

# Bias estimation and correction for satellite data assimilation

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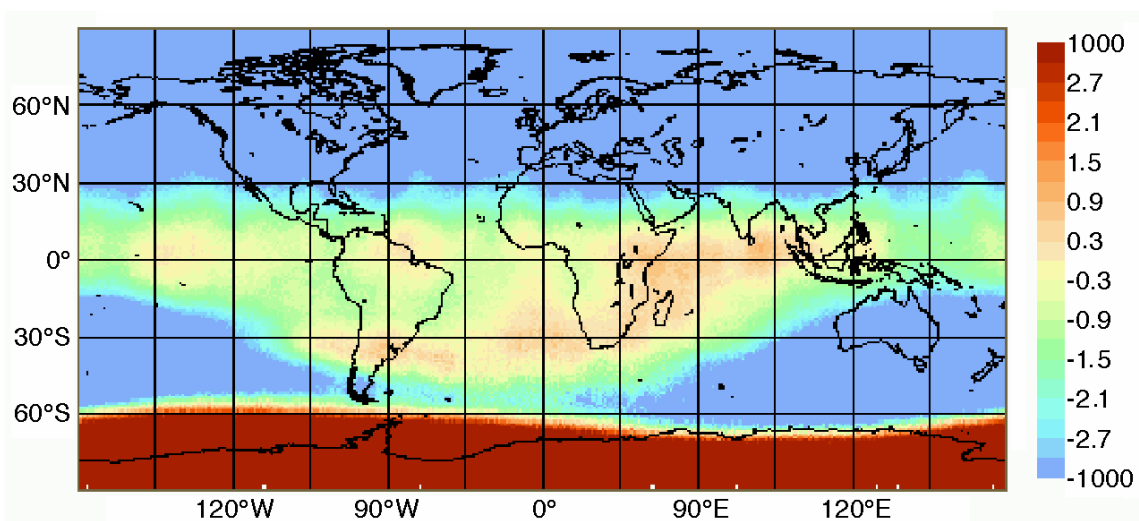
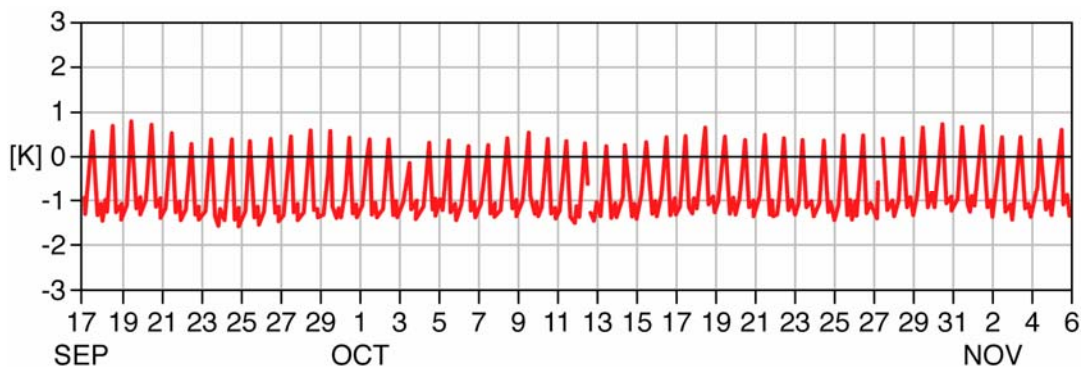
ECMWF

(Refer to online slide presentation:

[http://www.ecmwf.int/newsevents/meetings/workshops/2005/NWP\\_SAF/presentations/presentations.html](http://www.ecmwf.int/newsevents/meetings/workshops/2005/NWP_SAF/presentations/presentations.html))

## 1. What biases do we observe with satellite data?

For many years NWP centres have monitored satellite radiance observations for systematic departures (or biases) relative to the assimilation system. Usually the observed radiances are compared to equivalent values computed from the NWP short-range forecast (or background) and/or analysis estimates of the atmospheric state using a radiative transfer (RT) model. In general the biases are found to take a number of forms: (a) Time varying (e.g. diurnal or seasonal), (b) Geographically varying or air-mass (inc. underlying surface) dependent, (c) Varying with the scan position of the satellite instrument, (d) Varying with position of the satellite around its orbit. Examples of some of these (a, b and c) are shown in figure 1.



