

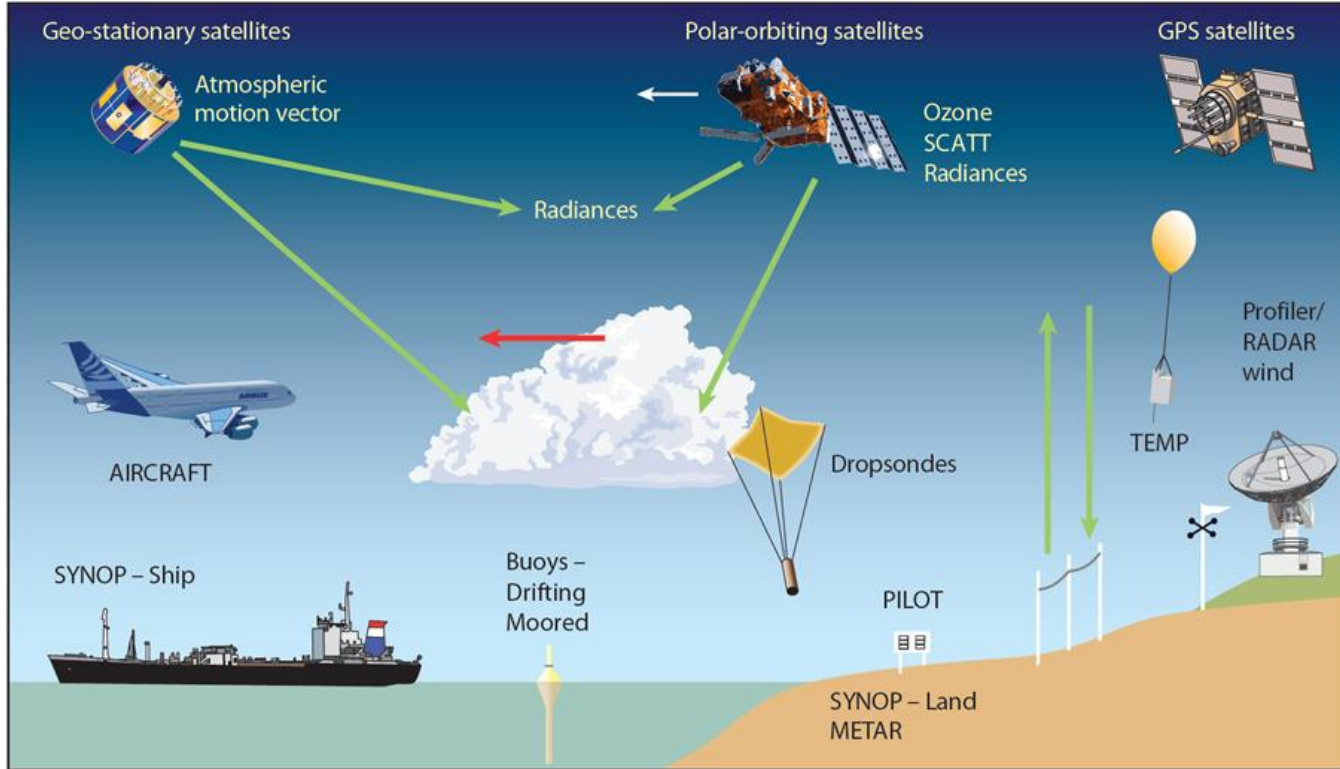
Recent experiences with the IASI L2 data assimilation at ECMWF

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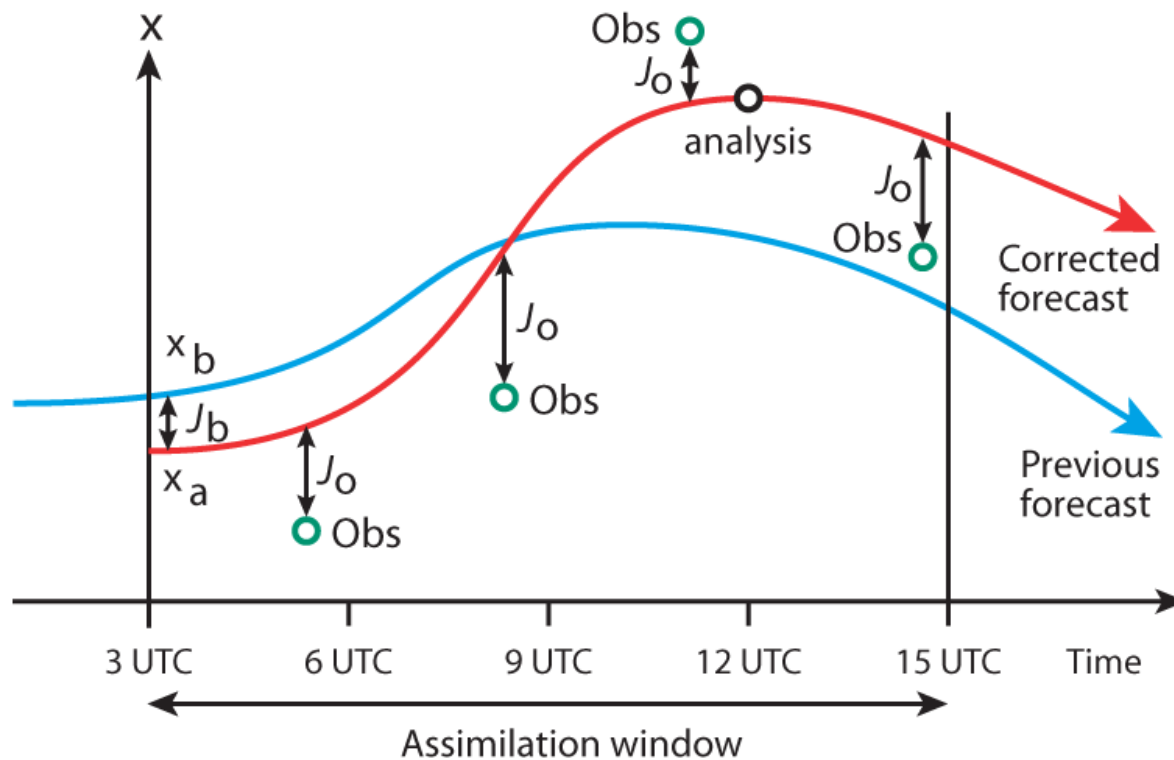
ECMWF model and use of observations



- ECMWF develops and operates a global numerical weather prediction system.
- Currently ~400 million observations are present in a 12-hour assimilation window, the vast majority of these are satellite measurements.
- Radiance assimilation, together with conventional observations, are the main drivers of the headline scores.
- Alternative approaches to radiance assimilation
 - PC scores or reconstructed radiances
 - Retrievals, traditional or transformed

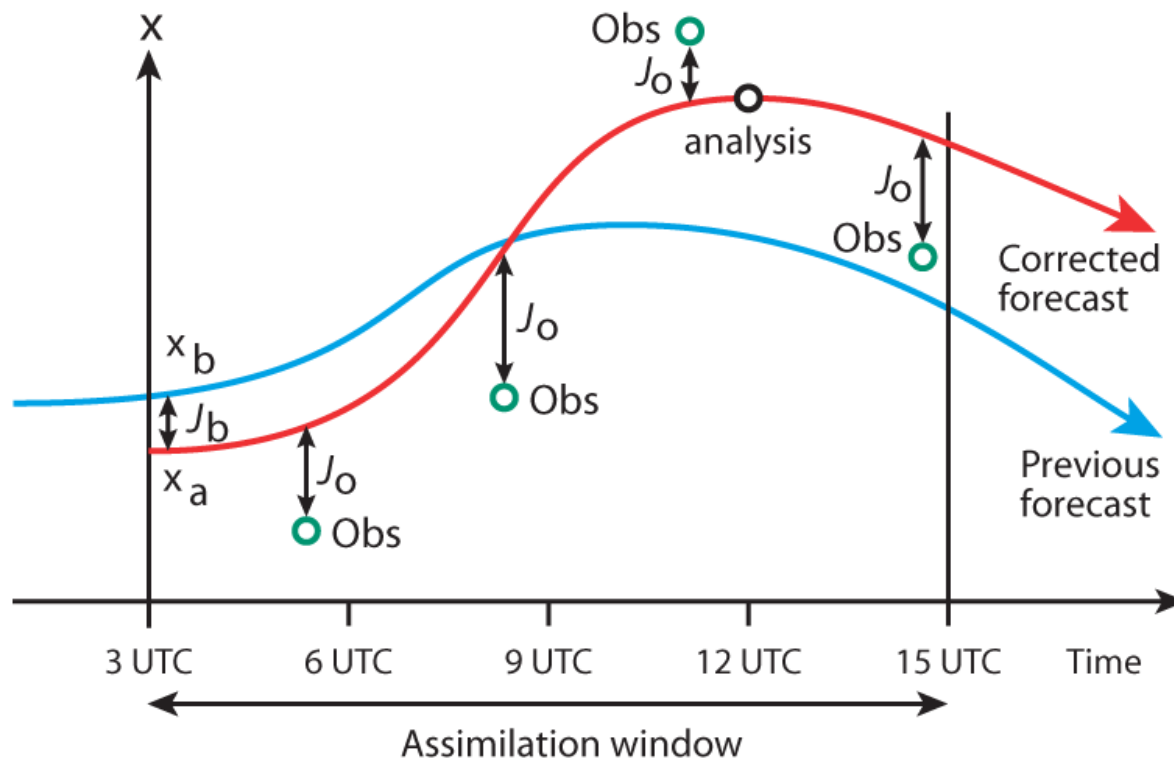
Data assimilation

- Combination of information from a model (typically a short-range forecast) and observations to produce the best estimate of the state of the atmosphere, analysis.



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Key elements of the assimilation system:

- Forecast model
- Observations
- Assimilation algorithm

4D variational data assimilation: cost function $J(x)$

The diagram illustrates the cost function $J(x)$ used in 4D variational data assimilation. The equation is presented with arrows pointing to its various components, which are labeled as follows:

- model state**: Points to the variable x in the first term.
- background error covariance**: Points to the matrix \mathbf{B}^{-1} in the first term.
- observations**: Points to the variable y in the second term.
- observation* error covariance**: Points to the matrix \mathbf{R}^{-1} in the second term.
- observation operator** (maps the model state to the observation space): Points to the operator $H[x]$ in the second term.

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

Introducing a new observation type into the system: observation operator

The diagram illustrates the cost function $J(x)$ used in data assimilation. It features the following components and labels:

- model state**: Labeled above the term $(x - x_b)$ with a downward arrow.
- background error covariance**: Labeled above the term \mathbf{B}^{-1} with a downward arrow.
- observations**: Labeled below the term $(y - H[x])$ with an upward arrow.
- observation* error covariance**: Labeled below the term \mathbf{R}^{-1} with an upward arrow.
- observation operator**: Labeled below the term $H[x]$ with an arrow pointing to it. This label is enclosed in a red oval and includes the subtext "(maps the model state to the observation space)".

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

Introducing a new observation type into the system: realistic observation errors

The diagram illustrates the cost function $J(x)$ used in data assimilation. The equation is centered on the slide, with arrows pointing from descriptive labels to its various parts. The labels are: 'model state' pointing to x , 'background error covariance' pointing to \mathbf{B}^{-1} , 'observations' pointing to y , 'observation* error covariance' (circled in red) pointing to \mathbf{R}^{-1} , and 'observation operator (maps the model state to the observation space)' pointing to \mathbf{H} .

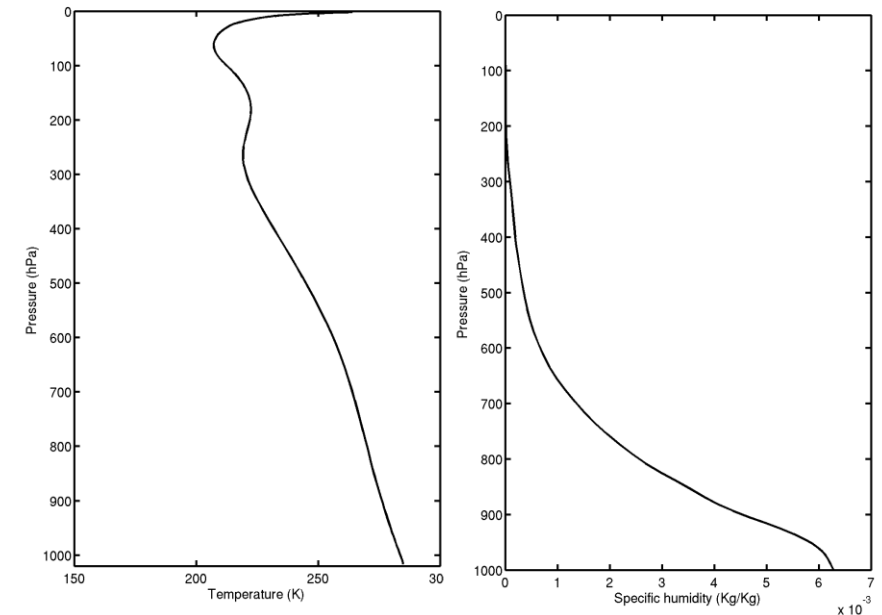
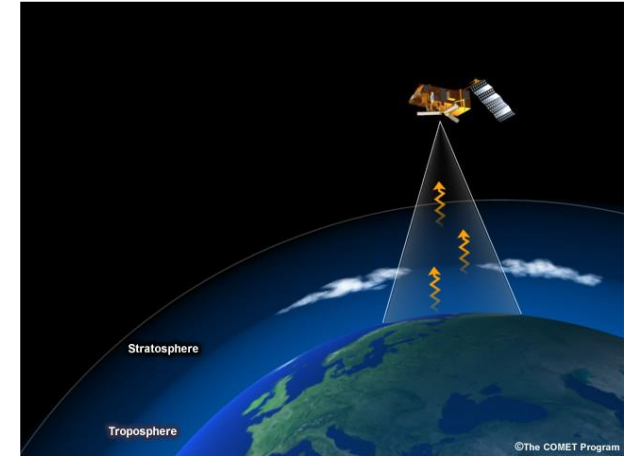
$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - \mathbf{H}[x])^T \mathbf{R}^{-1} (y - \mathbf{H}[x])$$

Annotations:

- model state
- background error covariance
- observations
- observation* error covariance
- observation operator (maps the model state to the observation space)

Forecast independent infrared only statistical retrievals from IASI

- Baseline for MTG-IRS L2 retrievals.
- Atmospheric temperature, humidity and ozone profiles, surface temperature and emissivity with quality information.
- Retrieval technique based on piece-wise linear regression.
- Training data set from ERA-5.
- All sky conditions.



What we need to do to introduce the data into the DA system?

- Design observation operator to produce the model counterpart for the observations
 - For the T and q retrievals, model T and q fields are interpolated to the observation locations in horizontal and in vertical
 - So called averaging kernels can be provided with the retrievals to take into account the actual vertical sensitivity and resolution of the retrievals (not yet used in this study)
- Perform quality assessment
 - Learn the characteristics of the new data
 - Extremely important step to estimate realistic observation errors and error correlations
- First assimilation trials
 - Start with best consistent quality observations, easier to find reasons why results are what they are
 - For L2 retrievals the focus has been first on clear sky retrievals over sea
- Step by step move to more complex experimentation.

Quality assessment

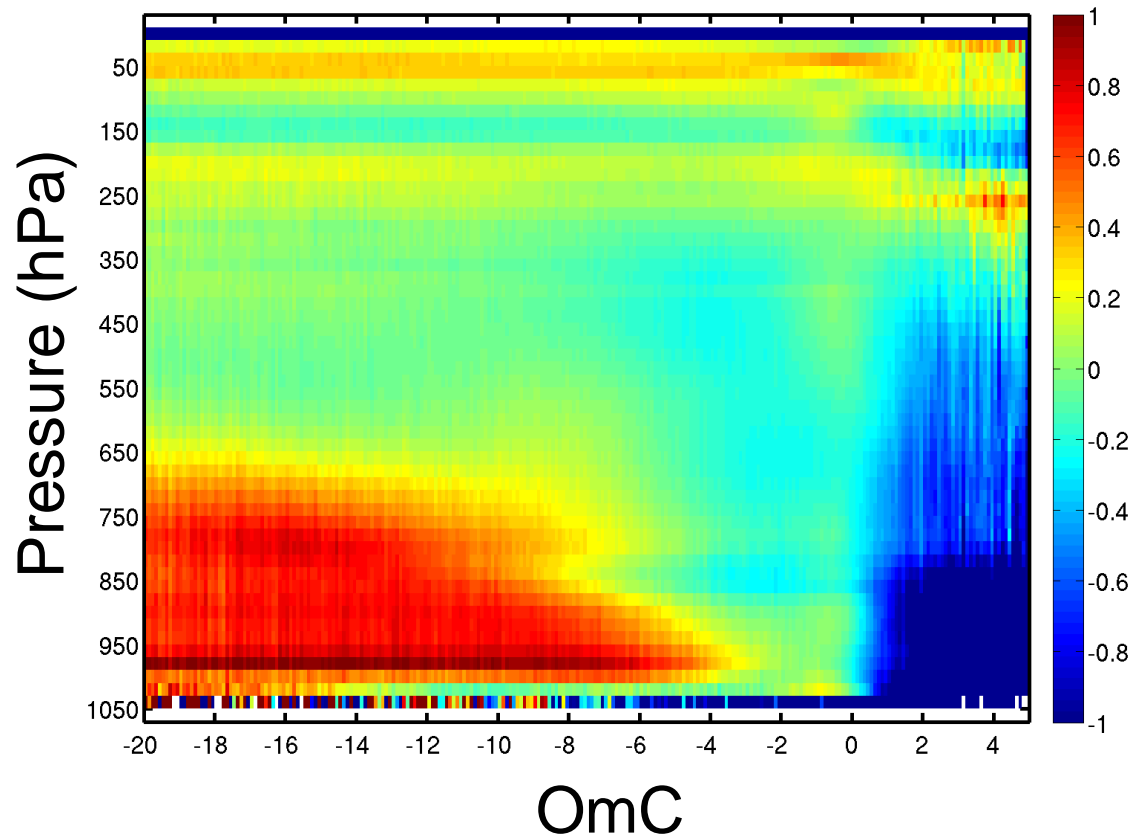
Observation minus model background statistics

- Extremely useful for investigating the observation quality and characteristics

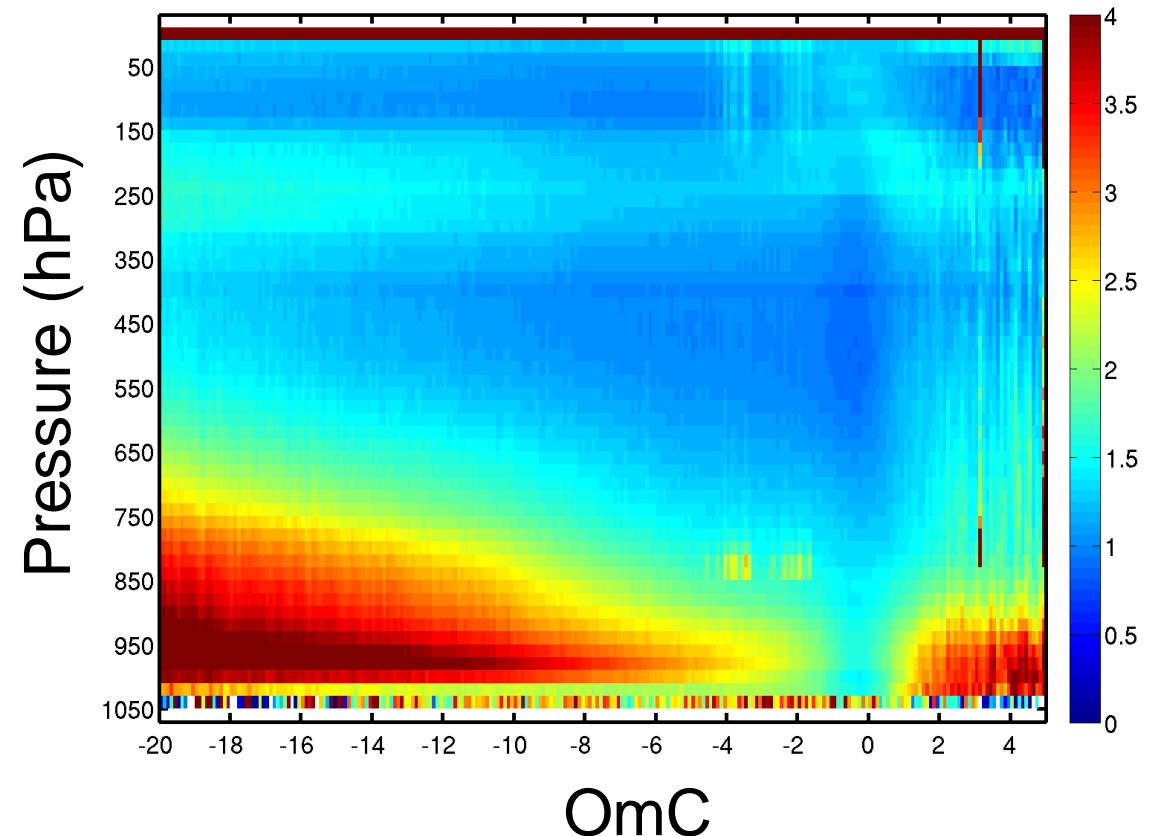
Measure of cloudiness OmC

- OmC: observed window channel brightness temperature minus the corresponding brightness temperature computed by a forward model with clear-sky assumption
- Criterion used to select cloud free data $|\text{OmC}| < 1$

