Progress towards better representation of observation and background errors in 4DVAR

Niels Bormann[1],
Massimo Bonavita[1], Peter Weston[2], Cristina Lupu[1],
Carla Cardinali[1], Tony McNally[1], Kirsti Salonen[1]

[1] ECMWF [2]Met Office

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

ECMWF

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

R and B in the cost function

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}(\mathbf{y}-\mathbf{H}[\mathbf{x}])^T \mathbf{R}^{-1}(\mathbf{y}-\mathbf{H}[\mathbf{x}])$$

- **Specifying B and R is essential for data assimilation:**
  - **B: Background error covariance: describes random errors in the background field**
  - **R: Observation error covariance: describes random errors in the observations and the comparisons observations/model field**
- **Together, they determine the weighting of observations/background.**

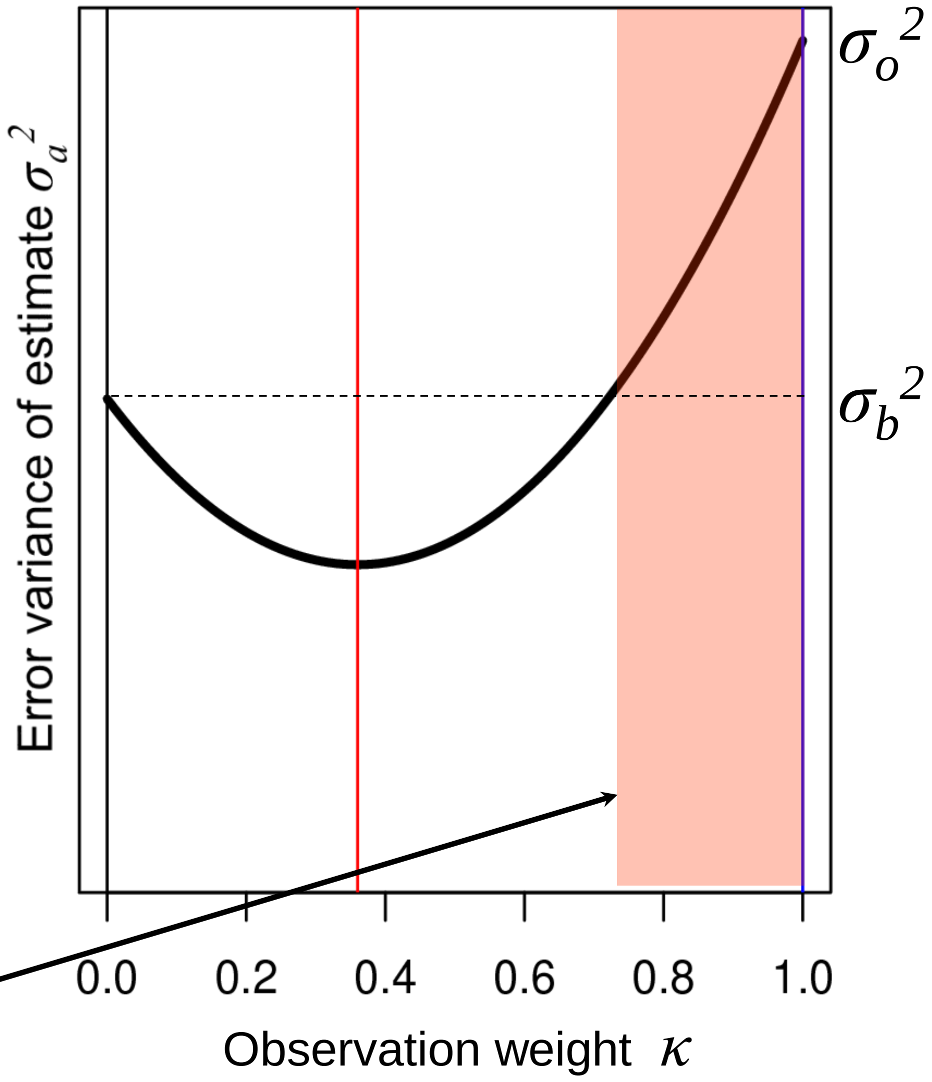
Weights given by R and B

- **Consider linear combination of two estimates x_b and y:**

$$x_a = \kappa y + (1-\kappa)x_b$$

- **Optimal weighting:**

$$\kappa = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}$$



Danger zone: Too small *assumed* σ_o or too large *assumed* σ_b can lead to an analysis worse than the background if the (true) $\sigma_o > \sigma_b$.

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

Observation error covariance

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}(\mathbf{y}-\mathbf{H}[\mathbf{x}])^T \mathbf{R}^{-1}(\mathbf{y}-\mathbf{H}[\mathbf{x}])$$

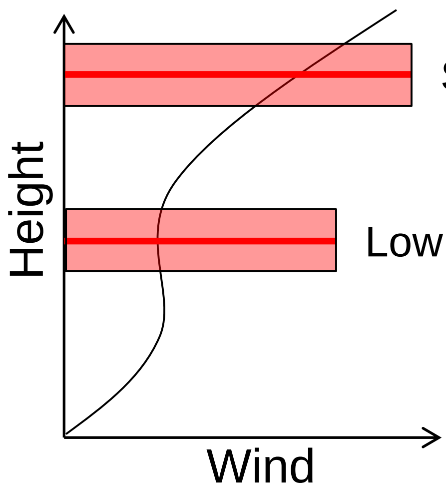
- **R: Describes random errors in the observations and the comparisons observations/model field.**
- **Systematic errors (biases) are treated separately through bias correction.**

Contributions to observation error

- **Measurement error**
  - **E.g., instrument noise for satellite radiances**
  - **Globally constant and uncorrelated if we are lucky.**
- **Forward model (observation operator) error**
  - **E.g., radiative transfer error**
  - **Situation-dependent, likely to be correlated.**
- **Representativeness error**
  - **E.g., point measurement vs model representation**
  - **Situation-dependent, likely to be correlated.**
- **Quality control error**
  - **E.g., error due to the cloud detection scheme missing some clouds in clear-sky radiance assimilation**
  - **Situation-dependent, likely to be correlated.**

Situation-dependence of observation error

- **Examples:**
  - **Cloud/rain-affected radiances: Forward model error and representativeness error are much larger in cloudy/rainy regions than in clear-sky regions (see Alan Geer's talk).**
  - **Effect of height assignment error for Atmospheric Motion Vectors (see Mary Forsythe's talk):**



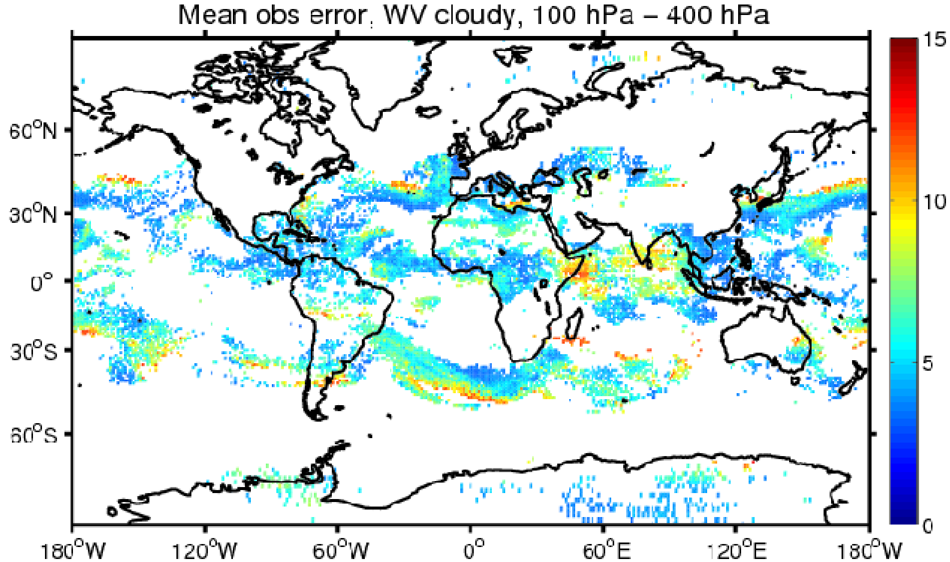
Strong shear – larger wind error due to height assignment error

Low shear – small wind error due to height assignment error

ECMWF

Situation-dependence of observation error

- **Examples:**
  - **Cloud/rain-affected radiances: Forward model error and representativeness error are much larger in cloudy/rainy regions than in clear-sky regions (see Alan Geer's talk).**
  - **Effect of height assignment error for Atmospheric Motion Vectors (see Mary Forsythe's talk):**



(Kirsti Salonen)

Current observation error specification for satellite data in the ECMWF system

- Globally constant, dependent on channel only:
  - AMSU-A, MHS, ATMS, HIRS, AIRS, IASI
- Globally constant fraction, dependent on impact parameter:
  - GPS-RO
- Situation dependent:
  - MW imagers: dependent on channel and cloud amount
  - AMVs: dependent on level and shear (and satellite, channel, height assignment method)

- Error correlations are neglected.

Outline

1. Introduction
2. **Observation errors**
   - Overview
   - **Estimation and specification**
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

How can we estimate R?

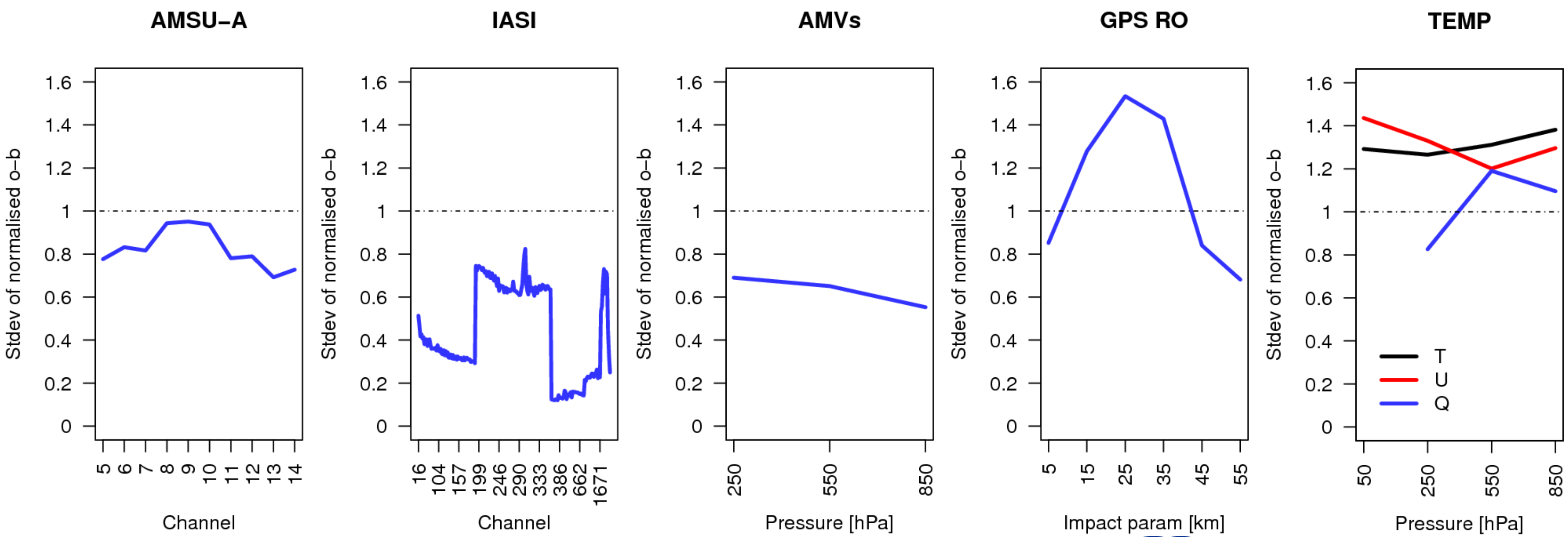
- **Several methods exist, broadly categorised as:**
  - **Error inventory:**
    - Based on considering all contributions to the error/uncertainty
  - **Diagnostics with collocated observations, e.g.:**
    - Hollingsworth/Lönnberg on collocated observations
    - Triple-collocations
  - **Diagnostics based on output from DA systems, e.g.:**
    - Hollingsworth/Lönnberg
    - Desroziers et al 2006
    - Methods that rely on an explicit estimate of B
  - **Adjoint-based methods**

Departure-based diagnostics

- **If observation errors and background errors are uncorrelated then:**

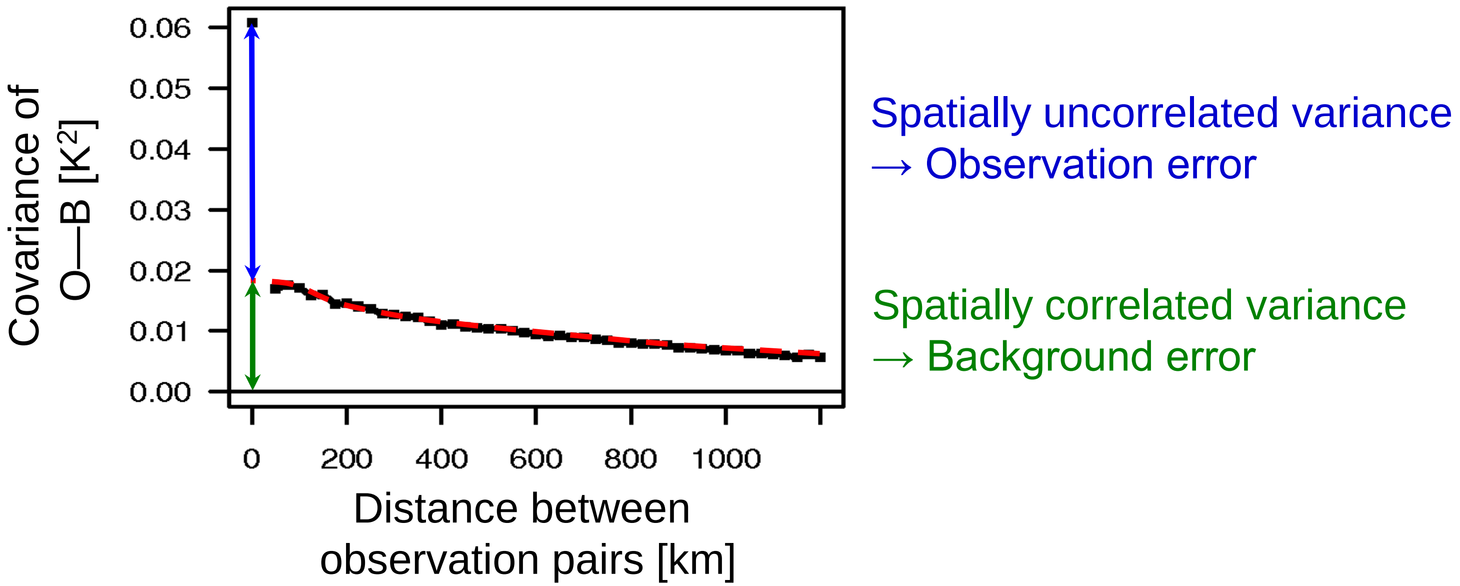
$$Cov[(\mathbf{y}-\mathbf{H}[\mathbf{x}_b]),(\mathbf{y}-\mathbf{H}[\mathbf{x}_b])] \quad = \quad \mathbf{HB}_{true}\mathbf{H}^T + \mathbf{R}_{true}$$

- **Statistics of background departures give an upper bound for the *true* observation error.**
  - Standard deviations of background departures normalised by *assumed* observation error for the ECMWF system:



Observation error diagnostics: Hollingsworth/Loennberg method

- Based on a large database of pairs of departures.
- Basic assumption:
  - Background errors are spatially correlated, whereas observation errors are not.
  - This allows to separate the two contributions to the variances of background departures:



Observation error diagnostics: Desroziers diagnostic

- **Basic assumptions:**
  - Assimilation process can be adequately described through linear estimation theory.
  - Weights used in the assimilation system are consistent with true observation and background errors.
- **Then the following relationship can be derived:**

$$\tilde{\mathbf{R}} = Cov[\mathbf{d}_a, \mathbf{d}_b]$$

with $\mathbf{d}_a = (\mathbf{y} - \mathbf{H}[\mathbf{x}_a])$ (analysis departure)

$\mathbf{d}_b = (\mathbf{y} - \mathbf{H}[\mathbf{x}_b])$ (background departure)

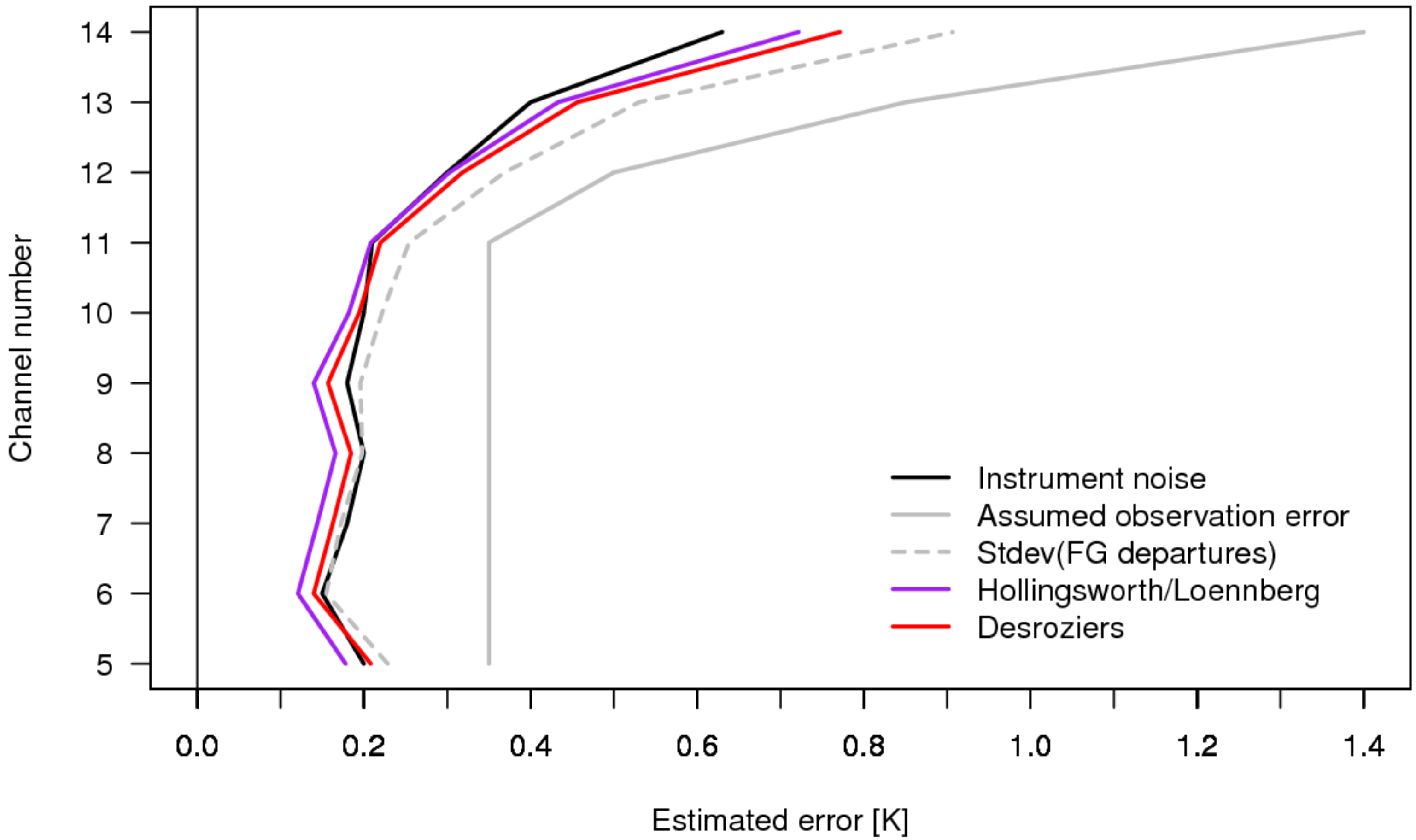
(see Desroziers et al. 2005, QJRMS)

- **Consistency diagnostic for the specification of R.**

ECMWF

Examples of observation error diagnostics: AMSU-A

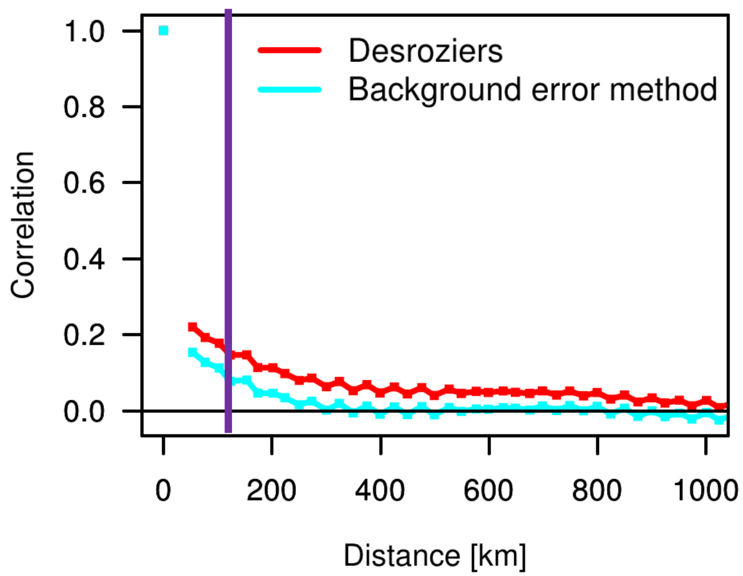
Diagnostics for σ_O, for NOAA-18



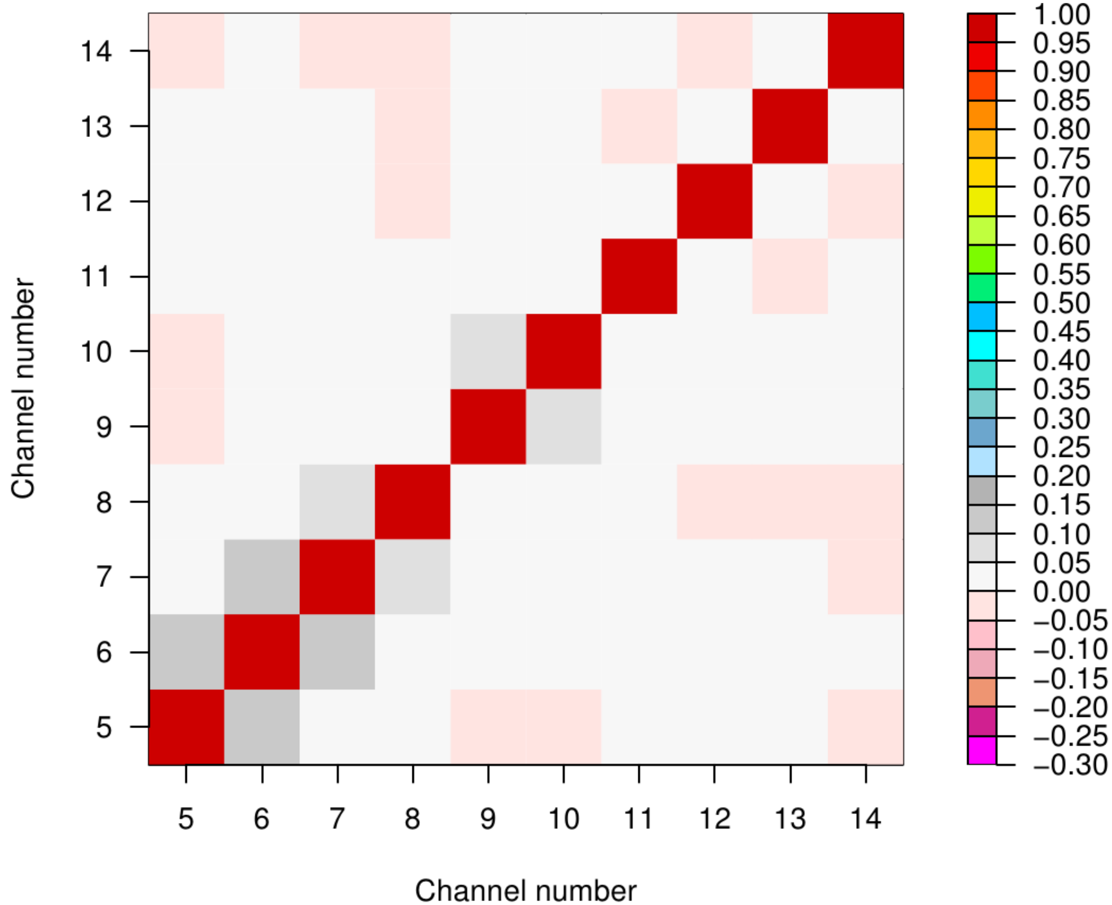
Example: AMSU-A

- **After thinning to 120 km, error diagnostics suggest little correlations…**

Spatial error correlations for channel 7:

