Handling of systematic model errors: Numerical Weather Prediction & Reanalysis

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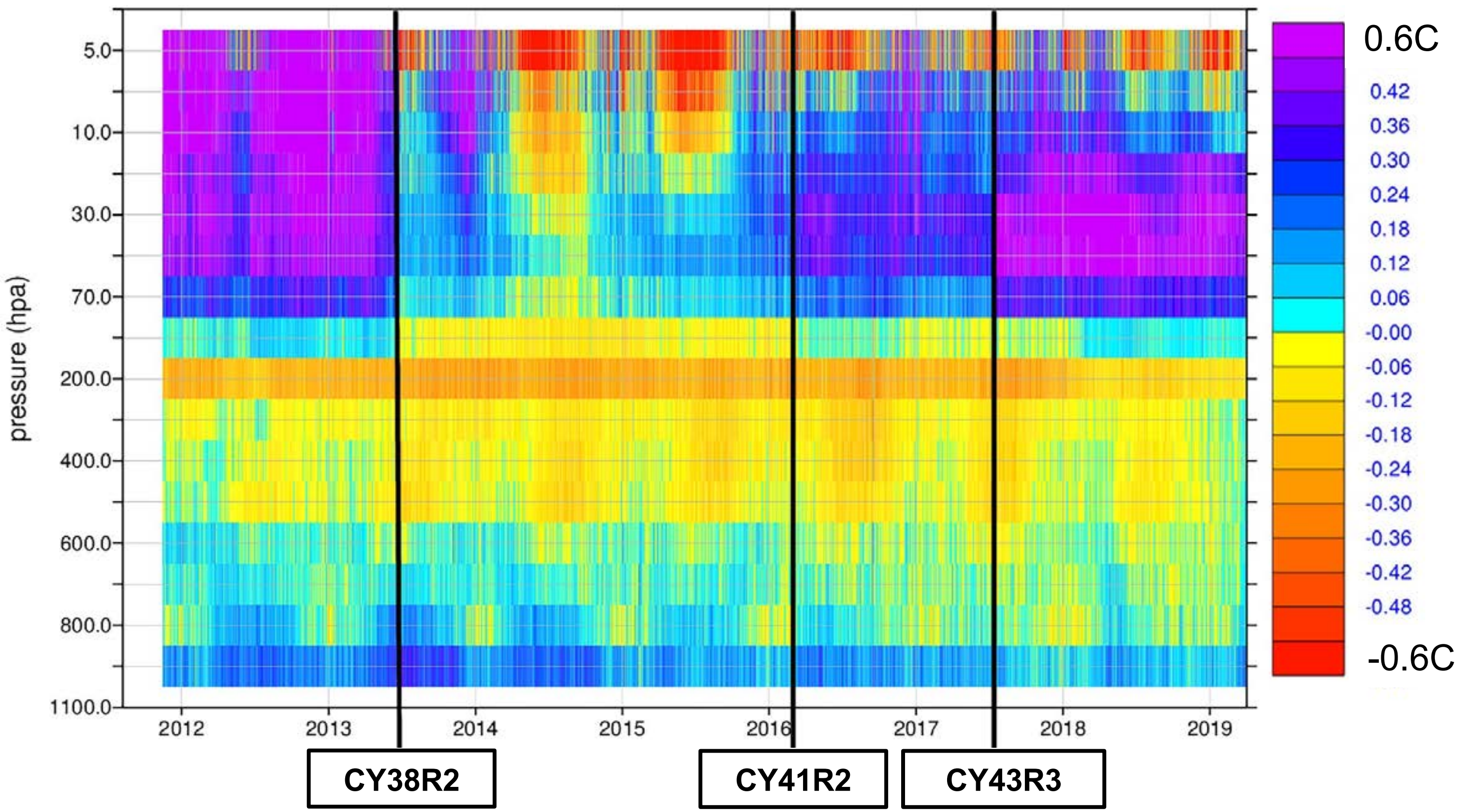
Introduction to systematic model errors

ECMWF has been developing a comprehensive Earth system model which forms the basis for all our data assimilation, forecasting and reanalysis activities. In this talk we concentrate on the stratosphere



The short-term model bias is estimated by comparing the 12-hour first-guess trajectory with radiosondes

Largest bias in the stratosphere:

→ bias reduced with new vertical resolution (L137 in CY38R2)

→ bias increased with new horizontal resolution (Tco1279 in CY41R2)

