Adaptive bias correction of satellite data at ECMWF

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1. Introduction

Several operational Numerical Weather Prediction (NWP) centres currently rely on variational analysis systems to define their initial state. Radiances measured by satellite sounding instruments provide one of the major sources of information. Variational assimilation requires that the observations and the model have normal and unbiased distributions. Nevertheless, departures between the observations and the equivalent from the NWP model first-guess (first-guess departures) show systematic errors.

The aim of bias correction is to remove the systematic errors corresponding to the observation, the radiative transfer and pre-processing steps. These errors are called observation bias though they rarely correspond to a real statistical bias. Different bias models have been developed to reproduce the shape and magnitude of the observation bias. Whatever the bias model, its parameters (or coefficients) are usually estimated intermittently (*e.g.* if a new radiative transfer model is introduced) and then held static for long periods. There are scientific and technical incentives to consider an adaptive bias correction, *i.e.* a correction with a bias model updated at each assimilation cycle.

In an adaptive context the bias parameters can be updated independently (Offline scheme) or they can be controlled (as any meteorological variable) by the main analysis in a Variational Bias Correction scheme (VarBC). Initial testing of VarBC compared to the static bias correction has shown a number of positive benefits as reported in Dee (2004).

The purpose of this study is to understand some processes associated with adaptive bias correction independently from the bias model. In Section 2, we define three modes of implementation with different adaptivity for the same bias model. In Section 3, we use artificial perturbations in the model fields and in the observations to study the ability of discriminating the sources of bias. Section 4 demonstrates that there are interactions between bias correction and data quality control. Section 5 presents the conclusions from the current work.

2. Bias correction adaptivity

2.1. Bias model

The bias model currently used operationally at ECMWF is instrument dependent. For AIRS and AMSUA, the model from Watts (2004) is applied. Assuming that most of the observation bias is due to a radiative transfer error, a corrective absorption coefficient γ is introduced inside the radiative transfer model. An offset δ is used to correct any residual calibration error. For each channel a duet $[\gamma,\delta]$ is adjusted to minimize the first-guess departures.

For other instruments (HIRS, AMSUB, SSMI, GEOS) the bias model follows Harris & Kelly (2001). It consists in a linear regression based on a few predictors from the NWP model as described in Eyre (1992). The coefficients corresponding to these predictors and an offset are adjusted to reduce the analysis departures near the radiosondes. The predictors that are used are summarized in Table 1.

Instruments	Predictors
HIRS	1000-300 hPa thickness 200-50 hPa thickness
AMSUB	1000-300 hPa thickness 200-50 hPa thickness
SSMI	Surface wind speed Skin temperature Total column water vapour
GEOS	1000-300 hPa thickness 200-50 hPa thickness Total column water

Table 1: Predictors used in Harris & Kelly (2001) bias correction for different satellite instruments.

A scan bias correction is also applied for all instruments aboard polar orbiting satellites. For each field of view a constant adjustment is calculated with respect to the centre of the swath.

2.2. Adaptive Bias Correction

A bias correction that is automatically calculated at each assimilation cycle is technically appealing for NWP centres. With no need for manual intervention, adaptive schemes have the potential ability to correct an observation drift or failure before it causes some damage on the meteorological analysis. The introduction of new instruments becomes easier if the bias correction is embedded inside the NWP system. This is particularly important for long-term experiments involving many different satellites like the ERA-40 reanalysis experiment (Uppala, 2001).

Static bias corrections usually involve a learning process where the data is carefully chosen in order to avoid considering model bias. Assuming that the learning dataset is sufficient, the calculated bias parameters are then assumed to apply statically over time. On the contrary adaptive bias corrections estimate the bias over the dataset of the current assimilation. The learning dataset also being the set where the bias correction is applied, any potential discrepancy is removed. On the other hand, more flexibility is given to the bias model to correct for systematic NWP model error. In theory it is the role of the bias model to keep the information within the observations that can correct model errors. In practise it is very difficult to disentangle systematic model error from observation bias.

2.3. Variational Bias Correction

The Variational Bias Correction (VarBC) is an adaptive bias correction system, which updates the bias parameters inside the NWP assimilation system. It has been implemented at NCEP by Derber and Wu (1998) and more recently at ECMWF by Dee (2004). The ECMWF 4DVar assimilation scheme has been modified to include the regression coefficients of the bias correction (so-called bias parameters) in the analysis control variable. This can be interpreted as an extension of the observation operators, which become a function of the NWP model state and the bias parameters. In order to avoid fitting in terms of bias any local feature of the data (*e.g.* cloud contamination) a background term is introduced. This constraint to the first-guess of the bias parameters can be considered as an inertia term.

The bias parameters provide extra degrees of freedom for the variational assimilation to converge toward the solution. The main advantage of this formulation is that the bias and the model state are considered together to determine the best solution for the analysis. If the introduction of new parameters in the control variable does not create local minima in the 4DVar cost function (which should not be the case with a linear bias model, a quadratic formulation for the background term of the associated cost function and an adequate preconditioning) these extra degrees of freedom can potentially be used by the variational assimilation system to better approximate the BLUE (Best Linear Unbiased Estimate). Studies of the reduction in the norm of the gradient of the cost function for the 4DVar system with and without VarBC (not shown) did not indicate any significant influence of VarBC on the convergence.

There is an obvious computational overhead to having VarBC inside the minimisation (particularly as it is inside the critical path). This overhead might be manageable for a limited number of data types with a simple bias model (*i.e.* involving only a few parameters), but more complicated bias models will increase the expense. In addition, data needed for quality control but not assimilated must also be provided to the minimisation to be bias corrected (thus increasing the data volume in the analysis). The introduction of new parameters in the control variable also presents new complications for the pre-conditioning of the analysis system (Dee, 2004) and the specification of background errors. However, adaptive bias correction can be performed outside the main analysis (or offline) by simply computing new estimates of the bias parameters before or indeed after the main analysis without any of the previously mentioned complications. Thus we have to justify scientifically why we would wish to perform adaptive bias correction inside the analysis.

2.4. Implementations for bias correction

We define the Offline scheme as an adaptive bias correction scheme identical in every point to VarBC except that the update of the bias parameters is calculated outside the meteorological analysis. For each cycle, prior to the assimilation, an extra minimisation is performed with a control variable composed of the bias parameters only. The corresponding bias that results from this calculation is then applied without evolving during the following analysis.

