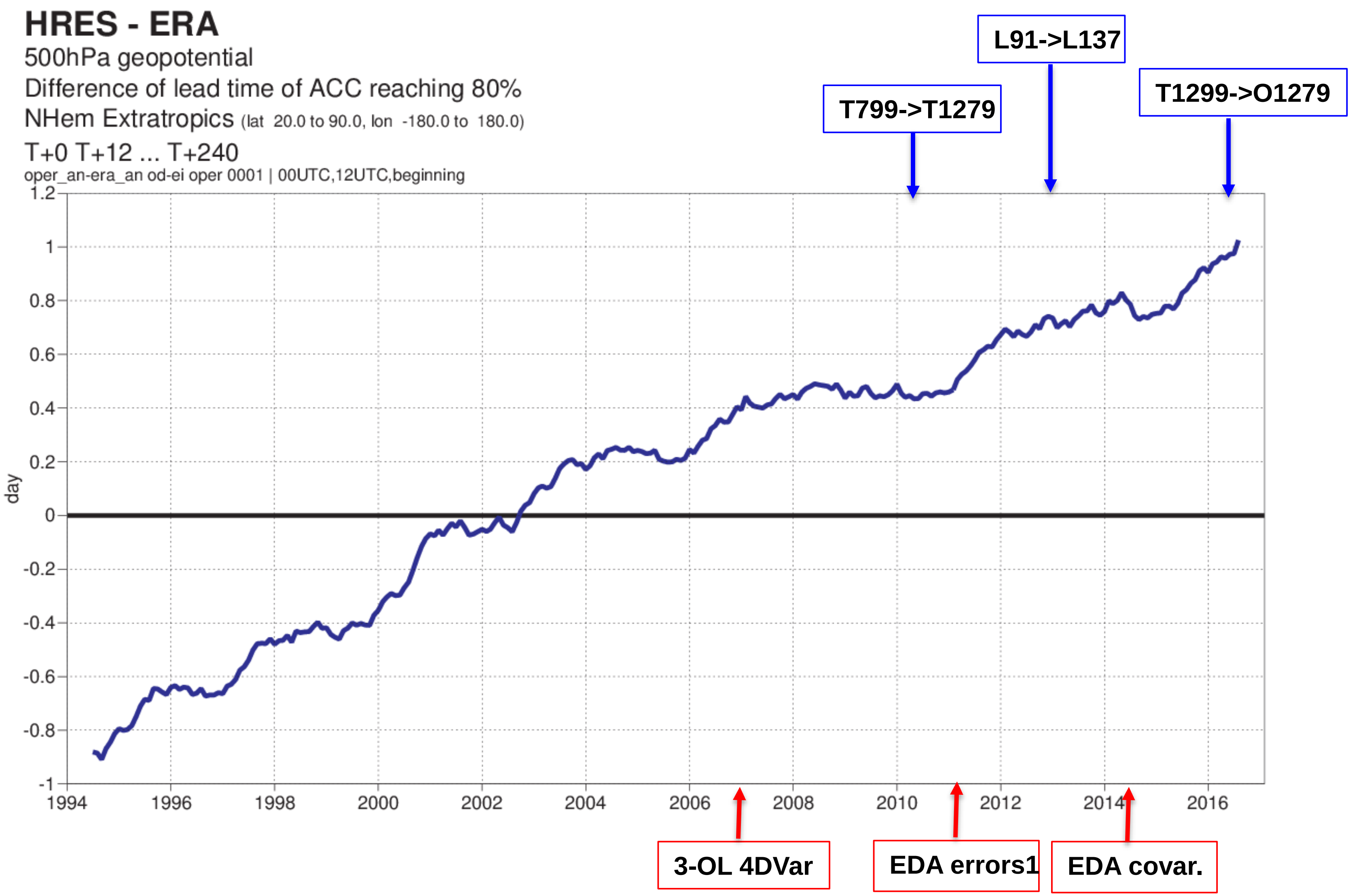
RMSE of t+24h ECMWF geopot. fcst, October 2016



from Lars Isaksen

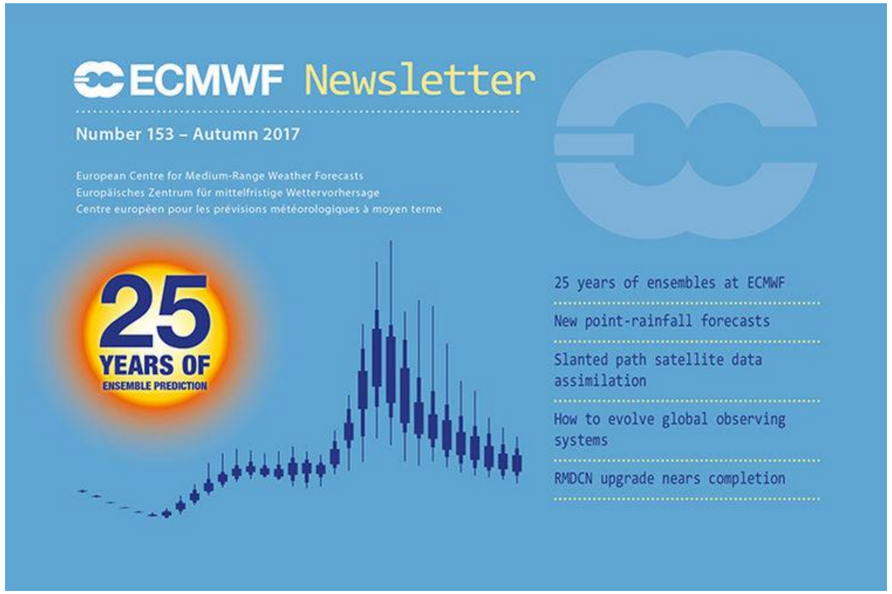
The past 10 years

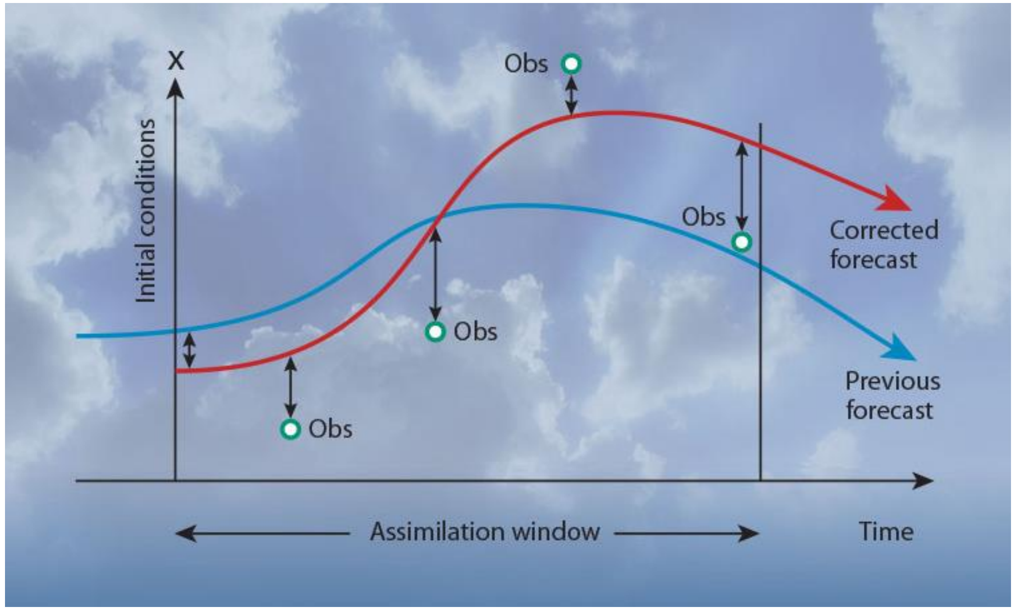
“Victory is claimed by all, defeat by none”
Tacitus



The past 10 years

- **Ensemble prediction** (Toth and Kalnay, 1993; Molteni et al., 1996; Houtekamer et al., 1996) and **variational DA** (Parrish and Derber, 1992; Courtier et al., 1994) came of age in the mid-1990s





The past 10 years

- **Ensemble prediction** (Toth and Kalnay, 1993; Molteni et al., 1996; Houtekamer et al., 1996) and **variational DA** (Parrish and Derber, 1992; Courtier et al., 1994) came of age in the mid-1990s

- But initially they were going along separate roads…

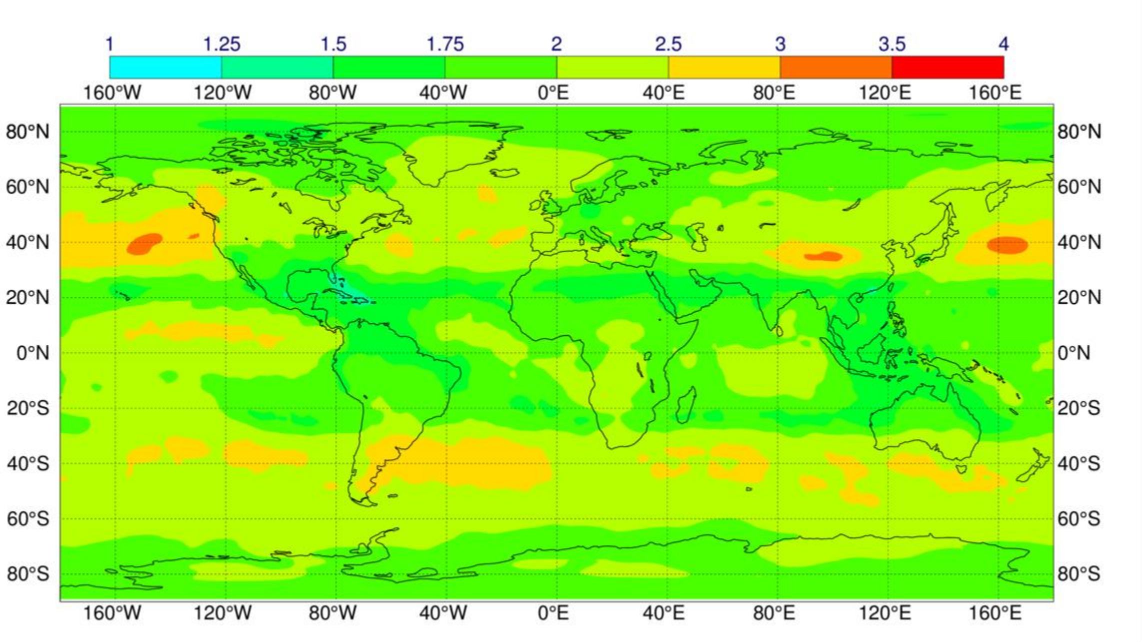
    - Ensemble forecasts initialised from singular vectors (ECMWF), bred vectors (NCEP), though the connection between DA and ensemble prediction was made early on at Env. Canada

    - Initial 3/4D-Var implementations based on climatological estimates of background error covariances, or very simplified models of error evolution (Fisher and Courtier, 1995)

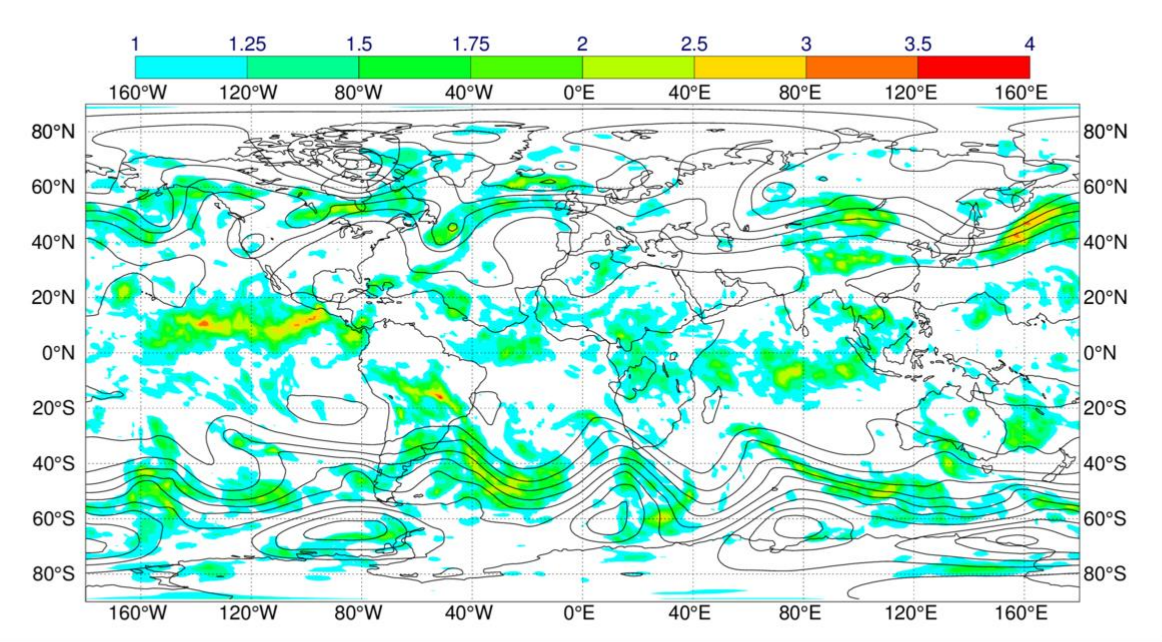
The past 10 years

- But background errors (like long range forecast errors) show large space and time variability ("*errors of the day*")

