NWP SAF

Satellite Application Facility for Numerical Weather Prediction

Report of Visiting Scientist Mission

Channel selection for AIRS radiance assimilation

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NWPSAF-EC-VS-001 Version 1.0, April 2002

This documentation was developed within the context of the EUMETSAT Satellite Application Facility on Numerical Weather Prediction (NWP SAF), under the Cooperation Agreement dated 25 November 1998, between EUMETSAT and the Met Office, UK, by one or more partners within the NWP SAF. The partners in the NWP SAF are the Met Office, ECMWF, KNMI and Météo France.

Change record			
Version	Date	Author / changed by	Remarks
1.0	Apr 2002	N Fourrie	

Visiting Scientist Mission Report

Channel selection for AIRS radiance assimilation

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Contents

Abstract

The Atmospheric InfraRed Sounder (AIRS) on board AQUA will provide 2378 channels for each field of view of the instrument. As it is neither feasible nor efficient to assimilate all the channels in a numerical weather prediction system, a policy of channel selection has to be designed in this context. This paper attempts to assess the quality of the selected AIRS radiance channels that will be available to the scientific community in near real time by NOAA/NESDIS (called thereafter NESDIS NRT). This assessment is done by comparing this channel selection with a more "optimal" method as the one presented in Rabier et al. (2002) and based on Rodgers (1996). It turns out that although the selected channel sets are different and that the information content as measured by the Entropy reduction (ER) and the Degreee of Freedom for Signal (DFS) is slightly weaker for the NESDIS NRT set than for the optimal set, both channel selections give similar results in terms of analysis error for temperature, humidity and ozone.

The robustness of the results of the comparison is then evaluated by varying a range of input parameters to the channel selection scheme: the background error covariance matrix (used as a metric in Rabier at al. 2002) and the atmospheric training dataset on which the channel selection is based. The results are robust to the specification of the background error covariances (as long as they represent reasonably well the NWP short-range forecast errors). It is also found that the Rabier et al. channel selection based on a polar air mass training dataset performs poorly when applied (in a 1D-Var context) to tropical air masses. Overall, the "manual" channel selection of NESDIS NRT provides a good compromise between robustness and quality.

1 Introduction

By measuring radiation in many thousands of different channels, advanced infrared sounders such as the Atmospheric InfraRed Sounder (AIRS) and the Infrared Atmospheric Sounding Interferometer (IASI) have the potential to provide atmospheric temperature and composition information at a much higher vertical resolution and accuracy that can be achieved with the current generation of operational sounding instruments. The successful exploitation of these next generation of satellite instruments is one of the major challenges for Numerical Weather Prediction (NWP) centres in the next decade.

However, it is neither feasible nor efficient to assimilate all of the channels (approximately 2400 in the case of AIRS and 8400 in the case of IASI) and a policy of data compression such as channel selection has to be designed in the context of Numerical Weather Prediction (NWP). The challenge is to find a set of channels that is small enough to be assimilated efficiently in a global NWP system (with operational time constraints) but which is still large enough to capture important atmospheric variability. In an ideal world, the channels selected should not be fixed but change with a variety of atmospheric conditions. It is expected that they will change geographically (e. g. from polar to tropical locations), but also dynamically with the presence of clouds and degree of baroclinic instability.

Following the launch of the NASA AQUA satellite, a reduced set of AIRS radiance channels will be made available to the scientific community in Near Real Time (NRT) by NOAA/NESDIS and ECMWF is planning to exploit this reduced set at day one. Currently, simulated AIRS data are already generated daily (from the NCEP model) for scientific trial purposes. Each simulated AIRS Field Of View contained 228 channels at the beginning of the SAF visit (281 channels are now available). It is expected that the channels provided for the real AIRS data will only depart marginally from this reduced set. On the other hand, several information content studies for advanced sounders aim at identifying the "best" channels for NWP in order to minimise the reduction of pieces of information from advanced infrared sounders. In particular, Rabier et al.(2002) have tested several methods and found that the most suitable is a method following Rodgers (1996) reducing the number of IASI channels (in clear sky conditions) in an optimal way which preserves the information content of the instrument. The main goal of this study is to apply Rabier et al. (2002) methodology to the AIRS instrument in order to assess the quality of the NRT NESDIS channel selection versus a more optimal channel selection.

In section 2, the experimental framework of the study as well as the optimal channel selection method are briefly described. The "efficiency" of the NRT NESDIS channel selection is then compared to the Rabier et al. selection in terms of information content and linear 1DVAR performance (section 3). The robustness of the results to the inputs specified to the channel selection is then evaluated. The sensitivity of the results to the specification of the background error covariance matrix is described in section 4. Section

5 addresses the problem of representativeness of the training dataset required to apply Rabier et al. channel selection. Conclusions and perspectives are finally discussed in section 6.

2 Experimental framework

The general framework of this channel selection study is linear optimal estimation theory in the context of Numerical Weather Prediction. One follows the framework presented at length by Rabier et al. (2002) from which we summarize the main elements. The atmospheric profile in temperature, humidity and ozone at a given location is represented by a vector x and the satellite observations by a vector y. The observations are linked to the atmospheric state by the radiative transfer equation :

$$y = \mathcal{H}(x) + \varepsilon_{\mathbf{O}} + \varepsilon_{\mathbf{F}} \tag{1}$$

where the measurement and the forward model errors $\varepsilon_{\mathbf{O}}$ and $\varepsilon_{\mathbf{F}}$ are assumed to be gaussian noises with error covariance matrices $\mathbf{O}$ and $\mathbf{F}$. We will denote $\mathbf{R} = \mathbf{O} + \mathbf{F}$ the resulting observation error covariance matrices. The background state vector x_b has an error covariance matrix denoted $\mathbf{B}$. The radiative transfer equation is assumed to be weakly non-linear, making the tangent linear assumption valid in the vicinity of the background state :

$$\mathcal{H}(x) = \mathcal{H}(x_b) + \mathbf{H}(x - x_b) \tag{2}$$

where $\mathbf{H}$ is the tangent linear model of the radiative transfer model $\mathcal{H}$.

The optimal analysed state x_a is given by

$$x_a = x_b + \mathbf{K}(y - y_b) \tag{3}$$

with $\mathbf{K} = \mathbf{A}\mathbf{H}^{\top}\mathbf{R}^{-1}$ and $\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^{\top}\mathbf{R}^{-1}\mathbf{H})^{-1}$. $\mathbf{K}$ is the Kalman gain matrix and $\mathbf{A}$ is the analysis error covariance matrix. $\mathbf{K}$ can be interpreted as the generalized inverse of $\mathbf{H}$, allowing one to reconstruct the atmospheric profile from the observations.

Rabier et al. (2002) introduce two addtitional concepts: the Entropy Reduction ($ER = -\frac{1}{2}\log_2 det(AB^{-1})$, Rodgers, 2000) and the Degrees of Freedom for Signal ($DFS = Tr(I - AB^{-1})$. Both concepts are very useful in that they quantify the gain in information brought by the observations with respect to the background information.

In this study, the radiative transfer model for AIRS (RTAIRS) described by Matricardi et al. (2001) has been used for $\mathcal{H}$. This model uses a fixed 43 pressure level vertical discretization (see Matricardi and Saunders, 1999). The $\mathbf{B}$ matrix has been interpolated from the current operational 60-level ECMWF background error covariance matrix representing short range forecast errors of the ECMWF model. The covariance matrix $\mathbf{R}$ has been derived from the latest estimation of the AIRS instrument noise (Hannon, pers. comm.) displayed in Figure 1.

2.1 Channel selection

The iterative method for channel selection, as proposed by Rodgers (1996) and used in Rabier et al. (2002), consists in performing successive analyses, each one using only one channel at a time. The resulting analysis error covariance matrix is updated accordingly and used at the next step. This ensures that all the information coming from previous channels is taken into account for the selection of the new channel. The channel selection in our case is based on maximizing the ER (and is therefore "optimal" in that sense).

In this study, the background fields and the AIRS data have been simulated from a set of representative atmospheric situations. This set is part of the ECMWF atmospheric data base (Chevallier, 1999 and Chevallier et al, 2000) and forms a set of 108 profiles of temperature, humidity, ozone and surface pressure covering most of atmospheric variability. All atmospheric scenes are assumed to be cloud-free, over sea and for nadir views. The 108 profiles are divided into 75 midlatitude (20N-70N,20S-70S), 14 tropical (20N-20S) and 19 polar (70N-90N, 70S-90S) profiles.

