Roadmap toward a model-insensitive water vapour climate data record based on radio occultation measurements

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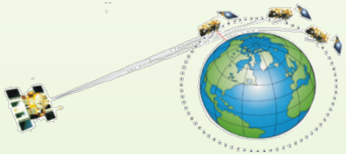
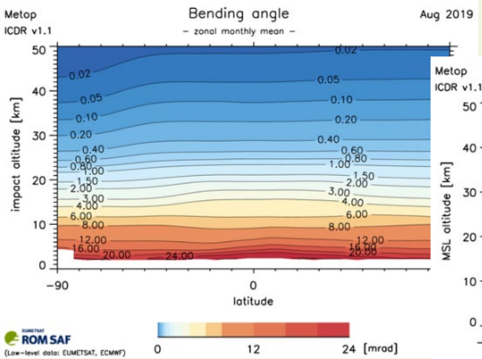
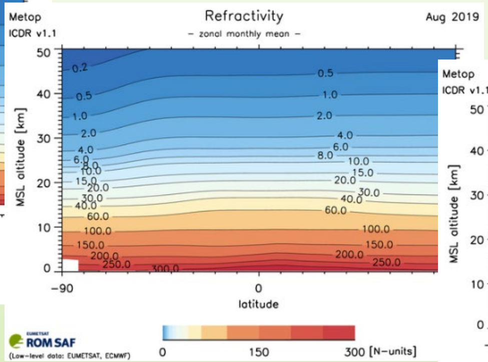
Outline

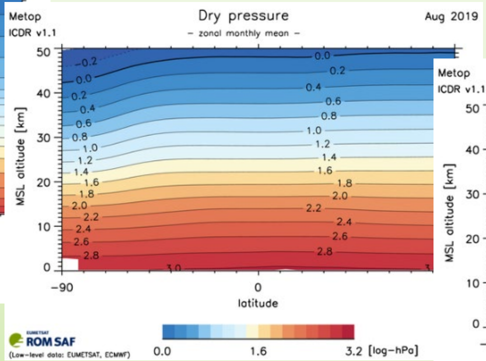
- ROM SAF Climate Data Records (CDRs) based on Radio Occultation (RO) data
- Tropospheric humidity from 1D-Variational retrieval
- Sensitivity of 1D-Var
- Climate trends:
  - issue with spurious effects in background data
  - issue with orbits (sampling)
- 3-step strategy for improved CDRs for climate applications:
  - Error-covariance matrix, detrending, sampling corrections
- Conclusions

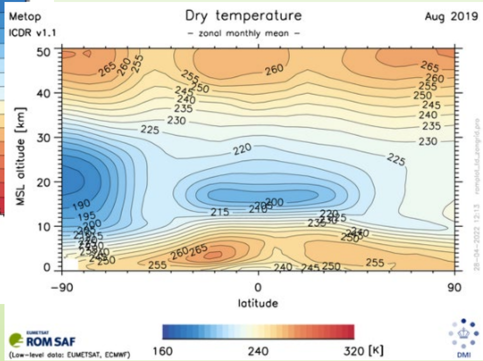
Climate Data Records: geophysical variables

