Chapter 12

IMPORTANCE OF DATA: A METEOROLOGICAL PERSPECTIVE

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Abstract: The importance of data in meteorological data assimilation can be quantified in the context of re-analyses performed at Numerical Weather Prediction centres. The increasing quality and quantity of satellite data is seen to play a major role in the improvement of forecast performance, particularly in the Southern hemisphere. Further optimisation of the use of observations is possible through proper evaluation of the data impact, optimisation of the amount of data to be assimilated and of their error characteristics, and a relevant selection of data based on information content concepts. A more interactive forecasting system including an adaptive observation component is a new challenge to bring additional improvement in the forecasting of high-impact weather.

Keywords: Observations, Numerical Weather Prediction, data assimilation, observation targeting, data impact, optimisation, data selection, information content.

1. Introduction

Atmospheric data assimilation consists in combining information coming from a forecast model together with available observations. It is usually performed in a sequential way, with a time series of "assimilation cycles" including a model integration and a correction due to observations. As a new set of observations becomes available every six or twelve hours, a short-range forecast (so-called "background") is updated with the new set of data into a new "analysis" of the atmosphere. This analysis is then propagated in time with the forecast model to provide a new background field for the next "assimilation cycle". This series of steps in the data assimilation process shows that the atmospheric model is the basic ingredient which allows time continuity in our evaluation of the atmospheric flow. It also means that the observations are the crucial elements allowing to constantly re-adjust the model trajectory to produce a reasonable estimate of the true atmospheric state. From these analyses of the atmosphere, the model is run daily up to a few days to produce the forecast products which will guide the forecasters in their prediction of the weather. At the beginning of the 80's, data assimilation was a minor sub-discipline of numerical weather prediction, where the emphasis was mainly on the forecasting model itself. Simple correction methods were used to update the forecast such as nudging and linear optimal interpolation. Over the last two decades or so, this subject has expanded into quite a mature and motivating area of research and applications, with in particular the advent of variational methods. Such major scientific advances, combined with a large increase in available observations, has brought data assimilation to the forefront of operational weather forecasting. Its use is also spreading to climate applications through re-analyses and oceanography/chemistry applications. The experience gained in data assimilation in meteorology can be shared with scientists interested in other areas, such as oceanography. This paper will mainly address the issue of the importance of data in the assimilation process, in the context of global atmospheric modelling.

Firstly, the impact of observations on the forecast performance will be illustrated through the 40-year reanalysis performed at ECMWF (European Centre for Medium-range Weather Forecasts). Secondly, tools will be described which can help to perform an optimal use of observations, through data selection and error tuning. Finally, current developments towards an adaptive system will be described in the context of the THORPEX programme.

2. Impact of observations on forecast performance

Operational data used at Numerical Weather Prediction (NWP) centres are consisting of various data types provided by the global observing system. The backbone of this system is formed by surface observations from land and ship stations, and vertical soundings from radiosonde and pilot balloons. From the 1970s, other data types emerged such as drifting buoys, aircraft measurements, wind profilers, satellite radiances, satellite cloud-drift winds and scatterometers. On the one hand, observations such as land stations and radiosonde observations have been providing a stable source of information throughout the years, but their horizontal distribution is far from being homogeneous. On the other hand, satellite observations are blooming and becoming a major and horizontally homogeneous source of information in current systems. How did this increase in available observations translate into analysis and forecast quality? As a partial answer to this question, an illustration of the impact of observations is now provided in the context of the ERA-40 project (www.ecmwf.int/research/era). As summarized in

Simmons (2003), a re-analysis was conducted from September 1957 to August 2002 based on cycle 23r4 of ECMWF forecasting system operational from June 2001 to January 2002. It uses six-hourly variational analysis, a degraded version of the operational analysis scheme. The T159 horizontal resolution (~125km grid) is coarser than current operations which uses T511 (~39km grid). This re-analysis can then be seen as a cheaper version of the current ECMWF operational system. Figures 1 and 2 show anomaly correlations of 12UTC 500hPa height forecasts as a function of forecast range for the extratropical northern hemisphere (Figure 1) and for a smaller region encompassing Australia and New Zealand (Figure 2). These anomaly correlation scores quantify the quality of the forecasts, 100% being the maximum score and 60% the score below which the forecast is not generally considered useful. Results are shown for many of the ERA-40 years, verified against corresponding ERA-40 analyses, denoted by the colour scale shown in legend and for ECMWF operations (verified against the corresponding operational analyses, labelled Ops) for the calendar years of 1980 and 2001 and for the year ending 31 August 2003.

