# All-sky observations: errors, biases, and Gaussianity

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**ABSTRACT**

Microwave imager observations are sensitive to surface properties, water vapour, cloud and precipitation, and are assimilated in 'all-sky' conditions at ECMWF. The first guess departures give information on biases between the model and observations, and can be used as a guide for determining the observation error. There can be substantial discrepancies in the position and magnitude of cloud and precipitation features between first guess and observations. Partly as a result of this, and partly because of larger modelling errors in cloudy situations, the standard deviation of all-sky first guess (FG) departures increases quite predictably as a function of mean cloud amount. The mean cloud amount is a 'symmetric' predictor in that it does not suffer from the sampling biases inherent in using first guess or observed cloud amount alone. This knowledge of the size of FG departure errors as a function of cloud amount can be used to derive a model for observation error, and also gives a new approach to quality control. Ways of dealing with bias in all-sky observations are also discussed.

## 1 Introduction

At the frequencies used by microwave imagers, the atmosphere is semi-transparent except in heavy cloud and precipitation. For the moment, these observations are only assimilated over oceans, where clear sky radiative transfer is dominated by water vapour absorption. Hence, the observations are sensitive to ocean surface properties (e.g. surface temperature and windspeed), atmospheric water vapour, cloud and precipitation. The intention is to use all of this information to improve analyses and forecasts. To achieve this is not just a matter of providing the appropriate forward model and assimilation algorithm. Observation and background error characteristics need to be properly described for the assimilation algorithm to work. In particular, the errors are supposed to be Gaussian and unbiased. Quality control (QC) schemes and adaptive bias correction (e.g. Variational Bias Correction, VarBC, Dee, 2004) help ensure this.

Cloud- and precipitation- affected microwave radiances have been assimilated at ECMWF since June 2005. Initially, Special Sensor Microwave / Imager (SSM/I) observations were assimilated using a 1D+4D-Var approach (Bauer et al., 2006a,b). More recently, additional sensors have been included. Direct assimilation of cloud and rain-affected radiances was introduced in March 2009 (Bauer et al., 2010; Geer et al., 2010), using an all-sky approach, where no distinction is made between clear, cloudy or rainy observations. This removes the need to separate clear and cloudy scenes before assimilation, and avoids biases that can come from an incomplete sampling. Most recently, the weight of these observations in the assimilation system has been substantially increased (Geer and Bauer, 2010). This required a new approach to quality control and observation error. This paper describes some of the concepts underlying the new approach and explores the feasibility of bias correction. In all of these areas, approaches that have worked well in the past for clear-sky data need re-examining for cloud- and rain- affected observations.

For more detail on any aspect discussed in this paper, the reader is referred to Geer and Bauer (2010).

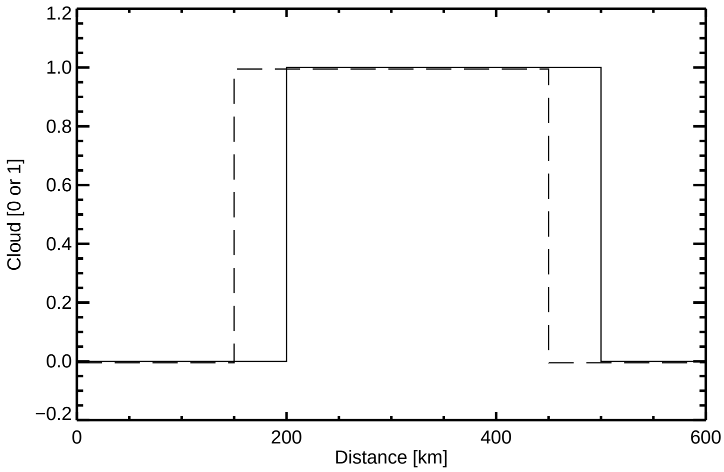


*Figure 1: Displacement error between hypothetical first guess (FG, dashed) and observed (solid) binary clouds.*

# 2 Observation errors and cloud sampling effects

## 2.1 Cloud sampling

Differences between modelled and observed cloud and rain are typically large. Some of these differences may be due to displacement errors, but there are also errors in the structure and intensity of forecast cloud and rain. Figure 1 shows a hypothetical system in which the only difference between model and observation is a displacement error. Typically we may wish to make observation error and bias correction vary as a function of the cloud or rain amount. However, it is very easy to do this in the wrong way.

