Recent Advances in Profile Soil Moisture Retrieval

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Summary

Remote sensing provides a capability to make frequent and spatially distributed measurements of surface soil moisture, whilst recent advances in affordable Time Domain Reflectometry probes allow continuous monitoring of profile soil moisture at specific points. We believe that reliable estimation of the spatial and temporal variation of profile soil moisture on a routine basis will require a combination of calibration and evaluation of an unsaturated soil moisture model using point measurements, and model updating using remote sensing observations to account for spatial inhomogeneities. This study investigates which of two commonly used assimilation techniques is most efficient for the retrieval of soil moisture and temperature profiles, over what depth soil moisture observations are required, and the effect of update interval on profile retrieval. These questions are addressed through a desktop study using synthetic data.

Introduction

Soil moisture in the root zone is a key parameter in numerous environmental studies, including meteorology, hydrology and agriculture. The significance of soil moisture is its role in the partitioning of energy at the ground surface into sensible and latent (evapotranspiration) heat exchange with the atmosphere, and the partitioning of precipitation into infiltration and runoff [1, 2].

Soil moisture can be estimated from: (i) point measurements; (ii) soil moisture models and (iii) remote sensing (see Figure 1). Traditional techniques for soil moisture estimation yield data on a point basis [3, 4], which does not always represent the spatial distribution [5]. The alternative has been to estimate the spatial distribution of soil moisture using a distributed hydrologic model [6, 7]. However, these estimates are generally poor, due to the fact that soil moisture exhibits large spatial and temporal variation [8], as a result of inhomogeneity in soil properties, vegetation and precipitation [4]. Remote sensing can be used to collect spatial data over large areas on a routine basis, providing a capability to make frequent and spatially comprehensive measurements of the near surface soil moisture. However, problems with this data include the current satellite repeat time (typically 25 days) and the depth over which soil moisture estimates are valid, consisting of the top few centimetres at most [2, 8, 9]. These upper few centimetres of the soil are the most exposed to the atmosphere, and their soil moisture varies rapidly in response to rainfall and evaporation [10]. Thus to be useful for hydrologic, climatic and agricultural studies, such observations of surface soil moisture must be related to the complete soil moisture profile in the unsaturated zone [11-13].

The problem of relating soil moisture content at the surface to that of the profile as a whole has been studied for the past two decades. Four approaches have been adopted: (i) regression, (ii) knowledge-based, (iii) inversion, and (iv) combinations of remotely sensed data with soil water balance models [14]. As remote sensing observations have a poor resolution in time, it is necessary to apply the water balance approach in order to obtain soil moisture estimates during the inter-observation period.

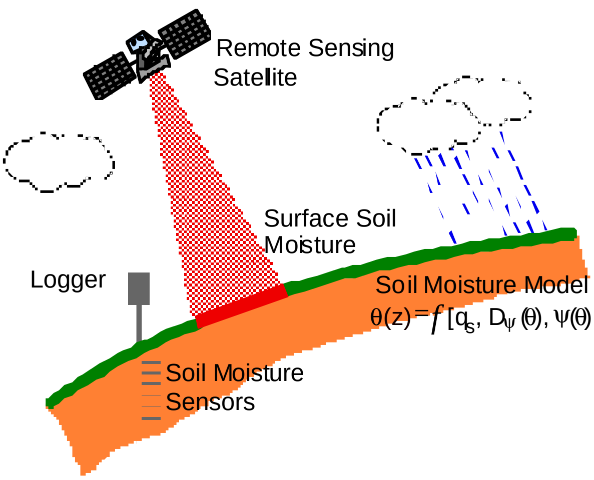

Figure 1: Illustration of the soil moisture estimation problem.

