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Variational bias correction of satellite radiance data in the ERA-Interim reanalysis

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ABSTRACT: This article 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 formulation of the method and its ability to automatically develop bias estimates when radiance measurements from newly available satellite sensors are first introduced in the reanalysis. We then present several results obtained from the first 19 years (1989–2007) of ERA-Interim. These include the identification of Microwave Sounding Unit (MSU) instrument calibration errors, the response of the system to the Pinatubo eruption in 1991, 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. Copyright © 2009 Royal Meteorological Society

KEY WORDS data assimilation; MSU calibration; climate monitoring

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1. Introduction

ERA-Interim is the latest global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), covering the data-rich period since 1989. The reanalysis of the 20-year period 1989–2008 is now complete and will be extended forward in time for some years to come. The assimilating model uses a T255 spherical-harmonic representation for the basic dynamical fields, on 60 vertical levels extending from the surface up to 0.1 hPa. The data assimilation is based on a 12-hourly four-dimensional variational analysis (4D-Var) that includes the adaptive estimation of biases in satellite radiance data. With some exceptions, ERA-Interim uses input observations prepared for ERA-40 until 2002, and data from ECMWF's operational archive thereafter. The ERA-Interim data assimilation system is described in more detail by Simmons *et al.* (2007a, b) and Uppala *et al.* (2008).

The ERA-Interim Product Archive is documented in Berrisford *et al.* (2009). The Archive is part of ECMWF's Meteorological Archive and Retrieval System, which is accessible to registered users in ECMWF Member States and Co-operating States. A substantial subset of the Archive is available for download from the ECMWF Research Data Server at http://data.ecmwf.int/data. A copy of the complete set of ERA-Interim data will be maintained at the National Center for Atmospheric Research (NCAR) for research and educational purposes (http://dss.ucar.edu/pub).

The ERA-Interim project was initiated in 2006 as part of the preparations for a new, more ambitious, next-generation reanalysis to succeed ERA-40 (Uppala *et al.*, 2005). The main goal of the project has been to apply lessons learned from ERA-40 in order to address certain well-documented weaknesses in first- and second-generation reanalyses. These include problems with the representation of the hydrological cycle (Andersson *et al.*, 2004), unrealistic stratospheric transport due to an excessive Brewer–Dobson circulation (Schoeberl *et al.*, 2003; van Noije *et al.*, 2004), and contamination of climate signals by changes in the observing system (Dee, 2005; Bengtsson *et al.*, 2007).

Many of these difficulties are related, either directly or indirectly, to the assimilation of radiance measurements from satellites. Satellite data now comprise the vast majority of all existing atmospheric observations, and the way they are used in reanalysis strongly affects the quality of the primary output parameters such as temperature, wind, and humidity, as well as the additional information generated by the assimilating forecast model such as precipitation, cloud cover, and radiative fluxes. Most radiance data in fact require substantial adjustments for bias before they can be usefully assimilated. Space agencies and other data providers are now investing substantial efforts to reprocess the raw measurement data from satellites in order to remove inter-satellite biases and generally to improve the information content of the data (e.g. the Global Space-Based Inter-Calibration System project; http://www.star.nesdis.noaa.gov/smcd/spb/calibration/icvs/GSICS).

In addition to the effects of instrument and calibration errors, biases in radiance data assimilation are affected

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by systematic errors in the radiative transfer models that are embedded in the assimilation system. In general, the bias associated with a given instrument and frequency band (channel) varies in space and time, and may depend on atmospheric conditions at the time of observation. To account for this complexity, radiance bias is typically represented by a predictor model involving properties of the observed atmospheric column (such as the integrated lapse rate) as well as the state of the instrument (such as its field of view). The bias in the input observations is then described by a relatively small (say, < 10) number of parameters, which are the unknown coefficients for the predictor model. These bias parameters can be estimated separately for each channel, for example, by regression to some reference dataset (Harris and Kelly, 2001).

In ERA-Interim, the estimation of bias parameters for satellite radiance data is handled automatically by a variational bias correction system. This system detects the appearance of a new satellite data stream, and it then initialises, updates, and keeps track of bias estimates for radiance observations from all channels for each sensor flying on the satellite. The bias parameters are updated during each analysis cycle by including them in the control vector used to minimise the 4D-Var cost function. This ensures that the bias estimates are continuously adjusted to maintain consistency of the bias-corrected radiances with all other information used in the analysis, which includes the conventional observations as well as the model background. An important practical advantage of this approach is that it removes the need for manual tuning procedures, which are prone to error and simply impractical in the modern age.

The ERA-Interim reanalysis is the first to use such a highly automated bias correction system. Previous operational experience with variational bias correction of radiance data has been confined to numerical weather prediction (NWP) applications, first at the National Centers for Environmental Prediction (NCEP) and more recently at ECMWF. For an NWP system, the ability to automatically detect newly available 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 not previously been documented.

This article describes the scientific performance of the variational bias correction system in ERA-Interim. A specific concern is the ability to accurately represent climate trends and variability. This is clearly a key requirement for reanalysis to be able to support climate monitoring, impact assessment of climate change, and the improvement of climate models (Bengtsson *et al.*, 2004; Trenberth *et al.*, 2007). The main difficulty is that changes in the observing system, combined with the presence of biases in models and observations, can cause shifts and trends in reanalyses that interfere with the true climate signal. There is a general tendency over time towards increasing data coverage in all dimensions, but this occurs in bursts and spurts, rather than continuously. The challenge is to smoothly handle these events in reanalysis and to minimise their effect on the representation of trends and variability in the reanalyzed fields.

2. Variational bias correction

Variational bias correction of satellite radiances was first implemented for operational NWP at NCEP (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

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

where the $\mathbf{p}_i$ are the predictors and β_i are unknown bias parameters associated with the channel. We take $\mathbf{p}_0 \equiv 1$ to allow for a globally constant component of the bias.

