Data Assimilation with the Noah Land Surface model in NLDAS

Dag Lohmann, Pablo Grunmann, Helin Wei, Kenneth Mitchell
NOAA/NCEP/EMC, 5200 Auth Rd., Suitland, MD, 20746, USA

1. Introduction

Improving weather and seasonal climate prediction by dynamical models requires multidisciplinary advances in providing reliable initial states for the atmosphere, land and ocean components of the earth system. For two decades, advances in providing atmospheric initial states via 4-dimensional data assimilation (4DDA) have paved the way for the development of counterpart 4DDA systems for the ocean and land.

In 4DDA, a geophysical model provides temporally and spatially continuous background states into which temporally and spatially discontinuous observations are assimilated from various observing platforms (in situ, satellite, radar). The backbone then of any atmospheric, ocean or land 4DDA system is the geophysical model whose day-to-day execution provides the continuous timeline of background states. A land data assimilation system (LDAS) blends sparse land observations with the background fields of a reliable land surface model (LSM). The accuracy of the LSM background field (and the attendant surface and sub-surface water/energy fluxes that drive those background fields) is crucial to the viability of an LDAS.

We present the progress within NOAA/NCEP/EMC to develop such a land surface data assimilation system. This progress includes the development of the adjoint model / tangent linear model for the Noah LSM (Ek et al., 2003) and it's incorporation into the North American Land Data Assimilation System (Mitchell et al., 2004), referred to as NLDAS. We demonstrate here the improvement achieved in Noah LSM 1-D column-model simulations of soil moisture by means of an "identical twin" experiment, which assimilates the land surface temperature (LST) produced by a Noah LSM control run. We will show results of the assimilation of hourly satellite-derived LST retrieved from NOAA GOES satellites with a simplified 4D-Var procedure.

2. Influence of soil moisture on LST in the Noah LSM

Before embarking on LST assimilation to improve the Noah LSM simulation of soil moisture, it is important to quantify the impact of soil moisture changes on the LST simulations of the Noah LSM. To assess this impact, we performed Monte-Carlo simulations for the year 1998, preceded by one year of spin-up (1997). Herein the 1-D Noah LSM column model was forced with surface meteorological data observed at 30-minute intervals from a Champaign, Illinois flux station (40.01 N latitude, 88.37 W longitude) operated by NOAA/ARL (Tilden Meyers, personal communication). We executed an 8000-member ensemble of Noah LSM simulations, in which each simulation utilized a different random specification of model parameter values, wherein we constrained the parameters by our knowledge (belief) in reasonable parameter ranges.

The resulting ensemble-mean of the simulated LST and the LST standard deviation of the ensemble are shown in Figures 1a and 1b. Additionally, the ensemble mean and standard deviation of the derivative of LST with respect to soil moisture -- d (LST) /d (soil moisture) -- in the Noah model are shown in Figures 1 c and 1d. During the warm season (April – October) this ensemble mean derivative is negative with values up to -0.4K per one percent volumetric soil moisture change (total column), while the ensemble shows a variance of up to 2K.

We therefore can expect to successfully assimilate LST into the Noah LSM if we can find parameters that yield unbiased estimates in the Noah LSM of LST and other state variables and fluxes, assuming that the LST measurements themselves are unbiased. This will be explored further in our workshop presentation in the context of A) parameter optimization (especially for NLDAS regions with limited available measurements) and B) the assimilation of GOES-derived LST.

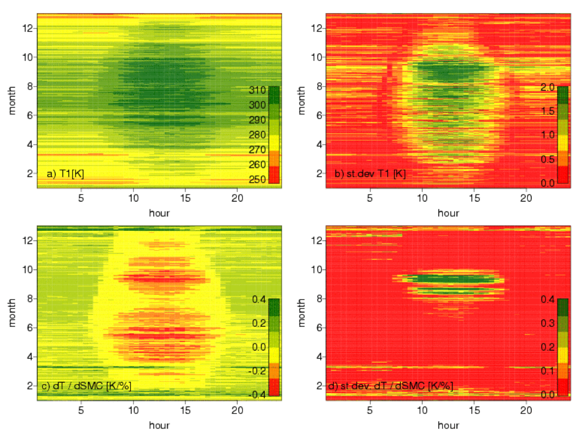
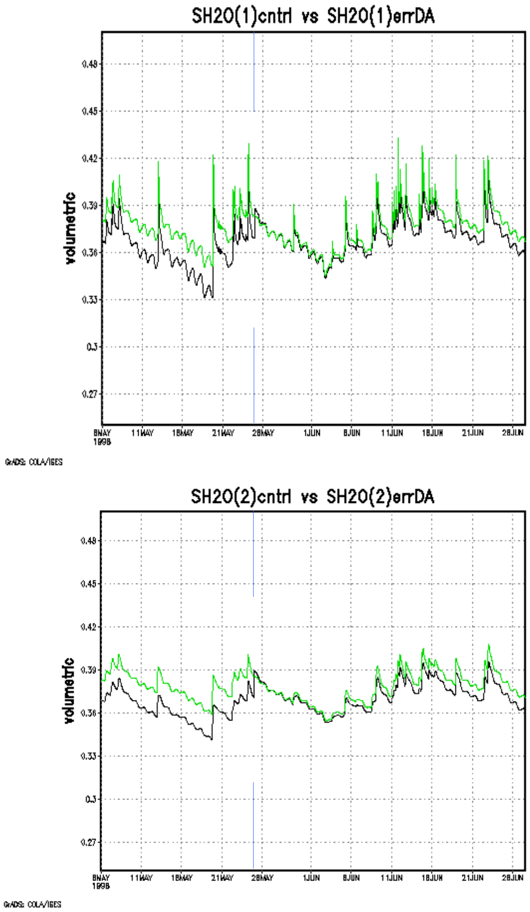


