

Bias correction in data assimilation

Hans Hersbach and Dick Dee

ECMWF

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Data Assimilation

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Overview of this lecture

In this lecture the variational bias correction scheme (VarBC) as used at ECMWF is explained. *VarBC replaced* the tedious job of estimating observation bias *off-line* for each satellite instrument or in-situ network *by an automatic* self-adaptive *system*.

This is achieved by making the bias estimation an *integral part* of the ECMWF variational data *assimilation* system, where now both the initial model state and observation bias estimates are updated simultaneously.

By the end of the session you should be able to realize that:

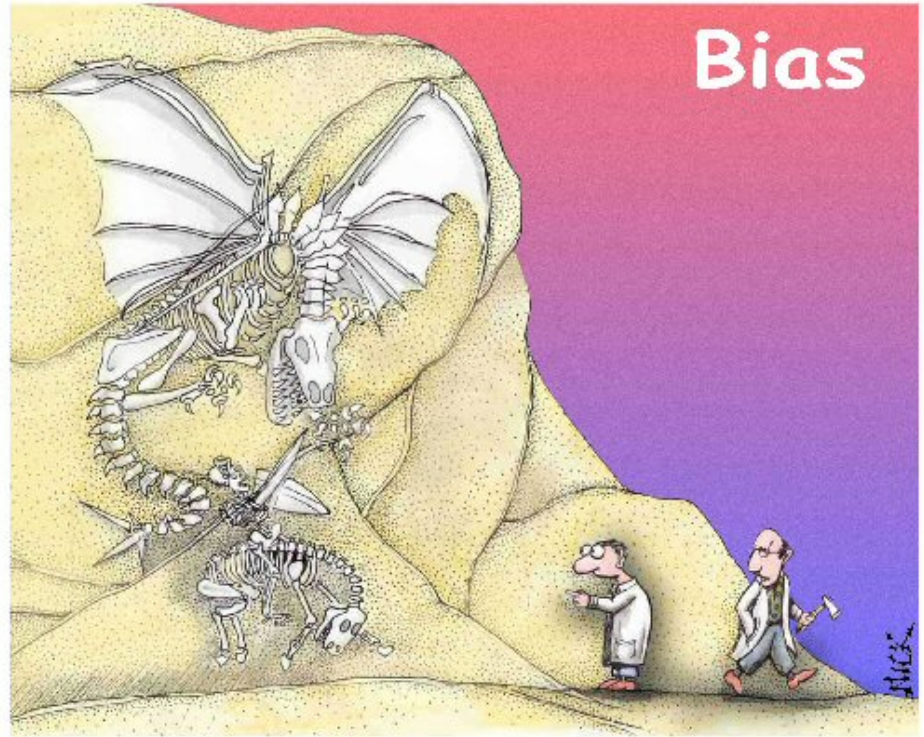
1. many observations are biased, and that the characteristics of bias *varies widely* between types of instruments,
2. *separation* between *model* bias and *observation* bias is often *difficult*,
3. the success of an adaptive system implicitly relies on a *redundancy* in the underlying observing system.

Bias: Ignorance is bliss...

Everyone knows that models are biased

Not everyone knows that most observations are biased as well

So... where is the bias term in this equation?



"Ignore it, Jeffries. It's unscientific."

$$\mathbf{J}(\mathbf{x}) = \underbrace{(\mathbf{x}_b - \mathbf{x})^T \mathbf{B}^{-1} (\mathbf{x}_b - \mathbf{x})}_{\text{background constraint}} + \underbrace{[\mathbf{y} - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{h}(\mathbf{x})]}_{\text{observational constraint}}$$

Outline

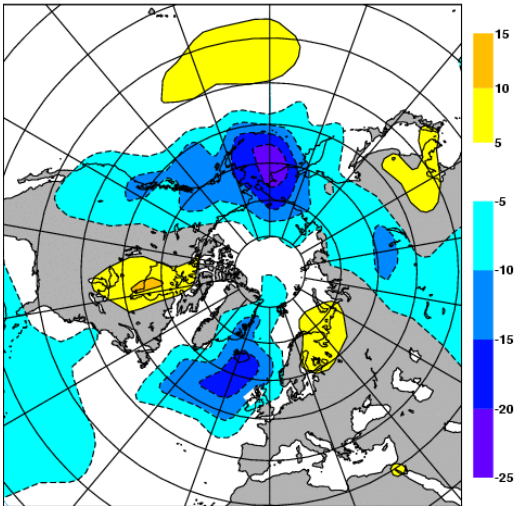
- Introduction
 - Biases in *models*, *observations*, and *observation operators*
 - *Implications* for data assimilation
- Variational analysis and correction of observation bias
 - The need for an adaptive system
 - Variational bias correction (VarBC)
- Extension to other types of observations
- Limitations due to the effects of model bias

Model bias:

Systematic Day-3 Z500 errors in three different forecast models

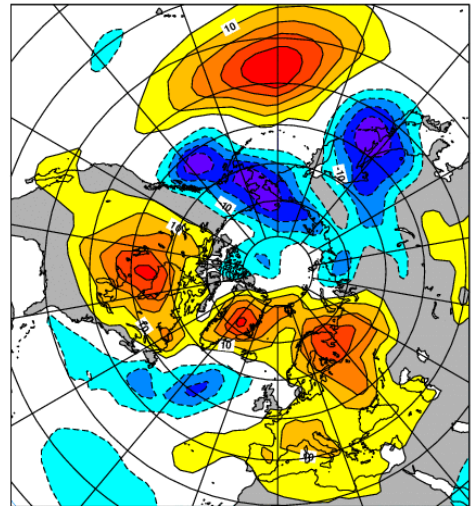
ECMWF

Systematic Z500 Error (ECMWF DJF 01-03)



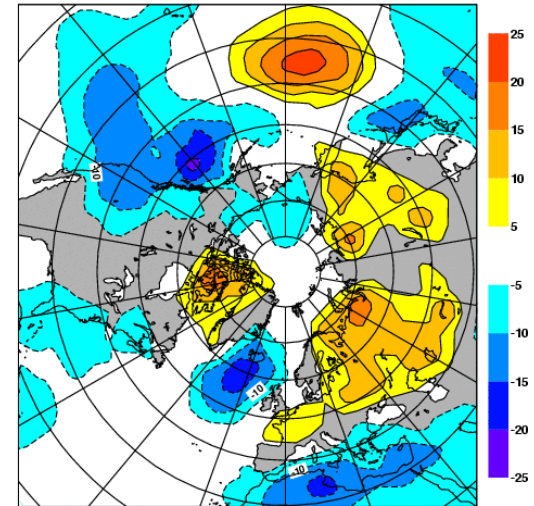
Meteo-France

Systematic Z500 Error (France DJF 01-03)



DWD

Systematic Z500 Error (DWD DJF 01-03)