As a starting point, we have considered the fact that 228 channels were available in the NESDIS NRT dataset produced on a regular basis on the NESDIS WEB server[1]. Since surface temperature is excluded in the first place from the study (the reason being that firstly it is difficult to specify realistic correlations between surface temperature and lowest model level background errors and secondly that, even if these correlations were kwown , they could be difficult to incorporate in 4D-Var, as Ts is treated indepedently of upper-air fields), the NESDIS NRT "window" channels were removed from the comparison. Two separate checks were performed for the mean sea mid-latitude profile, to define a "window" channel:

- a channel for which the surface-to-space transmittance is smaller than .6 is not a window channel
- a channel for which the departure between the computed brightness temperature and the model sea surface temperature is larger than 4K is not a window channel

Applying this check, the total number of AIRS channels was reduced from 2378 to 1576 channels, NESDIS NRT channel set being reduced from 228 to 186 channels. In order to perform a fair comparison between the NESDIS NRT remaining channels and the optimally selected ones, the optimal channel selection was therefore restricted to selecting the first 186 channels which maximize the ER.

As pointed out by Rabier et al. (2002), this method if applied bluntly (one optimal channel selection per atmospheric profile) can be very CPU time consuming and would

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[1] http://orbit35i.nesdis.noaa.gov/crad/st/airs_near_realtime/level1b/

certainly be impossible to apply in an operational context. Therefore a constant channel selection has been computed as an average selection based on the set of 108 different optimal channel selections (one per atmospheric profile).

Different criteria can be used to compare the quality of the different channel selections. One can for example investigate the information content of AB^{-1} represented by its eigenvalues that provide the number of independent pieces of information brought by the observations. The Degrees of Freedom for Signal (DFS) is another quantity that gives a global measure of the reduction of uncertainty brought by the analysis.

2.2 Linear 1D-Var

Besides the quality criteria described above, the efficiency of each channel selection has been evaluated in terms of linear 1D-Var. The linear 1D-Var is briefly described in the following.

The optimal analysed state x_a is given by

$$x_a = x_b + \mathbf{K}(y - y_b) \tag{4}$$

with $\mathbf{K} = \mathbf{A}\mathbf{H}^{\top}\mathbf{R}^{-1}$ and $\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^{\top}\mathbf{R}^{-1}\mathbf{H})^{-1}$. $\mathbf{K}$ is the Kalman gain matrix and $\mathbf{A}$ is the analysis error covariance matrix introduced above. $\mathbf{K}$ can be interpreted as the generalized inverse of $\mathbf{H}$, allowing to reconstruct the atmospheric profile from the observations. The parameter space is the temperature, humidity and ozone profile defined on the 43 RTAIRS pressure levels (Matricardi et al., 2001).

3 Comparison between NESDIS NRT and Rabier et al. selection

As stated above, a constant channel selection has first been built as an average selection based on the set of 108 individual channel selections. This average selection will be called thereafter "constant". This selection is compared with the NESDIS NRT selection and with the "optimal" channel selection (where individual channel selections are performed for each individual profile). Worth mentioning is that only 31 channels are always selected throughout the 108 channel selections (corresponding to very different atmospheric situations), whereas 1763 channels are never selected. The resulting constant channel selection shares 65 channels with NESDIS NRT selection. Figure 2 displays the AIRS spectrum corresponding to the mean atmospheric profile (averaged over the 108 profiles) with the location of the NESDIS NRT selected channels (blue circles) and Rabier et al. (pink stars) selected channels. As a first sight, the NESDIS NRT channel set spans more evenly the IR spectrum than the constant channel set which privileges specific small spectral domains. 50% of NESDIS NRT channels are located in the 649-1150 cm^{-1} (longwave and ozone) band while 44% of the constant channels are located in the 1150-1650 cm^{-1} (water vapour) band. The 4.5 μm band is hardly covered by the constant channel selection, whereas both NESDIS NRT and constant channels describe evenly the 4.2 μm CO2 band. The ozone band (1050 cm^{-1}) is also well captured by the two selections.

Jacobians of the channels exclusively selected by NESDIS NRT (left panels) and constant (right panels) are represented in figure 3 for temperature (top panels) and humidity (bottom panels). This figure indicates an overrepresentation of the upper stratosphere by the constant selection. This can be explained by the large background error variances at these levels. The corresponding channels are located in the CO_2 band at around 2350 cm^{-1}. Conversely, NESDIS NRT has a large number of channels peaking in the low troposphere corresponding to the 700-750 cm^{-1} band and to the 2400 cm^{-1} area. The constant channels located in the 1470-1500 cm^{-1} band are sensitive to temperature between 400 hPa and 600 hPa. The bottom panels illustrate the dominating choice of the water vapour band in the constant channel selection, partly driven by the vertical structure of the humidity background error covariance matrix.

When looking at the "efficiency" of the two channel selections, one can see that the ER and DFS are slightly smaller for the NESDIS NRT selection (see Table 1). The number of independent pieces of information brought by the 186 channels (as defined in the section above) is also smaller (23.7 against 25.85) in the case of NESDIS NRT selection. The standard deviations of the background error and of the 1D-Var analysis error have then been studied for temperature, humidity and ozone parameter for all the 108 profiles (Figure 4). The NESDIS NRT and the constant selection, as well as the optimal selection provide similar temperature retrieval errors in the lower troposphere, while constant and optimal selection give analysis errors in general smaller than 2 K in the upper-troposphere and in the stratosphere (versus 2.5 K or more with the NESDIS NRT selection). Note that temperature analysis errors are similar when the optimal or the constant sets are used, whereas a small degradation is observed with the constant selection versus the optimal selection for humidity. This indicates that the constant selection has difficulty to capture the larger variability in the 108 humidity profiles. In addition, NESDIS NRT and constant selections provide similar humidity and ozone analysis errors.

Comparisons with retrieval errors using all the AIRS channels and 1576 channels (corresponding to the remaining channels after exclusion of the "window" channels) show that these additional channels lead to a further reduction of temperature analysis error of about 0.1 K in the troposphere and roughly of 0.2 K in the stratosphere. The improvement in the humidity analysis is also very important in the lower troposphere when all the channels are used in the assimilation. Likewise, the ozone retrieval error is largely improved when the 2378 or the 1576 channels are used. Note that the 3 selections (NESDIS NRT contant and optimal) give almost identical results. The further gain in ER is respectively 19.8 and 18.5 for the whole channel set and the 1576 channels (Table 1) compared with the optimal selection (ER=50). Similarly a further gain of about 5 unit in DFS is observed when the 1576 or the 2378 channels are used in the analysis.

In conclusion, if a loss of information content is to be expected by using around one tenth of the total number of AIRS channels, the NESDIS NRT selection seems reasonable for NWP applications. Even though the information content is slightly smaller than for the two other selections, the respective performance of NESDIS NRT and constant selections is very comparable in terms of 1D-Var retrieval error (and this applies for temperature, humidity and ozone).

In the two following sections, the robustness of the results to various inputs to the channel selection is assessed.

4 Robustness of the selection to the specification of the background error covariance matrix

The current background error covariance matrix used at ECMWF only provide a climatology of short-range forecast errors. On the other hand, previous information content studies, such as those of Prunet et al (1998) and Collard (1998), have suggested that advanced sounders such as AIRS and IASI could resolve some of the small scale baroclinic structures that have been identified by the sensitivity studies (Rabier et al., 1996) as being crucial to forecast error development.

One month of "key analysis errors" (as described in Klinker et al., 1998) has been computed at a resolution of T159 (120 km): these "errors" represent perturbations that, if added to the operational analysis, reduce the 48 hour forecast error (defined as the global difference between the 48h forecast and the verifying analysis). Up to now, humidity perturbations are not considered in the sensitivity computations, therefore only temperature will be included in the study described below. These structures are generally of small amplitude (meaning that a small atmospheric perturbation in this area can have a very large impact on the forecast quality) and can be fairly sharp both in the horizontal and in the vertical. One can clearly see that the associated covariance matrix (averaged over one month) is sharper in vertical (Figure 5) and horizontal (Figure 6) than the operational background covariance error. In addition, the error standard deviations are relatively large in the troposphere and in the high stratosphere (although they remain altogether of much smaller amplitude than the assumed averaged background errors used operationally).

