Biases in observations

Patrick Laloyaux

based on material from Niels Bormann, Hans Hersbach and Dick Dee

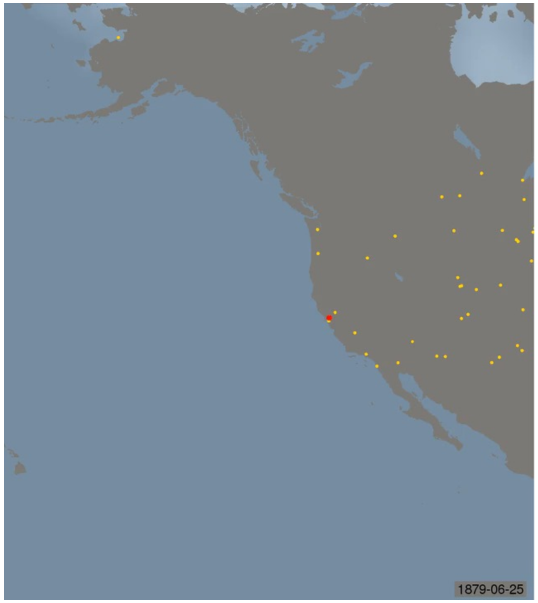
To illustrate biases in observations

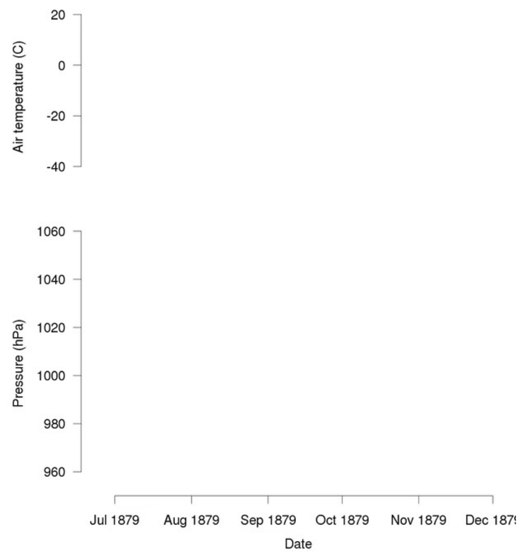
To construct bias models for specific instruments

To understand the challenges of observation bias correction

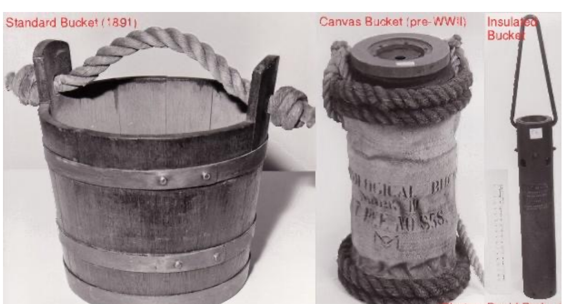
Examples of biases in observations (1/3)

The USS Jeannette (1879, Artic, 33 crew members)





SST measurements from standard buckets have a cold bias (~0.4C)



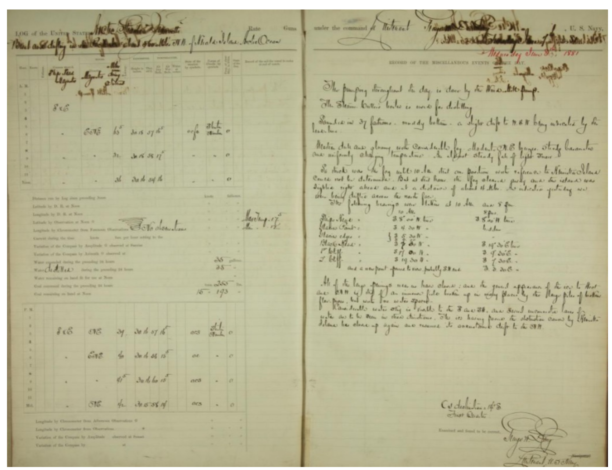
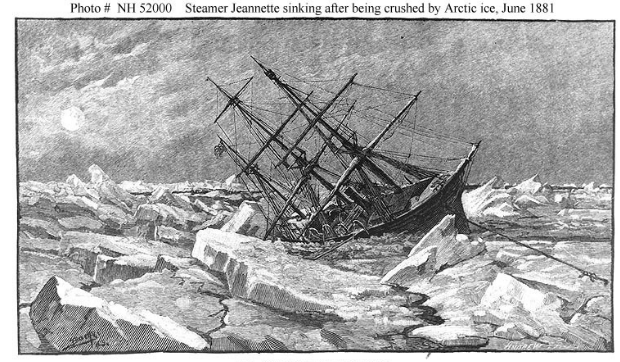


Photo # NH 52000 Steamer Jeannette sinking after being crushed by Arctic ice, June 1881



THE SINKING OF THE JEANNETTE.

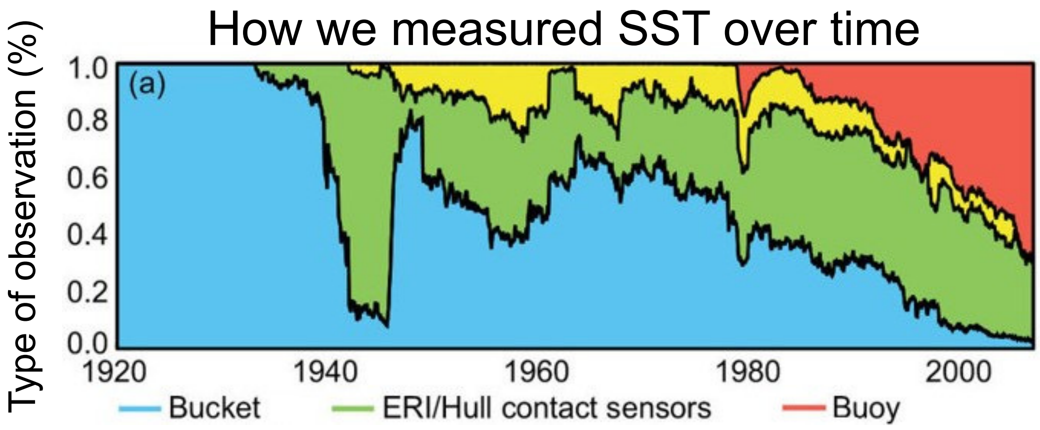
Photo # NH 52002 Jeannette's crewmen drag their boats over the Arctic ice, June-August 1881

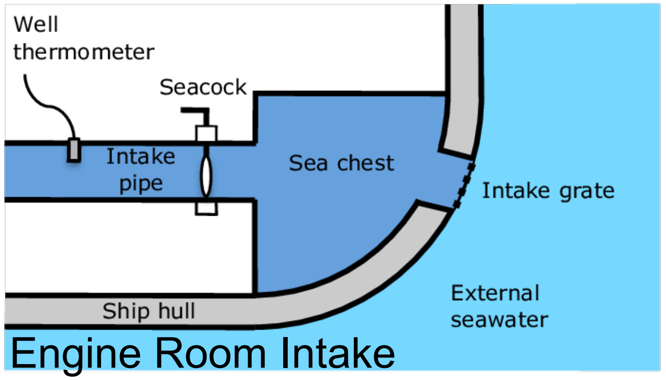
DRAGGING THE BOATS OVER THE ICE

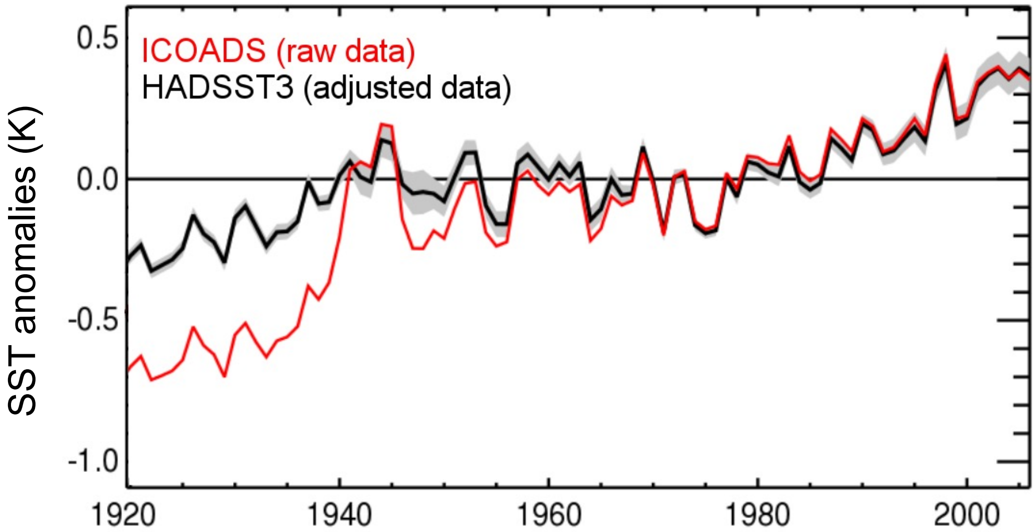
Photo # NH 92142 LCdr. DeLong and his party wading ashore on the Lena Delta, Siberia, 17 Sept. 1881

WADING ASHORE.