Figure 1. Results of the Monte Carlo Noah LSM simulations for 1998, showing ensemble mean of LST (upper left) , standard deviation of the ensemble LST (upper right), ensemble mean of the derivative of LST with-respect-to soil moisture (lower left) and standard deviation of the latter (lower right). The x-axis is the hour of the day and the y-axis is the month of year.

3. 1D Identical-Twin Experiments

To test our basic assimilation approach, we performed a 1-D identical-twin experiment with the Noah LSM column model. In this experiment, the control run used the Noah LSM default parameter values and the one-year spin-up initialization and forcing data of the Champaign, IL site as in Section 2. The companion data assimilation run was identical to the control run, with two exceptions. First, following the spin-up year (1997), we degraded the forcing throughout 1998 by imposing a 30% reduction to all moderate or greater amounts in the 30-minute precipitation forcing. Second, we assimilated the control-run LST during the 3½-day period beginning 0000 UTC on May 25.

Figure 2 shows the layer-1 and layer-2 soil moisture of the control run (‘cntrl’, green line) and the data assimilation run (‘errDA’, black line) for a nearly two-month interval (May-June) of 1998. The vertical blue lines in Figure 2 denote the beginning of the 3½-day assimilation period. During this period, the assimilation routine calculates the cost function and the tangent linear of the Noah LSM and finds the optimal correction to the soil moisture content for 0000 UTC on May 25 that minimizes the difference between the "control" and simulated LST over the subsequent 3½ days. No assimilation was performed after this 3½-day period and therefore the two runs drift apart in June. Our presentation will include more examples and give more details of the setup. The numerical optimization was performed using a Truncated-Newton scheme, adapted from Nash, Stephen G., 1984: SIAM J. Num. Anal.770-788.



Figures 2. Volumetric soil moisture content for model soil layers of 0-10 cm depth (upper panel) and 10-40 cm depth (lower panel) for the control run (green) and data assimilation run (black).

4. Simplified 4D-Var Data Assimilation in NLDAS

The NOAA operational partners in NLDAS include NCEP/EMC and OHD of the NWS and NESDIS/ORA, who have joined with the NLDAS research partners of NASA/GSFC, Princeton and Rutgers University, and the Universities of Maryland, Oklahoma and Washington. These partners have developed, executed, and evaluated a realtime and retrospective uncoupled NLDAS. The NLDAS generates hourly surface forcing (anchored by observation-based solar insolation and precipitation fields) and uses this forcing to drive four LSMs running in parallel to produce hourly output on a common 1/8° grid over a CONUS domain. The paper of Mitchell et al. (2004) contains all the references of other papers published within this project that measure the quality of the forcing data and assess the model results.

We present a highly simplified method of how to assimilate skin temperature data into the Noah land surface model soil moisture state variable. Based on the cost function

$$J(x) = (x - x_b)^T B^{-1}(x - x_b) + \sum_{i=1}^{n} (y_i - H_i[x_i])^T R_i^{-1}(y_i - H_i[x_i])$$

where J is the cost function, X the model state (soil moisture), Xb the model background state, B the background error covariance matrix, n the number of observations, Y the observed state, H the observation operator, and R the error covariance matrix for observation errors. The 4D-Var starts with the following assumptions:

$$\boldsymbol{x}_i = \boldsymbol{M}_i \boldsymbol{M}_{i-1} \ldots \boldsymbol{M}_1 \boldsymbol{x}_1$$

1) The Noah model can be linearized around its background state and be written as a succession of linear operators.

