

Chaojiao Sun*

University of Maryland Baltimore County and NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

Jeffrey P. Walker

University of Melbourne, Parkville, Victoria, AUSTRALIA

Paul Houser

NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

1. INTRODUCTION

Snow plays an important role in the Earth's global energy and water budgets, due to its unique qualities (high albedo, low thermal conductivity, and spatial and temporal variability). However, the modeling and prediction of snow is difficult because of its subgrid-scale variability and errors in the forcing data. Remotely sensed observations can provide information on snow cover, snow water equivalent and snow depth, which can be assimilated into models to improve predictions of snow.

Previous work in assimilating snow observations has typically used the direct insertion technique, which may cause excessive water fluxes due to erroneous snowmelt arising from a warm temperature bias. Our work seeks to develop an assimilation scheme that addresses these problems. Snow observations are assimilated into the Catchment-based Land Surface Model (CLSM), which is being used by the NASA Seasonal-to-Interannual Prediction Project (NSIPP) (Koster *et al.*, 2000; Ducharme *et al.*, 2000).

2. SNOW MODEL

The snow model component used by the CLSM incorporates various complicated snow physics including evaporation/sublimation/condensation, radiation, precipitation as rain or snowfall, mechanical compression, overflow, underflow, snowmelt, etc (Lynch-Stieglitz, 1994; Stieglitz *et al.*, 2001). To ensure a smooth transition from snow-bare to snow-covered state, it is assumed that snow accumulates to 13 mm of snow water equivalent before it spreads to the other regions of the catchment. A snowpack is treated as a single layer if the catchment is not completely covered by snow, i.e., its snow water equivalent W_p (averaged over the whole catchment) is less than 13 mm; otherwise, the snow pack is treated as three distinct layers of snow.

There are nine prognostic state variables in this snow model: snow water equivalent W_1, W_2, W_3 ; heat content H_1, H_2, H_3 ; and thickness Z_1, Z_2, Z_3 for each snow layer. Subscripts 1, 2, 3 refer to, respectively, the top layer (in direct contact with the atmosphere), middle layer and bottom layer (in direct contact with the ground). The

total snow water equivalent of the snowpack W_p is the sum of W_1, W_2 and W_3 . When there is no snow in the forecast, all state variables have values of zero.

When a catchment is only partially covered by snow, the snowpack is assumed to be homogeneous and the model treats the snowpack as a single layer: the snowpack exchanges heat and water with the atmosphere and the ground as a single entity. At the output time, the nine state variables are assigned values as if there are three layers of snow according to the following formula: the snowpack is divided into three layers of snow, the thickness of the top layer is 25% the snowpack, and the bottom layer is the lower 25% of the pack, while the middle layer occupies the remaining 50% of the pack. The three layers have similar fractions of snow water equivalent and heat content with respect to the snowpack.

When a catchment is completely covered by snow, the snowpack has three distinct layers, each with different density and temperature. The top layer is very thin, being less than the thermal damping depth of snow (about 6 cm) in order to capture the diurnal range in the surface radiation temperature. The other two layers may be thick. In this three-layer mode, meltwater may flow from one layer to another. In the lower layer, it may freeze, remain in the lower layer as liquid water, or flow through to the next layer. Liquid water leaving from the bottom layer is gone from the pack. There is also heat flow between the layers, the soil and the atmosphere.

3. METHODOLOGY

A one-dimensional extended Kalman filter (EKF) is applied to 24 catchments in North America. This is a focused study designed to test and evaluate the assimilation scheme with the CLSM. In a later study, the EKF will be applied to the entire North American continent using the bias-corrected forcing data of Berg *et al.* (2000) and snow observations from the SMMR and SSM/I space-borne instruments over the last 20 years.

To test our snow assimilation strategy, a synthetic study has been undertaken using the bias-corrected ECMWF forcing for 1987. To mimic the space-borne observations inferred from the passive microwave brightness temperature measurements, we have used model output of the total snow water equivalent of the snowpack at each catchment. The snow observation and truth data sets were generated by the CLSM after it had been spun-up to equilibrium. A degraded simulation

* Corresponding Author Address: Chaojiao Sun, NASA-GSFC, Mail Code 974, Greenbelt, MD 20771, USA; Tel: +1-301-614-5804; Email: csun@hsb.gsfc.nasa.gov

was then made using a poor initial condition for the snow states. Specifically, it is prescribed that there is no snow present. The assimilation run starts from the poor initial state, and uses the observations generated from the truth run. The assimilated results are then compared with the truth and degraded model simulations. Observations are assimilated once every three days.