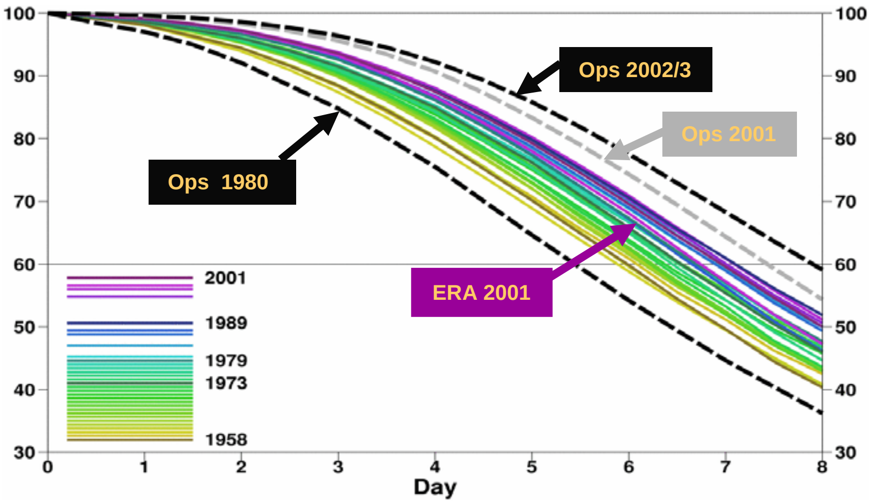

Figure 1. Anomaly correlations of 500hPa height forecasts over the Northern Hemisphere. From Simmons (2003).

These figures provide some evidence of the general improvement of the analyses over time, with interannual variations in predictability. The northern hemisphere results in Figure 1 show that whilst the observing system for medium-range prediction has improved over the years, a greater improvement in forecasts has been derived from the improvements in data assimilation and forecast models achieved since 1980. This can be seen by comparing the improvement in the coloured solid lines (same system, improvement entirely due to global observing system) and the larger improvement in the dashed lines (both changes in the observations and in the NWP system). A different picture is seen for the southern hemisphere, where forecast performance is mainly driven by satellite data (Bouttier and Kelly, 2001). The area chosen for the score calculation in Figure 2 includes Australia and New Zealand where observational coverage is sufficient for some reliance to be placed on the quality of the verifying analyses throughout the period. Forecast quality is poor in the 1950s and 1960s. A dramatic jump in forecast quality occurs at the end of 1978 when the observing system was improved considerably with the introduction of radiances from the TOVS instruments and the addition of winds from geostationary satellites and many more data from drifting buoys and commercial aircraft. Observing-system improvements beyond 1979 have had larger impact on southern- than northern-hemisphere forecast accuracy, bringing forecast skill levels closer. In any case, observing system improvements have had a major impact on the forecast scores globally.

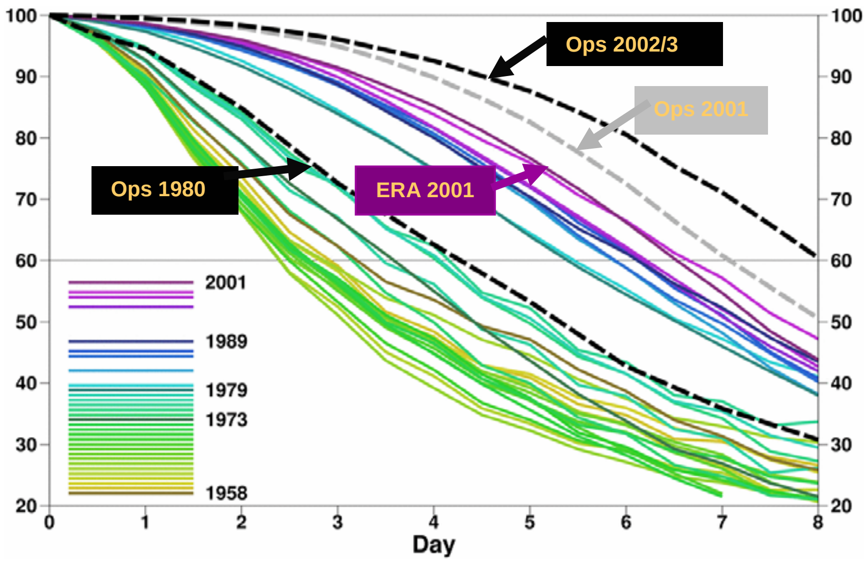

Figure 2. Anomaly correlations of 500hPa height forecasts over Australia-New Zealand. From Simmons (2003).

Such a large impact of observations has been made possible through the large increase in number and quality of observations combined with new approaches for their assimilation. One of the major advances has been the direct use of raw radiance observations in data assimilation in variational systems in the last few years in most NWP centres (and in the ERA-40 re-analysis). To explain this approach, let us start with the basics of satellite data assimilation. Radiometers provide a set of radiance measurements at various frequencies in the electromagnetic spectrum. Each of these radiance measurements provides information about temperature and/or humidity integrated over a layer of the atmosphere. A set of a few of these measurements thus describes broad vertical structures in temperature and humidity. Data assimilation in some way or another converts these radiance measurements in temperature/moisture profiles. Different possibilities exist to process this information. One can use externally generated retrievals (profiles deduced from a set of radiances through regression typically), interactive retrievals using in-house information about short-range forecasts (e. g. 1D-Var retrievals), or the direct use of radiances (e.g. 3D-Var or 4D-Var). In NWP at least, the direct assimilation of satellite raw radiances has progressively replaced the assimilation of retrievals (Thépaut, 2003). This has been made possible because 3D and 4D-Var allow for some (weak) non linearities in the observation operator, and radiances are non-linearly linked with the atmospheric profiles. Retrievals always need prior background information, which either comes from independent statistics or from the short-range forecast. The direct assimilation of radiances has the advantage to avoid the contamination by such an external background information for which error characteristics are poorly known. Another advantage of global variational methods is that increments brought by satellite radiances are further constrained by many other observations/information. Finally, raw radiance observations exhibit less spatially correlated errors than processed retrieved information. In current data assimilation schemes, this allows to use observations with more spatial density, a subject which will be discussed further in the next section. Of course this use of raw data comes at the cost of developing the observation operator and the quality control appropriate for each observation for each data assimilation system in each NWP centre, but some of this effort is collaborative through EUMETSAT facilities for instance.

