

Variational bias correction of radiance data in the ECMWF system

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Workshop on assimilation of high spectral
resolution sounders in NWP

ECMWF, June 28 – July 1 2004

Outline

- Current scheme for radiance bias correction at ECMWF
- Variational bias correction
- Implementation aspects
- Some preliminary assimilation results
- Summary and conclusions

Acknowledgements

Graeme Kelly, Tony McNally, Jean-Noël Thépaut
Erik Andersson, Lars Isaksen, Yannick Tremolet

Current scheme for radiance bias correction at ECMWF

Scan bias and air-mass dependent bias for each sensor/channel are estimated off-line (Harris and Kelly 2001)

Error model: $y = h(x) + b^{scan} + b^{air} + e^{obs}$

where $b^{scan} = b^{scan}$ (latitude, scan position)

$$b^{air} = \beta_0 + \sum_{i=1}^N \beta_i p_i(x)$$

e^{obs} = random observation error

Predictors:

- 1000-300 hPa thickness
- 200-50 hPa thickness
- surface skin temperature
- total precipitable water

In the absence of model bias:

$$\langle y - h(x_b) \rangle = b^{scan} + b^{air}$$

Estimate scan bias and predictor coefficients based on

- typically 2 weeks of background departures
- 2-step regression procedure
- careful masking and data selection

This scheme has been very successful, but it is becoming difficult to manage

Variational bias correction: The general idea



The **bias** in a given instrument/channel is usually modelled in terms of a relatively small number of parameters

It is possible to estimate these parameters and correct the observations during the analysis
(Derber and Wu, 1998)

The **standard variational analysis** minimizes

$$J(x) = (x_b - x)^T B_x^{-1} (x_b - x) + [y - h(x)]^T R^{-1} [y - h(x)]$$

Modify the observation operator to account for bias: $\tilde{h}(z) = \tilde{h}(x, \beta)$

Include the bias parameters in the control vector: $z^T = [x^T \quad \beta^T]$

Minimize instead

$$J(z) = (z_b - z)^T B_z^{-1} (z_b - z) + [y - \tilde{h}(z)]^T R^{-1} [y - \tilde{h}(z)]$$

What is needed to implement this:

1. the modified operator $\tilde{h}(x, \beta)$ and its TL + adjoint
2. background error covariances for the bias parameters
3. an effective preconditioner for the joint minimization problem

Variational bias correction: Implementation

1. The modified operator and its adjoint:

- bias parameters are the predictor coefficients: $\tilde{h}(x, \beta) = h(x) + b^{air}(x, \beta)$
- predictors are computed from the reference trajectory: $b^{air}(x, \beta) \approx b^{air}(\bar{x}, \beta)$

2. Background error specifications:

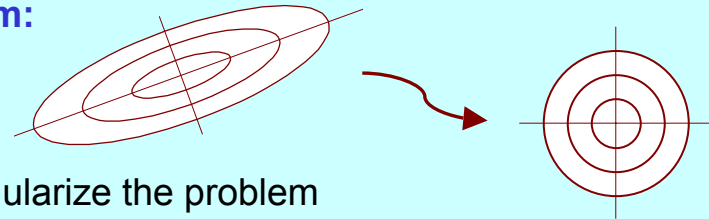
- parameter background value = final estimate from previous analysis
- set $\sigma_\beta^2 = \sigma_o^2 / N$ (N large means strong constraint – less adaptivity)
- neglect cross-covariances between state and parameter background errors:

$$\begin{aligned} J(x, \beta) = & (x_b - x)^T B_x^{-1} (x_b - x) && \text{'traditional' background term} \\ & + (\beta_b - \beta)^T B_\beta^{-1} (\beta_b - \beta) && \text{parameter background term} \\ & + [y - \tilde{h}(x, \beta)]^T R^{-1} [y - \tilde{h}(x, \beta)] && \text{modified observation term} \end{aligned}$$

Variational bias correction: Minimization

3. Preconditioning the joint minimization problem:

- joint minimization problem is ill-conditioned
- use a transformation of the control variable to regularize the problem



The **ideal change-of-variable** would be the square-root of the Hessian: $B_x^{-1} + H^T R^{-1} H$

background information

observational information

The standard variational analysis uses $\chi_x = B_x^{-1/2} (x_b - x)$

This works well as long as the background information dominates the analysis

For the parameter estimates, the observational information dominates instead

An effective **change-of-variable for the parameter section** of the control vector is

$$\chi_\beta = L (\beta_b - \beta), \quad L = \left[B_\beta^{-1} + \frac{p}{\sigma_o^2} \langle X^T X \rangle \right]^{1/2}$$

predictor covariances

Convergence for the modified problem is similar to that of the original

Assimilation results

- **Reference:**

Current operational system (Cycle 26r3, as of 9 March 2004)