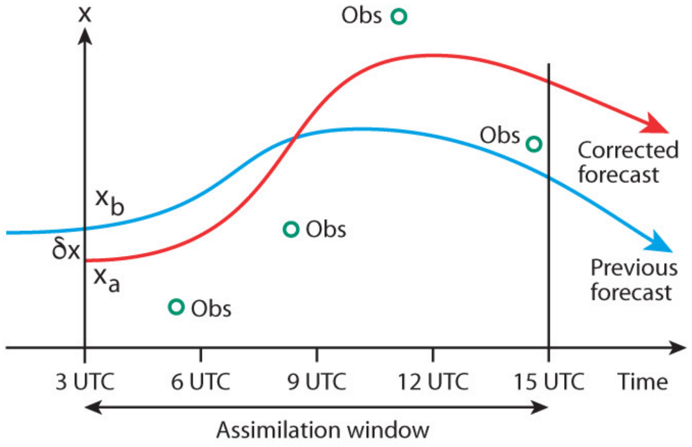
→ bias increased with new radiative scheme (CY43R3)

One of the best models in the world, but it still contains some residual biases that must be taken into account

Model biases in data assimilation for Numerical Weather Prediction (1/3)

ECMWF has been developing a DA system that can handle model biases

Strong constraint 4D-Var

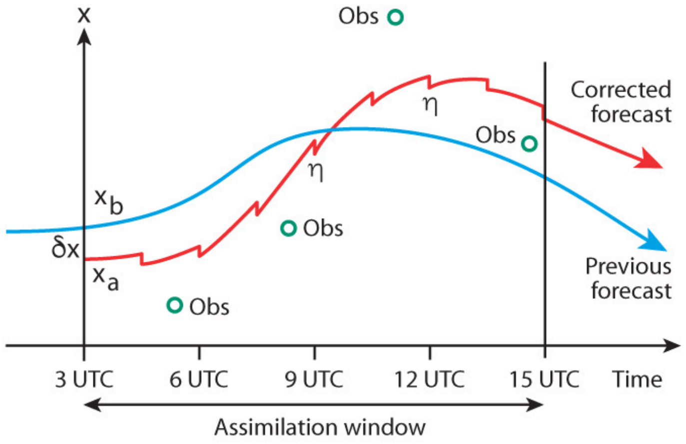


$$x_k = \mathcal{M}_k(x_{k-1})$$

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

Any model bias is affecting the quality of the analysis

Weak constraint 4D-Var



$$x_k = \mathcal{M}_k(x_{k-1}) + \eta \quad \text{for } k = 1, 2, \cdots, K$$

Model bias correction

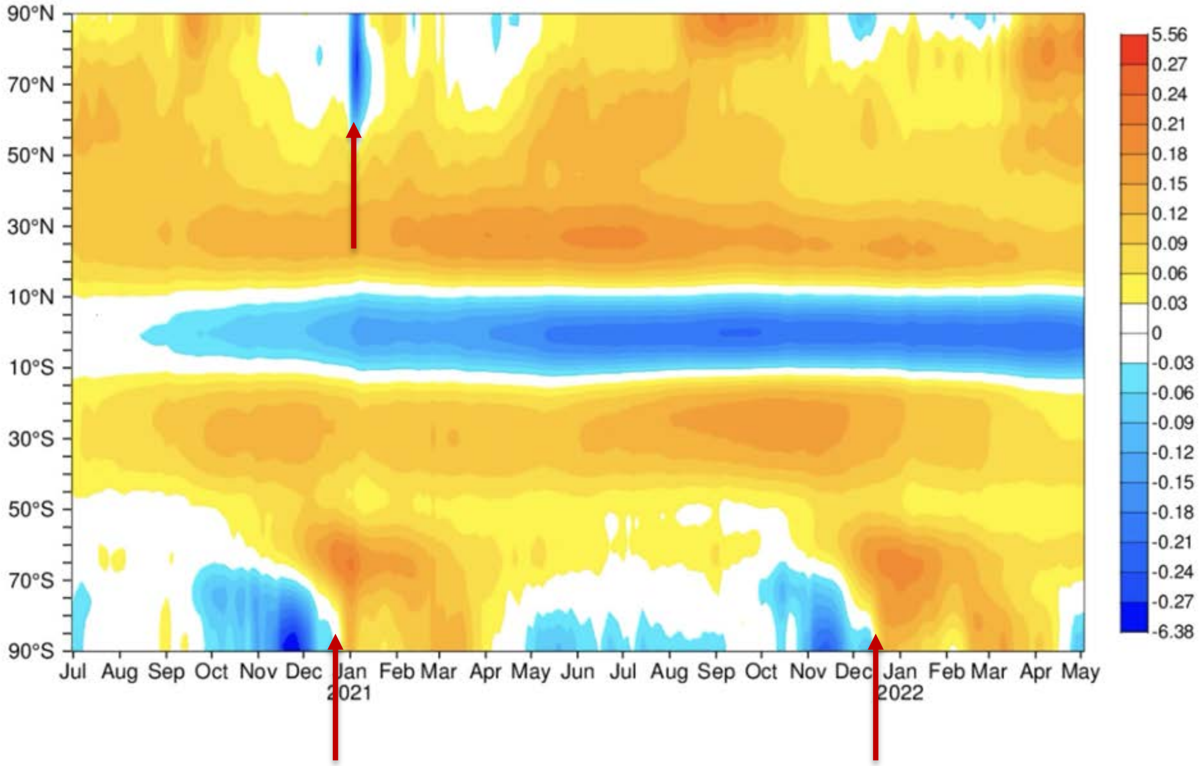
$$\begin{aligned} J(x_0, \eta) &= \frac{1}{2}(x_0 - x_b)^T \mathbf{B}^{-1}(x_0 - x_b) \\ &+ \frac{1}{2}\sum_{k=0}^{K}[y_k - \mathcal{H}(x_k)]^T \mathbf{R}_k^{-1}[y_k - \mathcal{H}(x_k)] \\ &+ \frac{1}{2}(\eta - \eta_b)^T \mathbf{Q}^{-1}(\eta - \eta_b) \end{aligned}$$