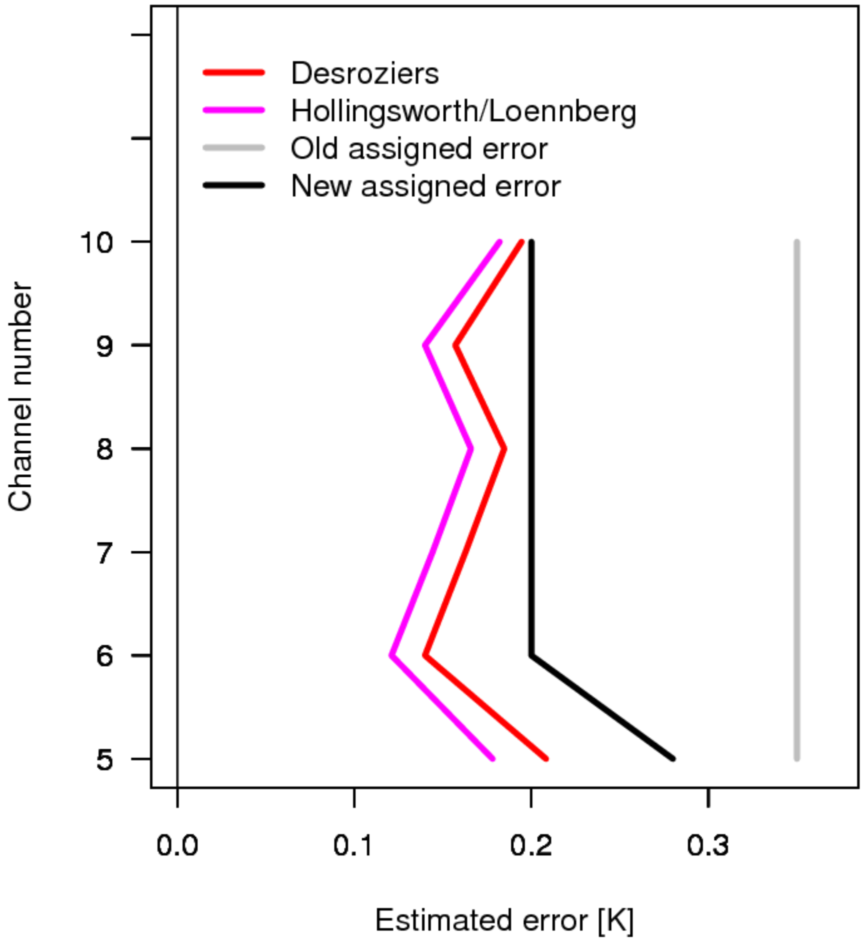


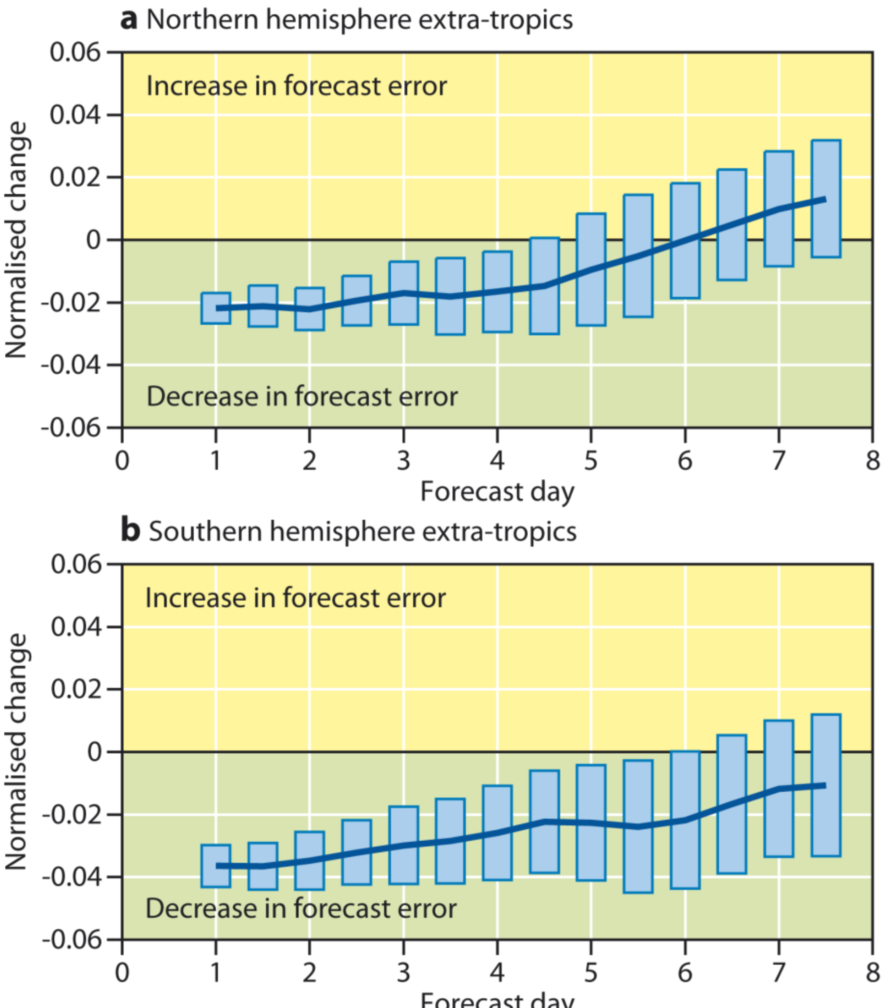
Inter-channel error correlations:



Example: AMSU-A

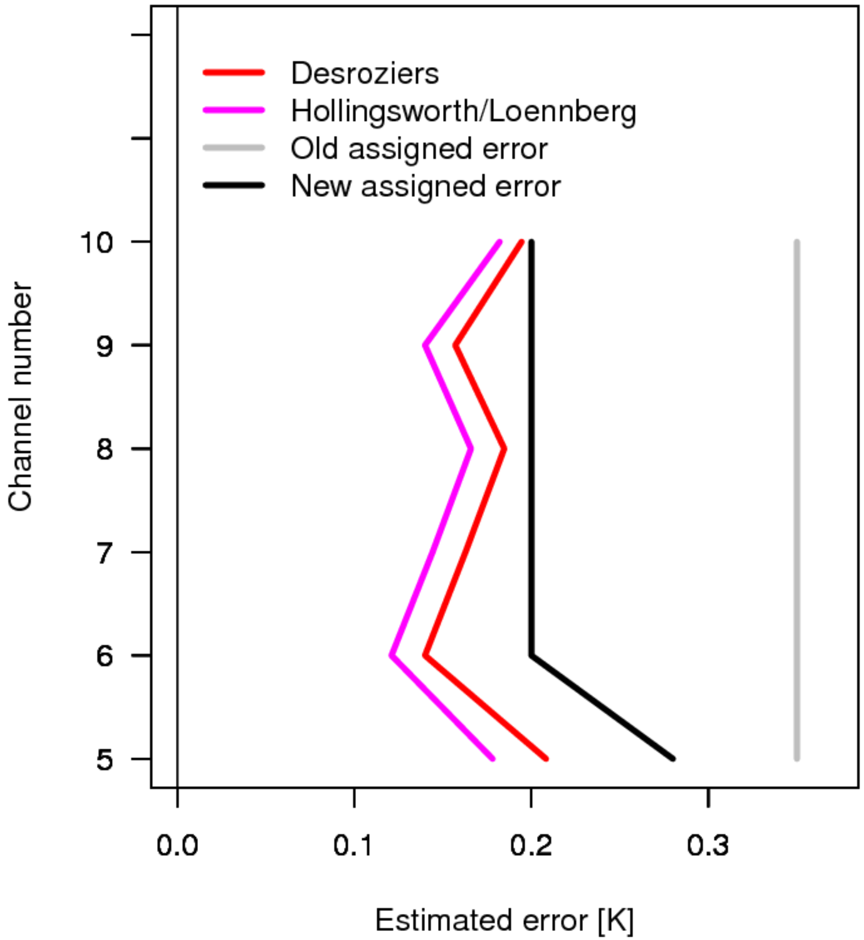
- … diagonal R a good approximation.

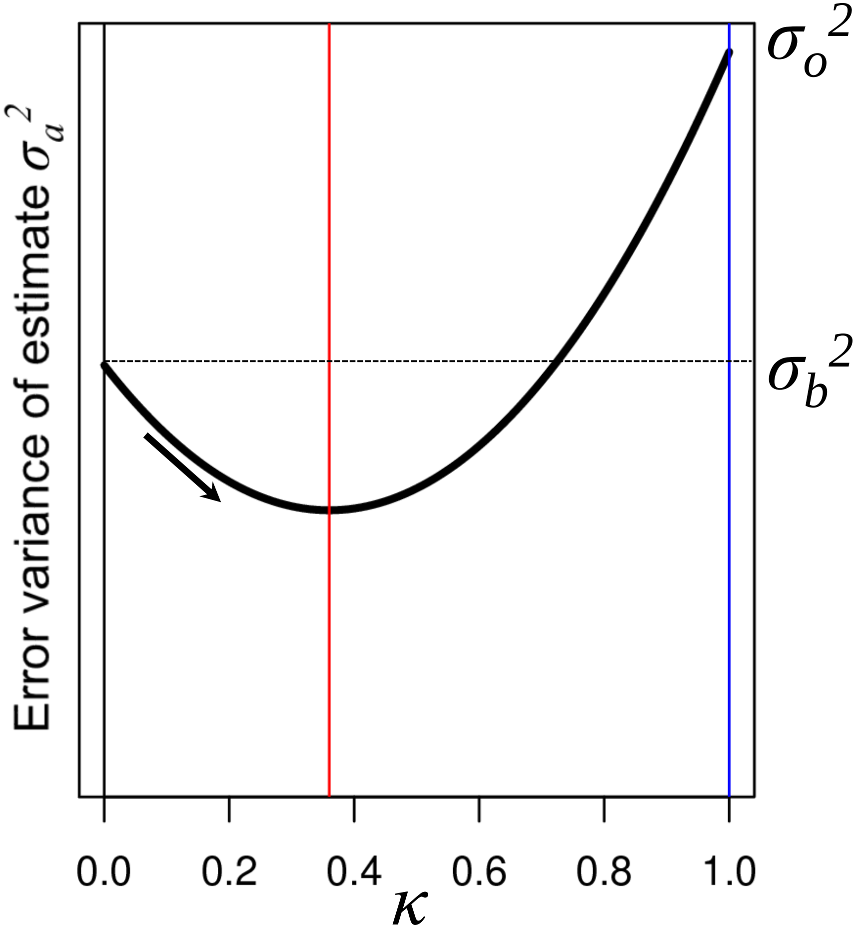




Example: AMSU-A

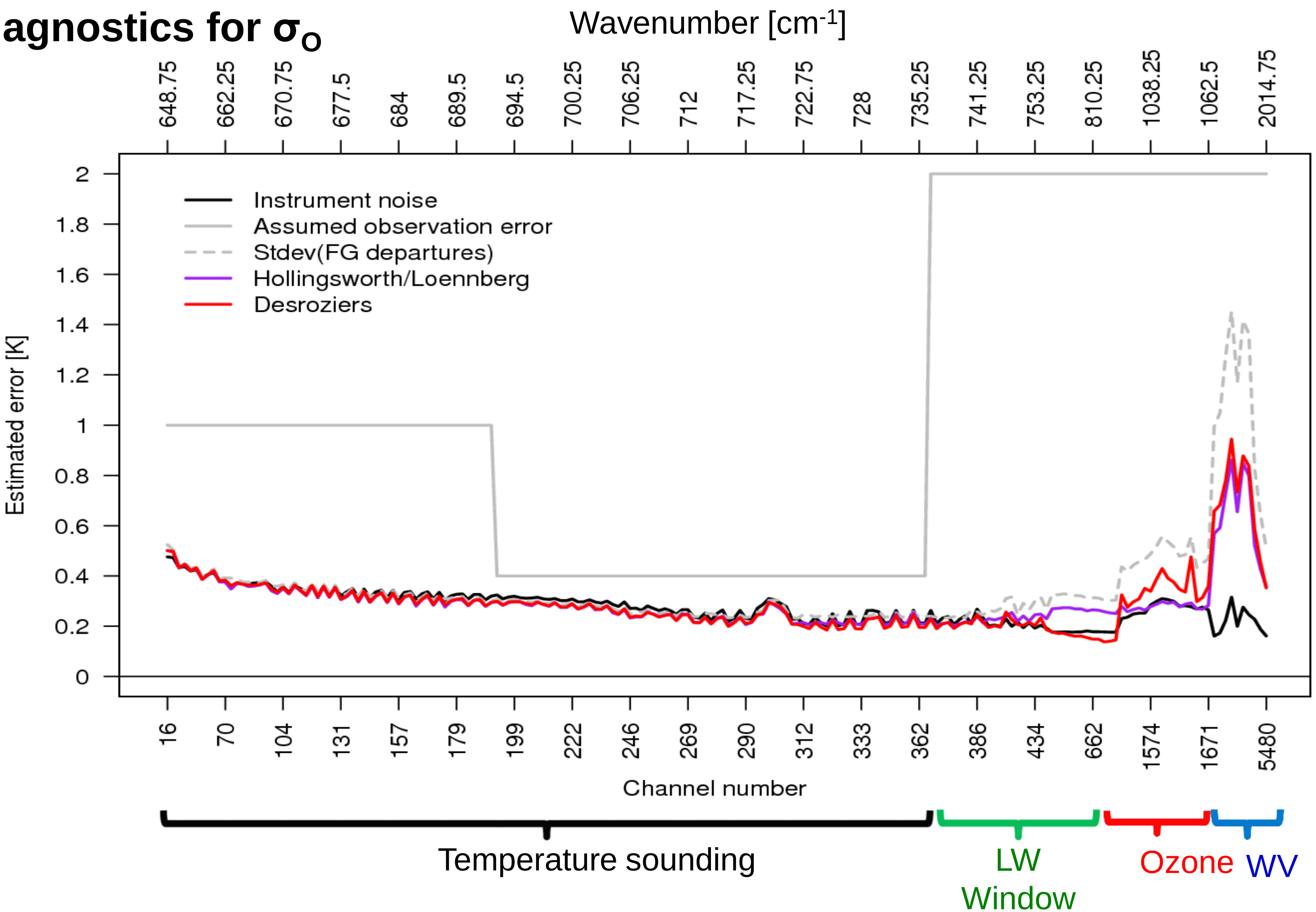
- … diagonal R a good approximation.





Examples of observation error diagnostics: IASI

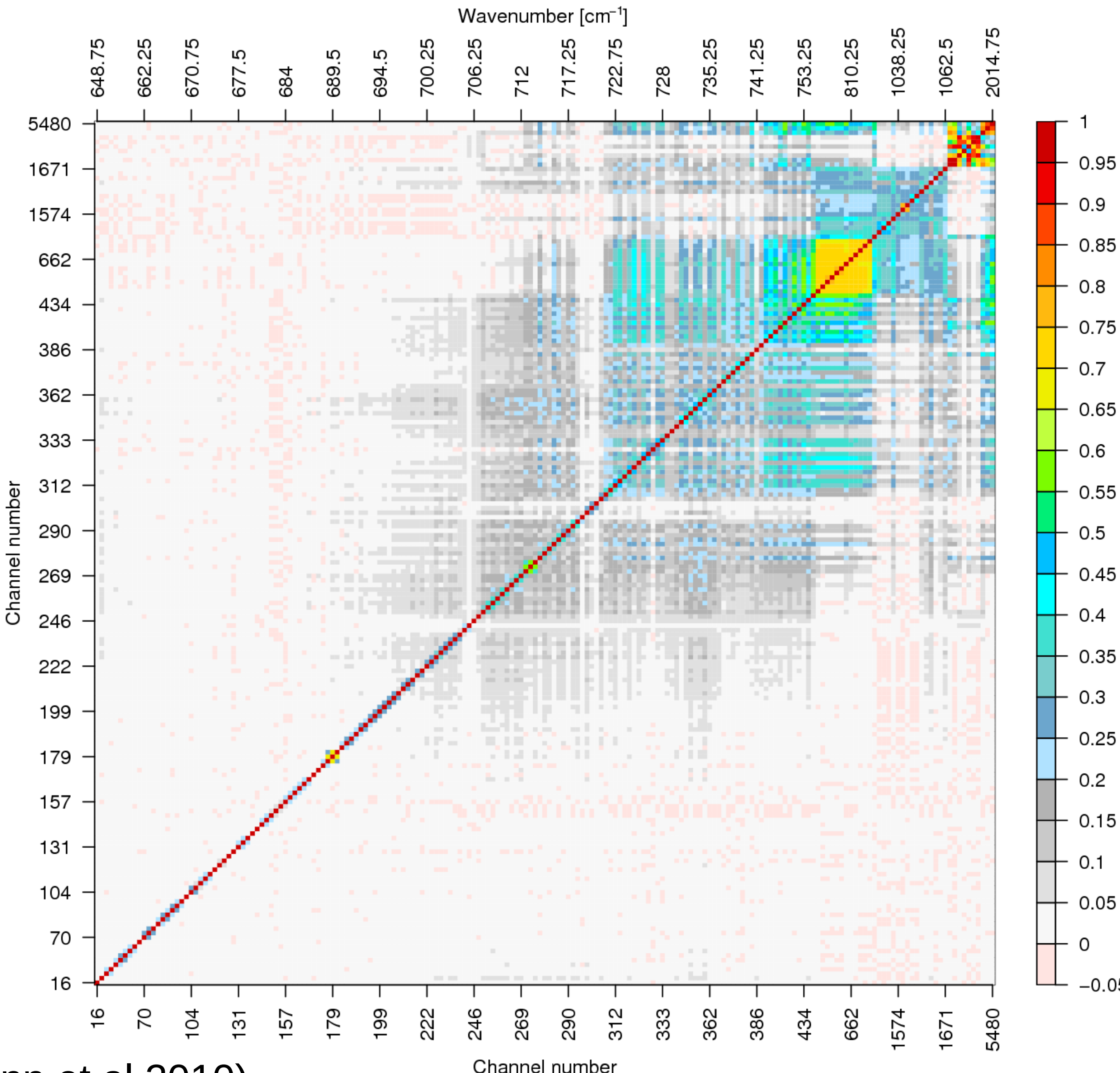
Diagnostics for σ_O



ECMWF

Example: IASI

Inter-channel error correlations (Hollingsworth/ Lönnberg):



(Updated from Bormann et al 2010)

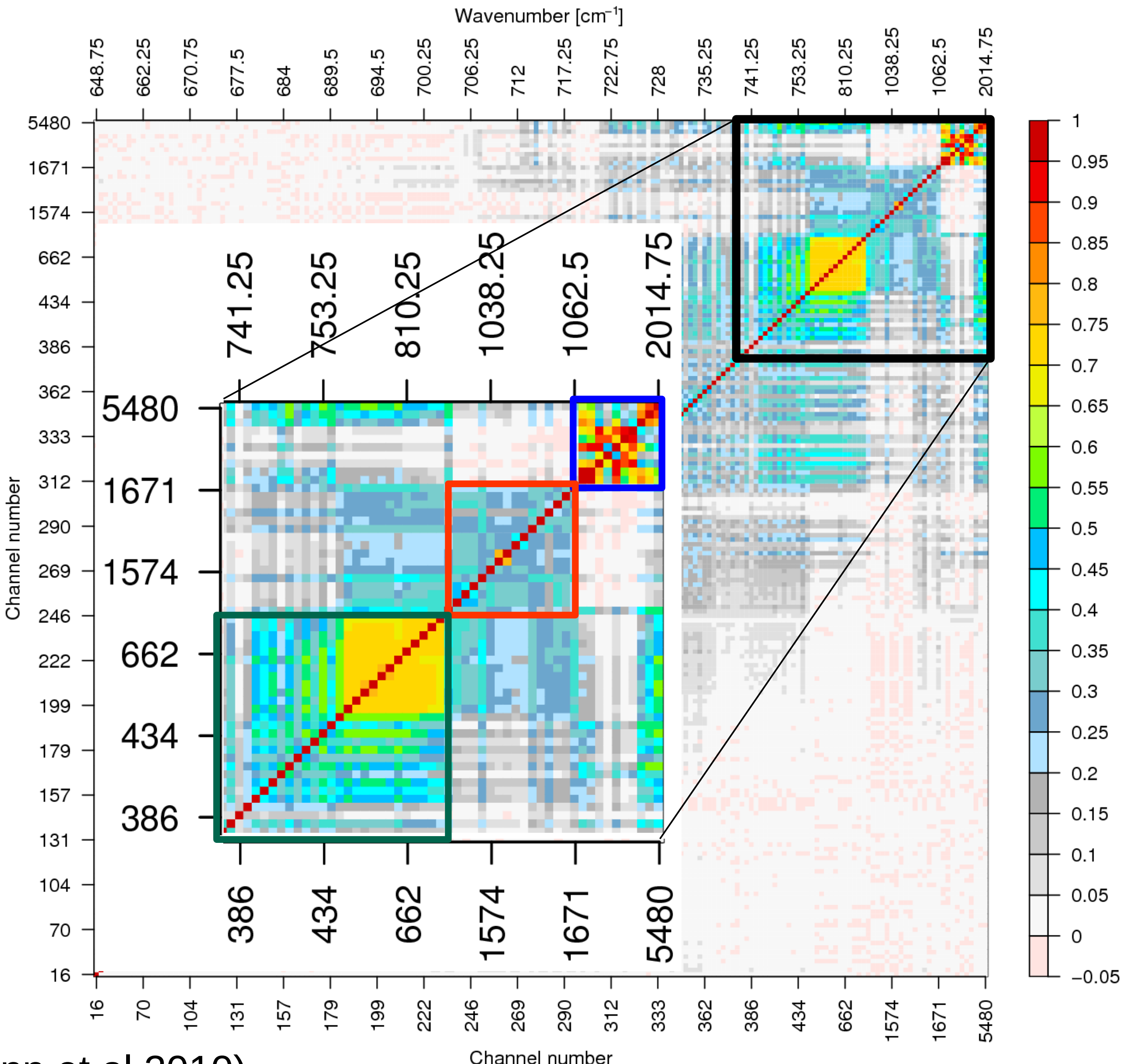
Example: IASI

Inter-channel error correlations (Hollingsworth/ Lönnberg):