Temperature OmB bias, sea



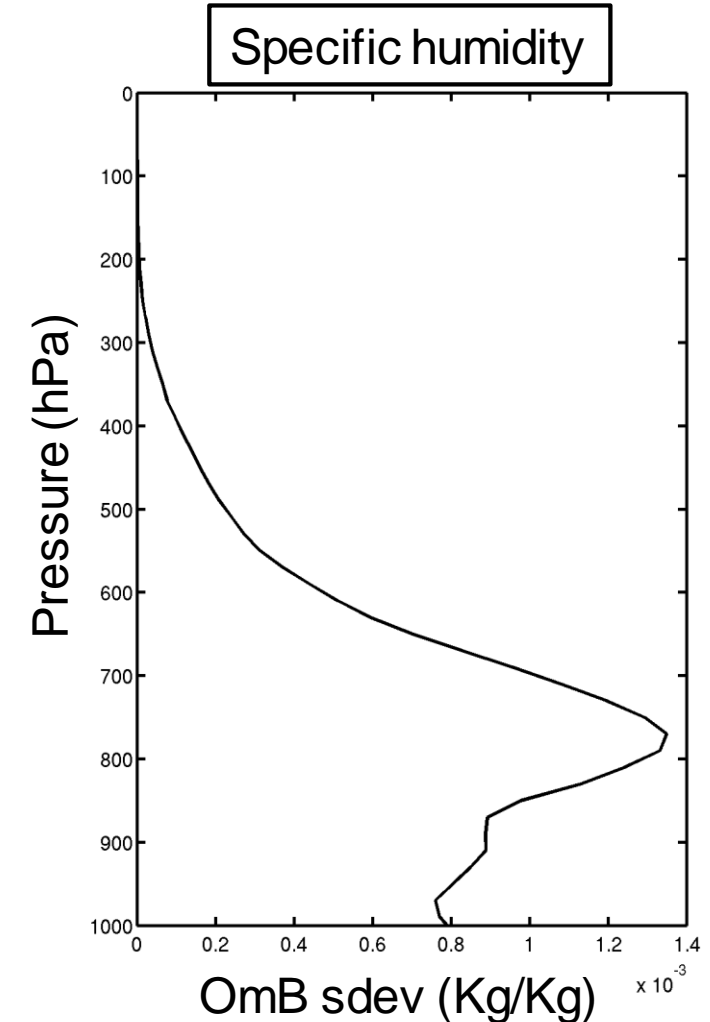
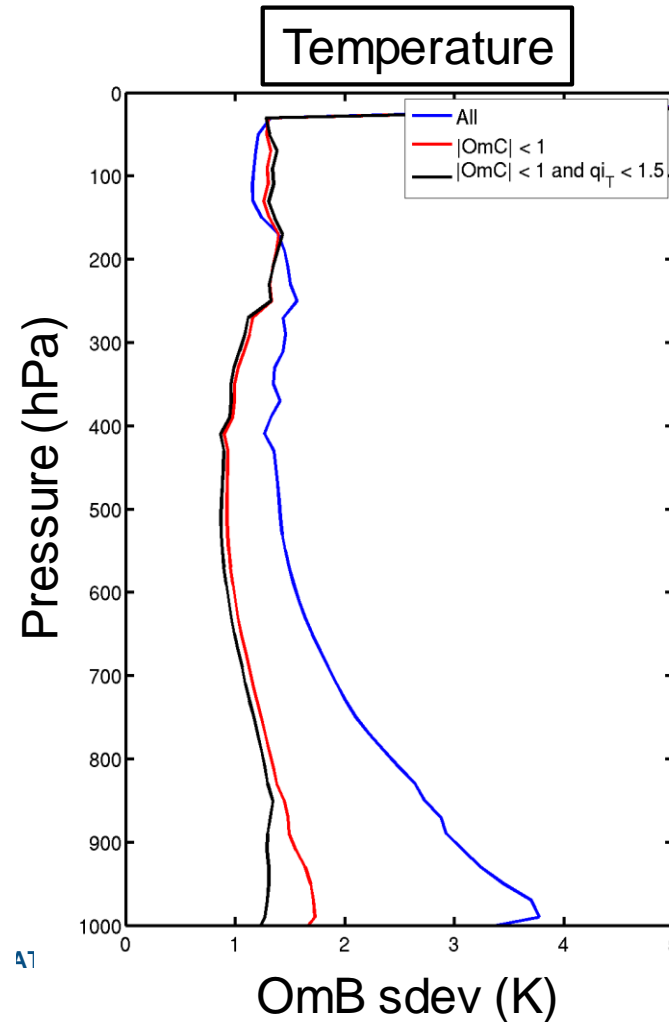
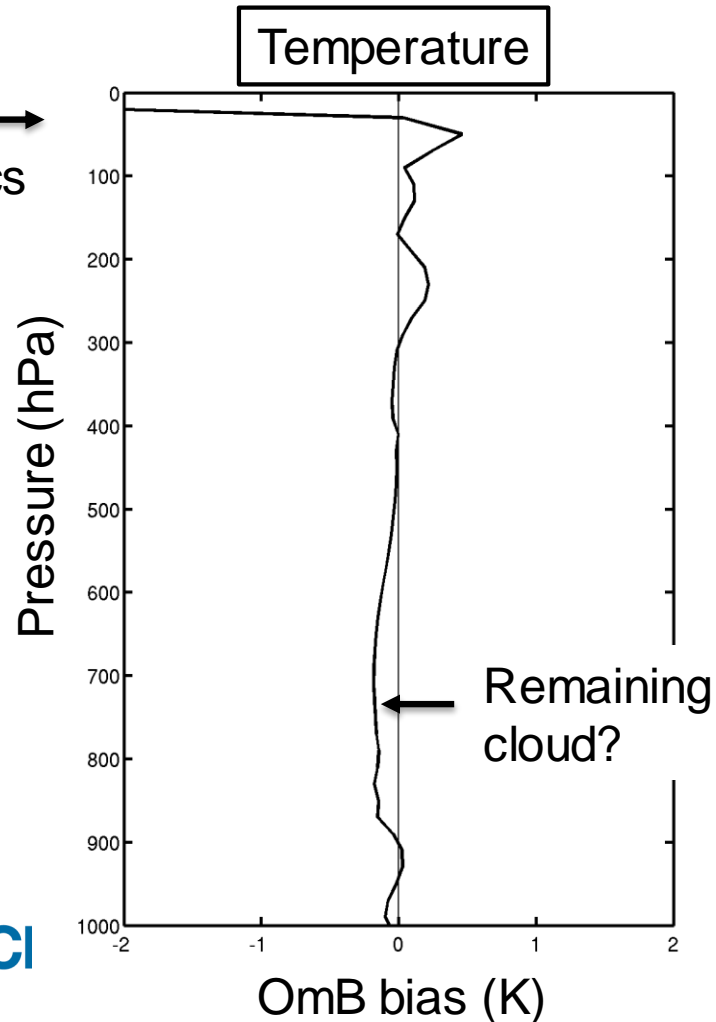
Temperature OmB sdev, sea



Applying quality criteria

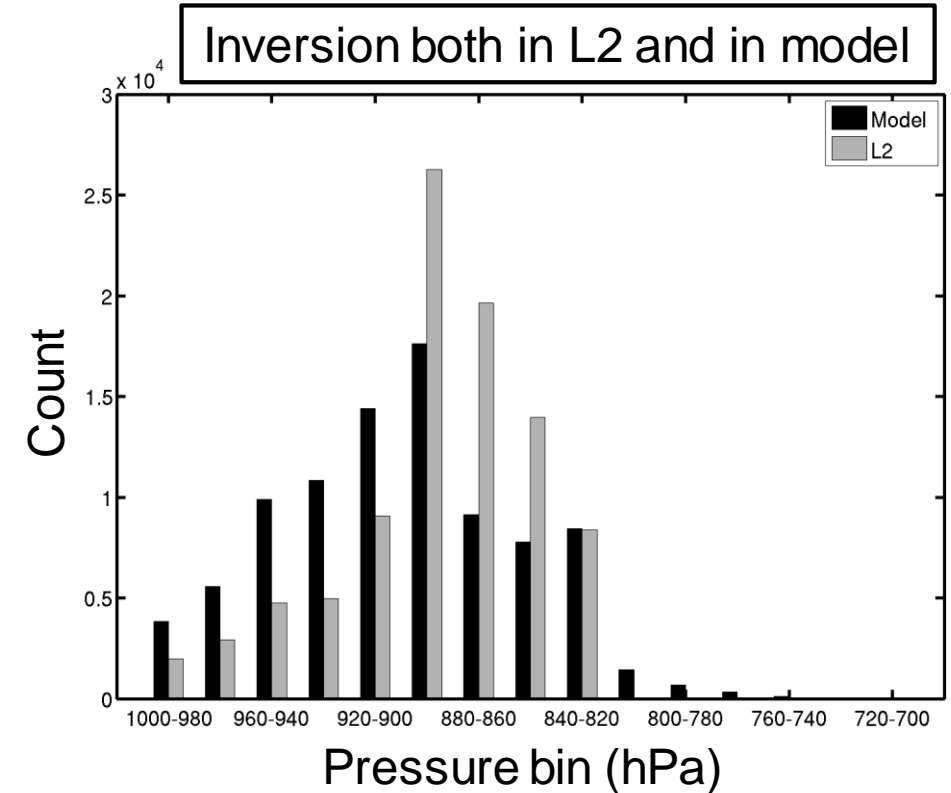
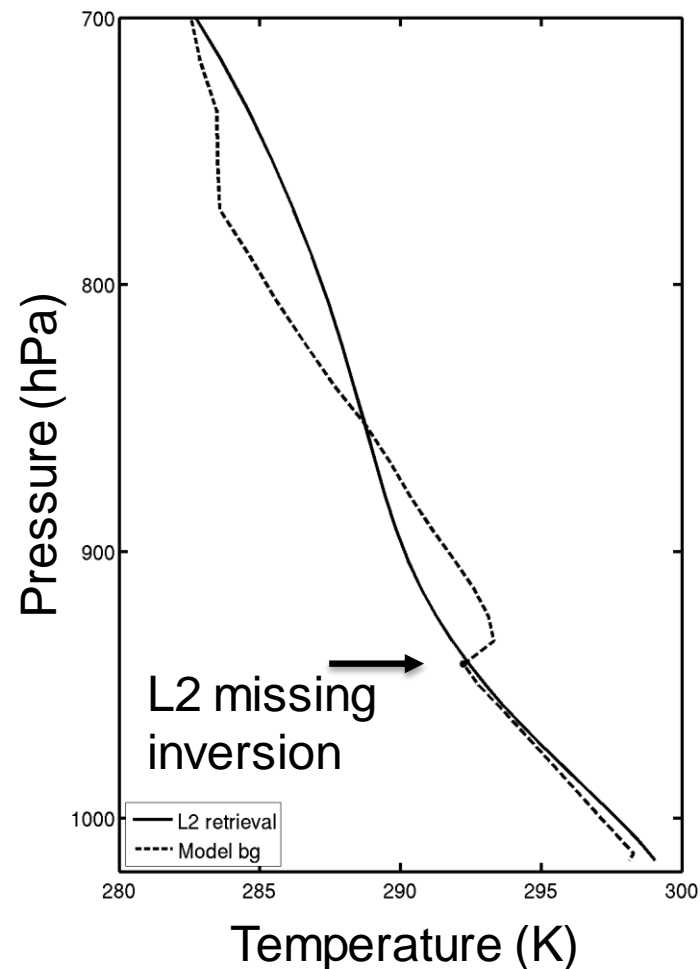
- The overall quality of the retrievals is relatively good as long as strict quality criteria are applied to exclude cloudy scenes. (Focus on data over sea only.)
- All, cloud free retrievals $|\text{OmC}| < 1$, additional quality screening for cloud free retrievals $\text{QI}_T < 1.5$

Error characteristics from ERA5



L2 has challenges to capture low level inversions

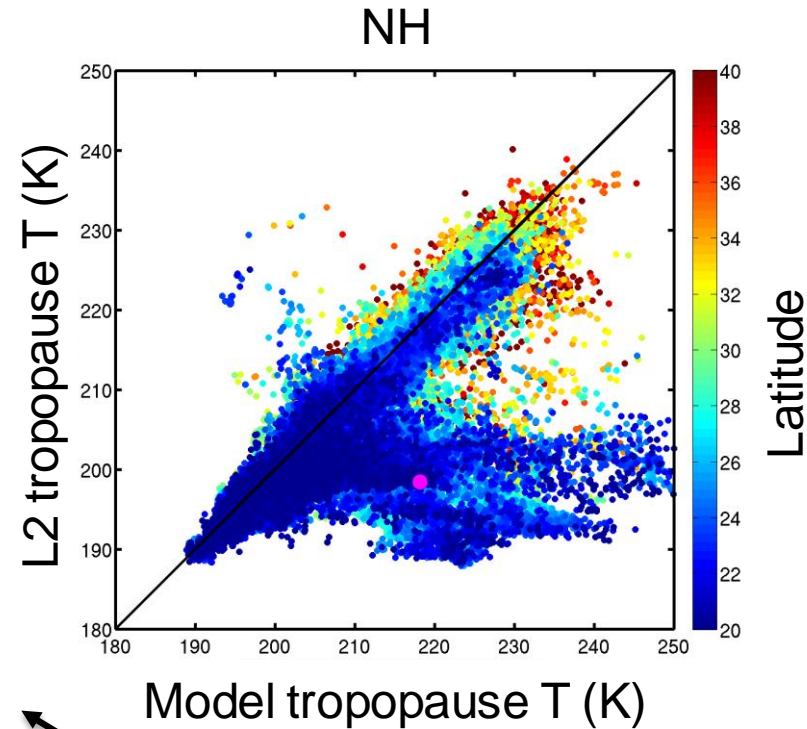
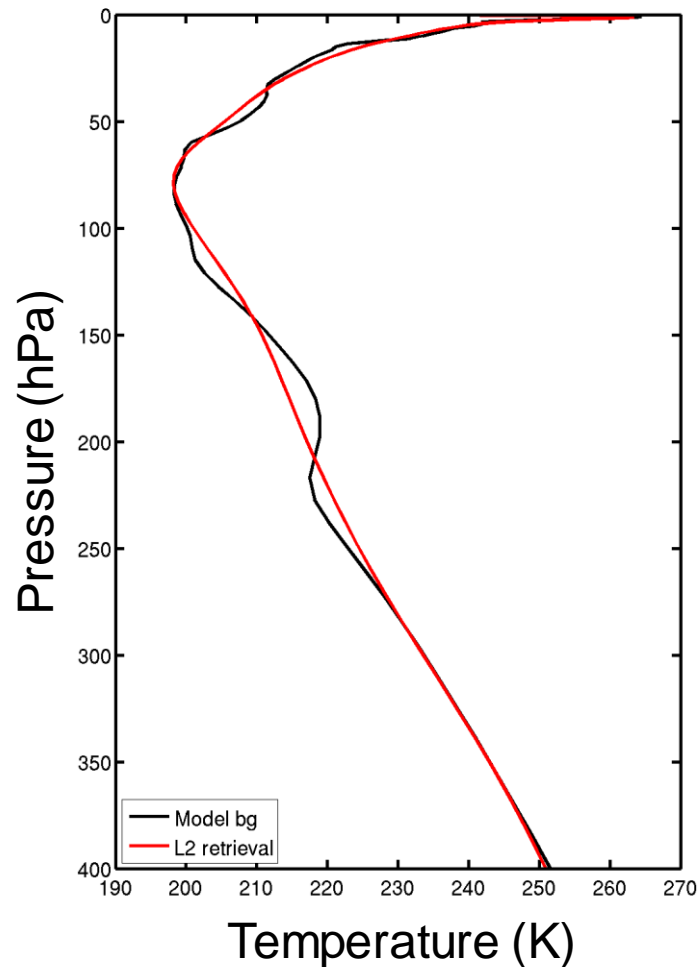
- Model is capturing the low level temperature inversions much more frequently than L2.
- L2 inversions are smooth, and on average found from higher altitudes than the model inversions.