Fig. 2a shows the mean first guess (FG) departures (observation minus FG) of the hypothetical cloud in Fig. 1, as a function of cloud. In the area where the FG is clear, there are some cloudy observations, and where the FG is cloudy, part of the area is observed to be clear. This causes mean departures to be positive where the FG is clear and negative where the FG is cloudy. For the mean departure as a function of observed cloud, the opposite applies. This behaviour may seem trivial, but its consequences are very important.

When correcting observational bias as a function of cloud amount, the choice of predictor is crucial. In clear-sky assimilation it is typical to use the FG forecast to provide predictors for bias correction. The bias is calculated as a function of these predictors, and then removed from the observations. However, the bias as a function of FG cloud in Fig. 2 is simply a feature of the sampling, and not a real bias. The only difference between FG and observation is a displacement. Hence it is incorrect to use the FG cloud or rain as a bias predictor. Treating the sampling bias as a real bias and removing it from the observations will tend to reduce their impact in the assimilation. Here we will define as 'symmetric' any predictor that does not produce a sampling bias in mean FG departures. The mean of observed and FG cloud amount (Fig. 2) and the maximum of FG and observed cloud amount (not shown) are both symmetric.

It is typical to prescribe observation error as a function of cloud amount (e.g. Bauer et al., 2010), and an asymmetric predictor can cause problems here too. Consider assimilating the observations in Fig. 1 with a large error for those which are cloudy, and a small error for those which are clear. If the background

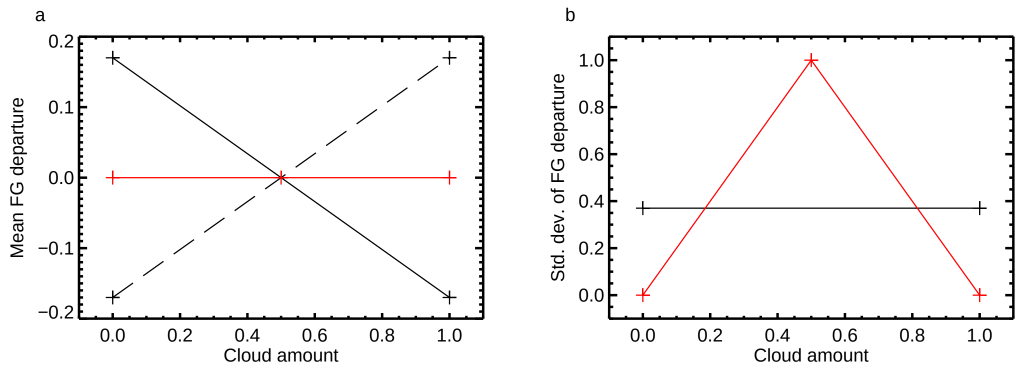


*Figure 2: **(a)** Mean and **(b)** standard deviation of FG departures of the cloud distribution shown in Fig. 1, as a function of FG cloud (black, solid), observed cloud (black, dashed) and mean cloud (red, solid)*

error were the same in each case, the cloudy observations would be relatively less influential than the clear observations. The clear observations have a sampling-induced bias of -0.17 and would cause the analysis to dry. The cloudy observations have a sampling bias of +0.17 which should counterbalance this, but it does not, because these observations have less influence in the analysis. The net effect would be a spurious drying of the analysis relative to the FG. Hence, just as for bias correction, if observation error is defined as a function of cloud or rain, the cloud or rain predictor must be symmetric.