Examples of biases in observations (2/3)







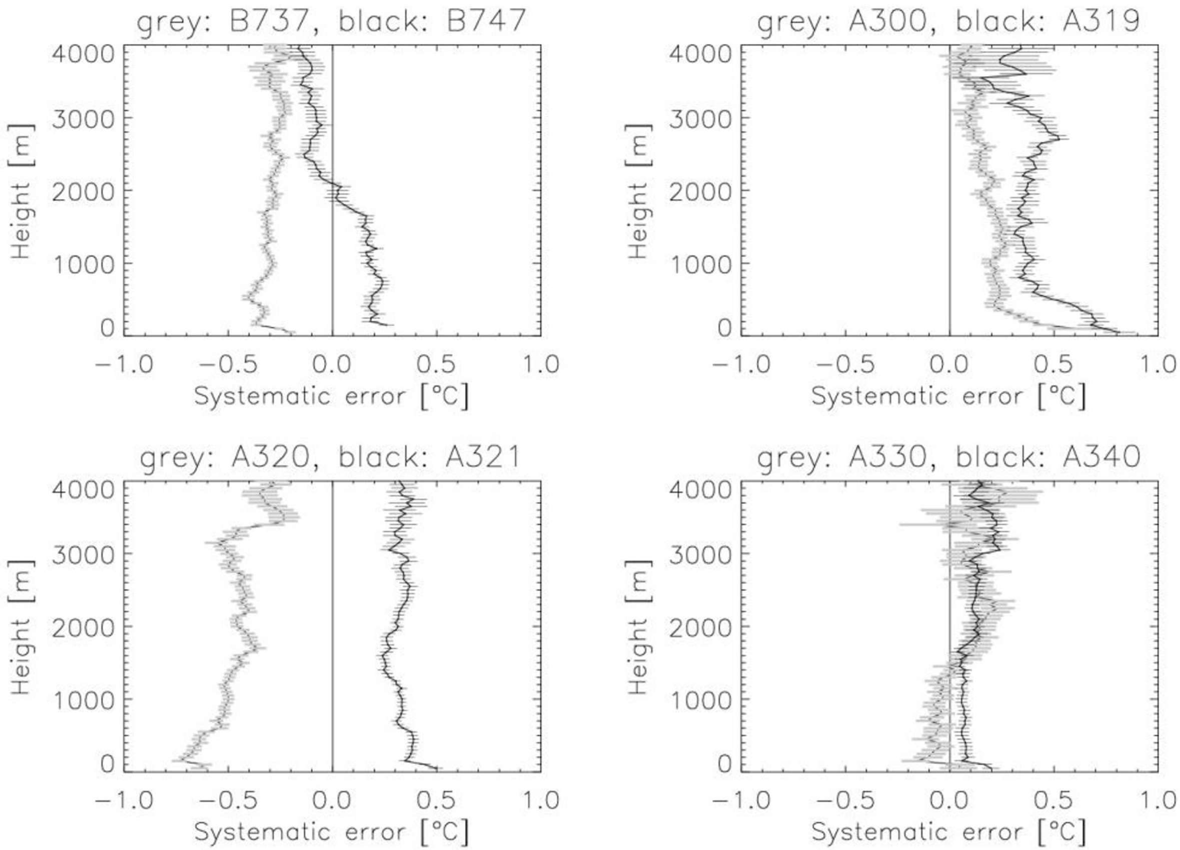
Estimation of observation biases done by inter-comparison between instruments

➔ Involve experts knowing the instruments

➔ Not straightforward as incomplete metadata

Examples of biases in observations (3/3)

One year of measurements from aircrafts landing at Frankfurt



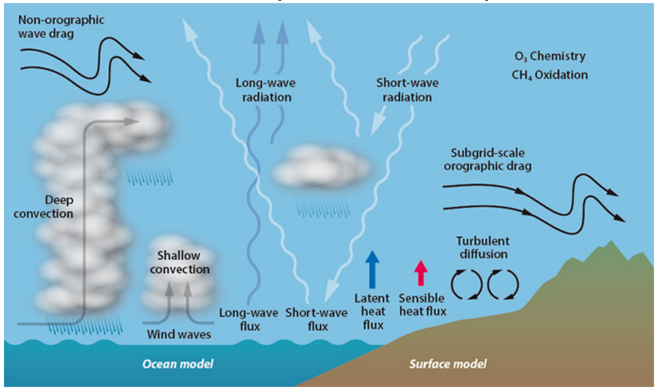
Estimation of observation biases done by inter-comparison between instruments

➔ Involve experts knowing the instruments

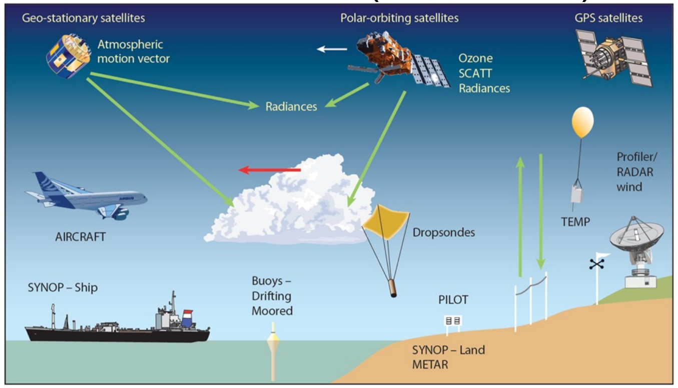
➔ observation bias is estimated using the hourly mean of all measured profiles

What you have seen so far on data assimilation

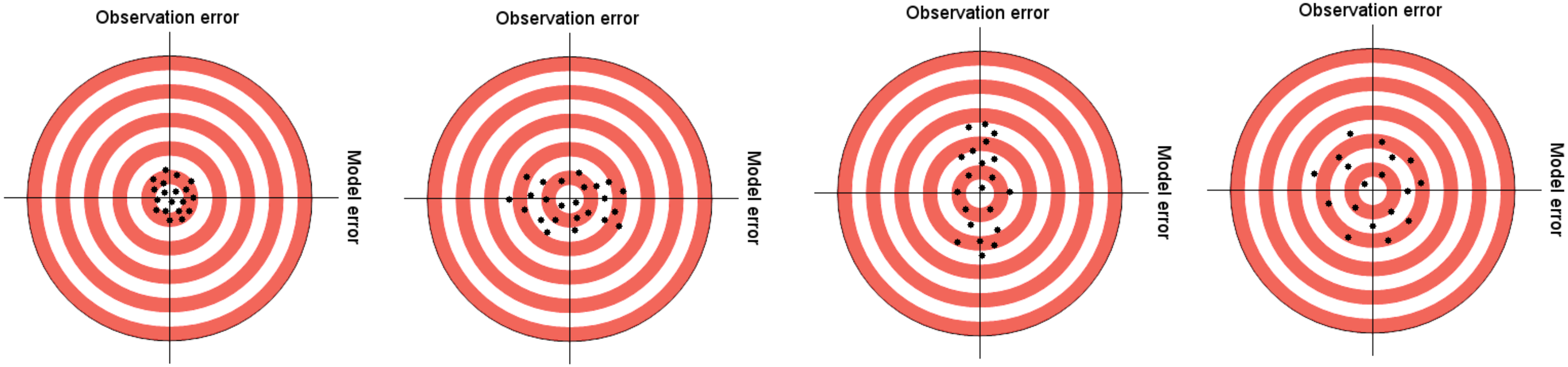
Model (with errors)



Observations (with errors)



