Bias correction in data assimilation

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Reanalysis Section

ECMWF

Meteorological Training Course
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.

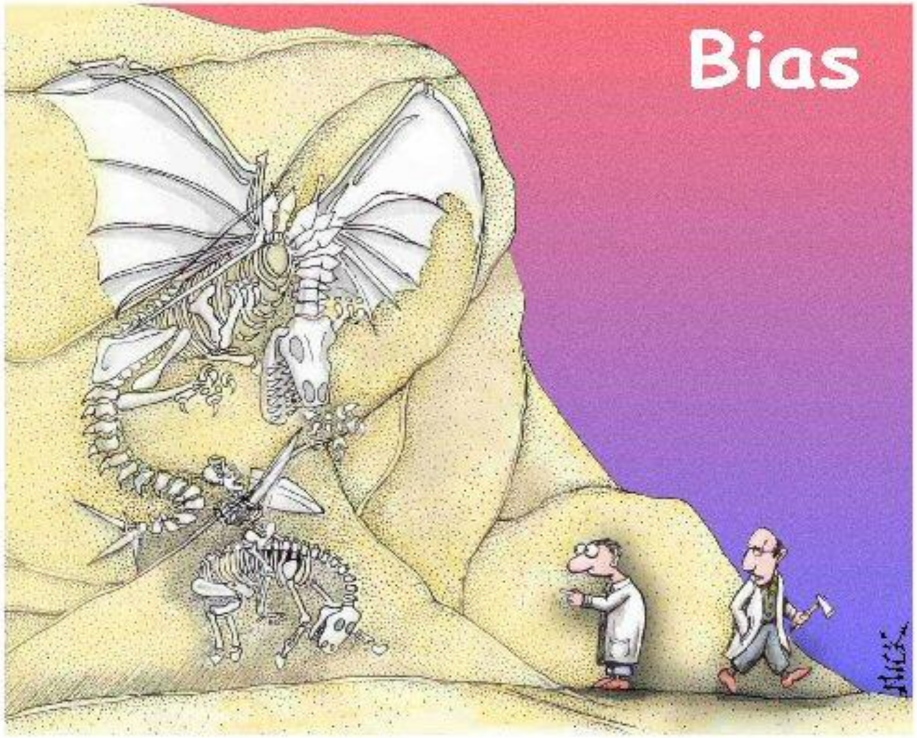
By the end of the session you should be able to realize that:

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.

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."

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

model background constraint

observational constraint

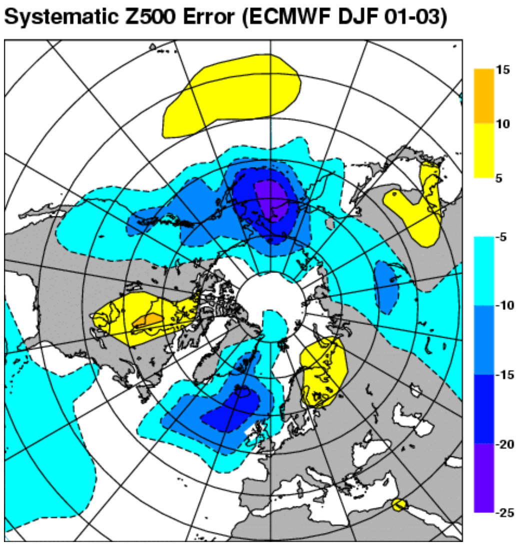
Outline

- 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

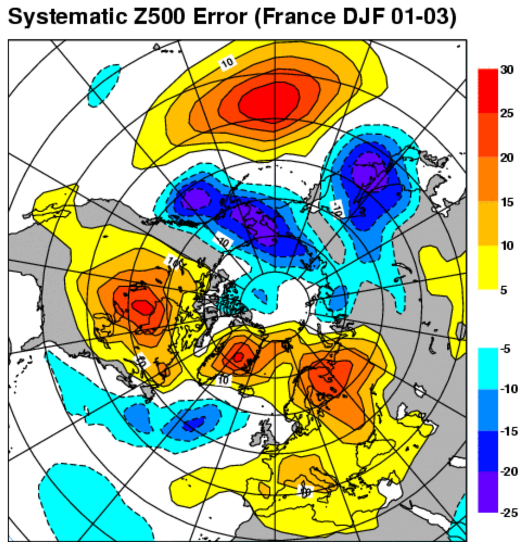
Model bias:

Systematic Day-3 Z500 errors in three different forecast models

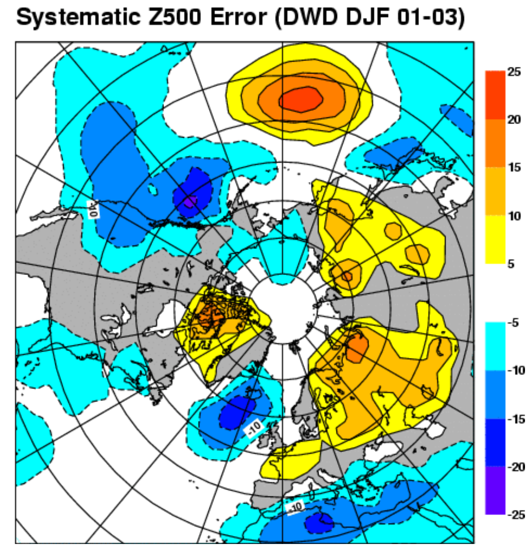
ECMWF



Meteo-France



DWD



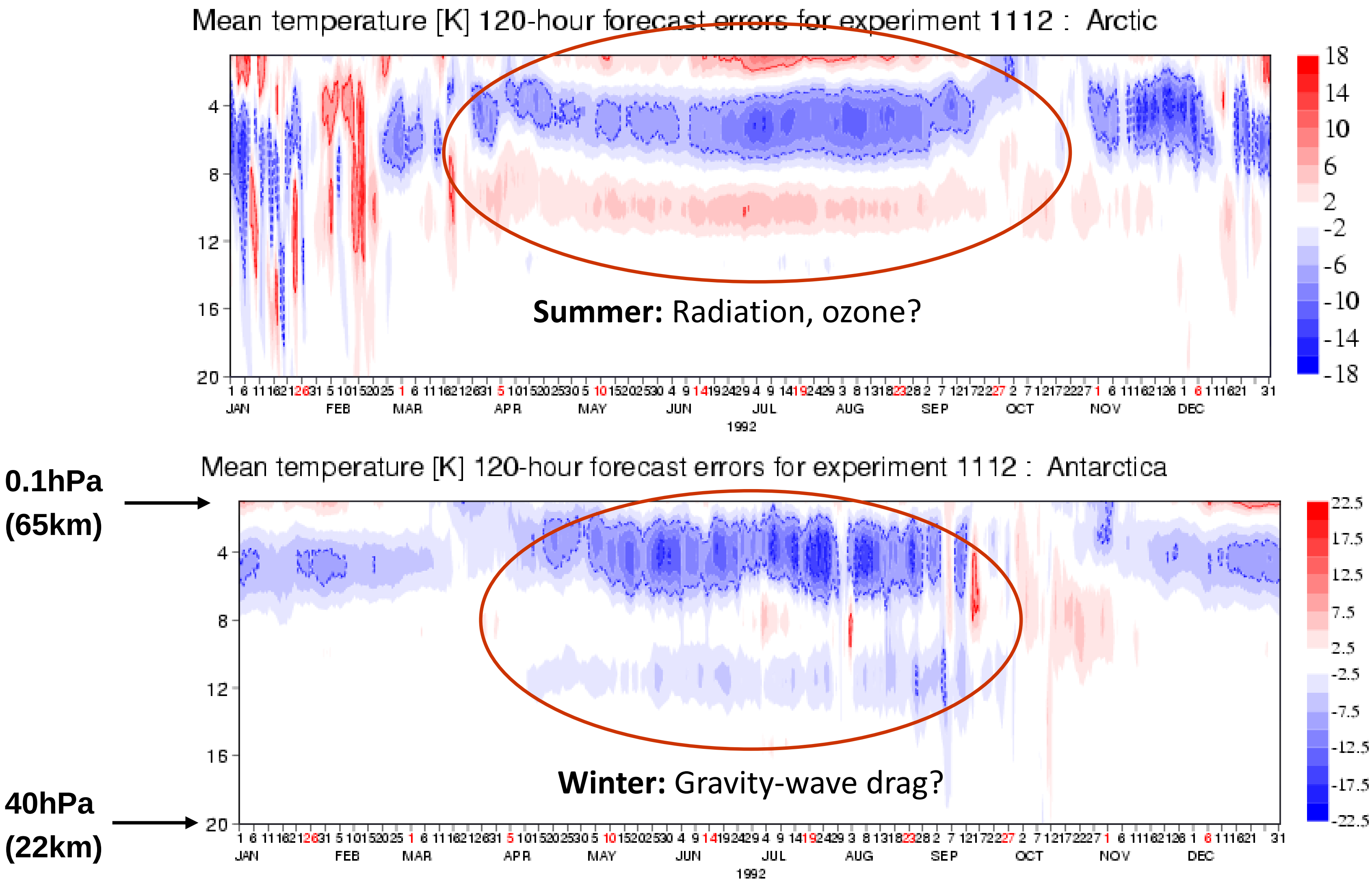
Different models often have similar error characteristics