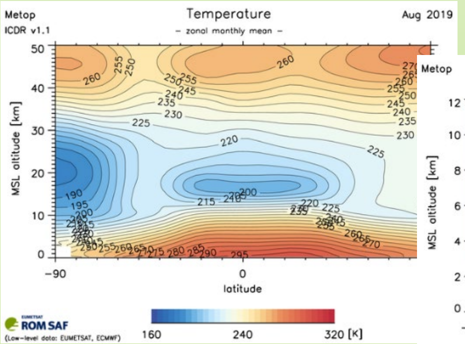


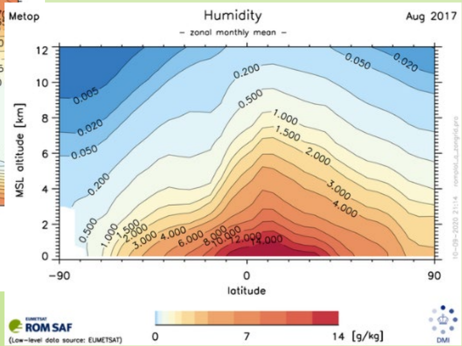


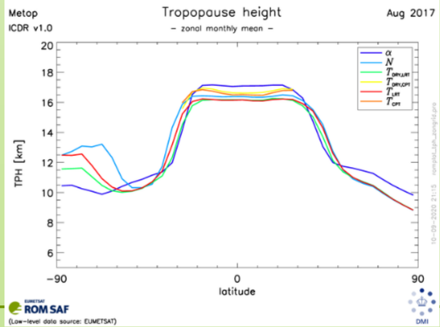




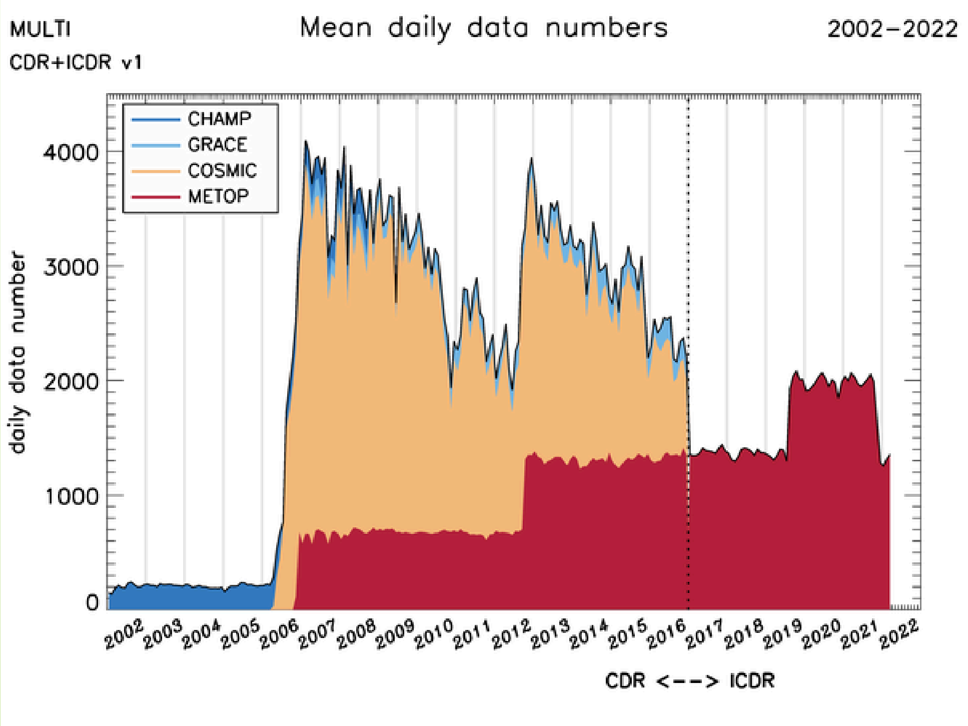








ROM SAF Climate Data Records



Climate data record (CDR v1.0)

- CHAMP, GRACE, COSMIC-1, Metop, MULTI
- Input data from EUMETSAT Secr (Metop) and from UCAR (CHAMP, GRACE, COSMIC)
- Reprocessed 15+ years, Sep 2001 - Dec 2016
- Released in February 2019

Interim climate data record (ICDR v1)

- Metop
- Input data from EUMETSAT Secretariat
- Processed 5+ years, Jan 2017 - Mar 2022
- First release in May 2019
- New data added monthly

ROM SAF: Radio Occultation Meteorology Satellite Application Facility (EUMETSAT)

http://rom-saf.eumetsat.int

1D-Variational retrieval of tropospheric humidity

$\boldsymbol{x}$ = (temperature, specific humidity, surface pressure)

$\boldsymbol{x}_b$ = model background

$\boldsymbol{y}$ = observed RO data (refractivity profile)

$\boldsymbol{h}$ = forward model ($\boldsymbol{H} = \partial \boldsymbol{h} / \partial \boldsymbol{x}$)

Minimize the cost function:

$$J(\boldsymbol{x}) = \frac{1}{2}(\boldsymbol{x} - \boldsymbol{x}_b)\,\boldsymbol{B}\,(\boldsymbol{x} - \boldsymbol{x}_b)^T + \frac{1}{2}(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x}))\,\boldsymbol{R}\,(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x}))^T$$

$\boldsymbol{B}$ = Background error covariance

$\boldsymbol{R}$ = Observation error covariance

$\boldsymbol{S}$ = Solution error covariance: $\boldsymbol{S}^{-1} = \boldsymbol{B}^{-1} + \boldsymbol{H}^T \boldsymbol{R}^{-1} \boldsymbol{H}$

