Importance of data: A Meteorological Perspective

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With contributions from

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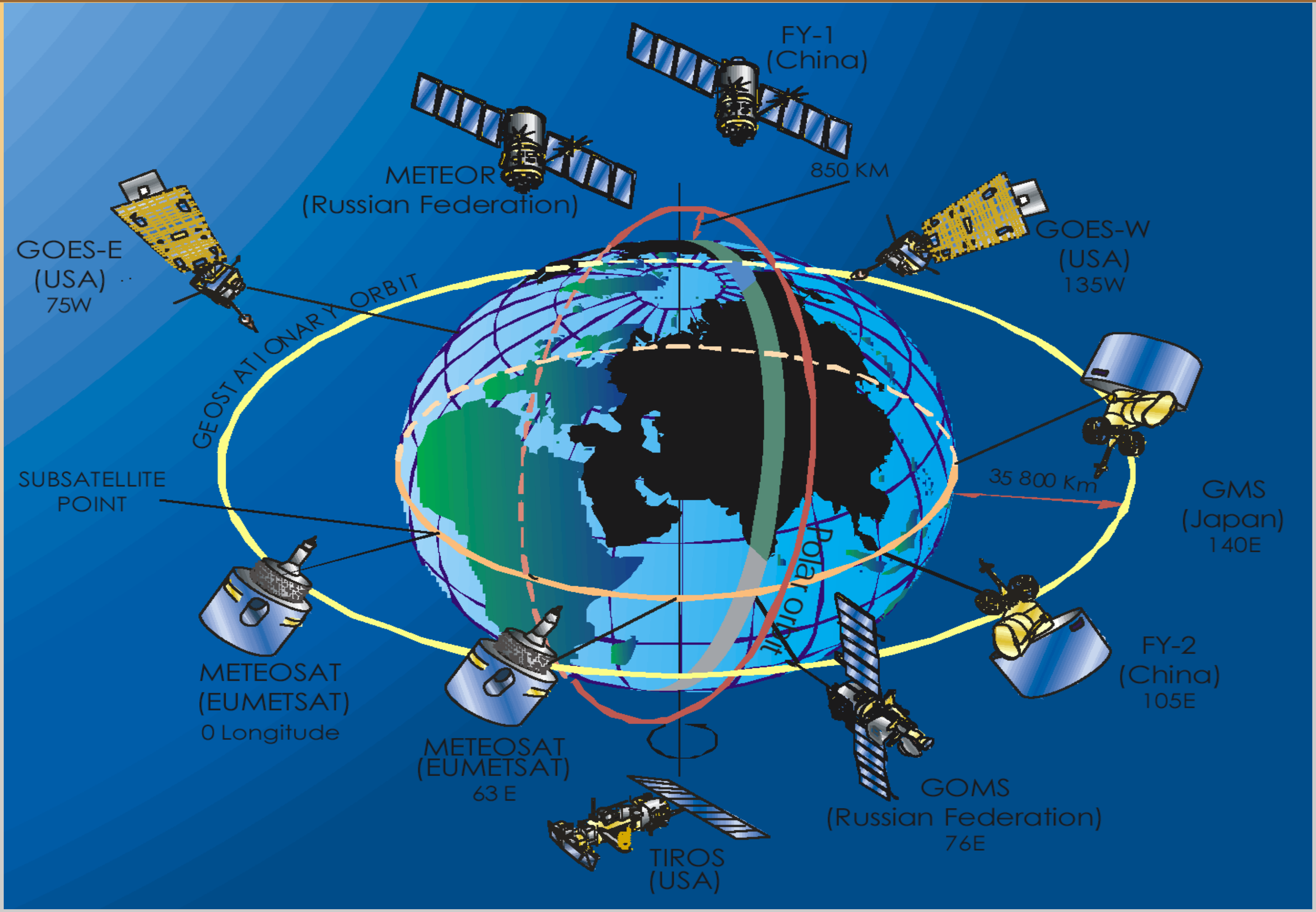
- Adrian Simmons, Jean-Noël Thépaut, Carla Cardinali (ECMWF)

Presentation

- Introduction: impact of observations on forecast performance
- Data selection, information content, and error tuning
- Towards an adaptive system

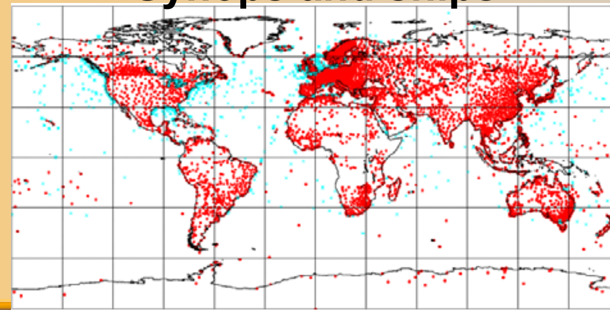
Available satellites



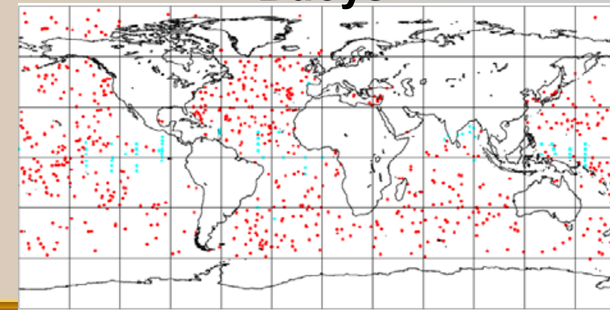
Data coverage

09 – 15 UTC
5 September 2003

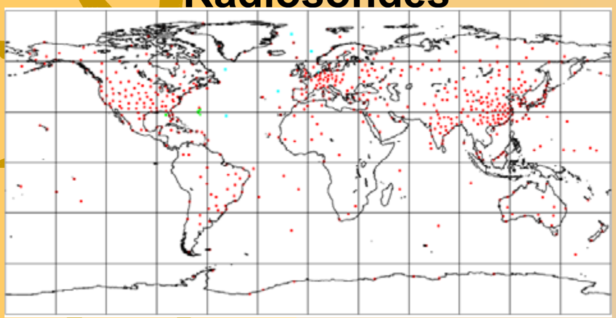
Synops and ships



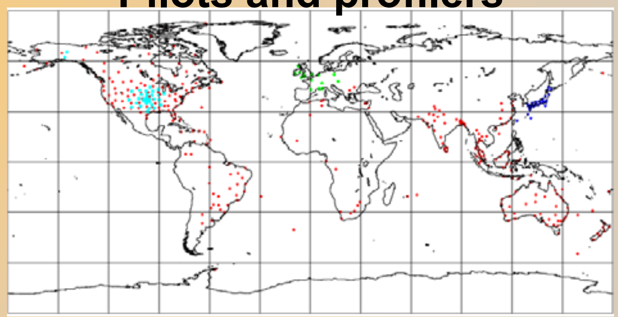
Buoys



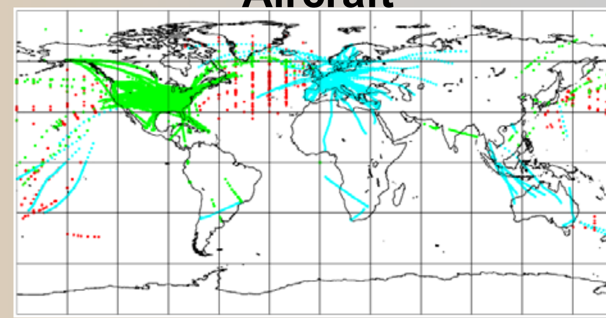
Radiosondes



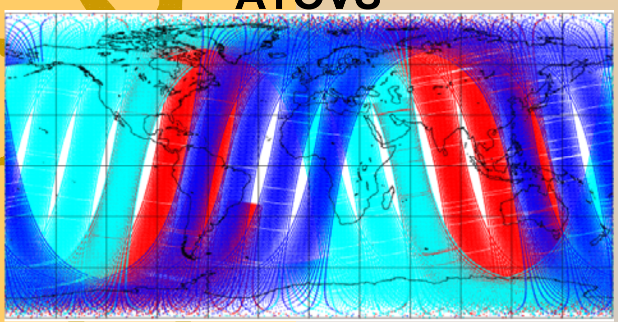
Pilots and profilers



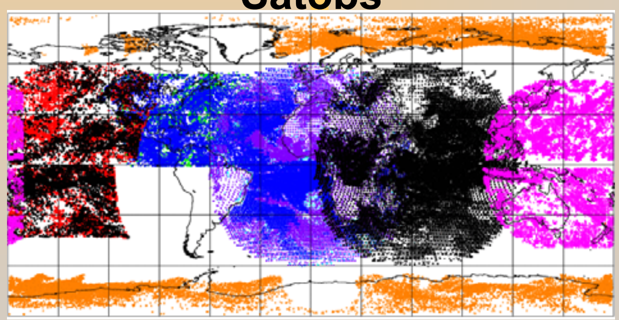
Aircraft



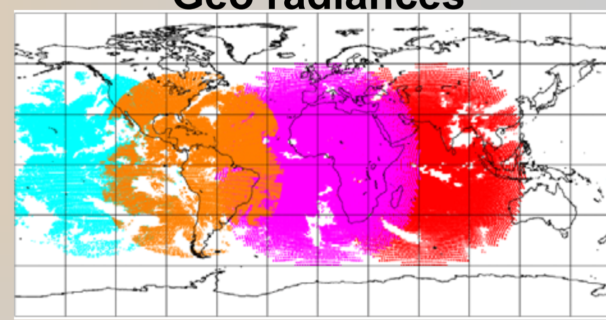
ATOVS



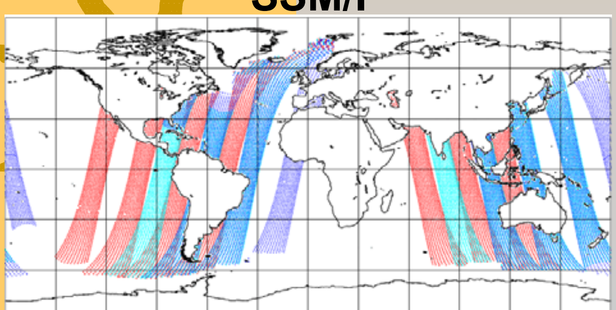
Satobs



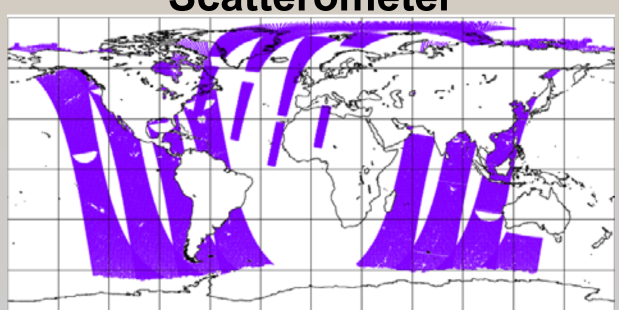
Geo radiances



SSM/I



Scatterometer



Ozone

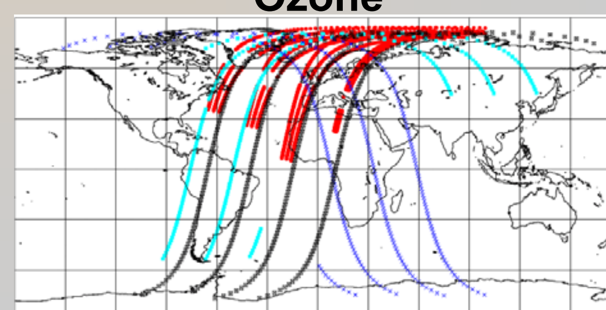


Illustration of the impact of observations:
ERA-40 (www.ecmwf.int/research/era)