The complete set of bias predictors used in ERA-Interim is listed in Table I. Predictors $p_1 - p_7$ depend on the atmospheric state at the observed location; these are mainly intended to account for systematic errors in the radiative transfer model. Predictors $p_8 - p_{10}$ are included for scanning instruments, to allow for bias components that depend on viewing angle relative to nadir. Broadly, bias predictors used for instruments on polar orbiters are $p_0, p_1, p_2, p_5, p_6, p_8 - p_{10}$, with the exception of microwave imagers which use $p_0, p_3, p_4, p_7, p_8 - p_{10}$. Bias predictors used for clear-sky radiances from geostationary satellites are p_0, p_1, p_2, p_4. Radiances from atmospheric window channels on some instruments are used for cloud detection; these data are adjusted for constant offset and scan bias ($p_0, p_8 - p_{10}$). Temperature sounding channels used to anchor the upper stratosphere (briefly discussed in section 6) are corrected for scan bias only ($p_8 - p_{10}$).

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 given by

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

Table I. Bias predictors used in ERA-Interim.

p_0:	1 (constant)
p_1:	1000–300 hPa thickness
p_2:	200–50 hPa thickness
p_3:	skin temperature
p_4:	total precipitable water
p_5:	10–1 hPa thickness
p_6:	50–5 hPa thickness
p_7:	surface wind speed
p_8:	viewing angle
p_9:	(viewing angle)^2
p_{10}:	(viewing angle)^3

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which is to be minimised with respect to the model state control parameters $\mathbf{x}$ and the bias control parameters β. Here $\mathbf{x}^b$, β^b are prior (background) estimates for $\mathbf{x}$, β, with $\mathbf{B_x}$, $\mathbf{B}_\beta$ 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 Equation (2) is the familiar background constraint for the state vector. The second term similarly represents a background constraint for the bias parameters. In a fully adaptive system, the background estimates for the bias parameters are simply the final estimates obtained from the previous analysis. When newly available radiance data enter the system for the first time, the background estimates must somehow be initialised; in ERA-Interim this is done by computing the mode of the uncorrected radiance departures. This is sufficient to initialise the parameter β_0 associated with a constant offset; the remaining predictors then adjust during subsequent minimisations (Dee and Uppala, 2008). Alternatively, or additionally, one can use information from passive monitoring of the data, from a previous reanalysis, or from other sources.

The specification of the background constraint on the bias parameters affects the adaptivity of the estimates. A weak constraint (i.e. large $\mathbf{B}_\beta$) allows the parameter estimates to respond more quickly to the latest observations. For radiance data, the precise formulation of the background constraint does not matter very much, because the number of parameters is typically much smaller than the number of data available to estimate them. In ERA-Interim, $\mathbf{B}_\beta$ is a diagonal matrix, with each element on the diagonal controlling the adaptivity of a specific predictor coefficient for a specific radiance channel. These are set to $\sigma^2/10^4$ where σ is an estimate of the error standard deviation for the observed radiance for the associated channel. As explained in Dee (2004), this means that the weight given to the prior (i.e. background) parameter estimate is equivalent to that of 10^4 additional radiance observations.

The third term in Equation (2) is the bias-adjusted observation term, which provides most of the control for the bias parameters. The variational analysis can use the additional degrees of freedom provided by the bias parameters to improve the mean fit to observations. The interpretation of a bias estimate generated in this fashion may be ambiguous, since the variational analysis can adjust bias parameters to account for the effect of both instrument errors and errors in the observation operators. For example, an instrument miscalibration that causes radiances to be systematically too warm by 1 K should produce a bias estimate of 1 K, resulting in corrected departures $(\mathbf{y} - 1) - \mathbf{h}(\mathbf{x})$. However, the same bias estimate results if the observation operator $\mathbf{h}$ is too cold by 1 K due to errors in the radiative transfer model. The purpose of the variational bias correction is to correct the combined effect of both types of error.

An alternative, more worrisome possibility is that the bias estimates compensate for systematic errors in the model state estimate $\mathbf{x}$. In that case, the data are wrongly adjusted to render them consistent with the model prediction, when in fact the model should be corrected. We return to this point in section 6 below.

3. Basic performance aspects

As in any modern NWP system, the quality of a reanalysis increasingly depends on the way that satellite data are handled. This is certainly the case for ERA-Interim which covers the data-rich period from 1989 onward. The ability of the analysis system to generate optimal bias corrections for satellite observations should therefore be reflected in standard quality measures, such as the fit to conventional observations and the quality of forecasts initialised with ERA-Interim analyses.

Figure 1 compares temperature errors for ERA-Interim and ERA-40 in the Arctic region, based on January 2000 radiosonde reports north of 70°N. Figures 1(a) and (b) respectively show analysis and background departures from observations, with central curves indicating the mean departures for ERA-Interim (solid) and ERA-40 (dashed). Analysis departures below 200 hPa are very similar, showing the consistency of both reanalyses with radiosonde temperature data in the Arctic troposphere. The mid- and upper-stratospheric temperatures are more uncertain, especially in polar winter. Radiosonde departures for ERA-Interim have clearly improved overall, both in terms of magnitude and vertical structure. While this improvement is due to many factors, including the use of a better forecast model, the consistency in the mean between the bias-corrected radiances and the radiosondes in ERA-Interim is significant. It demonstrates that the mean state of the reanalysis is effectively constrained by the radiosonde observations, as well as any other data not subject to variational bias correction, even though the radiance data vastly dominate in number.

The prominent oscillatory vertical structure in the ERA-40 departures visible in Figure 1 is connected with spurious features in the reanalysis of the upper troposphere and stratosphere. These features typically occur in polar regions in winter, and are symptomatic of a long-standing problem in satellite data assimilation (McNally, 2004). They are fundamentally caused by the presence of large and systematic discrepancies between the forecast model and the radiance information (Dee, 2005). The ERA-Interim variational analysis adjusts the bias parameters for the radiance data in order to optimise the consistency among all available sources of information, thereby reducing the vertical oscillations while maintaining a good mean fit to radiosondes. In addition, as can be seen by comparing the analysis and background departures in Figure 1, ERA-Interim shows a much improved time consistency between the analysis cycles; the forecast model requires smaller corrections yet is better able to retain the information introduced by these corrections.

