Variational bias correction of radiance data in the ECMWF system

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1 Introduction

This paper describes the implementation of a method for adaptive estimation and correction of radiance biases in the ECMWF variational data assimilation system. Biases are partly caused by problems with the measurements themselves, but are also affected by errors in the radiative transfer calculations that are used to simulate radiance observations from the model state. These errors are different for each sensor and each channel, and tend to depend on the state of the instrument (e.g., scan position, poor calibration) as well as on local properties of the geophysical parameters being sensed (McNally *et al.*, 2000). Over the years, sufficiently effective schemes have been developed for screening the data and estimating their biases, so that the quality-controlled and bias-corrected radiance data can be usefully assimilated in an NWP system. At the same time, the number and variety of available sensors and the quantity of measurements they produce have increased to the point that the processing and management of the data now presents a tremendous challenge.

The radiance bias correction scheme currently in use at the ECMWF is largely manually operated. First, the bias for a given channel is modeled by an expression that depends on a relatively small number of parameters. The parameters for all sensors on a particular satellite are estimated from time series of radiance departures (observed-minus-background residuals) and stored on file. The files with bias parameters are then ingested by the data assimilation system as needed, and the data are corrected accordingly in real time. The need to periodically re-estimate the bias parameters is primarily determined on the basis of monitoring; if the bias correction for a given channel is still effective then the mean departures for that channel should remain small. Changes in the bias can occur with the aging of an instrument, or when the radiative transfer operator is modified. Additionally, changes in the error characteristics may depend in a complex manner on changes in the configuration of the data assimilation system. The introduction of a new data type (or the removal of an old one), adjustments to the model physics, or a change in surface characteristics—any of these events may affect the biases in some of the sensors.

There are obvious practical advantages to having an adaptive bias correction scheme that can automatically sense a change in the bias for a given channel and will then respond accordingly. Such a scheme was in fact implemented by Derber and Wu (1998) in the context of their global variational analysis system, and it has been operational at NCEP for many years. Conceptually it is straightforward to estimate bias parameters (or any other parameters, for that matter) along with the model state in a variational framework. The implementation in an existing data assimilation system requires: (1) formulation of a parameterized bias model for the observations; (2) the tangent linear and adjoint of this bias model; (3) an algorithm for cycling the bias parameter estimates; and (4) an effective preconditioner for the joint (state/parameter) minimization problem.

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2 Methodology

2.1 Current scheme for radiance bias correction

The current scheme for radiance bias correction in use at the ECMWF is described in Harris and Kelly 2001. Bias corrections are pre-computed for all available sensors and applied to the brightness temperature observations prior to their assimilation. The scheme is based on a separation of the biases into scan-angle dependent and state dependent components. It is assumed that the data y in a given channel are related to the true model state x at the observed time and location by

$$y = h(x) + b^{scan} + b^{air}(x) + \tilde{e}_o, \qquad < \tilde{e}_o >= 0 \tag{1}$$

where $h(x)$ represents the radiative transfer for the channel in question. In the current version of the system (Cy26r3), the scan bias b^{scan} is a function of latitude as well as scan position. The air-mass dependent bias b^{air} is expressed as a linear combination of a set of state-dependent predictors $p_i(x), i = 1, \ldots, N$:

$$b^{air}(x) = b^{air}(x, \beta) = \beta_0 + \sum_{i=1}^{N} \beta_i p_i(x) \tag{2}$$

with scalar coefficients $\beta_i, i = 0, \ldots, N$. The selection of predictors $p_i(x), i = 1, \ldots, N$ is flexible and depends on the instrument and channel. Available predictors and their use in Cy26r3 are listed in Tables 1 and 2.

Table 1: Bias predictors implemented in Cy26r3

p_0: 1 (constant)
p_1: 1000-300hPa thickness
p_2: 200-50hPa thickness
p_3: skin temperature
p_4: total column water
p_5: 10-1hPa thickness
p_6: 50-5hPa thickness
p_7: surface wind speed

If the background x_b contains no systematic errors, then (1) implies

$$< y - h(x_b) >= b^{scan} + b^{air}(x_b) \tag{3}$$

A carefully selected sample of background departures for a given sensor and channel set is used to estimate the biases, in a two-step procedure. First, scan bias coefficients are computed by separating the scan-position dependent component of the mean departures in latitude bands. Second, after removing the scan bias from the departures, the predictor coefficients $\beta_i, i = 0, \ldots, N$ for the state-dependent component of the bias are obtained by linear regression. See Harris and Kelly (2001) for further details.

At the end of this estimation procedure, bias coefficients for each sensor are stored on file. The data assimilation system can then access the coefficients in order to compute bias corrections for the latest observations, using updated state information for evaluating the air-mass dependent component of the bias. The brightness temperatures are corrected accordingly, just prior to assimilation.

The success of this method depends strongly upon a careful selection of the data sample. Data locations used for bias estimation are restricted to the vicinity of radiosonde sites where the background is likely to be most accurate. Furthermore, an attempt is made to remove the effect of residual cloud/rain contamination in the departures, so that those effects will not influence the bias estimates. Thus, the data selection and quality control for the bias estimation can be very different from the data selection and quality control used in the analysis. When we later introduce the new variational bias correction scheme, we shall see that all data used in the analysis will influence the bias estimates, so that is no longer possible to restrict and/or weight the data differently for the bias estimation.

Table 2: Usage of bias predictors in Cy26r3, by sensor type

HIRS	NOAA-16, NOAA-17	p_0, p_1, p_2, p_3, p_4
AMSU-A	NOAA-15, NOAA-16, NOAA-20	p_0, p_1, p_2, p_3, p_4
AMSU-B	NOAA-16, NOAA-17	p_0, p_1, p_2, p_3, p_4
SSM/I	DMSP-13, DMSP-14, DMSP-15	p_0, p_3, p_4, p_7
GEOS	METEOSAT-5, METEOSAT-7, GOES-9, GOES-10, GOES-12	p_0, p_1, p_2, p_4
AIRS	NOAA-20	p_0

2.2 Standard variational analysis

All analysis methods rely on a precise description of the relationship among the available data and the unknown model state. Information from past data is incorporated in a background estimate, which is usually a short-term forecast issued from the previous analysis. Current data consist of a heterogeneous set of quality-controlled meteorological observations. The standard statistical description of these data and their errors is

$$y = h(x) + e_o, \qquad < e_o > = 0, \qquad < e_o e_o^T > = R \tag{4}$$

$$x_b = x + e_b, \qquad < e_b > = 0, \qquad < e_b e_b^T > = B, \qquad < e_b e_o^T > = 0 \tag{5}$$

where x is the unknown model state, x_b the background estimate, and y the observations. The function $h(x)$ is the observation operator, which is supposed to describe the deterministic relationship between the observations and the state of the system. The observation and background error covariances R and B are assumed known.

In a variational analysis, the model state is estimated by minimizing

$$J(x) = \frac{1}{2}(x_b - x)^T B^{-1}(x_b - x) + \frac{1}{2}\left[y - h(x)\right]^T R^{-1}\left[y - h(x)\right] \tag{6}$$

with respect to x. The minimizing solution $x = x_a$ is the best linear unbiased estimate (BLUE) when the statistical assumptions in (4–5) are valid. The usefullness of this estimate depends on whether the error distributions can be adequately described by their first two moments.

