Approaches to accounting for spectrally-correlated observation errors at ECMWF

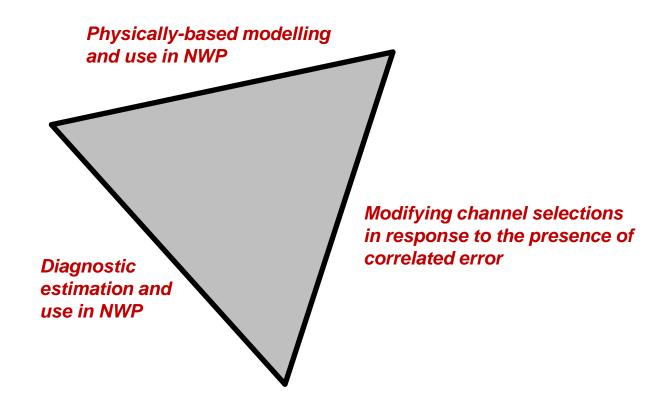
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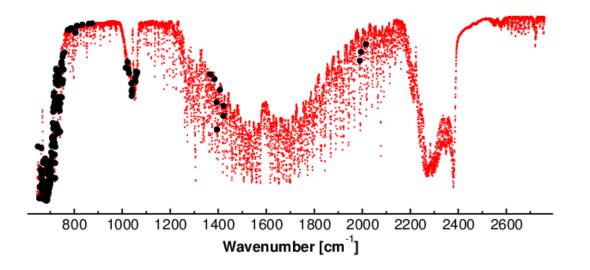




Currently operational use of IASI radiances at ECMWF

191 active channels but mostly using clear data only

Assuming uncorrelated observation errors



Globally constant observation error specification

Active use of data over sea and seaice only

Pre-screening and horizontal thinning applied

Variational bias correction



1. Updating the observation error covariance matrix



Diagnosing observation error covariance

The available tool 1: Method of Hollingsworth and Lönnberg (HL; 1986)

- Assuming observation errors are not correlated from one field-of-view to another
- Assuming no correlation between observation and background errors
- Making use of background departure data only

The available tool 2: Diagnostic tool of Desroziers et al. (2005)

- Assuming ~correct weighting of observations and background in the assimilation process
- Assuming no correlation between observation and background errors
- Making use of background and analysis departure data

The innovative approach taken at ECMWF consists of three major steps:

- 1) Obtain the first estimate by applying the HL method on previously produced data
- 2) Run an assimilation experiment using the covariance as diagnosed in step (1)
- 3) Obtain an updated estimate by applying the Desroziers diagnostic on the output from (2)

To optimize the covariance for practical use, step (2) is **repeated with a range of inflation factors**

- The optimal inflation factor is chosen by subjective assessment from background fit to independent data

The diagnosed covariance is adjusted by removing smallest eigenvalues to improve numerical efficiency

Bormann et al. (2016): Enhancing the impact of IASI observations through an updated observation error covariance matrix. DOI:10.1002/qj.2774 (QJRMS)



Motivation:

- Diagnostic tools for covariance estimation are imperfect and rely on potentially invalid assumptions
- Good understanding of statistical error characteristics increases our confidence to use diagnostically-derived covariance matrices
- Possibility to build up a situation-dependent observation error covariance
- Hassle-free transitioning from one channel selection to another (or from any specific assimilation system setup to another)

Requires some understanding on sources of observation error:

- Instrument noise
- Failures in cloud detection
- Radiative transfer model
- Representativeness issues