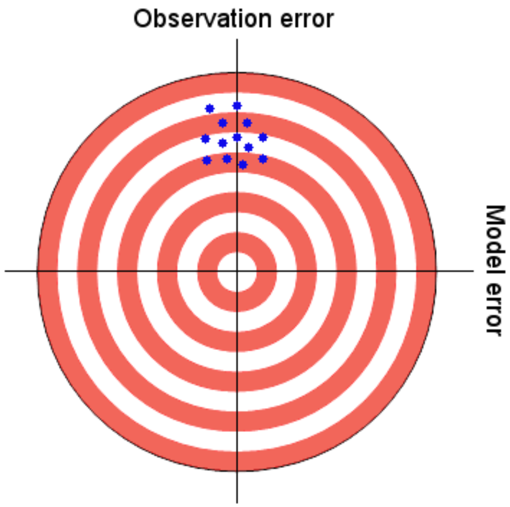
If you are lucky, model and observations are **accurate** (no biases, mean error is zero)



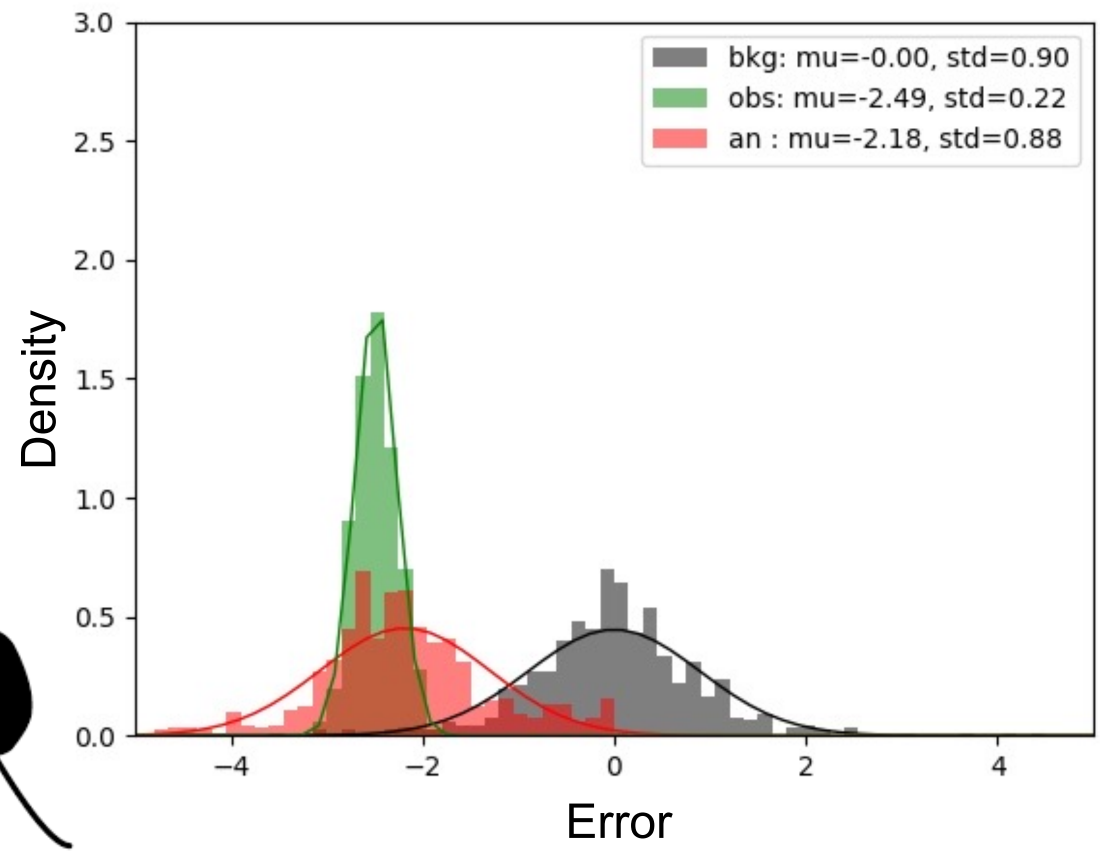
$$J(x_0) = \frac{1}{2}(x_0 - x_b)^T\mathbf{B}^{-1}(x_0 - x_b)$$
$$+ \frac{1}{2}\sum_{k=0}^{K}[y_k - \mathcal{H}(x_k)]^T\mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)]$$

Most of the time, we are unlucky!

Observation biases matter

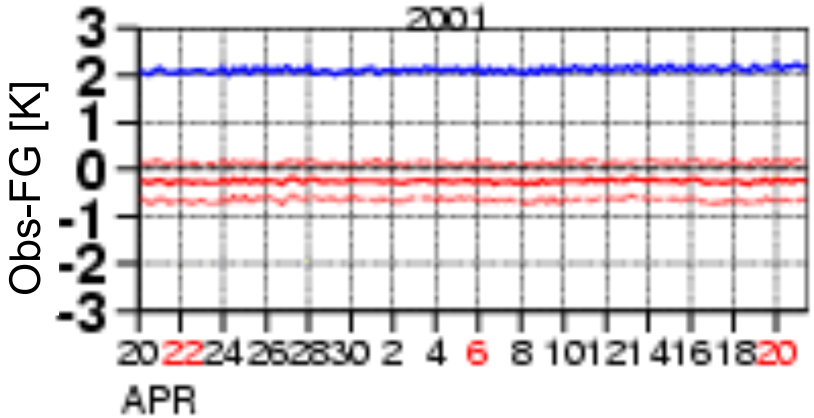


- If standard 4D-Var is used to assimilate biased observations (systematic errors), the resulting analysis will be biased.
- In this case the background is more accurate than the analysis!

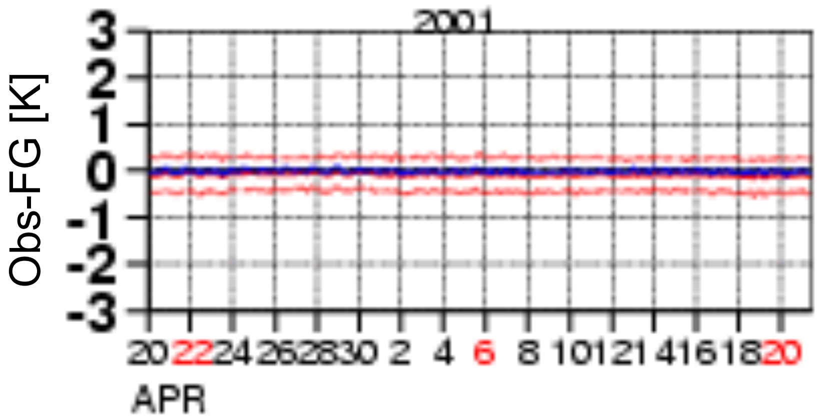


How do we know about observation biases?

By comparing the observations with the model, we learn a lot about the quality of both. Monitoring the background departures (averaged in time and/or space) is done in operations for all the observations



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



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

➔ Instrument inter-comparison (redundancy) shows that discrepancies between observation and bias is coming from an observation bias

➔ Bias model = $b(\beta) = \beta$

Changing the 4D-Var formulation (introducing VarBC)

$$
\begin{aligned}
J(x_0, \beta) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\
&+ \frac{1}{2}(\beta - \beta_b)^T \mathbf{B}_\beta{}^{-1}(\beta - \beta_b) \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Radiosonde}} [y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{NOAA-16}} [y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{NOAA-14}} [y_k - \beta - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \beta - \mathcal{H}(x_k)]
\end{aligned}
$$

Model state

Observation bias parameters

Unbiased observations (anchor)

Biased observations

Bias model

Variational Bias Correction (VarBC)

- We choose which observations we want to correct and which observations we trust
- We choose the bias model
- 4D-Var minimization estimates the value of the VarBC parameters

Changing the 4D-Var formulation (introducing VarBC)

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\begin{aligned}
J(x_0, \beta) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\
&+ \frac{1}{2}(\beta - \beta_b)^T \mathbf{B}_\beta{}^{-1}(\beta - \beta_b) \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Radiosonde}} [y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{NOAA-16}} [y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{NOAA-14}} [y_k - \beta - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \beta - \mathcal{H}(x_k)]
\end{aligned}
$$