Zooming now on the period covering the most recent years, Figure 3 shows the number of data used in the ECMWF analysis between 1997 and 2003. This illustrates the tremendous increase in terms of observation numbers which took place lately, and most of this progression in data numbers comes from non-conventional asynoptic observations.

Such observation numbers have a significant impact, especially in an advanced data assimilation scheme such as 4D-Var which has been used since 1997 (Rabier et al, 2000). 4D-Var stands for Four-Dimensional Variational Data assimilation and it performs a global optimization of the model trajectory over a period of 6 to 12 hours typically. It performs an adjustment of the model trajectory with the observations taken explicitly at the precise time of the observation, thus allowing for a consistent use of data spread in time throughout the optimization period, such as satellite observations. In the linear approximation, 4D-Var is equivalent to a Kalman smoother: at any time in the assimilation window, information from past and future observations within this window will be taken into account to provide the best estimate of the flow (Rabier and Liu, 2003). It can also use the timetendency between various observations to adjust the model, which is particularly beneficial in the case of rapidly-developing weather systems (Järvinen et al, 1999). It is then particularly suited to the use of a large number of observations spread in time.

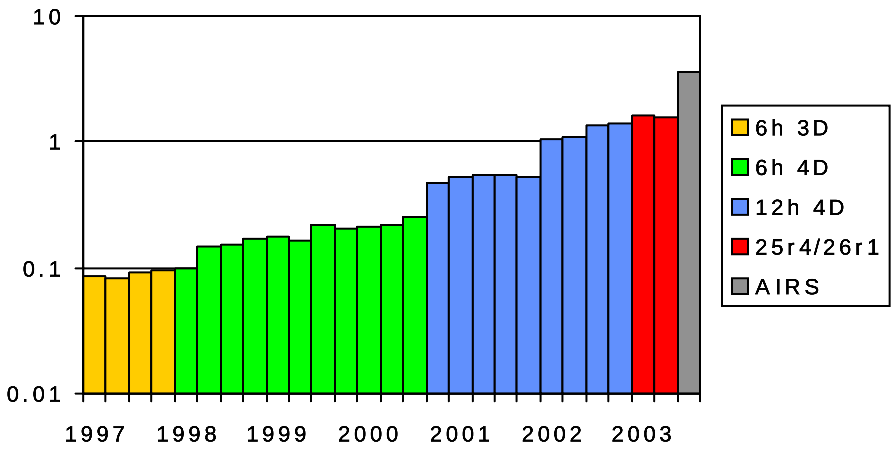

Figure 3. Number of observational data used in the ECMWF assimilation system, in millions. From Thépaut (2003).

What should be kept in mind after this introductory presentation is that data assimilation techniques now allow to make full use of observations, and in particular satellite measurements. These have become a major source of information in NWP systems, and their increase in number and quality is currently booming. It is then the right time to investigate their use in the view of optimally extracting the information contained in these data.

3. Optimal use of observations

3.1 Optimal resolution of observations

As already seen in the previous paragraph, the performance of current NWP systems benefits to a large extent from the increasing amount of globally available remotely-sensed observations used together with conventional observations to generate initial conditions for forecasts. Some of these data have fine horizontal resolution. The observation spacing can be smaller than the analysis grid of global NWP models. Not all of these observations are used in data assimilation systems because of various considerations. Firstly, current computing and storage power limits the use of all observations. Secondly, the errors affecting these observations may be horizontally correlated (instrument errors and/or representativeness errors);

current assimilation systems do not generally consider this correlation in the modelling of the observation-error covariance, because of a lack of accurate information on the correlation statistics and the technical difficulty of implementation. Alternatively, most NWP centres tend to use sub-optimal schemes for which the observation-error covariance matrix is designed to be diagonal. At the same time, horizontal thinning of remotely sensed observations is performed in order to reduce their effective error correlation.

Liu and Rabier (2002) have used a simple one-dimensional context to evaluate the optimal resolution of the observations leading to the best analysis. The framework is a 1D circle of a length of 8000km, with a grid-size of 100km. Background and observation errors have the same standard-deviation equal to 1 (arbitrary value).The background error correlation length-scale is taken equal to 200km. The analysis error covariance matrix is calculated for various observation spacings. Various scenarios were tested: uncorrelated observation errors and correlated observation errors with a correlation length of 100km. In the case of correlated observation errors, two analysis schemes were tested: the optimal one taking into account the proper observation error covariance matrix and a sub-optimal one neglecting the observation error correlations (similar to operational practice). Figure 4 shows the analysis error variance resulting from these combinations of observation density/observation correlation/analysis scheme. The main results are that, for uncorrelated observation errors, increasing the density always improves the analysis (dash-dotted line). This is the case even when the observation density is finer than the background error correlation length-scale and the analysis mesh. For correlated observation errors, increasing the observation density beyond a threshold can be harmful in a sub-optimal scheme for which no correlations are included in the observation error covariance matrix, as in current systems (dashed line). These results have been confirmed by a further study in a more realistic 4D context (Liu and Rabier, 2003) and might explain some of the results found in practical NWP experience.