It is therefore interesting to verify the robustness of the NESDIS NRT channel selection to the specification of such an "extreme" error covariance matrix in the 1D-Var algorithm. Beforehand, Figure 7 shows the location of the channels chosen from the constant selection computed with the operational background error covariance matrix (constant set) and the "key analysis error" covariance matrix (constant-sensitivity set) for an analysis in temperature only. Both selections share 131 channels. Main differences appear in the 668-683 cm^{-1} band and in the vicinity of 2370 cm^{-1} where channels are selected by the constant method using the operational background error while the constant selection computed from the key analysis error selects more channels in the water vapor band (1200-1560 cm^{-1}), channels obviously having some sensitivity to temperature as well and located in layer where the temperature background error variance is large.

The standard deviation of the analysis performed with NESDIS NRT and the optimal selection are shown in Figure 8. Even though the superiority of the dedicated channel selection is observed, NESDIS NRT gives good results in that it manages to substantially reduce the original "key analysis error" variance.

This only gives a flavour of the efficiency of the NESDIS NRT channel selection to cope with sensitivity perturbations, since it is now well recognised that thes sensitive areas are generally affected by clouds that will badly affect the performance of the AIRS instrument altogether.

5 Impact of the air mass on the quality of the NESDIS NRT channel selection

In this section we investigate the robustness of the different channel selections to the air mass under consideration. Two questions have been considered: 1) Is the NESDIS NRT selection performing well regardless of the atmospheric type (polar, mid-latitude, tropical)? 2) What happens to the constant selection if it is trained with a given air mass and applied to a very different one?

5.1 Variation of the channel selection with respect to the airmass type

Let us remind that three air mass classes have been defined: the mid-latitude air mass class is made of 75 profiles, the tropical one consists of 14 profiles and the last 19 profiles represent the polar type. Figure 9 displays the constant channel selection with respect to the air mass class (in that case the average has been performed on the profiles representing each airmass type).

The global constant channel selection (averaged over the whole dataset) shares 185 channels in common with the mid-latitude constant selection, 170 channels with the tropical constant selection and 148 channels with the polar selection. The polar and tropical selections only share 132 channels. In particular, the polar selection does not pick any channel in the longwave between 750 -770 cm^{-1} in contrast to the two other selections. As expected, the global constant selection is dominated by a mid-latitude signal and this points out to a poor representation of polar and tropical air mass in the sampling dataset.

Figures 10, 11 and 12 display the standard deviations of background and analysis errors for the mid-latitude, tropical and polar airmass types respectively.

- For temperature, the results are quite similar to those obtained with the global constant selection and this for all air mass types.
- For humidity, the optimal channel selection gives systematically slightly better results than the constant and NESDIS NRT selections. Note that the analysis error for the constant selection is outperformed by the NESDIS NRT selection for the polar air mass type. This is due to missing sounding channels in the low troposphere in this selection.
- For ozone, the 3 selections give similar results with the exception of the tropical set, where the optimal and constant selections provide slightly smaller analysis errors than NESDIS NRT.

Altogether, the NESDIS NRT seems to be fairly unsensitive to the air mass category, pointing out to a careful "manual" choice of these channels.

5.2 Importance of the training dataset for the quality of the channel selection

It has been shown above that the channel selection can vary depending on the air mass type the selection is trained with. We want to illustrate here the impact of performing a 1D-Var analysis for certain atmospheric situations using a channel selection based on a completely different atmospheric training dataset.

Figure 13 displays the 1D-Var performance of the NESDIS NRT, and polar constant selection averaged over the 14 tropical profiles available in our dataset. One can clearly see the degradation in humidity below 700 hPa of the polar constant selection, due to a poor sampling of the tropospheric water vapour channels. One also note a loss of around 1 unit in term of DFS and 6 % in term of entropy reduction (table 2). This tells us that for an optimal selection to be robust and competitive with the day-1 NESDIS NRT selection, an exhaustive training dataset is absolutely required, especially for highly variable quantities such as humidity.

6 Conclusions

The NESDIS NRT AIRS channel selection which will be provided to the operational weather centres has been assessed through the comparison with an optimal iterative channel selection following Rodgers (1996) and a constant selection deduced from this iterative method. NESDIS NRT and constant channel sets are very different, only 65 channels are indeed identical between the two selections. However both constant sets lead to similar results in terms of DFS and temperature, humidity and ozone 1D-Var analysis errors. The humidity analysis is mostly affected by the use of a constant selection instead of the optimal selection, pointing out to the difficulty of a constant selection to capture the entire variability of the humidity field.

The impact of the background error covariance matrix has been assessed. A background error covariance matrix representative of key analysis errors felt crucial for the quality of the short range forecasts (and exhibiting smaller amplitude errors and sharper temperature structure functions) has been used to validate the robustness of the NESDIS NRT selection. It was shown that under those "extreme" circumstances, NESDIS NRT performs almost as well as a dedicated optimal channel selection.

The impact of the air mass on the channel selection has then been studied. The outcome is that a poorly trained optimal channel selection can perform very badly especially for humidity.

All the experiments show that despite the overall slightly smaller information content of the NESDIS NRT versus optimally derived channel selections, this set seems very reasonable for NWP applications and appears to be robust to various inputs to the method. This gives some confidence about our day-1 strategy which consists in taking for granted the NESDIS NRT selection.

Several limits of the method will be overcome in the near future. First the study will be extended to the final NESDIS NRT channels (281 simulated channels are now daily broadcasted). The impact of including surface temperature in the control variable and adding surface channels in the selection will also be addressed. This could potentially modify the selection of the lower tropospheric channels. Finally, the software has been extended to a non linear 1D-Var which will be used to validate the findings described above.

Acknowledgements

The authors acknowledge Frédéric Chevallier for providing the atmospheric sampling dataset used to train the different channel selections, and Marco Matricardi and Tony McNally for helpful discussions and suggestions.

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7 Tables

Experiment	DFS in T	DFS in Q	DFS in O	DFS	ER	EV
NESDIS	8.10	6.54	1.55	16.19	41.35	23.72
Optimal	9.29	7.77	1.74	18.80	50.02	26.67
Constant	9.18	7.35	1.70	18.23	48.33	25.85
1576 channels	11.59	8.99	2.53	23.10	68.51	31.81
2378 channels	11.66	9.10	2.59	23.34	69.76	32.14

Table 1: Values of DFS (Degrees of Freedom of Signal), ER (Entropy Reduction) and the mean of eigenvalues (EV) for the different experiments conducted in this study.

Experiment	DFS in T	DFS in Q	DFS in O	DFS	ER	EV
Midlatitude						
NESDIS	8.12	6.47	1.56	16.16	41.25	23.69
Optimal	9.34	7.62	1.75	18.70	49.53	26.61
Constant	9.23	7.27	1.72	18.23	48.33	25.90
Tropical						
NESDIS	8.75	5.67	2.07	16.49	40.11	24.63
Optimal	9.85	6.38	2.51	18.74	46.88	26.50
Constant	9.77	6.14	2.50	18.41	46.11	26.00
Polar constant	9.62	5.98	1.95	17.55	43.41	26.21
Polar						
NESDIS	7.51	7.45	1.11	16.08	42.70	23.21
Optimal	8.68	9.42	1.16	19.27	54.29	27.00
Constant	8.63	8.95	1.15	18.72	52.31	26.63

Table 2: Values of DFS (Degrees of Freedom of Signal), ER (Entropy Reduction) and the mean of eigenvalues (EV) for the different experiments conducted in the study of the impact with respect to the air mass.

8 Figures

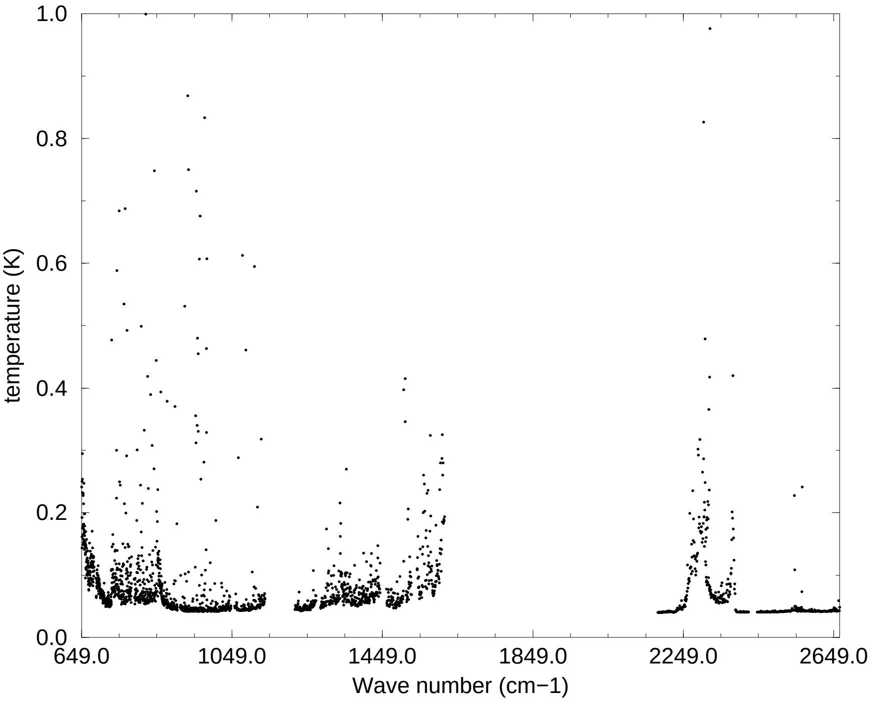

Figure 1: Typical spectrum of the AIRS observation-error values.

