Status of Assimilating Satellite Data at Deutscher Wetterdienst

— tuning observation and background errors for 1D-Var —

Reinhold Hess

Deutscher Wetterdienst
Offenbach, Germany

Introduction

Deutscher Wetterdienst (DWD) has recently enforced efforts to assimilate satellite radiances. Hitherto only satellite retrievals (SATEMS) and atmospheric motion wind products (SATOBS) were assimilated.
At a first step more satellite data is used in a quite innovative way: In order to take part at ECMWF's great expertise in using satellite data, profiles of temperature, humidity and wind of IFS analyses over sea are assimilated as conventional radiosonde data with the operational Optimal Interpolation analysis system. These data (named Pseudo-Temps) are used one time per day in an update run. In this way the global system takes part in the abundance of satellite data used at ECMWF, whereas it is still driven independently with its own analysis and forecast modules. Humidity profiles are assimilated only above 700 hPa in order to not affect the boundary layer climate of the global model GME of DWD.
Meanwhile development of 1D-Var retrievals for ATOVS has progressed towards operational application. In the northern hemisphere the forecast quality of the Pseudo-Temps method is almost reached using 1D-Var retrievals of AMSU-A instead. In the southern hemisphere, however, it seems that it is required to assimilate more satellite data in order to approach the quality of the IFS profiles, that are rich in satellite information.
Among many other developments required for assimilating satellite radiances the tuning of the observation and background errors is an important factor to realize best positive impact in forecast quality. In the following a method is described briefly that is simple and effective: The sizes of the error matrices are tuned so that the method is theoretically consistent and that the resulting retrievals best fit IFS profiles that are considered good approximations of truth.

Tuning of Observation and Background Error Covariance Matrices R & B

Observation and background errors are usually specified along with their correlations by the constant matrices $\mathbf{R}$ and $\mathbf{B}$. These matrices are required to formulate the cost function of variational analysis schemes. Although the cost function of 3D-Var and 4D-Var has the same shape, in the following only 1D-Var (one-dimensional vertical retrievals of temperature and humidity) is considered.

The cost function $\mathcal{J}(x)$ consisting of observation term $\mathcal{J}_o(x)$ and background term $\mathcal{J}_b(x)$ reads

$$\begin{aligned} \mathcal{J}(x) &= \mathcal{J}_o(x) + \mathcal{J}_b(x) \\ &= \frac{1}{2}\,(y - H(x)\,)^T \mathbf{R}^{-1} (y - H(x)\,) + \frac{1}{2}\,(x - x_b)^T \mathbf{B}^{-1} (x - x_b) \end{aligned} \tag{1}$$

with standard notation.

Commonly $\mathbf{R}$ is defined diagonal neglecting observation error correlations. The correlations of $\mathbf{B}$ are however essential for variational data assimilation. The specification of the sizes and the relation of the errors matrices $\mathbf{R}$ and $\mathbf{B}$ is an important tuning problem for variational data assimilation and a number of methods exist (e. g. Chapnik et al. [1]).

Two Inequalities for Consistency

Minimisation of $\mathcal{J}(x)$ results in the retrieved profile x_a. The size of the cost function at the minimum $\mathcal{J}(x_a)$ may be used for some theoretical study. If the error matrices $\mathbf{R}$ and $\mathbf{B}$ are specified correctly (and if the errors are Gaussian and no biases exist), then the empirical distribution of a large sample of $2\,\mathcal{J}(x_a)$ should meet a χ^2-distribution with n_o degrees of freedom (e. g. Talagrand [2]) (n_o denotes the order of $\mathbf{R}$, i. e. the number of channels in y). The expectation E and variance Var of $\mathcal{J}(x_a)$ are given by

$$E\Big(\mathcal{J}(x_a)\Big) = \frac{n_o}{2} \qquad \text{and} \qquad Var\Big(\mathcal{J}(x_a)\Big) = \frac{n_o}{2} \qquad .$$