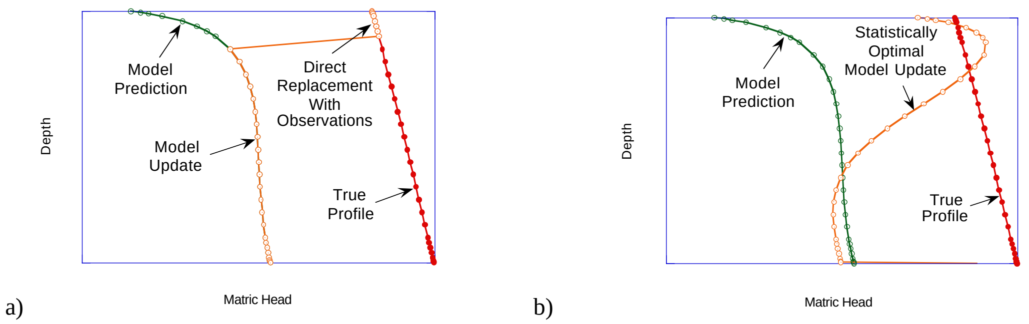

Figure 2: Illustration of data assimilation techniques: a) Direct-insertion; b) Kalman-filter.

The water balance approach uses a soil water balance model that has been adapted to accept remote sensing data as input to track soil moisture status in time. As surface observations of soil moisture become available they are assimilated into the model. A review of approaches used for assimilation of remote sensing observations into soil moisture models found that the direct-insertion and Kalman-filter techniques have been used most frequently.

The direct-insertion approach is performed by directly substituting simulated values of soil moisture and temperature with the observed values, as they become available. This is illustrated in Figure 2a, where the model profile (open circles) is replaced by the observations of the true profile (solid circles) to yield the model update profile (open symbols with dot). The governing equations for flow of moisture through unsaturated soil are highly non-linear. Therefore the direct-insertion approach is the simpler of the two approaches suggested, as it allows for the non-linear problem to be solved directly. However, the only way in which this surface information is transferred to greater depths is through the physics of the model.

The Kalman-filter is a statistical approach that yields a statistically optimal update of the soil moisture profile based on the relative magnitudes of the covariances of both, the model's profile estimate and the surface observations. The principal advantage of this approach is that the Kalman filter provides a statistical framework in which the entire profile may be modified as illustrated in Figure 2b (open symbols with dot), with covariances representing the degree of belief in the observations (solid circles) and model predictions (open circles). This characteristic of Kalman-filtering reflects our intuition that surface measurements provide some knowledge, albeit limited, of soil moisture values below the depth over which observations are made. The disadvantage of this approach is that the governing equations require linearisation.

Model Equations

The most commonly used physically based model for estimating the flow of soil moisture and heat in unsaturated soil is that of Phillip and de Vries [15]. By assuming isothermal conditions and that vapour flux is negligible, the well known Richards equation is obtained in (1). The heat flow equation in (2) is obtained by assuming the effects from differential heat of wetting and vapour flux are negligible.

$$C_\psi \frac{\partial \psi}{\partial t} = \nabla\left[D_{\psi l}\nabla\psi + D_{\psi l}\right] \quad (1)$$

$$C_T \frac{\partial T}{\partial t} = \nabla\left[\lambda\nabla T - c_l\left(T - T_{ref}\right)\mathrm{q}_l\right] - c_l\rho_l\left(T - T_{ref}\right)\frac{\partial \theta_l}{\partial t} \quad (2)$$

where ψ is the soil matric suction, $D_{\psi l}$ is the isothermal liquid hydraulic conductivity, T is the soil temperature, T_{ref} is a reference soil temperature, λ is the thermal conductivity, c_l is the specific heat capacity of liquid water, q_l is the liquid moisture flux, ρ_l is the density of liquid water, θ_l is the liquid volumetric soil moisture, t is time, C_ψ is the soil capillary capacity factor, C_T is the volumetric heat capacity of the bulk soil medium, and z is elevation taken as positive upward.

The soil moisture equation in (1) is decoupled from soil temperature by the assumption of isothermal conditions. Hence modelling of soil moisture could be performed without the soil temperature equation in (2). The necessity for modelling soil temperature is the relationship between microwave remote sensing observations and soil dielectric constant, and the temperature dependence of the relationship between soil dielectric constant and volumetric soil moisture. The magnitude of this dependence is illustrated in Figure 3 for both dry and wet soil conditions. As surface soil temperatures can have diurnal variations in excess of 40°C in some parts of the world, it is necessary to have an estimate of the surface soil temperature in order to retrieve surface soil moisture from microwave remote sensing observations. Current generation microwave remote sensing platforms do not