Laloyaux et al., Exploring the potential and limitations of weak-constraint 4D-Var, 2020
Laloyaux et al., Towards an unbiased stratospheric analysis, 2020

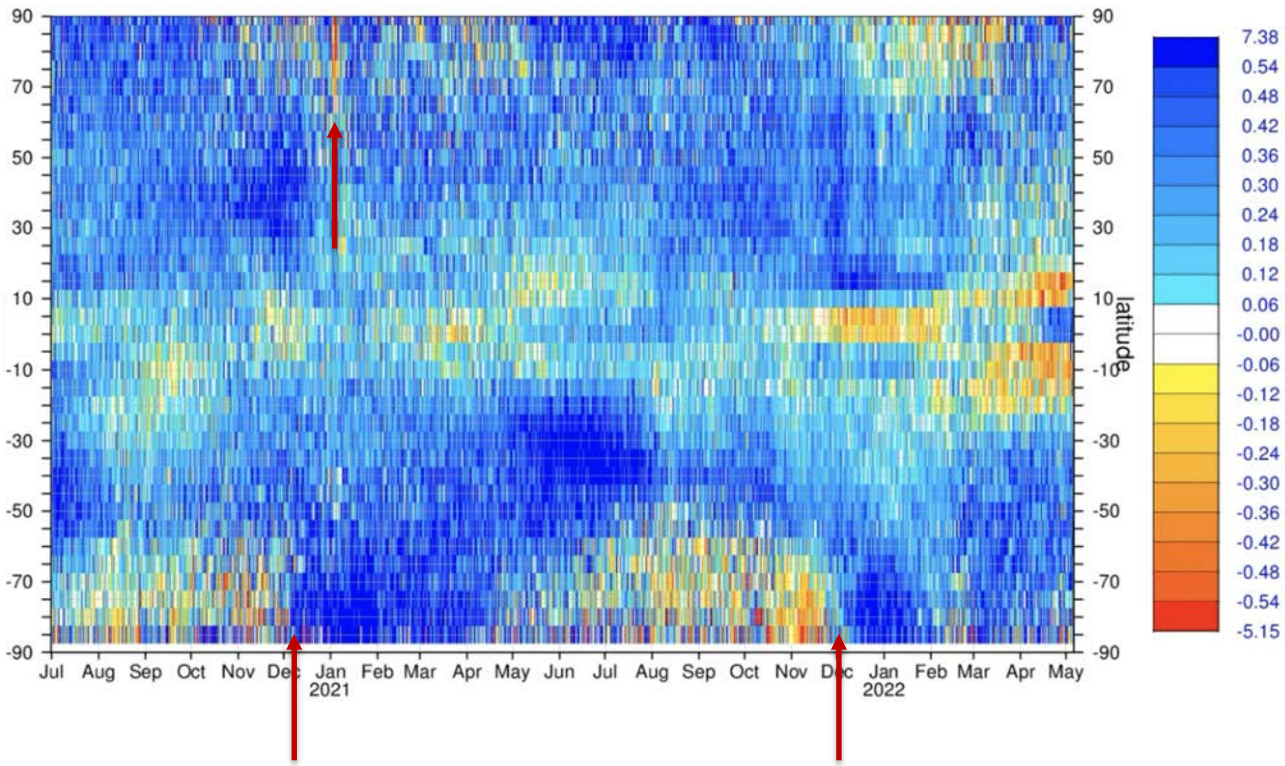
Model biases in data assimilation for Numerical Weather Prediction (2/3)

