

Soil moisture assimilation in a coupled water/energy scheme in a semiarid region

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Abstract Soil moisture assimilation in a coupled water/energy scheme in a semiarid region is investigated using the Ensemble Kalman Filter theory. The method is used to improve the model estimates but also to account for the seasonal evolution of the hydrologically active soil depth. It is shown that this method significantly improves the soil water content predictions and the daily stream flows estimates.

Key words Kalman filtering; online parameterization; soil water assimilation; water balance

INTRODUCTION

Surface processes are particularly complex due to the numerous interactions and the large variability of the temporal and spatial scales involved (Blösch & Sivapalan, 1995). These complex interactions, coupled with the scarcity of relevant data, led to the development of simplified schemes. These schemes do not explicitly take all the processes into account but integrate them into a conceptual parameterization (Wood *et al.*, 1992; Franks *et al.*, 1997). Parameters that can not be derived from measurements are calibrated to fit an objective function over a given period. They are then considered to be constant for the rest of the simulation.

In regions characterized by a high seasonality, such as semiarid regions, some parameters are bound to vary during the year and thus, impact the simulation results. In particular, the hydrologically active depth used in surface processes modelling is definitely not a constant value and may vary significantly between the dry and wet seasons. It influences the average available soil water content for evapotranspiration and drainage. Accurate description of surface processes thus requires accounting for the seasonal variability of local conditions. This is even more important in areas where water availability is limited.

This paper presents a method to account for the seasonal variability of parameters in a coupled Hydrology/Soil–Vegetation–Atmosphere Transfer (SVAT) model using data assimilation (Pellenq *et al.*, 2003). The method relies on the Ensemble Kalman Filter theory (Evenson, 1994) and allows one to take soil moisture measurements into account to improve simulations and adjust the parameter values. Evaluation of the method is carried out for a small Australian drainage basin.

DATA

The experimental site used in this study is located in the Williams River basin (New South Wales, Australia) on a property called Nerrigundah. It is a small basin of 6 ha running east to west with a relief of 27 m. The climate is characterized by a summer dominant mean annual rainfall of 1000 mm and a high mean potential evapotranspiration (1600 mm). The soil is essentially duplex, with a shallow clay-loam A layer (30 to 90 cm) on a clay B horizon (55 to 290 cm). The stream is ephemeral and important baseflows only occur when precipitation is significant.

The Nerrigundah experimental basin was permanently instrumented from 28 October 1996 through to 7 April 1999, for soil moisture content, soil temperature, runoff, rainfall and meteorological data (Walker *et al.*, 2001). The data set includes: high resolution (20 m) Digital Elevation Model (DEM) data; soil moisture profile measurements made at 13 locations for 38 measurement days (once every two weeks on average) using Time Domain Reflectometry (TDR); soil temperature profile measurements; daily streamflow measurements and supporting meteorological measurements. Soil information including field measurements of saturated hydraulic conductivity and soil depth were performed at 19 locations.

COUPLED MODEL

The water and energy model used in the numerical experiment couples a simple SVAT model (SVATsimple; Boulet *et al.*, 2000) with the TOPMODEL formalism (Beven & Kirkby, 1979). TOPMODEL takes the topography into account to estimate the surface runoff and baseflow at the basin scale. SVATsimple simulates the evolution of the water content and the vertical water and energy fluxes at the surface-atmosphere interface. The soil is described by a single "bucket" for vertical fluxes with a bulk surface of mixed vegetation and bare soil. The depth d of this bucket corresponds to the average depth of the infiltration and evaporation fronts. The only state variable is the depth integrated water content θ . A complete description of the coupling is given in Pellenq *et al.* (2003).

ASSIMILATION METHODOLOGY

Data assimilation aims at assessing the real state of a system using all the available information in an optimal way. The Kalman Filter methods use all the available ancillary (sequential) data to adjust the state variables in order to obtain better model outputs. These methods take model and data uncertainties into account but usually suppose the parameter values to be exact.

In this study, an Ensemble Kalman Filter (Evenson, 1994) was used: (a) to assimilate soil water content information into the water and energy scheme, and (b) to account for the variability of parameters. First, the overall philosophy of the filter is described.

