Further study of bias correction

for 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 RT 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 (Static, Offline, VarBC) for the same bias model. In Section 3, we study their response to perturbations in the model fields and in the observations. 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

2.1 Bias model

The bias model 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. The coefficients corresponding to these predictors and an offset are adjusted to reduce the analysis-guess departures near the radiosondes. The predictors that are used are summarized in Table 1.
All instruments aboard polar orbiting satellites also have a scan bias correction. A constant adjustment is calculated for each field of view with respect to the centre of the swath.

Instruments	Predictors
HIRS	1000-300 hPa thickness
	200-50 hPa thickness
AMSUB	1000-300 hPa thickness
	200-50 hPa thickness
SSMI	1000-300 hPa thickness
	200-50 hPa thickness
	Total column water
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.

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.

Static bias corrections usually involve a learning process where the data is carefully chosen in order to avoid considering model bias. Provided that the learning dataset is sufficient, the calculated bias parameters are then assumed to apply statically over time. Adaptive bias corrections estimate the bias over the dataset of the current assimilation. The learning dataset also being the set where the bias parameters are applied, any potential discrepancy is removed. On the other hand, more flexibility is given to the bias model to correct NWP model error. In theory it is the role of the bias model to make sure not to remove from the observations any piece of information that could 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 at ECMWF by Dee (2004). The ECMWF 4DVar assimilation scheme has been modified to include the coefficients of the bias correction regression (bias parameters) in the 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 seen as an inertia term.

The bias parameters are fully integrated into the 4DVar control variable, thus we can consider the bias parameters as 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 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, 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. Results

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 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 by bias correcting the data, while it is mostly ignored by inline VarBC. This demonstrates the ability of the inline system to distinguish (at least partially) between different sources of systematic error.
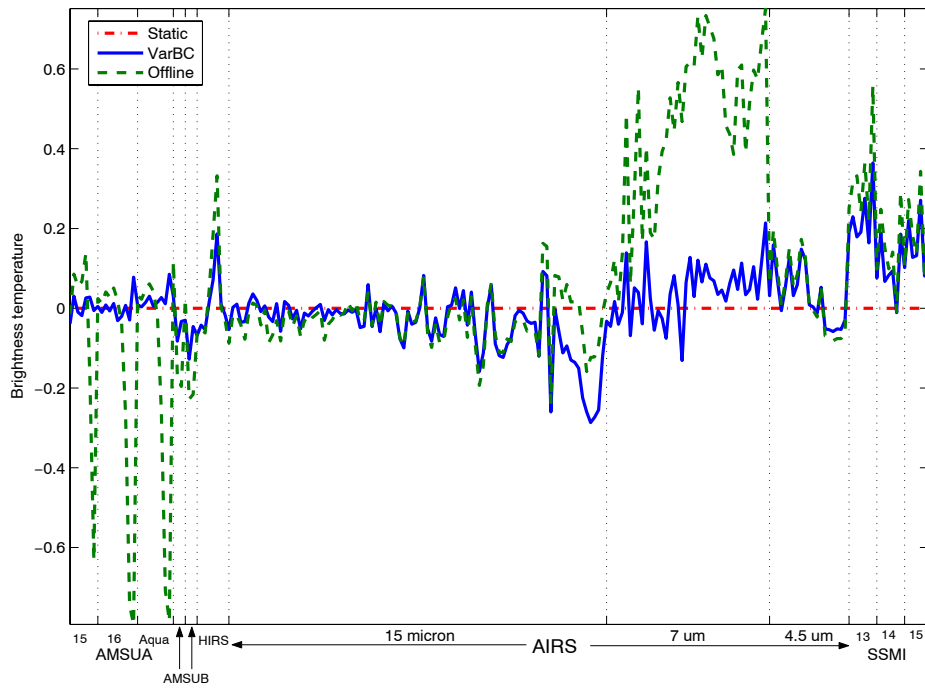
Figure 1: Mean bias correction from 2005/03/01 at 00UTC to 2005/03/05 at 12UTC minus the initial bias value. The blue and green curves correspond to the Offline and VarBC experiments respectively. The abscise represents different satellite data types.
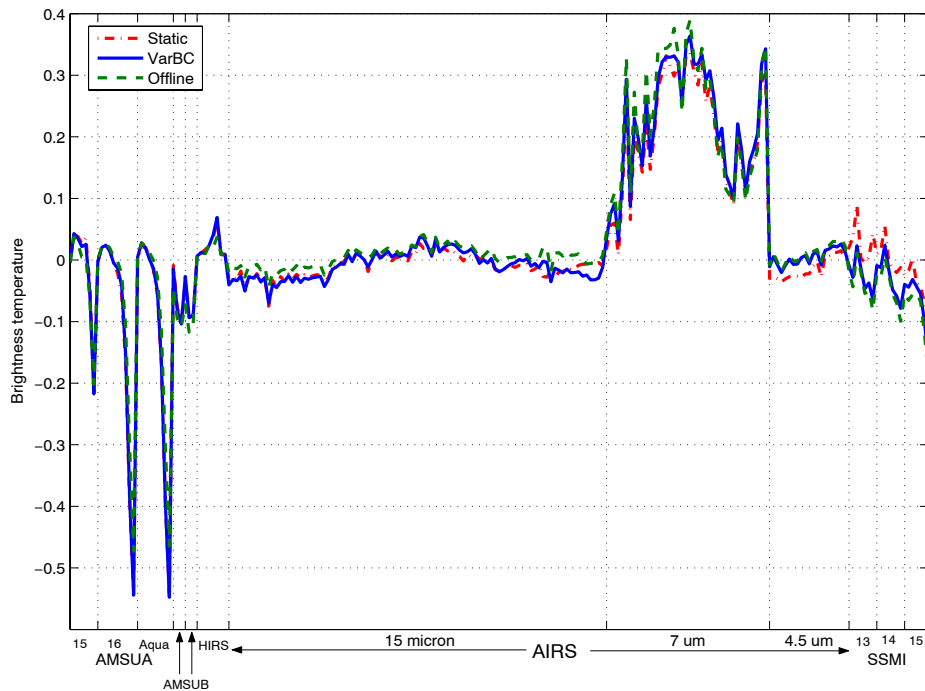

