Towards an unbiased stratospheric temperature analysis

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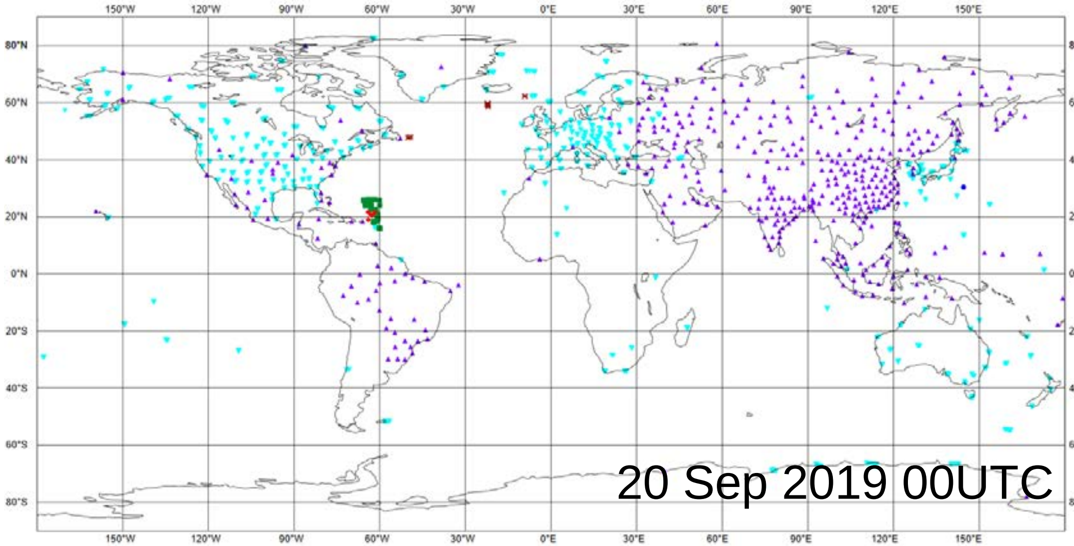
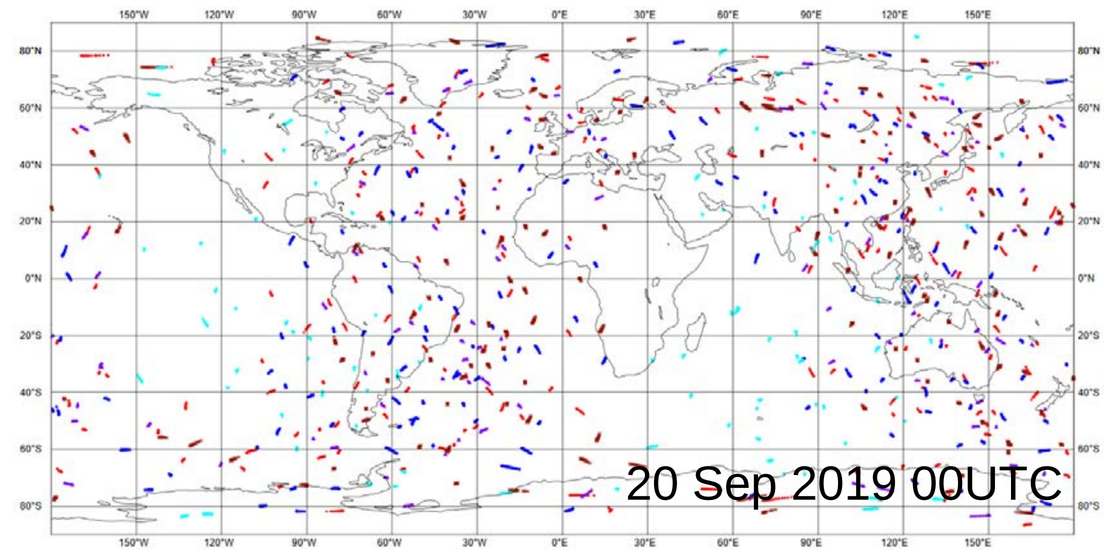
How we observe stratospheric temperature

