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Variational bias correction in ERA-Interim

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Abstract

This paper describes the performance of the variational bias correction system for satellite radiance data in ERA-Interim, and considers implications for the representation of climate signals in reanalysis. We briefly review the variational formulation of the method and its ability to automatically develop bias estimates when newly available radiance measurements are first introduced. We then present several results obtained from the first 16 years (1989-2004) of ERA-Interim. These include the identification of MSU instrument calibration errors, the response of the system to the Pinatubo eruption in 1991, some difficulties in constraining model errors in the upper stratosphere, and the detection of a long-term drift in biases of tropospheric AMSU-A data. We find that our results support the notion that global reanalysis provides an appropriate framework for climate monitoring and climate change assessment.

1 Introduction

In recent years, reanalyses of multi-decadal series of past observations have become an important and widely utilized resource for the study of atmospheric and oceanic processes and predictability. Reanalysis data have been used in numerous studies that require an observational record of the atmosphere and its underlying land and ocean surfaces. Estimation of renewable energy resources, calculation of microwave telecommunication signal losses, insurance risk assessment, and study of bird migration patterns are just a few examples of the many interesting applications of reanalysis products. Reanalysis clearly has a useful role to play in climate monitoring and the assessment of climate change, although there is some debate about the accuracy by which climate signals can be represented in a reanalysis system.

Two major ECMWF reanalyses have exploited the substantial advances made in operational weather forecasting since operations began at ECMWF in 1979. The first project, ERA-15 (1979-1993), was completed in 1995 and the second extended reanalysis project, ERA-40 (1957-2002), in 2002. Products of ERA-15 and ERA-40 have been used extensively by ECMWF Member States and by the wider user community. They are also increasingly important to many core activities at ECMWF, particularly for validating long-term model simulations, for helping develop a seasonal forecasting capability and for establishing the climate of EPS (Ensemble Prediction System) forecasts needed for construction of forecaster-aids such as the Extreme Forecast Index.

ECMWF is currently producing ERA-Interim, a global reanalysis of the data-rich period since 1989 based on cycle 31r2 of the Integrated Forecasting System (IFS). As the name suggests, ERA-Interim represents a step towards ECMWF's next generation reanalysis system, which is currently in planning and is expected to be developed within the next few years. Relative to the ERA-40 system, which was based on IFS cycle 23r4, ERA-Interim incorporates many important IFS improvements such as model resolution and physics changes, the use of four-dimensional variational (4D-Var) assimilation, and various other changes in the analysis methodology. The configuration of the ERA-Interim system and many aspects of its performance are described in several recent ECMWF Newsletter articles (Nos. 110, 111, and 115). After it catches up with real-time in early 2009 ERA-Interim will be maintained as a Climate Data Assimilation System (CDAS), opening new opportunities for climate monitoring.

A key component of ERA-Interim is the variational bias correction system for satellite radiances developed at ECMWF (Dee 2004) and implemented in operations in 2006. The system handles data events such as the appearance of a new radiance data stream, and it initialises, updates, and keeps track of bias estimates for radiances from all satellites and sensors present. Biases are estimated during the analysis by including parameters for that purpose in the control vector used to minimise the 4D-Var cost function. This ensures that radiance bias corrections are continuously adjusted to optimise consistency with all information used in the analysis. An important practical advantage of this automated system is that it removes the need for manual tuning procedures, which are tedious and prone to error, especially in view of the increasing number and variety of sensors being assimilated (Thépaut 2003).

ERA-Interim is the first reanalysis using adaptive and fully automated bias corrections of satellite observations. Previous operational experience with variational bias correction has been limited to numerical weather prediction (NWP) applications, originally at NCEP (Derber and Wu 1998) and more recently at ECMWF (McNally *et al.* 2006, Aulígné *et al.* 2007). For an NWP system the ability to automatically detect new data and quickly develop bias estimates without human interference is not as crucial as it is for reanalysis, where data events happen much faster than they do in real time. And since the natural mindset in the NWP context is to look forward rather than backward, the long-term performance and stability of the adaptive approach to bias correction has never been documented.

The purpose of this paper is to assess the performance of the variational bias correction system in ERA-Interim, based on the first sixteen years (1989-2004) of production. The ability to accurately represent climate trends and variability will be an important quality measure for the ERA-Interim CDAS. This touches on a key issue for future reanalyses, since there has been considerable debate about the role that reanalyses can play in climate change assessment (e.g. Bengtsson *et al.* 2004, Trenberth *et al.* 2007). Changes in the observing system and the presence of biases in models and observations can cause shifts and trends in reanalyses that interfere with true climate signals. There is a general tendency over time towards increasing data coverage in all dimensions, but this occurs in bursts and spurts, rather than continuously; cf. Fig. 1. Most observations require bias corrections before they can be usefully assimilated, and the biases may depend not only on instrument characteristics but also on atmospheric conditions. A major challenge for reanalysis therefore is to smoothly handle data events and bias changes, to minimise their effect on the representation of trends and variability, and, where possible, to quantify the associated uncertainties in the reanalysis products.

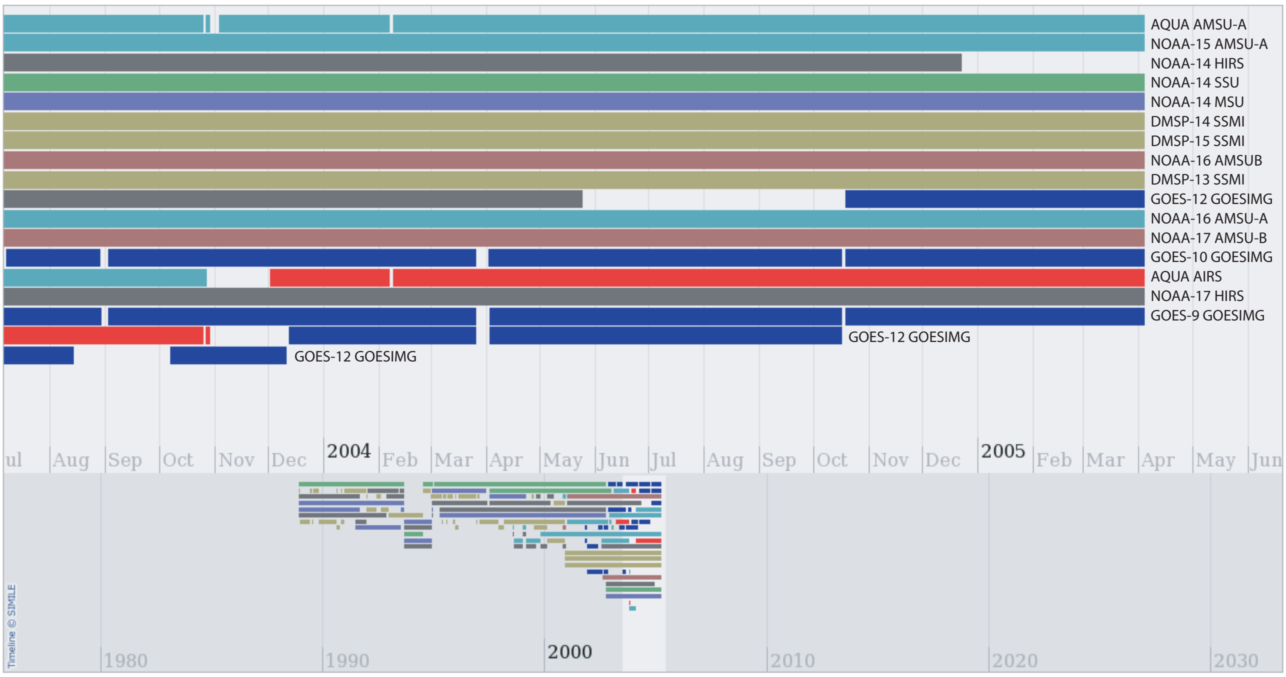

Figure 1: ERA-Interim web-based event monitoring, displaying radiance data usage on moveable timelines. Each horizontal bar represents a different sensor. The top and bottom sections contain the same information but on different time scales. A user can drag the timelines with a mouse and click on each bar to bring up detailed information for that sensor.

The paper is organised as follows. Section 2 provides a brief overview of the variational bias correction scheme, and section 3 illustrates its ability to spin up new bias estimates, using the introduction of NOAA-14 in April

1995 as an example. The effect of the bias correction scheme on the overall performance of ERA-Interim is briefly discussed in section 4. In section 5 the ability of the scheme to identify instrument calibration errors in MSU data is presented. Section 6 reviews the performance following the Pinatubo eruption, which caused several difficulties in ERA-40. The impact of model errors on variational bias correction is discussed in general terms in section 7, and specifically in relation to model biases in the upper-stratosphere in section 8. Section 9 discusses observed drifts in the bias estimates for tropospheric AMSU-A data, and conclusions are presented in section 10.

2 Variational bias correction

Variational bias correction of satellite radiances was first implemented at the National Centers for Environmental Prediction (NCEP) in their Spectral Statistical Interpolation analysis system (Derber and Wu 1998), and more recently at ECMWF (Dee 2004). Both implementations rely on a linear predictor model for the bias $\mathbf{b}$ in each radiance channel, of the form

$$\mathbf{b}(\beta,\mathbf{x}) = \sum_{i=0}^{N_p} \beta_i \mathbf{p}_i(\mathbf{x}) \tag{1}$$

where the $\mathbf{p}_i$ are the predictors and β_i are unknown bias parameters. By convention $\mathbf{p}_0 \equiv 1$ so that β_0 represents a global offset. The remaining predictors may depend on the observed atmospheric column, on the state of the instrument itself (e.g. the field of view), or on any other available information. Different radiance channels can use different predictors, although a similar selection is used in most cases.

Estimation of the bias parameters for each channel is achieved by including them in the control vector for the variational analysis. This leads to a modified penalty function, to be minimised with respect to the model state control parameters $\mathbf{x}$ and the bias control parameters β, given by

$$\begin{aligned} J(\mathbf{x},\beta) = (\mathbf{x}^b-\mathbf{x})^T\mathbf{B}_{\mathbf{x}}^{-1}(\mathbf{x}^b-\mathbf{x}) \\ + (\beta^b-\beta)^T\mathbf{B}_{\beta}^{-1}(\beta^b-\beta) \\ + [\mathbf{y}-\mathbf{h}(\mathbf{x})-\mathbf{b}(\mathbf{x},\beta)]^T\mathbf{R}^{-1}[\mathbf{y}-\mathbf{h}(\mathbf{x})-\mathbf{b}(\mathbf{x},\beta)] \end{aligned} \tag{2}$$

with $\mathbf{x}^b, \beta^b$ *a priori* (background) estimates for $\mathbf{x}, \beta$, and $\mathbf{B}_{\mathbf{x}}, \mathbf{B}_{\beta}$ their prescribed error covariances. The vector $\mathbf{y}$ represents the uncorrected observations, $\mathbf{h}(\mathbf{x})$ is the observation operator, and $\mathbf{R}$ is the prescribed error covariance for the observations. Further details about the notation and other aspects of the formulation can be found in Dee (2004).

The first term in (2) is the usual background constraint for the state vector. The second term similarly represents a background constraint on the bias parameters; it affects the adaptivity of the estimates. A weak constraint (or no constraint at all) allows the parameter estimates to respond more quickly to the latest observations. For radiance data the background constraint on the bias parameters is usually not very important, because the number of parameters is typically much smaller than the number of data available to estimate them. The third term is the bias-adjusted observation term, which provides most of the control for the bias parameters.

The interpretation of the variational bias estimates is ambiguous, since the analysis can use the bias parameters to correct both instrument errors and errors in the observation operators. For example, an instrument miscalibration that causes radiances to be too warm by 1K should produce a bias estimate of 1K, resulting in corrected departures $(\mathbf{y}-1)-\mathbf{h}(\mathbf{x})$. Alternatively, if the observation operator $\mathbf{h}$ is too warm by 1K, then the analysis produces a bias estimate of -1K, giving corrected departures $\mathbf{y}-(\mathbf{h}(\mathbf{x})-1)$. The purpose of the variational bias correction is to correct both types of error.

A third, more worrisome possibility is that the bias estimates reflect systematic errors in the model state estimates. In that case the data are wrongly adjusted to render them consistent with the model, when in fact the model should be corrected. We will discuss this possibility at length in sections 7 and 8 below.

3 Initialising the bias parameters

To illustrate the ability of the system to automatically detect new data and develop bias estimates for these data, we describe in some detail the introduction in ERA-Interim of radiance data from the Microwave Sounding Unit (MSU) and the High Resolution Infrared Radiation Sounder (HIRS) on NOAA-14. These data first appeared in the input data stream for ERA-Interim at 12 UTC on 9 April 1995.

The 4D-Var analysis is normally preceeded by a screening step, in which bias corrections are applied to the data as needed, background departures are computed for all observations, and various quality control checks are applied. During the screening on 12 UTC 9 April 1995 the system detects the presence of data not previously seen—in this case, radiances from MSU and HIRS on NOAA-14. In the absence of any prior information on biases for these data, an initial bias estimate for each channel is defined as the mode of the global distribution of (uncorrected) background departures. The mode rather than the mean is used for this purpose since it is less sensitive to outliers and asymmetries in the distribution resulting from, for example, cloud detection algorithms applied during quality control.

Due to the parallel implementation of the screening algorithm, the initial bias estimate is not available until the very end. At this point the screening step would have to be repeated in order to allow immediate use of the new data in the 4D-Var analysis. Instead, in ERA-Interim the first use of the data is simply postponed by one analysis cycle.