- A re-analysis from September 1957 to August 2002

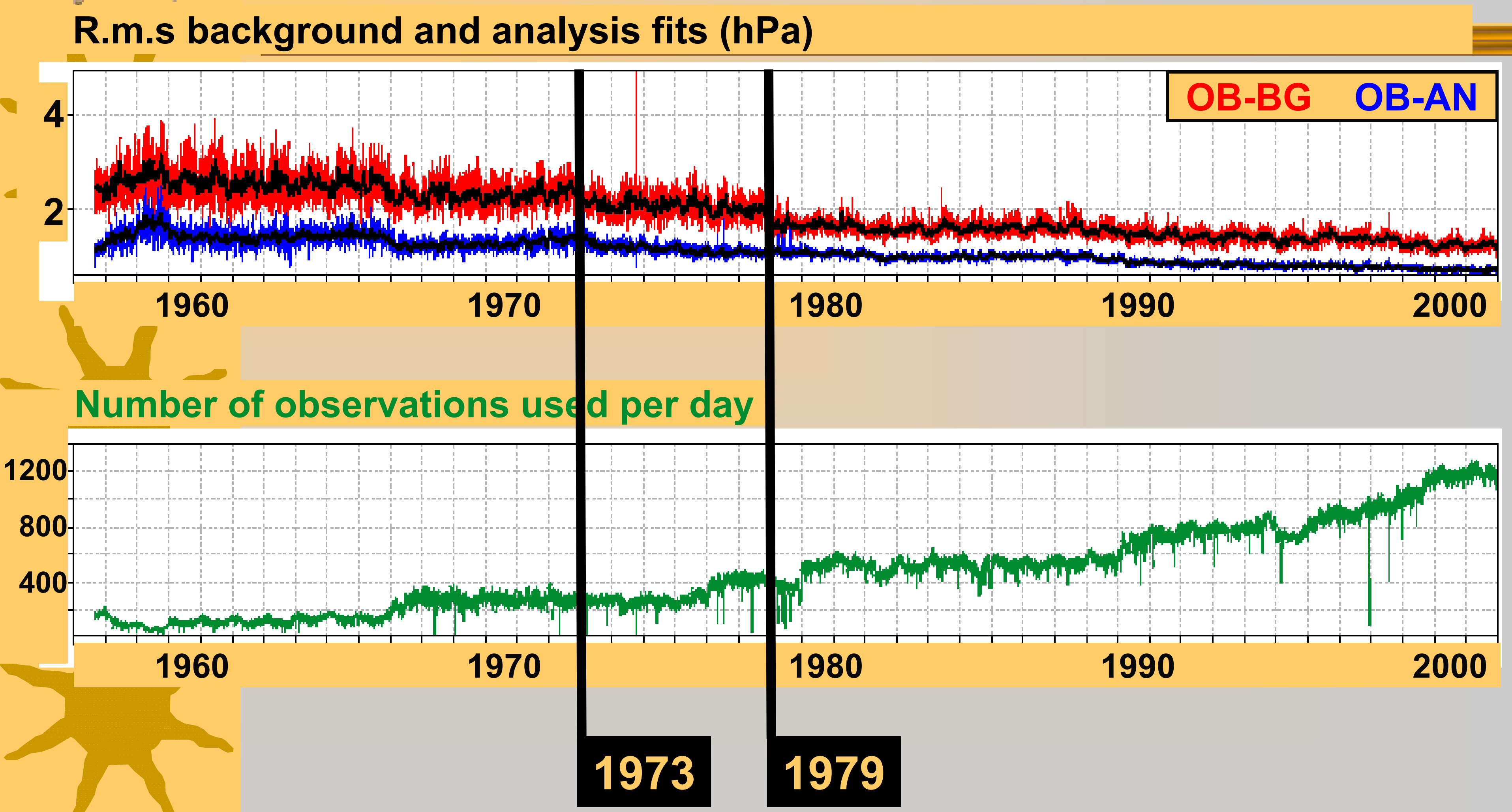
- Based on cycle 23r4 of ECMWF forecasting system - operational from June 2001 to January 2002

- Six-hourly 3D-Var analysis
  - operations uses 12-hourly 4D-Var

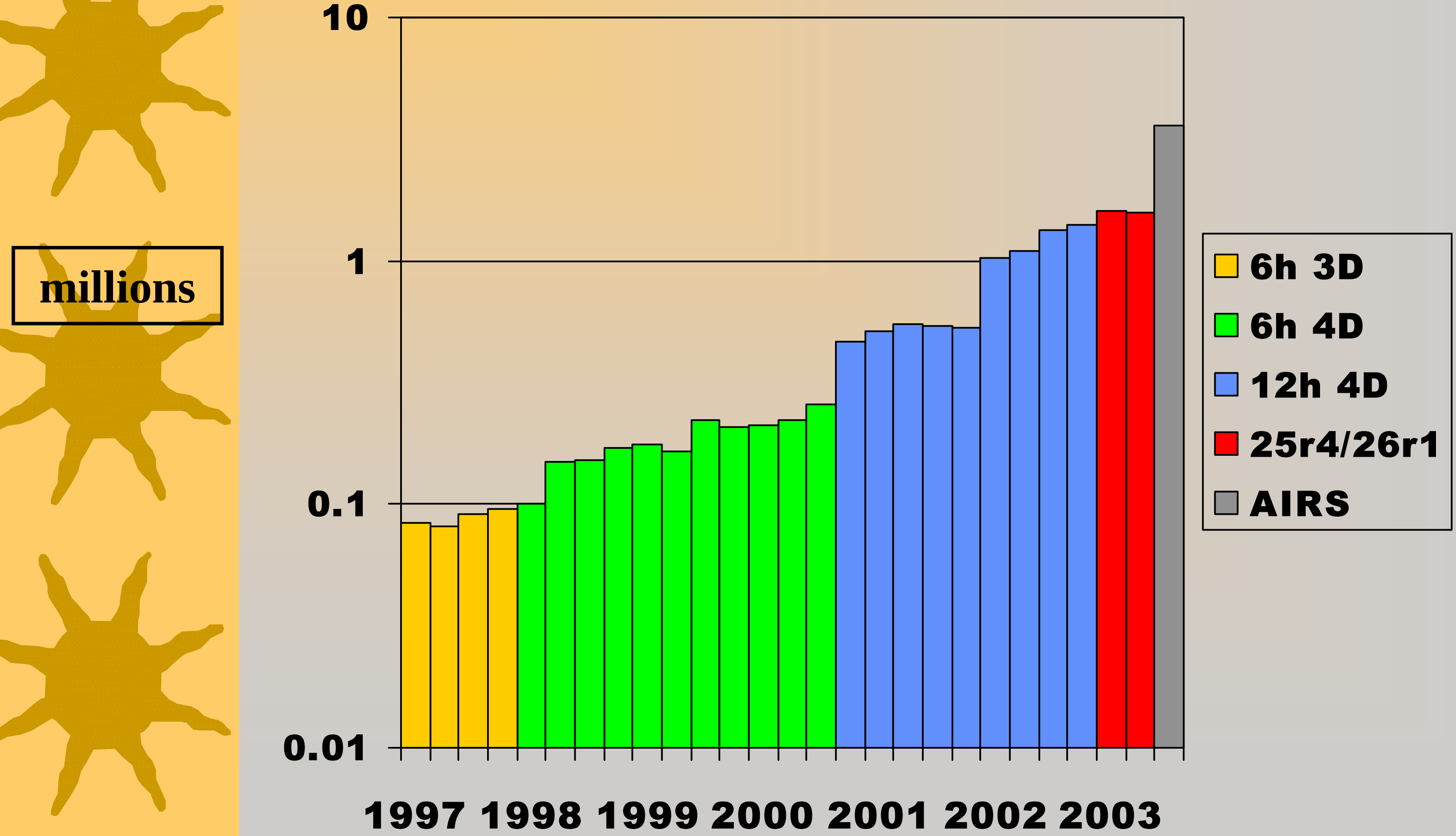
- T159 horizontal resolution (~125km grid)
  - operations uses T511 (~39km grid)

Simmons (2003)

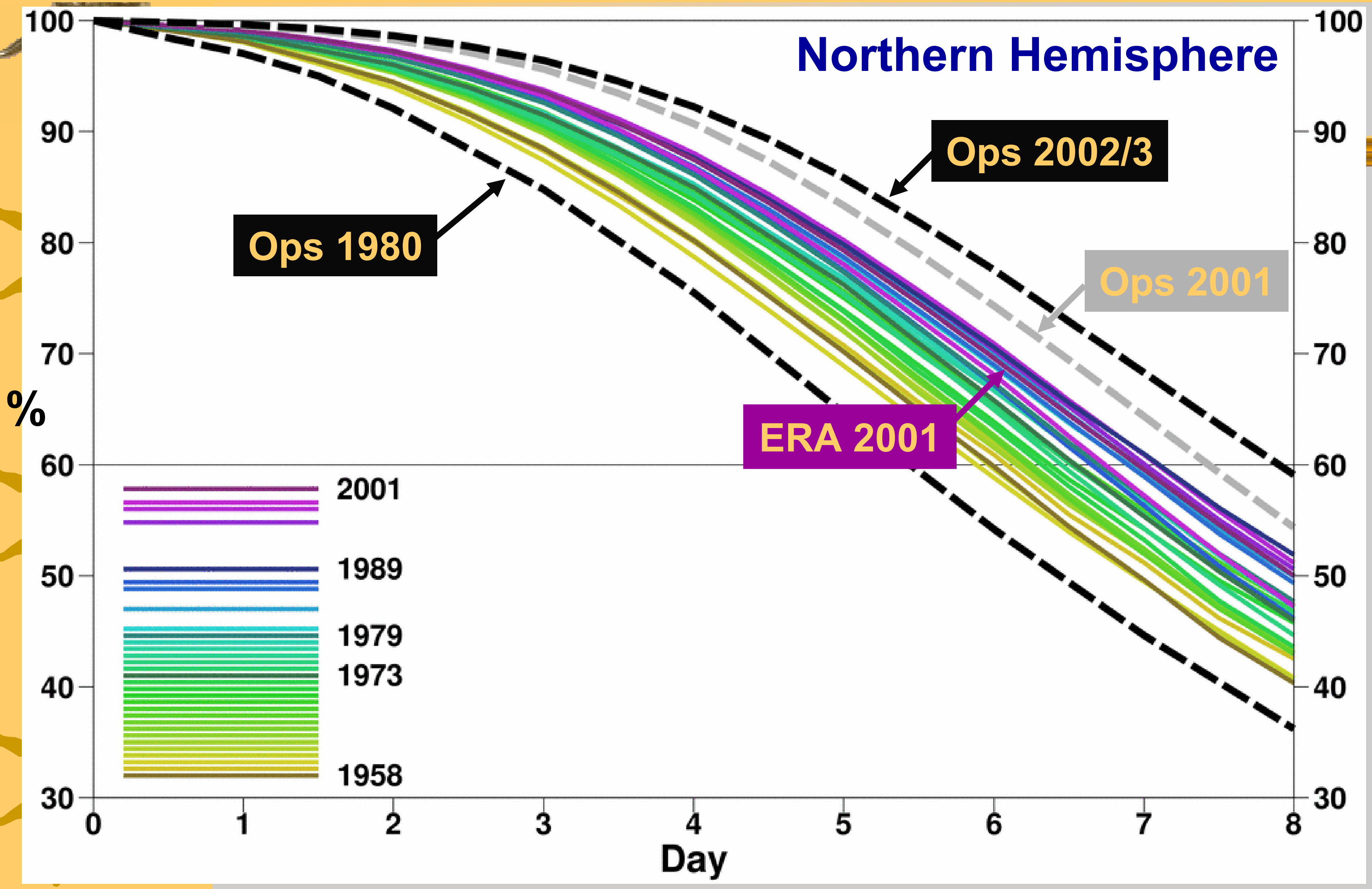
Use of SYNOP surface pressure observations over the extratropical southern hemisphere in ERA-40