Figure 2: Mean analysis minus first-guess increments from 2005/03/01 at 00UTC to 2005/03/05 at 12UTC. The blue, green and red curves correspond to the Static, VarBC and Offline experiments respectively. The abscise represents different satellite data types.

3.2 Responses to 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.

3.2.1 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).
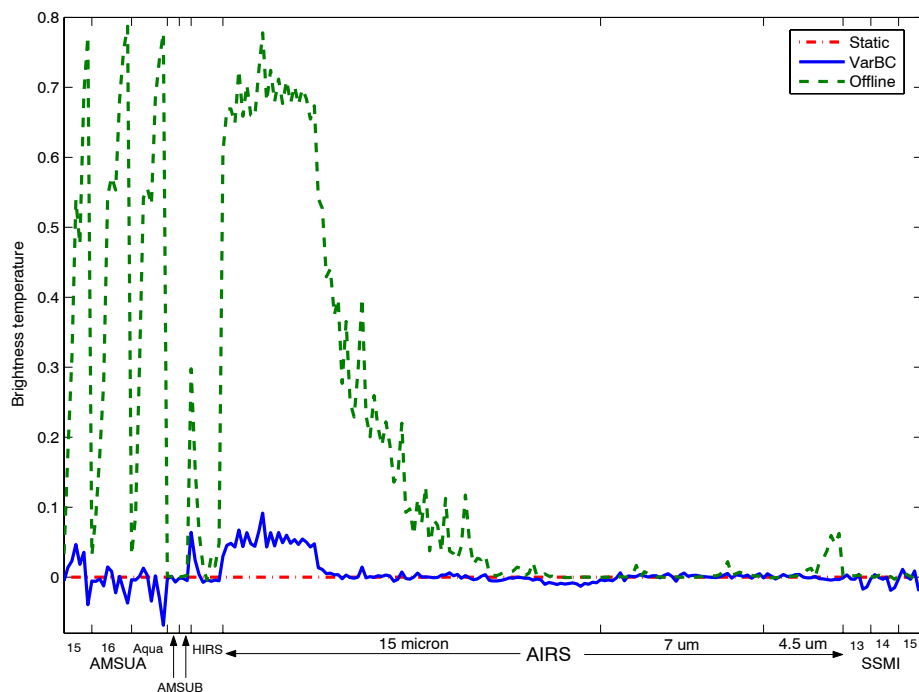