So as to initialize the simulation, an ensemble of N initial state vectors $\{x_i(t=0), i = 1, \dots, N\}$ is computed from a normal distribution with a mean \bar{x} equal to the first

guess and covariance $P_{ij}(t = 0)$ equal to the estimated uncertainties on the variables (model). These N points are propagated in time until an observation is available (errors are implicitly propagated and are estimated by the scatter of the points). Once an observation (or a set of observations) is available, the vector of observations z is used to generate a set of N observation vectors $\{z_i(t), i = 1, \dots, N\}$ from a normal distribution of variance equal to the estimated observation uncertainty σ_z . For each point of the ensemble, the state variables are then re-adjusted, according to the uncertainties on the observed data and on the simulated variables:

$$x_i^a = x_i^f + K_e(z_i - z_{s,i}) \quad (1)$$

where x_i^f is the *forecast* state vector, x_i^a is the *analysed* state vector after re-adjustment and $z_{s,i}$ is the simulated variable equivalent to the observation variable. The difference $(z_i - z_{s,i})$ in equation (1) is called the *measurement innovation* and reflects the discrepancy between the predicted measurement $z_{s,i}$ and the actual measurement z_i . K_e is the *Kalman gain* that minimizes the analysed error covariance.

It can be shown (Evenson, 1994) that the expression for K_e is given by:

$$K_e = \frac{(x_i^f - \bar{x}^f)(z_{s,i}^f - \bar{z}_s^f)^T}{(z_{s,i}^f - \bar{z}_s^f)(z_{s,i}^f - \bar{z}_s^f)^T + \sigma_z^2} \quad (2)$$

The filter algorithm is schematized Fig. 1.

This method is efficient because it does not (unlike the Extended Kalman Filter) require the computation of the system derivatives along the state variables and can be used for nonlinear systems. Moreover, if the state variables re-adjustment is not sufficient to correct the output estimate, some chosen parameters can be calibrated "online" in order to match the observations. This can easily be done by considering the parameter as a state variable (constant in time if no observation is given) and by using equations (1) and (2) to re-adjust the parameter value every time a new observation is available.

This method was applied on the coupled SVATSimple-TOPMODEL scheme for the Nerrigundah catchment. Soil moisture measurements (averaged over the basin) were assimilated to re-adjust the soil moisture state variable θ and the hydrological soil depth d every time a measurement was done. Impacts on continuous soil water content simulations, cumulated evapotranspiration and streamflow predictions were studied.

RESULTS

The model was implemented over the 907 days of observations from October 1996 to April 1999 during which 38 soil moisture measurements were available. Parameters that could not be measured were considered constant and calibrated on half of the soil moisture data using a genetic algorithm. Three different simulations were performed: (a) without any assimilation, (b) with assimilation but without online parameterization of the hydrological depth, and (c) with assimilation and on line parameterization.

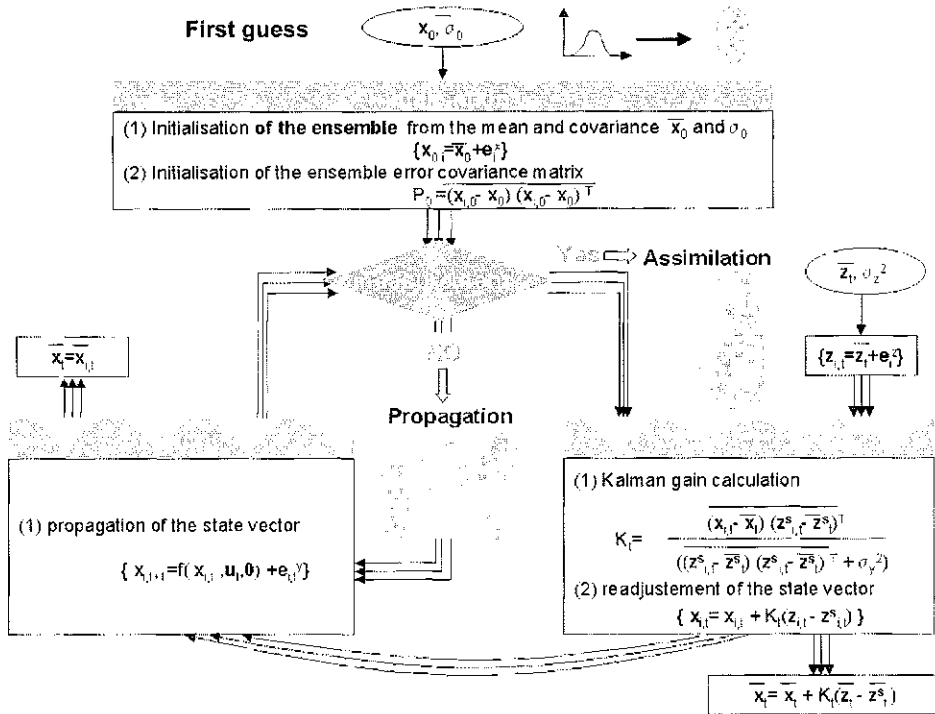


Fig. 1 Schematic representation of the Ensemble Kalman Filter used in this study.

Table 1 Efficiency criteria for soil moisture and daily streamflow predictions for the three simulations: (a) without assimilation, (b) with assimilation of soil moisture, (c) with assimilation and on line parameterization.