It is also interesting to examine the standard deviation of FG departure as a function of cloud (Fig. 2b). In our example standard deviation does not vary with observed or FG cloud (this is because cloud makes up exactly half of the domain). However, as a function of mean cloud, standard deviations are zero where both model and FG agree, i.e. where mean cloud is either 0 or 1. A mean cloud amount of 0.5 is associated with situations where model and FG disagree, and here, for binary cloud, the standard deviation is 1. Large departures are associated with areas where the model and observation disagree. We can use this effect to our advantage for the quality control of cloud and rain observations.

## 2.2 The symmetric behaviour of all-sky FG departures

The behaviour of all-sky FG departures is remarkably similar to what our conceptual model would predict. Figure 3 shows the mean and standard deviation of FG departures from the all-sky system, calculated as a function of FG, observed, or symmetric ‘cloud’. Of course, cloud is not a binary quantity here. More importantly we need to be careful with our definition of ‘cloud’, since we are working with a radiance observation. It would be easy to determine the FG cloud amount from the model, but cloud is only one of several quantities to which the radiances are sensitive. We need to use a measure of cloud that can be computed consistently for both FG and observations.

The solution is to work in radiance space, and to apply a simple approximate retrieval of the cloud amount. Here, we take the normalised 37 GHz polarisation difference $P37$ (Petty and Katsaros, 1990; Petty, 1994), which is roughly proportional to the square of the slant path cloud and precipitation transmittance at this frequency. Note that cloud and precipitation have much lower optical depth in the microwave than in the visible or infrared, so only the most intense convection is opaque at 37 GHz. To be consistent with our earlier discussion, we use $C37$ as the x-axis in Fig. 3, where

$$C37 = 1 - P37 \tag{1}$$

and hence $C37$ increases with cloud amount. We compute $C37_{FG}$ and $C37_{OBS}$ for the FG and observed