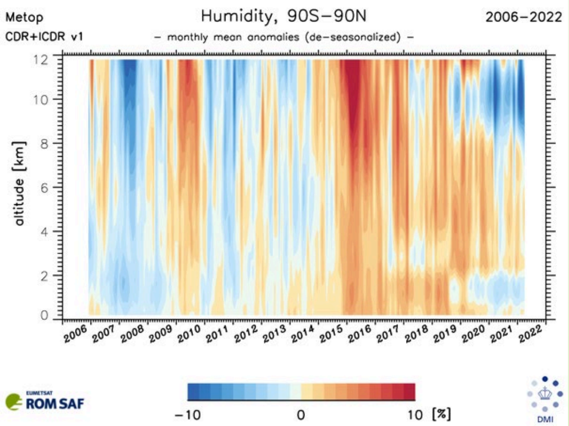
The averaging kernel $\boldsymbol{KH}$ expresses the solution's sensitivity to the specific humidity:

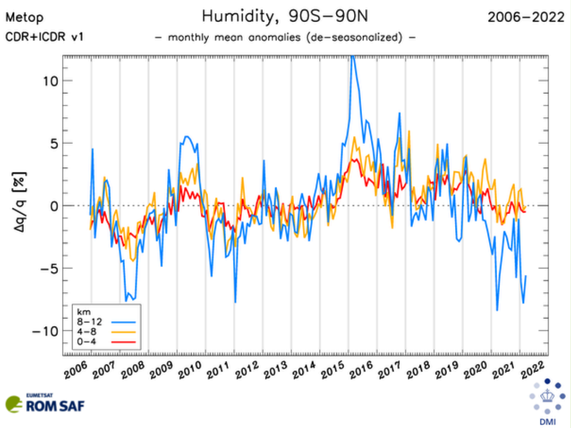
$$\boldsymbol{KH} = (\boldsymbol{H}^T \boldsymbol{R}^{-1} \boldsymbol{H} + \boldsymbol{B}^{-1})^{-1} \boldsymbol{H}^T \boldsymbol{R}^{-1} \boldsymbol{H}$$

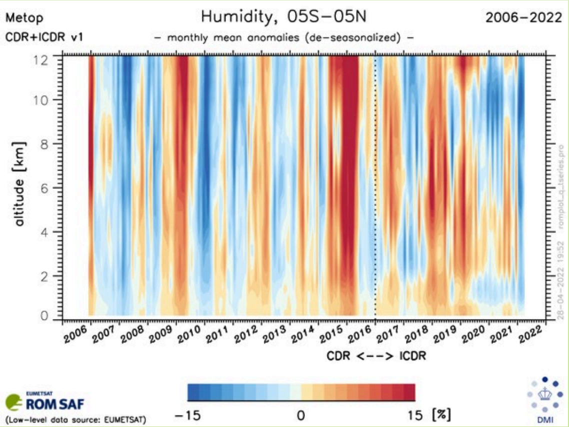
Weighting between real signal and background:

$$\boldsymbol{\delta x}_s = \boldsymbol{KH}\,\boldsymbol{\delta x} + (\boldsymbol{I} - \boldsymbol{KH})\boldsymbol{\delta x}_b$$

Tropospheric humidity time series

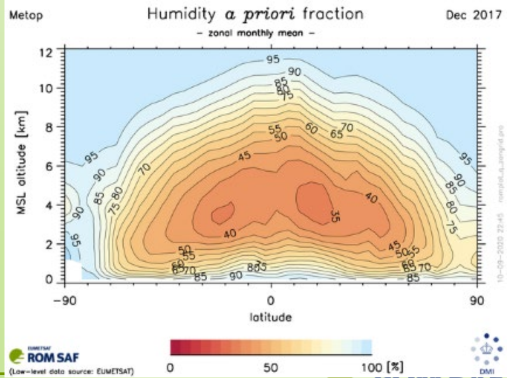




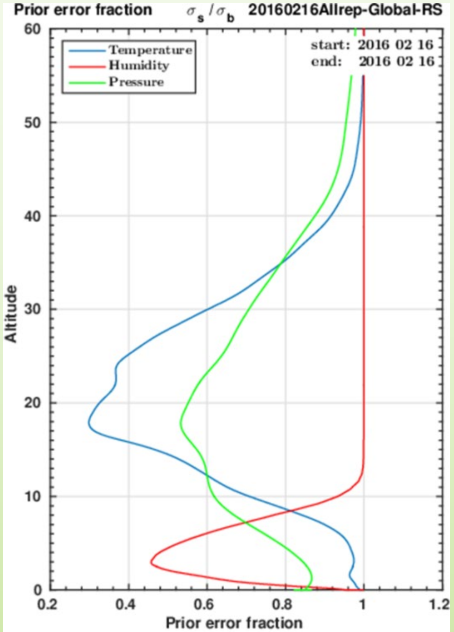


1D-Var retrievals (using background information from ECMWF reanalyses) yields humidity

