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Adaptive bias correction for satellite data in a numerical weather prediction system

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ABSTRACT: Adaptive bias corrections for satellite radiances need to separate the observation bias from the systematic errors in the background in order to prevent the analysis from drifting towards its own climate. The variational bias correction scheme (VarBC) is a particular adaptive scheme that is embedded inside the assimilation system.

VarBC is compared with an offline adaptive and a static bias correction scheme. In simulation, the three schemes are exposed to artificial shifts in the observations and the background. The VarBC scheme can be considered as a good compromise between the static and the offline adaptive schemes. It shows some skill in distinguishing between the background-error and the observation biases when other unbiased observations are available to anchor the system. Tests of VarBC in a real numerical weather prediction (NWP) environment show a significant reduction in the misfit with radiosonde observations (especially in the stratosphere) due to NWP model error. The scheme adapts to an instrument error with only minimal disruption to the analysis.

In VarBC, the bias is constrained by the fit to observations – such as radiosondes – that are not bias-corrected to the NWP model. In parts of the atmosphere where no radiosonde observations are available, the radiosonde network still imposes an indirect constraint on the system, which can be enhanced by applying a mask to VarBC.

KEY WORDS bias estimation; model bias; observation bias; radiance assimilation; systematic error; variational bias correction

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1. Introduction

Satellite instruments, like any other measurement system, are imperfect and prone to error. While errors that are purely random – such as noise at the radiation detector – are undesirable, their adverse effects can be significantly reduced within a data assimilation scheme by a combination of spectral, spatial and temporal filtering. However, errors that are systematic (i.e. biases) cannot be handled in this way. Observation bias can systematically damage the data assimilation scheme, and ultimately the quality of the forecasting system. Biases in satellite observations are of particular concern, as they have the potential, if uncorrected, to damage the NWP system globally in a very short period of time.

The bias in a particular satellite observation can only be determined by comparison with some unbiased reference. Special measurement campaigns involving surface or aircraft-mounted radiometers and balloon-borne sensors launched to coincide with the satellite overpass provide a highly accurate reference, but are inevitably limited to certain locations and times. Therefore NWP centres often monitor and diagnose satellite biases using the NWP assimilation system itself. The obvious advantage of this approach is the in-house real-time availability of what is arguably (in the case of the NWP analysis or short-range forecast) the best estimate of the global atmospheric state. However, this approach has the disadvantage that it does not provide a completely unbiased reference. Indeed, for some atmospheric variables and regions of the atmosphere, the biases in the NWP system can be comparable to the biases that one is attempting to diagnose in the satellite information. Despite these concerns, the overwhelming benefits of monitoring satellite biases against the NWP system have led to its widespread adoption.

In general, the observed biases when satellite data are monitored against the NWP model are not fixed offsets. Rather, they can vary with time (e.g. diurnally or seasonally), with geographical location, including changes in the air mass and in the underlying surface (e.g. land, sea or ice), and even with the scan position of the satellite instrument.

Biases between the data and the model arise because of systematic errors in any one (but usually a combination) of the following sources: the satellite instrument itself (e.g. poor calibration or characterization, or adverse environmental effects); the radiative transfer model (RTM) linking the atmospheric state to the radiation measured by the satellite (e.g. errors in the physics or spectroscopy, or from non-modelled atmospheric processes); and systematic errors in the background atmospheric state provided by the NWP model used for monitoring. In principle,

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we do not wish to correct the observations for the latter, because such correction could reinforce the systematic model errors. Ideally, biases in the NWP should be handled explicitly by the system. Otherwise, they can produce biased analyses and hinder attempts to diagnose and correct observation bias. Such explicit treatment is under way in various NWP centres (Trémolet, 2007), but is beyond the scope of this paper. Here we will only consider how NWP model error alters the observation bias correction scheme, and demonstrate that some approaches are more robust than others. Given the complexities of the various sources of systematic error (and of how they may combine), it is not surprising that a considerable amount of effort has been directed towards bias correction.

The very first attempts to assimilate satellite data at the European Centre for Medium-Range Weather Forecasts (ECMWF) assumed fixed constant offsets applied to each channel, but these were quickly exposed as inadequate (Kelly and Flobert, 1988): a more sophisticated correction was needed. A scheme that aimed to apply a geographically-varying bias correction (depending on air mass) was proposed by Eyre (1992). The air-mass dependence of the bias was parametrized by a number of predictors based on the radiance observations themselves. The coefficients of the predictors were then generated by linear regression, trained on a representative sample of observed-minus-background radiance departures. A modification of this scheme, where the observation-based predictors were replaced by predictors based on an NWP model, was proposed by Harris and Kelly (2001). In both of these schemes, the aim was to correct the radiance data completely towards the NWP model. The bias correction was given many predictors and the regression coefficients were updated frequently to capture any possible drift of the bias in time. More recently, as satellite instruments and RTMs have improved, there has been a slow evolution towards a simpler and more constrained bias correction of the satellite radiances, which aims to correct only biases in the observations and RTM, and not to remove NWP model error (Watts and McNally, 2004). However, to this day any constraint placed upon the bias correction has always been rather subjective and ad hoc. It has ultimately depended on which predictors have been selected for the bias correction scheme and how frequently the bias coefficients have been updated.

Three different approaches for the bias correction are proposed in Section 2 below: a static scheme, an adaptive offline scheme, and an adaptive variational bias correction scheme (hereafter referred as 'Static', 'Offline' and 'VarBC' respectively). In Section 3 we study results from simulations using artificial perturbations in a real assimilation system. The performance of VarBC in an NWP system is examined in Section 4. Section 5 examines the constraint imposed by the radiosonde data on the bias correction, and shows that it can apply remotely. Conclusions are presented in Section 6.

2. Three approaches to bias correction

The radiance departures are defined as

$$\mathbf{y} - H(\mathbf{x}),$$

where $\mathbf{y}$ is the observation vector, $\mathbf{x}$ is the NWP model state vector, and $H(\mathbf{x})$ is the observation operator.

Following Harris and Kelly (2001), the parametric form used here to represent the observation bias is a linear regression based on N state-dependent predictors $p_i(\mathbf{x})$, with associated coefficients β_i. Since the bias correction is applied to the radiance departures, this is equivalent to using the modified definition of the observation operator:

$$\tilde{H}(\mathbf{x}, \boldsymbol{\beta}) = H(\mathbf{x}) + \sum_{i=0}^{N} \beta_i p_i(\mathbf{x}). \quad (1)$$

The training of the bias correction consists in finding the vector $\boldsymbol{\beta}$ that allows the best fit between the NWP fields $\mathbf{x}$ and the observations. This is obtained by minimizing the following cost function:

$$J(\boldsymbol{\beta}) = \frac{1}{2}[\mathbf{y} - \tilde{H}(\mathbf{x}, \boldsymbol{\beta})]^{\mathrm{T}}[\mathbf{y} - \tilde{H}(\mathbf{x}, \boldsymbol{\beta})]. \quad (2)$$