Period DJF 2001-2003

Model bias:

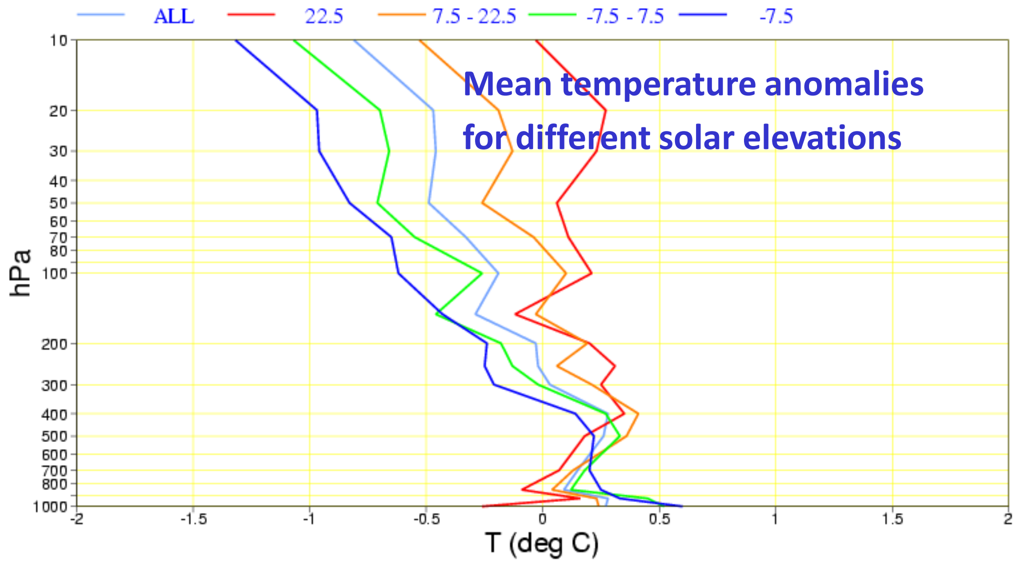
Seasonal variation in upper-stratospheric model errors

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

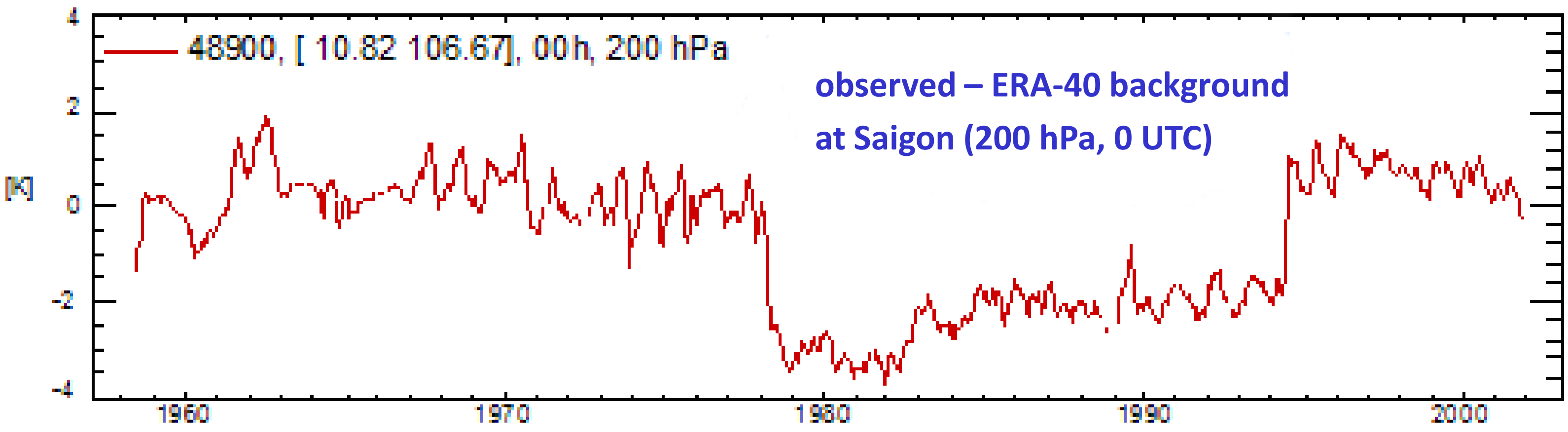


Observation bias:
Radiosonde temperature observations

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



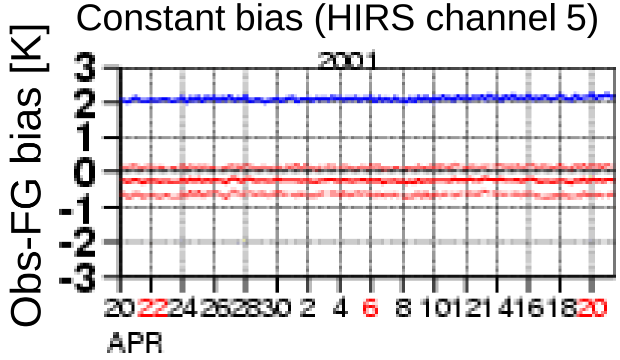
Bias changes due to change of equipment



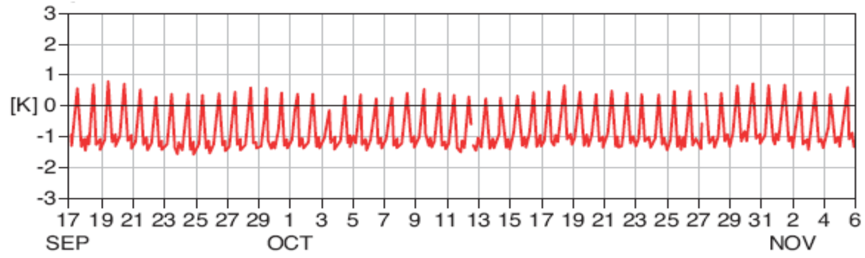
Observation and observation operator bias:
Satellite radiances

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

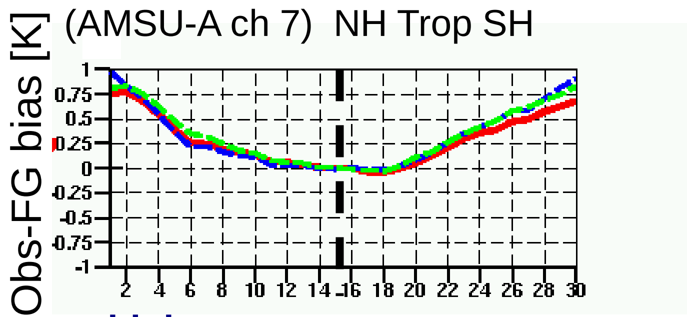
Constant bias (HIRS channel 5)