2.3 Observation bias parameters

In practice many observations contain non-negligible systematic errors, so that the standard assumptions (4) do not apply; i.e.,

$$< e_o > = < y - h(x) > \neq 0 \tag{7}$$

The quantity $< e_o >$ is often referred to as 'observation bias' because $< \cdot >$ has traditionally been calculated as a time average. This terminology can be misleading when systematic non-zero departures are caused by errors in the implementation of the observation operator $h(x)$ (e.g. inaccurate weighting functions for the radiative transfer), which depend on the true state x and possibly on other unknown parameters as well.

In any case, suppose the systematic observation errors can be described in terms of a limited set of parameters β. We can then modify the observation operator $h(x)$ such that

$$< \tilde{e}_o > = < y - h(x, \beta) > = 0 \tag{8}$$

for some (unknown) parameter vector β. In practice this means that we incorporate some degrees of freedom in the observation operator that will be adjusted in order to reduce the bias. For example, a modified observation operator could be defined using a linear predictor model such as that given by (2),

$$h(x,\beta) = h(x) + \sum_{i=0}^{N} \beta_i p_i(x) \tag{9}$$

In more meaningul, physically-derived error models, the modified operator refers to uncertain parameters or coefficients that are known to have a significant impact on the systematic errors in (1). For example, Watts (2004) has introduced a bias correction scheme for AIRS data which is based on a modification of the transmittance coefficients in the RTTOV model (Saunders *et al.*, 1999). This scheme involves, for each AIRS channel, two global parameters that can be adjusted to reduce the systematic errors in the RTTOV calculations.

If the parameters β vary slowly in time and space, then it should be possible to obtain statistically meaningful estimates using appropriate techniques, even though the 'observation bias' itself is flow-dependent. In the case of the linear predictor model, for example, it is tacitly assumed that the predictor coefficients β are globally valid and approximately constant in time. This makes it possible to estimate them from timeseries of localized departures, and it also justifies the use of those estimates for predicting and extrapolating appropriate bias corrections for future data.

2.4 Modified variational analysis

The error parameters of a modified observation operator can be estimated along with the model state using state augmentation techniques. This is a standard approach that can be implemented in sequential estimation schemes as well as in a variational framework. State augmentation has been widely used in many applications to estimate parameters related to, for example, uncertainties in model forcing, the boundary conditions, diffusion coefficients, and other model components. At the ECMWF, state augmentation is used operationally to estimate the surface temperature at radiance data locations (Simmons 2000), and experimentally to estimate CO2 concentration using AIRS data (Engelen *et al.* 2004). Developments are currently underway to add model error parameters to the control vector (Trémolet 2003).

For the purpose of radiance bias estimation, we define the augmented control vector

$$z^T = \left[x^T \, \beta^T\right] \tag{10}$$

Assume we have some prior estimate β_b of the parameters, obtained, for example, from a previous analysis cycle. The standard assumptions in terms of the augmented control vector z and the modified observation operator $\tilde{h}$ are

$$y = \tilde{h}(z) + \tilde{e}_o, \qquad <\tilde{e}_o> = 0, \qquad <\tilde{e}_o \tilde{e}_o^T> = R \tag{11}$$

$$z_b = z + \tilde{e}_b, \qquad <\tilde{e}_b> = 0, \qquad <\tilde{e}_b \tilde{e}_b^T> = Z, \qquad <\tilde{e}_b \tilde{e}_o^T> = 0 \tag{12}$$

with

$$z_b^T = \left[x_b^T \, \beta_b^T\right] \tag{13}$$

Therefore the BLUE of the modified control vector z is obtained by minimizing

$$J(z) = \frac{1}{2}(z_b - z)^T Z^{-1}(z_b - z) + \frac{1}{2}\left[y - \tilde{h}(z)\right]^T R^{-1}\left[y - \tilde{h}(z)\right] \tag{14}$$

Inclusion of the bias parameters in the control vector means that they are jointly estimated with the model state, based on the same set of observations y. It is therefore not possible in this approach to maintain a separate, more restrictive, data selection for the estimation of bias parameters.

2.5 Adjoint of the bias model

The first implementation of adaptive bias correction in the ECMWF variational was designed to co-exist with the current operational bias correction scheme. For the moment, the scan bias correction is still handled outside the variational analysis. The adaptive bias parameters are therefore the predictor coefficients for the air-mass dependent component of the bias, so that the modified observation operator is given by (9).

In the incremental formulation of the variational analysis, nonlinear observation operators are linearized about the latest outer-loop estimate $\bar{x}$ of x. Similarly, for the modified operator we use

$$h(x,\beta) \approx h(\bar{x},\beta) = h(\bar{x}) + \sum_{i=0}^{N} \beta_i p_i(\bar{x}) \tag{15}$$

The modification to $h(x)$ is therefore additive and linear in the bias parameters, and its adjoint with respect to these additional control parameters is trivial to implement.

2.6 Cycling the bias parameters

The first term in (14) expresses the joint background constraint for the state vector x and bias parameters β. As usual x_b is a short-term forecast, and for β_b we take the parameter estimates obtained in the previous analysis cycle.

In general the parameter estimation errors will be correlated with the state estimation errors, because they depend on the same data. We know of no practical way to account for this statistical dependence, and therefore take

$$Z = \begin{bmatrix} B_x & 0 \\ 0 & B_\beta \end{bmatrix} \tag{16}$$

where B_x denotes the usual (state) background error covariance, and B_β the parameter background error covariance. Written in terms of x and β, (14) then becomes

$$J(x,\beta) = \frac{1}{2}(x_b - x)^T B_x^{-1}(x_b - x) + \frac{1}{2}(\beta_b - \beta)^T B_\beta^{-1}(\beta_b - \beta) + \frac{1}{2}\left[y - \tilde{h}(x,\beta)\right]^T R^{-1}\left[y - \tilde{h}(x,\beta)\right] \tag{17}$$

The second term represents the background constraint on the bias parameters. It controls the adaptivity of the estimates: a strong constraint means that the parameter updates in each cycle are small, while a weak constraint (or no constraint at all) implies that the parameter estimates respond quickly to the latest observations.

We take B_β diagonal:

$$B_\beta = \mathrm{diag}(\sigma_{\beta_1}^2, \ldots, \sigma_{\beta_n}^2) \tag{18}$$

with

$$\sigma_{\beta_j}^2 = \sigma_{o_j}^2 / N_j, \qquad j = 1, \ldots, n \tag{19}$$

Here β_j denotes the j^{th} bias parameter, σ_{o_j} is the error standard deviation of the observations associated with β_j, and N_j is a positive integer.

Equation (19) gives the error variance of an estimate of the mean of N_j independent noisy observations whose individual error variances are $\sigma_{o_j}^2$. Thus, the interpretation of (19) is that the background estimate for the parameter β_j is assigned the same weight as N_j current observations. For example, taking $N_j = 10,000$ for all parameters, the system will adapt quickly to changes in the bias for a clean channel generating thousands of radiances per analysis cycle. On the other hand, it will respond slowly to a cloudy channel that generates only a few hundreds of data per cycle. This is appropriate for the estimation of global parameters, which should not be determined solely on the basis of a few localized patches of data.

