

Validation of the NESDIS Near Real Time AIRS channel selection

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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 optimality of the selection of the AIRS radiance channels that will be available to the scientific community in near real time by NOAA/NESDIS (called hereafter NESDIS NRT). This assessment is done by comparing this channel selection with another method presented in Rabier *et al.* (2002), the so-called “constant” method. It turns out that although the selected channels are different and the information content as measured by the Entropy Reduction (ER) and the Degree of Freedom for Signal (DFS) is slightly smaller for the NESDIS NRT channel set than for the “constant” set, both channel selections give similar results in terms of analysis error for temperature, humidity and ozone. The robustness of the results is then evaluated by varying a range of input parameters to the channel selection scheme, in particular the atmospheric training dataset on which the channel selection is based and the background error covariance matrix. It is found that the performance of the “constant” channel selection is very sensitive to the training dataset, while the NESDIS NRT channels selection remains robust to different background error specifications. Altogether, the “manually selected” NESDIS NRT channels provide 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, 2378 channels) and the Infrared Atmospheric Sounding Interferometer (IASI, 8461 channels) 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 (High InfraRed Radiation Sounder - HIRS, 20 channels). Successful exploitation of this new generation of satellite instruments is one of the major challenges for Numerical Weather Prediction (NWP) centres for the next ten years.

It is neither feasible nor efficient to assimilate all of the channels and most centres are following effective channel selection strategies for radiance assimilation in NWP. The challenge is to find a set of channels that is small enough to be assimilated efficiently in a global NWP system (within operational time constraints), and large enough to capture important atmospheric variability.

Following the launch of the NASA¹ AQUA satellite in May 2002, a reduced set of AIRS radiance channels have been selected by the AIRS Science Team (Susskind, pers. comm.) and will be made available to the scientific community in Near Real Time (NRT) by NOAA²/NESDIS³. Several information content studies for advanced sounders aim at identifying the “best” channels for NWP in order to minimise the reduction of information from advanced infrared sounders. In particular, Rabier *et al.* (2002) have tested several methods in the context of the IASI instrument. They found that the channel selection method following Rodgers (1996) selects 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 the Rabier *et al.* (2002) methodology to the AIRS instrument in order to assess the quality of the NESDIS NRT channel selection versus a more “optimal” (as defined by information content considerations) channel selection.

In section 2, the experimental framework of the study as well as the optimal technique leading to the “constant” channel selection method are briefly described. The efficiency of the NESDIS NRT channel selection is then

¹National Aeronautic and Space Agency

²National Oceanic and Atmospheric Administration

³National Environmental Satellite Data and Information Service

compared to the “constant” selection in terms of information content and linear 1DVAR performance (section 3). The robustness of the results to the different inputs to the channel selection is then evaluated. Section 4 addresses the problem of representativeness of the training dataset used for the “constant” channel selection. The sensitivity of the results to the specification of the background error covariance matrix is described in section 5. Conclusions are discussed in section 6.

2 Experimental framework

The general framework of this channel selection study is linear optimal estimation theory in the context of NWP. We follow the framework presented at length by Rabier *et al.* (2002) from which we summarize the main elements. The atmospheric profile in temperature, humidity, ozone and surface temperature at a given location is represented by a vector \mathbf{x} and the satellite observations by a vector \mathbf{y} . The observations are linked to the atmospheric state by an observation operator representing the radiative transfer equation :

$$\mathbf{y} = \mathcal{H}(\mathbf{x}) + \boldsymbol{\varepsilon}_O + \boldsymbol{\varepsilon}_F \quad (1)$$

where the measurement and the forward model errors $\boldsymbol{\varepsilon}_O$ and $\boldsymbol{\varepsilon}_F$ are each assumed to be gaussian noises with error covariance matrices \mathbf{O} and \mathbf{F} . We denote $\mathbf{R} = \mathbf{O} + \mathbf{F}$ the resulting observation error covariance matrix. The background state vector \mathbf{x}_b has an associated 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 : $\mathcal{H}(\mathbf{x}) = \mathcal{H}(\mathbf{x}_b) + \mathbf{H}(\mathbf{x} - \mathbf{x}_b)$ where \mathbf{H} is the tangent linear model of the radiative transfer model \mathcal{H} .