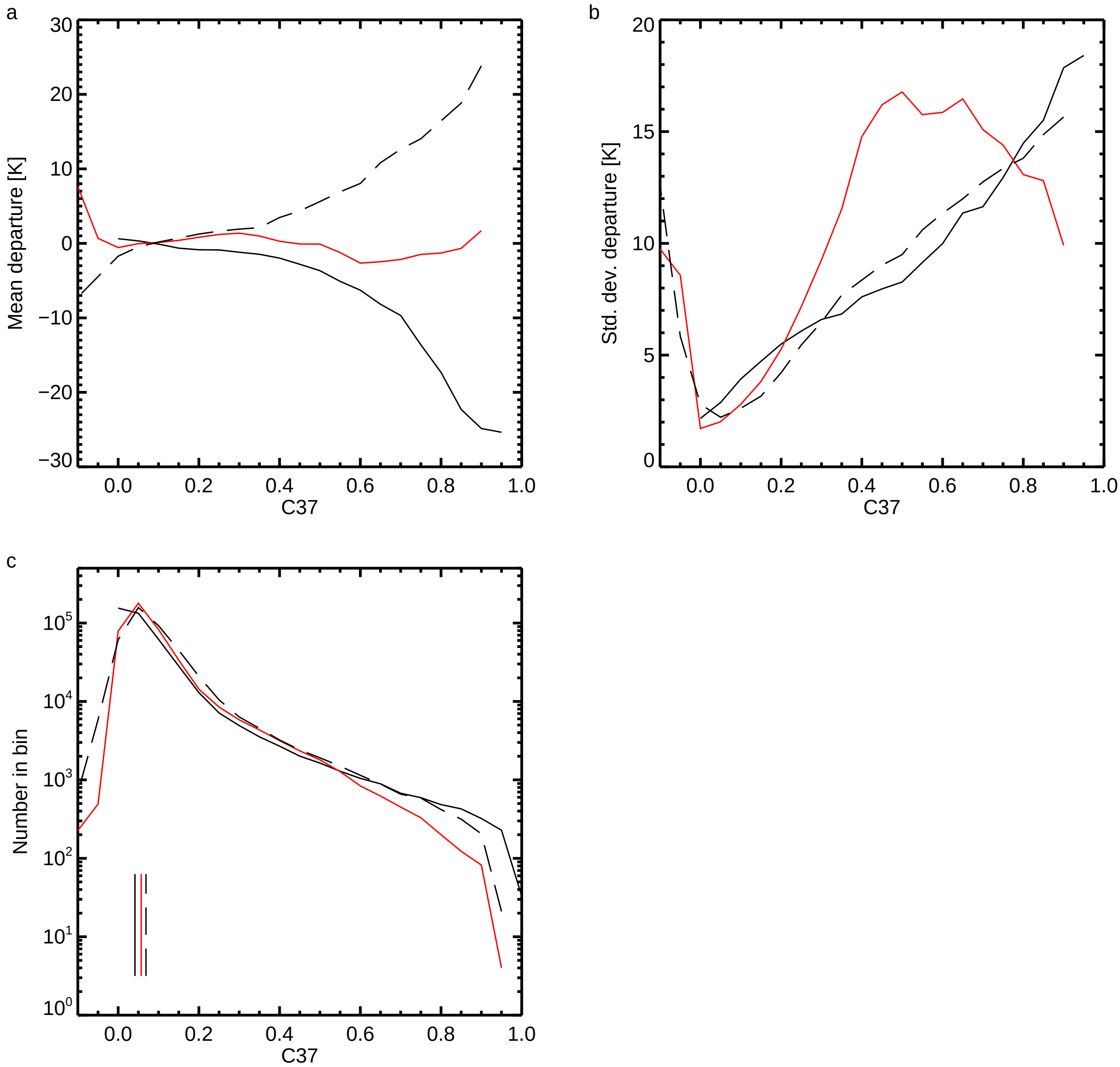


*Figure 3: **(a)** Mean and **(b)** standard deviation of SSM/I channel 19v FG departures binned as a function of 'cloud' derived from 37 GHz brightness temperatures (C37) and **(c)** number per bin, for a sample of 419159 observations from 1 - 10 October 2009. C37 is derived from the FG (black, solid), observations (black, dashed) or is the mean of the two (red, solid). Vertical lines on panel c show the medians. Bin size is 0.05 in C37. Standard deviations and means are only shown when there are more than 50 observations in a bin.*

values and then the 'symmetric' or mean cloud,

$$\overline{C37} = \frac{C37_{FG} + C37_{OBS}}{2}. \tag{2}$$

As expected, selecting a cloudy FG ($C37_{FG} > 0.8$) gives a positive mean departure and selecting a completely clear FG ($C37_{FG} = 0$) gives a negative mean departure (Fig. 3a). Mean departure as a function of observed cloud is almost a mirror image. Against $\overline{C37}$, the mean departure is generally quite close to zero. Deviations from zero probably indicate true biases between modelled and observed cloud.

In contrast to the simple binary model, standard deviation increases as a function of FG or observed cloud (Fig. 3b). We would expect FG or observation error to be larger in cloudy situations than in clear sky because: (i) both the model and the observation operator are less accurate and (ii) the dynamic range of brightness temperature is much larger in cloud and rain than in clear skies. Against mean cloud, standard deviation peaks at 17 K between 0.45 and 0.65, and declines for higher mean cloud amounts, as increasingly the FG and observation agree that cloud is present.

Overall, Fig. 3 suggests that mean cloud, as represented by $\overline{C37}$, should be useful in all-sky assimilation as a symmetric predictor for bias correction and observation error.

### 2.3 Application to quality control and observation error

The lesson from Fig. 3b is that the standard deviation of FG departures is well predicted by the mean cloud amount. The FG departures give the 'total error', and in terms of variance, this should be the sum of the observation error and background error in observation space (see, e.g. Desroziers et al., 2005):

$$t^2 = r^2 + b^2, \tag{3}$$

where t, r and b are respectively the total, observation, and background error standard deviations. Here, as is conventional, observation error includes errors of representativity and of the observation operator. Based on Fig. 3, we can predict $t$ as a simple function of mean cloud amount. This has some useful applications for quality control and for helping estimate the observation error.