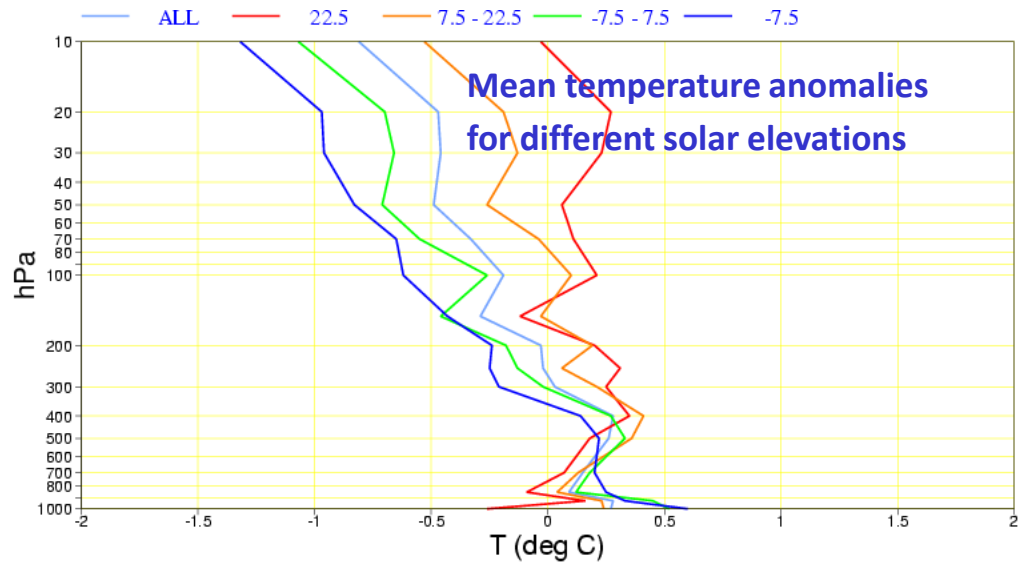


Different models often have similar error characteristics

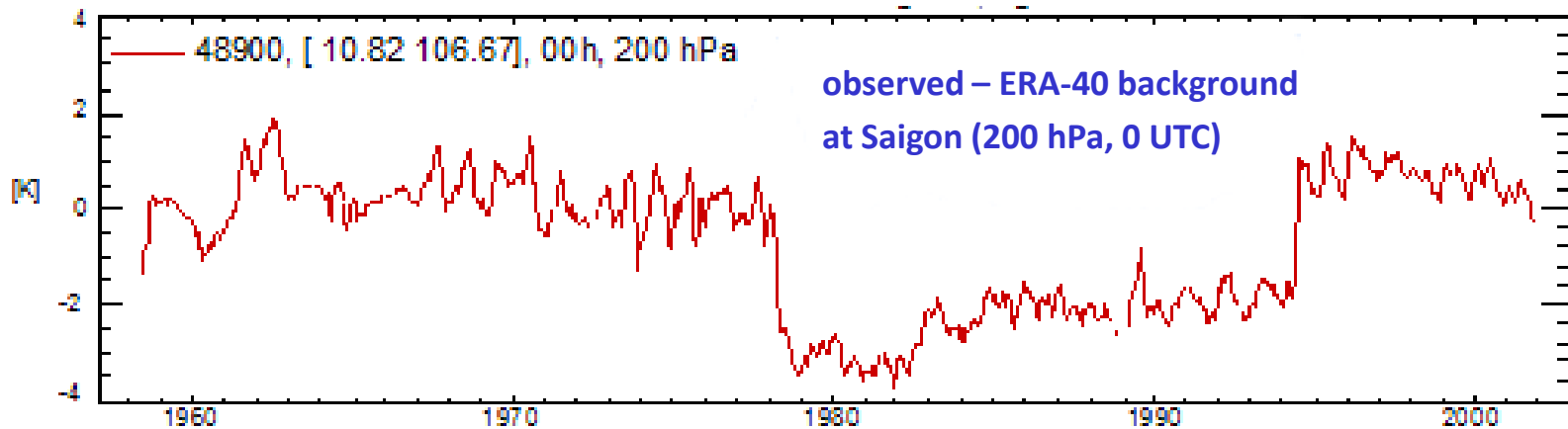
Period DJF 2001-2003

Observation bias: Radiosonde temperature observations

Daytime warm bias due to radiative heating of the temperature sensor
(depends on *solar elevation* and *equipment type*)

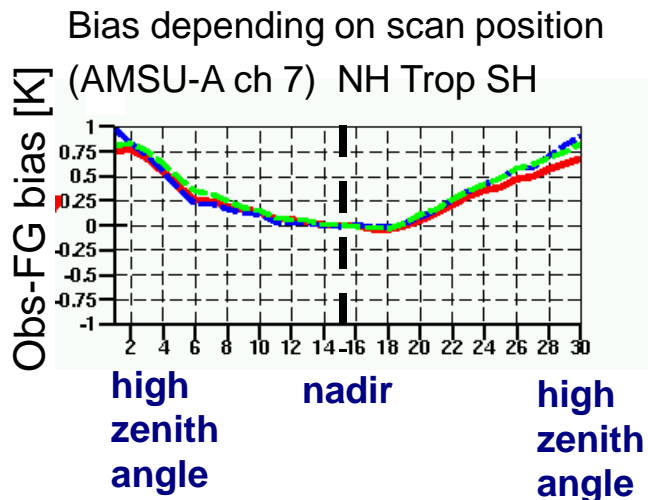
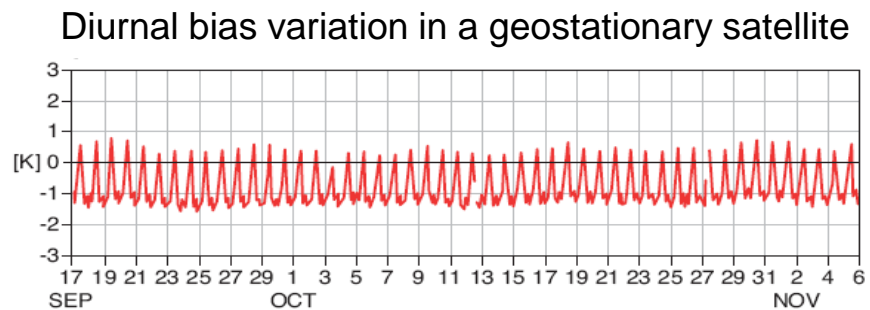
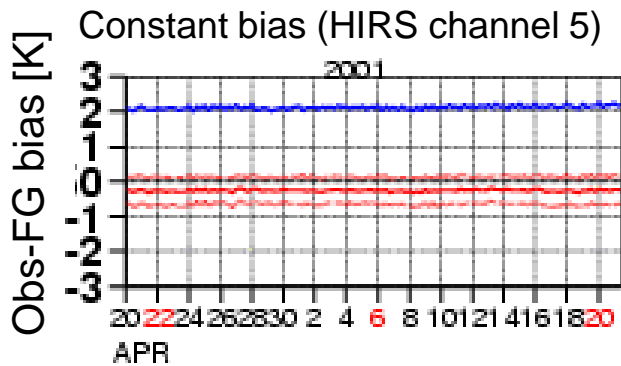


Bias changes due to change of equipment

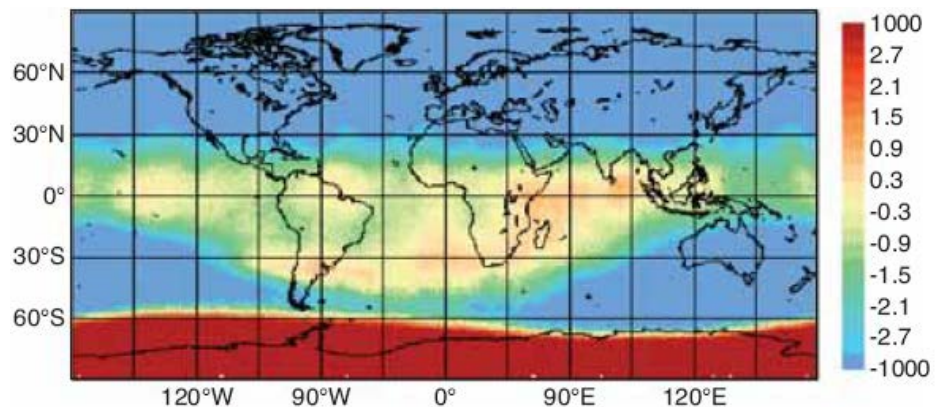


Observation and observation operator bias: Satellite radiances

Monitoring the background departures (averaged in time and/or space):