Using 3*AMSU-A
 2*AMSU-B
 2*HIRS
 3*SSM/I
 2*METEOSAT
 3*GOES
 AIRS

- **Experiment:**

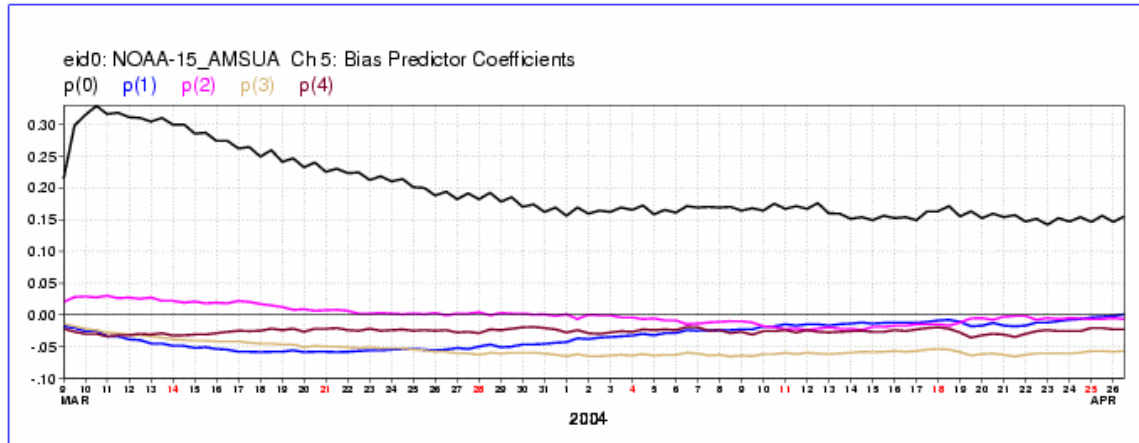
Variational bias correction on all T_B data

Keeping scan bias correction fixed (for now)

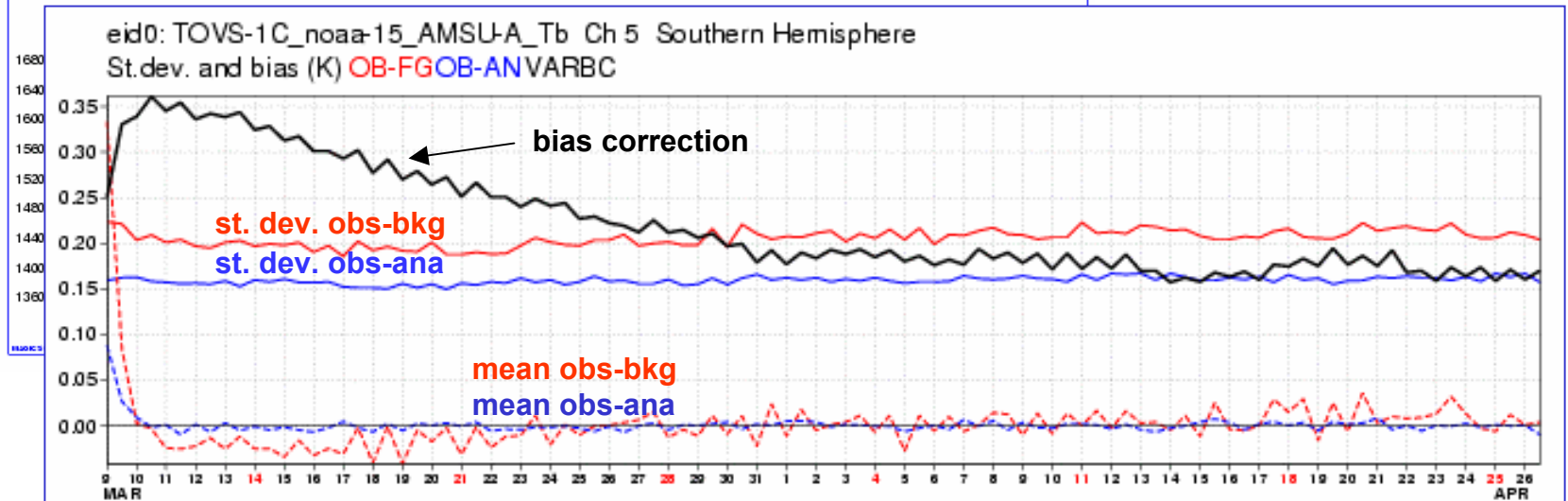
Cold start for air-mass dependent bias parameters