It is also found that an optimal thinning of the dataset can extract most of the information contained in the data, and this approach is the pragmatic one used in most centres. The “optimal” observation density is usually found by trial and error. Another ad-hoc approach is to use most of the observations but to inflate artificially their errors to compensate for their correlations. More general solutions would of course be preferable. In particular, instead of performing a thinning of the observations, one might prefer to perform an averaging of neighbouring observations. The best theoretical framework might well be to model the correlations in the long term, if feasible.

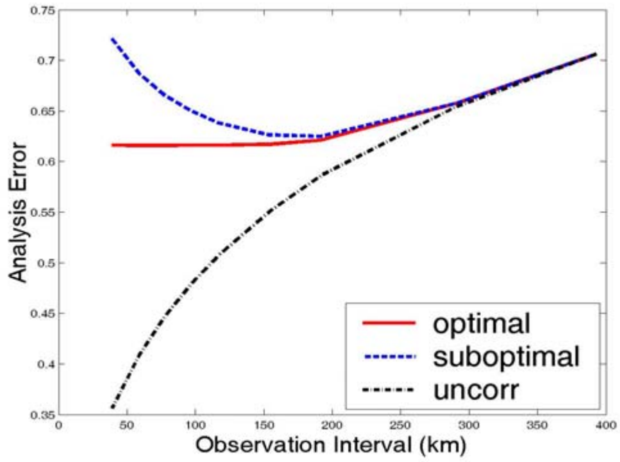

Figure 4. Analysis error standard-deviation as a function of the observation interval in a simple one-dimensional framework. The black dash-dotted line corresponds to uncorrelated observation errors. The solid red line corresponds to correlated observation errors, fully accounted for in the analysis. The dashed blue line corresponds to correlated observation errors, not accounted for in the analysis. From Liu and Rabier (2002).

3.2 Advanced diagnostics

Apart from the density issues explained in the previous section, another important question might arise in the use of observations, such as: what is the actual information content of the data? A simple data count might be misleading as not all observations are equal in what they measure and with what accuracy. In the perspective to diagnose the impact of observations on the data assimilation, some diagnostics were developed which are presented here.

Firstly, let us recall the equations relevant for statistical estimation, from the point of view of least squares. Let us assume that observations $\mathbf{y}$ are available, with a known observation operator $\mathbf{H}$ linking them to the atmospheric state vector $\mathbf{x}$

$$\mathbf{y} = \mathbf{Hx} + \varepsilon_{\mathbf{r}} \tag{1}$$

together with a background vector (which usually comes from a short range forecast)

$$\mathbf{x_b} = \mathbf{x} + \varepsilon_{\mathbf{b}} \tag{2}$$

The least-squares method for estimating the analysed state $\mathbf{x_a}$ is to minimize the cost-function

$$J(\mathbf{x})=1/2\ (\mathbf{x}-\mathbf{x_b})^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x_b}) + 1/2\ (\mathbf{y}-\mathbf{Hx})^T\mathbf{R}^{-1}(\mathbf{y}-\mathbf{Hx}) \tag{3}$$

where **B** is the covariance matrix of the background error ε_b and **R** the covariance matrix of the observation error ε_r which includes the instrument error and the representativeness error.

The solution in this linear case is given by

$$\mathbf{x_a} = \mathbf{x_b} + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x_b}) \quad (4)$$

with the gain matrix **K**

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}. \quad (5)$$

The corresponding analysis error is given by

$$\varepsilon_a = (\mathbf{I} - \mathbf{K}\mathbf{H})\,\varepsilon_b + \mathbf{K}\varepsilon_r. \quad (6)$$

The analysis error covariance is

$$\mathbf{A} = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{B} = (\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}. \quad (7)$$

This is the Optimal least-square estimator, which leads to the minimum variance for the analysis error, or BLUE= Best Linear Unbiased Estimator. If all errors are Gaussian, then it is also the maximum likelihood estimate.