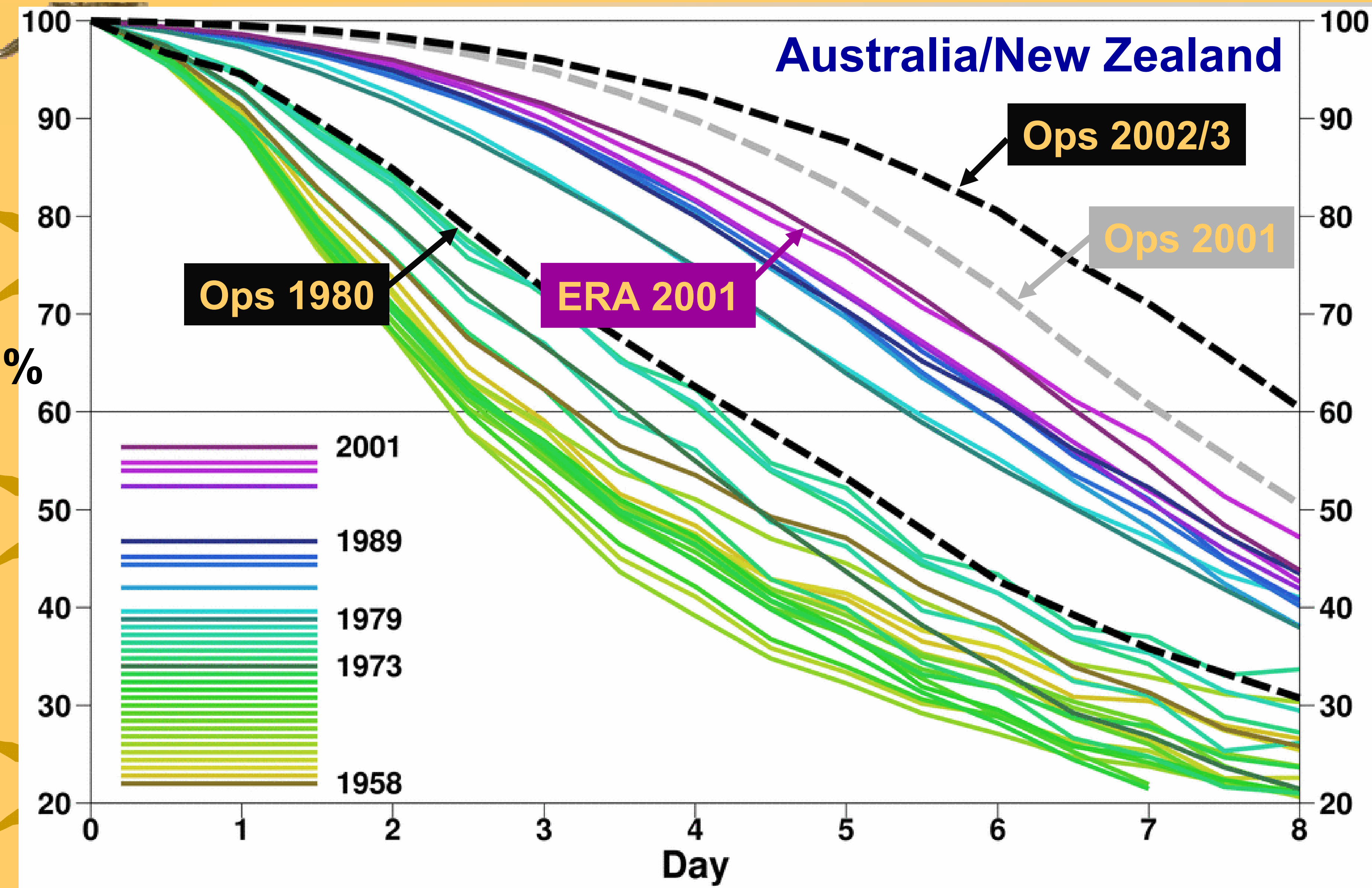
Number of observational data used in the ECMWF assimilation system (with AIRS)



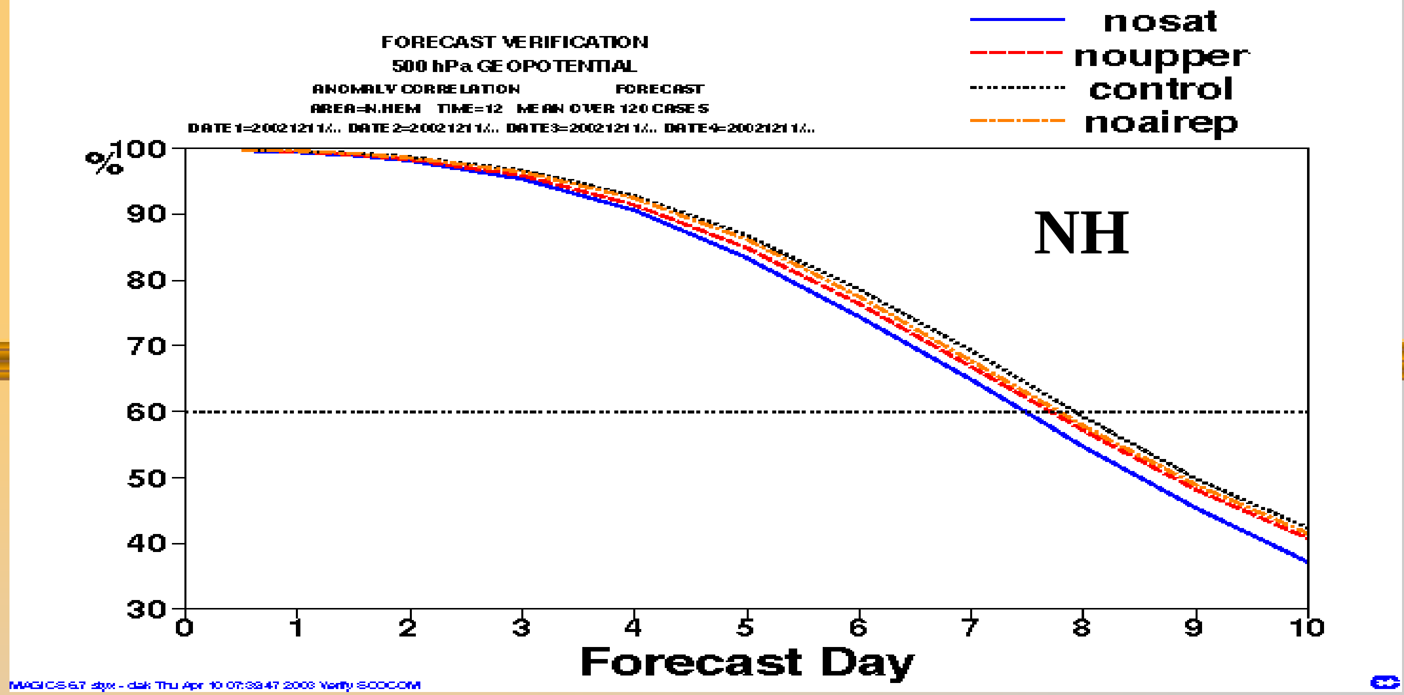
Anomaly correlations of 500hPa height forecasts