Three experiments are set with the same bias model described in Section 2.1. The implementation of the bias correction is respectively Static (as opposed to adaptive), Offline and VarBC. The initial value of the bias is the same for the three experiments. For the two adaptive schemes (Offline and VarBC), the scan correction and the γ radiative transfer absorption correction are kept constant; all the other bias parameters are updated at each analysis cycle.

3. Discrimination in the sources of bias

3.1. Mean bias correction

The mean bias corrections over a 5-day period are compared to their common initial values in Fig 1. The two adaptive schemes show an evolution in the bias estimates. For most of the channels, VarBC gives biases comparable to the static values, except for AIRS window channels with a negative evolution in the bias which is significant with regard to the corresponding observation error statistics. On the other hand, Offline diverges quite significantly from the initial bias for several channels (namely AMSU-A mesospheric channel 14, HIRS channel 12 and AIRS 7 micron channels). These channels have a large systematic forcing in the assimilation system (as measured by the analysis minus background radiance departures shown in Fig 2) most likely due to known systematic model errors. The Offline scheme removes the signal from the observations by bias correcting the data, while it is mostly ignored by VarBC. This demonstrates the ability of the inline system to distinguish (at least partially) between different sources of systematic error.

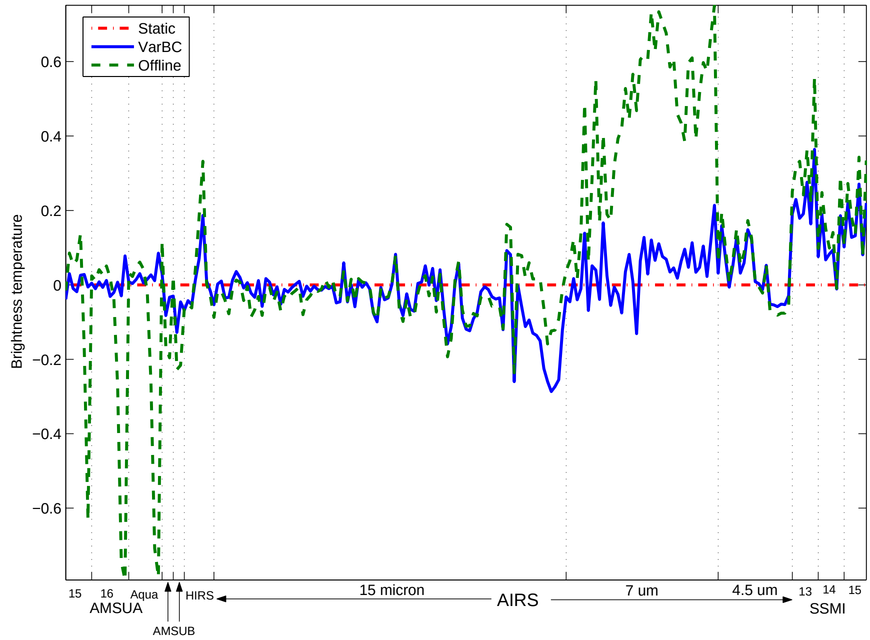

Figure 1: Mean bias correction minus the initial bias value for a 5-day period starting from 2005/03/01 at 00UTC. The red, blue and green curves correspond to the Static, Offline and VarBC experiments respectively. The abscise represents different satellite instruments and channels.

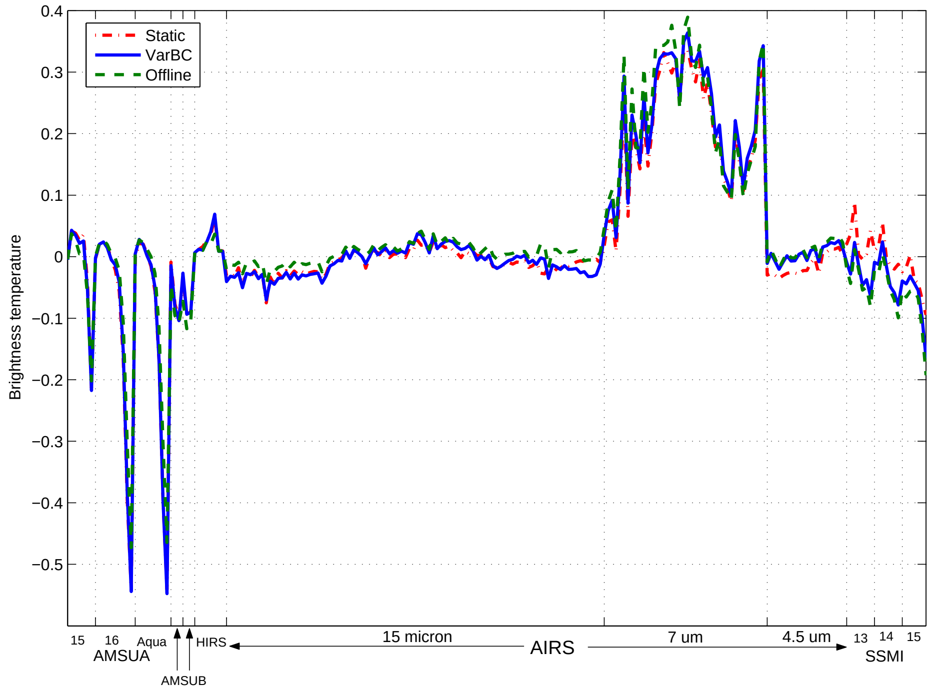

Figure 2: Idem to Figure 1 representing the mean analysis minus first-guess increments.

3.2. Responses to artificial perturbations

The characteristics of the adaptive bias corrections have been further explored in a more hypothetical environment where model and observation biases are simulated by artificial perturbations.

(i) *NWP model artificial perturbation*. A sudden shift is introduced in the NWP model temperature. All model levels from 1 to 25 (i.e. over about 100 hPa) are perturbed by -1K prior to all observation operators, resulting in a shift of the first-guess departures. Fig 3 shows the response of the three experiments using static, VarBC and Offline bias corrections. The Offline scheme treats each instrument independently from the meteorological part of the control variable and thus we expect it to adjust for the perturbation with a change to the bias correction (even though in this case it is the model which is biased). Indeed we see a very significant shift in the bias for the channels peaking above 100 hPa. The maximum shift is less than 1K because of the constraining influence of the background term and Quality Control (QC). In comparison, VarBC shows a much smaller adjustment of the bias, due to the additional constraint imposed by other observations (e.g. radiosondes) inside the minimisation. Most of the model bias is then (correctly) adjusted by the 4DVar system through analysis temperature increments (and not a bias correction of the satellite data). Fig 4 shows the analysis differences (with respect to their own unperturbed control) with the three bias corrections. The Static and VarBC experiments show important analysis differences above level 25 correcting the perturbation in the model at these levels, while the Offline experiment results in a very small correction in the analysis temperature.