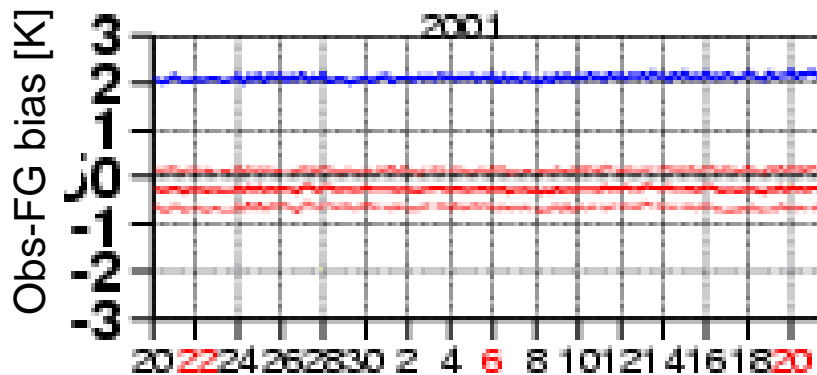


Air-mass dependent bias (AMSU-A channel 14)

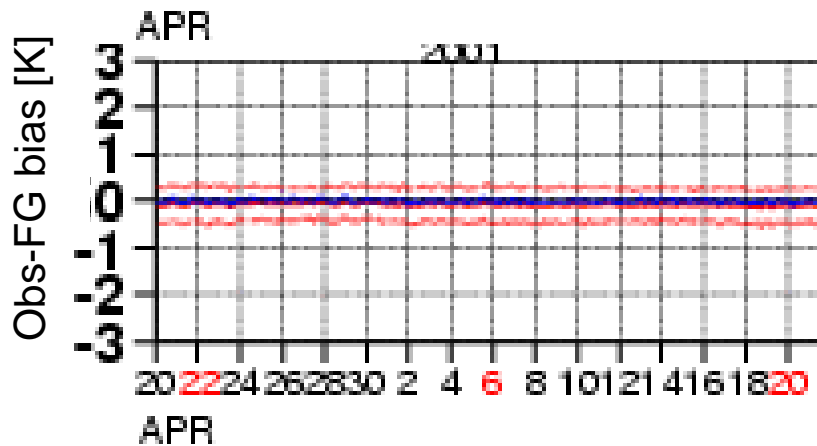


Observation and observation operator bias: Satellite radiances

Monitoring the background departures (averaged in time and/or space):



HIRS channel 5 (peaking around 600hPa) on **NOAA-14** satellite has +2.0K radiance bias against FG.



Same channel on **NOAA-16** satellite has no radiance bias against FG.

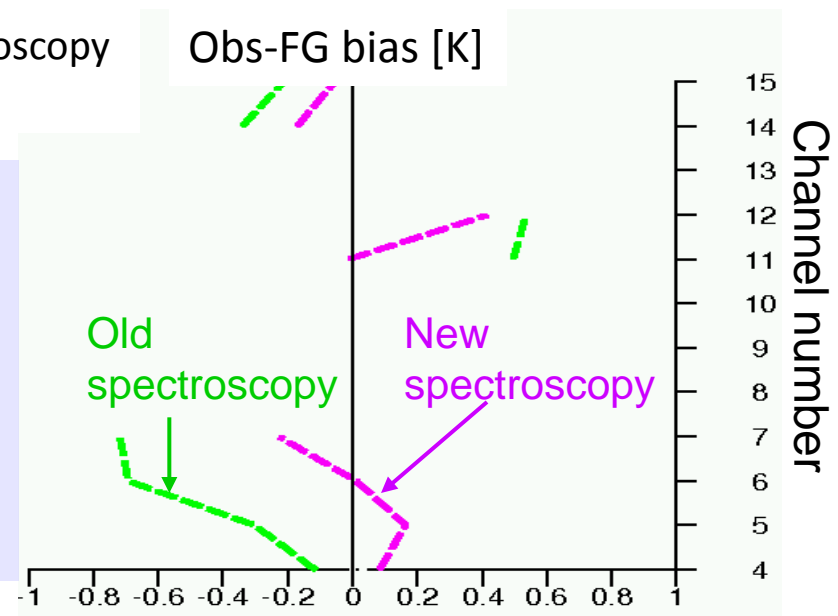
→ NOAA-14 channel 5 has an instrument bias.

Observation and observation operator bias: Satellite radiances

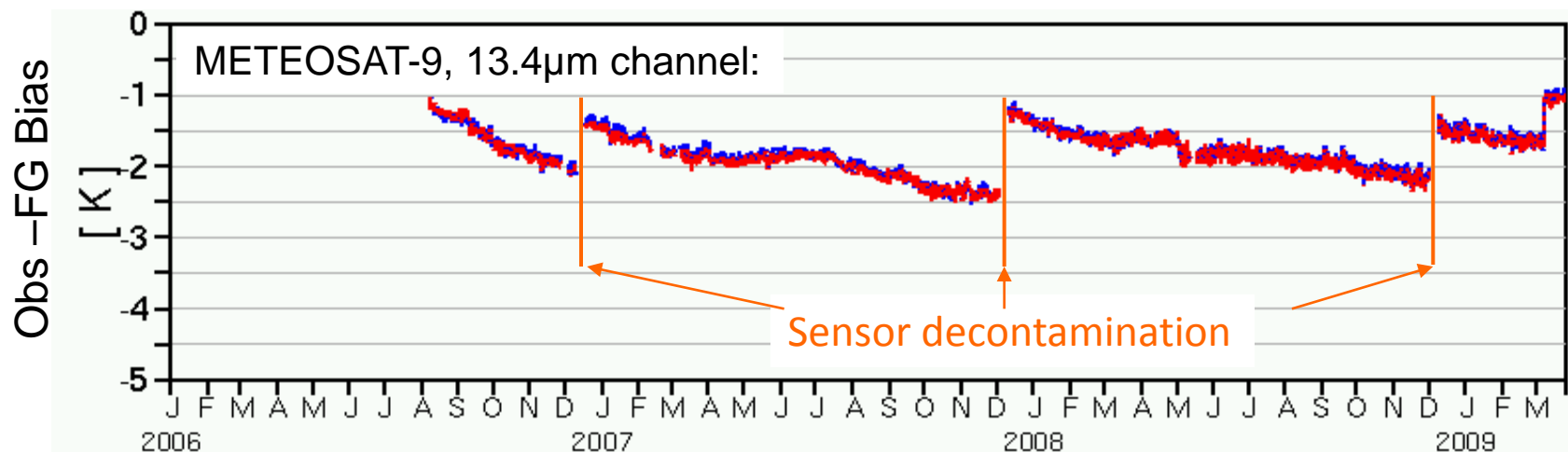
Different bias for HIRS due to change in spectroscopy used in the *radiative transfer model*:

Other common causes for biases in radiative transfer:

- Bias in assumed concentrations of atmospheric gases (e.g., CO₂, aerosols)
- Neglected effects (e.g., clouds)
- Incorrect spectral response function
-



Drift in bias due to ice-build up on sensor:

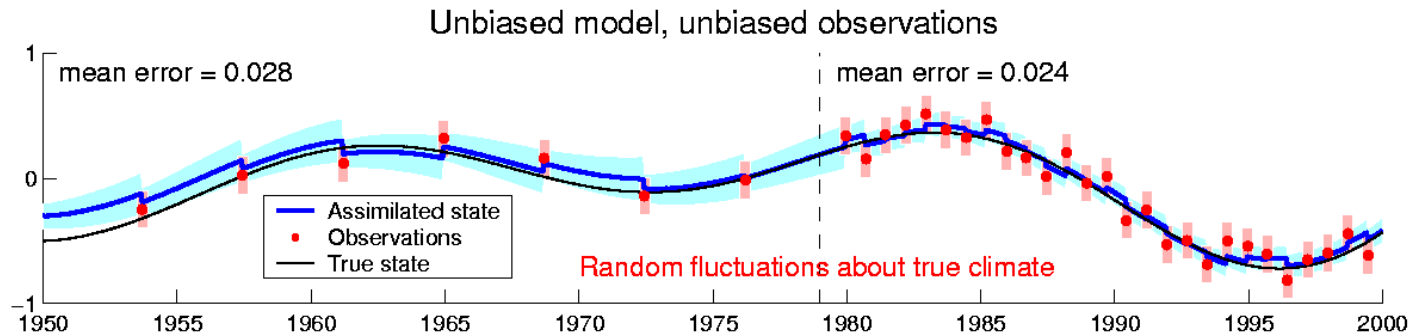


Implications for data assimilation: Bias problems in a nutshell

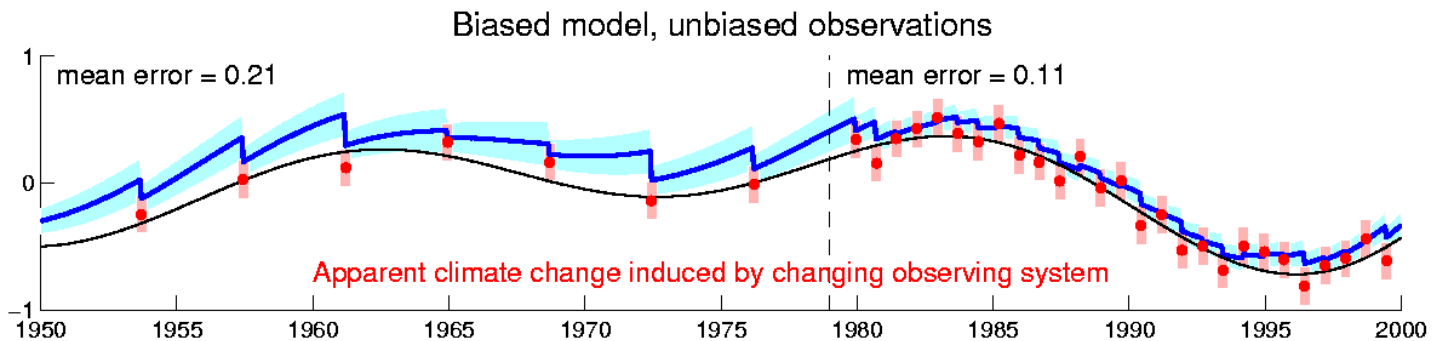
- **Observations and observation operators have biases, which may change over time**
 - Daytime warm bias in radiosonde measurements of stratospheric temperature; radiosonde equipment changes
 - Biases in cloud-drift wind data due to problems in height assignment
 - Biases in satellite radiance measurements and radiative transfer models
- **Models have biases, and changes in observational coverage over time may change the extent to which observations correct these biases**
 - Stratospheric temperature bias modulated by radiance assimilation
 - This is especially important for reanalysis (trend analysis)
- **Data assimilation methods are primarily designed to correct small (random) errors in the model background**
 - Large corrections generally introduce spurious signals in the assimilation
 - Likewise, inconsistencies among different parts of the observing system lead to all kinds of problems

Implications for data assimilation: The effect of model bias on trend estimates

Most assimilation systems assume unbiased models and unbiased data



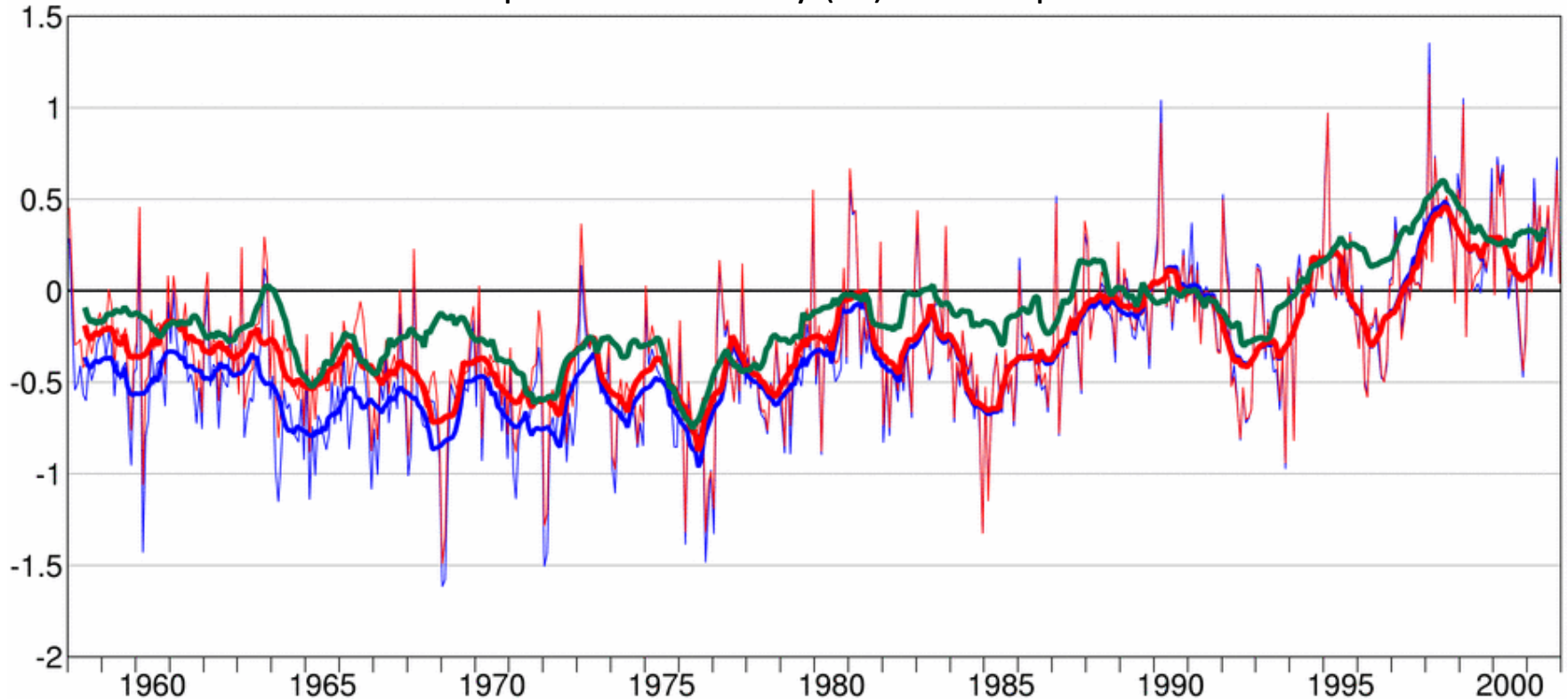
Biases in models and/or data can induce spurious trends in the assimilation



Implications for data assimilation:

ERA-40 surface temperatures compared to land-station values

Surface air temperature anomaly ($^{\circ}\text{C}$) with respect to 1987-2001



— Based on monthly CRUTEM2v data (Jones and Moberg, 2003)

— Based on ERA-40 reanalysis

— Based on ERA-40 model simulation (with SST/sea-ice data)

Outline

- Introduction
 - Biases in models, observations, and observation operators
 - Implications for data assimilation
- Variational analysis and correction of observation bias
 - The *need* for an adaptive system
 - The variational bias correction scheme: *VarBC*
- Extension to other types of observations
- Limitations due to the effects of model bias

Variational analysis and bias correction: A brief review of variational data assimilation

$$\text{Minimise } \mathbf{J}(\mathbf{x}) = \underbrace{(\mathbf{x}_b - \mathbf{x})^T \mathbf{B}^{-1} (\mathbf{x}_b - \mathbf{x})}_{\text{background constraint } (\mathbf{J}_b)} + \underbrace{[\mathbf{y} - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{h}(\mathbf{x})]}_{\text{observational constraint } (\mathbf{J}_o)}$$

- The input \mathbf{x}_b represents past information propagated by the forecast model
(the **model background**)
- The input $[\mathbf{y} - \mathbf{h}(\mathbf{x}_b)]$ represents the new information entering the system
(the **background departures**)
- The function $\mathbf{h}(\mathbf{x})$ represents a model for simulating observations
(the **observation operator**)
- Minimising the cost function $\mathbf{J}(\mathbf{x})$ produces an adjustment to the model background based on all used observations
(the **analysis**)

