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Bias correction of window channels on microwave and infrared sounders

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Abstract

This study is focused on the bias correction of window channels on microwave and infrared sounders (e.g. AMSUA and HIRS). These channels are primarily used to quality control other sounding channels by virtue of their enhanced sensitivity to cloud contamination. In general these channels may be suceptable to systematic errors like any other channel and as such must be bias corrected before they are used.It will be shown that their sensitivity to clouds poses particular problems for the evaluation and correction of systematic errors and some potential solutions are proposed.

1 Introduction

Window channels on infrared and microwave sounders are often used to detect and reject scenes that are contaminated by cloud and / or precipitation. In its simplest form the detection may be based on a threshold test applied to observed minus clear-sky calculated radiance departures in a chosen window channel. A large departure would indicate the presence of some degree of contamination and result in the rejection of some or indeed all of the sounding channels at that particular location. Other schemes use the window channels inside a more complex multichannel cloud or rain detection algorithm. Whatever the complexity of the approach, the window channels are of central importance due to their acute sensitivity to cloud and rain - more than that of any of the other sounding channels measured by the instrument.

In general the window channels (like any other channel) may be prone to systematic errors due to instrument or radiative transfer problems and, just like any other channel, require some degree of bias correction before they are used. Bias corrections are usually based upon long time averaged statistics of observed minus calculated radiance departures evaluated in clear sky conditions. However, it can be seen that there is a fundamental problem if the identification of clear sky conditions itself relies on bias corrected window channel departures.

This study investigates the problem of bias correcting infrared and microwave window channels. Firstly the window channel departures will be studied in detail to look at what systematic errors may be present and require bias correction. The success of the current approach to bias correction is evaluated and found to be problematic. It is shown that these problems are generic to infrared and microwave window channels, but for illustrative purposes the study then focuses on data from the Advanced Microwave Sounder (AMSUA) channel 4. An approach to resolve these problems based on using the mode of the departure statistics is tested in simulation and a real assimilation environment. Finally a summary and conclusions are presented.

2 Diagnosis of first guess departures in AMSUA channel 4

In the case of AMSUA channel 4 (henceforth AC4) the population entering the statistics presented here is controlled by a simple symmetric threshold test of 0.7K applied to the observed minus calculated departure. This aims at selecting only clear sky locations and the same test is currently being used operationally at ECMWF for this channel. This data selection produces a geographic distribution of mean departures shown in figure 1 (averaged over a three month period). The plots instantly show that the AC4 on METOP is biased relative to the same channel on the two NOAA platforms - understood to be a result of differing antenna correction and calibration approaches used by the data provider(Nigel Atkinson pers. com.). However, within each satellite there are clearly geographic variations in mean departure and we will return to the likely origin of these variations.

In addition to the geographic variations the radiance departures have a distinct dependence on instrument scan position. This is shown in figure 2 where a histogram density plot of departures for all data is shown (i.e. without the 0.7K threshold applied). The variation with scan position is significant compared to the overall mean departure and distinct inter-satellite variations can again be seen (also understood to originate from differing antenna correction processing applied to different satellites). While there are known instrumental problems that could give rise to scan dependent biases (related to the fact the diffraction limited microwave beam can interfere with the spacecraft itself) the accuracy of the surface emissivity model may be angle dependent. Another important consideration is that AC4 is not a very clean window channel and increasing absorption with view angle raises the channel weighting function above the surface (reducing its sensitivity to the surface emission).

The time variation of the AC4 departures is shown in figure 3 as another histogram density plot for all observations (i.e. without the 0.7K threshold applied). Only data from NOAA-15 are shown as this satellite provides the longest contiguous time series. The results suggest that whatever the sources of systematic error in AC4 - these combine to produce a mean departure structure that is very stable in time.

A final characteristic that has been investigated is the degree of symmetry displayed by the radiance departures. A hint of asymmetry is evident in the histograms of figures 2 and 3, but is more clearly seen in the spatial and time averaged histogram of figure 4. There is a distinct warm tail to the AC4 departures which could result from a number of physical causes. Modelling of the microwave surface emissivity may contribute to this, but another important source of asymmetric systematic warm departure that must be considered is cloud contamination. At microwave window channel frequencies the sea surface has a very low emissivity and obscuring this dark surface with an absorber such as cloud leads to a warming of the observed brightness temperature and a corresponding positive departure compared to a clear sky calculation (note the opposite signal to cloud contamination in the infrared). If the source of the warm tail is cloud contamination we must question if the population selected by the 0.7K threshold to calculate the bias correction also contains residual cloud contamination and that this may be responsible for some of the variations seen in figure 1.

In summary, it is obvious that there are significant systematic departures in the AC4 departures and some of these undoubtedly require bias correction before the data are used. However, recalling the intended use of AC4 to detect the presence of clouds in other sounding channels - it is also obvious that any bias correction scheme should not remove systematic departures due to cloud.

3 Bias correction of AMSUA channel 4

The ECMWF implementation of Variational Bias Correction scheme (VarBC) is described in Auligne et al 2007 and is based on removing the mean of observed minus calculated radiance departures. The system is adaptive in the sense that the required correction is updated every 12 hour assimilation cycle and can thus account automatically for any sudden shifts in the instrument performance without the need for human intervention.

The correction of the mean departure is constrained in a three ways. Firstly, the VarBC has an explicit inertia term (or weight) that limits the size of the bias adjustment that can be made in any one analysis cycle. This is currently set to be very weak - allowing almost instantaneous changes equal to the change in the mean departure. Secondly, the bias correction has a limited parametric form primarily determining how many spatial degrees of freedom are allowed. While some channels have bias corrections which are allowed to vary significantly around the globe depending on air-mass predictors, AC4 has only a flat global offset and a globally constant scan dependent correction. This choice of highly restricted parametric form is also used for infrared window channels and is intended to limit the ability of the bias correction to correct for cloud contamination. Thirdly the VarBC is constrained by estimating the satellite bias correction inside the main 4D-Var analysis - simultaneously with all other analysis variables (temperature, humidity, wind etc...). Applying a bias correction to a particular satellite instrument that degrades the overall fit of the analysis to other observations in the system will have an associated detrimental cost and should not be allowed. This constraint or anchoring to other data helps avoid applying erroneous bias corrections when the source of the systematic departure is an error in the NWP model fields on which the calculated radiance is based. Unfortunately this constraint is very weak in the case of window channels as the only observations that are sensitive to the surface are satellite data and these are all bias corrected independently of each other (i.e. they cannot anchor the system).