The three bias correction schemes studied here are essentially defined by their choice of $\mathbf{x}$. The Static scheme calculates the optimal vector $\boldsymbol{\beta}$ for a set of observations supposed to be representative of the actual bias. In this implementation, $\mathbf{x}$ is usually taken to be the background fields $\mathbf{x}_{\mathrm{b}}$ from a control assimilation over a period of the order of one month. The coefficients are then fixed and applied in all subsequent analyses. This scheme does not account for changes in the nature of the bias (e.g. instrument problems or contamination). Therefore it is interesting to consider an adaptive bias correction that updates $\boldsymbol{\beta}$ regularly (but not the choice of predictors). In the Offline scheme, the bias coefficients are updated at each new analysis (e.g. every 12 hours), using a background $\boldsymbol{\beta}_{\mathrm{b}}$ issued from the former analysis cycle. The bias is calculated from the same dataset as the one used for the analysis. But the update is performed independently (or 'offline'), and in this case prior to the analysis, by minimizing the cost function

$$J(\boldsymbol{\beta}) = \frac{1}{2}[\mathbf{y} - \tilde{H}(\mathbf{x}_{\mathrm{b}}, \boldsymbol{\beta})]^{\mathrm{T}}\mathbf{R}^{-1}[\mathbf{y} - \tilde{H}(\mathbf{x}_{\mathrm{b}}, \boldsymbol{\beta})] + \frac{1}{2}(\boldsymbol{\beta} - \boldsymbol{\beta}_{\mathrm{b}})^{\mathrm{T}}\mathbf{B}_{\beta}^{-1}(\boldsymbol{\beta} - \boldsymbol{\beta}_{\mathrm{b}}), \quad (3)$$

where $\mathbf{R}$ represents the observation error covariance matrix and $\mathbf{B}_{\beta}$ the bias parameter background error covariance matrix. The second term in Equation (3) controls the adaptivity of the bias parameters (the 'inertia constraint').

VarBC has been implemented at ECMWF (Dee, 2004, 2005), and has been operational since 12 September 2006. Like the Offline scheme, it updates the coefficients of the satellite bias correction every analysis cycle. It is based

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on ideas developed at NCEP and used in the operational system there (Derber and Wu, 1998). It updates the bias inside the assimilation system by finding corrections that minimize the systematic radiance departures while simultaneously preserving (or improving) the fit to other observed data inside the analysis. This is achieved by including the regression coefficients in the control vector of the variational analysis, so that they are adjusted together with other analysis variables, taking all available information into account. The adjustment is optimal in that it respects the uncertainty of the observations and any background or inertia constraints we wish to impose on changes to the satellite bias estimation. The cost function, to be minimized with respect to the bias parameters $\boldsymbol{\beta}$ and the model state $\mathbf{x}$, is:

$$J(\mathbf{x}, \boldsymbol{\beta}) = \frac{1}{2}[\mathbf{y} - \tilde{H}(\mathbf{x}, \boldsymbol{\beta})]^{\mathrm{T}}\mathbf{R}^{-1}[\mathbf{y} - \tilde{H}(\mathbf{x}, \boldsymbol{\beta})] + \frac{1}{2}(\boldsymbol{\beta} - \boldsymbol{\beta}_{\mathrm{b}})^{\mathrm{T}}\mathbf{B}_{\boldsymbol{\beta}}^{-1}(\boldsymbol{\beta} - \boldsymbol{\beta}_{\mathrm{b}}) + \frac{1}{2}(\mathbf{x} - \mathbf{x}_{\mathrm{b}})^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_{\mathrm{b}}), \tag{4}$$

where $\mathbf{B}$ represents the model background error covariance matrix.

VarBC is fundamentally different from an offline scheme, where the bias is estimated before each analysis, assuming the NWP model fields to be correct (or after the analysis, assuming that the observation bias does not change abruptly). As the simple simulation in Appendix A illustrates, offline adaptive systems cannot distinguish observation bias from NWP model bias, and they gradually alter the radiances to fit the NWP model. VarBC, on the other hand, uses extra observations, such as radiosondes, to constrain the observation bias correction in order to prevent the contamination of the observation bias estimates by systematic NWP model errors. The simple simulation in Appendix B illustrates this ability of VarBC to separate the sources of bias inside the departures and to ignore most of the NWP model bias.

This approach also goes a long way towards automating the updating and management of satellite bias corrections. With the current assimilation at ECMWF of about 30 satellite instruments providing radiance information in more than 500 channels, automation constitutes a significant benefit. The need for an adaptive bias correction system also became obvious during the production of reanalyses such as ERA-40 (Uppala *et al*., 2005), which had to be interrupted and restarted on many occasions for manual retuning of the bias corrections.

3. The performance of VarBC with artificial perturbations to the NWP system

The characteristics of the adaptive bias corrections are explored in a hypothetical environment where model and observation biases are simulated by artificial perturbations. The bias correction is studied within the ECMWF 4D-Var assimilation system (Rabier *et al*., 2000; Mahfouf and Rabier, 2000) at a reduced resolution (T159L60). The predictors that are used for the bias correction are summarized in Table I. On top of this parametric form, a constant scan-dependent bias correction, consisting in an adjustment for each field of view with respect to the centre of the swath, is also applied for the instruments aboard polar orbiting satellites. Furthermore, a constant γ coefficient is applied to AMSUA and AIRS channels to adjust the RTM to the observations (as explained in (Watts and McNally, 2004)). Three assimilation experiments (Static, Offline and VarBC) are run using three different bias corrections. They all use the same bias predictors, but differ in how the bias coefficients are updated. The Static scheme uses regression coefficients pre-computed from a representative sample of radiance departures and fixed for the duration of the experiment. The Offline and VarBC schemes use adaptive bias corrections that start from the same coefficients as the Static scheme. In both these experiments, the coefficients are updated every analysis cycle, subject to an inertial damping. In the cost function, an inertia term applies a constraint which limits the magnitude of changes for the coefficients within a single update. In the Offline scheme, the update is performed prior to the analysis; in VarBC, the coefficients are updated within the analysis.

3.1. Response to an artificial instrument perturbation

An instrumental failure or contamination usually has a signature in the observation bias that is either a sudden shift or a slow drift (which can be considered as a succession of small shifts). An artificial shift is simulated for the NOAA-16 AMSU-A channel 6 (a temperature sounding channel with a weighting function peaking around 400 hPa) with a magnitude equal to the assumed observation standard deviation (0.2 K) specified for this channel. Figure 1 shows the analysis responses (temperature increments) averaged over the entire globe for the three experiments during the first cycle following the observation shift.

The Static scheme has no information about the changed observations, so that the perturbation leads to erroneous analysis increments around 400 hPa. The Offline scheme reacts to the perturbed observations by updating the bias estimates; this significantly reduces the impact of the perturbation on the analysis. However,

Table I. Predictors used in the bias parametric form for different satellite instruments. The pressure differences represent thicknesses; TCWV is the total column water vapour; V_s is the surface wind speed; and T_s is the skin temperature.