Figure 3: Bias correction differences between experiments with and without the model perturbation. The green and blue curves correspond to experiment with Offline VarBC and VarBC respectively. The abscise represents different satellite data types.
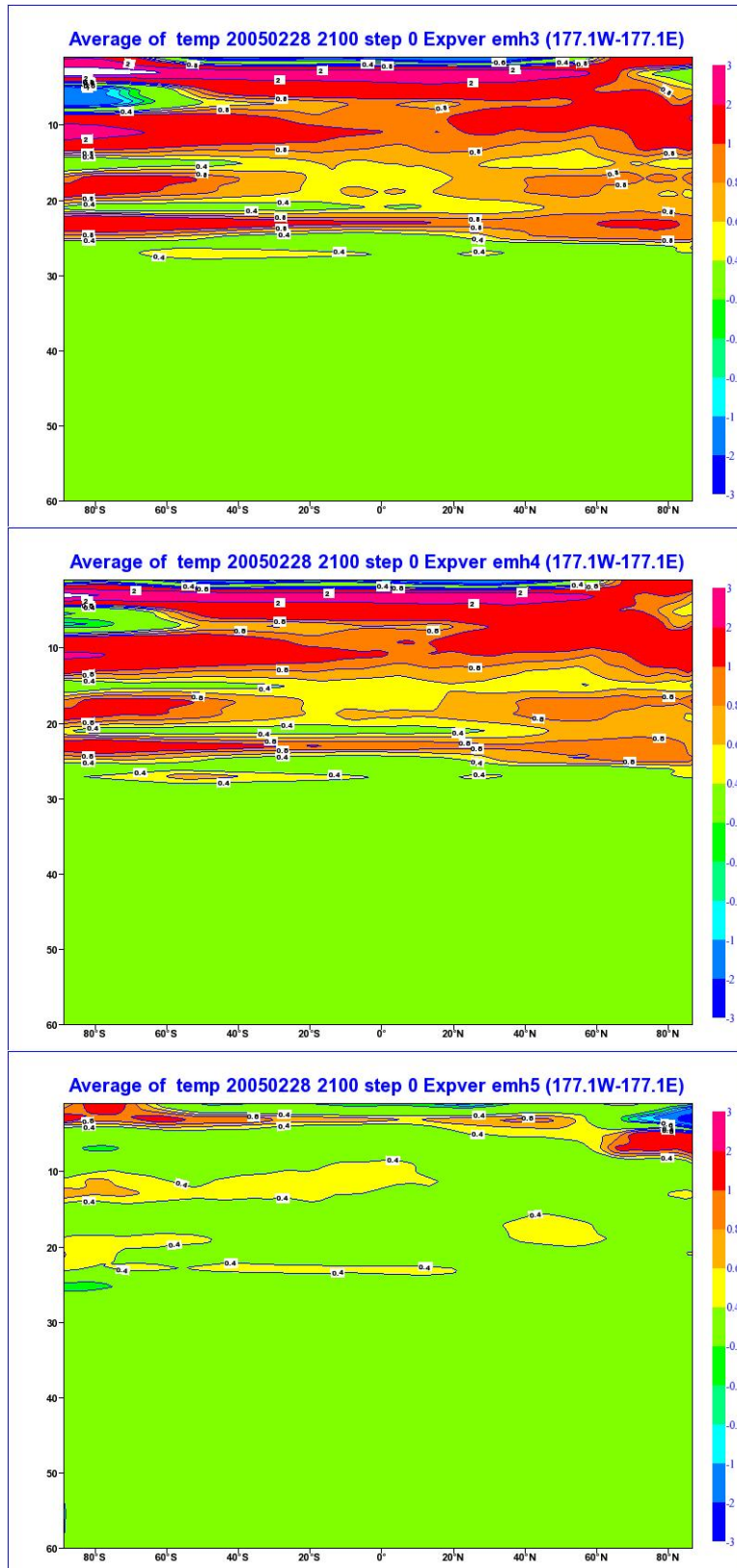
Figure 4: Mean analysis differences as a function of latitude and model levels for experiments:
a) Static bias correction, respectively with and without the model perturbation.
b) VarBC, respectively with and without the model perturbation.
c) Offline VarBC, respectively with and without the model perturbation.