4. RESULTS

The EKF scheme is tested by running for one month over the 24 catchments, starting from February 1, 1987. Simulation results from the poor initial condition (no snow everywhere) predicts very little snow on February 22, 1987 (Fig. 1a). The average amount of snow water equivalent is 16 mm, while the average for the true state is 90 mm (Fig. 1b). The average for the assimilated snow water equivalent is very close to the truth, at 92 mm (Fig. 1c). Hence, the EKF is able to correctly estimate snow water equivalent. This is to be expected,

however, since the observation is the measurement of the snow water equivalent of the snowpack.

The estimate of snow depth is less successful. The model simulation from the poor initial condition (Fig. 2a) is very different from the truth (Fig. 2b), being significantly less, while the EKF tends to significantly overestimate the snow depth (Fig. 2c). The average of assimilated snow depth over the 24 catchments is 611 mm (with a standard deviation of 76 mm), almost doubling the average of the true state (366 mm with standard deviation of 26 mm). This indicates that the information of snow water equivalent measurement is not effectively propagated to the snow depth estimate by the EKF. However, one must keep in mind that we have started from a very poor initial condition and there have only been relatively few updates to this point.

The snow temperature (heat content) is well estimated by both EKF and model simulation (Fig. 3), probably because it is strongly influenced by the forcing, which is assumed to be perfect in this identical twin experiment.

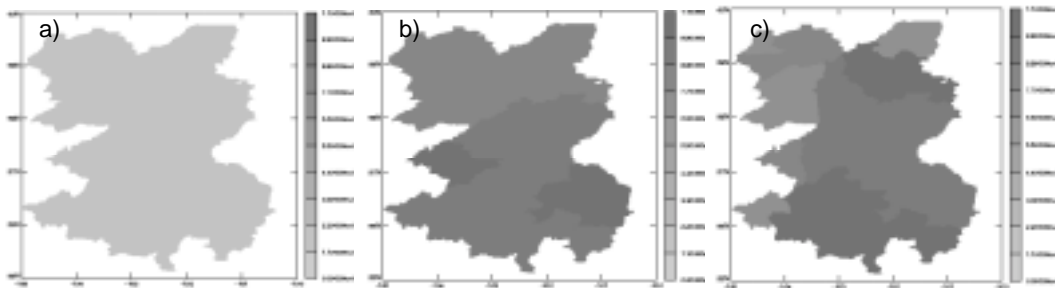


Fig. 1 Snow water equivalent on Feb. 22, 1987 for a) model simulation with poor initial condition b) truth c) assimilation With poor initial condition.

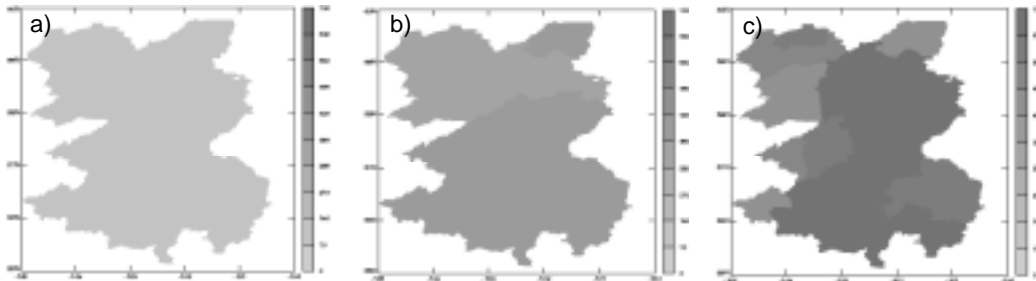


Fig. 2 Snow depth on Feb. 22, 1987 for a) model simulation with poor initial condition b) truth c) assimilation With poor initial condition.

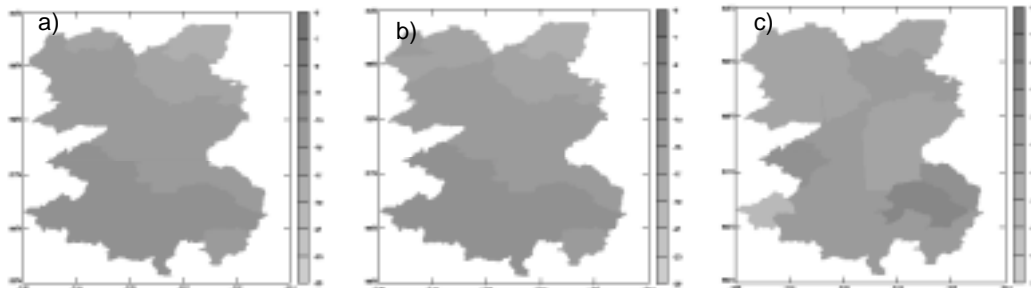


Fig. 3 Snow temperature on Feb. 22, 1987 for a) model simulation with poor initial condition b) truth c) assimilation With poor initial condition.