Rabier *et al.* (2002) use two additional concepts introduced by Rodgers (2000): the Entropy Reduction ($ER = -\frac{1}{2} \log_2 \det(\mathbf{A}\mathbf{B}^{-1})$) and the Degrees of Freedom for Signal ($DFS = Tr(\mathbf{I} - \mathbf{A}\mathbf{B}^{-1})$), where \mathbf{A} represents the analysis error covariance matrix. Let λ represent eigenvalues of $\mathbf{A}\mathbf{B}^{-1}$ (a small λ corresponding to a direction where the measurements have reduced a lot the analysis error variance). It can be shown that:

$$DFS = n - \sum_{\lambda \in \sigma(\mathbf{A}\mathbf{B}^{-1})} \lambda \quad (2)$$

$$ER = -\frac{1}{2} \sum_{\lambda \in \sigma(\mathbf{A}\mathbf{B}^{-1})} \log_2 \lambda \quad (3)$$

where n represents the total number of degrees of freedom of the analysis problem.

Both concepts are very useful in that they quantify the gain in information brought by the observations with respect to the background information (the larger the ER or the DFS the better).

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 vertical discretization with 43 pressure levels (see Matricardi and Saunders, 1999). The \mathbf{B} matrix has been interpolated from the current (2002) operational 60-level ECMWF background error covariance matrix representing short range forecast errors of the ECMWF model. The surface temperature background error standard deviation has been included (1.04K corresponding to an inflation of 0.5^2 to the lowest model level temperature background error variance) in the \mathbf{B} matrix and a correlation with the lowest tropospheric level has been added (it is assumed that the vertical correlation between the surface and the first model level is identical to the correlation between that level and the one above). The covariance matrix \mathbf{R} has been derived from the latest estimation of the AIRS instrument noise (Hannon, pers. comm.).

2.1 Channel selection

The iterative method for channel selection, proposed by Rodgers (1996) and used in Rabier *et al.* (2002), entails performing successive analyses, each one using only one extra channel at a time. The resulting analysis error covariance matrix is updated accordingly and used at the next iterative 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). It has been verified that the channel selection does not change if one considers the DFS as the choice criterion for the channel selection.

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, surface temperature 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 (20°N-70°N, 20°S-70°S), 14 tropical (20°N-20°S) and 19 polar (70°N-90°N, 70°S-90°S) profiles.

As a starting point, we have considered that 324 channels will be available in the NESDIS NRT selection. Since some channels of the original 2378 are known to be of poorer quality, they are excluded from the optimal selection. Applying this check, the total number of AIRS channels is reduced from 2378 to 2140.

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 certainly be impossible to apply in an operational context. Therefore, as in Rabier *et al.* (2002), a “constant” channel selection has been computed as an average of the 108 different optimal channel selections and is used here as a benchmark for the validation of the NESDIS NRT selection.

Different criteria can be used to compare the quality of the different channel selections. One can for example investigate the information content of $\mathbf{A}\mathbf{B}^{-1}$ represented by its eigenvalues that provide the number of independent pieces of information brought by the observations. As already mentioned, DFS and ER are other quantities that give 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 \mathbf{x}_a is given by $\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{y}_b)$ with $\mathbf{K} = \mathbf{A}\mathbf{H}^T\mathbf{R}^{-1}$ and $\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}$. \mathbf{K} is the Kalman gain matrix and \mathbf{A} is the analysis error covariance matrix introduced above. The parameter space is the temperature, humidity and ozone profile defined on the 43 RTAIRS pressure levels (Matricardi *et al.*, 2001) and the surface temperature. $\|\mathbf{A}\|$ is usually used as a criterion for quality of 1D-Var retrieval (the smaller the better).