In the ECMWF system, background quality control (BgQC, Järvinen and Unden, 1997) rejects observations with large normalised departures, i.e. where

$$\frac{d}{\sqrt{r^2 + b^2}} > \delta \tag{4}$$

Here, $d$ is the bias-corrected FG departure. The rejection threshold $\delta$ is set to 2.5 for all-sky observations. Since we can estimate $t$ as a function of cloud amount, this can be used in BgQC in place of $\sqrt{r^2 + b^2}$. Figure 4 shows histograms of actual departures $d$ and normalised FG departures $d/\sqrt{r^2 + b^2}$ for SSM/I channel 37v, along with roughly fitted Gaussians. The actual histogram emphasises how hard it is to do all-sky quality control in brightness temperature space. The distribution of departures is very non-Gaussian, with the largest departures occurring where observation and model disagree in terms of the rain or cloud amount. It is impossible to use a threshold to distinguish erroneous observations from real information. When normalised, the departures become far more Gaussian. Normalised departures with magnitudes greater than 2.5 are infrequent and quite often associated with gross observation error. An example is shown in Fig. 5. SSM/I suffers from occasional bad scan-lines, such as those around 40N, 165W. however, only when the departures are normalised can a threshold check be used to identify the problem. The large positive departures around 5N, 150W, for example, indicate a cloud system that is observed but not present in the first guess.

Being able to predict the total error as a function of mean cloud amount is also useful for providing observation errors as a function of cloud amount. However, we have no easy way of knowing how to split

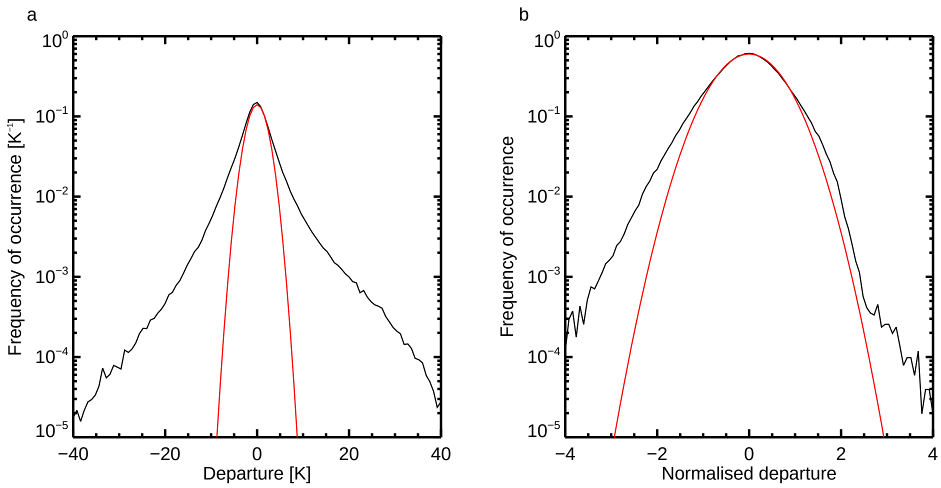


*Figure 4: Histograms of SSM/I channel 37v FG departures* ***(a)*** *as brightness temperatures* ***(b)*** *normalised by the symmetric error model. Sample is from 27 June to 6 July 2009. The red curves show Gaussians fitted by eye to the peak of the distribution.*