Instrument	Predictors			
AIRS	1000–300 hPa	200–50 hPa	10–1 hPa	50–5 hPa
ATOVS	1000–300 hPa	200–50 hPa	10–1 hPa	50–5 hPa
GEOS	1000–300 hPa	200–50 hPa	TCWV	
SSMI	V_s	T_s	TCWV	

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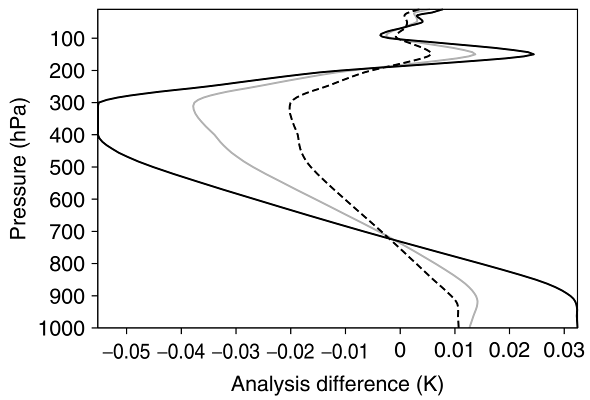

Figure 1. Response to a simulated instrument contamination. Mean analysis temperature response as a function of pressure, following a 0.2 K artificial perturbation for NOAA-16 AMSU-A channel 6. The solid black, solid grey and dashed curves correspond to the Static, VarBC and Offline bias correction schemes respectively.

the Offline scheme is not optimal, since it does not immediately correct for the whole observation shift. This is due to the inertia constraint imposed in the Offline scheme, and also to the effect of the quality control (based on the bias-corrected departures), which rejects observations that would otherwise contribute to updating the bias coefficients.

The VarBC scheme identifies, and partly corrects for, the observation shift with a change to the bias coefficients. Compared with the Static scheme, it significantly reduces the impact of the perturbation on the analysis. However, it is slightly inferior to the Offline scheme, which benefits from the a priori knowledge that the NWP model is correct (and thus any departure signal goes exclusively to changing the bias correction of the observations). It should be noted that in the Offline scheme considered here, the adaptive system is run before the meteorological analysis. If it had been run after the analysis, the perturbed (bad) data would indeed have damaged the analysis.

3.2. Response to an artificial NWP model perturbation

When new versions of the NWP forecast model are implemented, there can be significant changes in the systematic errors. To simulate this scenario, a sudden shift (of -1 K) is introduced in the NWP model temperature for levels above 100 hPa. In this case the Static scheme does exactly the right thing: it does not change the bias correction of the observations, and the signal in the radiance departures causes an adjustment of the analysis (Figure 2). The Offline scheme does exactly the wrong thing, by assuming that the NWP model is correct. It accounts for most of the NWP model error with a large change to the bias correction (again limited by the inertia), seen in Figure 3. This results in only a small correction to the analysis. Compared with the Offline scheme, the VarBC scheme shows almost no adjustment of the bias. Most of the NWP model error is (correctly) adjusted through analysis increments (almost identical to those of the Static scheme). The VarBC scheme benefits from the presence of *in situ* temperature data (such as radiosonde and aircraft data) that are not adaptively bias-corrected, and thus identify the source of the perturbation as an NWP model error.

4. The performance of VarBC in a real NWP system

4.1. Response to a real instrument problem

From previous reanalyses (Uppala *et al*., 2005), there are a number of well-documented cases where a satellite instrument has suddenly degraded or been contaminated by an extreme event (e.g. volcanic emissions). If the event is unexpected, this can result in a serious contamination of the analysis. Even if the event is expected, blacklisting the affected channel can still disturb the time-consistency of the analysis. VarBC has demonstrated an ability to handle sudden systematic changes to the data and minimize damage to the analysis. An example is shown in Figure 4, for August 2006 when the Meteosat-5 calibration changed unexpectedly for both the IR and the WV channels, resulting in changes greater than 1 K in the observed temperatures.

In this example, most of the erroneous data are not rejected by the quality control process. For the Static scheme (top panel), this results in a significant modification of the mean first-guess and analysis departures. The VarBC scheme (bottom panel) automatically corrects the shifted data. With very little disruption to the analysis system, a completely new bias correction is established, differing by nearly 2 K (the black line of Figure 4) from the stable bias correction prior to the incident. Once the calibration has returned to its nominal level (from 1 September), the bias correction quickly returns to a stable state which is slightly different from (0.2 K below) its prior values.

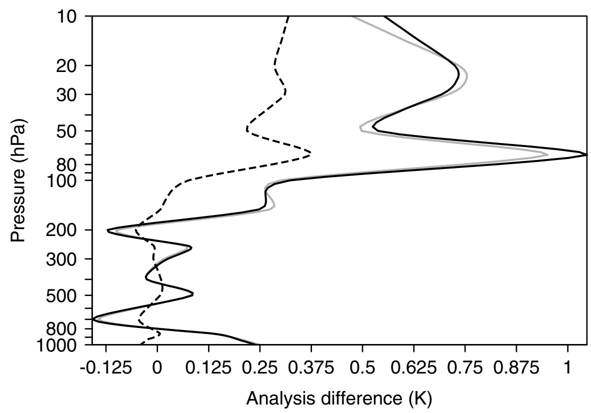

Figure 2. Response to an artificial uniform NWP model error. Mean analysis temperature response as a function of pressure, following an artificial -1 K NWP model perturbation above 100 hPa. The solid black, solid grey and dashed curves correspond to the Static, VarBC and Offline bias correction schemes respectively.