3 Comparison between NESDIS NRT and “constant” channel selections

The “constant” channel selection is an average selection based on the set of 108 individual optimal channel selections. In fact only 63 channels are always selected through the 108 channel selections (corresponding to very different atmospheric situations), whereas 1504 channels are never selected. The resulting “constant” channel selection shares only 119 channels with the NESDIS NRT selection. Figure 1 displays the AIRS spectrum

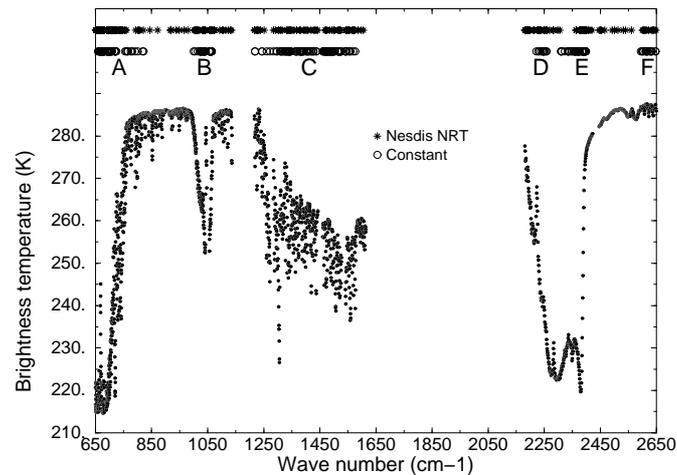


Figure 1: Typical spectrum of AIRS superimposed at the top of the figure by the location of the channels chosen by the NESDIS NRT selection (stars) and picked by the "constant" channel selection. See Table below for the description of the letters corresponding to different spectral bands.

Band	
A	Temperature sounding
B	Ozone
C	Water vapor
D	Temperature sounding (troposphere)
E	Temperature sounding (stratosphere)
F	surface window

corresponding to a midlatitude profile together with the location (at the top of the figure) of the NESDIS NRT (stars) and "constant" selected channels (circles). The different spectral bands are labelled by letters to facilitate the discussion. At first sight, the NESDIS NRT channel selection spans the IR spectrum more evenly than the "constant" channel selection which privileges specific small spectral domains. This choice for the NESDIS NRT selection is obviously aiming at representing as uniformly as possible the whole AIRS spectrum. The fact that only 119 out of 324 channels are commonly selected between the two approaches could seem worrying. However, as can be seen from Fig. 1, large spectral areas are covered by both sets (longwave CO₂, ozone, water vapour,...) and obviously "constant" and NESDIS NRT have selected neighbouring wavenumbers.

A closer look to both selections indicates that 53% of NESDIS NRT channels are located in bands A and B against 36% of the "constant" channels while 40% of this latter set are chosen in band C. Band D is hardly covered by the "constant" channel selection, whereas both NESDIS NRT and "constant" selected channels describe evenly band E. Band B is also well captured by the two selections. The study of the Jacobians of the associated selected channels in both selections indicates an overrepresentation of the upper-stratosphere (bands A and E) in the "constant" selection. This overrepresentation of the upper-stratosphere can be explained by the large temperature background error variances at these levels. There is also a dominating choice for band C (water vapour) in the "constant" channel selection, most likely driven by the vertical structure of the humidity background error covariance matrix. Conversely, NESDIS NRT selection has a large number of channels peaking in the low troposphere corresponding to bands A and F.

Figure 2 and Tab. 1 show that the ER and DFS are slightly smaller for the NESDIS NRT selection than for the "constant" selection. The number of independent pieces of information brought by the 324 channels (as defined

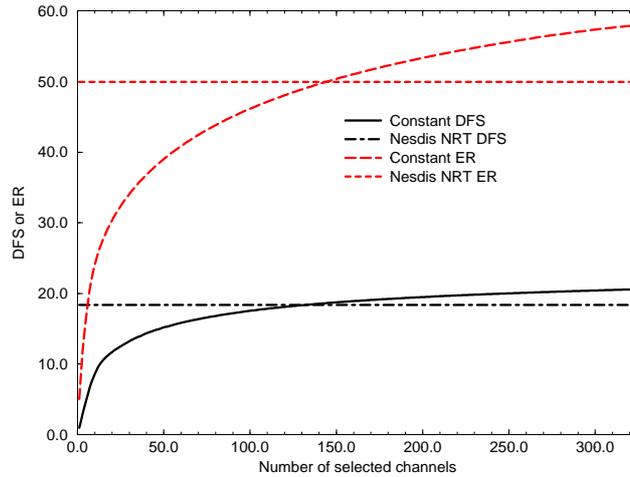


Figure 2: Evolution of the Degree of Freedom of Signal and the Entropy Reduction for the “constant” channel selection with respect to the number of selected channels, averaged over the 108 profiles. The corresponding values of DFS and ER for the NESDIS NRT channel set is also appended.