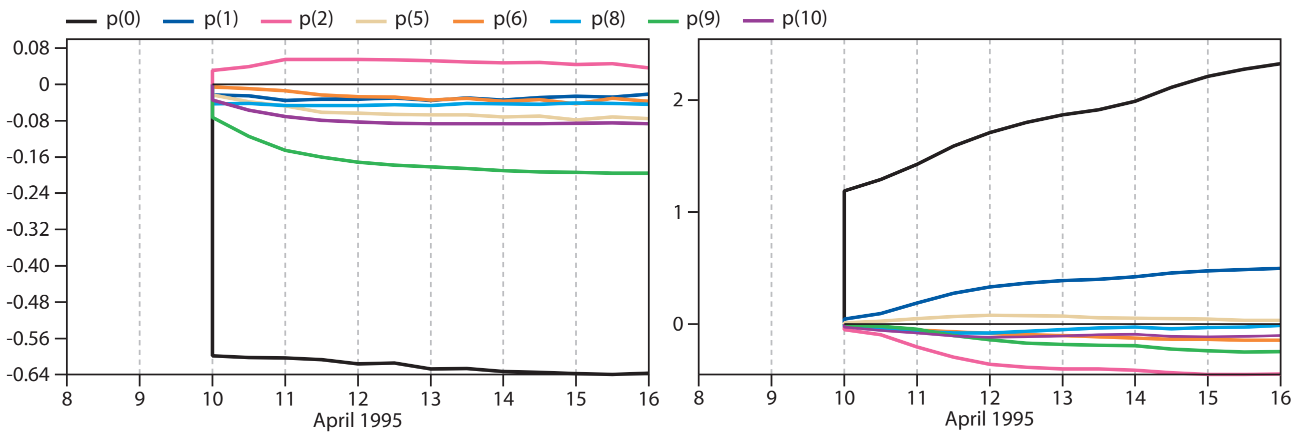

Figure 2: Development of bias parameter estimates produced by the variational analysis, for NOAA-14 MSU channel 2 (left) and HIRS channel 4 (right). The curves in each panel correspond to the bias predictors used for these particular channels: a global offset p(0), four state-dependent predictors p(1), p(2), p(5), p(6), and three field of view-dependent predictors p(8), p(9), p(10). The global offset is initialised based on uncorrected background departures from the initial data screening at 12 UTC, 9 April 1995. The data are first used in the 00 UTC, 10 April 1995 analysis, which then produces parameter estimates for all predictors.

Figure 2 shows the evolution of the bias parameters during the first days of assimilation, for MSU channel 2 (left) and HIRS channel 4 (right). The black curve in each panel corresponds to the global offset; it is initialised at the beginning of the screening step on 00 UTC 10 April 1995 based on the estimate obtained in the previous analysis cycle, while all other parameters are initially set to zero. All bias parameters for these two channels settle down smoothly, within a few cycles for MSU and somewhat more slowly for HIRS.

Figure 3 shows global mean bias estimates and mean bias-corrected departures for MSU channels 2, 3, and 4, for the first analysis cycle in which they were used (left panel), and averaged for the first week of assimilation (right panel). The magenta curves correspond to the bias estimates, while the black curves denote the global mean background (solid) and analysis (dashed) departures for the bias-corrected radiance data. These curves confirm that the system is able to correct the global mean analysis departures as expected. Note that the bias correction applied to the background departures in the very first analysis at 00 UTC 10 April 1995 is the global offset obtained during the initial screening, as described above.

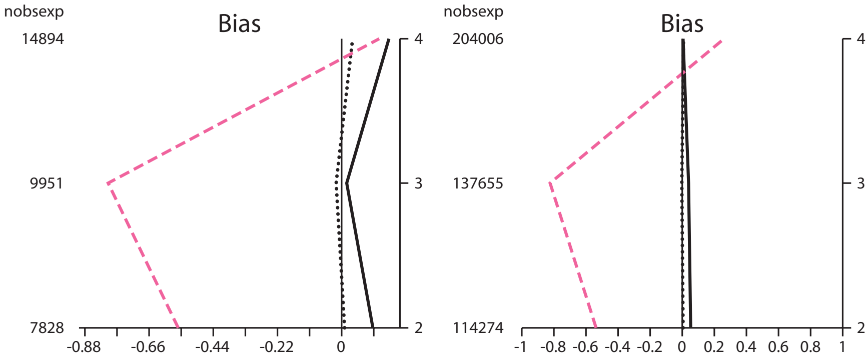

Figure 3: Global mean bias estimates and bias-corrected departures for NOAA-14 MSU channels 2, 3, and 4, in degrees Kelvin. The left panel corresponds to the first analysis in which the data were used (10 April 1995, 00 UTC); the right panel to the first week (10-16 April 1995). Each panel displays mean bias estimates (magenta dashed), and mean bias-corrected background (black solid) and analysis (black dashed) departures. The number of used observations are indicated along the left-vertical axes. Note that the horizontal scales for the two panels are different.

For further illustration we focus on MSU channel 2 in more detail. Fig. 4 shows mean bias estimates and corrected departures for this channel as a function of field-of-view, after the initial cycle and during the first week of assimilation. Convergence of the parameters associated with the scan bias predictors requires several analysis cycles, so that the bias correction is not fully optimised during the first few days. Fig. 5 is a global map of bias estimates averaged for the first week, showing a roughly zonal structure combined with a dependence on field of view; the latter is clearly visible at the high northern latitudes that are only seen by slant views of the instrument when it passes near the pole.

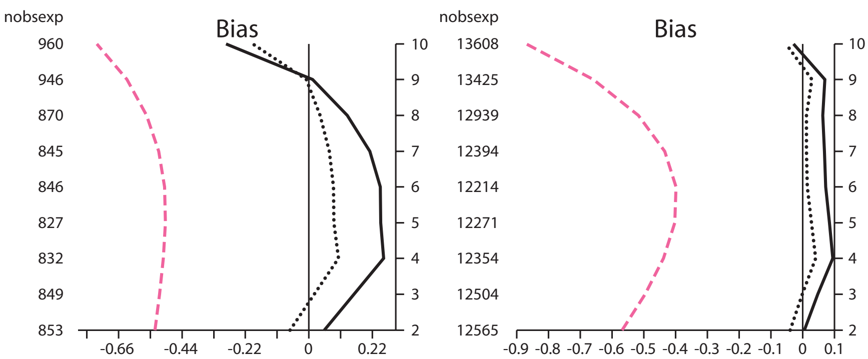

Figure 4: As Fig. 3 but for NOAA-14 MSU channel 2 only, for each field of view as indicated along the right-vertical axes.

The impact of the sudden introduction of NOAA-14 MSU and HIRS data on the reanalysis is visible in the mean analysis increments for temperature, shown as a function of time and model level in Fig. 6. This diagnostic of the assimilation system is extremely sensitive to changes in the observing system, and a moderate impact in the stratosphere of spinning up the bias corrections can be detected in this way.

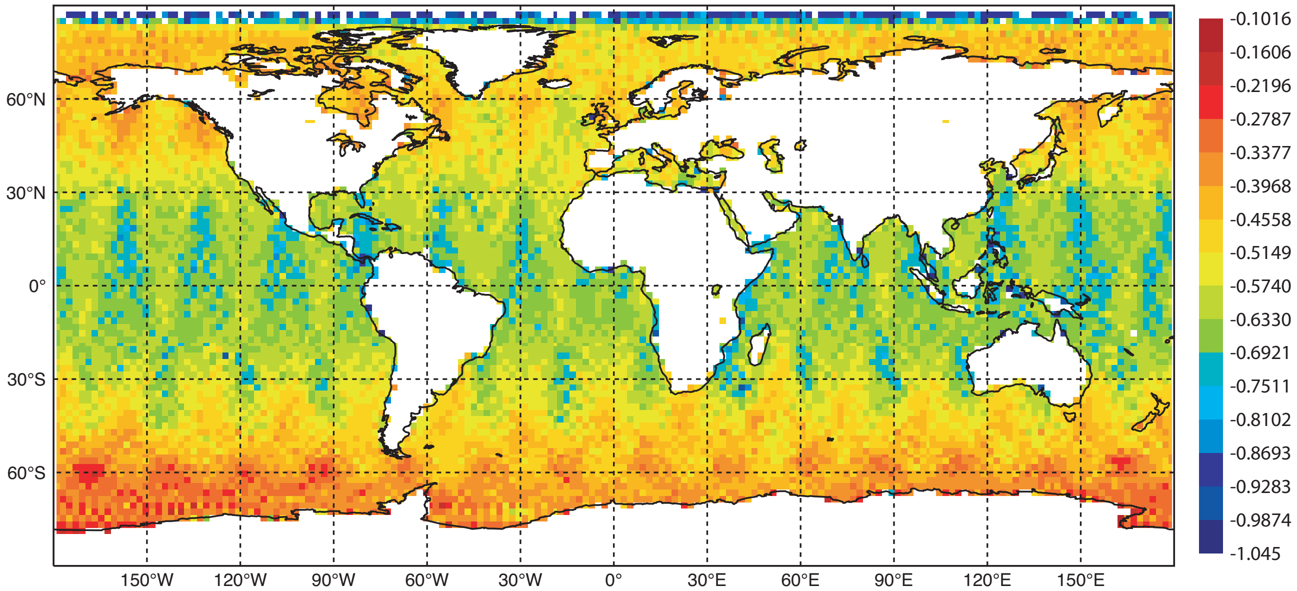

Figure 5: Bias estimates for MSU channel 2, averaged over all fields of view for 10-16 April 1995.

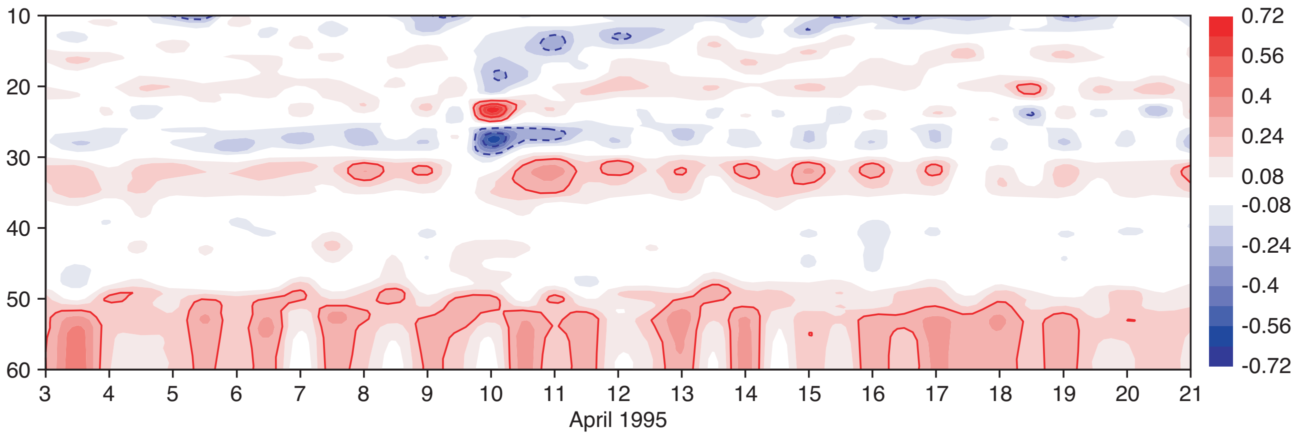

Figure 6: Evolution of mean temperature analysis increments, averaged over tropical latitudes (20S-20N). The vertical axis indicates model levels; level 60 corresponds to the model surface, level 30 to 200 hPa, level 10 to about 5 hPa. MSU and HIRS data from NOAA-14 were first used in the analysis on 10 April 1995, 00 UTC.

4 Basic performance aspects

As in any modern NWP system, the quality of reanalysis products increasingly depends on the way satellite data are used. This is certainly the case for ERA-Interim, which covers the data-rich period from 1989 onward. Various aspects of ERA-Interim product quality have been documented in recent ECMWF Newsletter articles (Simmons *et al.* 2007a,b; Uppala *et al.* 2008). They demonstrate important improvements over ERA-40 in many areas, including the representation of the hydrological cycle and the strength of the Brewer-Dobson circulation that have been identified as two special difficulties in ERA-40 (Uppala *et al.* 2005). Other key performance measures such as the fit to observations and the quality of forecasts initialised with ERA-Interim

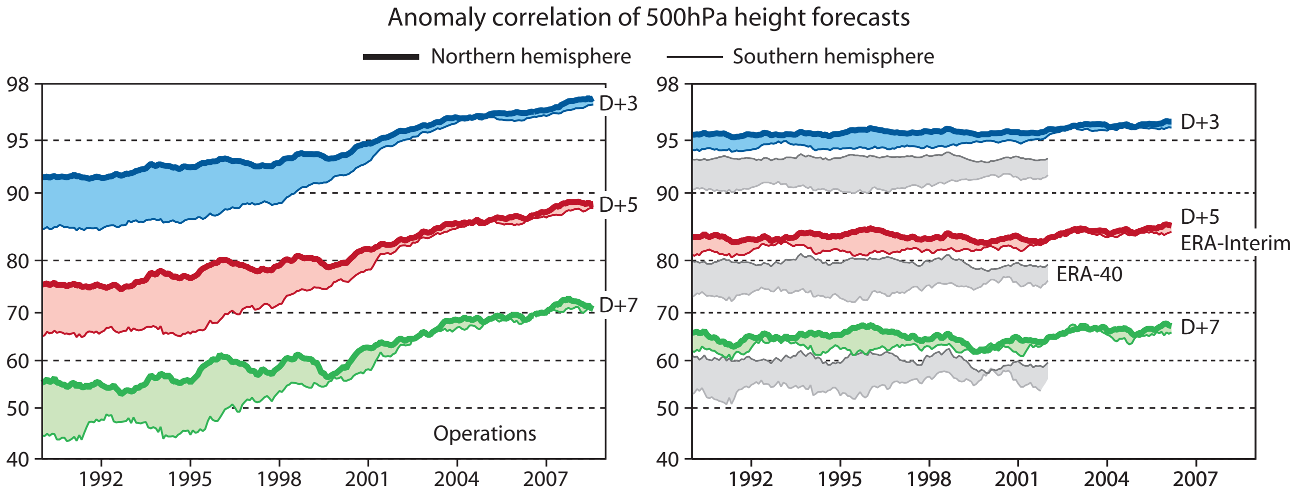

Figure 7: Mean anomaly correlations for 3-day, 5-day, and 7-day forecasts of 500 hPa geopotential height in northern and southern hemispheres. The left panel shows operational scores; the right panel shows scores for ERA-Interim and ERA-40. All forecasts are verified against their own analyses.

analyses are equally impressive. For example, Fig. 7 shows that 500 hPa geopotential height forecasts produced with ERA-Interim are consistently better than both the original operational forecasts and those from ERA-40.

