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REANALYSIS LAND DATA ASSIMILATION USING ENSEMBLE TECHNIQUES

Susan C. Dunne *[1], and Dara Entekhabi [1]

[1]Ralph M. Parsons Laboratory, M.I.T.

ABSTRACT

The objective of this research is to develop a data assimilation framework in which microwave brightness temperatures at various temporal and spatial resolutions, and frequencies may be merged with a mainstream land surface model using an ensemble Kalman smoother to obtain consistent estimates of soil moisture and surface fluxes. Land data assimilation using filters, such as extended or ensemble Kalman filters, the data is ingested sequentially as it becomes available. This framework is appropriate for forecasting problems where the observations up to the current time are used to update the initial conditions for forecasts into the future. In the land data assimilation problem, the objective is often reanalysis rather than forecasting. Smoothing combines future and past data to make an estimate. This additional information on how the system evolves yields improved estimates of the state at the present time. The hypothesis of this research is that developing an ensemble smoother from a successful ensemble Kalman filter algorithm would lead to improved estimates by extracting more information from the observational data available. This hypothesis is founded on the principle of smoothing and analysis of results from the ensemble Kalman filter approach. The final data assimilation framework will be used to make mission design decisions for future soil moisture missions and will demonstrate the suitability of ensemble smoothing to reanalysis-type problems in hydrology.

1 FILTERING AND SMOOTHING

There are three fundamental types of problem in data assimilation, namely filtering, forecasting and smoothing. Filtering techniques are ideal for control problems as they estimate the state as each new observation becomes available. Forecasting techniques are used to determine the state at a time later than the last measurement, and so are used in Numerical Weather Prediction and flood forecasting. Smoothing is ideal for analysing historic data, so that the state estimate at a given time is determined by including subsequent observations. As hydrologists our goal is not likely to be forecasting soil moisture as its future state is largely dictated by future precipitation. We are often,however, interested in performing a reanalysis of soil moisture data obtained during field campaigns (e.g. SGP97,SGP99 and SMEX02), or from future pathfinder missions such as HYDROS and SMOS. As we will have data for the entire study interval, using a smoothing technique rather than a filtering technique enables us to extract information from later observations to improve our estimate of the current state.

2 ENSEMBLE TECHNIQUES

The classic Kalman filter provides the optimal state estimate for linear systems. It is therefore of limited use in hydrological applications where the physical models are often non-linear. In the extended Kalman filter approximate expressions are found for the propagation of the conditional mean and its associated covariance matrix. The structure of the propagation equations is similar to those of the classic Kalman filter for a linear system, as they are linearized about the conditional mean. Linearization of the Kalman filter is seriously prone to unstable growth of the covariance matrices (Ljung, 1979). Any artificial limits on the propagation of the covariance matrix results in suboptimal filters and poor estimation. To use an Extended Kalman Filter in the soil moisture estimation problem would require derivation of a tangent linear model to approximate the Land Surface Model, as well as techniques to treat the instabilities which may arise from this approximation. Fortuitously, Ensemble techniques offer a means to avoid such linearizations. In the Ensemble Kalman filter an ensemble of model states is integrated forward in time and used to calculate the mean and error covariance when required. The traditional update

*Corresponding author address: Susan Dunne, Mass. Inst. of Tech., Dept. of Civil & Environmental Engineering, Cambridge, MA 02139; email: susan@mit.edu

equation from the classical Kalman filter is used, with the Kalman Gain calculated from the error covariances provided by the ensemble.Our goal is to develop an ensemble-based smoother from a successful Ensemble Kalman filter algorithm for use in the land data assimilation problem. The hypothesis of this research is that estimates obtained using ensemble smoother techniques will improve on those obtained by ensemble filtering, as they include information on the future state as well as its prior state.

3 ENSEMBLE MOVING BATCH SMOOTHER

Our ensemble smoother algorithm is an extension of the the sequential Ensemble Kalman filter used in Margulis *et al*. (2002). The Kalman filter equations are identical, except that the state vector and covariance are augmented to include the states at times subsequent to the time of interest. The interval over which we smooth is bound by observations, as observations are the means by which information is incorporated into the smoother. The augmented state vector will therefore consist of the states at the observation times, but can include states at any times at which we desire an estimate. By controlling the number of observations over which the smoother extends and the number of intermediate states we can effectively limit the computational burden.

4 OTHER COMPONENTS OF THE DATA ASSIMILATION FRAMEWORK

4.1 Forward Model

The NCAR Land Surface Model Version 1.0 (Bonan *et al*. (1996)) shall be used as the forward model in this data assimilation framework. NCAR LSM is a 1D model of energy, momentum, water, and CO_2 exchanges between the atmosphere and land accounting for ecological differences among vegetation types, thermal and hydrological differences among soil types and multiple surface types including lakes and wetlands within a grid cell. The biophysical and biogeochemical fluxes depend on the ecological and hydrologic state of the land, which are updated by ecological and hydrologic sub-models. Hydrologic processes modeled include interception, throughfall and stemflow, snow accumulation and melt, infiltration and run-off, soil hydrology, including water transfer in a six-layer soil column

4.2 Meteorological Forcing Data

In this experiment, we use forcing data recorded at El Reno during SGP97. Precipitation forcing was generated using the Rectangular Pulses Model using parameters from Hawk and Eagleson (1992) appropriate to Oklahoma City . This ensemble was conditioned on the five-day total from the real precipitation. This enables us to have temporal uncertainty as well as uncertainty in the amount of precipitation which occurred. (Margulis, 2003).

