Single Column Variational Assimilation Experiments with Atmospheric Radiation Measurement Data

J.-F. Louis and M. Živković
Atmospheric and Environmental Research, Inc.
Cambridge, Massachusetts

In this paper we present results of variational data assimilation experiments using Atmospheric Radiation Measurement (ARM) observations over the Southern Great Plains Cloud and Radiation Testbed (CART) Site. Large scale forcing for the single column ALFA model (AER Local Forecast and Assimilation model) is provided by data from the Mesoscale Analysis and Prediction System (MAPS), and we are currently assimilating data from radiosondes, surface observations, Bowen ratio measurements, and broad band radiometers. The experiments were designed to explore two issues relevant to successful assimilation of the ARM observations: 1) definition of the adjustment terms required for data assimilation, and 2) representativeness of the observations from different CART facilities on the scale of the entire CART site. More detailed results related to the second issue are presented in the second paper by the same authors (see Živković and Louis 1997). The results presented here focus on the first of these issues—defining the adjustment terms and on the convergence characteristics of the minimization algorithm used in the variational data assimilation.

Variational Method

Variational data assimilation is based on minimization of an objective function that is constructed as a weighted sum of all the square differences between observations and model computations over an assimilation window. The analysis is obtained by modifying the model simulation to minimize this objective function. We could simply modify the initial state for the simulation over a 24-hr assimilation window, and we have experimented with this approach. However, it strongly constrains the analysis to the model and implies that the model errors are much smaller than the initial state errors. This assumption is probably not correct, and we have relaxed these constraints by using adjustment terms as control variables. The adjustment terms are added to the model tendencies and are modified until they minimize the objective function. The final analysis is then only weakly constrained by the model.

One can symbolically write the modified forecast model equations representing the step from time t_{i-1} to t_i as

$$\psi^i = A^i(\psi^{i-1}) + \nu^i \qquad (1)$$

where A^i is the nonlinear model operator acting upon the generalized variable ψ^{i-1}. In our experiments, we define the adjustment term ν^i to be a smooth function of time and height by representing it as a combination of basis functions

$$\nu^i(z,t) = \sum_k^6 Z_k(z) \cdot \left(\lambda_1^k + \lambda_2^k \cdot \sin\left(\frac{2\pi i\Delta t}{24}\right) + \lambda_3^k \cdot \cos\left(\frac{2\pi i\Delta t}{24}\right)\right). \qquad (2)$$

where the functions Z_k are Gaussian curves with maxima at heights that correspond to standard pressure levels and Δt is the time step. The λ coefficients are the control variables for the minimization of the objective function.

A necessary requirement for a practical variational data assimilation is fast convergence of the minimization algorithm. The convergence rate of the minimization algorithm is related to the condition number of the Hessian matrix of the problem (Luenberger 1984). Problems with an ill-conditioned Hessian matrix usually have large condition numbers (the ratio between its maximum and minimum eigenvalue). This results in a low convergence rate since the isopleths are very distorted and the calculated descent direction may be almost orthogonal to the optimal direction. One way to speed up the algorithm convergence in such cases is preconditioning by a diagonal matrix based on diagonal elements of an estimated Hessian (e.g., Yang et al. 1996; Nash 1985; Županski 1993).

The minimization algorithm (a version of the conjugate gradient method) goes through a number of iterations for each 24-hour period. At the end of each iteration, a new set of adjustment coefficients becomes available, and a new simulation is produced. With each iteration the simulation more closely approaches the observations. The diagrams in Figure 1 illustrate this process for six consecutive iterations. Adjustment coefficients are optimized when the minimum of the objective function is reached. Usually, it takes fewer than 20 iterations to find the minimum of the objective function.

Data

We started analyzing data from the CART site soon after they became operationally available. In our analysis we used sounding data from four boundary facilities and the central site. Also, we used energy balance Bowen ratio (EBBR) observations at ten facilities, surface meteorological observation system (SMOS) observations at five facilities, and Baseline Surface Radiation Network (BSRN) observations at the central facility. In this paper, we present results for the central facility. The data processing is detailed in Živković and Louis (1997) in this volume.

Our analyses were limited to the intensive observation period (IOP) days when complete MAPS data (Mesoscale Analysis and Prediction System of the NOAA Forecast System Laboratory) were available. The MAPS data are needed to calculate horizontal advection terms for the ALFA model. Unfortunately, many of the MAPS data sets were incomplete over the 24-hour assimilation window periods that we considered in our applications, and they were entirely missing after 1994. This limited the number of days of single column model (SCM) IOPs when we could perform the analyses. Among the 1994 IOPs, only 15 days of complete MAPS data were available: 4 days in April, 3 days in July, and 8 days in October.

