The MTG-IRS Level 2 Processor: Background

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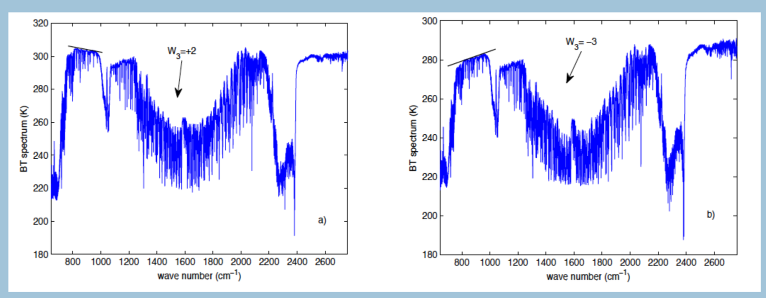
The Level 2 processor

For the generation of level 2 products from MTG-IRS observations a processor is needed. The high level processing functionality are documented in an ATBD. Here some key elements of this document are presented. The level 2 processor is an end-to-end processor and considers a Scene Classification, A Product Generation and a Post Processing module.

Scene Classification

To detect the presence of clouds with the FOV a scene classification method consisting of a number of statistical tests has been developed. Besides traditional tests involving surface temperature, also more elaborate tests regarding the shape of the spectrum are used. To determine the optimal settings of the thresholds for the tests, all tests are considered simultaneously (**?**). It is important to realize that scene classification has to rely on the spectra themselves as no additional observations are available like for IASI. That this is not necessarily a limitation shows the results below. *Illustration:* The figure to the left shows two IASI spectra.



As can be seen the two spectra are very similar. Traditional test will classify both cloud free. However the slope test indicate that the left panel is an observation collected over a FOV which contained a this cirrus cloud, while the right one over a cloud free area.

Product Generation

The Product Generation module is a basic 1DVAR routine based on the Optimal Estimation theory described by **?**. The state vector consists of $\mathbf{x} = (\mathbf{T}, \log(\mathbf{q}), \log(\mathbf{O_3}), T_s, logit(\epsilon))^T$. Background information is extracted from the ECMWF deterministic model for the state and from the ensemble system for the associated covariances (**?**). This information is currently available on 137 hybrid sigma coordinates but only twice per day. The radiative transfer code adopted is the Optimal Spectral Sampling described by **?**. The minimization is a standard Marquardt-Levenberg minimization, and convergence criterion is based on state, if change in state is smaller than uncertainty of the state, the iterative process is stopped.