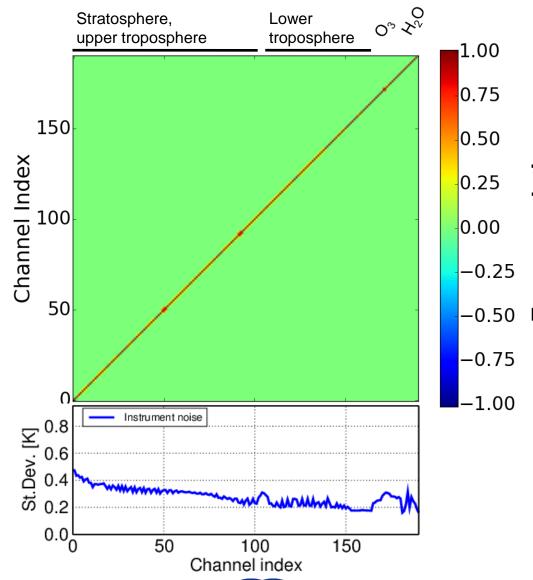


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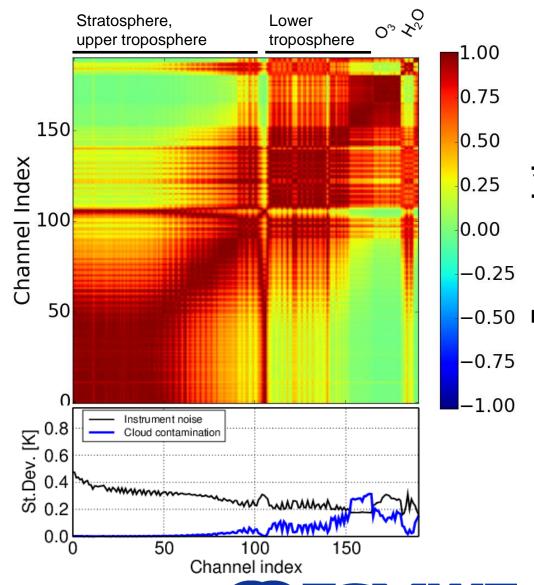


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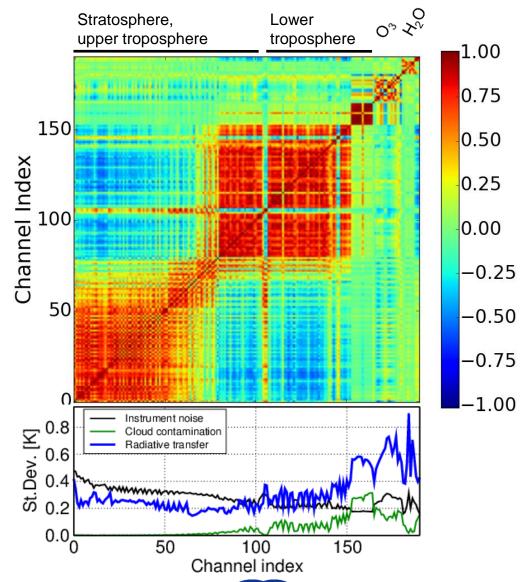


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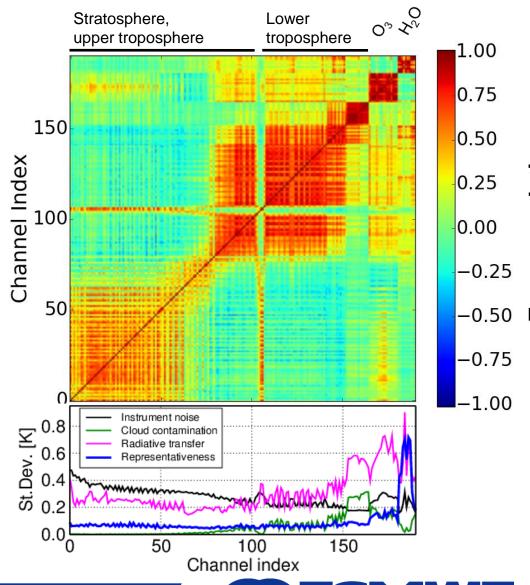


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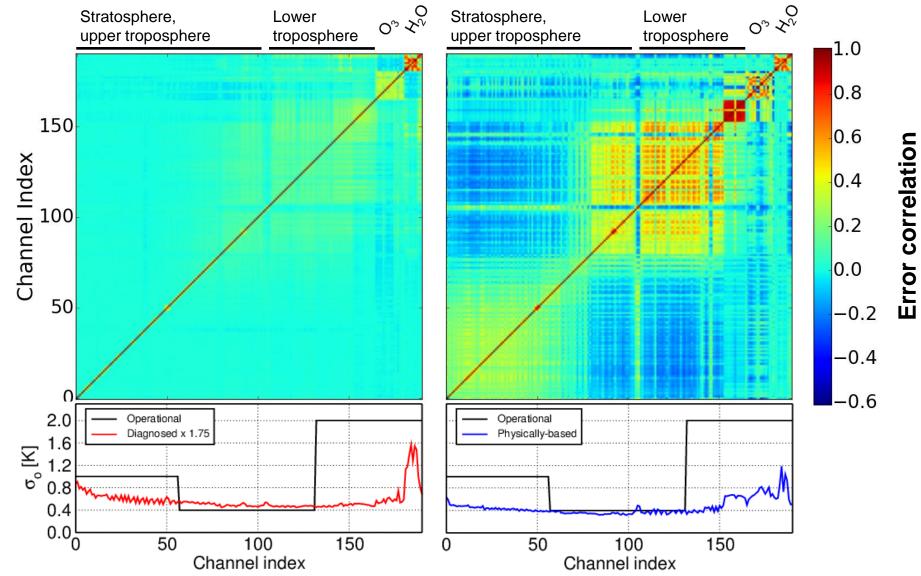
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Diagnosed-and-scaled vs. physically-based covariance matrix