The VarBC bias corrected radiance departures for AC4 are shown in figure 5 averaged for the same period as figure 1. It can be seen that while geographic variations still exists (expected since the correction is restricted to a global flat offset) the inter-satellite bias has been successfully removed and the global bias is now closer to zero. The VarBC also successfully removes most of the scan dependent bias although this is not shown.

Unfortunately, a closer analysis suggests that the bias correction has been very effective at reducing the mean radiance departure to near zero in locations known to be affected by large amounts of cloud cover. Cloud fraction from the ECMWF high resolution model averaged for the same time period shows consistent large amounts of low cloud in exactly the areas where the bias correction has removed most of the mean departure. As was stated in the introduction - this is exactly what we do not want the bias correction to do as it limits the ability of this channel to detect clouds for the other sounding data.

This dragging of the mean bias correction towards the removal of cloud contamination was identified in Auligne and McNally 2007 a feature of any bias correction (adaptive or static) based upon the mean of the departure distribution. The use of the mode of the distribution was proposed - being less affected by outliers than the mean - and the advantage of this is shown very clearly in figure 7. Here the three months of radiance departures for all data are corrected using a static evaluation of the mean (0.4K) and the mode (0.27K).

It can be seen that where the mean based bias correction renders the departures close to zero in cloudy areas, the mode based correction does not. Conversely the mode based correction estimates that the required bias correction is very close to zero in regions known to be free from clouds. This is in itself is a very encouraging result which suggests that the AC4 observations and associated radiative transfer model (including the surface emissivity model) are almost unbiased in clear areas. Moreover, given its intended use for cloud detection, the mode based bias correction is clearly more suitable for AC4.

4 Simulation of adaptive mean and mode based bias correction

Before discussing a practical adaptive implementation of a bias correction based upon the mode we look at some simulations with a toy adaptive model and establish to what extent they are an accurate representation of the behaviour of the full ECMWF VarBC.

If we define radiance departures as **d** as:

$$\mathbf{d} = \mathbf{y} - \mathbf{H}(\mathbf{x}) \tag{1}$$

where **y** is the observation vector, **x** is the NWP model state vector, and $H(\mathbf{x})$ is the observation operator, the VarBC bias estimation is incorporated inside the main analysis cost function as follows:

$$J(\mathbf{x},\beta) = [\mathbf{x}-\mathbf{x_b}]^{\mathbf{T}}\mathbf{B_x}^{-\mathbf{1}}(\mathbf{x}-\mathbf{x_b}) + (\beta-\beta_{\mathbf{b}})^{\mathbf{T}}\mathbf{B}_{\beta}^{-\mathbf{1}}(\beta-\beta_{\mathbf{b}}) + [\mathbf{y_o^i}-\mathbf{H}(\mathbf{x_b})]^{\mathbf{T}}\mathbf{R}^{-\mathbf{1}}[\mathbf{y_o^i}-\mathbf{H}(\mathbf{x_b})] \tag{2}$$

Where the observation operator now includes a bias correction with parametric form based on N state-dependent predictors $p_i(\mathbf{x})$ and coefficients β_i:

$$\mathbf{b} = \mathbf{c_0} + \sum_{\mathbf{i=1}}^{\mathbf{N}} \beta_{\mathbf{i}}\mathbf{p_i}(\mathbf{x}) \tag{3}$$

Figure 8 shows the time evolution of the METOP AC4 bias correction estimated by the real VarBC inside a real assimilation system. The bias correction is initialised at zero and after about 2 weeks of assimilation the flat global offset (black line) converges upon a value of around 0.4K when the aforementioned population selection threshold of 0.7K is applied to departures.

If we ignore the inertia or background constraints and interactions inside the analysis we can simplify the above as a toy model and minimise:

$$J(b) = \frac{1}{2N}\sum_{i=1}^{N}\frac{(d_i - b)^2}{\sigma^2} \tag{4}$$

$$b = \frac{1}{N}\sum_{i=1}^{N} d_i \tag{5}$$

where the first guess departures, $d_i = {y_i}^o - H(x^b)$

This simplified expression represents adaptive updating of a bias correction defined by the mean of a selected population, but obviously ignores the other constraints present in VarBC (particularly the inertia and the influence of other observations).

Using the same initial input population of AC4 departures described by the histogram shown in figure 9 we iteratively calculate and update the bias correction using the simplified expression above (note: just the global flat offset - the toy model does not attempt to estimate the parameters describing the scan dependent part of the bias correction). The time evolution of the estimated correction using a variety of QC thresholds is shown in figure 10. It can be seen that when the same selection threshold of 0.7K is applied the simplified toy model converges on a value very close to that obtained by the real VarBC system. From this we can conclude that the additional constraints inside the full VarBC system do not have a strong impact on the bias estimation for AC4 and that we may use the simplified toy model predict the behaviour of the full VarBC (at a small fraction of the computational cost).

The effect of other selection thresholds is seen in figure 10 to alter the convergence value of the bias estimate - with tighter values converging slower to bias estimates dragged less by the warm tail of cloud affected outliers. While it may be obvious, this is a clear illustration that estimated bias correction can be a strong function of how stringently the departure population is selected.

Returning to the use of the mode for bias correction we can also simulate a formulation of this in the iterative toy model.

Mode estimation:

$$m = \arg\max p(d_i) \tag{6}$$

in practice we minimise a proxy for the mode estimation

$$J(m) = \frac{1}{2N}\sum_{i=1}^{N}\frac{(d_i - b)^2}{\sigma^2} w_i \tag{7}$$

, where w_i is weight ,$w_i = p(d_i)^\gamma$,where γ is a positive number essentially ”sharpening” the histogram about the mode This proxy for the mode is still based upon the mean, but departures with low frequency in the histogram are down-weighted in the calculation.

This iterative mode formulation has been applied to the same population of METOP AC4 departures as before and the time evolution of the bias correction estimate is shown in figure 11. The reduced of sensitivity of the mode to warm tail outliers is evident - with the estimated bias correction and the speed of convergence almost insensitive to the choice of population selection threshold.

Using the iterative mode all estimates converge to near the true mode of the population (0.27K). However, it is interesting to note that the mean based bias estimate with a very tight thresholds of 0.1 or 0.2 also converge around this value confirming the similarity of these to the mode.

