The revival of L2 assimilation. Radiances or profiles? That is the question!

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Introduction

You should stop assimilating radiances and start assimilating profiles instead. You might think that the radiances work well for you, but they are not without problems. The use of a forward model as observation operator introduce forward model errors. While you might be able to characterize the covariance of the forward model errors, the problem is that they are not random. On the contrary, they depend on the atmospheric state, and this is why you end up having to use ad hoc inflated observation errors and horizontal thinning to get a good impact from the radiances. With profiles, there is a similar problem - the null space errors, which are not random at all. But with appropriate observation operators based on the averaging kernels these systematic errors are removed and we get a promising alternative to the radiances.

In the early days of satellite data assimilation, the information on temperature and humidity from atmospheric sounders was assimilated in the form of retrieved profiles. This soon led to problems because of the inherent limited vertical resolution of the retrieved profiles, which damaged the fine scale vertical structures of the NWP model profiles. It became clear that an observation operator was needed to transform the model profiles into an alternative representation excluding vertical structures, which do not influence the measured radiances. Thus, the assimilation of L1 radiances using a radiative transfer forward model as observation operator was introduced and became the dominant approach. The alternative, more direct, approach of representing the profiles as coordinates with respect to a truncated basis spanning only the broader vertical structures which are actually observed by the sounder, was hardly considered. More recently, following a paper in 2012 by Migliorini where the equivalence of L2 and L1 assimilation was demonstrated, there has been a renewed interest in L2 assimilation. But we want more from L2 assimilation than just a technical transformation of the radiance assimilation allowing the application of the forward model to take place before the assimilation. In a recent study performed by ECMWF, temperature and humidity profiles, retrieved from IASI observations with the piecewise linear regression (PWLR) machine learning approach, were assimilated using observation operators based on the averaging kernels of the retrievals. In a depleted system, a positive impact similar to the assimilation of radiances was achieved (see poster 15p.14).

We think, that these promising first results can be further improved and that L2 assimilation is an interesting alternative because it avoids some of the drawbacks associated with the use of a radiative transfer model as observation operator - in particular, the dependency of further geophysical parameters which are not part of the NWP model, as for example surface emissivity, trace gases and the part of the profiles above the model top. Errors in these parameters are problematic because they are not random and have temporal and spatial structure. L1 assimilation is mostly restricted to clear sky (or channels peaking above the cloud top), because the cloud radiative transfer is challenging. Whereas the PWLR retrievals are able to extract temperature and humidity information in partly cloudy scenes, which can be fed into the NWP models without the need to model the clouds. The L2 scene dependent observation error covariance can be incorporated in the observation operators, and we believe that the difficulties of deriving a suitable observation error covariance matrix, which are sometimes observed for L1 assimilation, can be alleviated with L2 assimilation.

The approach presented here is an evolution with respect to the study, where the observation operator was simply the leading left singular vectors of the averaging kernel (not taking the atmospheric variability into account) and no scaling was applied. A practical aspect of L2 assimilation is the data volume of the scene dependent observation operators H and observation error covariance matrices R_x, which approach or even exceeds the data volume of the radiances. But as H and R_x stay constant within each regression class, they can be distributed in advance as a look up table. If you are interested in L2 assimilation, don't hesitate to contact tim.hultberg@eumetsat.int

HSIR assimilation

m-dimensional measurements $\boldsymbol{y}$ n-dimensional profiles $\boldsymbol{x}$ *Both carry information on temperature and humidity*

$$(F(x)-\boldsymbol{y})^T R_y^{-1}(F(x)-\boldsymbol{y}) \qquad (x-\boldsymbol{x})^T R^{-1}(x-\boldsymbol{x}) \qquad (Hx-H\boldsymbol{x})^T R_x^{-1}(Hx-H\boldsymbol{x})$$

Observation errors:

$(F(x)-y)$: random instrument noise S_y and forward model errors

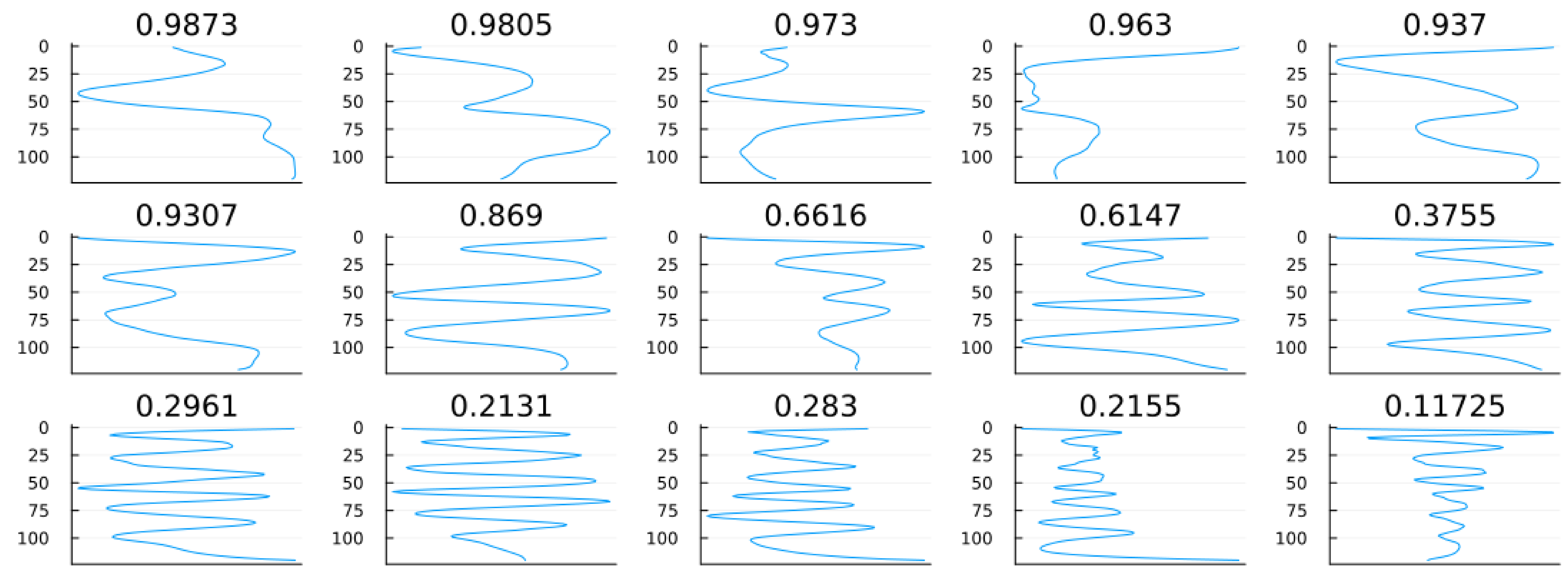
$(x-\boldsymbol{x})$: random retrieval noise GS_yG^T and null space error $(I-A)C_x(I-A)^T$

$(Hx-H\boldsymbol{x})$: random retrieval noise $HGS_yG^TH^T$ and $H(I-A)C_x(I-A)^TH^T$