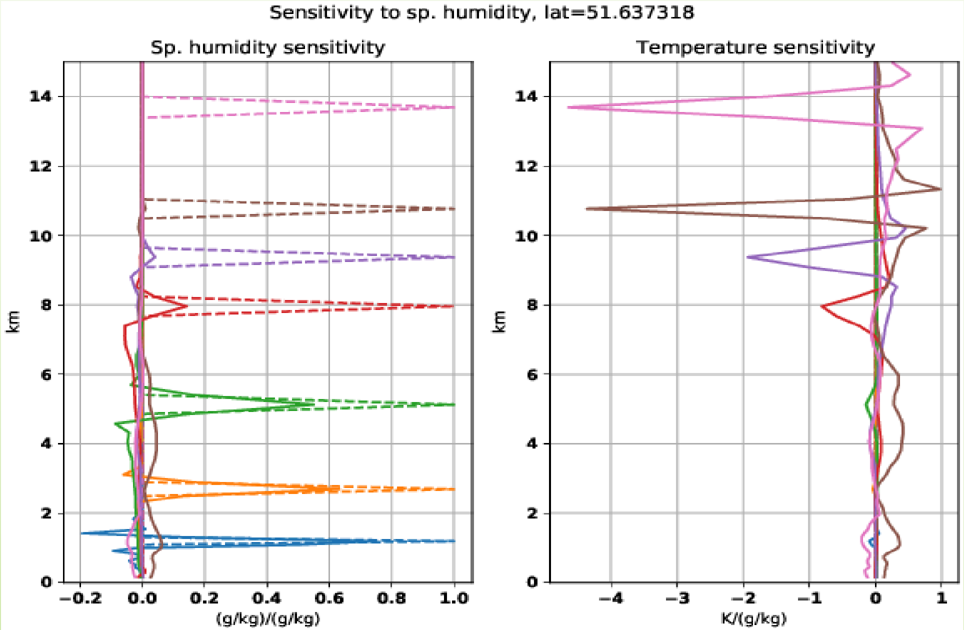
Highest observational information content is in the height range 2 - 8 km



1D-Var sensitivity



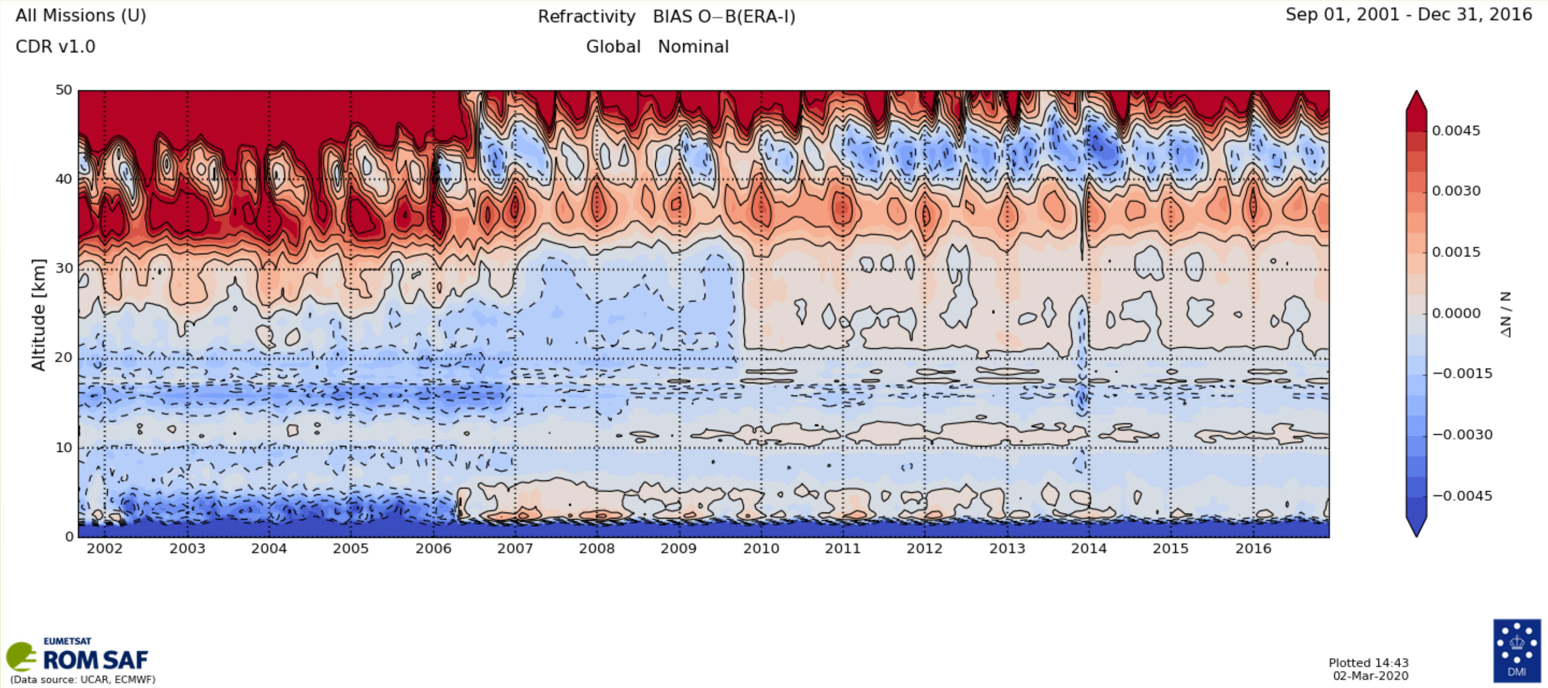
Prior fraction: shows the reduction of uncertainty diag(S) / diag(B)