When one wants to evaluate the gain brought by the observations, a pure data count can be misleading. If practically feasible, the computation of the analysis error covariance **A** and its comparison with the background error covariance matrix **B** will indicate how much benefit was brought by the observations, in terms of decreasing the error covariance of the estimation of the atmospheric state. Another approach is to compute the sensitivity of the analysis with respect to the observations. This leads to estimating the information content of data types. For example, one can compute the DFS = Degrees of Freedom for Signal (Rodgers, 2000)

$$\mathrm{DFS} = \mathrm{Tr}(\mathbf{K}\mathbf{H}) \quad (8)$$

where the trace of the matrix **KH** quantifies the gain in information brought by the observations. As shown by

$$\mathbf{H}\mathbf{x_a} = (\mathbf{I} - \mathbf{H}\mathbf{K})\,\mathbf{H}\mathbf{x_b} + \mathbf{H}\mathbf{K}\mathbf{y} \quad (9)$$

The **HK** matrix quantifies the sensitivity of the analysis to the observations

$$\partial_y \mathbf{H} x_a = (\mathbf{HK})^T \ . \tag{10}$$

DFS=Tr($\partial_y \mathbf{H} x_a$)=Tr(**HK**) characterizes how the assimilation system uses the observations to pull the signal from the background. In the optimal case (i.e $\mathbf{K} = \mathbf{K}_{true}$), this is also the relative reduction of variance (Tr (**KH**)=Tr (($\mathbf{B}$-$\mathbf{A}$)*$\mathbf{B}^{-1}$) = Tr($\mathbf{I}$-$\mathbf{AB}^{-1}$)). It is only an upper bound in non-optimal cases. It indicates what the system does. One would need other information to give insight about what should be done to get the best analysis.

How to estimate Tr (**HK**) ? This is not straightforward for large-dimension systems where the matrices are often implicitly known and not explicitly computed. Cardinali et al (2003, 2005) compute an estimate using the singular vectors of the hessian of the cost function provided by the Lanczos/Conjugate gradient minimizer. Another method was introduced in Desroziers and Ivanov (2001) and is used in Chapnik et al (2005), based on Girard (1987) for the evaluation of the trace of a matrix only known as an operator. Let us present the basis of this method, which is relatively easy to implement.

Let us consider a vector $\boldsymbol{\varepsilon}$ following a normal (Gaussian) distribution with mean **0** and covariance matrix the identity **I**. Girard (1987) proposed to use the following mathematical identity in order to evaluate the trace of a matrix **A** only known as an operator

$$E(\boldsymbol{\varepsilon}^T \mathbf{A} \boldsymbol{\varepsilon}) = \mathrm{Tr}(\mathbf{A}). \tag{11}$$

The evaluation of the trace of **KH**, or equivalently the trace of **HK** can be perfomed based on this equation. The basic idea is to produce two analyses, one being deduced from the other by perturbing the observations. The difference between these two analyses will then be equal to the operator **K** applied to the perturbation, and applying **H** to this difference of analyses will give access to the **HK** operator needed. This method, as presented in Chapnik et al (2005) involves several steps

1. Perform a normal analysis from the information ($\mathbf{x_b}$,$\mathbf{y}$) producing the analysis vector $\mathbf{x_a}$
2. Perform a perturbed analysis from the information ($\mathbf{x_b}$,$\mathbf{y}$*) with perturbed observations $\mathbf{y}^* = \mathbf{y} + \mathbf{R}^{1/2}\varepsilon$ leading to $\mathbf{x_a}$*. One notes that $\mathbf{x_a}^* - \mathbf{x_a} = \mathbf{K}(\mathbf{y}^* - \mathbf{y})$.
3. Then $(\mathbf{y}^* - \mathbf{y})^T \mathbf{R}^{-1} \mathbf{H}(\mathbf{x_a}^* - \mathbf{x_a})$ provides an approximation to Tr(**HK**).

If the number of observations is large, one sequence of such steps might be enough to get a reasonable estimation of the trace. Otherwise, one can use several realizations of the analysis, and concatenate the results.

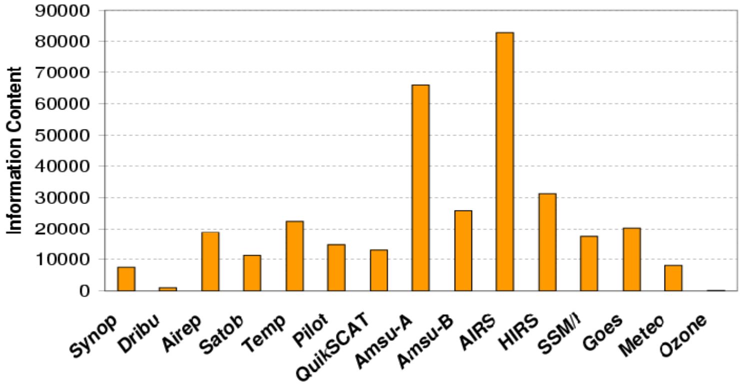

Figure 5. Information Content. Partition by observation type for the ECMWF system. Synop= surface observations, Dribu=drifting buoys, Airep=aircraft obs, Satob=winds from geostationary images, Temp=radiosonde obs, Pilot=wind profiler, QuikSCAT=scatterometer, Amsu-A +Amsu-B +AIRS +HIRS +SSM/I +Goes +Meteo =satellite radiances, Ozone=ozone information. From Cardinali et al (2003).

For non-linear cases, $\mathbf{H}(\mathbf{x_a}^*)-\mathbf{H}(\mathbf{x_a})= (\partial_{\mathbf{y}}\ \mathbf{H}(\mathbf{x_a}))\ (\mathbf{y}^*-\mathbf{y})$. Therefore,$(\mathbf{y}^*-\mathbf{y})^T\mathbf{R}^{-1}(\mathbf{H}(\mathbf{x_a}^*)-\mathbf{H}(\mathbf{x_a}))$ gives an approximation of $\mathrm{Tr}(\partial_{\mathbf{y}}\ \mathbf{H}(\mathbf{x_a}))$. This shows that this method allows the computation of DFS like quantities even for non-linear schemes.