Anomaly correlations of 500hPa height forecasts

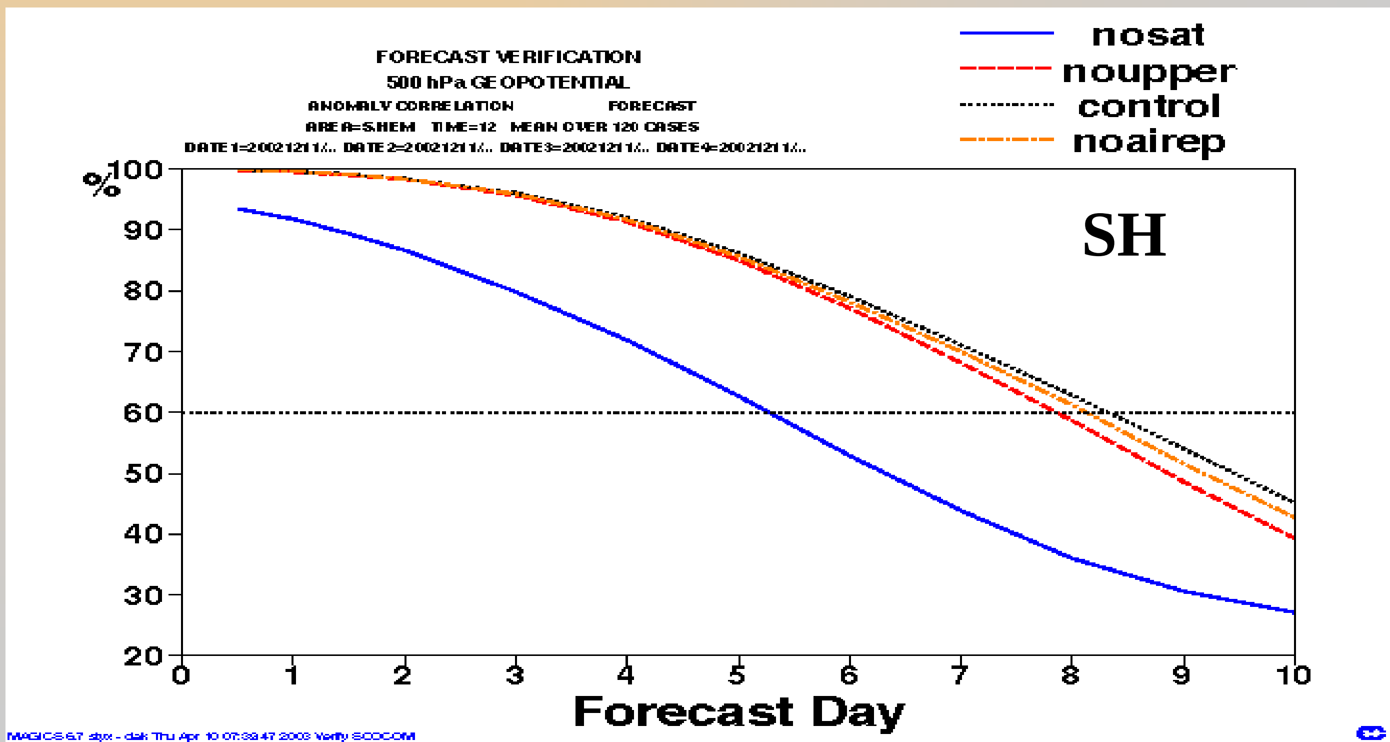


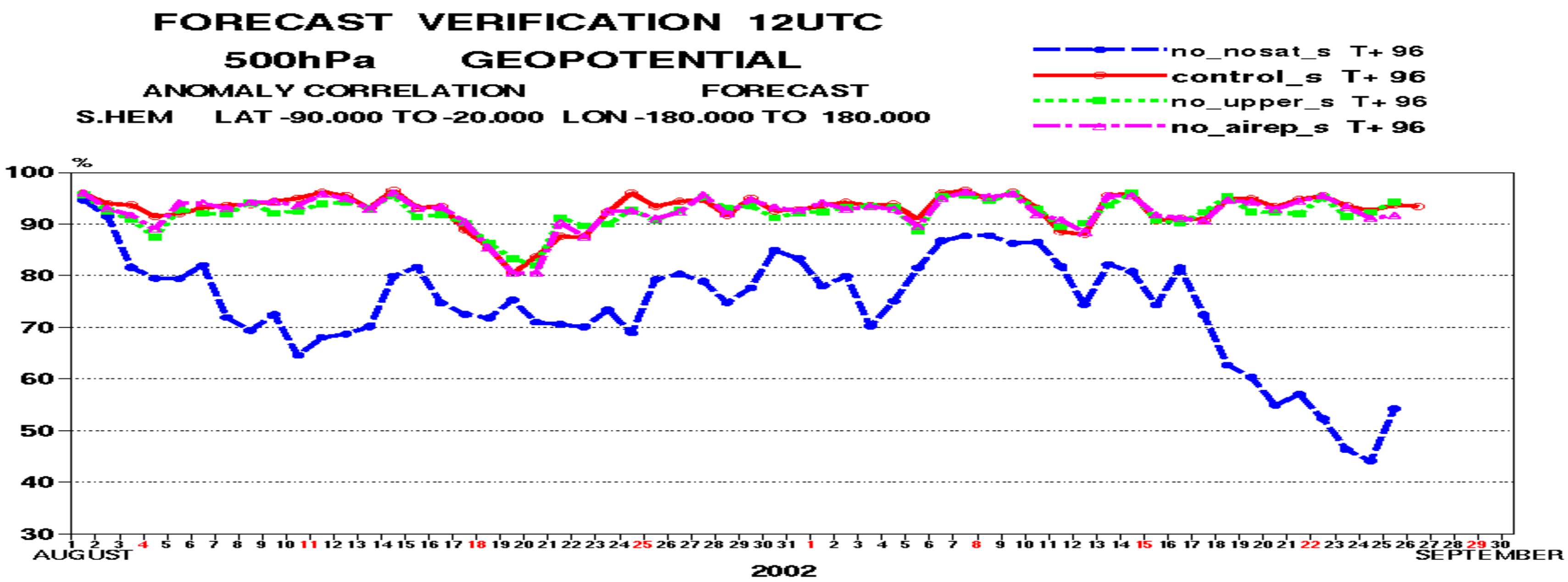
N. Hemisphere

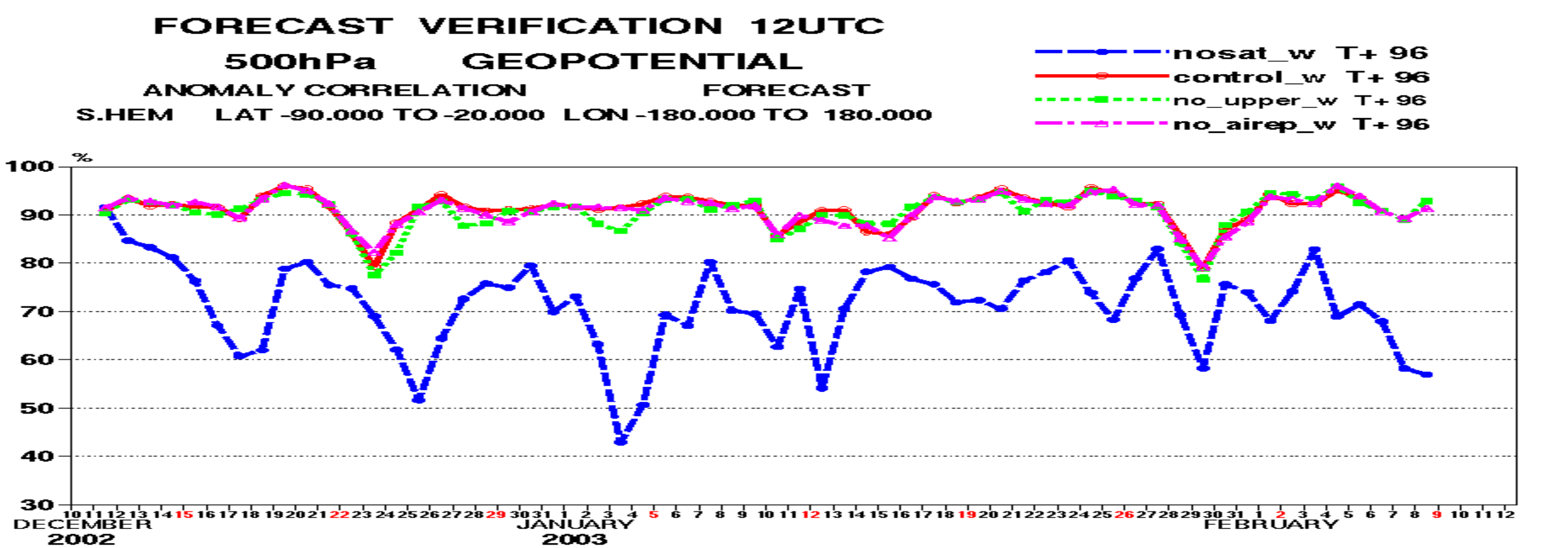


120 days 500 hPa Z scores

S. Hemisphere




FORECAST VERIFICATION 12UTC
500hPa GEOPOTENTIAL
ANOMALY CORRELATION FORECAST
S.HEM LAT -90.000 TO -20.000 LON -180.000 TO 180.000
no_nosat_s T+ 96
control_s T+ 96
no_upper_s T+ 96
no_airep_s T+ 96
%
AUGUST
SEPTEMBER
2002


FORECAST VERIFICATION 12UTC
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nosat_w T+ 96
control_w T+ 96
no_upper_w T+ 96
no_airep_w T+ 96
%
DECEMBER
2002
JANUARY
2003
FEBRUARY

Impact of observations: how?

- Large increase in number and quality of observations

- New approaches: direct use of radiance observations in data assimilation in variational systems

Radiative transfer problem

- Radiance: energy at a given wavenumber
- $R_\upsilon = (I_0)_\upsilon \tau_\upsilon(z_0) + \int_{z_0} B_\upsilon(T(z)) K_\upsilon(z)dz$

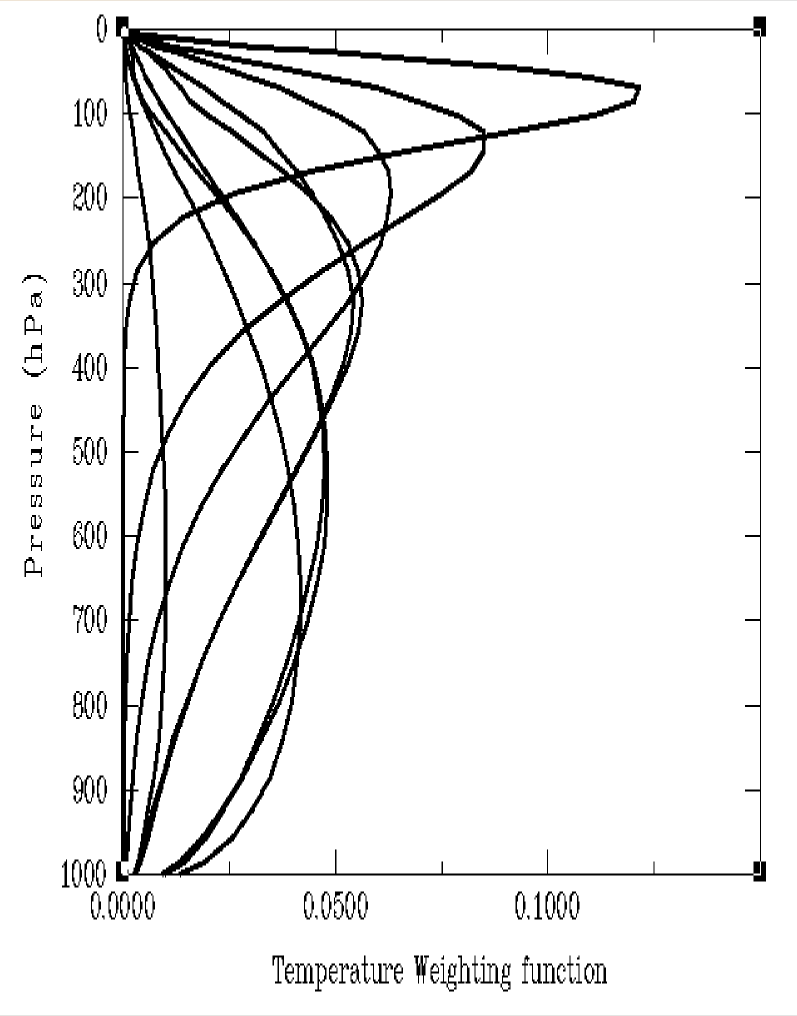
$K_\upsilon(z) = d\tau_\upsilon(z)/dz$ is a weighting function, depends on absorption and emission of various gases.

B(T) is the Planck function (emission of a black-body at temperature T)

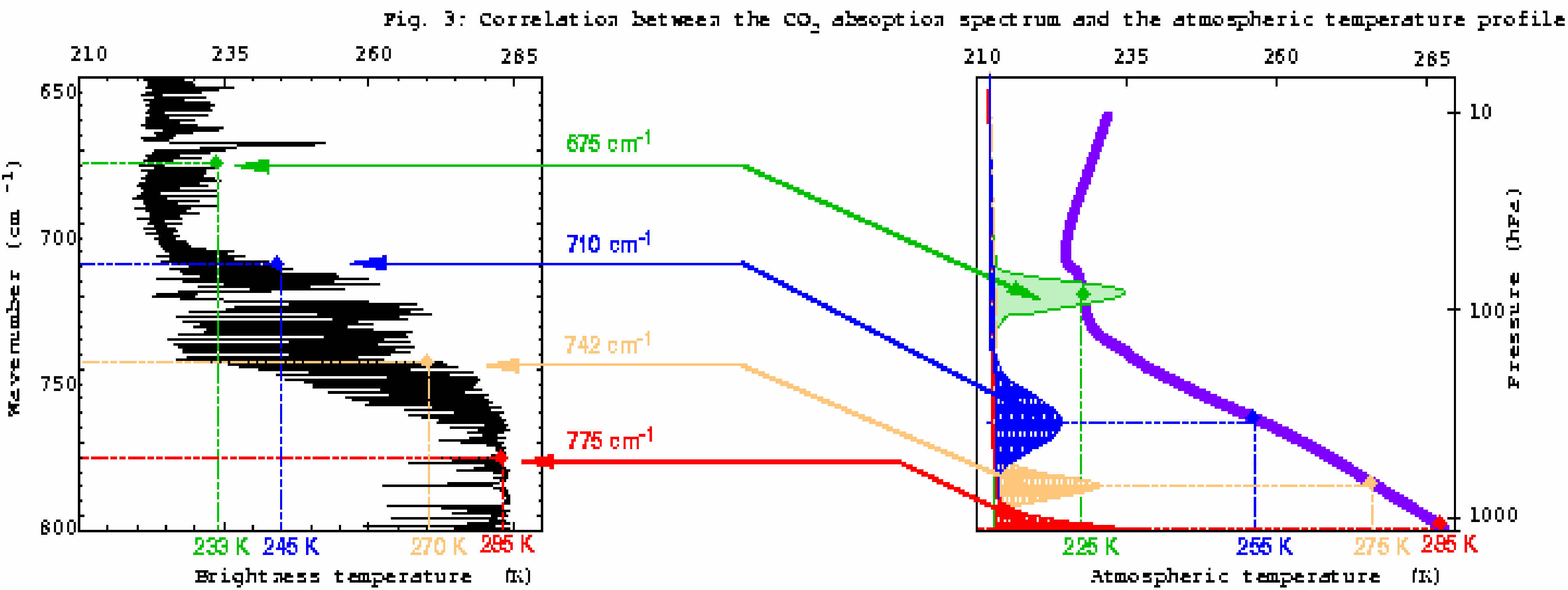
AMSU-A

- Illustration of weighting functions

- Various channels (wavenumbers) provide information at various levels in the vertical



IASI example



How can radiances be used?

