Diagnosing the impact of satellite observations in data assimilation

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Abstract

This paper gives a short overview of the currently employed tools for quantifying the impact of satellite observations in data assimilation as employed at ECMWF. Tools range from standard model-vs.-observation statistics, dedicated observing system experiments to advanced diagnostics based on model and observation operator adjoints. Due to the complexity of the data assimilation system and the complicated response of the forecast model to the initial conditions the optimization of the observational impact remains a difficult task, in particular given the large variety of satellite observations available for NWP.

1. Introduction

The impact of observations in data assimilation is determined by the sensitivity of a certain observation type to a particular model state variable, the associated observation error and the confidence that is given to the forecast model. In the case of satellite observations the bulk of the data is assimilated as radiances that usually combine sensitivities to atmospheric temperature, moisture, the concentration of selected trace gases, clouds and surface conditions. Given the latter range, the estimation of the impact of satellite radiances can be rather complex; however, in most cases the choice of instruments and radiometer channels is sufficiently conservative so that most of the individual signal contributions are separable.

Figure 1 aims at illustrating this with two examples, one related to the Advanced Microwave Sounding Unit (AMSU-A) channel 9 that is mostly sensitive to temperatures near 100 hPa and another related to the Special Sensor Microwave / Imager (SSM/I) that is mostly sensitive to total column water vapour. Figure 1a (top panel) shows that, at 100 hPa, radiance structures are rather smooth and that the mean differences between model and observation (middle panel) exhibit large scale structures with only small differences (tenths of degrees K). These structures are consequently found in similar patterns of mean increments, i.e. where the observations are used to correct the model. The large-scale temperature structures and the small differences between observations and model produce a consistent and easily traceable picture of data impact in this case.

Figure 1b (top panel) shows the mean SSM/I radiance structures are already more complex because they represent water vapour, cloud and surface effects together. The middle panel illustrates how large local variations between model fields and observations can be and the mean increments in the bottom panel exhibit how these departures are propagated into increments through the complex moist model physics. The second example illustrates that the impact of, say, a moisture sensitive instrument is much more difficult to evaluate due to the combined sensitivity of the observation to a number of state variables and through the involvement of much more complicated physical processes during assimilation.