Model state

Observation bias parameters

Parameter estimates from previous analysis

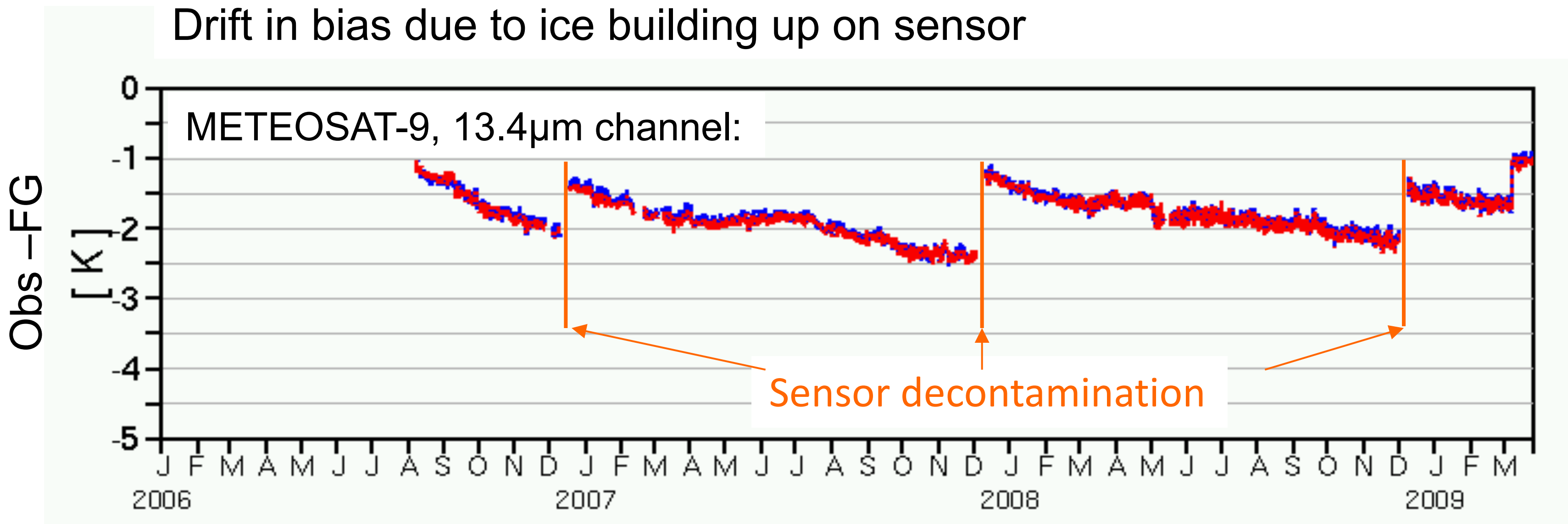
Background covariance matrix for VarBC parameters

Variational Bias Correction (VarBC)

- A cycling scheme for updating the bias parameter estimates
- Specification of the background covariance matrix $\mathbf{B}_\beta$ (large value ➔ fast adaptation, small value ➔ slow adaptation)

$$
\mathbf{B}_{\boldsymbol{\beta}} = \begin{bmatrix} \mathbf{B}_{\boldsymbol{\beta}}^{(1)} & & 0 \\ & \ddots & \\ 0 & & \mathbf{B}_{\boldsymbol{\beta}}^{(J)} \end{bmatrix}
$$

Building models of observation biases

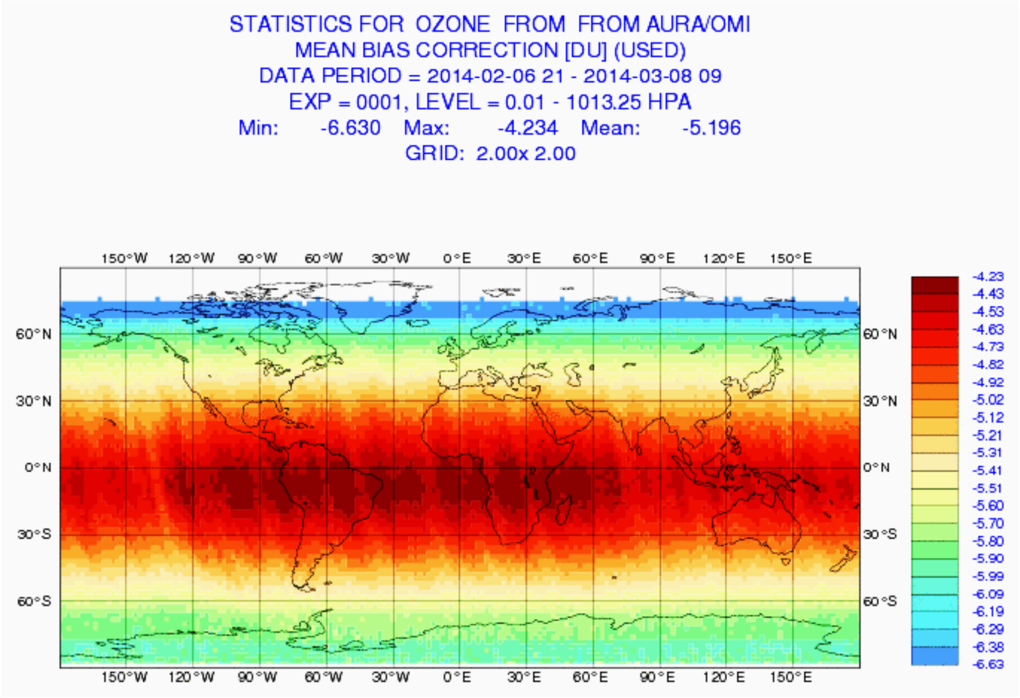


VarBC can correct for such an observation bias

- Bias model = b(β) = β
- β is evolving over time depending how much ice is building up
- Specification of $\mathbf{B}_{\beta}$ is crucial to ensure a good performance

Building models of observation biases (Ozone)

VarBC correction for Ozone observations



Model bias = $b(\beta) = b(\beta_0, \beta_1) = \beta_0 + \beta_1$ * solar elevation

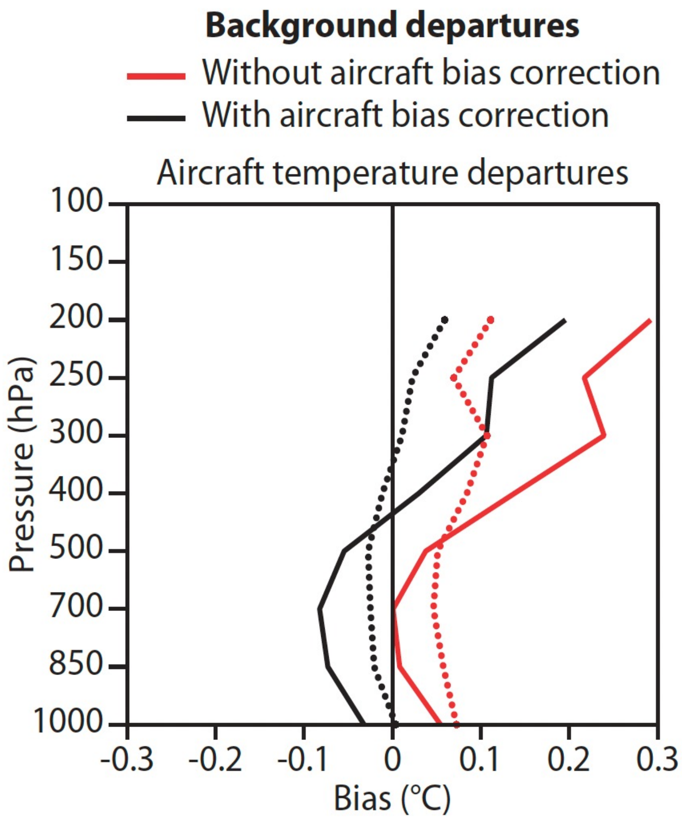
the predictor

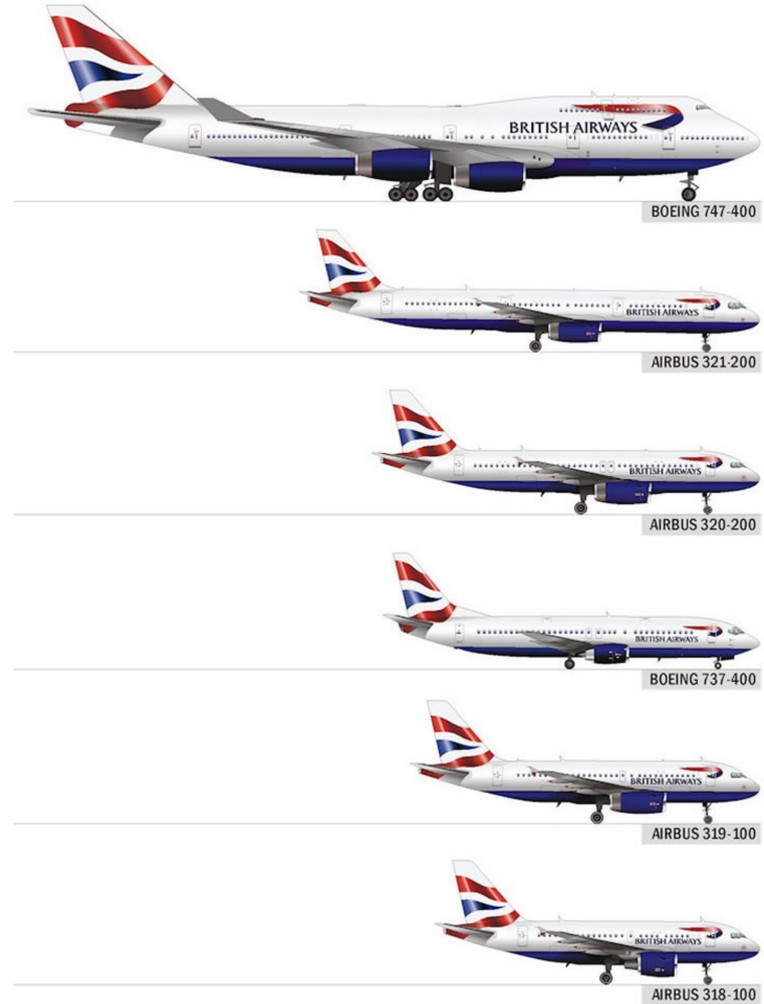
the parameters

Any bias correction requires a good model for the bias $b(\beta)$

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

Building models of observation biases (aircraft)