	Soil water content efficiency	Daily streamflow efficiency
Without assimilation	0.84	0.65
With assimilation	0.96	0.75
With assimilation and online parameterization of d	0.97	0.78

Predicted soil moisture evolution and daily streamflow were compared to observations and an efficiency criteria (Nash & Sutcliffe, 1970) was computed. Results in terms of efficiency are presented in Table 1. Soil moisture assimilation seriously improves estimates of simulated soil water content compared to the simulation without assimilation, but it also significantly improves predictions of daily streamflows. As total initial soil moisture controls lateral fluxes, improvement of the soil moisture estimate helps to better represent the streamflow. Accounting for variability of the hydrologically active depth d also improves both soil moisture and streamflow prediction.

Figure 2(a) shows the temporal evolution of the observed and predicted soil water content for the three simulations and the evolution of the re-adjusted active soil depth d for the last simulation. Results show that assimilation of soil moisture and re-adjustment of d significantly influence the soil moisture trajectory, even for a small

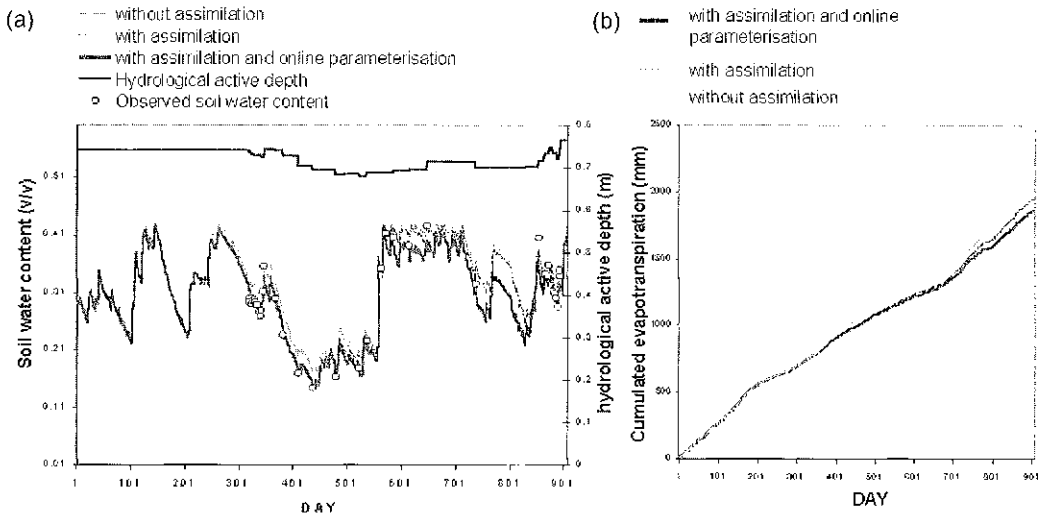


Fig. 2 (a) Evolution of: (i) the predicted soil water content without assimilation, (ii) the predicted soil water content with assimilation, (iii) the predicted soil water content with assimilation and online parameterization, (iv) the observed soil water content, and (v) on line parameterization of the hydrological active depth.

(b) Evolution of the predicted cumulated evapotranspiration for the whole period of simulation: (i) without assimilation, (ii) with assimilation, (iii) with assimilation and online parameterization.

re-adjustment of the soil depth. Indeed, the active soil depth is constant in time and equal to its constant calibrated value of 0.74 m until the first observation is available, then, it is re-adjusted to minimize the variance between estimated and observed soil moisture. The active soil depth decreases during the wet season and increases during the dry winter period by about 10% of its mean value. These variations are not dramatic but sufficient to induce significant changes of the soil moisture values, especially during the wet period when the scheme without online parameterization overestimates the soil moisture. This impacts positively on the streamflows with an efficiency increasing from 0.65 to 0.78 when accounting for the active soil depth seasonal variability. The scheme with online parameterization also has an important impact on the predicted evapotranspiration as can be seen on Fig. 2(b). This figure shows the cumulated evapotranspiration for the whole simulation period and for the three experiments. It can be seen that small variations of the active soil depth can lead to important differences in the cumulated evapotranspiration fluxes at the interface.

CONCLUSION

The sequential assimilation method presented in this study allows one to account for all the available information so as to get close to the best estimate of the system state, and secondly to account for seasonal variations of some chosen parameters.

It was shown that:

- sequential assimilation of soil moisture information into a coupled hydrological/SVAT significantly improves both the soil moisture temporal evolution prediction at the catchment scale and the daily streamflow prediction;
- not accounting for the seasonal changes of the hydrologically active soil depth induces some significant differences in predicted fluxes that should not be neglected.

This method is simple and is applicable to either ground measurements or remotely sensed data.

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