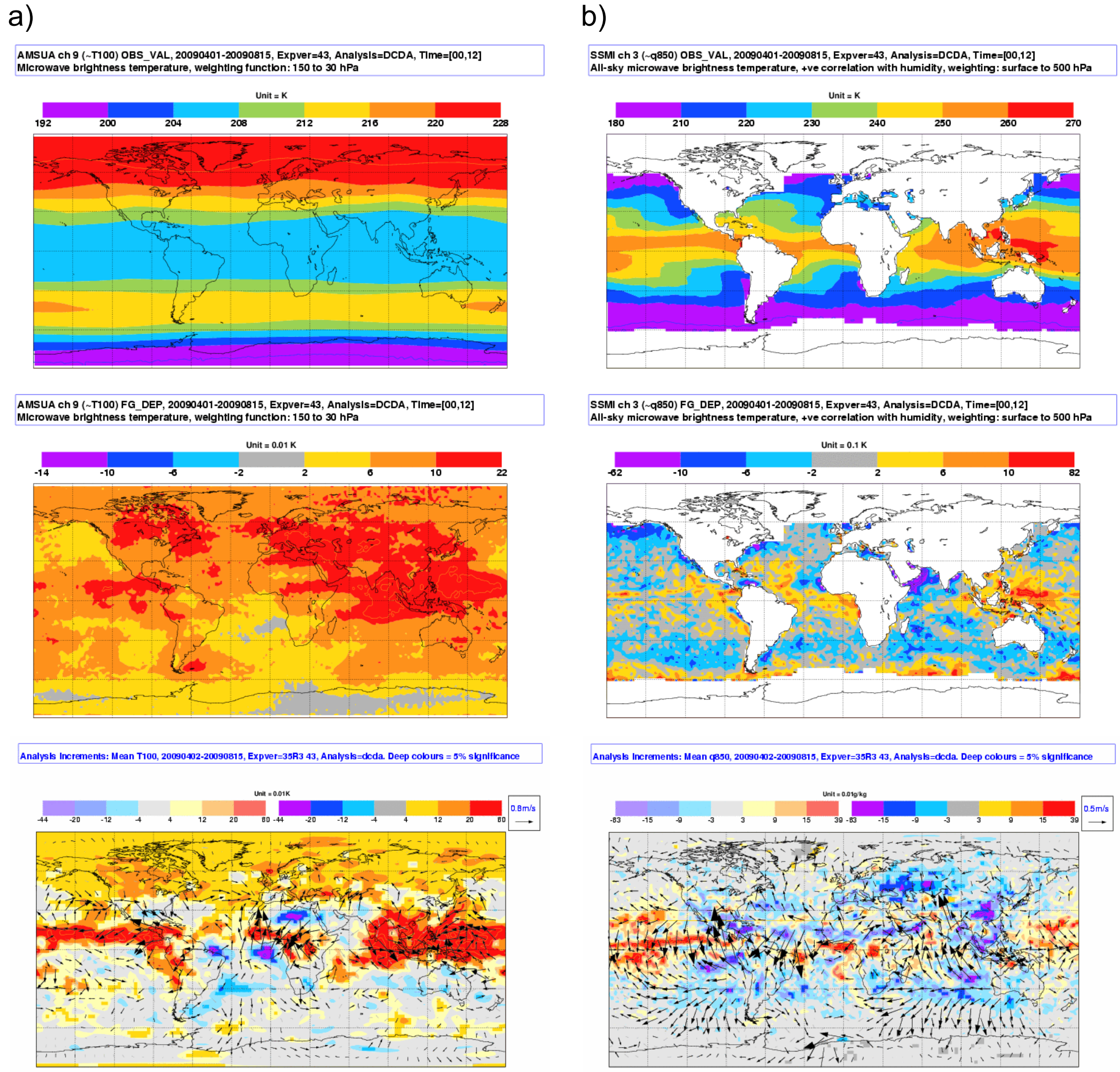

Figure 1 a) AMSU-A channel 9 mean observation (top), mean observation minus model (middle) and mean 100 hPa temperature and wind increments (bottom); b) SSM/I channel 3 mean observation (top), mean observation minus model (middle) and mean 850 hPa specific moisture and wind increments (bottom). Period 01/04-15/08/2009.

Given the large number of observations used in NWP analyses and the complexity of variational data assimilation systems, diagnostics are performed at various levels, namely for the purpose of (1) routine sanity checks (both model and observations), the assessment of individual observational types in the system through (2) observing system experiments and (3) adjoint diagnostics (Cardinali 2010). Note that in the presence of significant model errors (Rodwell 2010) the data assimilation system must be carefully tuned to keep the analysis stable and to avoid strong spin-up effects in the forecast. This means that the obtained observational impact represents a compromise between the exploitation of the observation's information content and the ability of the assimilation system to digest the information.

2. Data monitoring

An essential part of the routine data impact assessment is the monitoring of data quality before and after the data has been assimilated. Given the large data volumes and the great variety of data types (Bauer 2009) this routine monitoring has been automated at ECMWF and the derived information is accessible though the ECMWF website (http://www.ecmwf.int/products/forecasts/satellite_check).

An example of data monitoring is shown in Figure 2a that displays a time series of channel 10 from NOAA-16 AMSU-A in early 2009. The instrument has been intermittently affected by an increase of noise that is not necessarily visible in the observation values themselves (third panel from top) but easily identified from the observation-minus-model departure standard deviation (second panel from top). After quality control (Fig. 2b) the data is removed from the assimilation system before it can negatively affect the analysis.

