Assimilation of Remote Sensing Data in a Hydrologic Model to Improve Estimates of Spatially Distributed Soil Moisture

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***Abstract* - A data assimilation scheme has been applied using field data to determine the effects of the temporal frequency at which remote observations are assimilated to adjust model soil moisture profiles. It was found that, in terms of near-surface soil moisture, there is generally a gradual decrease in performance as the update frequency decreases. Performance for update periods longer than 8 days is nearly identical to that of a simulation performed without assimilation.**

I. INTRODUCTION

Soil moisture profiles estimated by land surface models are affected by errors in (1) meteorological inputs, particularly precipitation, (2) soils, vegetation, and topography parameters, and (3) model physics. Assimilating accurate observations into such models may reduce the impact of errors and improve soil moisture estimates. In this paper, we discuss a system for assimilating remote microwave measurements into a land surface model using a Kalman filter. Data from the Southern Great Plains 1997 (SGP '97) Hydrology Experiment are used in a series of model simulations designed to examine how model performance changes as the time period between times of data assimilation is altered. Model performance is evaluated based on surface layer soil moisture estimates.

II. ASSIMILATION SYSTEM

The assimilation system consists of three components: (1) a land surface model to estimate soil moisture and temperature profiles, (2) a microwave radiobrightness model to estimate brightness temperatures, and (3) a Kalman filter to assimilate remotely-sensed brightness temperatures. The land surface model used is SHEELS, the Simulator for Hydrology and Energy Exchange at the Land Surface [1],[2]. SHEELS simulates three soil 'zones', with each zone being divided into a variable number of 'layers'. SHEELS estimates volumetric water content for each soil zone and layer using Darcy flow to model sub-surface fluxes and a kinematic wave approach to simulate overland flow. In this study, the upper, root and bottom soil zones extend to depths of 100, 1000 and 2000 mm, and are sub-divided further into five, five and three layers, respectively.

Six basic meteorological variables plus precipitation are required as surface boundary conditions. The basic meteorological inputs were applied uniformly in space, while precipitation was treated as spatially variable as described below. Soil properties were derived from the CONUS 1 km soil characteristics data set, and vegetation properties were based on a landcover classification from Landsat-TM data [3].

The radiobrightness model used in this study is a coherent radiative transfer (CRT) model [4]. The model is based on the vertical profiles of temperature and emissivity, the latter of which is strongly controlled by the soil moisture content. Required input variables to the CRT are surface temperature, vegetation water content, and profiles of soil moisture, temperature and porosity.

An extended Kalman filter is used to update the model soil moisture profile by assimilating remote measurements [1]. In the Kalman filter, intermittent microwave brightness temperature observations and the model soil moisture state are blended to yield an optimal estimate of the soil moisture profile. The amount of nudging toward the observations is based on the relative uncertainties of the model state and the observations and the difference between the two.

III. DESCRIPTION OF NUMERICAL EXPERIMENT

One of the most useful gridded rainfall data sources in the US is the NOAA Stage IV hourly 4-km product. However, these estimates are still prone to large errors. Because we had a very dense rain gauge network in our study domain, we were able to create gridded hourly rainfall estimates that we believe have much smaller errors than do

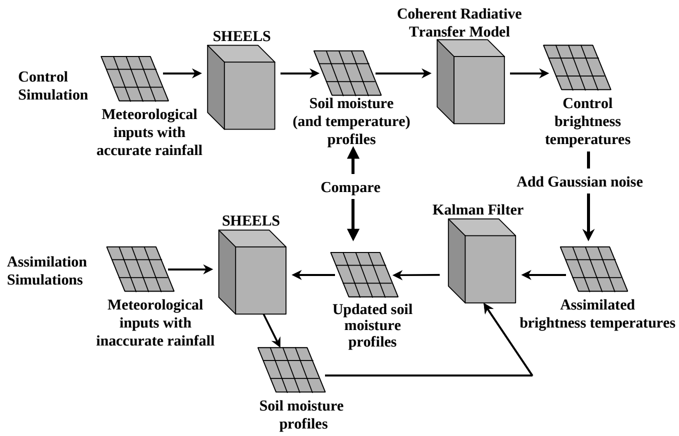

Fig. 1. Schematic showing coupling of model system components in control and assimilation simulations