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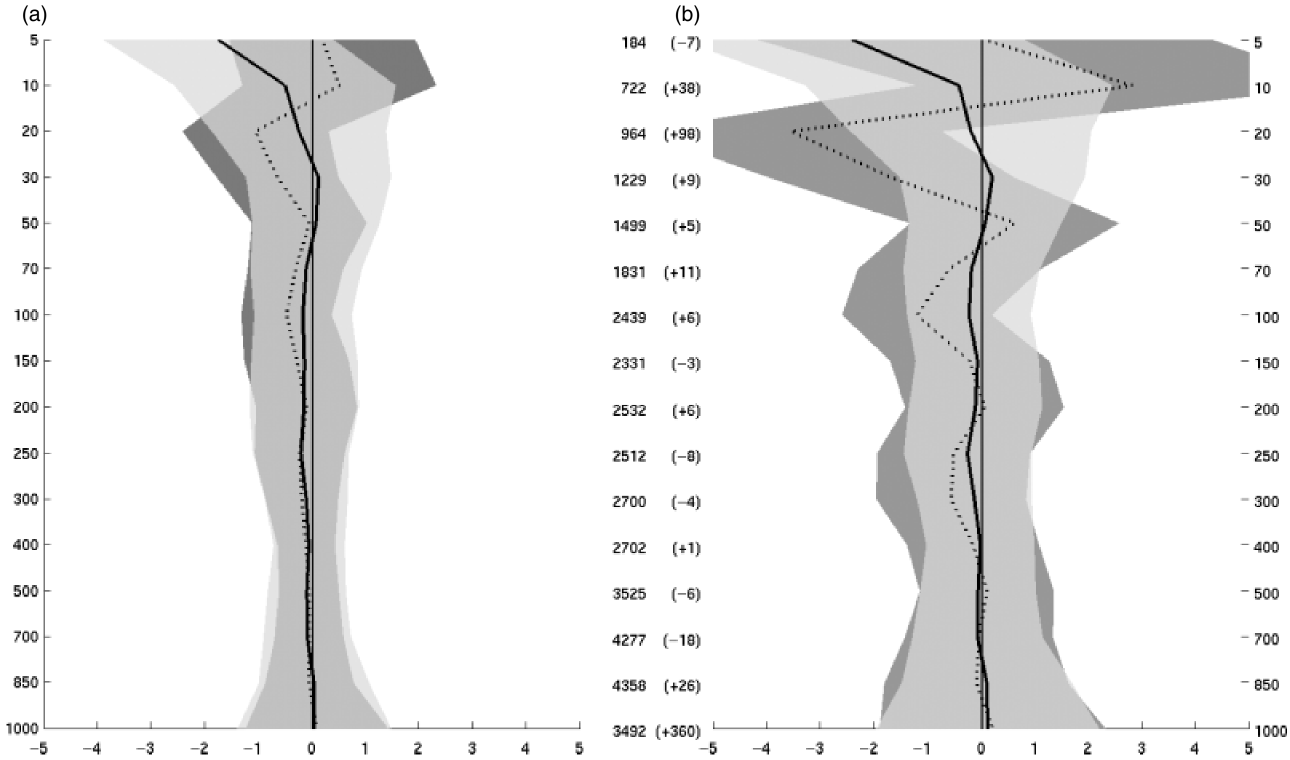

Figure 1. January 2000 fit to radiosonde temperatures from stations north of 70°N, on pressure levels (hPa) indicated on the outer vertical axes. (a) shows analysis departure means and standard deviations (K, horizontal axis) for both ERA-Interim and ERA-40. The solid curve shows mean ERA-Interim departure values, with light shading indicating ±1 standard deviation from the mean. The dashed curve and darker shading show ERA-40 analysis departure statistics. (b) similarly shows background departure means and standard deviations. Data counts for ERA-Interim are printed between the two panels, with differences from ERA-40 counts in parentheses.

Figure 2 shows the quality of ERA-Interim analyses as measured by forecast skill. For reference, Figure 2(a) shows the skill of the ECMWF operational forecast system since 1989, in terms of anomaly correlations of 500 hPa geopotential height forecasts at 3, 5, and 7 d, for both hemispheres. The gradual improvement in skill is the result of numerous factors, including model upgrades, resolution changes, advances in data assimilation, and the evolution of the observing system (Simmons and Hollingsworth, 2002). Figure 2(b) shows the same measure of skill for the set of reforecasts that were produced twice daily along with the ERA-Interim and ERA-40 reanalyses. The ERA-Interim forecasts are clearly superior to those of ERA-40, with scores that are nearly uniform in time and space. There is a noticeable improvement in forecast skill after 2002, especially in the Southern Hemisphere, which is most likely the result of the increasing availability of high-quality satellite observations. The ERA-Interim skill is comparable to that of the 2002 configuration of the operational forecast system throughout the entire reanalysis period, even though the resolution of the latter was substantially higher in 2002 than that of ERA-Interim (T511 compared to T255).

Relative to ERA-40, ERA-Interim product quality has also significantly improved in several challenging areas, including the representation of the hydrological cycle and the strength of the Brewer–Dobson circulation (Simmons *et al.*, 2007a, b; Uppala *et al.*, 2008). As a measure of the quality of the stratospheric circulation in ERA-Interim, Monge-Sanz *et al.* (2007) have shown that the mean age-of-air in the reanalysed lower stratosphere now lies well within the error bars associated with independent estimates derived from *in situ* observations of trace gas concentrations.

The observations used in ERA-Interim are not very different from those in ERA-40, so that the improvements in the reanalysis products must be due to progress in modelling and data assimilation since the completion of ERA-40. The contribution of improved radiance bias corrections to this general picture cannot be isolated. However, as we will show below, the variational approach to bias correction clearly results in better use of observations in some important situations, and this can only benefit the reanalysis.

4. MSU instrument errors

The long record of radiance bias estimates produced in ERA-Interim for multiple sensors flown on different satellites provides a wealth of information. We first focus on the behaviour of Microwave Sounding Unit (MSU) channel 2, which measures radiances determined by temperatures in a deep layer of the troposphere, with maximum sensitivity near 600 hPa. Figure 3 shows the evolution of the biases in this channel, for each of the four NOAA satellites that carried the MSU sensor during the period 1989–2007. Each point plotted represents the global mean of a bias estimate generated by the 12-hourly