2) The observation operator can be linearized

$$y_i - H_i M_{1\to i}(x) \cong y_i - H_i M_{1\to i}(x_b) - \mathbf{H}_i \mathbf{M}_{1\to i}(x - x_b)$$

We then apply the following simplifying assumptions:

a) M = I, soil moisture doesn't change more than 1% of total soil moisture in a day due to ET

b) Hi = [dT/d(soilm)] is constant throughout the daily data assimilation window (6 hours)

c) B, R = diagonal for the estimation of the cost function. Weighting coefficients chosen based on empirical evidence

This leads to the following gradient of the cost function (without the background term)

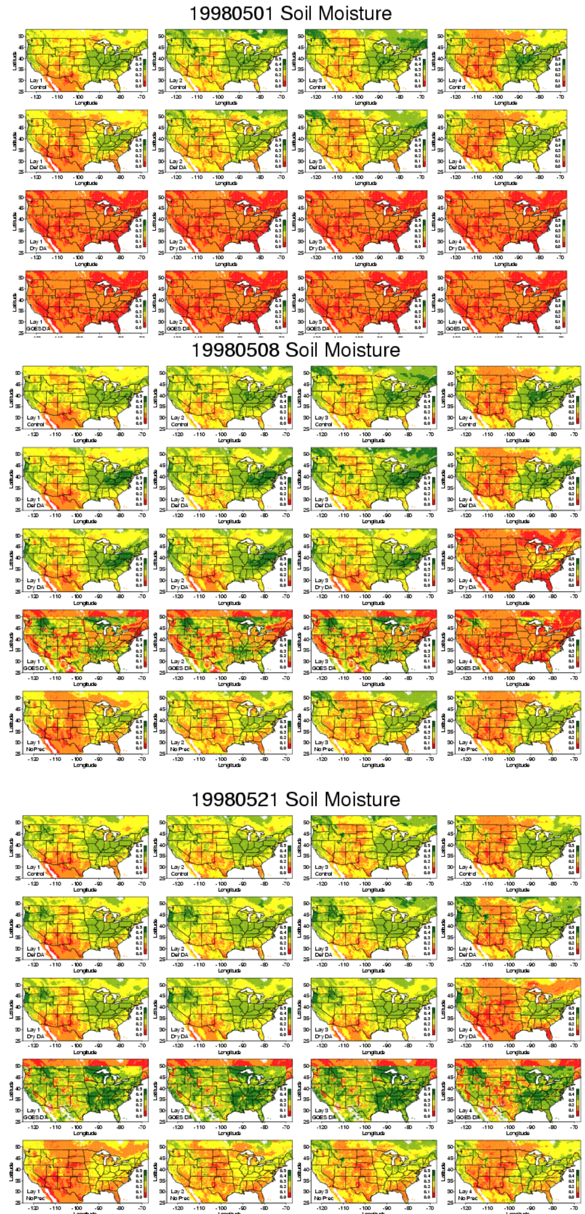
$$-\tfrac{1}{2}\nabla J(x) = \sum_{i=1}^{n} H_i^T (y_i - H_i x_i) = H^T \sum_{i=1}^{n} (y_i - H_i x_i)$$

The cost function for the analysis increment has a minimum where the gradient equals zero, therefore the sum of the differences has to be zero.

$$x = x_b + \frac{1}{n * H} \sum_{i=1}^{n} (y_i - H_i x_b)$$

This is the state update equation for the case that the measurements are perfect and the background has no weight. Timescales of adjustement can be choosen by only using fractions of the increment, e.g. 50%.

This method was used in an Identical Twin-Experiment over the NLDAS region for May to September 1998, as well as with skin temperature data from the GOES satellite. For all the data assimilation runs precipitation is set to zero, the DA model run just gets the hourly surface temperature from the control run or the GOES satellite as information for a 6 hour assimilation window per day. No soil moisture was assimilated into layer four. The columns in Figure 3 show the volumetric soil moisture for the four soil layers at six different times (initial conditions, 8 days and 21 days). In row four we replaced the surface temperature of the control run with GOES based skin temperature. We will introduce a simple bias correction scheme to adjust for the different climatologies in the GOES data compared to the Noah model output.



Figures 3. Row 1 = Control experiment; Row 2 = Data assimilation run initialized from Row 5; Row 3 = Data assimilation run initialized with wilting point
Row 4 = Data assimilation with GOES skin temperature run initialized with wilting point, Row 5 = Initialized 3/1/1998, no precipitation used for initializing data assimilation runs

References

Mitchell, K., D. Lohmann, P. Houser, E. Wood, A. Robock, J. Schaake, B. Cosgrove, J. Sheffield, L. Luo, Q. Duan, D. Lettenmaier, R. T. Pinker, D. Tarpley, W. Higgins, J. Meng, A. Bailey, F. Wen, The Multi-institution North American Land Data Assimilation System (N-LDAS): Leveraging multiple GCIP products in a real-time and retrospective distributed hydrological modeling system at continental scale, J. Geophys. Res. 109,D07S90,doi:10.1029/2003JD003823, 2004.

Ek, M. B., K. E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, G. Gayno, and J. D. Tarpley, Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta model, J. Geophys. Res., 108(D22), 8851, doi:10.1029/2002JD003296, 2003.