When the N_j are sufficiently large (say, $N_j \gg 100$) the effect of neglecting off-diagonal elements of the parameter background error covariance matrix should be insignificant. This is because $O(N_j)$ observations are used to estimate just a few bias parameters; the estimation errors will be small even when the estimation is sub-optimal. The situation is, of course, very different for the state estimation, which can be extremely sensitive to the specification of the background error covariances, especially in data-sparse areas.

2.7 Preconditioning the joint minimization problem

For general background on minimization algorithms for variational data assimilation, with particular emphasis on preconditioning methods, see Fisher (1998).

Preconditioning in the current ECMWF system is partly accomplished by a carefully constructed transformation from the physical model state variables to an abstract control space. The idea is to define this transformation in such a way that the shape of the cost function in control space is nice enough (i.e., similar in all directions) that the minimization algorithm can rapidly converge to the solution, with uniform error reduction in all directions. For a quadratic cost function, the shape at the minimum is completely described by the Hessian, which is

$$\left.\frac{\partial^2 J}{\partial x^2}\right|_{x=x_a} = B_x^{-1} + H_x^T R^{-1} H_x, \qquad H_x = \left.\frac{\partial h}{\partial x}\right|_{x=x_a} \tag{20}$$

The ideal change of variable would therefore be the symmetric square root of the Hessian, since this would result in a perfectly isotropic cost function in control space.

The first term on the right-hand side of (20) represents the information contained in the background, while the second term represents the additional information provided by the observations. The second term is, of course, unknown at the outset of the minimization, and difficult to evaluate in general. The change of variable used for preconditioning is therefore normally defined in terms of just the background covariance operator:

$$\chi_x = B^{-1/2}(x_b - x) \tag{21}$$

Usually this works quite well, because the information in the background tends to dominate the information in the observations. For the state estimation problem, therefore, the inverse background error covariance is not too far removed from the Hessian. When occasional convergence problems do occur, they are often associated with the use of densely spaced and/or highly accurate observations. Such a case of poor convergence was analyzed and explained in detail by Andersson *et al.* (2000).

For the parameter estimation problem, on the other hand, observational information tends to dominate because the number of data per unknown is typically very large. The standard change of variable based on the background contribution alone is therefore not an effective preconditioner. The Hessian with respect to the parameter vector is

$$\left.\frac{\partial^2 J}{\partial \beta^2}\right|_{\beta=\beta_a} = B_\beta^{-1} + H_\beta^T R^{-1} H_\beta, \qquad H_\beta = \left.\frac{\partial h}{\partial \beta}\right|_{\beta=\beta_a} \tag{22}$$

The change of variable for the parameter vector should incorporate an estimate of the second term in this expression, which represents the observational contribution to the available information about the parameters.

For the linear predictor model (9), the derivatives with respect to the parameters are simply the values of the predictors at the observation locations. The observational contribution to the Hessian depends primarily on the number of observations (the number of rows of H_β), on the observation error variances (the diagonal of R), and on the second moments of the predictors (the elements of $H_\beta^T H_\beta$). We will construct a change of variable for the bias parameters based on a simple approximation of this term for each single group of observations.

Suppose that we have designated K distinct groups of data (i.e., single channels) for bias correction. Consider a single group k, containing m observations with error standard deviation σ_o. Suppose that the bias model for that group is based on N predictors, and let the $N \times N$ matrix C denote an estimate of the globally averaged covariances of those predictors. Then let

$$L^k = \left[(B^k_\beta)^{-1} + \frac{m}{\sigma_o^2} C \right]^{1/2} \tag{23}$$

where B^k_β is the $N \times N$ matrix of background error covariances associated with the N bias parameters for group k. This expression is easy to compute prior to the minimization. We then define the change of variable for the bias parameters by

$$\chi_\beta = L(\beta_b - \beta) \tag{24}$$

where the operator L is block-diagonal with blocks $L^k, k = 1, \ldots, K$ defined by (23).

Extensive experimentation has shown that this change of variable for the parameter vector, when combined with the standard change of variable for the state vector, provides an effective preconditioner for the joint parameter/state minimization problem. The conjugate-gradient algorithm used for the minimization typically requires the same number of iterations with or without bias parameters. There is no measurable increase in the cost of each iteration, since the number of bias parameters is relatively small and the computational overhead is therefore insignificant.

2.8 Bias correction of passive data

In some cases it is necessary to estimate biases for data that are not normally used in the analysis except for quality control. For example, the ECMWF cloud-detection scheme for HIRS and AIRS data involves checks on channels that are otherwise excluded from the analysis (McNally and Watts 2003). These channels must be bias-corrected for the cloud detection scheme to be effective. Now that the bias correction is done jointly with the state estimation in the variational analysis, it is unavoidable that channels needed for quality control be included in the analysis.

Bias correction of otherwise passive data can be achieved by artificially inflating the observation error standard deviations for those data. We will clarify this point with a simple scalar error analysis. Suppose that the number of observations in a particular group of data is m, and that the observation error standard deviation assigned to that group is such that

$$\sigma_{x_b} \ll \sigma_o \ll m \tag{25}$$

where σ_{x_b} is the background error standard deviation, which we assume to be roughly $O(1)$. For a linear analysis the error standard deviation σ_{x_a} satisfies

$$\frac{1}{\sigma_{x_a}^2} \approx \frac{1}{\sigma_{x_b}^2} + \frac{1}{\sigma_o^2} \qquad \longrightarrow \qquad \sigma_{x_a} \approx \sigma_{x_b} \tag{26}$$

so that the impact on the state estimates at any particular location is negligible. On the other hand, for the parameter estimation we have

$$\frac{1}{\sigma_{\beta_a}^2} \approx \frac{1}{\sigma_{\beta_b}^2} + \frac{m}{\sigma_o^2} \tag{27}$$

which, when combined with (19) gives

$$\sigma_{\beta_a} \approx \frac{\sigma_o}{\sqrt{N+m}} \ll 1 \tag{28}$$

which means that the impact on the parameter estimates is large. It is therefore possible to inflate the observation error standard deviation for a group of data in such a way that the impact of the data on the state estimates is negligible, but the bias parameters estimates are accurate all the same.

3 Results

We now present results of an assimilation with variational bias correction applied to all available brightness temperature data. All comparisons are made against the ECMWF 4D-Var assimilation system (Cy26r3) which became operational on March 9, 2004. The sensors available to the system are listed in Table 2. The experimen-