Averaging kernel KH (dashed curves) illustrates humidity perturbation, δx_s. Full curves show corresponding response in solution δx_s.

KH expresses the weighting of observation in the retrieval.
Dependence on covariance matrices R and background covariance B is crucial.

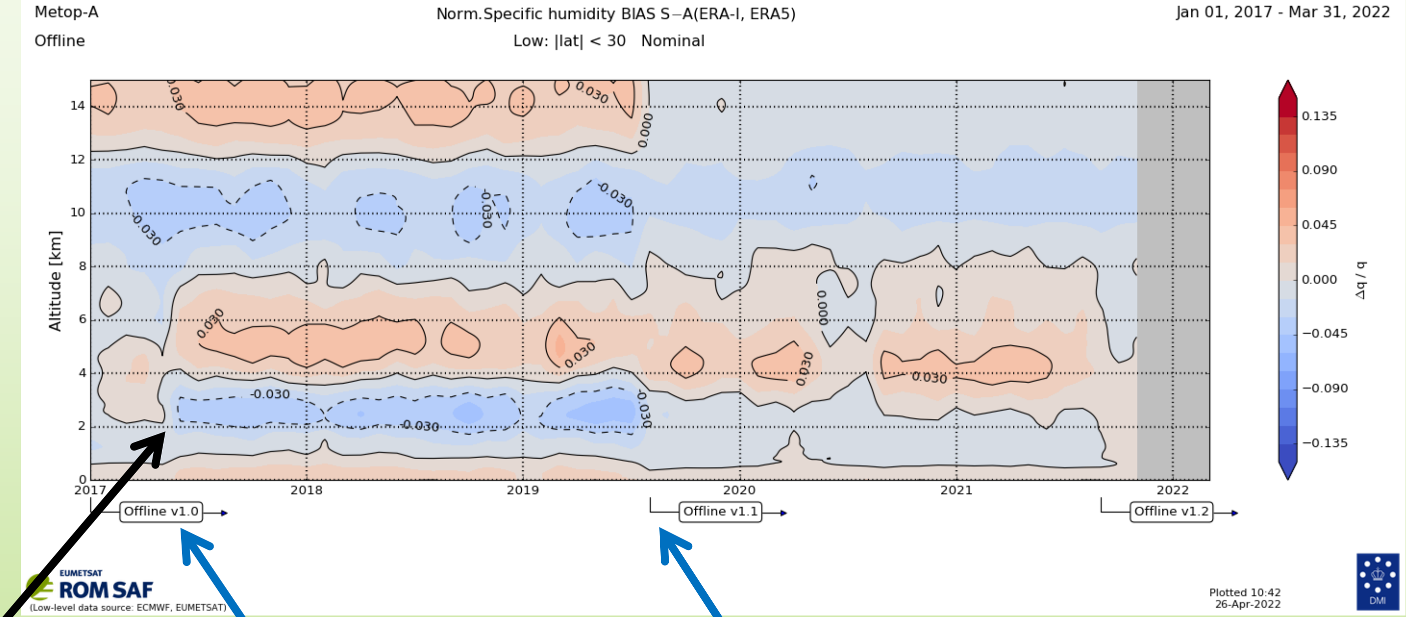
Spurious features in ERA-Interim 1D-Var background fields