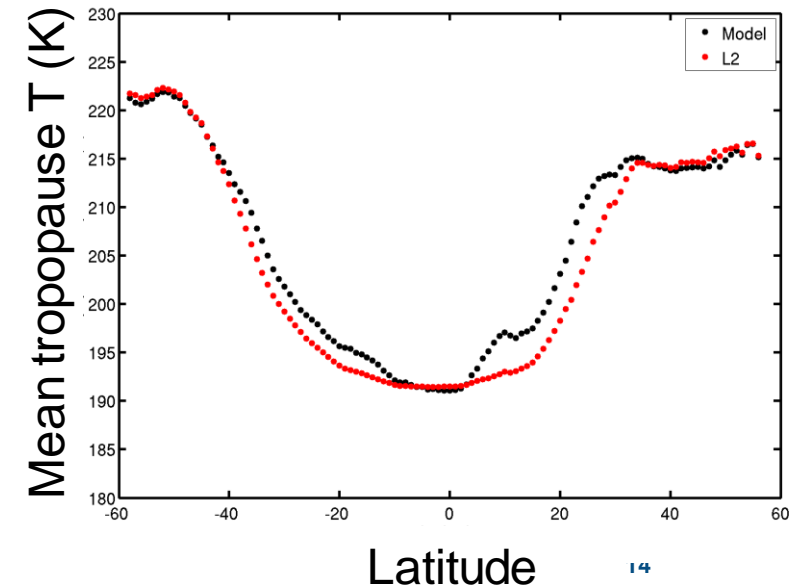
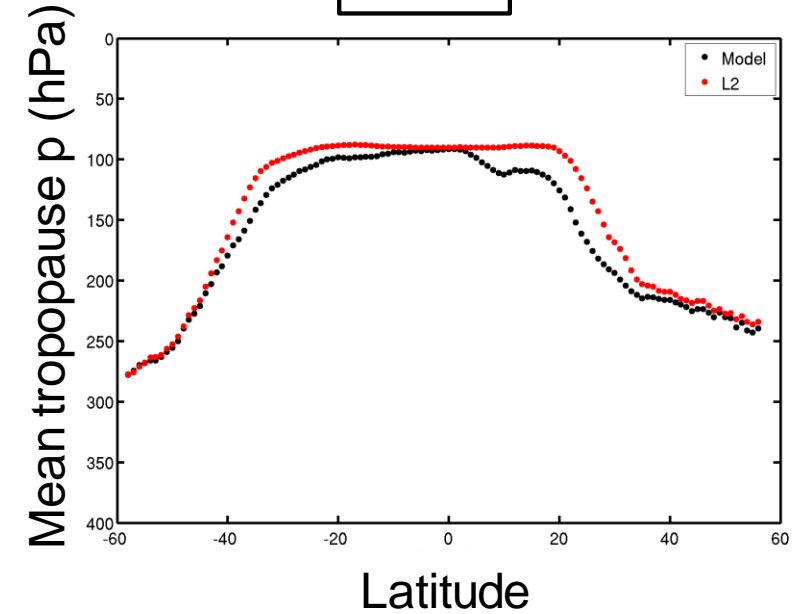
	Model: % of low level inversions 1.1-31.3.2017	L2 profiles: % of low level inversions 1.1-31.3.2017	Model: % of low level inversions 1.6-31.8.2017	L2 profiles: % of low level inversions 1.6-31.8.2017
Geodisc NH	64.6	10.8	79.3	33.4
Geodisc TR	67.3	17.6	67.0	18.2
Geodisc SH	67.6	19.4	68.5	14.0

Tropopause structure

- The model tropopause is on average warmer and at lower altitude than the L2 tropopause.
- Model captures more often the double tropopause structure in the midlatitudes



• Example profile



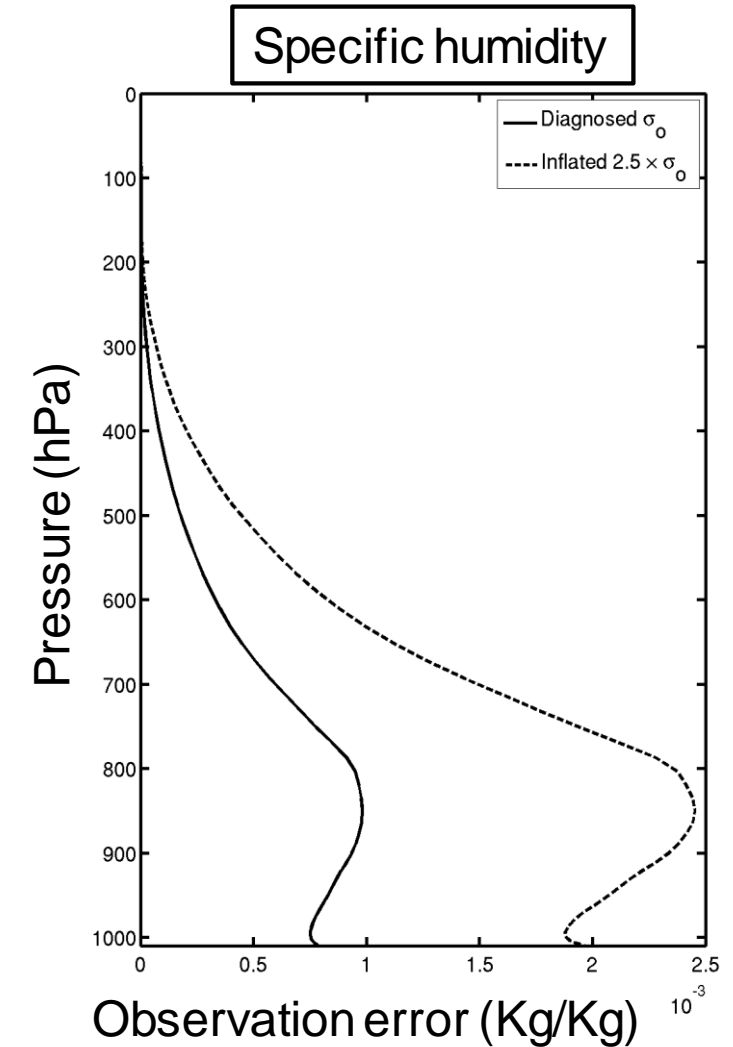
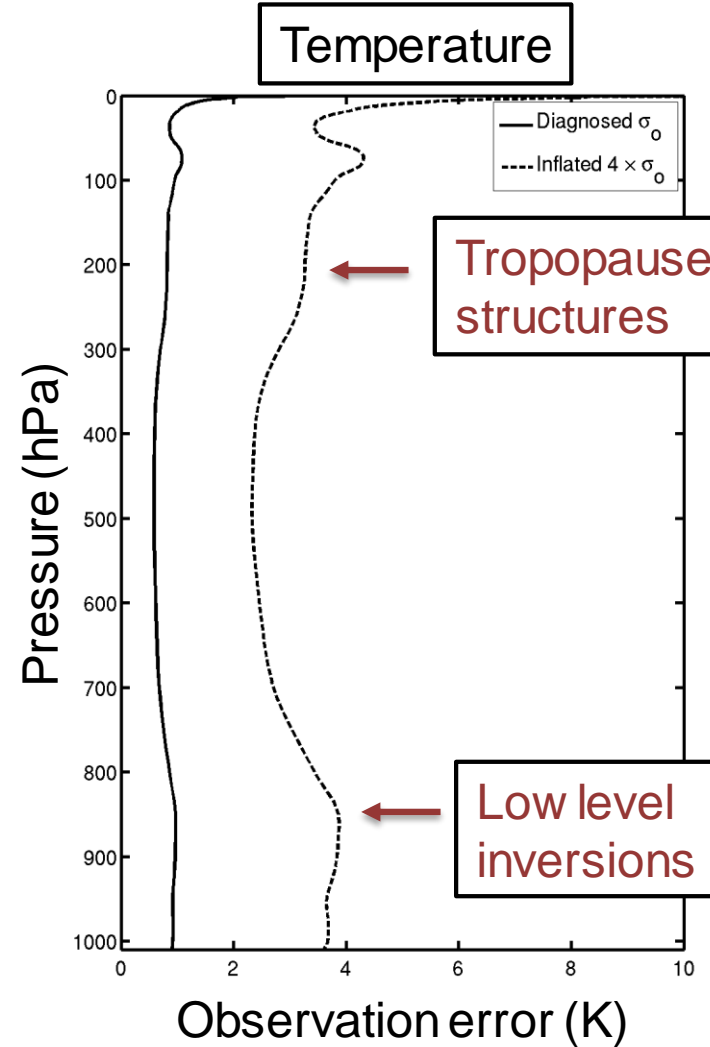
Summary of the quality assessment

- Quality of the retrievals is highly situation and location dependent
 - Cloud free profiles have the best quality
 - Errors increase rapidly for cloud affected data
 - Generally the data quality is better over sea than over land
- QI_T is useful for filtering good quality data especially over land
 - $|OmC| < 1$, 11% of all data
 - $QI_T < 1.5$ K, 35% of all data
 - $|OmC| < 1$ and $QI_T < 1.5$ K 9 % of all data
- Model is capturing the low level inversions much more frequently than L2.
- The model tropopause is on average warmer and at lower altitude than the L2 tropopause
 - Model has more often the double tropopause structure in the midlatitudes

Impact assessment of clear sky retrievals

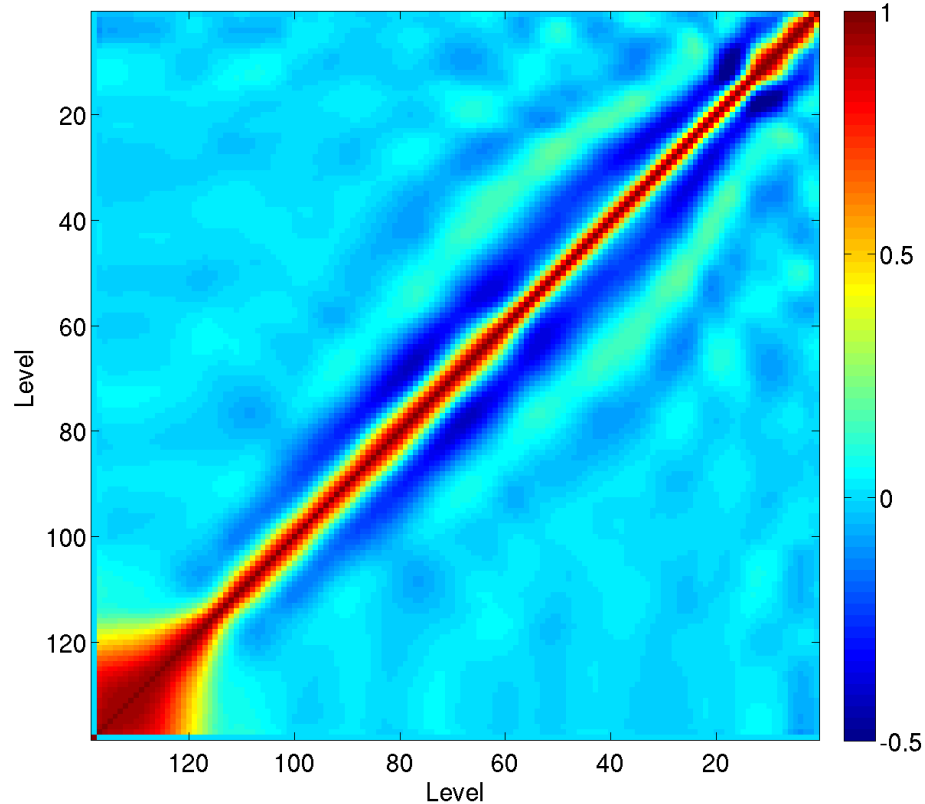
Estimating observation errors in clear sky

- Observation errors diagnosed with Desroziers method.
- Temperature errors require significant inflation, $4 \times \sigma_{oT}$ used in the assimilation experiments.
 - Increased errors at low level inversion and tropopause levels.
- Inflation for humidity errors moderate, $2.5 \times \sigma_{oq}$

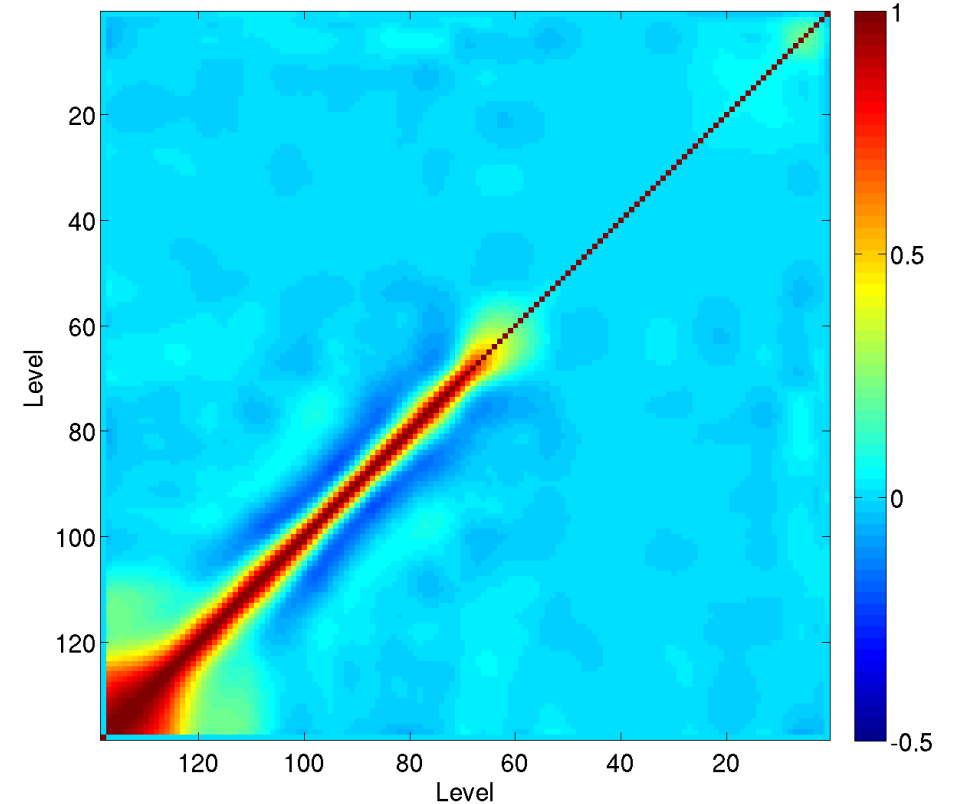


Observation error correlations in clear sky

IASI L2 temperature



IASI L2 specific humidity



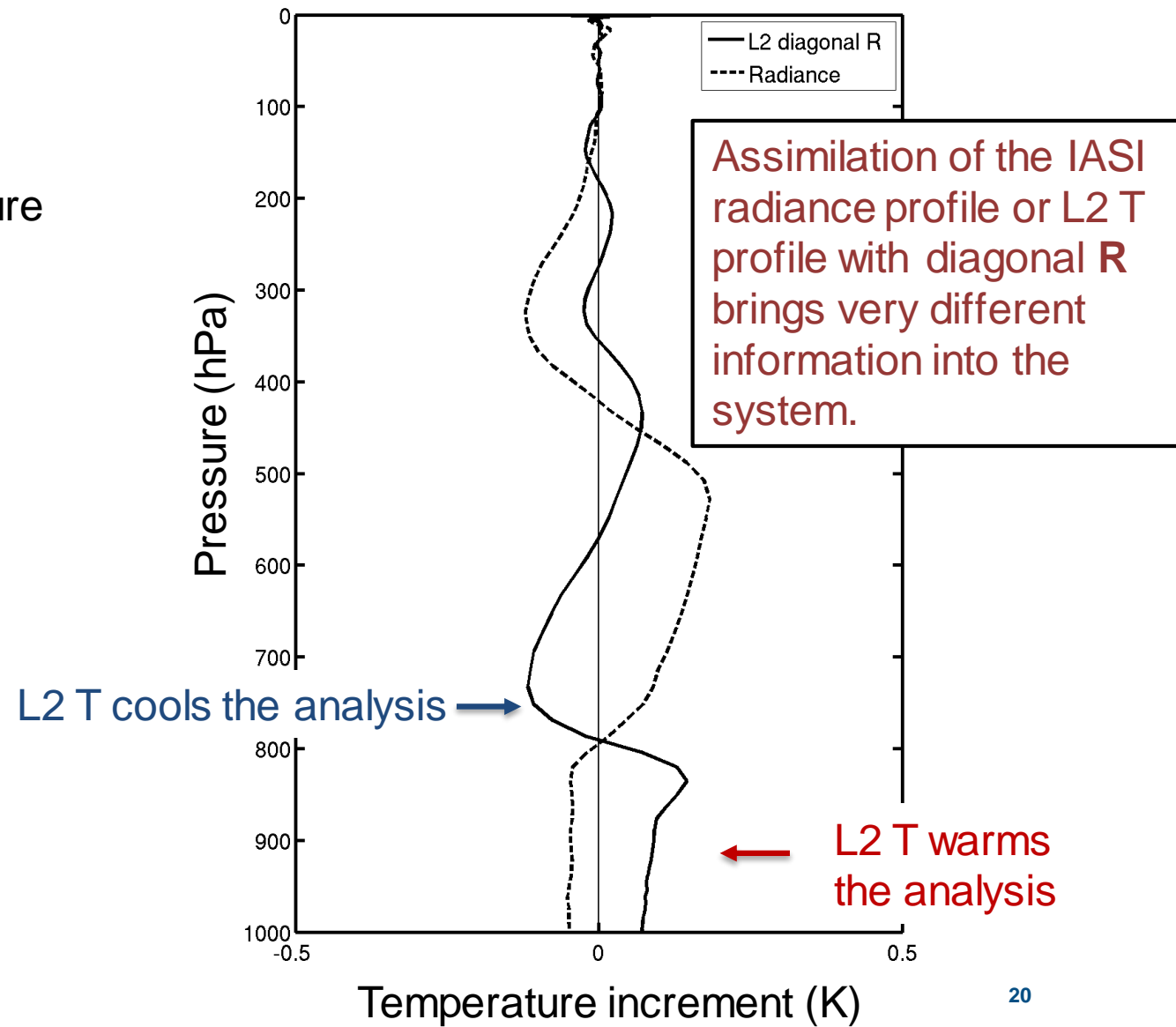
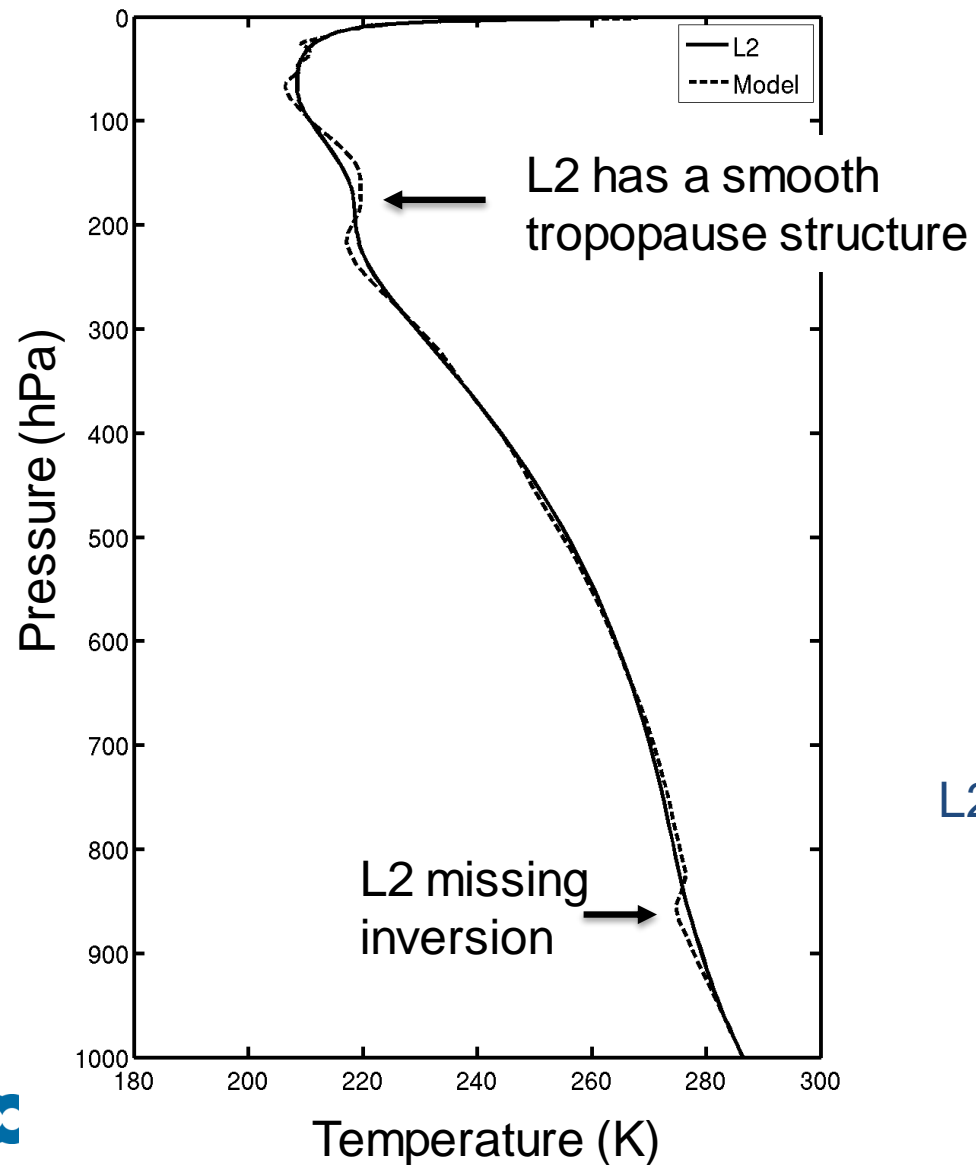
Reconditioning required, especially for the humidity R

Single observation experiment, temperature

- 1.1.2017, 12.38 UTC
- 39.26 N, 33.41 W
- All IASI channels are cloud free according to ECMWF cloud detection scheme
- High quality clear sky L2 temperature profile
 - $OmC = 0.36$
 - $QI_T = 0.75$