An example of the use of the DFS as a diagnostic is shown in Figure 5. The partition by observation types allows to diagnose which observing system is pulling the analysis more or less than the other types. It can be seen that globally, the satellite observations have become a dominant source of information.

3.3 Observation error estimation

Apart from its use in pure diagnostic mode, it is possible to use DFS related quantities to improve specified covariance matrices. Following Desroziers and Ivanov (2001) and Chapnik et al (2004), suppose one can write the "true" perfect covariance matrices as a function of the ones actually used in the analysis

$$\mathbf{B}_{true}= s_b\ \mathbf{B} \qquad (12)$$
$$\mathbf{R}_{true}=s_o\ \mathbf{R} \qquad (13)$$

s_o and s_b being tuning coefficients. If

$$J(\mathbf{x})=1/2\ (\mathbf{x}-\mathbf{x_b})^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x_b}) + 1/2\ (\mathbf{y}-\mathbf{Hx})^T\mathbf{R}^{-1}(\mathbf{y}-\mathbf{Hx})= J_b +J_o \qquad (14)$$

is the cost function used in the sub-optimal system, with J_b the first term on the right-hand side and J_o the second term on the right-hand side, then

$$J_{true}(\mathbf{x}) = J_b/s_b + J_o/s_o \quad (15)$$

is the cost function using « true » matrices.
Let $\mathbf{x_a}$ be the minimizer of this cost function, then, following Talagrand (1999)

$$E(2J_o(\mathbf{x_a})/s_o) = \mathrm{Tr}\,(\mathbf{I} - \mathbf{HK}) \quad (16)$$
$$E(2J_b(\mathbf{x_a})/sb) = \mathrm{Tr}\,(\mathbf{KH}) \quad (17)$$

yielding the following condition for the tuning coefficients

$$s_o = 2J_o(\mathbf{x_a}) / \mathrm{Tr}\,(\mathrm{I} - \mathbf{HK}) \quad (18)$$
$$s_b = 2J_b(\mathbf{x_a}) / \mathrm{Tr}\,(\mathbf{KH}) \quad (19)$$

As $\mathbf{K}$ depends on s_o and s_b, this is a fixed-point relation, and a fixed point algorithm can be used to estimate the tuning coefficients. The denominator of those expressions can be computed using Girard's method, which is also used to compute the DFS.

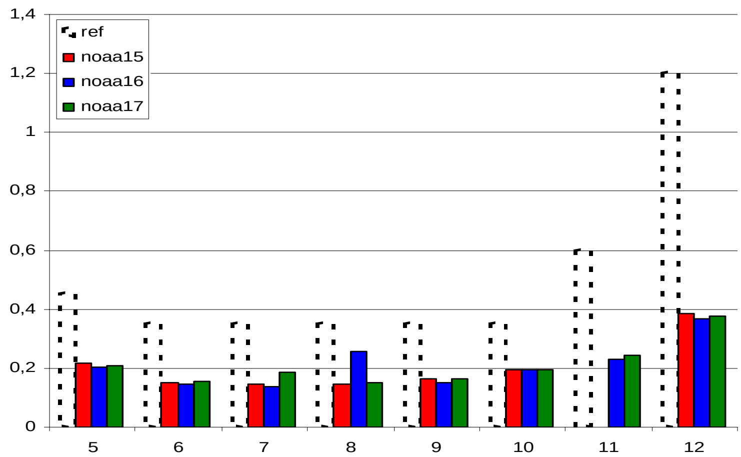

Figure 6. Observation errors, specified in the data assimilation system (dashed bars) and estimated by the optimisation method, for several channels of the AMSU-A instrument on board 3 NOAA satellites of the ATOVS series (coloured bars). From Chapnik et al (2005).

An example of the tuning of the error standard-deviations for satellite radiances of the ATOVS series is shown in Figure 6. One can see that the errors are generally over-estimated in the operational French global NWP model, and that the method can pick up small differences between the various satellites (which have been confirmed by the individual monitoring of the data). This type of information can be very valuable for a real-size NWP system, for which there are too many parameters to allow to perform a fine tuning on each by trial and error methods.

3.4 Channel selection for satellite sounders

Another optimisation of the use of observations can be the selection of the most valuable subset of data, if some of the global observing systems are providing too many pieces of information for the data processing capabilities. In particular, advanced infrared sounders provide thousands of radiance data at every observation location. The first instrument with kilo-channel data is the Atmospheric InfraRed Sounder (AIRS) on the Aqua satellite launched by the National Aeronautics and Space Administration (NASA) in 2002. On the European side, the French space agency Centre National d'Etudes Spatiales (CNES) and the European Meteorological Satellite organization (EUMETSAT) have developed the Infrared Atmospheric Sounding Interferometer (IASI) to be launched at the end 2005. For operational NWP systems, these data will provide temperature and humidity information with a fine vertical resolution. The number of individual pieces of information is not usable in an operational NWP context, and several possibilities are being investigated to choose an "optimal" subset of data. This would allow to extract the maximum information content from hyperspectral sounders, with a reduced number of individual data. Solutions proposed to solve this problem include the selection of relevant limited spectral bands (Aires et al, 2002), the grouping of highly correlated channels in the same spectral area into super-channels, the use of a partial eigen-decomposition of the radiance data (Joiner and Da Silva, 1998), and the selection of individual channels based on objective criteria (Rodgers, 1996).