5. DISCUSSIONS

The EKF requires the calculation of the state transition matrix M , whose elements are numerical derivatives of the nonlinear model with respect to the state variables. The numerical differentiation method commonly used treats the model as a black box. Only one state variable is perturbed at a time, while all other state variables are held constant (their values are those of the model state at the current time step).

This calculation of numerical derivatives in the EKF does not fit well with the model formulation in this case. The problem is the switch between a one-layer and three-layer model. In this synthetic study, the observation used is the total snow water equivalent of the snow pack W_p , to mimic remotely-sensed passive microwave measurements, from which the total snow water equivalent of the snowpack can be derived, but not the snow depth (without an assumption about the snow pack density) or the heat content of the snowpack. The nature of this observation in combination with the setup of the model causes difficulty under certain conditions. The problem arises when there is a big difference between model forecast states and observed states, especially when there is very little or no snow in the model state (snow water equivalent < 13 mm), while the snow water equivalent of the observed snowpack W_p is greater than 13 mm. In this case, the model has only one layer of snow, but the proper assimilation of the observation requires three layers of snow. The following discussion is concerned with this situation.

When there is no snow in the model forecast, adding perturbations to the state variables causes the model to crash, because all snow variables are zero in this case. It is not possible to have nonzero water equivalent W_i (due to perturbations) while the depth of the snow layer Z_i has zero values (where $i=1,2,3$). In this case, propagation of forecast error by the model dynamics is not possible. We simply set the state transition matrix to the identity matrix.

6. CONCLUSIONS

A framework to assimilate snow water equivalent into the catchment-based land surface model using a one-dimensional extended Kalman filter (EKF) has been developed. Some numerical difficulty arises with implementation of the EKF due to the nature of observation used here. Snow may not be predicted in the model simulation at certain time steps while observation indicates snow on the ground. The state transition matrix cannot be computed in a conventional way in this case. When the snow model switches from one-layer snow physics to that of three layers, the state transition matrix needs to be calculated with special care.

The EKF scheme we developed produces satisfactory estimates of snow water equivalent but overestimates the snow depth. It is conceivable that snow water equivalent alone could not provide information about the density of the snow, which is needed to correctly estimate the thickness of snow. To improve snow depth estimation from snow water equivalent observations, we need to improve the “known” statistics of model-error covariance and initial forecast-error covariance, especially the estimate of covariance between snow depth and snow water equivalent. We also need to deal with the problem of unknown snow density. The snow water equivalent measurement does not provide information about snow density, which results in difficulty in estimating snow depth.

In assimilating real observations, we also need to consider temperature biases in the model and forcing, which can melt or freeze the snow unrealistically. This is necessary to maintain a meaningful water budget in the land system.

7. REFERENCES:

- Berg, A. A., J. S. Famiglietti, J. P. Walker and P. R. Houser, 2001: Development of a catchment-based hydrometeorological forcing data set for land surface modeling applications, *Proceedings of the 12th Symposium on Global Change and Climate Variations*. The American Meteorological Society, 197—198.
- Ducharne, A., R. D. Koster, M. J. Suarez, M. Stieglitz and P. Kumar, 2000: A catchment-based approach to modeling land surface processes in a general circulation model. 2. Parameter estimation and model demonstration. *J. Geophys. Res.*, **105**, 24,823—24,838.
- Koster R.D., M. J. Suarez, A. Ducharne, M. Stieglitz and P. Kumar, 2000: A catchment-based approach to modeling land surface processes in a general circulation model. 1. Model structure. *J. Geophys. Res.*, **105**, 24809—24822.
- Lynch-Stieglitz, M., 1994: The development and validation of a simple snow model for the GISS GCM. *J. Clim.*, **7**, 1842—1855.
- Stieglitz, M., A. Ducharne, R. Koster, and M. Suarez, 2001: The Impact of Detailed Snow Physics on the Simulation of Snow Cover and Subsurface Thermodynamics at Continental Scales. *J. Hydrometeor.*, **2**, 228—242.