Table 1: Values of DFS (Degrees of Freedom of Signal), ER (Entropy Reduction) and mean number of Eigenvalues (EV - as defined in Thépaut and Moll 1990 and Rabier et al. 2002) for ‘NESDIS NRT’, ‘constant’, ‘all channels’ and ‘HIRS-like’ selections. ‘All channels’ corresponds to the experiment when 2140 channels are used. ‘HIRS-like’ corresponds to the experiment when 15 AIRS channels closest to the current channels of the High resolution Infrared Radiation Sounder (HIRS) are used.

Experiment	DFS	ER	EV
NESDIS NRT	18.36	49.93	25.7
Constant	20.59	57.94	28.5
All channels	24.34	76.16	33.2
Hirs-like	6.44	14.06	9.29

in the section above) is also smaller (25.2 against 28.8) in the case of NESDIS NRT selection. However, both selections greatly improve the DFS, ER and the number of eigenvalues compared to the use of the 15 channels corresponding to the current HIRS instrument (see Tab. 1).

We have examined the standard deviations of background error and of linear 1D-Var analysis error for temperature, humidity and ozone profiles as well as for surface temperature, averaged over the 108 profiles (Fig. 3). Both NESDIS NRT and “constant” selections outperform the “HIRS-like” set in terms of analysis error reduction, and this for temperature, humidity and ozone. NESDIS NRT and “constant” selections provide similar temperature retrieval errors in the lower troposphere, while the “constant” selection produces analysis errors generally smaller than 2 K in the upper-troposphere and in the stratosphere versus 2.5 K or more with NESDIS NRT selection. Otherwise, both selections provide similar humidity and ozone analysis errors.

For surface temperature, the analysis error standard deviation is decreased to 0.05 K for both selections to be compared with 1.04K for the background and 0.3 K for the “HIRS-like” channel set. This result should be taken with great care since the very small analysis error is explained by the somewhat “empirical” value specified for the surface temperature background error. This quantity is poorly known in NWP models as is the background error vertical correlation between surface temperature and lowest model level temperature.