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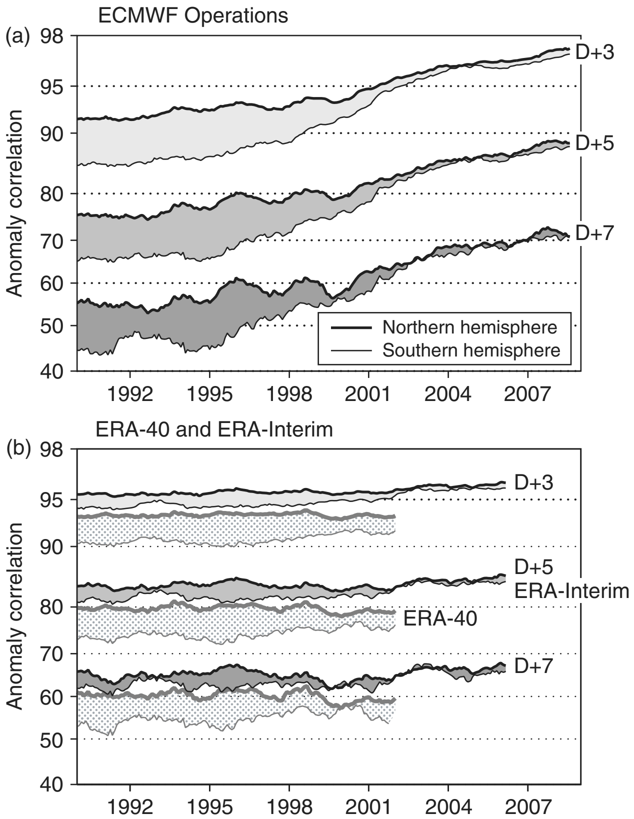

Figure 2. Mean anomaly correlations for 3 d, 5 d, and 7 d forecasts of 500 hPa geopotential height in Northern and Southern Hemispheres. (a) is for the ECMWF operational forecast system, and (b) for ERA-Interim and ERA-40. In all cases forecasts were verified against their own analyses.

variational analysis. The estimates are based implicitly on all observations available to the reanalysis system; they do not depend on any prior information about the biases.

Figure 3 has several notable features. First, the bias estimates are coherent on short time-scales; the successions of dots look like curves. However, they vary considerably on monthly and interannual time-scales. The hemispheric averages (not shown) are very similar to the global averages, implying that the variation in time is mainly due to global changes in the bias, i.e. the spatial structure of the bias is approximately stationary. There is some considerable 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.

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 dataset 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 mean 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 all variants rely to some extent on overlaps between pairs of satellites, comparisons with radiosonde observations, and modelling of physically based calibration errors.

In deriving their corrections to the MSU record, Grody *et al.* (2004) used a calibration model for the instrument that includes the effect of orbital drift of the satellite. The change in Equator-crossing time due to this 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 Figure 4(b), taken from Grody *et al.* (2004), shows recorded fluctuations of warm-target temperature for NOAA-14 MSU. This is independent information not used by the reanalysis. Nevertheless, the temperature variations are remarkably similar to those of the bias estimates obtained in ERA-Interim, which are reproduced in the Figure 4(a) to facilitate the comparison. The close correspondence between the two curves, which represent different quantities, shows that the MSU bias estimates in ERA-Interim effectively correct for the documented drift in satellite orbit.

This case provides a powerful example of the ability of a variational bias correction system to adapt to large and unexpected changes in the behaviour of instruments. Moreover, it clearly shows that fast adaptivity is necessary in order to extract a maximum of useful information from satellite observations. The viability of this approach depends on the presence of sufficient redundancy in the observing system, in order to enable simultaneous identification of biases in multiple sources. As used in reanalysis, the variational bias correction is fundamentally a statistical method for cross-calibration of observing systems. It uses all available data from a variety of instruments, in addition to the physical constraints provided by the forecast model.

5. Response to the Pinatubo eruption

A well-known difficulty with the ERA-40 reanalysis is the excessive precipitation produced over tropical oceans after 1991 (Uppala *et al.*, 2005). This was partly due to the method used for analysing humidity at the time, combined with the effect of assimilating increasing numbers of humidity-sensitive radiance observations from the High-resolution Infrared Sounder (HIRS) and the Special Sensor Microwave/Imager (SSM/I) during the 1990s (Andersson *et al.*, 2004). As a result, the humidity analysis methodology used in ERA-Interim has been completely revised (Hólm *et al.*, 2002).

The tropical precipitation problem in ERA-40 was exacerbated by effects of the eruption of Mount Pinatubo in June 1991. Large amounts of aerosol were injected into the lower stratosphere, resulting in significant cooling of

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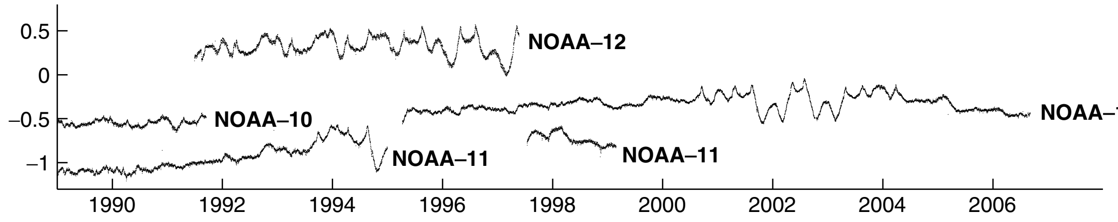

Figure 3. Global mean 12-hourly variational bias estimates (K) for MSU channel 2 radiance data from NOAA-10, NOAA-11, NOAA-12, and NOAA-14.