Variational analysis and bias correction: Error sources in the input data

$$\text{Minimise } \mathbf{J}(\mathbf{x}) = \underbrace{(\mathbf{x}_b - \mathbf{x})^T \mathbf{B}^{-1} (\mathbf{x}_b - \mathbf{x})}_{\text{background constraint } (\mathbf{J}_b)} + \underbrace{[\mathbf{y} - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{h}(\mathbf{x})]}_{\text{observational constraint } (\mathbf{J}_o)}$$

- **Errors in the input $[\mathbf{y} - \mathbf{h}(\mathbf{x}_b)]$ arise from:**
 - errors in the actual observations
 - errors in the model background
 - errors in the observation operator
- **There is no general method for separating these different error sources**
 - we only have information about differences
 - there is no true reference in the real world!
- **The analysis does not respond well to conflicting input information**

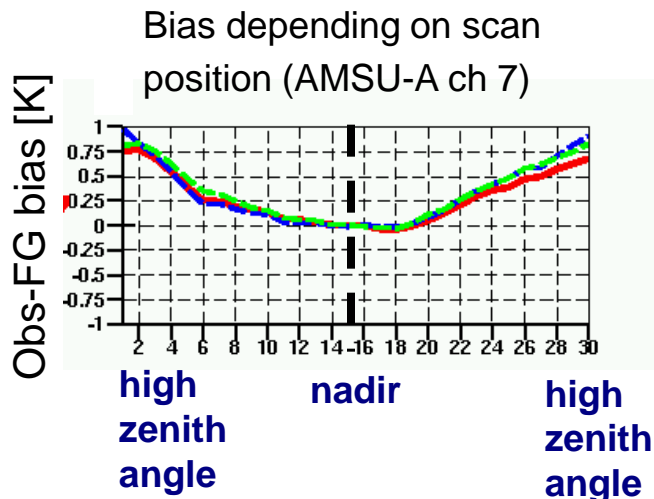
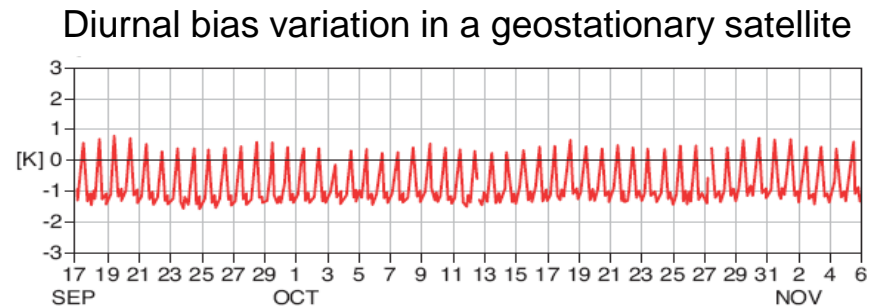
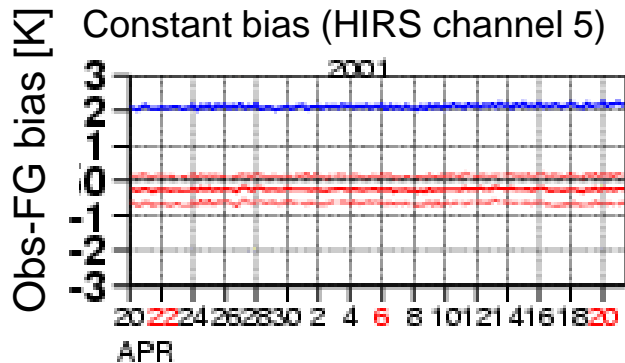
A lot of work is done to remove biases prior to assimilation:

 - ideally by removing the cause
 - in practise by careful comparison against other data

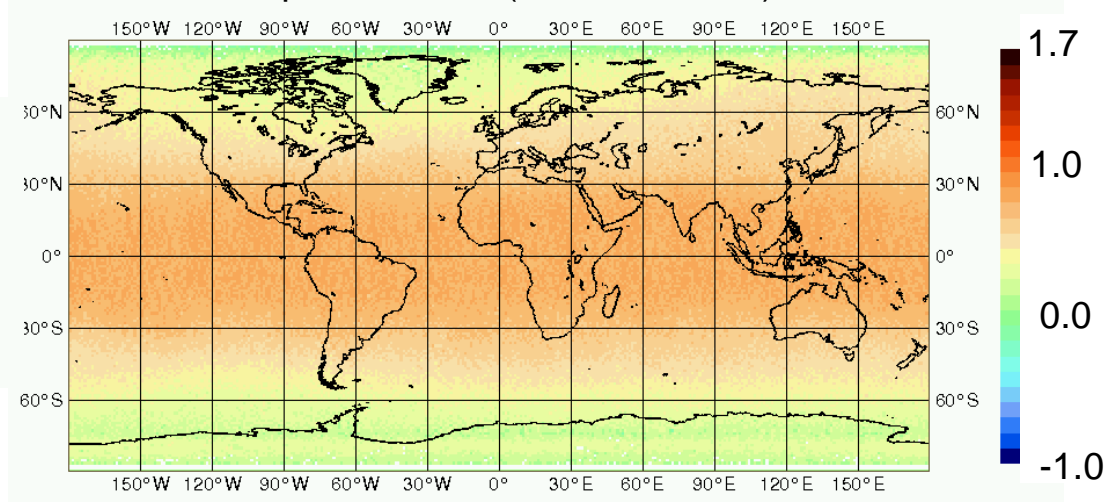
The need for an adequate bias model

Prerequisite for any bias correction is a good model for the bias ($b(x,\beta)$):

- Ideally, guided by the physical origins of the bias.
- In practice, bias models are derived empirically from observation monitoring.



Air-mass dependent bias (AMSU-A ch 10)



Satellite radiance bias correction at ECMWF, prior to 2006

Scan bias and **air-mass dependent bias** for each satellite/sensor/channel were estimated off-line from background departures, and stored in files (**Harris and Kelly 2001**)

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

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, for instance:

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

Average the background departures:

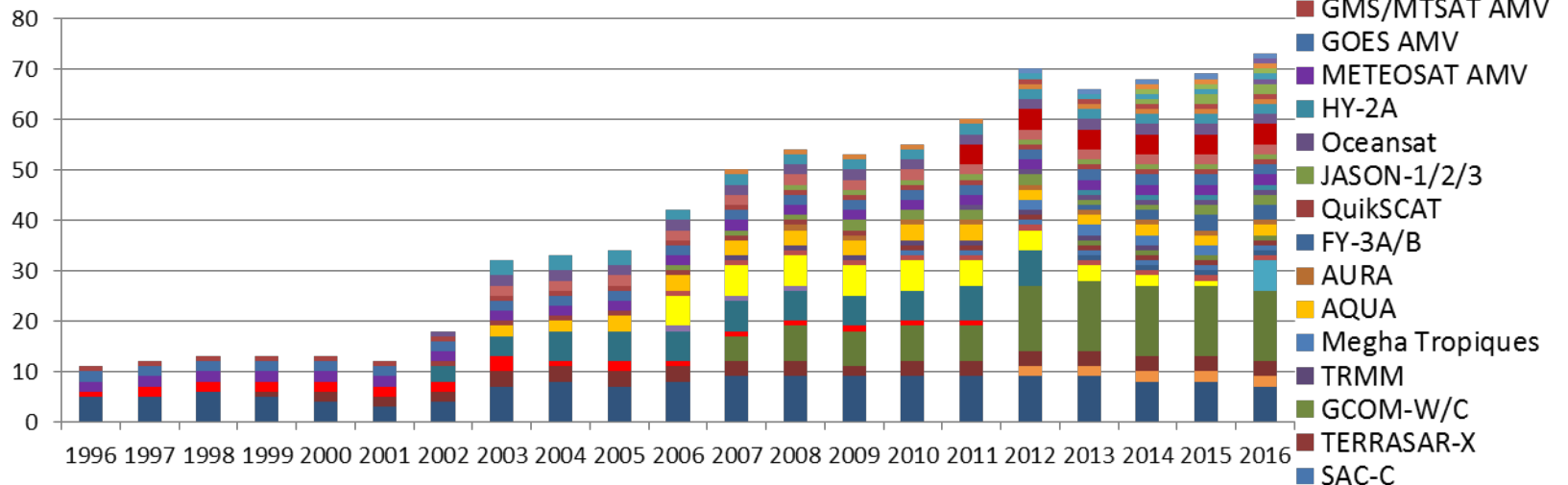
$$\langle y - h(x_b) \rangle = b^{scan} + b^{air}(x)$$