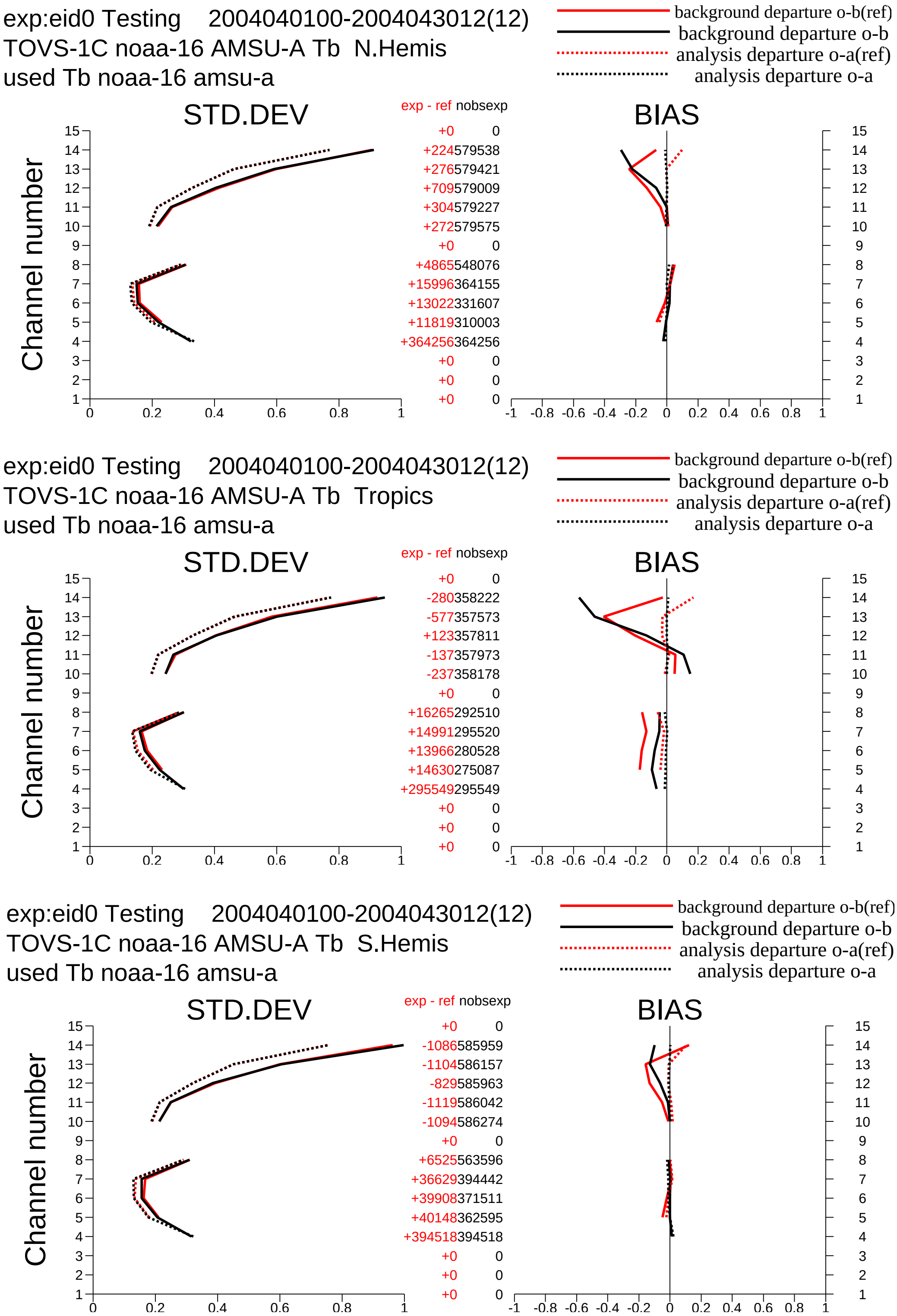

Figure 1: NOAA-16 AMSUA brightness temperature departure statistics

tal system is identical to the operational system, except that the air-mass component of the bias for all sensors and all channels is made adaptive. Scan bias correction is still performed prior to the assimilation, based on the precomputed scan bias files used in operations. A number of additional channels are assimilated in the experiment with inflated observation errors, as explained in the previous section (HIRS channels 1,2,3,8,9,10,13, AMSU-A channel 4, AMSU-B channel 2, and a number of AIRS channels).

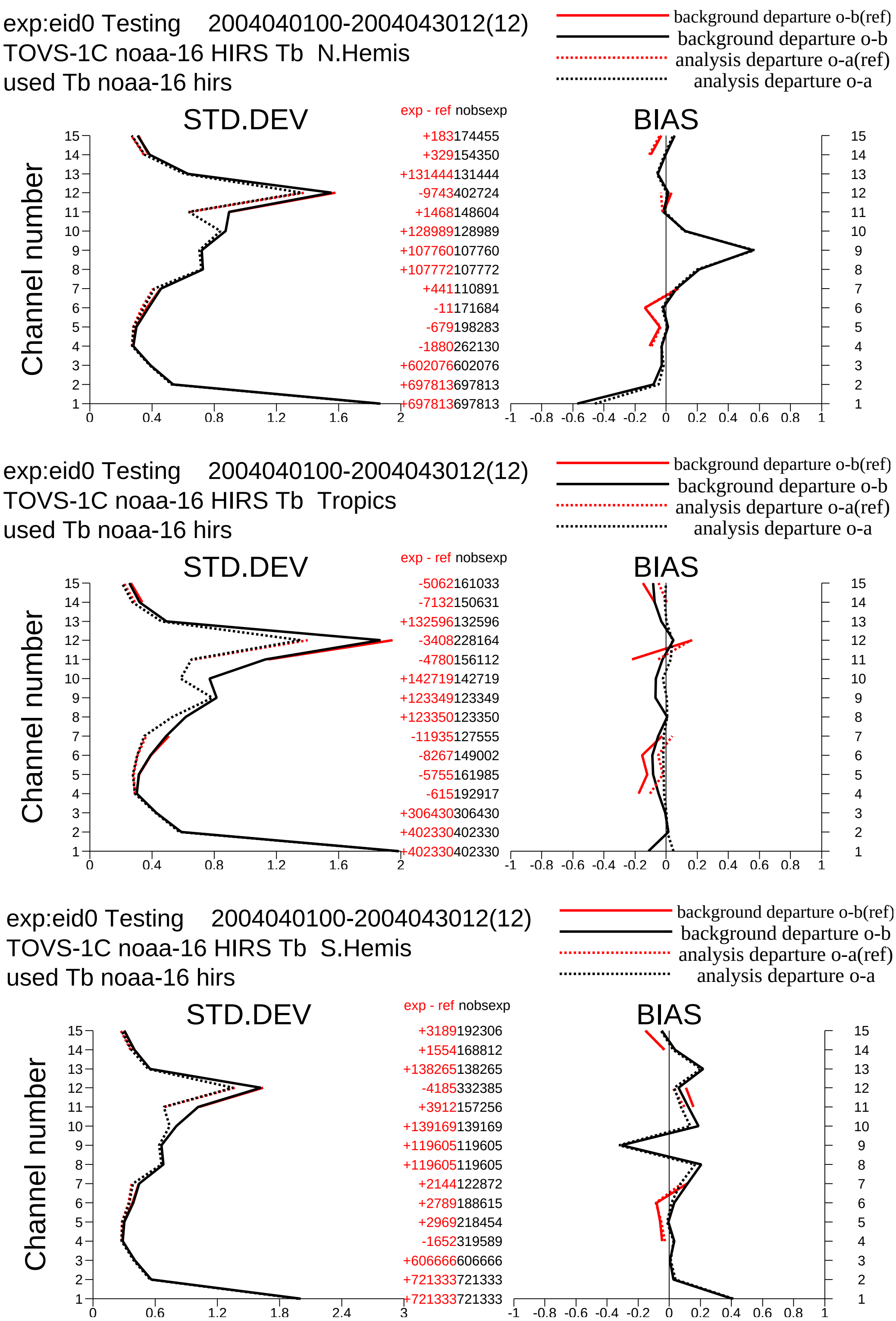

Figure 2: NOAA-16 HIRS brightness temperature departure statistics

Figure 1 shows departure statistics for NOAA-16 AMSU-A brightness temperatures, computed over April 2004 for the Northern Hemisphere (top panels), Tropics (center panels), and Southern Hemisphere (bottom panels). Biases are shown on the right, standard deviations on the left; solid curves are background departure statistics, dashed curves are analysis departure statistics; black for the experiment (eid0), red for the reference (Cy26r3). The vertical axes indicate channel numbers; data counts are printed along the vertical axes in the center.