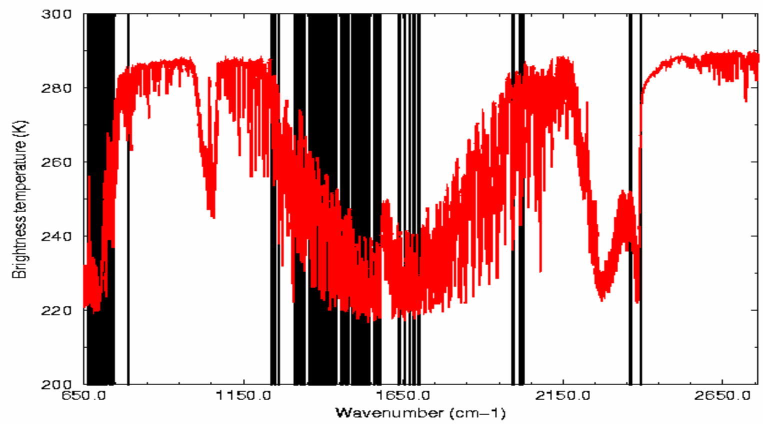

Figure 7. Location of 300 channels (black lines) selected by an iterative procedure based on information content for the retrieval of temperature and humidity for a IASI spectrum (red line). From Rabier et al (2002).

An example of such a channel selection procedure is presented in Rabier et al. (2002). The selection of individual channels is performed for simulated

IASI spectra (8461 radiance data). The procedure is iterative, based on Rodgers, (1996). At each step, one channel is picked. It is the most informative channel among those which have not been previously selected. The analysis error covariance matrix is then updated before proceeding to the next channel selection step. The choice of channels is based on information content with respect to the background or current analysis information. The selection criterion is the entropy reduction ER=-1/2 $\log_2 \det(\mathbf{AB}^{-1})$ or the DFS= Tr $(\mathbf{I}- \mathbf{AB}^{-1})$. At each step, one optimises ER=-1/2 $\log_2 \det(\mathbf{A_{i+1}}\ \mathbf{A_i}^{-1})$ or the DFS= Tr $(\mathbf{I}- \mathbf{A_{i+1}}\ \mathbf{A_i}^{-1})$ with $\mathbf{A_i}$ the analysis error covariance when using the first i selected channels, and $\mathbf{A_{i+1}}$ the analysis error covariance when using the first i+1 selected channels. Figure 7 shows the location of the "optimal" 300 channels selected for the retrieval of temperature and humidity information for a typical IASI spectrum. This type of work illustrates the benefit of using information content diagnostics for the benefit of the optimisation of data assimilation, through data selection.

4. Towards an adaptive system

Despite the notable increase in forecast skill over the past quarter-century, there is a necessity for further improvements, particularly in high-impact weather defined by their effect on society and the economy. The international programme THORPEX is a response to the challenge of improving the skill of high-impact weather forecasts. Its mission Statement is "Accelerating improvements in the accuracy of high-impact 1-14 day weather forecasts for the benefit of society and the economy". Information on this programme, and in particular the science plan, can be found on the World Meteorological Organisation web page (www.wmo.int). Research objectives are developed under four Sub-programmes: Predictability and Dynamical Processes, Observing Systems, Data Assimilation and Observing-Strategies, Societal and Economic Impacts. Among the core objectives, THORPEX plans to Contribute to the design and demonstration of interactive forecast systems which include the new concept of "targeted observations" and to perform THORPEX Observing-System Tests (TOSTs) and Regional field Campaigns (TReCs) to test and evaluate experimental remote-sensing and in-situ observing systems, and when feasible, demonstrate their impact on weather forecasts.

What is Targeting? In the last decade, strategies were developed that identify locations where additional observations would provide maximal improvements in the expected skill of forecasts. Targeting strategies are based on techniques that predict, prior to the actual measurements, the influence of an observation (or set of observations) on the uncertainty of a subsequent forecast. Different targeting techniques have been developed: some involve the adjoint of the linearized version of the forecast model or of the assimilation scheme, others manipulate ensembles of forecasts. This concept is currently operational in the US and is called the Winter Storm Reconnaissance Program. The National Centers for Environmental Prediction uses the dispersion of the ensemble of forecasts run routinely and a set of pre-defined flight plans to evaluate which of the flight scenario would bring the maximum reduction in the dispersion of the forecasts. This flight scenario leads to a designated aircraft flying in the area and dropping dropsondes at regular intervals to provide additional observations. Majumdar et al (2002) provide a detailed comparison of various targeting techniques.