4.3 Radiative Transfer Model

The radiative transfer model relates the states of the model to the radio brightness observations. The radiative transfer model used is based on that used in Jackson *et al*. (1999) to retrieve soil moisture from ESTAR observations during SGP97. However, we include the effects of soil moisture on soil dielectric properties by including the mixing model of Wang *et al*. (1980). Surface roughness and vegetation effects from Choudhury *et al*. (1979) and Jackson *et al*. (1991) respectively are also included.

5 EXPERIMENTAL SET-UP

To test the smoother algorithm, we will use an Observing System Simulation Experiment (OSSE). The model is forced with the true precipitation recorded at El Reno during SGP97. The model parameters are just one realization of the possible ensemble of parameters, so the simulated truth is effectively one realization from the ensemble. We generate the observations which would have been obtained has this sythetic truth been observed. The experimental objective is to try to estimate this synthetic truth using the land surface mode, the ensemble moving batch smoother and the synthetic observations.

6 RESULTS

It will be shown that using the ensemble moving batch smoother can yield improved estimates of the desired states. For example, Figure 1 shows that the Ensemble Kalman Filter improves on the estimate obtained using the Ensemble Open Loop and that this estimate can be further improved by implementing the Ensemble Moving Batch Smoother. Alternatively, this improvmenent can be shown in terms of the covariance as in Figure 2. The covariance across the updated ensemble when the Ensemble Kalman Filter is used is lower than that of the Ensemble Open Loop. A greater reduction in covariance can be achieved if we use the Ensemble Moving Batch Smoother rather than the Ensemble Kalman Filter.

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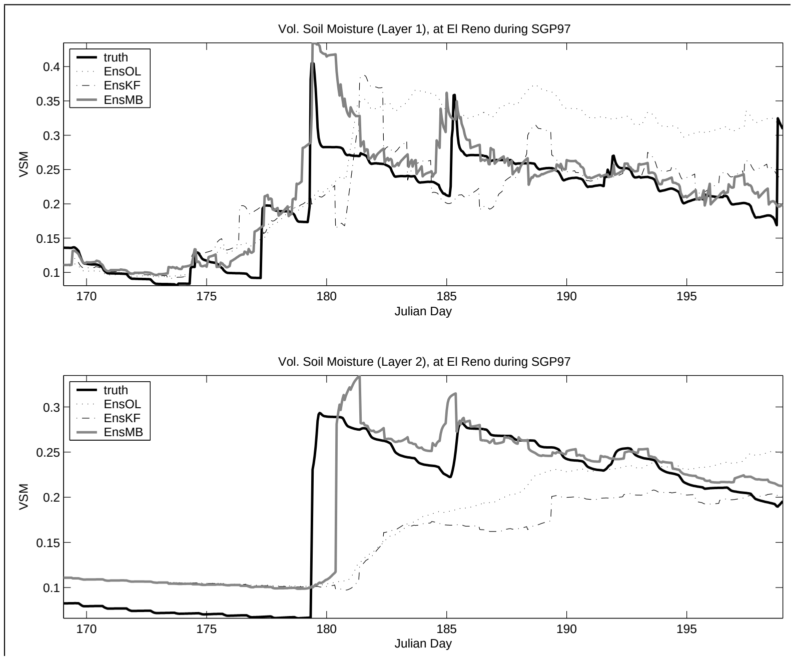

Figure 1: Volumetric Soil Moisture in the surface layer (top panel) and the second layer (lower panel) at El Reno during SGP97. Estimated volumetric soil moisture from the Ensemble Moving Batch Smoother (EnsMB) is compared to the truth as well as estimates from the Ensemble Open Loop (EnsOL) and the Ensemble Kalman Filter (EnsKF).

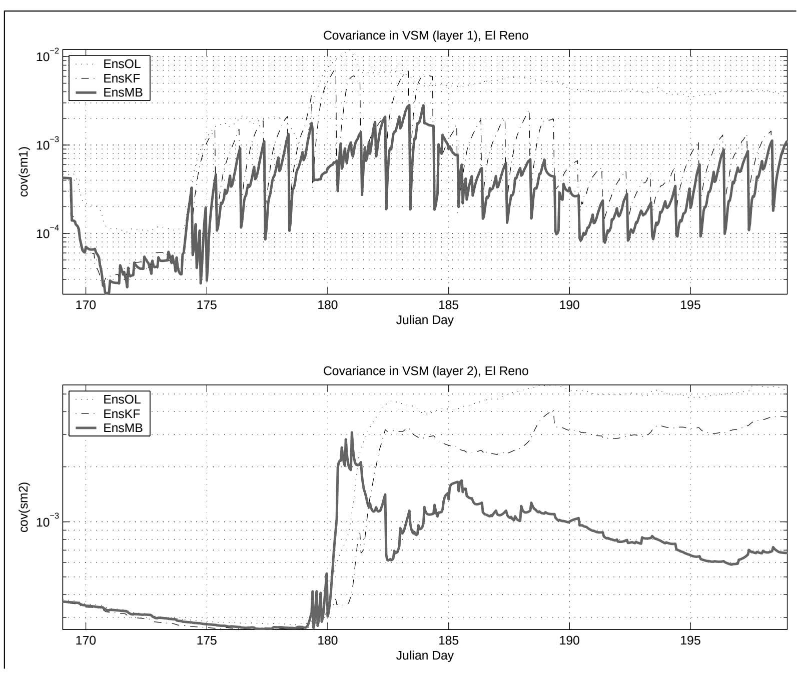

Figure 2: Volumetric Soil Moisture in the surface layer (top panel) and the second layer (lower panel) at El Reno during SGP97. Estimated volumetric soil moisture from the Ensemble Moving Batch Smoother (EnsMB) is compared to the truth as well as estimates from the Ensemble Open Loop (EnsOL) and the Ensemble Kalman Filter (EnsKF).