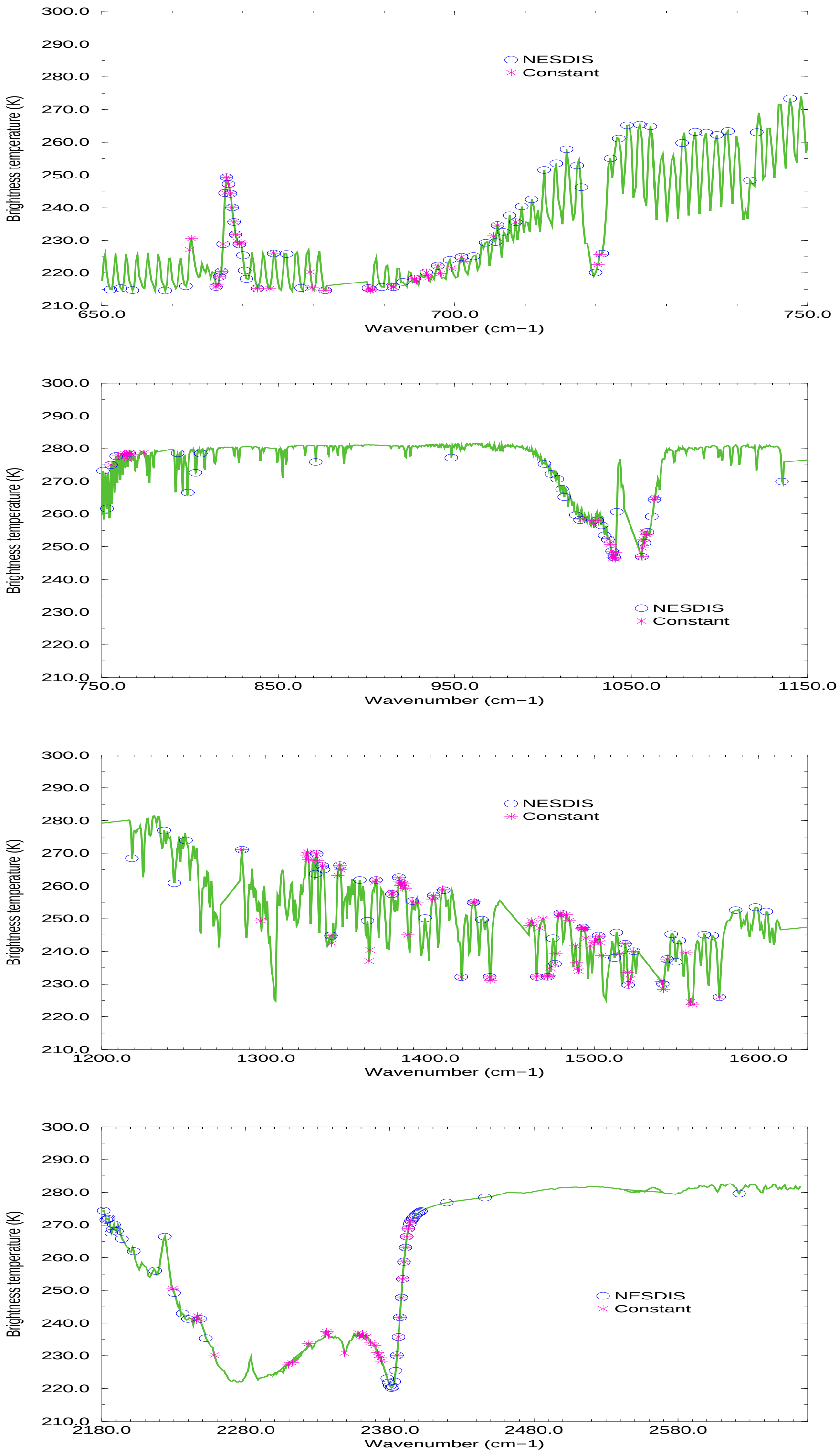

Figure 2: Typical spectrum of AIRS and location of the channels selected by the NESDIS NRT set and the constant method.

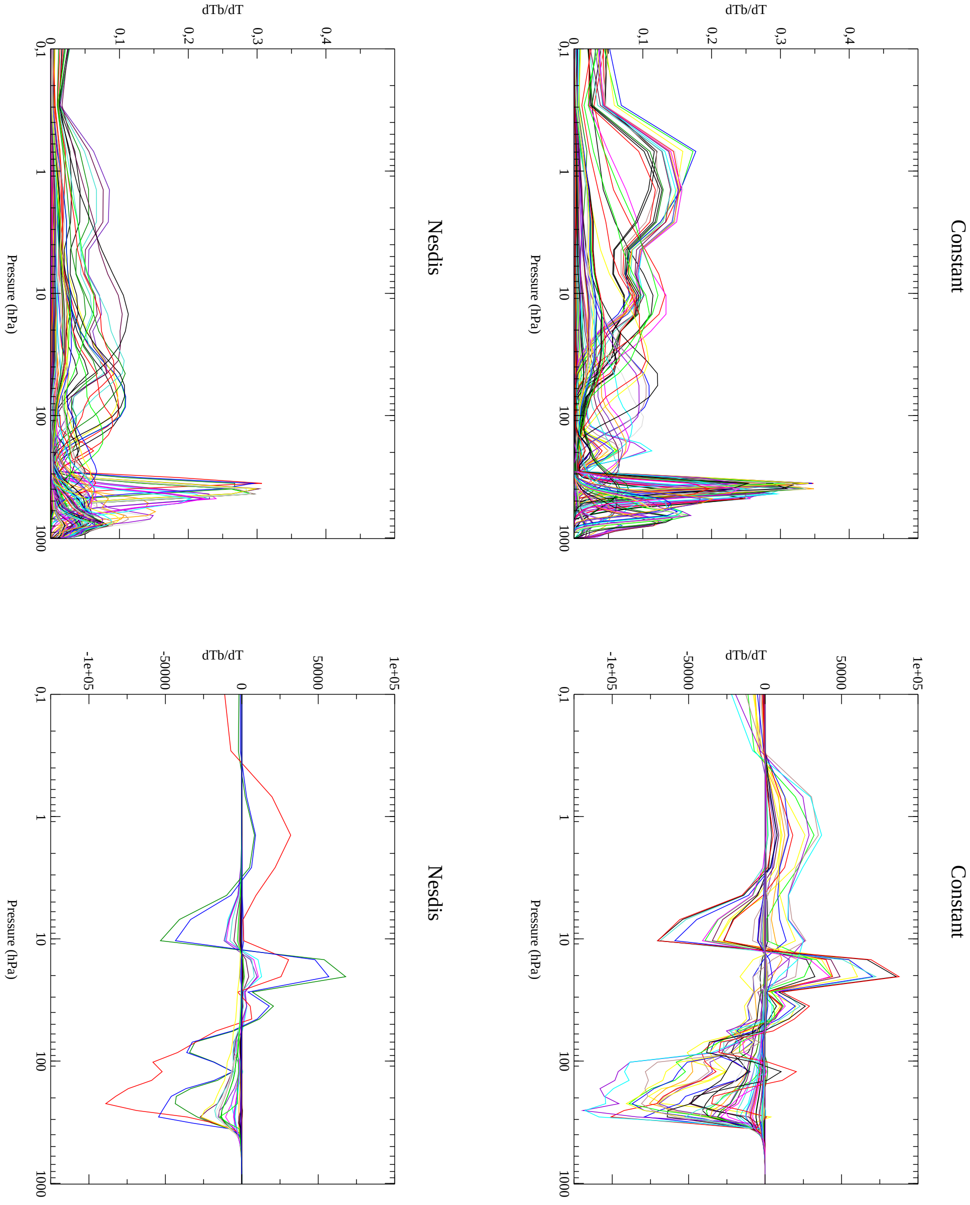

Figure 3: Jacobian relative to the temperature (top panels) and the humidity (bottom panels) of the different channel selections (NESDIS NRT set (left-hand panels) and constant set (right-hand panels)).