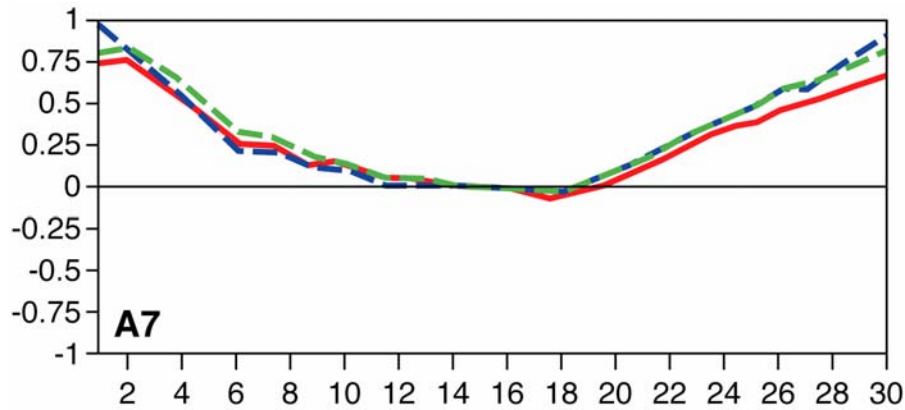


Figure 1 Examples of bias variation. Top panel, diurnal varying bias in a METEOSAT window channel. Centre panel, air-mass (geographically) dependent bias in AMSUA channel 14. Lower panel, scan dependent bias in AMSUA channel 7.

## 2. Where do the biases come from?

The biases arise due to systematic errors in any one of (but more usually a combination of) the following sources: The satellite instrument (i.e. due to poor calibration / characterization and adverse environmental effects). The radiative transfer (RT) model (errors in the physics / spectroscopy and non-modelled atmospheric processes e.g. non-LTE). The pre-processing of observations (such as residual contamination after cloud-precipitation detection and any systematic errors in level-2 processing). Systematic errors in the background atmospheric state provided by the NWP model. Table 1 shows the type of systematic errors we expect from each of the contributing sources.

	Time varying	Air-mass dependent	Scan dependent	Orbit dependent
<b>Instrument calibration</b>	Yes	No		
(hot surfaces)	Yes	Yes		
<b>RT model</b>	No	<u>Yes</u>	Yes	Yes
<b>NWP model</b>	Yes	Yes	<u>Yes</u>	No
<b>Observation preprocessing</b>	No	Yes	Yes	No

Most are capable of producing highly variable biases. Two possibly counter-intuitive examples are shown in figure 2, which illustrate that great care must be taken in any assumptions regarding the effect a particular systematic error is likely to have. In the top panel a constant absorption error of 5% in an AMSUA temperature sounding channel maps into a highly variable bias. The constant error is effectively a vertical shift in the channel's weighting function which, depending on the atmospheric lapse rate, may translate into a large (or small) change in brightness temperature.