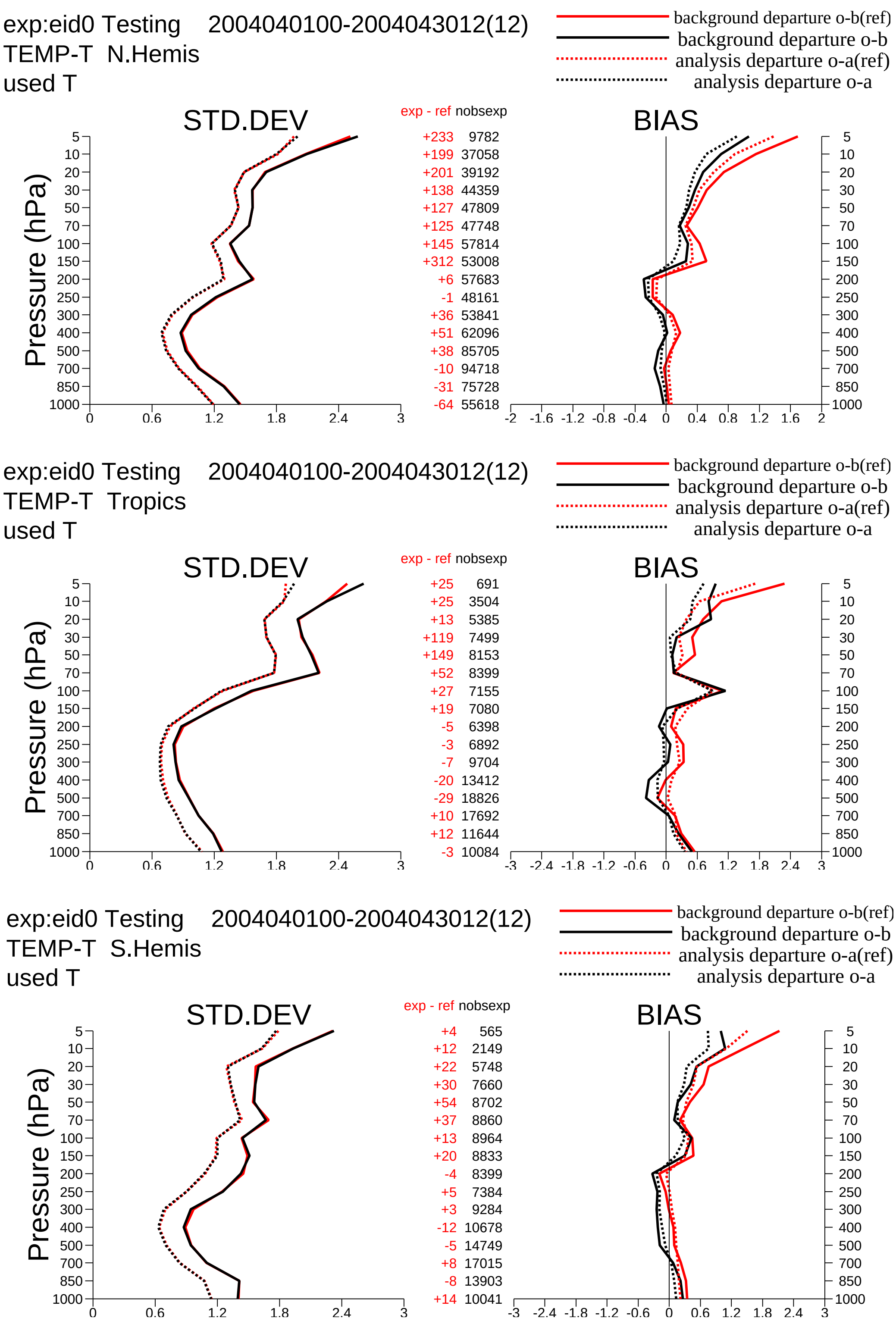

Figure 3: Radiosonde temperature departure statistics

The first thing to note is that the biases in the analysis departures have all but disappeared in the experiment. This shows that the inclusion of bias parameters in the variational analysis effectively reduces the mean departures for each channel, as expected. For most of the channels, the mean background departures are significantly reduced as well. This implies that the new bias correction scheme actually improves the analyses, in the sense that the ensuing short-term forecasts provide a better fit to future data. The most notable exception is channel