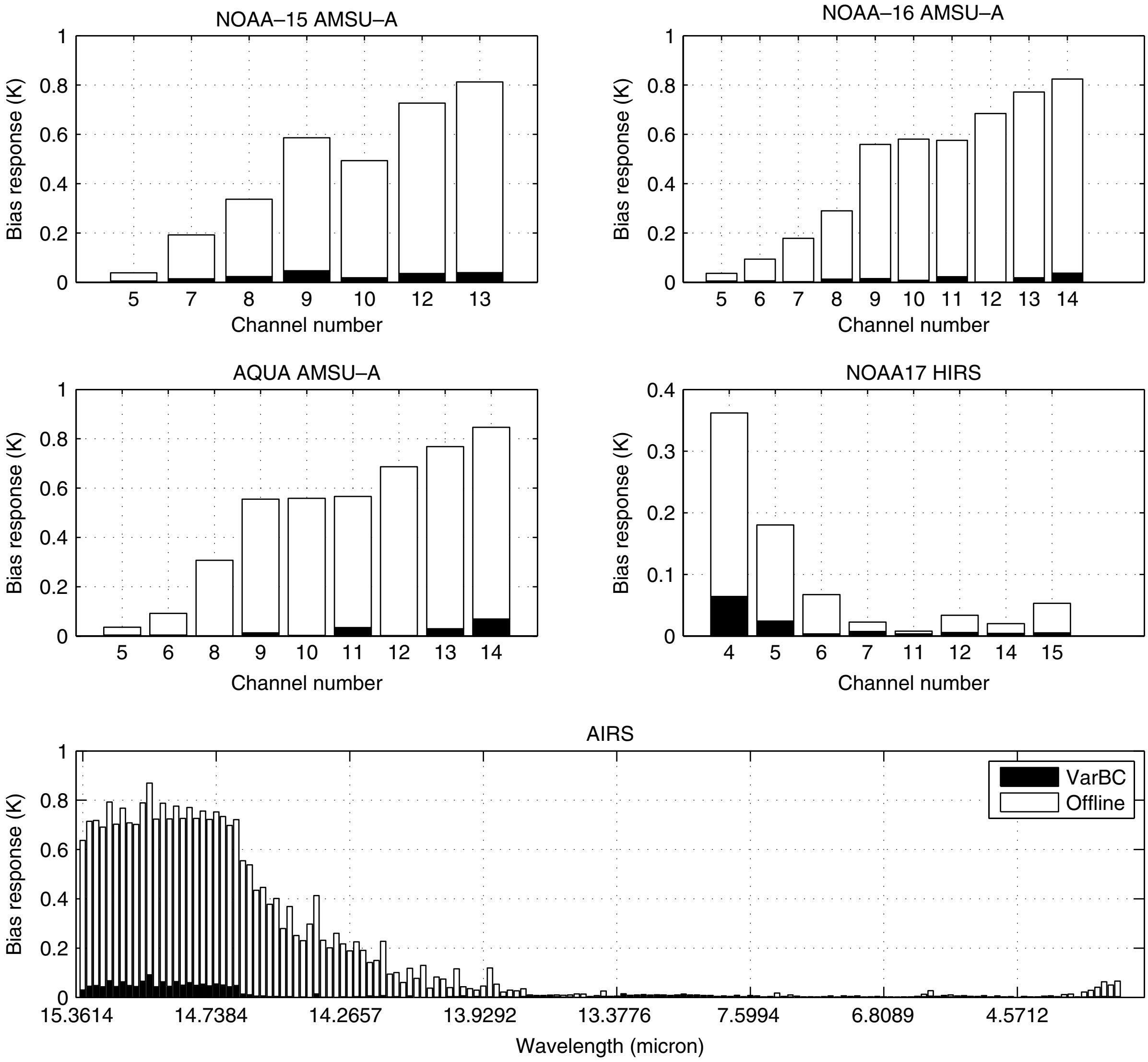

Figure 3. Response to an artificial uniform NWP model error. Observation bias correction response to a −1 K NWP model perturbation above 100 hPa for the VarBC (black) and Offline (white) bias correction schemes.

4.2. Response to a systematic NWP model error

Figure 5 shows the mean fit to radiosonde temperature data for two different assimilation systems. The grey lines correspond to a system using the Static bias correction scheme from ECMWF operations (version CY30R1). The radiosonde temperature data suggest that there is a cold bias in the assimilation (short-range forecast and analysis) in the lower stratosphere. Similar statistics for radiances from AMSU-A in channels sensitive to the lower stratosphere show no such disagreement. However, the radiances are only unbiased by virtue of their bias correction towards the model. This situation has been recognized for some time, and an obvious interpretation is that the forecast model does have a cold bias in the lower stratosphere, which is sustained in the analysis by the assimilation of wrongly bias-corrected radiances. Past attempts to manually resolve this problem – for example, by completely removing bias corrections from some of the upper AMSU-A channels – have failed to achieve an appropriate balance between different overlapping AMSU-A channels (Kelly, personal communication).

The same data fits after the VarBC scheme has been allowed to adjust the satellite bias correction are shown by the black lines of Figure 5. There is a striking improvement in the radiosonde agreement, achieved by VarBC adapting the bias correction applied to the stratospheric AMSU-A channels. The time series for AMSU-A channel 10 is shown in Figure 6, where the bias correction (black line) has been adjusted from 0.22 K to almost zero. By progressively reducing the amount of bias correction applied to the radiance data, more of the information from the AMSU-A forces mean increments and warms the analysis accordingly (as seen in the time series of the radiosonde fit in Figure 6(b)). Indeed, there is a gradient in the analysis cost function, which indicates that the observation bias can be reduced to improve the overall fit of the system to all observations. However, the successful removal of the cold bias has not been achieved quickly. The VarBC scheme has taken several weeks of

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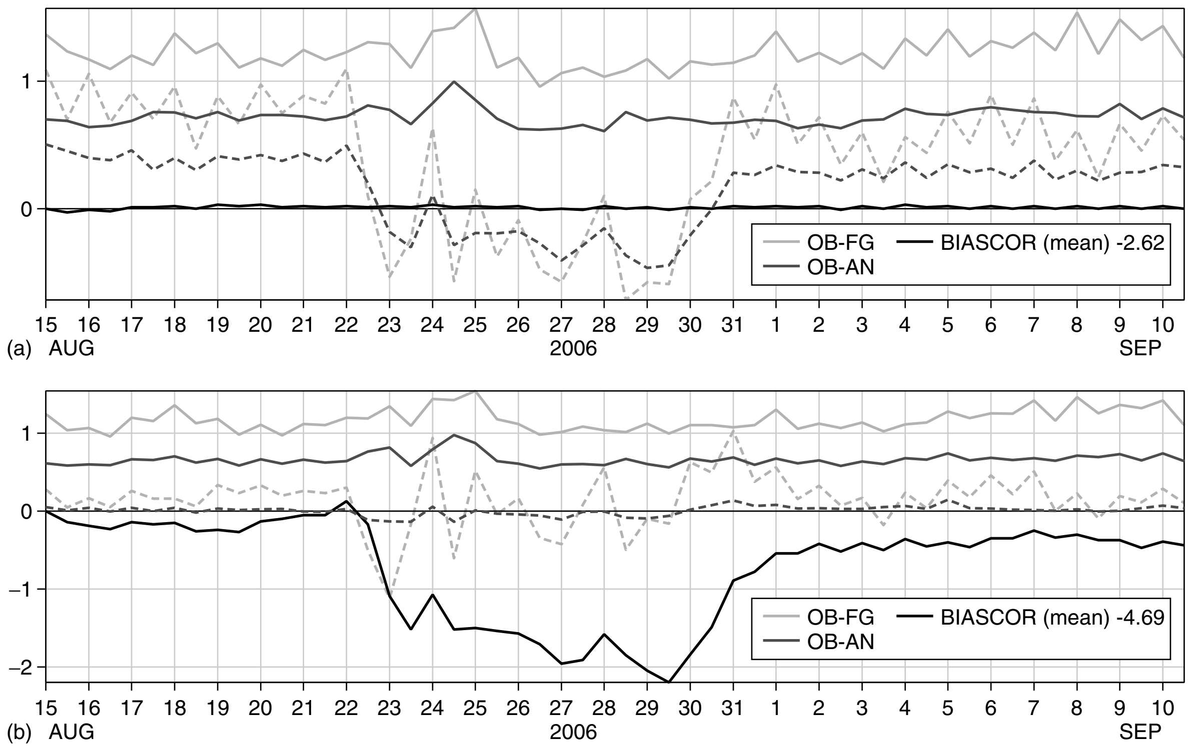

Figure 4. Standard deviation and bias of observed-minus-background (grey) and observed-minus-analysis fit (black) for the Meteosat-5 water-vapour channel in the Tropics. The bias (black dashed line) is estimated with (a) the Static bias correction scheme and (b) the VarBC scheme (with initial offsets of 2.62 K and 4.69 K respectively, for better visualization).

assimilation to gradually reduce the original satellite bias correction.

While an instrument failure or contamination is usually accounted for within a couple of days, in this case the cold bias observed in the stratosphere requires several weeks to be corrected. This cannot be explained by the inertia term (as it is deliberately relaxed for stratospheric channels). The potential damping influence of the quality control is similarly a small effect for stratospheric channels. As yet the reason for the slow evolution is not understood.