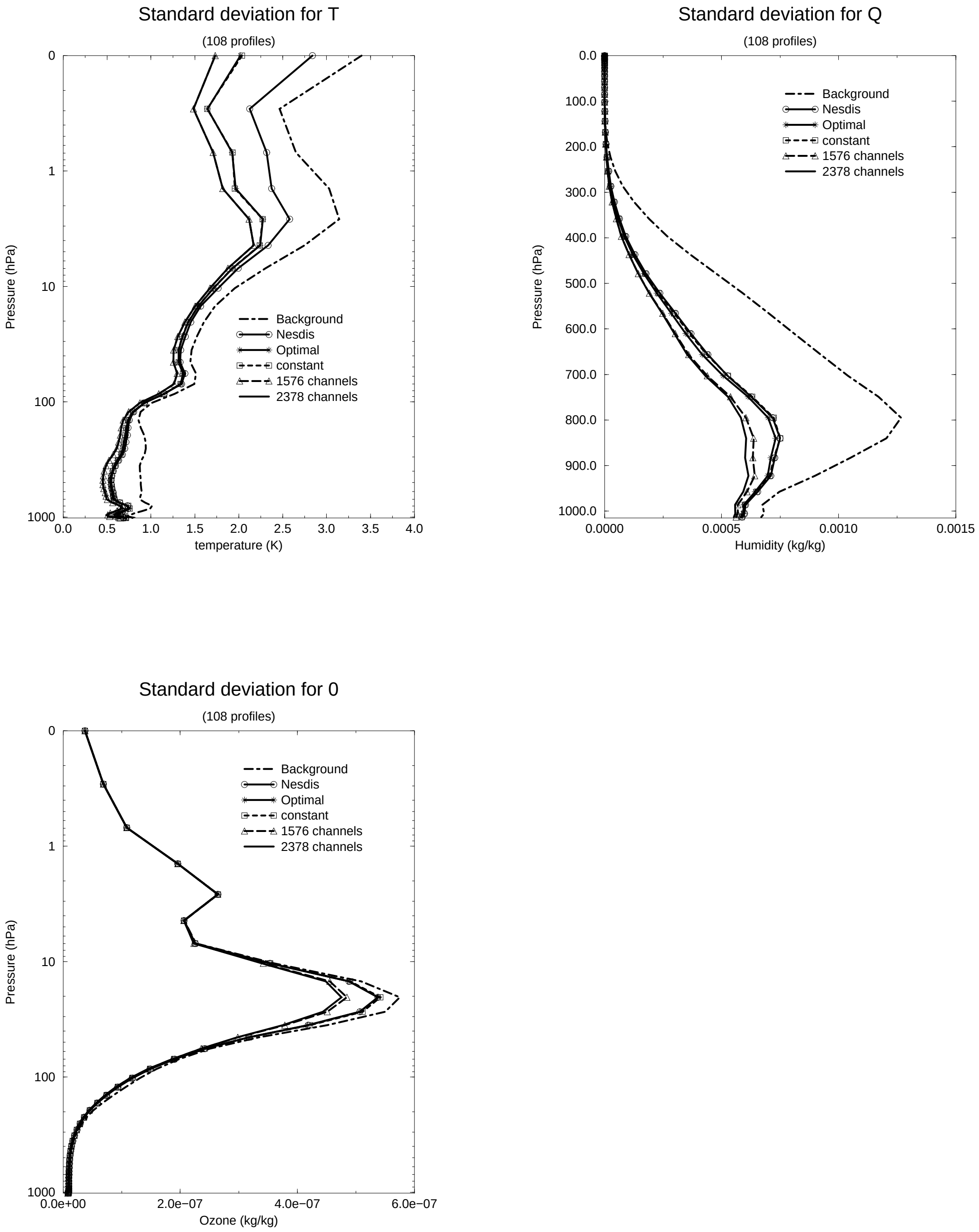

Figure 4: Standard-deviation of errors averaged over 108 profiles, for various channel selections to retrieve temperature (left-hand panel), humidity (right-hand panel) and ozone (bottom panel). 'Background' corresponds to the standard deviation of background errors. 'Nesdis', 'optimal' and 'constant' are related to the standard deviation of analysis errors obtained with the NESDIS Near Real Time set, optimal selection and constant set. '1576' corresponds to the standard deviation obtained with an analysis using the remaining channels after the exclusion of the 'window' channels and '2378' corresponds to the standard deviation obtained with an analysis using all the AIRS channels.

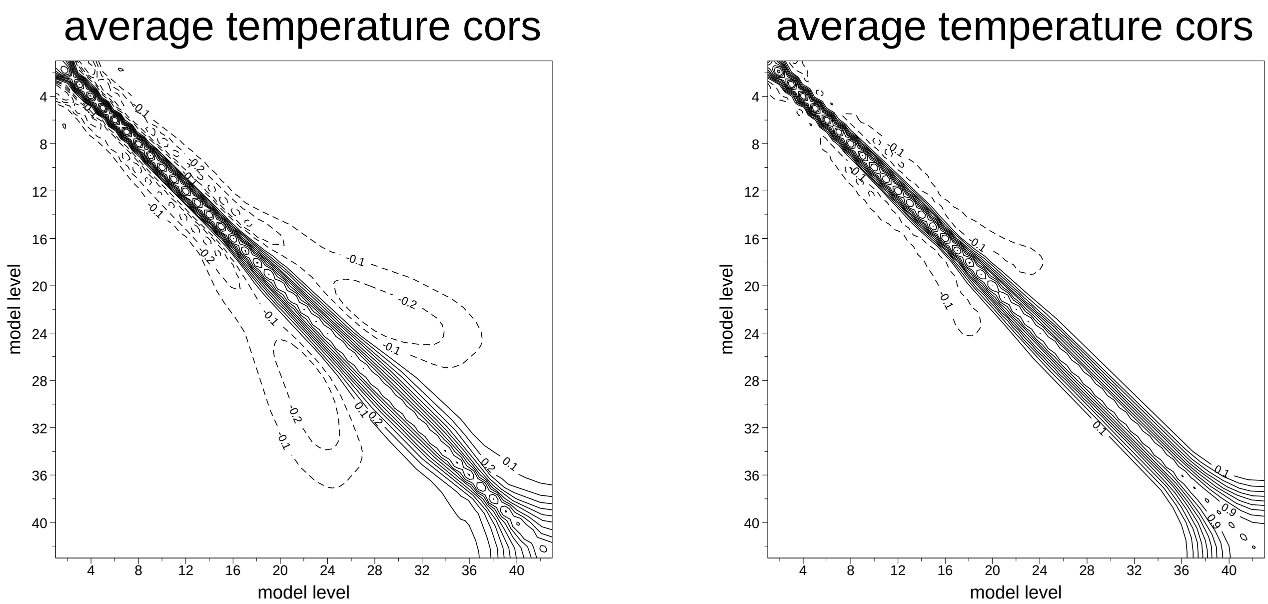
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Figure 5: Vertical correlation of the operational background error (left-hand panel) and of the key analysis error (right-hand panel) matrices.