3.2.2 Instrument artificial perturbation

We introduce an artificial -1 K shift in to radiances from NOAA16 AMSUA channel 6 (weighting function peaking about 400 hPa). This drift can be simulated by adding 1 K to the initial bias since the analysis only considers the bias corrected first-guess departures. In the first assimilation cycle VarBC removes 40% of the perturbation by bias correcting the data (Fig 5). The remaining 60% that is not bias corrected impacts the meteorological analysis as this signal is interpreted as adjustments to the temperature field. Fig 6 shows the analysis differences (around 500hPa) for the perturbed VarBC relative to an unperturbed VarBC. For reference, the differences for a static (perturbed and unperturbed) experiment are shown in the same figure. The patterns (unsurprisingly) fit the location of the NOAA16 AMSUA channel 6 active data. VarBC shows slightly smaller adjustments than the "static" experiment but is generally comparable in magnitude. 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 (Fig 7). 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. There are two reasons. Firstly the shift is very large compared to the observations error specified for this channel (0.2K) such that the background constraint restricts size of the bias adjustment in a single cycle. Fig 8 shows the same analysis differences when the background constraint on the bias parameters is removed. The analysis is now much closer to the unperturbed system showing the VarBC has corrected a larger proportion of the induced bias. For comparison the analysis differences for an offline VarBC system (which is similarly unconstrained by background information) are shown to be very similar. Secondly, 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) as shown in Fig 9.

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 the in 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.
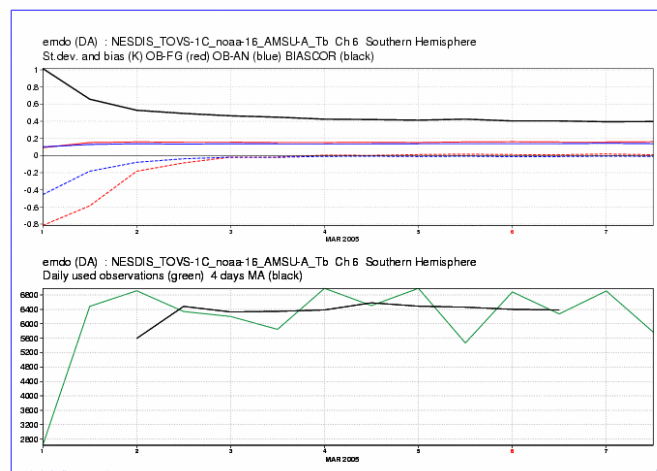