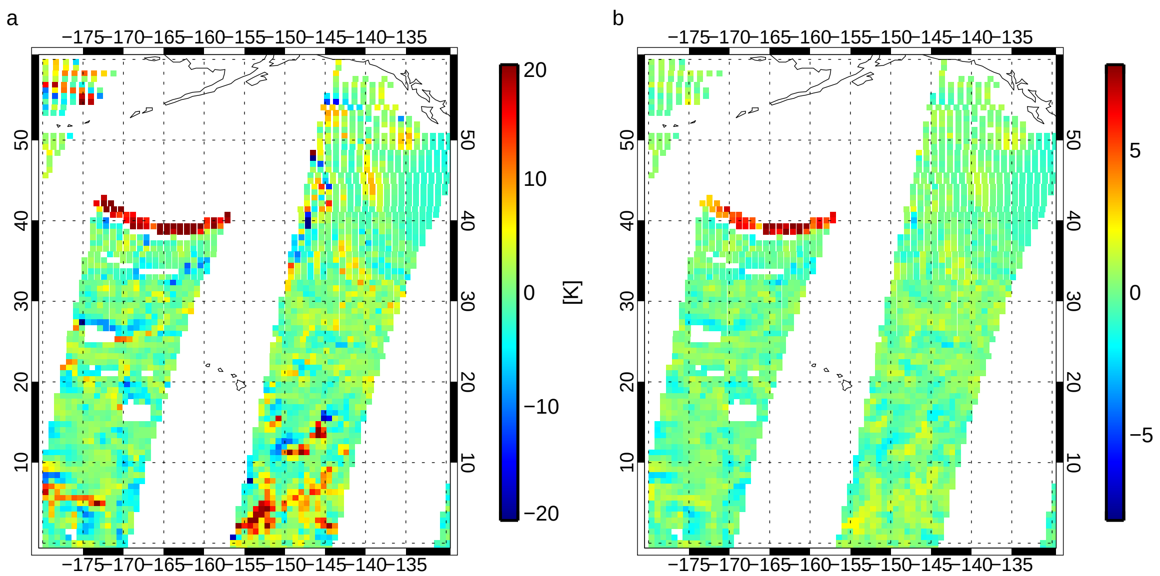


*Figure 5: Maps of SSM/I channel 37v FG departures* ***(a)*** *as brightness temperatures* ***(b)*** *normalised by the symmetric error model, on 1 July 2009, looking at the Defense Meteorological Satellite Program (DMSP) F-13 satellite only.*