5 Real assimilation test of mode based bias correction

Within the time allowed for this particular SAF Visiting Scientist study it has not been possible to code the mode based bias correction inside the full ECMWF VarBC system. Instead we have exploited the equivalence of the very tight threshold mean based estimate of the bias correction and used this to test the impact in a real assimilation system.

The experiments have been set up as follows: A control system CTRL equivalent to the CY32R3 version of ECMWF operational configuration except at T255 (rather than T799) horizontal resolution has been run from 12-01-2008 until 15-08-2006. The experimental system EXPT is identical except that the threshold for AC4 departures to enter the bias correction calculation for AC4 is reduced from 0.7K to 0.2K. This value has been chosen based on the simulation of the previous section which showed that 0.2 produces a bias estimate reasonably close to the mode, but converges significantly faster than the tighter 0.1K threshold. It should be noted that this changed threshold only influences the data that enters the AC4 bias calculation and all other QC thresholds - in particular those which define if the other sounder data - are left unchanged. To speed convergence to the anticipated mode value of just less than 0.3K, the EXPT VarBC is initialised with the same value of the AC4 bias correction as the CTRL (0.4K) and not zero. Despite this, it has been found that there was a spin-up period of several weeks before which the AC4 bias correction had not reached a stable value in the EXPT system. This period has been excluded for the results presented subsequently.

The effect of the changed bias correction in AC4 on the rejection of other AMSUA sounding channels (5 and 6) is shown in figure 12 for the three satellites concerned. The most obvious difference is that much more data is now rejected from the analysis in the EXPT system. However, this extra rejection is in areas known to be strongly influenced by cloud cover and is expected as the mode corrected AC4 now retains cloud signals (triggering rejection) that were previously weakened by the mean based bias correction. Conversely, although the signal is much smaller, the EXPT system used more data in areas known to be free from clouds. This again is expected as the same mean based bias correction was applying an erroneous correction in clear locations causing wrongful rejection of other channels.

Despite what is believed to be an improved rejection of cloudy scenes, the EXPT system does not show any improvements in the bulk analysis data fits for the other AMSUA channels. This is because the VarBC has adapted slightly new bias corrections to fit the new selected population. However, the changes to the data rejections have been found to influence the quality of forecasts made from the two assimilation systems. Figure 13 shows zonal mean cross sections of RMS forecast error differences (EXPT minus CTRL) averaged over more than 60 cases in the period. Blue areas prevail and indicate improved forecasts with the EXPT system - particularly in the areas of the Southern Hemisphere where the largest changes in data usage have occurred.

6 Summary and recommendations

The bias correction of window channels used in the identification of clouds has been studied - using channel 4 on the AMSUA as a test case. An analysis of systematic observed minus calculated departures suggest there are significant inter-satellite, geographic and scan dependent biases which are rather stable in time. However, there is strong evidence to suggest that a large proportion of the geographic variation in systematic departure is due to residual contamination that remains even after the input population has been selected for clear conditions. This cloud contamination produces a warm tail to the departure histogram.

Any bias correction scheme (adaptive or static) must avoid removing these signals due to cloud as this will negate the ability if the window channel to detect clouds for other sounding data. Also, any correction that does remove cloud signals will necessarily do the wrong thing in clear conditions and may lead to the erroneous rejection of data unaffected by clouds.

It has been shown that a bias correction scheme based upon the mean of the departure histogram will necessarily be dragged to some extent by the warm outlying cloud affected departures - and thus partially correct for the cloud signal. An analysis of the current operational ECMWF bias correction of AMSUA channel 4 (based upon the mean) shows clear evidence of this of this problem.

Simulations have been used to demonstrate the difference between a mean based bias correction and one based upon the mode of the departure histogram. It is seen that the latter is unaffected by the outlying cloudy departures and returns a more appropriate estimate of the observations bias in clear sky conditions. A proxy formulation to use the mode in the ECMWF VarBC is presented, but this has not been tested yet. Instead an approximation of the mode based on a very stringently selected mean population (the simulations suggesting this is a good approximation - although a rather slowly converging one) has been tested in a real assimilation environment.

Results from the real assimilation test show the improved window channel bias correction performing very well - causing more sounding data to be rejected in cloudy areas and more sounding data to be used in clear sky areas. The better selection of sounding data produces improved forecasts in the short to medium range. It should be noted how sensitive the assimilation and forecasting system is to the bias correction of AMSUA channel 4 - the mean and mode based bias corrections only differing by about 0.1K (0.4K to 0.3K).

While the study presented here used AMSUA channel 4 as a test case the issues are rather general. Results not shown show a similar problem for infrared data from HIRS channel 8 - with a cold tail of cloud affected departures dragging the mean in the toy model simulations (indeed the affect of cloud being much stronger and the problem more acute than for the microwave data). The reason this channel is not used in this study is that the current ECMWF clear sky data selection is more complex than a simple threshold applied to the window channel departure - and in this sense the toy model is not such an accurate proxy for the real assimilation system.

It is pertinent to ask if the problems discussed in this study could be avoided if clouds could be identified independently of a bias corrected departure threshold test. To some extent the answer is yes and an obvious candidate would be the use of coincident imager data to determine if a sounder footprint is free from clouds. It is suggested that this approach be pursued. However, there will inevitably be a tolerance or threshold below which cloud cannot be identified even with imager data and if the signal leaks into the input population we may still require an approach to stabilize the bias correction calculation against outliers.