Humidity

Ozone

Window channels

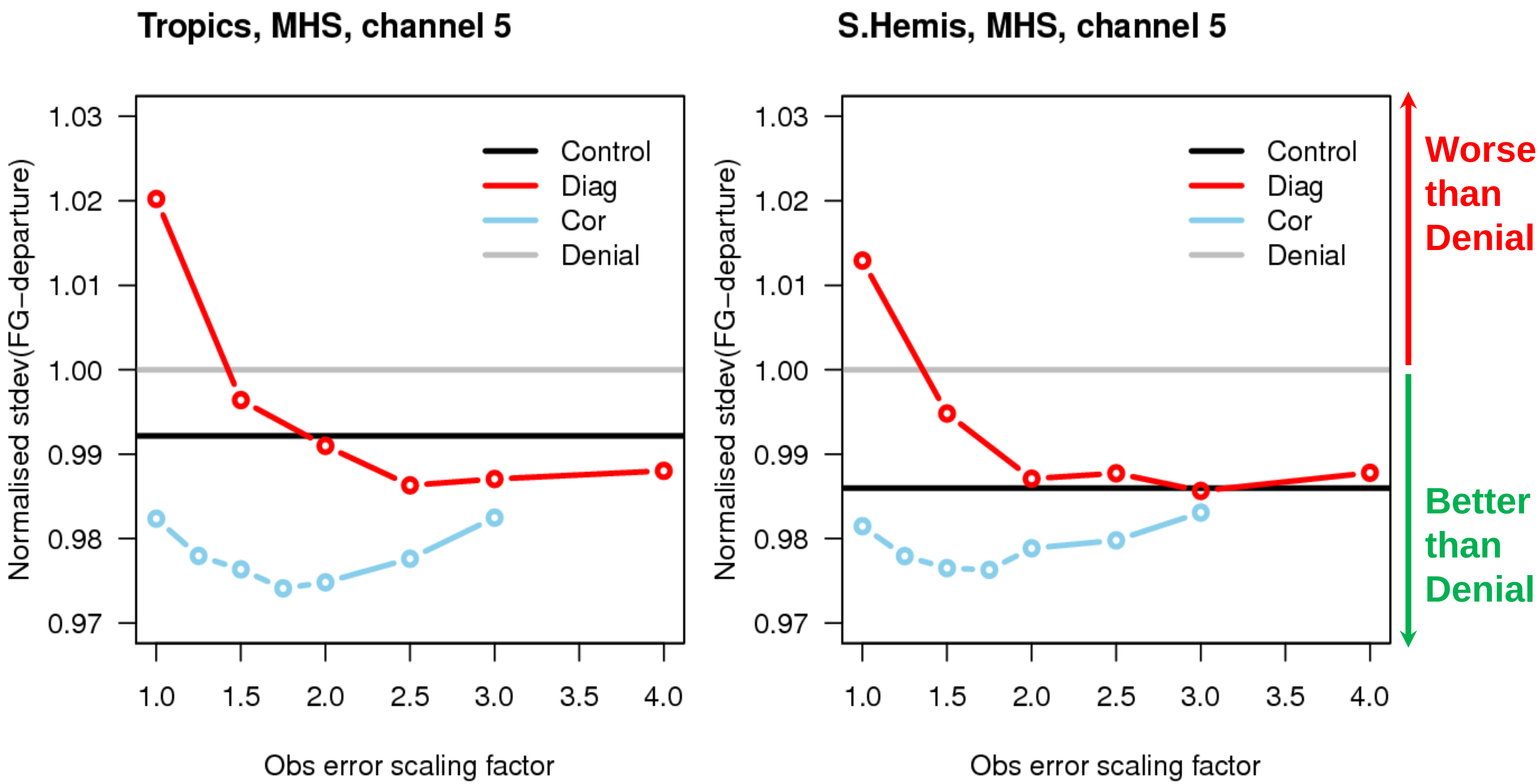


(Updated from Bormann et al 2010)

Role of error inflation and error correlation

- **Experiments:**
  - **<u>Denial:</u>** No AIRS and IASI.
  - **<u>Control:</u>** **Operational** (diagonal) observation errors for AIRS and IASI.
  - **<u>Diag:</u>** Series of experiments with **diagonal observation errors** for AIRS and IASI, with σ_O **from HL diagnostic**, scaled by a constant factor α:
    - $\sigma_O = \alpha \ \sigma_{O,\,HL}$, with a series of different α
  - **<u>Cor:</u>** Series of experiments with **full diagnosed observation error covariances** for AIRS and IASI, again scaled by a factor α:
    - $\mathbf{R} = \alpha^2 \ \ \mathbf{R}_{HL}$, with a series of different α
- **Setup:**
  - **4DVAR, T319 (~60km) resolution, 15 Dec 2011 – 14 Jan 2012**

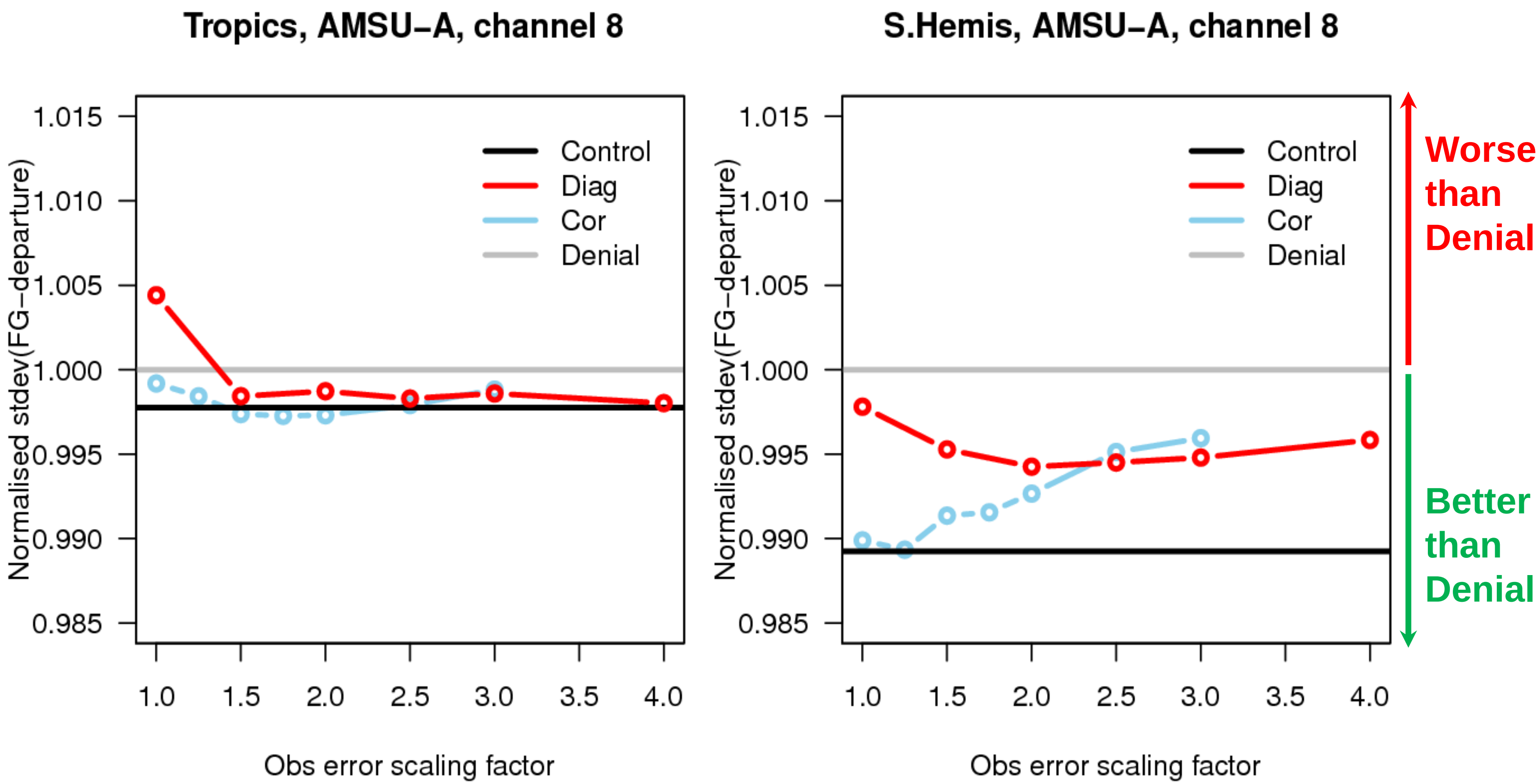
Role of error inflation and error correlation: Impact on mid-tropospheric humidity



Significant improvement for humidity for experiments with error correlations.

ECMWF

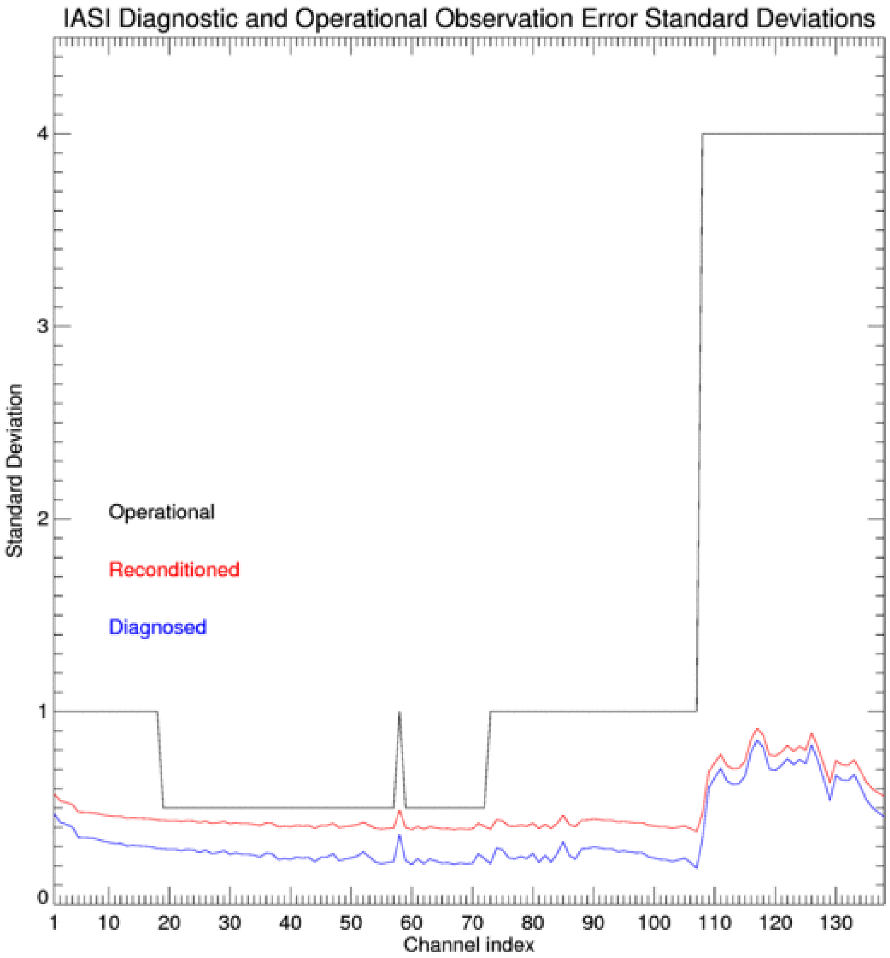
Role of error inflation and error correlation: Impact on upper tropospheric temperature



For tropospheric temperature, benefit over operations is less clear.

Benefits of taking inter-channel error correlations into account

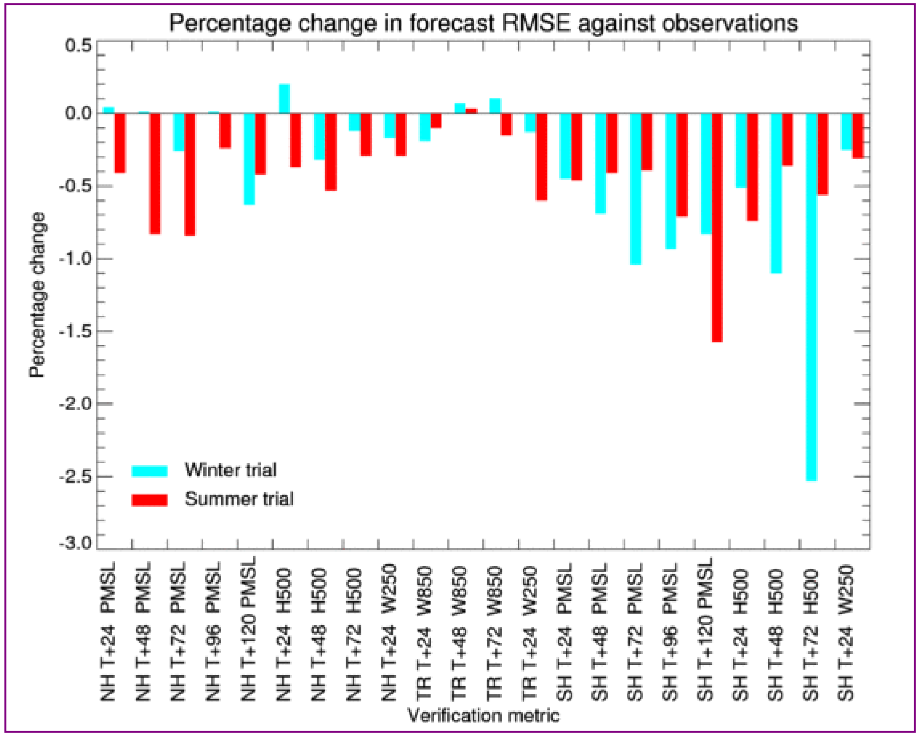
- Benefits have been found from taking inter-channel error correlations into account.
  - Some adjustments to diagnosed matrices needed/beneficial:
    - Scaling of σ_O (ECMWF)
    - Reconditioning (Met Office)

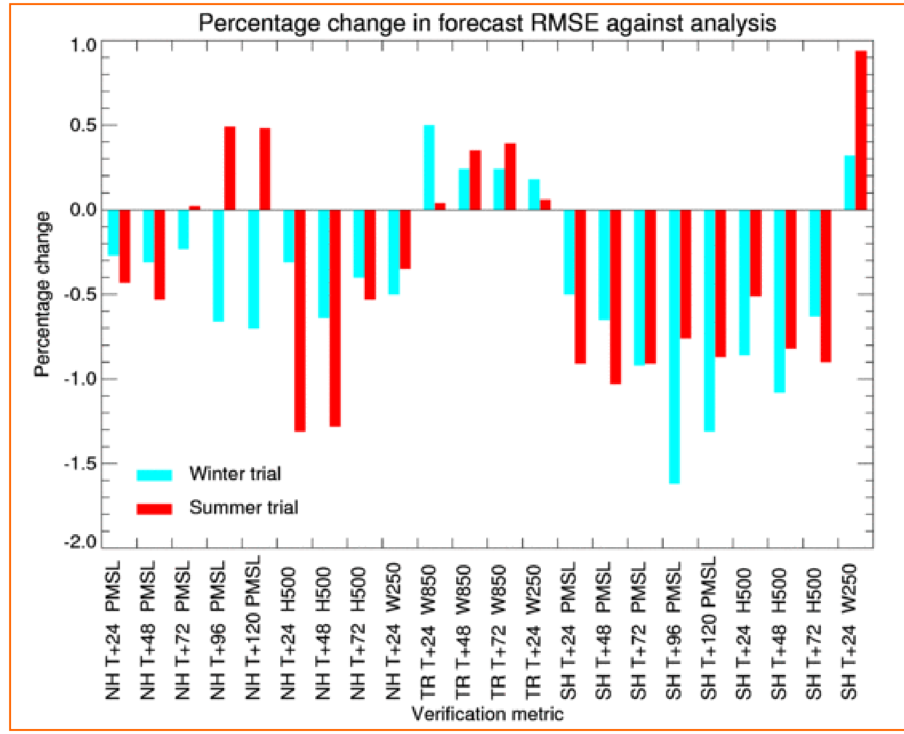


(Peter Weston, Met Office)

Trial results at Met Office

(Peter Weston, Met Office)





Verification v Observations

+0.209/0.302% UKMO NWP Index

Verification v Analyses

+0.241/0.047% UKMO NWP Index

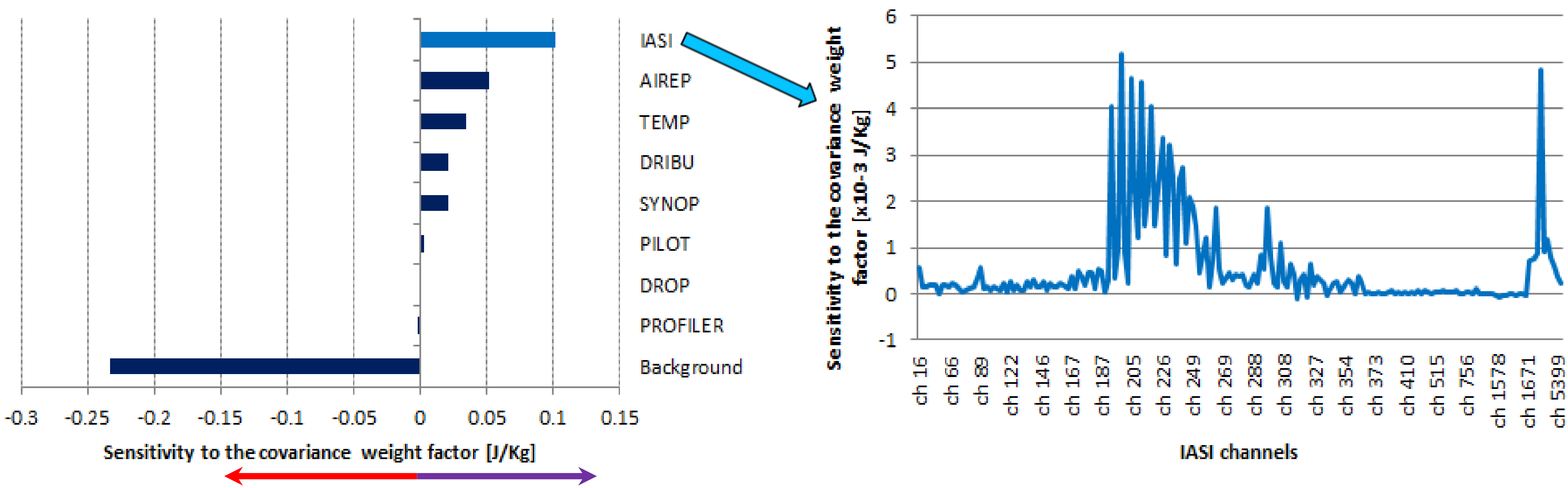
The use of correlated observation errors for IASI was implemented operationally at the Met Office in January 2013

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

Adjoint diagnostics for observation errors

- Adjoint diagnostics can be used to assess the sensitivity of forecast error reduction to the observation error specification (e.g., Daescu and Todling 2010).
- Example: Assessment of IASI in a depleted observing system with only conventional and IASI data.



Increase of assigned error beneficial

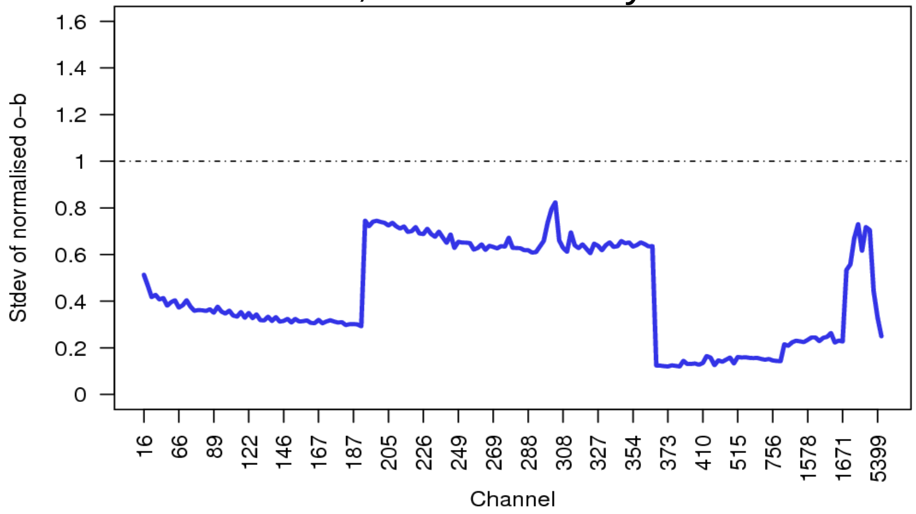
Reduction of assigned error beneficial

(Cristina Lupu, Carla Cardinali)

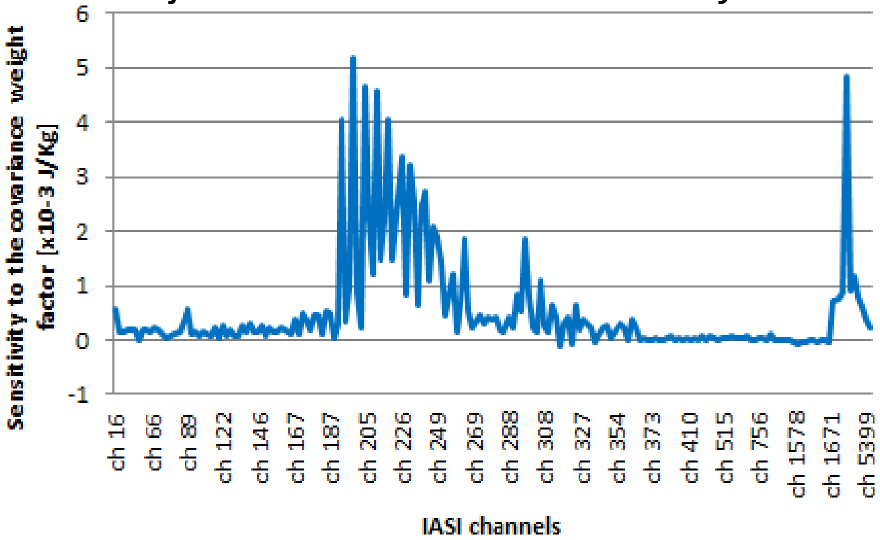
Adjoint diagnostics for observation errors

- Adjoint diagnostics can be used to assess the sensitivity of forecast error reduction to the observation error specification.
- Example: Assessment of IASI in a depleted observing system with only conventional and IASI data.

Stdev of o-b, normalised by assumed R:



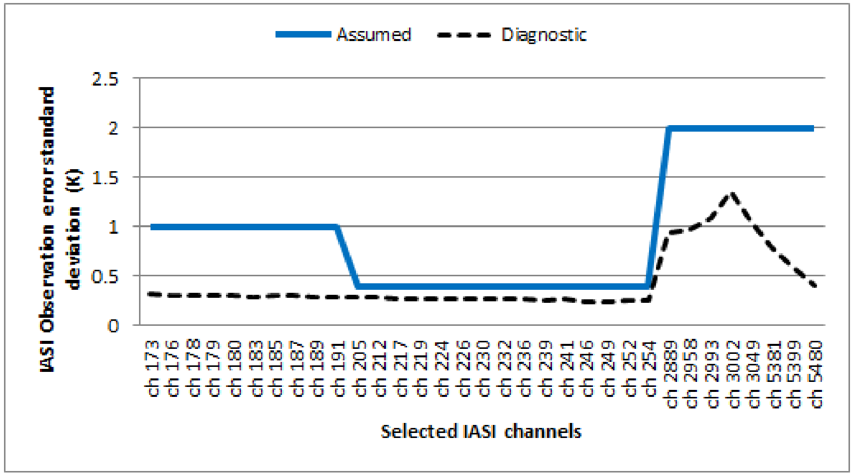
Adjoint-based forecast sensitivity to R:

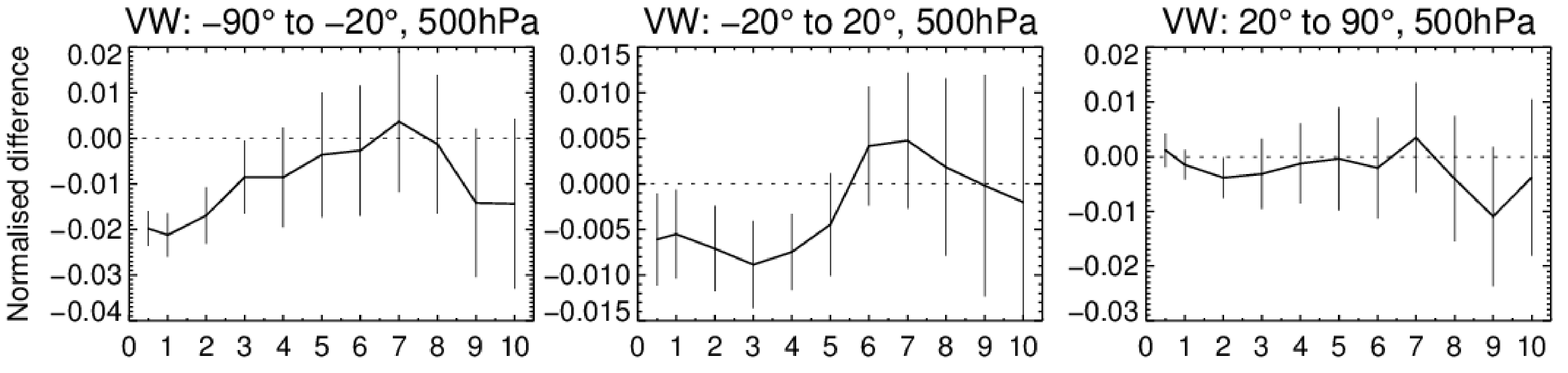


(Cristina Lupu, Carla Cardinali)

Adjoint diagnostics for observation errors

- Forecast impact from using observation error reduced to Desroziers values for selected 33 channels (no error correlations) in depleted observing system:





- Further work required regarding the applicability of this diagnostic (consistency of results with estimates of true observation errors).