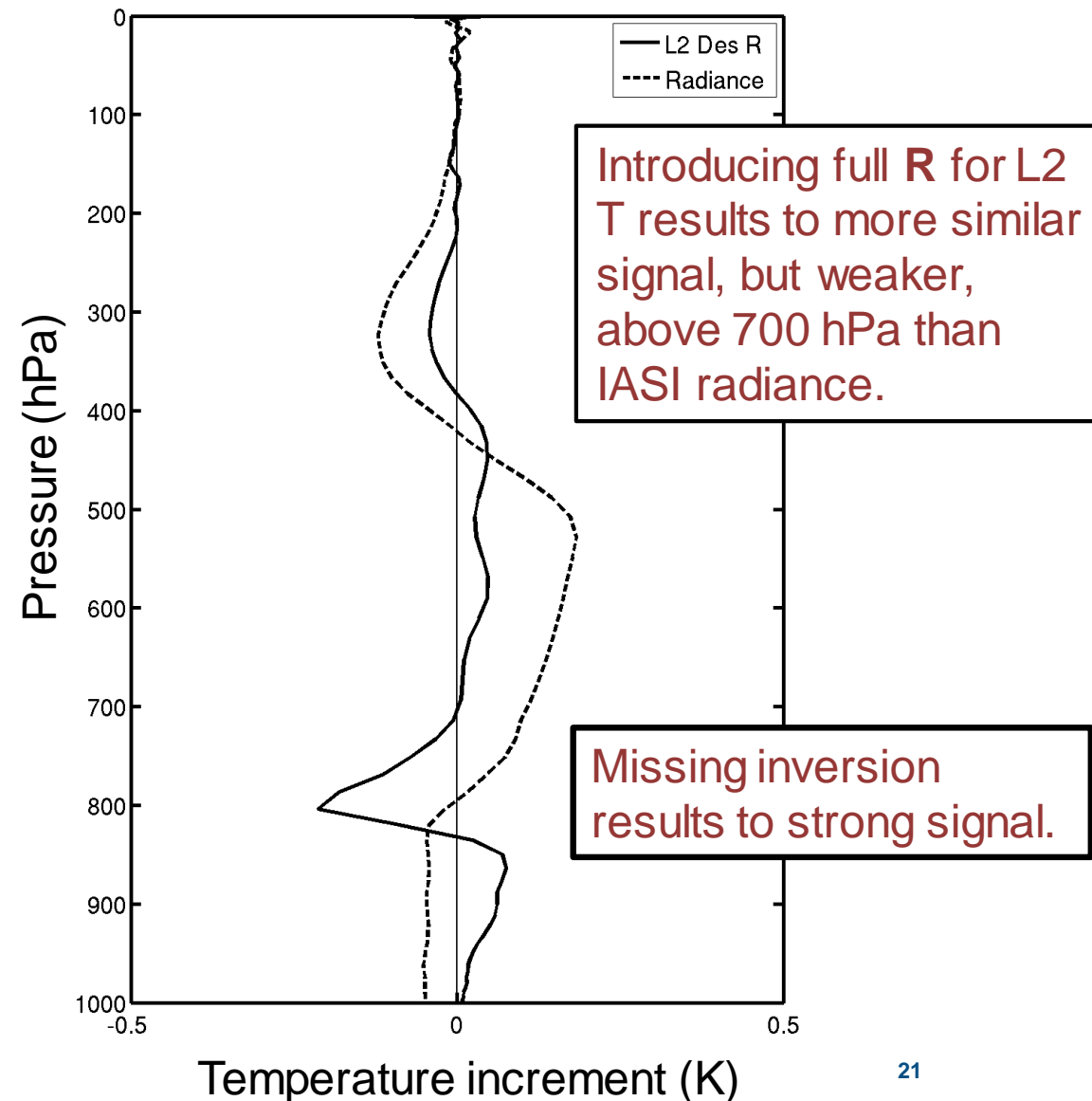


Single observation experiment, using diagonal R



Single observation experiment, using full R

- It is very important to take the vertical error correlations into account.
- Missing inversion results to strong signal in the analysis increment despite significantly inflated σ_{oT} .



Data assimilation experiments, Jan – Feb and Jun – Jul 2017

- Depleted observing system

CTL: Conventional observations + AMSU-A

L2: CTL + L2 temperature and specific humidity

IASI: CTL + IASI radiances

- Full observing system

CTL: Full observing system without IASI

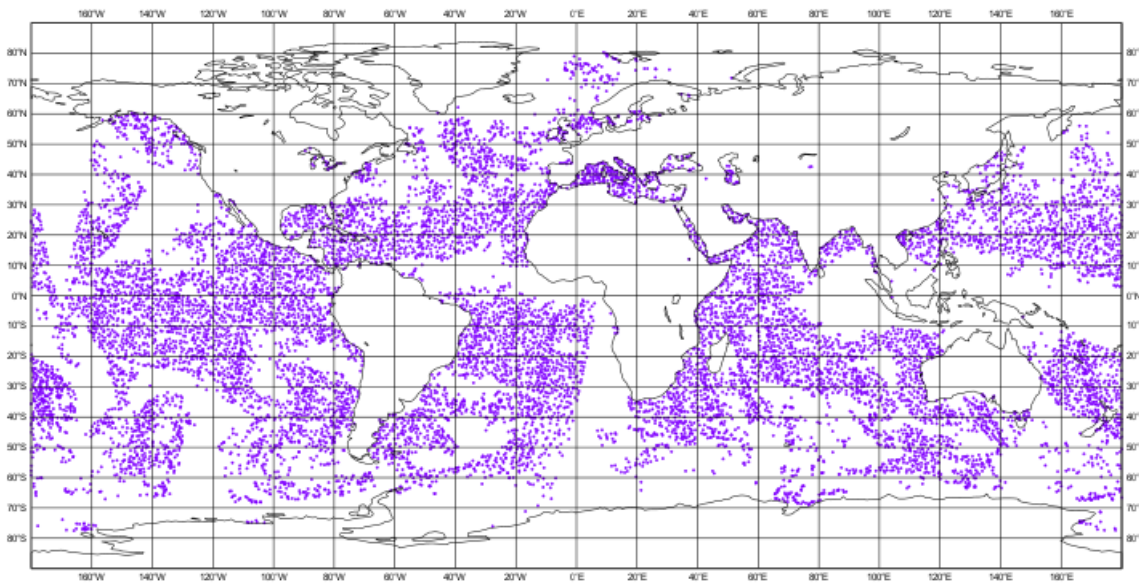
L2: CTL + L2 temperature and specific humidity

IASI: CTL + IASI radiances

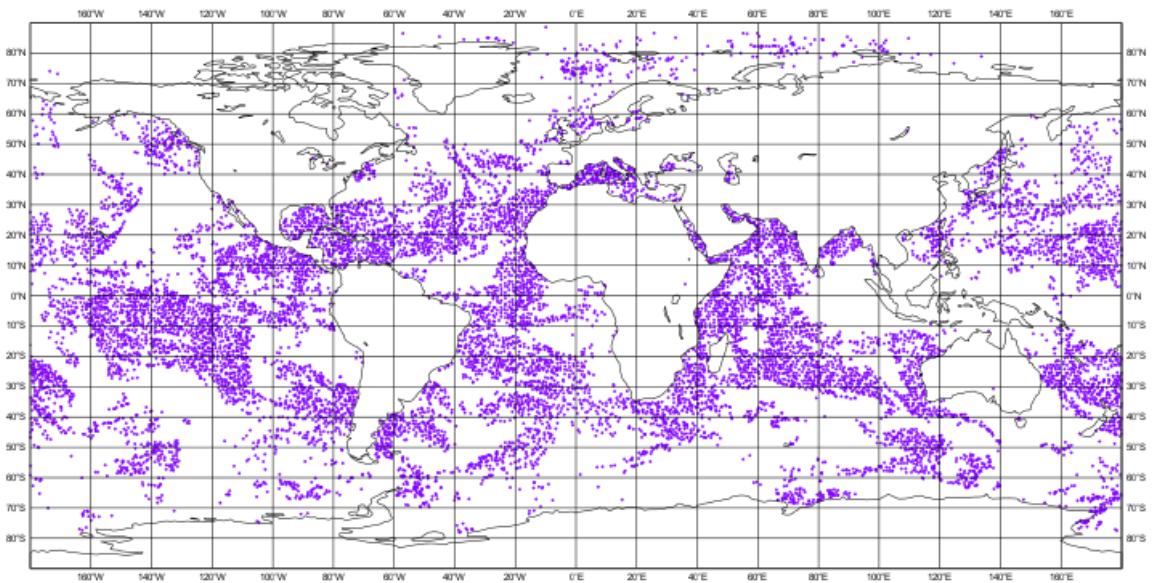
12-hour sample coverage for active data

- Data selection as similar as possible for L2 profiles and radiances
 - Horizontal thinning 125 km
 - Clear sky data over sea only
 - IASI radiances blacklisted at the edges of the swath
 - L2 data blacklisted above ~30 hPa due to large temperature bias

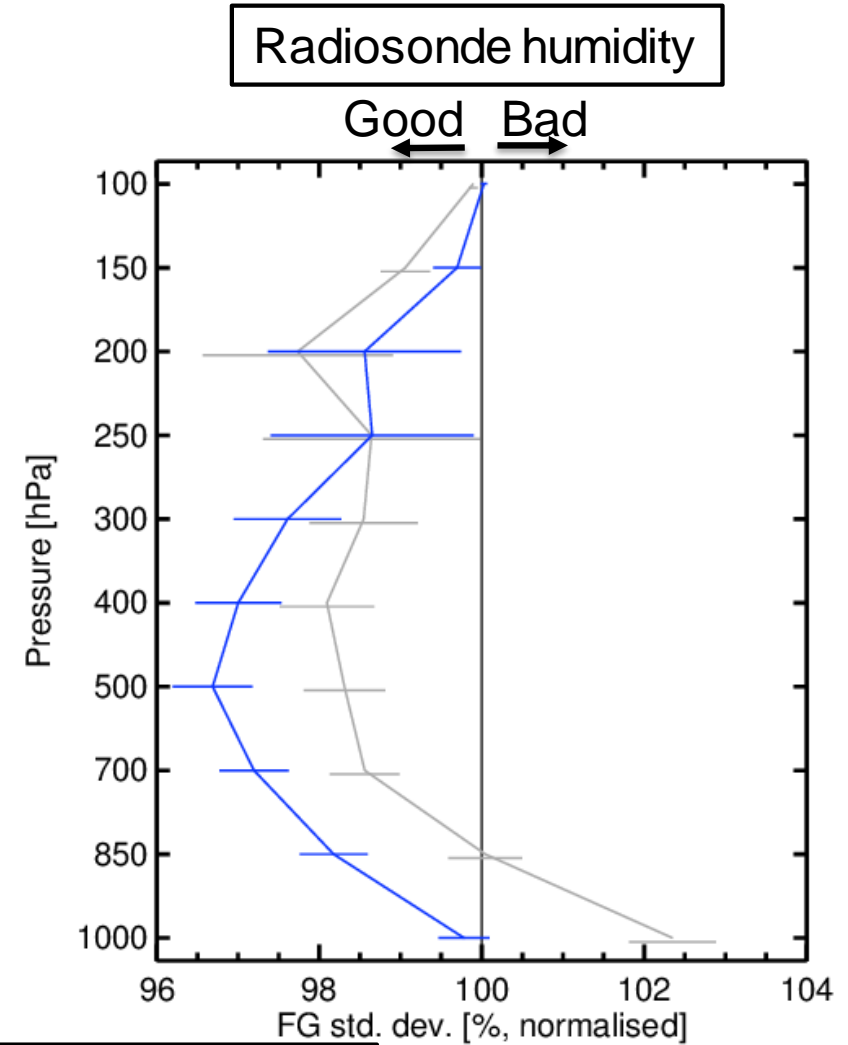
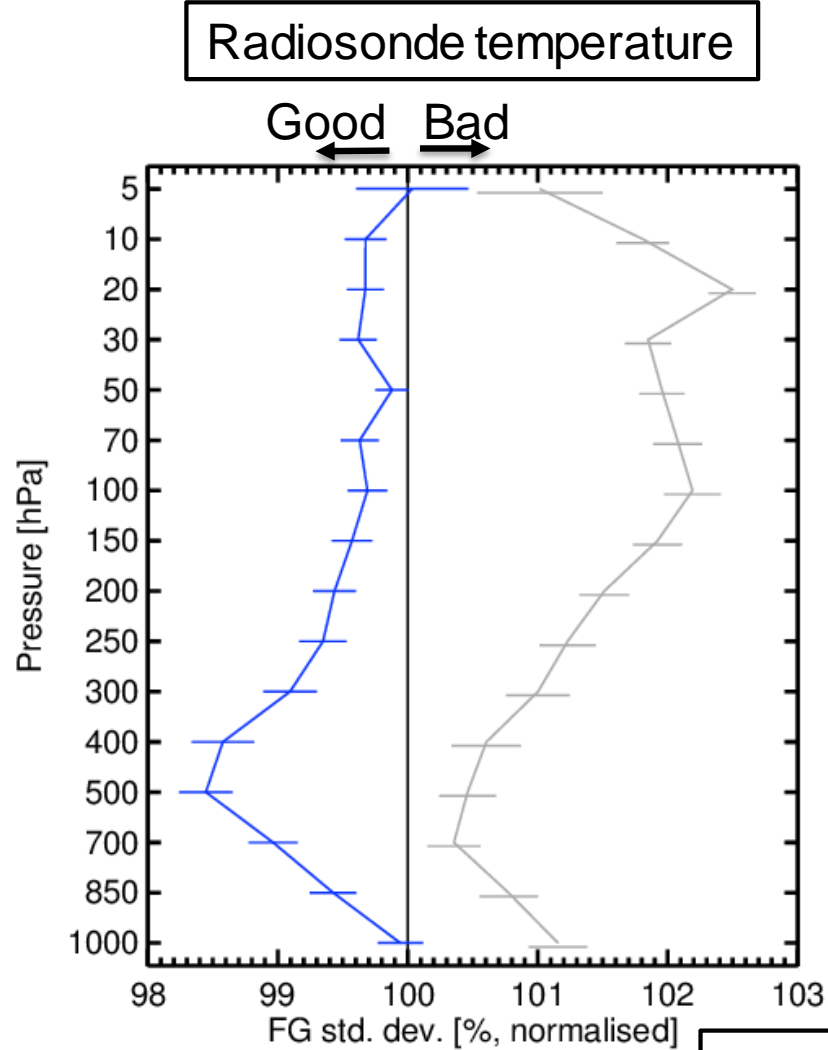
IASI radiances, channel 3049 (~11700 obs)



L2 humidity profiles (~12400 obs)

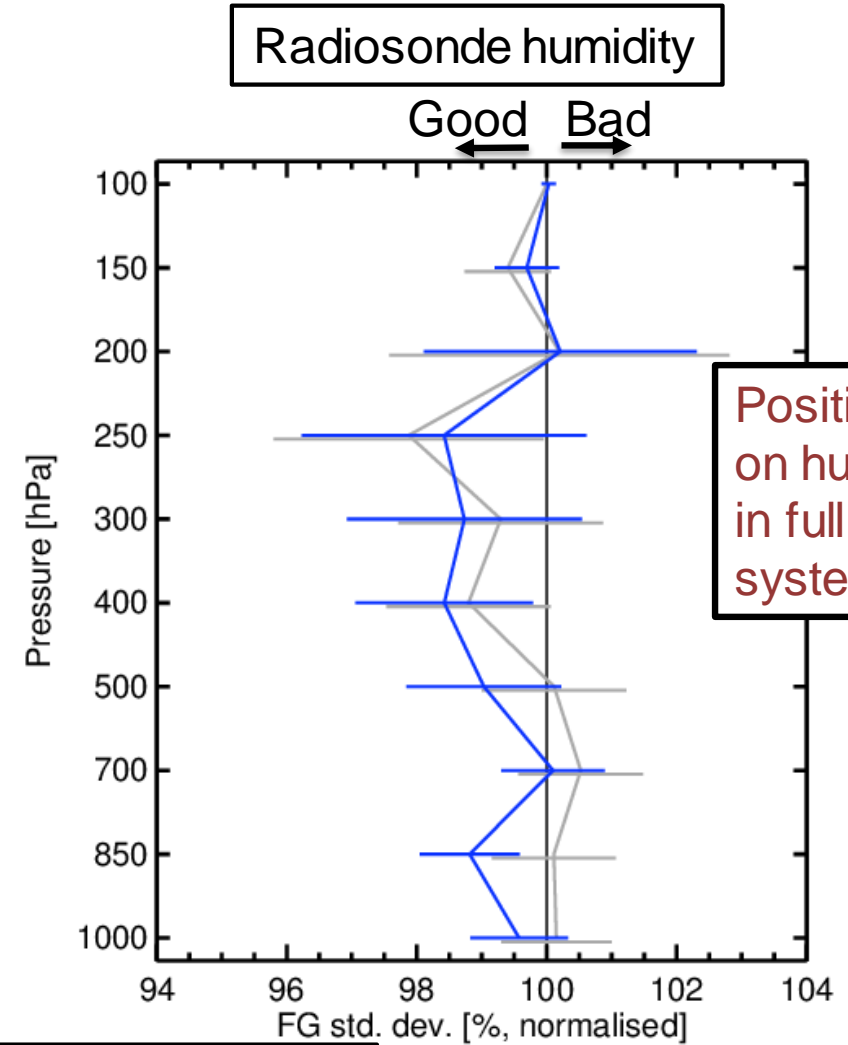
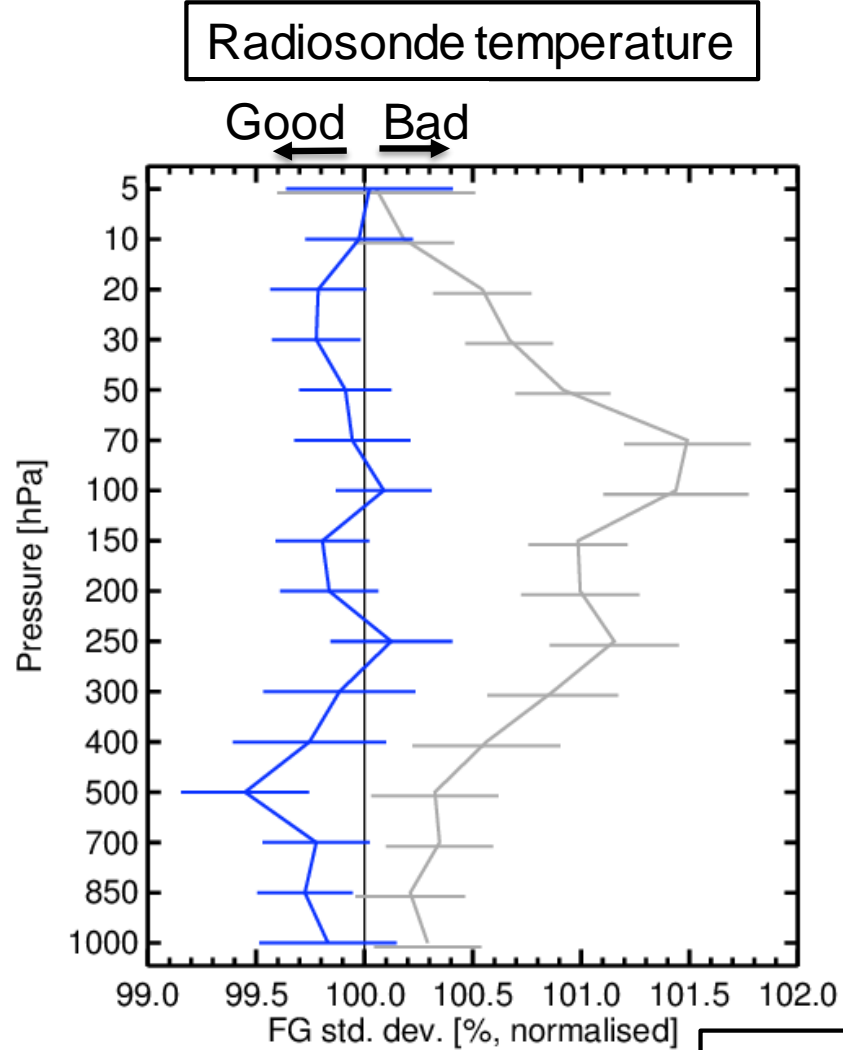


Short range forecast impact, depleted observing system



CTL (100%): Conv + AMSU-A
CTL + IASI L2 T and q with full R
CTL + IASI radiances

Short range forecast impact, full observing system



Positive impact
on humidity even
in full observing
system!