- Data assimilation in some way or another converts radiance measurements in temperature/moisture/winds,…

- Different possibilities
  - Use of externally generated retrievals
  - Use of interactive retrievals (e. g. 1D-Var retrievals)
  - Direct use of radiances (e.g. 3D-Var or 4D-Var)

- In NWP at least, the direct assimilation of satellite raw radiances has progressively replaced the assimilation of retrievals

Thépaut (2003)

- The direct assimilation of radiances has several advantages over that of retrievals:

  - avoid the contamination by external background information for which error characteristics are poorly known and correlated
  - 3D and 4D-Var allow for some (weak) non linearities in the observation operator
  - Increments further constrained by many other observations/information

- In particular, less correlated errors allows to use denser observations

Problems encountered with a complex H

- Bias removal: H is inaccurate , and introduces biases often larger than the signal.
- Contamination: measures can be affected by clouds (infra-red) and precipitation (micro-wave). Good quality control needed

Data Assimilation

Solution in the linear case

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}_b)$$

With the gain matrix

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$$

And Analysis error Covariance

$$\mathbf{A} = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{B}$$

- This is the Optimal least-squares estimator minimum variance for the analysis error
- Or BLUE= Best Linear Unbiased Estimator
- If all errors are Gaussian, then it is also the maximum likelihood estimate

Use of raw data: more effort on H, less on R

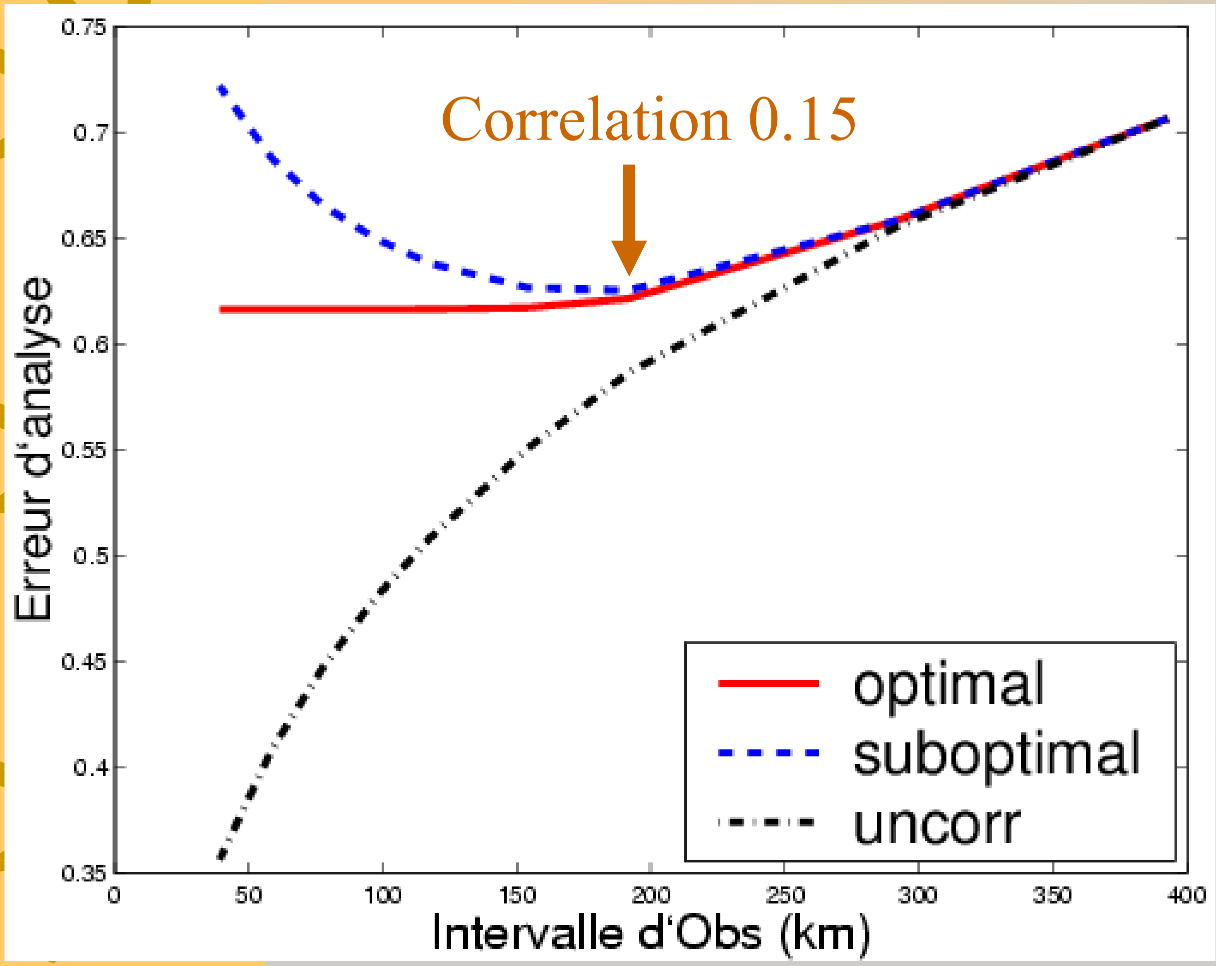
Evaluating the optimal resolution of the observations

- 1D circle: Length=8000km
- Δx=100km.
- Background and obs error σ=1.
- Background error correlation length-scale: 200km
- Observation spacing $\Delta\mathbf{y}$.
- Analysis Covariance matrix:

$$\mathbf{A} = (\mathbf{I} - \mathbf{KH})\mathbf{B}(\mathbf{I} - \mathbf{KH})^{\mathbf{T}} + \mathbf{KRK}^{\mathbf{T}}$$

Liu and Rabier (2002)

Optimal thinning of observations

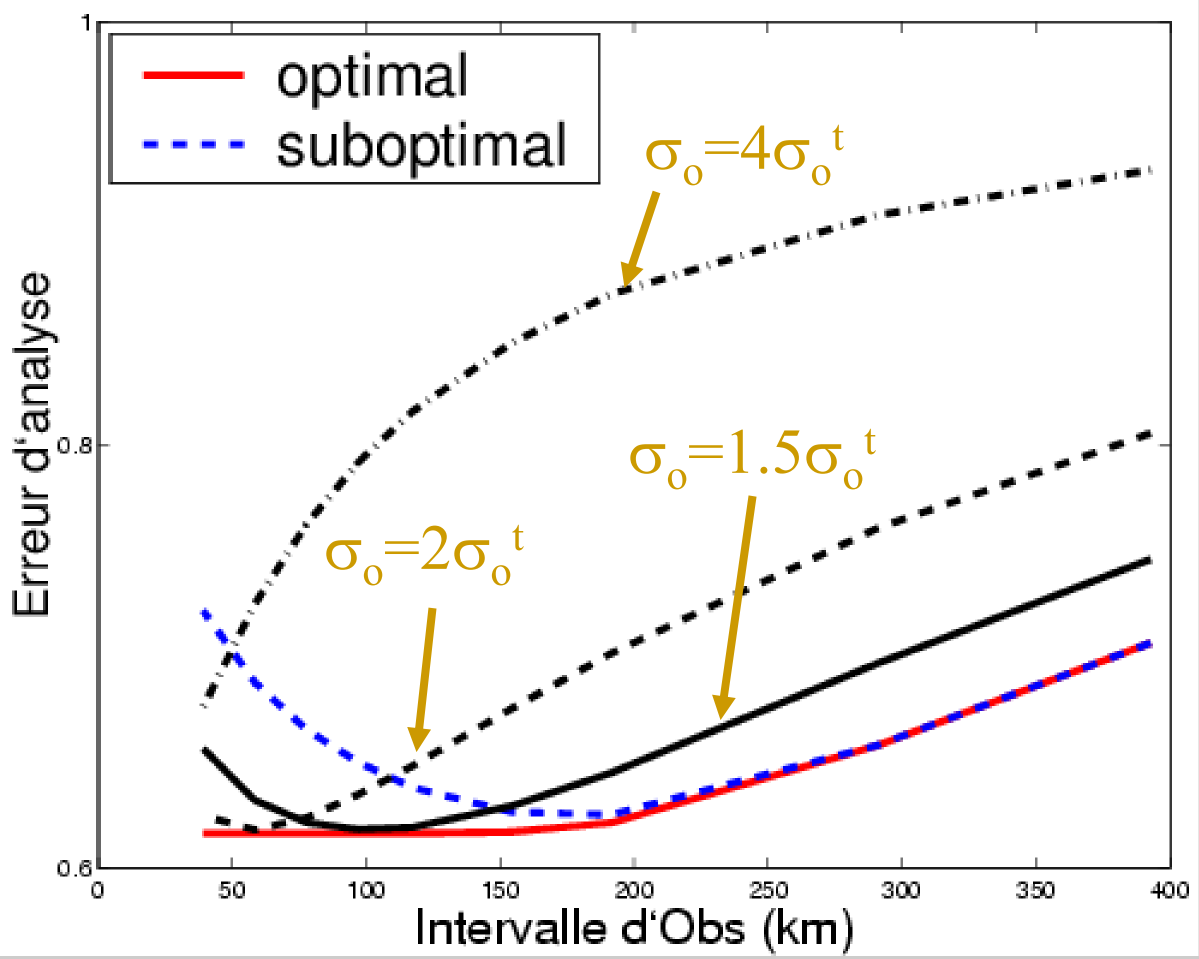


Tests with various Observation intervals

Correlated observation errors

- For uncorrelated obs errors, increasing the density improves the analysis
- For correlated obs errors,
  - Increasing the obs density beyond a threshold can be harmful in a sub-optimal scheme for which no correlations are included in R (current systems)
  - An optimal thinning can extract most of the information contained in the data
- More general solutions
  - Thinning or averaging?
  - Modelling the correlations?
  - Inflating the obs error?

Inflating the obs error



Information content

- A pure data count can be misleading
- There are various ways of estimating the information content of data types
- Example: *DFS* =Degrees of Freedom for Signal

$$DFS = tr\left(\mathbf{I} - \mathbf{A}\mathbf{B}^{-1}\right)$$

or

$$DFS = n - \sum_{\lambda \in \sigma\left(\mathbf{A}\mathbf{B}^{-1}\right)} \lambda$$

where

$$\mathbf{A} = \left(\mathbf{B}^{-1} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\right)^{-1}$$

$\mathbf{B}$ **Background error covariance matrix**

H **Observation operator**

$\mathbf{R}$ **Observation error covariance matrix**

$\mathbf{A}$ **Analysis error covariance matrix**

Why estimate Tr (HK) ?

$$Hx_a=(I-HK)x_b + HKy_o$$

$$\partial_{y_o}Hx_a=(HK)^T$$

Sensitivity of the analysis to the observations

$DFS=Tr(\partial_{y_o}Hx_a)=TR(HK)$ Characterizes how the assimilation system uses the observations to pull the signal from the background

- In the optimal case (i.e $K_{oper} = K_{true}$), This is also the relative reduction of variance (Tr (KH)=Tr ((B-A)*B^{-1}). It is only an upper bound in non-optimal cases.
- Says what the system does. Need other information to give insight about what it should do to get the best analysis.