In summary, for the model perturbation, the VarBC scheme shows considerable skill to distinguish between a model error and observation biases. It does this by using other (non adaptively bias corrected) observations (in this case radiosondes) to decide upon the likely source of the bias. However, this ability (obviously) depends upon the availability of other observations not being bias corrected with VarBC (or indeed adaptively in any way).

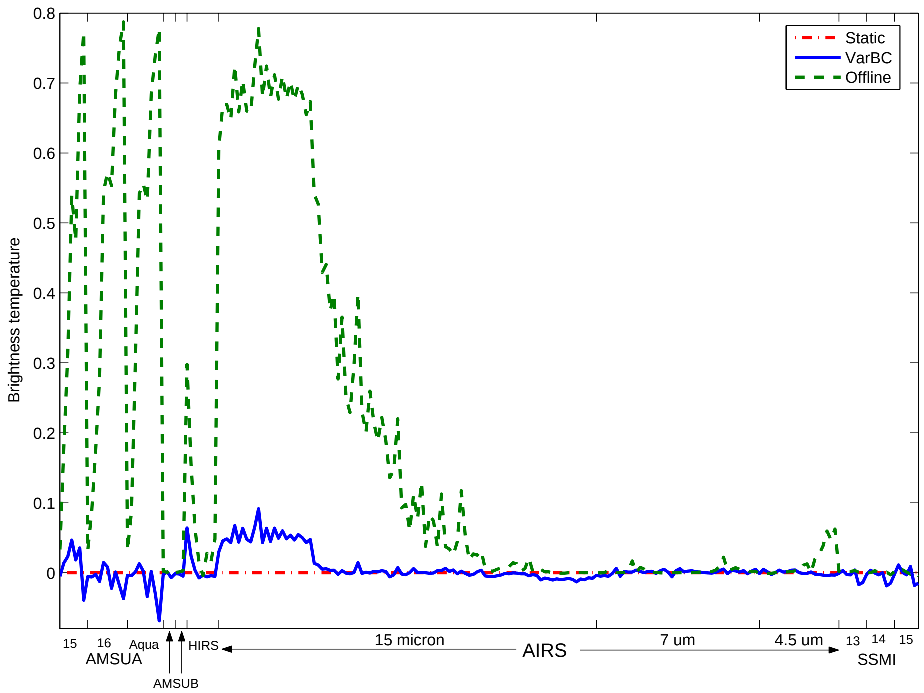

Figure 3: Bias correction differences between experiments with and without the model perturbation. The red, green and blue curves correspond to experiment with Static, Offline and VarBC respectively. The abscise represents different satellite data types.

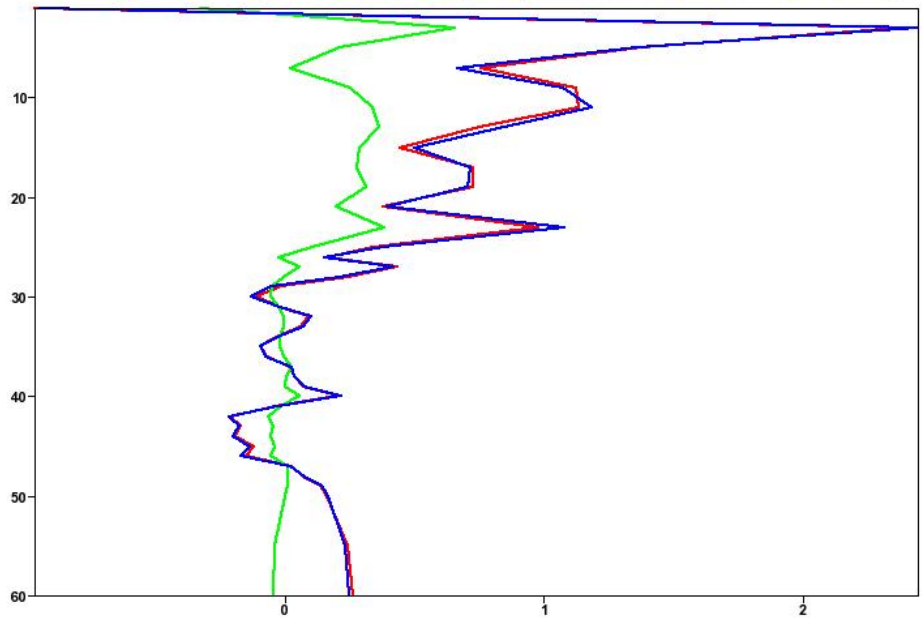

Figure 4: Mean analysis response to a 1K model perturbation above 100 hPa (NWP model level 25) as a function of the NWP model vertical levels. The red, green and blue curves correspond to experiment with Static, Offline and VarBC respectively. The abscise represents the analysis response in Kelvin.

(ii) *Instrument artificial perturbation*. We introduce an artificial -1 K shift in the radiances from AMSU-A channel 6 (with a weighting function peaking about 400 hPa) aboard NOAA16 platform for the three experiments with different bias correction implementations. This drift can be simulated by adding 1 K to the initial bias since the analysis only considers the bias corrected first-guess departures. This shift is very large compared to the observations error specified for this channel (0.2K) such that the background constraint would restrict the size of the bias adjustment in a single cycle. Therefore the background constraint on the bias parameters has been removed. Fig 5 shows the analysis differences for the perturbed relative to unperturbed experiments.

These erroneous temperature adjustments influence the fit of the analysis to other data (e.g. radiosondes) and the bias correction of other channels in the system. After 5 -7 days VarBC has fully corrected the induced perturbation, but the analysis is irreparably damaged compared to the control.

With such a simple and large perturbation we may wonder why VarBC does not manage to instantly correct the shift in AMSUA-6. The remaining inertia (even when the background constraint is removed) can be explained by the influence of the quality control. The induced perturbation is sufficiently large that the first-guess check significantly reduces the amount of active data in the system (which would otherwise have helped to evolve the bias correction).

