# Observational bias correction in data assimilation

Niels Bormann, with material from

Hans Hersbach and Dick Dee

Meteorological Training Course
Data Assimilation

13 March 2019

# Overview of this lecture

In this lecture we look at ***observational biases***, and 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 ***with 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 the ***characteristics of bias vary widely*** depending on the type of instrument,
2. ***Distinguishing model bias from observation bias*** is often difficult,
3. The success of an adaptive system implicitly relies on a ***redundancy*** in the underlying observing system.

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**?**

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

**model** background constraint — **observational** constraint

Bias: **mean(y-h(x))** (can be situation-dependent)

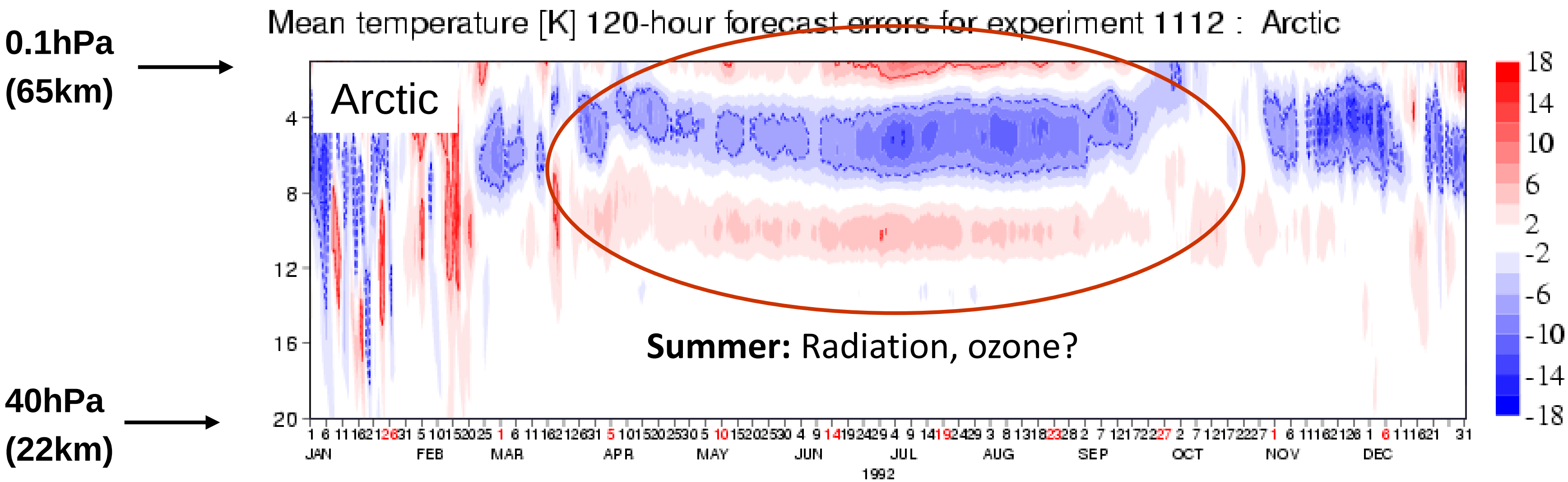
# Outline

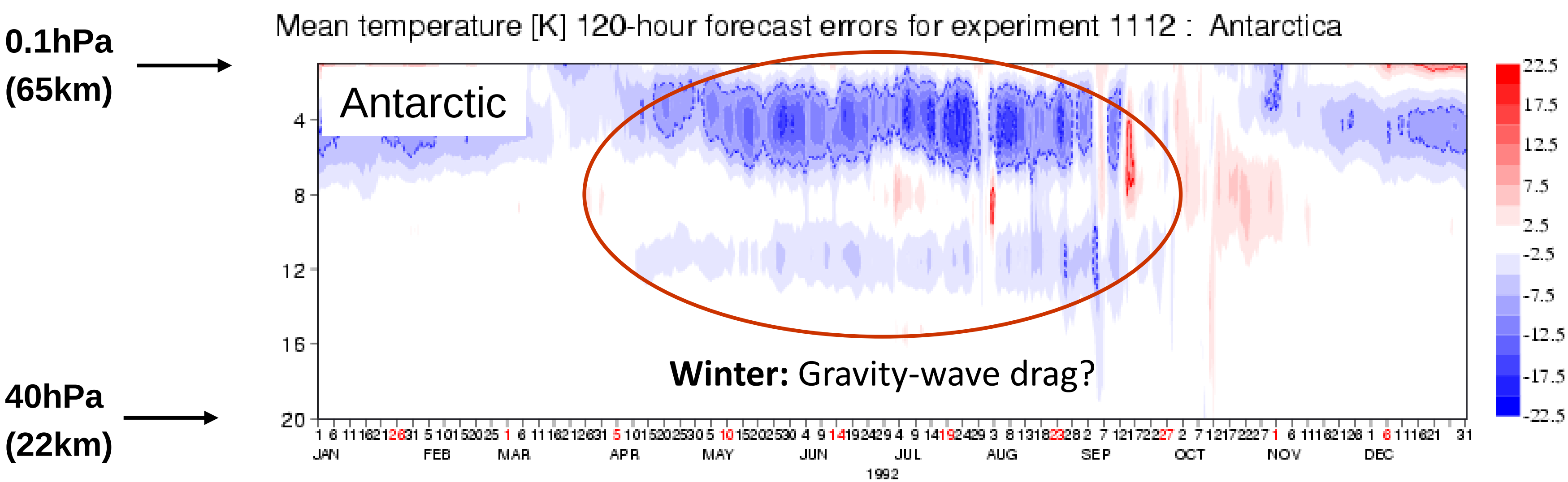
- Introduction
  - Biases in ***models***, ***observations***, and ***observation operators***
  - Implications for ***data assimilation***
- Variational analysis and correction of observation bias
  - The need for an adaptive system
  - Variational bias correction (VarBC)
- Limitations of VarBC

# Model bias:

## Seasonal variation in upper-stratospheric model errors

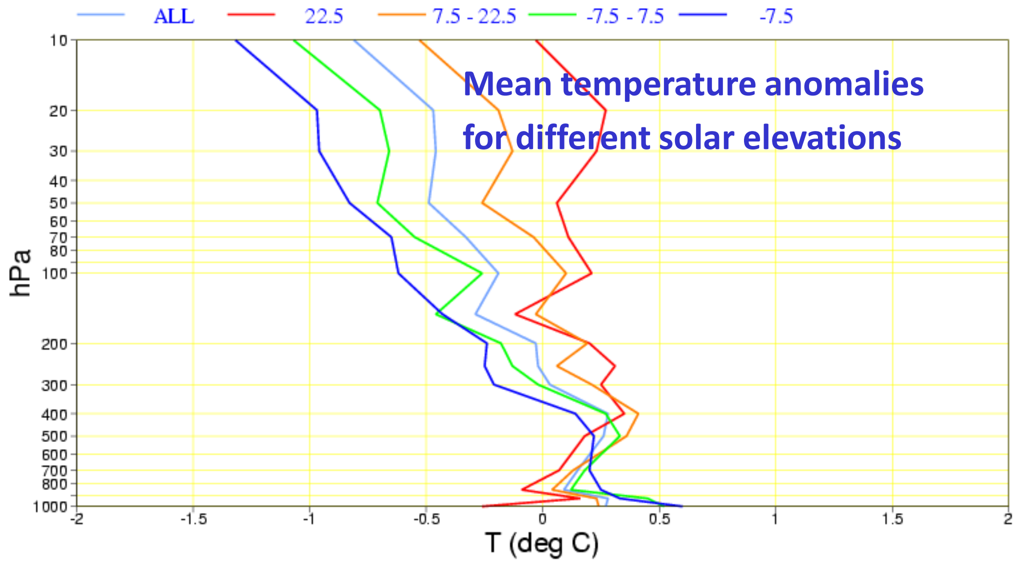
T255L60 model used for the ***ERA-Interim*** reanalysis