Figure 5: Evolution over time starting after the first cycle following the perturbation.
a) Total bias correction, first-guess departure and analysis departure (black, blue and red curves respectively). The solid curves correspond to mean values and the doted curves to standard deviation.
b) The green curve represents the number of active data and the black curve is an average over a 4 day window.
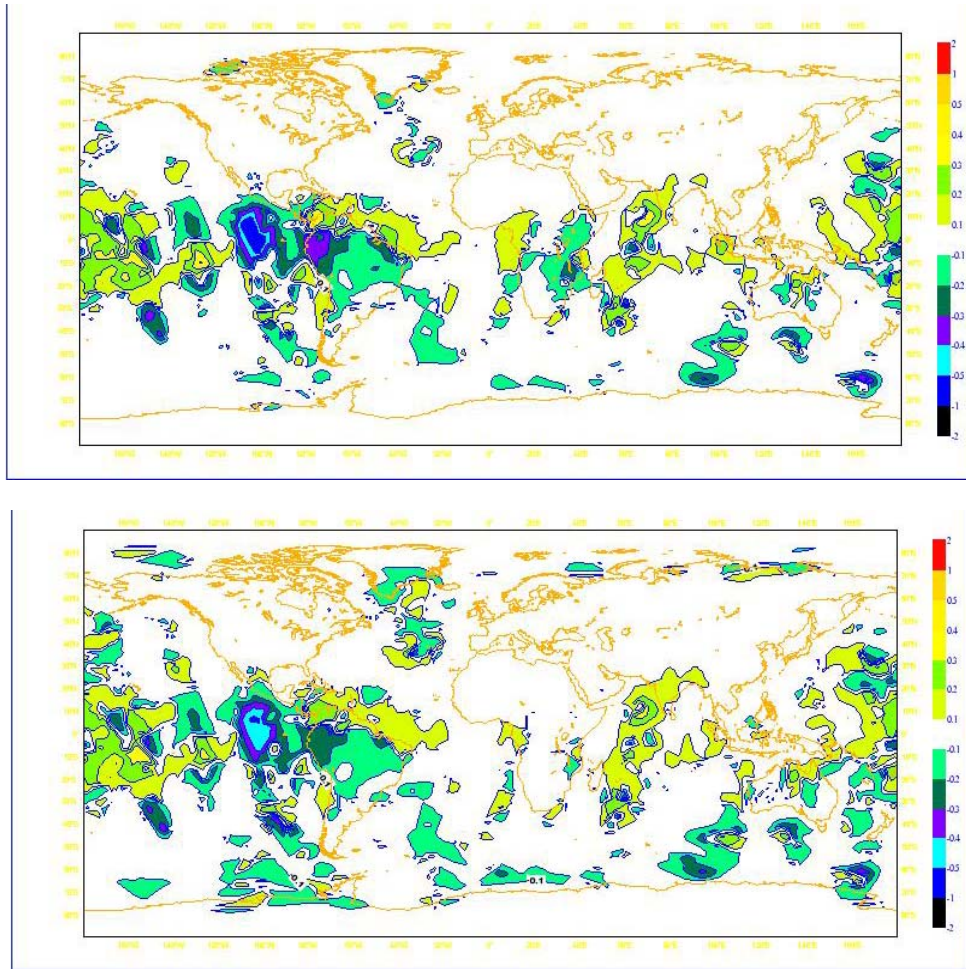
Figure 6: Analysis increments differences for model level 36 (about 500 hPa)

  a) Between experiments with a static bias correction respectively with and without the NOAA16 AMSUA6 perturbation
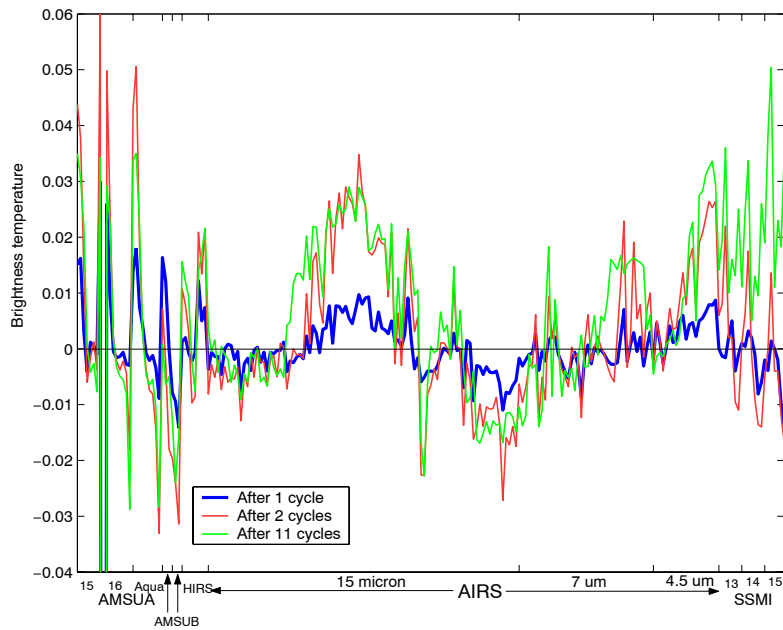 b) Between experiments with VarBC respectively with and without the perturbation

