Addressing soil moisture model error using adaptive ensemble Kalman filtering

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Abstract For several applications, the property that the assimilation of a soil moisture observation at one location in the horizontal space can affect neighboring locations is desirable. However, for computational efficiency, course scale land surface models often treat soil moisture profiles as independent individual land columns, introducing some model error by ignoring horizontal water flows. This study shows how this type of error in the CLM2.0 model can be overcome through adaptive filtering of point profile soil moisture data with an ensemble Kalman filter.

Method

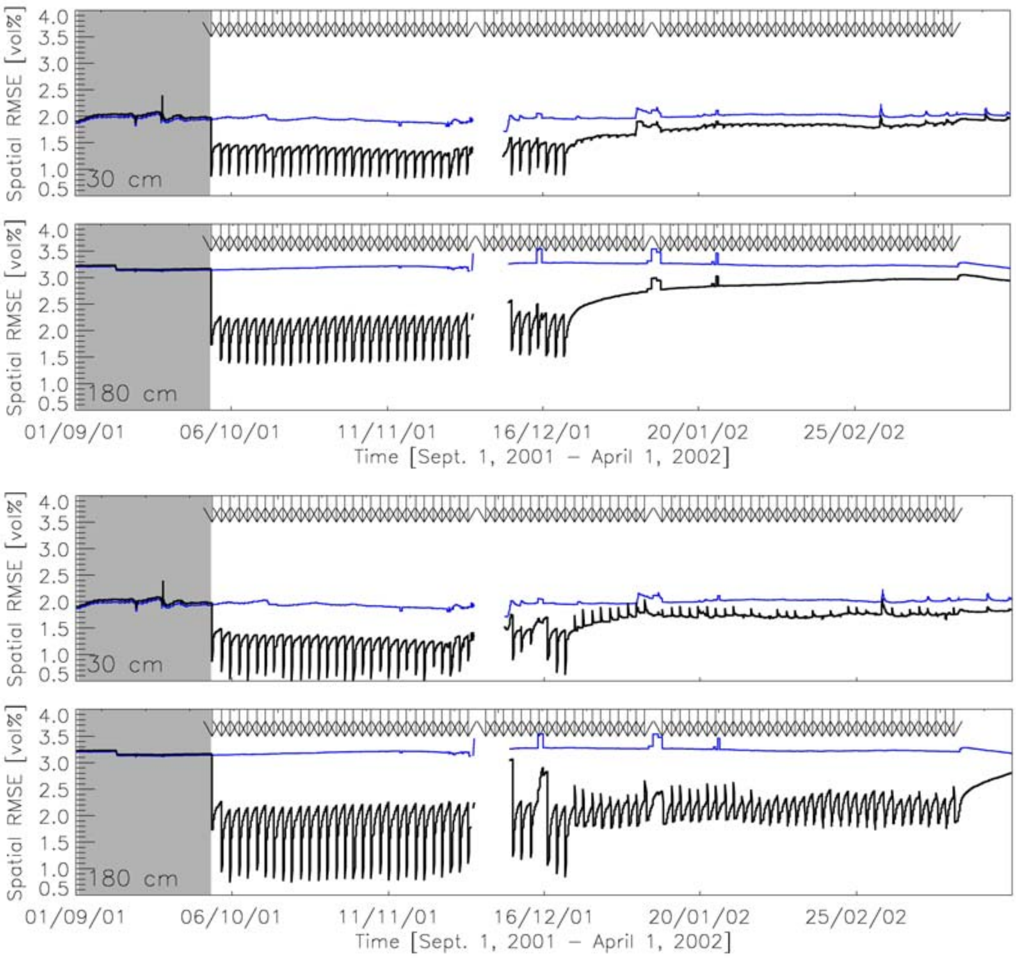
Soil moisture profiles are estimated with the Community Land Model (CLM2.0, Zeng, 2003) in a small agricultural field on which the Optimizing Production inputs for Economic and Environmental Enhancement (OPE[3], Gish et al., 2002) experiment is conducted. The goal was to use only a few profile soil moisture observations to enhance the soil moisture estimates at all simulated soil moisture profiles in the field. However, as the CLM2.0 does not model horizontal flow (the linearized system matrix is block diagonal), we imposed a horizontal flow of innovation information in between profiles by tuning the a priori error covariance matrix in the Kalman gain for an ensemble Kalman filter.

Adaptive filters typically seek to extract information on the model error covariance from some knowledge of the innovations or observation increments. Most adaptive filters aim at whitening the (mostly time) sequence of innovations or matching the innovation covariance matrix by tuning the filter parameters **Q** and **R**, i.e. the model and observation uncertainty. The deviation of adaptive filters is generally based on an assumption of a time-invariant linear system and observation model, resulting in steady state error covariance matrices and ultimately in constant blending matrices for filtering. Furthermore, not all adaptive filters allow estimating both the variances and the correlation: often only the variances are estimated. In this and many other studies, the time-invariance assumption does not hold, e.g. because of missing data (time varying observation operator) and different governing processes (time varying system model) for varying hydrological regimes. The method of Meyers and Tapley (1976) is selected for this research and changed so that the time averaging is replaced by batch processing.

In contrast to all original adaptive methods where (some parameters of) the complete **Q**-matrix is sought, we only determine the unknown part of **Q** or more generally, the unknown part of the a priori error covariance matrix. Because ensemble generation allows estimating some model error correlations and variances between variables in the same profile (i.e. soil moisture at different vertical soil layers), there is only need to look for the horizontal model error correlations and variances between variables of different profiles. The retrieved part of **Q** is then fed back into the cyclic assimilation system by adding multivariate random values (with the estimated model error structure) to the ensemble of land surface state members.

Result

After assimilating all available OPE³ field profile information for some time, the best estimate of the unknown part of **Q** can be used as first guess for subsequent assimilations (and **Q** updating) with limited observations. This greatly improves the effect of a single soil moisture profile assimilation on horizontally distant estimates. Figure 1 shows the spatial root mean square error over all profiles in the OPE³ field without and with adaptive filtering. In this figure, an assimilation period of all available profile information is followed by an assimilation period of data from only one profile. However, so far, the interaction between the **Q** estimation and the bias estimation was not successful; the combination of bias estimation and adaptive filtering only marginally improved the results.



a)

b)

Figure 1: Spatial root mean square error (RMSE) over 36 locations in the OPE³ field at 2 depths. Assimilation of observations at all 36 locations was from 2 October 2001 through 24 december 2001 and assimilation of a single profile thereafter, until 19 March 2002 at an assimilation frequency of once per week (a) with the ensemble Kalman filter and (b) with the adaptive ensemble Kalman filter. Black is for the filtering run, blue is for the calibrated control (ensemble mean without filtering) run.

References

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