In summary, for the case of the observation bias, VarBC is slightly inferior with respect to the offline system as the latter benefits from the a priori knowledge that the model is correct (and thus any departure signal goes exclusively to changing the bias correction). However, it should be noted that in this case the offline system is run before that meteorological analysis. If it had been run after the analysis the perturbed (bad) data would indeed have damaged the analysis. VarBC is not obviously better than the static system, but this is only due to the fact that the particular perturbation chosen was so large that in the static system most of the data was rejected by quality control. More generally (and with smaller observation bias shifts) the VarBC is expected to be superior to the static system.

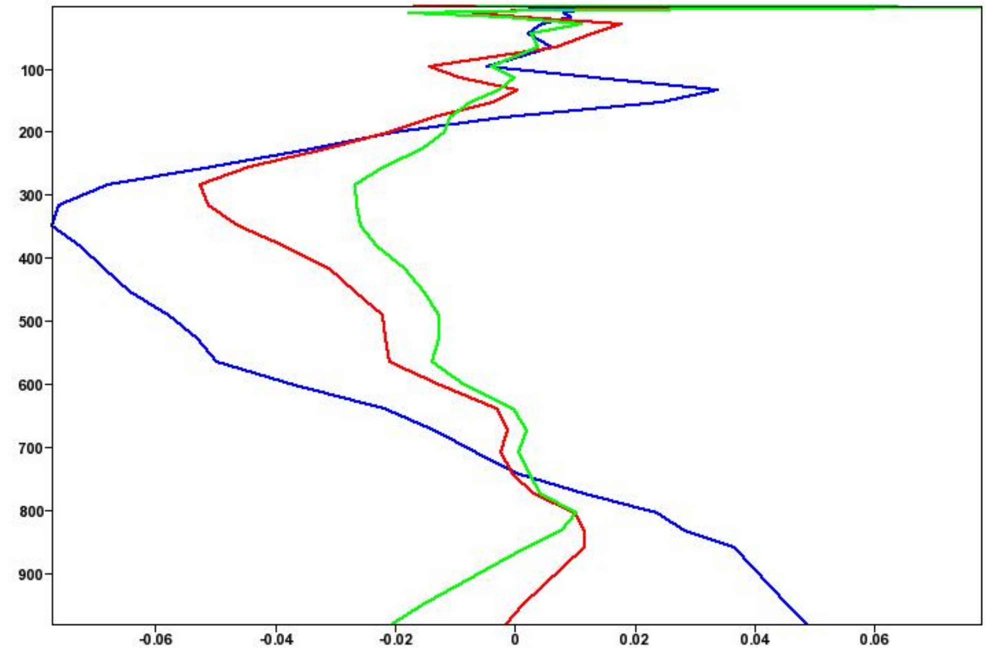

Figure 5: Mean analysis response to a 1K perturbation for NOAA16 AMSUA channel 6 for different pressure levels. The red, green and blue curves correspond to experiment with Static, Offline and VarBC respectively. The abscise represents the analysis response in Kelvin.

3.3. Separation between sources of bias

The role of discriminating in the departures what belongs to observation bias from what corresponds to model error is usually assigned to the bias model. This is usually achieved by assumptions on the shape of the bias that are either physical (*e.g.* the main source of bias is an error in the radiative transfer model) or statistical (*e.g.* careful selection of the predictors for a regression). A static implementation obviously equally forbids the scheme to adapt to instrument drifts or evolution in the model error. We focus on the ability of adaptive schemes (Offline or VarBC) to further separate between sources of bias. In this study, we have intentionally chosen very simple model and observation artificial perturbations that can be fully reproduced by the bias model (as described in Section 2.1).

The core information for any observation versus model bias discrimination is the redundancy between different types of observations. Conceptually, if several instruments indicate the same bias versus the model, we want the analysis to update the model itself (and not bias correct the observations). In the case of a single instrument disagreeing with the others, we probably wish to update the bias correction for that observation. When calculating the bias parameters and the meteorological variables in the same analysis (as performed in the VarBC scheme), there is a potential ability to discriminate in the departures what belongs to observation bias from what corresponds to model error through the background error statistics. Indeed the increments are determined within the 4DVar according to the relative importance of the background error covariance matrices. The system should potentially be able to decide, for each type of data, whether it is more relevant to adjust the bias or to modify the model state. In practise, it is very difficult to determine the exact background error statistics given the different number of data measuring the same model variable for a fixed location. The role of the background term in adaptive bias corrections is reduced to an inertia constraint in the response to a change in the departures. This is a simple way to consider that systematic (*i.e.* large time scale) errors in the departures can come from the observations while random (*i.e.* small time scale) errors are attributed to the model.

The Offline scheme introduces an artificial discrimination in the sources of error. Indeed, performing a bias calculation prior to the meteorological analysis tends to explain any departure signal through observation bias. This corresponds to the assumption that the NWP model is correct. Similarly, calculating the bias correction after the main analysis is equivalent to assuming that the observations are correct.

In the case of VarBC correcting the bias of only a part of the total available observations (for example satellite data), the data that are not VarBC related (for example radiosonde, aircraft or surface data) still contribute to the cost function through the meteorological part of the control variable. Thus they act as a constraint over the update of the control variable and especially VarBC parameters. Values for the bias parameters that would imply a strong degradation in the fit to these extra data become prohibited. If a model error is measured by data corrected through VarBC and also by other data without adaptive bias correction, it is likely that the optimal solution will modify the meteorological part of the control variable rather than the VarBC parameters.

4. Interaction between bias correction and quality control

4.1. Feedback mechanism

An adaptive bias correction scheme emphasis certain problems already present in a hidden manner in a static scheme. This is particularly true for the interaction between bias correction and quality control (QC). The data has to pass a quality control in order to detect failing observations and remove them prior to the analysis. In order to estimate biases we require a population of quality controlled observations representative of those we ultimately intend to assimilate. Most QC acts upon observed minus first guess departures (so called first-guess checks) to discriminate between good and bad data. However, to be useful, these departures themselves have to be bias corrected before the check. There is thus a fundamental link between bias correction and QC. This is the case in a static bias correction scheme. A different choice of QC threshold will result in a different estimate of the static bias. However, in an adaptive bias correction there is a potential feedback mechanism as mentioned in Eyre (1992). The value of the bias correction influences the population that successfully passes the QC which, in turn, will be used to define the new bias estimate. This interaction happens from one assimilation cycle to the next without being constrained. Thus any analysis scheme, whatever its performance, can be substantially degraded by this feedback mechanism.