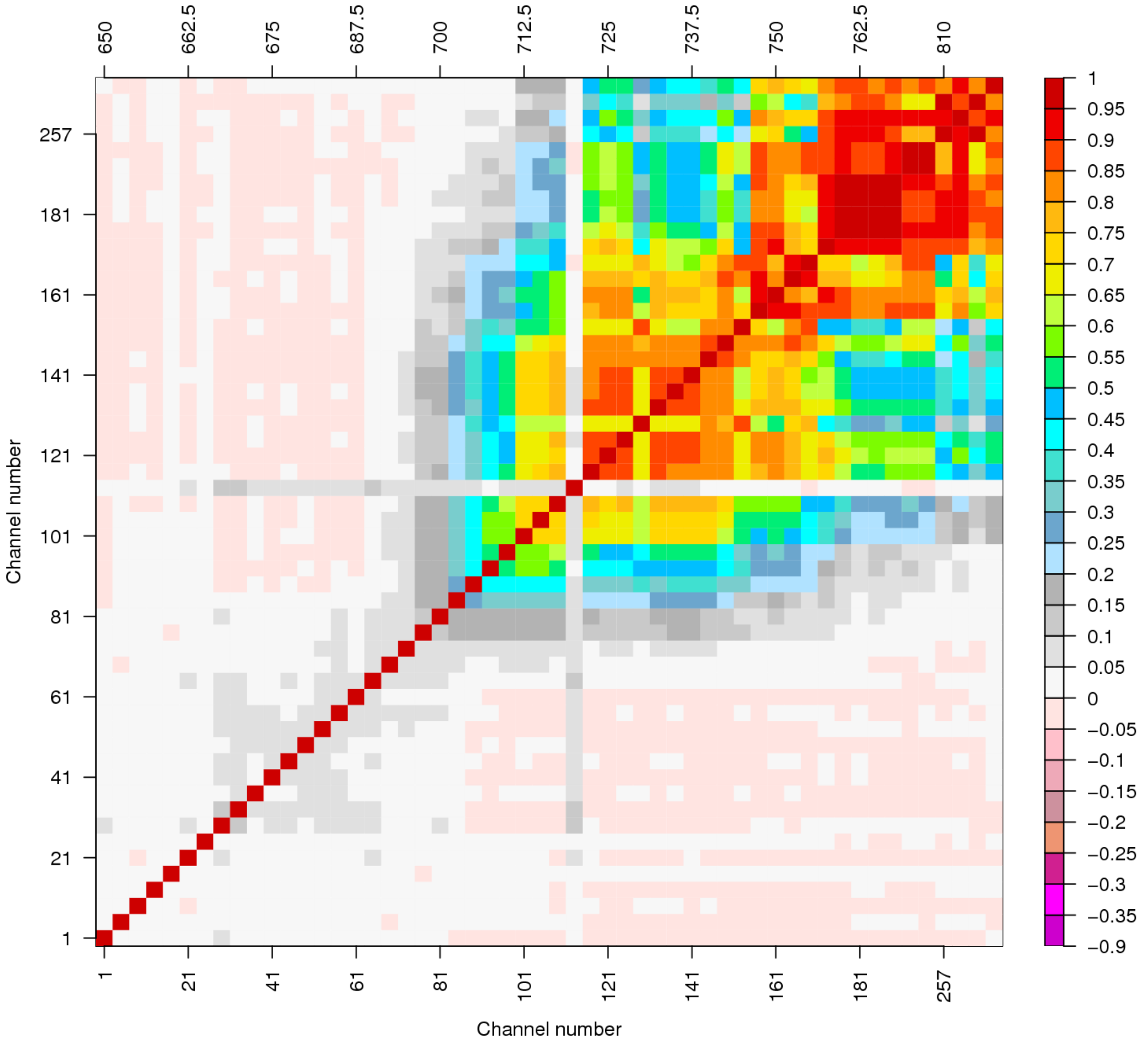
(Cristina Lupu)

Summary for observation errors

- **The representation of observation errors in current data assimilation systems is mostly fairly basic.**
  - **Common practice is to use globally constant, inflated errors without error correlations.**
  - **Representation of forward model error, representativeness error or quality control error is mostly rather crude.**
  - **Benefits are being seen from introducing a more sophisticated representation of these errors for some data (e.g., situation-dependence, inter-channel error correlations).**
  - **Efforts to take into account spatial observation error correlations are very limited.**

  - **Specification of error correlations is likely to be important to optimise the use of humidity channels and low-noise instruments (CrIS).**

Observation error correlation diagnostics for CrIS on S-NPP



Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

ECMWF

Background error covariance

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}(\mathbf{y}-\mathbf{H}[\mathbf{x}])^T \mathbf{R}^{-1}(\mathbf{y}-\mathbf{H}[\mathbf{x}])$$

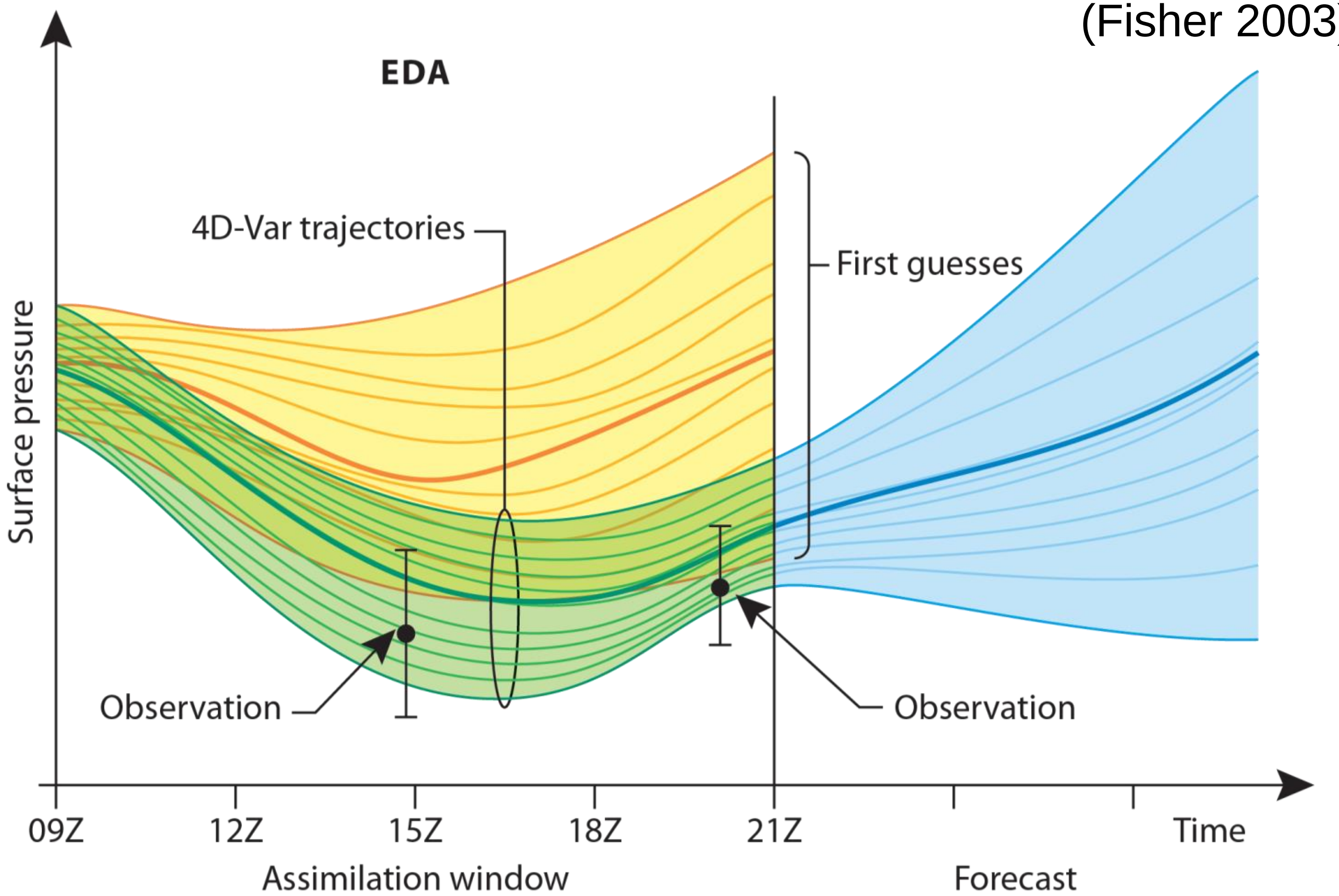
- **B: Describes random errors in the background fields**
- **Prescribes the structure of the analysis increments**
- **Crucial for carrying forward information from previous observations**

Development of B-modelling within 4DVAR at ECMWF

- January 2003, 25r3: Static B generated from an ensemble of data assimilations (EDA)
- April 2005, 29r1: Wavelet B
- June 2005, 29r2: Static B from an updated EDA
- May 2011, 37r2: Use of flow-dependent background error variances from an EDA for vorticity
- June 2013, 38r2: Use of flow-dependent background error variances from an EDA for unbalanced control variables
- November 2013, 40r1: Flow-dependent background error correlations from the EDA

Ensemble of data assimilations (EDA)

(Fisher 2003)



- E.g.,: 25 members of 4DVARs
- Perturbations from observations, SST, model parameterisations
- **Provides an estimate of the analysis and background uncertainty.**

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. Summary

Hybrid EDA 4DVAR

At ECMWF, the modelled B has this form:

$$\mathbf{B} = \mathbf{L}\ \Sigma_b^{1/2}\ \mathbf{C}\ \Sigma_b^{1/2}\ \mathbf{L}^T$$

$\mathbf{L}$: Balance operator => cross-covariances (mainly mass-wind balance)

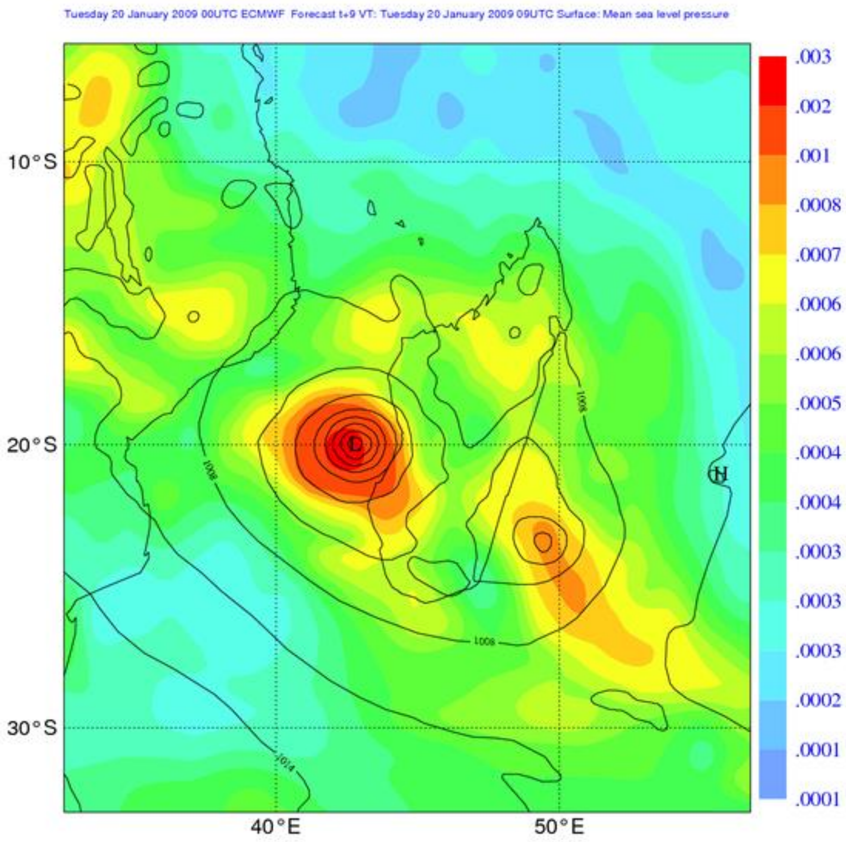
$\Sigma_b^{1/2}$: Standard deviation of BG errors in grid point space
$\mathbf{C}$: Correlation structures of BG errors (wavelet JB, Fisher 2003)

$\Sigma_b^{1/2}\mathbf{C}\ \Sigma_b^{1/2}$: univariate covariances of control variables

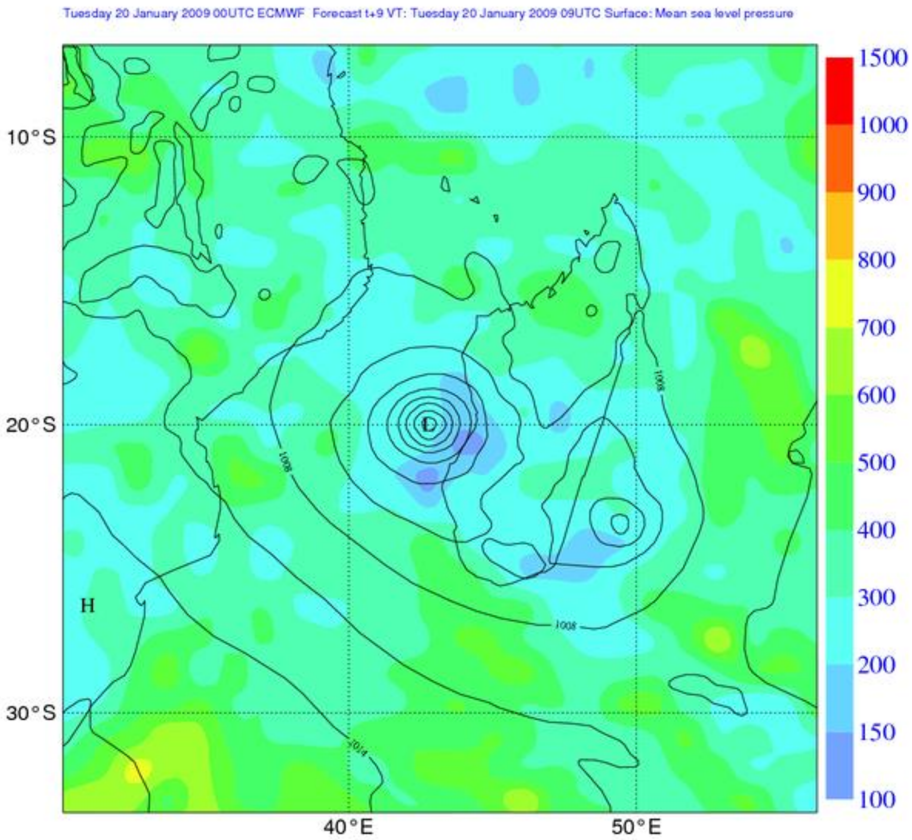
Hybrid EDA 4DVAR: Make $\Sigma_b^{1/2}$ and C flow-dependent.

Flow-dependent background errors from the EDA

EDA StDev of LNSP

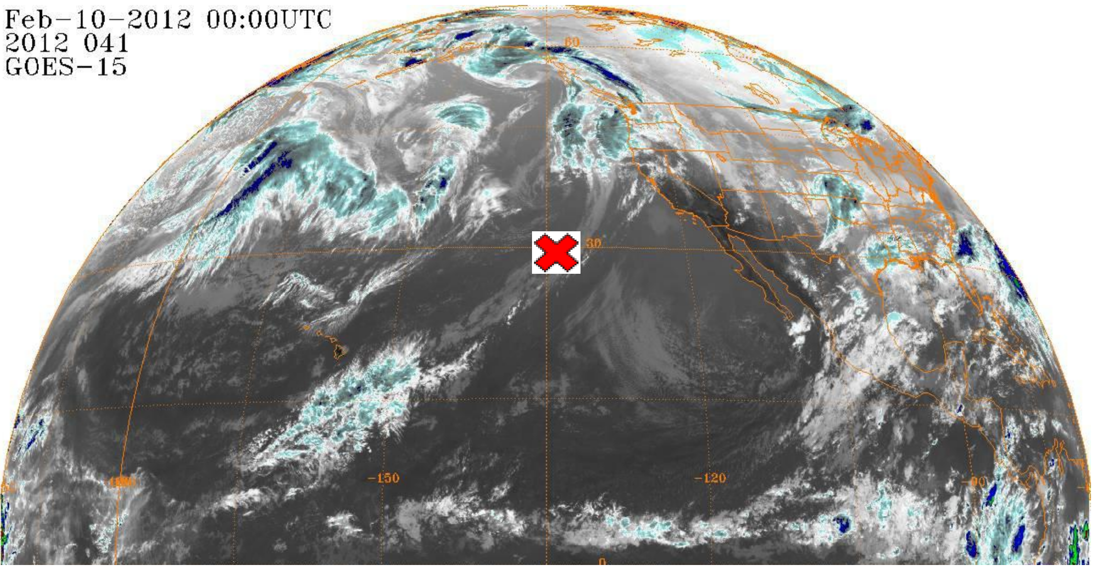


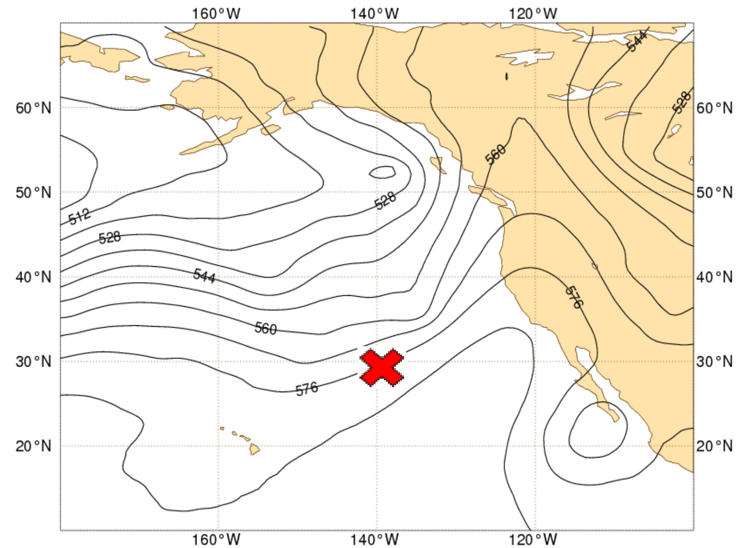
EDA Lscale of BG errors LNSP



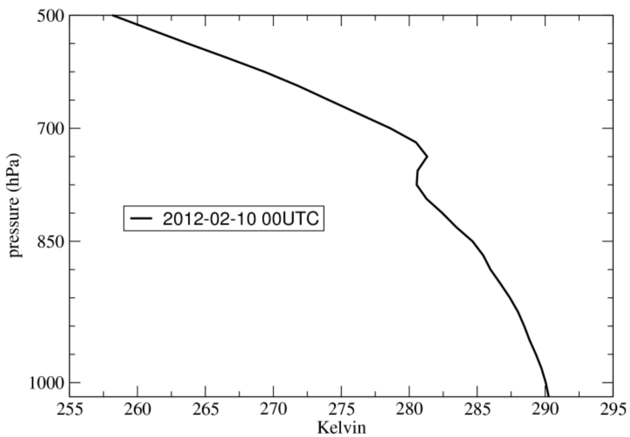
(Massimo Bonavita)

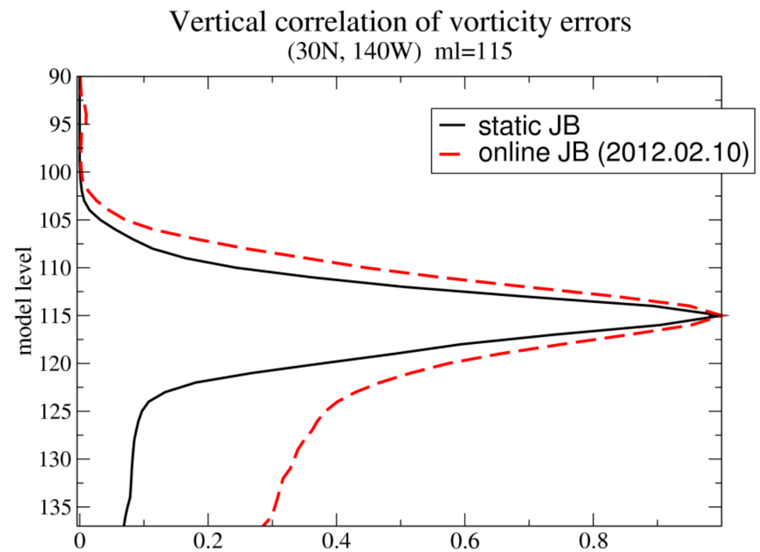
Vertical Error Correlation: Vorticity, 850 hPa





Temperature profile
2012/02/10 00Z - (30N, 140W)



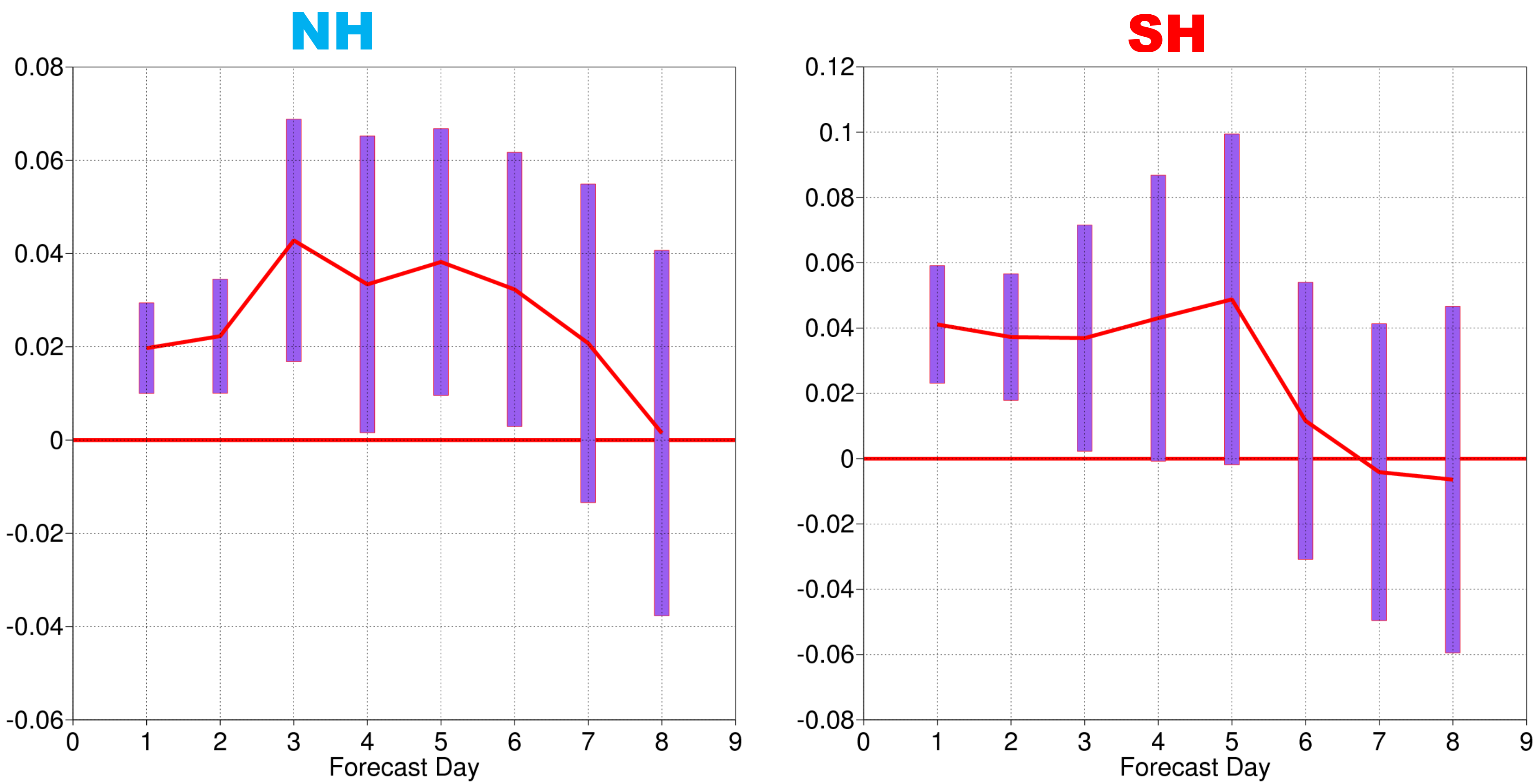


(Massimo Bonavita)

ECMWF

Impact of flow-dependent JB vs static

Normalised reduction in 500 hPa Geopotential RMSE, with 95% confidence, June/July 2012



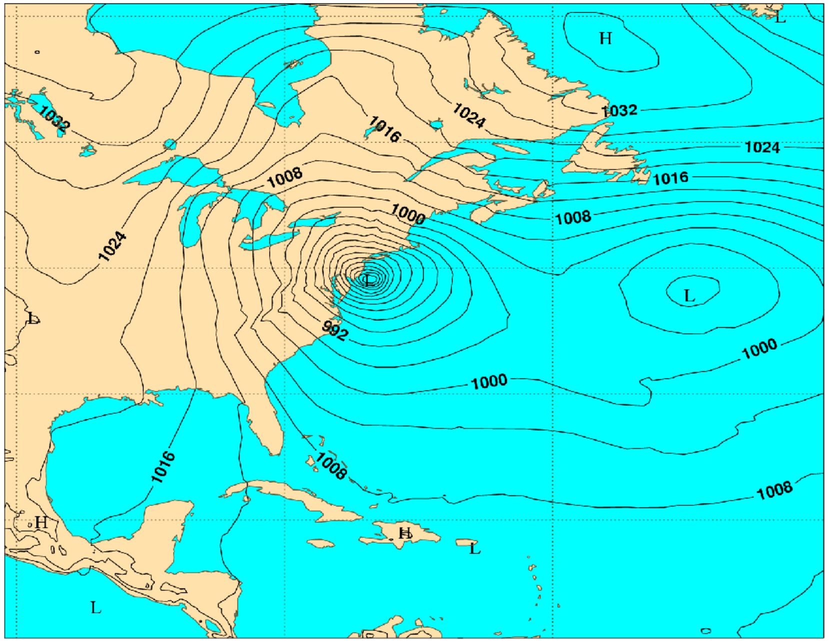
(Massimo Bonavita)

Example: Hurricane Sandy

Operational ECMWF forecast provided accurate guidance on landfall position around a week in advance.