V-wind errors, 500hPa, October climatology



V-wind errors, 500hPa, October 3rd 2017



The past 10 years

- Initial 3/4D-Var implementations based on climatological estimates of background error covariances, but background errors (like long range forecast errors) show large space and time variability (“*errors of the day*”, Kalnay et al., 1997)

- **Gradual convergence of ensemble forecasting and variational DA ideas**: use ensemble DA to estimate the errors of the day and use this information in the variational analysis and to initialise ensemble forecasts -> ensemble-variational data assimilation

The past 10 years

- Ensemble-variational DA (Clayton et al., 2012; Buehner et al., 2013; Berre et al., 2015; Kleist and Ide, 2015; Bonavita et al., 2012, 2016) has been gradually adopted in all global NWP centres

- The ensemble-variational paradigm: an ensemble DA system (EnKF, EDA) is run in parallel with the higher resolution "deterministic" Var analysis cycle with the explicit aim of providing estimates of:

  a) Initial uncertainty and starting point for ensemble prediction

  b) Background error covariance for cycling Var analyses

The past 10 years

Evolution of errors during the analysis-forecast cycle:

$$e^a = x^a - x^t = (\mathbf{I} - \mathbf{KH})e^b + \mathbf{K}e^o$$

$$e^b = x^b - x^t = \mathbf{M}e^a + e^M$$

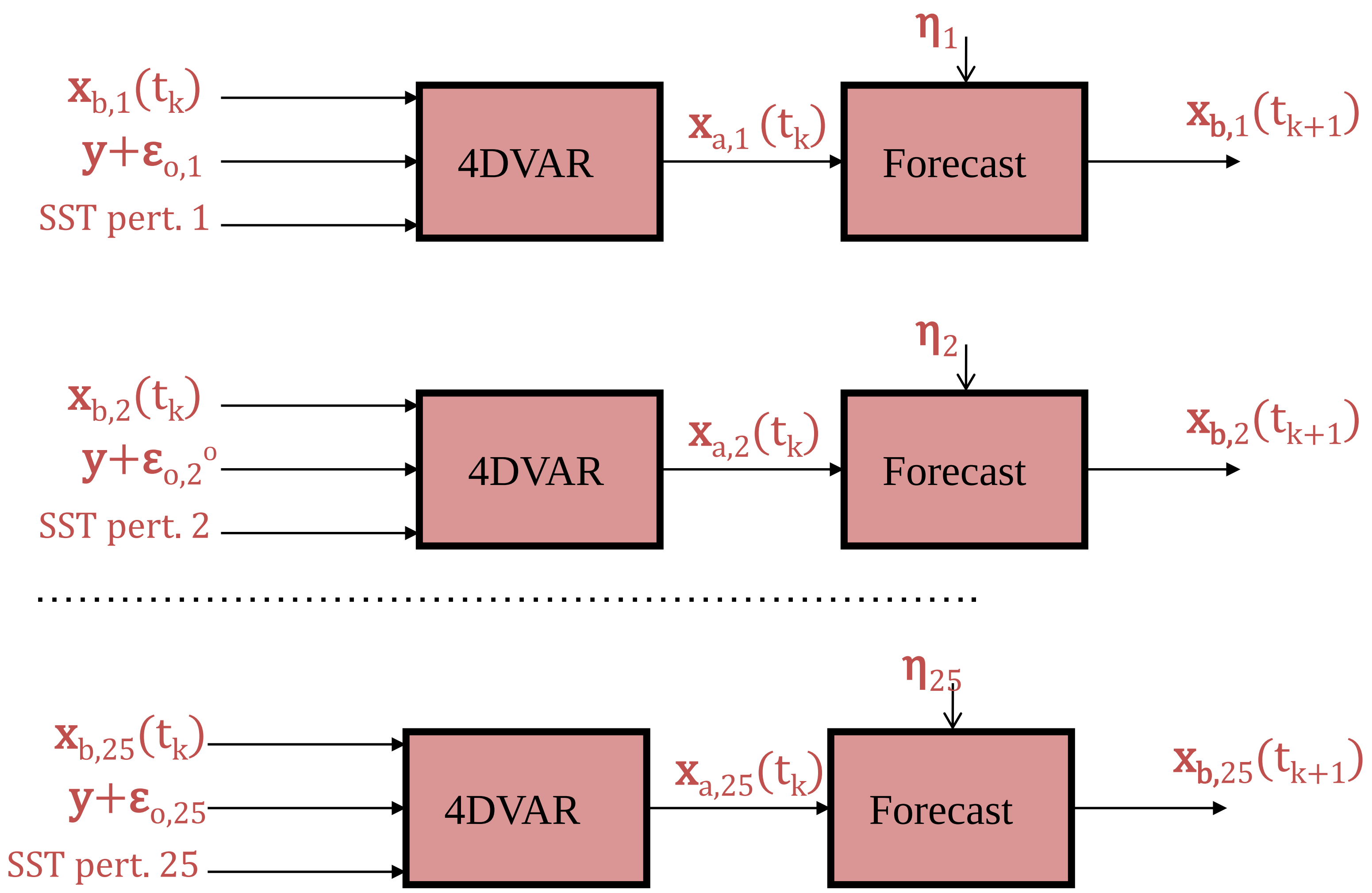
Evolution of perturbations in an ensemble DA system:

$$\varepsilon^a = x^a_{pert} - x^a_{ctrl} = (\mathbf{I} - \mathbf{KH})\varepsilon^b + \mathbf{K}\varepsilon^o$$

$$\varepsilon^b = x^b_{pert} - x^b_{ctrl} = \mathbf{M}\varepsilon^a + \varepsilon^M$$

- Monte Carlo sample of prior and posterior error distributions
- Requires adequate knowledge of DA system error sources
- Operational at CMC (Houtekamer et al., 1996), ECMWF, Météo-France

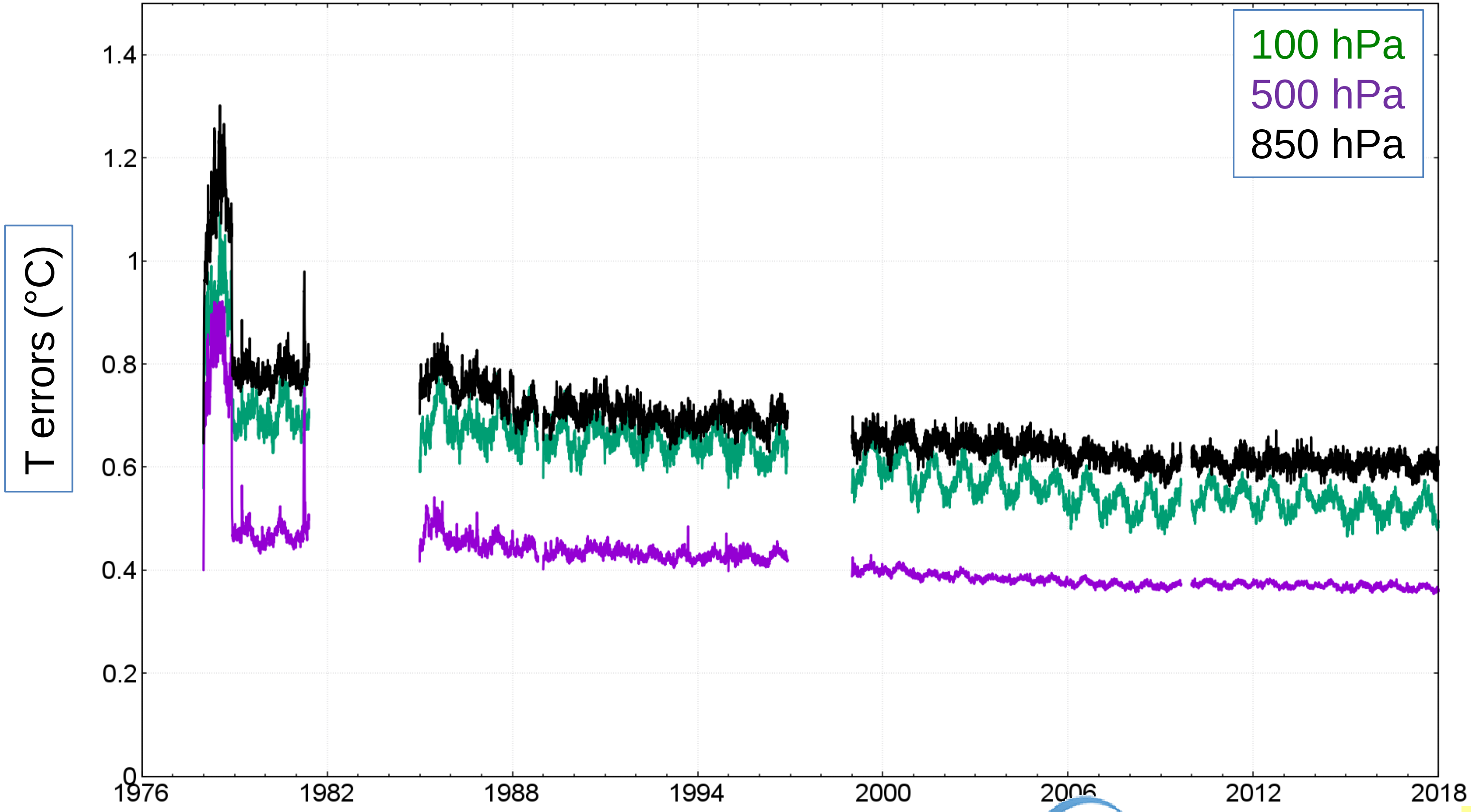
The Ensemble of Data Assimilations (EDA)