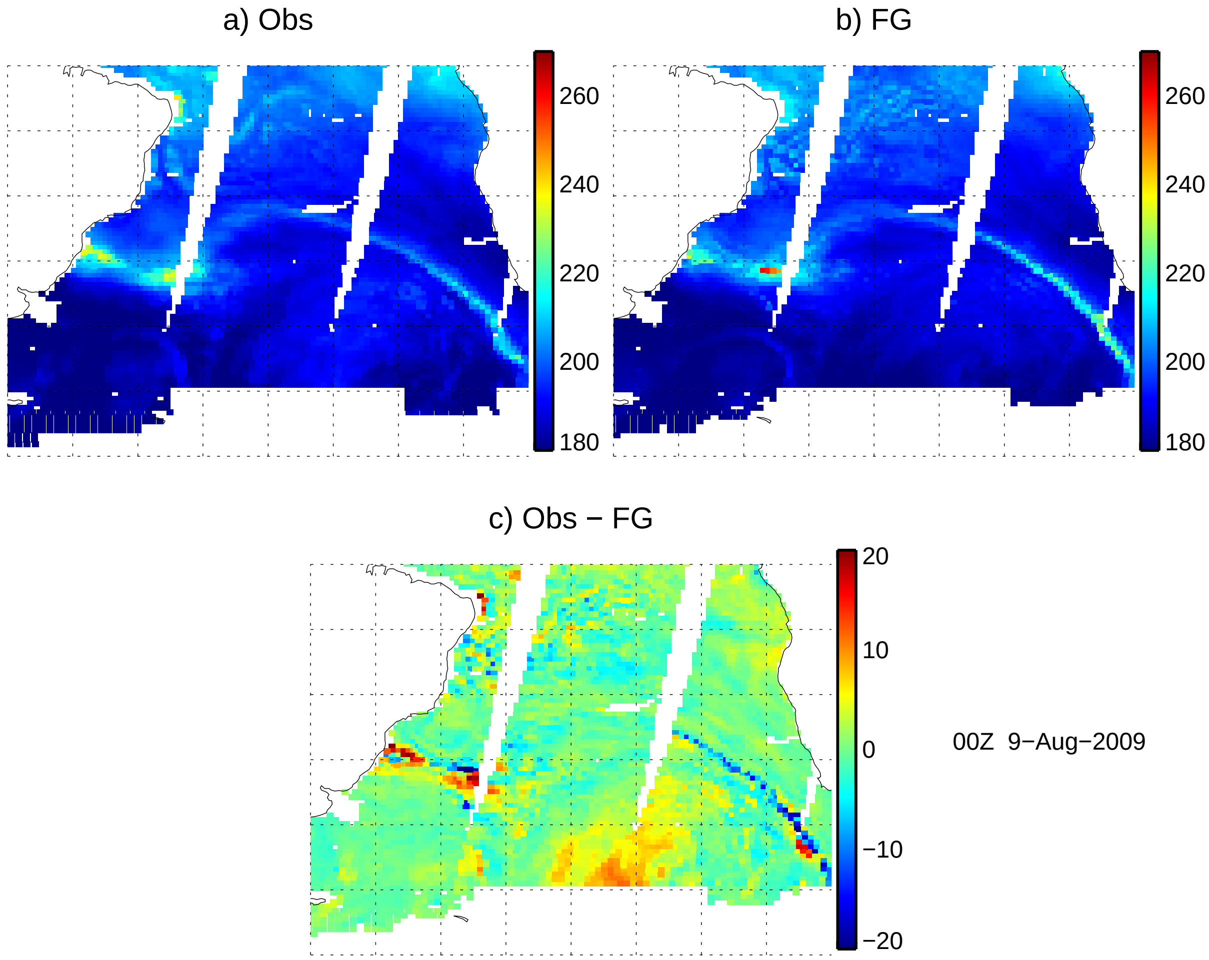


*Figure 6: Maps of SSM/I channel 19v **(a)** observations **(b)** first guess **(c)** departures on 9 August 2009 in the South Atlantic.*

total error between background error and observation error. The proportion of total error being assigned as observation error was made tunable and a series of experiments were performed with different values for this tuning parameter. Fits of FG forecasts to other observation types were used to determine the best value, which turned out to require 100% of total error in cloudy situations to be assigned as observation error. All this is explained in more detail in Geer and Bauer (2010). In summary however, in cloudy regions, observation error needs to be about the same size as the expected standard deviation of FG departures. This is strange, as we would expect a large component of the FG departure standard deviation to come from the model, which is not always able to predict cloud or rain in exactly the right place or intensity. Observation error correlations are not taken into account in our current all-sky assimilation system but may explain some of this. Also, if there are residual biases between observations and model, observation errors may need to be set quite large to avoid these biases being assimilated into the system as real information, and thus degrading forecasts. The next section examines these biases in more detail.

## 3 Biases

Figure 6 illustrates the kind of biases that affect the all-sky system. The broad area of positive departures in the centre at the bottom of the plot is a bias typically associated with cold, dry, air moving equatorward from the polar regions. Here, the observations are relatively warm, indicating the presence of water cloud, but the model produces very little cloud, giving lower brightness temperatures. This bias, known as the 'cold sector' bias, is most prevalent in the winter hemisphere, and shows up in monthly means in the regions where such equatorward transport occurs preferentially. A second bias occurs around the front on the lower right of the figure. Here, SSM/I measures relatively high brightness temperatures caused by elevated moisture and cloud amounts. The model's fronts appear to be typically too intense but not widespread enough, giving a band of negative departures (in blue) along the centre of the front, surrounded by a region of positive departures (in red). Monthly mean histograms of brightness temperatures (not shown) confirm that this is a systematic effect.

The traditional approach with an adaptive bias correction system such as VarBC is to determine biases as a function of predictors such as surface temperature, layer thicknesses, and total column water vapour (TCWV). It is natural to extend this for cloud and rain affected observations by adding a predictor for biases as a function of cloud amount. However, as Sec. 2.2 and Fig. 2 show, this must be done very carefully to avoid producing a sampling bias. We experimented with using mean cloud amount ($\overline{C37}$) as a predictor, as it is not subject to sampling biases. However, this proved to be of little practical benefit in the all-sky assimilation, for the following reasons:

1. As shown in Fig. 2a and b, the mean bias in cloudy areas is only 2 K. By comparison, the standard deviation of departures is around 15 K. Hence, the bias is insignificant compared to the variability in cloudy areas, and may not be worth correcting.