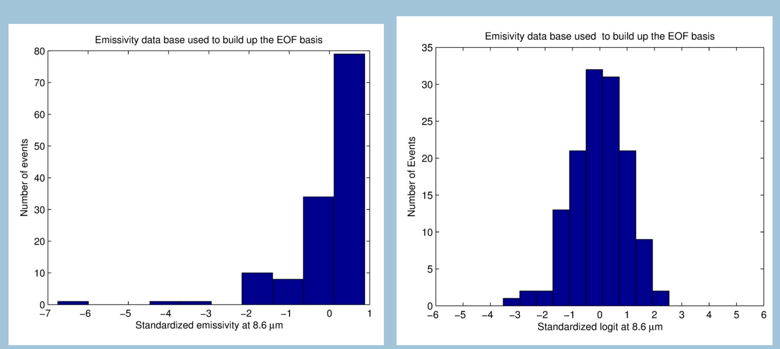


Fig. 2: Surface emissivity PDF in physical (left) and in logit (right) space

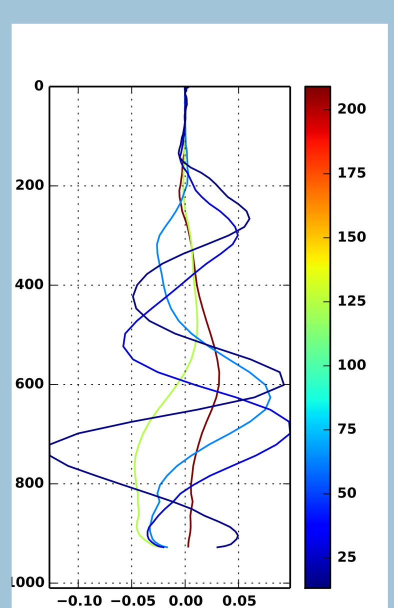
Logit of Surface Emissivity The logit transformation $(\log(\epsilon/[1.0-\epsilon]))$ ensuresthat the during the retrieval the surface emissivity remains within physical bounds $[0,1]$ and a better Gaussian distribution of the pdf as shown in the left figure. It should be noted that in the state vector not the logit is used but a principle component compression of the logit representation of surface emissivity. This to reduce the number of parameters in the state vector. The background consists of two elements the background for surface emissivity taken from Dan Zhou climatology, (PC compressed after transformation in logit space). The second component namely the atmospheric background (state and covariance) is taken from ECMWF diagnostic forecast (state) and ensemble system (covariance). Data is available twice per day, but higher frequency is expected at day-1 of operations.

Post Processing

Post processing consists of quality control and a scaling and projection of the L2 products for data assimilation. From a SVD of the information content signal to noise matrix ($\hat{\mathbf{S}}_s = \mathbf{S}_o^{-1/2}\hat{\mathbf{K}}\mathbf{S}_a^{1/2} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{V}^T$), it can be shown that the retrieved state is linear combination of true state and the background information (**?**, e.g.):

$$\hat{\mathbf{x}} = \hat{\boldsymbol{\Lambda}}^T\left(\hat{\boldsymbol{\Lambda}}\hat{\boldsymbol{\Lambda}}^T + \mathbf{I}\right)^{-1}\hat{\boldsymbol{\Lambda}}\mathbf{x} + \left(\hat{\boldsymbol{\Lambda}}\hat{\boldsymbol{\Lambda}}^T + \mathbf{I}\right)^{-1}\mathbf{x}_b + \hat{\boldsymbol{\Lambda}}^T\left(\hat{\boldsymbol{\Lambda}}\hat{\boldsymbol{\Lambda}}^T + \mathbf{I}\right)^{-1}\epsilon'. \quad (1)$$

By using only the eigenvectors with eigenvalue > 1, the contribution to the state $\hat{\mathbf{x}}$ can be minimized. This is used to generate a scaled projected state, which together with an observation operator is being provided to data assimilation applications. The assimilation of the scaled and projected state can provide identical results to radiance assimilation (**?**). Remove from the retrieved state $\hat{\mathbf{x}}$ the a-priori information according:



$$\mathbf{y}_{ret} = \hat{\mathbf{x}} - \mathbf{x}_a + \hat{\mathbf{G}}\hat{\mathbf{K}}\mathbf{x}_a, \quad (2)$$

Using the above transformations the parameter $\mathbf{y}'_{ret}$ can be defined as :

$$\mathbf{y}'_{ret} = \left(\hat{\boldsymbol{\Lambda}}\hat{\boldsymbol{\Lambda}}^T + \mathbf{I}\right)\hat{\boldsymbol{\Lambda}}^{-T}\hat{\mathbf{V}}^{-1}\mathbf{S}_a^{-1/2}\mathbf{y}_{ret}. \quad (3)$$