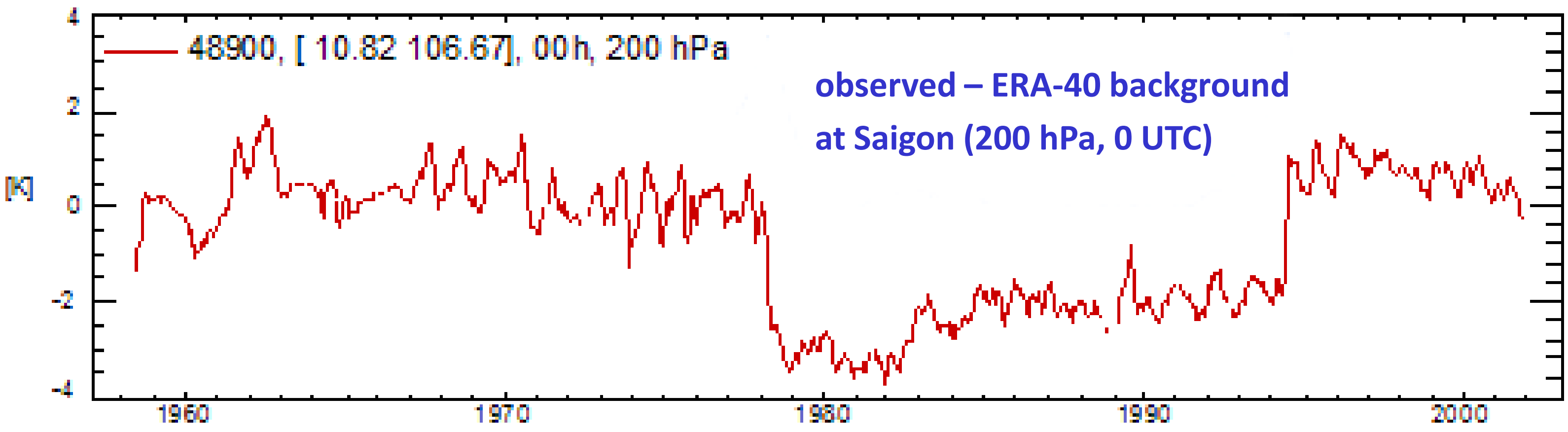



# Observation bias:
## Radiosonde temperature observations

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



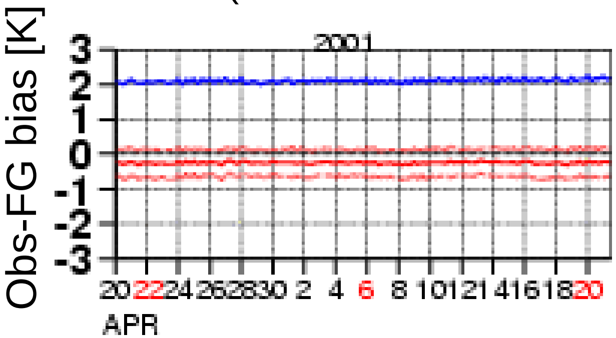

**Bias changes due to change of equipment**



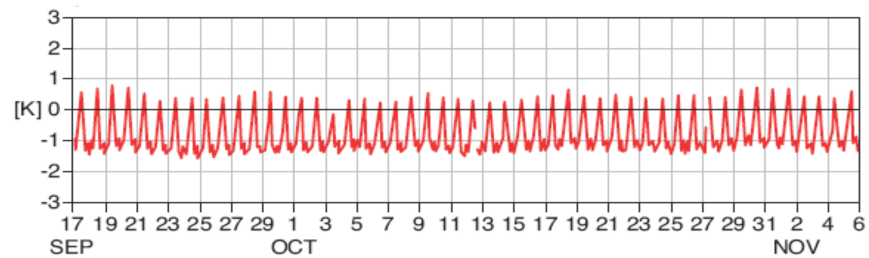
# Observation and observation operator bias:
## Satellite radiances

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

Constant bias (NOAA-14 HIRS channel 5)

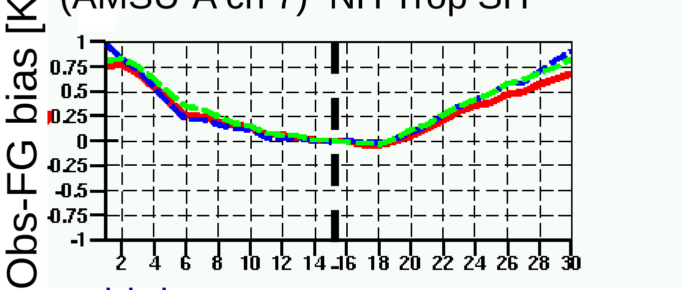



Diurnal bias variation in a geostationary satellite




Bias depending on scan position

(AMSU-A ch 7) NH Trop SH

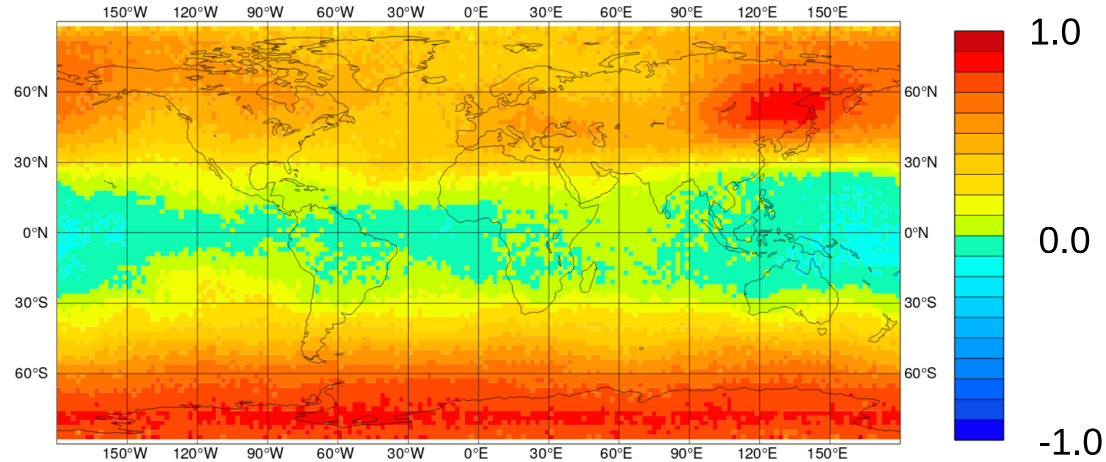



high zenith angle

nadir

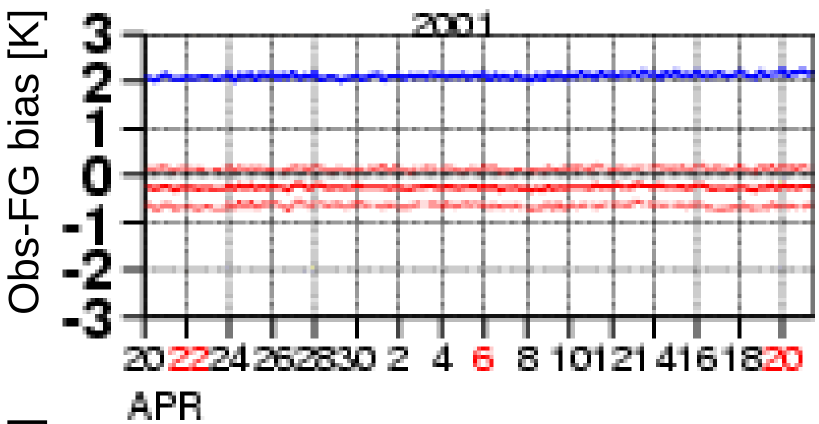
high zenith angle

Air-mass dependent bias (AMSU-A ch 8)

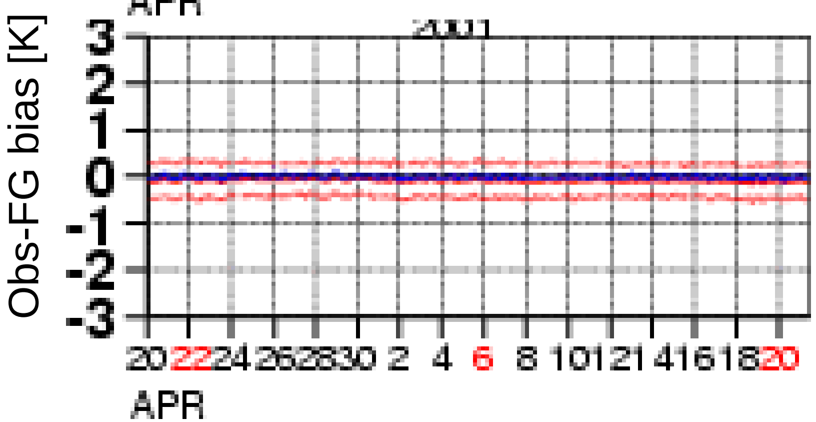


## Observation and observation operator bias:
### Satellite radiances – sources of bias

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.

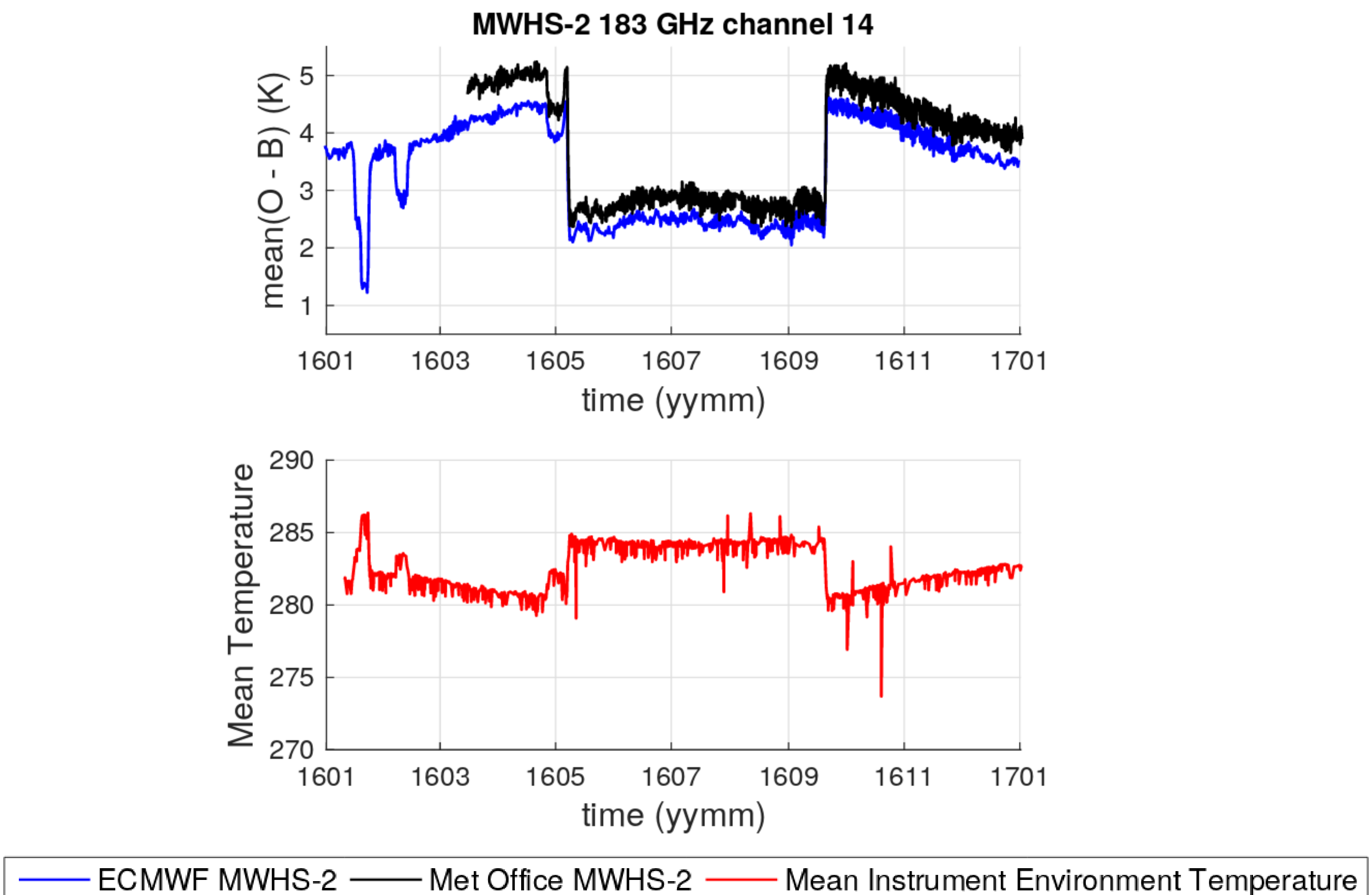



Same channel on NOAA-16 satellite has no radiance bias against FG.