Apart from being used for selecting additional observations, targeting observing systems can be extended to other applications such as controlling the sampling rate of satellite sensors or the timing and location of mobile upper-air soundings. Targeting can also be used to determine which observations are to be discarded, i.e., to conduct effective thinning of the observations. This capability will become increasingly important, given the very large numbers of observations that will be available from next-generation satellites. Among the tools which can be useful for targeting, being able to quantify the impact of any observation on the analysis and the subsequent forecast is crucial. Such a tool has been developed in particular using the adjoint of the various operations involved (analysis step and model forecast) by Baker and Daley (2000) and Doerenbecher and Bergot (2001).This sensitivity to observations is illustrated in Figure 8. The "forward" step consists in the analysis represented by the Kalman gain matrix $\mathbf{K}$ and the forecast model $\mathbf{M}$. From the background $\mathbf{x_b}$ and the observations $\mathbf{y}$, it creates the analysis $\mathbf{x_a}$ and the subsequent forecast $\mathbf{x_f}$. The "adjoint" step consists in the adjoint of the forecast model $\mathbf{M}^T$ followed by the adjoint of the analysis process $\mathbf{K}^T$. It allows to compute the sensitivity of any aspect of the forecast with respect to the observations and/or the background.

This sort of tools initially developed mainly for targeting can also allow to compute the sensitivity of the analysis or forecast to various satellite sounder channels (eg Fourrié et al ,2002) and can also be used to select channels in an adaptive manner (Fourrié and Rabier, 2004).

Beyond these targeting issues, NWP is also expected to progress (within THORPEX and also independently) in flow-dependent specification of various parameters used in assimilation. The major of these parameters is the background error covariance matrix $\mathbf{B}$, where a lot of work is ongoing to incorporate more flow-dependence in the statistics through 4D-Var or ensemble methods mainly. The link to the observations is then the estimation of background errors in observation space ($\mathbf{HBH}^T$) to perform first-guess check (Andersson et al, 2000). There are also interesting developments in the context of flow-dependent tolerances for outlier observations for an adaptive buddy check (Dee et al, 2001).

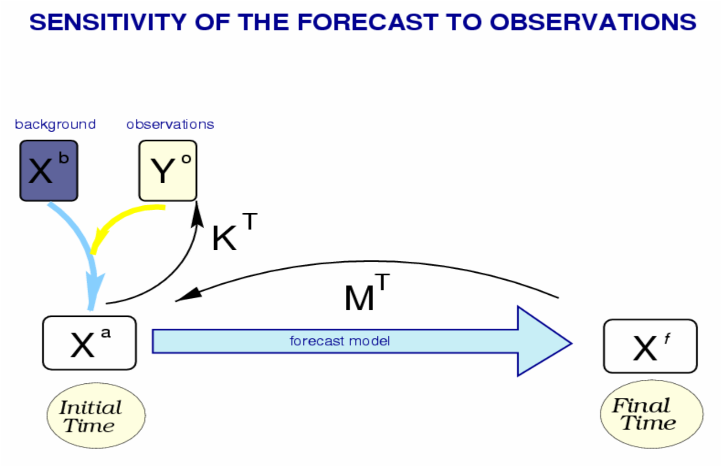

Figure 8: Schematic representation of the analysis and forecast steps K and M leading to the forecast and of its adjoints M^T and K^T leading to sensitivity computations.

5. Conclusion

In conclusion, there is ample evidence of the major improvements made in the last ten years or so in the context of Numerical Weather Prediction, and in particular in data assimilation. This can be seen in particular in the context of re-analyses programmes such a ERA-40, which highlight improvements coming from the increase in quantity and quality of data, mainly satellite observations, throughout the years. Satellite data are currently very successfully exploited by new data assimilation schemes (data assimilation schemes are now such that introducing additional well characterised satellite data generally improves the system). Variational methods have permitted to use such data in an innovative way, assimilating radiances directly in 3D/4D-Var, rather than using retrievals of temperature and humidity profiles obtained from the data. Furthermore, the proper inclusion of the time dimension in the assimilation period obtained in 4D-Var guarantees a near-optimal treatment of data which are not centred around the main synoptic times (0, 6, 12 and 18 UTC). In the future, the combined availability of new accurate satellite observations and improvement of models will allow an improved extraction of information content from these new data. In particular, observations related to the water cycle (clouds, rain…) will pose a great challenge to data assimilation. In general, the system can only cope with a small fraction of all available observations, and efficient tools have been built to evaluate observation impact. One of these tools is the Degrees of Freedom for Signal (DFS) quantity, which measures the sensitivity of the analysis with respect to observations. It can be used to investigate this sensitivity globally, data type per data type, of by geographical areas, or even by parameters (Temperature, humidity, wind…). Such a diagnostic can also be used to perform optimal observation selection and error tuning. Looking forward to the future, we are now in a position to further optimise the use of observations, including more flow-dependency and a more interactive forecast system through the WMO programme THORPEX. The basic idea beyond this programme is to use the forecast system itself to predict where and when additional observations or a better treatment of planned observations would bring a major improvement in the forecasting of high-impact weather likely to have a high economic and societal impact. The NWP community has achieved a major improvement in average forecast scores in the last decade and is now mature enough to concentrate some of its efforts on the challenge of improving the forecast of rare events such as storms and floods.

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