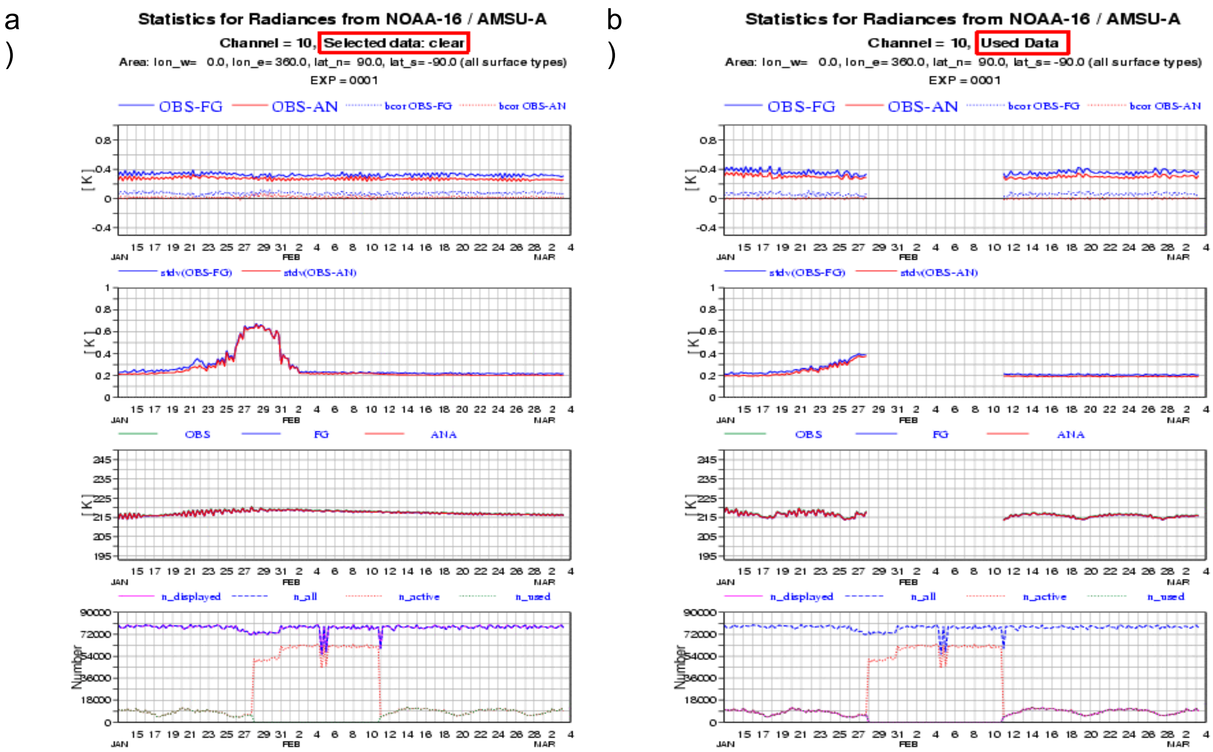

Figure 2: Time series of AMSU-A channel 10 from NOAA-16 before (a) and after (b) quality control for period 13/01-04/03/2009.

Figure 3 shows a different example but making use of the same kind of observation-vs-model statistics. Shown are departures, this time of channel 13 from two different AMSU-A instruments. In both time series a sudden increase in departures means and standard deviations can be seen that goes along with a slight increase of mean observed radiances as well. This effect is cause by a sudden warming of the stratosphere (channel 13 relates to ~5 hPa) that is not well modelled by the NWP model and that therefore generates large and systematic departures. Obviously, a model deficiency will be diagnosed by more than one instruments and thus single instrument failure can be excluded in this case.

