Testbed Model and Single Column Data Assimilation for the Atmospheric Radiation Measurement Program

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Atmospheric and Environment Research's (AER) project for the Atmospheric Radiation Measurement (ARM) project is to further develop and test a model originally designed for local weather prediction. This model will be used for three distinct but related purposes: 1) to provide a single column model testbed that simulates a global climate model, in order to facilitate the development and testing of new cloud parameterizations and radiation models; 2) to assimilate the ARM data continuously at the scale of a climate model, using the adjoint method, thus providing the initial conditions and verification data for testing parameterizations in single column model studies; 3) to study the sensitivity of a radiation scheme to cloud parameters, again using the adjoint method, thus demonstrating the usefulness of the testbed model.

In the first couple of years of the contract we will concentrate on developing the data assimilation system. Two of the big problems with using the ARM data will be its scale representativity (or lack thereof) and its incompleteness. Data assimilation is one way to address both problems. Data assimilation can be described as a way to generate a complete and continuous picture of the atmospheric profile above the Cloud and Radiation Testbed (CART) site. A model is used to define the characteristic scale of the solution, to provide time continuity, and to ensure dynamical balance of the fields. The model also provides an estimate of atmospheric quantities that are not directly measured. To the extent that the model is a reasonable representation of the atmosphere, these computed quantities are, at least, consistent with the observations.

One could argue that using the National Meteorological Center (NMC) analyses would be sufficient to describe the atmosphere and provide initial conditions and verification data for one-dimensional (1-D) general circulation models (GCMs), especially if some of the ARM data stream was used by NMC. However, a local model can be optimized for the site, producing a more accurate analysis. For practical reasons, the frequency of the NMC analyses and the amount of information available may not be sufficient; whereas, a local model can provide output with high temporal and vertical resolution, as well as fluxes, heating rates, etc.

The problem of scale representativity cannot be underestimated. A climate model output (even a "1-D GCM") can be compared with a point measurement only if everything, including surface boundary conditions, is completely uniform over the scale of the model grid point. This is a rare occurrence. Data assimilation can filter the data to the proper scale for use in single column models.

To develop our data assimilation system, we build upon an AER model which we have used to explore parameter optimization, using the adjoint technique. We call it the AER Local Forecast and Assimilation (ALFA) model. The scale of the ALFA model is determined by the horizontal derivatives and the values chosen for the ground parameters, which define the bottom boundary conditions.

The ALFA model is a single column model that solves the same equations as a climate model, but uses large scale, three-dimensional analyses or forecasts for all the horizontal derivatives. The parameterization schemes currently used are fairly similar to state-of-the-art climate models, including vertical eddy fluxes of momentum, heat and moisture, stratiform and convective precipitation, and a three-layer ground model. The Toon et al. (1989) radiation scheme is being incorporated.

The data assimilation will be based on variational principles in which the forecast computed by the model during the assimilation period is modified until the difference between forecast and observations (the "objective function" or "cost function") is minimized. These modification will be done by adjusting extra terms (the nudging terms) in the model equations, which are used as control variables. In a way, these extra terms account for the imperfections of the model. They pull the model solution towards the observations. They will be different for each prognostic variable, but will be constant during the assimilation period. The final result is close to the observations, but is approximately consistent with the model and is constrained by the characteristic scale of the model. Some of the parameters of the model, which represent physical quantities that are not well known, may also be used as control variables.

Figure 1 is a schematic comparison of the variational method and a more traditional assimilation method such as optimal interpolation. Using nudging terms produces a continuous description of the state of the atmosphere, which is consistent with the observations, while filtering out the unwanted small scales. In optimal interpolation, an intermittent series of analyzed fields is created by a linear combination of the background fields (or "first guess") and the observations.

To find the appropriate nudging terms, we use a standard minimum search algorithm. This requires the computation of the gradient of the objective function (the forecast error during the assimilation period) with respect to the control variables (the nudging terms). An efficient way to compute this gradient is to use the adjoint of the perturbation model.

Let us write the model as

$$\chi_{n+1} = \chi_n + f(\chi_n) + v_n \tag{1}$$

where χ is the vector of model variables, v is a nudging term and the subscripts indicate the time step. We can complete the model by adding the definition of the cost function, and a statement that the nudging terms are constant in time:

$$J_{n+1} = J_n + H_n(\chi_n) \tag{2}$$

$$v_{n+1} = v_n \tag{3}$$

H_n is a measure of the forecast error at time step n (typically, the squared difference between a forecast quantity and an observation)