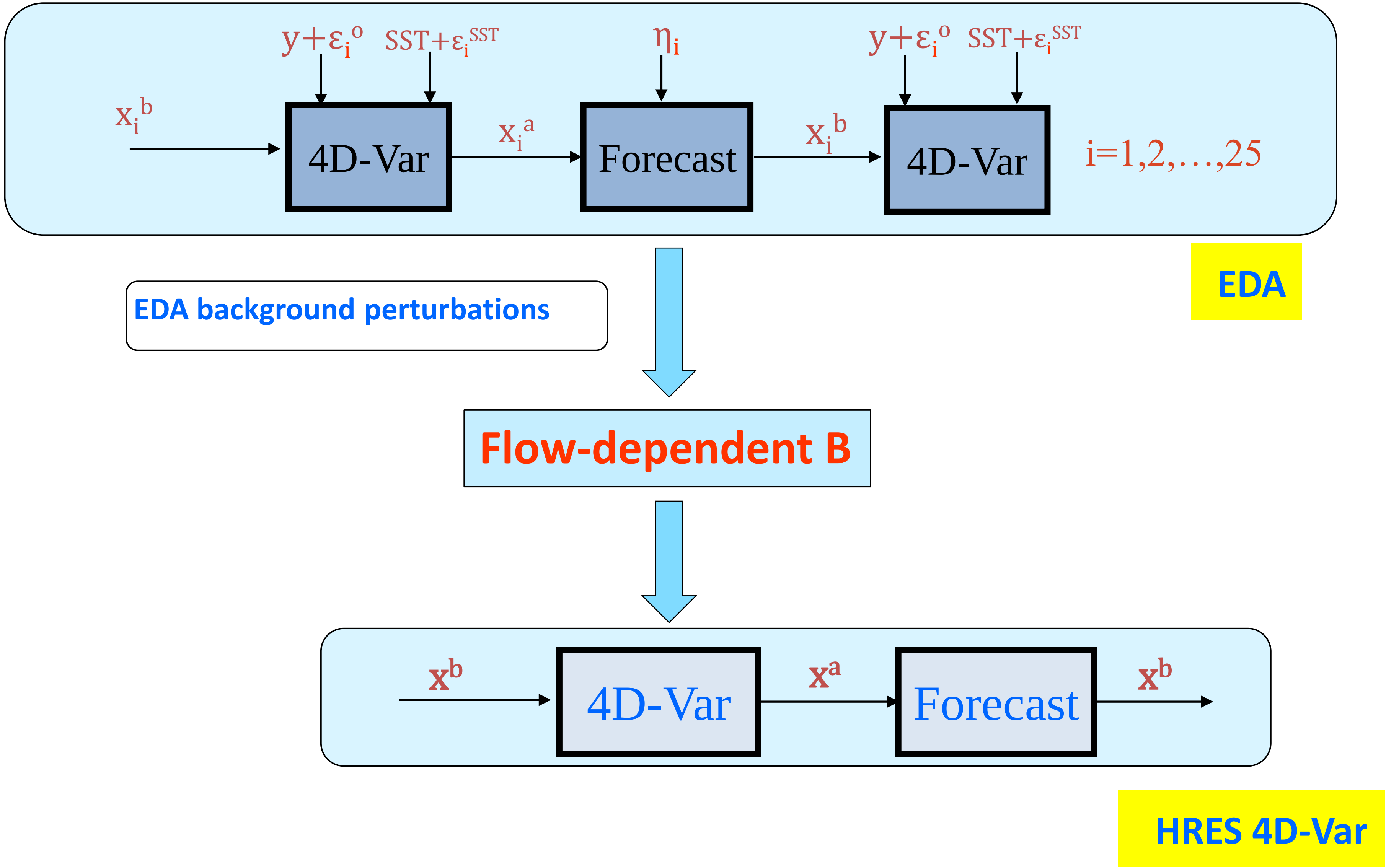
ECMWF

The past 10 years

- Estimates of temperature errors in the ERA5 re-analysis



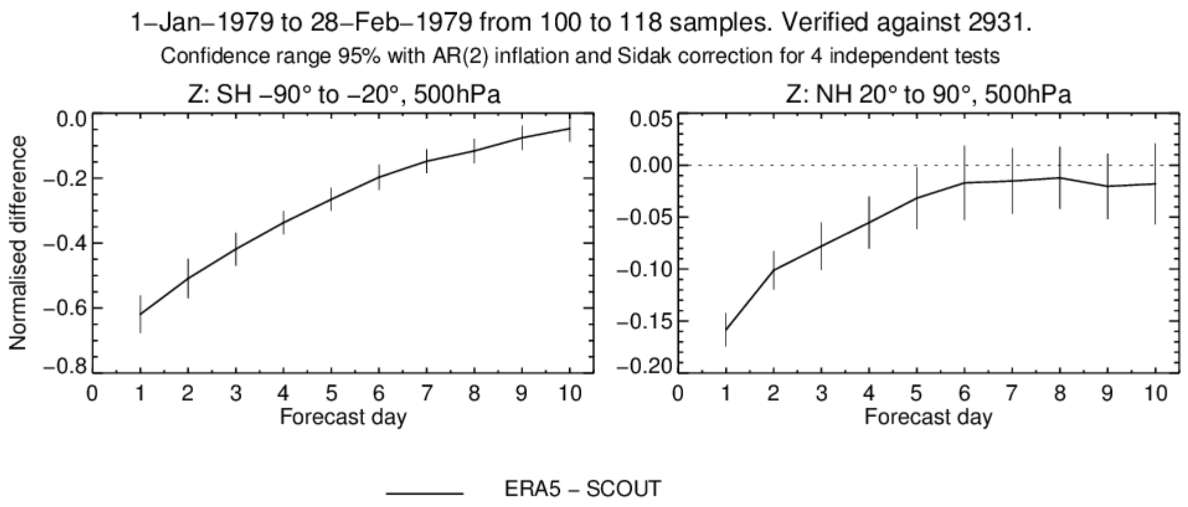
from Raluca Radu


$y+\varepsilon_i^o$
$SST+\varepsilon_i^{SST}$
η_i
$y+\varepsilon_i^o$
$SST+\varepsilon_i^{SST}$
x_i^b
4D-Var
x_i^a
Forecast
x_i^b
4D-Var
$i=1,2,\ldots,25$
EDA
EDA background perturbations
Flow-dependent B
x^b
4D-Var
x^a
Forecast
x^b
HRES 4D-Var

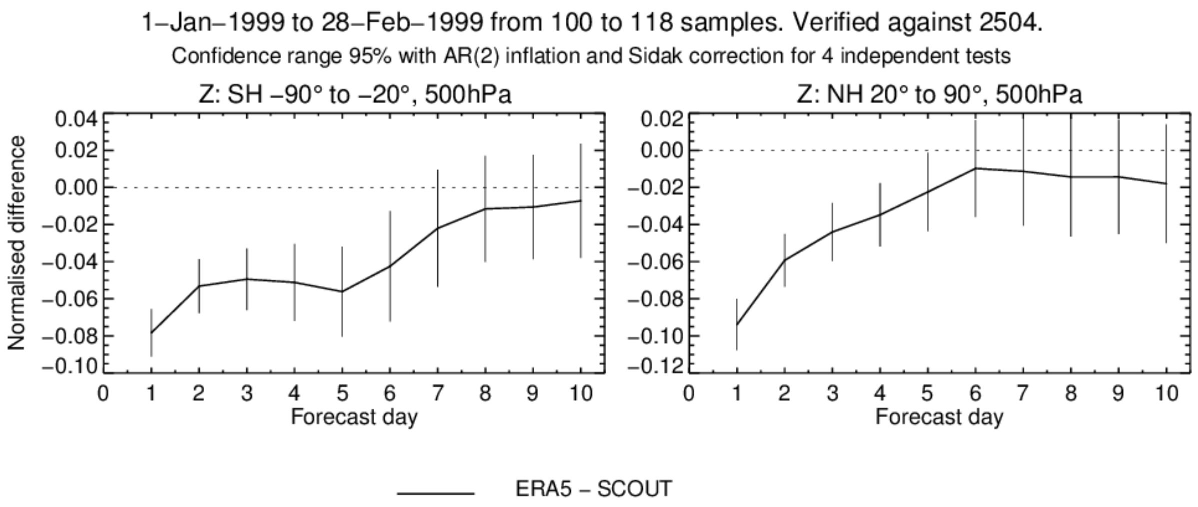
The past 10 years

- Forecast impact of using flow-dependent **B** matrix in 4D-Var for different ERA5 re-analysis streams (NB: using 10 member EDA!):

Relative difference in Z500 RMSE, 1979



Relative difference in Z500 RMSE, 1999

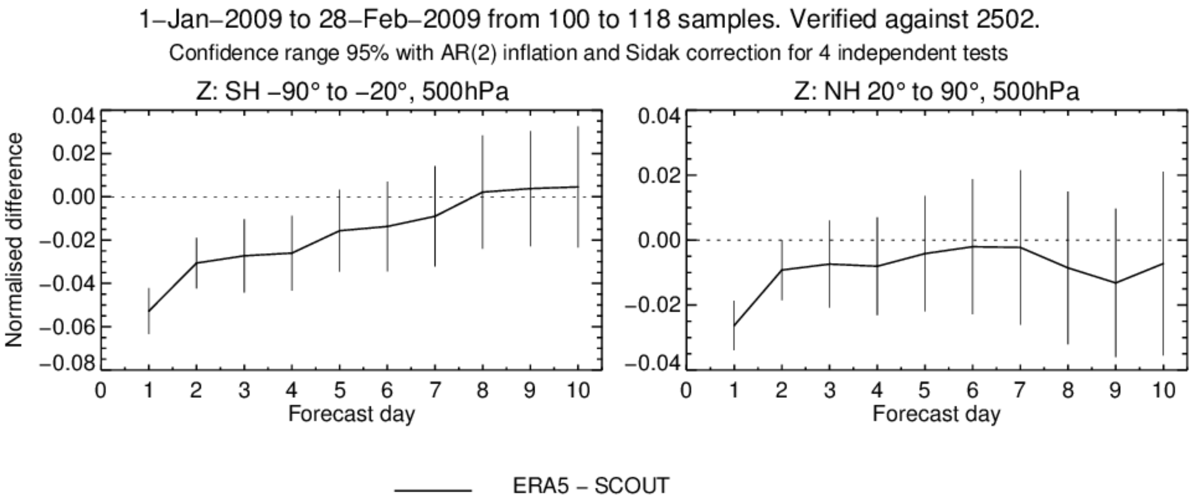


from Cornel Soci

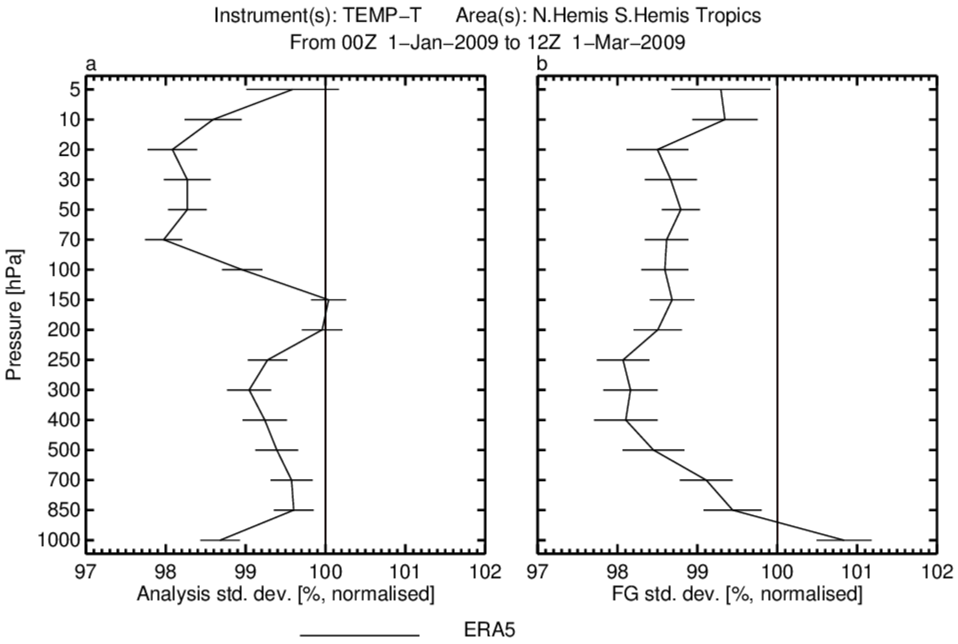
The past 10 years

- Forecast impact of using flow-dependent **B** matrix in 4D-Var for different ERA5 re-analysis streams (NB: using 10 member EDA!):

Relative difference in Z500 RMSE, 2009



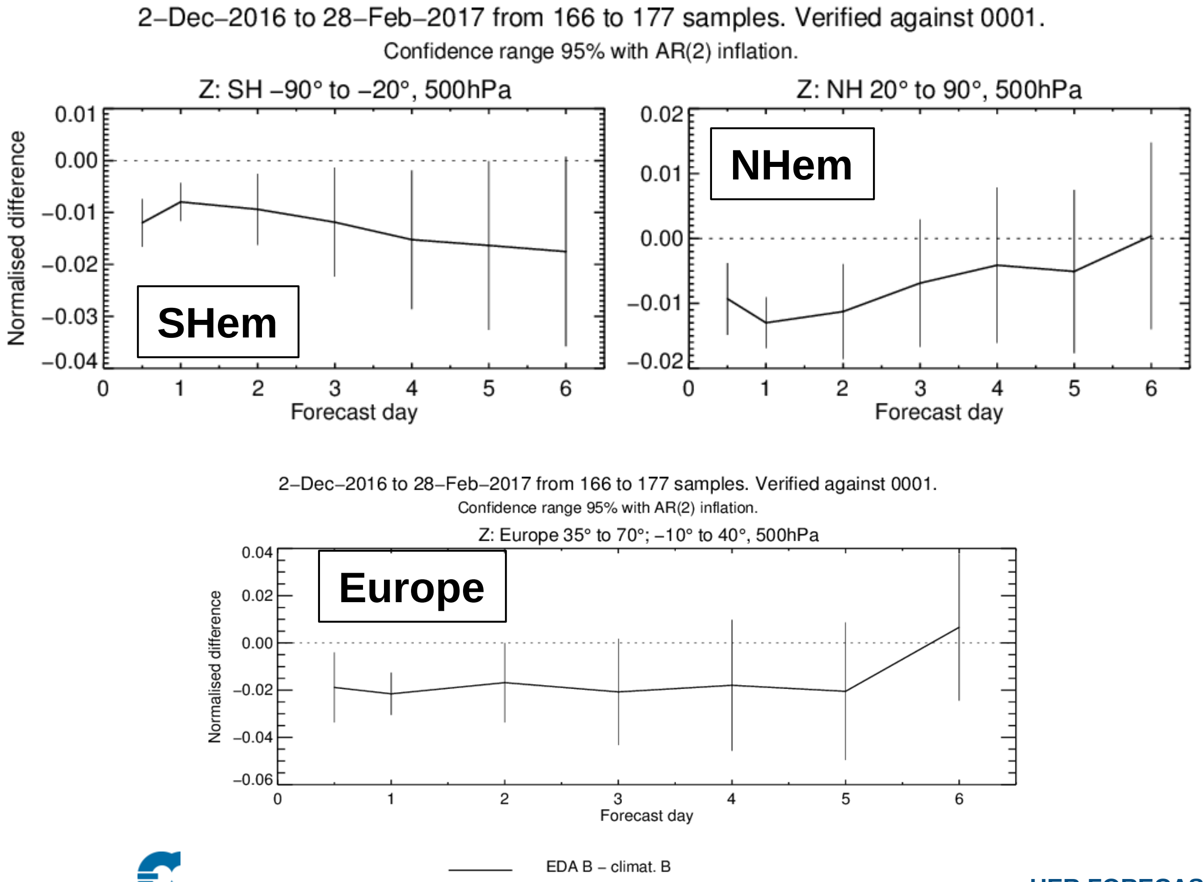
Relative difference in Radiosonde temp. fit, 2009