Periodically estimate scan bias and predictor coefficients:

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

The need for an adaptive bias correction system

- The observing system is increasingly complex and constantly changing
- It is dominated by satellite radiance data:
 - biases are flow-dependent, and may change with time
 - they are different for different sensors
 - they are different for different channels



- How can we manage the bias corrections for all these different components?
- This requires a consistent approach and a flexible, automated system

The Variational bias correction scheme: The general idea

The **bias** in a given instrument/channel (**bias group**) is described by (a few) **bias parameters**: typically, these are functions of air-mass and scan-position (the **predictors**)

These parameters can be estimated in a variational analysis along with the model state (**Derber and Wu, 1998 at NCEP, USA**)

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. A cycling scheme for updating the bias parameter estimates
3. An effective preconditioner for the joint minimization problem

Variational bias correction: The modified analysis problem

The original problem:

\mathbf{J}_b : background constraint

$$J(\mathbf{x}) = (\mathbf{x}_b - \mathbf{x})^T \mathbf{B}^{-1} (\mathbf{x}_b - \mathbf{x}) + \underbrace{[\mathbf{y} - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{h}(\mathbf{x})]}_{\mathbf{J}_o: \text{observation constraint}}$$

The modified problem:

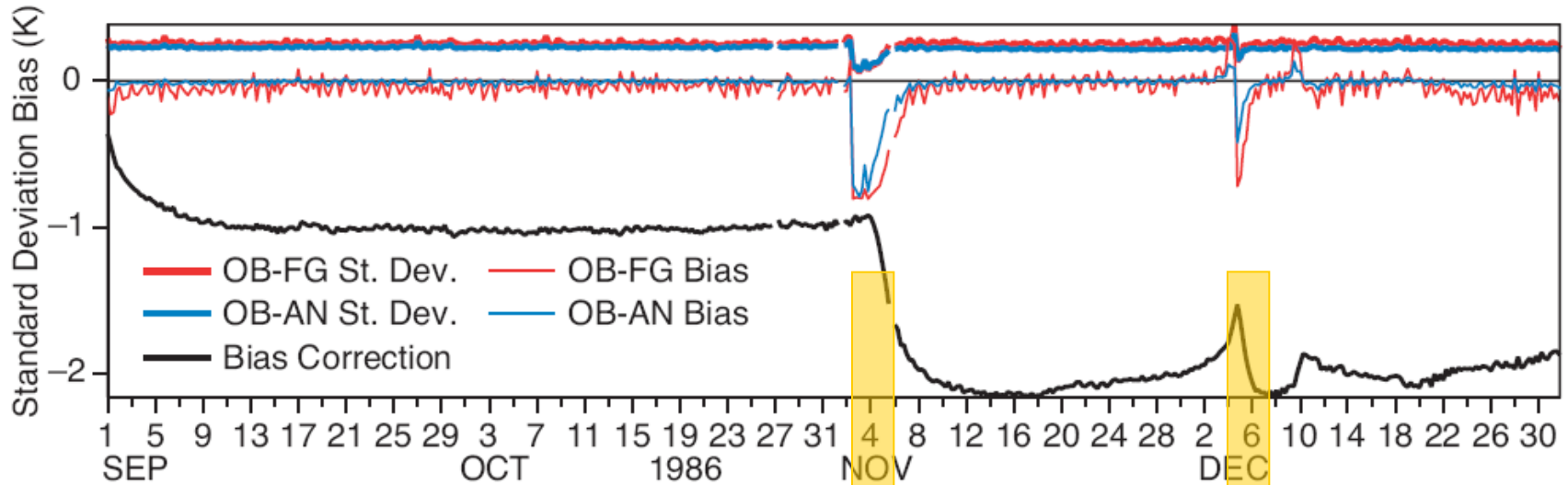
\mathbf{J}_b : background constraint for \mathbf{x} \mathbf{J}_β : background constraint for β

$$\mathbf{J}(\mathbf{x}, \beta) = (\mathbf{x}_b - \mathbf{x})^T \mathbf{B}_x^{-1} (\mathbf{x}_b - \mathbf{x}) + \underbrace{(\beta_b - \beta)^T \mathbf{B}_\beta^{-1} (\beta_b - \beta)}_{\mathbf{J}_\beta: \text{background constraint for } \beta} + \underbrace{[\mathbf{y} - \mathbf{b}_o(\mathbf{x}, \beta) - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{b}_o(\mathbf{x}, \beta) - \mathbf{h}(\mathbf{x})]}_{\mathbf{J}_o: \text{bias-corrected observation constraint}}$$

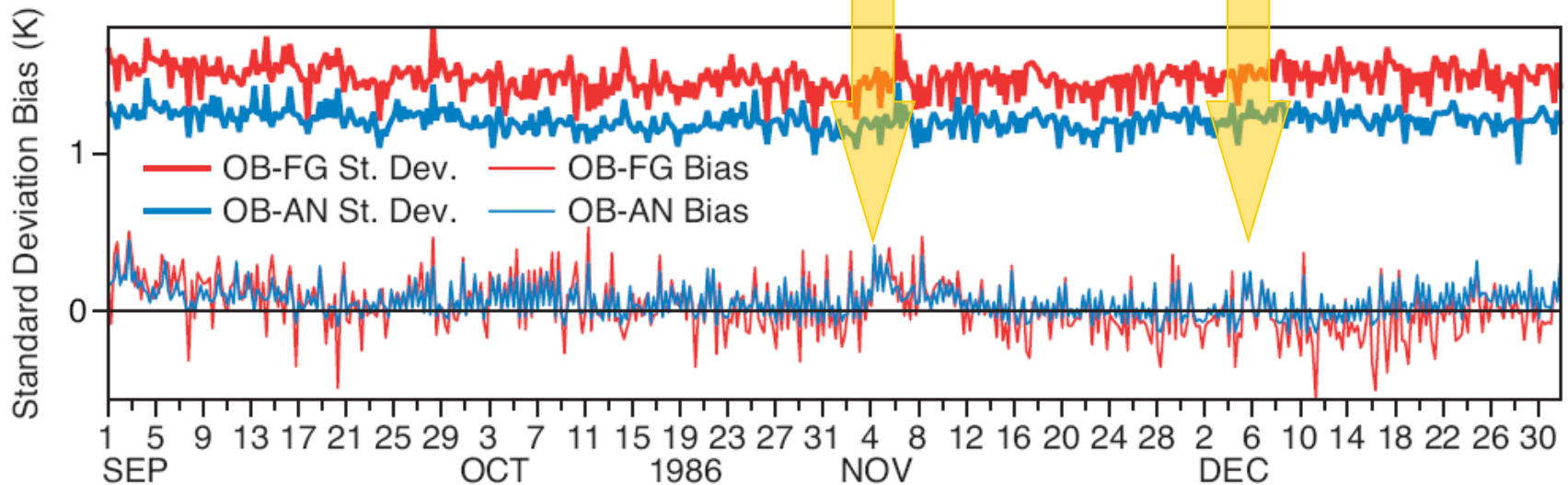
Parameter estimates from previous analysis →