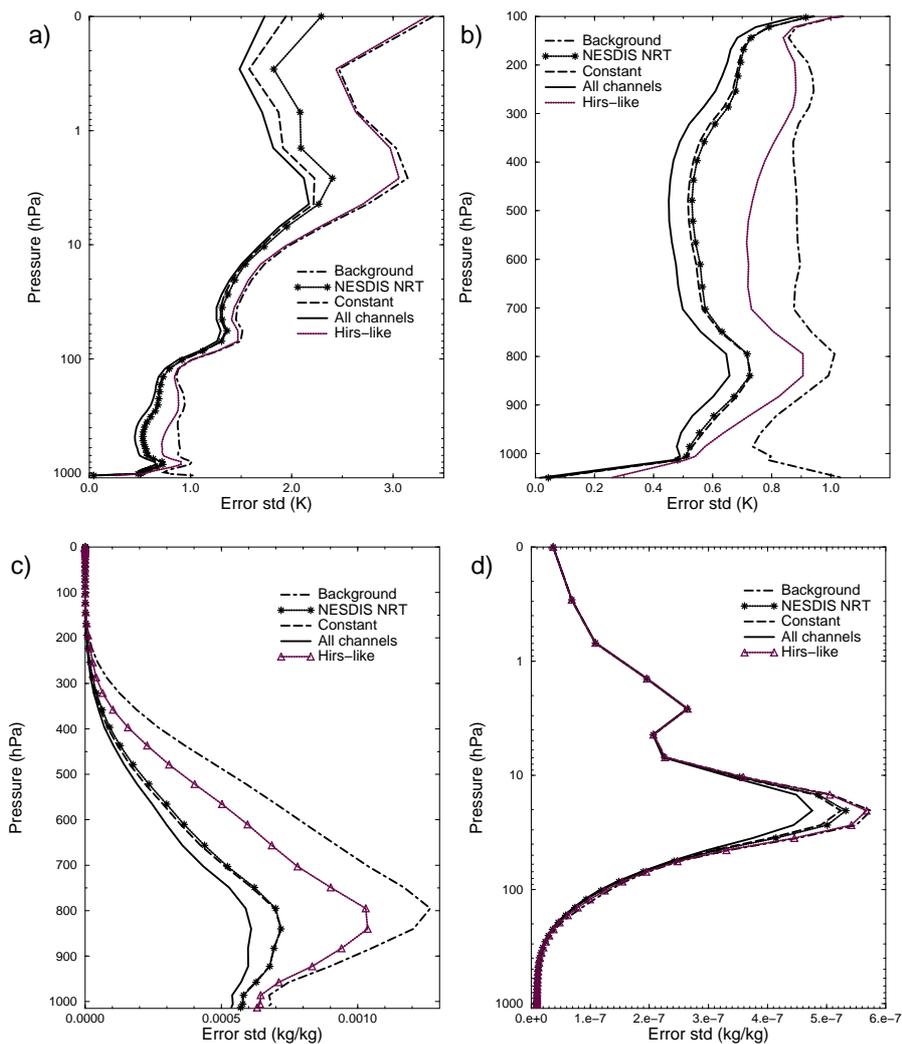


Figure 3: 1D-Var averaged (over 108 profiles) error standard deviation, for temperature (top left in log scale and top right in linear scale), humidity (bottom left) and ozone (bottom right). Experiment names as explained in table 1.

Comparisons with “all channels” retrieval errors (Fig. 3) provide some guidance about the loss of information entailed by the two channel selections tested. The use of all channels leads 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 very important in the lower troposphere when all the channels are used in the assimilation. Likewise, the ozone retrieval error is substantially decreased when the 2140 channels are used. The further gain in ER and in DFS is 18.2 and 3.75 respectively when all the channels are used in the analysis (Tab. 1).

We conclude that even though 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 “constant” selection, the respective quality of NESDIS NRT and “constant” selections is very comparable in terms of linear 1D-Var retrieval error for all retrieved parameters. This shows that despite a different choice of channels (only 119 out of 324 are in common), the spectral bands (and therefore the atmospheric layers) are sufficiently similarly covered by the two selections to provide equivalent performance.

Table 2: Values of *dfs* (Degrees of Freedom of Signal), *ER* (Entropy Reduction) and mean number Eigenvalues (*EV*) for the different channel selection with respect to the airmass type.

Airmass class	DFS	ER	EV
Mid-latitude	20.26	56.44	28.3
Polar	20.82	61.05	28.7
Tropical	20.33	54.20	27.9

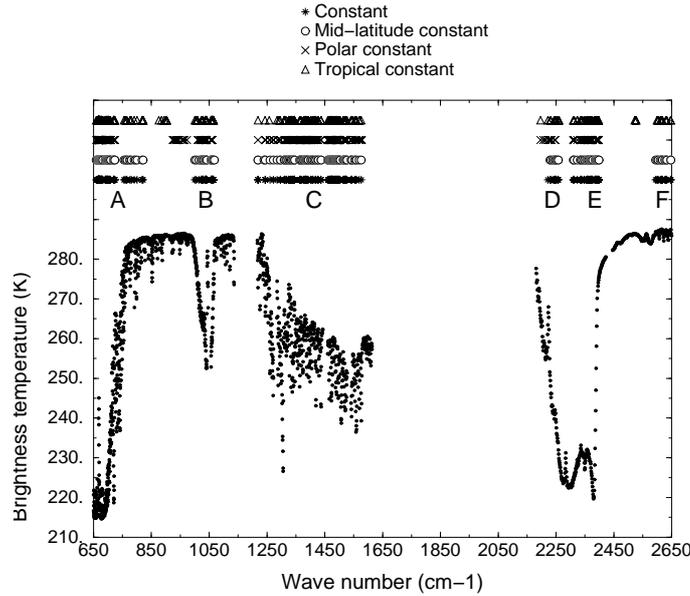


Figure 4: Typical spectrum of AIRS and location of the channels selected by the “constant” method averaged over all profiles (“constant”) and over different airmass profile classes (“mid-latitude constant”, “polar constant” and “tropical constant”). See Table of Fig. 1 for the description of the letter corresponding to spectral bands