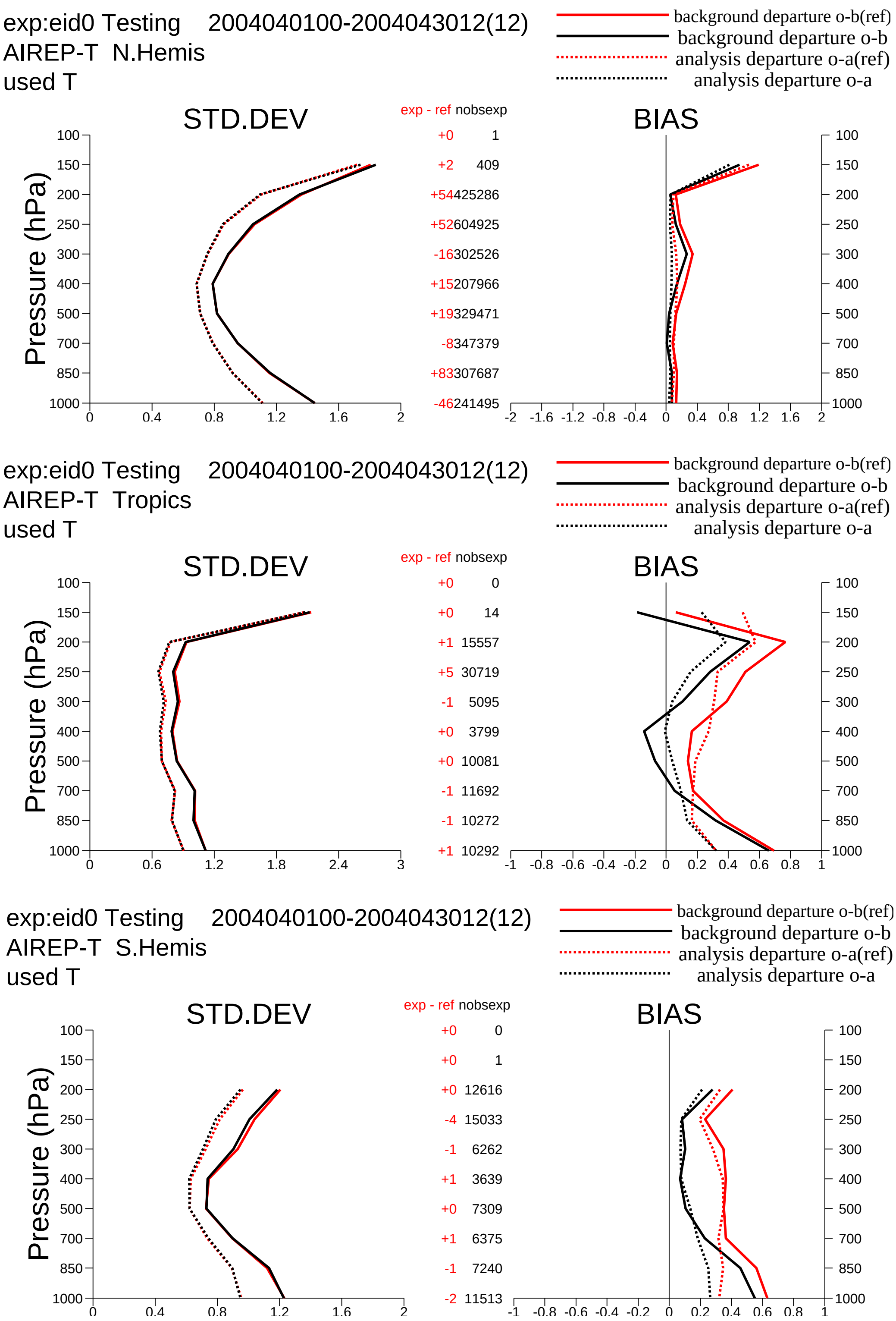

Figure 4: Aircraft temperature departure statistics

14, for which the background departures deteriorate quite a bit. This high-stratospheric channel is known to be much less biased than the background itself, and for this reason is not subject to any air-mass dependent bias correction in the operational system. The variational bias correction scheme cannot distinguish between model biases and data biases, and will therefore attribute any model bias component of the mean background departures to the observations. As a result, the data may be corrected in the wrong direction, and this can reinforce the model biases in the stratosphere. The obvious fix in this case is to disallow the bias correction on this channel, as is currently done in operations. Note also the slight deterioration in the Tropics for the mean background departures in channels 10 and 11, which peak in the lower stratosphere. Standard deviations of the departures are virtually unchanged in most channels, but slightly improved in the main tropospheric channels. Finally, the data counts for most channels show that the quality control allows significantly more data into the system, which is probably due to the overall reduction in background departures. The increase in AMSU-A channel 5 data in the Southern Hemisphere, for example, is about 11%, which is quite large.

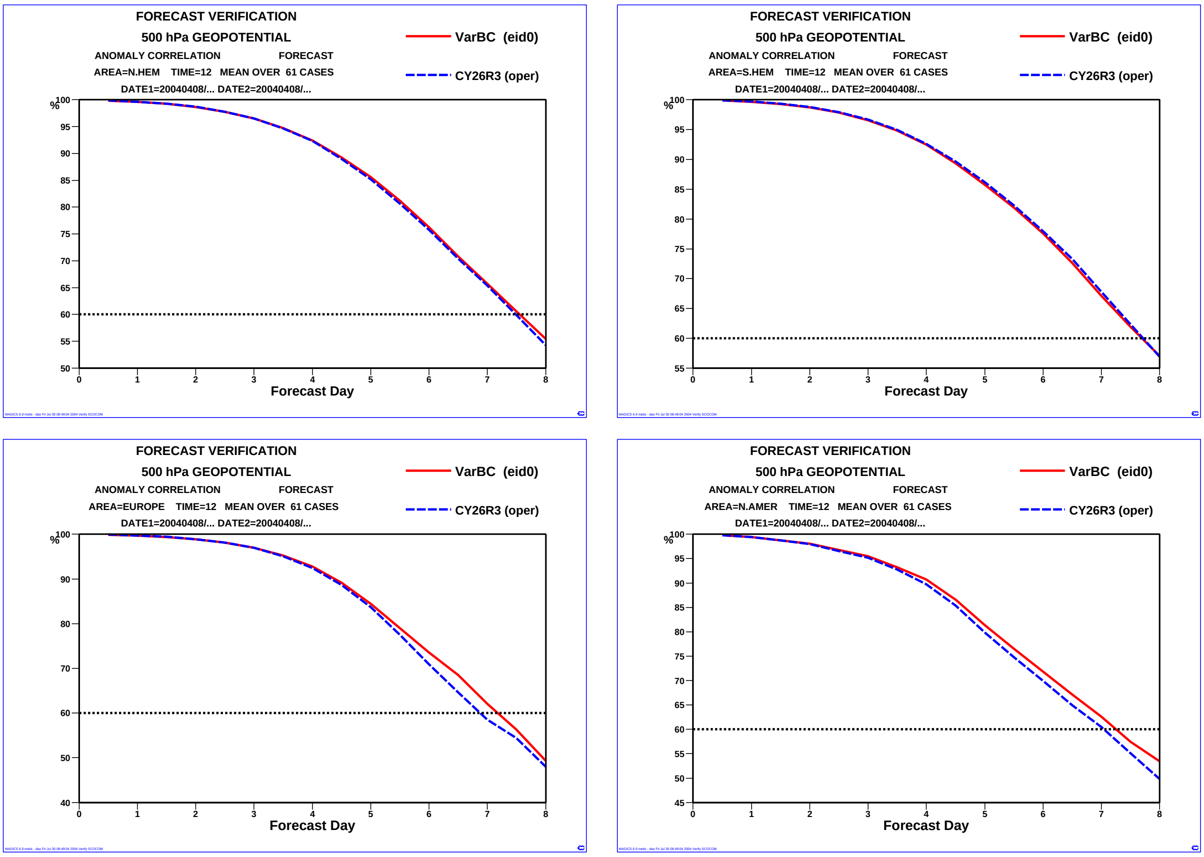

Figure 5: 500 hPa geopotential height anomaly correlations, verified against operational analyses

Figure 2 shows departure statistics for NOAA-16 HIRS. All HIRS channels are assimilated, since the cloud detection scheme requires bias-corrected departures from all channels. For this reason channels 1,2,3,8,9,10,13 are used passively, i.e. with inflated observation errors, in order to keep their bias estimates up-to-date. Departure statistics for the passive channels are not particularly interesting, since they do not affect the analysis directly except through the cloud detection. Departure statistics for the active channels (i.e., those for which there are red curves) are generally slightly improved. The changes in data usage in the active channels are probably mostly due to the cloud detection, which is sensitive to the bias correction. We note a global decrease of about 1.2% in the use of the water vapor channels 11 and 12.