To illustrate this problem we use observations from AMSU-A and the Atmospheric Infra-Red Sounder (AIRS) (Aumann, 2003) which are assimilated operationally or pre-operationally in several NWP centres (Auligne, 2003) (Collard, 2003) (McNally et al., 2005). While providing relatively few poor-quality data, this advanced sensor, like any other satellite infra-red instrument, is sensitive to clouds.

(i) *Influence of residual outliers.* This feedback can be demonstrated with a very simple model. We consider the population of first-guess departures for AMSU-A window channel 4on) provided to the ECMWF assimilation system over a particular 12-hour time window. The histogram (Fig 6) exhibits the well-known “warm tail” corresponding to cloud contamination for satellite micro-wave observations. For the sake of simplicity the bias model is hereafter limited to a global value. An adaptive bias correction scheme is simulated by calculating the bias iteratively as the mean value of the quality controlled departures. The QC is a simple box-car window applied to the bias corrected departures centred on zero with a pre-defined width. The initial bias estimate is set to 0K and different QC widths are investigated between -2K and +2K. After a number of iterations this process converges (Fig 7). Both the final estimate of the bias and the speed of convergence depend strongly on the chosen width of the QC window. The more stringent the QC, the more inertia the system has and the bias evolution is slower.

While this is a simple model - we neglect here the impact of the assimilation of the channel on the analysis - it does highlight the potential feedback between QC and bias correction. The main effect overlooked is that in a real system the assimilation of the data being bias corrected could cause the analysis itself to drift, which in turn affects the next update of the bias correction.

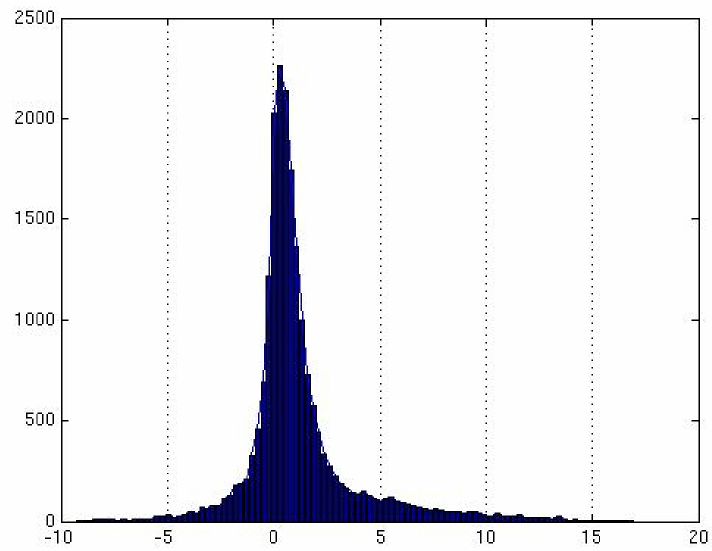

Figure 6: NOAA18 AMSUA window channel 4 first-guess departures histogram.

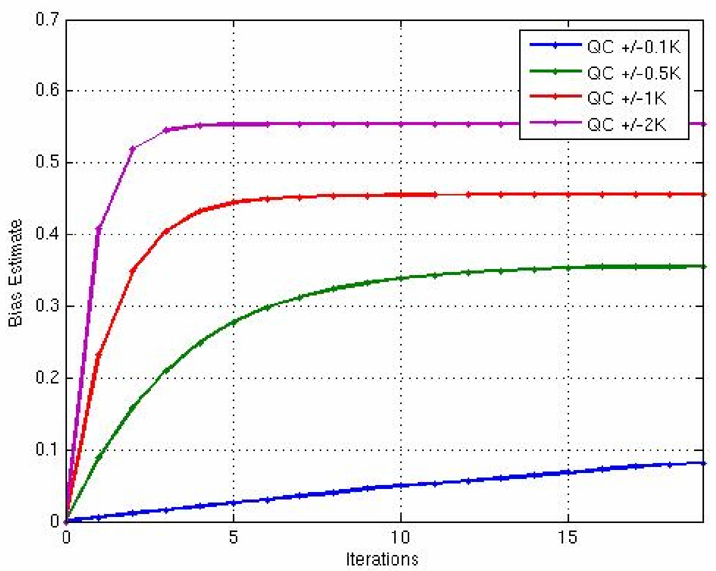

Figure 7: Bias estimation as a function of the number of iterations of the adaptive scheme for different quality control (QC) window widths.

(ii) Influence of biased quality control. Even without assimilating any bad quality or contaminated data, there is still a potential feedback mechanism between QC and adaptive bias correction. We take the example of cloud detection which can be considered as a special quality control focusing on the elimination of cloud contaminated data. Many schemes are simple first-guess checks applied to cloud sensitive window channels, and thus relate to the previous example. The cloud detection scheme used operationally at ECMWF for AIRS is more complicated and is described in details in McNally & Watts (2003). The scheme considers the first-guess departures for AIRS channels within different bands, ranked by the altitude of the channels weighting functions. A pattern-recognition algorithm is applied to define the characteristics of the cloud and reject the cloud contaminated channels. Within the water-vapour (7 micron) spectral band, the AIRS weighting functions are broader making the ranking less accurate. Significant NWP model errors are also observed with a signature very similar to a cloud contamination. Therefore most of the potentially cloudy observations are currently rejected. Fig 8 shows the total and active populations for AIRS mid-tropospheric water-vapor channel 1545 (7.23 micron). Most of the observations with a negative first-guess departure are withdrawn prior to the assimilation. This conservative approach induces a bias discrepancy between the active population and the actual clear population.