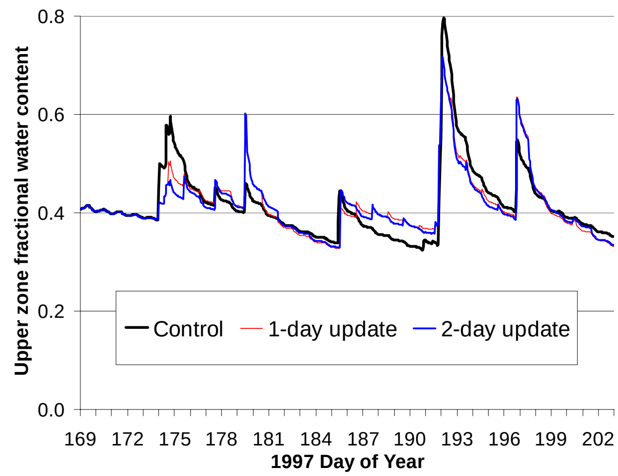

Fig. 2a. Hourly time series of upper zone fractional water content estimated by the control and 1- and 2-day assimilation simulations

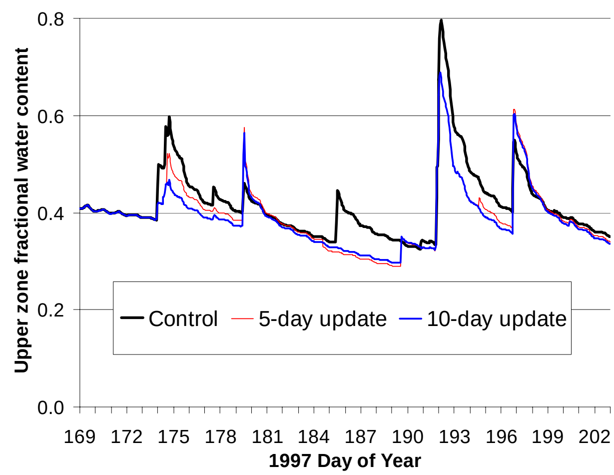

Fig. 2b. Same as fig. 2a except for 5- and 10-day assimilation simulations

Stage IV estimates. Our experimental design is based on two series of simulations, based on 'accurate' (gauge) and 'inaccurate' (Stage IV) rainfall inputs. Simulations using gauge input are referred to as 'control' runs, while those based on Stage IV data are called 'assimilation' runs. The control case was considered the 'truth', and the assimilation cases were compared to it. As shown in fig. 1, soil moisture and temperature profiles output from the control run at each model time step were passed to the CRT, which estimated L-band brightness temperatures. The control run brightness temperatures, with Gaussian noise added, provided the data needed for the assimilation simulations. Soil moisture estimates from each assimilation run were compared with values from the control case.

We applied the assimilation system using data from the 600 km^2 Little Washita River Basin in central Oklahoma. Data from SGP '97 were available for 18 June – 21 July (days of year 169-202). Meteorological data except rainfall were averaged over 40 USDA Micronet sites and applied uniformly across the domain. The control simulation was performed using these meteorological data and distributed rainfall estimates obtained from the rain gauge measurements.

Several assimilation runs were performed in which brightness temperatures output by the control run were assimilated at the following intervals: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 30 days, and no assimilation. In these runs, 'inaccurate' (Stage IV) precipitation inputs were applied to represent typical errors that can be expected in rainfall estimates. Daily differences between gauge and Stage IV rainfall estimates were both positive and negative, but the total basin-averaged Stage IV rainfall was 52 mm, significantly less than the 82 mm gauge rainfall estimate.

IV. Results

To illustrate the temporal behavior of soil moisture estimated by the assimilation simulations, figs. 2a-b show upper zone soil moisture estimates from simulations in which L-band brightness temperatures were assimilated at 1-, 2-, 5- and 10-day intervals. After the first rainfall on days 173-174, the assimilation runs underestimated soil moisture because the 'incorrect' Stage IV rainfall was only 6.0 mm while the 'correct' gauge rainfall was 13.7 mm. Data assimilation on day 175 reduced the differences for the 1- and 2-day update cases, but differences remained for the 5- and 10-day update cases until assimilation on day 179. Similar behavior is seen following the rainfall on day 179, but in this case the Stage IV rainfall estimates were greater than the gauge values, so the assimilation runs overestimated soil moisture. After the large rainfall on days 191-192, differences between the assimilation and control simulations persisted for several days. Assimilation slightly reduced these errors.