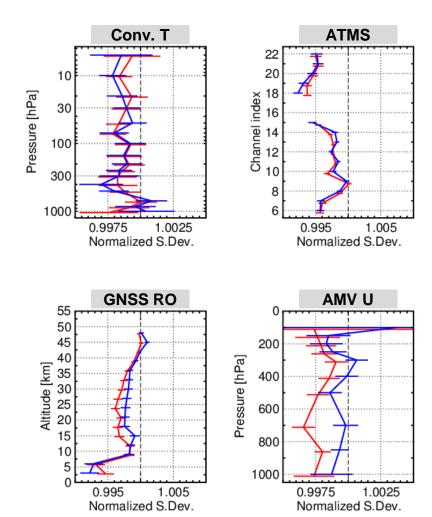


Physically-based error covariance matrix (on the right) contains

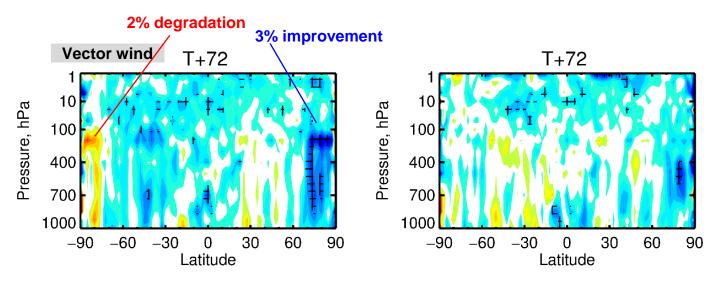
- lower standard deviations
- stronger correlations than diagnosed-and-scaled covariance matrix (on the left)



Control-normalized standard deviation of background departure



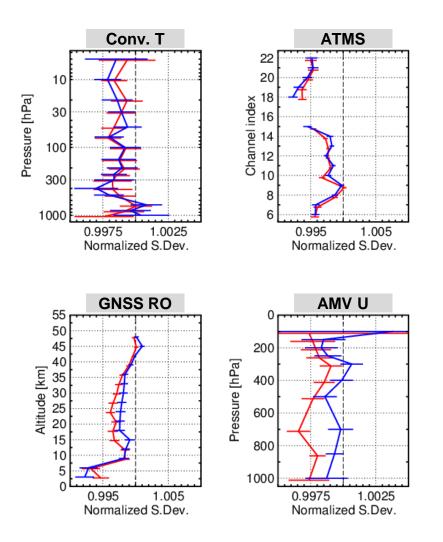
Control-normalized standard deviation of short-range forecast error



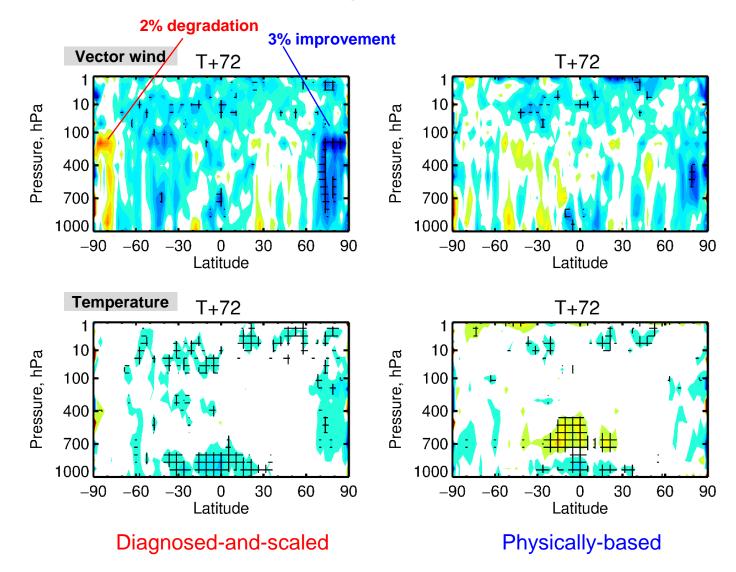
- → Normalized by a control run with the currently operational setup
- → Based on more than seven months of data
- → Reduced background departure standard deviation implies a positive impact
 - → Both diagnosed-and-scaled (red) and physically-based (blue) covariance matrices produce a mostly positive impact
- → Blue shades indicate areas where forecast impact is positive: forecast error standard deviation has become smaller
 - → Diagnosed-scaled matrix (left) produces a more consistent positive forecast impact than physically-based matrix (right)