For each aircraft separately (~5000 distinct aircraft)

Bias model = $b(\beta) = b(\beta_0, \beta_1, \beta_2) = \beta_0 + \beta_1$ * ascent rate + β_2 * descent rate

the parameters

the predictors

Building models of observation biases (a more complex case)

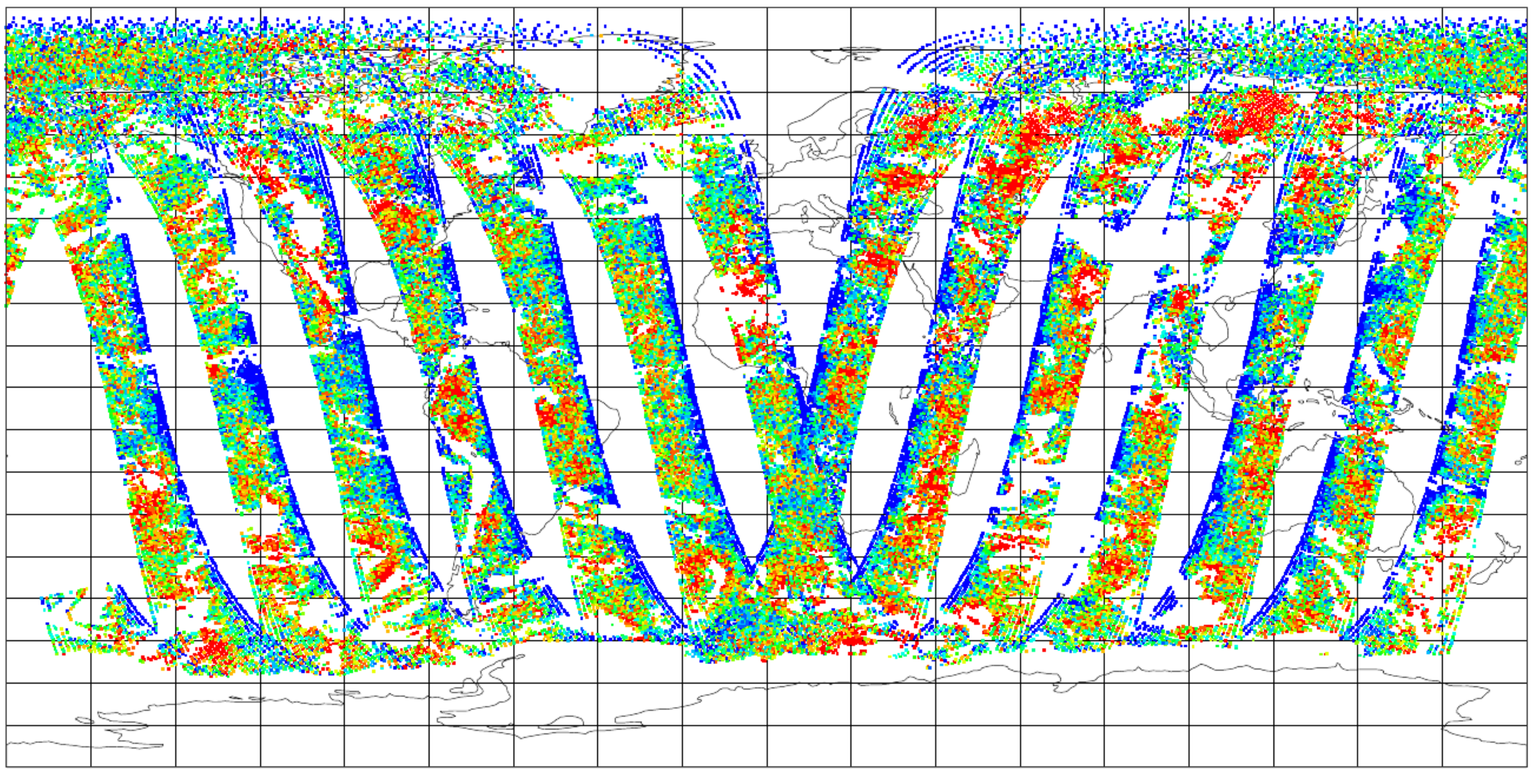
ECMWF is assimilating polar-orbiting Metop-C satellite (launched on 7 November 2018)

Observation bias is estimated inside 4D-Var

➔ comparing measurements with model

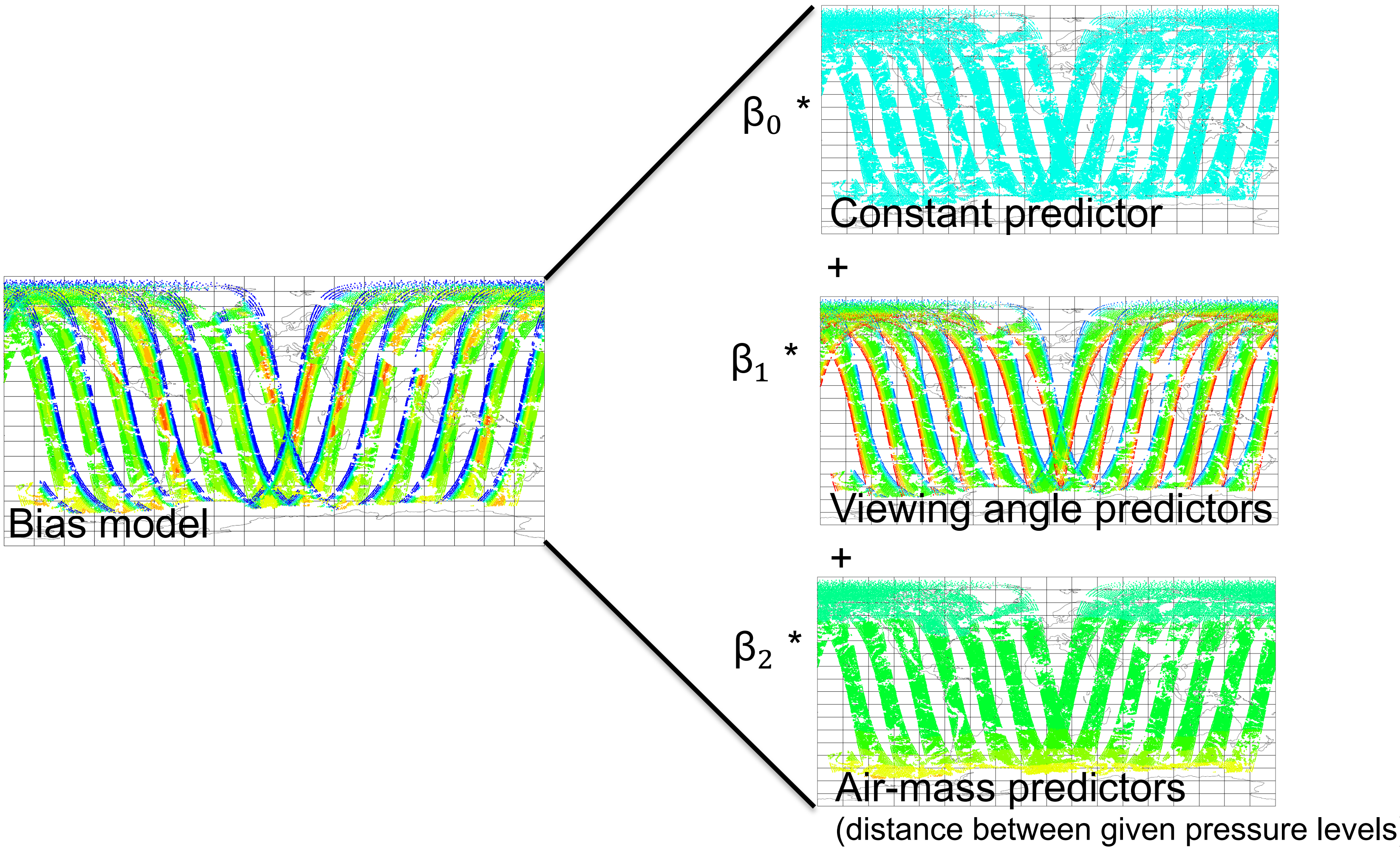
➔ specifying the structure of the model bias