Figure 7: Bias correction difference between VarBC experiments with and without the perturbation. The blue, red, green curves represent the bias differences respectively 1, 2 and 11 cycles after the perturbation. The abscise represents different satellite data types.
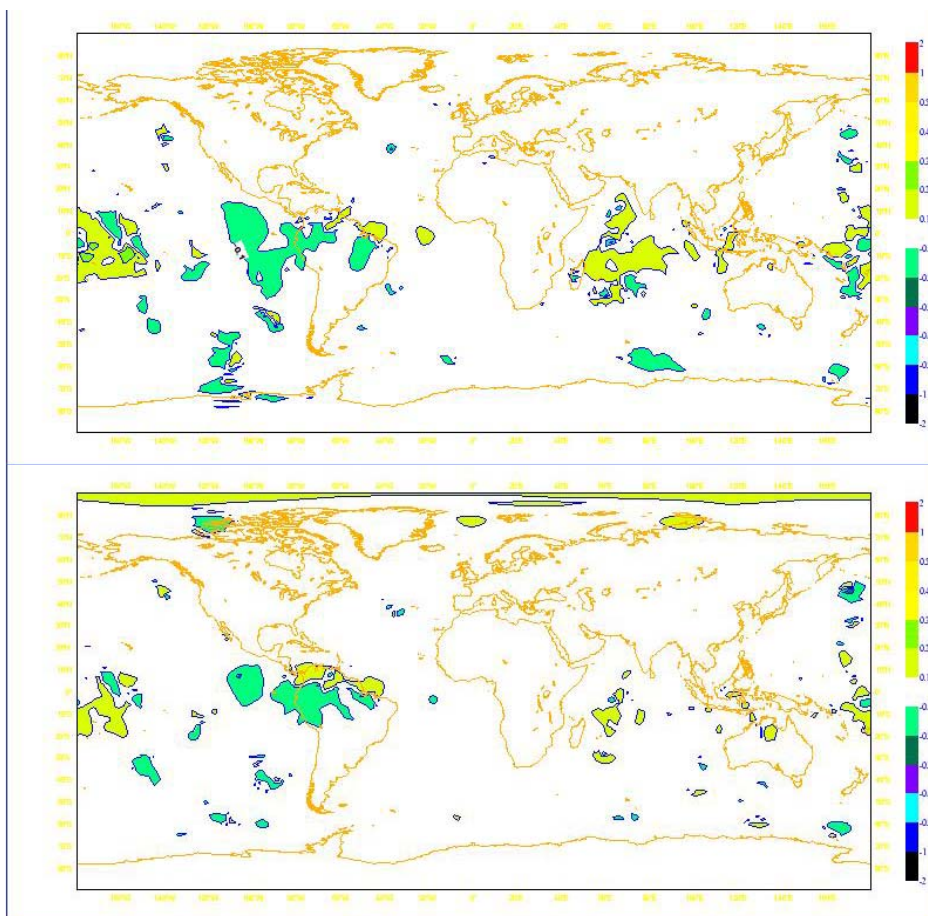
Figure 8: Analysis increments differences for model level 36 (about 500 hPa)
   a) Between experiments with VarBC and no background term for AMSUA6, respectively with and without the NOAA16 AMSUA6 perturbation.
   b) Between experiments with Offline and no background term for AMSUA6, respectively with and without the perturbation.
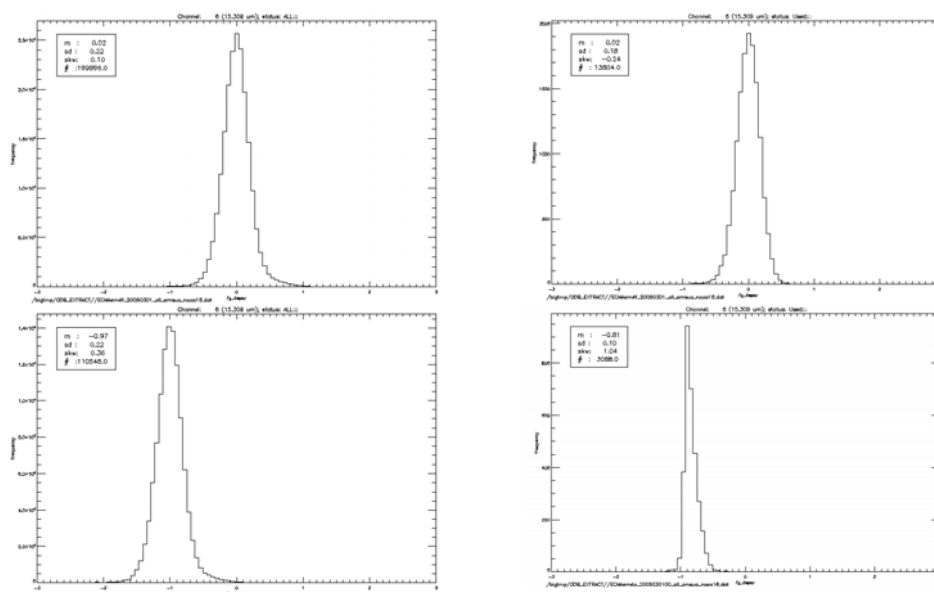

Figure 9: Histograms of observation minus first-guess departures. The top left and bottom left panels represent the departures for the VarBC experiments without and with the perturbation respectively. The top right and bottom right panels represent the corresponding departures for the data declared active for the analysis.