5. The indirect radiosonde constraint on the bias correction

The last section showed that *in situ* data (such as those from radiosondes), which themselves are not bias-corrected adaptively, can help the VarBC scheme to discriminate between NWP model error and satellite observation bias. These uncorrected observations provide an 'anchoring network' for the scheme. It is interesting to investigate the performance of the VarBC scheme in parts of the atmosphere not directly constrained by radiosondes (such as the upper stratosphere).

Figure 7(a) shows mean radiance departures for AMSU-A channel 14 from an assimilation that uses no satellite observations. The data are averaged over 8 days once the experiment has reached equilibrium (after about three weeks). This channel is sensitive to temperatures around 1 hPa. The large positive departures over the southern winter pole reflect a known systematic NWP model error that has been confirmed by a number of independent studies, for MIPAS (Dethof, 2004), GPS (Healy and Thépaut, 2006) and AIRS (McNally *et al.*, 2006).

Figure 7(b) shows the bias correction in AMSU-A channel 14 generated by the Offline adaptive bias correction scheme after three weeks of assimilation. The bias correction has compensated almost exactly for the NWP model error by generating a large correction to the observations. In contrast, the VarBC scheme generates a much smaller correction to the observations (Figure 7(c)), and uses more of the radiance signal to force analysis temperature increments (not shown). This part of the stratosphere (around 1 hPa) is not directly constrained by any radiosonde data, and yet VarBC and Offline show very different behaviours. This suggests that channels that are sensitive to layers where no radiosonde observations exist are at least partially constrained by neighbouring channels (through overlapping weighting functions), which are themselves constrained by radiosonde data below (in the lower stratosphere).

The radiosonde constraint can be further enhanced by calculating the bias only from the radiances in the vicinity of the radiosonde locations. We introduce a slightly different version of VarBC, called 'VarBC-Mask', which uses a mask to focus on data in the vicinity of radiosonde locations. This mask is fixed, and it includes land and sea locations within 1° of a predefined radiosonde location (see Figure 8). The sensitivity of the bias parameters to observations outside the mask is set to zero. Apart from this difference, VarBC-Mask is identical to VarBC, and in particular all observations are bias-corrected. Since

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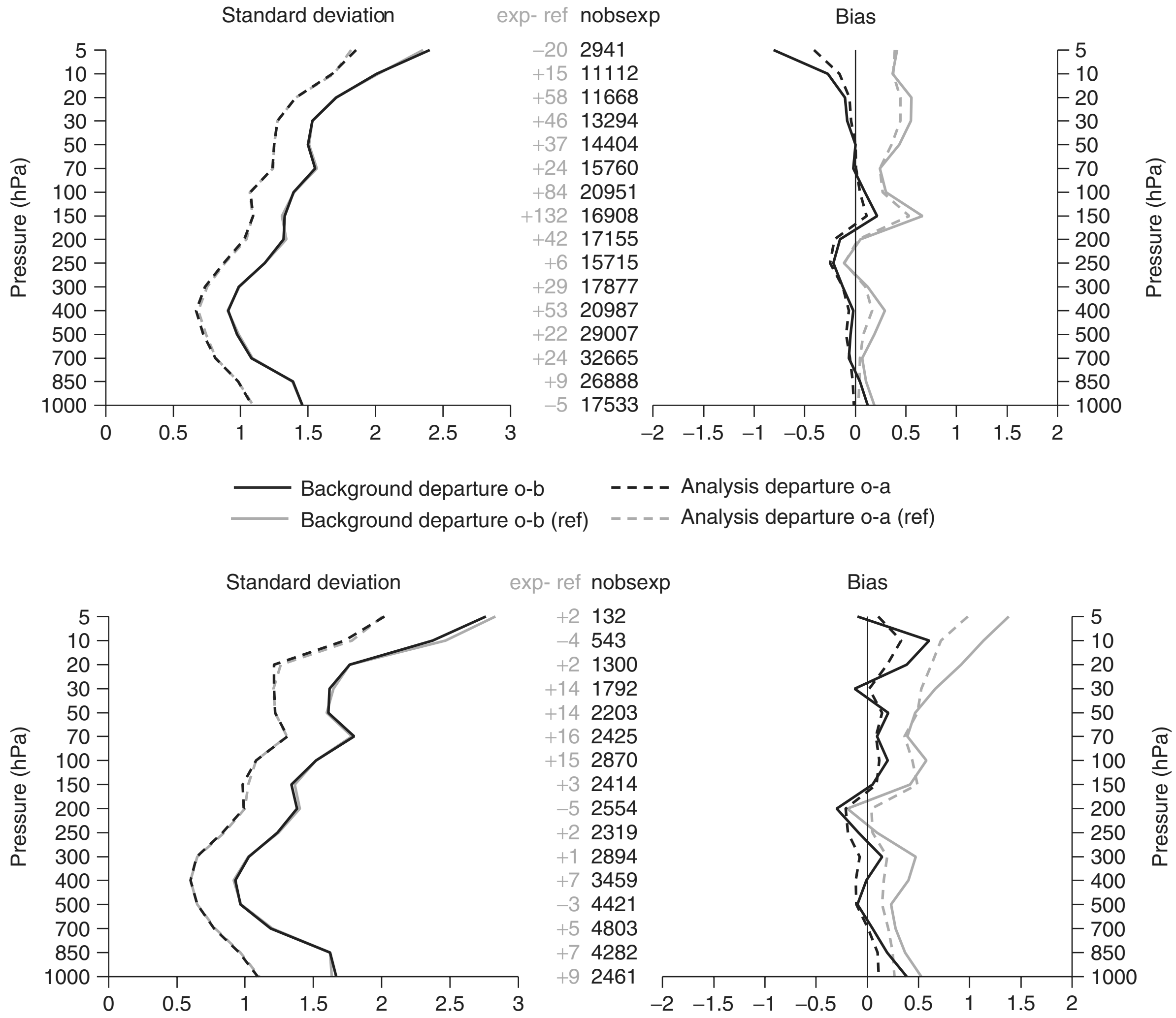

Figure 5. Standard deviation and bias of observed-minus-background (solid) and observed-minus-analysis fit (dashed) for radiosonde temperatures over the Northern Hemisphere (upper panels) and the Southern Hemisphere (lower panels). The statistics are calculated from 11 to 19 October 2005 for experiments using the Static bias correction scheme (grey lines) and the VarBC scheme (black lines) after 6 months of evolution.

VarBC-Mask focuses its update on the data that will most influence the fit to the radiosondes, it is expected to have a slightly better ability to discriminate between the sources of bias (NWP model error or observation error), and to be less contaminated by NWP model error. In addition, the bias calculation in the masked system is less exposed to NWP model error (especially over the southern oceans). The bias estimate from VarBC-Mask for AMSU-A channel 14 is shown in Figure 7(d). The corrections are generally comparable to those of the (unmasked) VarBC scheme, but with smaller values over the southern oceans and Antarctica.

6. Discussion and conclusions

A variational bias correction scheme has been studied, and the differences with an offline adaptive and a static bias correction scheme have been highlighted. In simulation, the three schemes have been exposed to artificial instrument and NWP model shifts.

The Static scheme equally forbids adaptation to instrument drifts and evolution in the NWP model error. While it rightly forces analysis increments to correct the NWP model (with no change to the bias), it is unable to adapt to the instrument problem, leading to significant damage to the analysis.