On the 30th of June 2022, we will celebrate the second weak-constraint 4D-Var anniversary in operations

Bias correction estimated by WC4DVar (20hPa and 30hPa)



Model bias diagnosed using RO retrievals (20hPa and 30hPa)



WC4DVar learns correctly the model bias from synoptic situations (e.g. SSW) and from seasonal cycles (e.g. sharp transitions in SH)

Model biases in data assimilation for Numerical Weather Prediction (3/3)

A collaboration between ECMWF and NVIDIA to develop a ML solution to correct model biases based on GNSS-RO

Deep learning to estimate model biases in an operational NWP assimilation system

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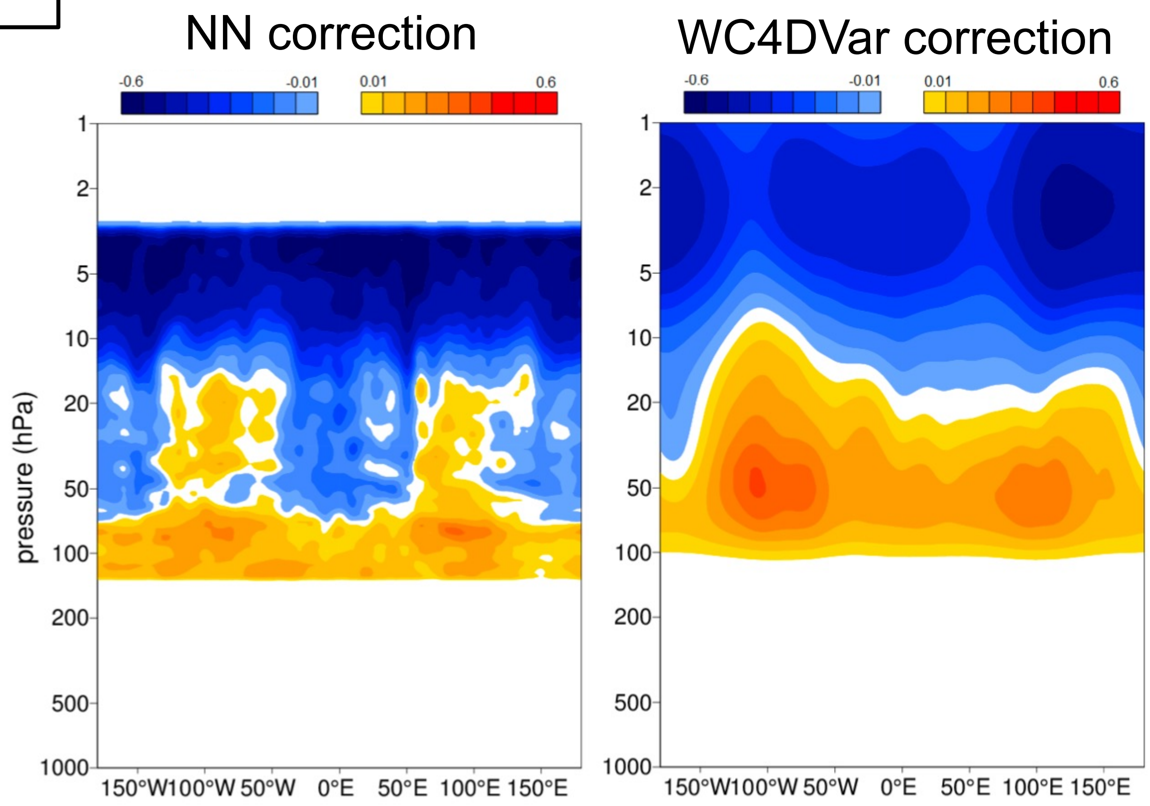
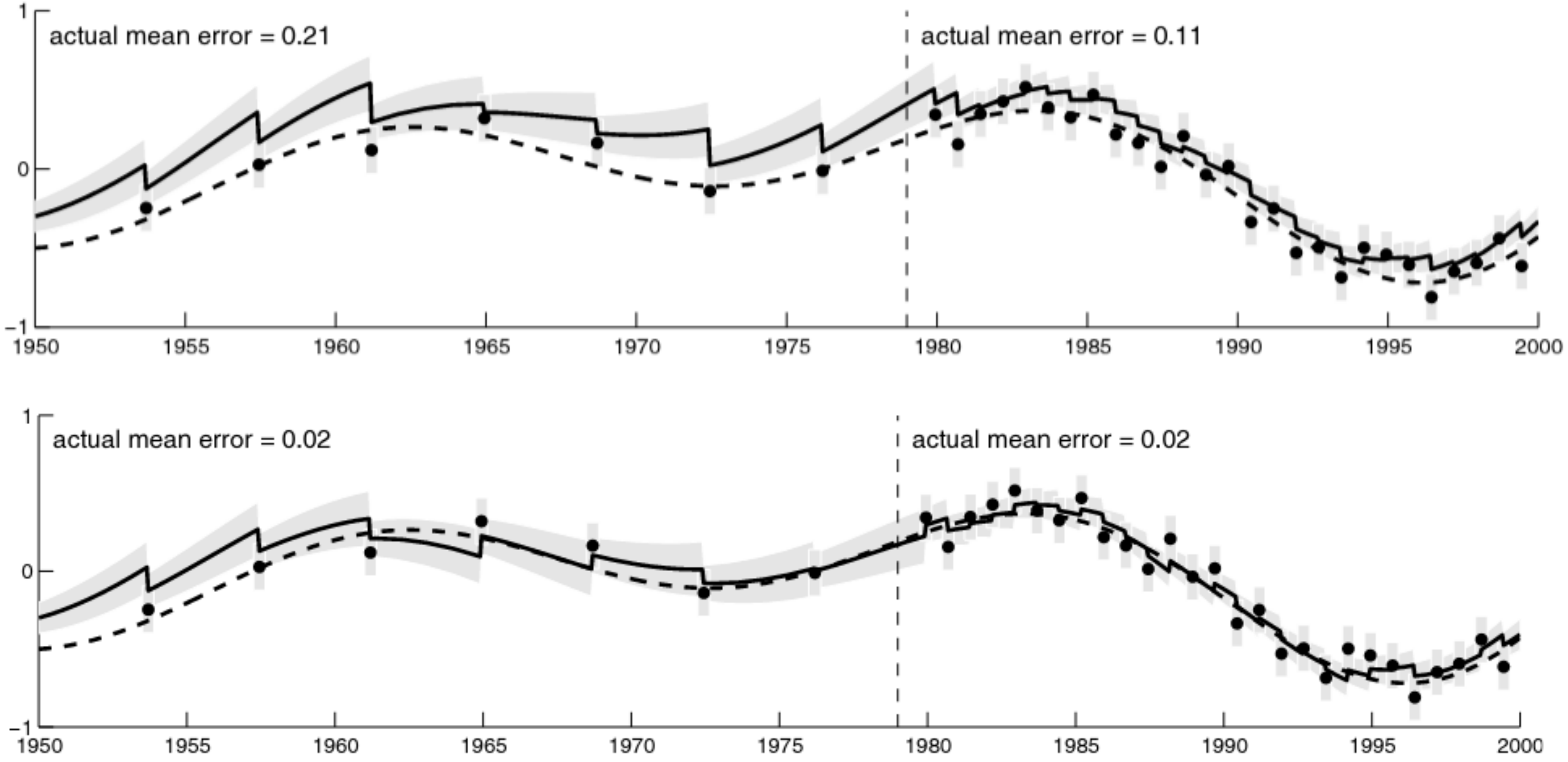
[2]Nvidia Corporation, Santa Clara, California, United States

Promising results but do not outperform WC4DVar



Model biases in data assimilation for Reanalysis (1/4)

Separate real signals and spurious climate trends is challenging because of model biases