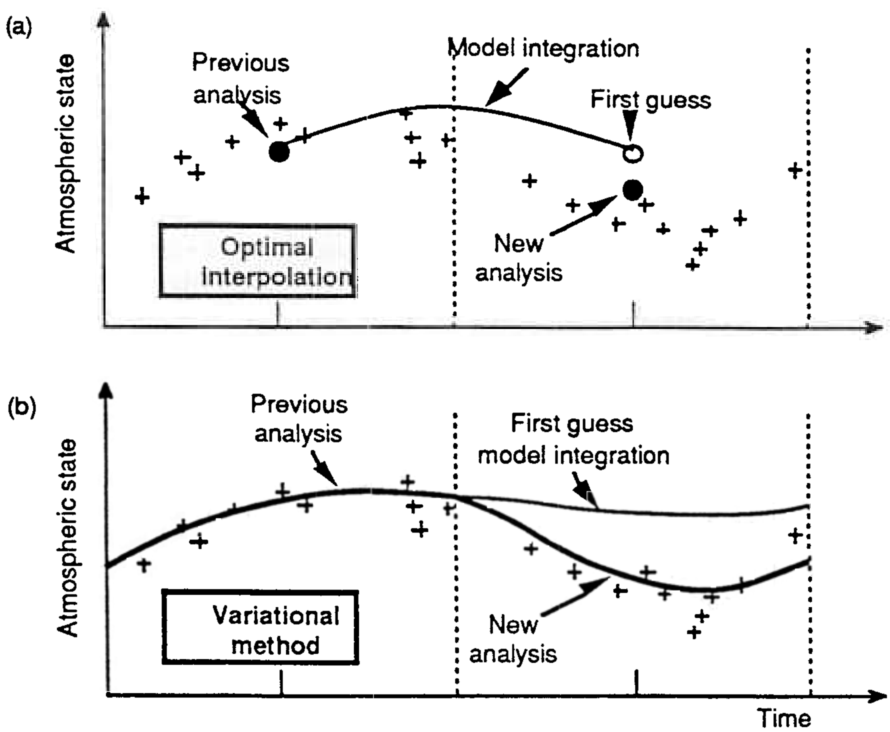

Figure 1. Comparison of two data assimilation methods. Each figure represents two assimilation cycles. The crosses represent observations, and the solid lines represent model integrations.

The perturbation (or linear tangent) equations corresponding to this model are

$$\begin{aligned} \delta\chi_{n+1} &= \delta\chi_n + \nabla_\chi f(\chi_n)\cdot \delta\chi_n + \delta v_n \\ \delta J_{n+1} &= \delta J_n + \nabla_\chi H_n(\chi_n)\cdot\delta\chi_n \\ \delta v_{n+1} &= \delta v_n \end{aligned} \tag{4}$$

or, in matrix form:

$$\begin{pmatrix} \delta\chi_{n+1} \\ \delta J_{n+1} \\ \delta v_{n+1} \end{pmatrix} = \begin{pmatrix} 1+\nabla_\chi f(\chi_n) & 0 & 1 \\ \nabla_\chi H_n(\chi_n) & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} \delta\chi_n \\ \delta J_n \\ \delta v_n \end{pmatrix} \tag{5}$$

The adjoint model is defined by taking the transpose of the matrix in (5):

$$\begin{pmatrix} \chi_n^* \\ J_n^* \\ v_n^* \end{pmatrix} = \begin{pmatrix} 1+\nabla_\chi f(\chi_n) & \nabla_\chi H_n(\chi_n) & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} \chi_{n+1}^* \\ J_{n+1}^* \\ v_{n+1}^* \end{pmatrix} \tag{6}$$

When this model is integrated backwards from the last time step N to time step 0 with initial conditions: $\chi^*_N = v^*_N = 0$ and $J^*_N = 1$, it can be shown that

$$v_O^* = \nabla_v J_N \tag{7}$$

where $\nabla_v J_N$ is the gradient of the objective function with respect to the nudging term, which we want for the minimization algorithm.

Figure 2 is a rather complicated diagram that attempts to show schematically how the adjoint method works. It represents one cycle of the data assimilation. Currently,

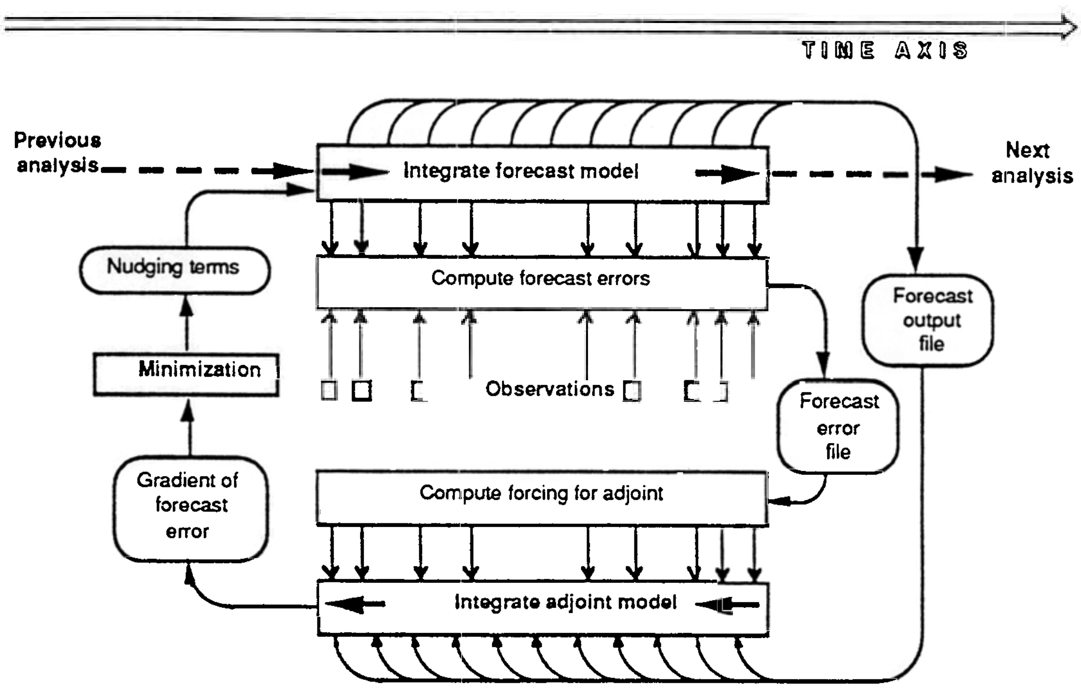

Figure 2. Schematic diagram of one cycle of the variational data assimilation, showing the flow of data.

we are finishing writing the adjoint of the Toon et al radiation scheme.

Reference

Toon, O. B., C. P. McKay, T. P. Ackerman, and K. Santhanam. 1989. Rapid calculation of radiative heating rates and photodissociation rates in inhomogeneous multiple scattering atmospheres. *J. Geophys. Res.* D13, 16287-16301.