Diurnal bias variation in a geostationary satellite

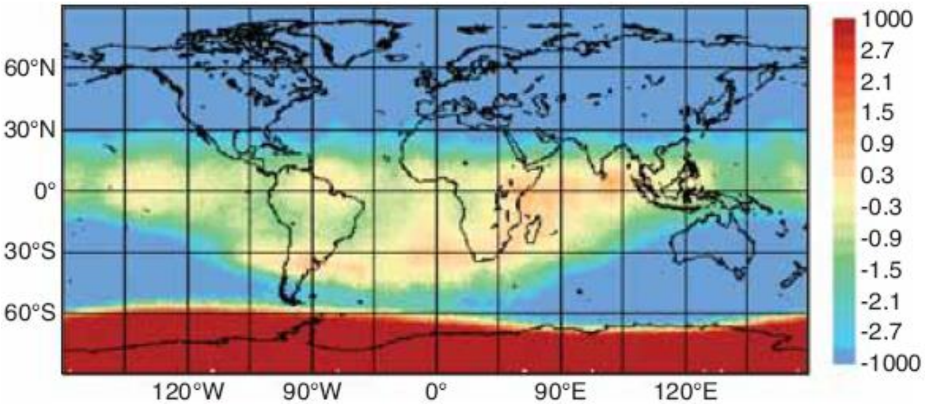


Bias depending on scan position (AMSU-A ch 7) NH Trop SH



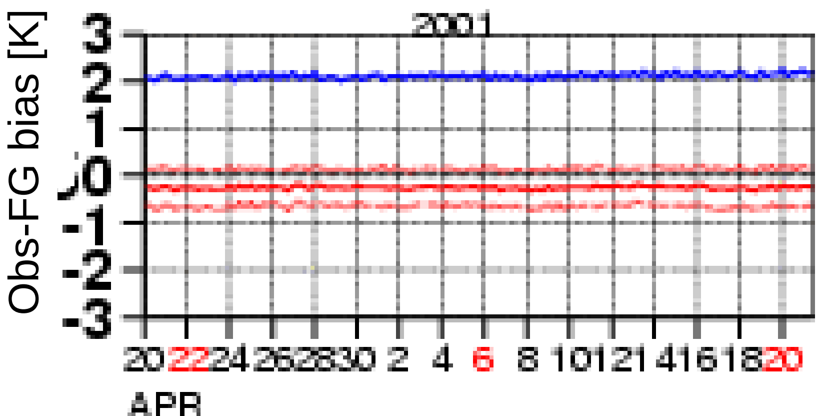
high zenith angle **nadir** **high zenith angle**

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

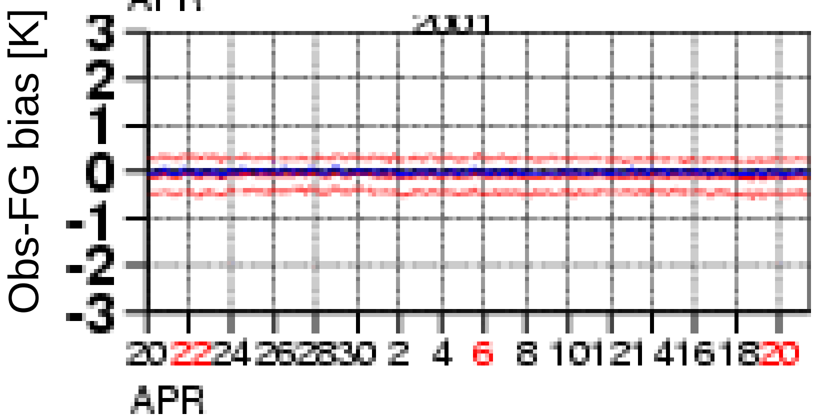


Observation and observation operator bias:
Satellite radiances

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.

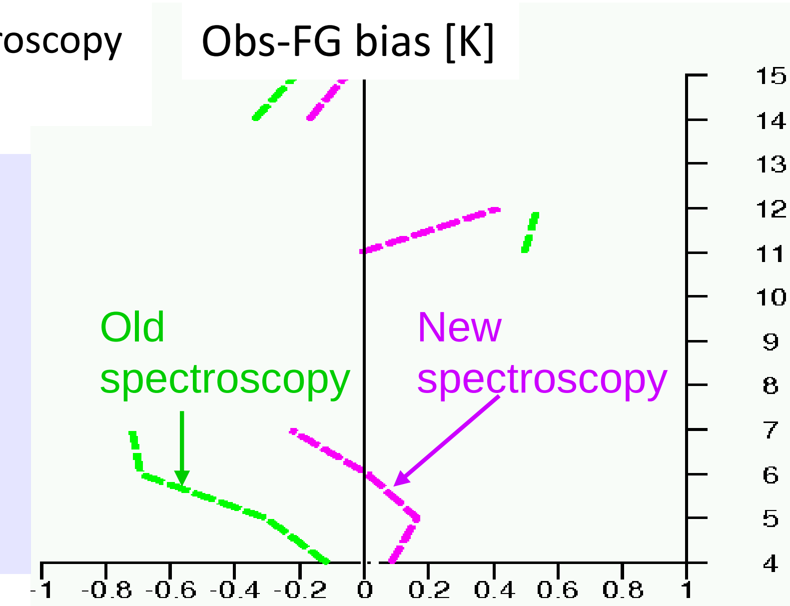


Same channel on NOAA-16 satellite has no radiance bias against FG.

→ NOAA-14 channel 5 has an instrument bias.

Observation and observation operator bias:
Satellite radiances

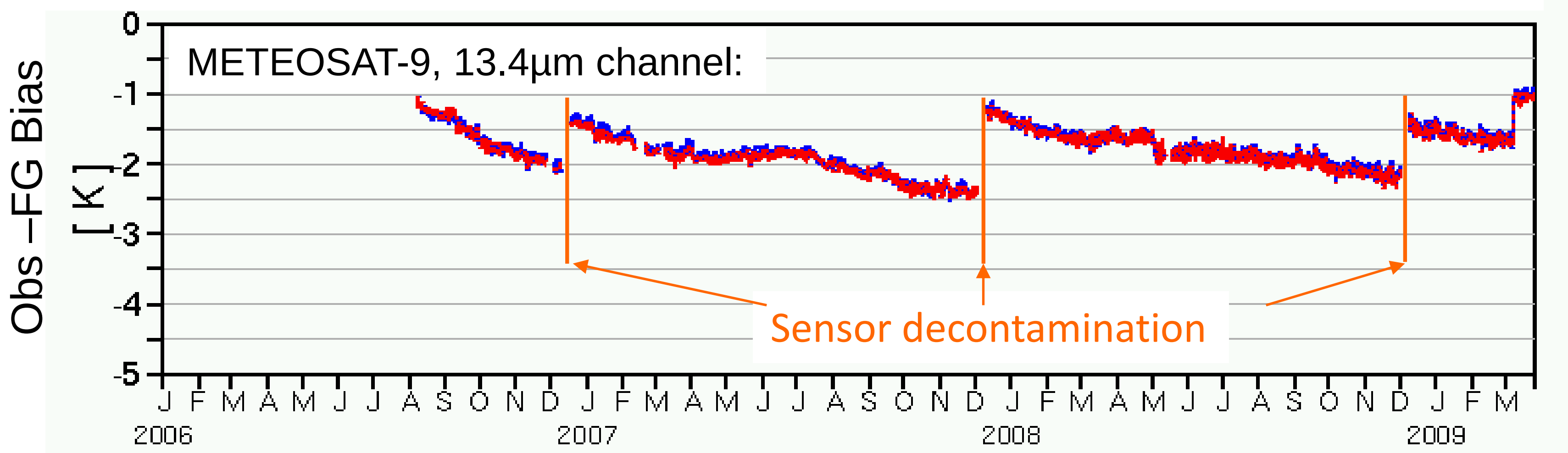
Different bias for HIRS due to change in spectroscopy used in the ***radiative transfer model***:



Other common causes for biases in radiative transfer:

- Bias in assumed concentrations of atmospheric gases (e.g., CO_2, aerosols)
- Neglected effects (e.g., clouds)
- Incorrect spectral response function
- ….