Radiosondes

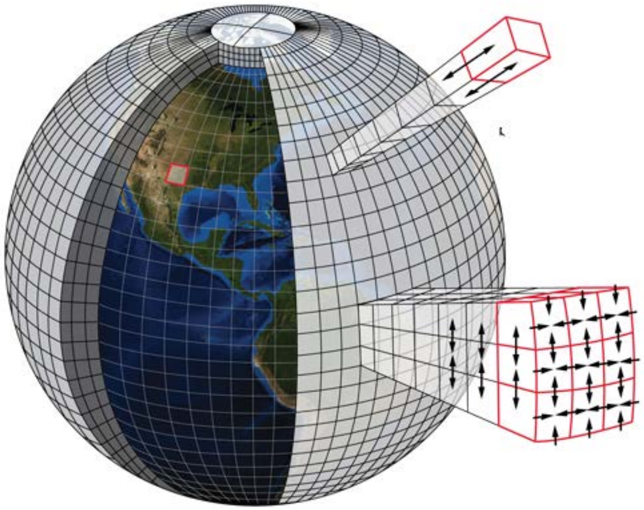


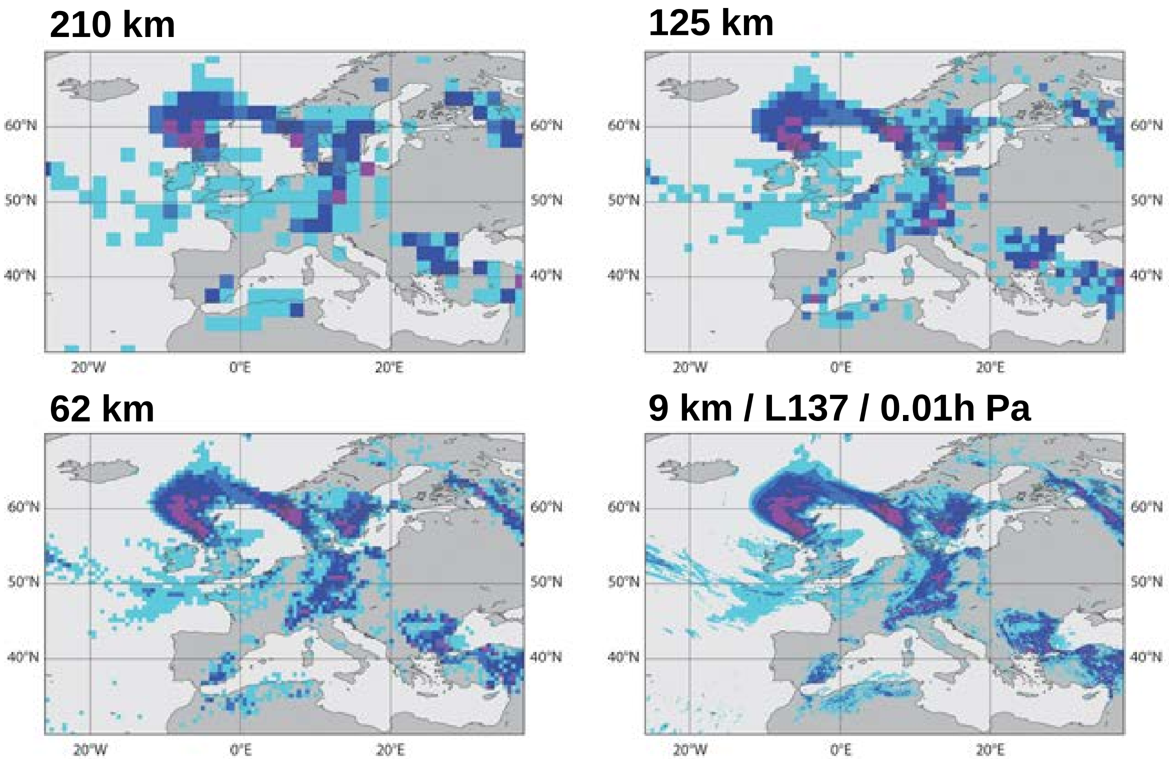
Radio occultation



Radiosondes and RO are used as anchoring observations in the atmosphere

How we model stratospheric temperature (IFS)





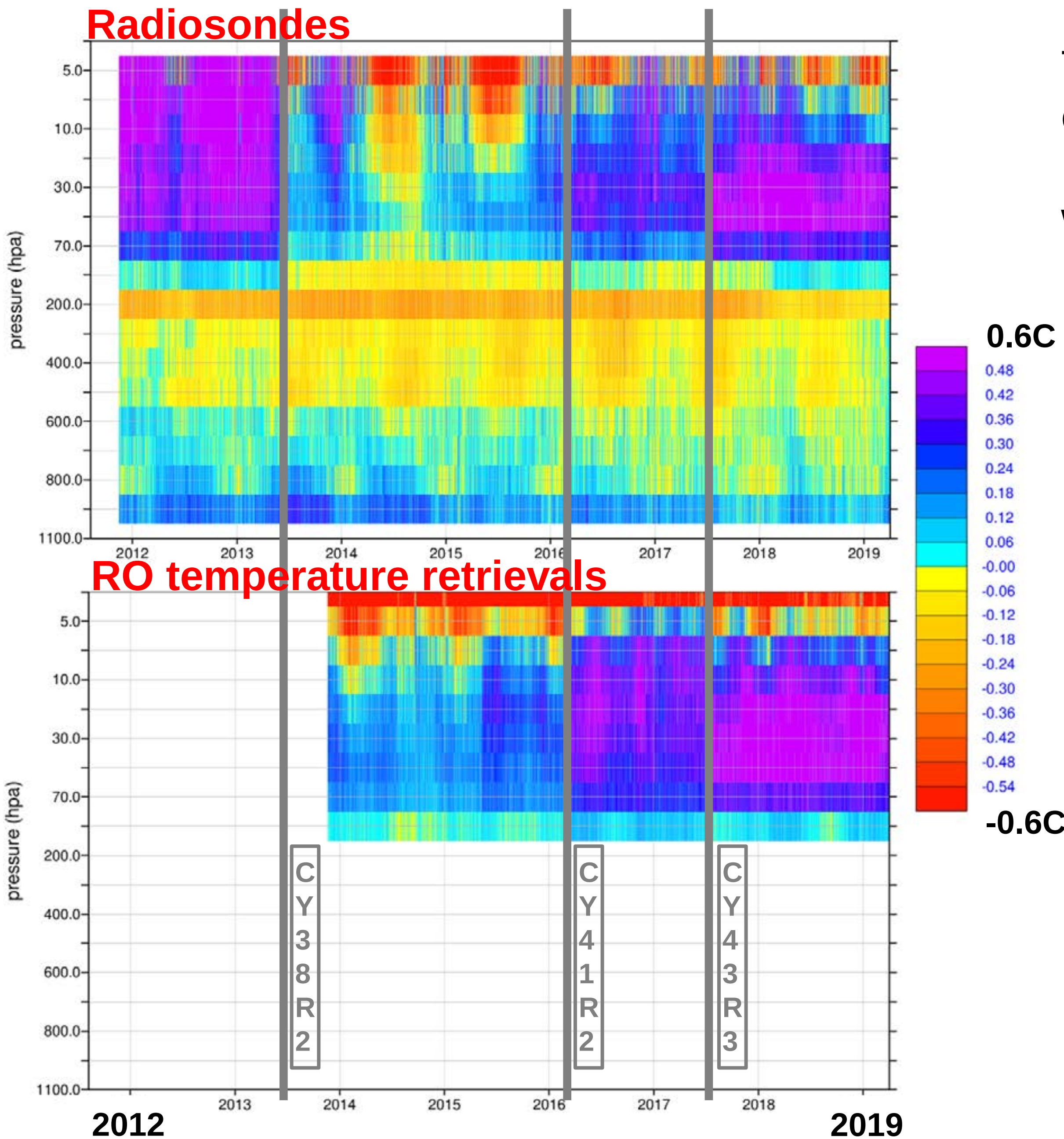
Model upgrades include
- resolution
- dynamic
- physic