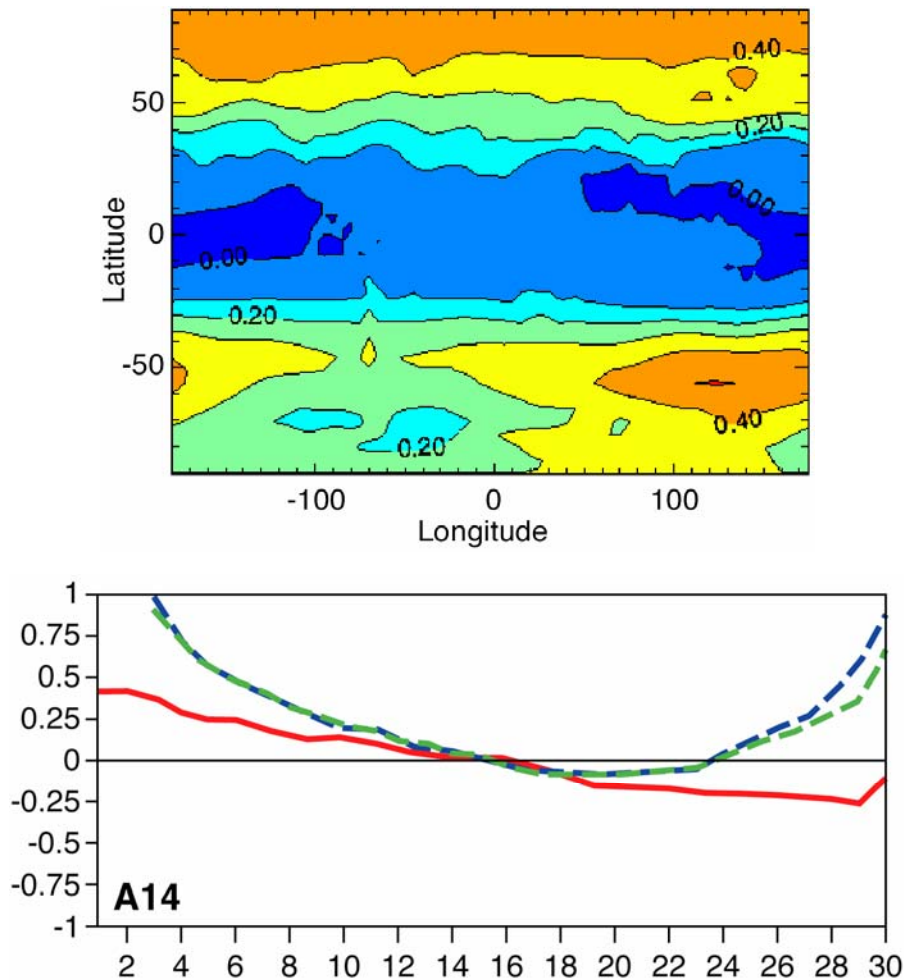


Figure 2 Top panel, an air-mass dependent bias introduced by a constant 5% error in the absorption coefficient for AMSUA channel 7. Lower panel, A scan dependent bias introduced in AMSUA channel 14 due a systematic error in the NWP model lapse rate

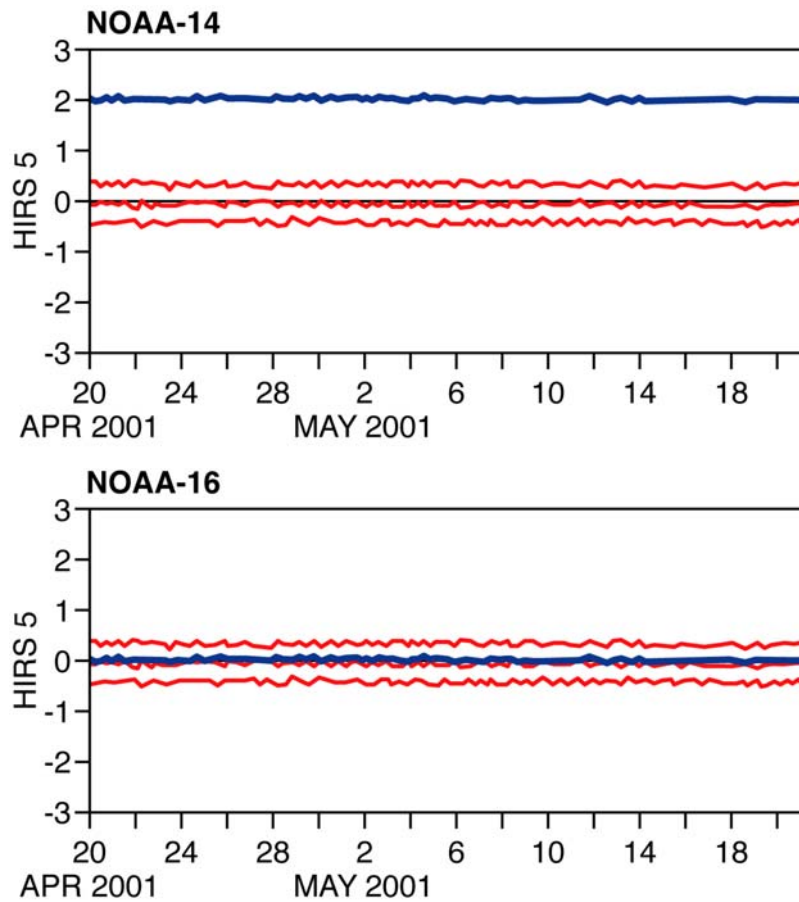
In the lower panel we see that a bias in the atmospheric lapse rate of the NWP model (common in the polar stratosphere) produces the wrong limb effect in the computed radiances. When compared to the true limb effect in the observed radiances this error manifests as a scan dependent bias (a type of bias traditionally attributed to instrument or RT problems).