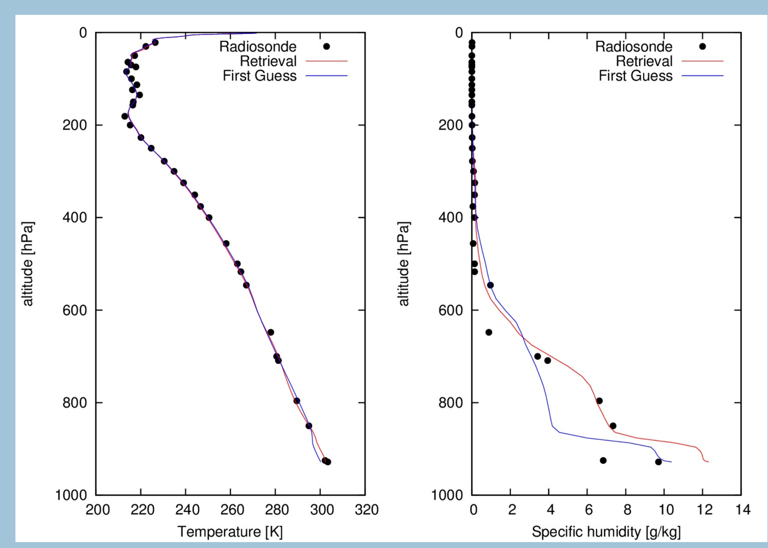
Also a linear relation between the projected observation $(\mathbf{y}'_{ret})$ and the true state $\mathbf{x}$ is found. The operator to project the true state onto the observation is named by **?** $\mathbf{H}'_{ret}$ and is given by:

$$\mathbf{H}'_{ret} = \hat{\boldsymbol{\Lambda}}\hat{\mathbf{V}}^T\mathbf{S}_a^{-1/2}. \quad (4)$$

The scaled projected state distributed to the users consists of two elements as indicated above, namely the state which is referred to as y'_{ret} and the observation operator referred to as H'_{ret}. Though the data volume of the state is relatively small, the data volume of the observation operator can be large. Note that for the method not all state vector elements needs to be consider. Only those elements which are part of the assimilation system are considered (e.g. T(p), q(p)). An example of the eigenvectors used in the projection to generate the projected state and the observational operator is shown to the right.

Illustration of retrieval result

The current figure shows the retrieved temperature (left panel) and specific humidity (right panel), together with a collocated radio sonde ascent for a location over Germany. Retrieval results in red line while the radiosonde observations are indicated by dots. Also shown in the same figure are the values of the ECMWF first guess in blue. Results are for the baseline configuration. The ECMWF forecast indicates a shallow moist layer near the surface followed by a relative dry layer above. the ECMWF forecast is significant dryer than the radiosonde observations. The retrieval indicates a relatively large specific humidity value near the surface but similar values as given by the radiosonde observations in the dry layer.



The Next Cycle

We are working now towards an alternative way of solving the 1dvar equation. Fundamentally

$$\left(\boldsymbol{\Gamma}\mathbf{S}_a^{-1} + \mathbf{K}^T(\mathbf{x})\mathbf{S}_\epsilon^{-1}\mathbf{K}(\mathbf{x})\right) \quad (5)$$

is not well conditioned and hence this could lead to instabilities in the method. Using the scaled jacobians

$$\mathbf{S}_s = \mathbf{S}_\epsilon^{-1/2}\mathbf{K}(\mathbf{x})\mathbf{S}_a^{1/2} \quad (6)$$

it can be shown that the kernel matrix can be written as

$$\mathbf{S}_a^{-1/2}\left(\boldsymbol{\Gamma} + \mathbf{S}_s^T\mathbf{S}_s\right)\mathbf{S}_a^{-1/2}. \quad (7)$$

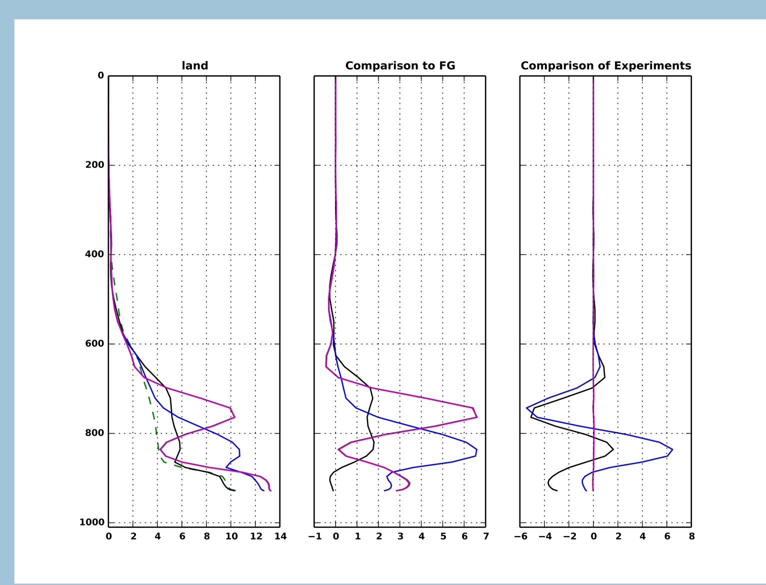
And after a SVD of this the fundamental 1dvar translates into