Assuming uncorrelated observation errors two inequalities can be deferred for the diagonal terms r_i, $i = 1, \ldots, n_o$ of $\mathbf{R}$: From

$$\mathcal{J}(x_a) \leq \mathcal{J}(x_b) = \mathcal{J}_o(x_b) = \frac{1}{2} \sum_{i=1}^{n_o} \frac{(\,y_i - H_i(x_b)\,)^2}{r_i}$$

it follows that

$$\frac{n_o}{2} \le \frac{1}{2} \sum_{i=1}^{n_o} \frac{\overline{(\, y_i - H_i(x_b)\,)^2}}{r_i} \qquad .$$

The overbars denote the mean of the squares of the sample. This is true for any number and combination of channels, thus also for each individual channel as well and thus

$$r_i \le \overline{(\, y_i - H_i(x_b)\,)^2} \qquad \text{for all } i = 1, \ldots, n_o \qquad . \tag{2}$$

Equation (2) means that the observation errors should be smaller than the standard deviation of observed minus background radiance departures for all channels (no biases assumed). This provides an upper bound for the observation errors[1]. However, in reality the observation errors are correlated; taking these correlations into account leads to a larger variability of the background departures than reflected by the diagonal terms only. Larger observation errors should be considered therefore when assuming uncorrelated observation errors. In this case Eq. (2) may become invalid. Correlated observation errors are considered a much more serious problem for infrared high spectral resolution sounders (AIRS, IASI, e. g.), but they should be kept in mind for ATOVS as well.

On the other hand,

$$\mathcal{J}(x_a) = \mathcal{J}_o(x_a) + \mathcal{J}_b(x_a) \ge \mathcal{J}_o(x_a) = \frac{1}{2} \sum_{i=1}^{n_o} \frac{(\, y_i - H_i(x_a)\,)^2}{r_i}$$

leads to

$$r_i \ge \overline{(\, y_i - H_i(x_a)\,)^2} \qquad \text{for all } i = 1, \ldots, n_o \qquad . \tag{3}$$

Equation (3) says that the standard deviation of observed minus analysed radiance departures should be smaller than the observation errors, which gives a lower bound for them. However this inequality is not very useful to define the observation errors as well, since the analysed radiances depend on the analysis x_a and as such on $\mathbf{R}$. When reducing the observation errors, the analysis is pulled to the observations and the remaining analysis departures reduce as well. No reasonable iterative limit can be found.

Although Eqs. (2) and (3) cannot be considered strictly valid in case of error correlations, they give realistic size limits for a consistent assimilation scheme.

[1] This inequality is better known as derived from $\overline{(\, y_i - H_i(x_b)\,)^2} = r_i + \mathbf{H}_i \mathbf{B} \mathbf{H}_i^T$, which says that the background departures consist of observation errors and the background errors in observation space.

Use Pseudo-Temps as Additional Information

Additional information is required for prescribing the observation and background errors, as it is not possible to derive them from a posteriori statistics of the data itself (Talagrand [2]). The basic idea proposed here is that the relation between observation and background errors is tuned so that the resulting retrievals are closest to truth. In order to define the truth, radiosonde data would be the first choice. They are in general however too sparse to provide collocations with satellite radiances over sea of significant large sample sizes.

Other approximations of truth are advanced numerical analyses that are as well used as reference for various surveys. For this study the Pseudo-Temps are used, that are derived from profiles of the IFS analyses, as additional information in order to tune the sizes of the observation and background errors. As they have no restrictions in spatial sampling they easily provide large sample sizes.

The tuning proposed here is performed according to two conditions:

1. The empirical distribution of the minima of the cost function should meet the statistical expectation $n_o/2$. Both matrices **B** and **R** simply can be multiplied with one scalar factor to guarantee that.

2. The relation of **R** and **B** is defined in order to get best collocations of the retrievals compared to the Pseudo-Temps. Only scalar factors have been applied on **B**, leaving the background error correlations untouched. This condition has been met by try and error.