### 3. Separating the sources of bias

It is clear that even simple errors can lead to complicated biases and we expect the biases we observe to be a mixture of errors from more than one source. In principle one could argue (from a purely theoretical point of view) that as long as all of the combined bias is removed by a suitable correction before the assimilation there is no need to understand or separate the sources of the bias. However, there are some strong arguments against this. Firstly, bias correction will never be perfect and it makes sense to identify and remove as much systematic error as possible at source. Secondly we (usually) do not wish to apply as bias correction to the observations (or RT) if it is the NWP model which is biased. In addition to producing a biased analysis, it is likely to re-enforce the model error and degrade the fit to other observations. There are ways to attempt to separate some of the bias contributions: Cross validation (i.e. using other independent satellites or in situ data). Time series analysis (exploiting the fact that some biases are likely to have well defined time scales such as diurnal effects of surface temperature). Monitor using independent well calibrated campaign data

(highly sample limited, but can sometimes be the only way to identify small biases). Prior knowledge (i.e. identifying a particular bias by its correlation with a known spectral signature or geographical pattern).

There are examples where the form and magnitude of the bias makes identification of the source relatively straight forward. An example is shown in figure 3 where the same infrared channel (HIRS-5) from two different satellites shows a very different bias. In this context it is most likely that an error in characterising the filter function response for NOAA-14 is the source of the error.



*Figure 3 An error in the specification of the NOAA-14 (top) spectral response for HIRS channel 5 results in a bias compared to*

*NOAA-16 (bottom)*

Another example shown in figure 4 demonstrates how corroborating evidence from a number of independent satellite sources makes systematic errors in stratospheric temperatures from the NWP model the most likely source of the observed bias.

#### **4. The treatment of NWP model error**

If we identify that systematic errors in the NWP model are the most likely source of a particular bias it is still not obvious what should be done. As mentioned previously, applying a bias correction to the data to compensate for the NWP model error is the wrong thing to do. This will produce a biased analysis and re-enforce the model error, possibly leading to the rejection of other (good) observations.