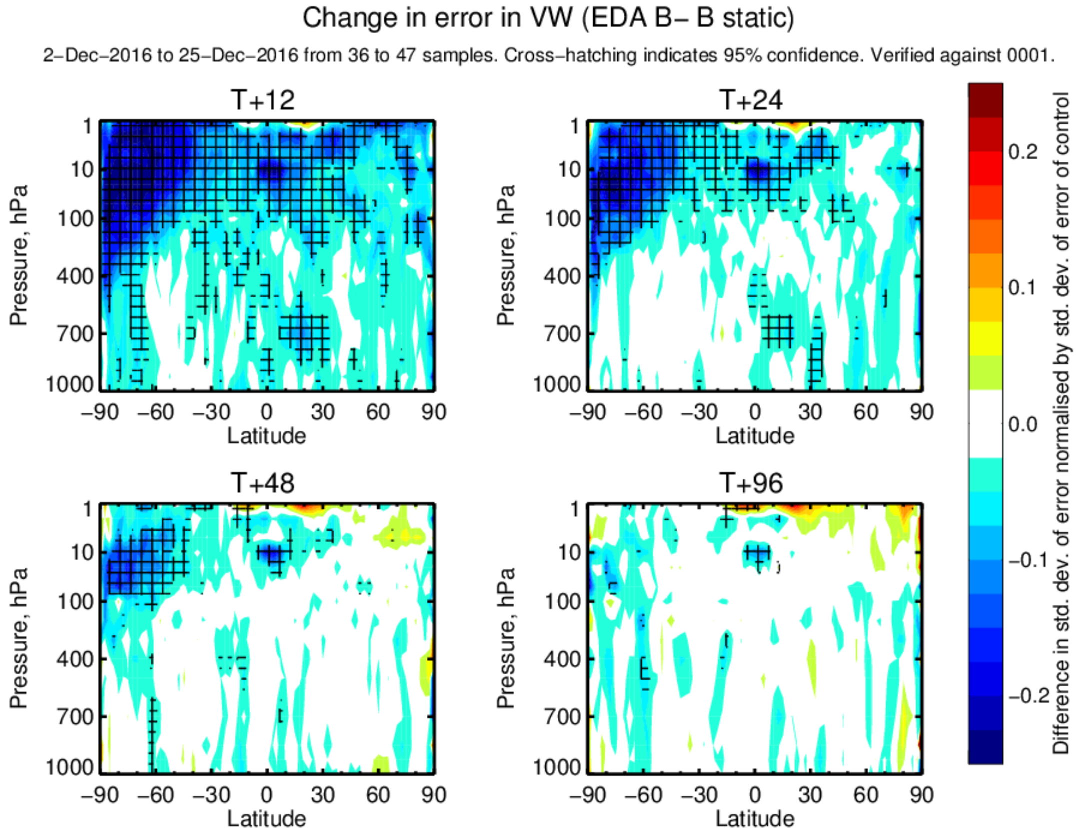
The past 10 years

- Forecast impact on HRES of using flow-dependent **B** matrix in 4D-Var for current operations:

Relative difference in Z500 RMSE, 2017



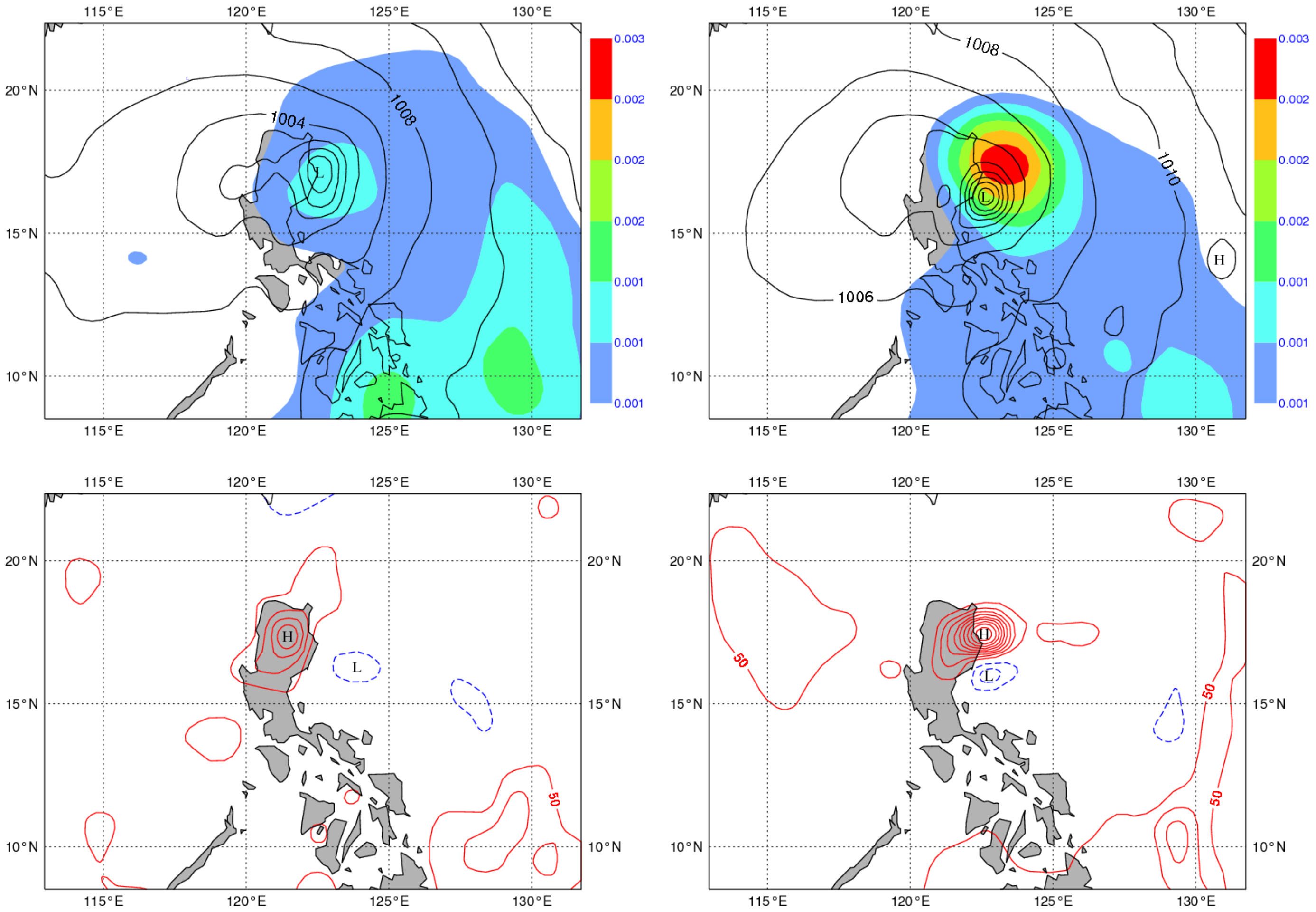
Relative difference in Wind errors 2017



The past 10 years

- Forecast impact of using flow-dependent **B** matrix in extreme weather:

Tropical Cyclone Aere, Philippines, 9 May 2011



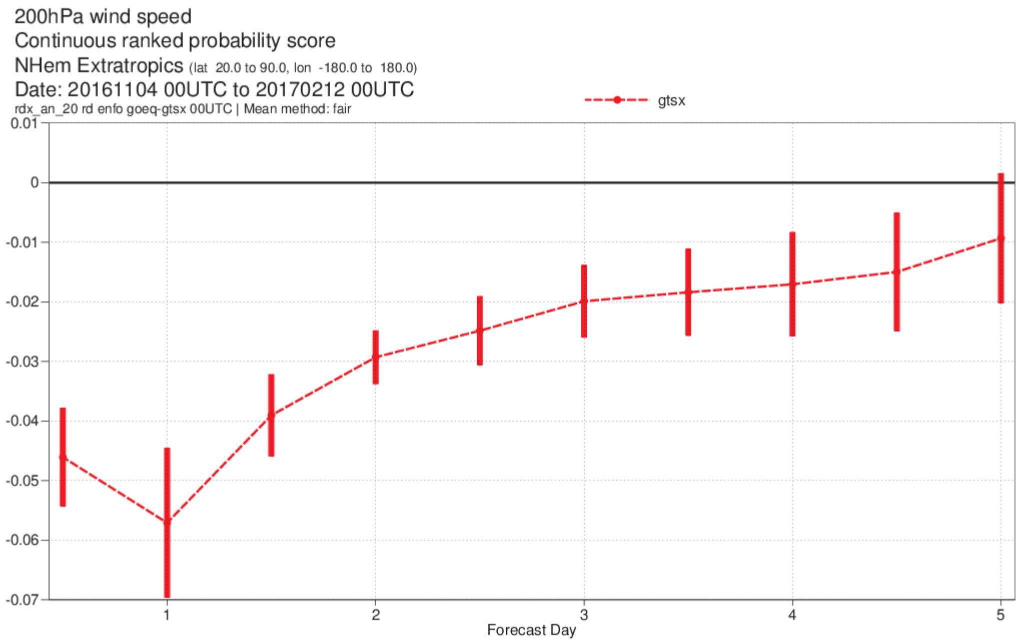
Bonavita et al., 2012

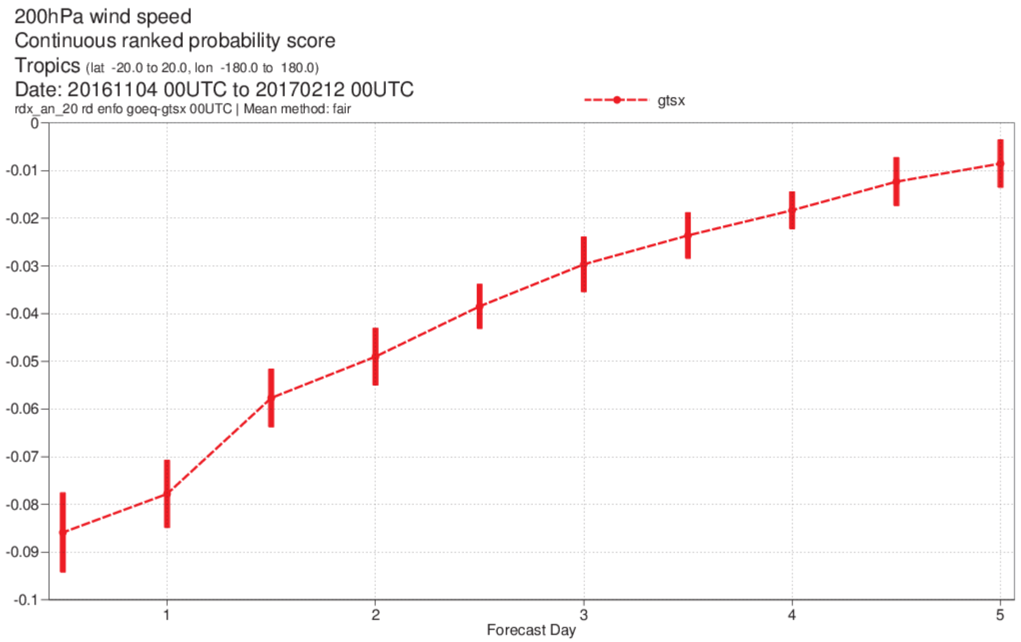
ECMWF

The past 10 years

- Current forecast impact on ENS of EDA perturbations (Note: this is additional to the degradation of the HRES control!):