Purpose of this talk is to demonstrate a new application of RO

→ RO used to diagnose temperature model biases

→ RO used to correct automatically those model biases in 4D-Var

Temperature bias in the operational IFS model (1/2)



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

Similar signal with the two types of observations:

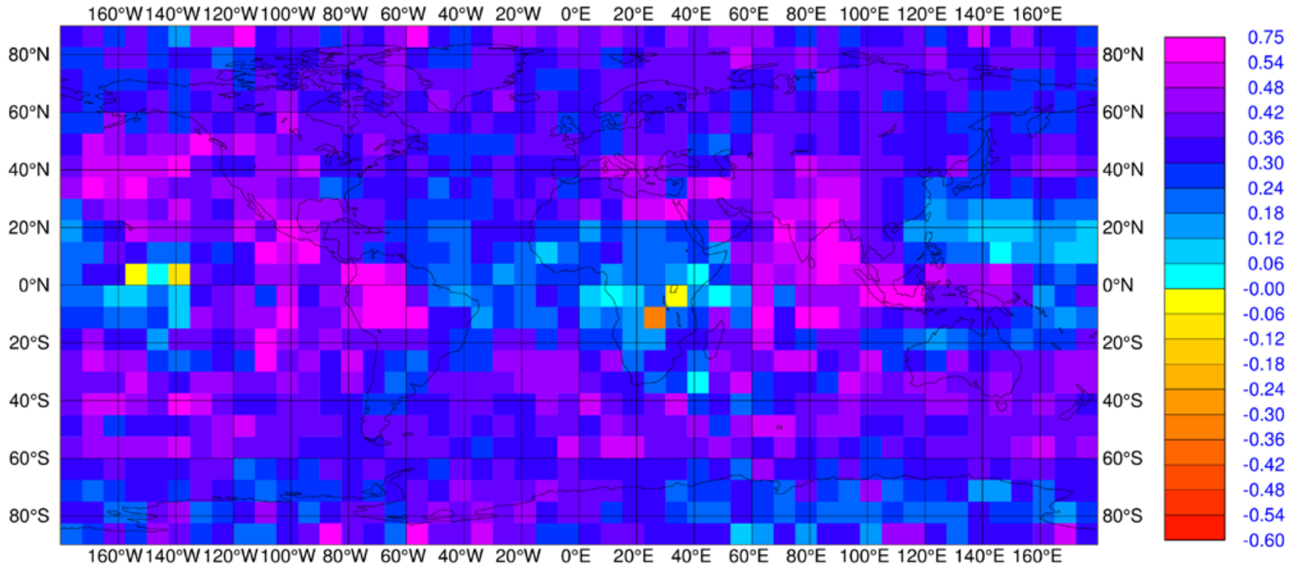
→ bias reduced with new vertical resolution (L137 in CY38R2)