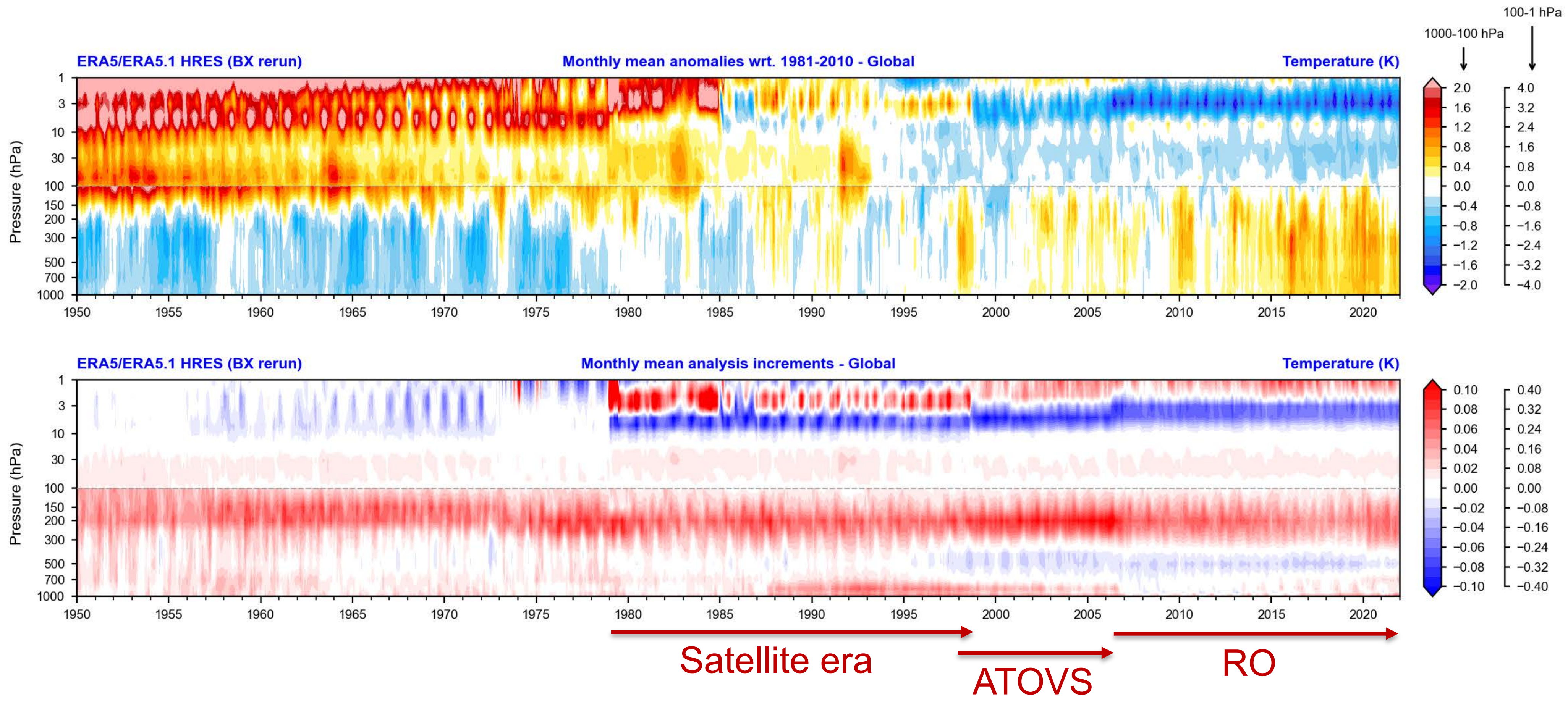
Biased model with less frequent observations create a spurious trend

Introducing a method correcting for model biases should alleviate the problem

D. Dee, Bias and data assimilation, 2005

Model biases in data assimilation for Reanalysis (2/4)

ERA5 has not used weak-constraint 4D-Var (not ready when production started). The climate trends are affected by model biases to some extend