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

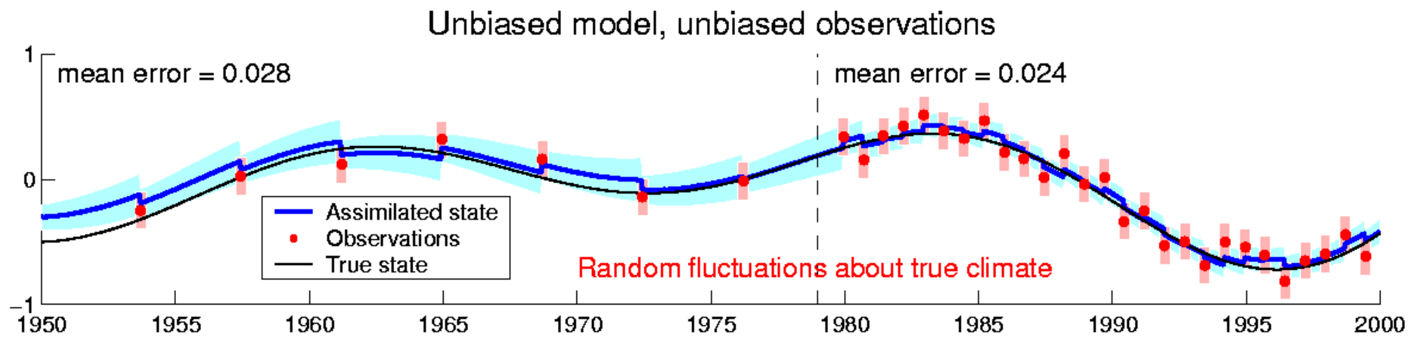


Implications for data assimilation:
Bias problems in a nutshell

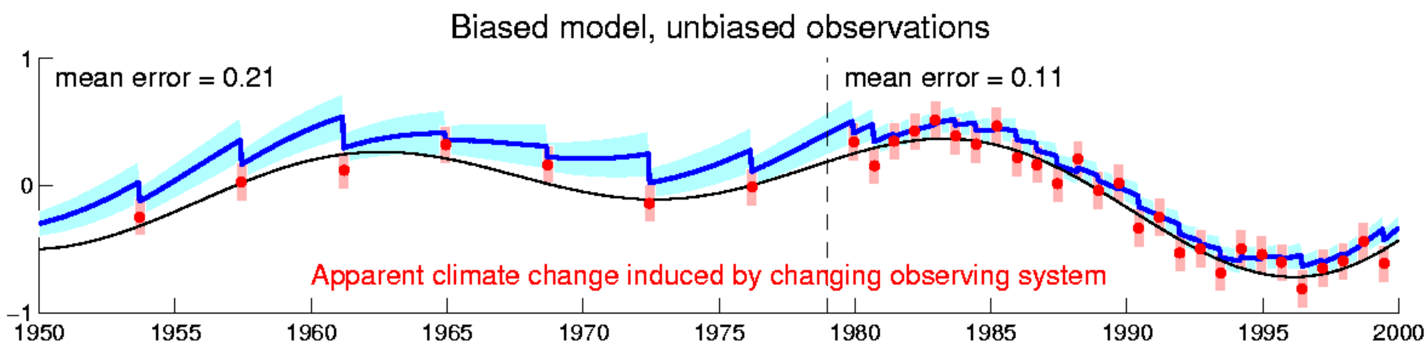
- **Observations and observation operators have biases, which may change over time**
    - Daytime warm bias in radiosonde measurements of stratospheric temperature; radiosonde equipment changes
    - Biases in cloud-drift wind data due to problems in height assignment
    - Biases in satellite radiance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

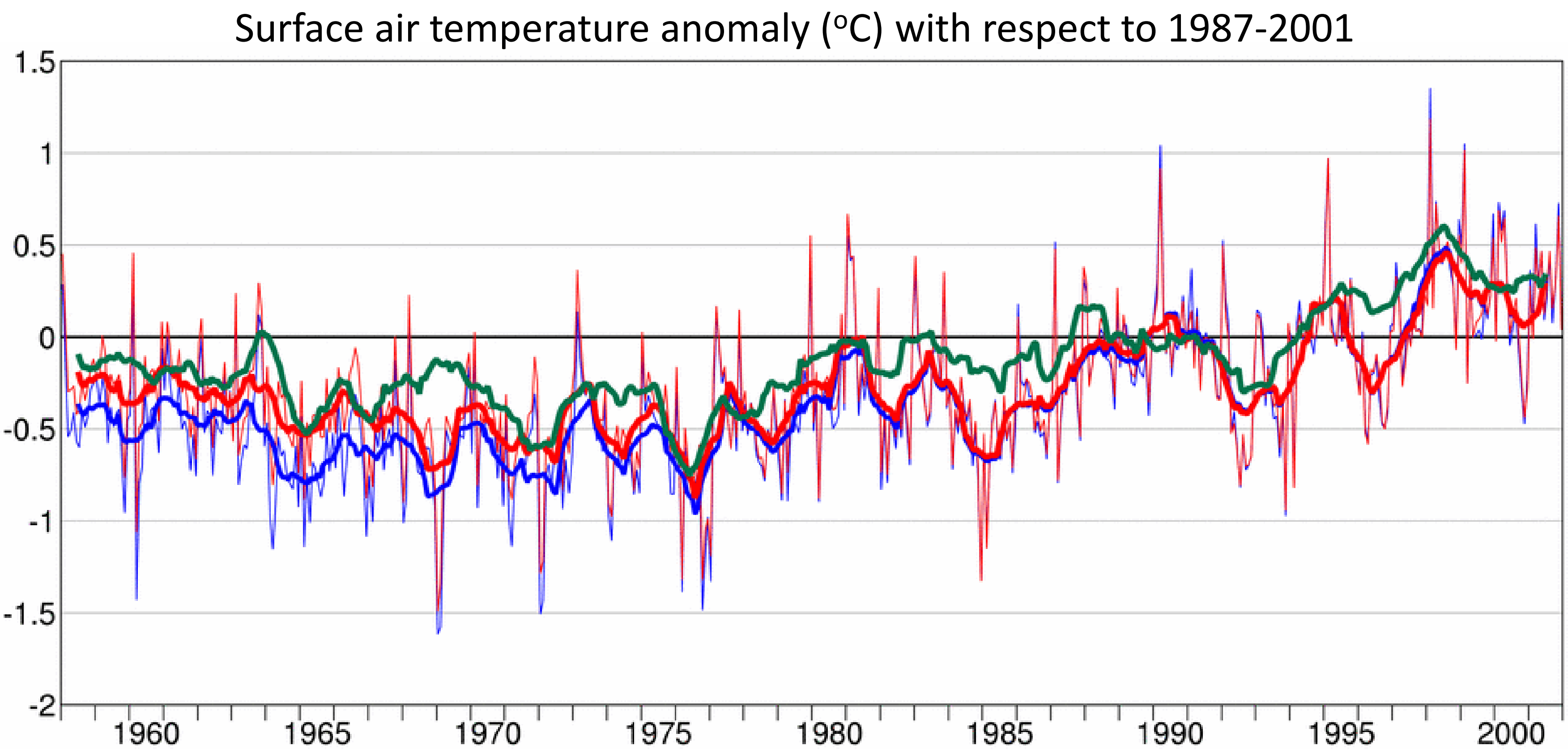


Biases in models and/or data can induce spurious trends in the assimilation



Implications for data assimilation:

ERA-40 surface temperatures compared to land-station values



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

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  - 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

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

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

- **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

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

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

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

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

Predictors, for instance:

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

Average the background departures:

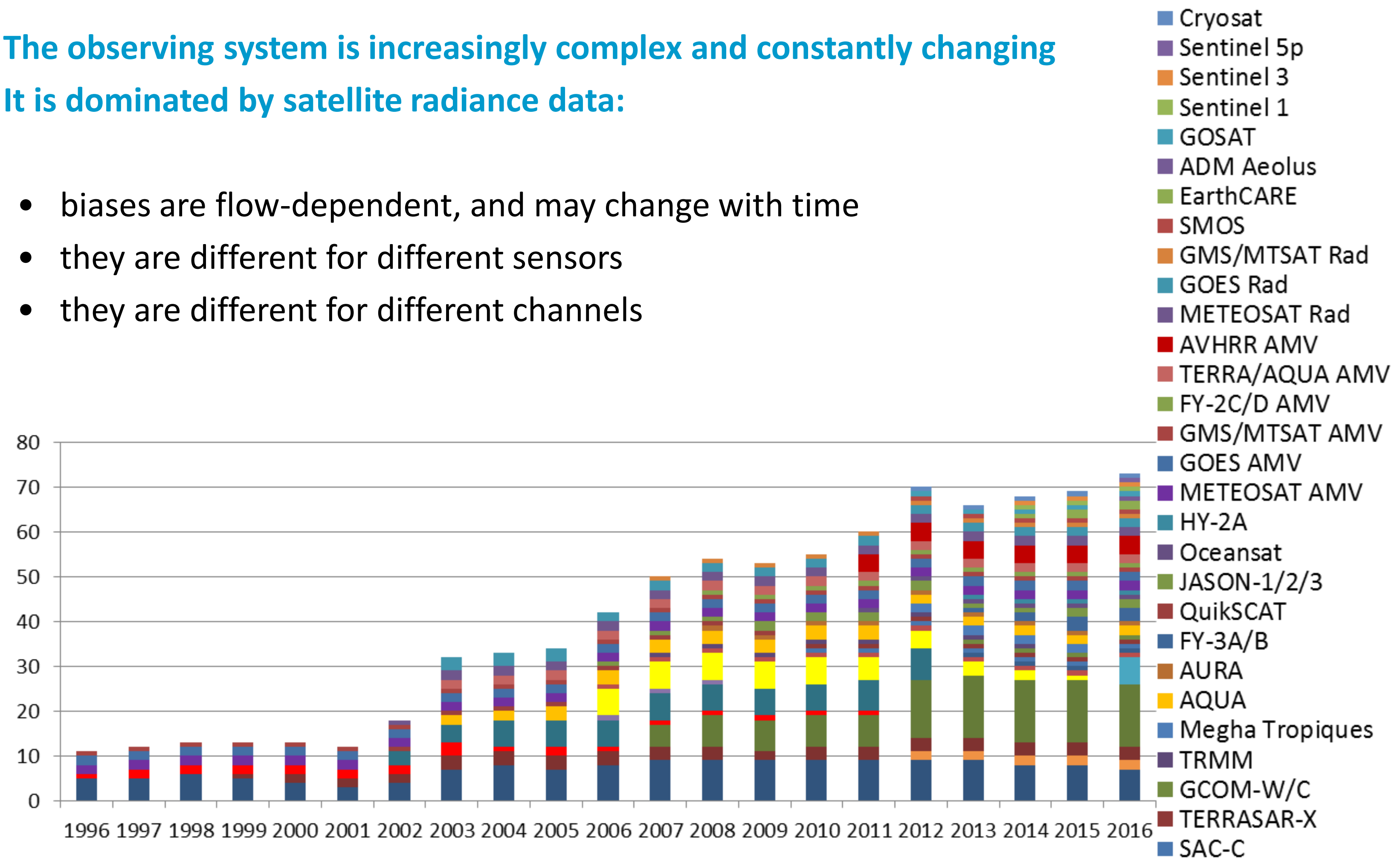
$$\langle y - h(x_b) \rangle = b^{scan} + b^{air}(x)$$

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_β: 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

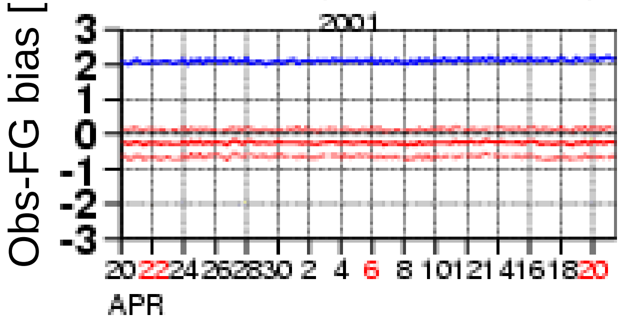
Form inspired by Harris and Kelly

The need for an adequate bias model

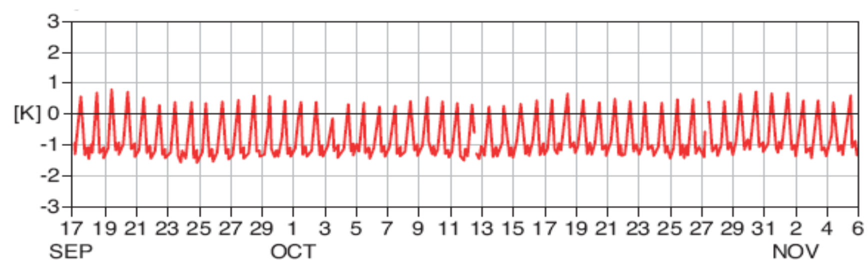
Prerequisite for any bias correction is a good model for the bias (b(x,β)):

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

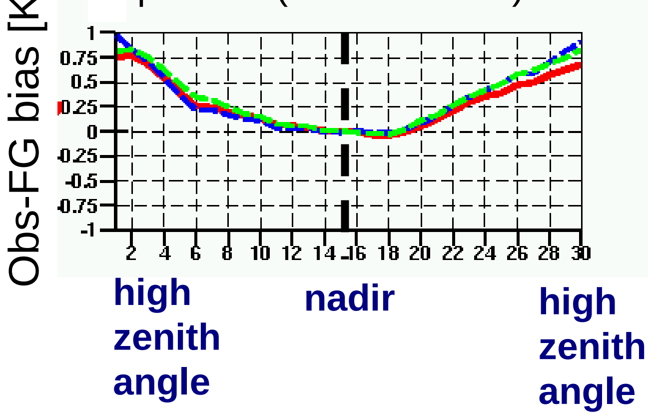
Constant bias (HIRS channel 5)



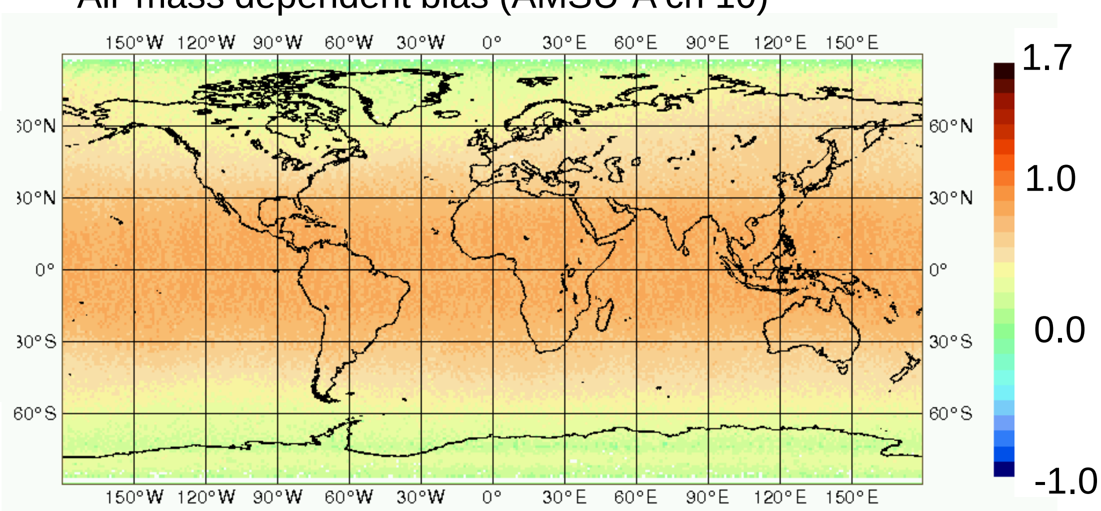
Diurnal bias variation in a geostationary satellite