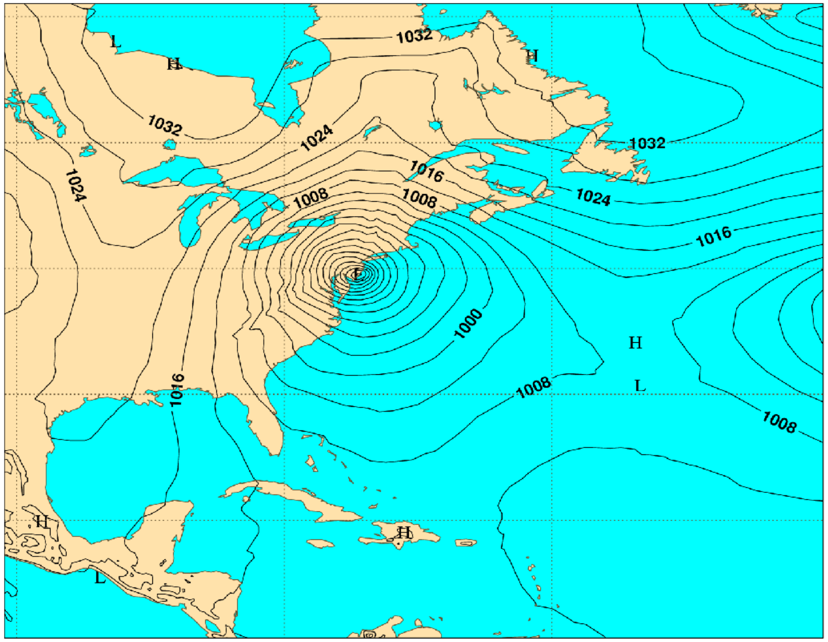
Mslp t+204h Fcst valid at 30/10/2012 00UTC

Monday 22 October 2012 00UTC ECMWF Forecast t+204 VT: Tuesday 30 October 2012 12UTC Surface: Mean sea level pressure



Mslp Analysis 30/10/2012 00UTC

ECMWF Analysis VT:Tuesday 30 October 2012 00UTC Surface: Mean sea level pressure

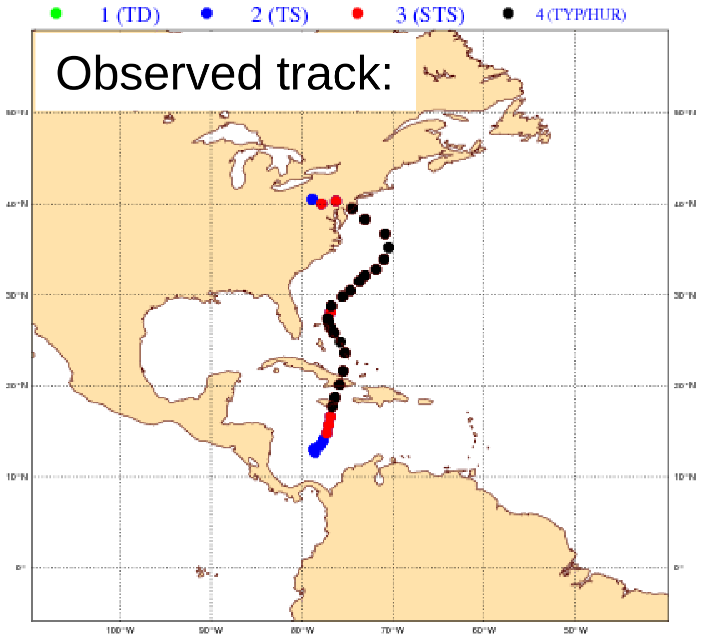


Hurricane Sandy

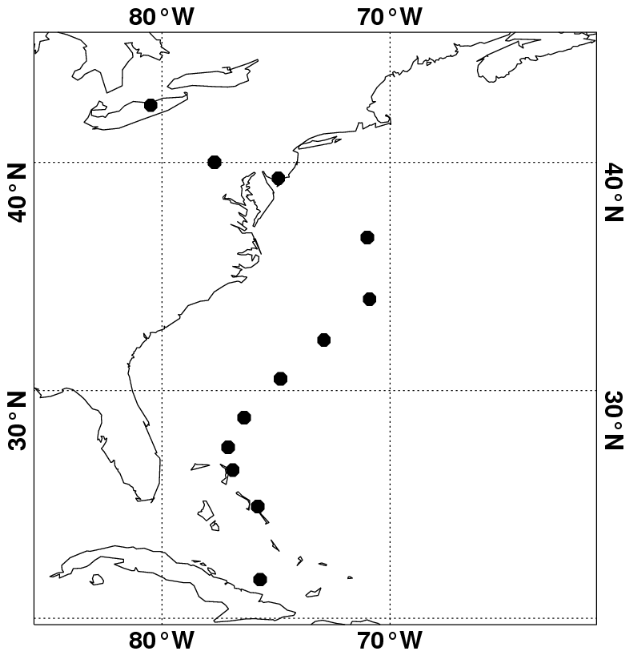
Influence of satellite data and EDA

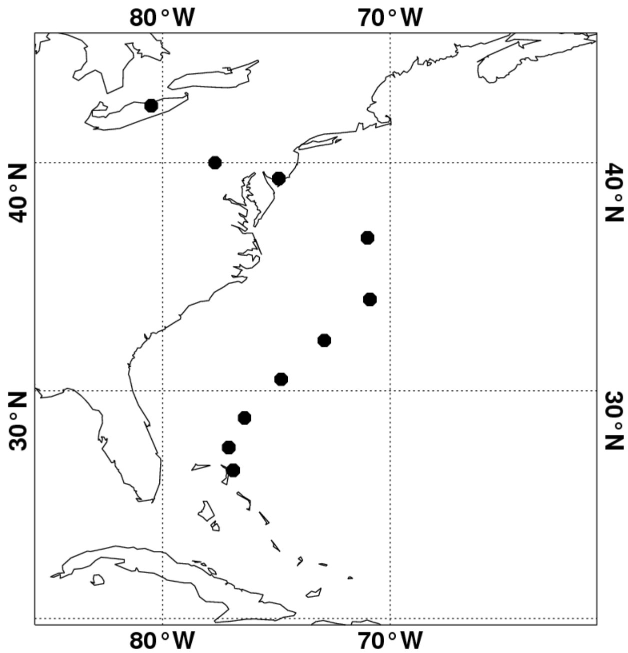
(McNally et al 2014, MWR)

- What happens if we withhold all satellite observations from polar-orbiters (i.e., approx. 90% of obs. counts)?



Track forecast from 25 Oct 2012 00UTC





Track forecast from 26 Oct 2012 00UTC

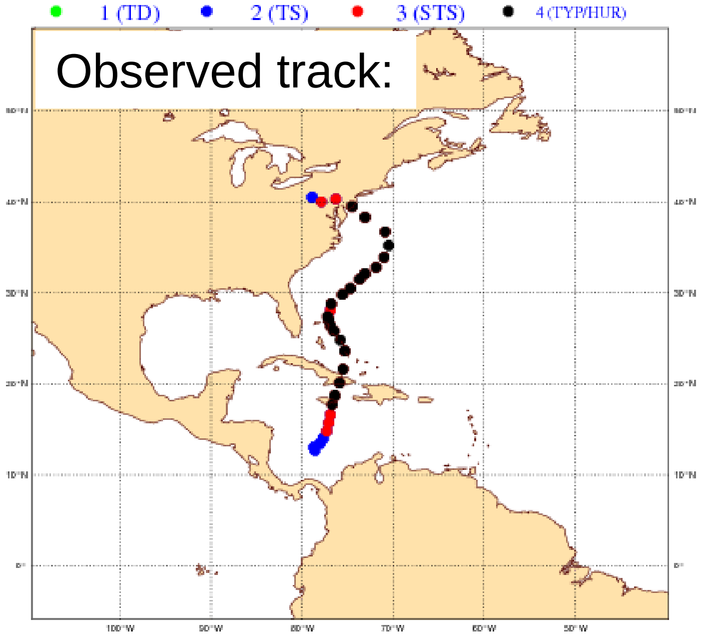
ECMWF

Hurricane Sandy

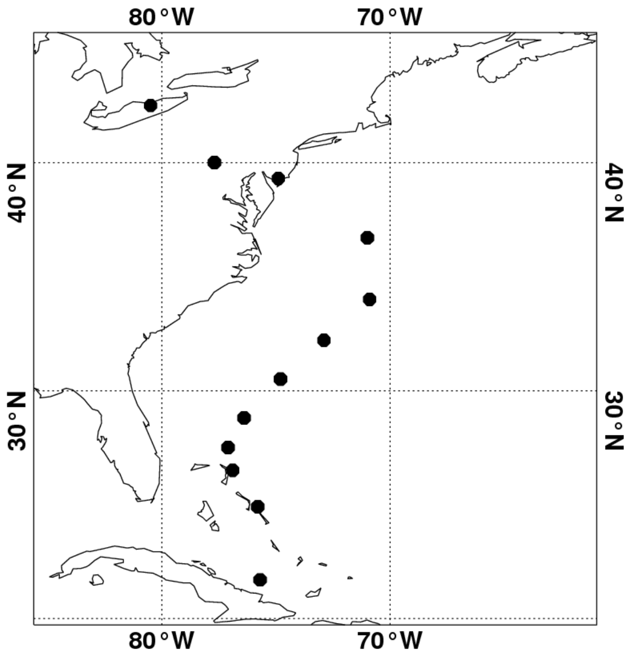
Influence of satellite data and EDA

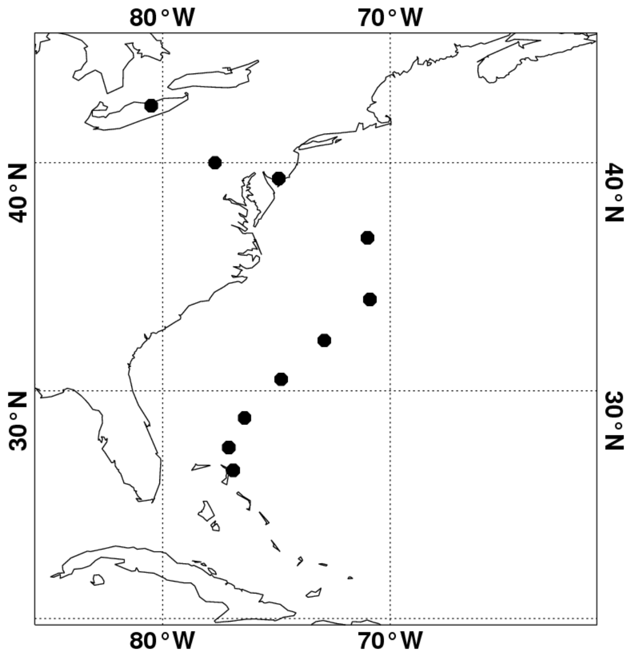
(McNally et al 2014, MWR)

Operational forecast



Track forecast from 25 Oct 2012 00UTC





Track forecast from 26 Oct 2012 00UTC

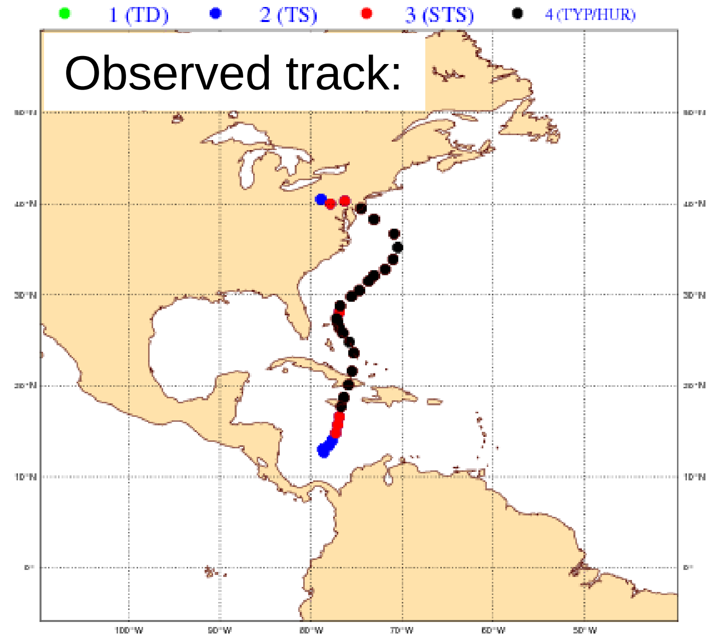
Hurricane Sandy

Influence of satellite data and EDA

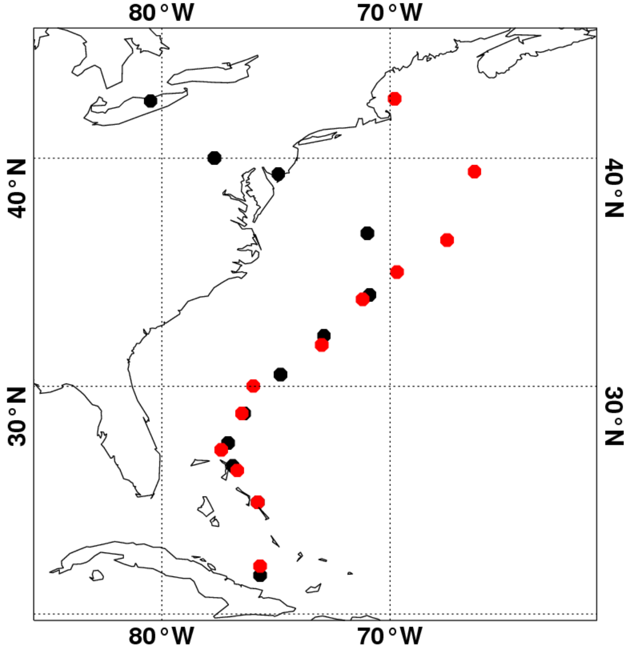
(McNally et al 2014, MWR)

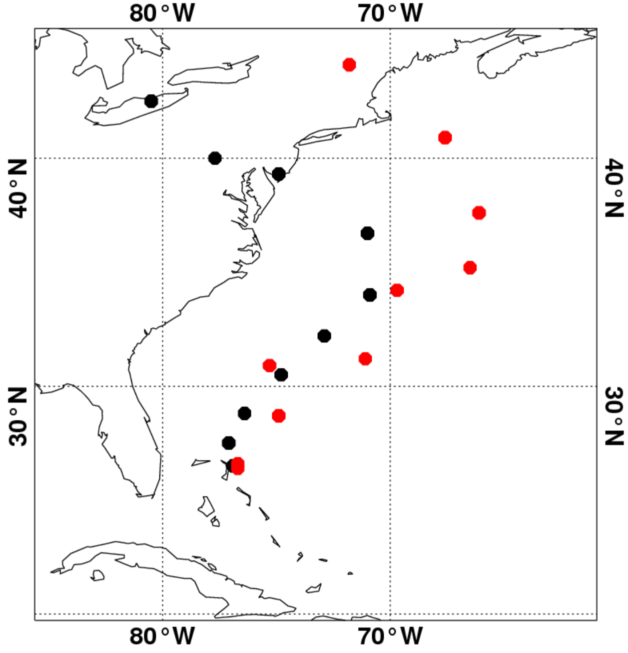
Operational forecast

Forecast without polar orbiters and background errors from operational EDA



Track forecast from 25 Oct 2012 00UTC





Track forecast from 26 Oct 2012 00UTC

Hurricane Sandy

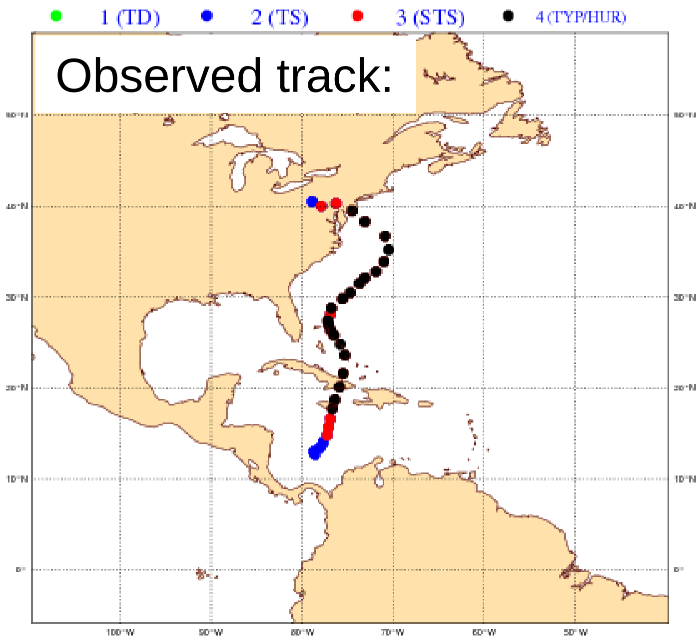
Influence of satellite data and EDA

(McNally et al 2014, MWR)

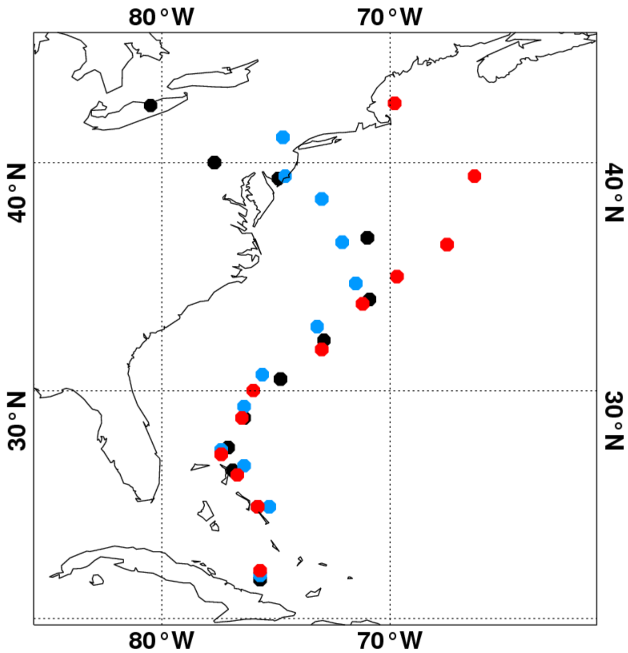
Operational forecast

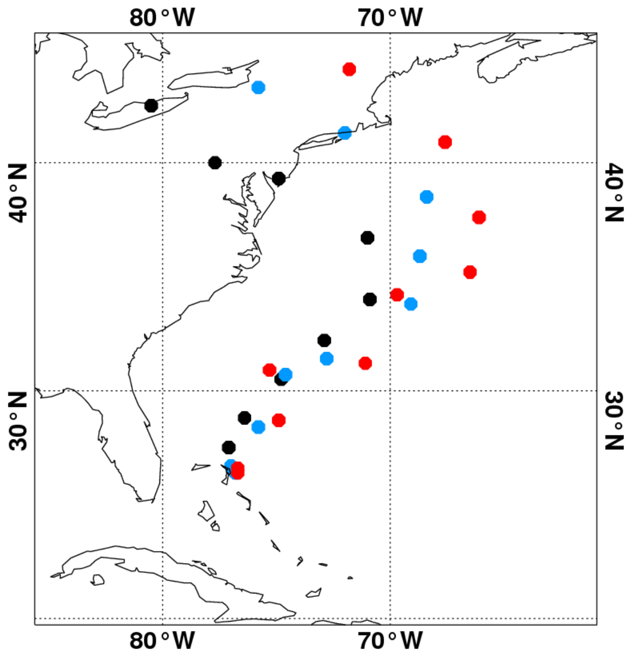
Forecast without polar orbiters and background errors from operational EDA

Forecast without polar orbiter data in EDA and 4DVAR



Track forecast from 25 Oct 2012 00UTC





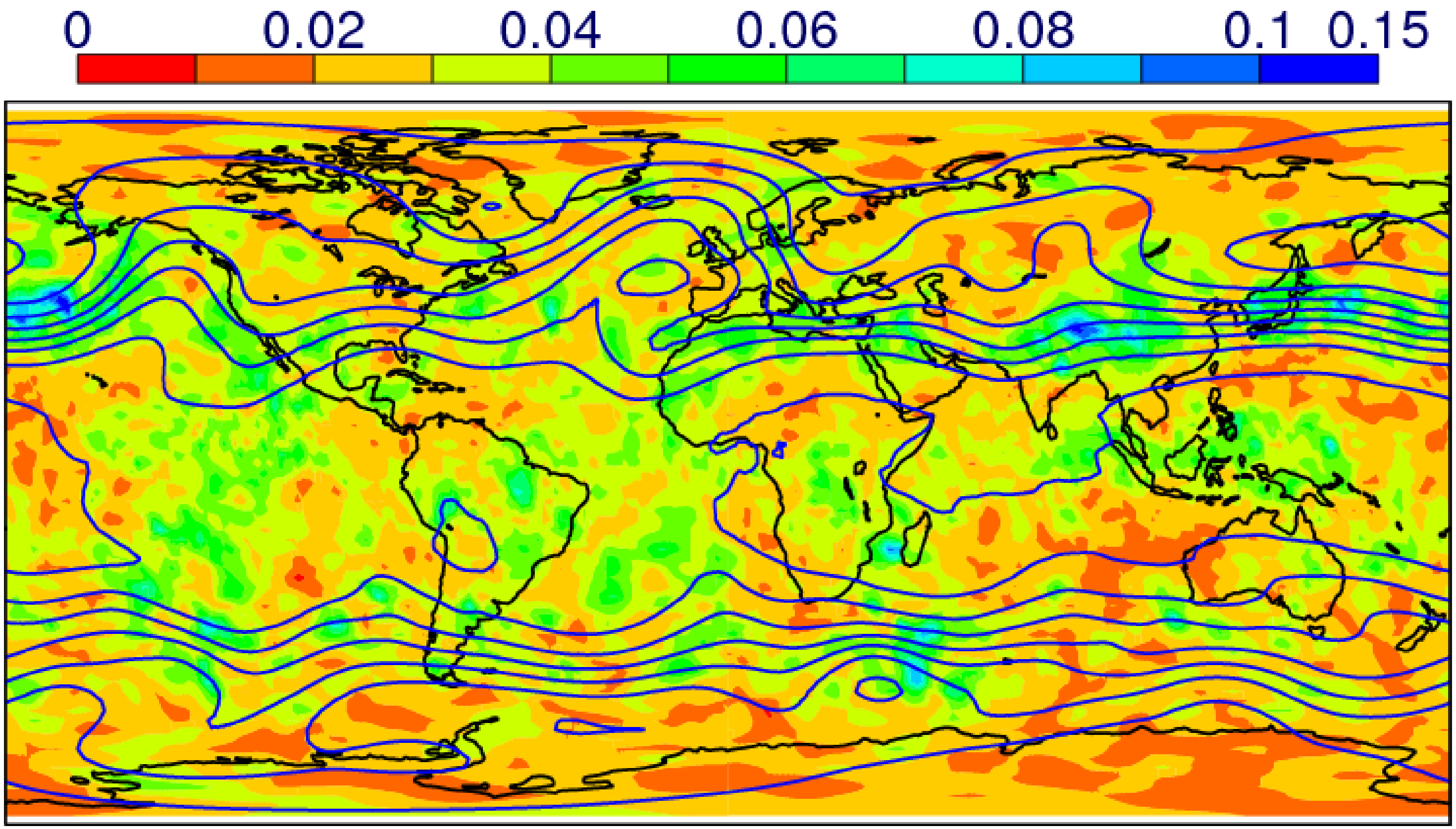
Track forecast from 26 Oct 2012 00UTC

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. **Background errors**
   - Introduction
   - Hybrid EDA 4DVAR
   - **Radiance diagnostics**
4. Balance of background and observation errors
5. Summary