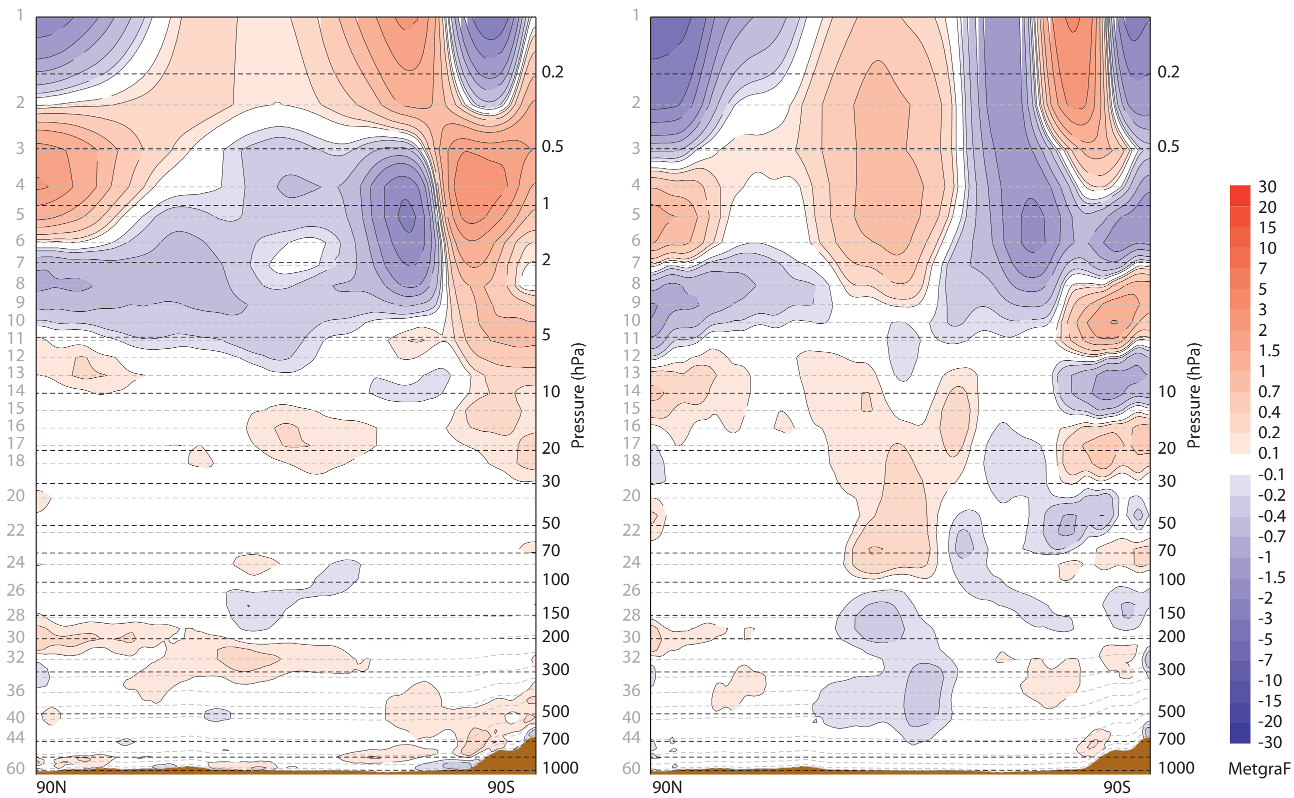

Figure 8: Zonal mean temperature analysis increments, in degrees Kelvin, averaged for August 2001 for ERA-Interim (left) and ERA-40 (right). Model levels and corresponding pressure levels are indicated along the left and right vertical axes, respectively.

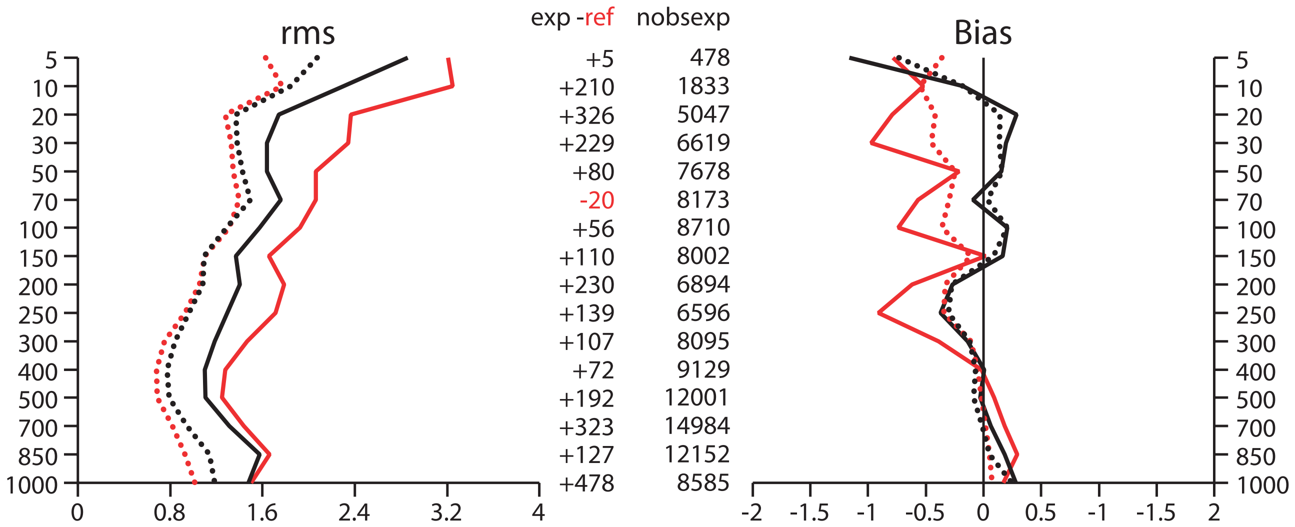

Figure 9: Root-mean-square (left) and mean (right) fit to southern-hemisphere radiosonde temperature reports for August 2001. Black curves are for ERA-Interim and red for ERA-40; dashed curves for analysis fit and solid for background fit.

The forecast quality in the southern hemisphere, which most strongly relies on satellite data, provides a measure of confidence in the performance of the variational bias correction system.

Figure 8 shows zonal mean temperature increments generated by the data assimilation, averaged for August 2001, for both ERA-Interim and ERA-40. The ERA-Interim increments are smaller and less systematic, and the oscillatory vertical structures near the poles, prominent in ERA-40, are largely absent. The qualitative picture is similar for all months, and it provides an additional indication of the overall improvement of the assimilation system. The spurious features in the analysis increments in the polar regions have been a longstanding feature in global data assimilation systems at various NWP centres (Dee 2005) and are known to be connected with the way radiance data are assimilated (McNally 2004). The variational bias correction in ERA-Interim enforces consistency among all radiance channels and all other observations as well, which has a clearly beneficial effect on the analysis increments for temperature. This can also be seen in Fig. 9, showing an improved mean fit to southern-hemisphere radiosonde temperature observations in ERA-Interim for the same month. While the root-mean-square analysis fit of ERA-40 to radiosonde temperatures is slightly better, the mean fit is significantly better in ERA-Interim, and the background errors are much smaller as well.

5 MSU instrument errors

The 16-year record of radiance bias estimates produced so far in ERA-Interim provides a wealth of information about the quality of the radiance data, the model, and the assimilation system. Here we consider the bias estimates for MSU channel 2, which measures temperatures in a deep layer of the middle troposphere, with maximum sensitivity near 600 hPa. Figure 10 shows the global mean bias estimates for this channel for 1989–2004, for each of the four NOAA satellites that carried the MSU sensor during this period.

The curves in Fig. 10 have several notable features. The variability of the bias estimates on monthly and interannual time scales is considerable. The curves for hemispheric averages (not shown) are very similar for this channel, implying that the variation in time is mainly due to global changes in the bias (i.e., the spatial structure of the bias as shown in Fig. 5 is approximately stationary). This is also confirmed by inspection of the evolution of the set of bias parameters for this channel, as in Fig. 2 but not shown here for the full period. There is some drift, especially for NOAA-11 during its first five years of operation, but this feature is not shared by other satellites and is therefore most likely due to an instrument-specific calibration issue. The global mean bias estimates for each satellite are stable, in the sense that they do not appear to drift indefinitely. Instruments on different satellites are biased relative to each other; for example, the offset between NOAA-11 and NOAA-12 is about 1.2 K on average.

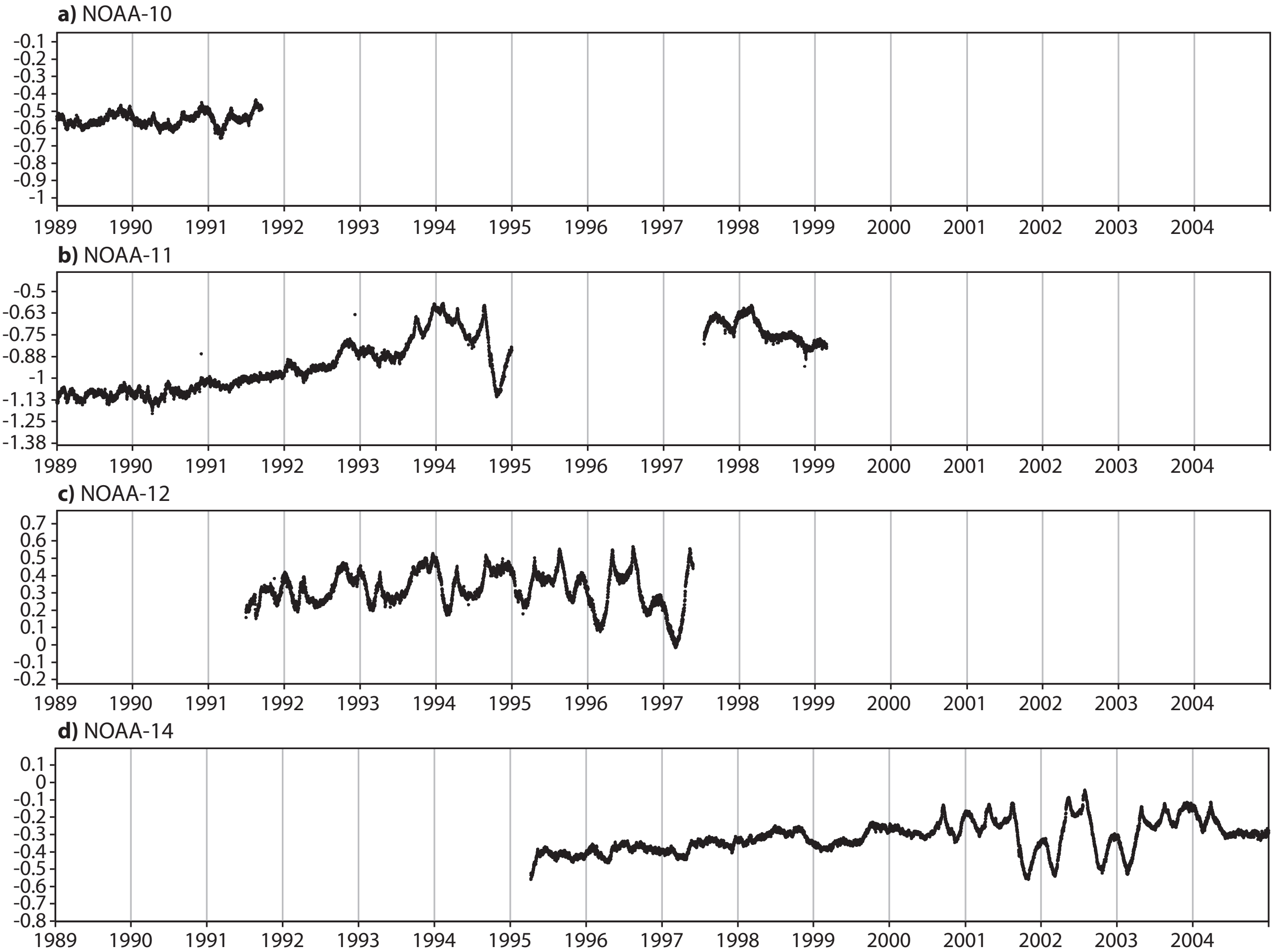

Figure 10: Global mean bias estimates in degrees Kelvin for MSU channel 2 brightness temperature data from NOAA-10 (a), NOAA-11 (b), NOAA-12 (c), and NOAA-14 (d).

The remarkable pattern of variability in the bias estimates begs an explanation. The MSU record, which extends back to late 1978, is considered a key data set for the assessment of climate change in the free atmosphere (IPCC 2007). Several groups (Christy *et al.* 2003, Mears *et al.* 2003, Grody *et al.* 2004) have used these data to reconstruct the tropospheric temperature record in order to estimate trends and other climate signals. This involves the application of various corrections to the data to account for calibration errors associated with each sensor, due to, for example, drift and/or decay of the satellite orbits (e.g., Mears 2008). There is no universal agreement on the optimal method of correction, but they all rely to some extent on overlaps between pairs of satellites, comparisons with radiosonde observations, and modeling of physically-based calibration errors.