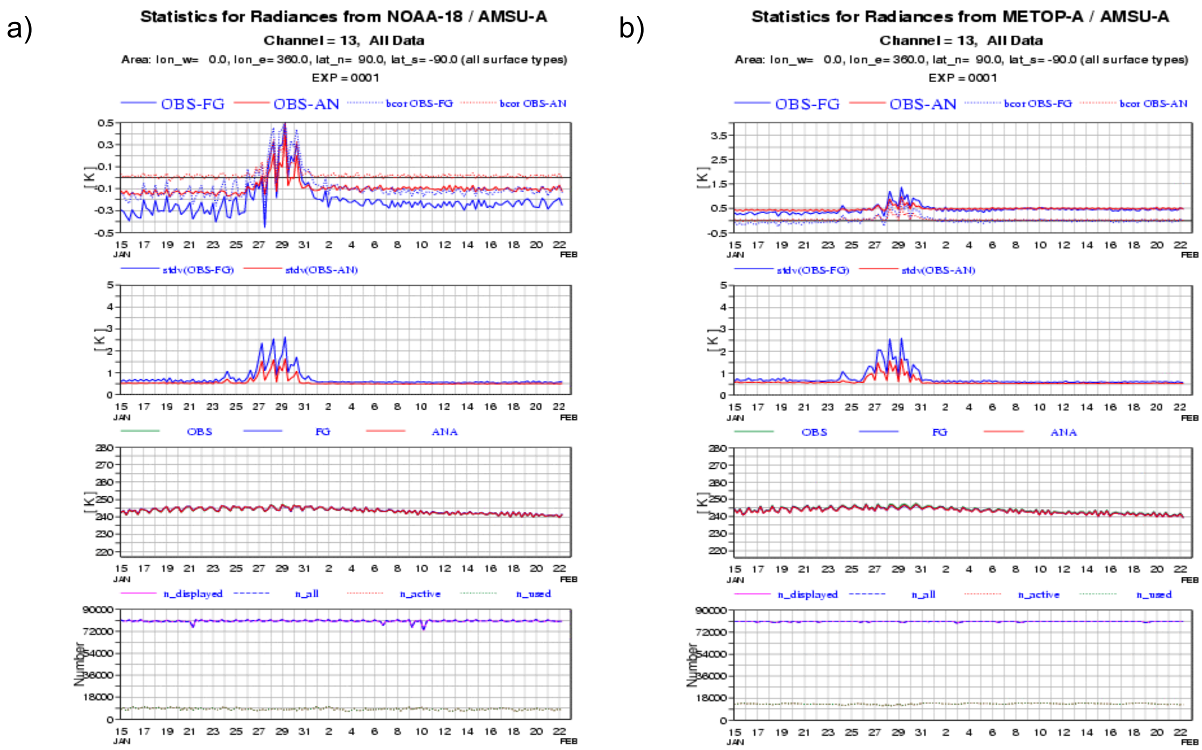

Figure 3: Time series of AMSU-A channel 13 from NOAA-18 (a) and Metop (b) between 15/01 and 23/02/2009

Both cases demonstrate basic but essential diagnostic output that is crucial for monitoring the data assimilation performance and for the safe exploitation of about 10 million satellite observations per day.

3. Observing system experiments

Observing System Experiments (OSEs) serve a number of different purposes, possibly the most important of which is related to the testing of new instruments to be assimilated in future model versions. The testing of new instruments is fundamental prior to their activation in an operational system and it occupies the largest resources associated with OSEs. Other applications in which OSEs play a fundamental role have been described by Bauer (2009) and will not be repeated here.

Many studies on OSEs performed in the context of model upgrades have been performed at ECMWF (refer to technical memoranda archive[1]). There have been various systematic studies of general observing system impact, for example Kelly and Thépaut (2007) and Bauer and Radnóti (2009). As instructive as these studies are they also demonstrate the often limited general validity of OSEs due to (1) insufficient statistical significance of the results produced by too short experimentation periods, (2) ambiguity of forecast verification from choice of verifying model analyses, (3) significant dependence of results on NWP system configuration that requires repetition of OSEs along with NWP system changes.

[1] http://www.ecmwf.int/publications/library/do/references/list/14

4. Adjoint diagnostics

Recently, new diagnostic methods for the assessment of the observational impact on both analyses and forecasts have been developed (Cardinali et al. 2004, Langland and Baker 2004, Cardinali 2009, Gelaro and Zhu 2009). These methods employ the basic operators available in the 4D-Var data assimilation systems to quantify the sensitivity of the analysis state or of forecast errors to individual observations. These tools are attractive in that they measure the impact of observations in the context of all other observations present in the assimilation system while OSEs require the removal or addition of observations relative to a control experiment. Adjoint methods are therefore the better option for routine monitoring because they can be run alongside sequential analysis/forecast cycles.