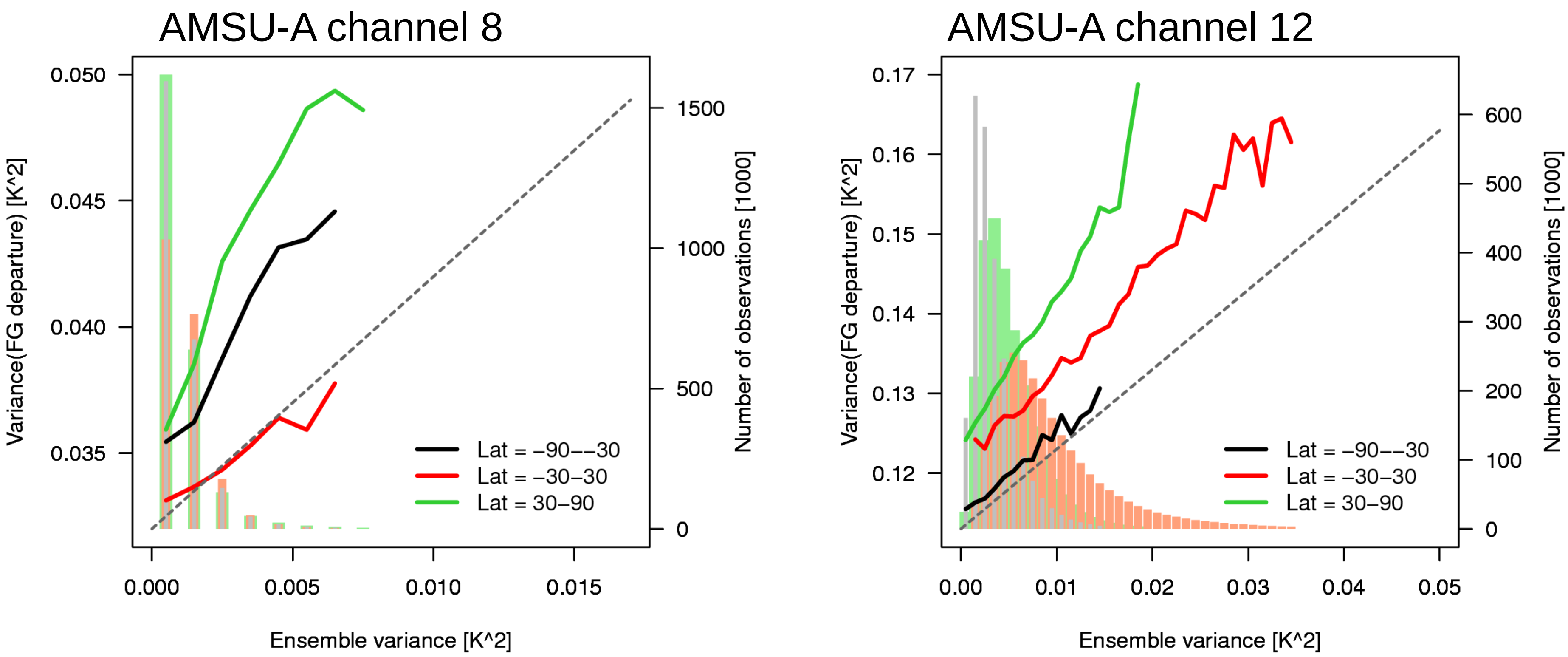
EDA spread in radiance space:
AMSU-A channel 8

15 February 2012, 9 Z



Skill of the EDA vs observation departures

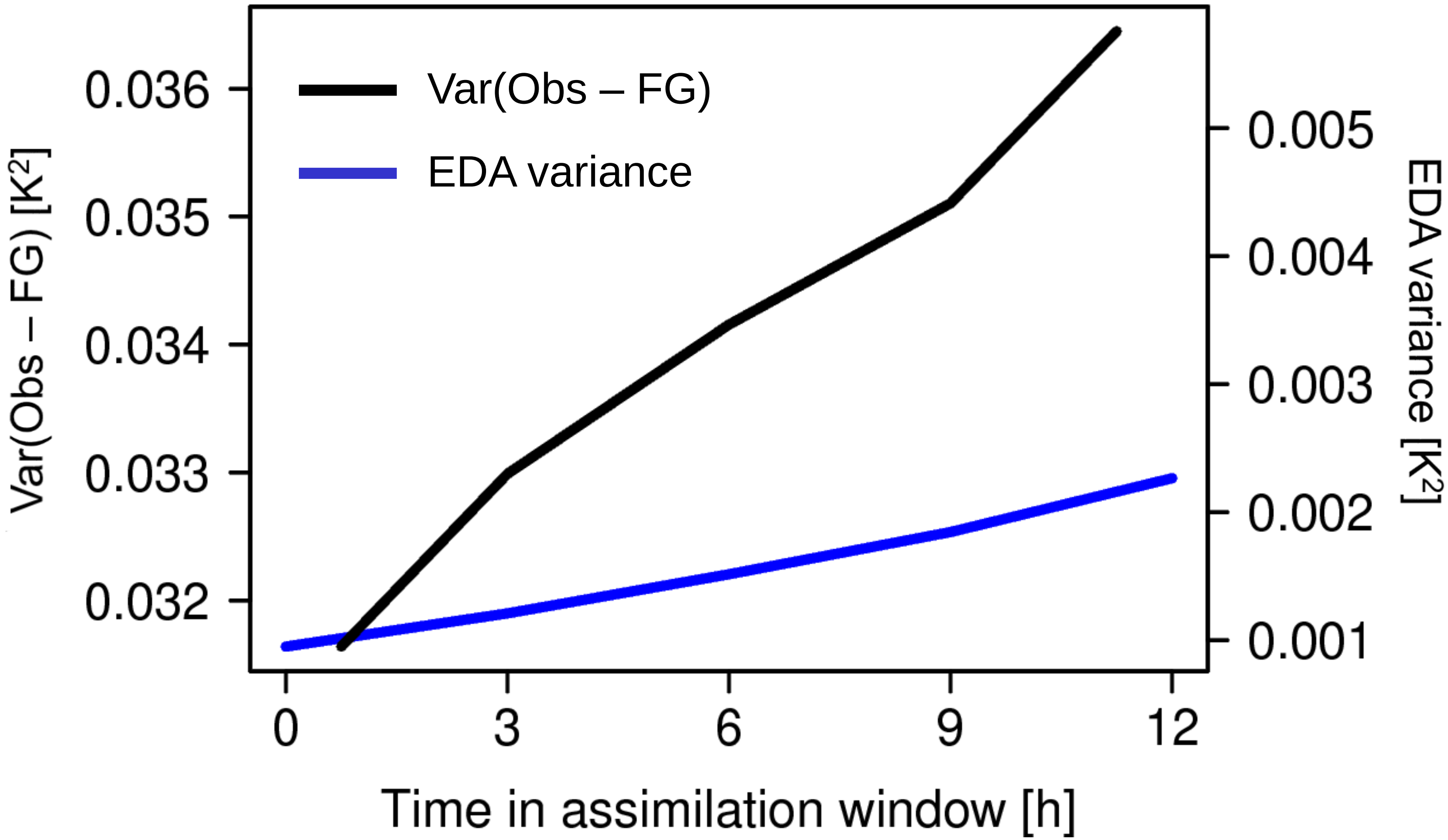
February 2012



Calibration required for EDA spread.

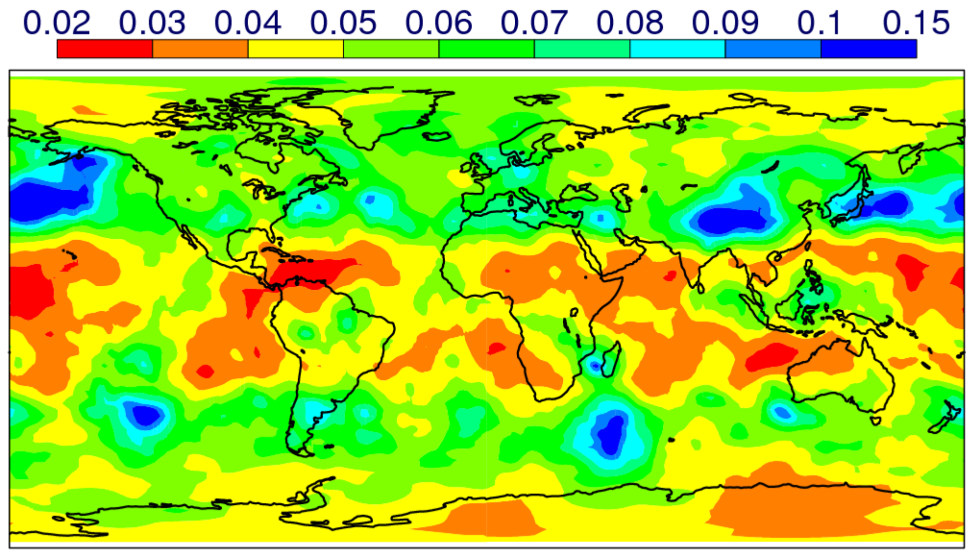
Evolution in assimilation window

Example: AMSU-A, channel 8 (100-300 hPa), N. Hem.

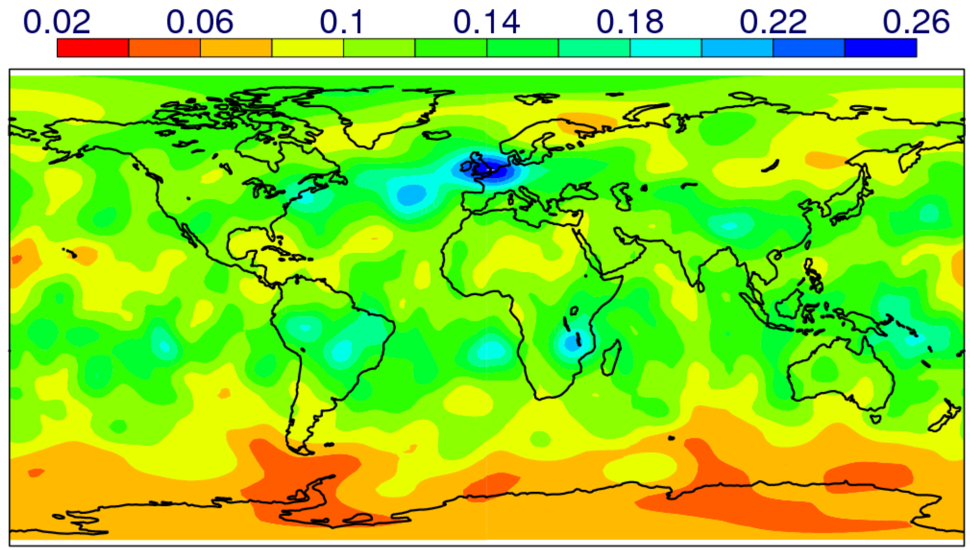


Background error estimates in radiance space [K]

AMSU-A
channel 8
(NeΔT ≈ 0.2 K)



AMSU-A
channel 12
(NeΔT ≈ 0.3 K)



15 February 2012, 9 Z

Outline

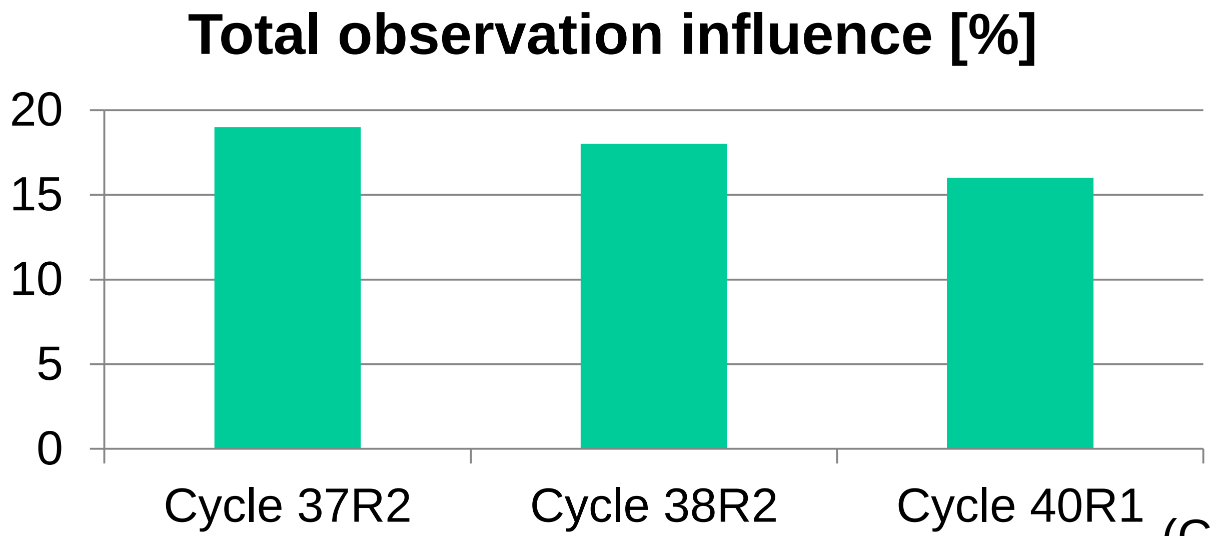
1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. **Balance of background and observation errors**
5. Summary

Observation/background influence

- **A measure of the observation influence on the analysis is:**

$$\mathbf{S} = \frac{\partial(\mathbf{H}[\mathbf{x}_a])}{\partial \mathbf{y}} \approx (\mathbf{HK})^T$$

With the Kalman gain $\mathbf{K} = \mathbf{BH}^T(\mathbf{HBH}^T + \mathbf{R})^{-1}$



(Carla Cardinali)

Outline

1. Introduction
2. Observation errors
   - Overview
   - Estimation and specification
   - Adjoint methods
3. Background errors
   - Introduction
   - Hybrid EDA 4DVAR
   - Radiance diagnostics
4. Balance of background and observation errors
5. **Summary**

Summary/conclusions

- **Observation errors for satellite data:**
  - Current specifications are mostly fairly basic; errors are mostly inflated.
  - A range of diagnostic tools are available, and these are being applied to:
    - Estimate and specify the size of observation errors, including situation-dependence
    - Test for error correlations
    - Specify inter-channel observation error correlations
  - Benefits are being obtained from accounting for inter-channel error correlations and situation-dependent observation errors for certain data.
- **Background errors:**
  - Ensemble methods are increasingly used to provide better, flow-dependent background error statistics.
  - This is resulting in significant gains in forecast accuracy.

Some future perspectives

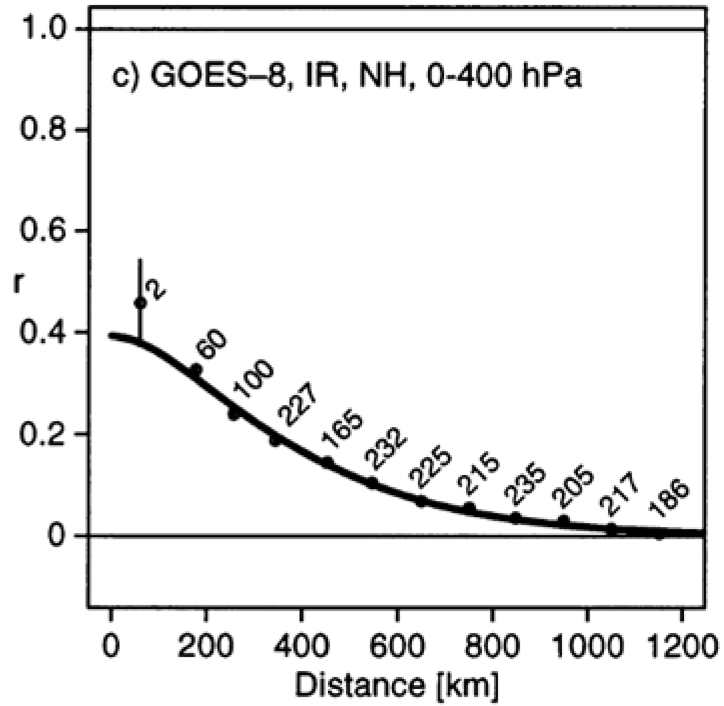
- There is a lot of potential for improved representation of observation errors in data assimilation systems.
- Better understanding of the contributions to observation error:
  - Different treatment for different aspects?
  - Interaction between correlated errors and bias correction
  - Possibilities to reduce or simplify errors?
  - Limitations of diagnostics
- Improved representation of background errors as described by the EDA:
  - Enhanced control variables (e.g., clouds, trace gases)
  - Refinements to EDA, e.g. in terms of applied perturbations (model and observations)

Backup

Observation error diagnostics: Hollingsworth/Loennberg method (II)

- Drawback: Not reliable when observation errors are spatially correlated.

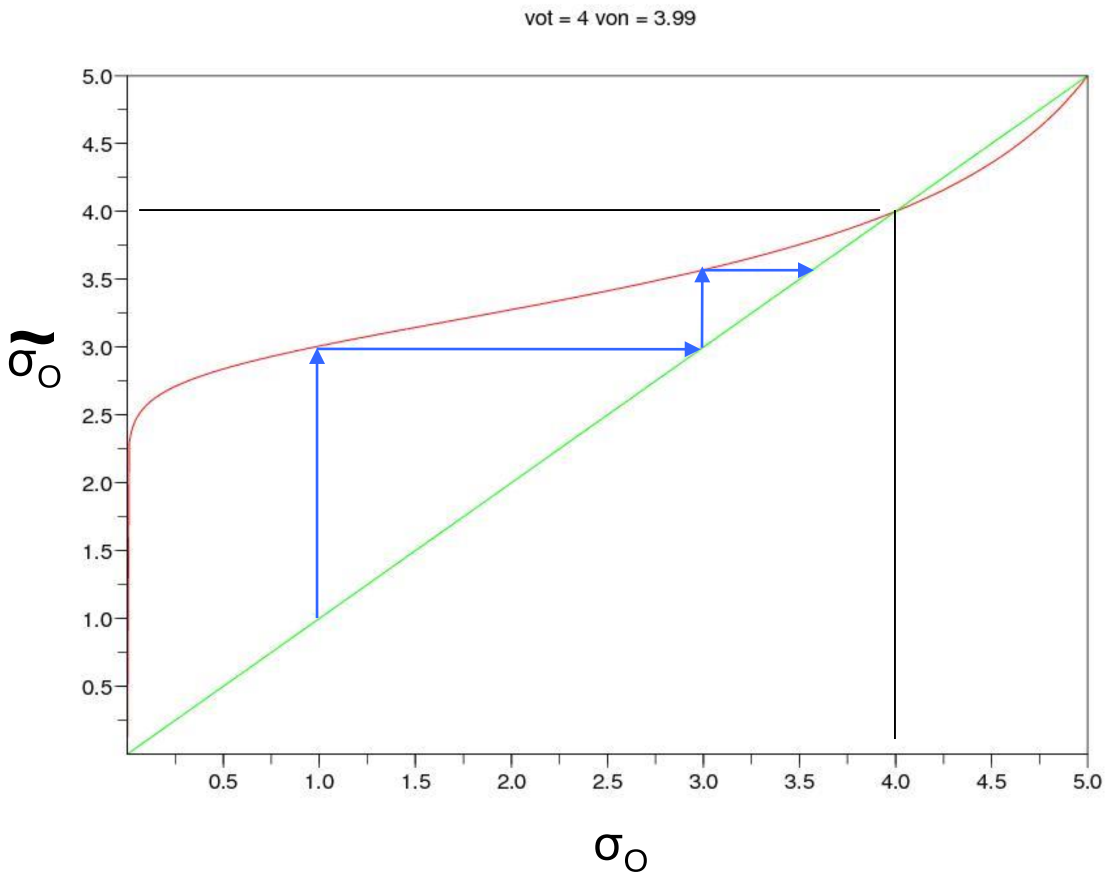
- Similar methods have been used with differences between two sets of collocated observations:
  - Example: AMVs collocated with radiosondes (Bormann et al 2003).
    - Radiosonde error assumed spatially uncorrelated.



Observation error diagnostics: Desroziers diagnostic (II)

- Simulations in toy-assimilation systems:
  - Good convergence if the correlation length-scales for observation errors and background errors are sufficiently different.
  - Mis-leading results if correlation length-scales for background and observation errors are too similar.
- For real assimilation systems, the applicability of the diagnostic for estimating observation errors is still subject of research.

Iterative application of Desroziers diagnostic

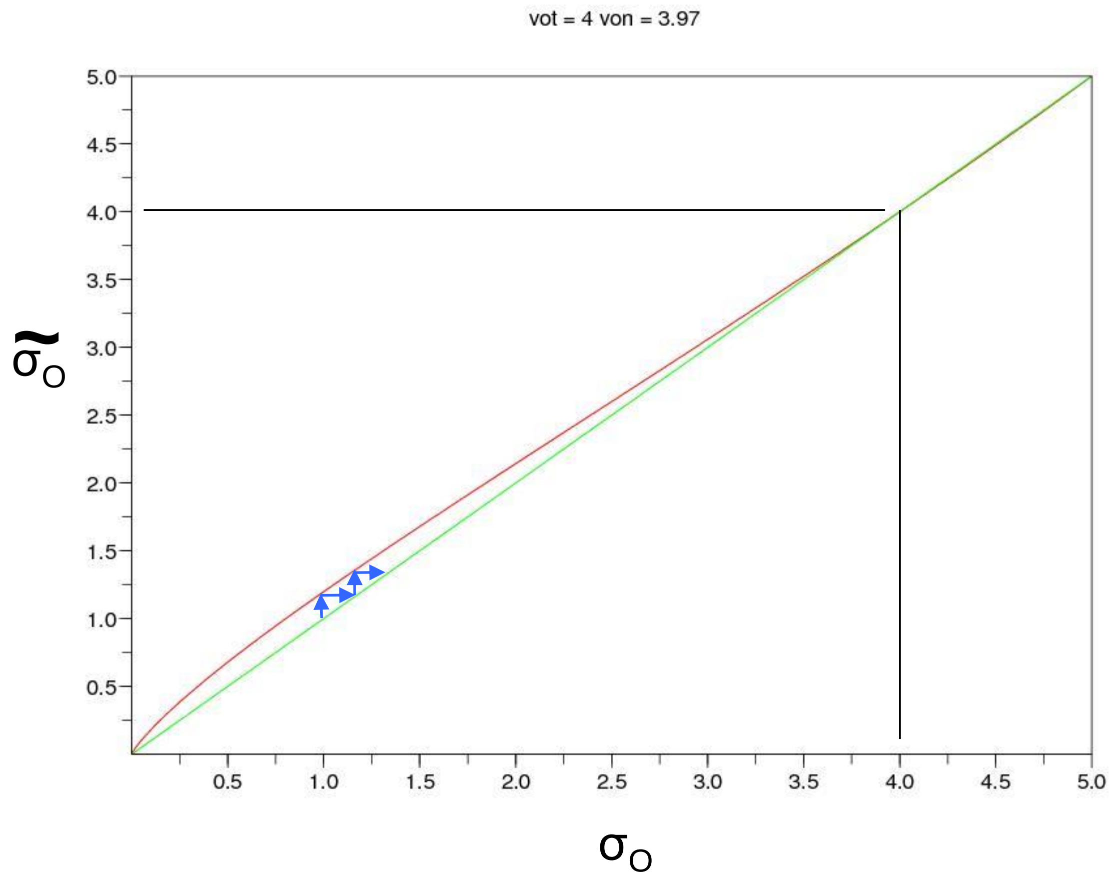


(Desroziers et al 2010)

Idealized case: analysis on an equatorial circle (40 000km) with 401 observations/grid-points.