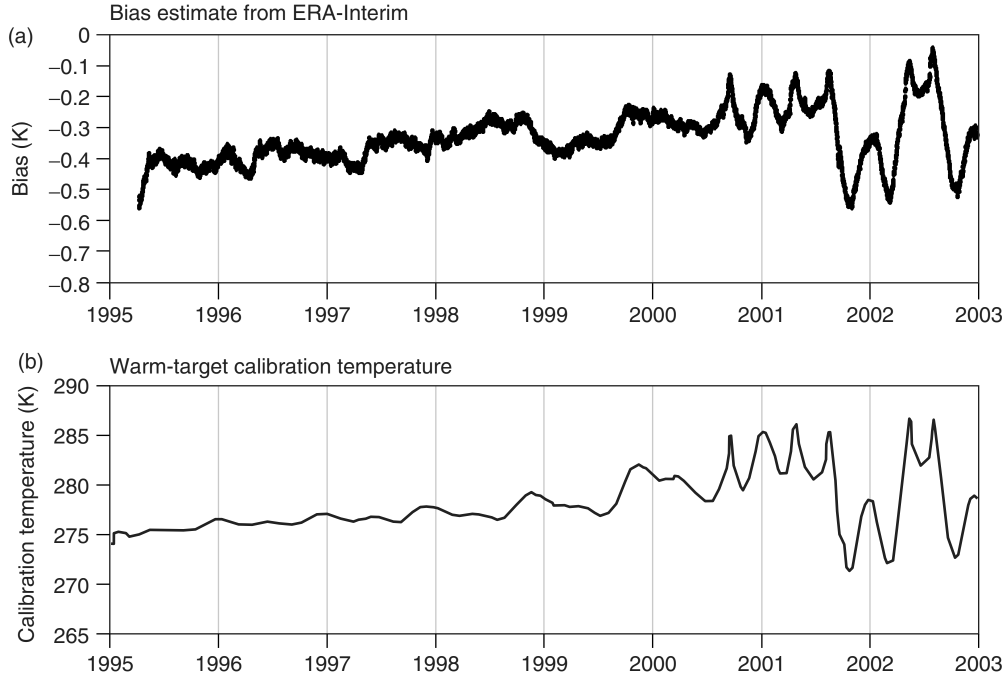

Figure 4. (a) shows global mean bias estimates from ERA-Interim for NOAA-14 MSU channel 2 radiances, as shown in Figure 3. (b) shows recorded variations of the warm-target calibration temperature on board NOAA-14 from Grody *et al.* (2004).

the HIRS infrared radiances. During the weeks following the eruption, the radiances in the water vapour band (channels 11 and 12) changed by approximately 0.5 K on average in the Tropics. The aerosols from the eruption persisted in the atmosphere for several years. The radiative transfer model used for the data assimilation does not account for this type of change in aerosol concentration, 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, which resulted in 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 system. In the absence of a realistic representation of the aerosols in the radiative transfer model, the only way to extract useful information from the HIRS water vapour channels is to absorb the aerosol signal in the bias estimates. Figure 5 shows that this is in fact what happens in ERA-Interim. In the Tropics, bias estimates for HIRS channel 11 on NOAA-11 drop swiftly by about 0.5 K during the second half of June 1991 to remove the aerosol effect from the signal. The estimates for NOAA-12 HIRS when introduced immediately reflect the prevailing anomalous 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 anomalous 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.

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

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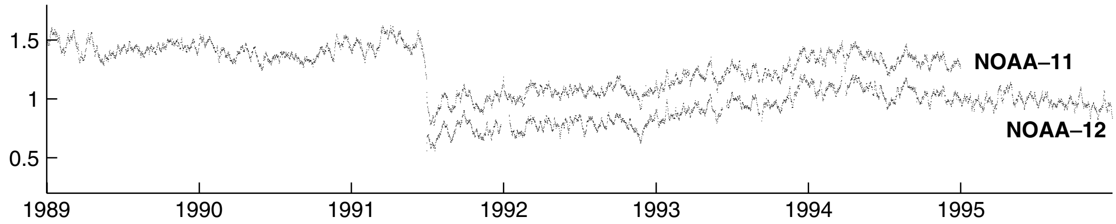

Figure 5. Tropical averages (for latitudes between 20°S and 20°N) of 12-hourly variational bias estimates (K) for HIRS channel 11 radiance data from NOAA-11 and NOAA-12.

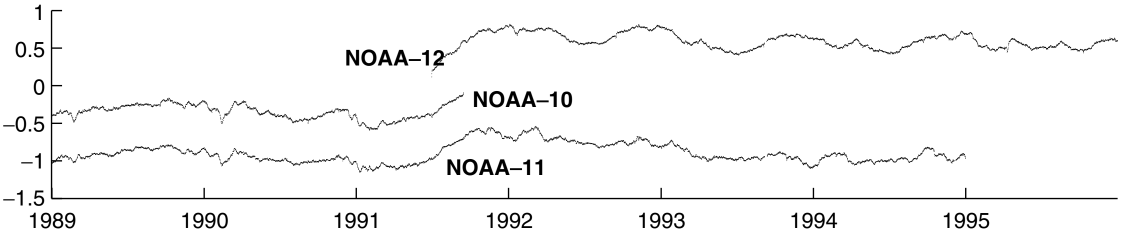

Figure 6. Tropical averages (for latitudes between 20°S and 20°N) of 12-hourly variational bias estimates (K) for MSU channel 4 radiance data from NOAA-10, NOAA-11, and NOAA-12.

is not equipped to do this. Instead the system gradually inflates bias estimates for MSU channel 4 radiances during the second half of 1991, by approximately 0.45 K in the Tropics, as shown in Figure 6. 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 as previously discussed.

6. 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, in accordance with the last term in Equation (2), adjusts the bias parameters in an attempt to remove any systematic discrepancy between the observations and the model-based simulation of these observations. This procedure amounts to a correction of the observations, regardless of the source of the bias. If the discrepancy is actually due to a bias in the model, then the observations are adjusted anyway. In a worst-case scenario, this could cause the assimilation to drift toward the model climate. However, there are two distinct factors that limit the potential for this to happen.

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, air-mass-dependent predictors often used for radiance bias correction could potentially explain model biases as well. These predictors normally comprise a small set of large-scale fields, such as the thickness of a deep layer of the atmosphere.

Second, the cost of making adjustments to any subset of observations depends on the implied changes to the fit of the resulting analysis to all other observations. The bias corrections produced for different channels and 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 observations by variational bias corrections due to the effect of model biases is therefore highest in sparsely observed situations where large-scale errors in the model background prevail. Given the reality that models do – and probably always will – generate biased forecasts, 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 for this.

In ERA-Interim, the effect of model biases on the data assimilation is most clearly seen in the stratosphere. To avoid excessive drift, the upper layers of the model were constrained by using uncorrected radiance data from the highest-peaking channel on successive Stratospheric Sounding Units (SSUs) and Advanced Microwave Sounding Units (AMSU-A). Since each instrument has somewhat different characteristics, this has resulted in spurious shifts in the reanalysis of the upper stratosphere that are visible, for example, in time series of global mean temperatures at 5 hPa and higher. Detailed discussions of these

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and other aspects of the stratospheric analysis in ERA-Interim appear in Dee and Uppala (2008) and Kobayashi *et al.* (2009).