There are other fundamental differences between adjoint methods and OSEs, for example, that the modification of the observing system in OSEs affects analyses and forecast cumulatively while adjoint systems perform an evaluation within the system for each cycle independently. It can be demonstrated that the results of OSEs and adjoint systems show similar features but that they are not identical due to the above mentioned differences. They should therefore be regarded as complementary tools (see Gelaro and Zhu for more details).

An example is shown in Figure 4 that illustrates the propagation of observational information through the analysis using the self-sensitivity diagnostics (Cardinali et al. 2004). Fig. 4a shows a weekly average of IASI channel 212 radiance departures that mainly reflects observation vs model differences of temperatures near 250 hPa. The two circles indicate areas where the mean departure standard deviations are rather large and therefore large increments should be applied in the analysis.

Fig. 4b shows the corresponding mean analysis sensitivity that expresses the sensitivity of the analysis system to exploit the information provided by the observation departures shown in Fig. 4a. Here, the two areas differ significantly in that the sensitivity is rather large in the Southern Pacific and very low in the Western Indian Ocean. This is mainly an effect from largely different background errors, i.e. larger errors in the Southern Pacific and lower errors in the Western Indian Ocean at that atmospheric level.

Fig. 4c finally shows the mean analysis increments for channel 212 that is the difference between first-guess and analysis departures. If the increments are large, the analysis has performed more work, which is actually the case in the Southern Pacific, opposite to the Western Indian Ocean. This example demonstrates clearly how a diagnostic tool such as the analysis sensitivity fills a gap between observation statistics, i.e. between first-guess departures and analysis increments, and thus helps to understand where observations drive the analysis as opposed to situations where they have little impact. More examples of such techniques are given in Cardinali (2010).