CTL (100%): Full observing system without IASI
CTL + IASI L2 T and q with full R
CTL + IASI radiances

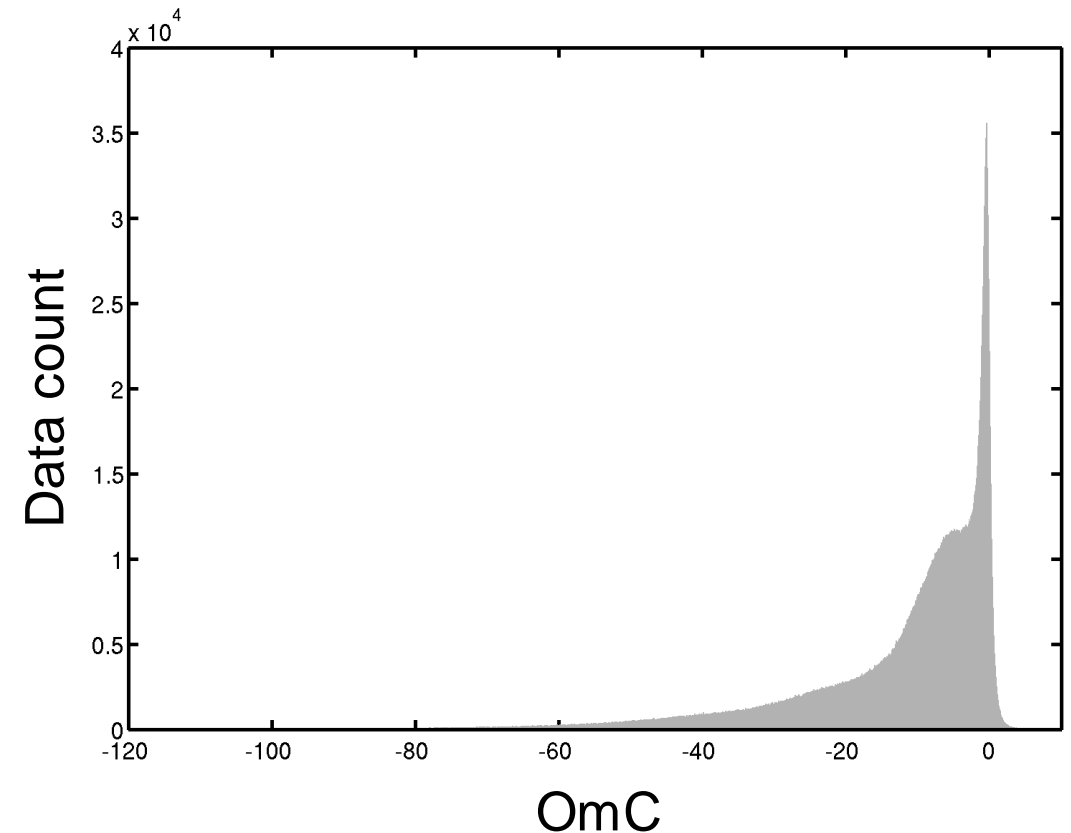
Summary of the L2 impact in clear sky conditions

- Positive impact from L2 humidity
 - Benefit comparable to IASI radiances
- Negative impact from L2 temperature
 - Most likely due to smoothing of inversions and tropopause structures
 - Vertical sensitivity not currently taken into account in the observation operator
- Results are consistent in depleted and full NWP systems
 - Smaller impact in full system
- L2 impact is very sensitive to the diagnosed error correlations
 - It is essential to take observation error correlations into account

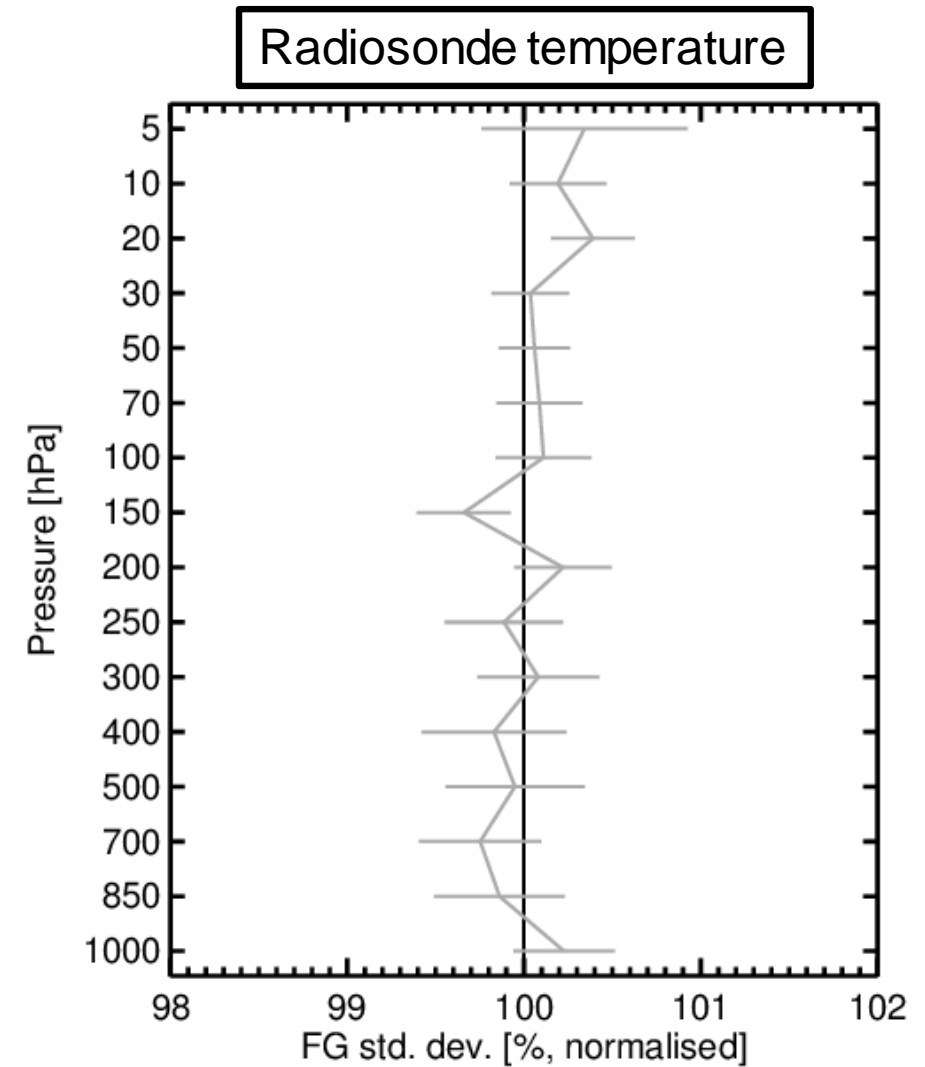
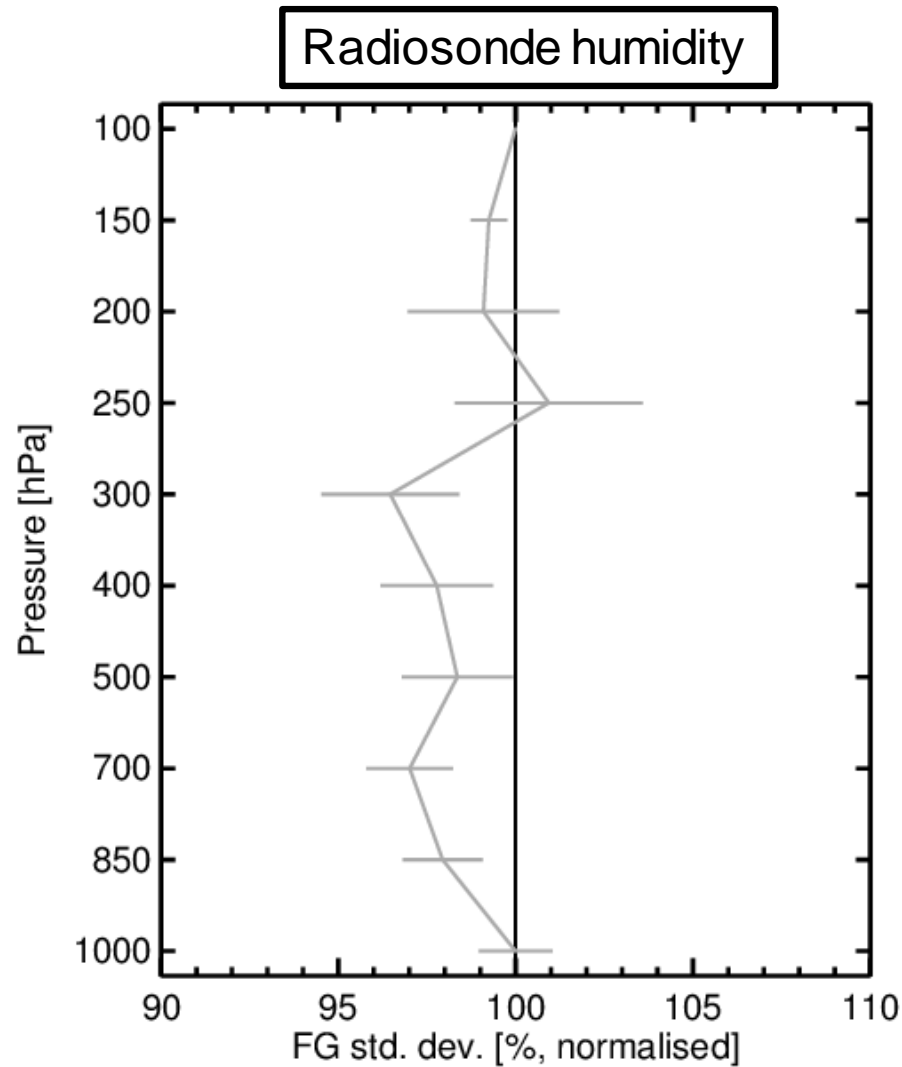
Impact assessment of cloud affected humidity retrievals

Depleted observing system experiments

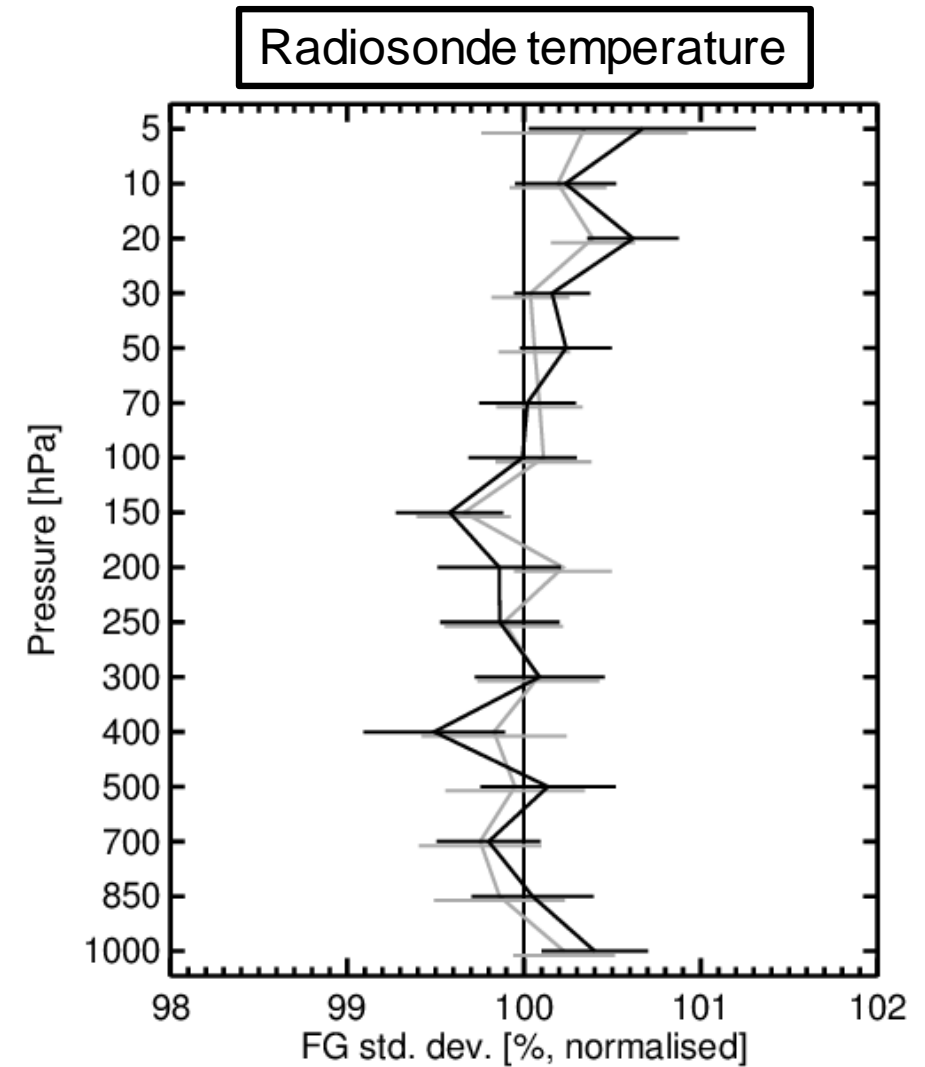
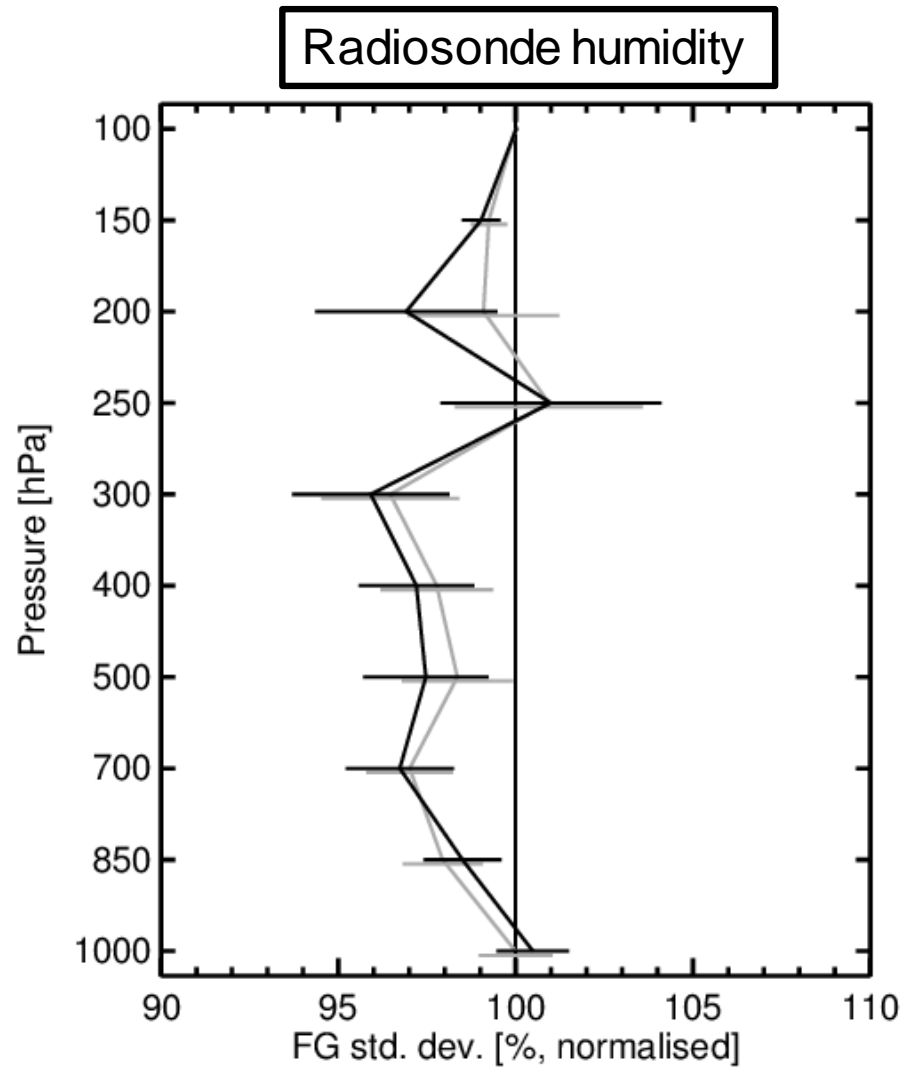
- **CTL**: Conventional observations + AMSU-A
- **L2**: **CTL** + L2 humidity profiles over sea
 - Varying criteria for accepted OmC
 1. $|\text{OmC}| < 1$
 2. $-5 < \text{OmC} < 1$
 3. $-15 < \text{OmC} < 1$
 4. $-30 < \text{OmC} < 1$
 5. $-45 < \text{OmC} < 1$
 6. $-60 < \text{OmC} < 1$
 - Observation errors and error correlations diagnosed for cloud free situations.



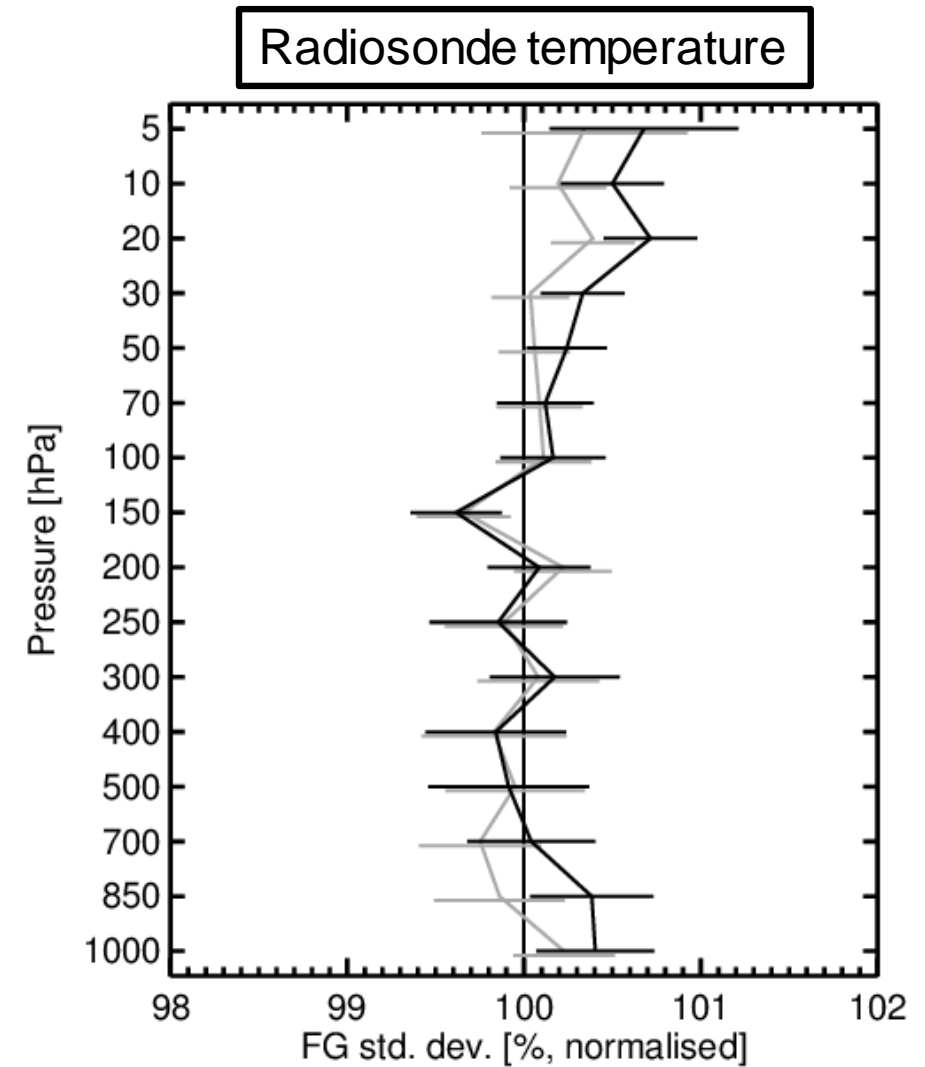
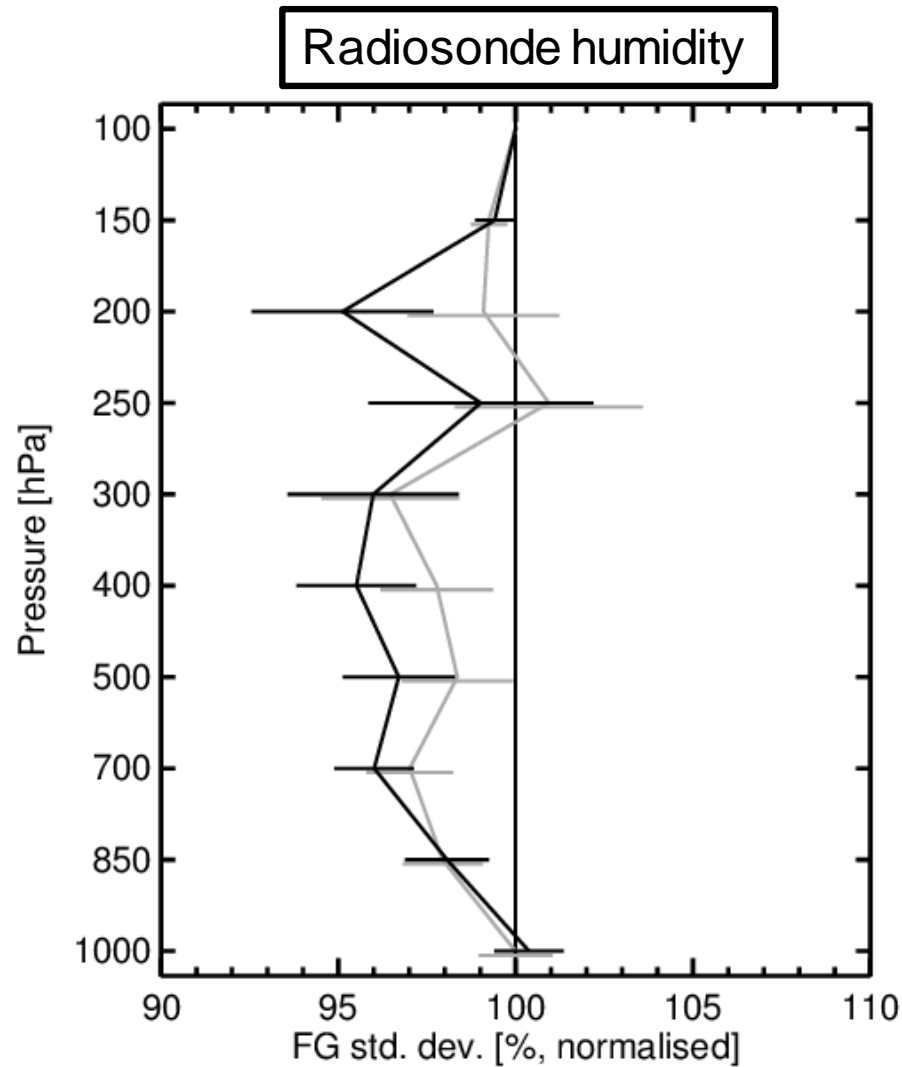
Short range impact on humidity and temperature, $-1 < \text{OmC} < 1$