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

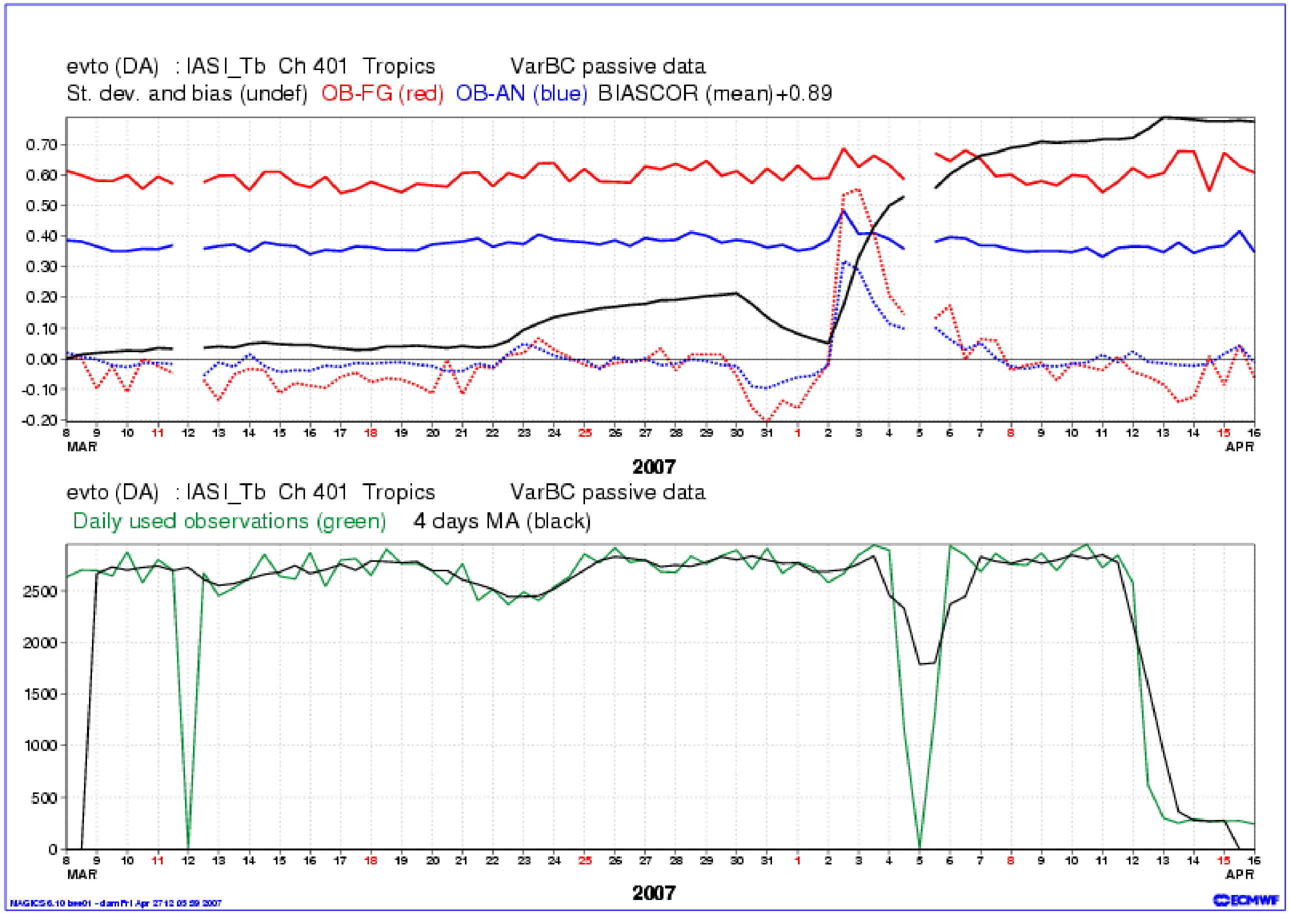


Air-mass dependent bias (AMSU-A ch 10)



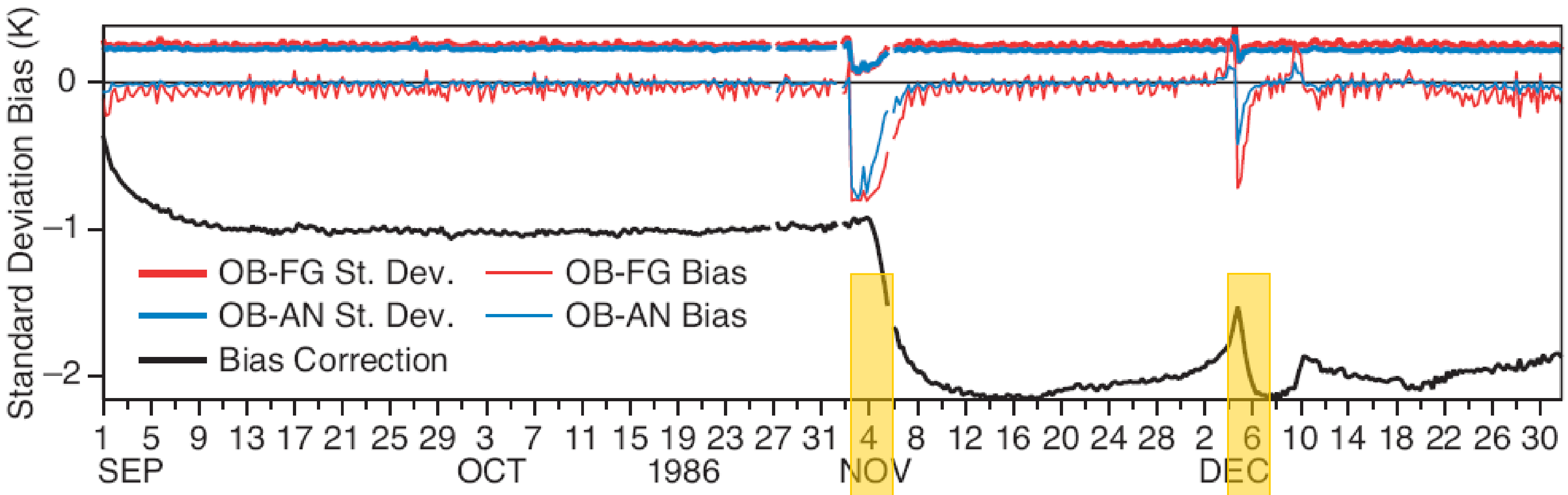
Example 1:
Spinning up new instruments – IASI on MetOp A

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

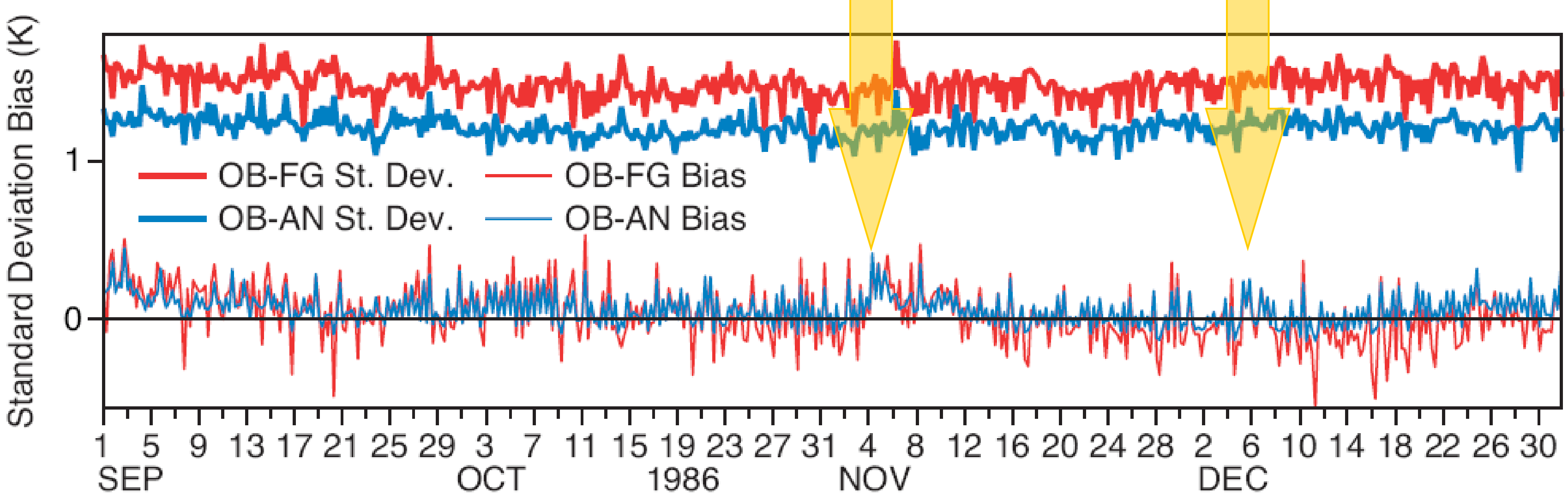


Example 2:

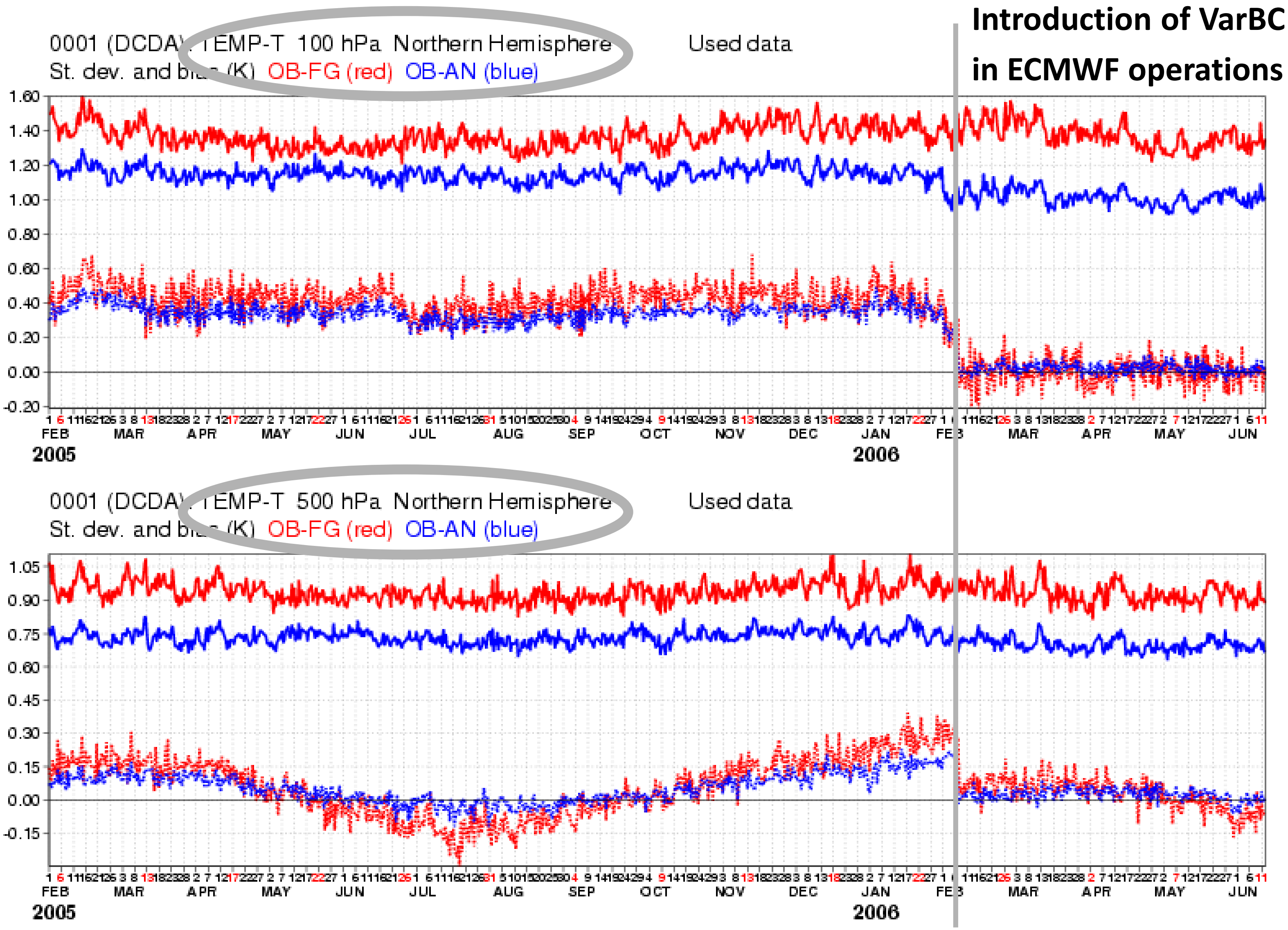
NOAA-9 MSU channel 3 bias corrections (cosmic storm)



200 hPa temperature departures from radiosonde observations



Example 3:
Fit to conventional data



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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
- Soil moisture (in SEKF surface analysis)

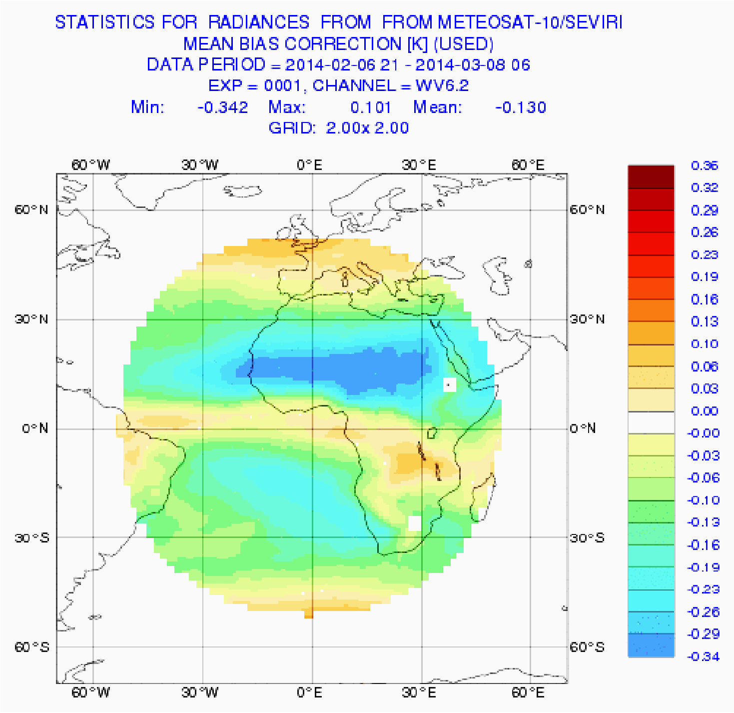
Specific:

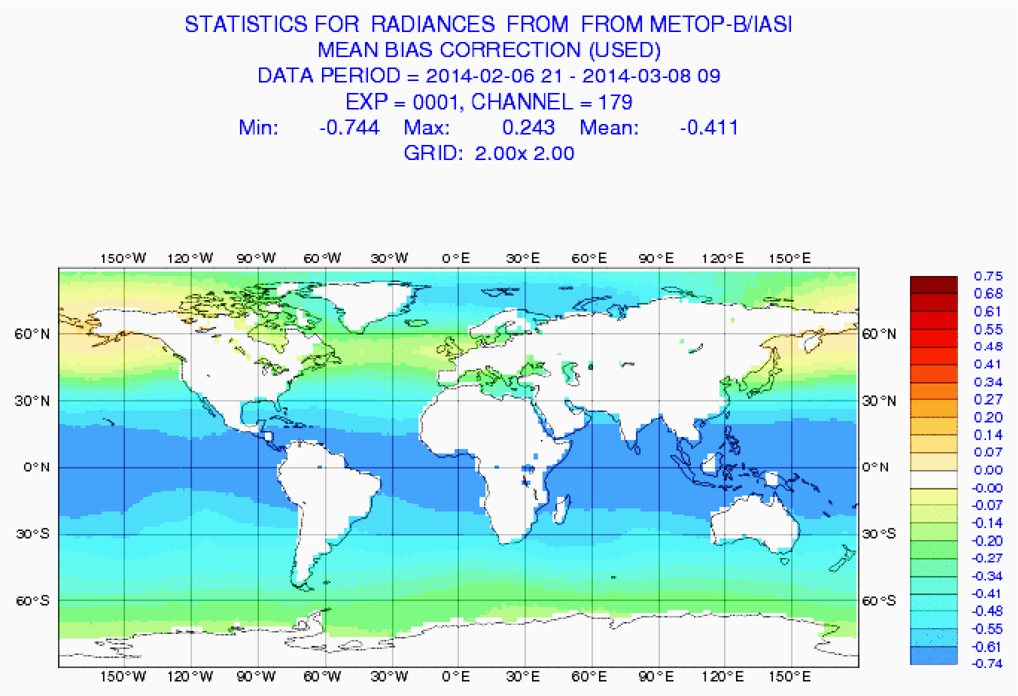
- ***ERA-Interim***: VarBC for radiances only
- ***ERA-20C:*** the 20th century reanalysis using surface observations only
- ***MACC***: atmospheric composition

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: $\beta_0 + \sum\beta_i\, p_i(\text{model state}) + \sum\beta_j\, p_j(\text{instrument state})$