$\sigma_{O,\ true} = 4$; $L^b = 300$ km / $L^0 = 0$ km.

Iterative application of Desroziers diagnostic



(Desroziers et al 2010)

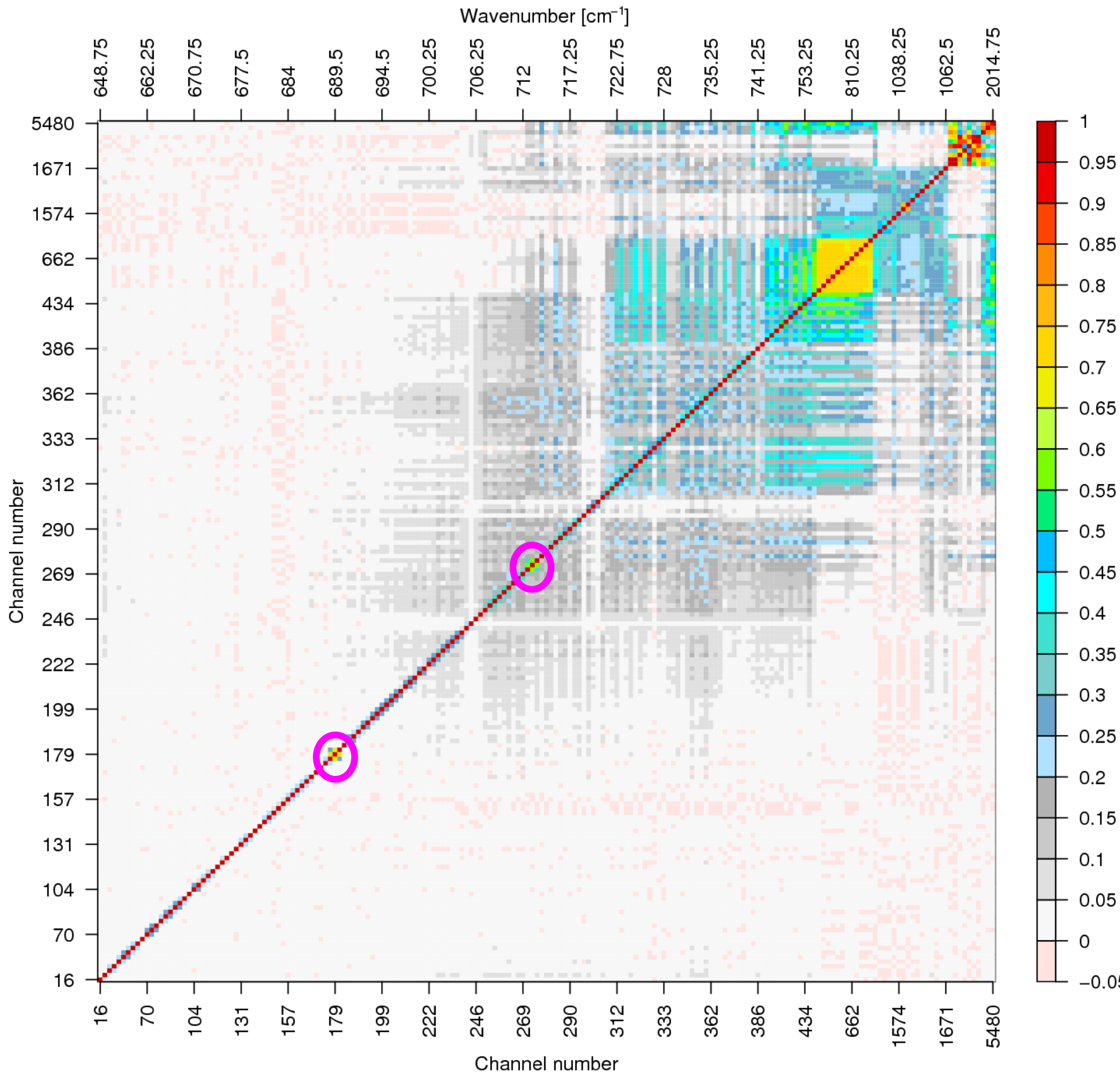
Idealized case: analysis on an equatorial circle (40 000km) with 401 observations/grid-points.

$\sigma_{O,\ true}$= 4; L^b = 300 km / L^0= 200 km.

Example: IASI

Inter-channel error correlations (Hollingsworth/ Lönnberg):

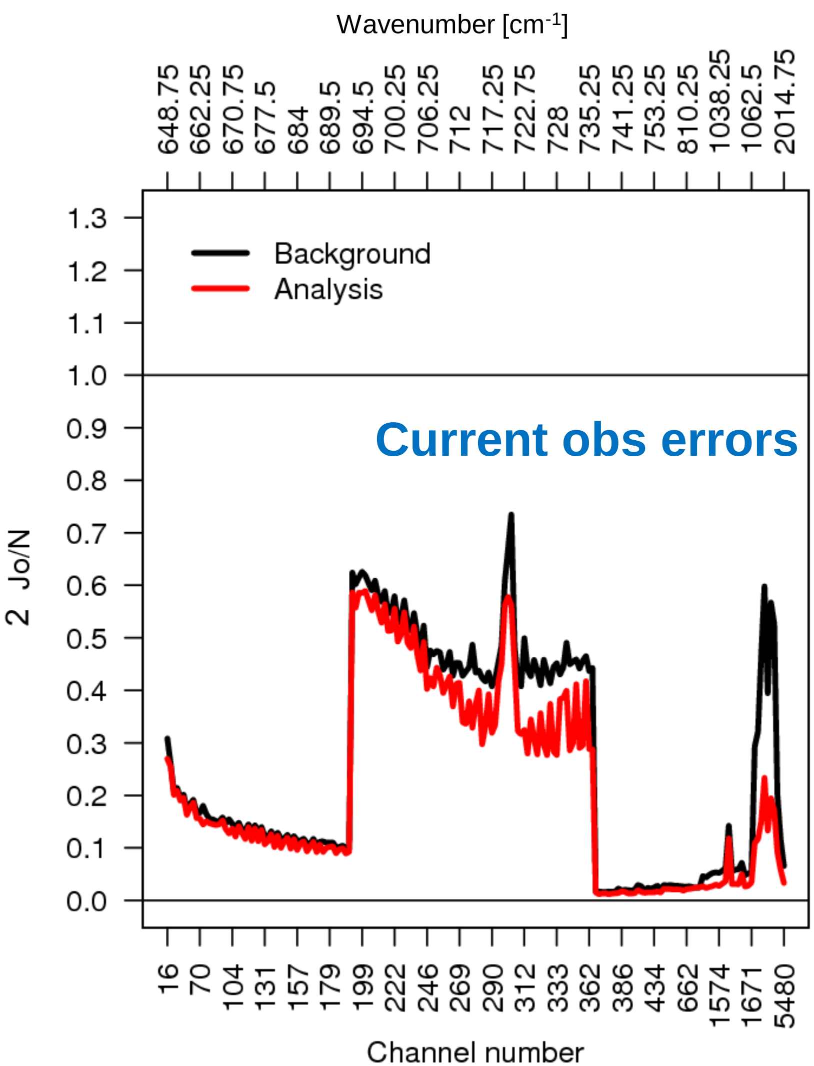
Apodisation

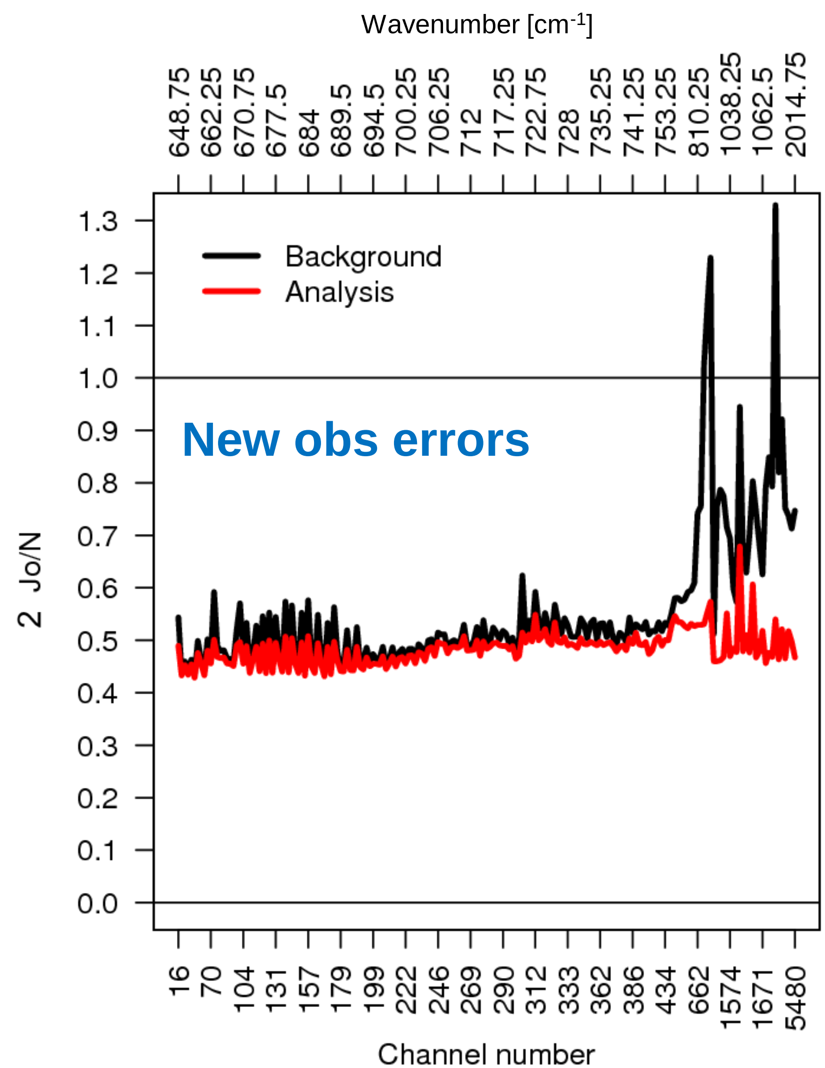


Bormann et al (2010)

J_o-statistics per channel: IASI

Based on effective departure: $\mathbf{d}_{eff} = (\mathbf{y} - \mathbf{H}(\mathbf{x}))^T \ \mathbf{R}^{-½}$

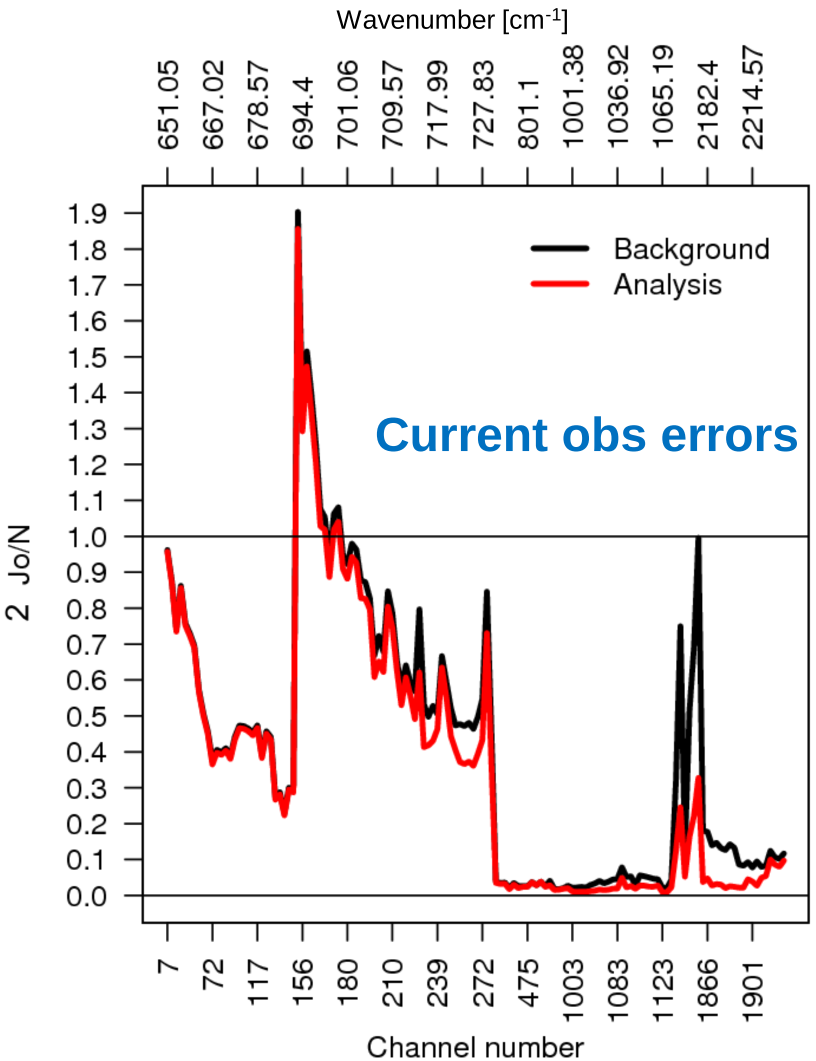


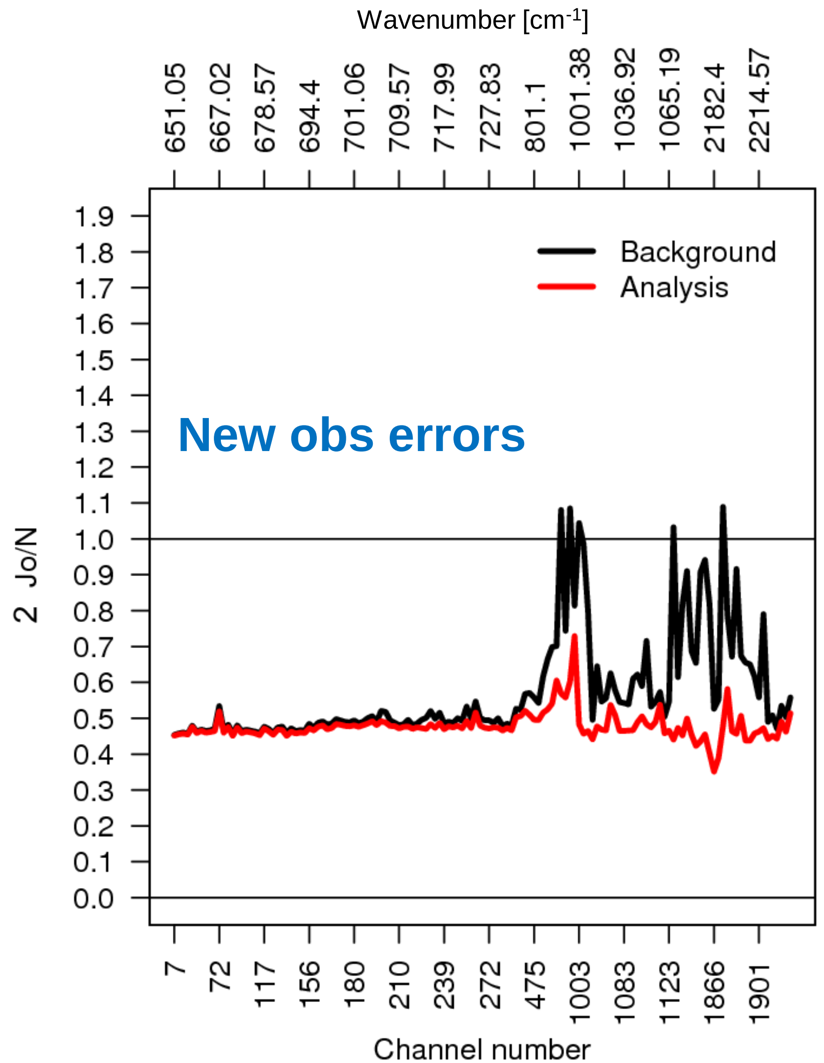


15 July – 4 August 2013

J_o-statistics per channel: AIRS

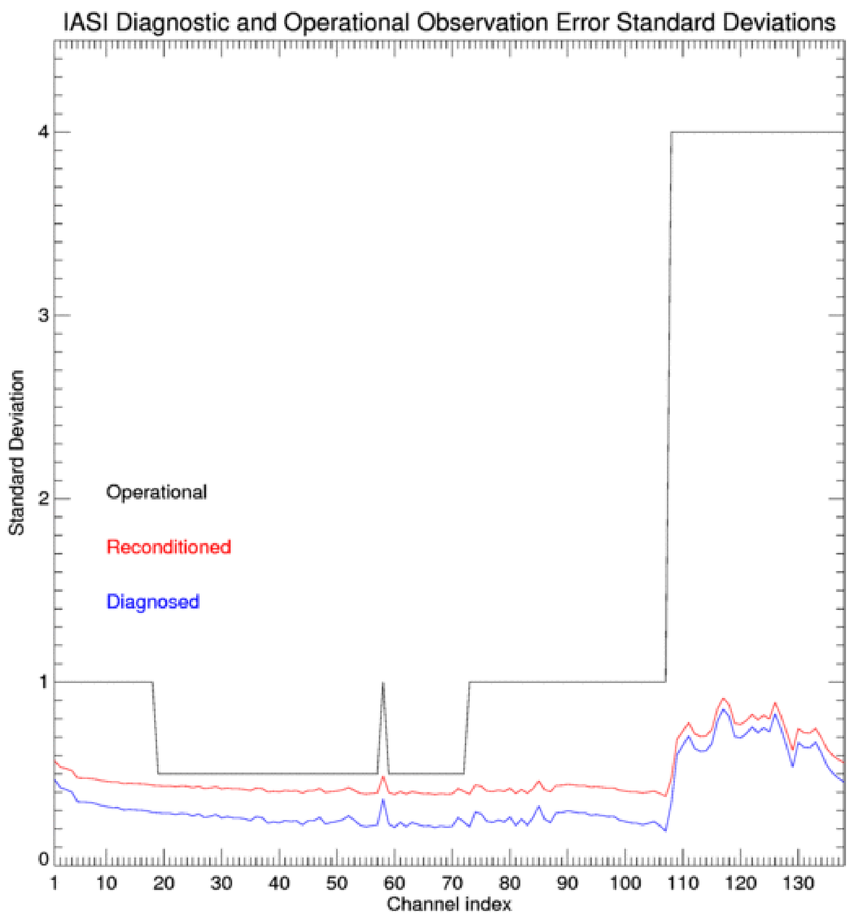
Based on effective departure: $\mathbf{d}_{\text{eff}} = (\mathbf{y} - \mathbf{H}(\mathbf{x}))^T \ \mathbf{R}^{-½}$

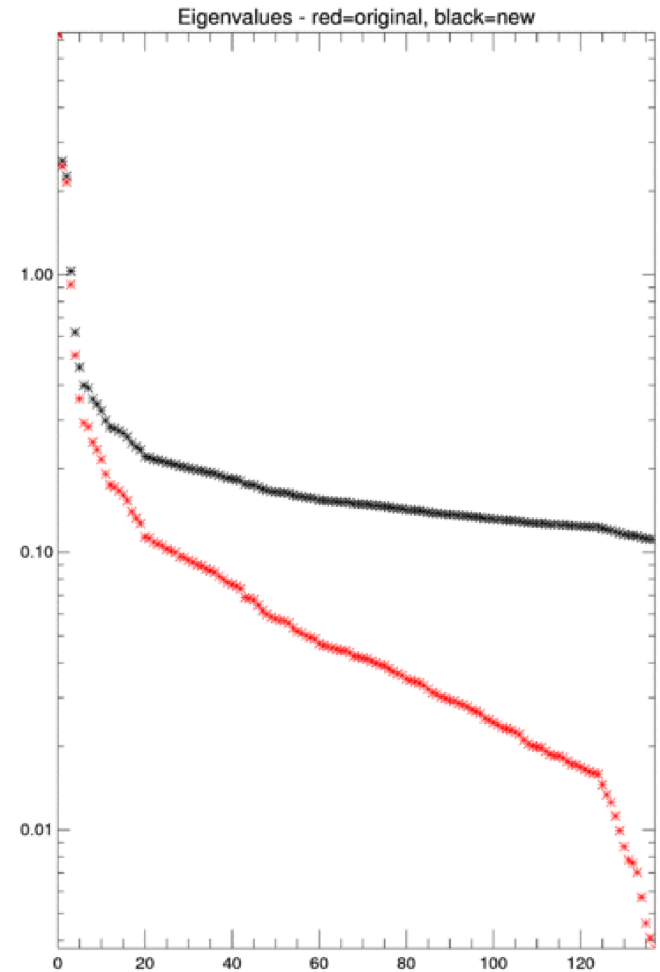




15 July – 4 August 2013

Reconditioning (shrinkage)

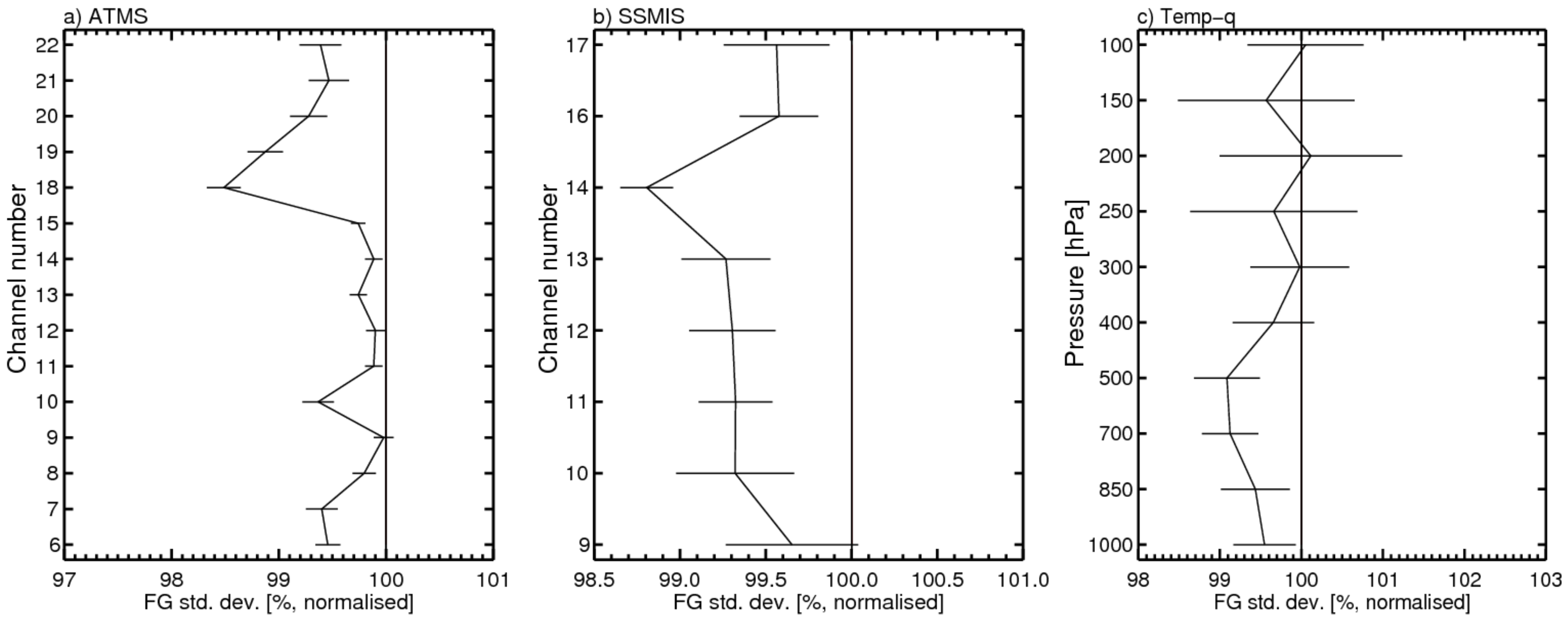




- Using reconditioned matrix results in:
  - Reduced weight given to IASI obs
  - Good convergence