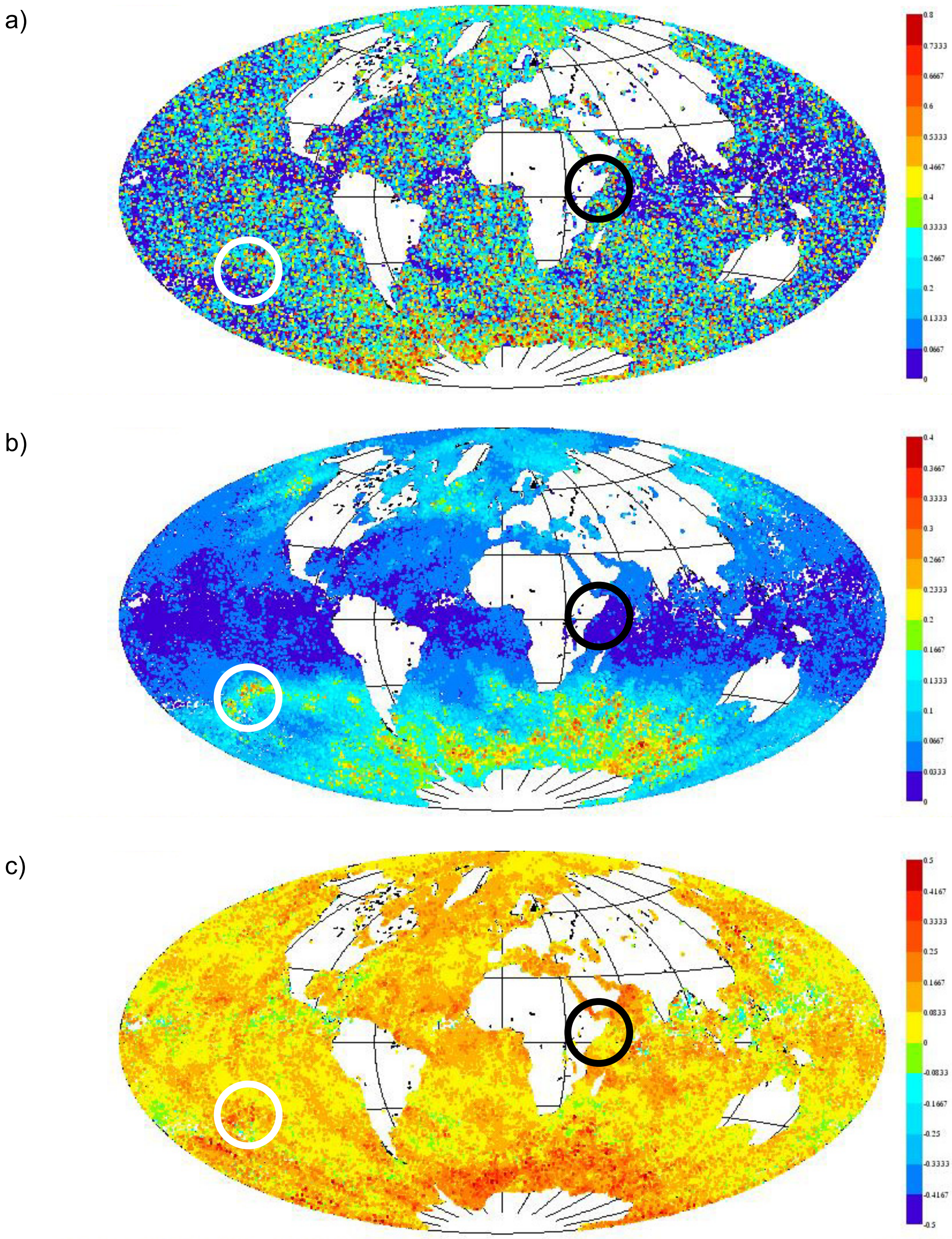

Figure 4 IASI channel 212 (250 hPa) 7-day mean observation-minus-model departure standard deviations (a), mean analysis sensitivities (b) and mean analysis increments (c). For explanation of white and black circles see text.

5. Summary and conclusions

In NWP, the estimation of the performance of the data assimilation system relies to a large extent on the assessment of the observational impact on the analysis. This covers several main aspects, namely (1) the monitoring of the health of the system in terms of instrument stability; (2) the effect of new observations on analysis and forecast accuracy and (3) the tuning of the trade off between observations and NWP model constraining the analysis.

At ECMWF item (1) is covered by a sophisticated monitoring tool that allows the routine assessment of instrument performance and permits quick response to both observation and model problems through an automated warning system.

Items (2) and (3) require dedicated research experiments and employ observing system experiments in which the data type under investigation is added or denied to/from a control system. Adjoint diagnostics represent a recent addition to the set of diagnostic tools.

While these tools represent a well established framework there are fundamental shortcomings of current observation impact assessment, namely:

- the evaluation of individual observation type impact on fit of model fields to other observation types is only available for analyses but *not* forecasts;
- standard diagnostics for tuning/optimization of the observing system is not available for the purpose of thinning, channel selection, definition of observation errors;
- general overview diagnostics require large and costly sets of observing system experiments, no continuous built-in evaluation is available yet;
- standard forecast scores often contradict the results from the analysis evaluation, e.g. when new observations add noise to the analysis (i.e. from performing more work in the analysis) and therefore may increase root-mean-square difference between forecasts and analyses used for verification.

In the future, the most potent evaluation tool is expected from the comparison of forecasts against all observations that are also available in the analysis through comparison in observation space. This will provide sufficient statistical significance, the observations can be considered independent with increasing forecast range and the available observations will provide a vast amount of information on the atmospheric state given the wide range of employed satellites/instruments/data types. The combined use of observing system experiments and adjoint diagnostics is further expected to provide complementary information on data impact in both analysis and forecasts. Adjoint diagnostics are computationally cheap and allow a continuous monitoring of performance.

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