Metop-C AMSUA-A Channel 5 (obs-model)

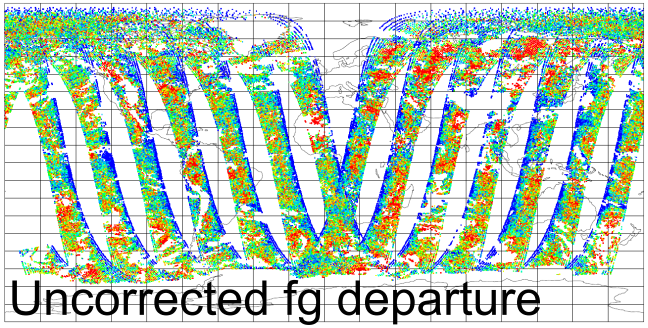


Building models of observation biases (a more complex case)

Bias model = $b(\beta) = b(\beta_0, \beta_1, \beta_2) = \beta_0 + \beta_1$ * viewing angle + β_2 * air-mass

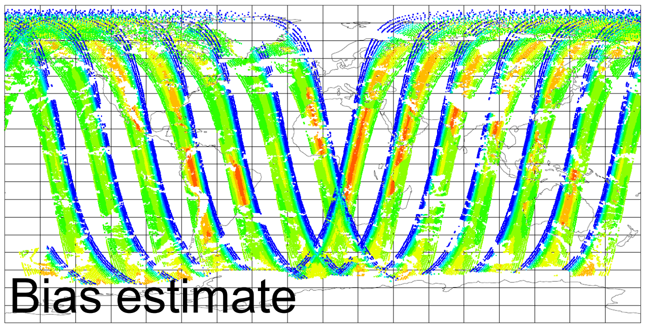


Building models of observation biases (a more complex case)



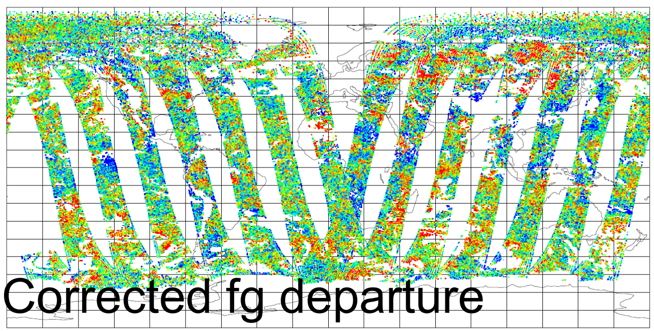
Uncorrected fg departure

-



Bias estimate

=



Corrected fg departure

$$
\begin{aligned}
J(x_0,\beta) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\
&+ \frac{1}{2}(\beta - \beta_b)^T \mathbf{B}_\beta{}^{-1}(\beta - \beta_b) \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Radiosonde}} [y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Metop-C}} [y_k - b(\beta, x_k) - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - b(\beta, x_k) - \mathcal{H}(x_k)]
\end{aligned}
$$

Do not include too many predictors in the bias correction models

➔ to avoid correcting for other sources of errors (background errors/model error)

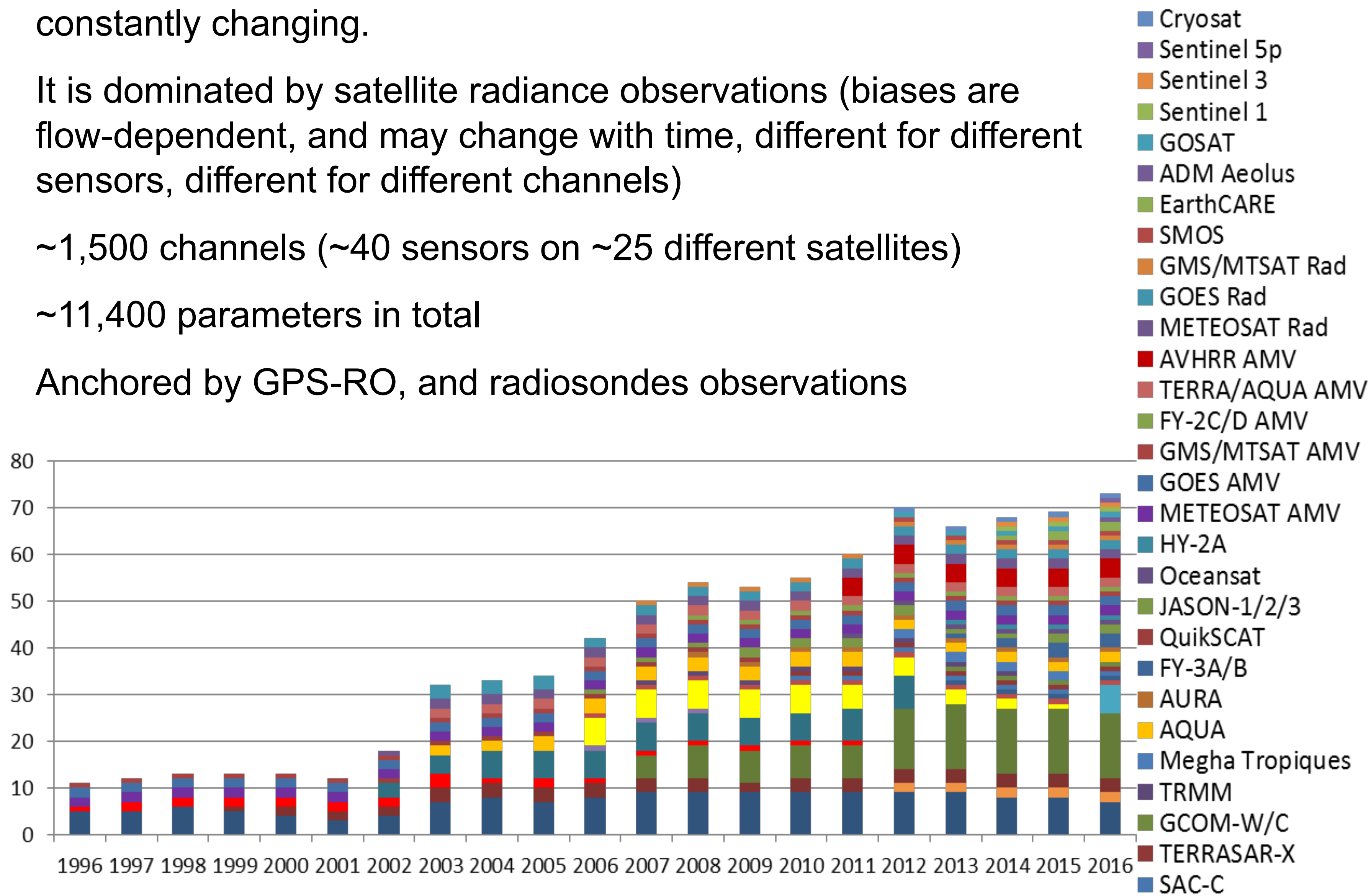
➔ corrected fg departure should still contain some information to constrain x_0