How to estimate Tr (HK) ?

1) **Cardinali et al (2003)**

Computes the estimate using the singular vectors of the hessian of the cost function provided by the Lanczos/Conjugate gradient minimizer.

How to estimate Tr (HK) ?

2) Girard (1987) method

Based on $\varepsilon^T \mathbf{A} \varepsilon \approx \mathrm{Tr}(A)$, $\varepsilon \sim N(\mathbf{0},\mathbf{I})$

Perform a normal analysis

$(x_b, y_o) \rightarrow x_a$

Perform a perturbed analysis

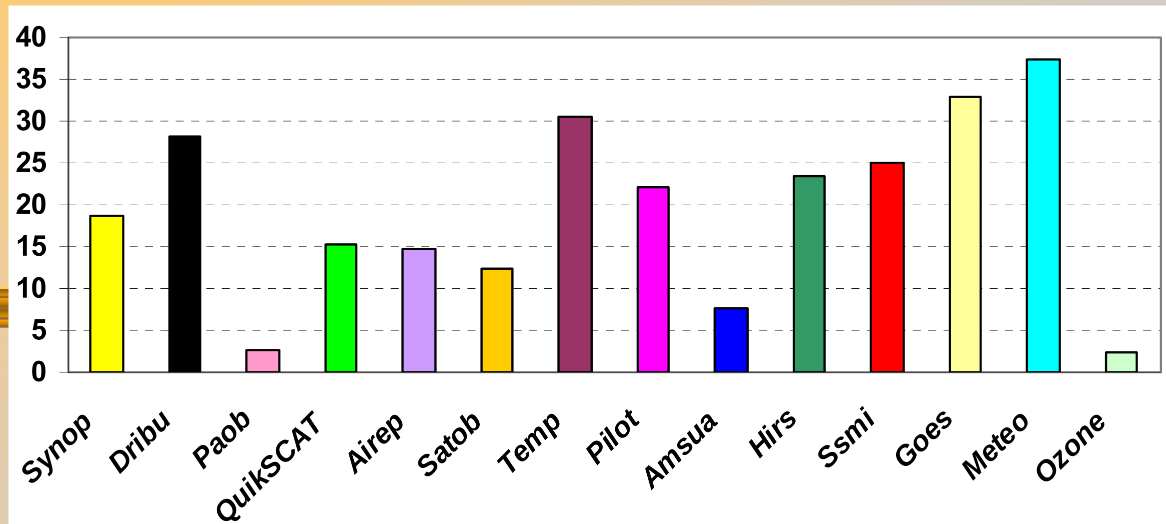
$(x_b, y_o^*) \rightarrow x_a^*$, $y_o^* = y_o + R^{0.5}\,\varepsilon$

Then

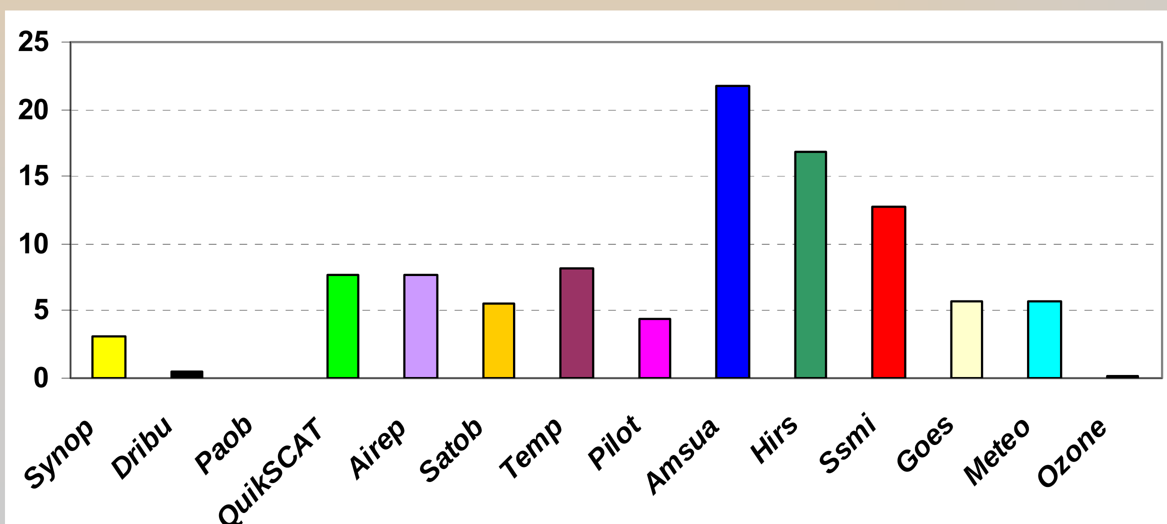
$(y_o^* - y_o)^T R^{-1} H(xa^* - xa) \approx \mathrm{Tr}(HK)$.

(Chapnik et al, 2004)

Average Influence and Information Content



Partition in obs types: individual data

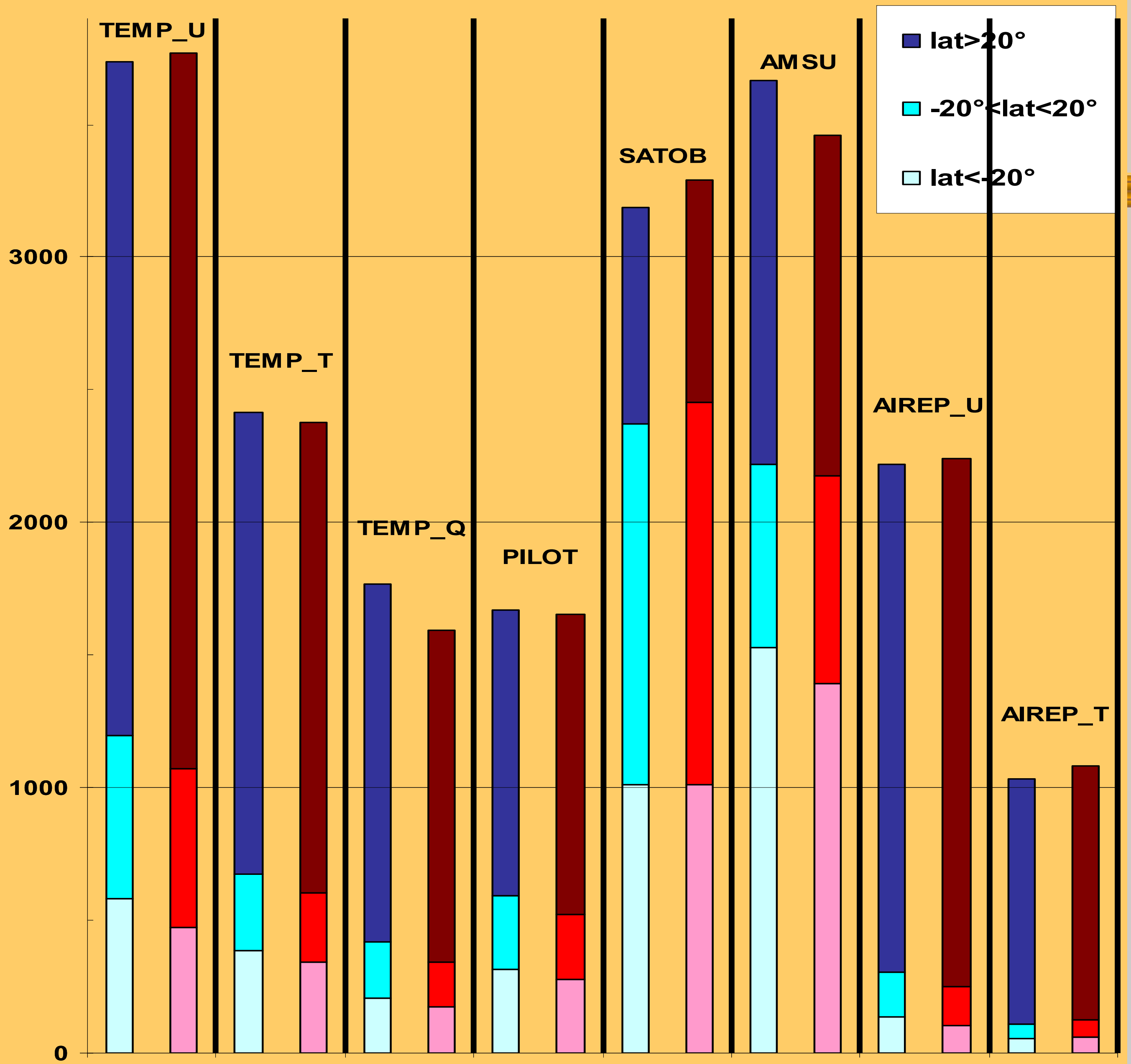


Partition in obs types: globally

Cardinali (2003)

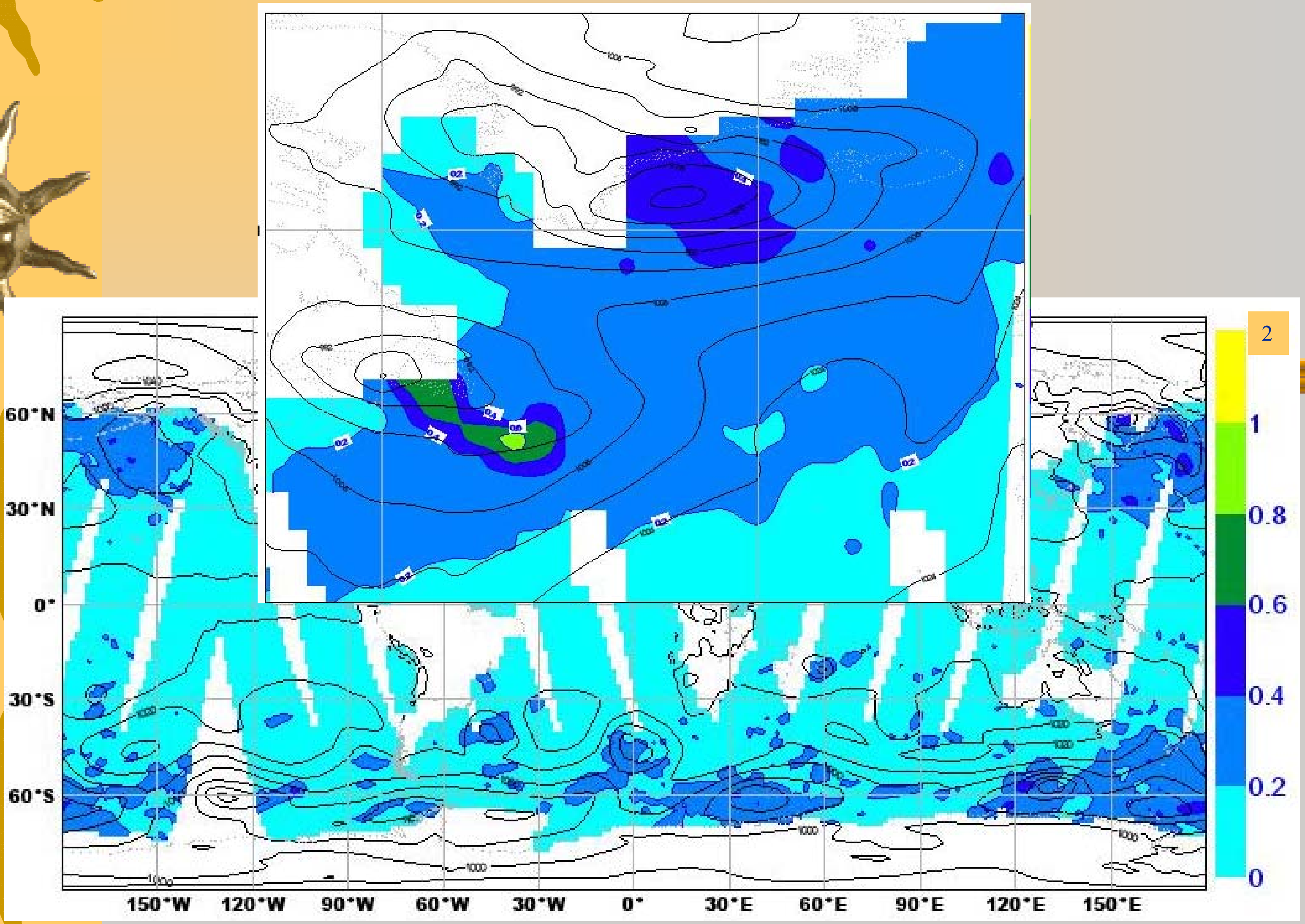
Evaluation of DFS

DFS of upper air observations on 4/02/2004



Partition in geographical areas

QuikSCAT U-Comp Influence



A way to use DFS related quantities to improve specified covariance matrices : Desroziers and Ivanov (2001)

Suppose one can write:

$$B_{true} = s_b\, B$$

$$R_{true} = s_o\, R$$

so and sb : tuning coefficients

If $J = J_b + J_o$
is the cost function used in a D.A system (suboptimal),

Then $J_o/s_o + J_b/s_b$
is the cost function using « true » matrices.