→ NOAA-14 channel 5 has an instrument bias.

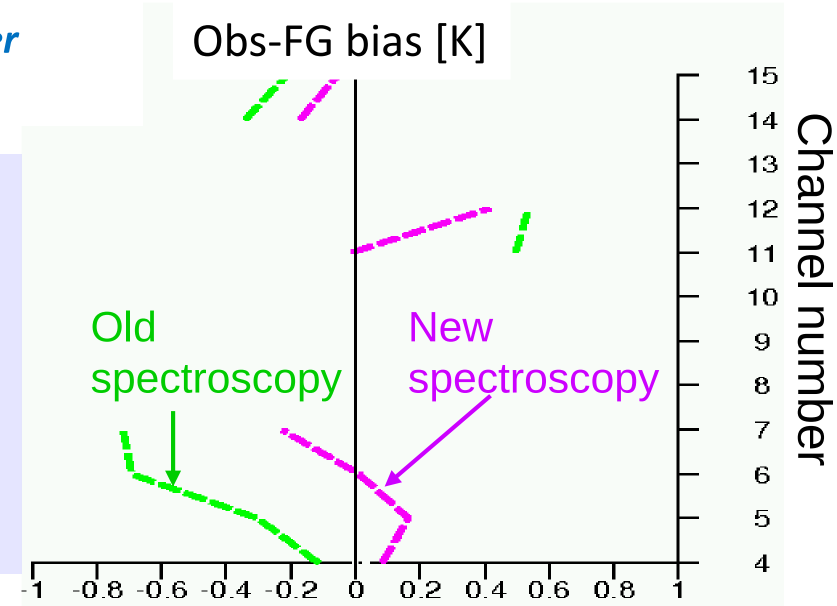
# Observation and observation operator bias:
## Satellite radiances – sources of bias

A time-varying bias, apparently dependent on the temperature of the satellite instrument:



# Observation and observation operator bias:
## Satellite radiances – sources of bias

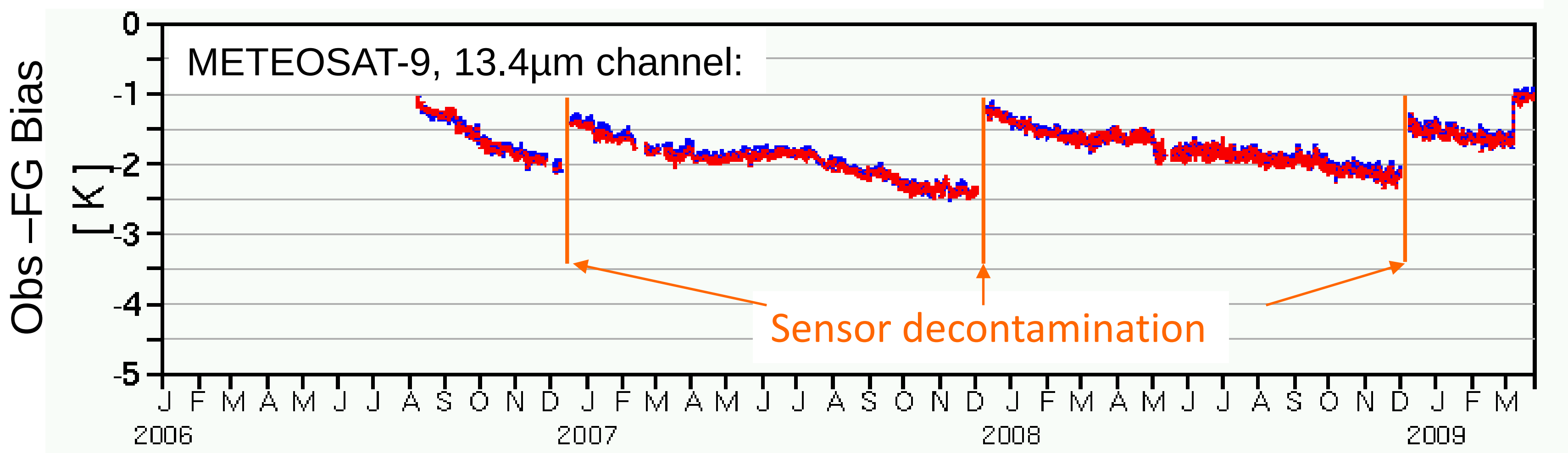
Different spectroscopy in the ***radiative transfer model*** can lead to different bias, e.g. for HIRS:




Other common causes for biases in radiative transfer:

- Bias in assumed concentrations of atmospheric gases (e.g., $CO_2$, 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

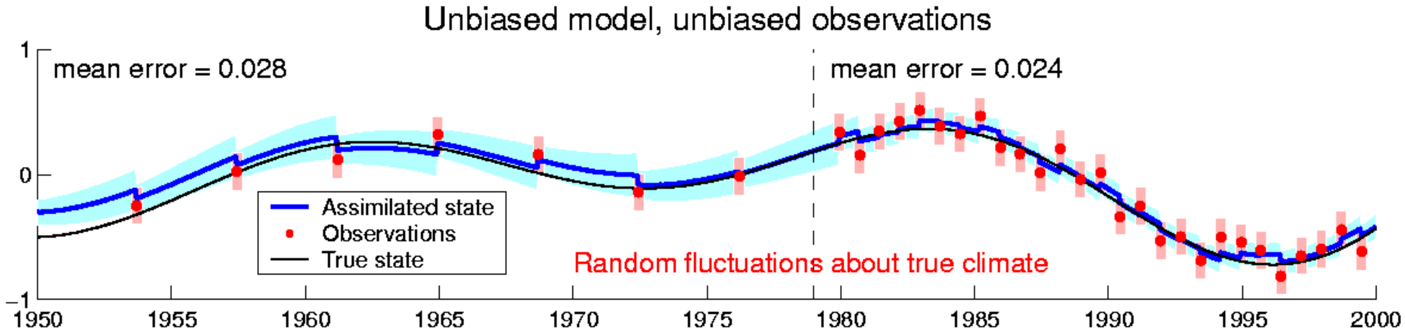
- **Observations and observation operators have biases, which may change over time**
  - Daytime warm bias in radiosonde measurements of stratospheric temperature; radiosonde equipment changes
  - Biases in satellite radiance measurements and radiative transfer models
  - Biases in cloud-drift wind data due to problems in height assignment

- **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)

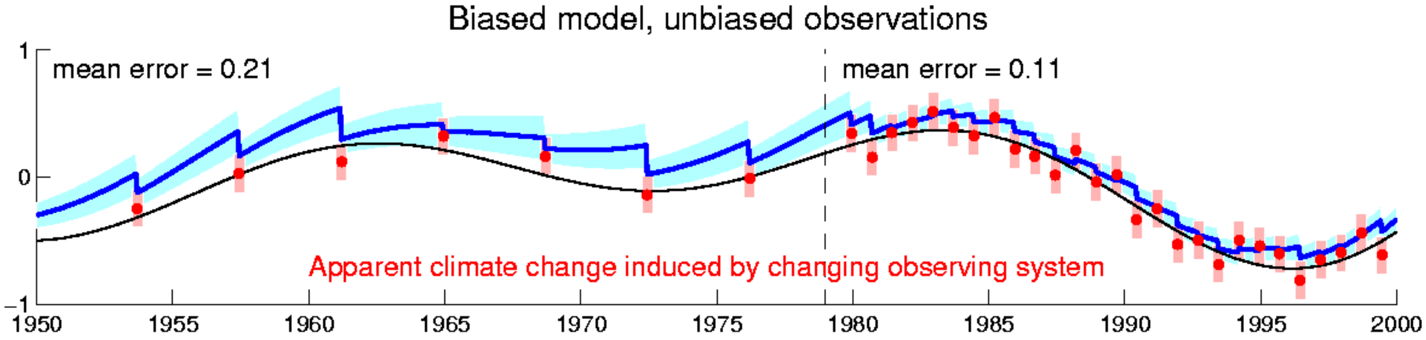
- **Data assimilation methods are primarily designed to correct *small random errors* in the model background**
  - Systematic inconsistencies among different parts of the observing system lead to all kinds of problems