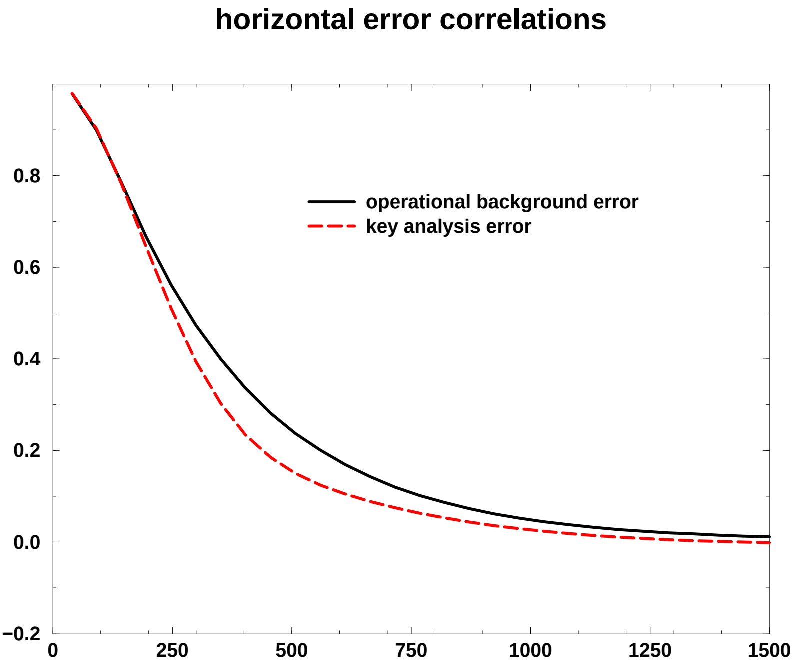


Figure 6: Horizontal correlation of the operational background error and of the key analysis error matrices.

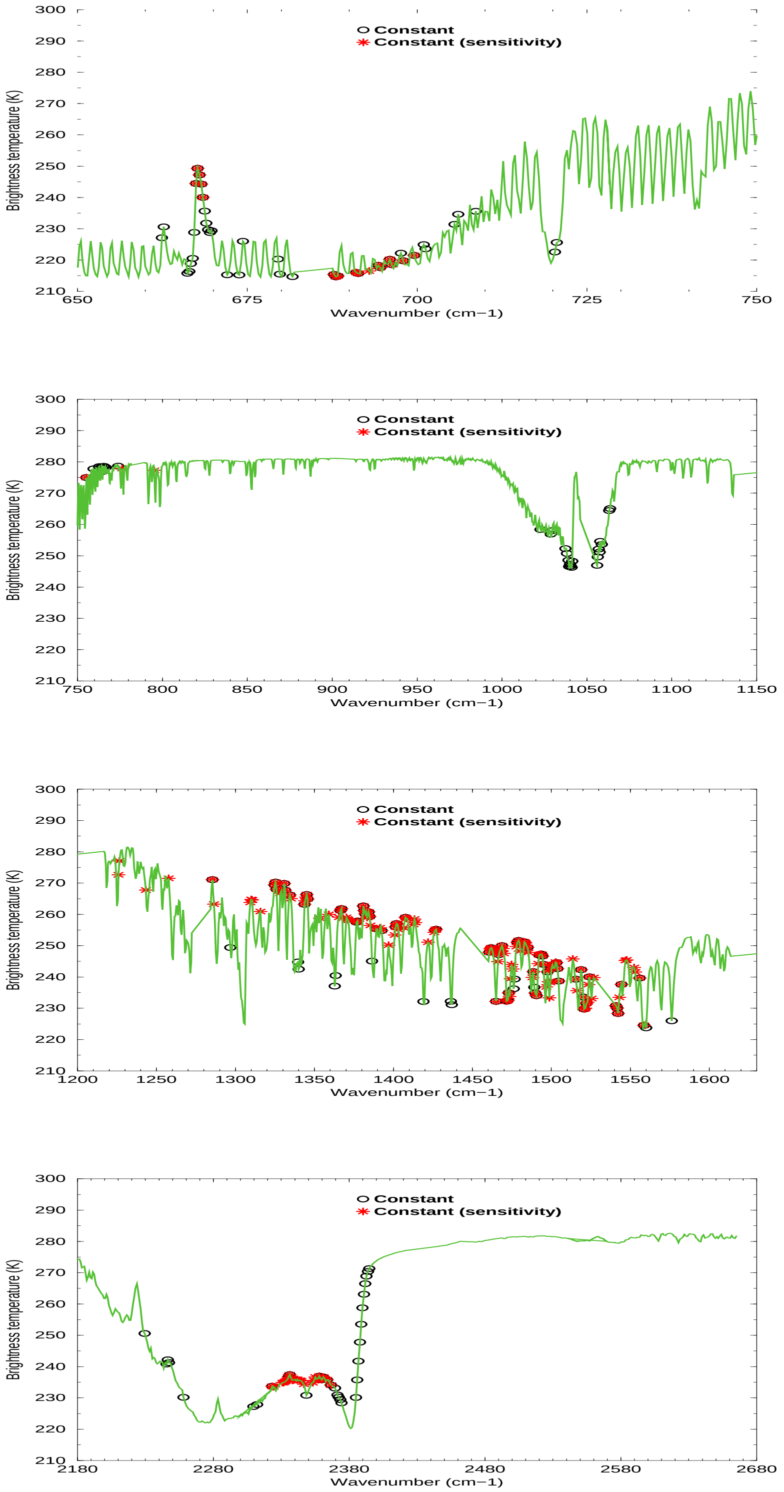


Figure 7: Typical spectrum of AIRS and location of the channels selected by the constant set and the constant method computed with key analysis error matrix for an analysis in temperature.

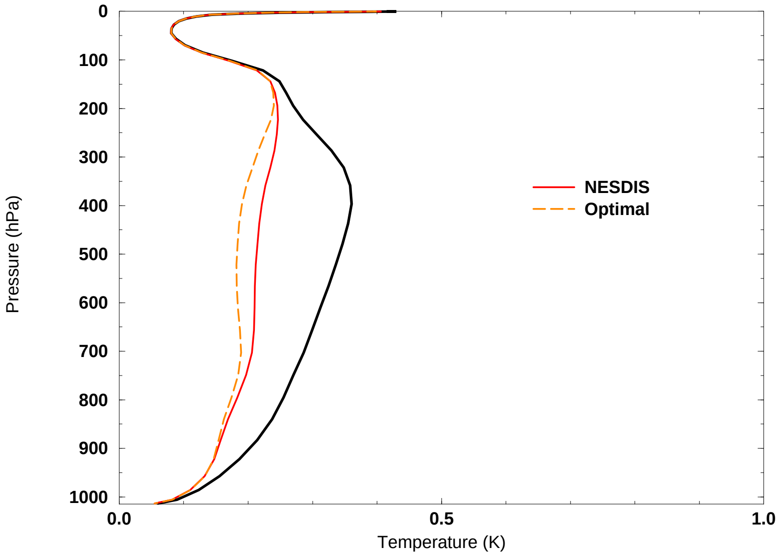


Figure 8: Standard-deviation of errors averaged over 108 profiles, for the NESDIS NRT channel set and the optimal channel selection to retrieve temperature and computed with the 'key analysis error' matrix. Black line represents the standard deviation of the key analysis error matrix.

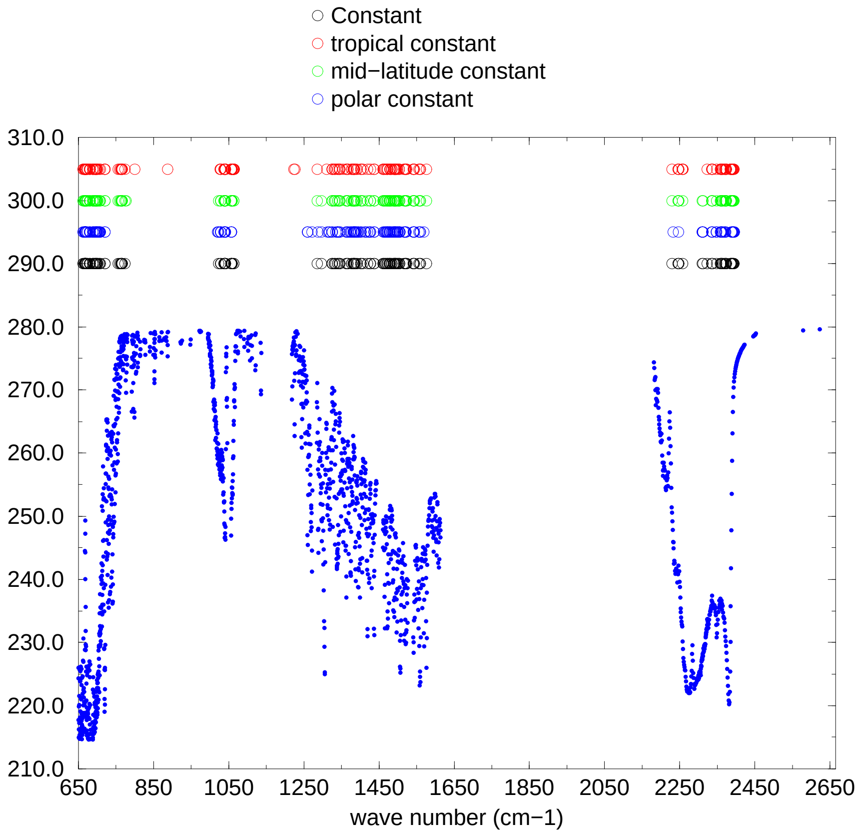


Figure 9: Typical spectrum of AIRS and location of the channels selected by the constant method with respect to the airmass classes (tropical constant, mid-latitude constant and polar constant) and for the whole data set (constant).