Activate some screening channels with large σ_0

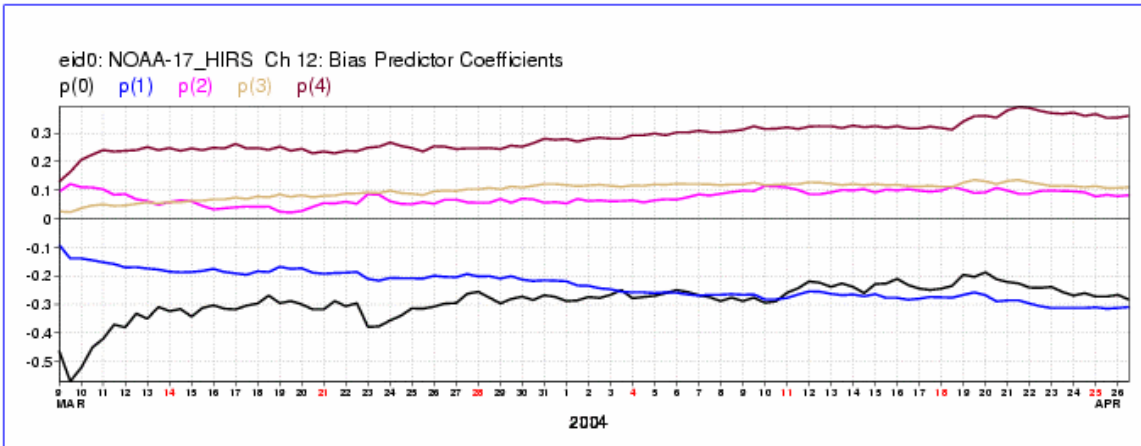
Evolution of the bias parameters: NOAA-15 AMSUA Ch5



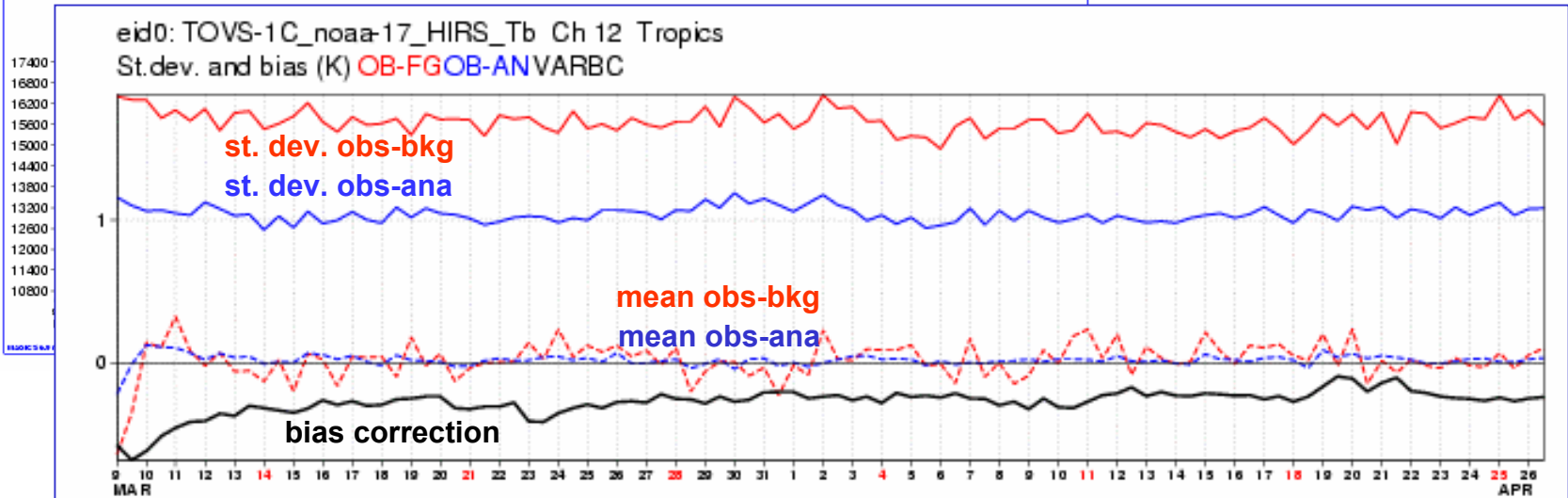
p(0): global constant
 p(1): 1000-300hPa thickness
 p(2): 200-50hPa thickness
 p(3): surface temperature
 p(4): total column water