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

Most assimilation systems assume unbiased models and unbiased data

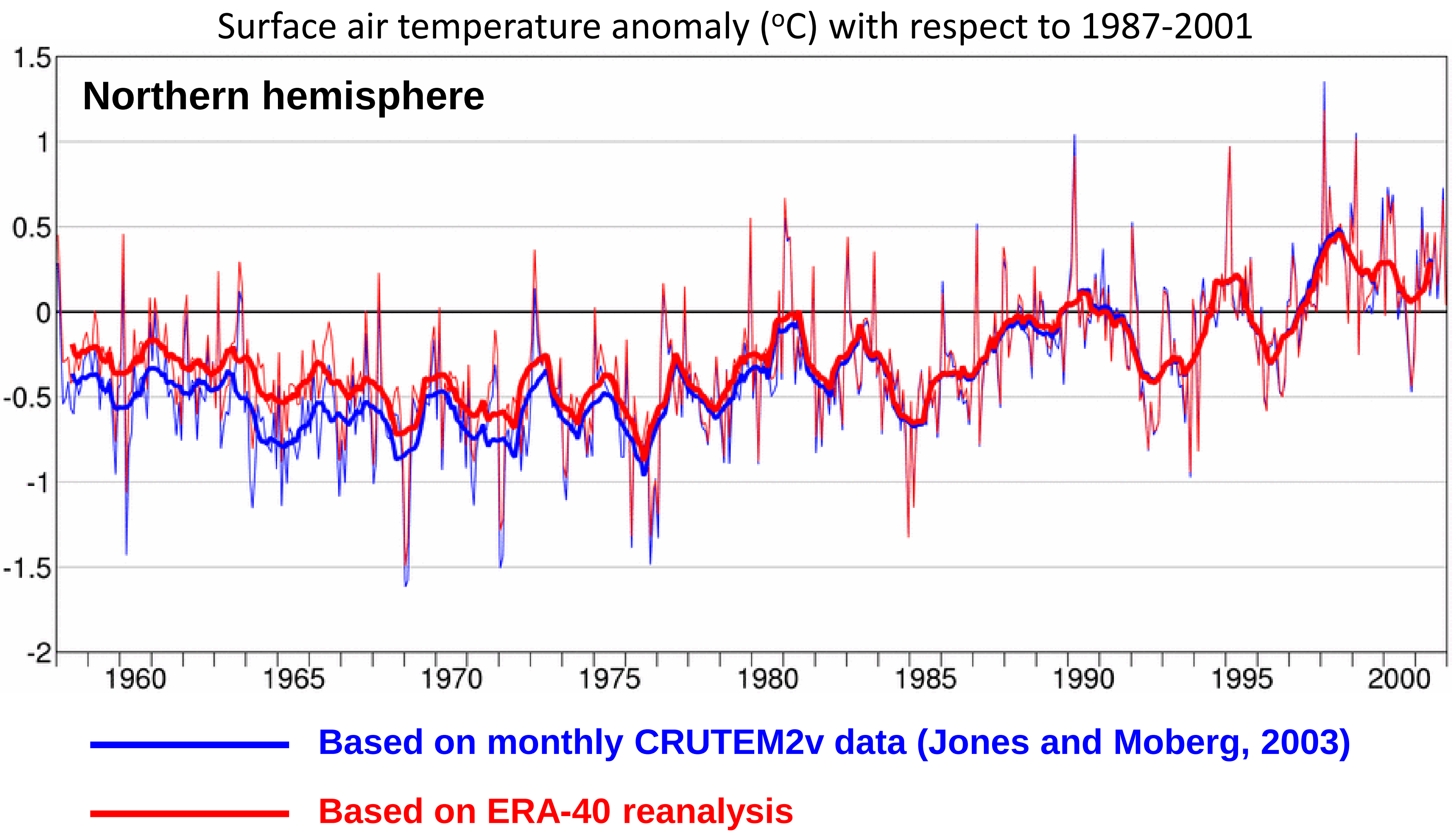



Biases in models and/or data can induce spurious trends in the assimilation



Implications for data assimilation:

ERA-40 surface temperatures compared to land-station values



# 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***

- Limitations of VarBC

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

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

- The input $x_b$ represents past information propagated by the forecast model

  (the model background)

- The input $[y - h(x_b)]$ represents the new information entering the system

  (the background departures)

- The function h(x) represents a model for simulating observations

  (the observation operator)

- Minimising the cost function J(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

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

- **Errors in the input [y – h($x_b$)] 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**

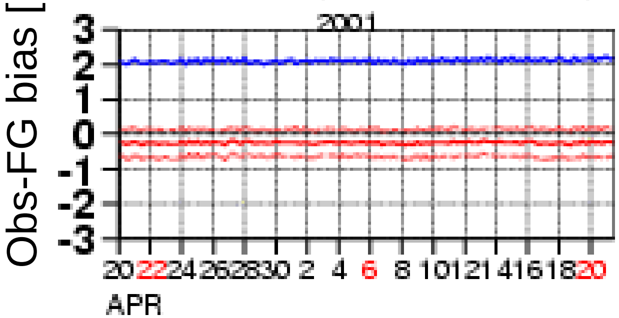
  A lot of work is done to remove biases prior to assimilation:
  - ideally by removing the cause
  - in practise by careful comparison against other data

# The need for an adequate bias model

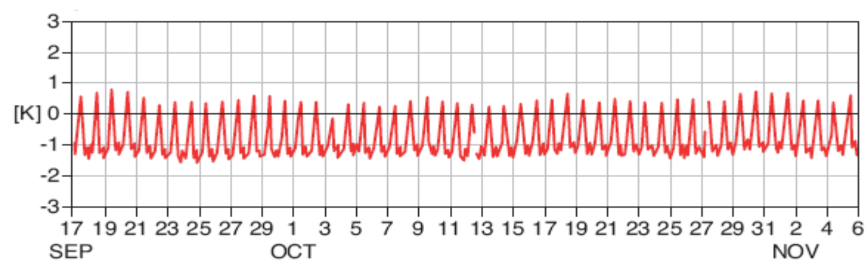
Prerequisite for any bias correction is a good model for the bias (b(x,β)):

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

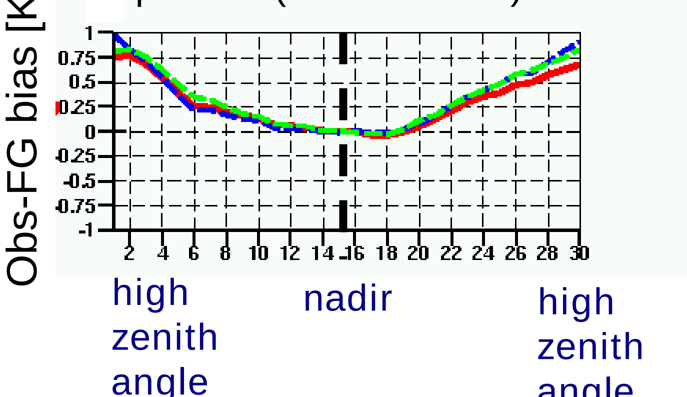
Constant bias (HIRS channel 5)



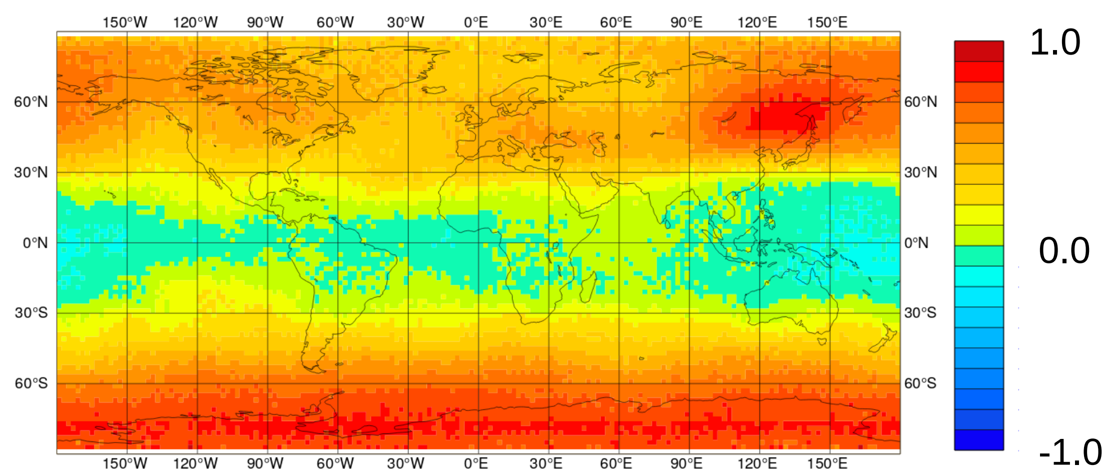

Diurnal bias variation in a geostationary satellite




Bias depending on scan position (AMSU-A ch 7)