Relative difference in 200 hPa Wind CRPS





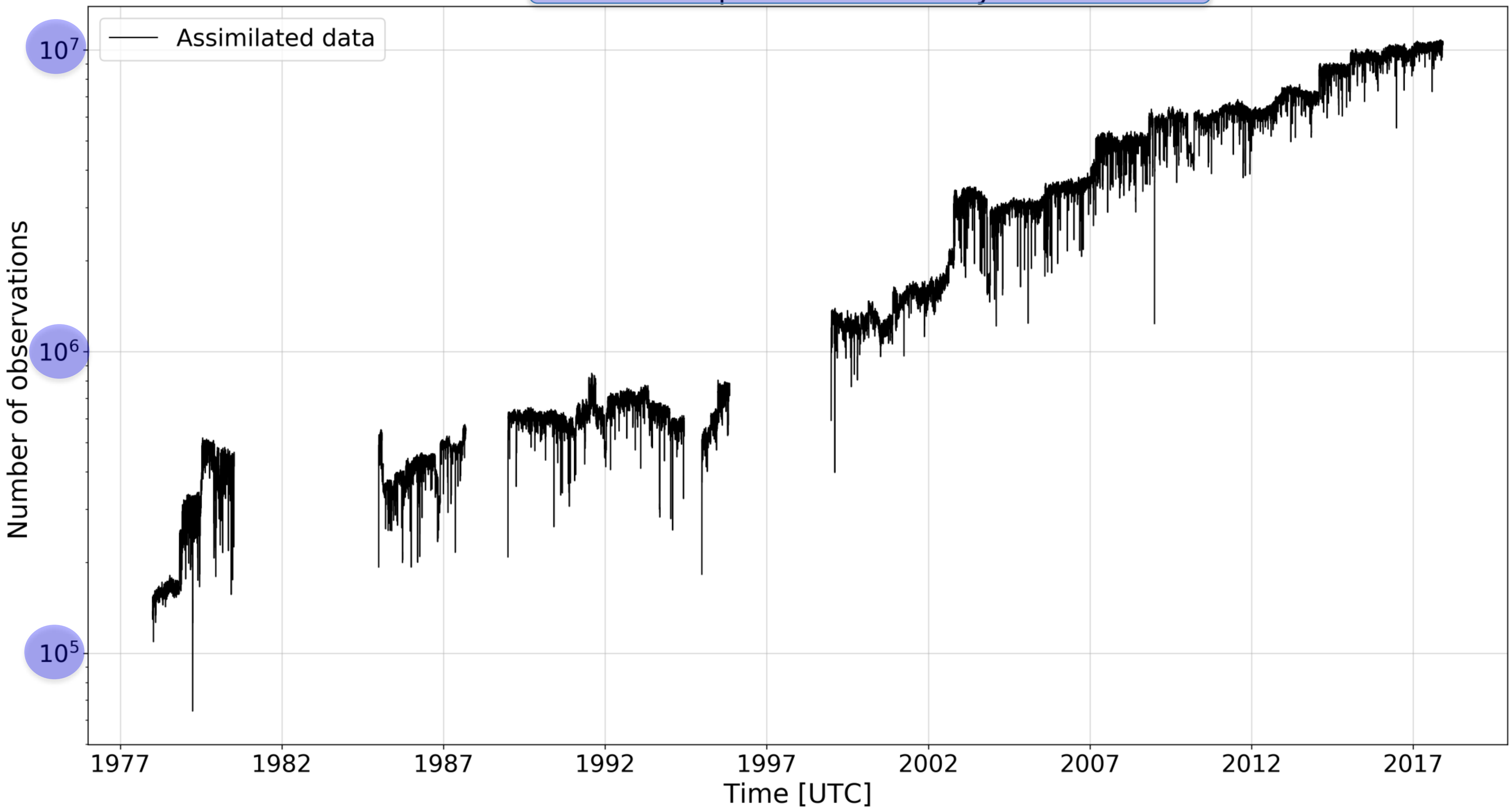
from Simon Lang

Outline

1. The past 10 years: where has the progress come from?

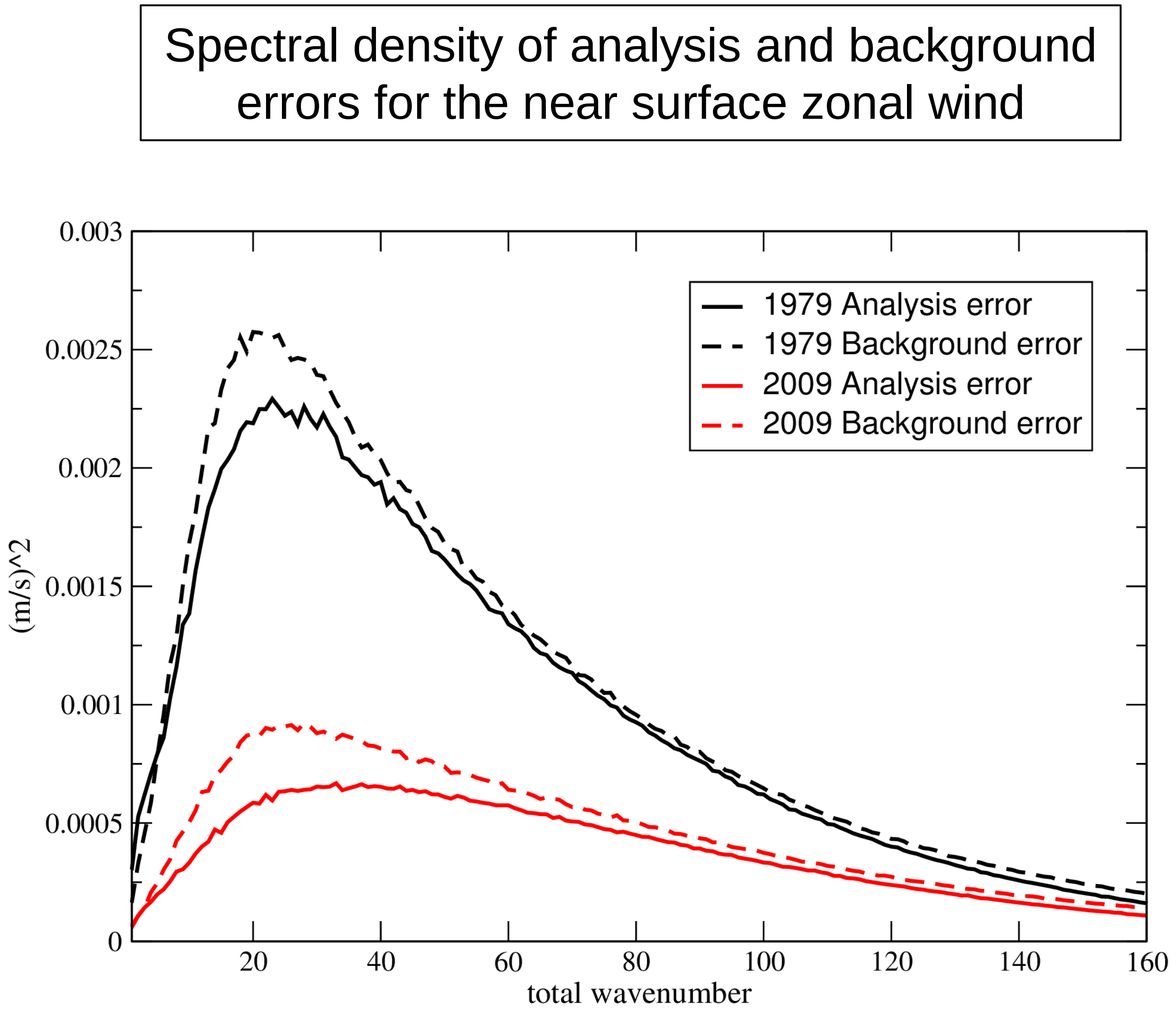
2. The next 10 years: where will the progress come from? (a data assimilation perspective…)

Used data per assimilation cycle in ERA5



from Gionata Biavati

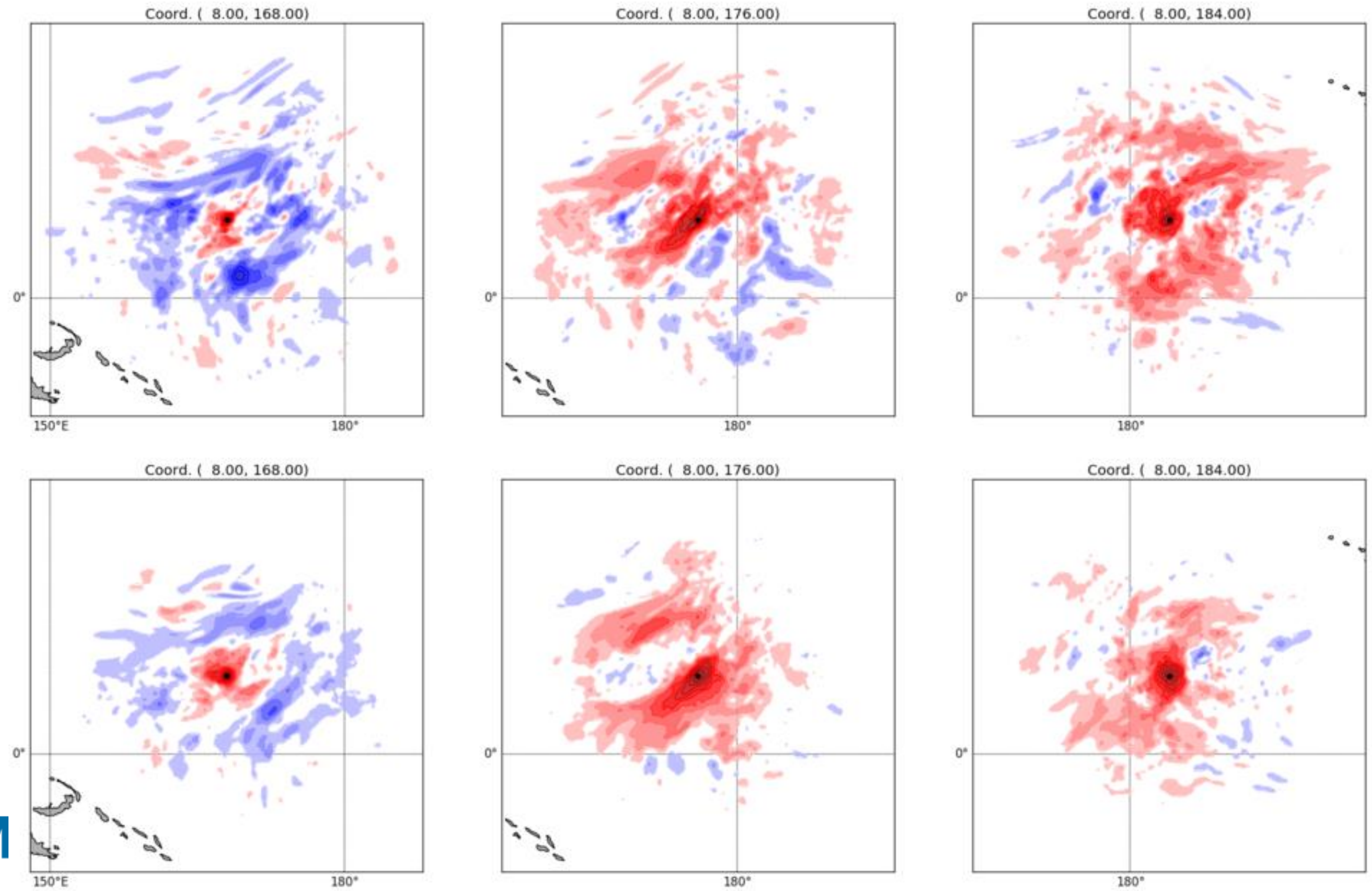
The past 10 years



The next 10 years

1) Larger, more efficient ensemble DA

- **Flatter spectra** of background and analysis errors require **larger ensemble** sizes for proper characterisation