7. Drift in tropospheric AMSU-A data

The benefits to numerical weather prediction of microwave radiance data from the AMSU-A sensor are well known (e.g. Thépaut and Andersson, 2003). AMSU-A is a 15-channel sounding instrument that measures atmospheric temperature and humidity profiles. It represents an improvement over MSU in terms of spatial resolution, both horizontally and vertically. AMSU-A sensors on five polar orbiting satellites are currently available for NWP, providing almost complete coverage of the Earth every four hours. The AMSU-A record is still relatively short, and its suitability for climate monitoring has not yet been carefully assessed.

Figure 7 shows globally averaged bias estimates produced in ERA-Interim for AMSU-A channels 7, 6, and 5, for four different satellites. These three channels with overlapping weighting functions contain a great deal of information about tropospheric temperatures; channel 7 peaks in the upper troposphere (400–150 hPa), channel 6 in the middle troposphere (600–300 hPa), and channel 5 in the lower troposphere (850–500 hPa).

The most obvious feature in the bias estimates is their collective, nearly linear, downward trend. The curves look similar when averaged over either hemisphere or over 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 or regional changes. The downward movement of the bias estimates for channel 7 on NOAA-16 exceeds that of NOAA-15, where a discernible trend appears only after 2004. The change in bias for channel 6 on NOAA-15 exceeds 0.5 K per decade and this appears consistent among all four satellites during the overlaps. The bias estimates for channel 5 reduce by approximately 0.15 K per decade for NOAA-15, with less consistency among the different satellites. With the exception of channel 6 on NOAA-15, which behaves erratically after 2003, the bias estimates are always positive (warm) on the three NOAA satellites. The estimates for the AQUA satellite are of the opposite sign (cold), most likely due to the different pre-processing algorithms used by the data providers.

Given the documented benefits of the AMSU-A instrument for NWP, these results are unexpected 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 – the worst-case scenario mentioned earlier. To investigate this possibility, we note first that the forecast model used in ERA-Interim has a slight but systematic cold bias in the troposphere, as can be seen, for example, from globally averaged 2 d forecast errors (cf. Figure 24 of Dee and Uppala, 2008). A drift towards the model climate would mean that the reanalysis gets increasingly cold relative to the data. To prove that this is inconsistent with the downward trend of the AMSU-A bias estimates, consider the departure bias $b = \overline{y - h(x)}$, where the overbar denotes averaging. A decrease in bias over time occurs when $\mathrm{d}\overline{y}/\mathrm{d}t < \mathrm{d}\overline{h(x)}/\mathrm{d}t$, which means that the temperature trend in the reanalysis exceeds the temperature trend implied by the (uncorrected) AMSU-A data. Thus, decreasing bias corrections imply that the reanalysis moves closer to the uncorrected AMSU-A data in a direction opposing the model bias. This is confirmed by the globally averaged temperature increments produced in the troposphere, which are systematically positive in ERA-Interim (not shown).

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 (2009), in which they attempt to merge recent AMSU-A data with the MSU record from earlier NOAA satellites in an effort to extend their MSU-based climate trend analysis for tropospheric temperatures. They find similar trends and inconsistencies in the AMSU-radiances from NOAA-15 and NOAA-16, and, in fact, most of these data are not included in their merged dataset.

Figure 8 shows globally averaged monthly mean temperature anomalies obtained from ERA-Interim, at three pressure levels (250, 500, and 850 hPa). To provide some measure of uncertainty, the anomalies computed from three other reanalyses are plotted as well. Anomalies were computed separately for each reanalysis based on its own mean annual cycle. The representation of temperature trends and variability is generally robust, with larger differences among reanalyses in the upper troposphere, suggesting larger uncertainty there. Each reanalysis clearly produces the tropospheric warming observed during the last two decades. The rate of warming in ERA-Interim is comparable with that in other reanalyses, although it appears slightly high in the upper levels.

The question remains: which information in the reanalysis drives the tropospheric warming? The decreasing bias estimates for AMSU-A show that ERA-Interim warms slightly faster than the uncorrected AMSU-A data, in spite of the model's systematic tendency to cool the troposphere. By design, the variational bias correction effectively reconciles the mean signal in the AMSU-A data (and the HIRS, SSM/I, and GOES radiances as well) with all other observations used in the analysis. The primary source of information for tropospheric temperature, apart from satellite radiance data, consists of radiosondes and aircraft. It follows that the tropospheric mean temperatures in ERA-Interim mainly derive from radiosonde and aircraft reports.

Figures 9 and 10 show time series of global mean departures for temperature data from radiosondes and aircraft, for three tropospheric layers that approximately correspond to AMSU-A channels 5, 6, and 7. When interpreting statistics for conventional observations, one needs to consider their numbers and locations, which are highly irregular in space and time. Both radiosonde