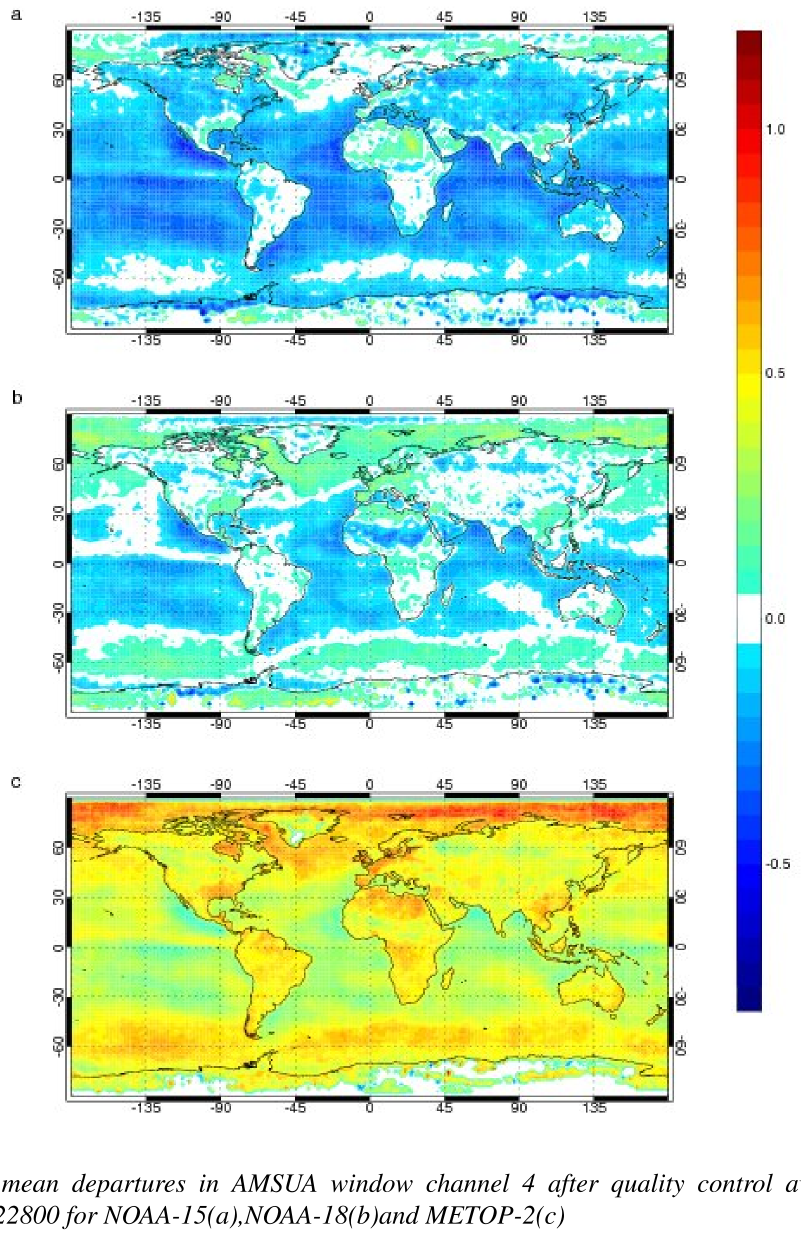

Figure 1: map of mean departures in AMSUA window channel 4 after quality control averaged over the period 2007120100-2008022800 for NOAA-15(a),NOAA-18(b)and METOP-2(c)

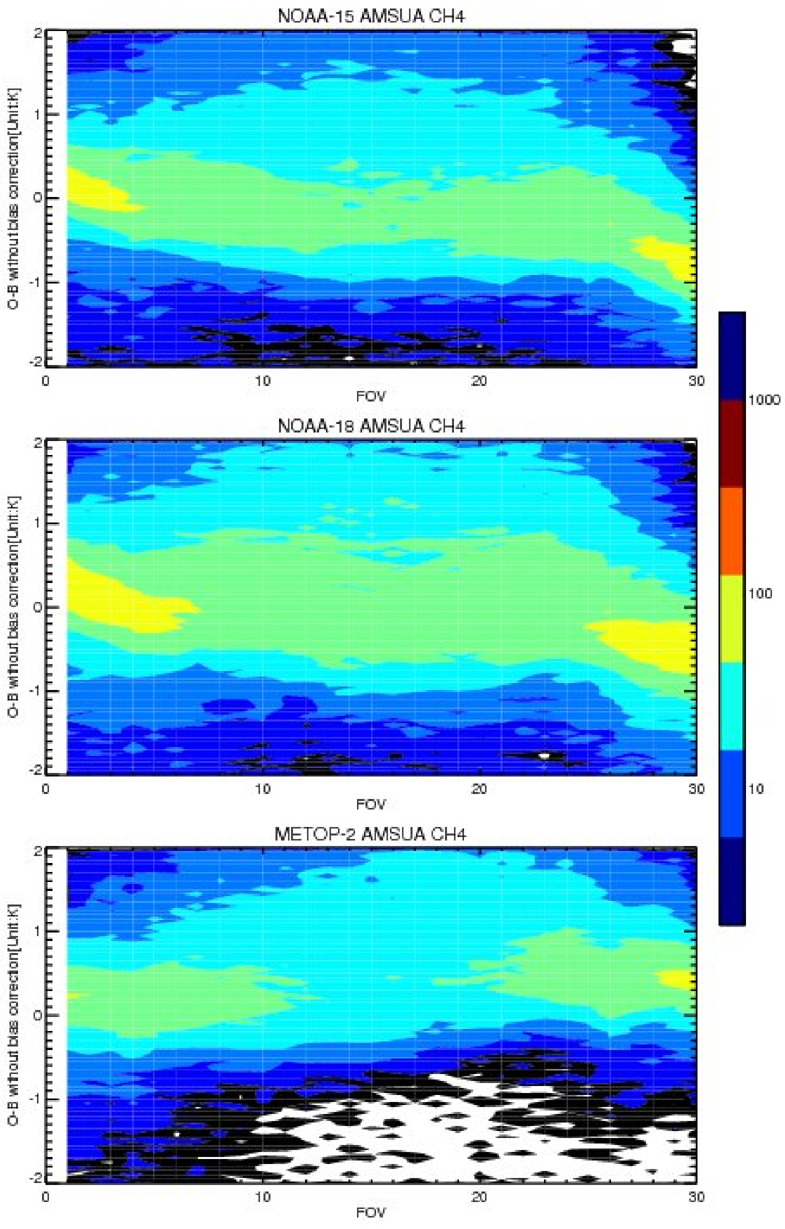

Figure 2: scan dependence of the histogram of departures (O-B) before quality control in AMSUA window channel 4 averaged over the period 20071212 .