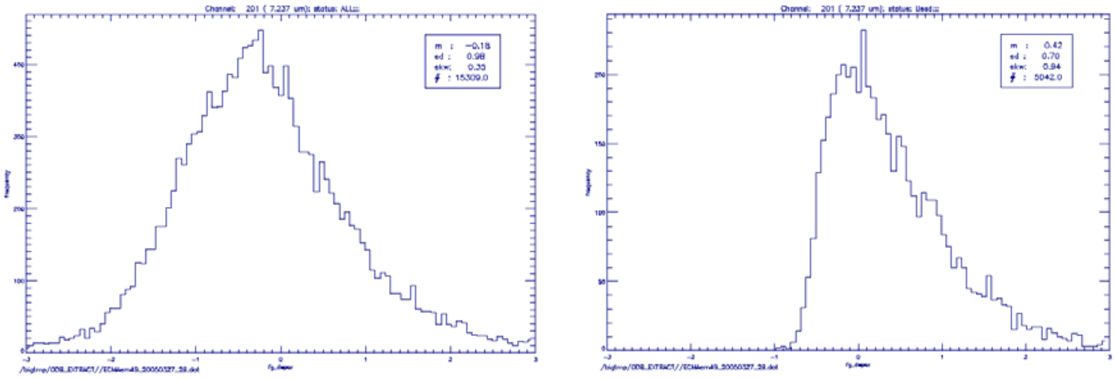

Figure 8: Histograms of observation minus first-guess departures for AIRS Water-Vapour channel 1545 (7.23µm) for a) all data and b) data declared active.

An assimilation experiment has been conducted over a one-month period using an offline adaptive bias correction with the initial bias estimation is provided by a static scheme. Fig 9 shows the evolution of the bias correction, residual statistics and data counts for a given AIRS mid-tropospheric water-vapour channel. The bias correction drifts away as the number of data accepted by the QC decreases dramatically. Indeed the bias introduced in the active population through the cloud detection step is picked by the bias correction scheme. This correction is then applied to all data prior to the meteorological analysis generating a feedback mechanism.

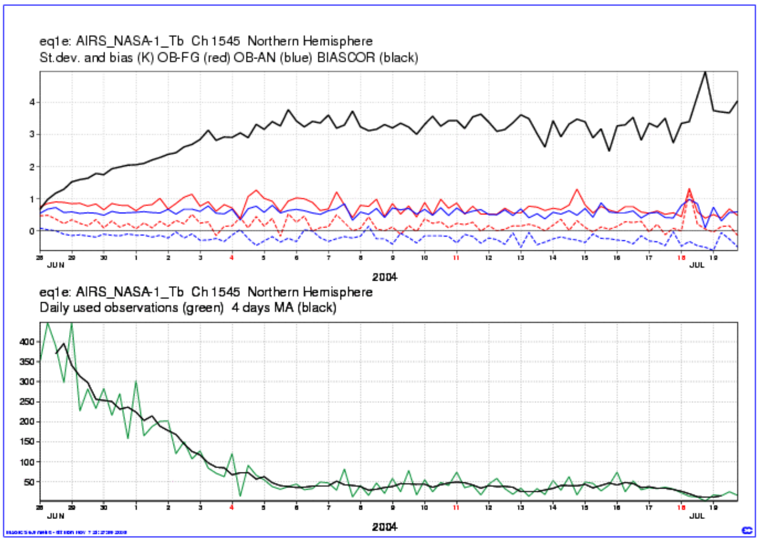

Figure 9 Top: Bias correction (black), first-guess and analysis departures (resp. red and blue) for AIRS mid-tropospheric water-vapor channel 1545 (7.23 micron). Standard deviation and bias are shown in solid and dashed lines respectively. Bottom: Number of active data in the analysis (green) and 4-value moving average (black).

4.2. Proposed solutions to the feedback process

(i) *Variational Bias correction*. The implementation of VarBC in a NWP system has been described in Section 2. The scheme implicitly constrains the calculation of the bias correction for each channel of each sensor with the fit of the analysis to all other observations. Any potential feedback process will modify the analysis and thus its fit to all data. Provided that a subset of observations is not bias corrected adaptively, the system is expected to reach a new equilibrium when it becomes too costly for the assimilation scheme to further update the bias parameters. Replacing the offline adaptive scheme by VarBC in the last assimilation experiment, we observe a different bias response for AIRS water-vapour channel 1545 (7.23 micron) as shown in Fig 10. The extra constraint provided by VarBC greatly reduces the feedback.

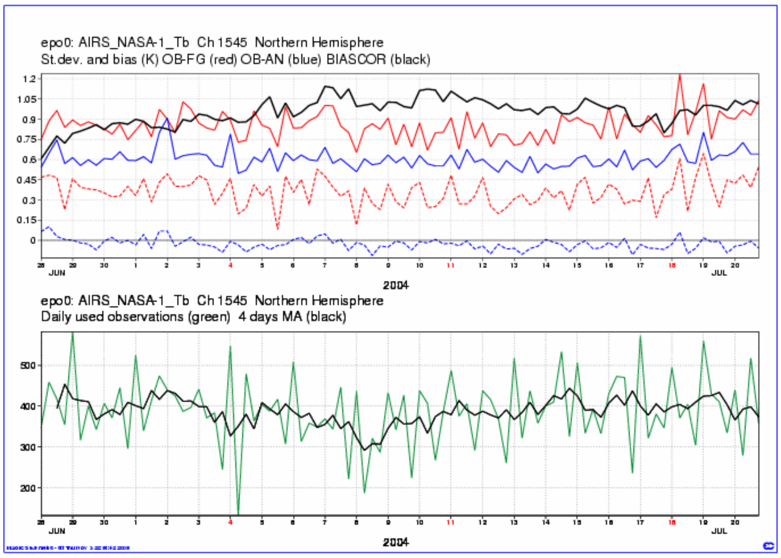

Figure 10: top) Bias correction (black), first-guess and analysis departures (resp. red and blue) for AIRS mid-tropospheric water-vapor channel 1545 (7.23 micron). Standard deviation and bias are shown in solid and dashed lines respectively. Bottom) Number of active data in the analysis (green) and 4-value moving average (black).