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

4 Impact of the airmass on the quality of the NESDIS NRT selection

In this section, we investigate the robustness of the different channel selections to the airmass under consideration. Two questions are considered: 1) Is the NESDIS NRT selection robust to the atmospheric airmass (e. g. polar, mid-latitude, tropical)? 2) What happens to the “constant” selection if it is based on a given airmass and applied to a very different one?

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

Three airmass classes have been defined: the mid-latitude airmass class consists of 75 profiles, the tropical one consists of 14 profiles and the last 19 profiles represent the polar type. Figure 4 displays the spectral location of the different “constant” channel selections tailored to the three different airmass classes (i.e. the average has

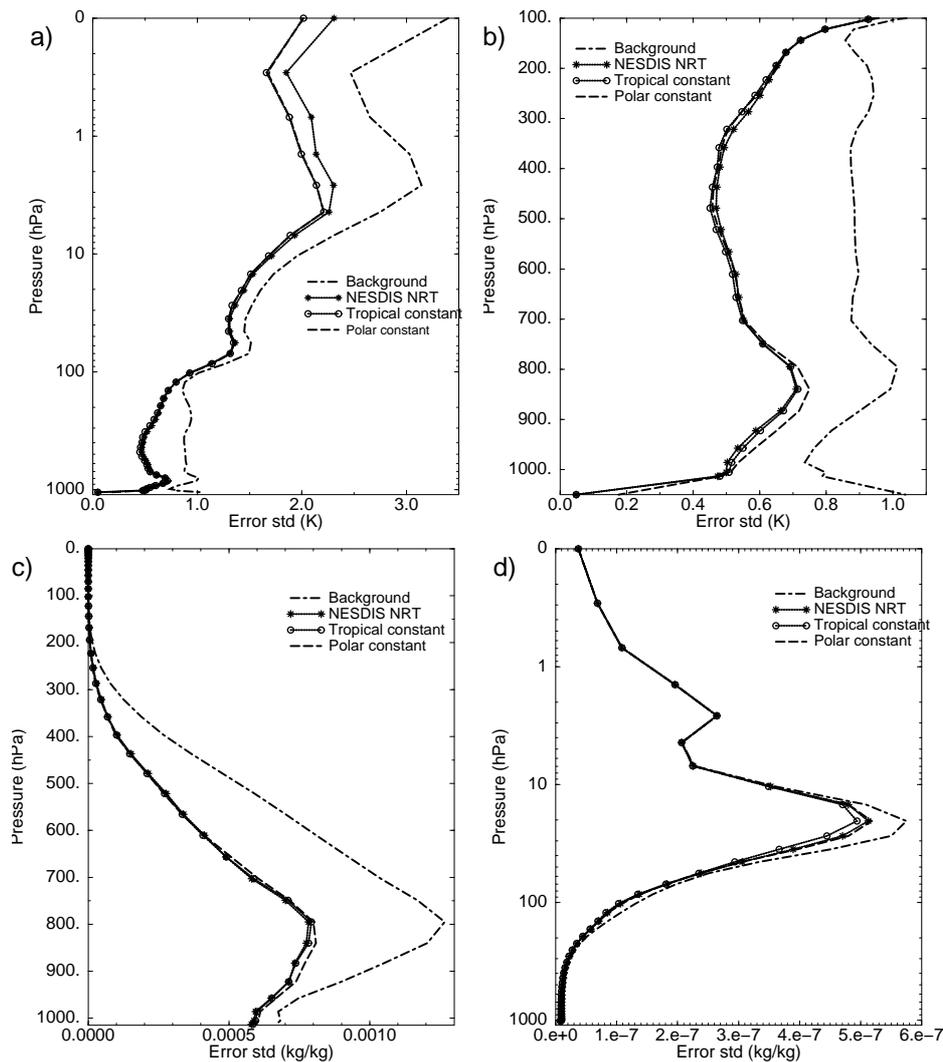


Figure 5: 1D-Var temperature (top panels), humidity (left-hand bottom panel) and ozone (right-hand bottom panel) error standard deviation averaged over the tropical airmass type (14 profiles). Errors are represented for “Background”, “Nesdis NRT”, “Tropical constant” and “Polar constant” channel selections

been performed on the representative profiles of each airmass type).

The “constant” channel selection (averaged over the whole dataset) shares 319 channels with the “mid-latitude constant” selection, 288 channels with the “tropical constant” selection and 254 channels with the “polar constant” selection. The “polar constant” and “tropical constant” selections share only 226 channels. In particular, the “polar constant” selection does not pick any channel in the right part of the band A ($12.5 \mu\text{m}$) in contrast to the “tropical constant” selection, but favours the pure window ($10.5 \mu\text{m}$). In fact, when the selection is based on tropical profiles the $12.5 \mu\text{m}$ region acts as a water vapour band and channels are selected in this area due to large specified humidity background errors, whereas the humidity signal is weak in this spectral region when dealing with very dry polar profiles which favour a selection in a cleaner window region and in band C ($6 \mu\text{m}$ water vapour band). As expected, the global “constant” selection is dominated by a mid-latitude signal due to a rather poor representation of polar and tropical airmass in the sampling dataset.

The outcome of the various 1D-VAR experiments using the different channel selection combinations (not

shown) can be summarised as follows:

- For temperature, NESDIS NRT and the different “constant” selections provide similar results for all airmass types.
- For humidity, NESDIS NRT gives similar performance as “mid-latitude constant” and “tropical constant”. “Polar constant” channel selection provides slightly better results than NESDIS NRT below 400 hPa for the polar airmass class, in agreement with a more massive selection in band C (157 channels for “polar constant” versus 61 for NESDIS NRT).
- For ozone, the selections give similar results with the exception of the tropical airmass, where the “tropical constant” selection provides slightly smaller analysis errors than NESDIS NRT.

Altogether, the NESDIS NRT selection seems to be fairly insensitive to the airmass category, thus confirming the quality of careful “manual” choice of these channels performed by the AIRS Science Team.

4.2 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 airmass type the selection is trained with. To document further this issue, we illustrate here the impact of performing a 1D-Var analysis for certain atmospheric situation using a channel selection based on a completely different atmospheric training dataset.

Figure 5 displays the 1D-Var performance of the NESDIS NRT, the “tropical constant” and “polar constant” selections 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 0.5 unit in term of DFS and 2.39 unit in term of ER. This indicates clearly the importance of an exhaustive training dataset if one plans to replace the day-1 NESDIS NRT selection by a more optimal method in the near future. It is of particular importance to capture all the weather regimes for highly variable quantities such as specific humidity.

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

The current background error covariance matrix used at ECMWF only provides 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 in clear air some of the small scale baroclinic structures that have been identified by sensitivity studies (Klinker *et al.*, 1998) as being crucial to forecast error development. It is therefore important to assess the ability of the NESDIS NRT selection to “observe” such important atmospheric patterns.

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 ECMWF operational analysis, reduce the 48 hour forecast error (defined as the global difference between the 48 hour forecast and the verifying analysis). Up to now, humidity perturbations are not considered in the sensitivity computations, therefore only temperature is included in the sensitivity study described here. 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)