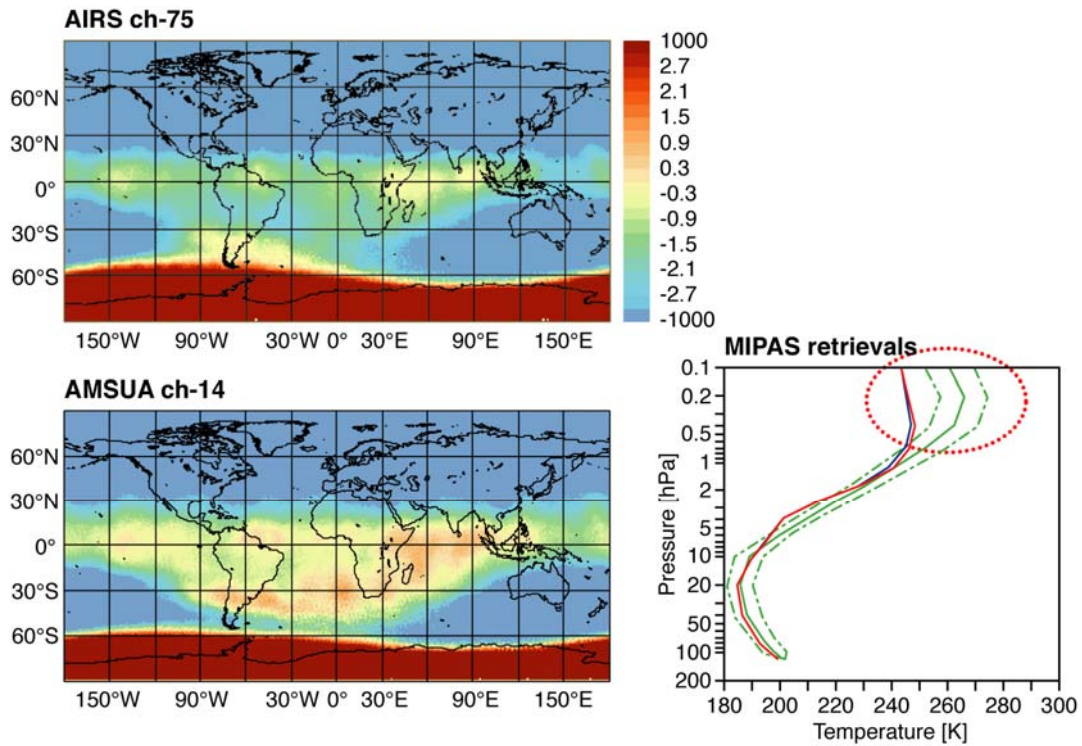


Figure 4 Agreement between independent satellite sources (AIRS, AMSUA and MIPAS) on the existence of a significant cold bias in the NWP model over Antarctica

However, it is not obvious that we can simply leave the error uncorrected and force the (unbiased) satellite observations into the assimilation system. Figure 5a shows an example where a systematic difference between radiances sensitive to upper tropospheric humidity and the NWP model which has not been removed by bias correction. Subsequent assimilation of the data has forced the analyzed tropical humidity field to a drier state which is in better agreement with radiosonde data.

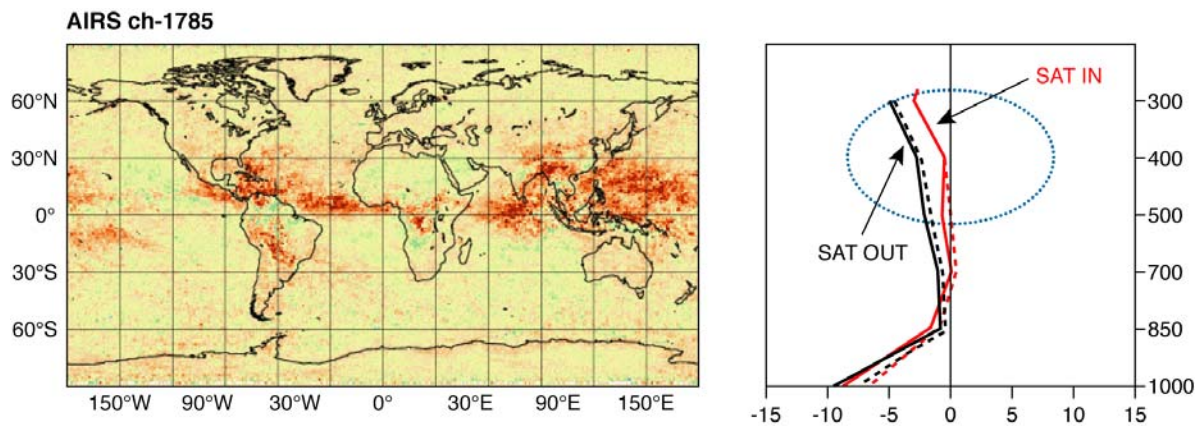


Figure 5a Forcing the systematic departures into the assimilation improves the fit of the analysis to tropical radiosonde data

In figure 5b, forcing stratospheric radiances into the assimilation to correct a known NWP temperature bias has improved the model top, but introduced significant spurious oscillations. This is a clear illustration that data assimilation schemes are tuned (in particular the statistics of the background formulation) to use observations with unbiased departures from the background.