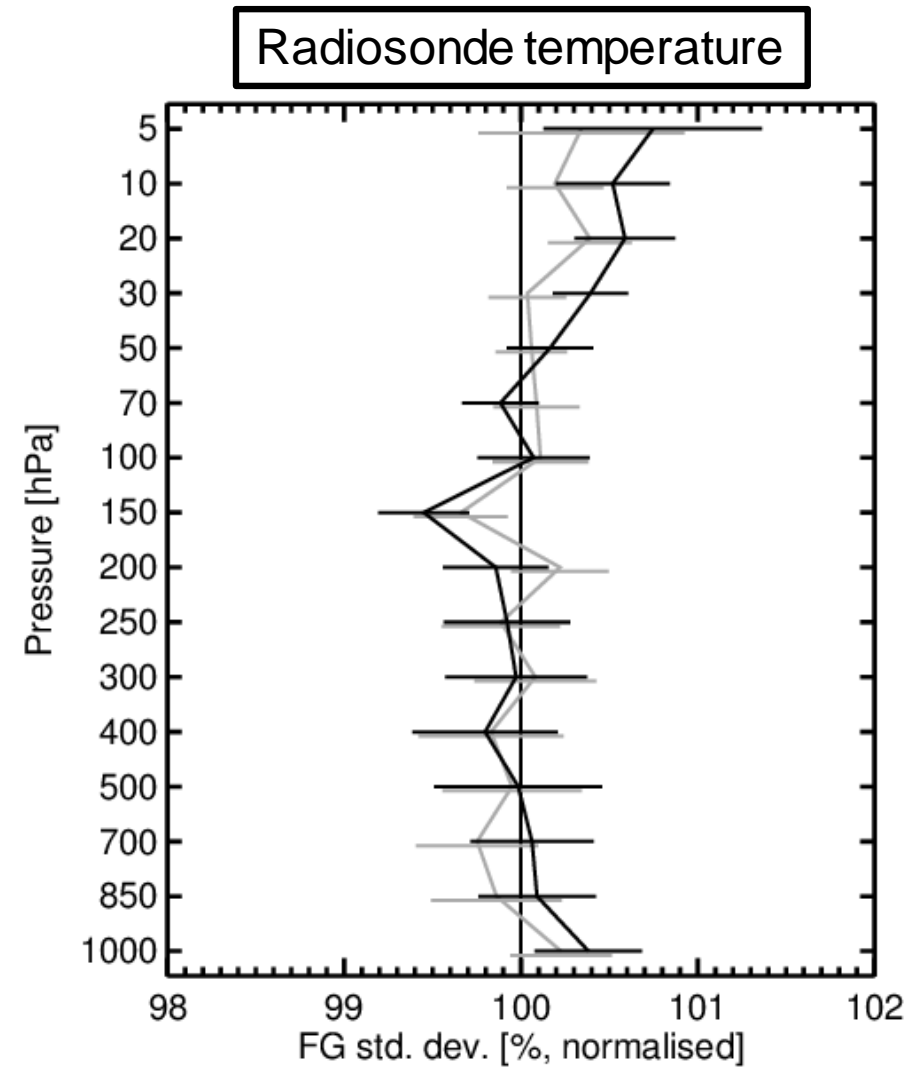
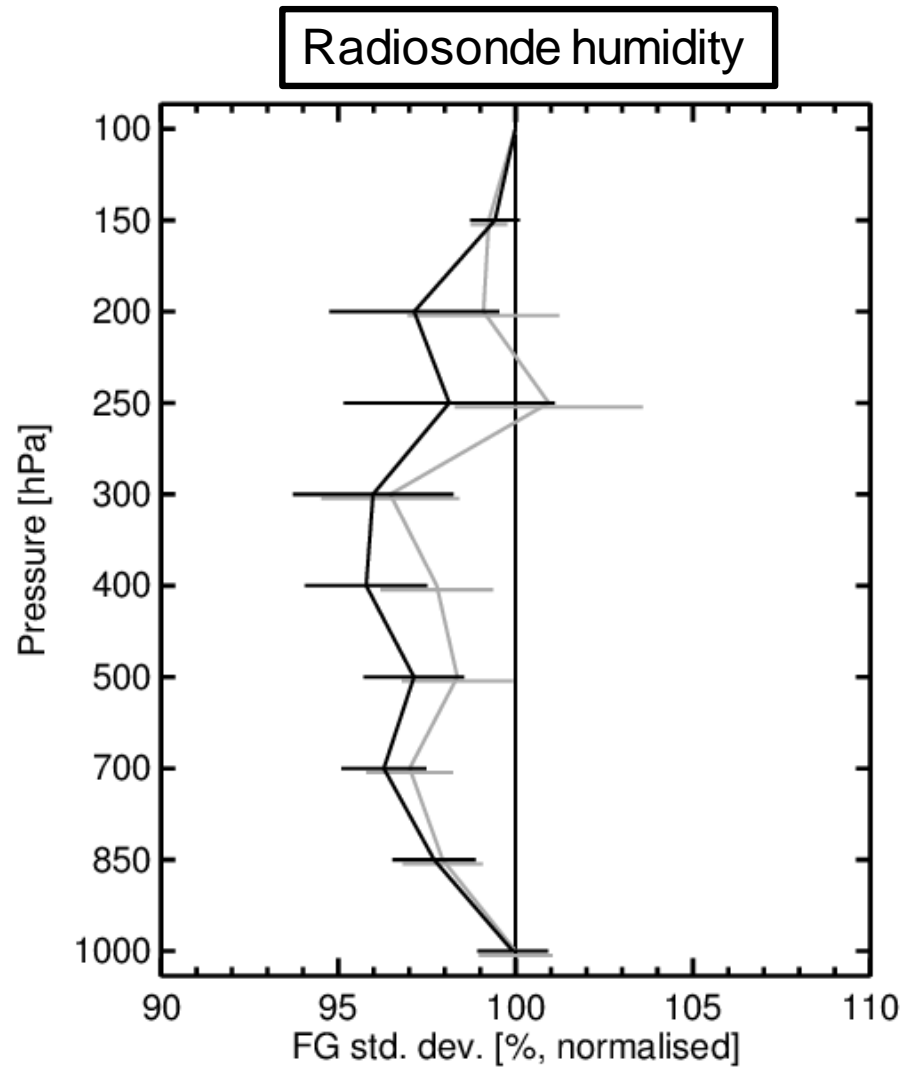
Short range impact on humidity and temperature, $-5 < \text{OmC} < 1$



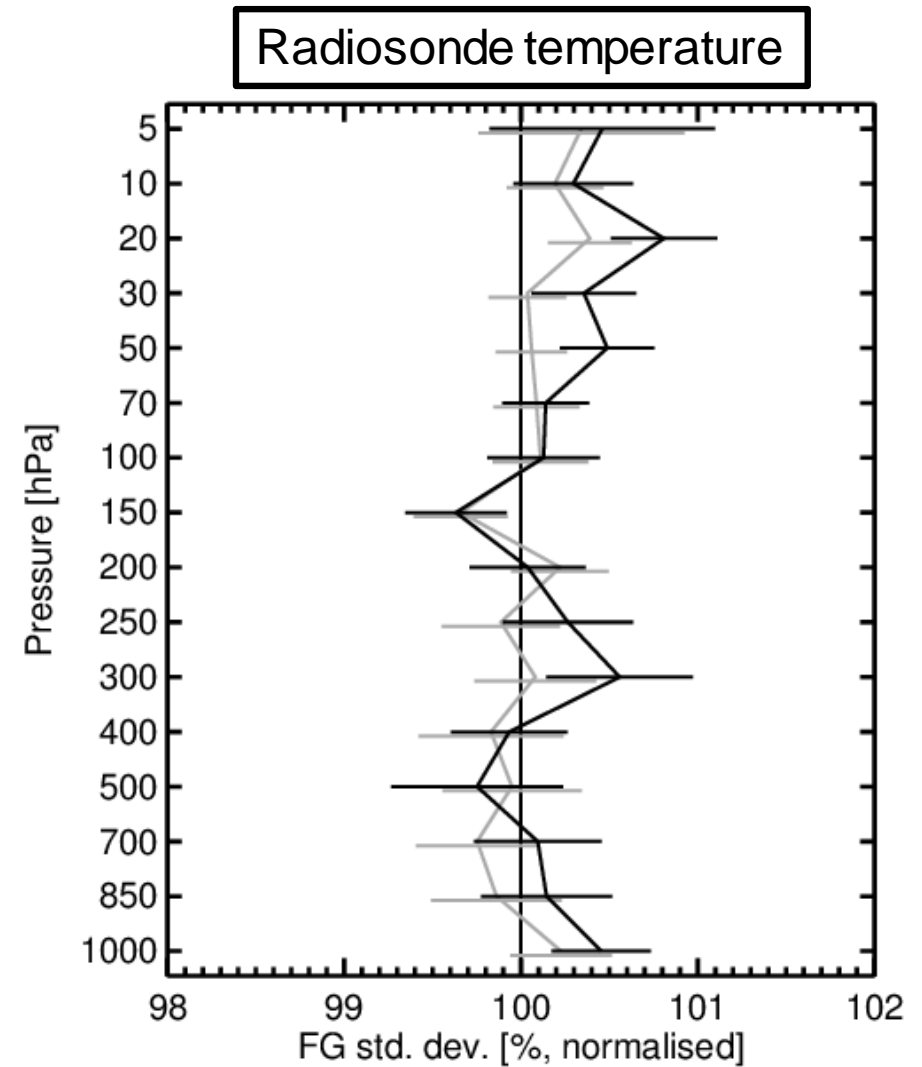
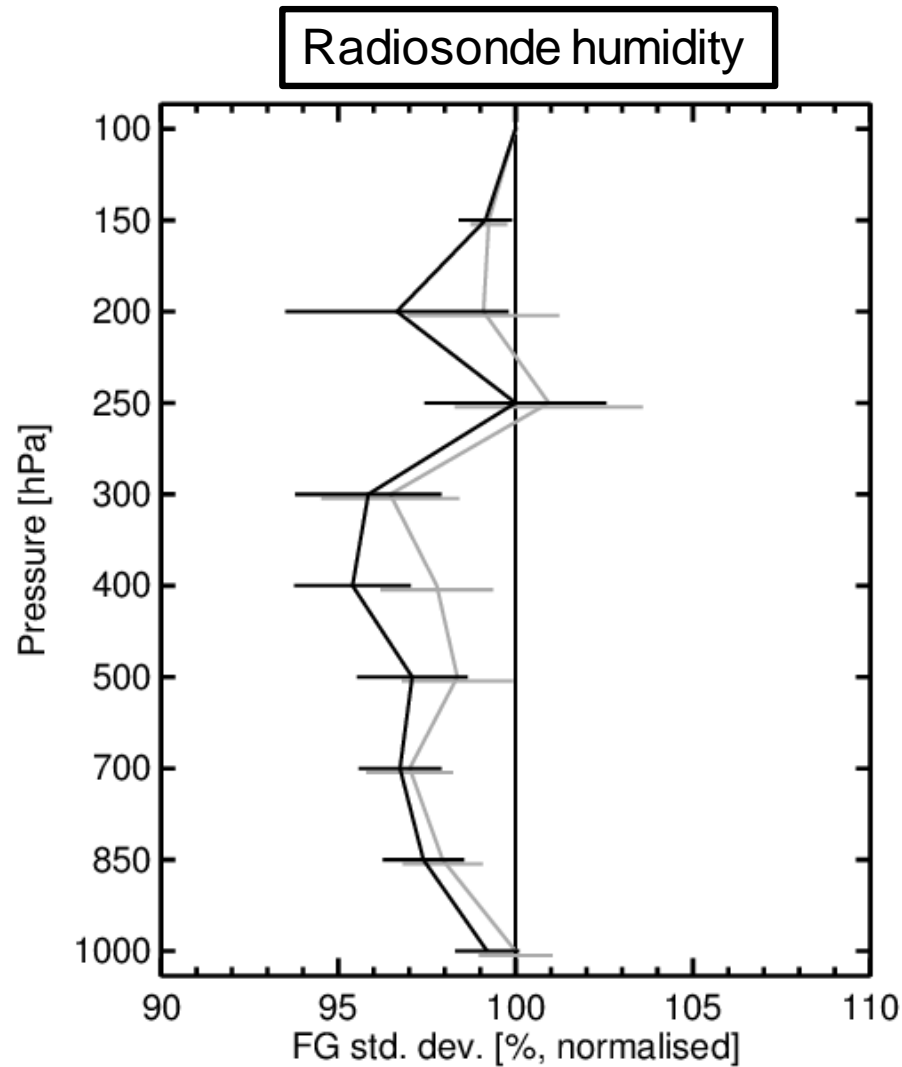
Short range impact on humidity and temperature, $-10 < \text{OmC} < 1$



Short range impact on humidity and temperature, $-15 < \text{OmC} < 1$

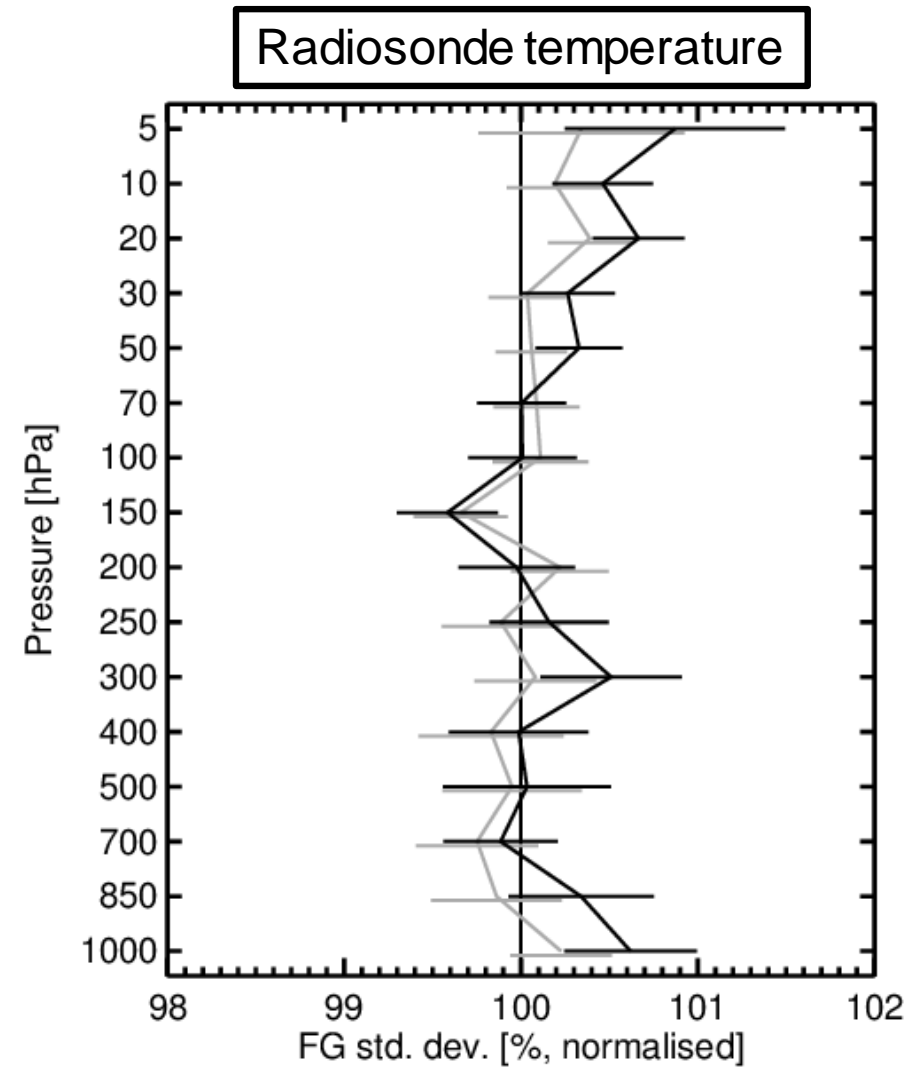
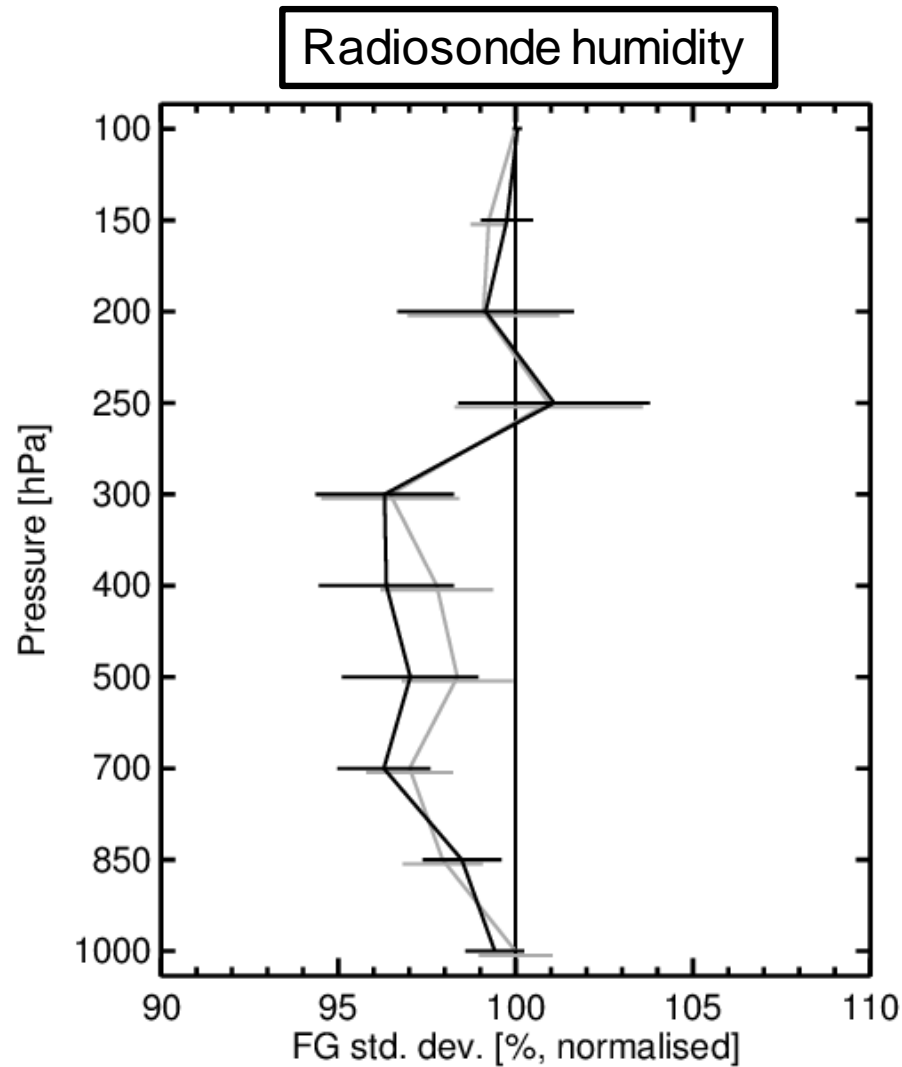