Sampled temperature gridpoint error autocorrelation, ml 74

25 member EDA

50 member EDA

from Sebastien Massart

The next 10 years

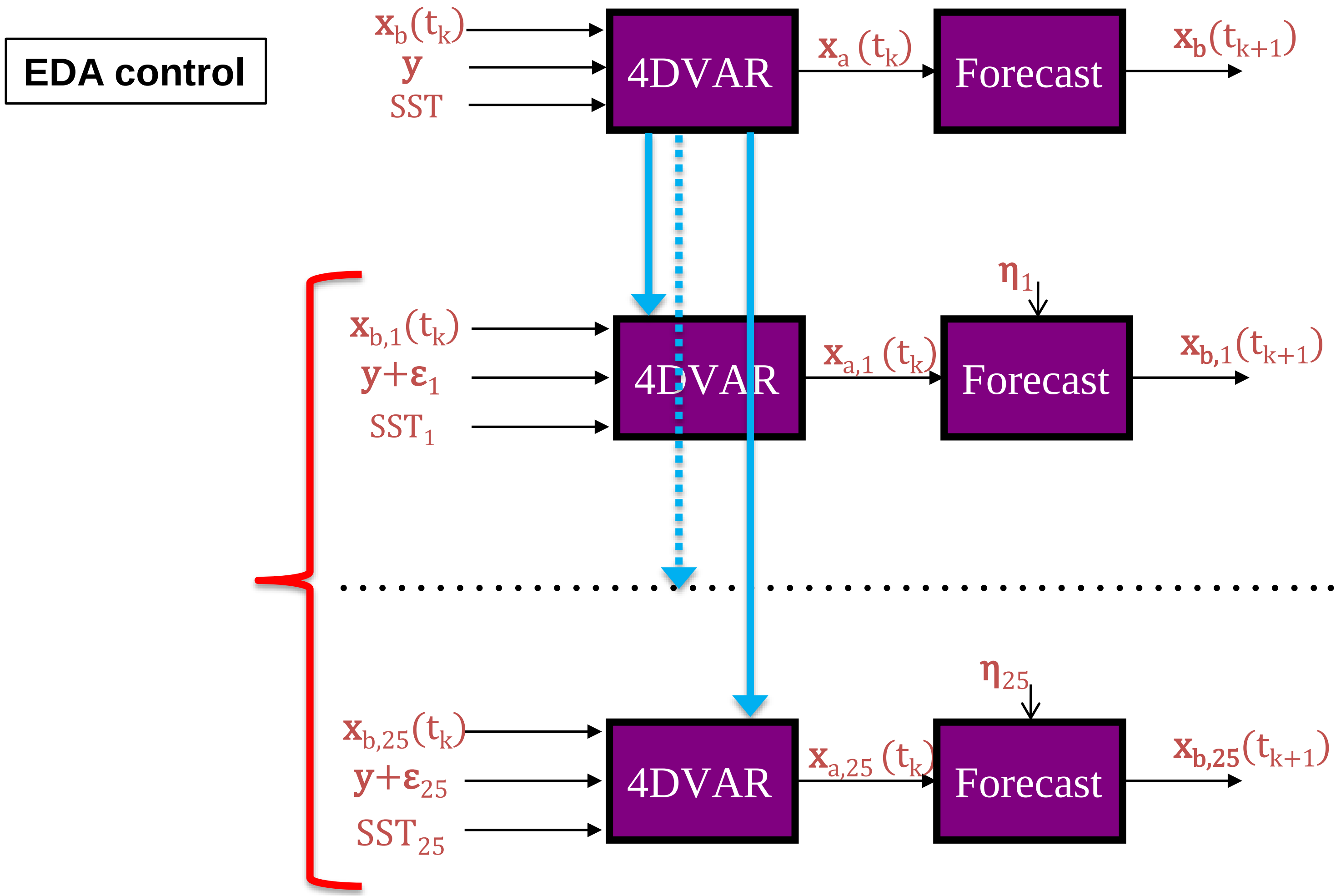
1) Larger, more efficient ensemble DA

- Flatter spectra of background and analysis errors require larger ensemble sizes for proper characterisation
- However EDA is a relatively costly component of the forecast system:

	% of total CPU cost 2017
Ensemble fcst	33.66%
Monthly fcst	25.55%
EDA	15.5%
HRES 4D-Var	13.33%
HRES fcst	6.43%
FSOI	2.65%
Seasonal fcst	1.89%
Wave model	1.01%

The next 10 years

- **Efficiency gains in the EDA**



Each EDA 4D-Var solves a series of linear problems of the form:

$$\mathbf{A}\delta\boldsymbol{u}^i = \mathbf{d}^i$$

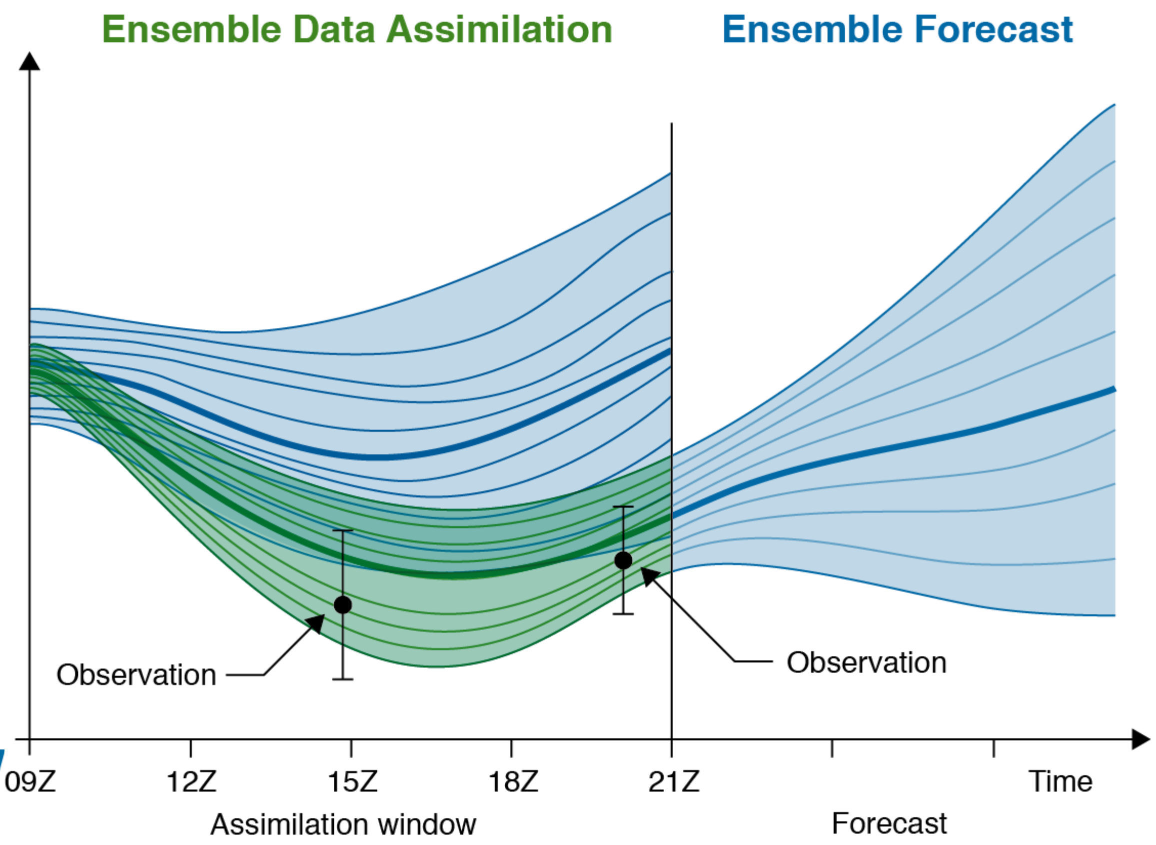
The system matrix **A** is ≈ the same for all the members, we can reuse information from the control solution to precondition and accelerate convergence in the perturbed members' 4D-Var.

This flow of information can be extended to first-guess and final analysis, at the cost of making more aggressive assumptions on linearity of errors

S. Lang, E. Holm, M. Chrust, M. Bonavita, A. Geer, N. Bormann

The next 10 years

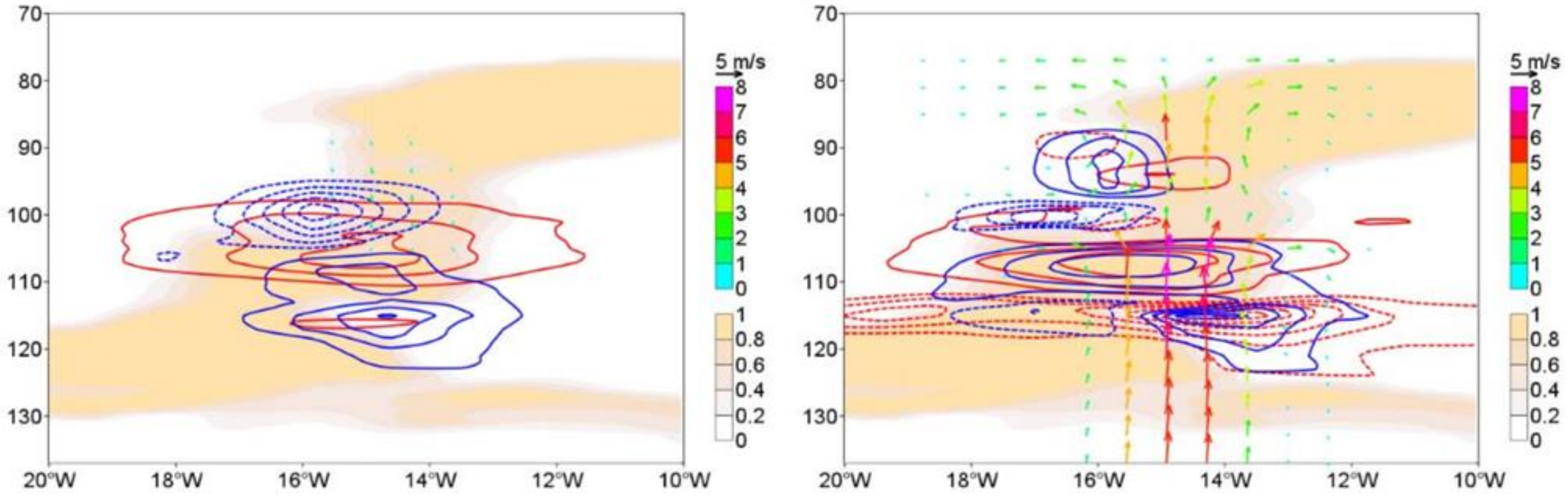
- **Efficiency gains in the EDA:**
  - These will allow to run a 50 member EDA at comparable cost to current 25 member EDA
  - This will be an important step towards a **seamless Ensemble DA – Ensemble Prediction** system (ECMWF Strategy 2016-2015)



The next 10 years

2) Extract more information from the EDA: improved B modelling

- Analysis increments (T, q, wind) from one all-sky µwave profile with current (left) and experimental (right) balance operators

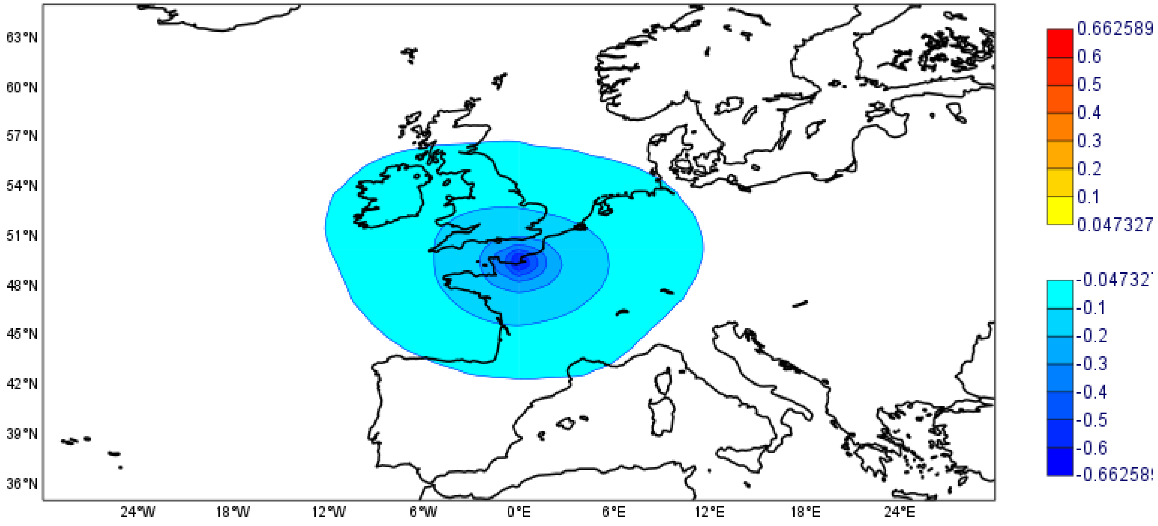


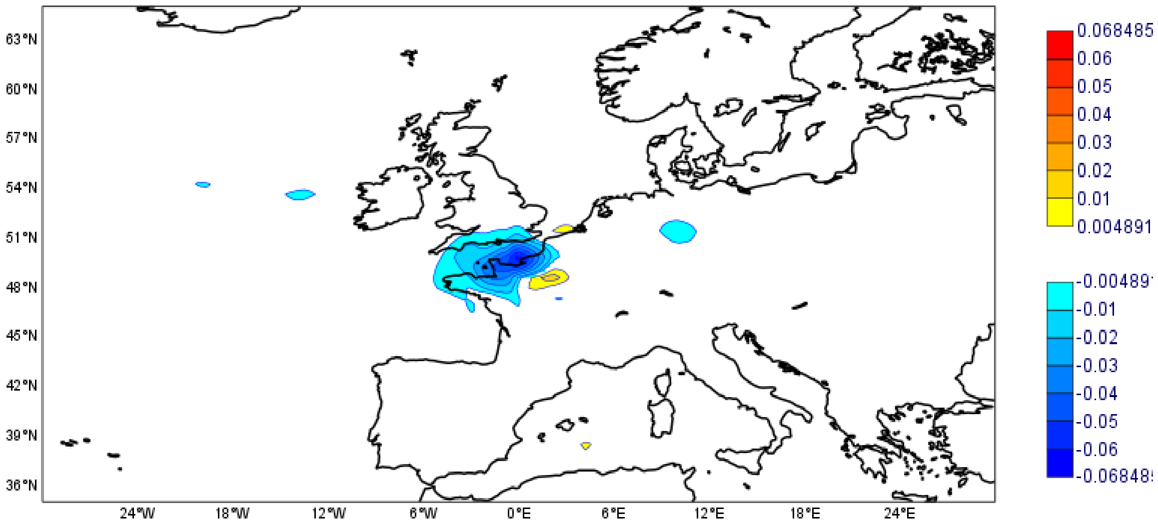
from Elias Holm

The next 10 years

2) Extract more information from the EDA: improved B modelling

- Increased flow-dependency in **B auto-correlations**, Augmented Control Variable