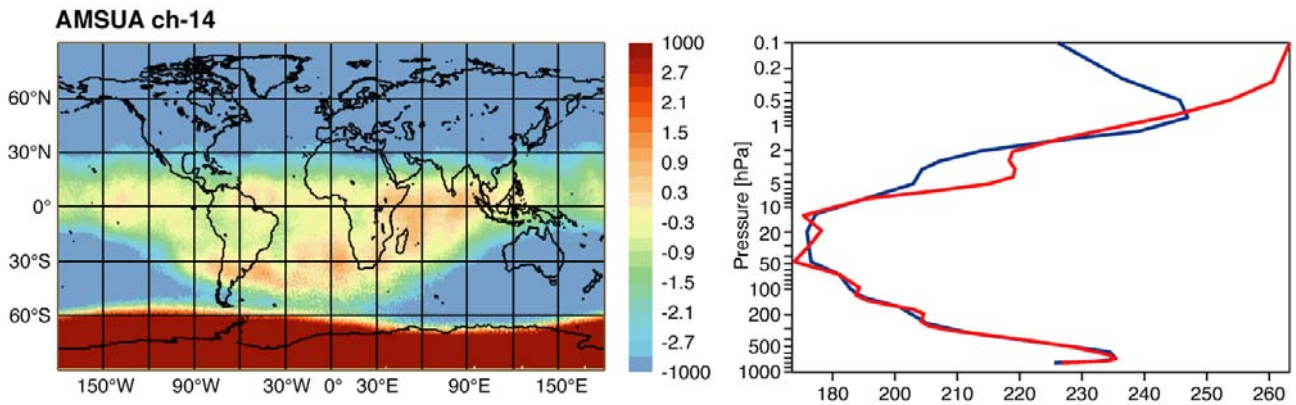


Figure 5b Forcing in systematic departures improves the model top, but introduces oscillations into the temperature analysis for the polar stratosphere.

Given the unpredictable nature of forcing observations into the assimilation, it is arguably better to remove the model systematic errors at source (i.e. improve the model or even tune parameterizations to the uncorrected data) or to assimilate the data within a weak constraint 4DVAR (where the bias can be accounted for explicitly with its own statistics). However, in some cases neither of these may be achievable, (particularly on the time scale we may wish to use the data) and we ultimately may have to absorb some proportion of the NWP error with a bias correction applied to the data.

## 5. How do we correct for biases

Before discussing possibilities for bias correction, it is useful to make the distinction between the *bias model* used for the correction and the *adaptivity* of the correction. The former determines the degrees of freedom of the bias correction to apply different values under different circumstances. Obviously a single flat global correction is an example of a very simple bias model. In contrast, a high order multi-variate regression (with many predictors) is an example of a highly flexible model and can produce corrections such as those shown in figure 6.

The adaptivity of the correction is how often we update the coefficients of the bias model (i.e. every hour, daily, monthly etc.). Together, these two attributes determine what the bias correction will remove and what it will not.