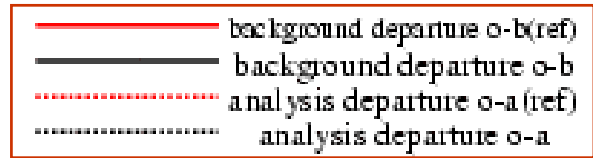
Evolution of the bias parameters: NOAA-17 HIRS Ch12



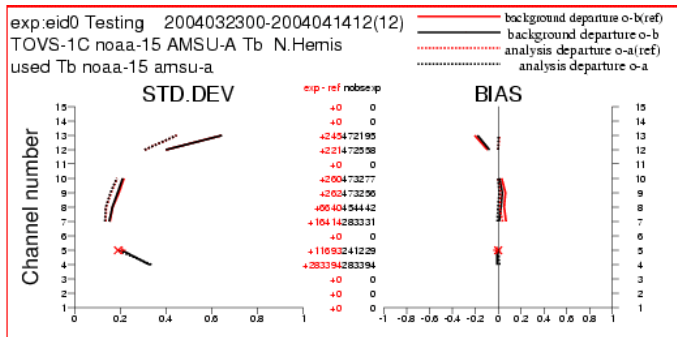
- p(0): global constant
- p(1): 1000-300hPa thickness
- p(2): 200-50hPa thickness
- p(3): surface temperature
- p(4): total column water



Departure statistics: 20040323 - 20040414 brightness temperatures

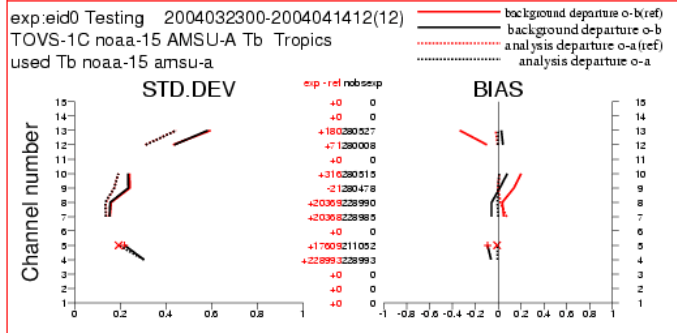
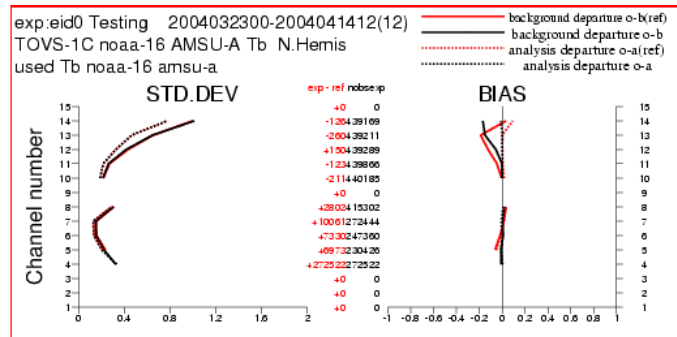


NOAA-15 AMSUA

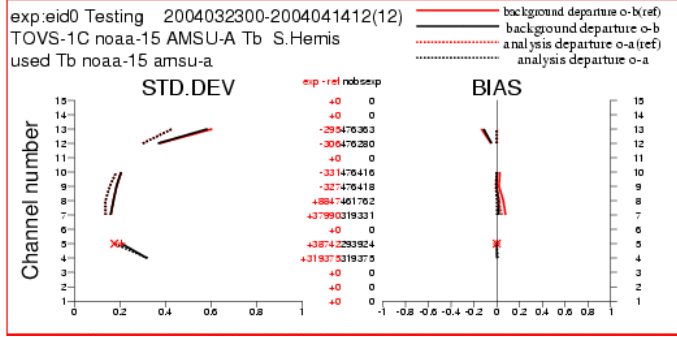
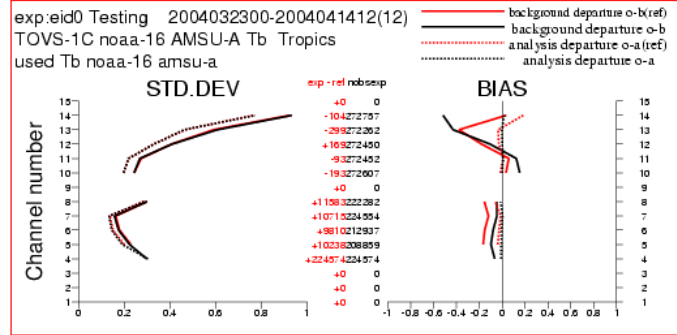