Experiments

We have performed several types of optimization experiments. In the set of experiments described here, we started from initial states interpolated from the MAPS data at 00Z for each day and used soil parameters (heat capacity, albedo, roughness length, etc.), which are representative of the type of terrain in the CART site. The experiments showed that the variational method works as expected with generally fast convergence of the minimization procedure. The resulting analysis follows the data fairly well. However, the initial state provided by interpolated MAPS data is clearly not accurate enough, especially near the surface, and we found indications that our soil parameters were not entirely appropriate.

Figure 2 illustrates results for five consecutive analyses for the central observational facility (we have generated analyses for another four sites as well [see Živković and Louis 1997]). The thin solid line is the short-wave surface flux observed by the broad-band radiometer (BSRN data). The lighter dotted line represents the first guess, i.e., the model solution with adjustment terms set to zero, at the start of the minimization. The dark dotted line represents the analyses, i.e., with the final adjustment terms.

The temperature time series during these five days reflect the synoptic situation with a cold front passing on 11/9, followed by three days of relatively clear skies, and finally a warm front passage (overcast sky) on 11/13. The analysis is noticeably poorer on the last day. This points to a deficiency in our cloud parameterization which cannot be rectified by the adjustment terms.

However, the analysis deficiency may not be related only to the cloud scheme since the analysis is fairly good in another cloudy case, on 11/9. It is likely that the model parameters describing the soil characteristics are also not quite correct. In the second set of experiments we then performed simultaneous optimization of the adjustment coefficients and the soil parameters. This showed that the definition of the parameters could be refined by this method, but that a longer time series would be necessary.

Finally, the third set of experiments consisted of optimizing the adjustment terms as we did in the first set, but with the initial state for each day's assimilation taken at the end of the previous day's analysis. This showed that cycling the data assimilation in this way can indeed provide better initial conditions. Figure 3 illustrates this for surface temperature at the central observational facility. Again, the thin solid line (with the shading) represents observations, in this case surface temperature as provided by the SMOS data. The dark dotted line represents the analyses from the first set of experiments (denoted as “opt6”). The lighter dotted line represents the analyses obtained with the initial state for each day’s assimilation taken at the end of the previous day's analysis (denoted as “opt8”). Clearly, the analyses for the first day (11/9) are identical. The following days show an improvement, particularly during the daylight. However, the most noticeable improvement is the last day, 11/13, when a warm front passage was characterized by an overcast sky condition.