In deriving their corrections to the MSU record, Grody *et al.* (2004) use a calibration model for the instrument that includes the effect of orbital drift of the satellite. The change in equator crossing time due to the drift causes a variation in the total heat budget of the spacecraft, which in turn affects the temperature of the on-board warm target used for calibration. The curve in the lower panel of Fig. 11, taken from Grody *et al.* (2004),

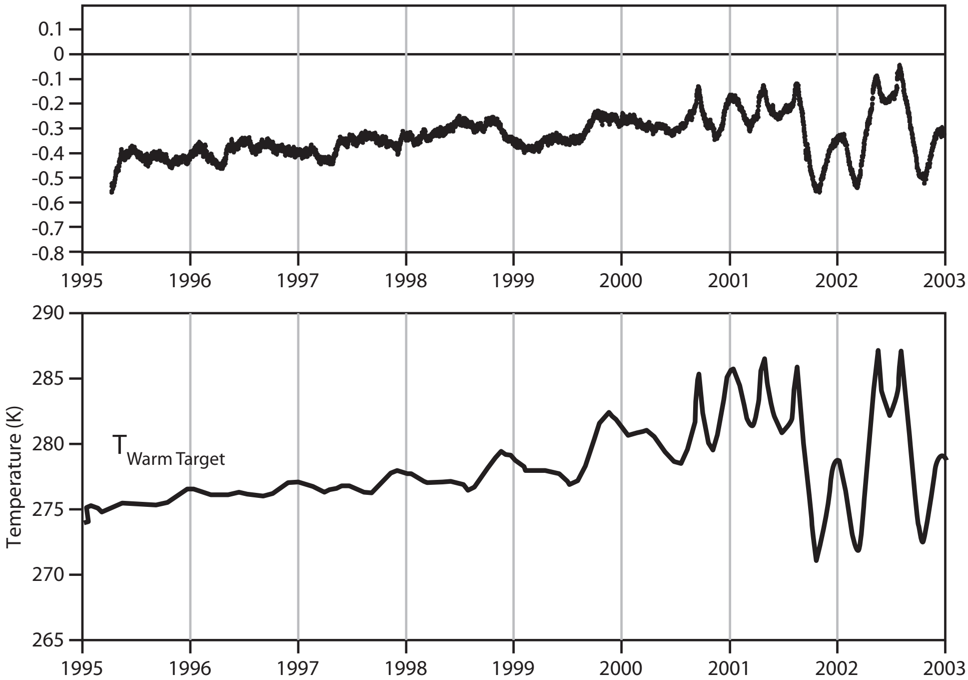

Figure 11: Bottom panel: recorded variations of the warm-target calibration temperature on board NOAA-14 from Grody et al. (2004). Top panel: global mean bias estimates from ERA-Interim for NOAA-14 MSU channel 2, as in Fig. 10b.

shows the NOAA-14 MSU warm target temperature changes during the lifetime of the instrument. This curve is remarkably similar to the bias estimates obtained in ERA-Interim, duplicated in the upper panel of Fig. 11 to facilitate the comparison.

Variational bias correction in reanalysis is essentially a statistical procedure for cross-calibrating and correcting the MSU data. It uses all available observational information, including that of other instruments, in addition to the physical constraints provided by the forecast model. With abundant data coverage in the lower troposphere, it is apparent that the bias correction of MSU channel 2 is successfull in identifying and correcting known calibration errors for these data.

6 Response to the Pinatubo eruption

A well-known problem with the ERA-40 reanalysis is the excessive precipitation over the tropical oceans after 1991 (Uppala *et al.* 2005). This was partly due to the method used for analysing humidity in ERA-40, combined with the increasing availability of humidity-sensitive radiance data from HIRS and SSM/I during the 1990s (Andersson *et al.* 2004). Based on the ERA-40 experience the humidity analysis methodology used in the IFS was completely revised (Hólm *et al.* 2002). Figure 12 reflects the improvements in the representation of the hydrological cycle in ERA-Interim compared to ERA-40, as well as other available reanalysis and data products. These improvements are almost certainly the result of a combination of factors, including changes to the model physics as well as the new humidity analysis.

The tropical precipitation problem in ERA-40 was exacerbated by effects of the eruption of Mt. Pinatubo in June 1991. A large amount of aerosol was injected in the lower stratosphere, resulting in a significant cooling of the HIRS infrared radiances. During the weeks following the eruption, the radiances in the water vapour band (channels 11 and 12) changed by approximately 0.5K when averaged over tropical latitudes. The aerosol

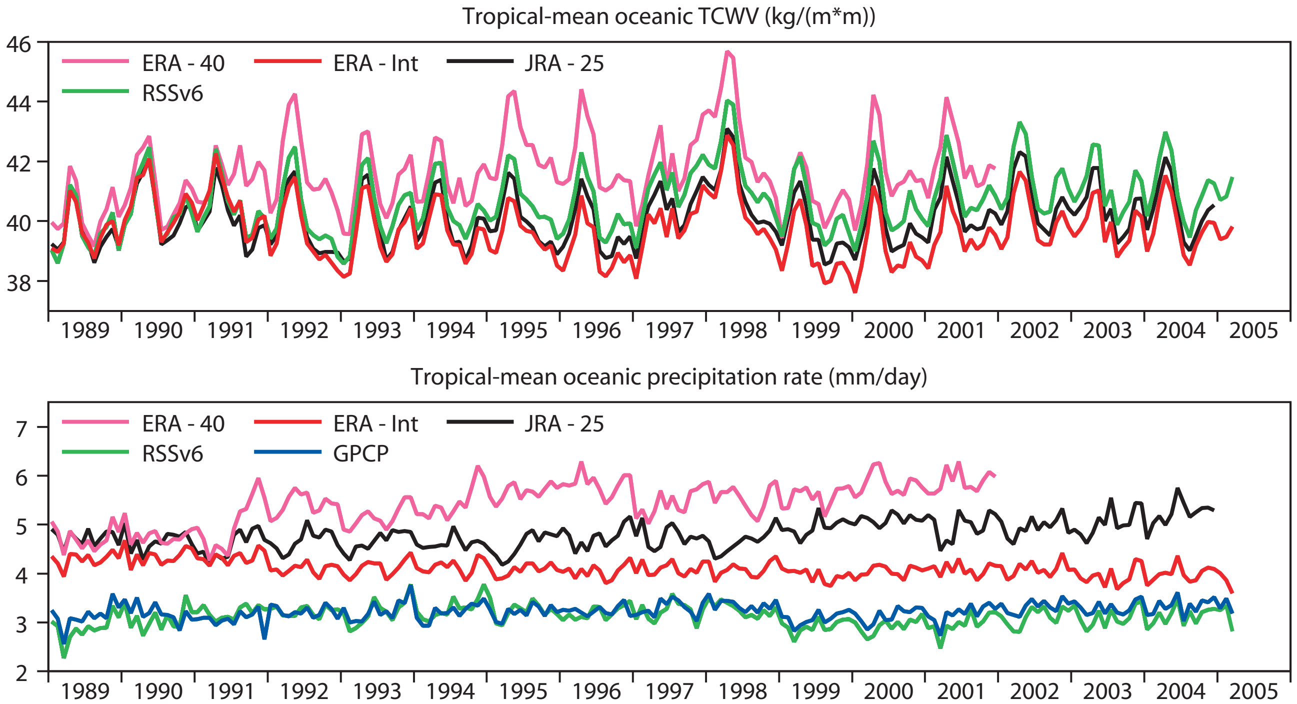

Figure 12: Tropical-mean oceanic total column water vapour (top) and precipitation rate (bottom), for ERA-40, ERA-Interim, and JRA-25. Data products from Remote Sensing Systems (RSSv6) and the Global Precipitation Climatology Project (GPCP) are included for comparison.

from the eruption persisted in the atmosphere for several years. The radiative transfer model used for the data assimilation does not account for these type of changes in aerosol concentrations, nor does the assimilating forecast model. The large signal seen by the HIRS data can therefore not be properly represented in the analysis. The response of the ERA-40 analysis was to adjust the humidity field in order to maintain the fit to HIRS data, causing a large injection of excess moisture in the tropical atmosphere. The introduction of NOAA-12 on 1 July 1991 with a second HIRS sensor made matters worse.

This situation presents an interesting challenge for the variational bias correction. In the absence of a realistic representation of the aerosol in the radiative transfer model, the only way to properly use the HIRS data is to absorb the aerosol signal in the bias estimates. Fig. 13 shows that this is in fact what happens in ERA-Interim. In the tropics, the bias estimates for HIRS channel 11 on NOAA-10 and NOAA-11 drop swiftly during the second half of June 1991 to remove the aerosol effect from the signal; this is a clear example of an adaptive correction to the observation operator, as discussed in section 2. The estimates for NOAA-12 HIRS when introduced immediately reflect the new situation. A gradual return of the bias estimates to normal (pre-Pinatubo) values then takes place during the next few years.

The effect of the Pinatubo eruption on MSU and SSM/I radiances is different. Due to the long wavelengths in the microwave spectrum these instruments are not directly sensitive to the stratospheric aerosols produced by the eruption (Spencer *et al.* 1998). On the other hand, absorption of radiation by the aerosols causes an increase in lower-stratospheric temperatures by several degrees. This signal is accurately measured by MSU channel 4, which has its peak sensitivity slightly above the tropical tropopause. The forecast model does not know about the anomolous stratospheric aerosol in this situation and therefore cannot predict its effect on temperature. As a result a slight cold bias develops in the model background, resulting in systematic departures from the MSU channel 4 radiances in the tropics.

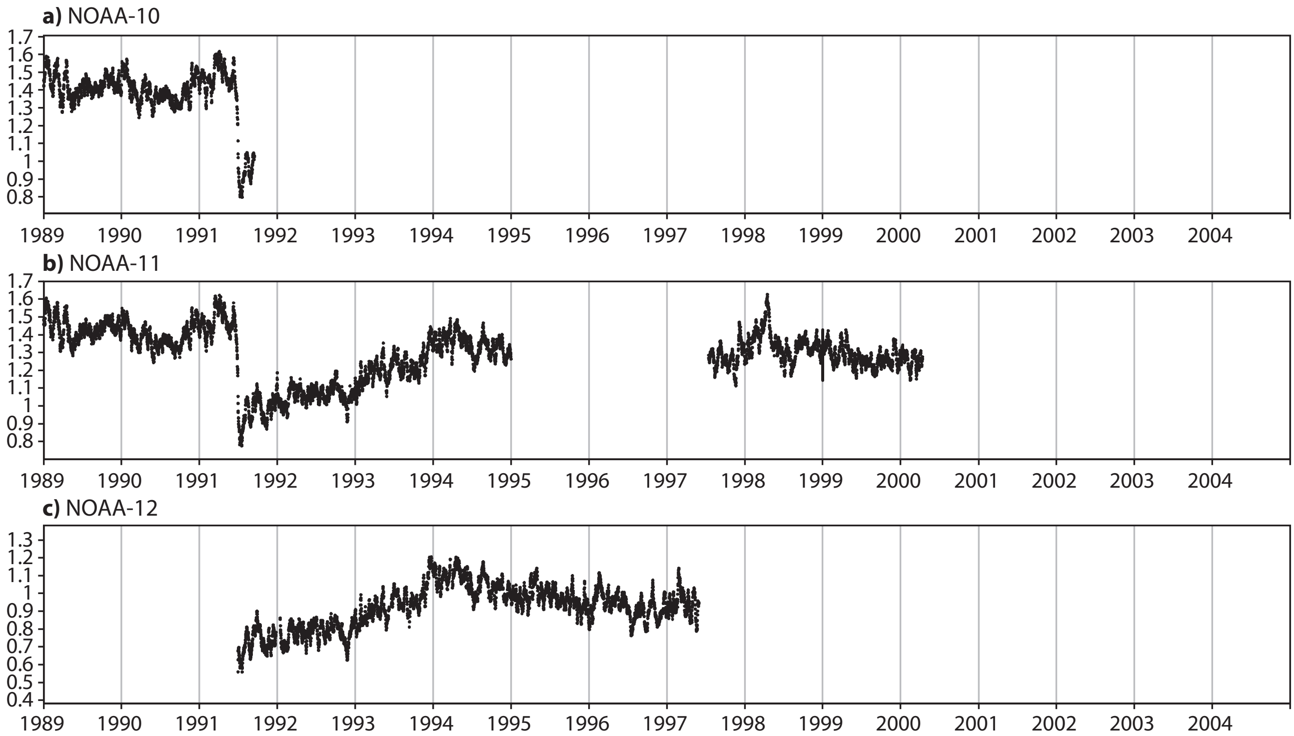

Figure 13: Tropical averages of variational bias estimates, in degrees Kelvin, for HIRS channel 11 brightness temperatures from NOAA-10 (a), NOAA-11 (b), and NOAA-12 (c).

The appropriate response in this case would be to correct the model bias in order to improve the agreement with the radiance observations, but the analysis system is not equipped to do this. Instead the system gradually increases the radiance bias estimates for MSU channel 4 during the second half of 1991, by approximately 0.45 K in the tropics, as shown in Fig. 14. The amplitude of the signal in the uncorrected radiance departures during this period is nearly 3 K, so that the true signal in the data is reduced by about 15%. This has a small, but nevertheless adverse, effect on the representation of the temperature signal in the lower stratosphere. The impact is ultimately limited by the other assimilated data, including the lower-peaking MSU channels, temperature observations from radiosondes, and the HIRS radiances discussed previously.

7 Impact of model errors

The adjustment of the MSU data following the Pinatubo eruption illustrates a potential weakness of the variational bias correction scheme in the presence of systematic model errors. The variational analysis (2) adjusts the observations in order to control the bias in the departures, regardless of its source. The obvious danger is that the data are falsely corrected to compensate for model bias, which could then cause the assimilation to drift toward the model climate. However, there are two distinct factors that limit the potential for such a scenario.

First, the nature of the bias model (i.e., the choice of bias predictors) determines the types of corrections that can be made, and this can restrict the possibilities for aliasing with systematic model errors. For example, the use of scan bias predictors for radiance data that depend only on the viewing angle of the instrument is likely to produce corrections that truly reflect biases in the data and/or in the radiative transfer model. On the other hand, the air-mass dependent predictors used for radiance bias correction could potentially explain model biases as well.