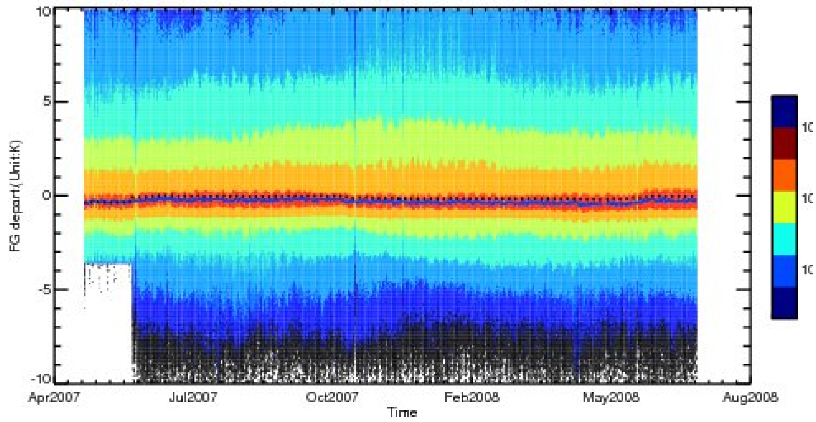

Figure 3: time evolution of the histogram of departures (O-B) before quality control in AMSUA window channel 4 during 2007 and 2008 for NOAA-15

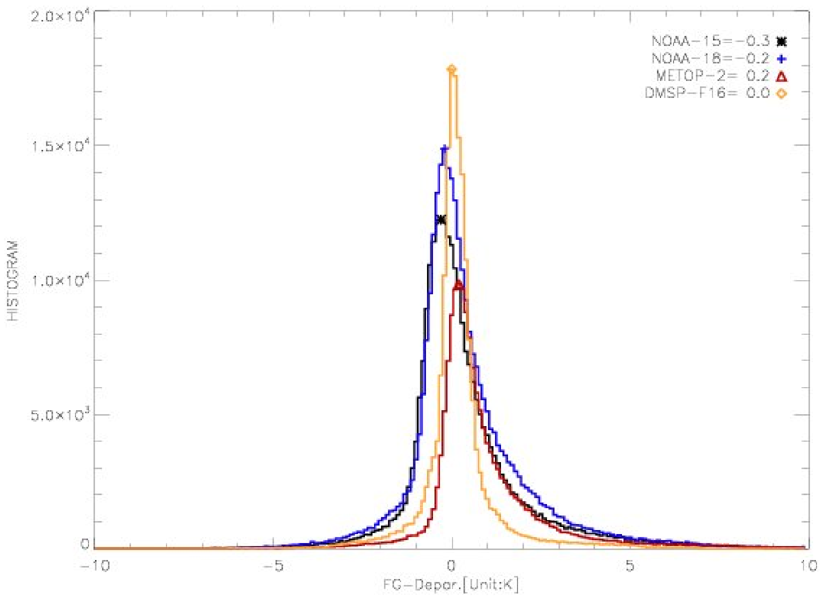

Figure 4: histogram of departures (O-B) before quality control in AMSUA window channel 4 on 2007120100 for NOAA-15, NOAA-18, METOP-2 and the equivalent frequency channel on F16 SSM/IS

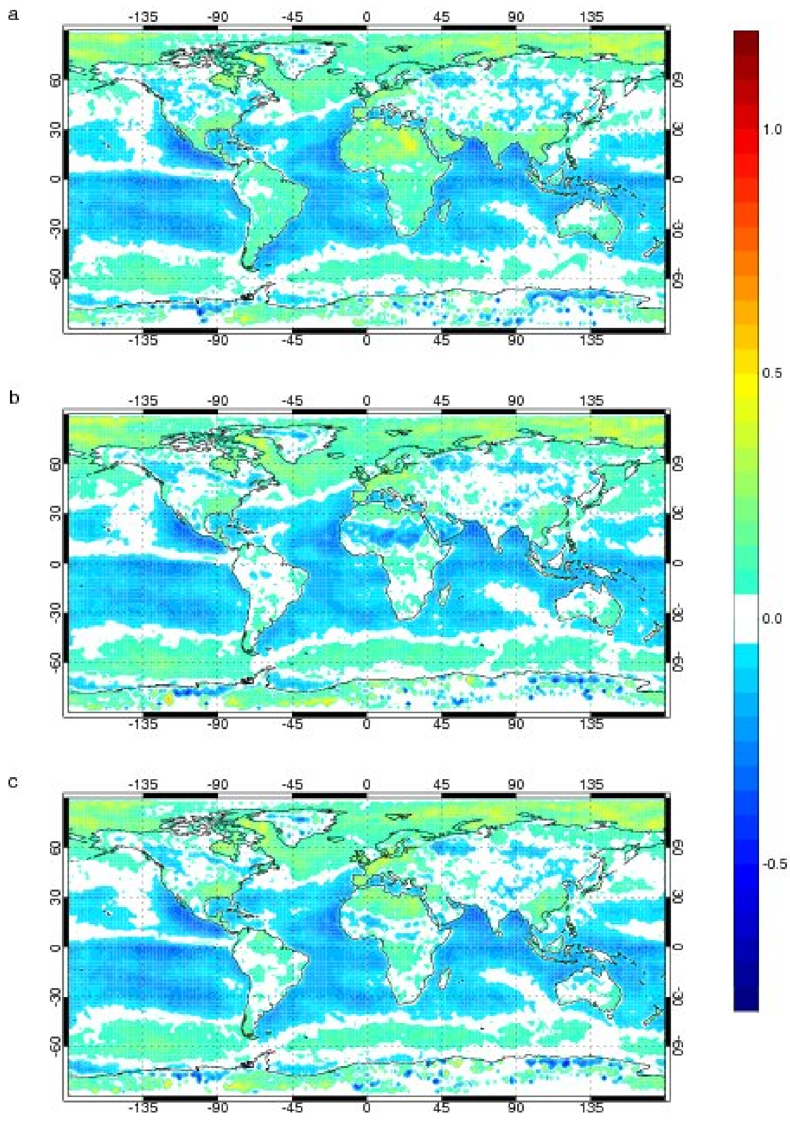

Figure 5: map of bias corrected mean departures in AMSUA window channel 4 after quality control averaged over the period 2007120100-2008022800 for NOAA-15(a),NOAA-18(b)and METOP-2(c)