Generic VarBC formulation

$$b(\beta, x_k) = \beta_0 + \sum_{i=0}^{N} \beta_i p_i(x_k)$$

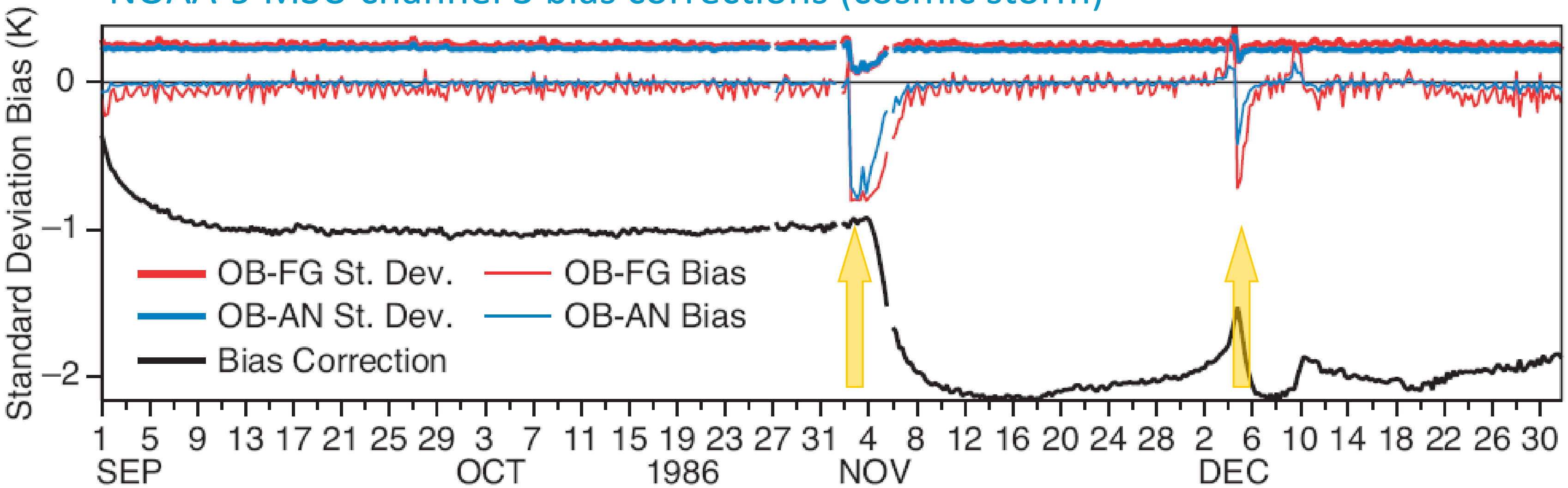
The power of VarBC

- The global observing system is increasingly complex and constantly changing.
- It is dominated by satellite radiance observations (biases are flow-dependent, and may change with time, different for different sensors, different for different channels)
- ~1,500 channels (~40 sensors on ~25 different satellites)
- ~11,400 parameters in total
- Anchored by GPS-RO, and radiosondes observations



The power of VarBC

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



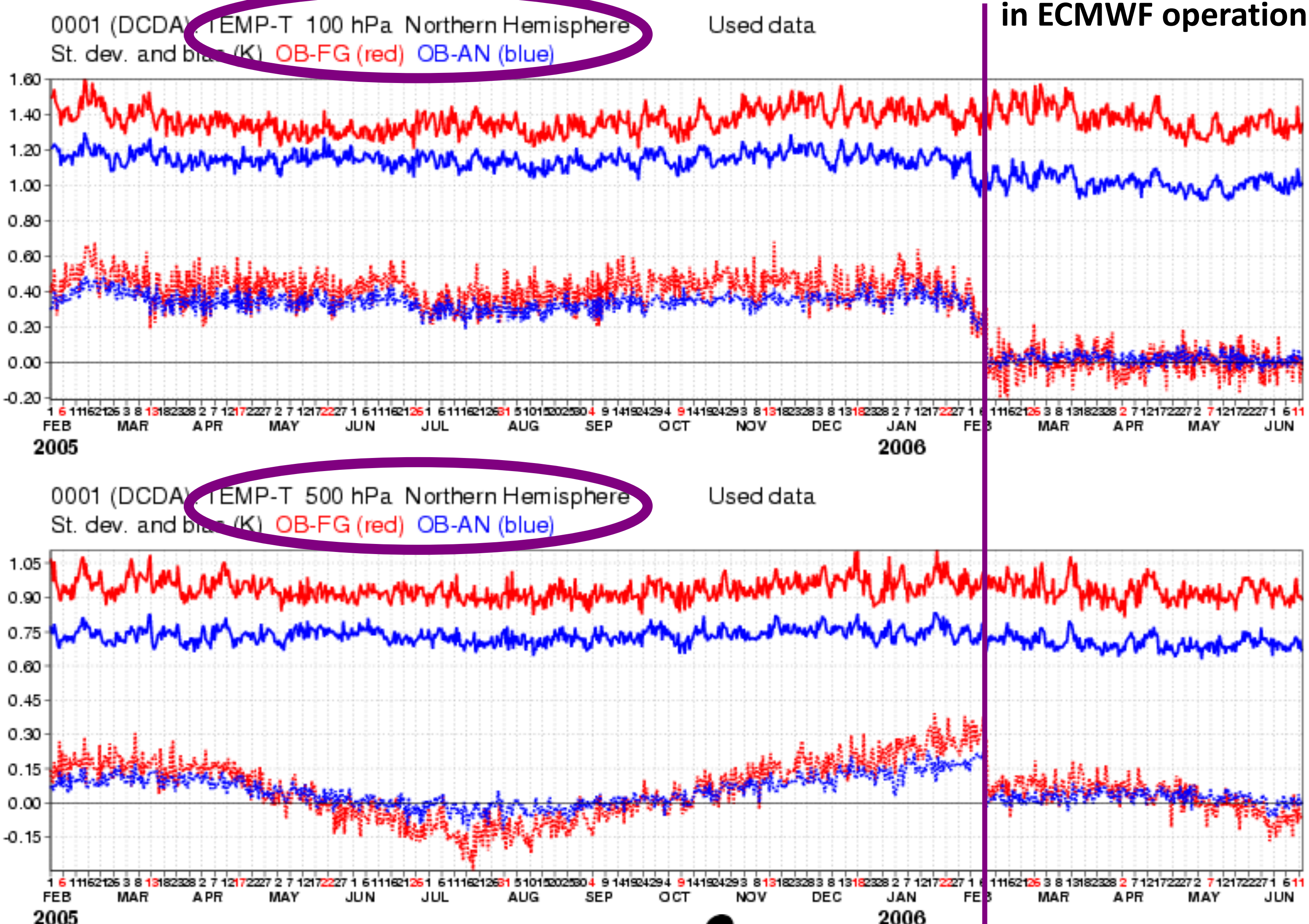
Two cosmic storms trigger large observation biases, but the whole 4D-Var system handles this automatically (thanks to VarBC)

1. Initially QC rejects most data from this channel
2. VarBC adjusts the bias estimates
3. Bias-corrected data are gradually assimilated again

No shock to the system!

VarBC introduced in operations at ECMWF

Introduction of VarBC in ECMWF operations

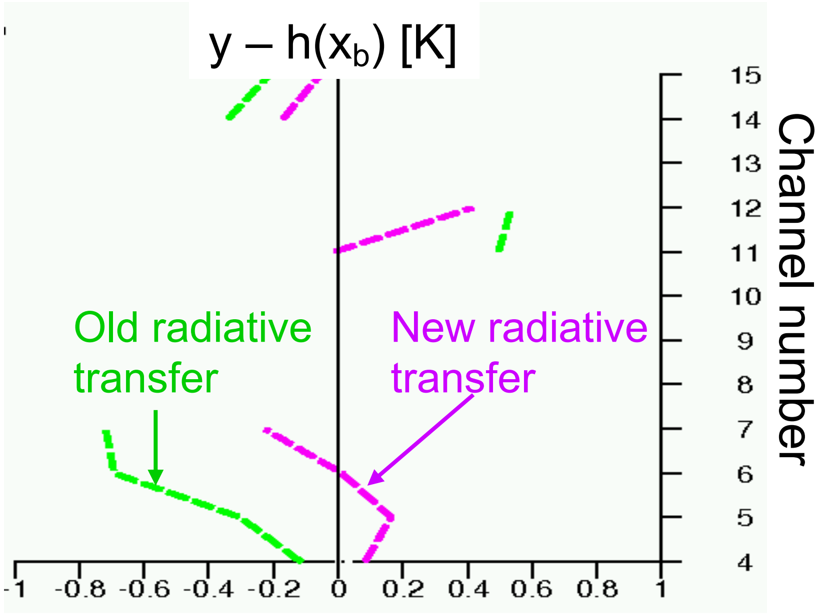


VarBC also handles biases from the observation operators

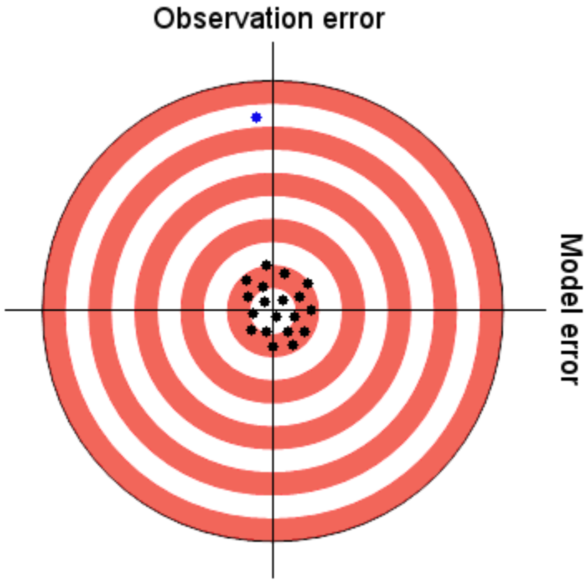
Examples of causes for biases in radiative transfer $y - h(x_b)$:
Bias in assumed concentrations of atmospheric gases (e.g., CO_2, aerosols)
Biases in the spectroscopy
Neglected effects (e.g., clouds)