Trend estimation is hindered by spurious trends in background data:

- 2007: COSMIC introduced
- 2009: Input data change
- 2014: Assimilation mishap

Spurious features in reanalyses fields



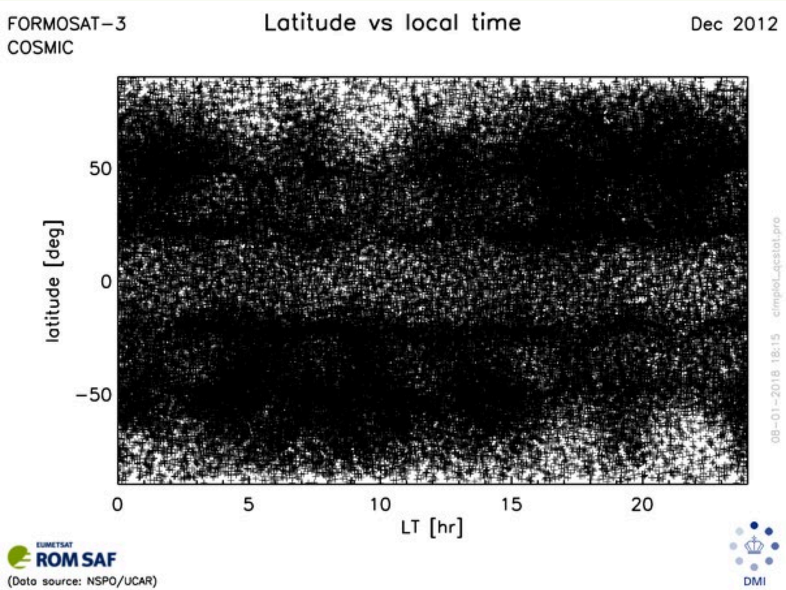
1D-Var with ERA-I

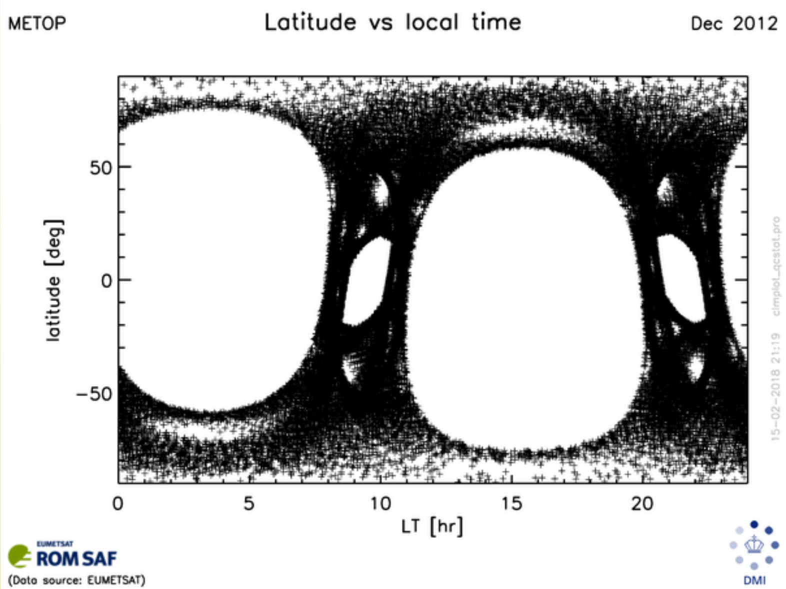
1D-Var with ERA5

Bias jump of 3% (~1.5 % per decade)

EUMETSAT ROM SAF

Spurious trends in observational data





If satellite data covering all local times (e.g., COSMIC) is combined with Sun-synchronous satellite data (e.g., Metop), the resulting multi-mission time series may exhibit spurious trends – unless the different sampling characteristics are accounted for.

➔ Important to correct for different sampling of the diurnal cycle

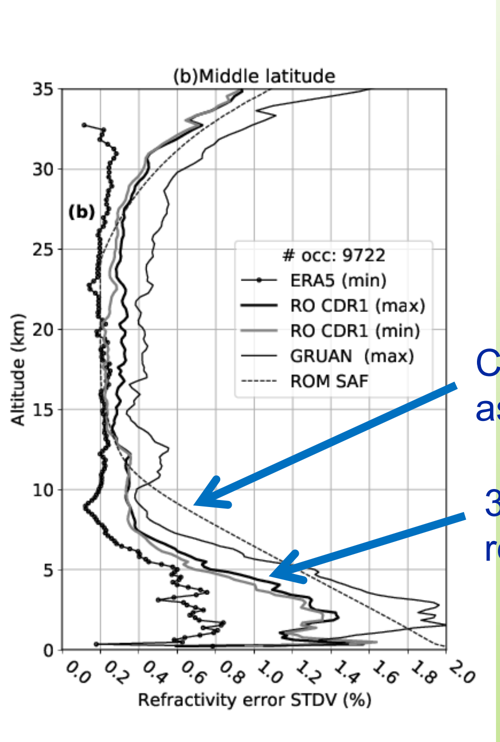
Three-step strategy for estimation of humidity trends