Short range impact on humidity and temperature, $-30 < \text{OmC} < 1$



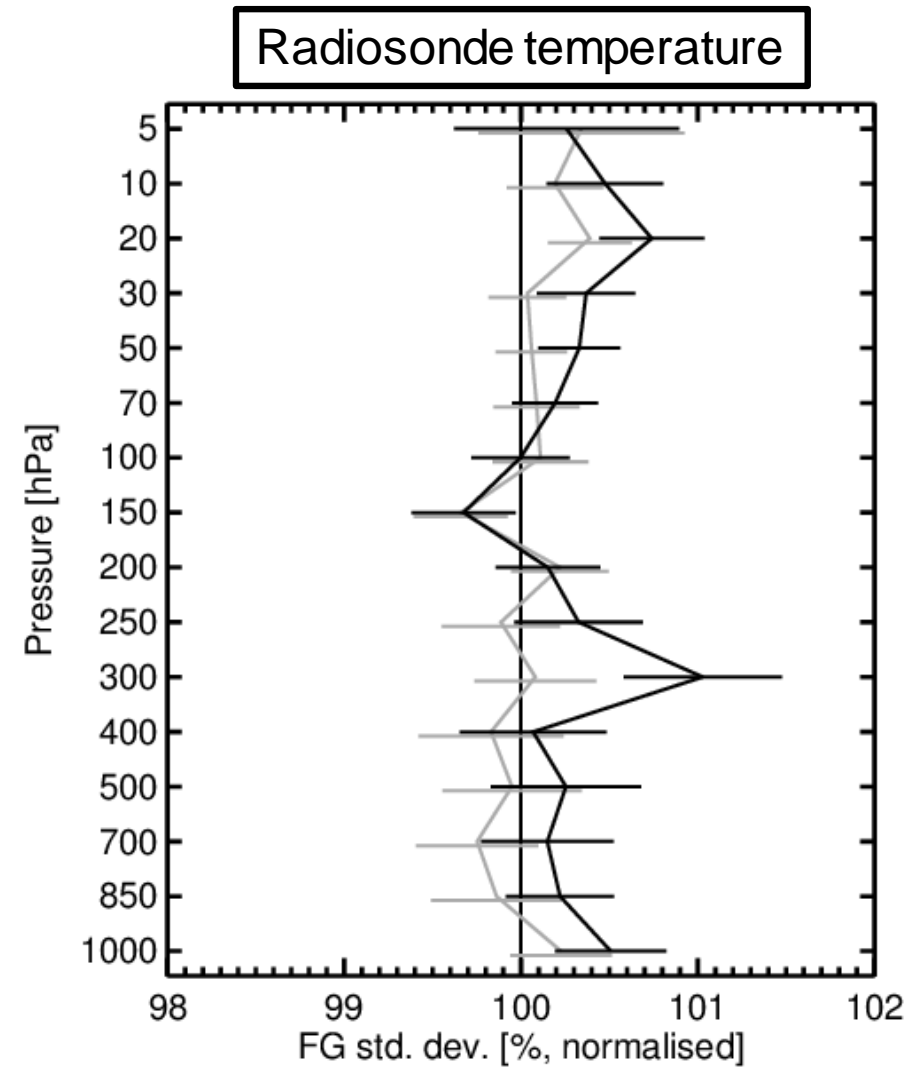
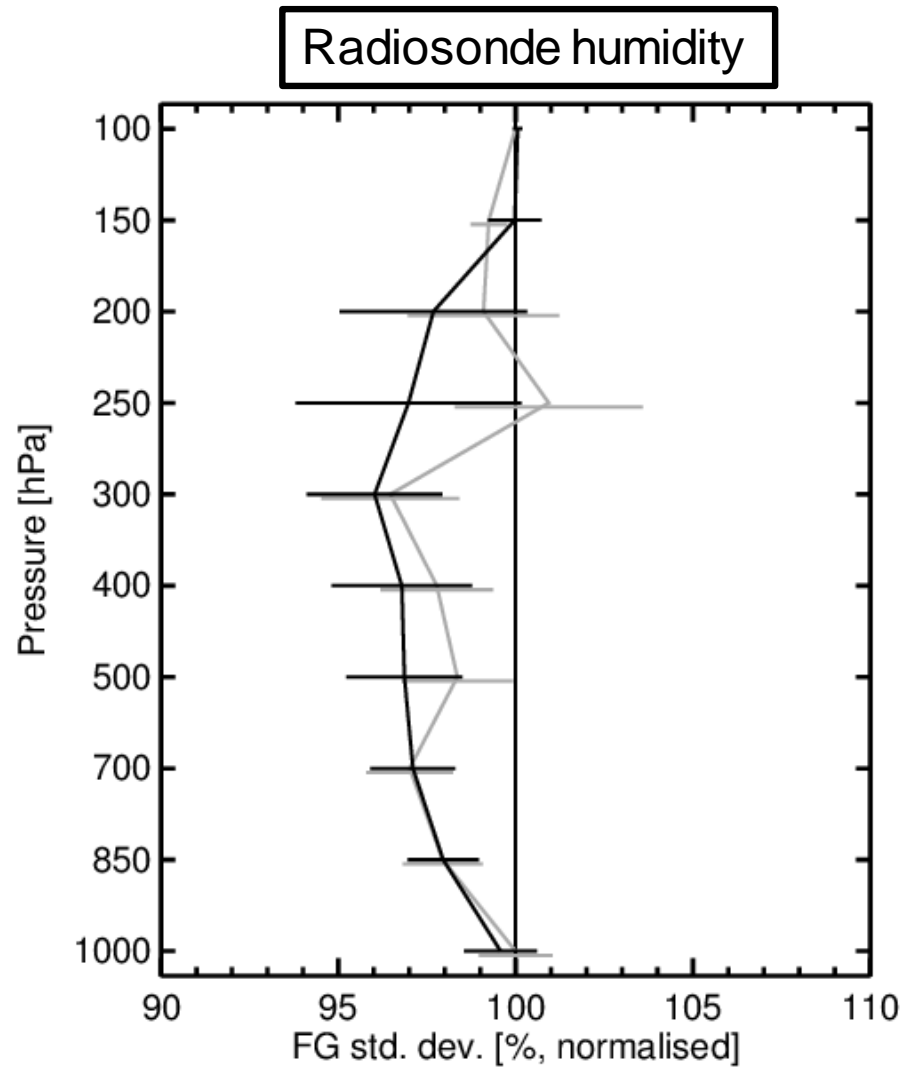
BUT the temperature forecasts starts to degrade for $\text{OmC} < -15$

Short range impact on humidity and temperature, $-45 < \text{OmC} < 1$



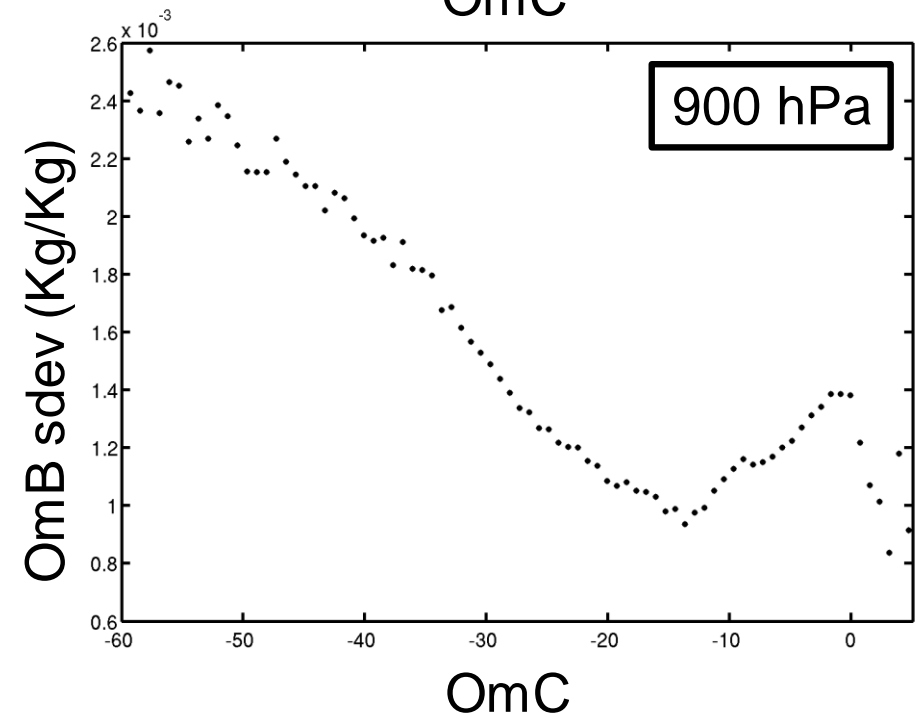
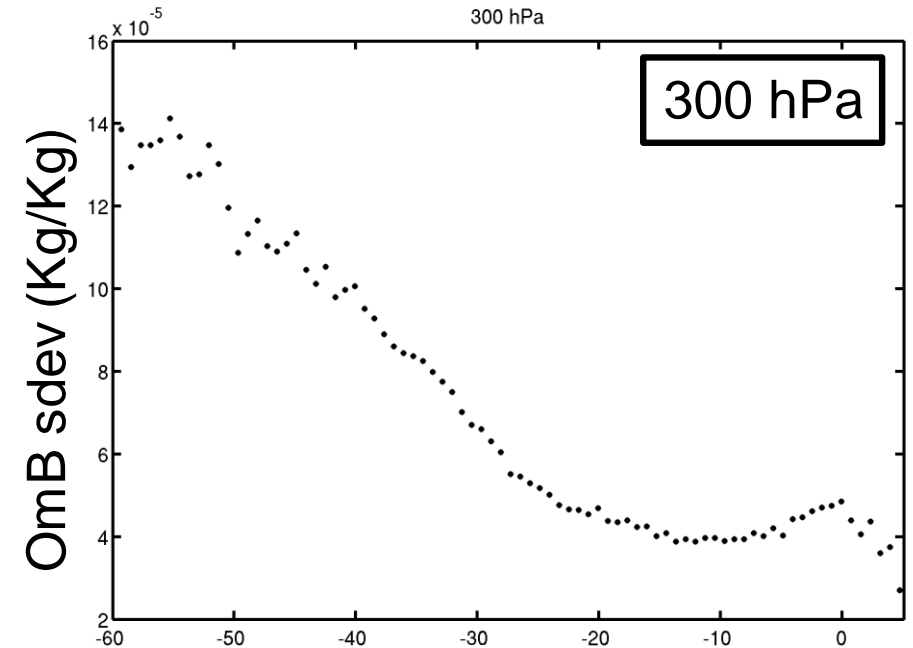
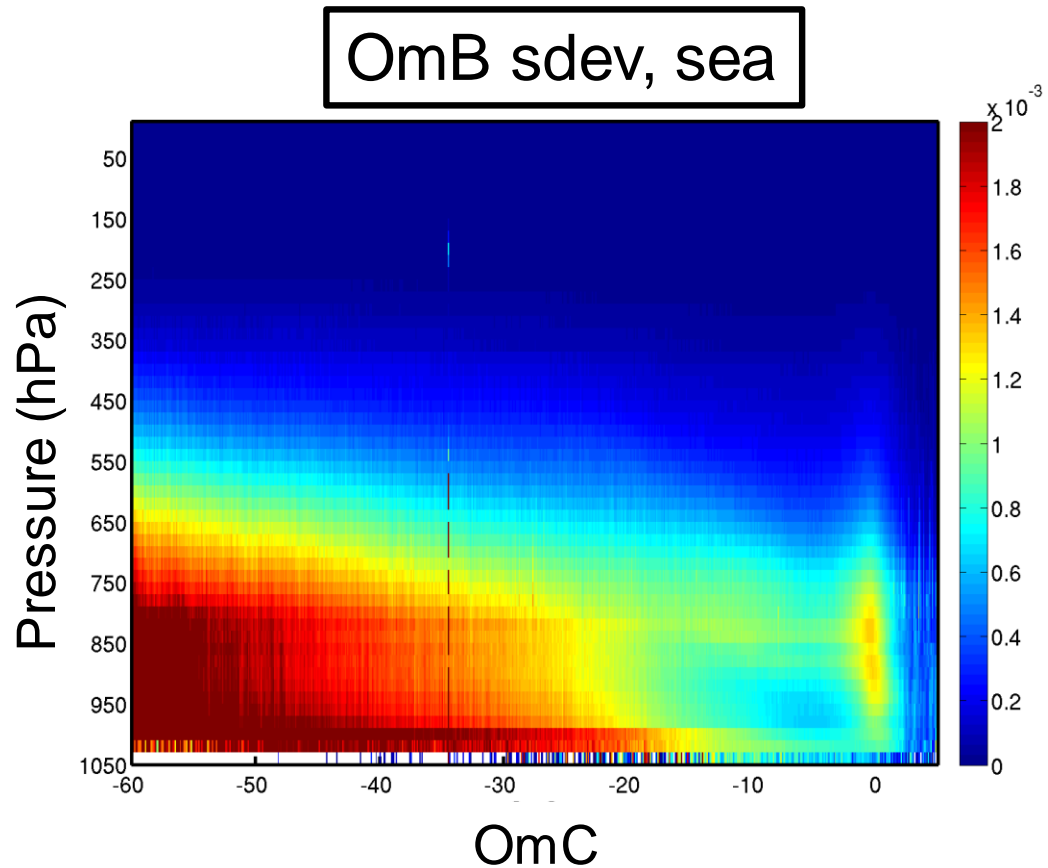
BUT the temperature forecasts starts to degrade for $\text{OmC} < -15$

Short range impact on humidity and temperature, $-60 < \text{OmC} < 1$

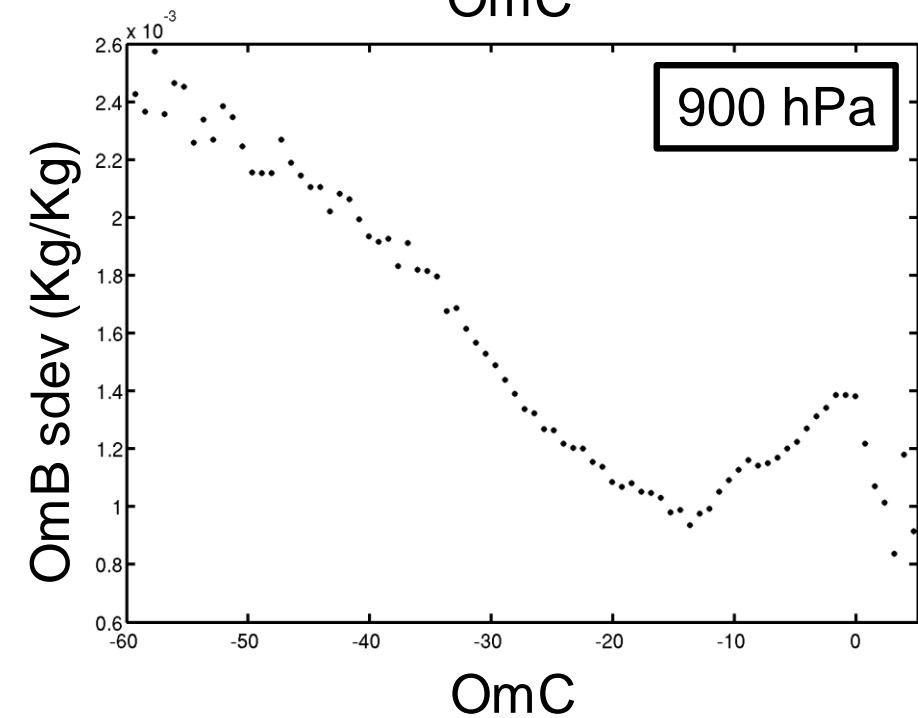
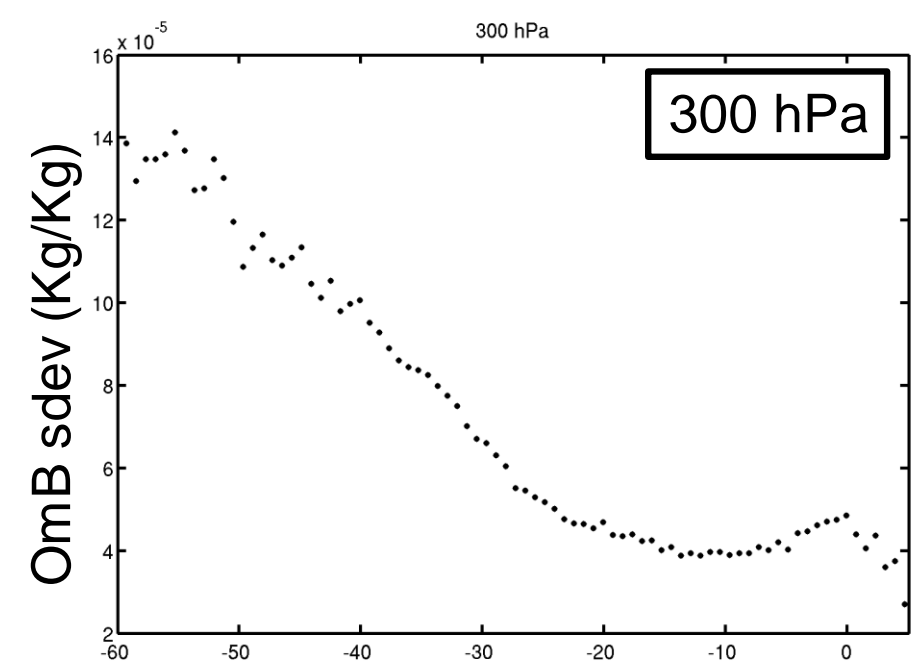
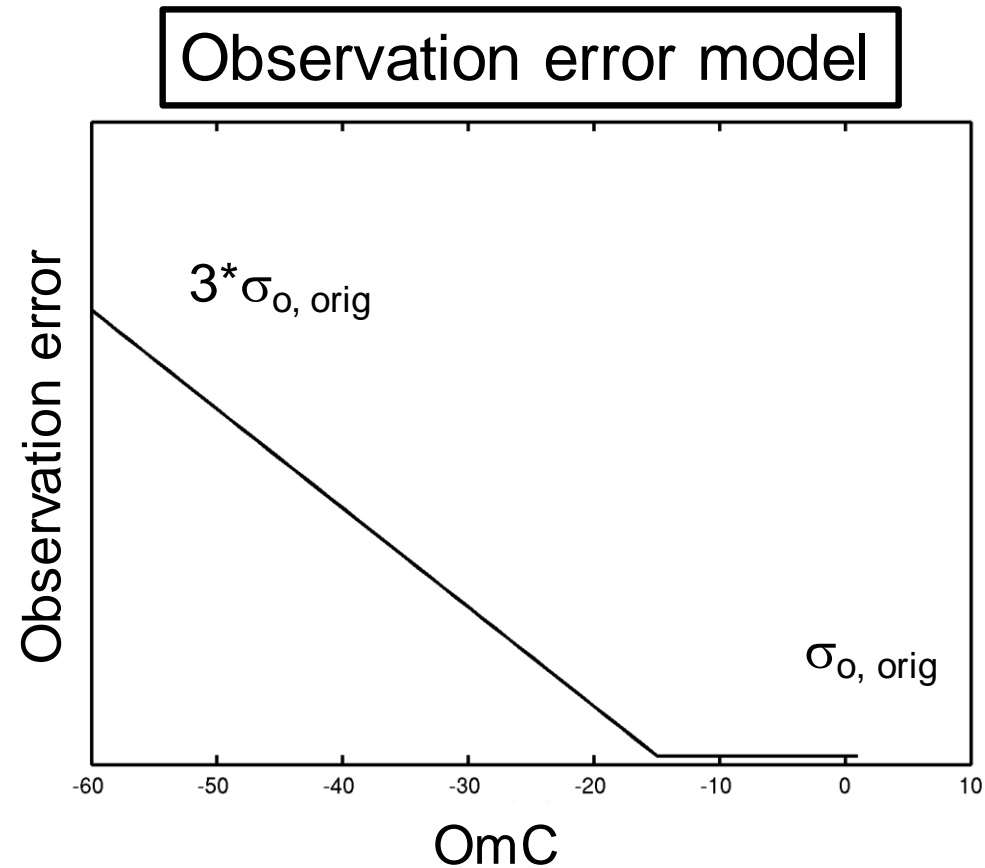