The Offline scheme benefits from the a priori assumption that the NWP model is correct, adapting appropriately to the instrument shift with very little damage to the analysis. (Note that this would not be the case if the bias were computed after the analysis.) However, an error in the NWP model is wrongly corrected by a change in the bias, resulting in limited analysis increments.

The VarBC scheme is better than the Static scheme in the case of an artificial instrument shift, where it limits damage to the analysis by partially adapting to the shift. This is confirmed by experiment with a real instrument error. A shift of more than 1 K for MSU channel 3 on NOAA-9 resulted in only minimal disruption to the analysis. VarBC is also better than

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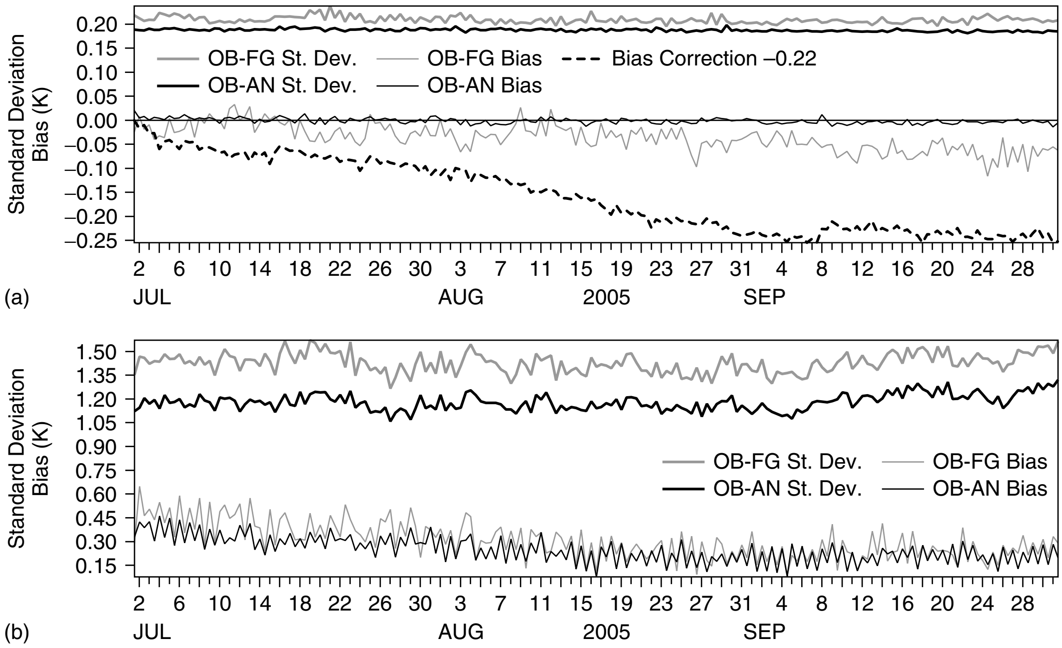

Figure 6. Standard deviation and bias of observed-minus-background (grey) and observed-minus-analysis fit (black) for (a) NOAA-16 AMSU-A channel 10 temperatures and (b) 50 hPa radiosonde temperatures in the Northern Hemisphere. The bias correction is represented by the black dashed line (with an initial offset of 0.22 K for better visualization).

Offline for an artificial error in the NWP model. Most of the signal in the radiance departures is correctly attributed to the NWP model (and not the observation bias), resulting in analysis increments to correct the NWP model. Extensive tests of VarBC in a real NWP environment show a significant reduction in the misfit to radiosonde observations (especially in the stratosphere) due to NWP model error. The VarBC scheme can therefore be considered as a useful compromise between the Static and Offline schemes.

VarBC has shown some skill in distinguishing between NWP model error and observation bias. It implicitly uses the redundancy of information between various observations to decide upon the likely source of the bias. Indeed, the data that are not VarBC-related (e.g. radiosonde, aircraft or surface data) still contribute to the cost function, and act as a constraint on the update of the control variable, and especially the VarBC parameters. Adjustments to 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 radiances and also by data not corrected with VarBC, it is likely that the optimal solution will modify the meteorological part of the control variable rather than the VarBC parameters. VarBC is believed to produce a better analysis at ECMWF in terms of fit to the radiosondes, but it must be noted that no significant improvement in forecast quality has been observed. Results have been shown for a particular assimilation system (the ECMWF 4D-Var system), and would not necessarily be the same in a system using different tuning parameters (for example, the background error covariances).

It must be stressed that the constraint of the radiosondes depends crucially on these observations not being bias-corrected to the NWP model, and thus acting as an 'anchoring network' to the system. It has been shown that the radiosondes can act remotely on VarBC. In parts of the atmosphere where no radiosonde observations are available (such as the upper stratosphere), the radiosonde network still imposes an indirect constraint on the system. This constraint is enhanced by applying a mask to the update of the bias in VarBC, considering only the radiances in the vicinity of the radiosonde locations.

Long-term drift linked with the interaction with the quality control is a potential concern when using an adaptive bias correction. We have evidence of only a small drift in the long-term experiments performed to date, reflecting the fact that VarBC is (at least) partially constrained either by the data that are not related to the VarBC or by the chosen bias predictors. However, significant effort is required to monitor the departures precisely (to detect systematic errors) and to better represent the characteristics of the observation biases (e.g. with the choice of predictors).

In order to detect failing observations and remove them prior to the analysis, the data have to pass a quality control (QC). Most QC algorithms act upon bias-corrected observed-minus-first-guess departures (so called 'first-guess checks'). Since the bias correction is calculated over the active population, a different QC results in a different bias correction, which will then influence the QC in the following cycle. This fundamental link (or 'feedback') between adaptive bias correction and QC is investigated in (Auligné and McNally, 2007). This study demonstrates that VarBC is usually more robust than other adaptive schemes performed outside the analysis. A new metric for the bias calculation, involving