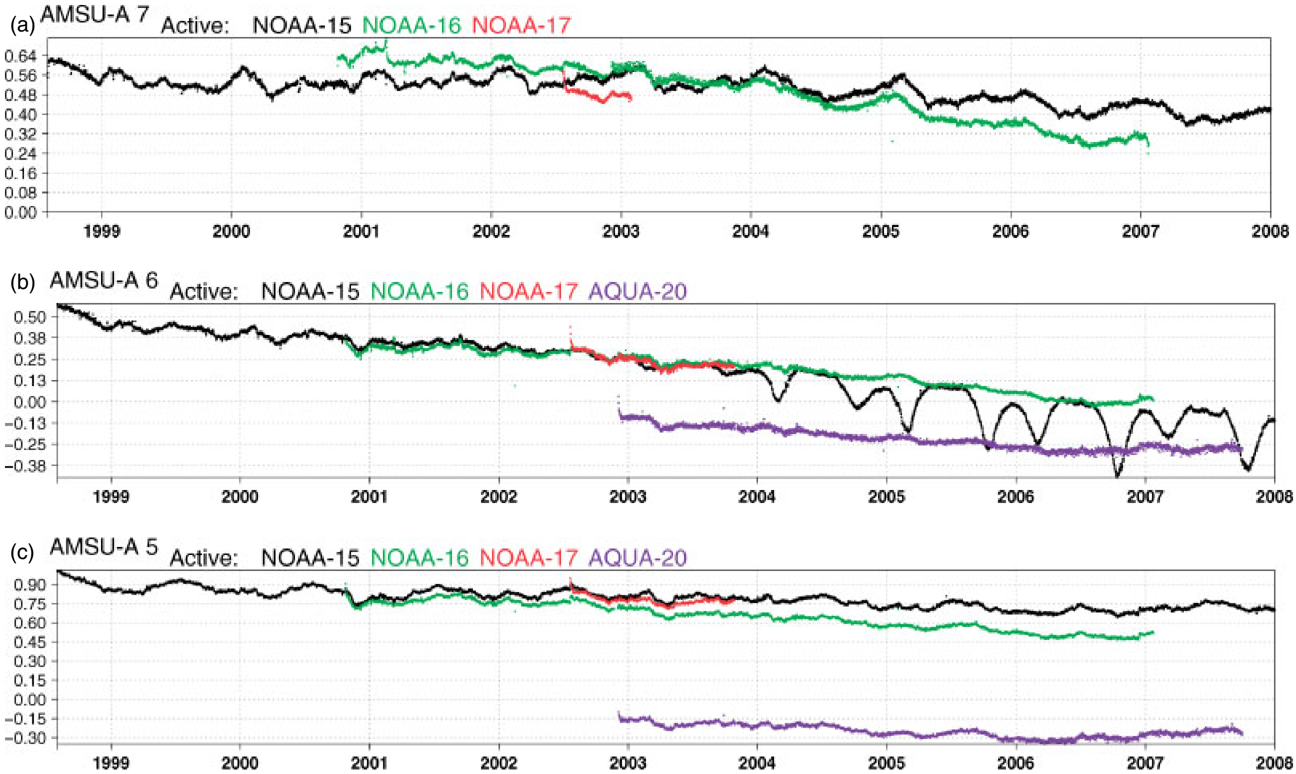

Figure 7. Globally averaged 12-hourly bias estimates (K) from NOAA-15, NOAA-16, NOAA-17, and AQUA for AMSU-A (a) channel 7, (b) channel 6, and (c) channel 5.

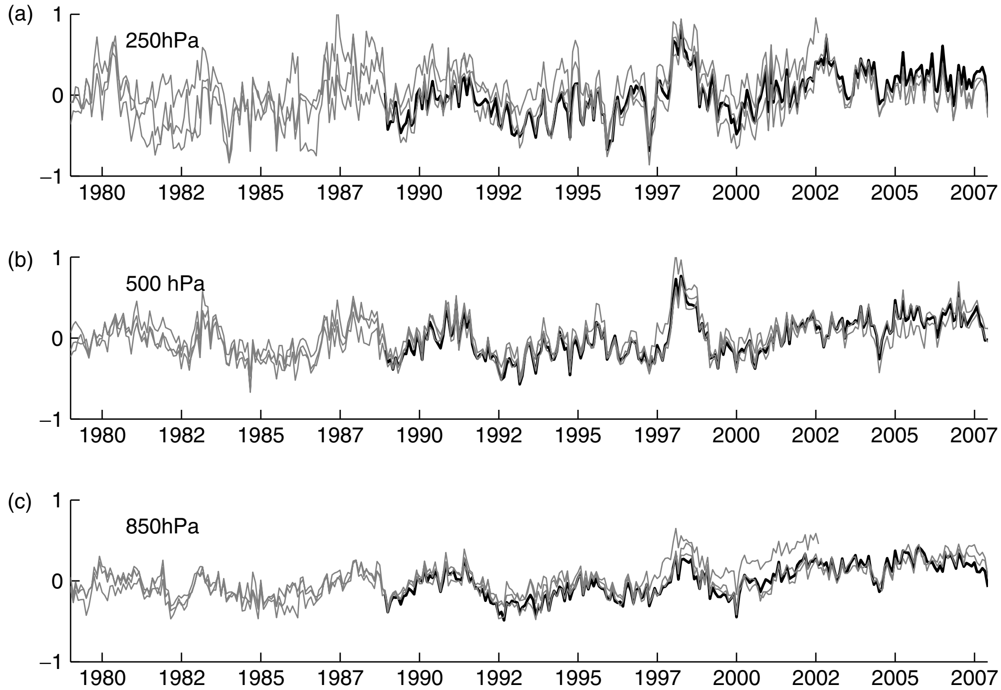

Figure 8. Global mean tropospheric temperature anomalies (K) at (a) 250 hPa, (b) 500 hPa, and (c) 850 hPa, from ERA-Interim (thick black curves) and three other reanalyses (thin grey curves): ERA-40, NRA2, and JRA-25. In each case the anomalies were computed relative to the mean annual cycle for that reanalysis. All calculations are based on monthly averaged fields.

and aircraft reports 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, although a noticeable decrease occurred in the late 1990s. 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

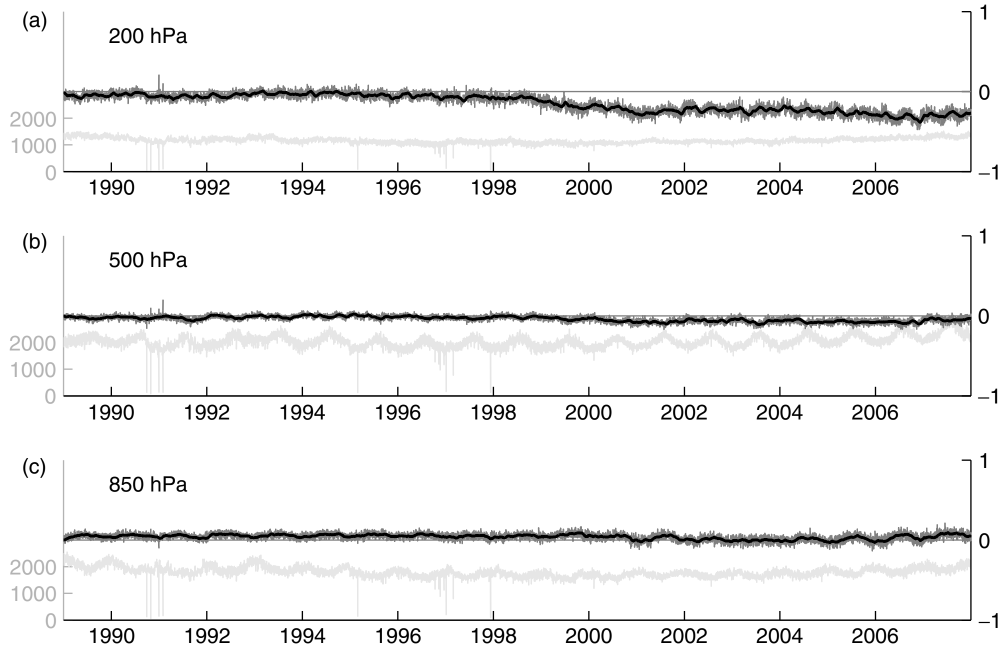

Figure 9. Global mean analysis departures from radiosonde temperature observations, at (a) 200 hPa, (b) 500 hPa, and (c) 850 hPa. Positive values mean that the observations are warmer, on average, than the analysis. The darkest curve in each panel shows the 30-day running average of the mean departures; the noisy curve behind it shows the 12-hourly values (K, right axis). Data counts per 12 hours are indicated on the left vertical axis and plotted as thin light-grey curves.