NH

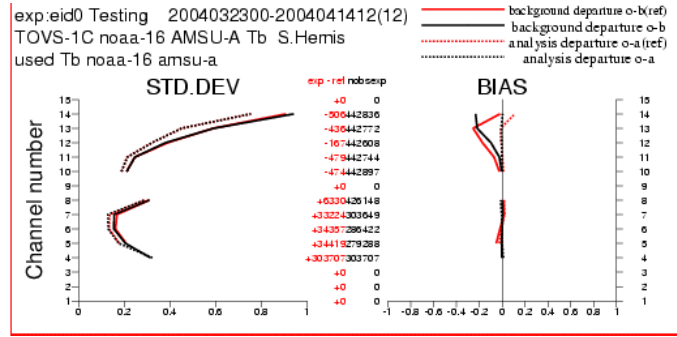
NOAA-16 AMSUA



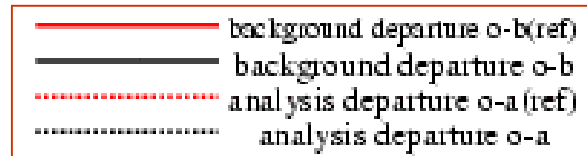
TR



SH

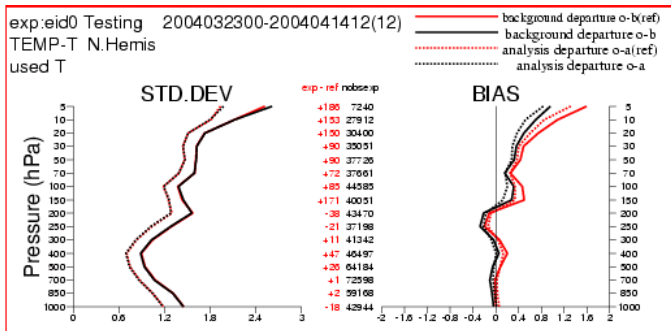


Departure statistics: 20040323 - 20040414 conventional temperatures

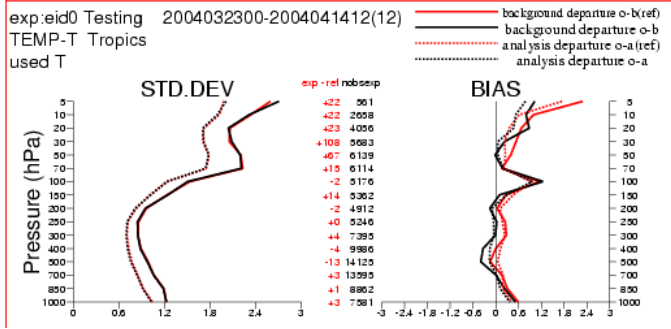
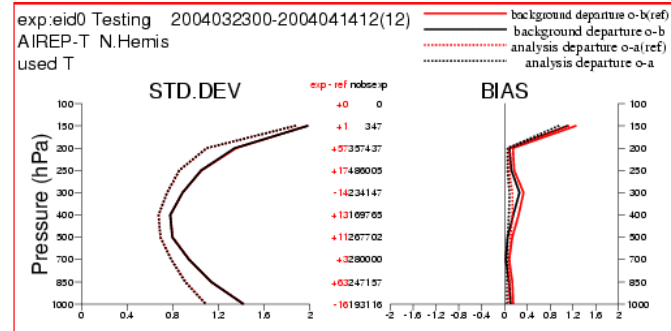