from Sebastien Massart

The next 10 years

3) Dealing with nonlinearities in DA

The next 10 years

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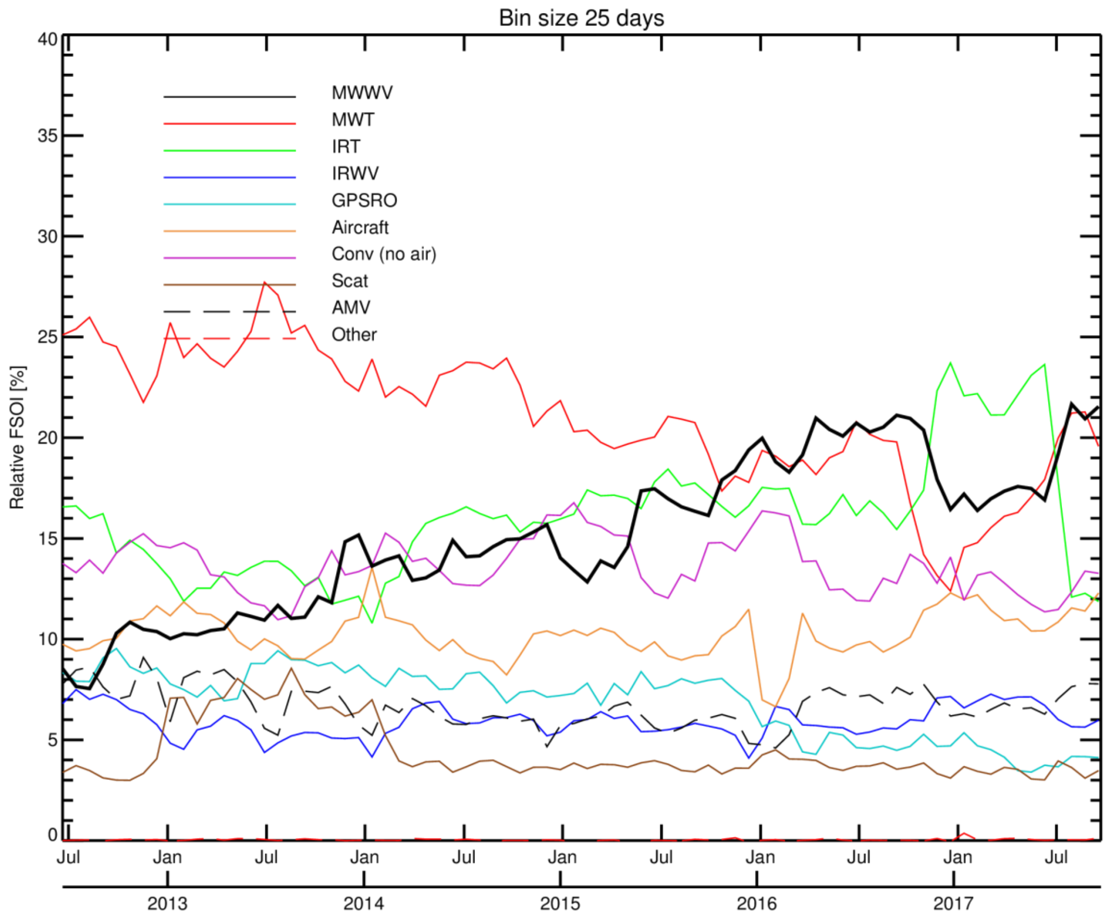
- Non-linear effects in 4D-Var become increasingly important with **ever increasing importance of nonlinear observations**:

Forecast sensitivity (FSO) of major observing systems in ECMWF DA



from Alan Geer

ECMWF EUROPEAN CENTR

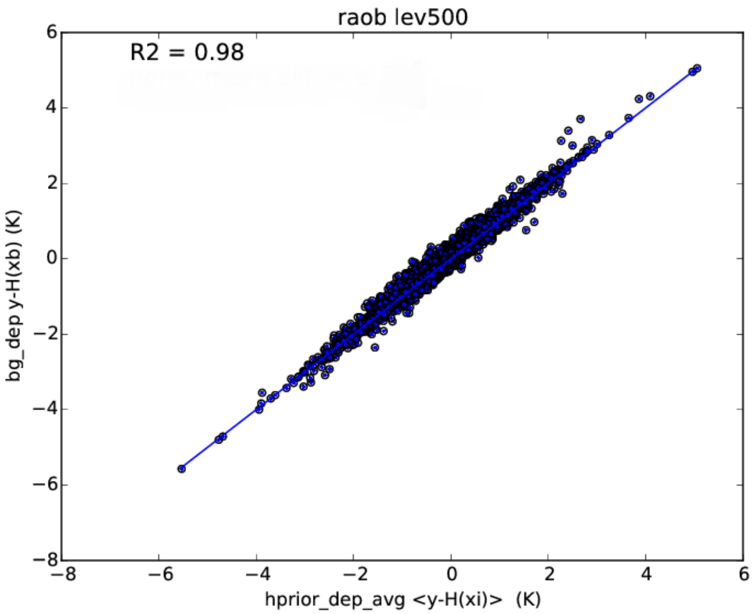
The next 10 years

3) Dealing with nonlinearities in DA

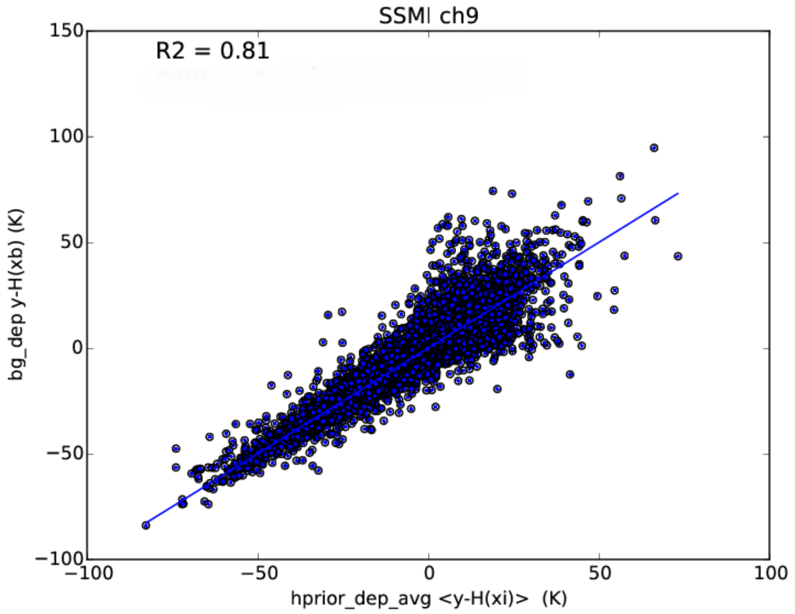
- Non-linear effects become increasingly important with an ever increasing use of observations nonlinearly related to the model state:

$$H\left(\mathbf{x}_b^{ctrl}\right) = H\left(M\left(\langle \mathbf{x}_a^i \rangle\right)\right) \approx \langle H\left(\mathbf{x}_b^i\right) \rangle \quad i = 1, \ldots, N_{ens}$$

Radiosonde Temp. 500 hPa



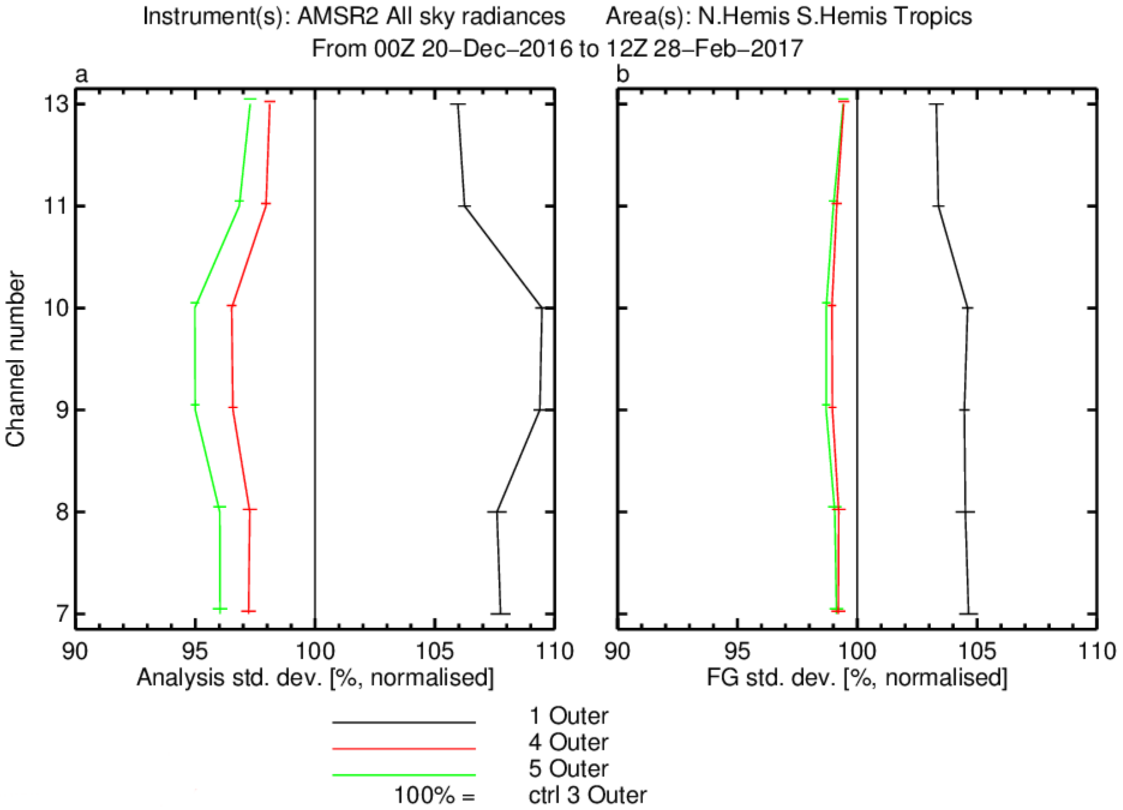
µwave humidity sounder, lower troposphere

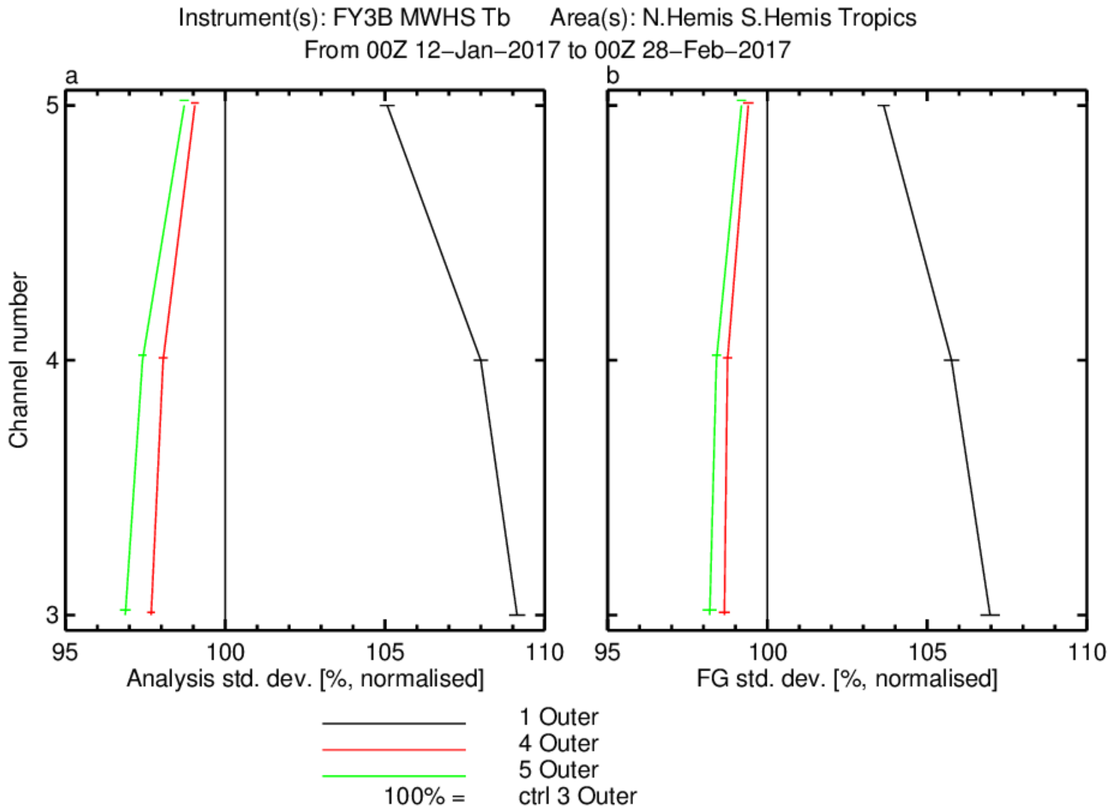


The next 10 years

3) Dealing with nonlinearities in DA

- Being able to run more outer loop in 4D-Var is key to exploit nonlinear observations