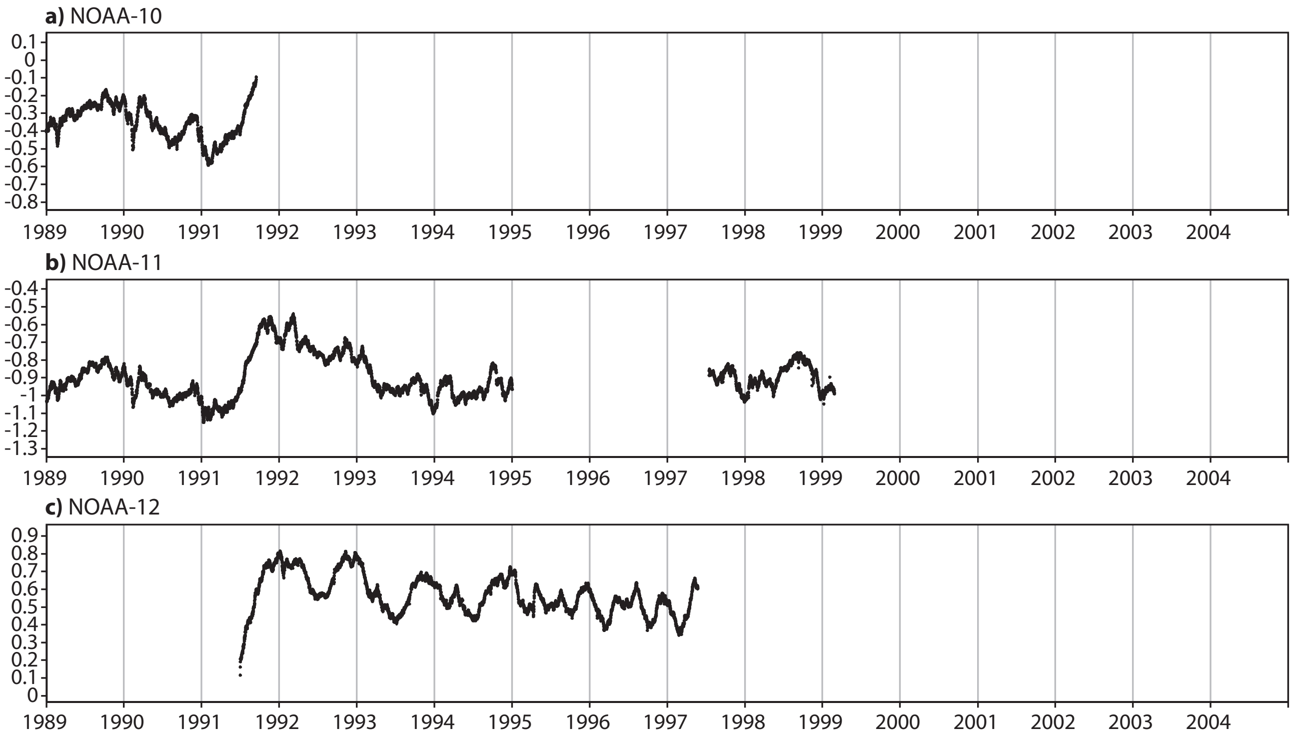

Figure 14: Tropical averages of variational bias estimates, in degrees Kelvin, for MSU channel 4 brightness temperatures from NOAA-10 (a), NOAA-11 (b), and NOAA-12 (c).

Second, the cost of making adjustments to any subset of observations depends on the resulting fit of the analysis to all other observations. The bias corrections produced for different sensors must therefore be consistent with each other as well as with any other data used in the analysis. This is a powerful feature of the variational approach to bias correction, which provides it with a major advantage over alternative schemes that estimate biases relative to a fixed reference state.

The risk of contaminating variational bias corrections of observations by the effect of model biases is therefore highest in sparsely observed situations with large-scale errors in the model background. Given the reality that forecast models have biases, it is clear that the assimilation system requires a certain amount of anchoring information to remain stable, in the form of uncorrected (and preferably unbiased) observations. It is not clear how much and what kind of anchoring information is needed.

8 Constraining the upper stratosphere

The effect of model biases on the data assimilation can be most clearly seen in the stratosphere, where observations are sparse while model errors are large. The forecast model used in ERA-Interim tends to be too warm in the upper stratosphere. Prior to 1998, stratospheric observations were dominated by radiance measurements from the Stratospheric Sounding Unit (SSU) flown on NOAA polar orbiting satellites, with three channels measuring temperatures in deep layers of the stratosphere. The main sensitivity of the highest-peaking SSU channel 3 is just below the stratopause where the model bias is largest.

Figure 15 shows the effect of allowing variational bias corrections for this channel. Since the data are systematically colder than the model, the variational analysis estimates a large negative bias for the SSU radiances

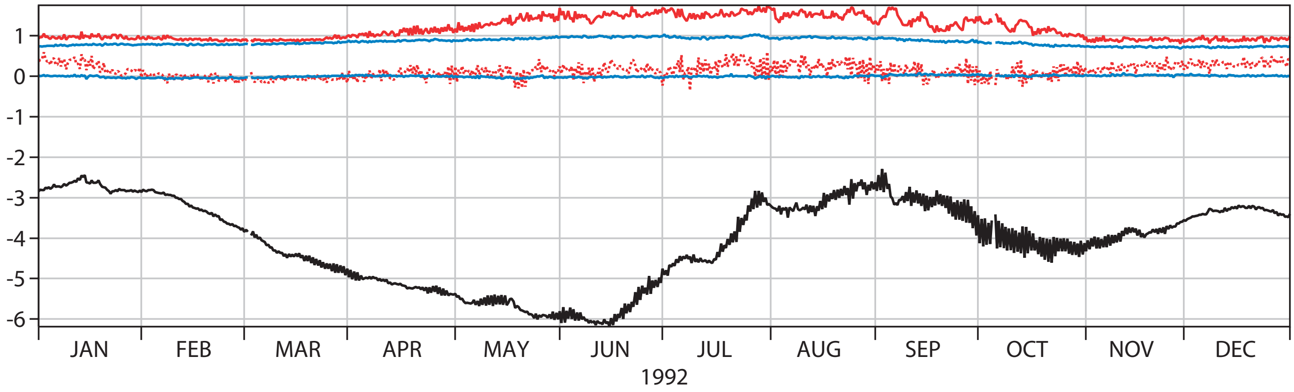

Figure 15: Evolution of mean bias corrections and mean bias-corrected departures, in degrees Kelvin, for SSU channel 3 brightness temperatures from NOAA-11 averaged for the Southern Hemisphere. Bias corrections are in black, analysis departures in blue, and background departures in red. The top two curves are the hemispheric standard deviations of the departures.

and adjusts the data accordingly. There are not enough other observations to prevent this, so that the reanalysed temperatures in the upper stratosphere inherit a warm bias from the model.

SSU is a relatively accurate instrument and corrections such as seen in Fig. 15 are probably excessive. The seasonal variations of the bias estimates, which are of opposite phase in the two hemispheres, are a further indication that the bias is due to model errors. Rather than allowing the forecast model to control the mean upper-stratospheric temperatures, more realistic upper-stratospheric temperatures can be obtained by using uncorrected SSU channel-3 radiance data. Following this approach, the variational bias correction in ERA-Interim was used to correct scan bias only for this channel (Simmons *et al.* 2007). Figure 16 shows the impact on zonal-mean temperatures for July 1993. Consistent with the SSU measurements, the upper stratospheric temperatures are reduced by several degrees Kelvin. Changes below 10hPa are small except in the Antarctic winter vortex, where temperature varies more smoothly with height.

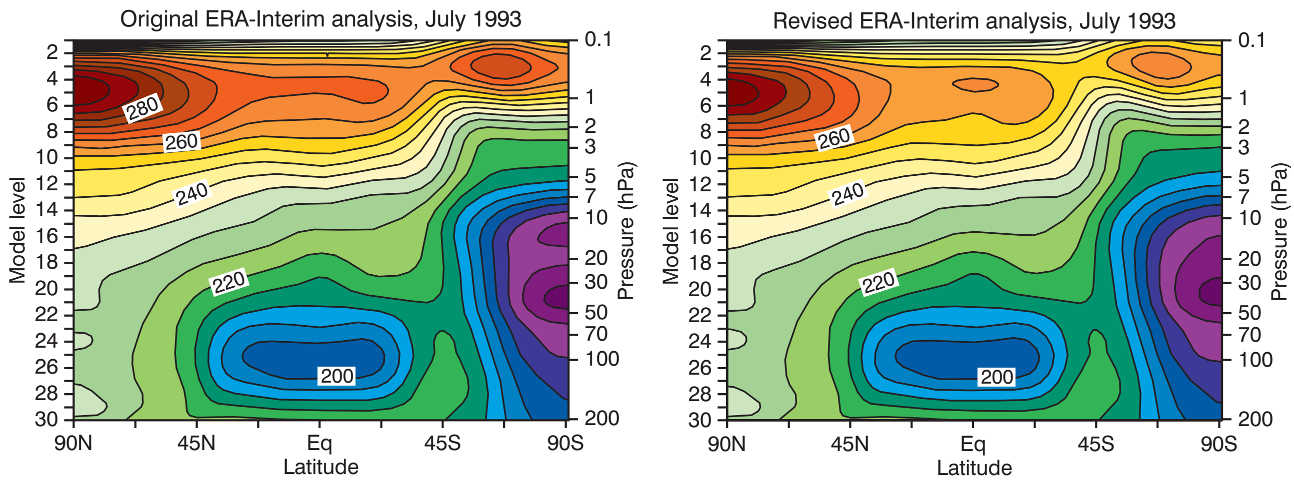

Figure 16: Pressure/latitude cross-sections of zonal-mean stratospheric temperature for July 1993, for an analysis obtained with bias-corrected SSU channel-3 radiances (left) as in Fig. 15, and for the corresponding analysis from ERA-Interim with only scan-bias correction applied to SSU channel-3 radiances (right).

The decision to use uncorrected satellite radiances for controlling the bias in the upper stratosphere raises a number of practical difficulties. First, the SSU data contain biases as well, which change in time and are different for each satellite (Kobayashi *et al.* 2008). Work is in progress to improve the radiative transfer modelling for SSU to account for instrument biases with known causes. However, any remaining inter-satellite differences will affect the reanalysis of the upper stratosphere. Second, at some point in time a transition must be made to the use of uncorrected AMSU-A radiances for constraining the stratospheric assimilation, since data from SSU are only available until 2006. This is a more serious difficulty, since the data can only partially constrain the model bias, and the nature of the constraints provided by the two sensors are quite different.

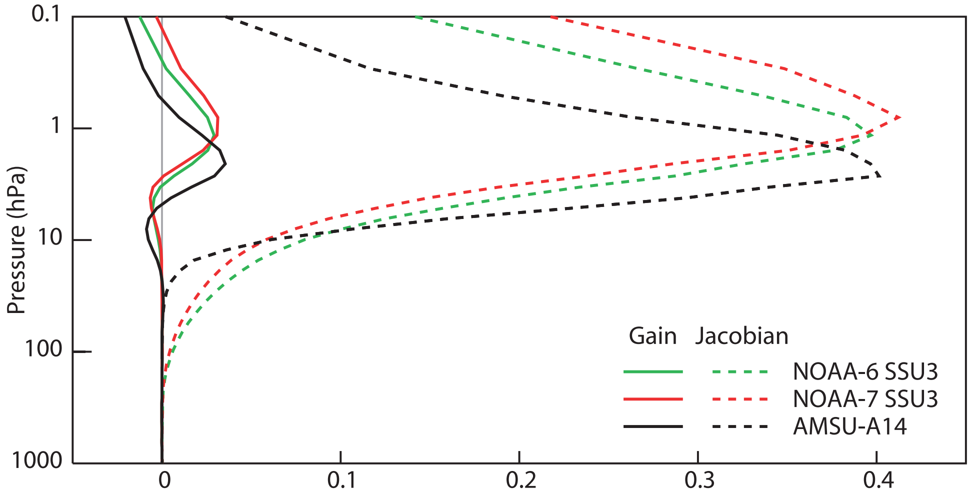

Figure 17: Jacobians and gain vectors for the highest-peaking channels of SSU and AMSU-A, from Kobayashi et al. 2008.

To help clarify these points, Fig. 17 shows the sensitivities of radiance measurements to the temperatures in an observed atmospheric column, for three simulated cases: SSU channel 3 on NOAA-6, SSU channel 3 on NOAA-7, and AMSU-A channel 14. The radiative transfer model used for computing the SSU sensitivities accounts for biases due to cell-pressure leaks, as described in Kobayashi *et al.* (2008). These biases cause a shift in the levels of the peak sensitivities and are different for each SSU instrument. The AMSU-A sensitivities were computed using a radiative transfer model that omits the parameterisation of the Zeeman splitting effect, which is a sufficiently accurate approximation for our purposes.

The solid curves in the figure show, for each of the three cases, the temperature corrections that would result

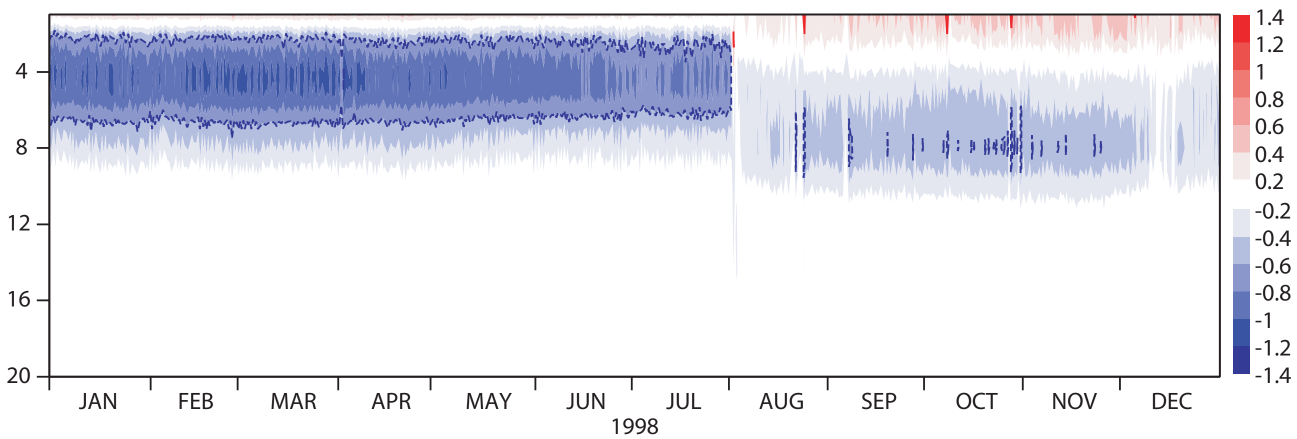

Figure 18: Globally averaged analysis increments for upper-stratospheric temperatures (30 hPa and up) in ERA-Interim during 1998, when the switch from SSU to AMSU-A took place.

from a single radiance measurement corresponding to a 1 K error in the background radiance estimate. These curves typify the impact of each sensor, which naturally depends on the background error characteristics for both scale and structure. However, the fact that the sensitivities are different for all three types of measurements guarantuees that the impacts will be different, regardless of the background error specifications.