Unfortunately VarBC does not always reduce the feedback between bias correction and QC. The evolution of bias correction for AIRS window channel 787 (10.89 micron) is plotted in Fig 11. The system using the offline adaptive scheme does not change much the bias correction from its initial value. This means there is no significant signal within the departures to modify the bias estimate. The first-guess and the observations are either unbiased or have very similar biases. Nevertheless the assimilation using VarBC modifies significantly the bias correction for this channel because it improves the global fit to all observations. However the cloud detection for AIRS window channels is mainly driven by a simple first-guess check and can therefore be considered as a box-car window check (with a threshold of 0.5K) on the bias corrected first-guess departures. The update of the bias correction triggers a feedback process as described previously. Fig 12 shows histograms of uncorrected first-guess departures for the initial active population (using a static bias correction) and after one month of assimilation using VarBC. While the first-guess check mainly rejects the coldest departures with the static bias correction, it removes mostly warm departures when adapting the bias with VarBC. Since infra-red window channels are greatly affected by clouds with a cold signature in the departures, there is a strong possibility of cloud contamination of the assimilation. To investigate that question, we introduce an independent source of information about the cloud amount derived from the collocated imager, the AIRS Visible/Near Infrared (VISNIR) instrument. During day time only, a percentage of cloud within the AIRS field of view is provided as described in Gautier (2003). We consider this derived cloud cover for population of data where AIRS window channel 787 is declared active. Fig 13 shows that more cloudy data (according to the VISNIR flag) is passed to the minimisation when the bias is updated with VarBC.

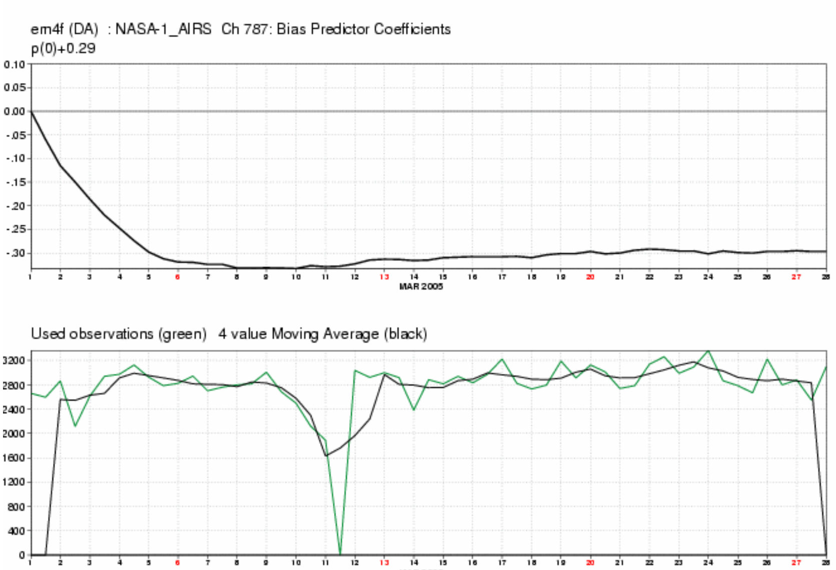

Figure 11: Bias correction for AIRS window channel 787 (10.89 micron) and number of active data in the analysis.

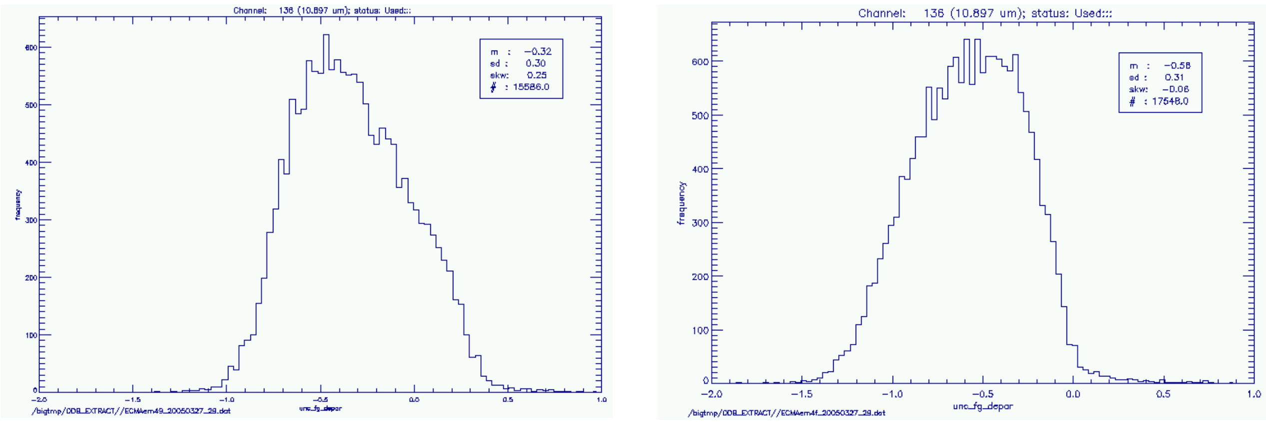

Figure 12: Histograms of observation minus first-guess departures for AIRS window channel 787 (10.89 micron) for data declared active with a bias correction that is a) static and b) adaptive.

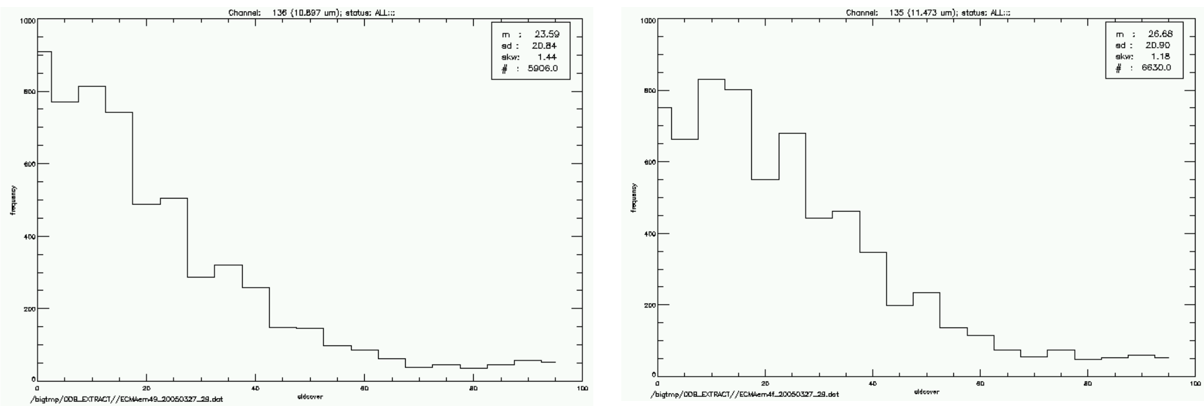

Figure 13: Histograms of VISNIR cloud cover (%) for AIRS window channel 787 (10.89μm) active data over 6 cycles with a bias calculated with a) static mean, b) VarBC.