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

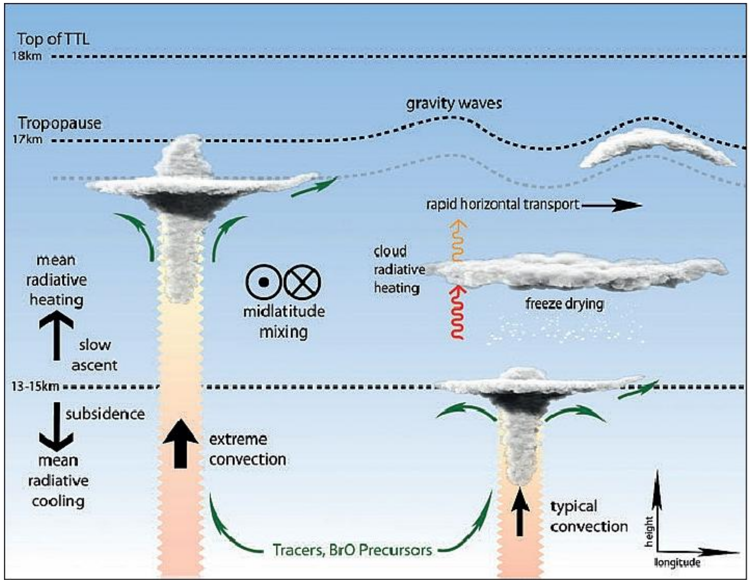
→ bias increased with new radiative scheme (CY43R3)

Temperature bias in the operational IFS model (2/2)

Temperature first-guess departure with respect to RO (~70hPa, January 2017)



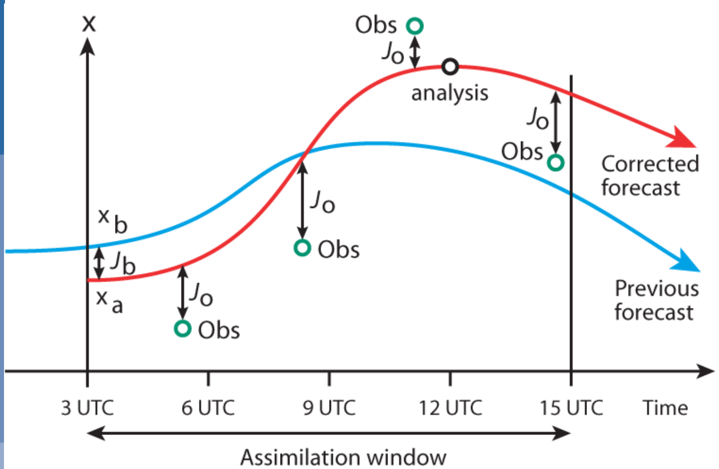
→ model error is large scale and presents specific features



The bias is due to
- discretization errors in the vertical advection (dynamical core)
- inadequate representation of gravity waves in the vertical direction

RO can be used to diagnose the spatial structure of the model error

4D-Var assimilation (1/3)



Strong-constraint

- First-guess trajectory
- Observations
- Compute a correction at initial time
- Analysis trajectory

The model is assumed to be perfect (strong-constraint)

$$\mathbf{x}_k = \mathcal{M}_{k,k-1}(\mathbf{x}_{k-1}) \qquad \text{for} \qquad k = 1, \ldots, N$$

Cost function depends only on the state at the beginning of the assimilation window

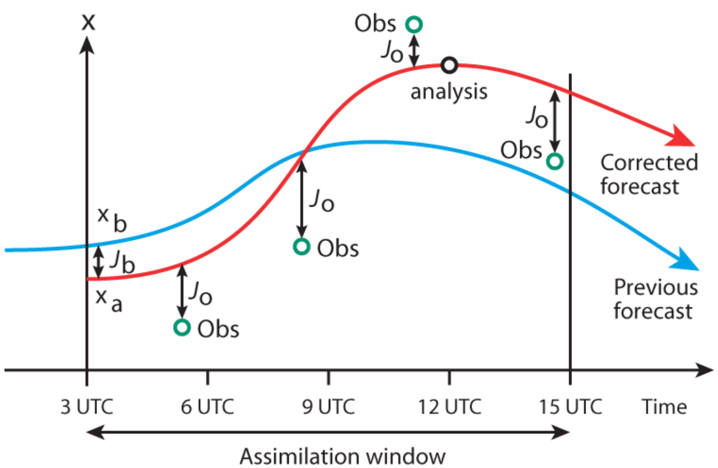
$$J(\mathbf{x}_0) = \frac{1}{2}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right)^{\mathrm{T}} \mathbf{B}^{-1}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right) + \frac{1}{2}\sum_{k=0}^{N}\left(\mathcal{H}_k\mathcal{M}_{k,0}(\mathbf{x}_0) - \mathbf{y}_k\right)^{\mathrm{T}} \mathbf{R}_k^{-1}\left(\mathcal{H}_k\mathcal{M}_{k,0}(\mathbf{x}_0) - \mathbf{y}_k\right)$$

4D-Var assumes **random zero-mean errors** for all sources of information, but the IFS model has biases

4D-Var assimilation (2/3)

Unknown forcing is introduced (additive, Gaussian, constant within the assimilation window, no cross-correlation with the background error).

$$\mathbf{x}_k = \mathcal{M}_{k,k-1}(\mathbf{x}_{k-1}) + \eta \qquad \text{for} \qquad k = 1, \ldots, N.$$



Weak-constraint

- First-guess trajectory
- Observations
- Compute a correction at initial time
- Compute a model forcing η
- Analysis trajectory