Control-normalized standard deviation of background departure

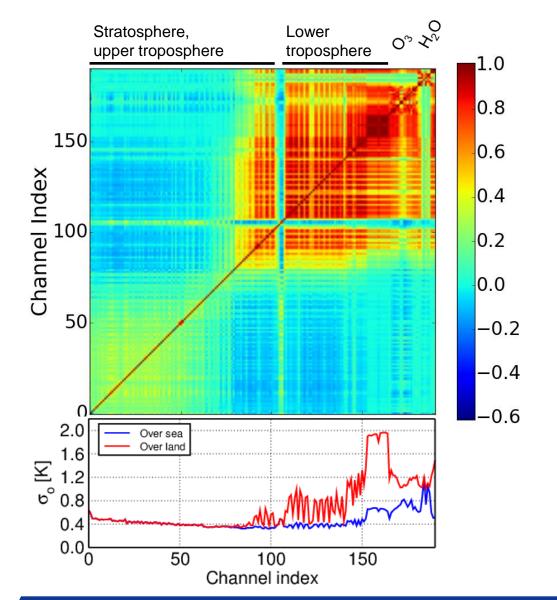


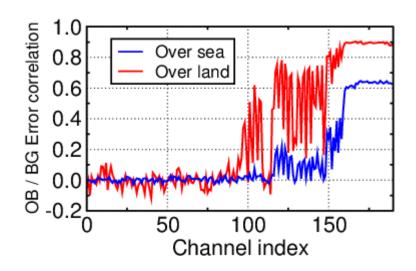
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An implication on the use of infrared radiances over land





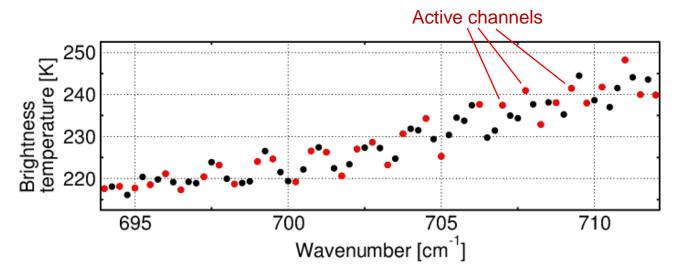
- → Much higher error standard deviation over land than over sea
- → Stronger error correlation over land than over sea
- → Considerable observation background error correlation when using a departure-based cloud detection scheme over land!
- →Need to work on background-independent cloud detection to facilitate the use of infrared radiances over land



2. Modifying channel selections in response to the presence of correlated error



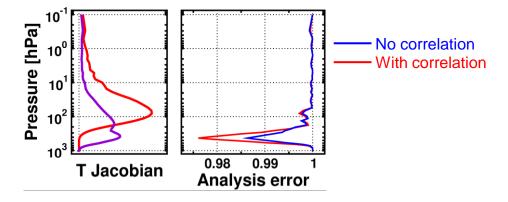
Motivation



Currently-used channel selections are based on theoretical information content assessments relying on the assumption of uncorrelated errors

→ An additional constraint not to select a channel if one (or two) of its immediate neighbours is already selected

Explicit treatment for correlated errors removes the additional constraint and makes it possible to assimilate pairs of spectrally-adjacent channels



Theoretical considerations demonstrate that presence of observation error correlation can be beneficial to analysis, given that the observations measure different things

→ Apodized interferometer radiances make an interesting test case because neighbouring channels can be sensitive to different atmospheric layers while still sharing correlated error