radiosondes

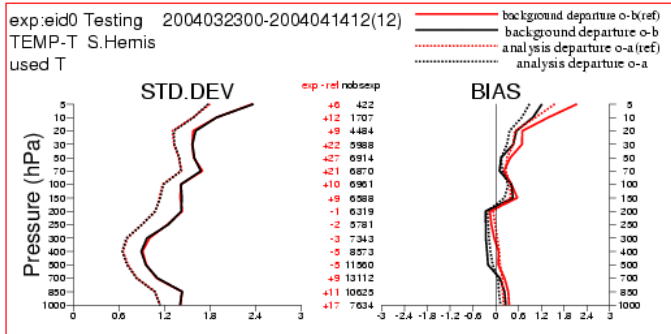
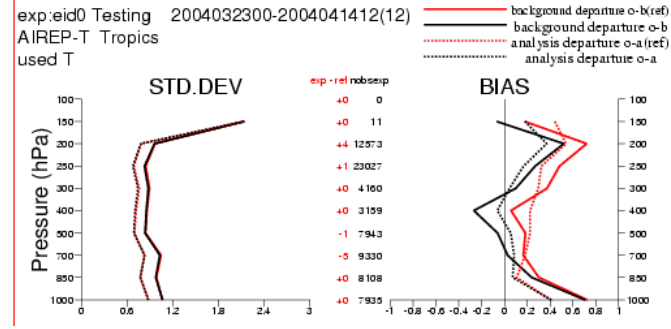
aircraft



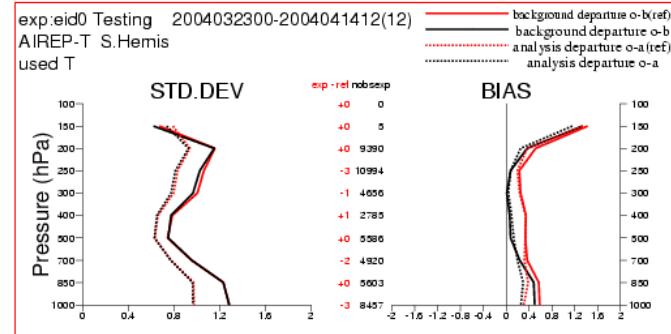
NH



TR



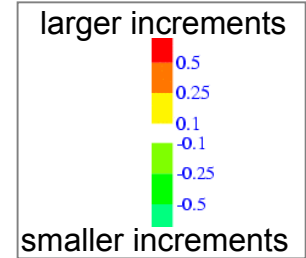
SH



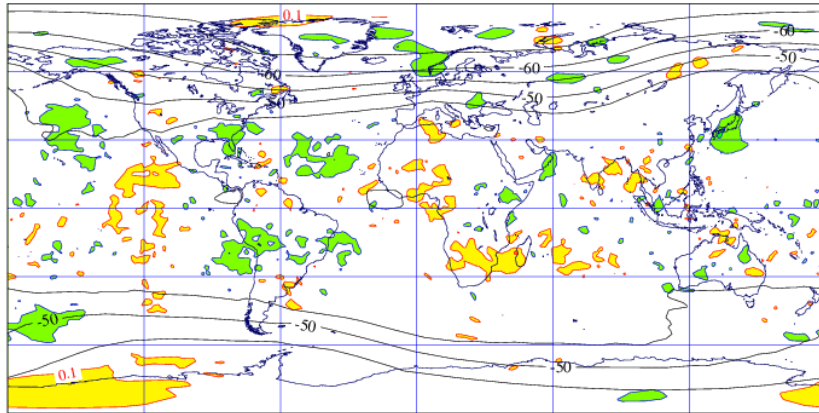
Temperature analysis increments dT_a

20040316 - 20040412

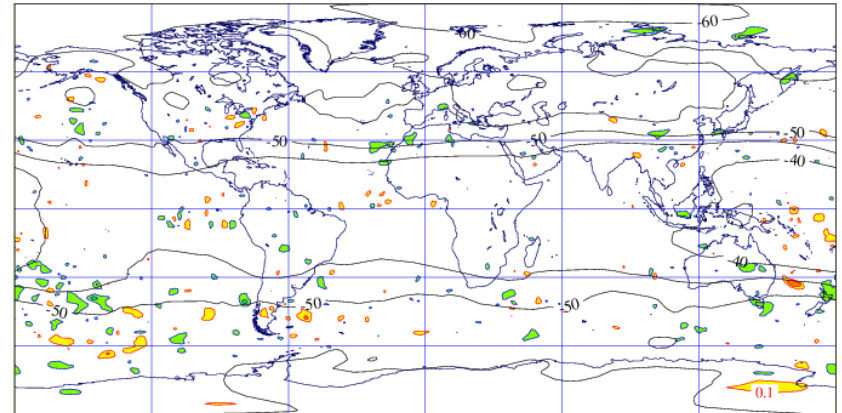
rms (experiment dT_a) – rms (reference dT_a)