$$-\boldsymbol{\Lambda}^T\Delta\bar{\mathbf{y}} + \Delta\bar{\mathbf{x}}^a + \left(\boldsymbol{\Gamma} + \boldsymbol{\Lambda}^T\boldsymbol{\Lambda}\right)\Delta\bar{\mathbf{x}}' = 0. \quad (8)$$

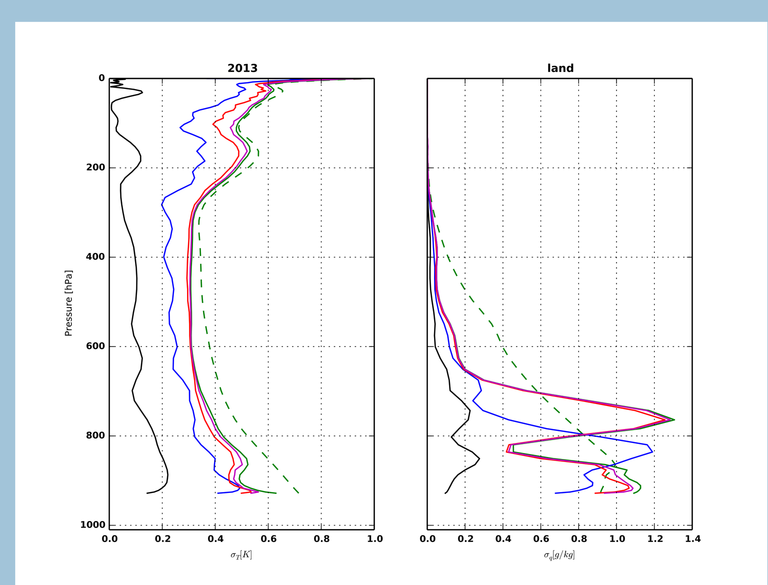
There are as many eigenvectors as there are element in the state vector, and the accuracy of the retrieved product depends on the number of eigenvectors used. As shown in the figures below where the number of eigenvectors changed from 15, 84, 125 and 297.

Illustration of new method

The figure to the right shows a result of the retrieval using the compression method described above. The results are for the same IASI FOV as used for the baseline results shown at the top of the poster. Shown is the retrieved specific humidity for varying numbers of eigenvectors ranging from 15 to 279,which is the maximum number of eigenvectors generated by the SVD of the scaled jacobian matrix. There are a maximum number of 279 elements in the state vector. Shown in the left panel is the retrieved specific humidity for the different number of eigenvectors. Black 15, blue: 22, red 85, magenta 125 and green 279.



The magenta and green solid line is are on top of each other. The dashed green line is the ECMWF first guess. The middle panel shows the difference between the retrieved state and the ECMWF first guess using the same color code as for the left panel, while the right panel shows the difference of the retrieval results to a retrieval using all 279 eigenvectors using the same color code as in the left panel. What can be seen is that the more eigenvectors are used the more the solution deviates from the first guess, and also from a certain number of eigenvectors adding more does not make a difference. The variances for the temperature and humidity are also shown and these figures indicate that the more eigenvectors are used the larger the variances. At one point the posterior variance is larger than the prior which is an undesired feature. Reason for this needs to be understood, as it is could also be a reflection of a undetected cloud (which given the very thin and moist PBL could be in the scene) or a problem with the surface emissivity.



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