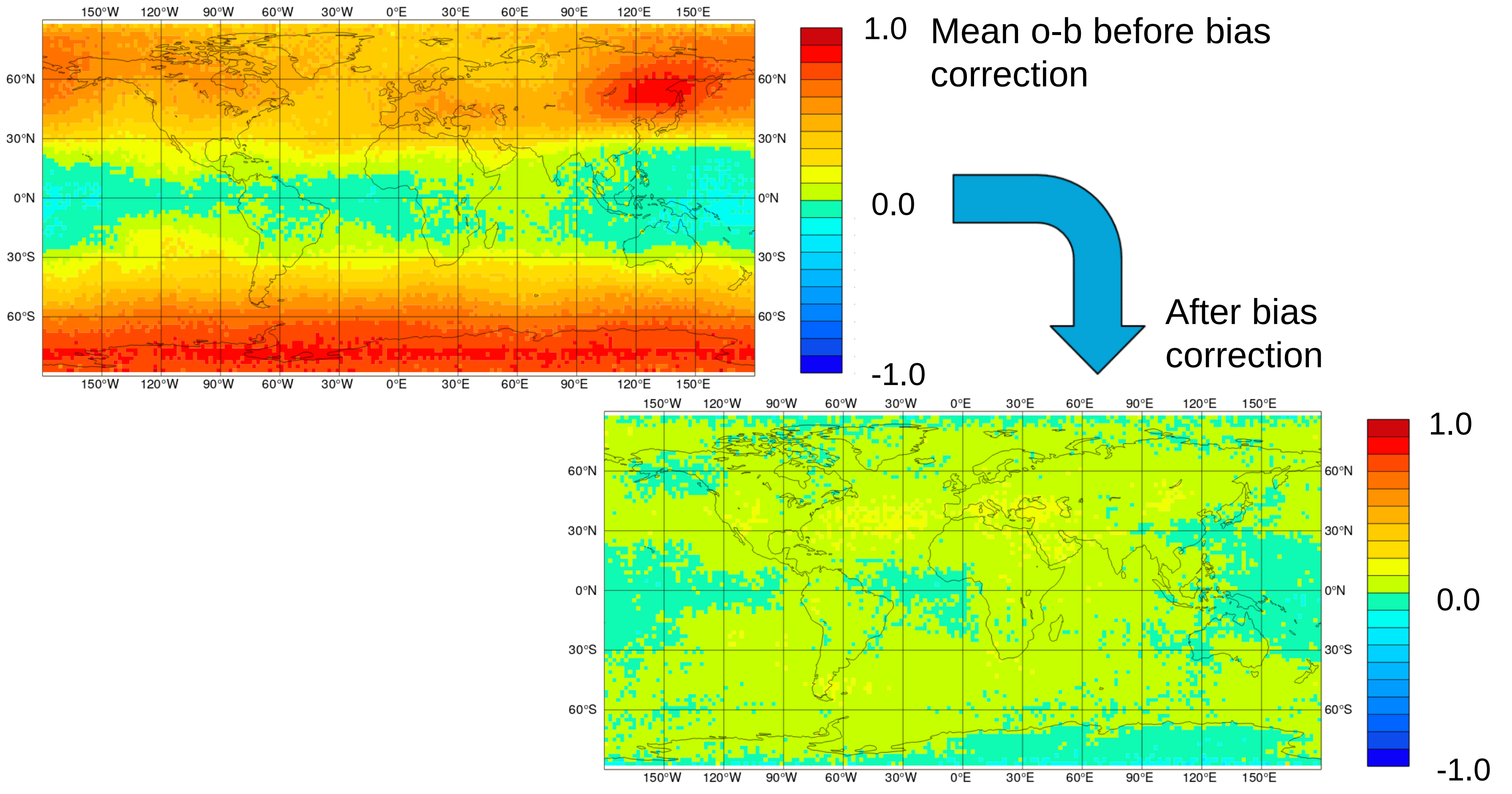

Air-mass dependent bias (AMSU-A ch 8)



# The need for an adequate bias model

Prerequisite for any bias correction is a good model for the bias (b(**x**,**β**)):

- For instance, a linear model with some predictors $p_1$, $p_2$, … $p_n$, and free parameters $\beta_0$, $\beta_1$, $\beta_{2,}$ … $\beta_n$ : $b(\mathbf{x},\boldsymbol{\beta}) = \beta_0 + \beta_1\, p_1 + \beta_2\, p_2 + \ldots + \beta_n\, p_n$
- Avoid models with too many free parameters.



# 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

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

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

$$e^{obs} = \text{random observation error}$$

**Predictors, for instance:**

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

Average the background departures:

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

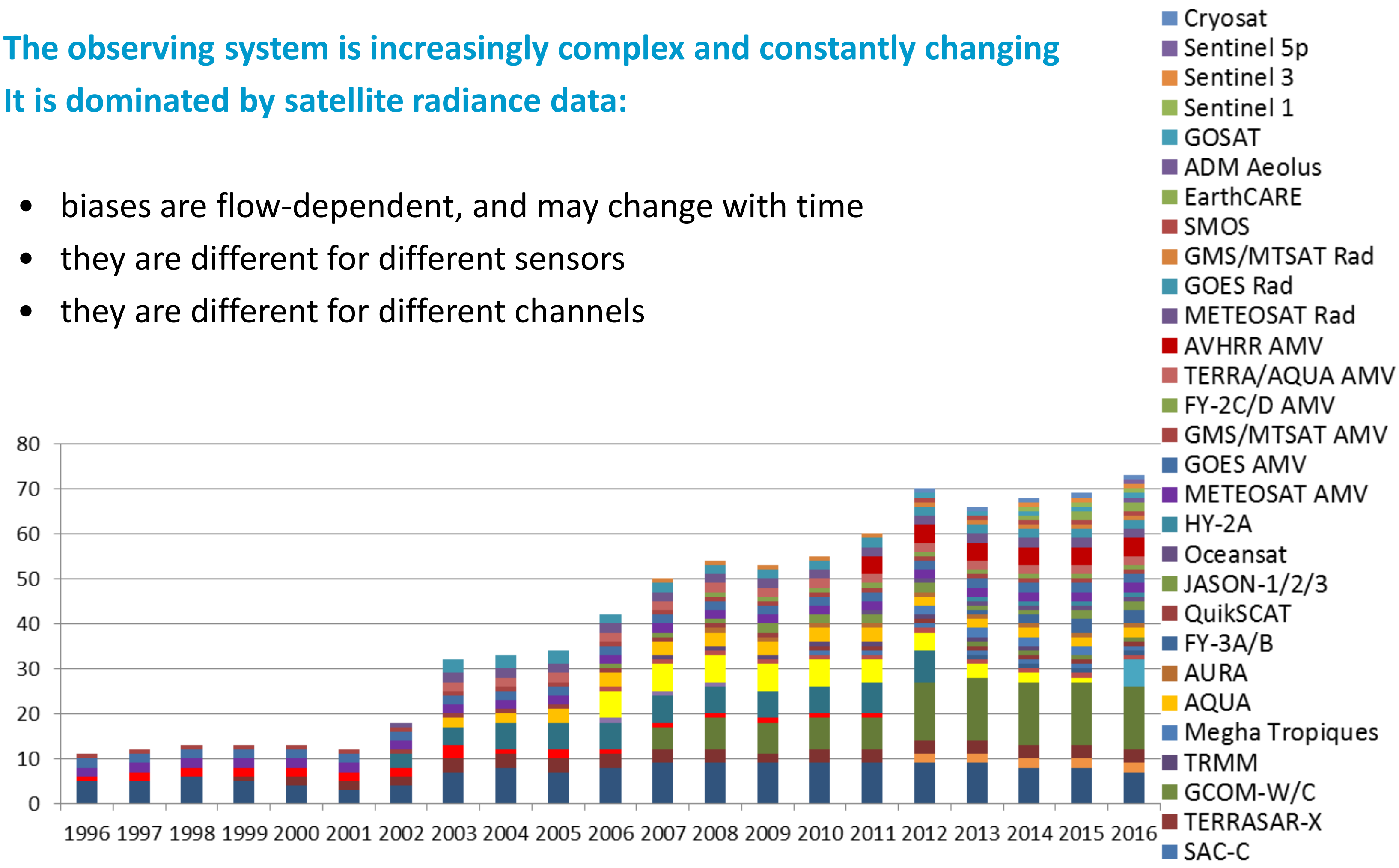
Periodically estimate scan bias and predictor coefficients:

- 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**

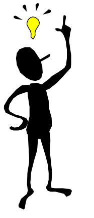
# The Variational Bias Correction scheme:
## The general idea

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: $z^T = [\, x^T \;\; \beta^T \,]$

**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:

$J_b$: background constraint

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

$J_o$: observation constraint

The modified problem:

$J_b$: background constraint for x

$J_\beta$: background constraint for β

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

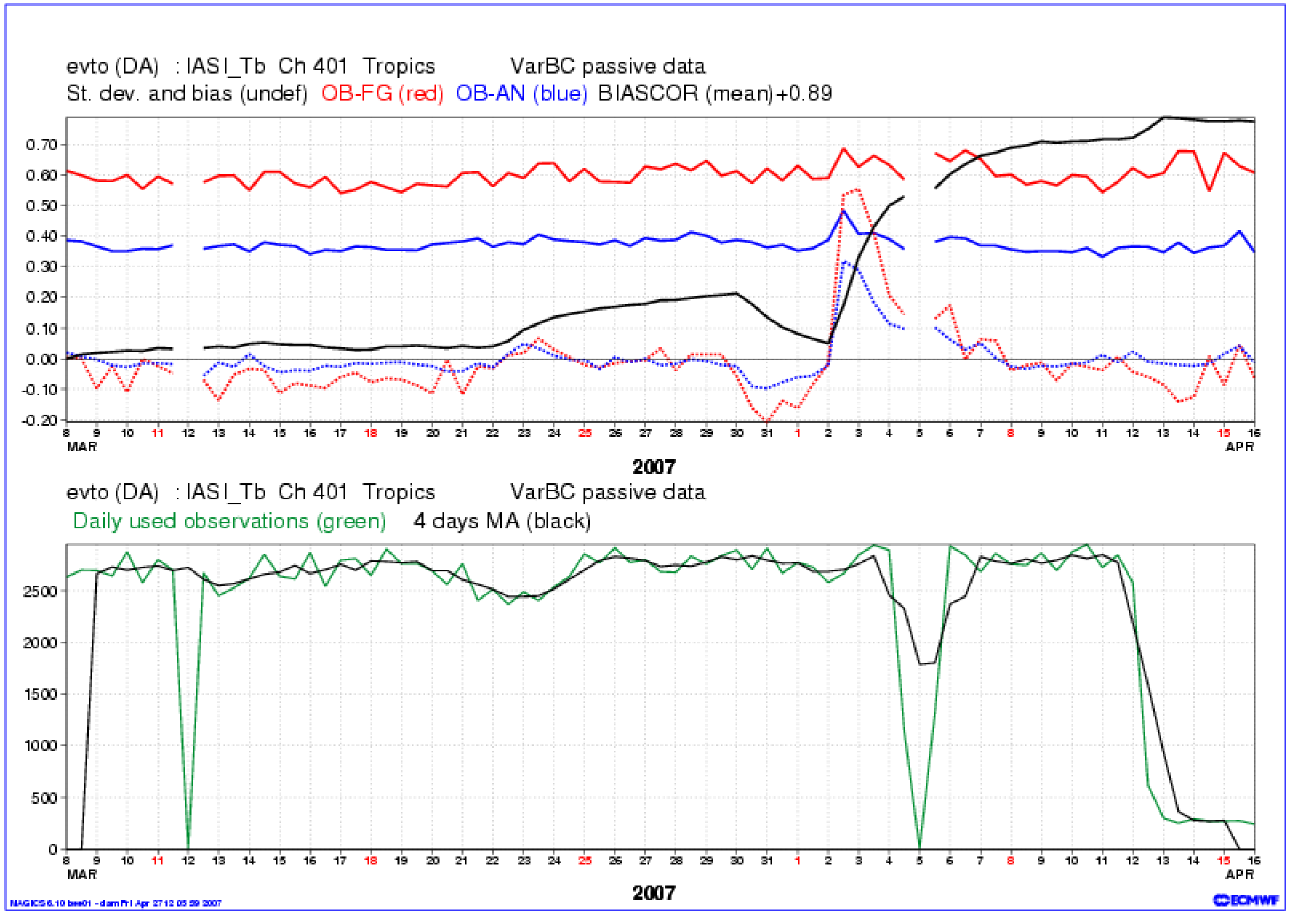
Parameter estimates from previous analysis