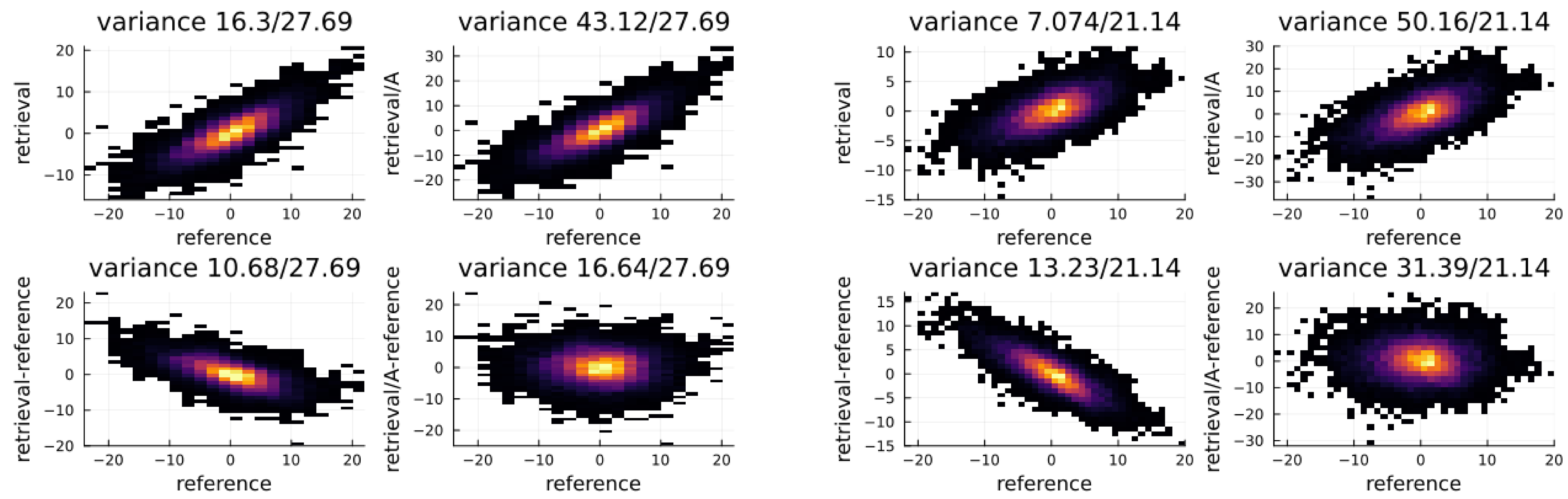
Choose H such that $H(I-A)C_x(I-A)^TH^T \sim 0$ (orthogonal to the null space in other words), while still retaining the retrieved information

➔ Leading eigenvectors of $AC_xA^T = GKC_xK^TG^T \approx GC_yG^T = C_{xy}C_y^{-1}C_{yx}$

We look at three versions of the observation term of the assimilation cost function. The observations are represented either as radiances, profiles in the vertical model grid or profiles with observation operator. The key to success lies in the behaviour of the observation errors. While the null space error covariance of the profile retrieval can be easily characterised, the problem is that it is not a random error, but depends on the profile. To eliminate the null space error, we derive an observation operator for each PWLR regression class. The classification, based on the observed radiances, is determined to achieve an approximately linear relationship between the profiles and the observed radiances, within each class. The linear approximation used for the retrieval is simply $G = C_{xy}C_y^{-1}$ (with regularization), where C_y is the covariance of the measurements and C_{xy} is the cross covariance between the reference profiles and the measurements. We see that the leading eigenvectors of $C_{xy}C_y^{-1}C_{yx}$ or equivalently the leading left singular vectors of $C_{xy}C^{-1/2}$ can be used as observation operator to eliminate the null space. The crucial remaining question is, how many vectors to include in H and how to assign an appropriate observation error R_x?



The figure shows the first 15 candidate H vectors (for temperature retrieval on 120 model levels below 2hPa) in a cloud free regression class along with their corresponding r^2 value. The r^2 value is the averaging kernel for the retrieval projected onto a given H-vector and it is clear that a value of (or very close to) one indicates the lack of null space error and the observation error is simply the propagated instrument noise. Likewise a value close to zero means that the observation does not provide any information about this component and it should not be assimilated. What to do for values in between?



When the averaging kernel drops below one, its means that the observations can not fully explain (retrieve) the atmospheric variance along the component and that the retrieval is biased towards the mean. This systematic bias can be avoided by scaling the retrieval with $1/A$ at the expense of increasing the random error. This is illustrated in the figure, where the left four scatter plots are for H-vector 9 (averaging kernel $A = 0.6147$) and the right four are for H-vector 10 (averaging kernel $A = 0.3755$). In this case we see that the error variance of the scaled retrieval exceeds the natural variability for H-vector 10 which should therefore not be assimilated.

Conclusions

Assimilation systems are equipped to handle observation errors - but only if they are random. Systematic errors, on the other hand, pose serious problems for assimilation. Retrieval errors are dominated by the null space errors, which are dependent on the model state and invalidates the assimilation of retrievals represented on a traditional pressure level grid. Forward model observation operators eliminate the null space error but introduce another source of systematic errors, the forward model errors (including the contribution from errors in their input, for example from the part of the profiles above the model top or from undetected cloud). To cope with the systematic errors, horizontal thinning and ad hoc inflation of the diagnosed observation errors are often required. L2 assimilation with observation operators constitute an alternative way to eliminate the null space errors without introducing forward model errors and might bring benefits over the usual L1 assimilation.