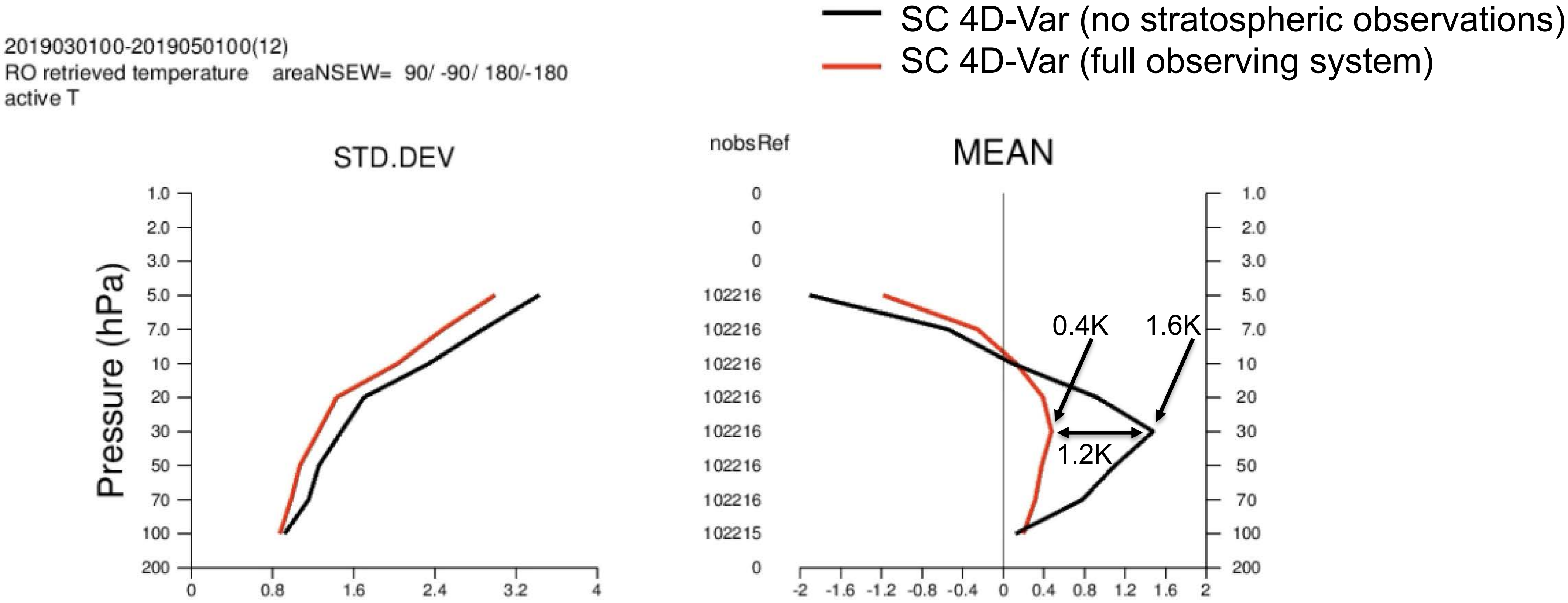


Model biases in data assimilation for Reanalysis (3/4)

Observing system experiments are carried out over 2019

- full observing system
- no stratospheric observations

RO temperature retrievals are used to assess the biases in the assimilation system

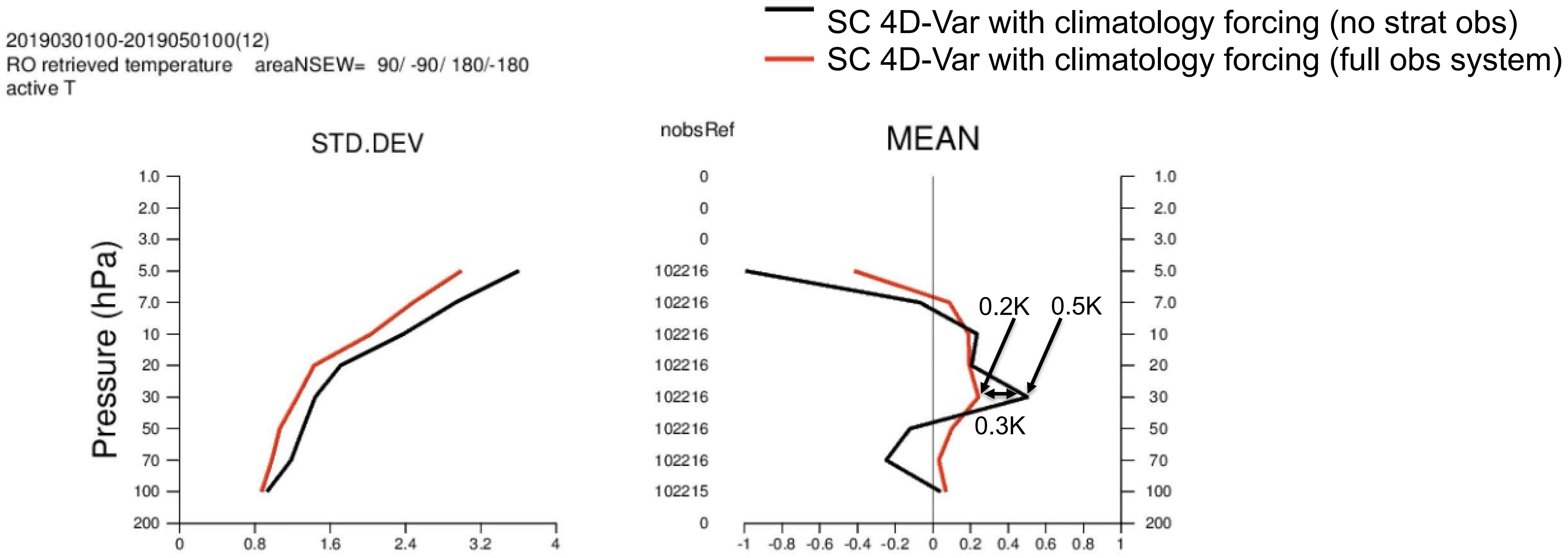


When model biases are present, SC4DVar mean state is very sensitive to changes in the observing system