$J_o$: bias-corrected observation constraint

A model for the observation bias

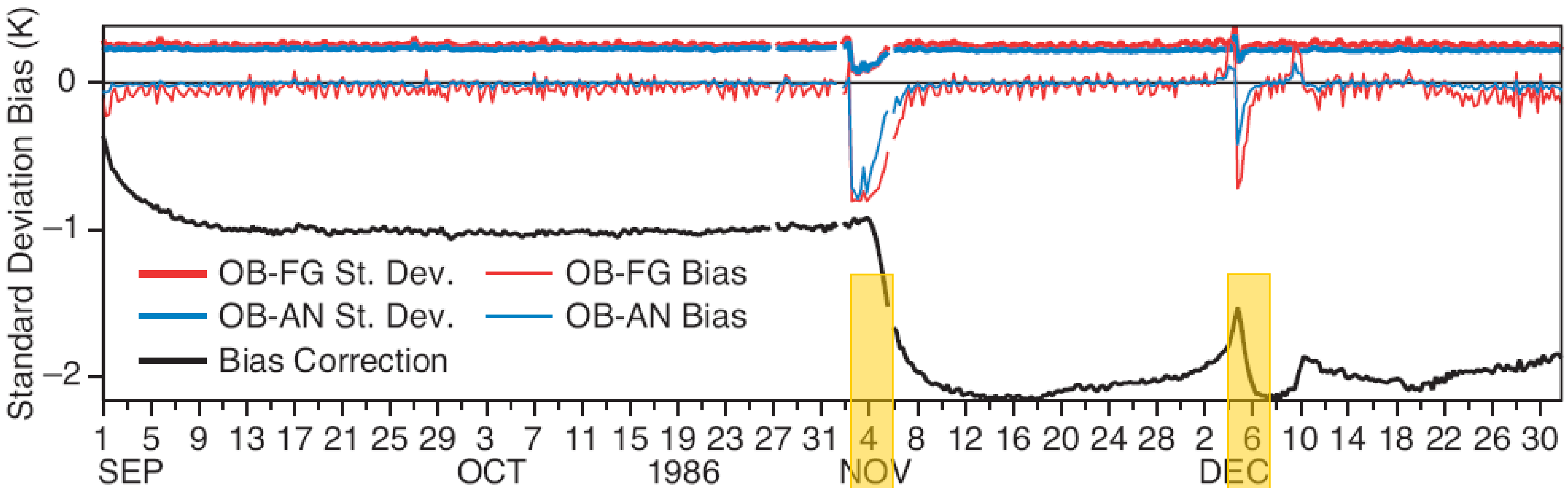
# Example 1:
## Spinning up new instruments – IASI on MetOp A

- IASI is a high-resolution interferometer with 8461 channels
- Initially unstable – data gaps, preprocessing changes

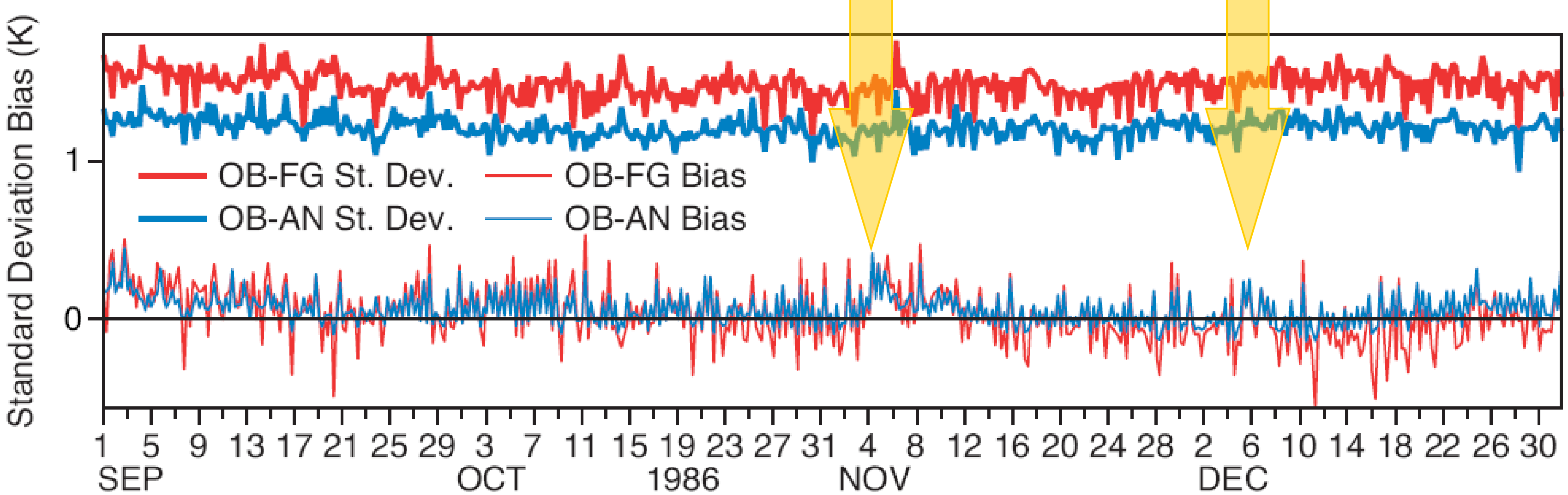


Example 2:

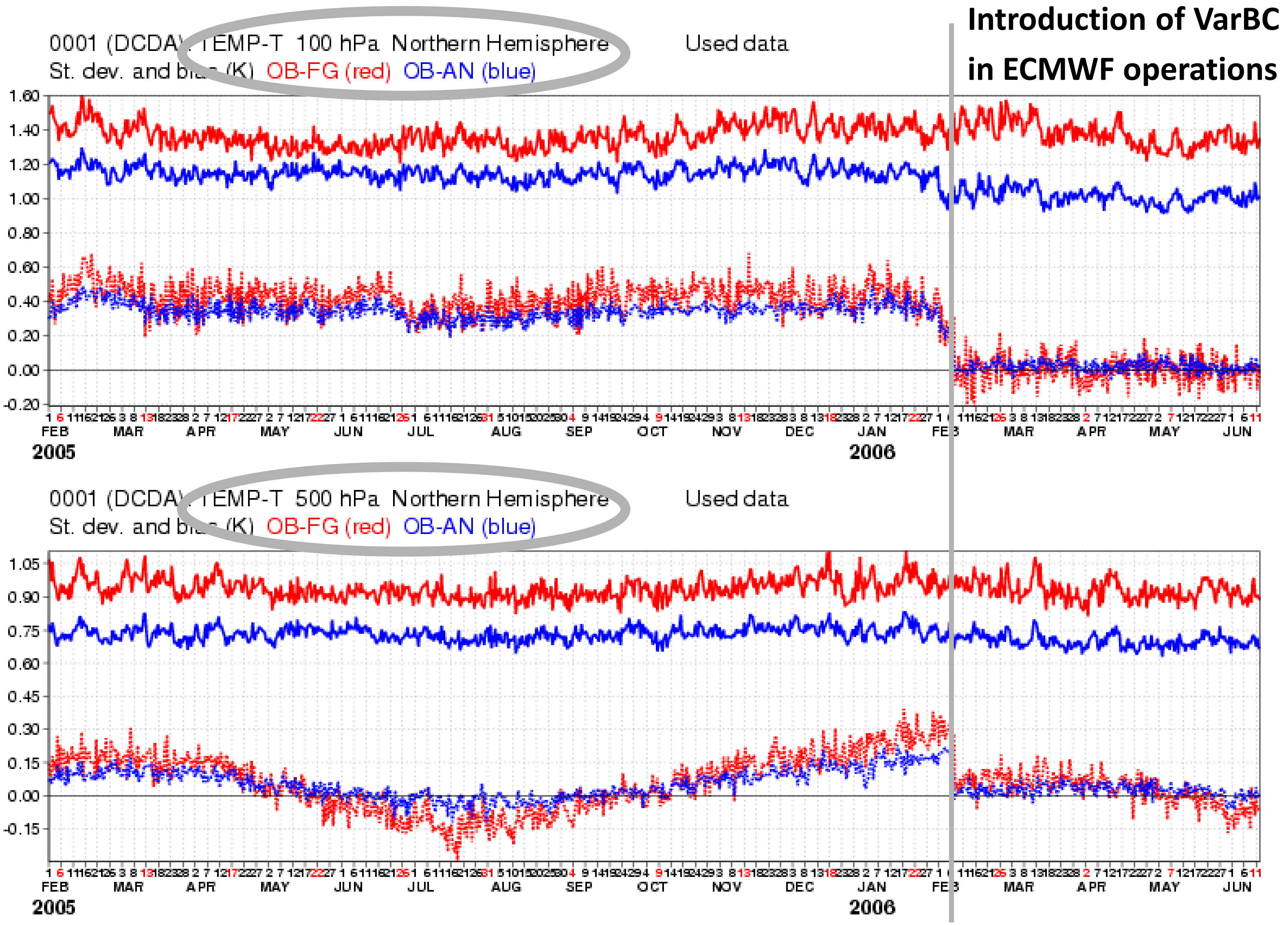
NOAA-9 MSU channel 3 bias corrections (cosmic storm)