Cost function depends on the initial state and the model forcing

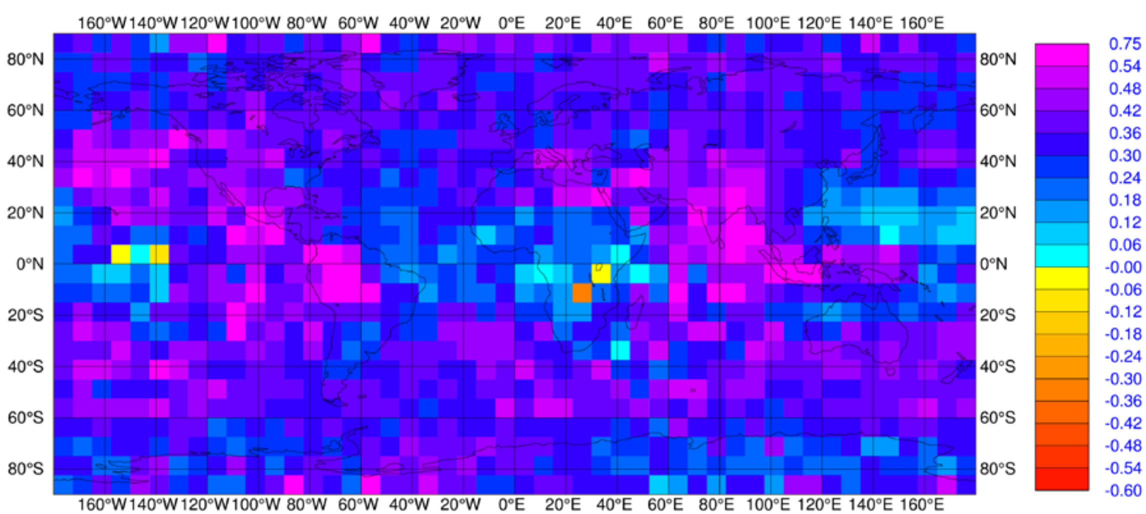
$$\begin{aligned} J(\mathbf{x}_0, \boldsymbol{\eta}) = &\frac{1}{2}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right)^{\mathrm{T}} \mathbf{B}^{-1}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right) \\ &+ \frac{1}{2}\left(\boldsymbol{\eta} - \boldsymbol{\eta}^b\right)^{\mathrm{T}} \mathbf{Q}^{-1}\left(\boldsymbol{\eta} - \boldsymbol{\eta}^b\right) \\ &+ \frac{1}{2}\sum_{k=0}^{N}\left(\mathcal{H}_k(\mathbf{x}_k) - \mathbf{y}_k\right)^{\mathrm{T}} \mathbf{R}_k^{-1}\left(\mathcal{H}_k(\mathbf{x}_k) - \mathbf{y}_k\right) \end{aligned}$$

4D-Var assimilation (3/3)

$$J(\mathbf{x}_0, \boldsymbol{\eta}) = \frac{1}{2}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right)^{\mathrm{T}} \mathbf{B}^{-1} \left(\mathbf{x}_0 - \mathbf{x}_0^b\right) + \frac{1}{2}\left(\boldsymbol{\eta} - \boldsymbol{\eta}^b\right)^{\mathrm{T}} \mathbf{Q}^{-1} \left(\boldsymbol{\eta} - \boldsymbol{\eta}^b\right) + \frac{1}{2}\sum_{k=0}^{N} \left(\mathcal{H}_k(\mathbf{x}_k) - \mathbf{y}_k\right)^{\mathrm{T}} \mathbf{R}_k^{-1} \left(\mathcal{H}_k(\mathbf{x}_k) - \mathbf{y}_k\right)$$