Model biases in data assimilation for Reanalysis (3/4)

ERA6 could use a method to correct model biases, option investigated at the moment:

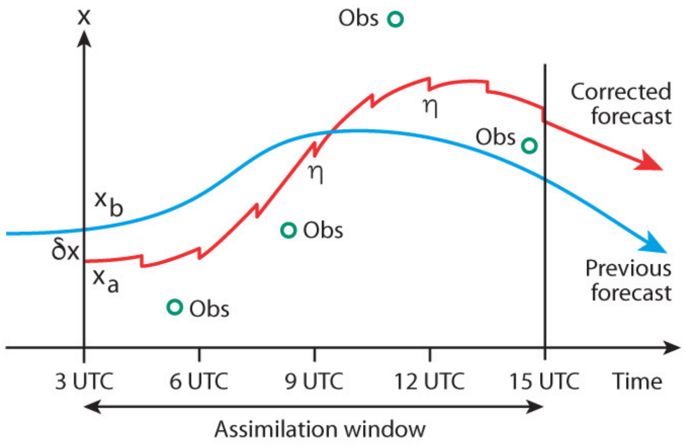
1. Run WC-4DVar over a recent period (e.g. 2020)
2. Use this year of model error estimate to derive a climatology (e.g. monthly average)
3. Apply this model error climatology to force the model for the whole reanalysis



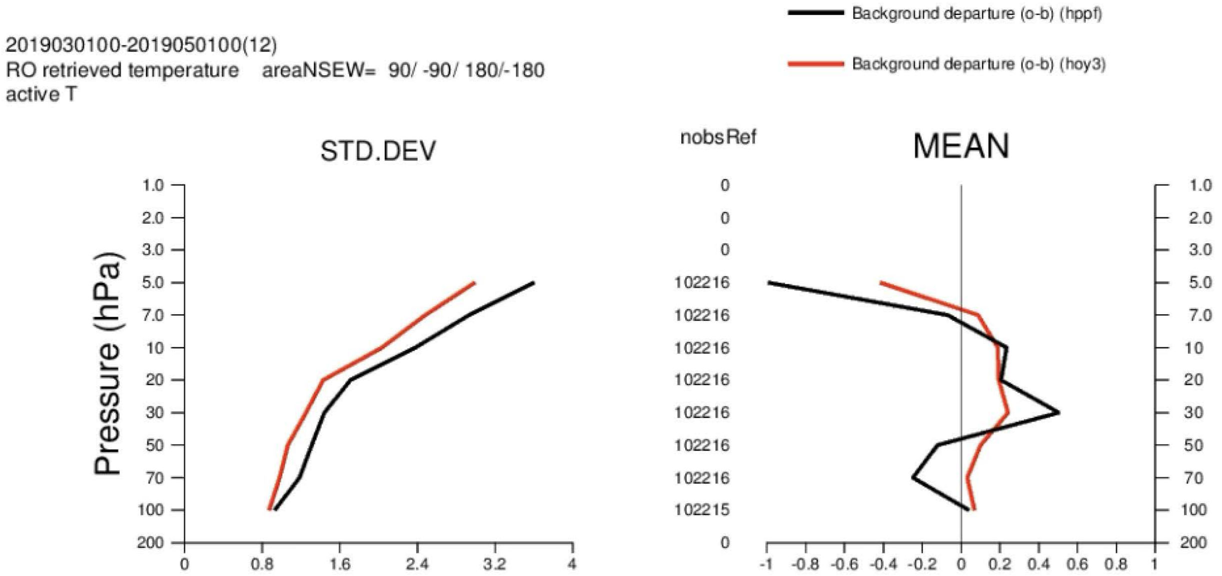
Mean states are less biased when the model is corrected by the climatology and impact of changes in the observing system is much reduced

Conclusions

- Data assimilation needs to take into account model biases in NWP and reanalysis. Both applications have a common goal (producing an unbiased analysis)



- Computing a model error climatology to force the model used in reanalysis looks promising, but other options are available



- Model biases have been discussed here, but observation biases are equally important