**200 hPa temperature departures from radiosonde observations**



# Example 3:
## Fit to conventional data



# Bias correction use at ECMWF

***Current VarBC bias 'classes' in the ECMWF operational system***:

- ***Radiances***
- ***Ozone***
- ***Aircraft data***
- ***Ground-based radar precipitation***

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

- Surface pressure
- Radiosonde temperature and humidity
- Soil moisture (in SEKF surface analysis)

# 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)

- Limitations of VarBC

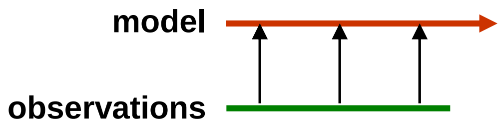
# Limitations of VarBC:
## Interaction with model bias

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

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

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 observation biases are poorly constrained (e.g., few anchoring observations; many bias-corrected observations with similar characteristics):

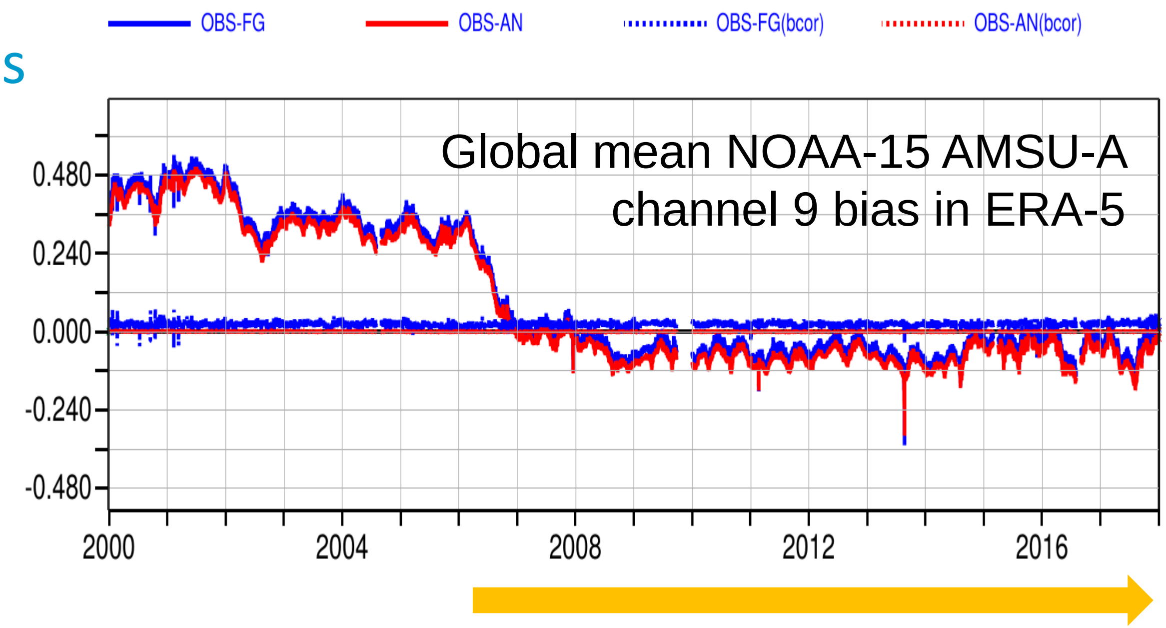



VarBC is not designed to correct model biases: Need for a **weak-constraint 4D-Var (Laloyaux)**

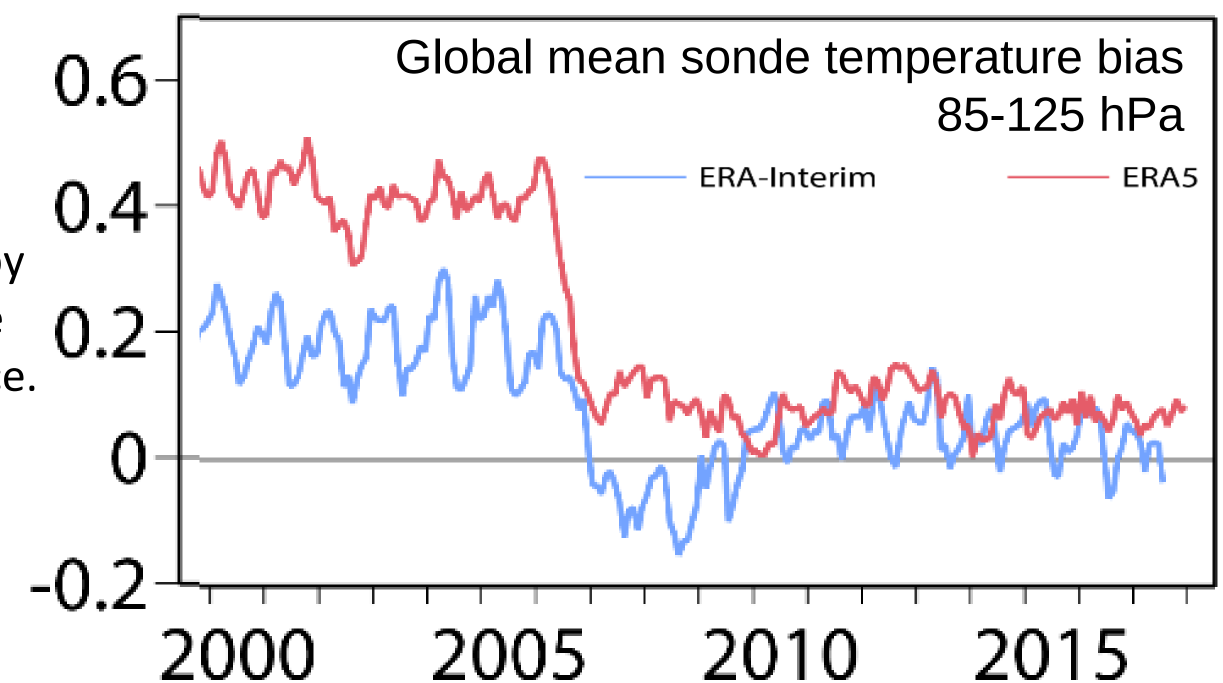
# Interaction with model bias and the role of anchor observations

***Example: Stratospheric temperature biases***

- Model biases affect the bias correction in the absence of sufficient anchor observations.
- GPS-RO provides a good anchor from mid-2006.
- The solution of the bias correction is also affected by other aspects, including the background error covariance.




Increased availability of GPS-RO data

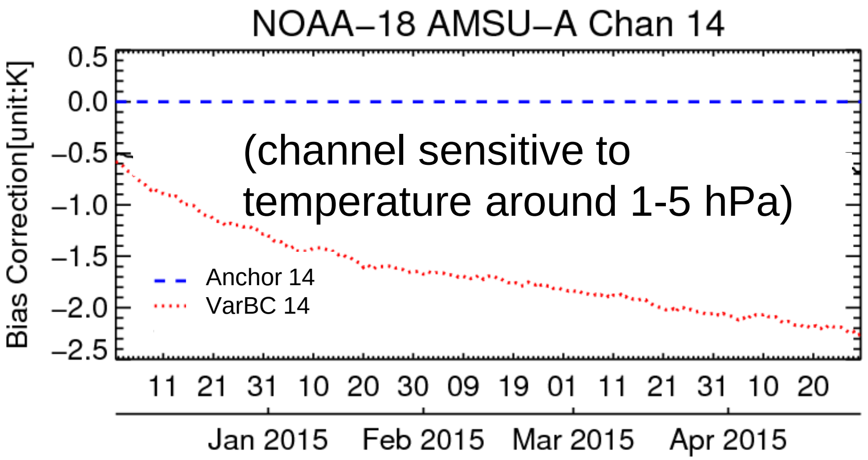


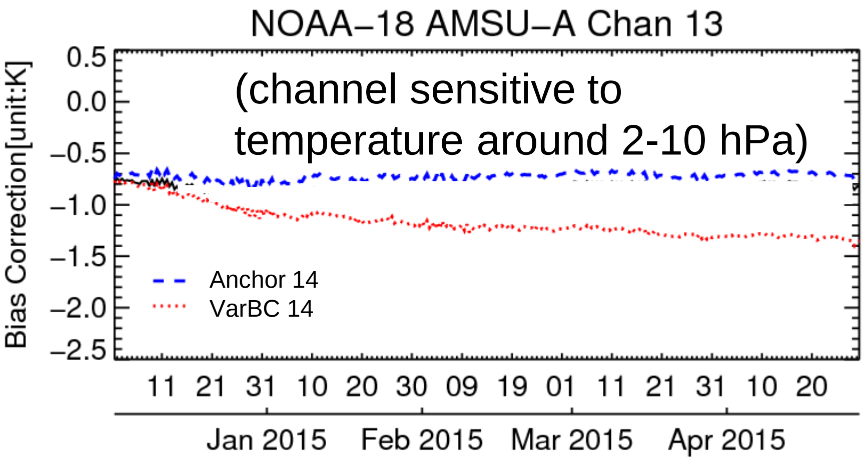
# Interaction with model bias: selecting an anchor