Bonavita, Lean and Holm, 2018

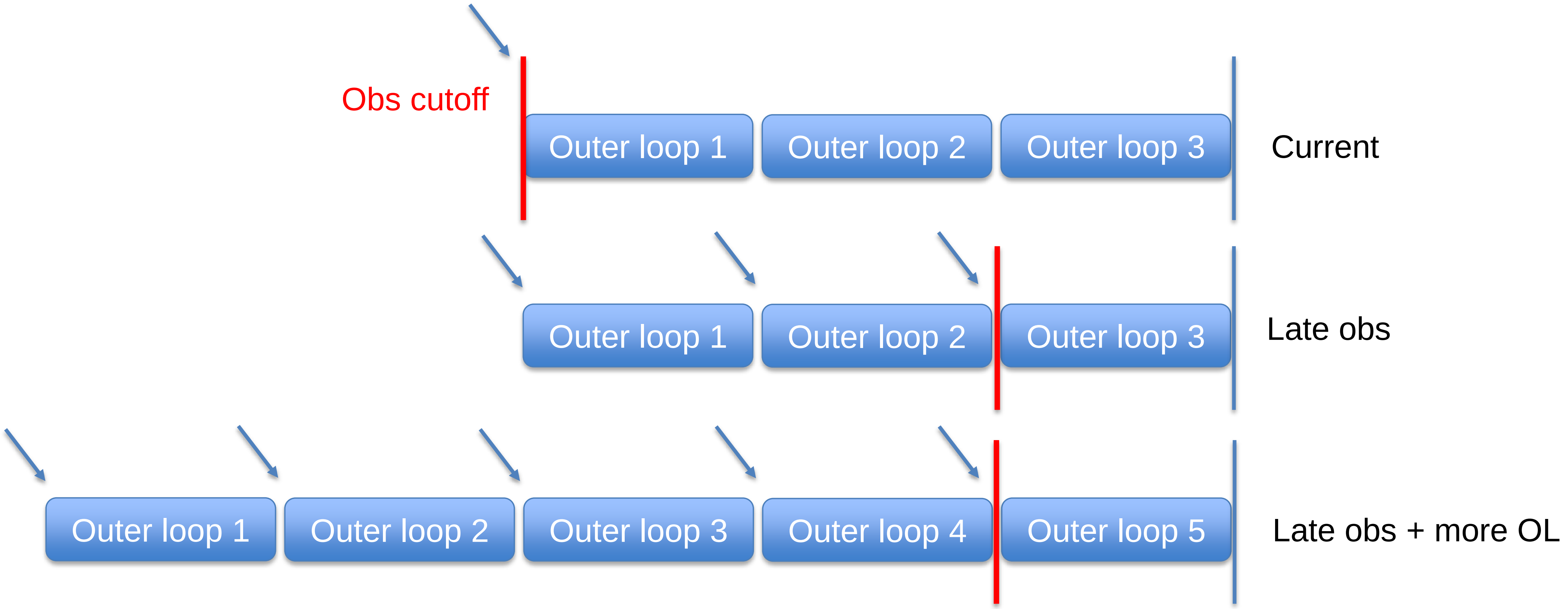
The next 10 years

3) Dealing with nonlinearities in DA

- Being able to run more outer loops in 4D-Var is key to exploit nonlinear observations and to deal with model non-linearities
- But can we fit additional outer loops inside an already tight operational schedule?

The next 10 years

- **Continuous DA concept**



from Peter Lean

The next 10 years

4) Model and Data Assimilation complexity

The next 10 years

4) Model and Data Assimilation complexity

- Common trend towards Earth system model paradigm (ECMWF Strategy 2016-2025)

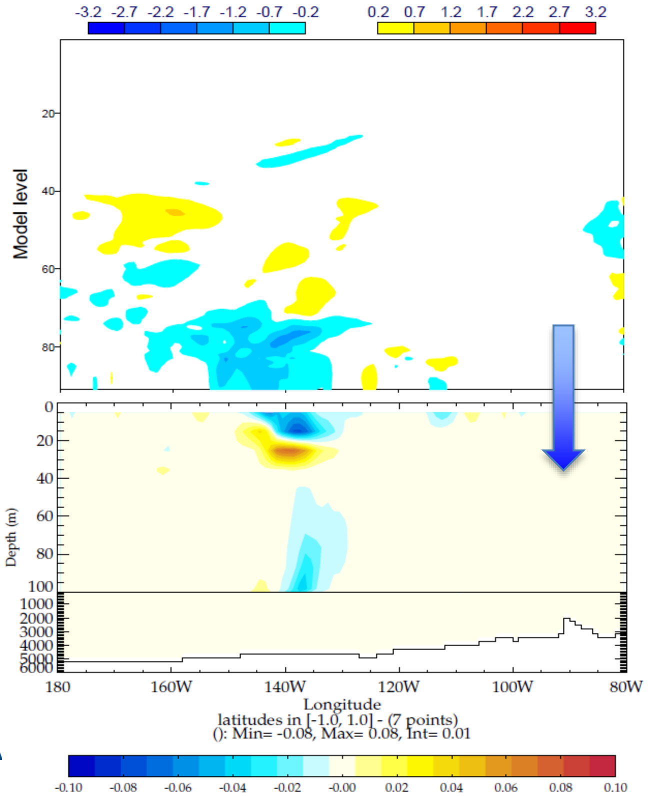
- What used to be fixed boundary conditions (ocean, land surface, sea ice) are becoming coupled models interacting with the atmospheric model

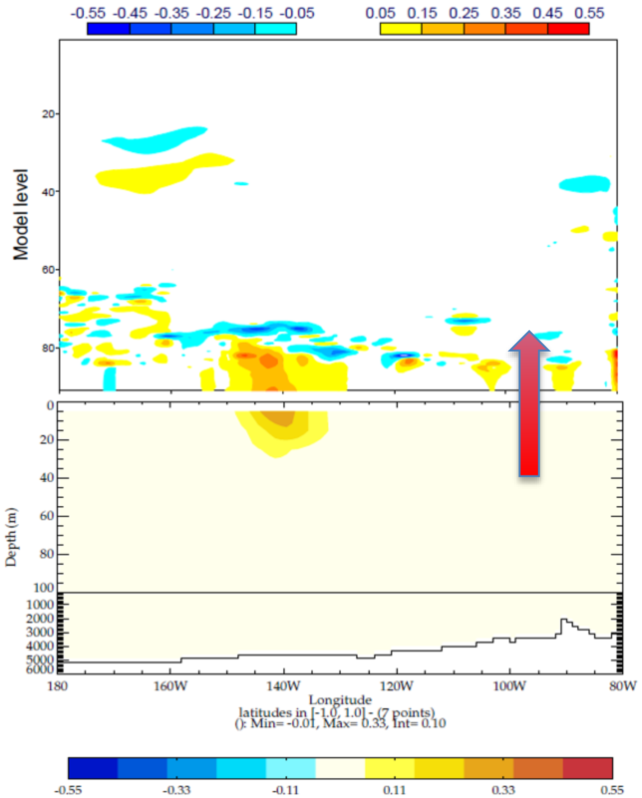
- Coupling atmosphere and ocean in forecast mode is already active in ECMWF ENS and will soon become operational for the deterministic (HRES) model, with clear benefits for forecast skill in the Tropics.

The next 10 years

4) Model and Data Assimilation complexity

- Similar trend towards **Earth system DA**
- Current ECMWF efforts towards evaluating “outer-loop” coupling of Laloyaux et al., 2016, in operational system



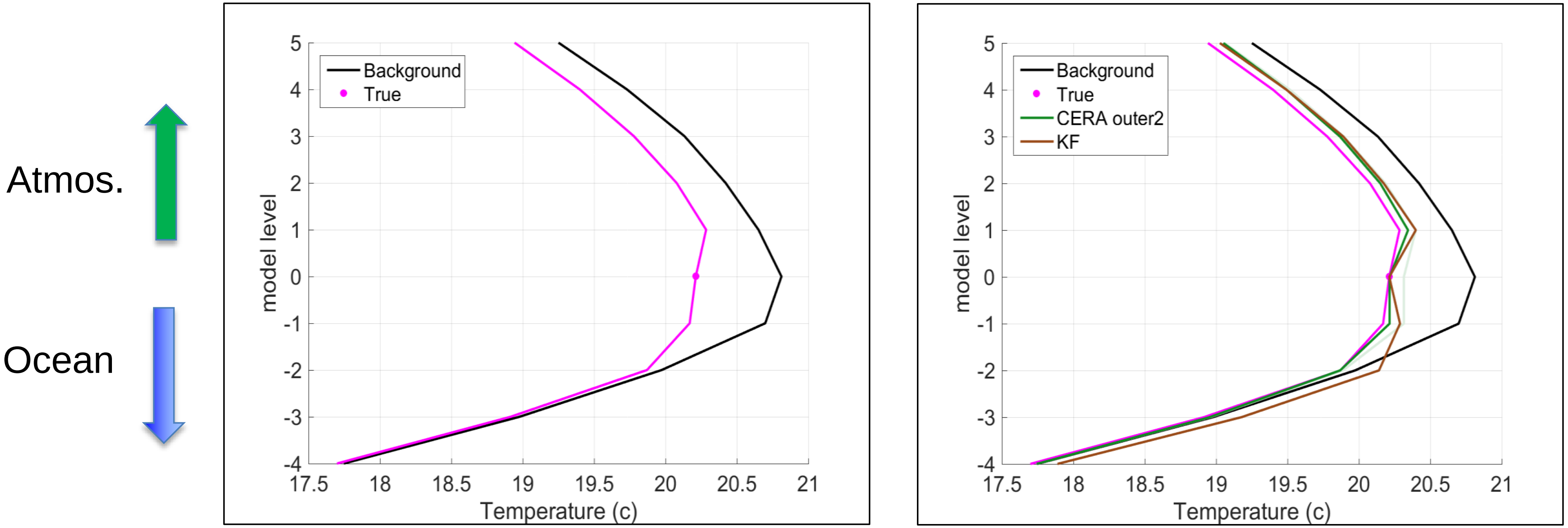


Laloyaux et al., 2016

The next 10 years

4) Model and Data Assimilation complexity

- For long enough assimilation windows (≈ 12 hours) the outer-loop coupling can be shown to be competitive with a full **B** covariance approach



Laloyaux et al., 2018

Conclusions and Perspectives

- Recent improvements in Data Assimilation methodology have been driven by increasing convergence of ensemble forecasting and 4D-Var ideas

- To further progress in this direction we need to:

    1. Increase ensemble DA size in an efficient manner;

    2. Extract more information from the ensemble through improved **B** modelling

- The envisaged long term goal is a seamless ensemble data assimilation and forecasting system

- Going from a 25 to a 50 member EDA is an important step in this direction, but significant scientific challenges remain:

    1. Can we improve each EDA member enough to avoid a HRES re-centring step?

    2. Can we start an ENS forecast directly from the EDA analyses?

Conclusions and Perspectives

- Even in a purely ensemble-based analysis and forecasting system, skill improvements will depend on the quality of each 4D-Var analysis

- The current, rapidly evolving global observing system requires data assimilation algorithms to deal effectively with nonlinear observations

- Incremental 4D-Var is uniquely positioned to tackle these problems in an efficient manner

- As observation availability has become approx. homogeneous in time, so operational DA will move towards a more continuous, data-driven process: Continuous DA is a first attempt in this direction

Conclusions and Perspectives

- NWP is evolving into Earth system analysis and prediction
- Practically difficult to perform a holistic variational analysis
- In the atmosphere-ocean context, outer loop coupling pioneered at ECMWF appears as effective as full B approach, at least for moderately long DA windows
- Augmented control variable approach is another promising idea to produce more coherent atmospheric and surface variable analyses, thus enhancing exploitation of satellite observations

Conclusions and Perspectives

- There are, of course, a number of challenges in this development path (and a number of other developments we did not have time to describe today!)

- One central issue is the continuous maintenance and development of accurate and efficient linearised models

- On balance, however, we still believe that the realised and potential benefits of a DA strategy based on incremental 4D-Var justify the additional overheads

Thank you for your attention!