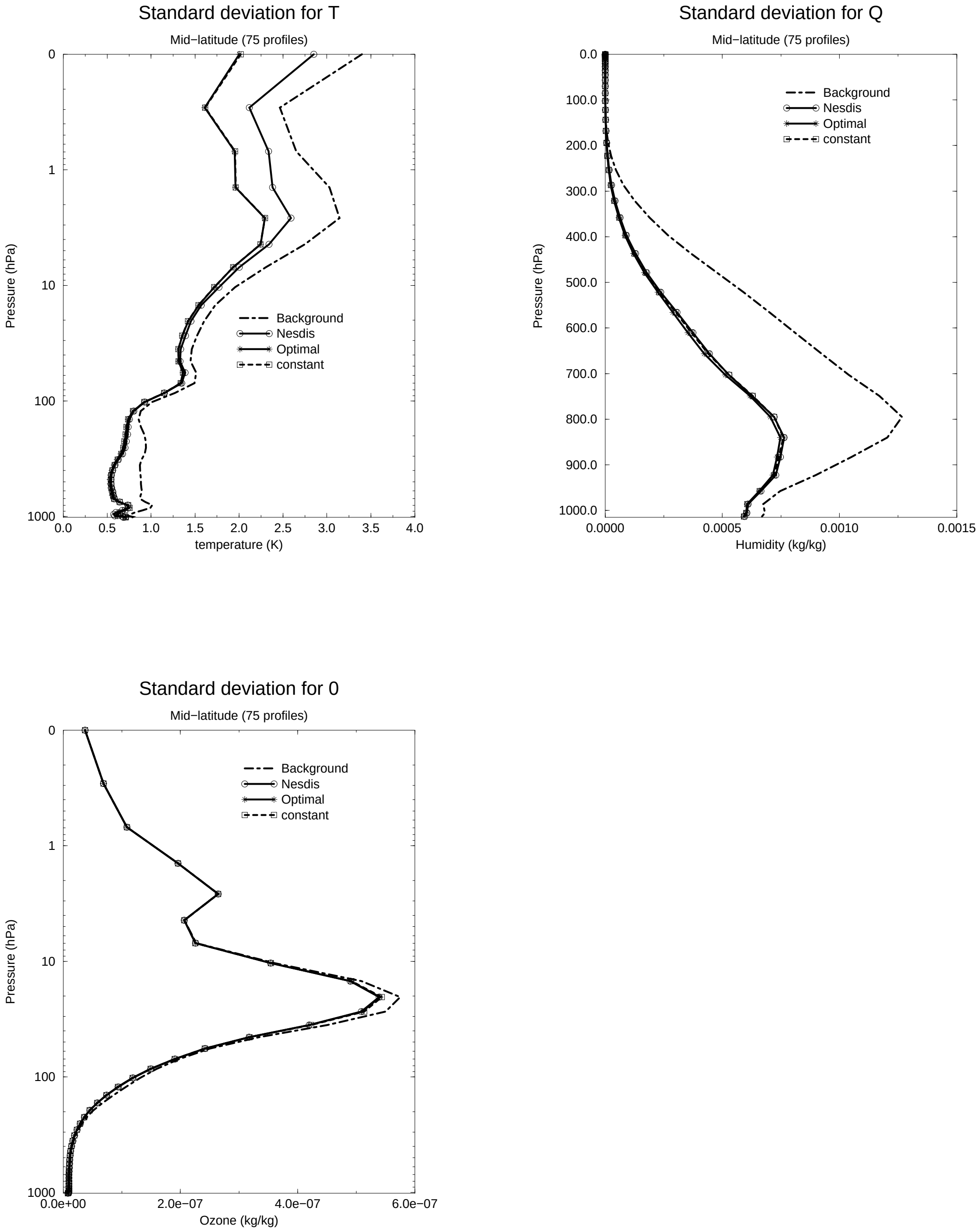
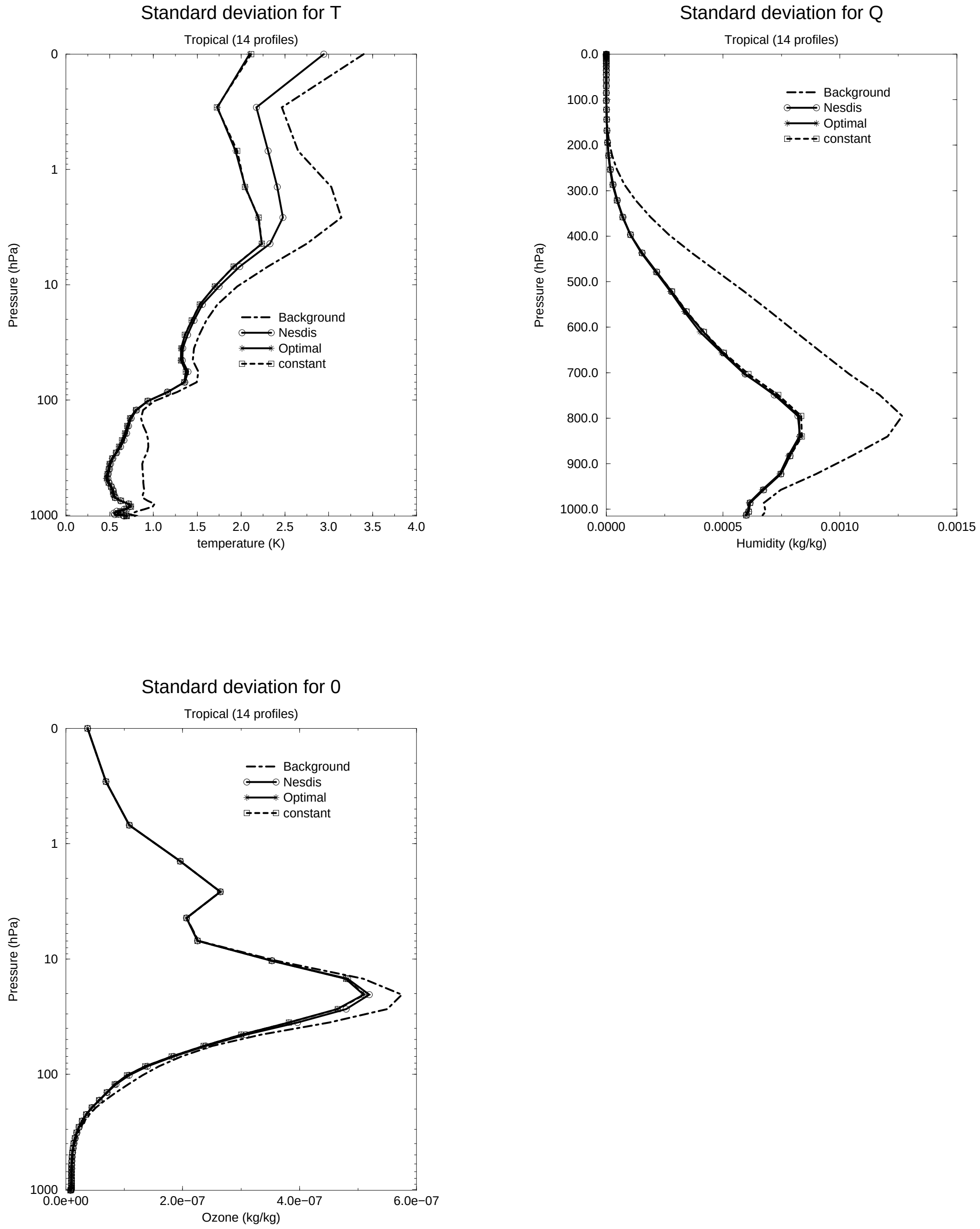


Figure 10: Standard-deviation of errors averaged over the mid-latitude airmass class, for the various channel selections to retrieve temperature (left-hand panel), humidity (right-hand panel) and ozone (bottom panel).