The fit to conventional observations provides an independent measure of the impact of the variational bias correction on the quality of the analysis. Figures 3 and 4 show, respectively, the fit to radiosonde and aircraft

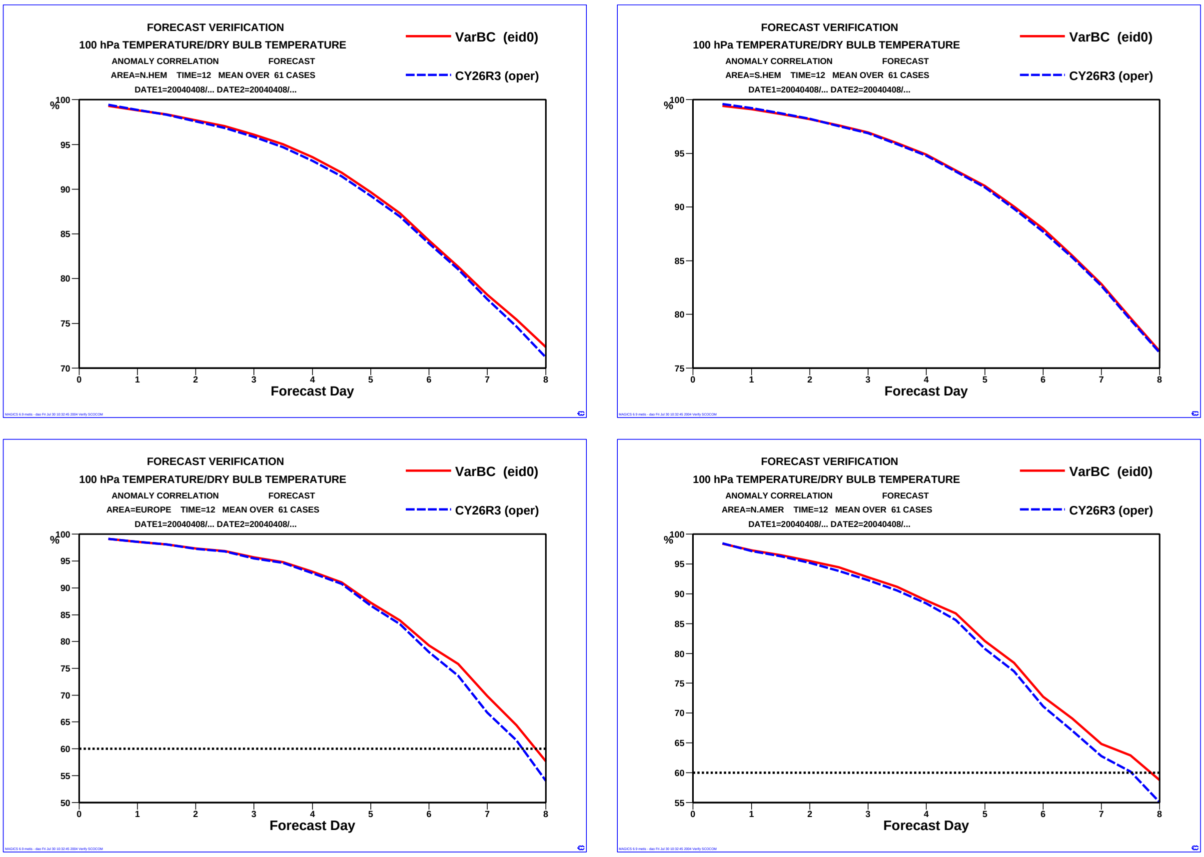

Figure 6: 100 hPa geopotential height anomaly correlations, verified against operational analyses

temperature measurements. From the mean analysis departures we can see that, roughly, the analysis at most levels is on average about 0.2K warmer in the Southern Hemisphere and Tropics, and about 0.1K warmer in the Northern Hemisphere. In the troposphere, biases with respect to aircraft observations are significantly reduced at all levels, and this is true for analyses as well as backgrounds. Temperature biases with respect to radiosondes in the troposphere are not uniformly smaller, although the reductions in biases at higher levels is impressive.

We next discuss the impact of the variational bias correction scheme on the medium-range forecast. Figure 5 shows mean anomaly correlations of the 500hPa height forecasts verified against operational analyses, averaged over 61 forecasts initialized at 12Z during the period 8 April – 7 June 2004. Red solid curves correspond to the experiment (eid0); blue dashed curves to the control (Cy26r3). We note a very slight deterioration in skill in the Southern Hemisphere (upper right panel), but a small improvement in the Northern Hemisphere (upper left). The scores for Europe (lower left) and North America (lower right) are significantly improved. At 100hPa (Fig. 6) the scores are slightly better in the Southern Hemisphere as well. These results, when considered together with the improved fit to temperature observations, suggest that the utilization of land-based conventional data has improved. This could be an interesting positive effect of the better spatial and temporal consistency among the different data sources enforced by the variational bias correction of satellite radiances.

We briefly turn to the impact of the variational bias correction scheme on forecast errors in the Tropics, verified against radiosonde observations. Figure 7 shows a small improvement in the vector wind forecast errors at 200hPa (left panels) and at 850hPa (right panels), for all lead times up to six days. Top panels display the root-mean-square errors, middle panels show the mean errors, and bottom panels the error standard deviations. Figure 8 shows a deterioration in the 200hPa temperature forecasts with respect to radiosonde observations, especially in the mean. This may be an effect of model errors at that level, which the variational bias correction wrongly attributes to the observations. Temperature forecast errors at 850hPa, on the other hand, are significantly improved.

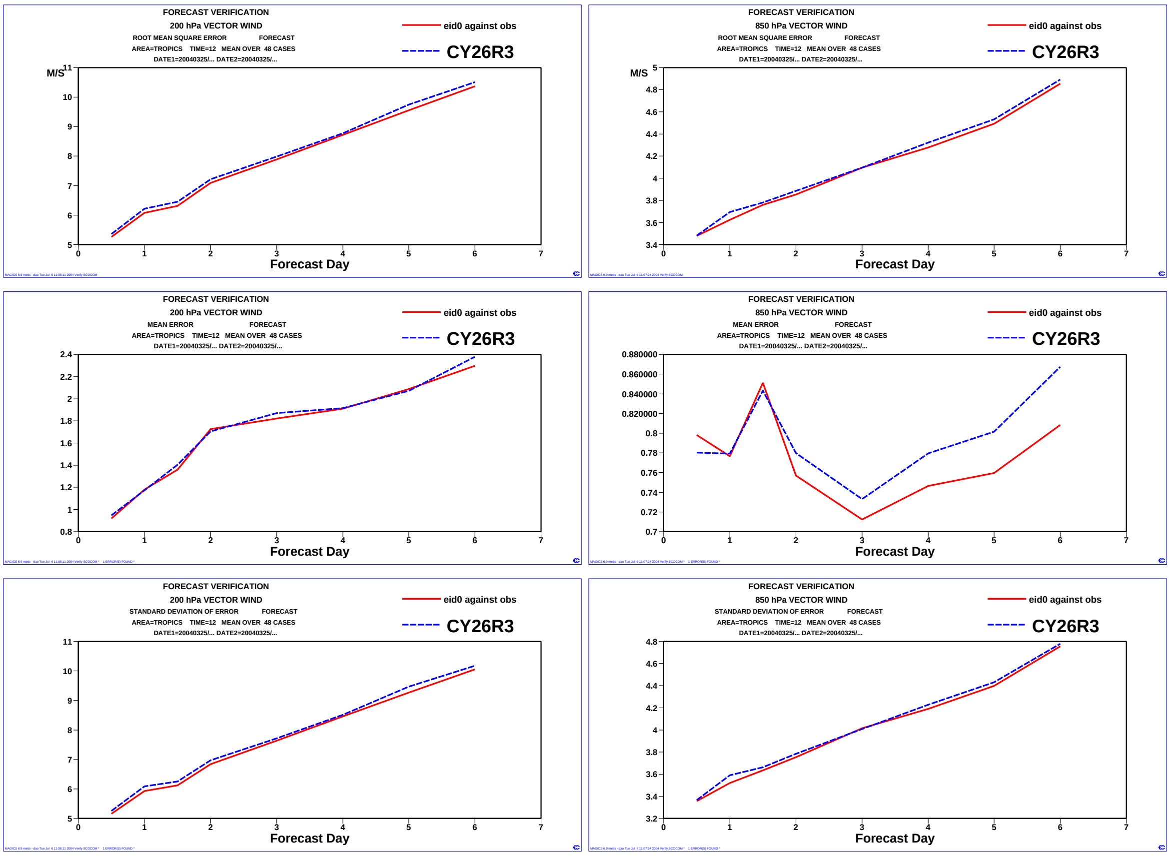

Figure 7: Tropical vector wind forecast errors at 200 hPA and 850 hPa, verified against radiosonde observations. Individual panels show root-mean-square, mean, and standard deviation of the forecast errors as a function of lead time.