The benefit of data assimilation has been evaluated in terms of the root mean square error (RMSE) in upper zone fractional water content (fwu) between the control simulation and each assimilation simulation. RMSE time series of fwu are shown for 1-, 2-, 3-, and 10-day update periods in figs. 3a-

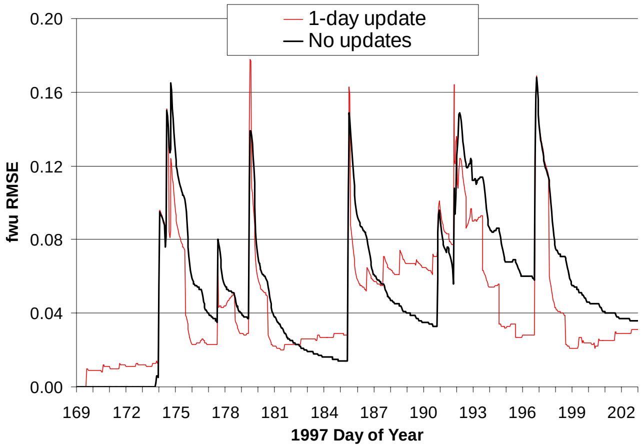

Fig. 3a. Root mean square errors in upper zone fractional water content for the 1-day assimilation simulation with respect to the control simulation

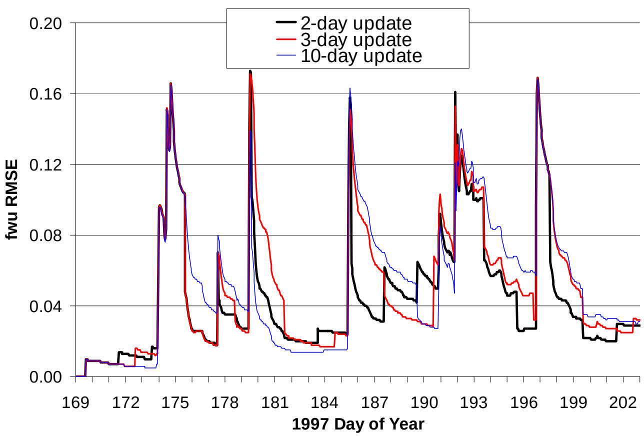

Fig. 3b. Same as fig. 3a except for 2-, 3-, and 10-day simulations

b. For update periods of 1, 2 and 3 days, RMSE values are generally lower than for the no-update case, particularly after rainfall events. The exceptions are the dry periods of days 182-184 and 187-190 for the 1- and 2-day update cases. For an update period of 10 days (fig. 3b), there is little overall improvement over the no-update simulation.

Time-averaged fwu RMSE values plotted in fig. 4 show a gradual increase in RMSE with update period, although 2-day updates give slightly better results than 1-day updates. Performance for update periods longer than 8 days is very nearly identical to that of the no-update simulation.

V. Summary and Conclusions

A modeling – data assimilation scheme has been applied using SGP '97 field experiment data to determine the effects of the temporal frequency at which microwave observations are assimilated into the system to adjust the soil moisture profile. A control simulation was performed using rainfall data from a dense rain gauge network, which is taken as ground truth. The control run served as a benchmark for a set of assimilation runs, which were based on Stage IV rainfall

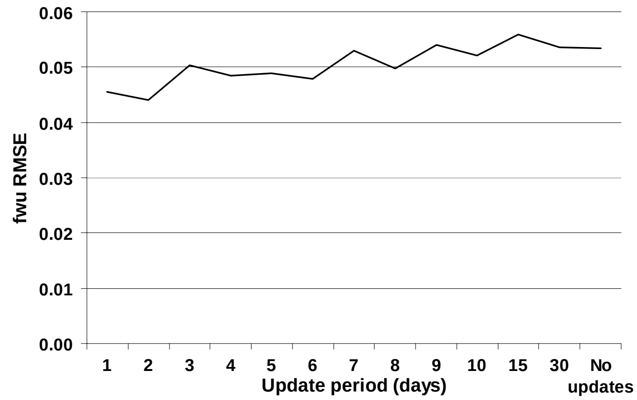

Fig. 4. Time-averaged RMS errors in upper zone fractional water content for all assimilation simulations with respect to the control simulation.

data. The radar estimates were found to differ greatly from the gauge data; these differences were considered errors in our study. L-band brightness temperatures derived from the control runs via a microwave radiobrightness model were used in the assimilation runs to update the moisture profile. Random noise was first added to the brightness temperatures to more realistically simulate application of the scheme. Because of the nature of our numerical experiment, it is not possible to draw inferences regarding the absolute value of the 'error' statistics shown here. Rather, the temporal behavior of errors and the changes in error statistics as the update period is increased is of relevance. We have shown, in terms of near-surface soil moisture, that there is generally a gradual increase in RMSE with update period.

Acknowledgment

This work was supported by Universities Space Research Association NCC8-140 under NASA Grant No. NCCW-0084 with Alabama A&M University. Contribution by the Center for Hydrology, Soil Climatology and Remote Sensing and the Agricultural Experiment Station, Alabama A&M University, Journal no. ???

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