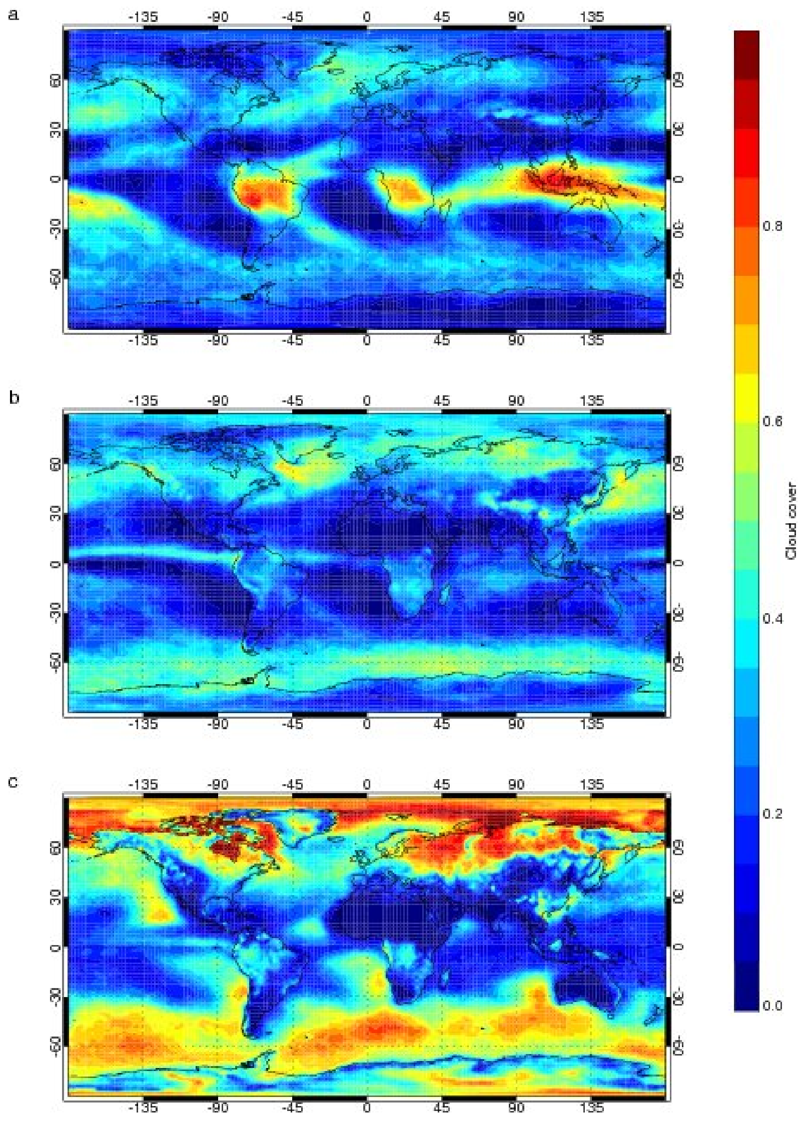

Figure 6: map mean cloud cover estimated by the ECMWF high resolution model averaged over the period 2007120100-2008022800 for (a) high, (b) medium and (c) low cloud conditions

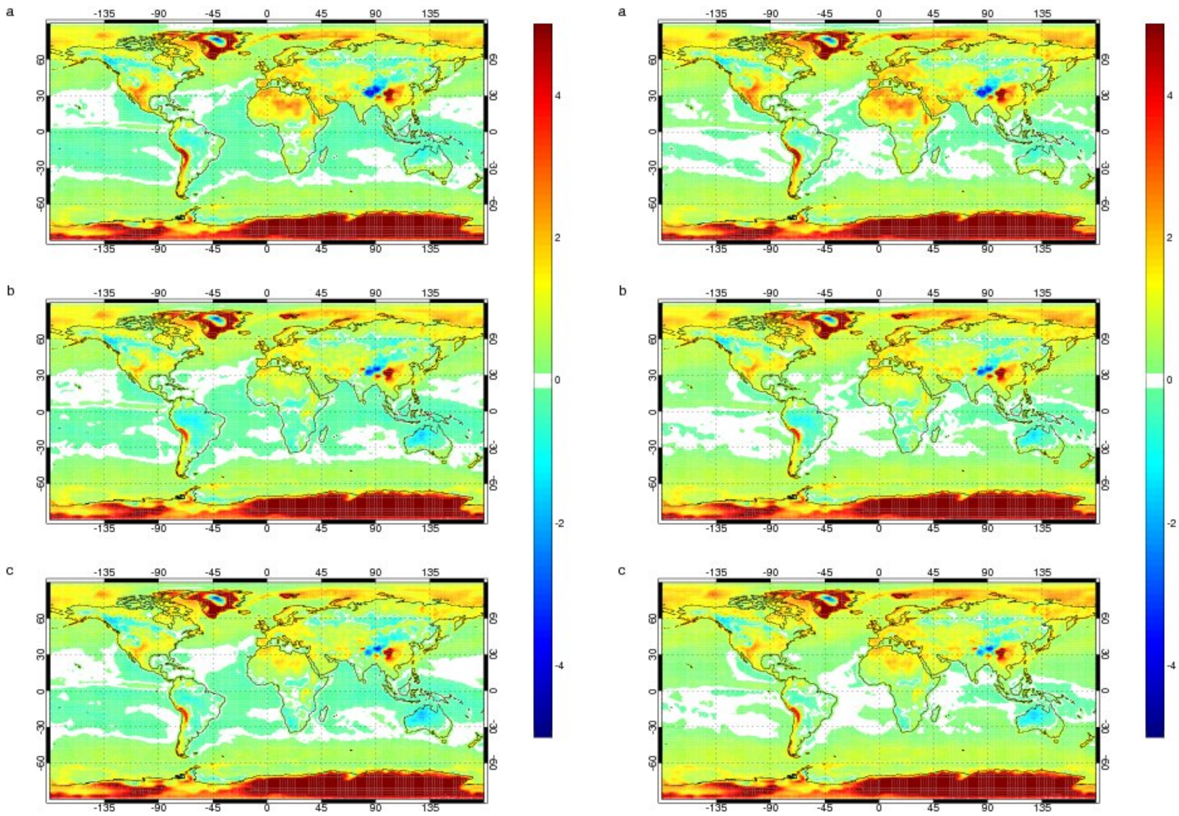

Figure 7: map of bias corrected mean departures in AMSUA window channel 4 after quality control averaged over the period 2007120100-2008022800 for NOAA-15(a),NOAA-18(b)and METOP-2(c) Left pannels use the mean and right panels use the mode for correction