Derivation of an alternative channel list

Operational setup makes active use of 191 channels

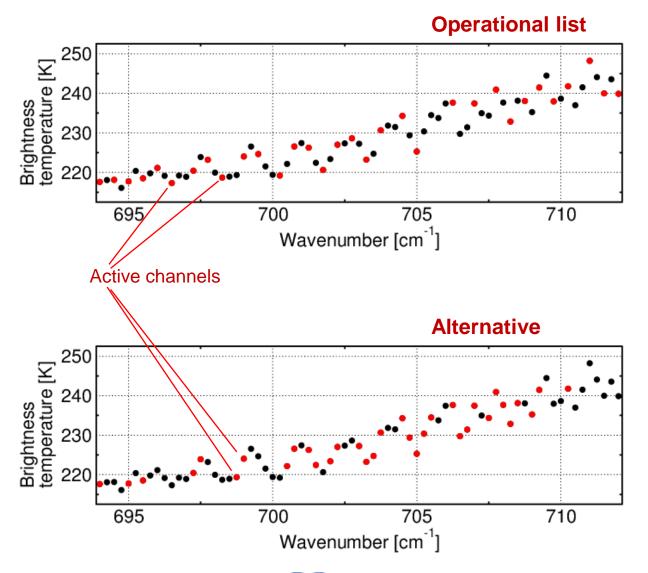
→ Can we retrieve more information from some other selection of 191 channels?

Approach: identify spectrally-adjacent channel pairs that contain the least amount of overlapping information

- → Use observed brightness temperature correlation as a proxy for the overlap
- → An alternative channel list for recent experiments using a diagnosed-and-scaled error covariance matrix

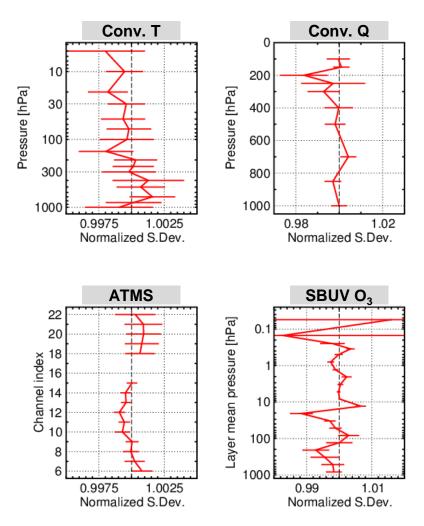
Changes limited to the long-wave CO2 absorption band

→ Use of channels in O₃ and water vapour –absorption bands is kept unchanged

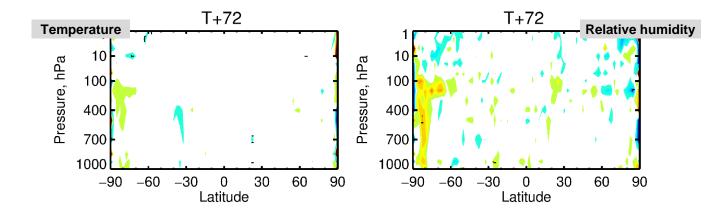




Control-normalized standard deviation of background departure



Control-normalized standard deviation of short-range forecast error



- →The impact of replacing the operational channel list with the alternative one
- →Normalized by a control run using the currently-operational channel list and diagnosed-and-scaled error covariance matrix
- →78 days of data in this sample
- →Neutral impact on background fit to independent observing systems: only a few marginally positive suggestions are seen
 - → Lower-stratospheric microwave sounding channels
 - → Conventional humidity data near tropopause
 - → SBUV ozone retrieval data
- → Neutral impact also on forecast verification



Concluding remarks

Using diagnosed-and-scaled error covariance matrices (with explicit treatment for correlated errors) is becoming a new baseline in infrared radiance assimilation

→ Operational change in 2016 for IASI and CrIS

Physically-based error covariance modelling is currently not reaching the new baseline, but this is a developing area

→ Improved understanding of error statistics has already proven very useful

There is no imminent need to modify channel selections for the presence of correlated error

- → Work on this issue will be continued as a low-priority activity
- → The next step is to increase the number of active channels from 191 to ~230
- → Later shifting the focus from the long-wave end to other parts of the IASI spectrum?



Backup



Diagnosed-and-scaled vs. physically-based covariance matrix for CrIS