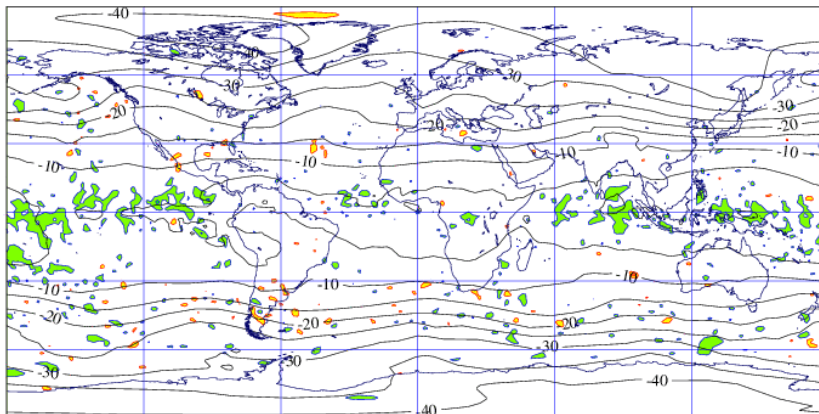
10 hPa



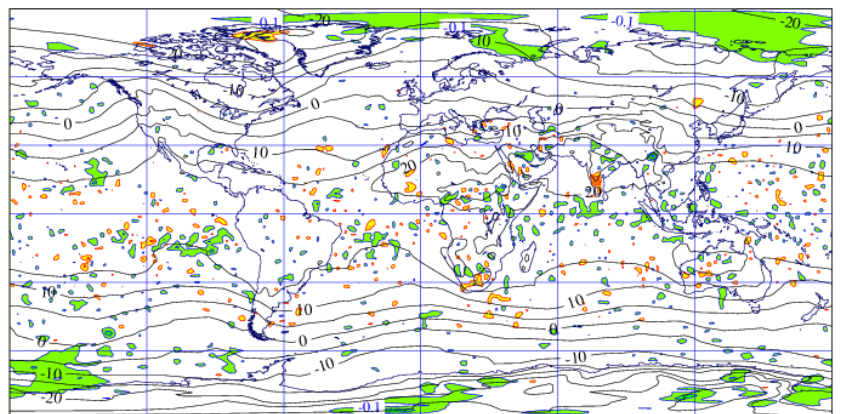
250 hPa



500 hPa



850 hPa

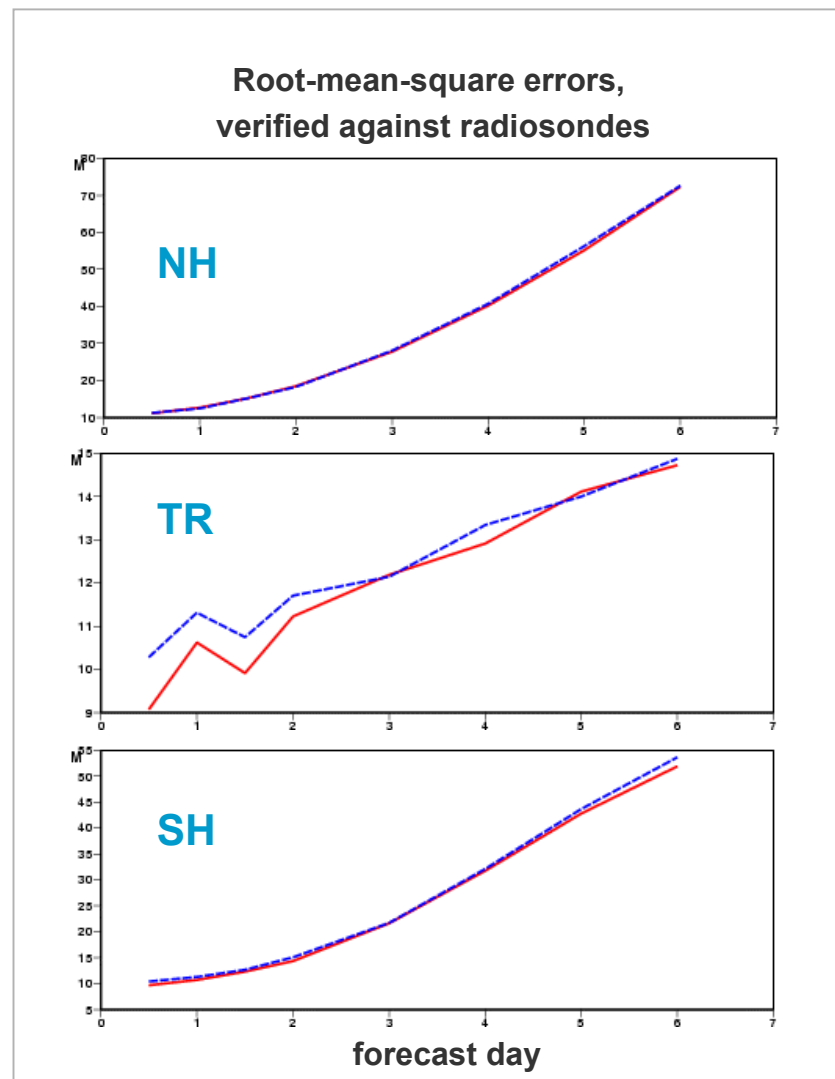
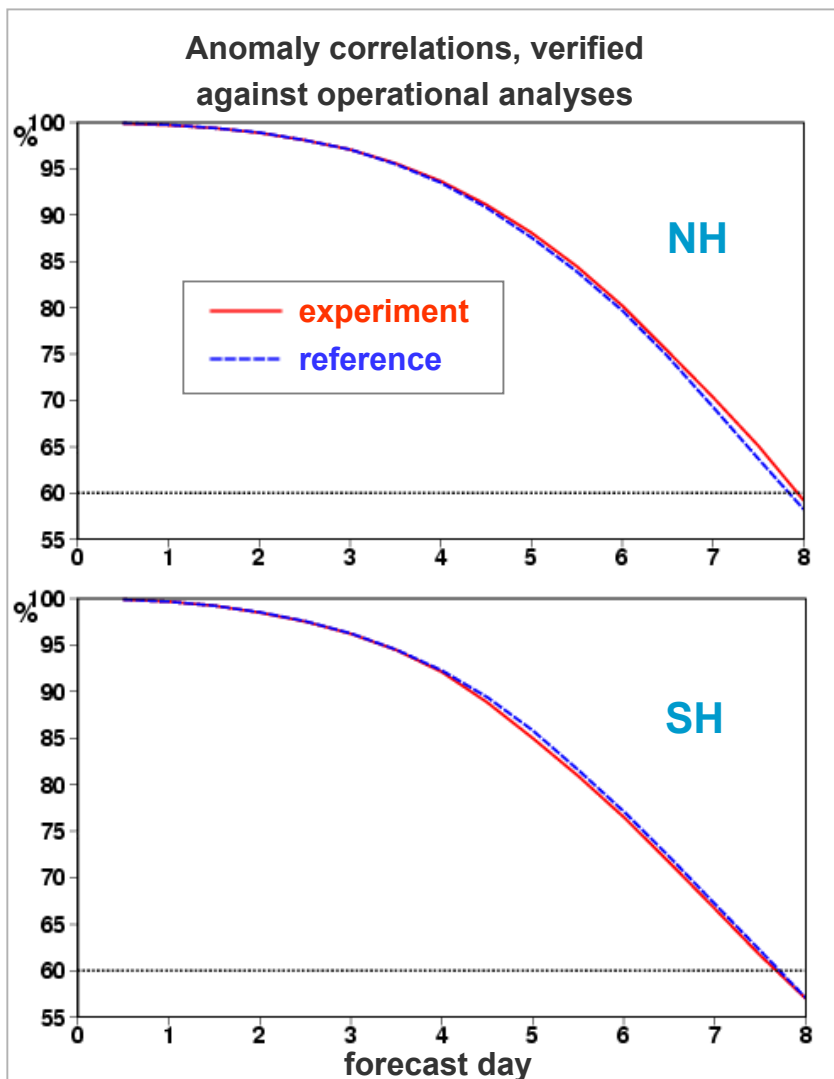


Zonal mean temperature analysis increments dT_a 20040316 - 20040412

larger
smaller



Forecast verification: 20040325 – 20040424 (31 cases) 500 hPa geopotential



Summary and conclusions

- Adaptive bias correction for radiance data implemented mainly for practical reasons
- Developed effective preconditioner for the joint parameter/state estimation problem
- First results look good, but need longer ERA-type experiments

Some issues to think about:

- How to obtain more meaningful bias models
- Danger of 'correcting' observations because of model errors
- Possible repercussions of adaptivity in a reanalysis
- How best to deal with systematic model errors in data assimilation