2. The bias correction was affected by interactions with quality control of the kind that are described by Auligné and McNally (2007). As shown in Fig. 2c, the highest cloud amounts are associated with very low numbers of observations. These observations are also associated with very large FG departures, which even with the new QC approach may still sometimes be removed. Hence, this makes the bias correction vulnerable to interactions with QC.

3. Biases such as the cold sector or frontal biases exemplified in Fig. 6 are not simple functions of cloud amount, but occur in particular synoptic situations. Hence, the cloud amount on its own is not well targeted towards the actual biases in the system. Many attempts were made to come up with predictors that could identify these biases, but none of them worked very well.

For these reasons, we decided not to include any cloud- or precipitation-related predictors in VarBC. Being unable to use the bias correction scheme to remove a bias, our options were either (a) to fix the problem at source, i.e. by improving the atmospheric model or observation operator, (b) not to assimilate the bias-affected observations or (c) to ignore the bias. Option (a) has been successful in the past: for example, Geer et al. (2007) identified a bias in the moist physics operator in the 1D+4D-Var assimilation and the moist physics was re-tuned as a result. Also, biases in the cloud-affected SSM/I departures helped identify an inaccuracy in the cloud overlap used in the radiative transfer operator, which was subsequently fixed (Geer et al., 2009). However, the causes of the remaining biases are harder to identify and fix. Instead, all observations affected by the cold-sector bias are eliminated from the system, based on identification criteria for cold, dry air masses with little water cloud. Unfortunately, this eliminates many good observations at the same time. The frontal bias is currently ignored, but given the relatively large observation errors applied in areas of heavy cloud and precipitation, it should not cause major problems.

# 4 Conclusion

One of the main difficulties in assimilating cloud- and precipitation-related observations is the fact the there are often substantial errors in the model forecast, so that clouds are in different places or have different structures in the model compared to the observations. Where these displacements occur, the size of the FG departures can be very large in terms of radiances. However, even when clouds are well located in the FG, the size of departures is still much larger in these areas, due to the inherent difficulty of modelling cloud and precipitation (both in the forecast model and in the observation operator) as well as the increased dynamic range of the radiances in these conditions. In order to assimilate cloudy radiances, we need to define an observation error that is larger in cloudy areas than in clear sky. Hence, we would like to vary the observation error as a function of cloud.

Through a simple model, and by studying the FG departures from the ECMWF assimilation system, we show that using FG or observed cloud amount on their own as a predictor for the size of the departures is incorrect, since they are affected by sampling biases, i.e. are 'asymmetric'. Only a 'symmetric' predictor should be used, i.e. one unaffected by sampling bias. This bears much similarity with the asymmetries encountered when using relative humidity as a control variable (Hólm et al., 2002). Here, we use the mean of FG and observed cloud amount as it is a good predictor of the standard deviation of FG departures. Normalising the FG departures by the predicted standard deviation gives a distribution that is very close to Gaussian. This is encouraging, as it suggests that non-Gaussianity may not be a problem in all-sky data assimilation. It also has a number of practical uses in the ECMWF system, both for quality control, and for developing a model of observation error as a function of cloud amount.

Ways of dealing with biases in all-sky data have been discussed. In a predictor-based system such as VarBC, it is also necessary to avoid sampling biases by using a symmetric predictor. However, in practice there is no large global bias that varies as a function of cloud, so no bias correction as a function of cloud has been introduced in the ECMWF system. Instead, the most damaging biases are typically found under specific meteorological situations which are quite hard to identify using a simple predictor in VarBC. To avoid damaging the analysis, the best solution is not to assimilate all-sky observations in such areas.

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