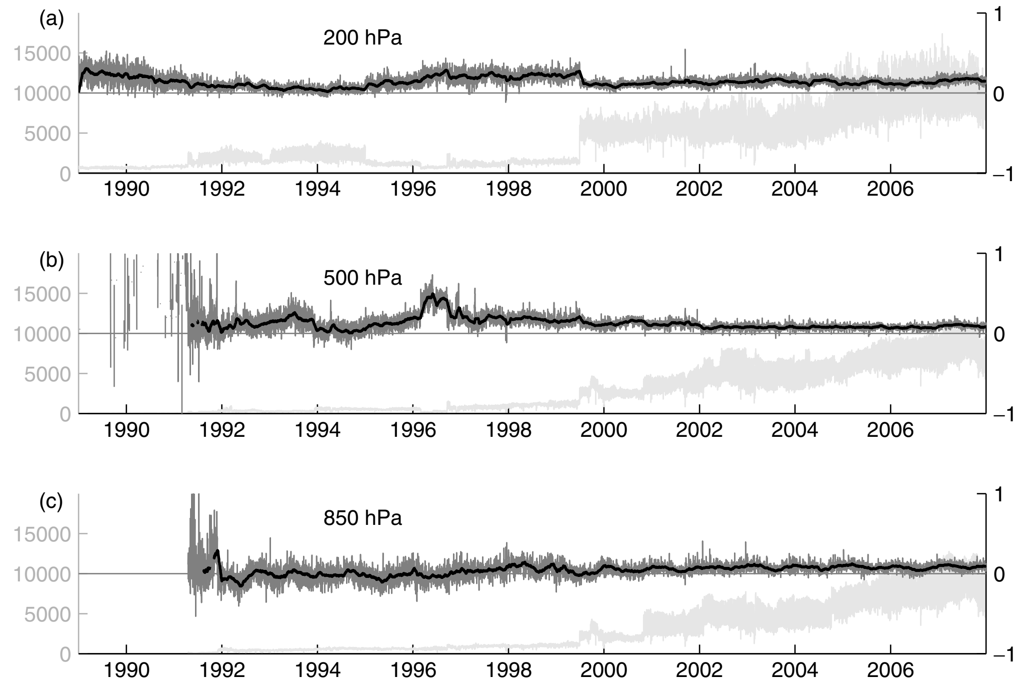

Figure 10. As Figure 9, but for aircraft temperature reports. Mean departures are not plotted for days when fewer than 50 observations were available globally.

sudden shift in mean departures with respect to the higher-level aircraft data noticeable in Figure 10.

It has been known for some time that temperature measurements for many types of aircraft are biased warm relative to radiosondes (e.g. Cardinali *et al.*, 2003). Together with the increasing number of aircraft reports, this explains the opposing mean departures for the two types of data, both at the 200 and 500 hPa levels. It is not clear, however, why the increase in bias with respect to radiosondes at higher levels apparently precedes the major increase in aircraft data counts, by about 6–9 months. After 1999 the 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 and may explain the slow decrease in bias corrections for these 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 1 K, and by a lesser amount in the lower troposphere.

8. Conclusion

A key challenge in reanalysis is to properly manage changes in the observing system. This involves difficult technical aspects such as detecting and initializing new data streams, keeping track of a large variety of instrument types, handling data gaps, monitoring data quality, and correcting data biases. Production of a multi-decadal reanalysis encompassing the modern satellite era requires that most of these tasks are performed automatically. The implementation of the variational bias correction system for satellite radiances is a major step in this direction. It has allowed the ERA-Interim reanalysis production to proceed essentially uninterrupted at a steady pace, without major mishaps.

The radiance bias estimates produced during the reanalysis contain a wealth of information, only a small fraction of which has been presented here. It is clear that the system is very effective in removing relative biases among different types of observations, and this has helped reduce the occurrence of spurious shifts and other artefacts in the reanalysed fields. The overall quality of the ERA-Interim 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 way that satellite data have been handled. More specifically, we found that long-term and seasonal variations in MSU bias estimates are consistent with known information about instrument problems documented elsewhere. The ERA-Interim system responded well to the Pinatubo volcanic eruption in 1991, which had caused difficulties in ERA-40 partly as a result of the bias corrections applied to data from NOAA-12. Unexpected drifts in tropospheric AMSU-A data detected by the variational analysis can be explained in part by instrument problems also noted by Mears and Wentz (2008). These drifts are probably somewhat overestimated in ERA-Interim, due to the assimilation of increasing numbers of biased aircraft reports in the upper troposphere.

Each of these cases demonstrates clearly the power of the variational approach to bias correction, which uses all available information to determine consistent bias estimates for multiple data sources. Our results also illustrate the importance of using an adaptive system that can respond quickly to changes in instrument behaviour, which, as we have seen, can occur on many time-scales.

Model errors can affect the variational bias corrections, especially in sparsely observed situations. The importance of anchoring data – accurate observations that do not require bias correction – is therefore evident, as is the need to use the best available forecast model. Fundamentally, observations can only partially correct model biases. It is therefore unavoidable that some residual signal associated with observing system changes remains in reanalysed data products. Advances in data assimilation, such as the application of weak-constraint variational analysis schemes (Trémolet, 2006; Lindskog *et al.*, 2009) will further reduce this effect in future reanalyses.

Is it possible to obtain accurate trend estimates for climate variables from a reanalysis system? Any observational study that involves the analysis of historical data records relies on quality control and bias adjustments based on uncertainty assessments of the input data. To obtain meaningful error estimates for the input data and the analysed products requires multiple sources of information, including observations but also the laws of physics. The use of an advanced prediction model as a framework for the assimilation of a diverse and changing data record is the best way to ensure that estimates of climate variables are consistent, not only with the available data, but also with each other.

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