Data Assimilation and the Atmospheric Radiation Measurement Program

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This paper is a brief introduction to data analysis and assimilation concepts; its purpose is to define the role of data assimilation in the Atmospheric Radiation Measurement (ARM) program. It may be useful to start with a very short, and probably oversimplified, historical perspective on the treatment of data in meteorology and, more specifically, in weather prediction.

The original concept of data analysis was a way of establishing a picture of a meteorological field on the basis of more or less randomly distributed observations. Long before the advent of computers, meteorologists were routinely contouring fields by hand, using synoptic observations. To a large extent, this was an art as much as a science, but it allowed the development of techniques, some mathematical and some purely graphical, to predict the evolution of the fields.

From very early on, it was recognized that data should not necessarily be taken at face value and that "drawing to the data" was not necessarily the best way to go. Not only did the data suffer from measurement errors, but it was understood that one should not draw fields that contained short waves of a scale that would not be properly sampled by the distribution of observations, waves which, furthermore, had little meteorological significance from the point of view of weather prediction. The question of representativity of the data had to be faced from the beginning.

Already in the days of hand analyses, models were used. These were conceptual models which allowed, for example, the introduction of sharp gradients in frontal zones, even when data were incomplete, and forced time continuity in the fields, in the same way as models are used today in data assimilation.

With the development of computers, a lot of effort was devoted to trying to automate the process of hand analysis of meteorological data. Two main directions were followed: curve fitting and statistical interpolation. In fitting techniques, the fields are represented locally by analytical spline functions whose coefficients are determined by a least square method. Somewhat simpler mathematically, and more often used, statistical interpolation defines the value of the field at each grid point as the weighted average of nearby data. The Cressman and the Barnes techniques are two examples of statistical interpolation, which differ mainly by the shape of the weighting function. Generally, several passes through the data are performed with different weighting functions, making successive corrections to the field to get as much information as possible out of the data. It can be shown that these interpolation techniques act as filters which eliminate the shorter wavelengths of the field. The filtering properties of the method can be controlled by the shape of the weighting function.

The use of successive corrections naturally led to the introduction of a first guess field which represented the a priori information known about the field either from climatology, persistence, or from a previous forecast. Analyzing the differences between a first guess and the observations, rather than the observations themselves, has distinct advantages, especially if the first guess is a forecast: it generates realistic fields even in data-void regions, and it ensures the time continuity of the fields. It can be said that the forecast model is a way to bring into the analysis the information of all the past data. Thus, the concept of assimilating data into a model was born.

At the same time as the concept of data assimilation was developed (in the sixties), new sources of data, mainly from satellites, were becoming available. It was realized then, that defining the weights purely on the basis of the filtering properties of the weighting function was no longer adequate. It was necessary to take into account the relative accuracy of the different observation types, as well as that of the first guess. The concept of optimal interpolation was then developed, pioneered by Gandin. In this method, the weights are determined by the error covariance matrices of the first guess and observations, including the representativity errors, so as to minimize the expected analysis error.

The optimal interpolation method has been very successful and is used today in many operational weather forecasting centers. Its main drawbacks are that it is difficult to use data that are not direct measurements of the model's prognostic variables and that it is an intermittent scheme. A new analysis is produced at periodic intervals, typically six hours. This means that it does not provide a continuous picture of the atmosphere, and asynoptic data cannot be used in the most effective way.

From the concept of optimal interpolation, there is only a short step to the principle of variational assimilation. Variational assimilation consists of finding the evolution of the atmosphere that is consistent with the model while minimizing a cost function which may include constraints such as smoothness, as well as the model simulation error. An equivalent framework is Bayesian estimation, which consists of finding the most probable evolution of the atmospheric state, given the observations, the a priori information contained in the model, and any constraints that might be imposed.

These methods are currently being developed. Their main drawback is their cost, which is due to the fact that the search for the minimum of the cost function or the maximum probability is an iterative procedure which requires the integration of the model and the computation of the gradient of the cost function at each iteration.

An efficient way of computing this gradient is to solve the adjoint model. With one forward integration of the model over the assimilation period and one backward integration of the adjoint, it is possible to compute the derivatives of the forecast error with respect to all the parameters that are used to bring the forecast closer to the observations. Additional details about the use of the adjoint are given in the description of our ARM project.

In the context of ARM, it is clear that the role of data assimilation will be mainly to provide a continuous, internally consistent picture of the atmospheric state over the Cloud and Radiation Testbed (CART) site, in order to provide appropriate initial conditions and verification data for models and parameterization experiments. Two distinct but complementary points of view can be adopted: mesoscale four-dimensional data assimilation (4DDA) or single column assimilation (SCA).

In mesoscale 4DDA we are interested in the detailed evolution on the fields with a resolution on the order of 10 km or so, to make it possible to describe mesoscale phenomena such as convective complexes. This will allow the study of the interaction between subgrid and large-scale processes, the development of hierarchical models, and the validation of parameterization schemes. Mesoscale 4DDA, however, is very expensive and will probably not be available on a routine basis for several years. In addition, mesoscale data assimilation is itself a subject of research. Techniques that have been developed for the large scale cannot necessarily be scaled down to mesoscale phenomena for which dynamic constraints may be different and error statistics are not well known.

Single column assimilation, which is the subject of our ARM research, uses a single column model. Its intent is to provide a picture of the evolution of the atmospheric fields at the scale of the CART site, which is typical of that of a climate model.