→ method described in Sasaki (1970), never worked properly at a NWP centre

→ error statistics (B and Q) need to be specified

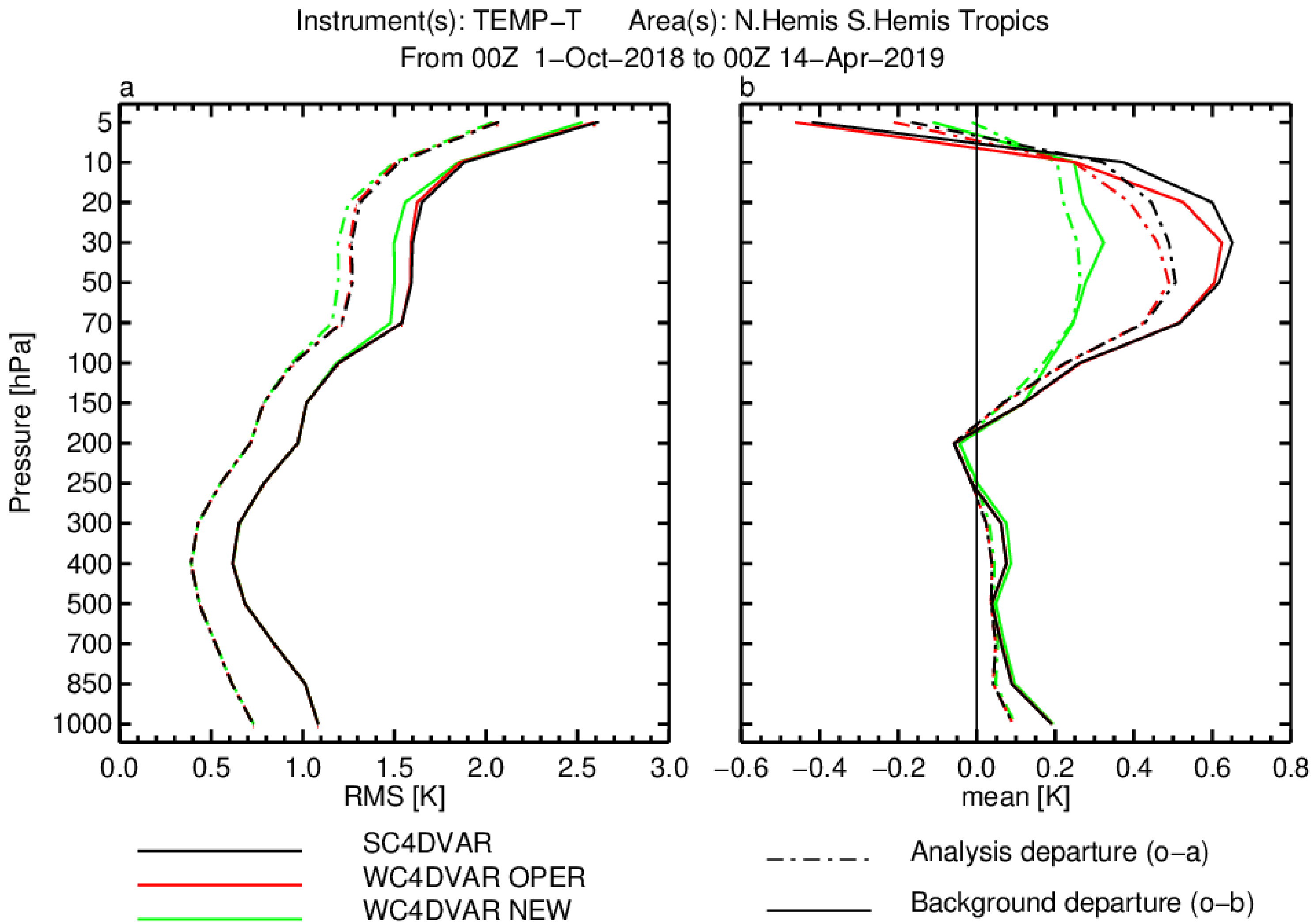


RO shows that model error (Q) is large scale

EDA shows that background error (B) is small scale

→ Scale separation

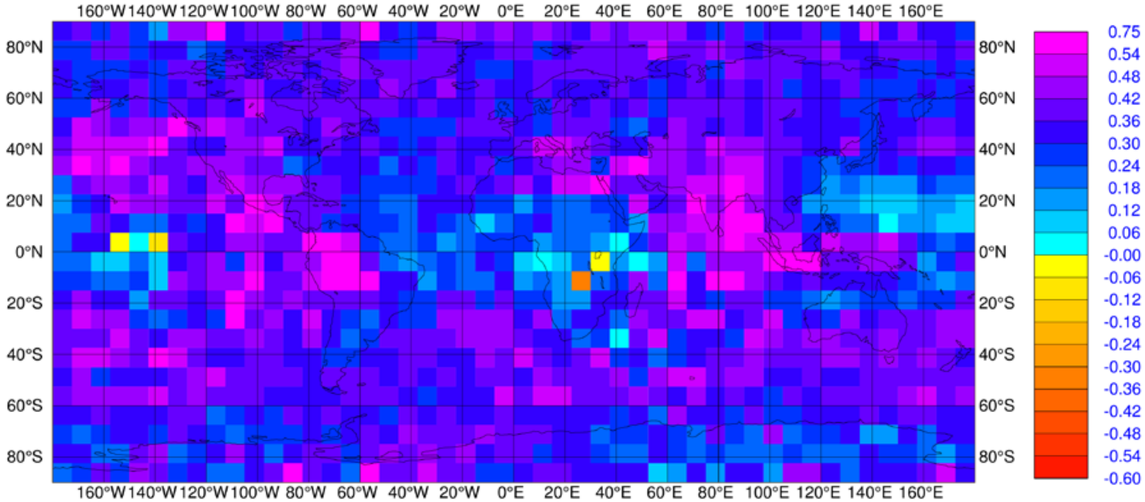
Weak-constraint 4D-Var with scale separation in IFS (1/2)