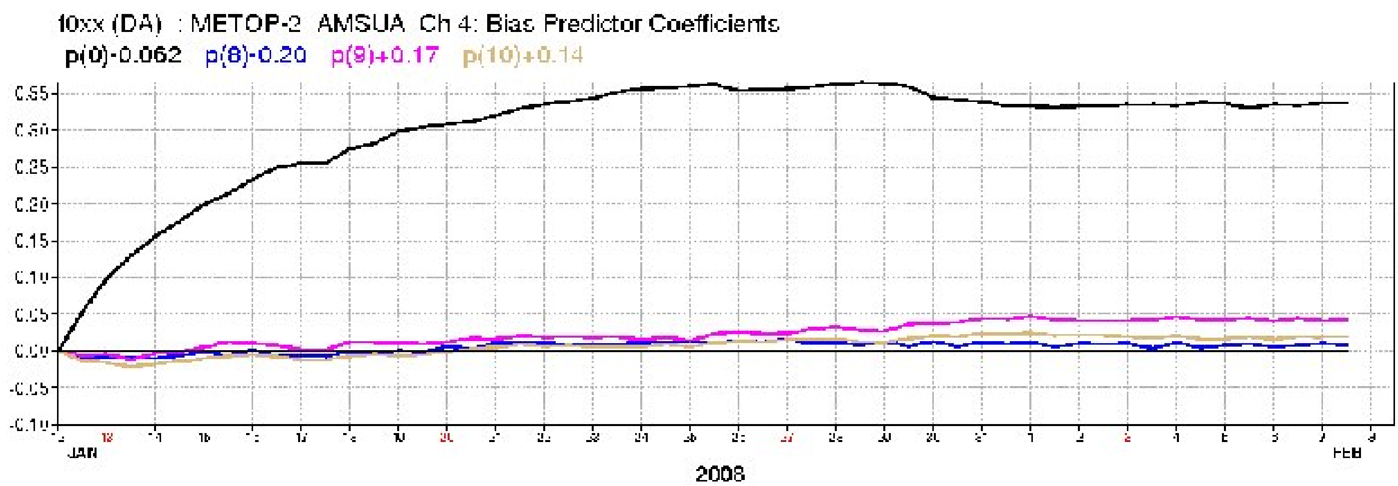

Figure 8: Time evolution of standard VARBC adaptive bias correction inside the 4DVAR analysis. The black line showing the global flat offset of the bias correction, the other colours relate to the coefficients that describe the scan dependent component of the bias correction

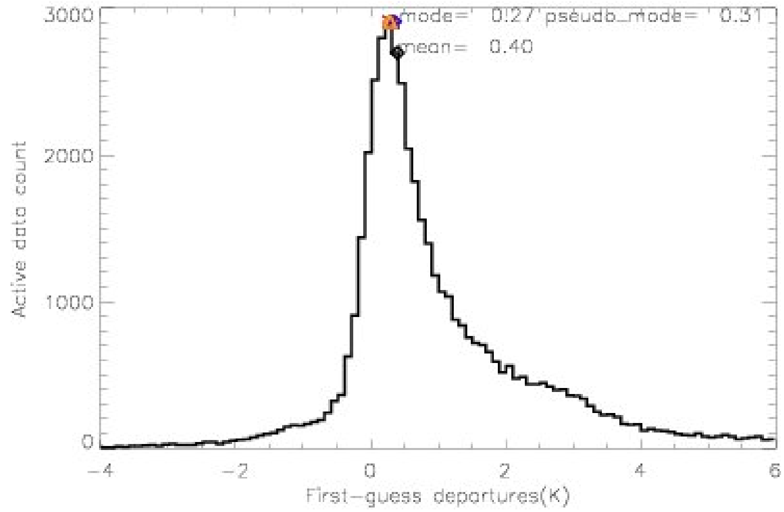

Figure 9: Histogram of uncorrected (O-B) departures in METOP AMSUA channel 4 forming the input to the toy model simulation

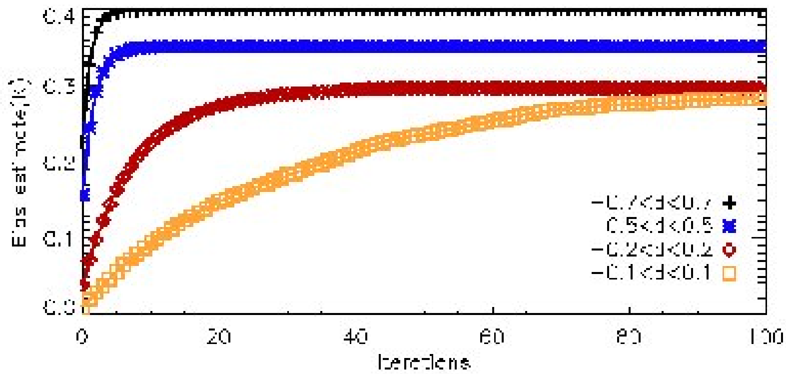

Figure 10: Time evolution of mean based adaptive bias correction simulated by the toy model for different QC thresholds

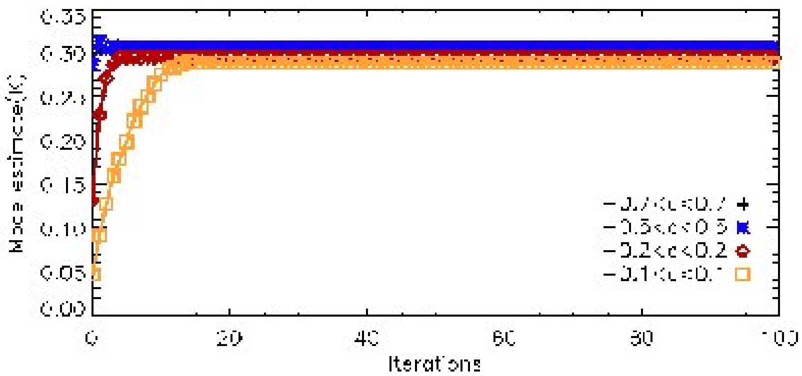

Figure 11: Time evolution of mode based adaptive bias correction simulated by the toy model for different QC thresholds