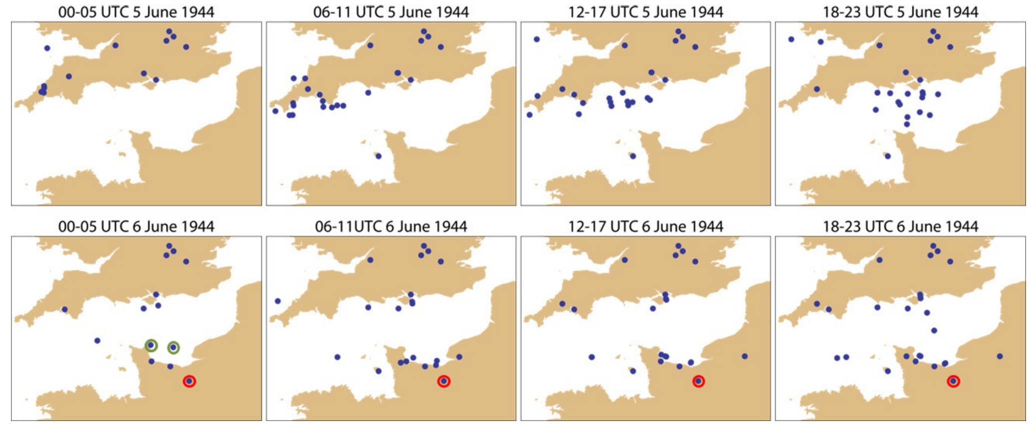
VarBC needs to handle these biases in its model!

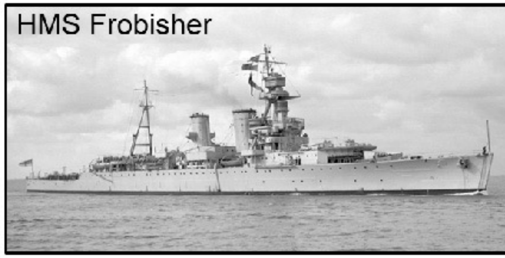
Change in bias for HIRS resulting from an update of the Radiative Transfer model:



Not the job of VarBC: Gross (obvious) errors

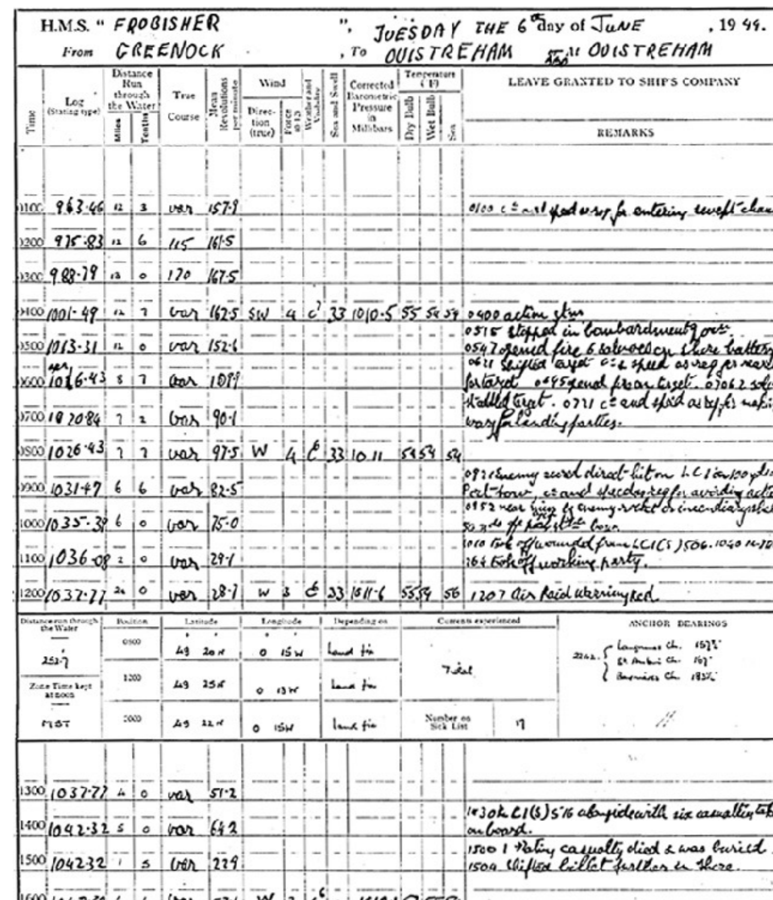






HMS Frobisher		
Pressure	1010.5hPa (mb)	
Temperature	285.95K	(55°F)
Dew point (wet bulb)	284.95K	(54°F)
Wind direction	225°	(SW)
Wind speed	6.7ms^{-1}	(Force 4)
(Weather/) Visibility	Code 97	(c/7)
Sea temperature	285.35K	(54°F)

HMS Hawkins		
Pressure	1014.8hPa (mb)	
Temperature	285.35K	(54°F)
Dew point (wet bulb)	283.35K	(52°F)
Wind direction	270°	(W)
Wind speed	6.7ms^{-1}	(Force 4)
(Weather/) Visibility	Code 96	(c/6)
Sea temperature	284.25K	(52°F)



H.M.S. "FROBISHER", TUESDAY THE 6th day of JUNE, 1944.

From GREENOCK, To OUISTREHAM, At OUISTREHAM

LEAVE GRANTED TO SHIP'S COMPANY

REMARKS

→ Preliminary analysis (blacklist,…)

→ Online Quality Control

Not the job of VarBC: Model biases

VarBC should not correct for biases in the model!

➔ We need another algorithm to do this job: weak-constraint 4D-Var (tomorrow)

Take-away messages (1/3)

To illustrate biases in observations

To construct bias models for specific instruments

Take-away messages (2/3)

Errors in the inputs y – h(x_b) arise from

- ➔ errors in the actual observations
- ➔ errors in the observation operator
- ➔ errors in the model background

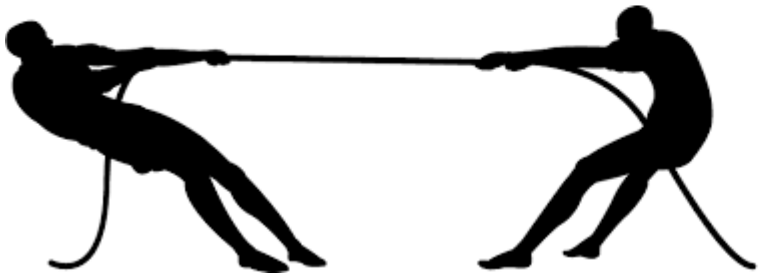
Challenges

- ➔ we only have information about differences
- ➔ there is no true reference in the real world!
- ➔ the success of VarBC relies on ***anchoring*** and ***redundancy***
- ➔ How to separate observation bias from model bias (error attribution)?

Take-away messages (3/3)

From bias-blind to bias-aware data assimilation

$$
\begin{aligned}
J(x_0) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\
&+ \frac{1}{2}\sum_{k=0}^{K}[y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)]
\end{aligned}
$$



$$
\begin{aligned}
J(x_0, \beta) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\
&+ \frac{1}{2}(\beta - \beta_b)^T \mathbf{B}_\beta{}^{-1}(\beta - \beta_b) \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Radiosonde}}[y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{GPSRO}}[y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\
&+ \frac{1}{2}\sum_{k=0}^{\text{Others}}[y_k - b(x_k, \beta) - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - b(x_k, \beta) - \mathcal{H}(x_k)]
\end{aligned}
$$

Any questions? Feel free to contact me patrick.laloyaux@ecmwf.int