When performing the tuning it was experienced that changing the sizes of **R** and **B** has only a small effect on the retrievals. Large changes of the errors are required to generate small changes in the profiles. On the one hand this makes the resulting error specification inaccurate, since small errors in the collocation statistics against the Pseudo-Temps may lead to much larger errors in the result of the tuning. On the other hand, as the resulting retrievals are what is important, this means that it is not required to be too accurate in the specification of the error sizes and that the accuracy provided by this method suffices.

Results

The tuning was performed for 1D-Var retrievals using AMSU-A radiances of channels 4 to 12 over sea. As the most important result of the study it came out that the previously defined errors were much too large in general and that the observation errors were too large compared to the background errors. This put too little weight on the observations in the variational retrieval. Figure 1 shows the collocation of temperature and humidity retrievals against ECMWF analyses for one week at the end of January 2005. The retrievals with tuned errors show better bias; the standard deviation around 800 hPa is significantly reduced.

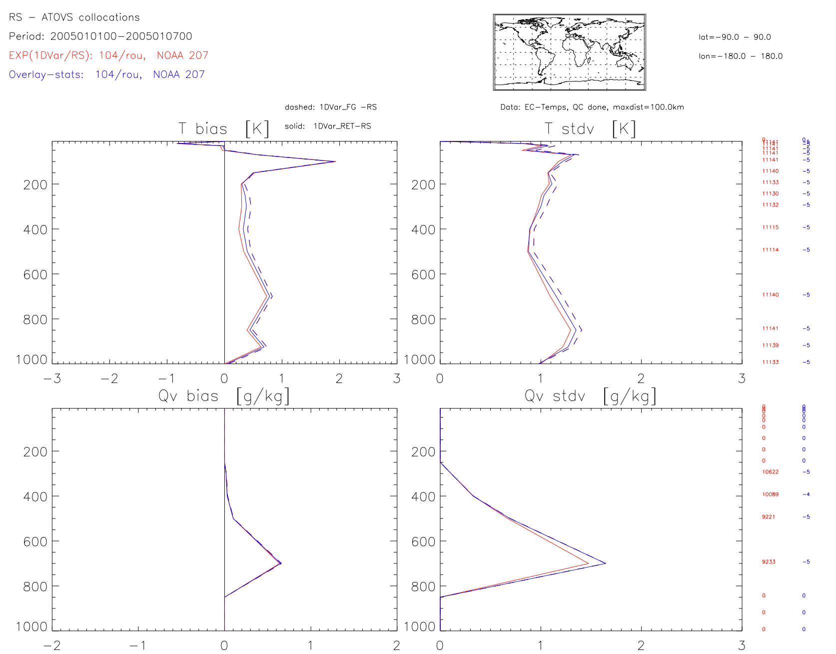

Figure 1: *Collocations of first guess and analysed profiles against Pseudo-Temps for one week. Dashed blue: first guess, solid blue: retrieval with old statistics, solid red: retrieval with tuned errors. Humidity below 800 hPa is not in statistics, since not assimilated as Pseudo-Temps at DWD.*

Table 1 compares the tuned observation errors with standard deviation of observed minus background and observed minus analysis radiance departures. For convenience the observation errors have been finally tuned as

$$r_i = \frac{||o_i - b_i||}{2} \qquad (4)$$

which is close enough to the optimal value that has been found according to the two conditions defined above. ($||o_i - b_i||$ is a more handy abbreviation for $\sqrt{\overline{(\,y_i - H_i(x_b)\,)^2}}$ as $||o_i - a_i||$ stands for $\sqrt{\overline{(\,y_i - H_i(x_a)\,)^2}}$). This definition of Eq. (4) clearly fulfills Eq. (2), but it also matches (at least almost) the requirement Eq. (3).

Channel	4	5	6	7	8	9	10	11	12
$\|\|o_i - b_i\|\|$	0.55	0.31	0.22	0.21	0.34	0.36	0.34	0.34	0.48
r_i	0.28	0.15	0.11	0.10	0.16	0.18	0.18	0.18	0.23
$\|\|o_i - a_i\|\|$	0.17	0.09	0.07	0.07	0.17	0.13	0.12	0.13	0.12

Table 1: *Standard deviation of observed minus background radiance departures ($||o_i - b_i||$) and of observed minus analysis radiance departures ($||o_i - a_i||$) in comparison with prescribed observation errors r_i*

Figure 2 shows the resulting histogram of $2\,\mathcal{J}(x_a)$ in comparison with the theoretical distribution. The resulting distribution has a mean of 8.2 which is only slightly smaller than the theoretical value of $n_o = 9$. The specified errors are little larger than theoretically optimal, but the difference is not considered to affect the retrieved profiles.