Let $\boldsymbol{x_a}$ be the minimizer of this cost function, then, following Talagrand (1999)

$$E(2J_o(\boldsymbol{x_a})/s_o) = \mathrm{Tr}\,(\mathbf{I_p} - \mathbf{HK})$$

$$E(2J_b(\boldsymbol{x_a})/s_b) = \mathrm{Tr}\,(\mathbf{KH})$$

Yielding the following condition for the tuning coefficients

$$s_o = 2J_o(\boldsymbol{x_a}) / \mathrm{Tr}\,(\mathbf{I_p} - \mathbf{HK})$$

$$s_b = 2J_b(\boldsymbol{x_a}) / \mathrm{Tr}\,(\mathbf{KH})$$

This is a fixed-point relation…

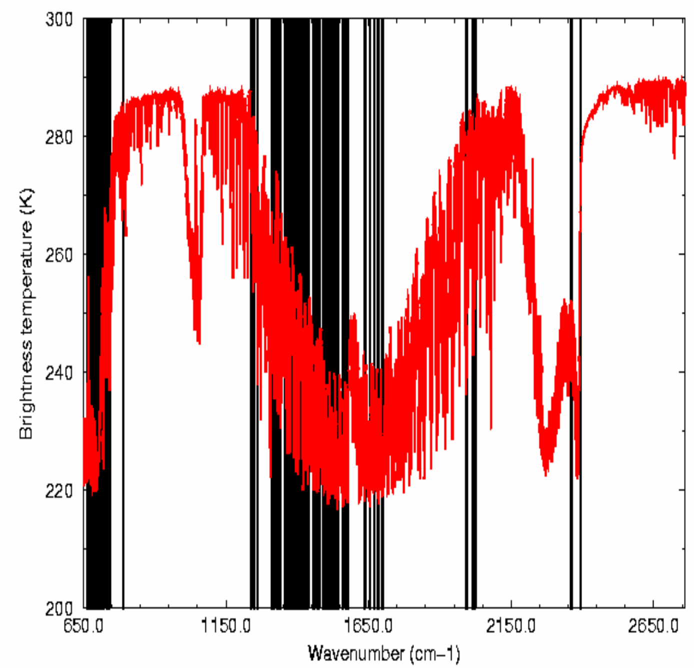
Channel selection (Rabier et al, 2002)

- ***Selection of individual channels***
- At each step, one channel is picked. It is the most informative channel among those which have not been previously selected.
- The analysis error covariance matrix is then updated

- *Iterative Method (Rodgers, 1996) or **Entropy Reduction** (ER) method*
  - ✓ This method is a step by step iterative selection scheme, based on information content wrt the background information.
    - The selection criterion is ER
      - $ER=-1/2 \log_2 \det(AB^{-1})$
      - Where B= background and A= analysis error covariance

Extract maximum information content from hyperspectral sounders

- Channel selection
  For IASI
  (CNES/EUMETSAT)



THORPEX

A GLOBAL ATMOSPHERIC RESEARCH PROGRAMME

Mission Statement - *Accelerating improvements in the accuracy of high-impact 1-14 day weather forecasts for the benefit of society and the economy*

http://www.wmo.int/thorpex/

http://www.mmm.ucar.edu/uswrp/programs/thorpex.html

How is THORPEX organised?

- THORPEX is part of the WMO
  - World Weather Research Programme (WWRP).
- Research objectives are developed under four Sub-programmes:
  - Predictability and Dynamical Processes;
  - Observing Systems;
  - Data Assimilation and Observing-Strategies;
  - Societal and Economic Impacts.
- International Science Plan available
  - Mel Shapiro and Alan Thorpe

A few core objectives

- Contribute to the design and demonstration of

  interactive forecast systems

  which include the new concept of targeted observations

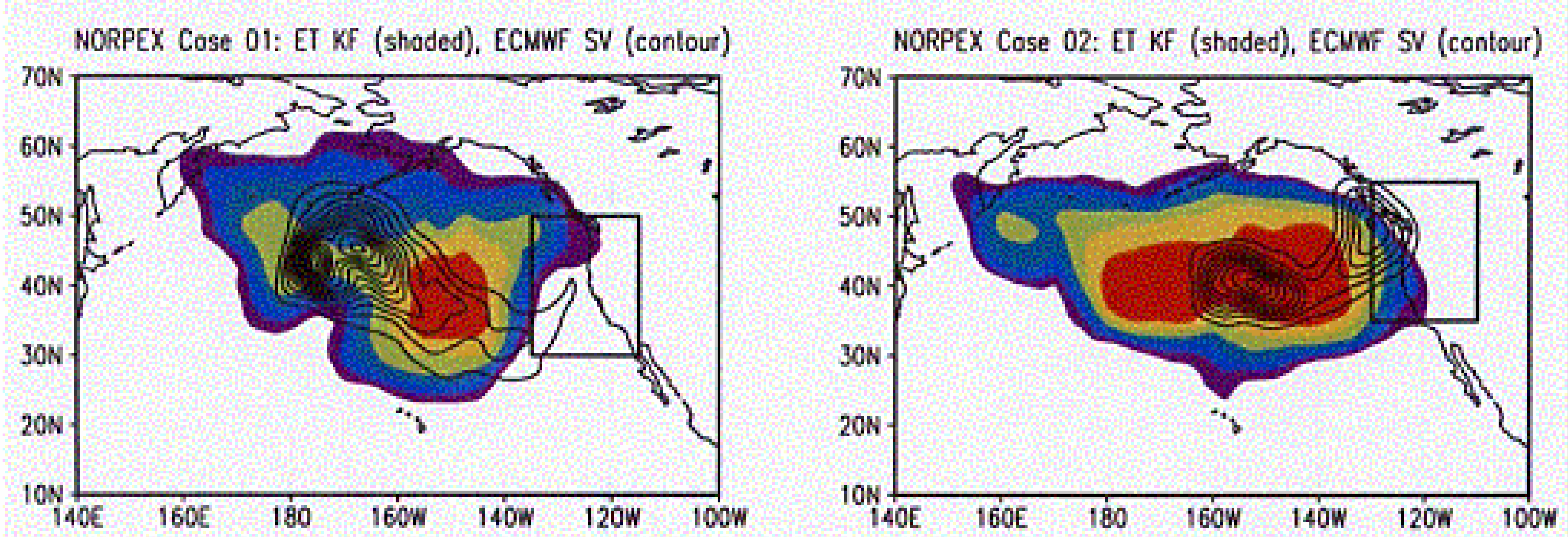
- Perform THORPEX Observing-System Tests (TOSTs)
  and Regional field Campaigns (TReCs)
  to test and evaluate experimental remote-sensing and
  in-situ observing systems,
  and when feasible, demonstrate their impact on weather forecasts

Targeting

- In the last decade, strategies were developed that identify locations where additional observations would provide maximal improvements in the expected skill of forecasts.
- Targeting strategies are based on techniques that predict, prior to the actual measurements, the influence of an observation (or set of observations) on the uncertainty of a subsequent forecast.
- Different targeting techniques: some involve the adjoint of the linearized version of the forecast model or of the assimilation scheme, others manipulate ensembles of forecasts.
- Operational in the US: WSRP

Targeting

Illustration of the differences between the results arising from different targeting algorithms. Two cases from the NORPEX field experiment are shown; the intent is to select the observation location that will minimize the expected 24-h forecast error in the box at right. Colored regions indicate the sensitive regions as determined by an ensemble-based filtering approach; contours indicate region of increasing observation sensitivity as determined by an adjoint-based singular vector approach. From Majumdar et al., QJRMS.



Targeting observing systems

- Examples include the control of the sampling rate of satellite sensors or the **timing and location** of mobile upper-air soundings.

- Targeting can also be used to determine which observations are to be discarded, i.e., to **conduct effective thinning of the observations**. This capability will become increasingly important, given the very large numbers of observations that will be available from next-generation satellites.

Diagnostics of data impact

Based on information content

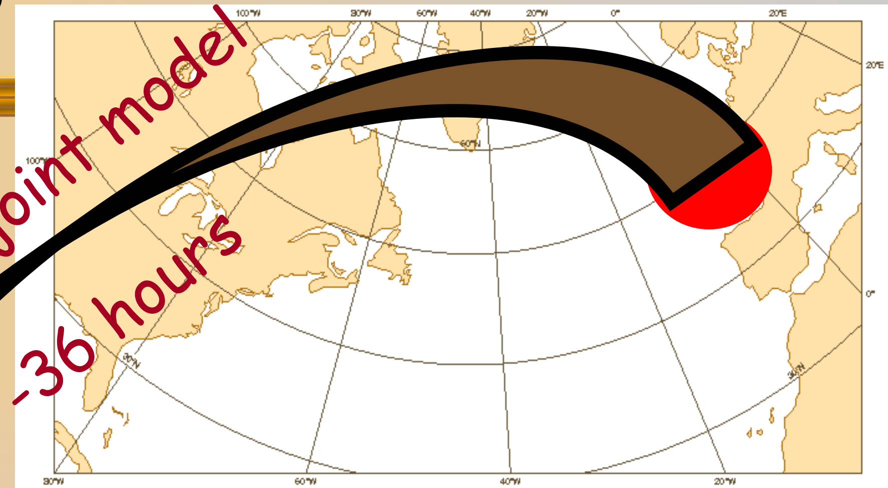
or

targeting information

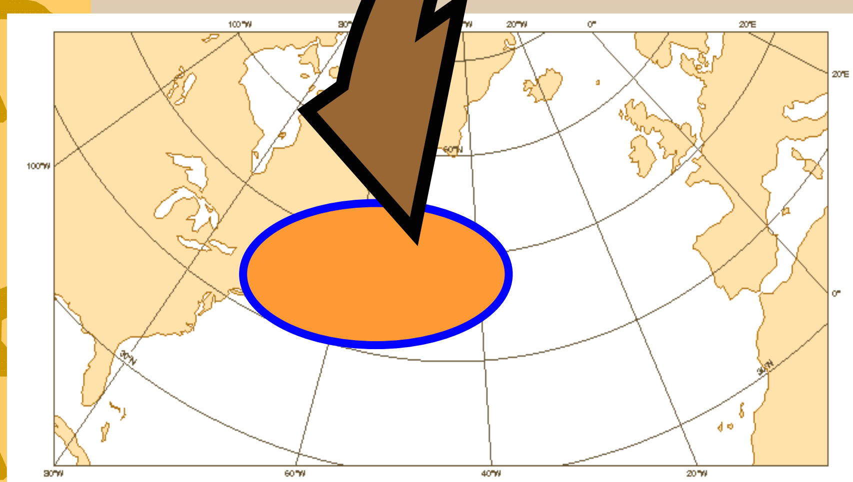
Sensitive areas

Diagnostic function: forecast of the mean sea level pressure over the region of interest on 19 Feb 1997,12 UTC