(ii) *New metric for bias correction calculation.* We have seen that feedback is initiated by residual outliers (e.g. poor quality data or observations contaminated by cloud or rain) or unbalanced QC that add a systematic component to the departures population. There is a theoretical advantage to consider a bias model based on the mode of the first-guess departures distribution instead of its mean. Indeed the mode is expected to be much less sensitive to outliers.

Let us take the example of observations contaminated by clouds. Their first-guess departures are much more heterogeneous than the one for the clear data, given the vast variety of cloud types, depths, altitudes and their corresponding radiative impact. Assuming that the NWP model is fairly accurate, the population of active departures can then be represented by the combination of a relatively gaussian-shaped population for the clear data and a more widely spread cloud residual. The mode is hardly influenced by the cloudy data and provides the mean of the clear population since the mean is equal to the mode for a gaussian distribution. The difference between clear and cloudy observations is sometimes very subtle and therefore a cloud detection step is still needed prior to the assimilation of the data. The simple model displayed in Fig 7 can be reproduced using the mode instead of the mean for each bias calculation. Fig 14 shows there is no feedback in this case. The adaptive bias correction converges immediately to a single value whatever the QC thresholds, provided that the peak of the distribution initially stands with the QC limits.

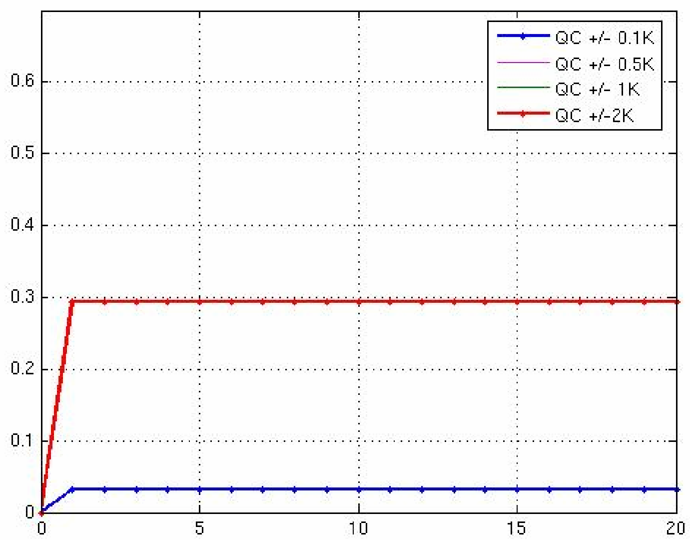

Figure 14: Bias estimation as a function of the number of iterations of the adaptive scheme based on the mode of the distribution for different quality control (QC) window widths.

The mode is applicable to a flat bias but a more complex bias model requires a different metric. The mode is also not derivable and thus cannot be included directly in a variational formulation. Therefore we define a new metric as an estimation of the mode that can then be used within the 4DVar system. During the bias update, instead of considering all observations equally and thus performing an average of all contributions, different weights are applied to the observation contributions. These weights are derived from the first-guess departures distribution. The histogram of the distribution is normalized to ensure an average value of one. Each observation is then weighted, according to its first-guess departure, by the value of the corresponding bin within the normalized histogram. Conceptually this is equivalent to applying, for the bias calculation, a confidence to the observations according to their relative position within the distribution of departures. Populations that have passed QC checks are usually near gaussian; therefore outliers have departures with a very low probability and will contribute much less to the evolution of the bias than data close to the peak of the distribution. This formulation is close to the M-estimator also called the Huber norm (Huber, 2003) which also defines a weight for each observation but it does not require any assumption on the shape of the distribution and it does not assume that the population is unbiased. This new metric can also be considered as a mask. Instead of using a standard Boolean mask - with weights equal to one inside the mask and no contribution elsewhere, we are now considering a mask with a soft transition from one to null with a sharpness that is defined by the accuracy of the first-guess departures.

This metric is applied to the simple model described in the former paragraph and results are shown in Fig 15. This method is less stable than the exact mode of the distribution. Nevertheless it is less sensitive than the mean of the distribution to the QC limits and it also converges faster.

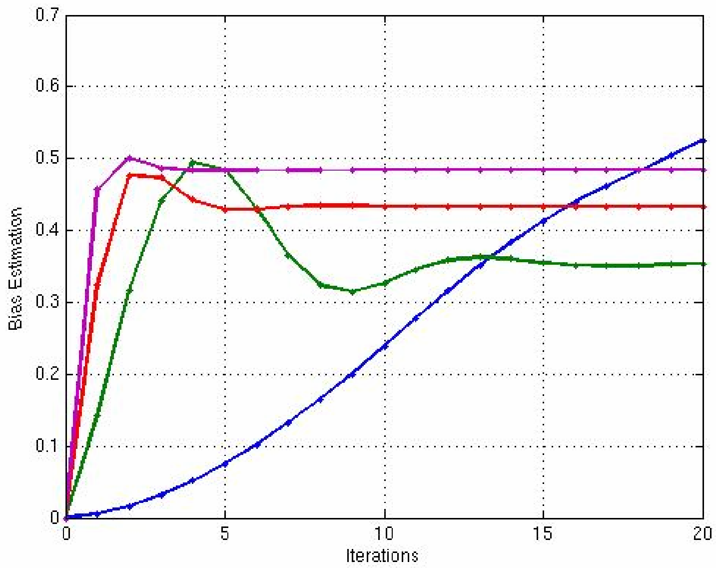

Figure 15: Idem to Figure 7 and Figure 14, but using the new metric for the bias calculation.

5. CONCLUSIONS

We have compared three different implementations of a given bias model. The Static scheme is applied statically over time while VarBC and Offline are two adaptive schemes respectively calculated inside and outside the main analysis.

Simple artificial NWP model and instrument artificial perturbation experiments have demonstrated that the VarBC system is a robust compromise between a Static and Offline bias correction. By implicitly using the redundancy of information between the observations, VarBC shows particular skills to disentangle the observation bias from systematic model error.

Nevertheless adaptive schemes exhibit unconstrained interactions with data quality control which influence the value of the bias estimation and the inertia of the system. The calculation of the bias from the mode of the first-guess departures distribution instead of the mean of the active population is expected to reduce this feedback process.

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