In ERA-Interim it was decided to begin using uncorrected radiance data from AMSU-A channel 14 as soon as they became available in August 1998, and to activate variational bias correction of SSU data at that point. Figure 18 shows the effect of this transition on the global mean temperature increments in ERA-Interim for the uppermost 20 model levels (corresponding to 30 hPa and up). Both sensors generate systematic increments to constrain the model bias, but their amplitudes and vertical structures are very different.

The fundamental point is that, in a variational analysis using the model as a strong-constraint, model bias can only be partially corrected by observations. In that case any change in measurement characteristics will introduce a systematic signal in the reanalysis. The only way to fully account for model bias in a statistical analysis system is to include explicit controls for this purpose (Dee and da Silva 1998), for example in a weak-constraint version of 4D-Var (Trémolet 2006, Lindskog *et al.* 2008).

Figure 19 shows the global mean bias corrections applied to the highest-peaking stratospheric channels in ERA-

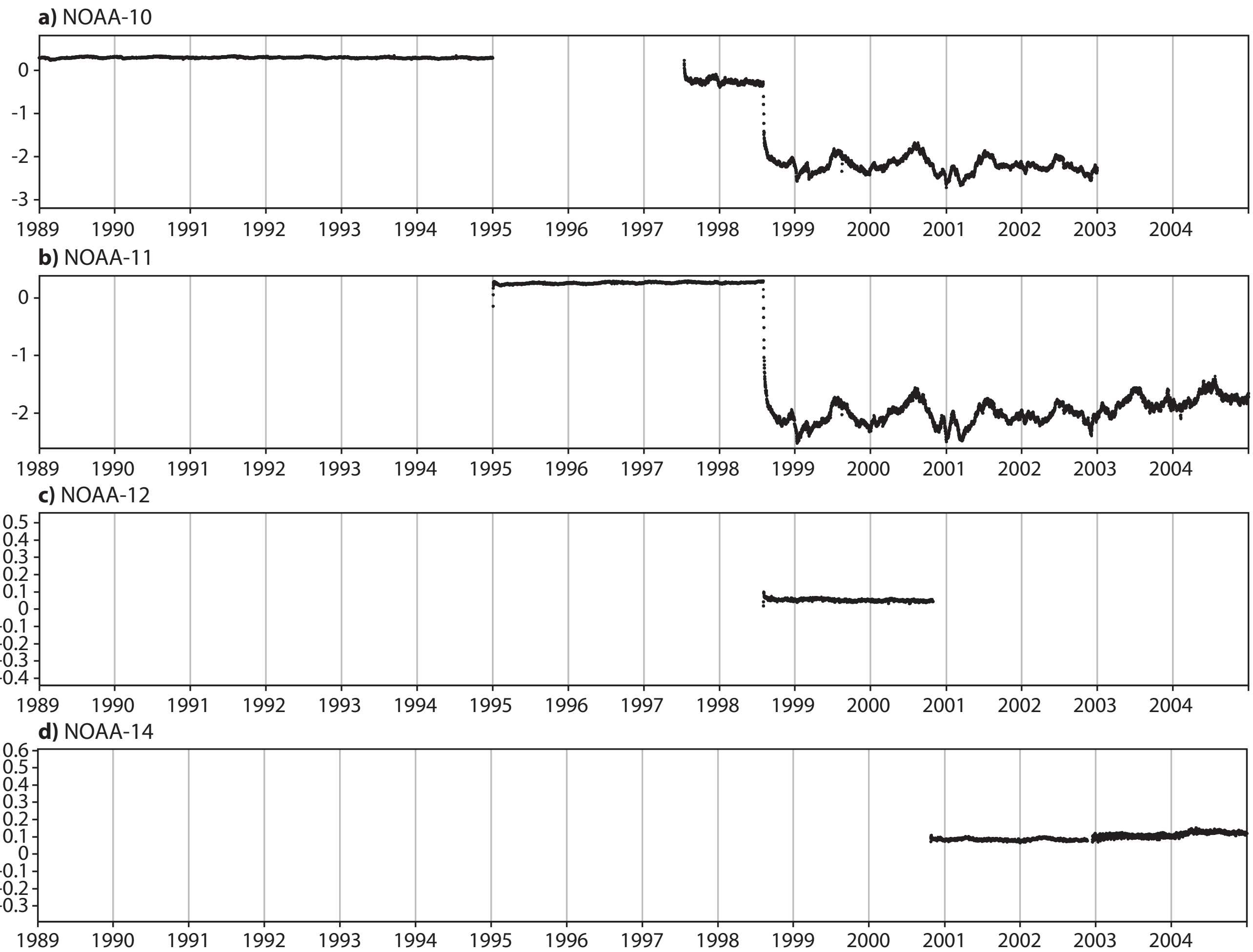

Figure 19: Globally averaged bias corrections, in degrees Kelvin, for SSU channel 3 brightness temperatures from NOAA-11 (a) and NOAA-14 (b), and for AMSU-A channel 14 data from NOAA-15 (c), and NOAA-16 (d).

Interim. The system was anchored to SSU channel 3 on NOAA-11, until SSU data from NOAA-14 became available in 1995. Variational bias correction was used to adjust SSU channel 3 data from NOAA-11 after it returned in 1997, to be consistent with those from NOAA-14. When AMSU-A was introduced on NOAA-15 in 1998, its channel 14 data were used uncorrected (except for scan bias) to anchor the system. As can be clearly seen from Fig 19, this has resulted in adjustments to the SSU radiances of about 2 K.

In summary, the need to constrain model bias in the upper stratosphere involves a number of practical choices and compromises. Inevitably, changes in the observing system have affected the time continuity of the reanalysed fields. This can be clearly seen in Fig. 20, showing the evolution of global mean temperature in ERA-Interim in the mid- and upper stratosphere. For comparison, global mean temperatures from ERA-40 are included, as well as from the recent reanalysis produced by the Japanese Meteorological Agency (JRA-25),

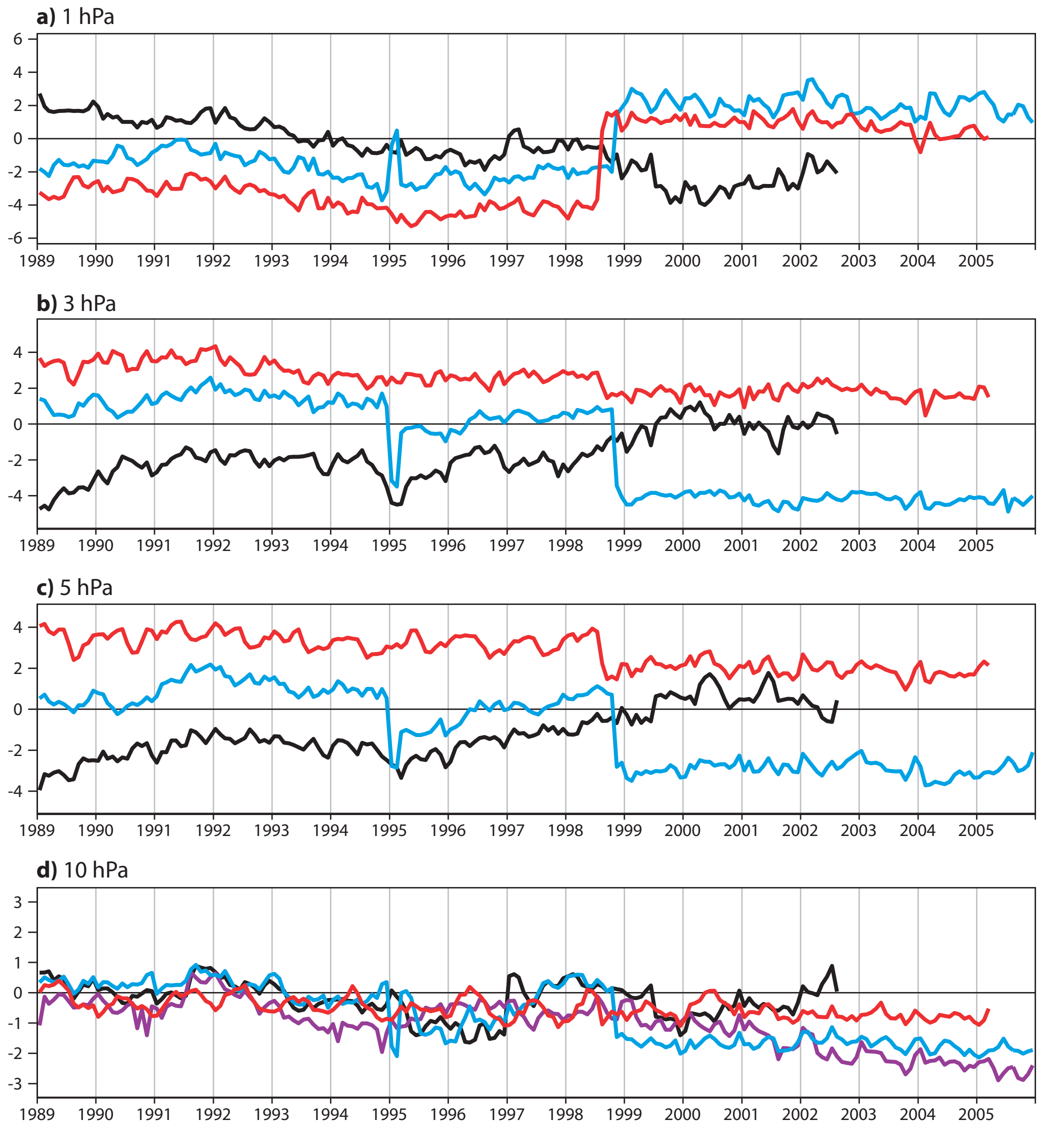

Figure 20: Global mean stratospheric temperature anomalies, in degrees Kelvin, at 1 hPa (a), 3 hPa (b), 5 hPa (c), and 10 hPa (d), from ERA-Interim (red), ERA-40 (black), JRA-25 (blue), and NRA2 (purple; 10 hPa only). ERA-Interim anomalies are defined relative to the ERA-40 climatology; anomalies for all other products are relative to their own climatologies.

and from the earlier reanalysis produced jointly by the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NRA2, at 10 hPa only). Shifts are clearly visible at levels 5 hPa and up when AMSU-A data are introduced, somewhat later in JRA-25 than in ERA-Interim. If these shifts are removed, a slight stratospheric cooling trend over the total period 1989-2004 can be detected.

9 Drift in tropospheric data from AMSU-A

The benefits of microwave radiance data from the AMSU-A sensor for numerical weather prediction at ECMWF and elsewhere have been well documented (e.g., Thépaut and Andersson 2003). AMSU-A is a 15-channel microwave sounder measuring atmospheric temperature and humidity profiles. It represents an improvement over MSU in terms of spatial resolution, both horizontally and vertically. At the time of this writing AMSU-A sensors on five polar orbiting satellites are available for numerical weather prediction, providing almost complete coverage of the earth every four hours. These data will become a mainstay of climate monitoring information for the ERA-Interim CDAS. However, since the AMSU-A record is still relatively short its suitability for this purpose has not yet been carefully assessed.

Figures 21, 22, and 23 show globally averaged bias estimates produced in ERA-Interim for AMSU-A channels 7, 6, and 5, respectively. These three channels with overlapping weighting functions provide the bulk of information about tropospheric temperature; channel 7 peaks in the upper troposphere (400–150hPa), channel 6 in the mid troposphere (600–300hPa), and channel 5 in the lower troposphere (850–500hPa).

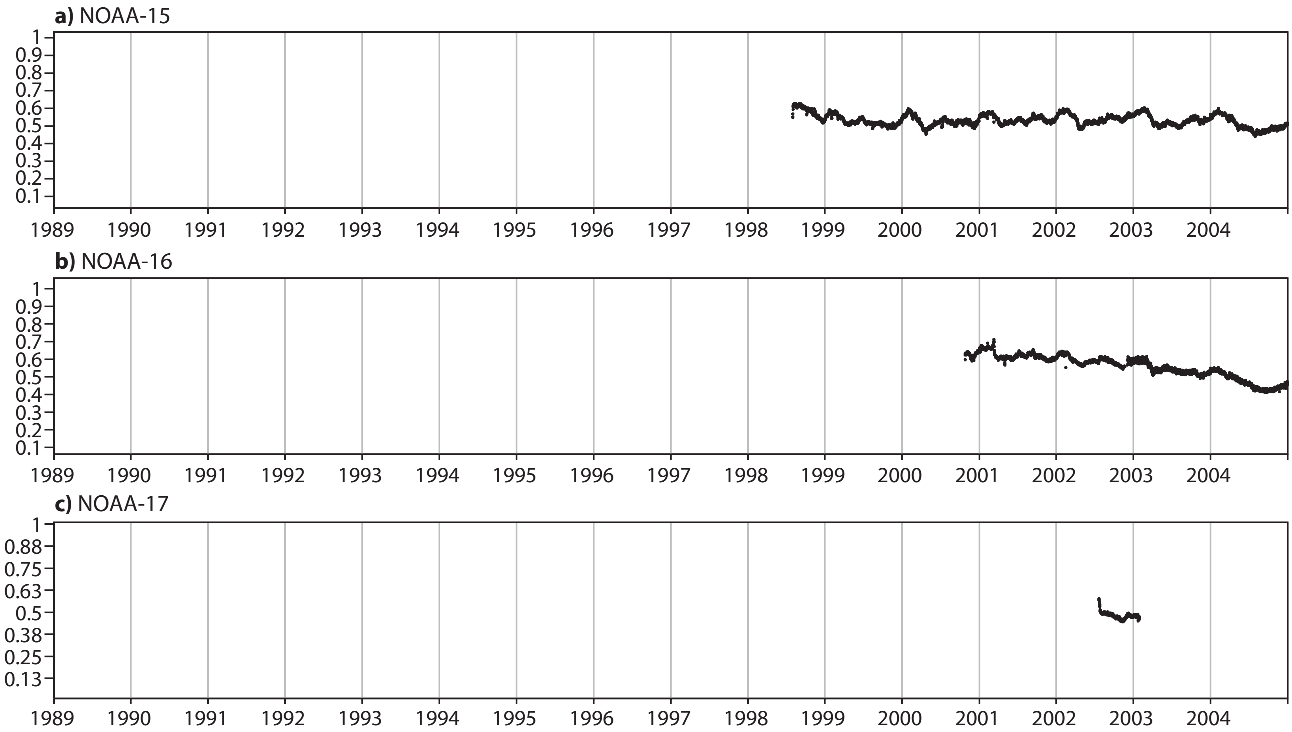

Figure 21: Globally averaged bias estimates, in degrees Kelvin, for AMSU-A channel 7 brightness temperature data from NOAA-15 (a), NOAA-16 (b), and NOAA-17 (c).