Example 2:

NOAA-9 MSU channel 3 bias corrections (cosmic storm)



200 hPa temperature departures from radiosonde observations



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Extension to other types of observations

Current bias 'classes' in the ECMWF operational system:

- ***Radiances***: clear sky/all sky, infrared/microwave, polar/geostationary
- ***Total column ozone***: currently only OMI
- ***Aircraft data***: one group per aircraft
- ***Total column water vapour***: ENVISAT MERIS until April 2012
- ***Ground-based radar precipitation***: one group embracing US stations

Other automated bias corrections, but outside 4D-Var:

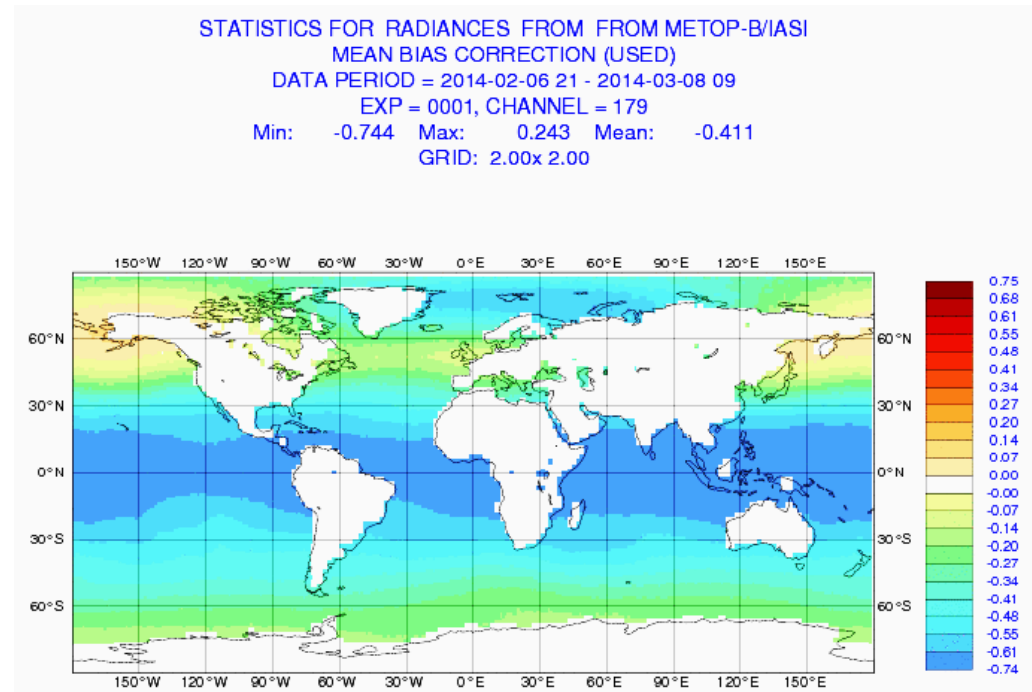
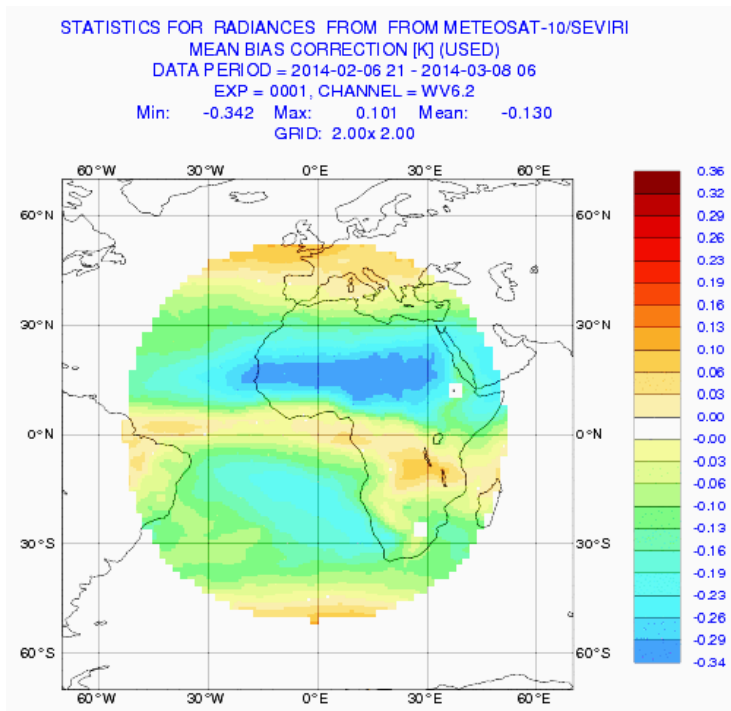
- Surface pressure
- Radiosonde temperature and humidity

Specific:

- ***ERA-Interim***: VarBC for radiances only
- ***ERA-20C***: the 20th century reanalysis using surface observations only
- ***MACC***: atmospheric composition

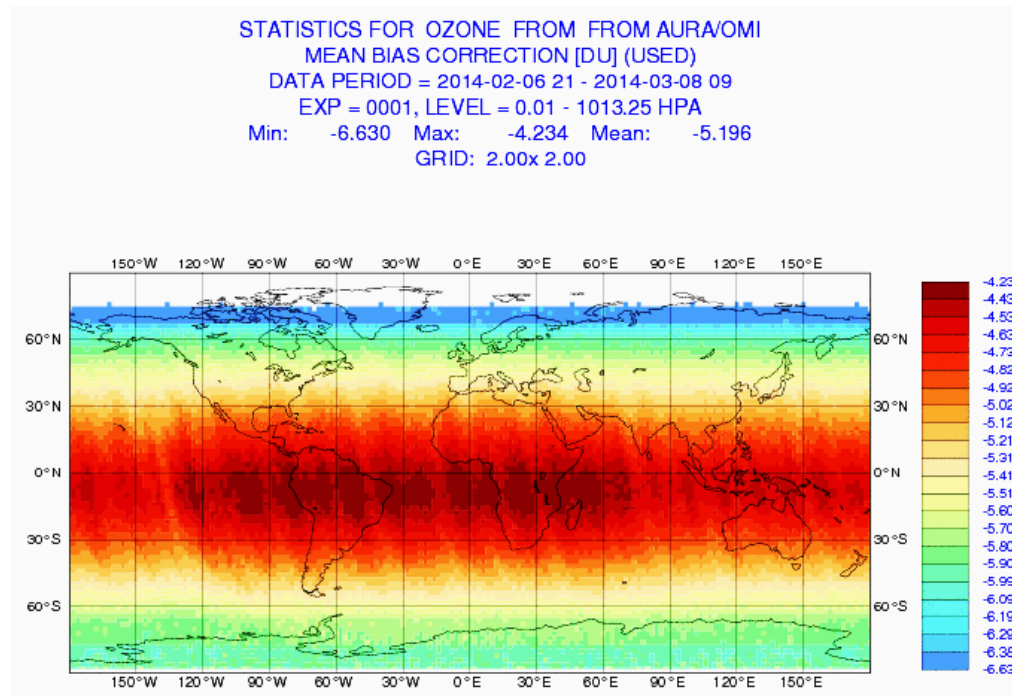
VarBC for satellite *radiances*

- **~1,500** channels (~40 sensors on ~25 different satellites)
- **Anchored** to each other, GPS-RO, and all conventional observations
- Bias model: $\beta_0 + \sum \beta_i p_i(\text{model state}) + \sum \beta_j p_j(\text{instrument state})$
(~11,400 parameters in total)