12 UTC 97/2/19

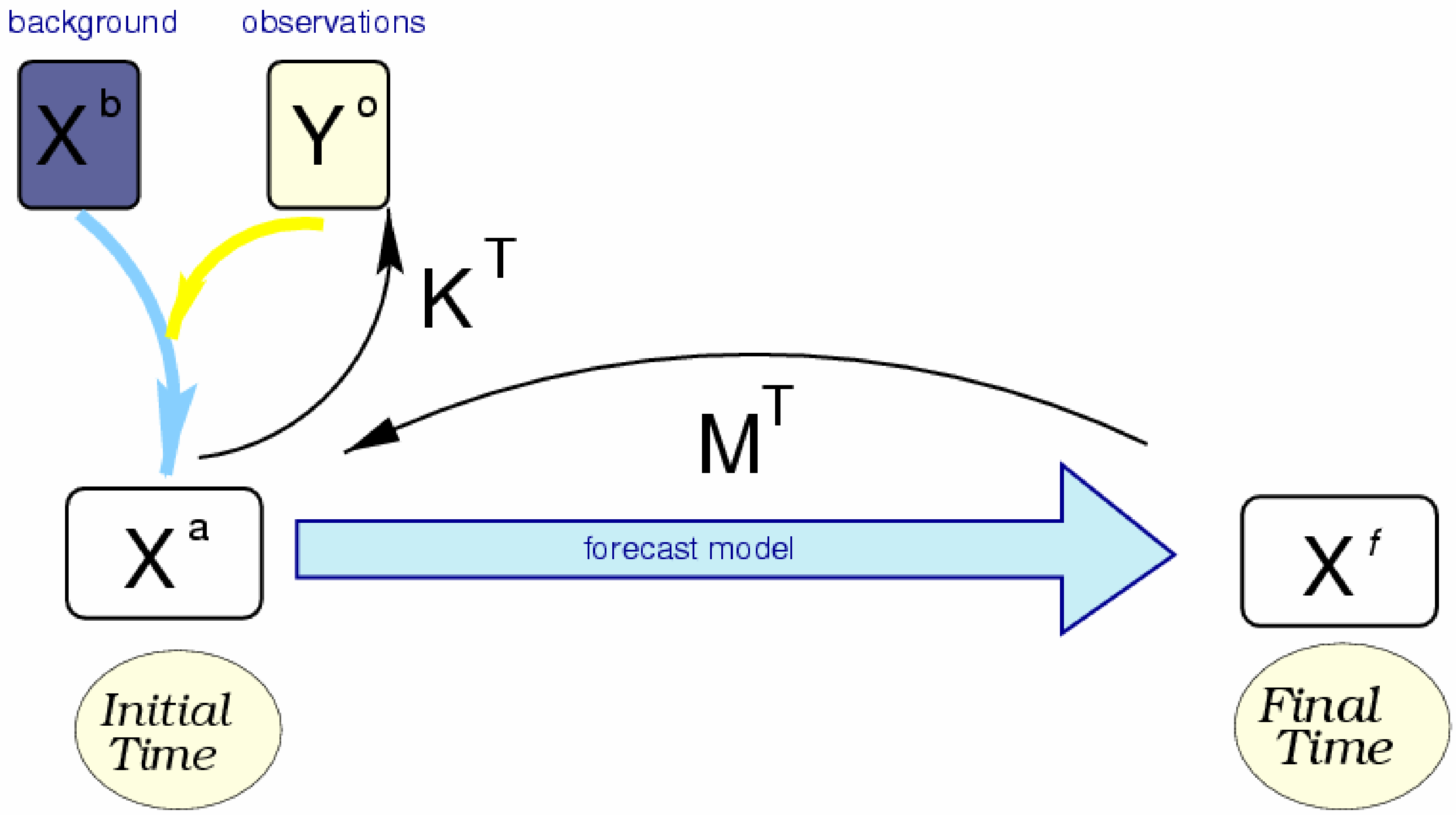


0 UTC 97/2/18



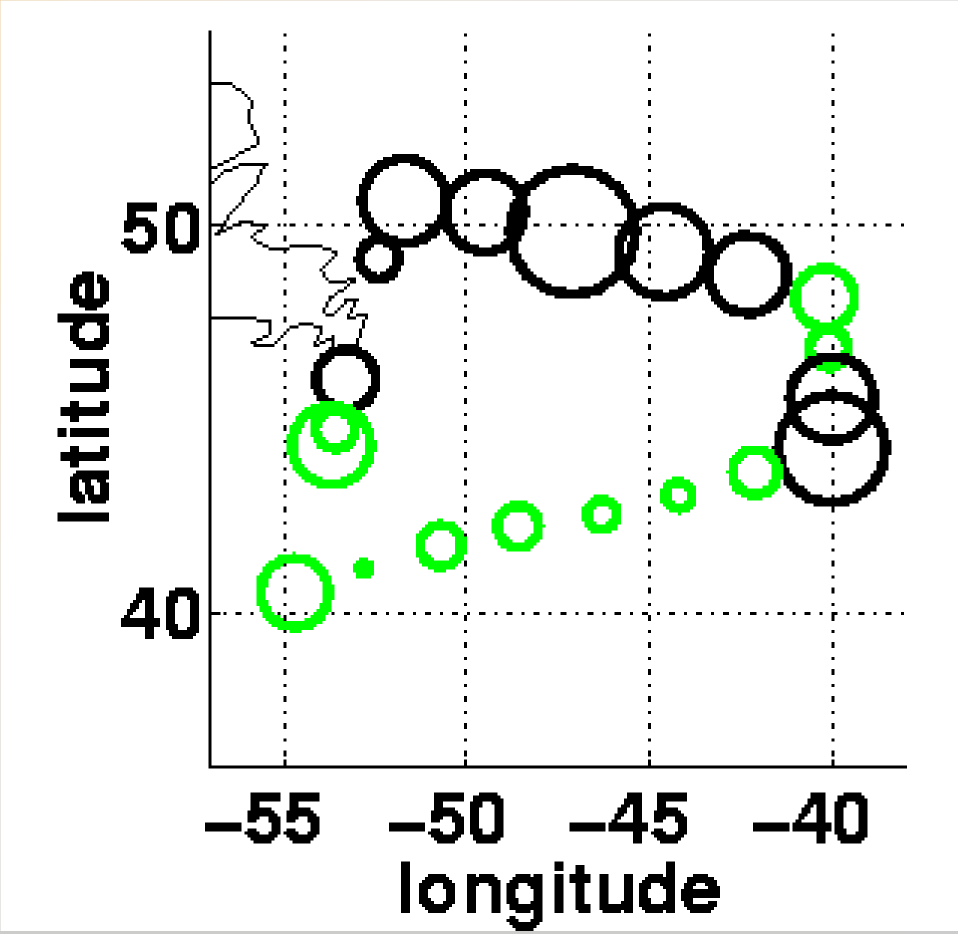
Sensitive area determined with temperature fields of the gradient of the diagnostic function with respect to initial conditions
(18 Feb 1997,0 UTC)

SENSITIVITY OF THE FORECAST TO OBSERVATIONS



Targeting: Quantifying impact of any obs

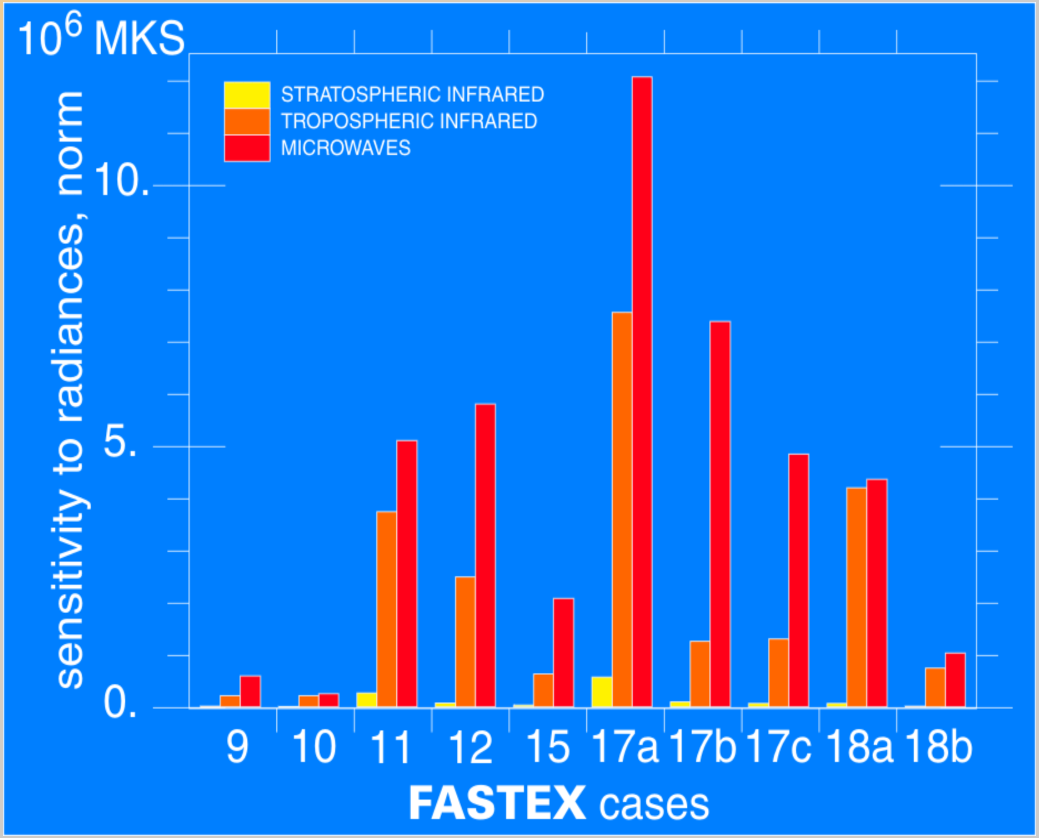
- Sensitivity of a cyclone to dropsonde wind profiles. FASTEX IOP17.
- Doerenbecher and Bergot, 2001.



Targeting: Compute sensitivity to sounder channels

Sensitivity to observations

- To see the importance of MW
- To select channels



Fourrié et al (2002)

Adaptive observation selection

- Estimation of background errors in observation space (HBH^T) to perform First-guess check (Andersson et al, 2000)

- Adaptive buddy check: flow-dependent tolerances for outlier observations (Dee et al, 2001)

Conclusions

Satellite data have been very succesfully exploited by new data assimilation schemes (DA schemes are such that introducing additional well characterised satellite data improves the system)

The combined availability of new accurate satellite observations and improvement of models will allow an improved extraction of information content from these new data (parallel upgrades of B and Y)

Conclusions

In general, the system can only cope with a small fraction of all observations

Efficient tools have been built to evaluate obs impact and perform tuning

In any case, we need to optimize their use, including more flow-dependency

References

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