Trial results from ECMWF

Better background fit to other observations over the tropics, especially for humidity-sensitive observations:



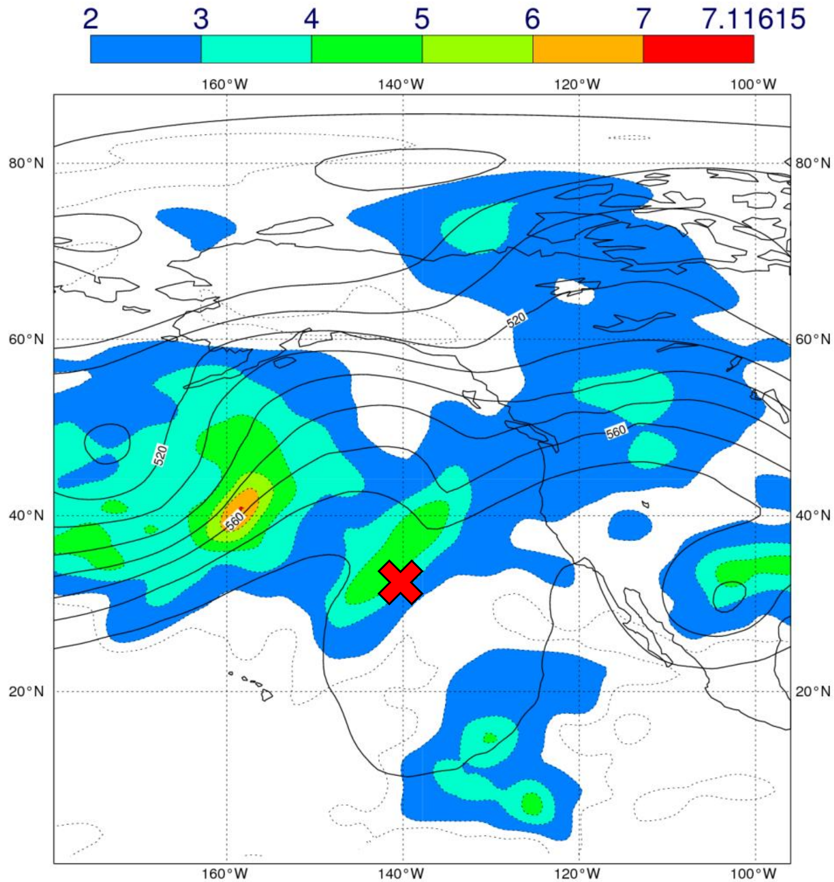
Diagnosing Background Error Statistics

- **Three approaches to estimating J_b statistics:**

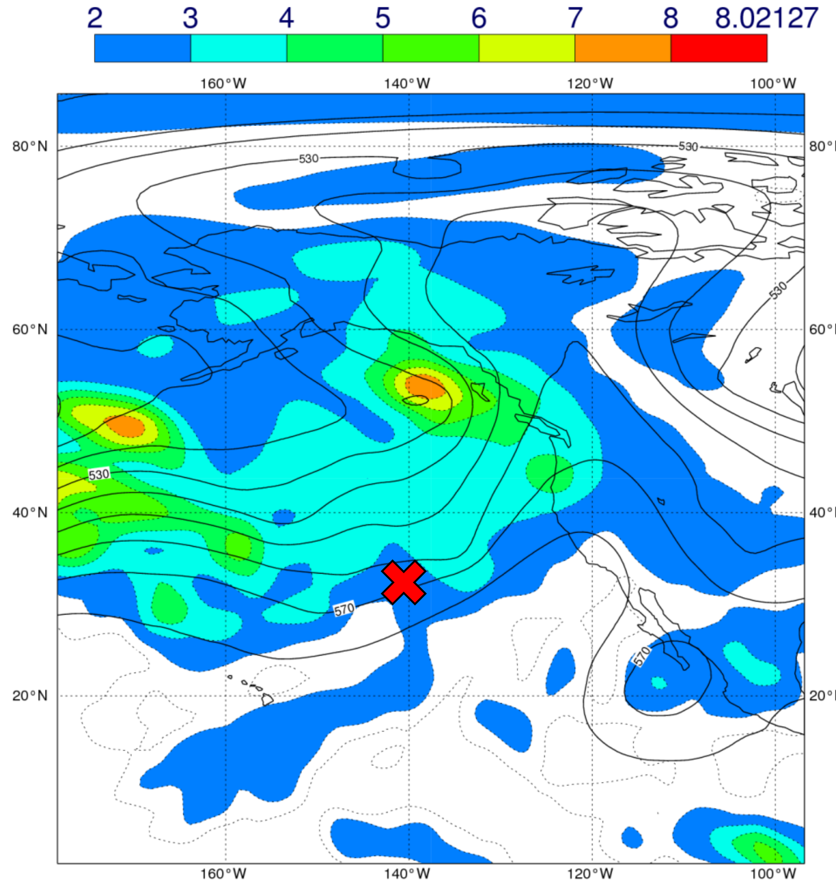
1. **The Hollingsworth and Lönnberg (1986) method**
   - Differences between observations and the background are a combination of background and observation error.
   - Assume that the observation errors are spatially uncorrelated.
2. **The NMC method (Parrish and Derber, 1992)**
   - Assume that the spatial correlations of background error are similar to the correlations of differences between 48h and 24h forecasts verifying at the same time.
3. **The Ensemble method (Fisher, 2003)**
   - Run the analysis system several times for the same period with randomly-perturbed observations and other perturbations.
   - Differences between background fields for different runs provide a surrogate for a sample of background error.

Flow-dependent background errors from the EDA

2012-01-10 00Z

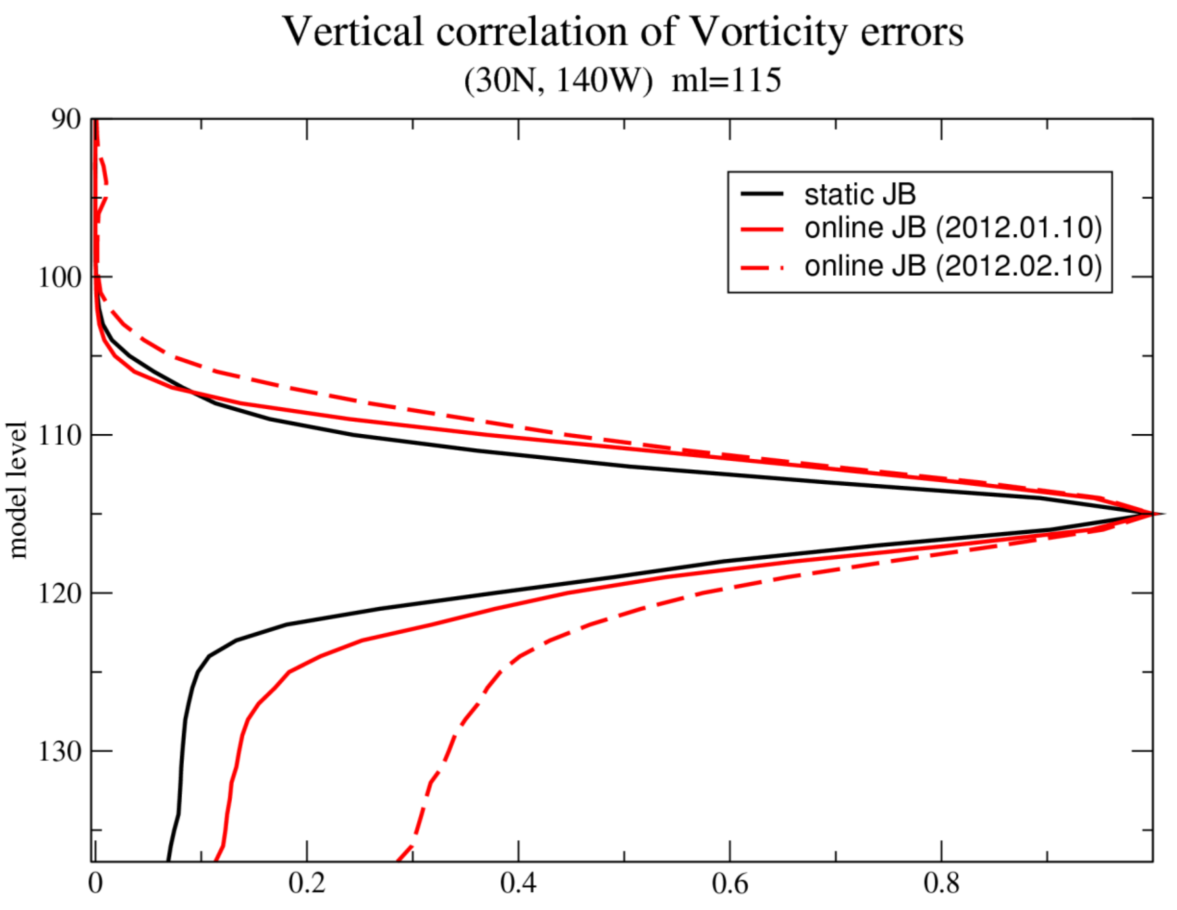


2012-02-10 00Z



(Massimo Bonavita)

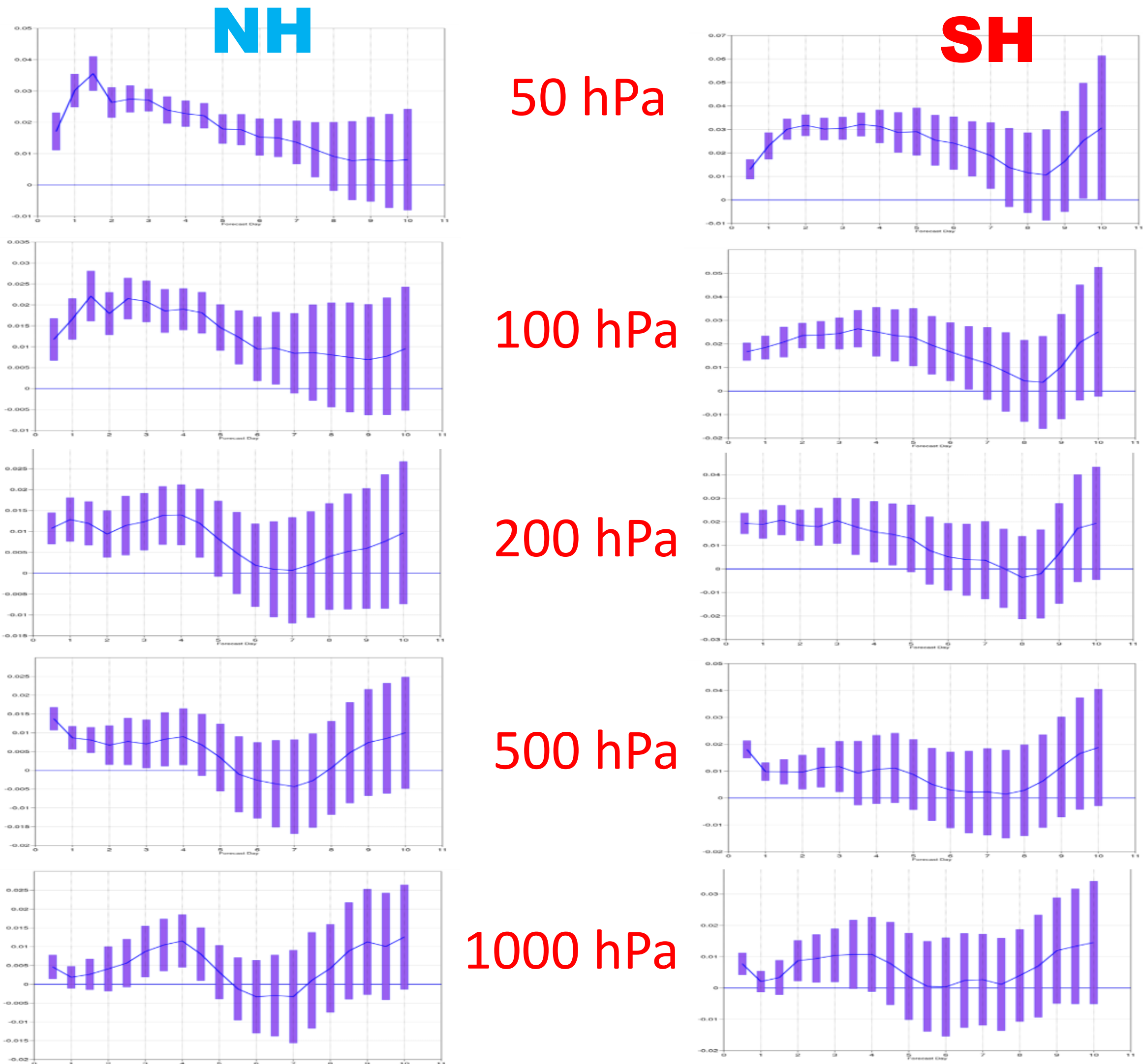
Flow-dependent background errors from the EDA



(Massimo Bonavita)

Impact of online JB

Reduction in Geopotential RMSE - 95% confidence



Period: Feb - June 2012

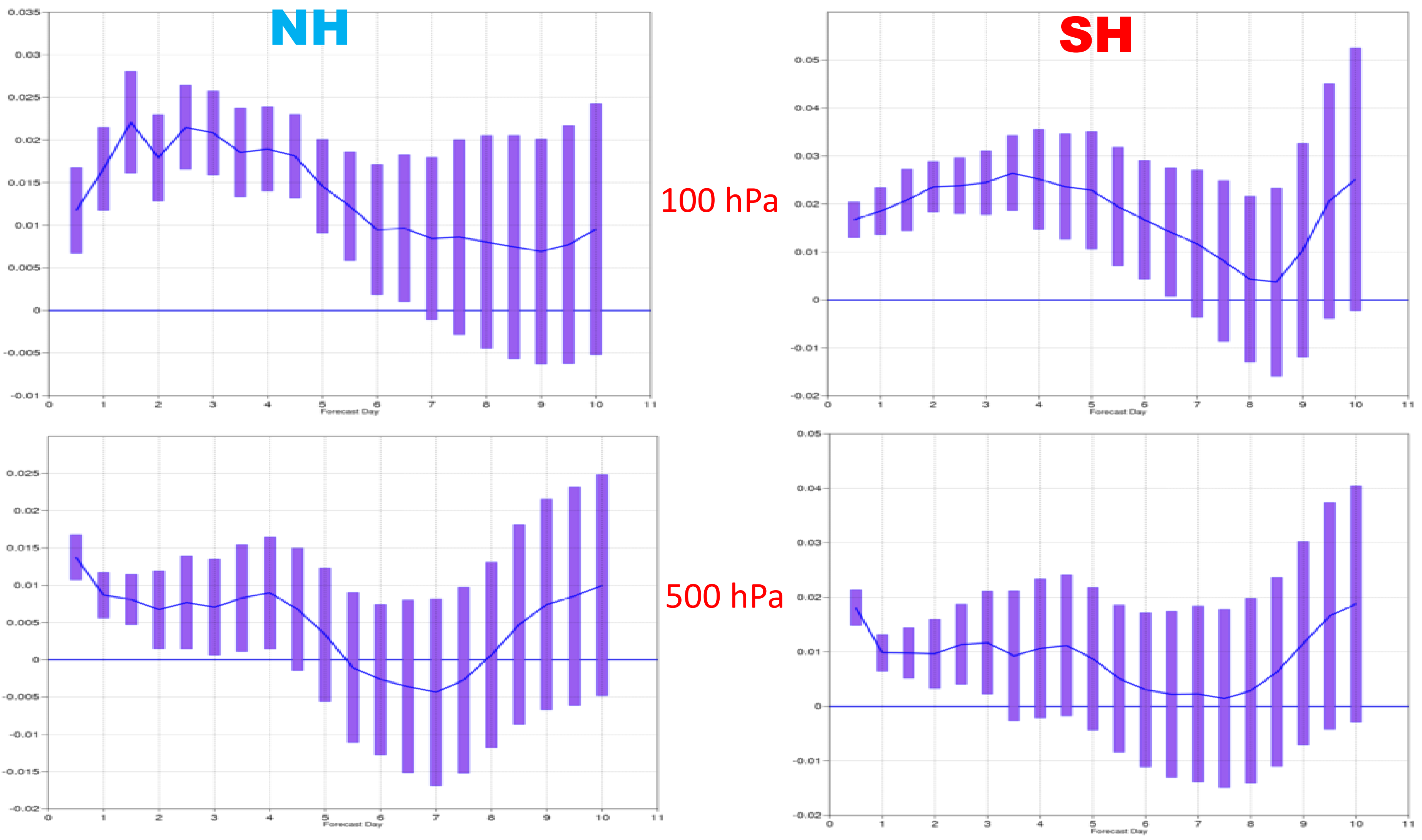
T511L91, 3 Outer Loops (T159/T255/T255)

Verified against operational analysis

(Massimo Bonavita)

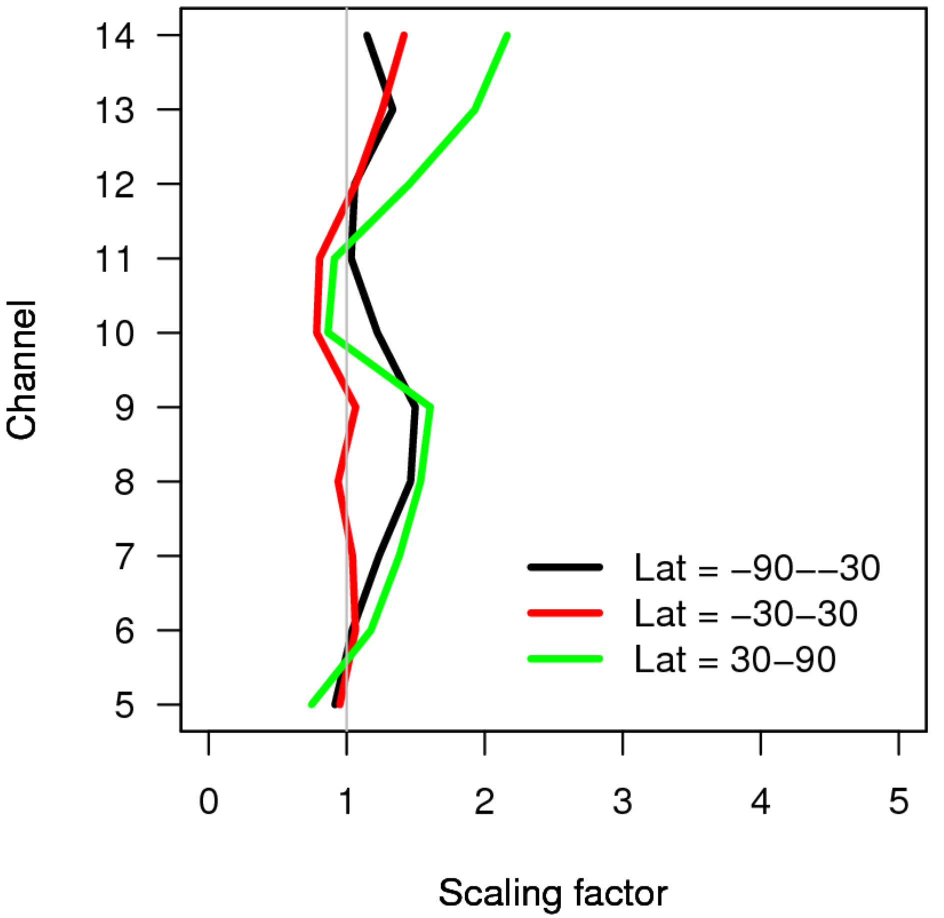
Impact of flow-dependent correlations

Reduction in Geopotential RMSE, including 95% confidence, Feb-June 2012



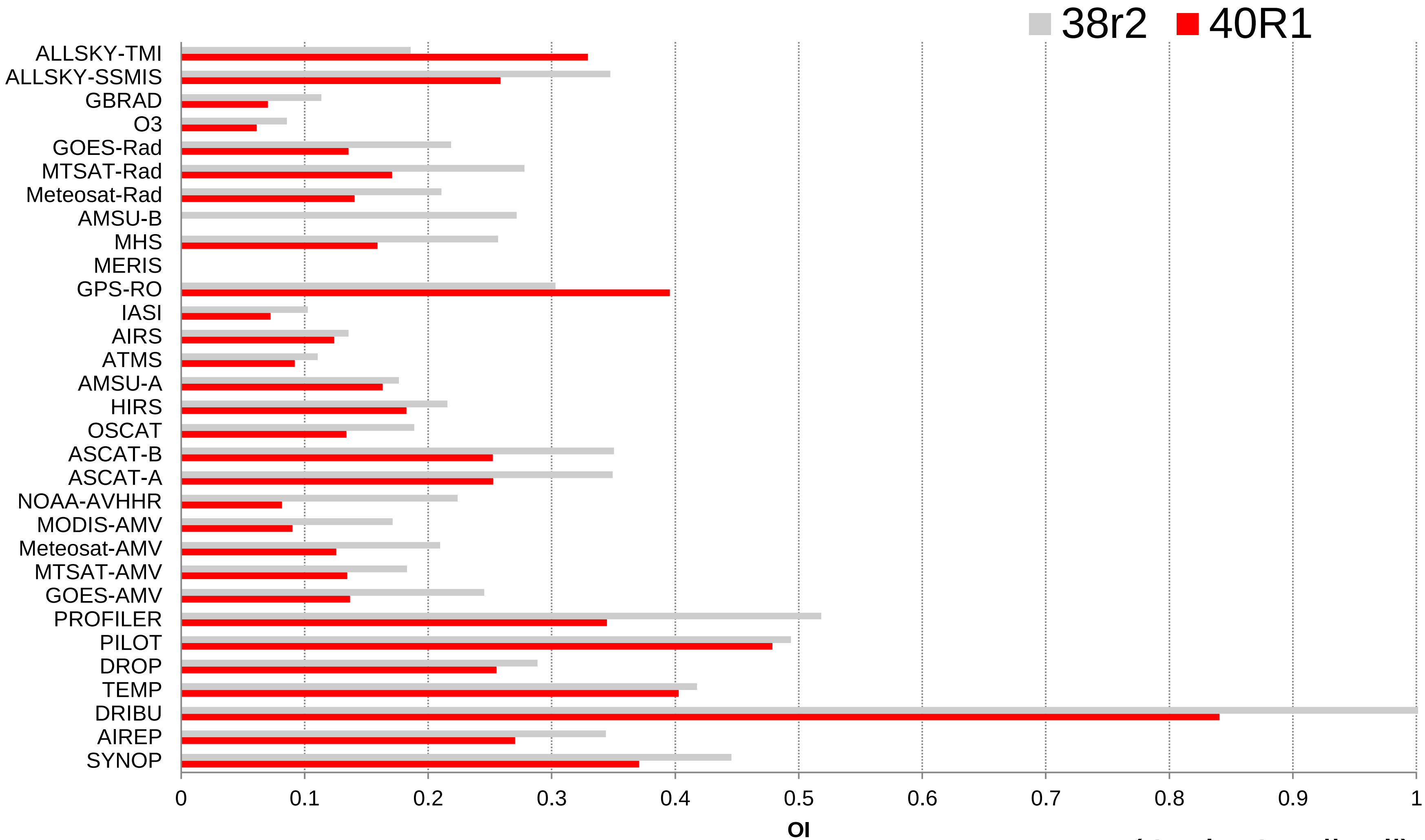
ECMWF

Calibration factors for AMSU-A observations



February 2012

Influence per observation by observation type



(Carla Cardinali)