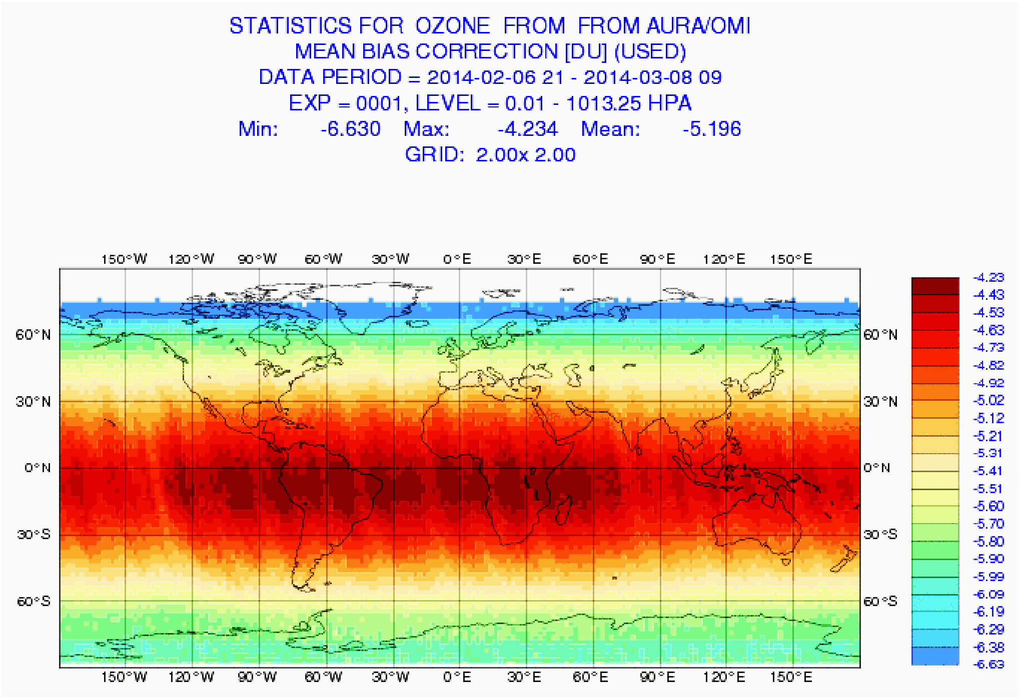
(~11,400 parameters in total)





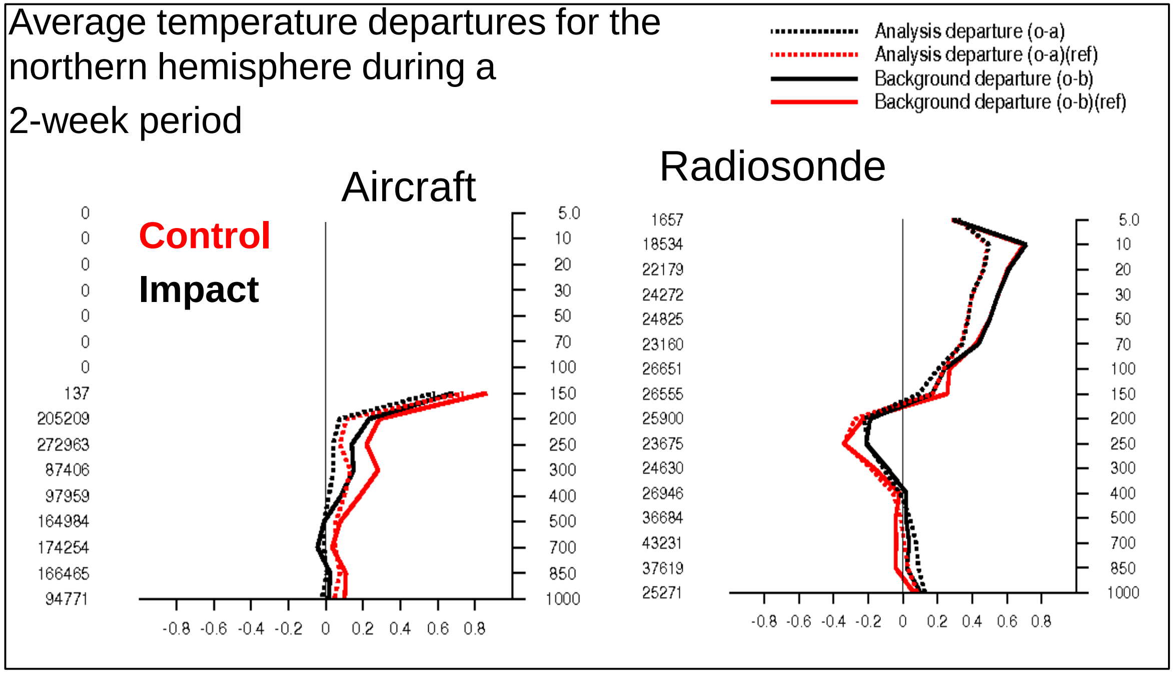
VarBC for ***ozone***

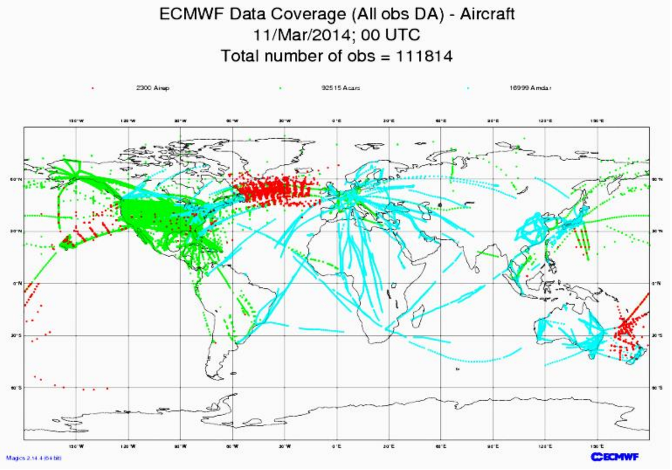
- OMI, (SCIAMACHY, GOMOS, SEVIRI, GOME2, GOME in past)
- ***Anchored*** to SBUV/2
- Bias model: $\beta_0 + \beta_1$ x solar elevation



VarBC for ***aircraft temperature***

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





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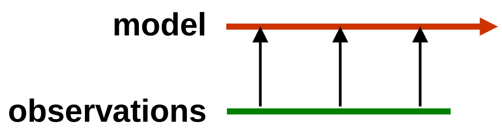
Limitations of VarBC:
Interaction with model bias

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:

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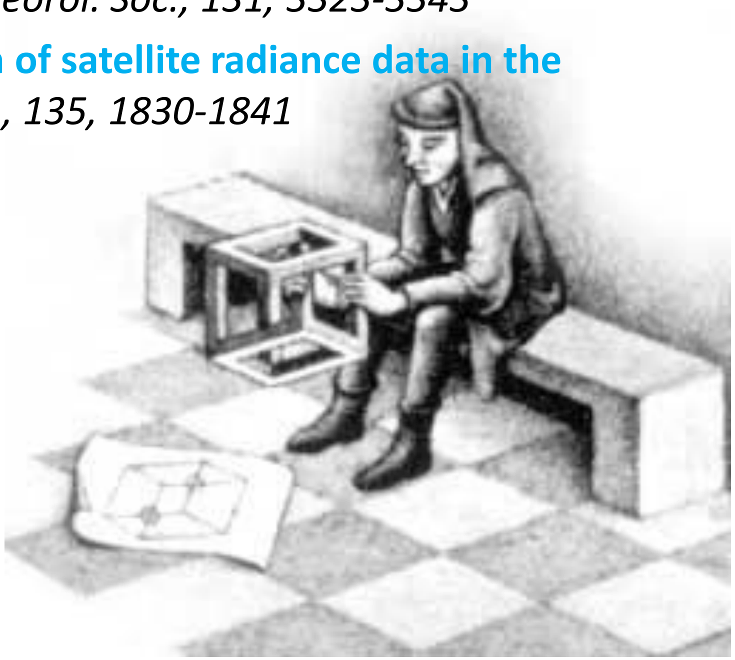

VarBC for ***total column water vapour***

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