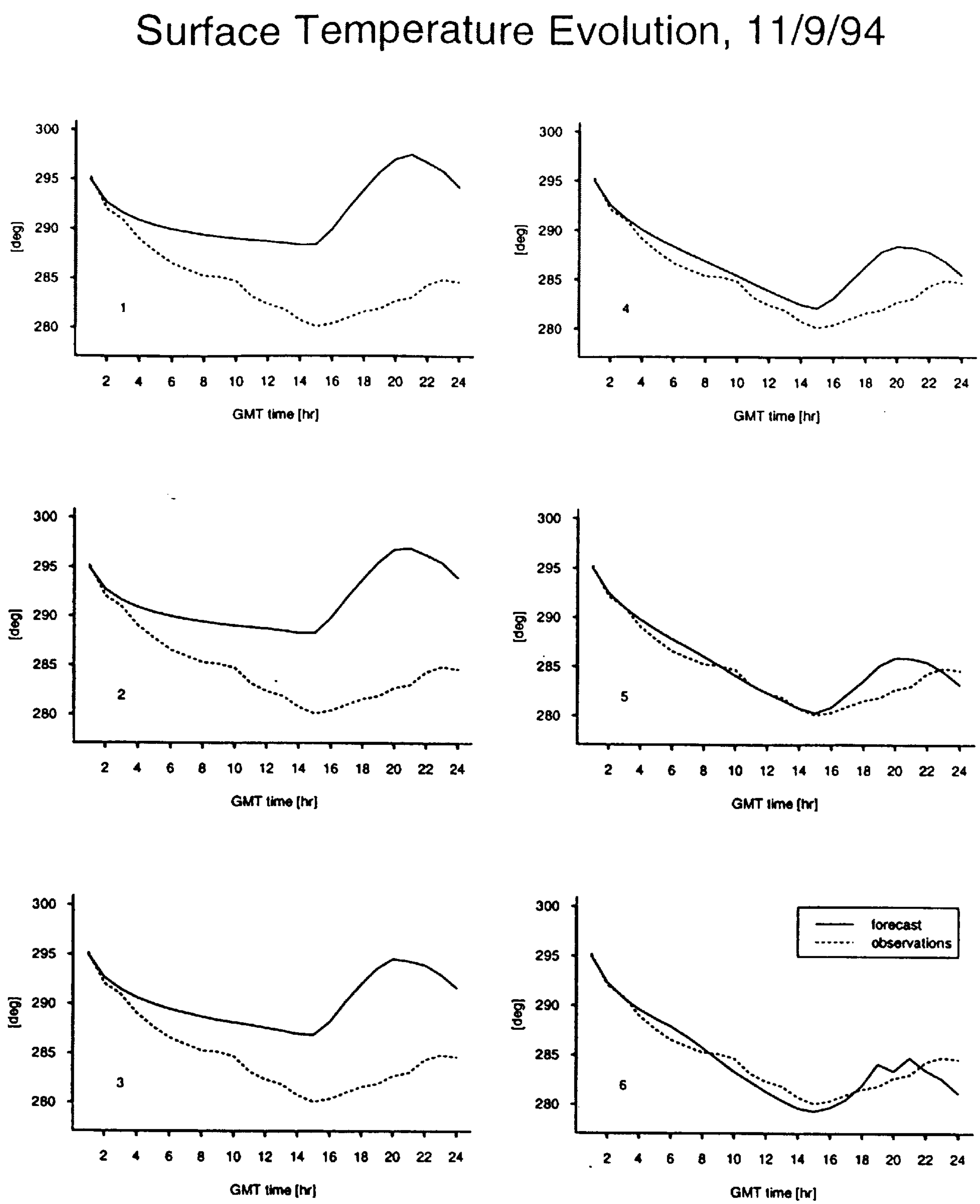

Figure 1. Comparison of 24-hr surface temperature forecast with observations during the first six iterations of the minimization algorithm.

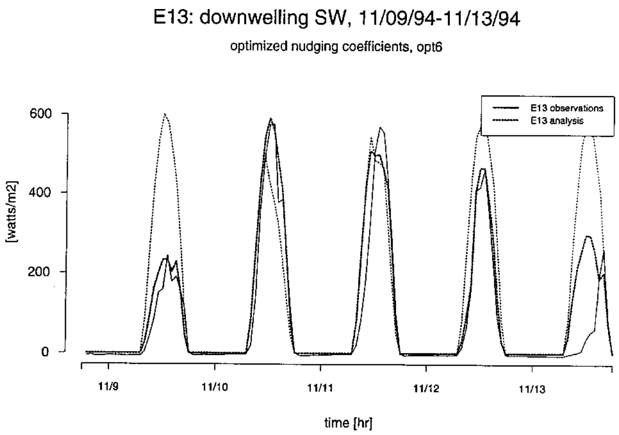

Figure 2. Time series of five consecutive short-wave flux analyses based on 24-hr data assimilation window started from independent initial states.

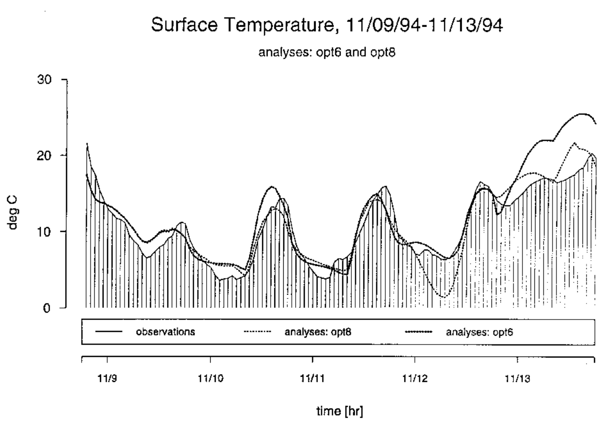

Figure 3. Time series of five end of the previous day's analysis.

References

Luenberger, D. L. 1984. *Linear and Non-linear Programming*. Addison-Wesley, 2nd edition, 491 pp.

Nash, S. G. 1985. Preconditioning of truncated-Newton methods. *SIAM J. Sci. Stat. Comput.* **6**, 599-616.

Yang, W., I. M. Navon and P. Courtier. 1996. A new Hessian preconditioning method applied to variational data assimilation experiments using a NASA General Circulation Model. *Mon. Wea. Rev.*, **124**, 1000-1017.

Živković, M., and J.-F. Louis. 1997. Subgrid-Scale Variability and Data Assimilation over Cloud and Radiation Testbed Observational Facilities. *Proc. Fifth Atmospheric Radiation Measurement (ARM) Science Team Meeting*. U.S. Department of Energy, Washington, D.C.

Županski, M. 1993. A preconditioning algorithm for large-scale minimization problems. *Tellus*, **45A**, 478-492.