4 Conclusions

We have described the implementation of an adaptive bias correction scheme for satellite radiances at the ECMWF. The scheme requires that the bias in any given channel be expressed in terms of a small number of unknown, global parameters. These bias parameters are then updated jointly and simultaneously with the model state during the variational analysis. The adaptivity of the bias estimates can be controlled by adjusting the background constraints for the bias parameters.

A major advantage of the adaptive scheme is that it has the potential to greatly simplify the manual bias tuning procedures currently in use at the ECMWF. In addition, the estimation of the bias parameters jointly with the model state has the theoretical advantage that the bias estimates are fully consistent with all observational information available to the analysis. On the other hand, it is no longer possible to impose a separate (more restrictive) data selection for bias estimation, as is done in the current scheme.

Results obtained with variational bias correction applied to all radiance data in an operational configuration of the ECMWF data assimilation system are mostly positive. Departure statistics for used radiance data confirm that mean analysis departures were greatly reduced compared to the control. More significantly, mean background departures were reduced as well for most channels on most sensors, and, as a result, the system was able to ingest a larger volume of data. The adaptive bias correction led to a much better fit to radiosonde temperature observations in the stratosphere and to aircraft temperatures throughout the troposphere. Anomaly correlations of 500 hPa height forecasts verified against operational analyses improved significantly over North America and Europe, suggesting a better use of observations over land. As a result, Northern Hemisphere scores improved

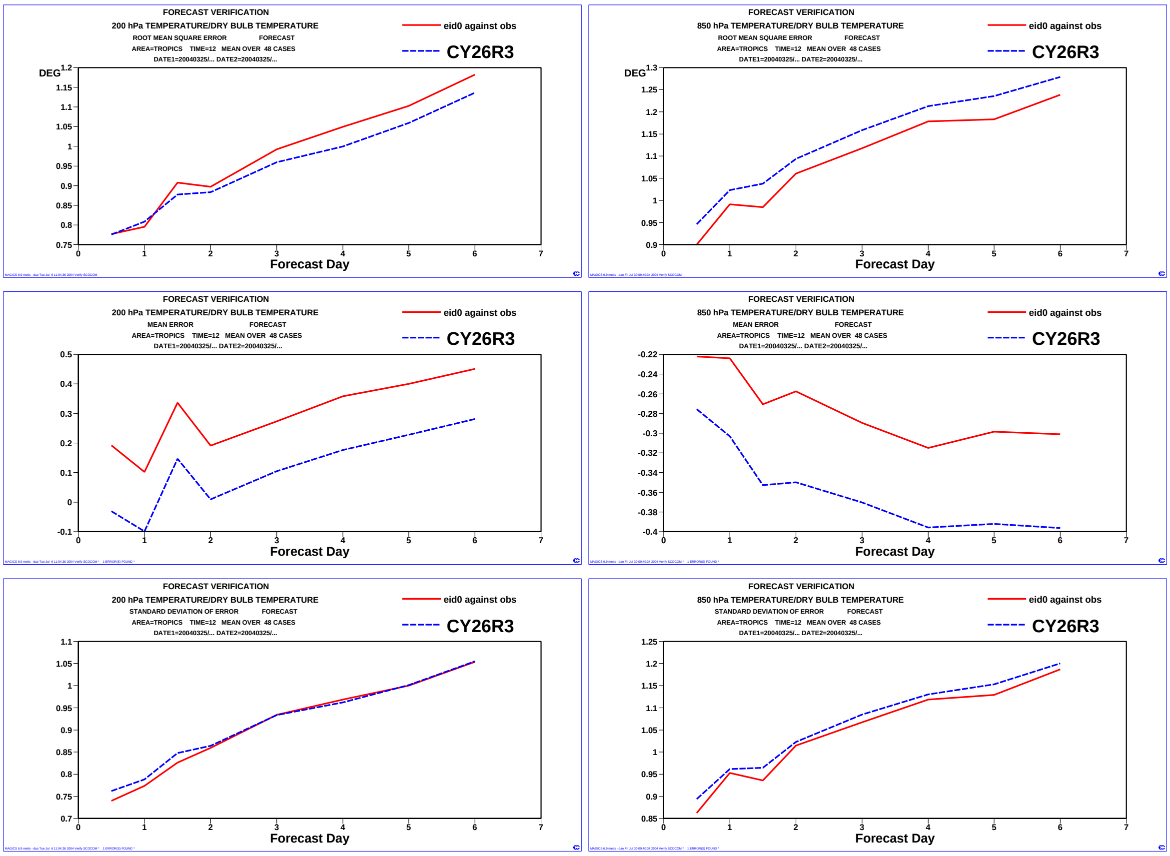

Figure 8: Tropical temperature forecast errors at 200 hPA and 850 hPa, verified against radiosonde observations. Individual panels show root-mean-square, mean, and standard deviation of the forecast errors as a function of lead time.

slightly overall, but a very small deterioration in forecast skill was noticeable in the Southern Hemisphere. In the Tropics, wind forecasts (verified against radiosonde observations) improved slightly at 850 hPa and at 200 hPa, while temperature forecasts were better at 850 hPa but worse at 200 hPa.

We noted in some cases (e.g., in the top AMSU channels) that mean background departures increased as a result of the adaptive bias correction. This may have been due to the presence of systematic model errors that the variational scheme falsely attributes to observation bias. Unless systematic model errors are explicitly accounted for in the data assimilation scheme, there is no general way to avoid this problem. After all, the variational analysis must be told which parameters to adjust in order to minimize the departures. The 4D-Var system at the ECMWF is being extended to allow the inclusion of model error terms in the analysis (Trémolet 2003), and experiments are currently underway to test this feature. In principle, the future system will support simultaneous adjustments of initial conditions, observation bias parameters, and model error forcing. It remains to be seen whether it is possible to design the constraints on all those additional degrees of freedom in such a way that the different sources of error can be adequately separated and meaningful state estimates can still be obtained.

Our first implementation of the variational bias correction scheme relied on the same linear predictor models currently used for radiance bias correction at at ECMWF. There are some known problems with the configuration of these models, and future investigations will consider more carefully the optimal selection of predictors for each sensor and channel. We would prefer to replace the predictor-based models by more meaningful, physically-derived error models (e.g. Watts 2004) as they become available. We also plan to include scan bias parameters in the scheme, to further reduce the need for manual tuning.

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