***Example: Upper stratospheric temperature biases***

- Unrealistic drift in the bias corrections due to model bias (red line)
- Additional *anchoring* can be imposed through assimilating AMSU-A channel 14 without a bias correction (blue line)

- Other anchoring in the ECMWF system: selected ozone-sensitive IR channels



# Interaction with model bias: alternative to anchor observations

- Alternative concept to reduce that VarBC corrects model bias:
  - **Constrained VarBC** (Han and Bormann 2016):
    - Penalise large bias corrections through an additional term in the cost function.

$$
\begin{aligned}
J(\mathbf{x},\boldsymbol{\beta}) = & \frac{1}{2}(\mathbf{x}_b-\mathbf{x})^T\mathbf{B}_x^{-1}(\mathbf{x}_b-\mathbf{x}) \\
& +\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\beta}_b)^T\mathbf{B}_\beta^{-1}(\boldsymbol{\beta}-\boldsymbol{\beta}_b) \\
& +\frac{1}{2}[\mathbf{y}-H(\mathbf{x})-b(\mathbf{x},\boldsymbol{\beta})]^T\mathbf{R}^{-1}[\mathbf{y}-H(\mathbf{x})-b(\mathbf{x},\boldsymbol{\beta})] \\
& +\frac{1}{2}[b(\mathbf{x},\boldsymbol{\beta})-\mathbf{b}_0]^T\mathbf{R}_b^{-1}[b(\mathbf{x},\boldsymbol{\beta})-\mathbf{b}_0]
\end{aligned}
$$

$\mathbf{b}_0$: Priori estimate of observation bias

$\mathbf{R}_b$: Priori estimate (or on orbit estimation) of radiometric uncertainty

$\boldsymbol{\beta}_b$: Background predictor coefficients

$\mathbf{B}_\beta$: Background predictor coefficients uncertainty

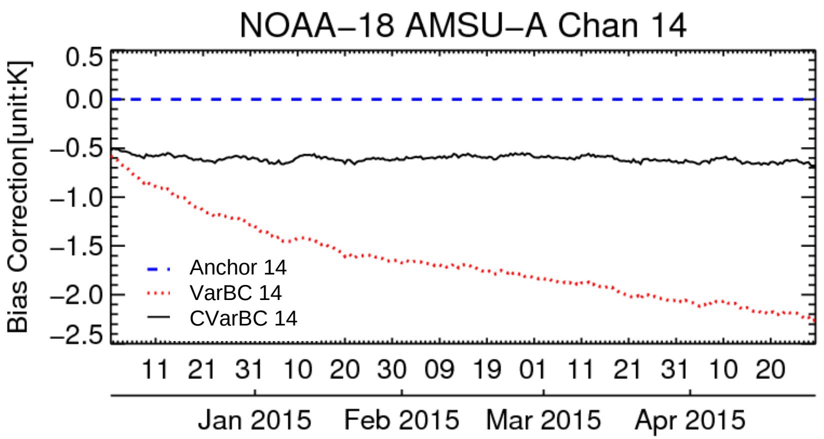
Adaptive

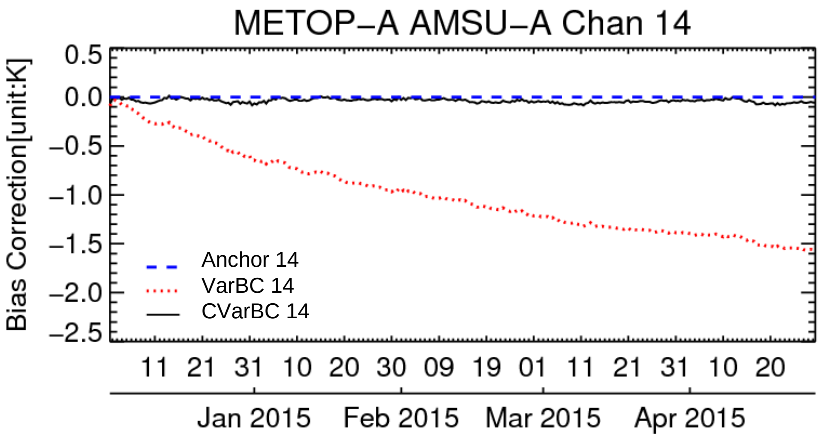
# Interaction with model bias: alternative constraints

***Example: Upper stratospheric temperature biases***

- Constrained VarBC is now used operationally for AMSU-A ch 14 and ATMS ch 15
  - Different bias characteristics for different satellites are now corrected. They were previously ignored when these channels were assimilated without bias correction.

- Further constraints could be introduced by using a more restrictive bias model (e.g., no air-mass component in bias model)

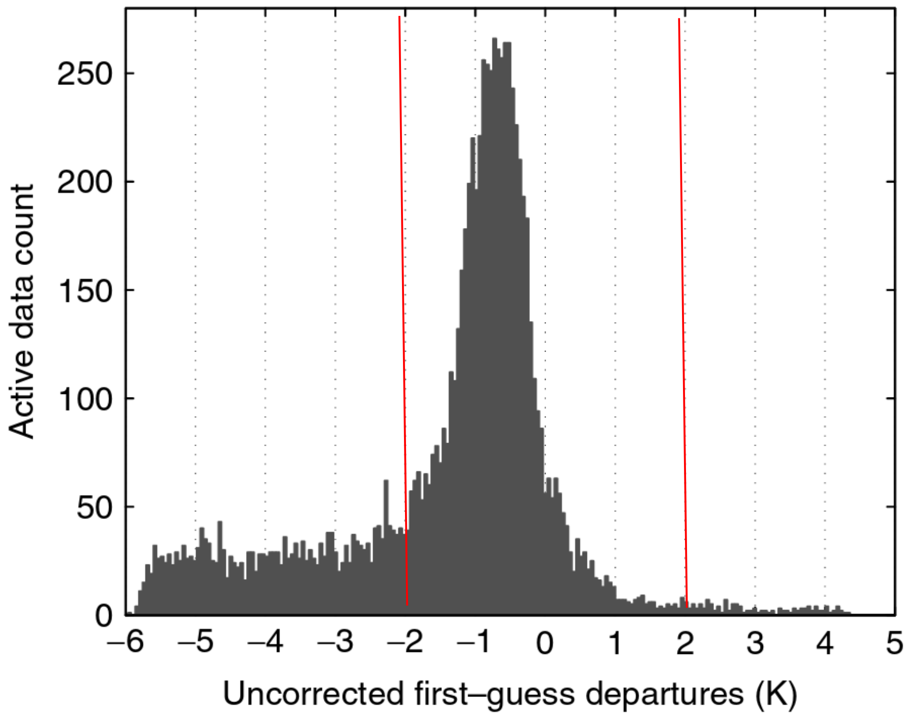


# Limitations of VarBC:

## Other pit-falls: Removing the signal

- Avoid bias correction models with too many predictors, to avoid correcting for situation-dependent background errors/biases to be incorrectly removed.
- Beware of interaction between VarBC and departure-based quality control and asymmetric distributions:
    - Can lead to unwanted drifts in the population after QC




Histogram of IR window channel departures with cold cloud tail

# Summary

Biases are everywhere:

- Most observations cannot be usefully assimilated without bias adjustments

- Manual estimation of biases in satellite data is practically impossible
- Bias estimates can be updated automatically during data assimilation

- 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*

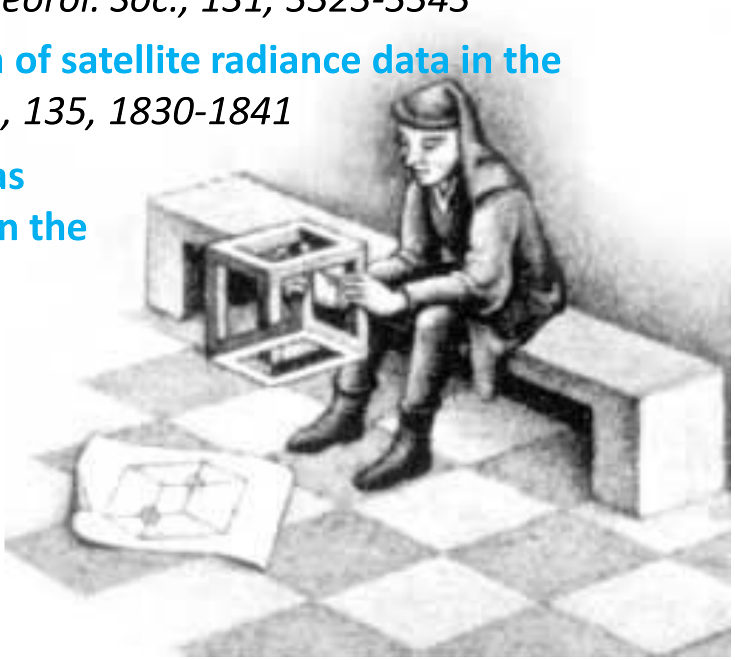
Derber and Wu, 1998: **The use of TOVS cloud-cleared radiances in the NCEP SSI analysis system.** *Mon. Wea. Rev., 126, 2287-2299*

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*

Han and Bormann, 2016: **Constrained adaptive bias correction for satellite radiance assimilation in the ECMWF 4D-Var system.** *ECMWF Technical Memorandum 783.*



Feel free to contact me with questions:

**Niels.Bormann@ecmwf.int**