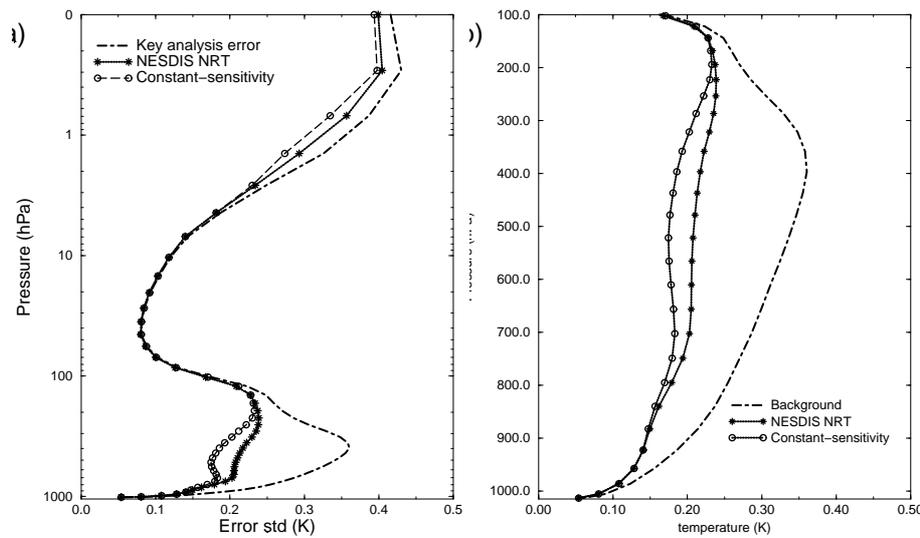


Figure 6: 1D-Var temperature error standard-deviation averaged over 108 profiles (left panel in log scale and right panel in linear scale), for various channel selections. 'Key analysis error' corresponds to the standard deviation of key analysis error. 'Nesdis NRT' and 'constant-sensitivity' correspond to 1D-Var analysis errors for NESDIS NRT and "constant" selection using the "key analysis" as background error.

and can be fairly sharp both in the horizontal and in the vertical. The associated covariance matrix (averaged over one month) is sharper in the vertical and horizontal than the operational background covariance error (not shown). In addition, as can be seen from Fig. 6, the error standard deviations are proportionally large in the troposphere and in the high stratosphere.

The optimal selections computed with the operational temperature background error covariance matrix ("constant") and "key analysis error" covariance matrix ("constant-sensitivity") share only 138 channels. The main differences appear in bands B, D and F where channels are solely selected by the "constant" method using the operational background error. "Constant-sensitivity" selects more channels in band C (water vapour), channels obviously having some sensitivity to temperature as well and located in layers where the temperature background error variance is proportionally large. Similarly, more channels are also selected in band E.

The 1D-Var temperature error standard deviation is shown on Fig. 6 for NESDIS NRT and "constant-sensitivity" selections, together with the "key analysis error" standard deviation. The two selections share only 67 channels. Even though the superiority of the "constant-sensitivity" channel selection is clear in the troposphere and high stratosphere, NESDIS NRT selection still manages to substantially reduce the original "key analysis error" variance in the troposphere.

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 these sensitive areas are generally affected by clouds that will badly affect the performance of the AIRS instrument altogether (McNally, 2002, Fourrié and Rabier, 2002). Our result implies that if these structures exist in reality and have some signature in clear sky areas, the current NESDIS NRT selection is able to observe them.

6 Conclusions

The NESDIS NRT AIRS channel selection to be provided to the operational weather centres has been assessed through comparison with a “constant” selection deduced from an optimal iterative method following Rodgers (1996). NESDIS NRT and “constant” channel selections are somewhat different, only 119 channels out of 324 are indeed identical between the two selections. However, both selected channels span sufficiently close spectral regions and lead to similar results in terms of DFS or ER, and also in terms of temperature, humidity, ozone and surface temperature linear 1D-Var analysis errors.

The impact of the airmass on the channel selection has then been studied. The outcome is that a poorly trained optimal channel selection can perform badly especially for humidity. On the other hand, NESDIS NRT selection seems to capture satisfactorily most of the variability of different atmospheric situations.

The impact of the background error covariance matrix has been assessed. A covariance matrix representative of key analysis errors felt crucial for the quality of the short range forecasts has been used to validate the robustness of the NESDIS NRT selection. It was shown that under those “extreme” conditions, NESDIS NRT performs again reasonably well as compared to a dedicated channel selection.

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

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