To get the improved amount of water vapor information from RO measurements, the following strategy is adopted for the ROM SAF reprocessing:

1. Estimate error covariance matrices empirically
2. Detrending background model data before 1D-Var retrieval
3. Sampling error correction

Step 1. Error covariances

Three cornered hat (3CH; triple colocation) estimate of refractivity uncertainty

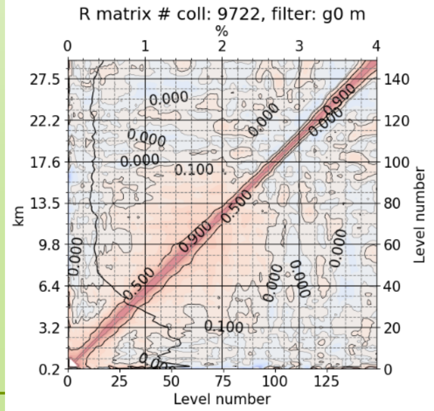


Current ROM SAF CDR assumed uncertainty

3CH estimate of refractivity uncertainty

3CH has been done for RO refractivities:
Uncertainty estimates based on collocated:
- ROM SAF CDRs
- ERA5 model forecasts
- GRUAN radio sondes

Estimated vertical refractivity error correlations.
Solid line is STDV relative to ERA5 background



Step 2. Detrending background

- Each ERA5 background profile to be normalized such that the variability is conserved but the background trend is zero:

$$\boldsymbol{x'}_{\boldsymbol{b}} = \boldsymbol{x}_{\boldsymbol{b}} \frac{\text{mean annual cycle}}{\text{monthly mean}}$$

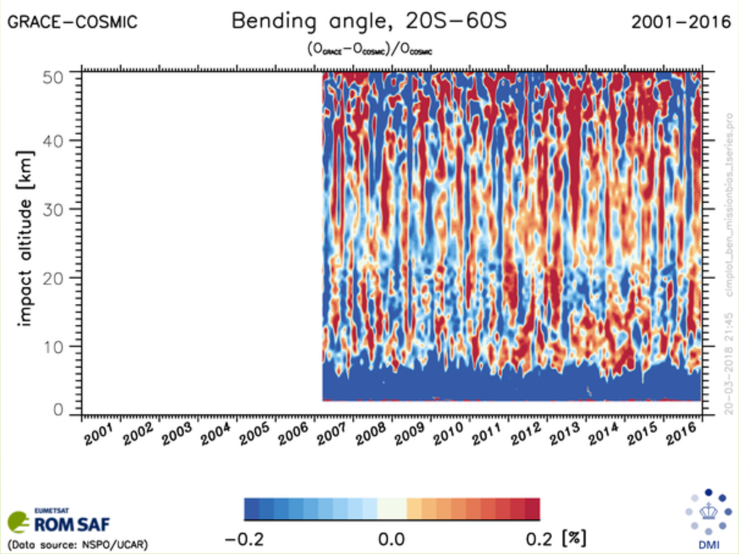
- Since $\boldsymbol{x'}_{\boldsymbol{b}}$ is trendless any trend or variability on monthly scale in the 1D-Var solution must come from the RO measurement.

- Since all trends are eliminated in $\boldsymbol{x'}_{\boldsymbol{b}}$, natural trends are also eliminated. Consequently the resulting 1D-Var climate data record underestimates the true trend. We shall seek to quantify the magnitude of this effect in order to reduce its impact.