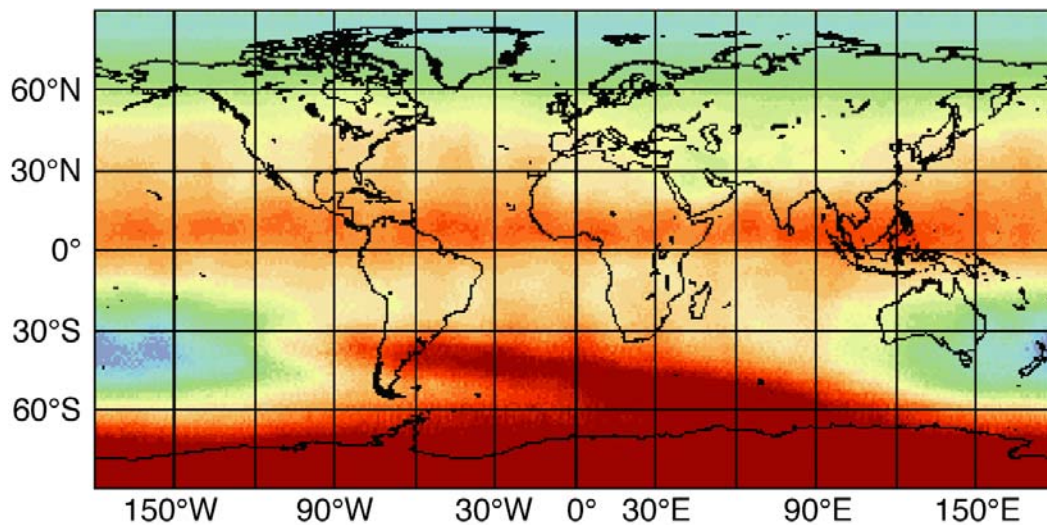


Figure 6 Bias patterns generated by a highly flexible bias model

Our particular choice of bias correction will depend on a number of factors. We should obviously make the bias correction flexible and adaptive enough to follow the expected evolution (spatial and temporal) of the systematic errors we wish to remove (e.g. instrument and RT errors). Conversely we may also construct the correction deliberately such that it will not correct certain systematic departures (e.g. from NWP errors) that we wish to retain. In addition to these scientific considerations, logistical factors may also be important. If we are running an assimilation system where many satellite instruments are used in rapidly changing configurations (such as re-analysis or indeed ECMWF operations) we may be forced to use a rapidly self-updating (i.e. adaptive) scheme. It may also not be feasible to separately determine which bias model is needed for each instrument and a highly flexible (one-size-fits-all) model may be required.

However, the danger of an over flexible and over adaptive bias correction is shown in figure 7 where a 90 parameter regression model is used to predict the bias with coefficients being evolved (i.e. re-computed) every analysis cycle. In this case, the correction is very detailed and has been able to remove systematic departures with a small horizontal scale that are actually related to humidity errors in the NWP model. The bias correction of the radiance data has negated much of the beneficial effect of the satellite radiances and produced an analyzed humidity field that is only as good (at least as measured by the fit to radiosonde data) as a system using no satellite data at all. In contrast a system where the radiances are corrected with a simple flat bias does not remove the tropical NWP humidity error before the assimilation, and the assimilation of the radiances produces an improved humidity analysis.

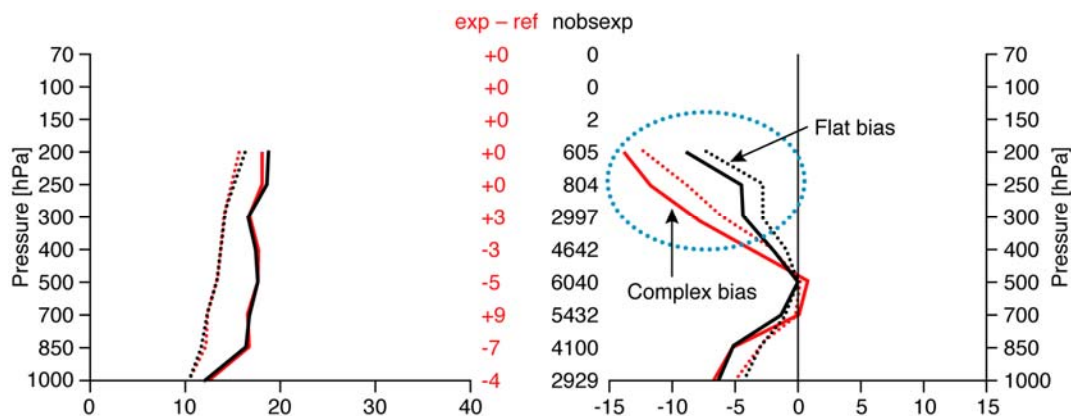


Figure 7 Correction of small scale systematic departures by a flexible bias correction scheme has removed useful information from the radiance data, compared to a flat correction

## 6. Constraining adaptive bias correction schemes

If an automated adaptive scheme must be used it is important to have constraints within the system to avoid problems of drift and to ensure that only components of the systematic departures we wish to correct are corrected. The most powerful constraint is the choice of bias model. The previous section showed how the choice of a flat bias ensured that tropical humidity errors were not removed. However, if we know that e.g. instrument or RT biases are not flat, we may need an air-mass varying correction. If a multi-variate regression must be used, computing the coefficients within the analysis scheme is recommended. In this case the presence of uncorrected in situ observations (e.g. radiosonde) represents a strong constraint upon the evolution of the bias correction. Computing the bias coefficients within the analysis also allows a suitable level of inertia to be imposed upon changes in the bias correction through the background constraint.

### Summary

The biases observed when we compare satellite observations with the NWP model can be highly variable with space / time and instrument view.

The sources of these biases are numerous (including the NWP model) and are generally not easy to separate. Great care must be taken in the correction of biases as they can have large scale significant impacts upon the quality of the NWP system.