BUT the temperature forecasts starts to degrade for $\text{OmC} < -15$

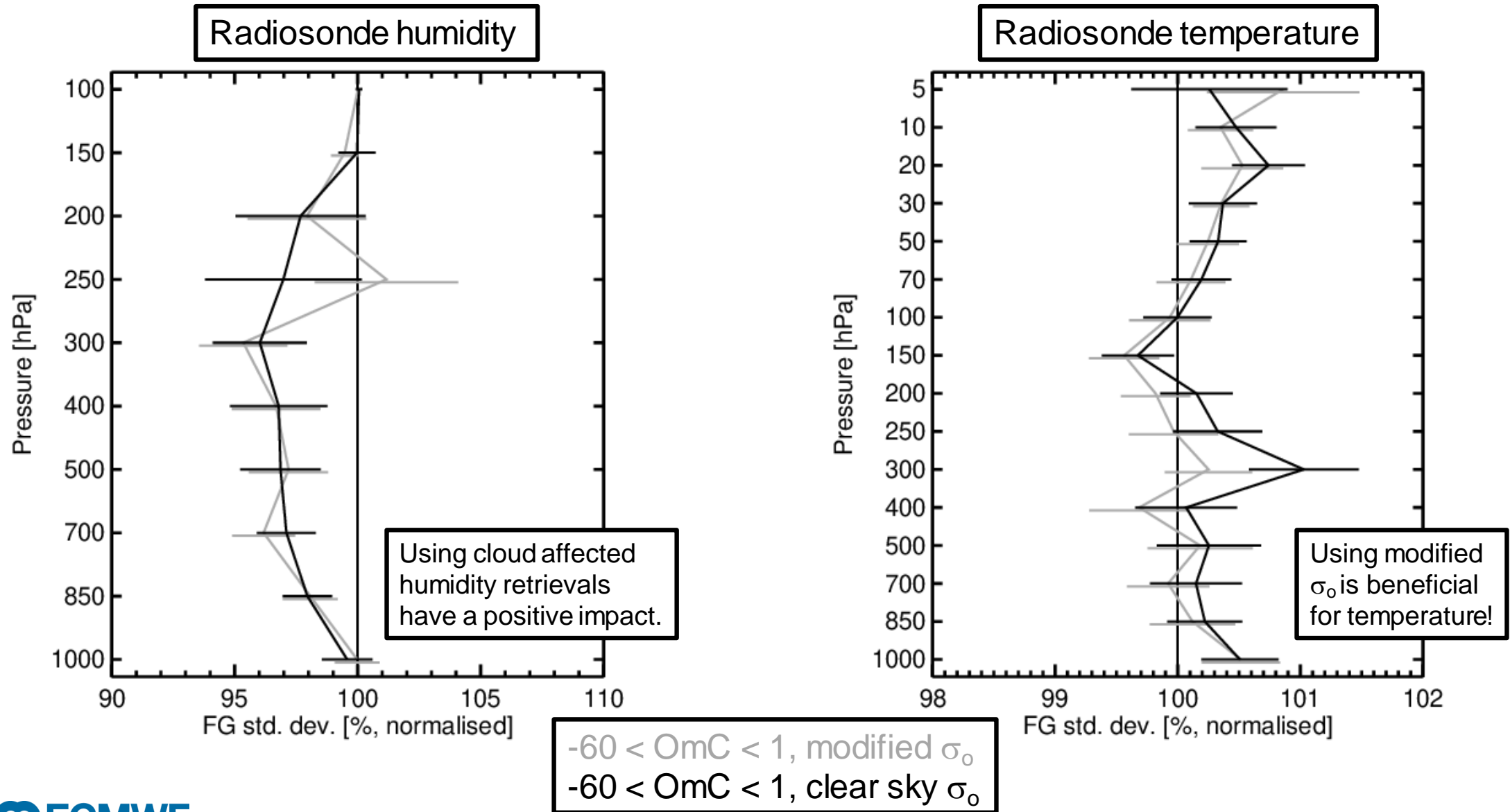
Behaviour of the OmB standard deviation



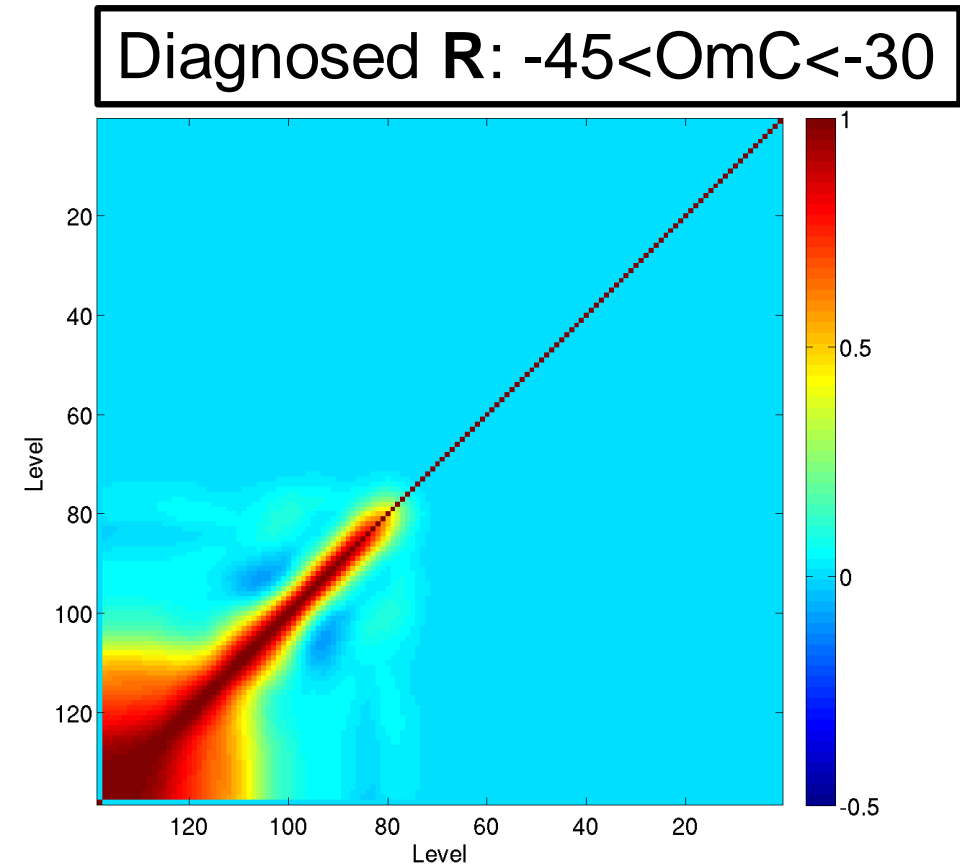
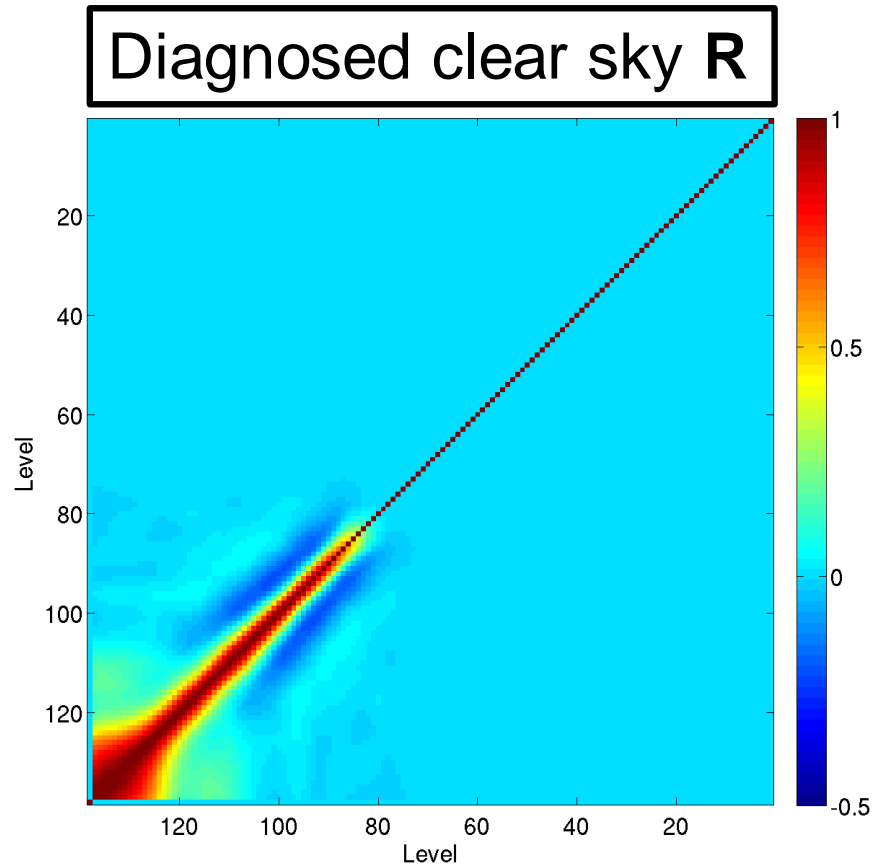
Modify the observation errors



Impact of using the observation error model, depleted observing system

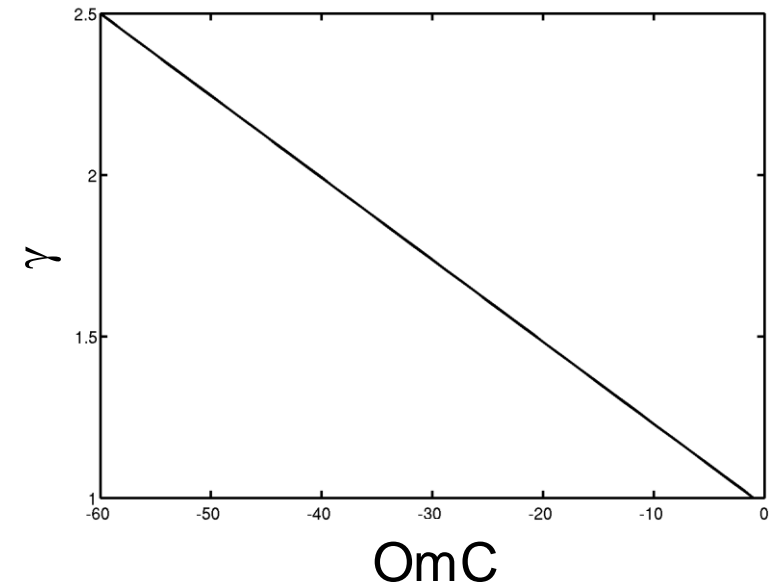


Clear vs cloud affected observation error correlations

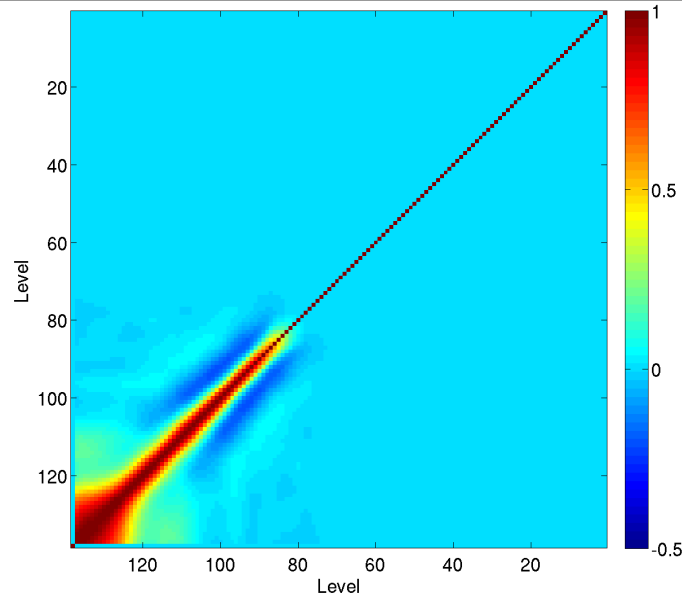


Modifying the observation error correlations

- Error correlation matrix can be sharpened/broadened by applying a multiplication factor γ to the eigenvalues of \mathbf{R} .
- Eigendecomposition: $\mathbf{R} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^{-1}$
- First test: modify the 1st eigenvalue.



Diagnosed clear sky \mathbf{R}

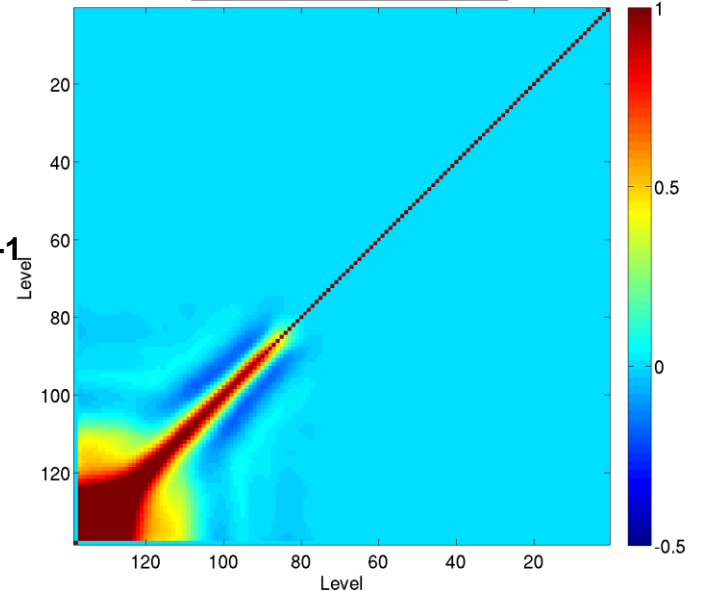


$$\mathbf{Q} \begin{bmatrix} \lambda_1 \\ \vdots \end{bmatrix} \mathbf{Q}^{-1}$$

$$\mathbf{Q} \begin{bmatrix} \lambda_1^\gamma \\ \vdots \end{bmatrix} \mathbf{Q}^{-1}$$



Inflated \mathbf{R}



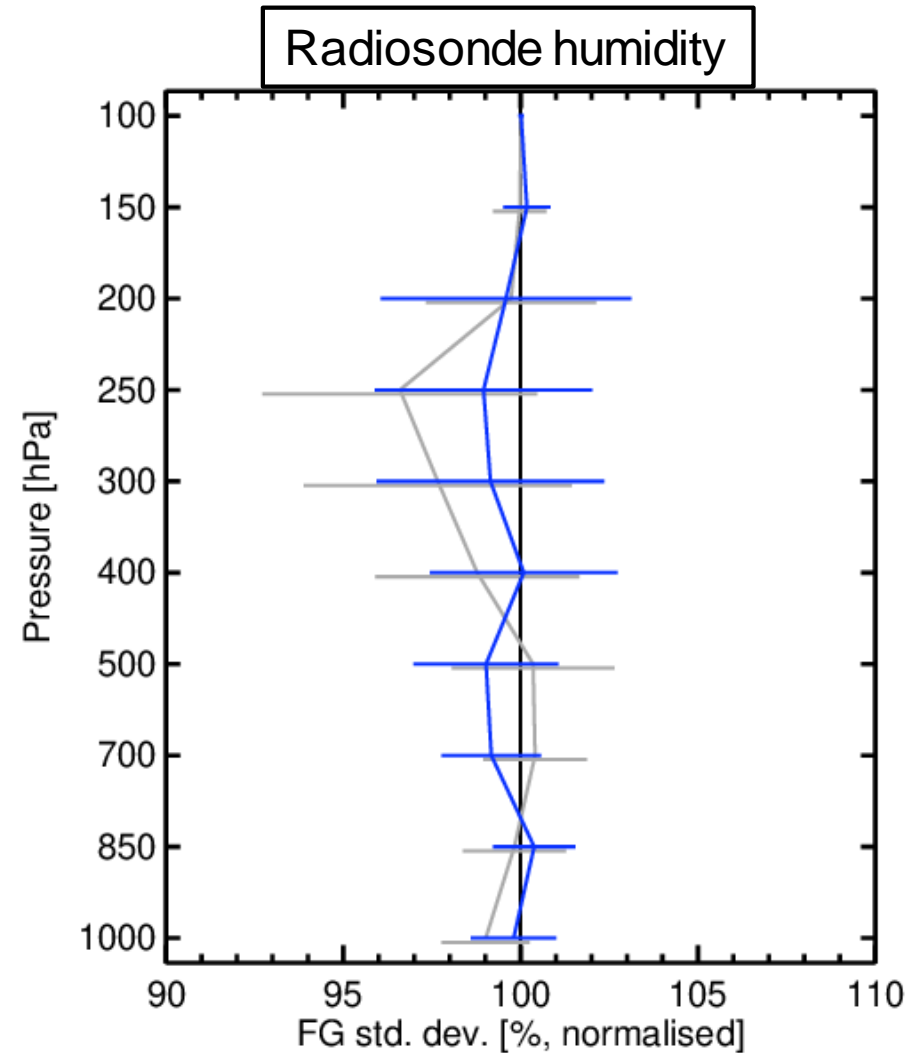
Preliminary impact of inflating the observation error correlations

- Further benefits can be obtained by introducing the scene dependent observation errors and error correlations.

CTL (100%): Conv + AMSU-A + L2 q with clear sky errors and correlation

CTL + IASI L2 q with scene dependent σ_o but clear sky error correlation

CTL + IASI L2 q with scene dependent σ_o and error correlations



Summary of assimilation of cloud affected humidity retrievals

- Assimilation of cloud affected humidity retrievals using observation errors and error correlation derived for clear sky situations indicate:
 - Improvements for the short range humidity forecasts
 - Temperature forecasts starts to degrade for OmC < -15
- Using the modified observation error model
 - Has neutral to positive impact on short range humidity forecasts
 - Is beneficial for temperature forecasts, the degradation is decreased significantly
- Inflating the observation error correlations
 - Brings further benefits on top of using scene dependent observation errors
- Results are consistent in full and the depleted system experiments

Overall conclusions

- Very clear **positive impact** from assimilation of humidity retrievals
 - Impact on humidity comparable to IASI radiances!
 - Assimilation of cloud affected humidity retrievals brings further benefits
- Very clear **negative impact** from assimilation of temperature retrievals
 - The degradation is most likely due to assimilating the smooth or missing vertical structures for temperature, without taking the limited vertical resolution of the retrievals fully into account.

Thank you for your attention!