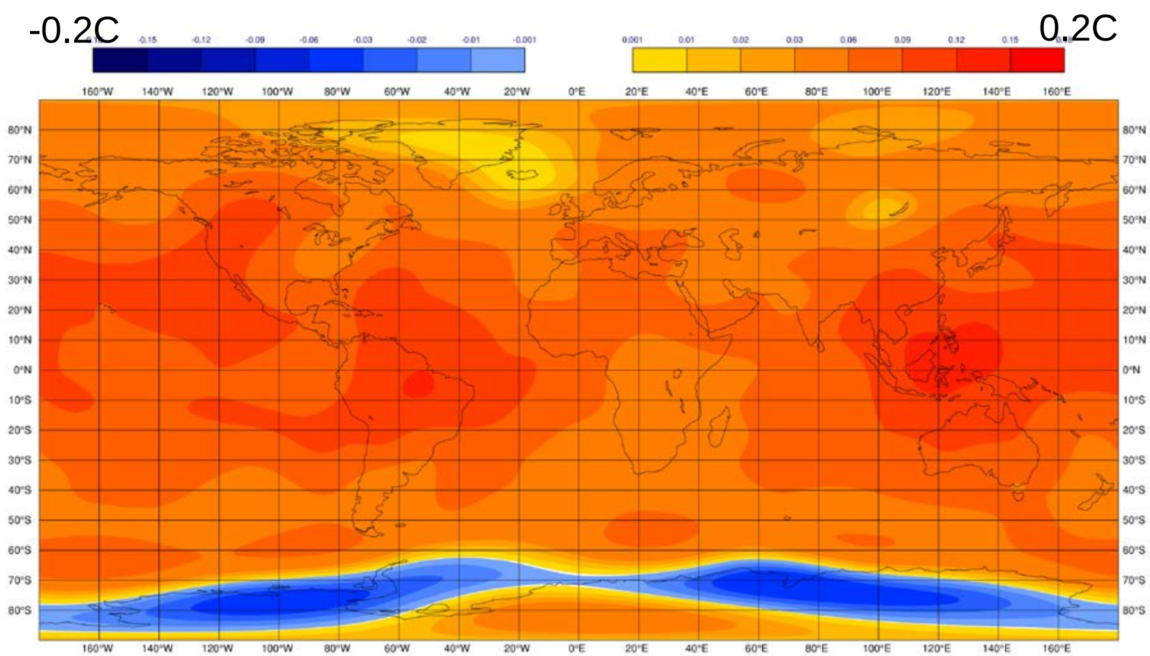
→ temperature bias is reduced up to 50% (0.6C to 0.3C) with respect to radiosondes and GPS-RO

→ temperature RMSE is reduced by 6%

Weak-constraint 4D-Var with scale separation in IFS (1/2)



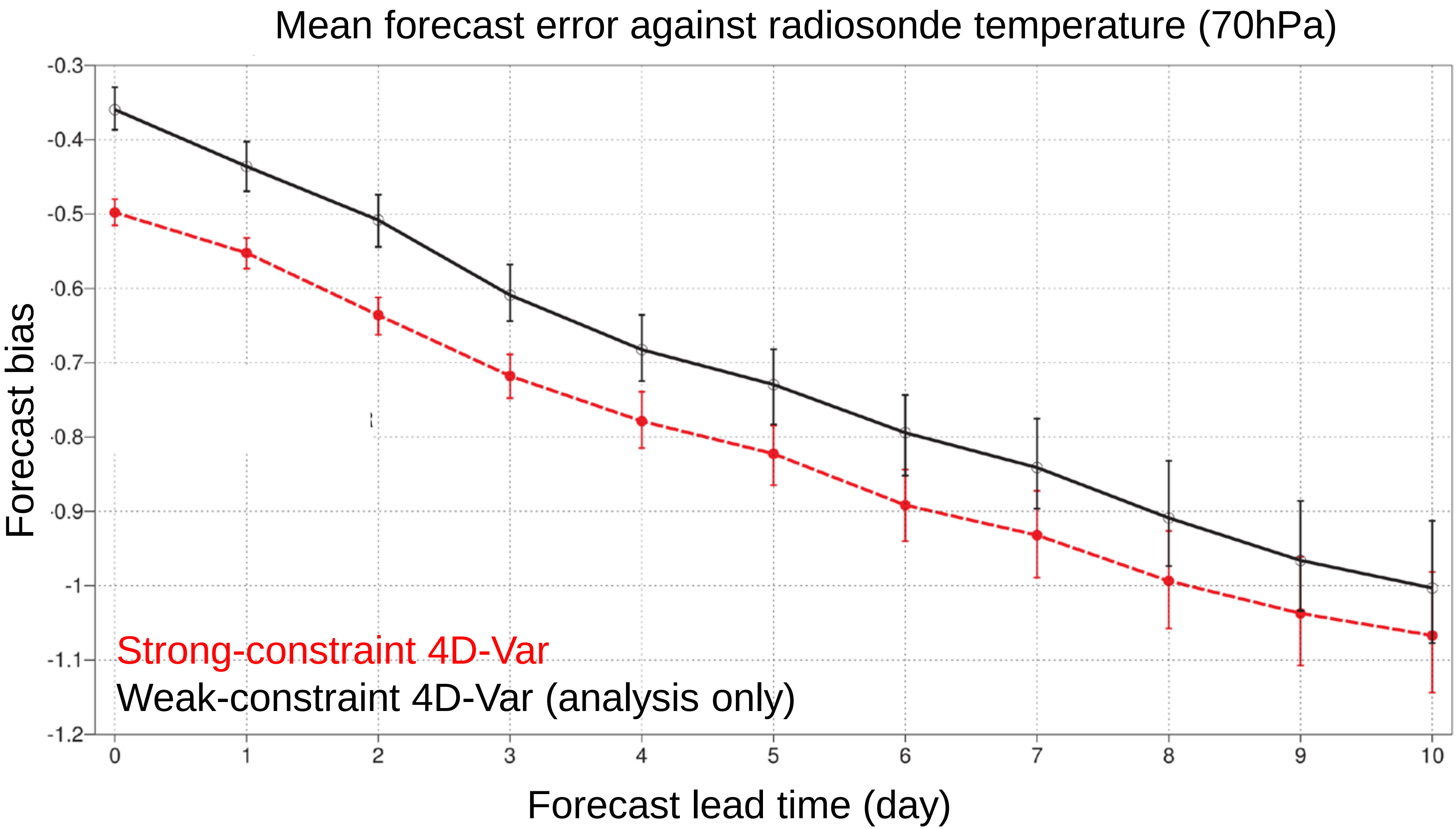
Cold biases in the lower/middle stratosphere over strong convective regions