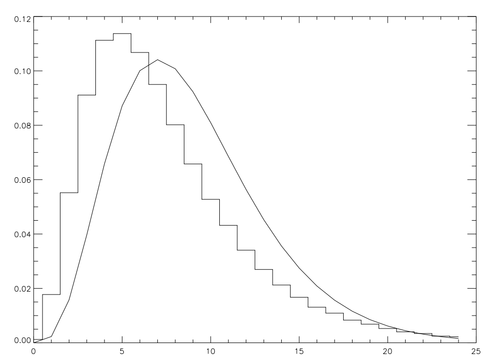

Figure 2: *Histogram of resulting minima of $2\,\mathcal{J}(x_a)$ (step function) and theoretical χ^2-distribution with $n_o = 9$ degrees of freedom (continuous line)*

A significant reduction of the standard deviation of the collocations against Pseudo-Temps around 800 hPa has been shown in Fig. 1 above. However what does in mean in terms of forecast quality? Fig. 3 shows anomaly scores of 500 hPa geopotential height of trial experiments with old and new error statistics compared to operational DWD forecasts (using Pseudo-Temps) for the southern hemisphere. A significant improvement of forecast quality has been achieved with the new error statistics. The anomaly scores with the tuned errors reach the operational forecast scores for that period. The

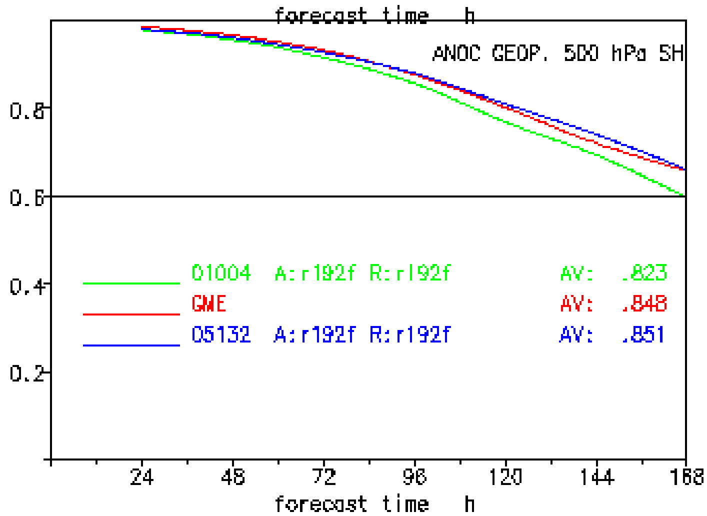

Figure 3: *Anomaly scores of the 500 hPa geopotential height for operational DWD forecasts (including Pseudo-Temps, red), experiment 1004 using ATOVS 1D-Var retrievals with old statistics (green) and experiment 5132 using ATOVS 1D-Var retrievals with tuned statistics (blue). (1004 and 5132 are without Pseudo-Temps and SATEMS, channel AMSU-A 4 has not been used). Sample is 10 days only, however similar improvements of new statistics compared to old errors have been confirmed with other experiments as well.*

large positive signal confirms that the tuning of the error statistics towards Pseudo-Temps is reasonable.

References

[1] Chapnik, B., G. Desroziers, F. Rabier and O. Talagrand, *Properties and first application of an error statistic tuning method in variational assimilation*, submitted to Q.F.J.M.S in 2003.

[2] Talagrand, O.,*A posteriori verification of analysis and assimilation algorithms.* In Proceedings of the ECMWF Workshop on Diagnosis of Data Assimilation Systems, 2–4 November, pages 17–28, Reading.