Standard deviation for T

Tropical (14 profiles)

Standard deviation for Q

Tropical (14 profiles)

Standard deviation for 0

Tropical (14 profiles)

Figure 11: Standard-deviation of errors averaged over the tropical airmass class, for the tropical constant channel selection to retrieve temperature (left-hand panel), humidity (right-hand panel) and ozone (bottom panel).

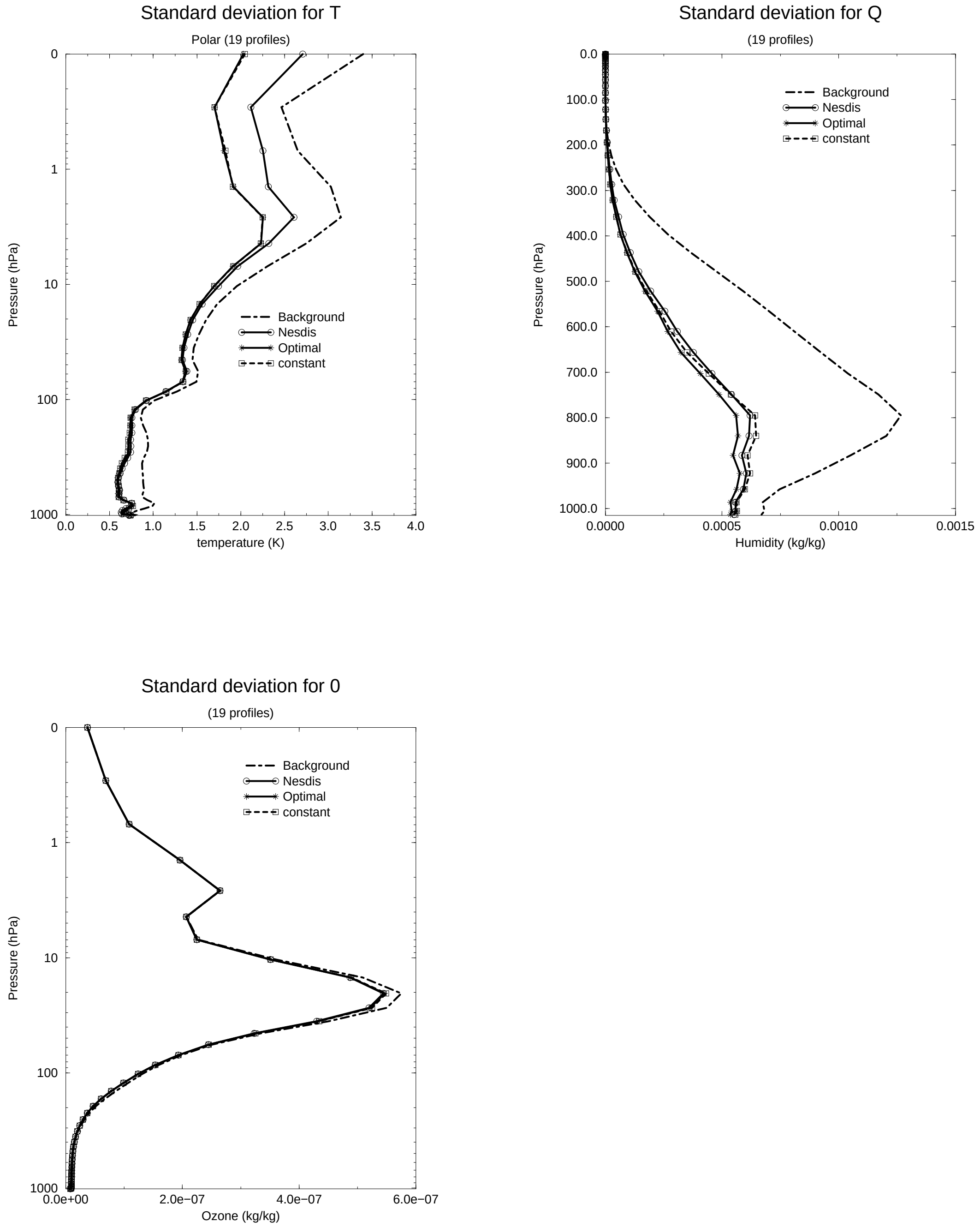


Figure 12: Standard-deviation of errors averaged over the polar airmass class, for the polar constant channel selection to retrieve temperature (left-hand panel), humidity (right-hand panel) and ozone (bottom panel).

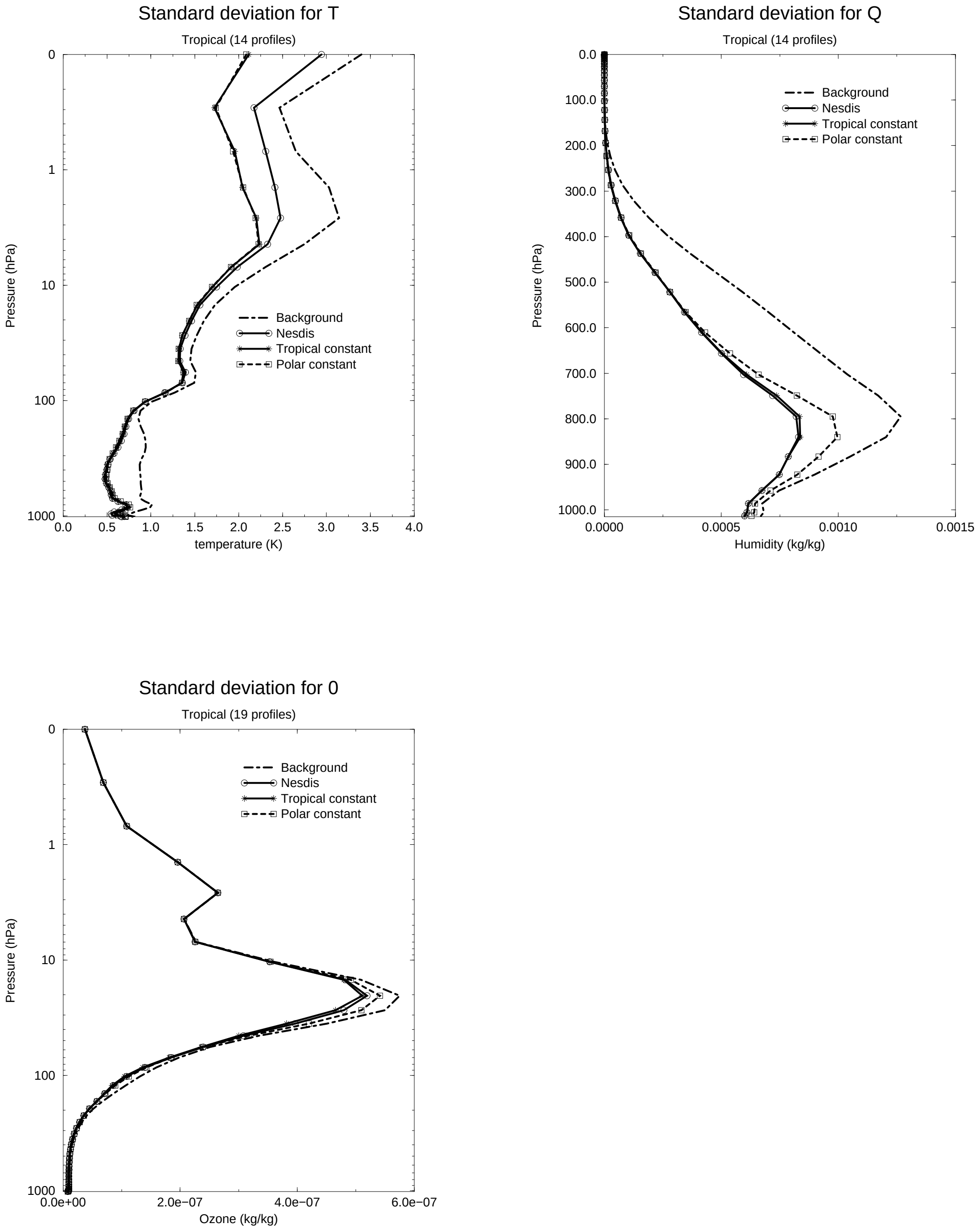


Figure 13: Standard-deviation of errors averaged over the 14 tropical profiles, for various channel selections (NESDIS NRT set, tropical constant set and polar constant set) to retrieve temperature (left-hand panel), humidity (right-hand panel) and ozone (bottom panel).