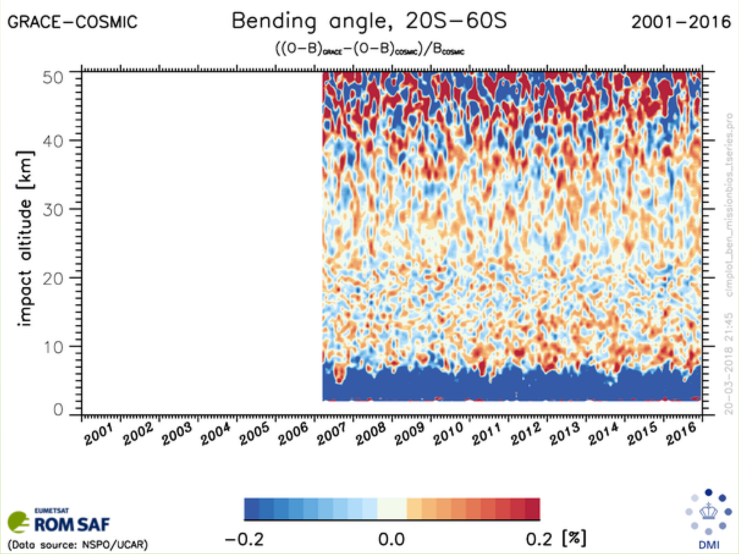
Step 3. Correct for sampling effects

Differences between data from the GRACE and COSMIC satellite missions.

No correction



Sampling-error corrected



Differences due to random errors, and due to systematic errors from input data or processing, remains. When the systematic errors are small, the differences appear as a “quasi-random” pattern.

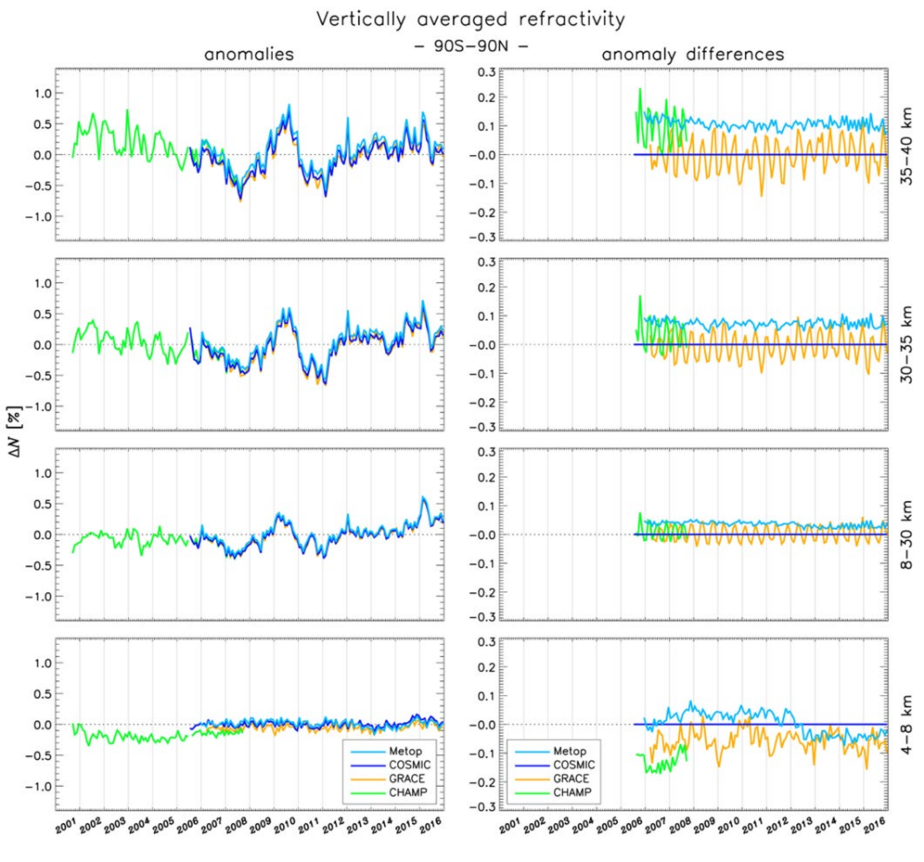
Step 3. Correct for sampling effects

35-40 km

30-35 km

8-30 km

4-8 km



In the <u>stratosphere</u>, we find sampling effects in the gridded data:

- Oscillating differences relative to COSMIC for satellite orbits that drift in local time;
- Constant offset relative to COSMIC for Sun-synchronous orbits.

In the <u>troposphere</u>, we find mission differences propagated from the Level 2 profile data to the Level 3 gridded data.

Conclusions

- Water vapour climate data records from RO is challenging because of insufficient knowledge of error covariances in input data, possible features in background data, and sampling errors due to different satellite orbits.
- Strategy for dealing with all three issues:
  - The observation error covariance matrices and the sampling errors have been resolved (and will be implemented in the next reprocessing).
  - The benefits and pitfalls in de-trended background data are still to be explored.