Model error forcing from WC4DVAR at 70 hPa

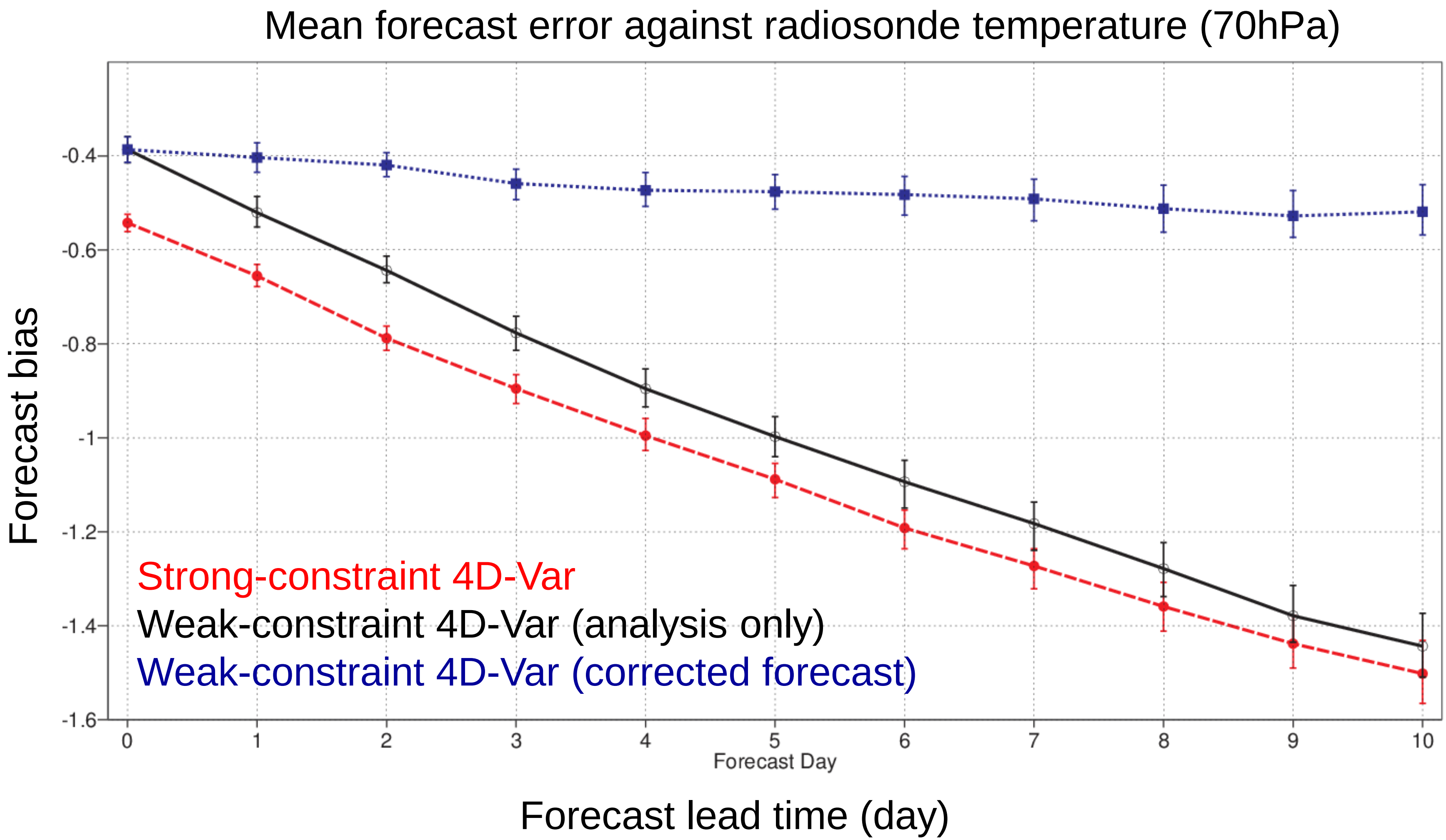
→ correcting the bias from the missing gravity waves and the dynamical core

Impact of new weak-constraint 4D-Var analysis on forecast skills



The better analysis can be seen in the forecasts

Impact of new weak-constraint 4D-Var forcing on forecast skills



→ The model error estimation η is applied as a constant model forcing over 10 days
→ The forecast model is not biased anymore and mean error does not increase
→ Approach will be tested in seasonal forecast (some model error variability required)

Conclusions and future work

New application of RO at ECMWF

- Diagnose model deficiencies and correct them in 4D-Var
- Bias reduced up to 50% with weak-constraint 4D-Var (from -0.6C to -0.3C)

How many RO do we need to estimate the model bias? Homogeneous network?

What is the impact of weak-constraint 4D-Var on the observation bias correction?

What is the best way to correct forecast/reanalysis bias? Climatology for η?