The most noticable feature in these figures is the collective, nearly linear, downward trend in the bias estimates. The curves look similar when averaged over either hemisphere or tropical latitudes rather than globally. This implies that the trends and other variations in time of the bias estimates reflect global shifts rather than seasonal

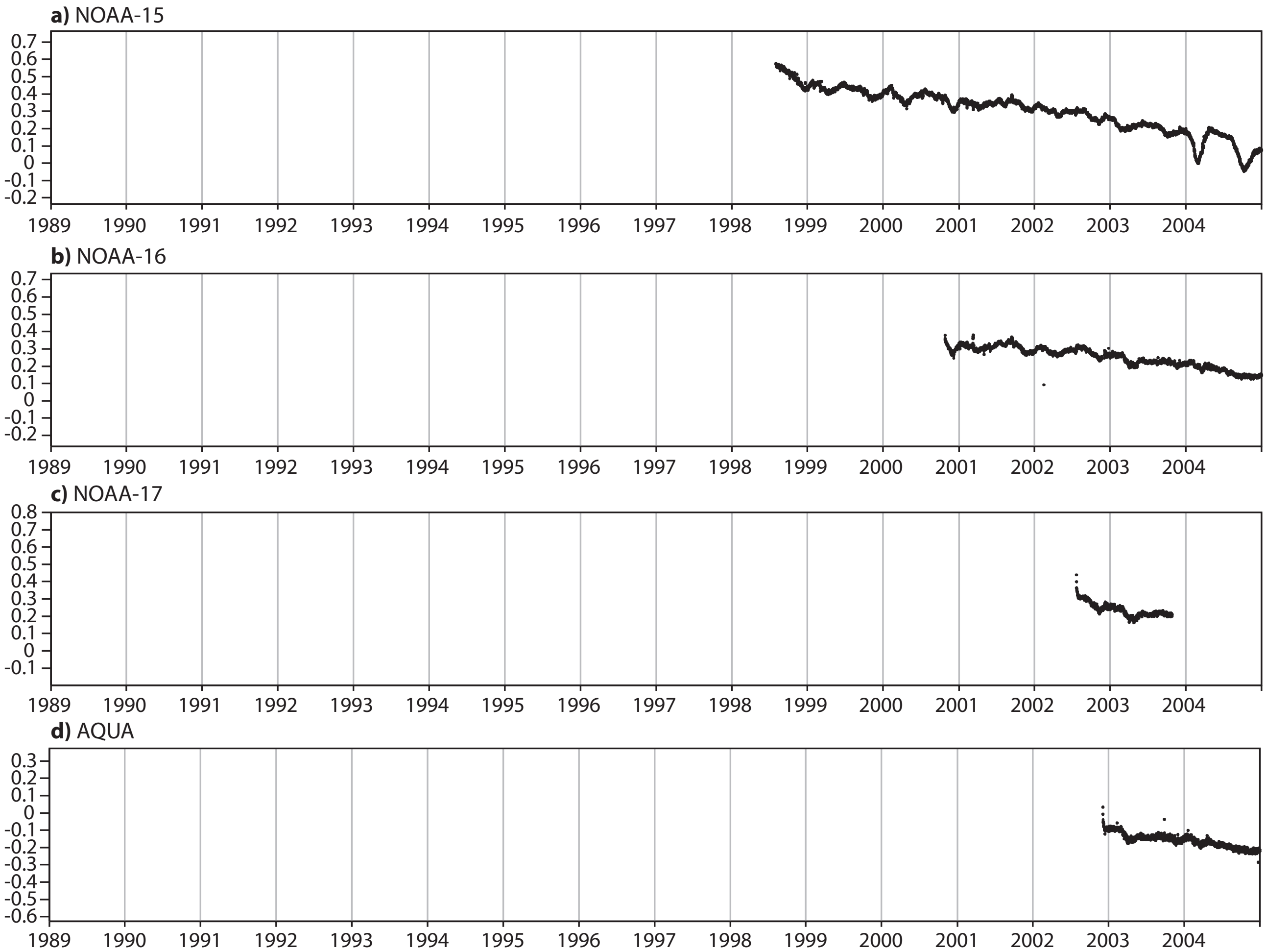

Figure 22: Globally averaged bias corrections, in degrees Kelvin, for AMSU-A channel 6 brightness temperature data from NOAA-15 (a), NOAA-16 (b), NOAA-17 (c), and AQUA (d).

or regional changes. The downward trend is largest for channel 6 on NOAA-15 (nearly 0.5 K per decade), and this appears to be consistent with the other satellites. The bias estimates for channel 5 reduce by approximately 0.15 K per decade for NOAA-15, with less consistency among the different satellites. There is no discernible trend in the bias estimates for channel 7 on NOAA-15, but on NOAA-16 they also appear to be slowly decreasing. On all three NOAA satellites the bias estimates are positive for all channels, which means that the measured radiances are biased warm relative to the analysis. The estimates for the AQUA satellite are of the opposite sign, probably because of different pre-processing algorithms used by the data provider.

In view of the positive reputation of the AMSU-A instrument, these results are remarkable and, at first glance, rather disconcerting. The first worry is that the trend in the bias estimates reflects a slow drift of the reanalysis towards the model climate, similar to the drift in the upper stratosphere discussed previously. However, the model has a slight cold bias in the troposphere, as can be seen, for example, in Fig. 24 which shows the general tendency of the model to cool the troposphere. If the true bias in the tropospheric AMSU-A data were actually stationary, then a drift of the reanalysis toward a colder model climate could only be accomplished by increasing the bias corrections to these data, because they would be increasingly warmer than the analysis. Instead, the corrections are decreasing, so that the analysis moves closer to the uncorrected data in a direction that opposes the model bias. This is confirmed by the fact that temperature increments produced by the analysis for the troposphere are systematically positive, as can be seen, for example, in Fig. 8.

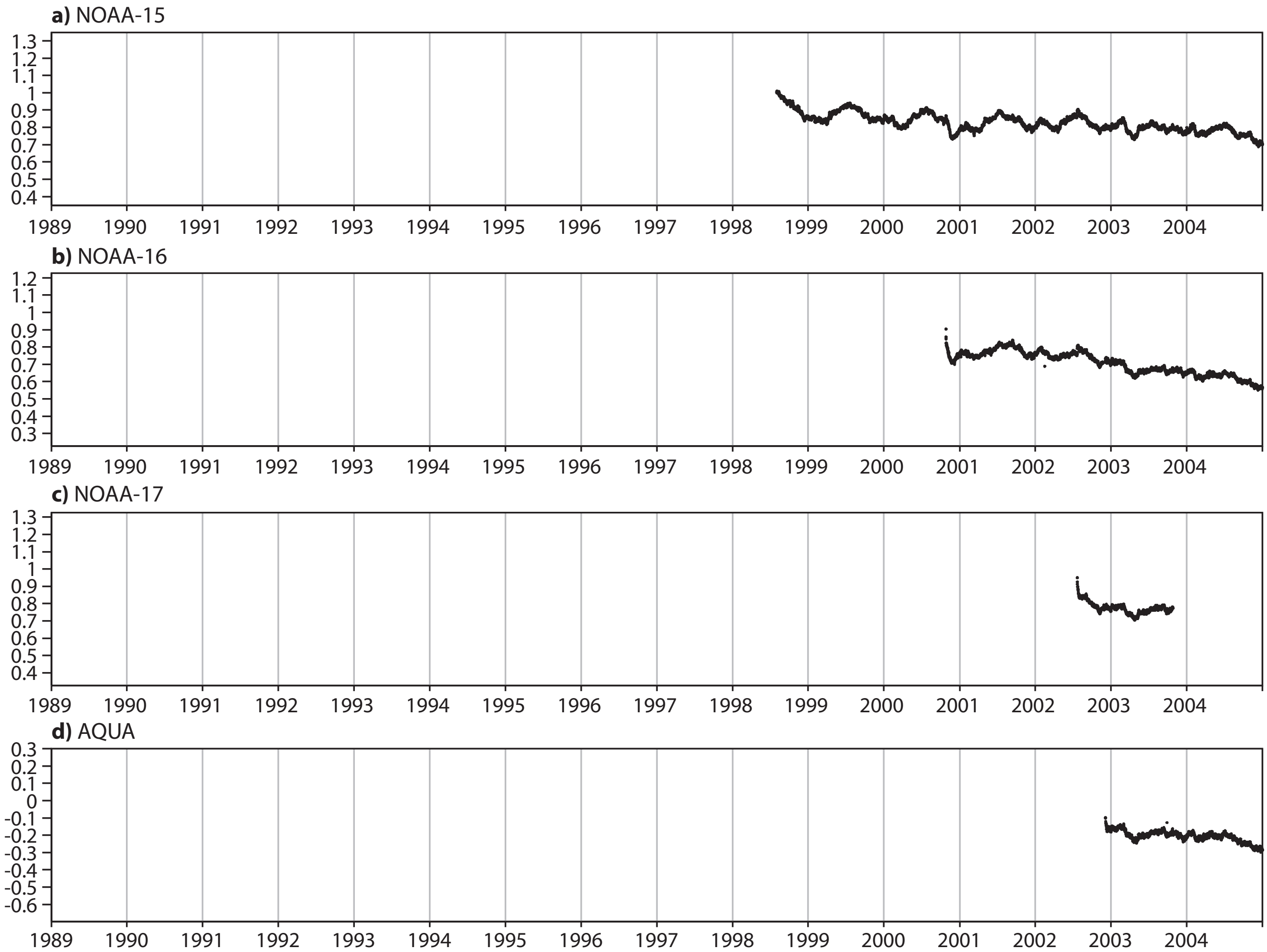

Figure 23: Globally averaged bias corrections, in degrees Kelvin, for AMSU-A channel 5 brightness temperature data from NOAA-15 (a), NOAA-16 (b), NOAA-17 (c), and AQUA (d).

We can state with confidence, therefore, that there is no insidious drift toward the model climate. An alternative explanation is that the changes in the tropospheric AMSU-A biases found in ERA-Interim are real and reflect actual instrument errors. This is partly supported in a recent study by Mears and Wentz (2008), who found trends and inconsistencies in the AMSU-A radiances from NOAA-15 and NOAA-16 that closely match the ERA-Interim bias estimate in magnitude, as well as in terms of the general behaviour. The purpose of the study was to merge recent AMSU-A data with the MSU record from earlier NOAA satellites, beginning with TIROS-N in 1979, in an effort to extend their MSU-based trend analysis for tropospheric temperatures. Based on their findings, they decided not to include any AMSU-A data NOAA-16 in the merged dataset, and not to use AMSU-A channel 6 data from NOAA-15 either. However, they do not provide a physical explanation for the observed behaviour, e.g. in terms of instrument characteristics, nor are we aware of any.

The question remains: Which information in the reanalysis is responsible for warming the troposphere? Figure 25 shows global mean temperature anomalies obtained from four different reanalyses (ERA-Interim, ERA-40, JRA-25, and NRA2) at three pressure levels (850, 500, and 250 hPa), for the period 1989–2005. ERA-Interim is consistently warmer in the lower troposphere, and its rate of warming during the AMSU-A period is at least equal to (and perhaps slightly exceeds) that in the other reanalyses. All radiance data (from AMSU-A, but also from HIRS, SSM/I, and GOES) are subject to variational bias correction, which effectively removes their mean signal and calibrates them to all non-radiance data used in the analysis. For tropospheric tempera-

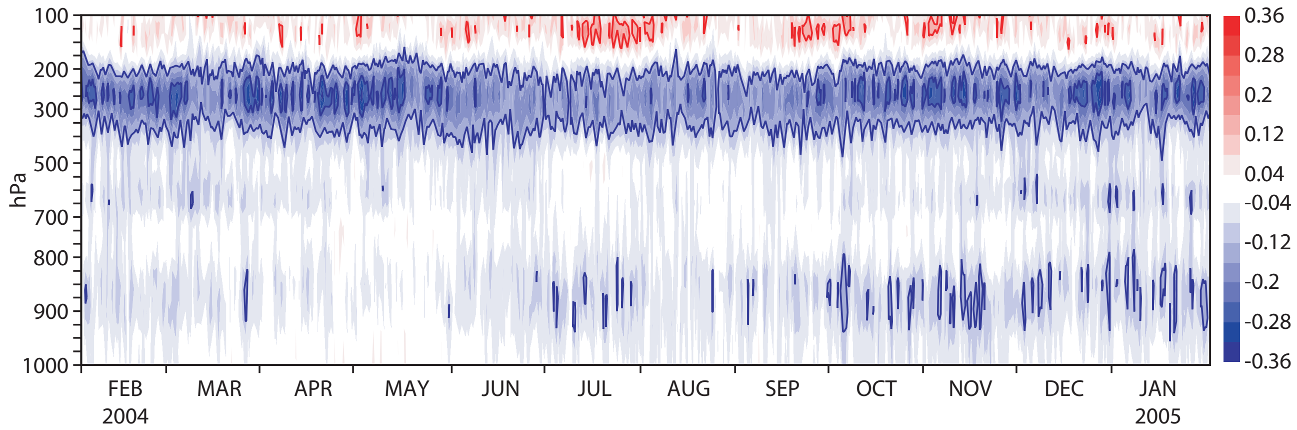

Figure 24: Global mean 24-h temperature forecast error for ERA-Interim, in degrees Kelvin, verified against its own analysis.

tures in particular, the latter primarily consist of radiosonde and aircraft observations. It must therefore be the case that the tropospheric warming in ERA-Interim largely responds to the information provided by radiosondes