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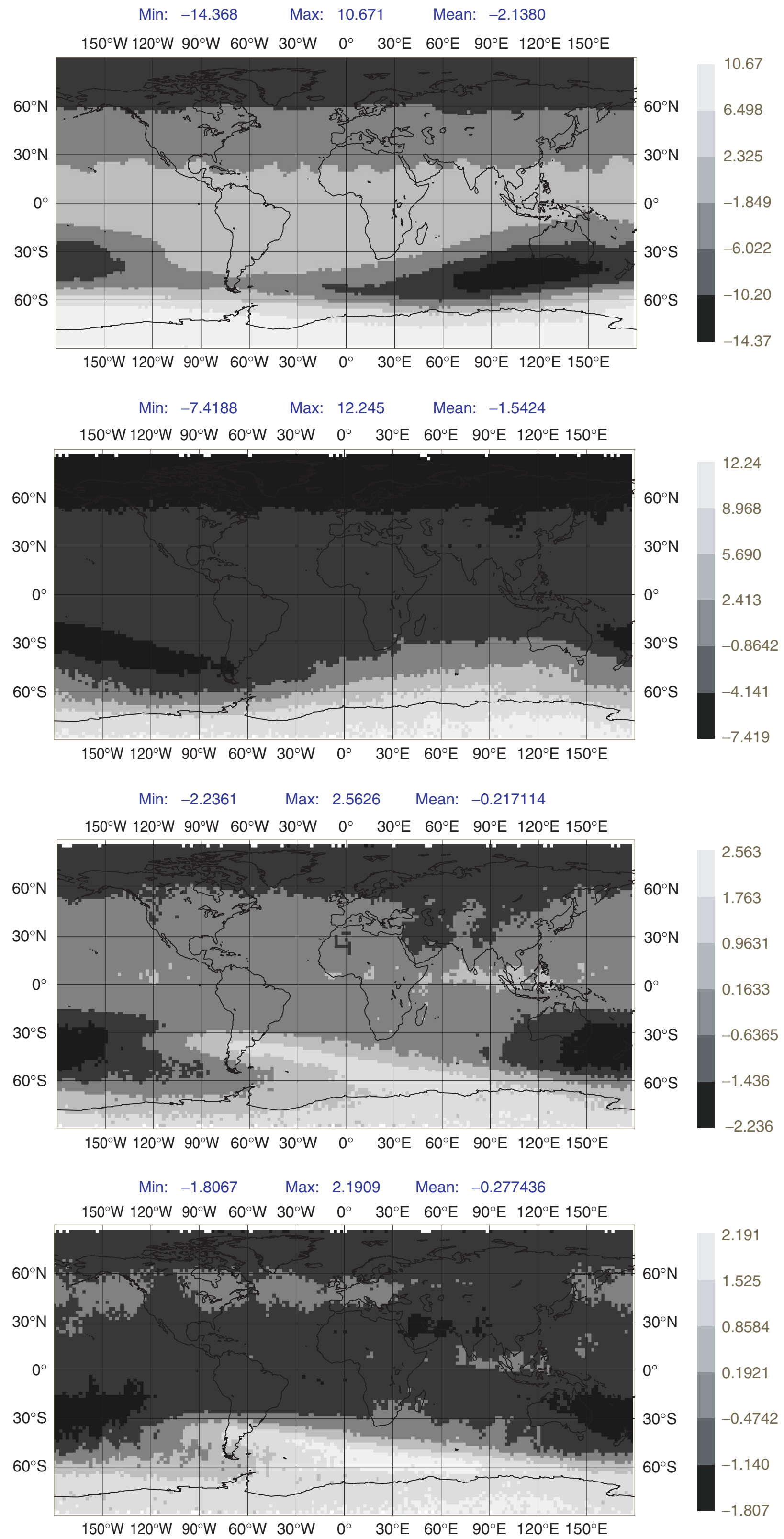

Figure 7. Mean values over a three-week period for AMSU-A channel 14 aboard the AQUA satellite. First panel: first-guess departures for an experiment where no satellite data is assimilated. Second, third and fourth panels: bias correction for experiments assimilating satellite data with the Offline, VarBC and VarBC-Mask schemes, respectively. This figure is available in colour online at www.interscience.wiley.com/qj

the use of a weighted mean instead of a simple average, is proposed in order to limit the influence of feedback on NWP model drifts.

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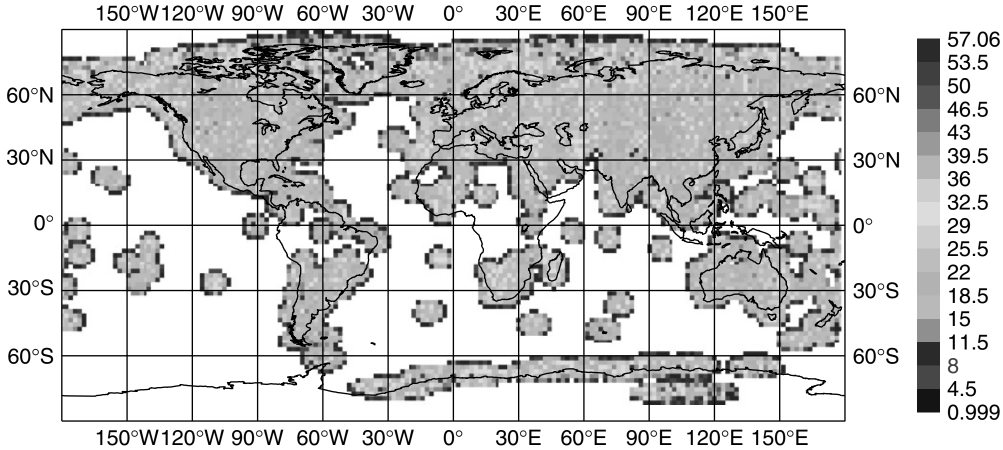

Figure 8. Number of data per 2° square contributing to the update of the bias in the VarBC-Mask experiment. The numbers are gathered over an 8-day period for AMSU-A channel 14 aboard the AQUA satellite.

for initiating fruitful discussions. Jean-Noel Thépaut provided helpful comments to improve the manuscript.

A. Appendix: Unconstrained adaptive bias correction

A very simple simulation is used to demonstrate that an NWP model bias will contaminate any adaptive bias correction that does not constrain the values of the bias estimates. We consider a temperature field represented by an NWP model that has a fixed 'climate' (i.e. the state the model would eventually reach in the absence of observations) that is biased relative to the true state by a constant offset $\mathbf{M}$. For a given analysis cycle k, the background $\mathbf{b}_k$ is a short-term forecast issued from the analysis of the previous cycle $\mathbf{a}_{k-1}$, which exhibits the tendency of the NWP model to creep back to its own climate $\mathbf{M}$. This can be simply modelled by the following formula:

$$\mathbf{b}_k = \mathbf{a}_{k-1} + \alpha(\mathbf{M} - \mathbf{a}_{k-1}), \qquad (A.1)$$

where α is a decay coefficient representing the tendency to the NWP model climate (arbitrarily set between 0 and 1).

The NWP model is confronted with satellite observations, which, for the sake of simplicity, directly measure the temperature with a constant offset $\mathbf{O}$. In each cycle, an analysis updates the model background according to the bias-corrected observation departures:

$$\mathbf{a}_k = \mathbf{b}_k + \beta(\mathbf{O} - \mathbf{b}_k - \mathbf{c}_{k-1}), \qquad (A.2)$$

where β is a coefficient set between 0 and 1, and $\mathbf{c}_{k-1}$ represents the bias correction calculated after the analysis for the cycle $k-1$. We suppose that no constraint is applied to the bias correction, which is simply calculated as the mean of the analysis departures:

$$\mathbf{c}_{k-1} = \mathbf{O} - \overline{\mathbf{a}_{k-1}}. \qquad (A.3)$$

Rearranging Equations (5), (6) and (7), we obtain:

$$\mathbf{a}_k = \mathbf{b}_k - \alpha\beta(\mathbf{M} - \mathbf{a}_{k-1}). \qquad (A.4)$$

Replacing $\mathbf{b}_k$ by its expression from Equation (5), and applying Equation (8) to k and $k+1$, we get:

$$\mathbf{a}_{k+1} - \mathbf{a}_k = \alpha(1-\beta)(\mathbf{M} - \mathbf{a}_k). \qquad (A.5)$$

Since the coefficients α and β are set between 0 and 1, it is easy to show that the sequence $\mathbf{a}_k$ is monotonic and bounded by $\mathbf{M}$ and that it converges towards $\mathbf{M}$:

$$\lim_{k\to\infty} \mathbf{a}_k = \mathbf{M},$$

and as a result,

$$\lim_{k\to\infty} \mathbf{b}_k = \mathbf{M},$$

and

$$\lim_{k\to\infty} \mathbf{c}_k = \mathbf{O} - \mathbf{M}.$$

Figure 9 shows the evolution of the model and observation values as the scheme is iterated. The information that pulled the NWP model away from its own climate is gradually removed from the observations by the bias correction as it gets contaminated by the model bias. The system converges when the model has reached its own climate. A bias correction with respect to the model background instead of the analysis would converge even faster to the same estimates, as this is implicitly equivalent to the assumption that the background is unbiased.