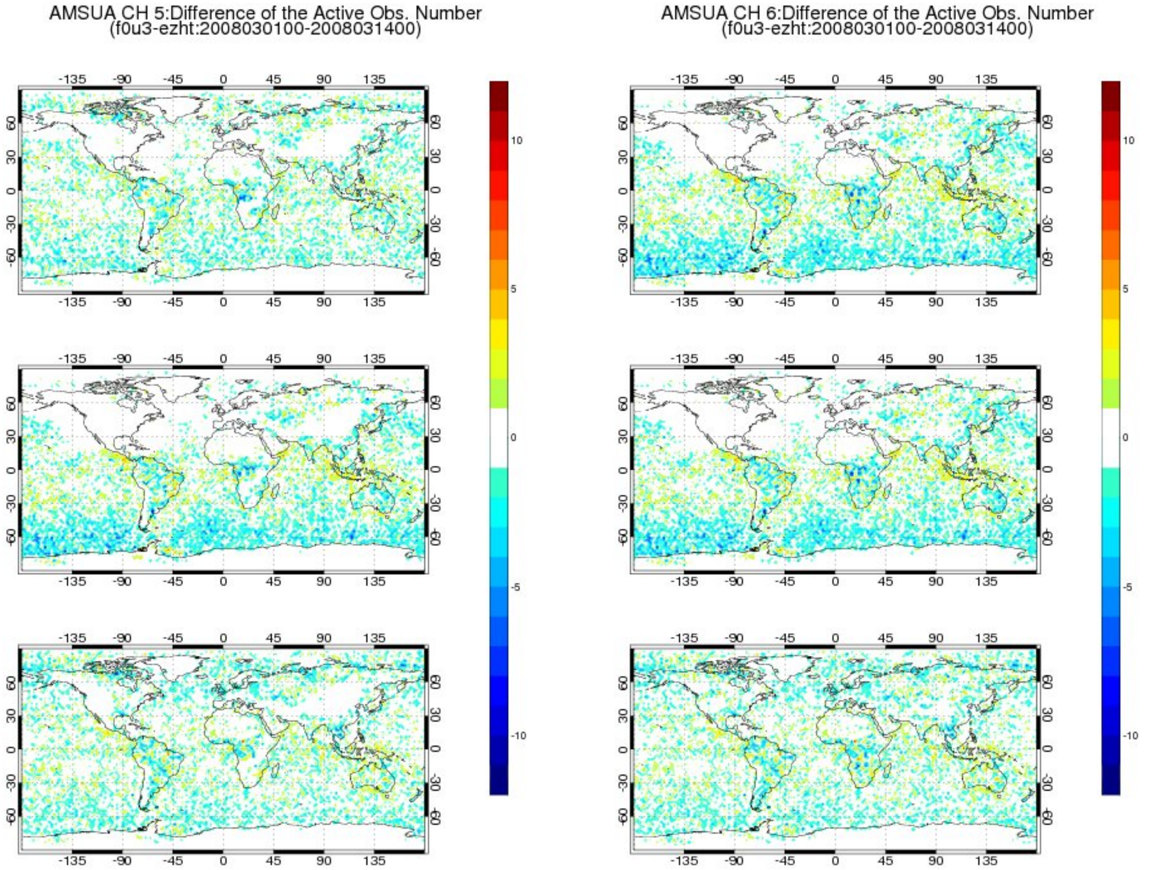

Figure 12: map of changes in AMSUA channels 5 and 6 usage experiment minus control averaged over the period 2007120100-2008022800 for NOAA-15(a),NOAA-18(b)and METOP-2(c) Blue indicates areas where the experiment uses less data, Red where it uses more

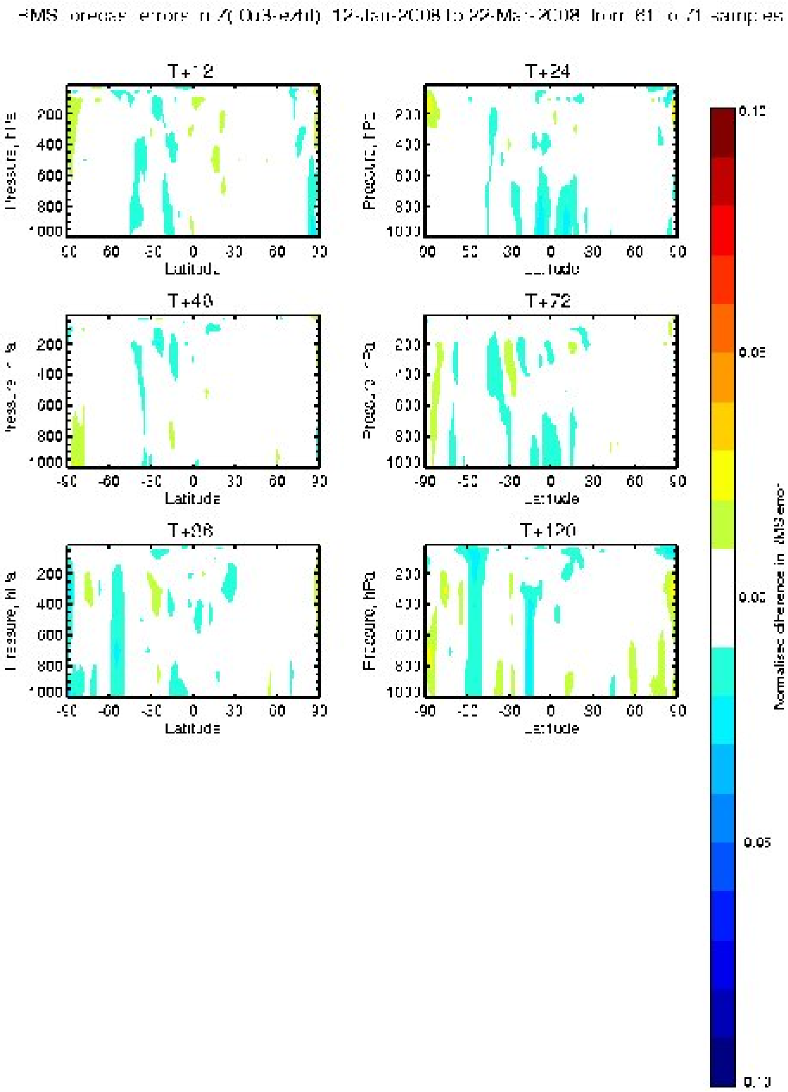

Figure 13: Zonal mean percentage changes in RMS forecast error averaged over the period 2007120100-2008022800 for various ranges.Blue indicates areas where the forecast errors are smaller with the revised channel 4 QC, Red where the errors are larger

References

Auligne, T. and A.P.McNally (2007). Interaction between bias correction and quality control. *Quart. J. Roy. Meteorol. Soc. 133*, 643–653.