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 with quality control

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. 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.

This feedback can be demonstrated with a very simple model. We consider the population of AIRS window channel 787 (10.89 micron) first-guess departures. An adaptive bias correction scheme is simulated by calculating the bias iteratively as the mean over the population declared active by the QC. This QC is a simple box-car window applied to the bias corrected departures centred on zero with a pre-defined width and the bias is the mean value of the quality controlled departures. Fig 10 shows an example of such a system with an initial bias estimate of -1K and a QC width of +/-2K. The adaptive scheme updates its estimate of the bias with each iteration, but with each iteration the population passed by the QC also changes. After a number of iterations this

process converges. It can be seen in Fig 11 that 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.

There are potential advantages to consider a bias model based on the mode of the first-guess departures distribution instead of the mean. Firstly the mode is expected to be much less sensitive to outliers such as bad quality data or observations contaminated by cloud or rain. Cloudy observations are much more heterogeneous that clear ones, given the vast variety of cloud types, depths, altitudes and their corresponding radiative impact. The population of departures can then be represented by a relatively gaussian-shaped population for the clear data and a widely spread cloudy population. The mode will not be influenced by the cloudy data and will provide the mean of the clear population (for a gaussian the mean is equal to the mode). We can consider calculating the mode over the total population of the departures and not only over the active data that have passed the QC. Thus there is no feedback between this bias correction (even when run adaptively) and the QC.
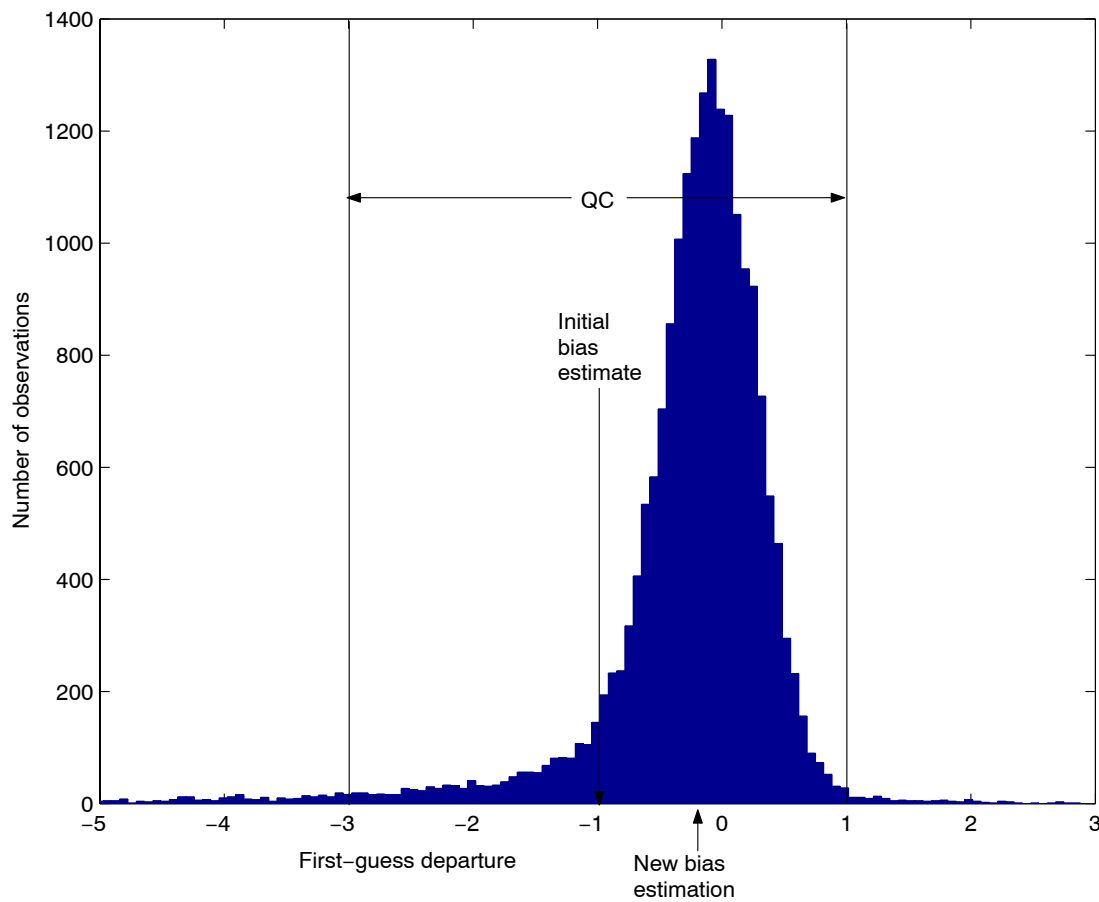