VarBC for *ozone*

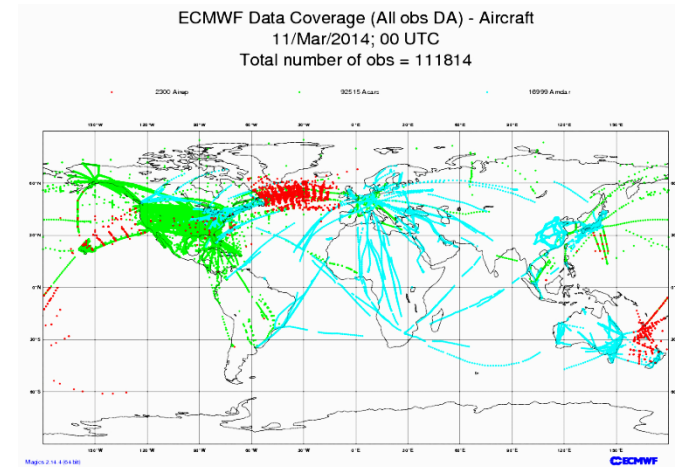
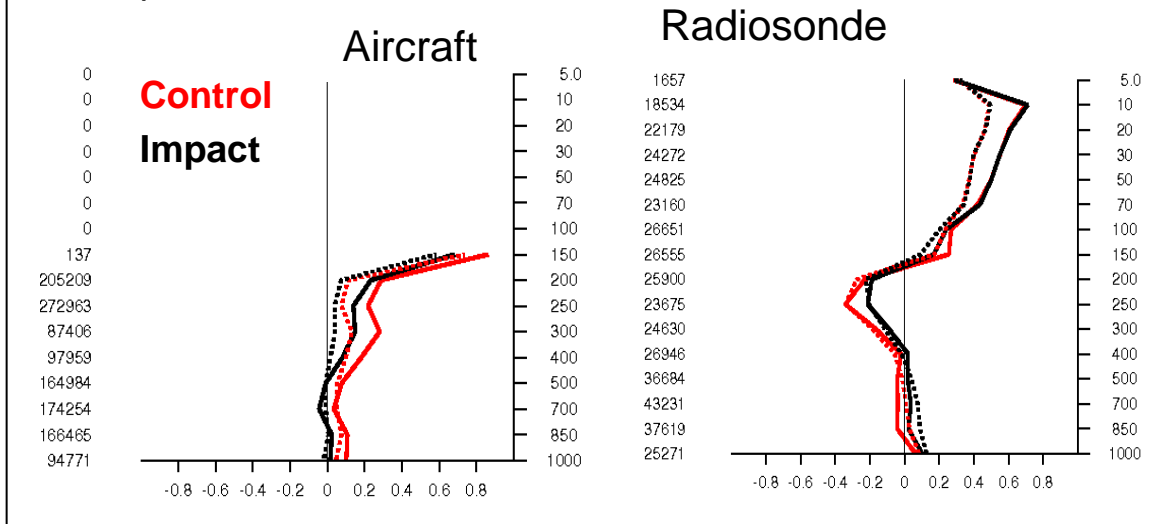
- OMI, (SCIAMACHY, GOMOS, SEVIRI, GOME2, GOME in past)
- **Anchored** to SBUV/2
- Bias model: $\beta_0 + \beta_1 \times \text{solar elevation}$



VarBC for *aircraft temperature*

- For each aircraft separately (~5000 distinct aircraft)
- **Anchored** to all temperature-sensitive observations
- Bias model: $\beta_0 + \beta_1 \times \text{ascent rate} + \beta_2 \times \text{descent rate}$

Average temperature departures for the northern hemisphere during a 2-week period



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Limitations of VarBC: Interaction with model bias

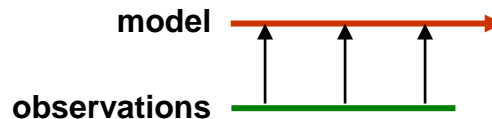
VarBC introduces extra degrees of freedom in the variational analysis, to help improve the fit to the (bias-corrected) observations:

$$\mathbf{J}(\mathbf{x}, \boldsymbol{\beta}) = (\mathbf{x}_b - \mathbf{x})^T \mathbf{B}_x^{-1} (\mathbf{x}_b - \mathbf{x}) + (\boldsymbol{\beta}_b - \boldsymbol{\beta})^T \mathbf{B}_\beta^{-1} (\boldsymbol{\beta}_b - \boldsymbol{\beta}) + [\mathbf{y} - \mathbf{b}(\mathbf{x}, \boldsymbol{\beta}) - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{b}(\mathbf{x}, \boldsymbol{\beta}) - \mathbf{h}(\mathbf{x})]$$

It works well (even if the model is biased) when the analysis is strongly constrained by observations:



It does not work as well when there are large model biases and few observations to constrain them:



VarBC is not designed to correct model biases: Need for a **weak-constraints 4D-Var (Trémolet)**

Summary

Biases are everywhere:

- Most observations cannot be usefully assimilated without bias adjustments
- Off-line bias tuning for satellite data is practically impossible
- Bias parameters can be estimated and adjusted during the assimilation, using all available information
- Variational bias correction works best in situations where:
 - there is sufficient redundancy in the data; or
 - there are no large model biases

Challenges:

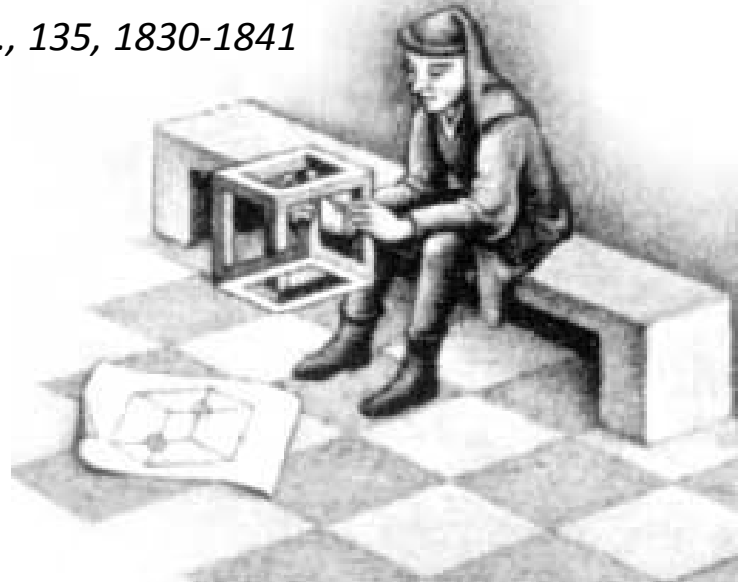
- How to develop good bias models for observations
- How to separate observation bias from model bias

Additional information

- Harris and Kelly, 2001: **A satellite radiance-bias correction scheme for data assimilation.** *Q. J. R. Meteorol. Soc.*, 127, 1453-1468
- Derber and Wu, 1998: **The use of TOVS cloud-cleared radiances in the NCEP SSI analysis system.** *Mon. Wea. Rev.*, 126, 2287-2299
- Dee, 2004: **Variational bias correction of radiance data in the ECMWF system.** Pp. 97-112 in *Proceedings of the ECMWF workshop on assimilation of high spectral resolution sounders in NWP, 28 June-1 July 2004, Reading, UK*
- Dee, 2005: **Bias and data assimilation.** *Q. J. R. Meteorol. Soc.*, 131, 3323-3343
- Dee and Uppala, 2009: **Variational bias correction of satellite radiance data in the ERA-Interim reanalysis.** *Q. J. R. Meteorol. Soc.*, 135, 1830-1841

Feel free to contact me with questions:

Hans.Hersbach@ecmwf.int



VarBC for *total column water vapour*

- ENVISAT/MERIS until April 2012
- Anchored to all other humidity-sensitive observations
- Bias model: $\beta_0 + \beta_1 \times \text{TCWV}(\text{model state})$

Statistics for Total Column Water Vapor from ENVISAT/MERIS
MEAN BIAS CORRECTION [kg/m²] (All)
Data Period = 2011-03-28 09 - 2011-05-07 09
EXP = 0001, Channel = 1
Min: -1.89736 Max: 0.250089 Mean: -0.630024