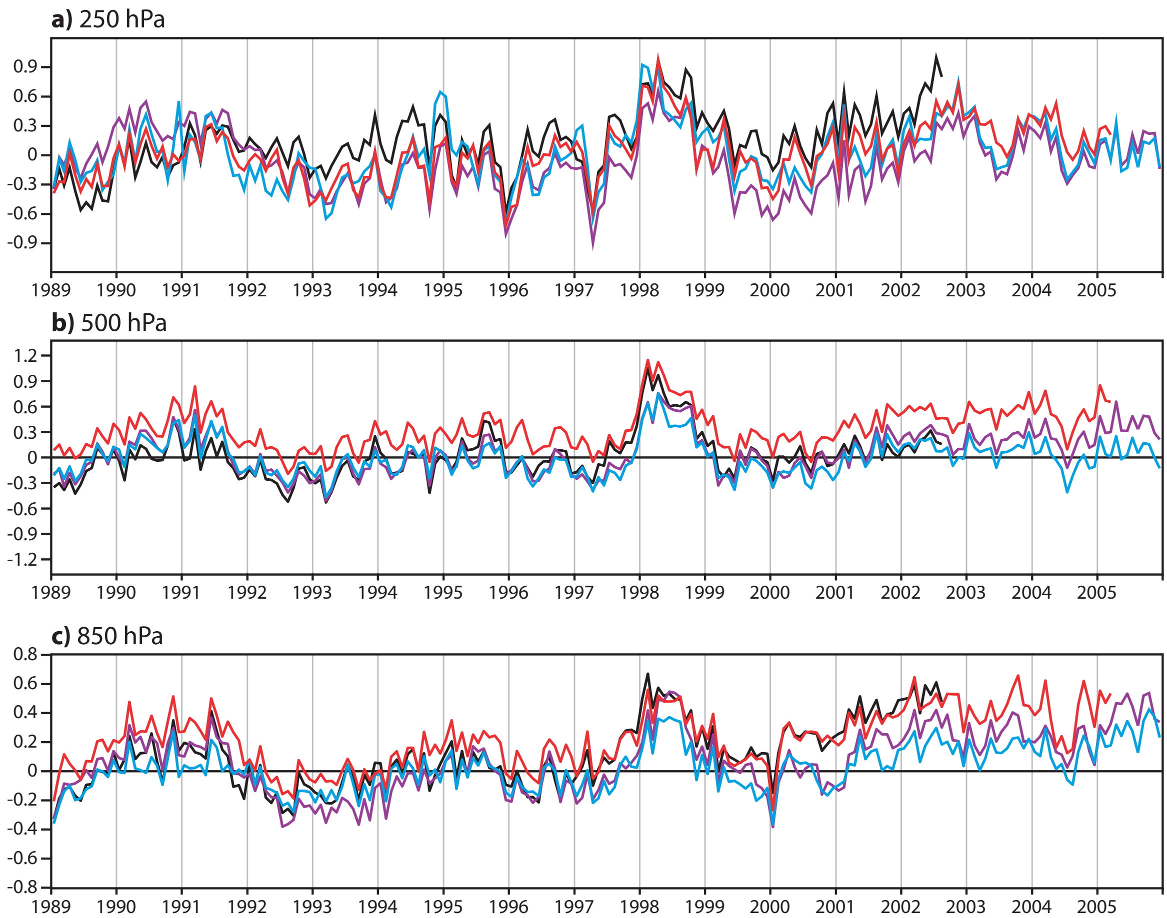

Figure 25: Global mean tropospheric temperature anomalies at 250 hPa (a), 500 hPa (b), and 850 hPa (c), from ERA-Interim (red), ERA-40 (black), JRA-25 (blue), and NRA2 (purple). ERA-Interim anomalies are defined relative to the ERA-40 climatology; anomalies for all other products are relative to their own climatologies.

and aircraft.

Figures 26 and 27 show global mean departures for radiosondes and aircraft temperature observations, for three layers of the troposphere that approximately correspond to AMSU-A channels 5–7. When interpreting statistics for conventional observations one needs to consider their numbers and locations, which are highly irregular in time and space. Both radiosonde and aircraft data are concentrated in the northern hemisphere. Most of the temperature measurements from aircraft occur at the jet-stream level; lower-level reports are predominately over land and especially in the vicinity of airports. Global radiosonde data counts do not vary a great deal during the ERA-Interim period. The number of temperature data from aircraft is small during the first few years (hence the noisy departure statistics), but increases dramatically in 1999. This explains the sudden shift in mean departures with respect to the higher-level aircraft data noticeable in Fig. 27.

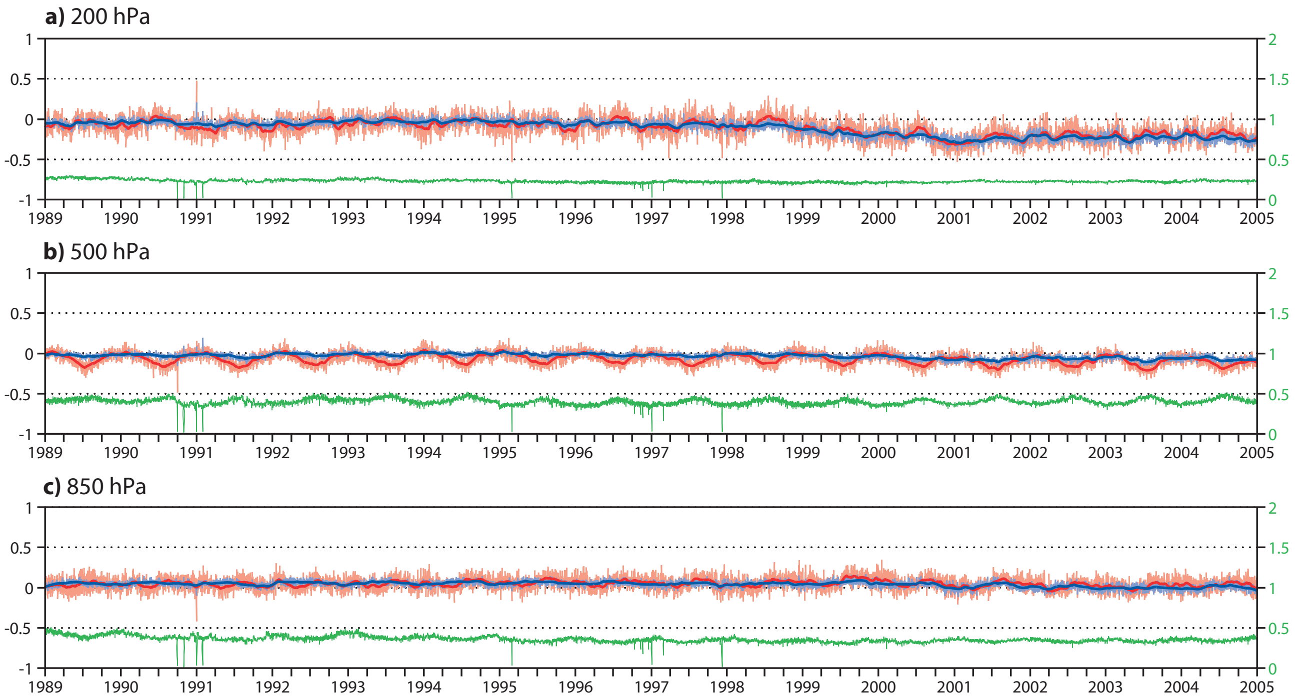

Figure 26: Global mean departures from radiosonde temperature observations, at 200 hPa (a), 500 hPa (b), 850 hPa (c). The thin curves show the mean background (red) and analysis (blue) departures for each analysis cycle; the thick curves are 30-day running averages; values in degrees Kelvin indicated on the left axes. Normalised data counts in green; in units of 10^4 *per day indicated on the right axes.*

It has recently been shown by Ballish and Kumar (2008) at NCEP that temperature measurements for many types of aircraft are biased warm relative to radiosondes, and this is also consistent with work performed by Cardinali *et al.* (2003) at ECMWF. Together with the increasing number of aircraft reports, this explains the opposing mean departures for the two types of data, both at the 200 hPa and 500 hPa levels. Beginning in 1999 mean analysed temperatures are increasingly determined by aircraft data, which greatly outnumber radiosonde reports at all levels. This also affects the anchoring of the radiance data from the AMSU-A tropospheric channels. Ballish and Kumar (2008) propose to apply bias corrections to the aircraft temperature measurements in order to render them consistent with the radiosondes. This would then have a global impact on reanalysed temperatures via the variational bias corrections of the AMSU-A channels. The net effect would be to slightly cool the reanalysis in the upper troposphere, by perhaps a few tenths of a degree Kelvin, and by a lesser amount in the lower troposphere.

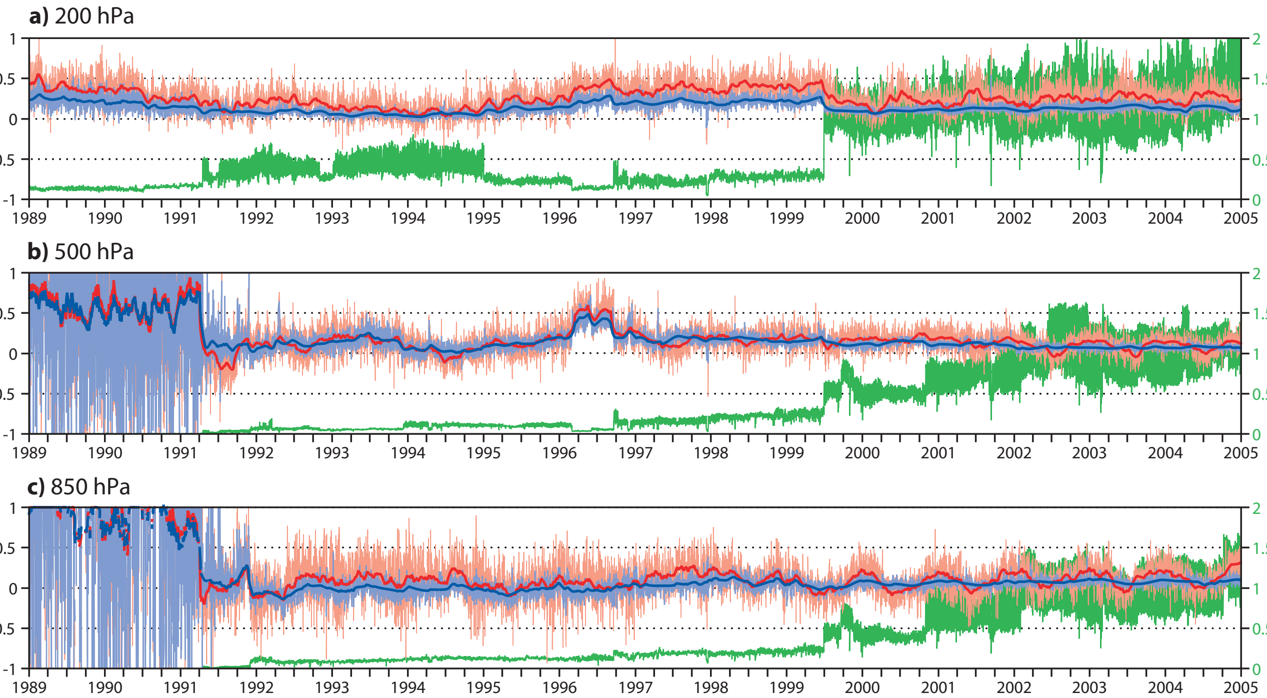

Figure 27: As Fig. 26, but for aircraft temperature reports.

10 Conclusion

The greatest challenge in reanalysis, both technically and scientifically, is the proper management of changes in the observing system. Detection of new data entering the assimilation, keeping track of the increasing variety of instrument types, handling data gaps, updating and monitoring the bias estimates—these activities are all fraught with pitfalls. Production of a multi-decadal reanalysis encompassing the modern satellite era requires that most aspects of data handling are performed automatically. The implementation of the variational bias correction system for satellite radiances in ERA-Interim is a major step towards meeting this requirement. It has allowed the reanalysis production to proceed essentially uninterrupted at a steady pace, without major mishaps.

This paper is primarily concerned with the scientific performance of the variational bias correction system in ERA-Interim. The high quality of the reanalysis products, as measured by forecast skill, fit to observations, representation of the hydrological cycle and other aspects of the global circulation, inspires confidence in the handling of radiance data in general, and hence in the quality of their bias estimates. The radiance bias estimates produced in ERA-Interim represent a wealth of information, a small fraction of which has been presented here. We were able to match long-term and seasonal variations in the bias estimates for MSU data with independent information about instrument calibration issues. The system responded well to the Pinatubo volcanic eruption in 1991, which had caused major problems in ERA-40. Unexpected drifts in AMSU-A biases seen in ERA-Interim have been confirmed in studies elsewhere as well. These cases clearly demonstrate the power of the variational approach to bias correction, which uses all available information to determine consistent bias corrections for multiple data sources. They also justify the need for an adaptive system that can respond quickly to changes in the biases, which, as we have seen, can occur on many timescales.

The fundamental problem in bias estimation is that biases are present in most data sources, and in the assimilating model itself, yet there is no objective way to separate them. In a reanalysis system this problem can manifest itself in the form of spurious signals caused by time-varying biases in the observations, and/or by changes in the way that model biases are constrained by the analysis as a result of changes in the observing system. We have seen examples of both phenomena in ERA-Interim. The switch from using SSU to AMSU-A in 1998 to constrain the model bias in the upper stratosphere has caused an abrupt change in global mean analysed temperatures at levels 5 hPa and higher. This cannot be helped unless model bias is reduced, preferably by improving the model but otherwise by changing the data assimilation method, perhaps by incorporating a weak-model constraint in the formulation of the variational analysis. The increasing numbers of temperature data from aircraft in recent years, some of which may be biased warm, is probably responsible for a modest over-estimate of the warming trend in the upper troposphere. This can be improved by correcting the biases in aircraft data, possibly with a variational scheme.

Is it possible to obtain meaningful trend estimates for climate monitoring from a reanalysis system? We believe that, in fact, reanalysis offers the best approach to do so. All observational studies involving the analysis of long (i.e. decades or more) data records require quality control and bias correction, based on an assessment of uncertainties in the data. This necessitates the use of additional, independent, sources of information. These may themselves be observational or they may be based on physical laws as expressed in prediction models. The reanalysis process is technically complex, and must be constantly improved, but it ultimately provides the right framework and the most powerful tools for integrating and reconciling diverse sources of climate information.

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