Figure 10: AIRS window channel 787 (10.89 micron) first-guess departures histogram.
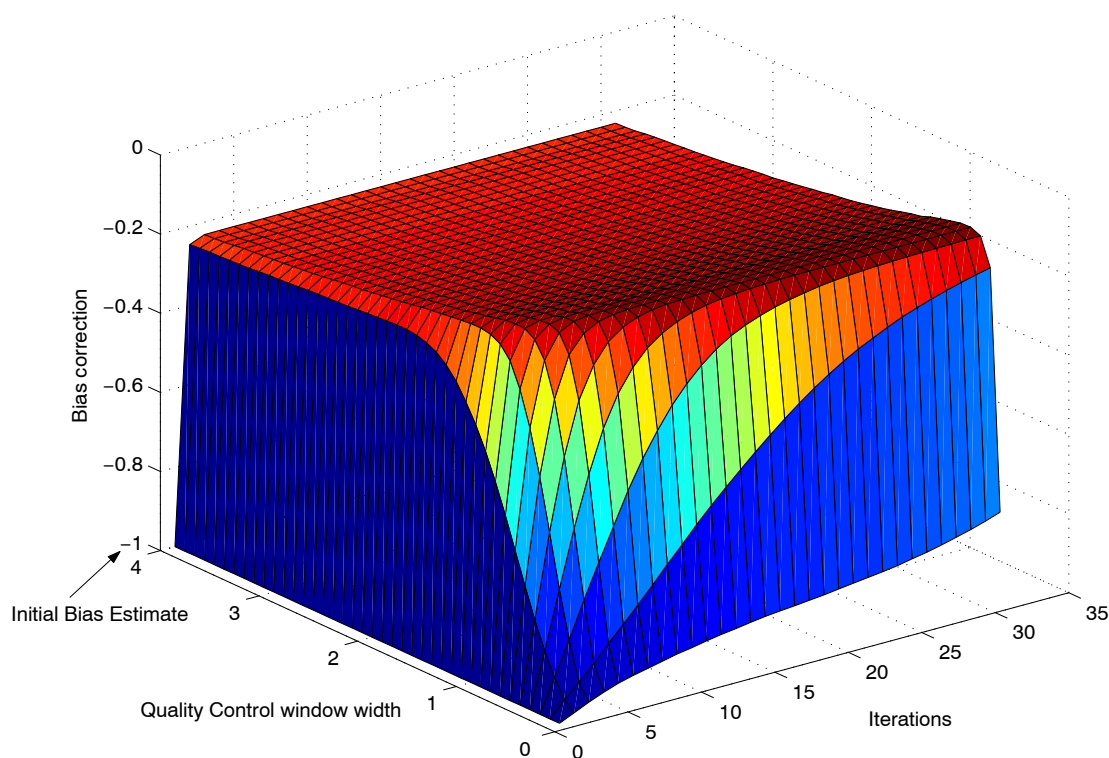
Figure 11: Bias estimation as a function of the number of iterations of the adaptive scheme and of the quality control window width.

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 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. Current work is in progress to calculate the bias from the mode of the first-guess departures distribution instead of the mean of the active population.

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