B. Appendix: Constrained adaptive bias correction

A different simulation is performed to illustrate the influence of a constraint on the bias correction. Focusing on a given analysis cycle, the model is assumed to have a systematic error that varies as the cosine of latitude. The bias correction scheme is defined as a linear regression, with two parameters β_0 and β_1, corresponding

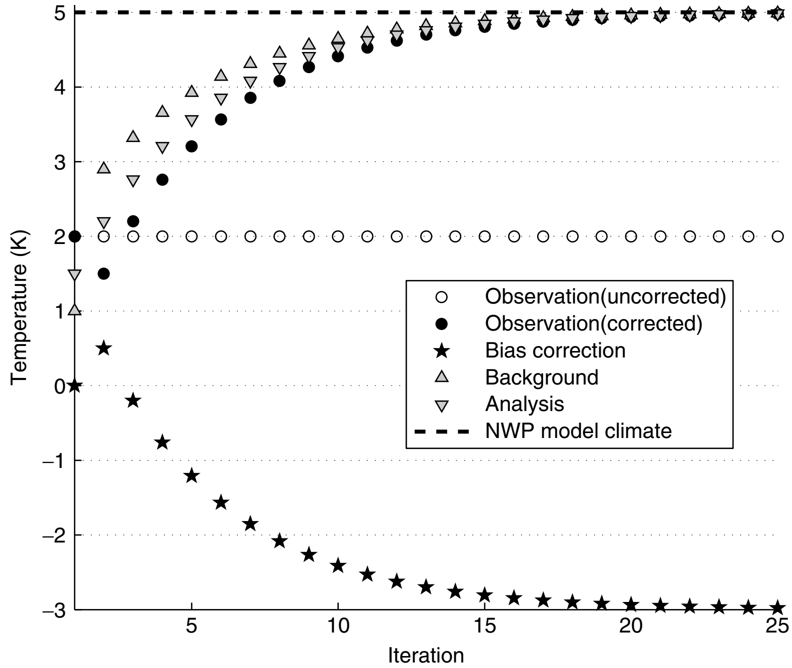

Figure 9. Theoretical simulation of an analysis system using an unconstrained adaptive bias correction. The evolution of the model state, the bias correction and the bias-corrected observations are represented as functions of the system iteration number.

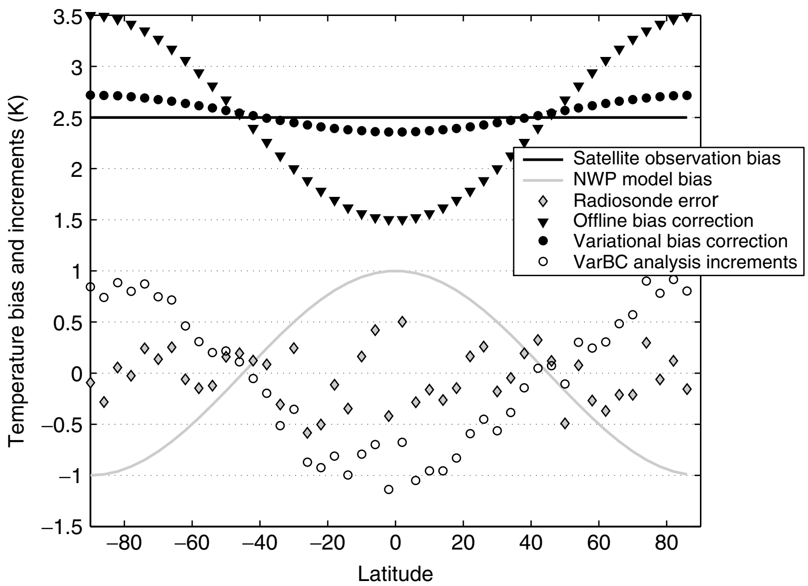

Figure 10. Theoretical simulation of two bias correction schemes (VarBC and Offline) confronted with a homogeneous satellite observation bias (black line) and a latitude-dependent NWP model bias (grey line). VarBC benefits from radiosonde measurements that have an unbiased random error.

respectively to a constant offset and a predictor defined for each observation n as

$$P_1(n) = \cos \lambda(n).$$

The bias estimate is thus of the following form:

$$B(n) = \beta_0 + \beta_1 P_1(n). \tag{B.1}$$

For the sake of simplicity, the N satellite observations X_{sat} and the corresponding NWP model values X_{m} are collocated temperatures (i.e. all observation operators are equal to the identity), and the N observations are distributed through the whole latitude range. The satellite observations are assumed to be uniformly biased relative to the true state. With the predictors defined in the parametric form, the bias correction has the potential to explain both the observation bias and the model error.

An offline adaptive bias correction scheme to the background, as described above, is equivalent for the given analysis cycle to the minimization of the following

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objective function:

$$J_{\text{offline}}(\beta_0, \beta_1) = \sum_{n=1}^{N} (X_{\text{sat}}(n) - X_{\text{m}}(n) - B(n))^2 , \tag{B.2}$$

where X_{m} is fixed, since the bias correction is performed independently of the analysis (i.e. offline).

Collocated radiosonde temperature observations X_{RS} are introduced with a Gaussian observation error. A bias correction performed inside the analysis (i.e. a variational bias correction) can be formulated for the given analysis cycle by the minimization of an objective function J_{VarBC}. To keep the formulation as simple as possible, the same weights are assigned to the satellite and the radiosonde observations. The number of observations is assumed to be large enough that one can neglect the effect of any prior knowledge (or 'background') on the bias parameters:

$$J_{\text{VarBC}}(X_{\text{m}}, \beta_0, \beta_1) = \sum_{n=1}^{N} (X_{\text{sat}}(n) - X_{\text{m}}(n) - B(n))^2 + \sum_{n=1}^{N} (X_{\text{RS}}(n) - X_{\text{m}}(n))^2 . \tag{B.3}$$

A simple gradient-descent algorithm is used to find the values that minimize the objective functions for the offline and variational formulations. The robustness of the solution has been assessed through several experiments using a varying Gaussian noise for the radiosonde observations. The results are shown in Figure 10. The offline scheme calculates a bias correction accounting for the full first-guess departures: a combination of the satellite observation bias and the systematic NWP model error. If the analysis of the temperature were performed after the bias correction calculation, the increments would be close to zero, since most of the signal from the departures would be removed by the bias correction. The variational scheme, constrained by the radiosondes, shows significant skill in distinguishing between the sources of bias. The bias correction is much closer to the actual satellite bias than that from the offline scheme.

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