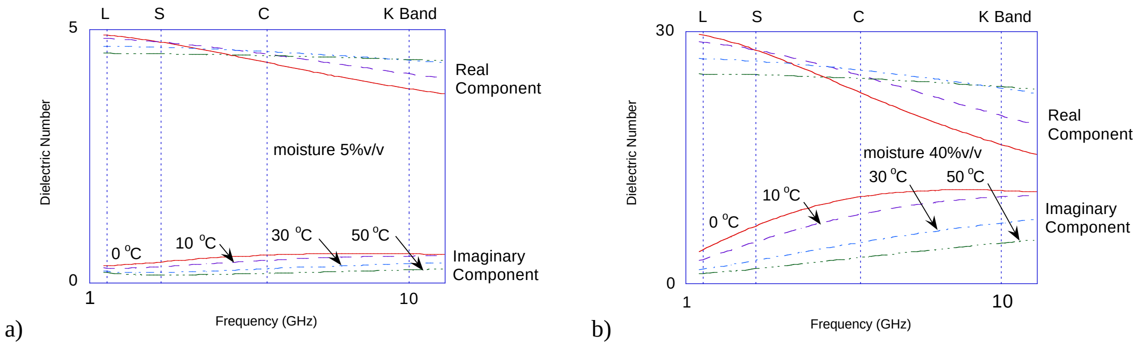

Figure 3: Temperature dependence of dielectric constant: a) low soil moisture; b) high soil moisture.

carry a thermal infra-red sensor on board, hence it is necessary to model soil temperature in addition to soil moisture.

Synthetic Study

A desktop study using synthetic data has been undertaken to illustrate the ability to retrieve soil moisture profiles using the direct-insertion and Kalman-filter assimilation techniques. Firstly, the soil moisture and temperature equations were used to generate a 40 day synthetic data set of "true" soil moisture and temperature profiles using the van Genuchten [16] moisture retention and hydraulic conductivity relationships. The soil parameters used by the model are given in Table 1, and initial conditions were 50 cm matric suction (51.5%v/v) and 20°C soil temperature uniform throughout the 1 m deep profile. The time variation of the "true" profiles were generated by subjecting the model to boundary conditions of 0.5 cm/day evaporation and a diurnal soil heat flux of 400 langley/day amplitude at the soil surface. The boundary condition at the base of the soil column was zero soil moisture and heat flux.

To test the direct-insertion and Kalman-filter profile retrieval algorithms, the soil moisture and temperature equations were initialised with a poor initial guess of 300 cm matric suction (35.5%v/v) and 15°C soil temperature, uniform throughout the profile. Subjecting the soil moisture and temperature equations to the same boundary conditions used for generating the "true" soil moisture and temperature profiles, the model was updated once every hour with soil moisture observations over depths of 0 (surface node), 1, 4 and 10 cm, and soil temperature observations at the surface node alone. Soil temperature observations were only for the surface node, as thermal infra-red sensors can only sense the soil temperature at the soil surface.

The profile soil moisture retrieval results from updating once every hour are given in Figure 4a for the direct-insertion assimilation technique and Figure 4b for the Kalman-filter assimilation technique. In these figures, the "true" profiles (closed symbol) are compared with the retrieved profile (open symbols) as well as the open loop profile (open symbol with a dot). The open loop refers to the situation where no observations are used and the system is simply propagated from the initial conditions subject to the surface flux boundary conditions.

Figure 4a shows that no retrieval is achieved for observations at the surface node alone using the direct-insertion assimilation technique, while full retrieval is achieved after approximately 7 days for an observation depth of 10 cm. It is also shown that retrieval of soil moisture profiles proceeds more slowly as the observation depth is reduced. This is a result of the direct-insertion assimilation technique relying on the physics of the model to translate surface observations to greater depths in the profile. The model translates these surface observations to greater depths in an attempt to achieve hdrostatic equilibrium within the soil profile. No retrieval was achieved for the soil temperature profile with updating of the surface node once every hour. When using a continuous

Table 1: Soil parameters used in simulations.

Saturated Hydraulic Conductivity K_s	25 cm/day
Porosity ϕ	54 %v/v
Residual Soil Moisture θ_r	20 %v/v
van Genuchten Parameter η	0.008
van Genuchten Parameter n	1.8
Proportion of quartz	3 %v/v
Proportion of other minerals	41 %v/v
Proportion of organic matter	2 %v/v

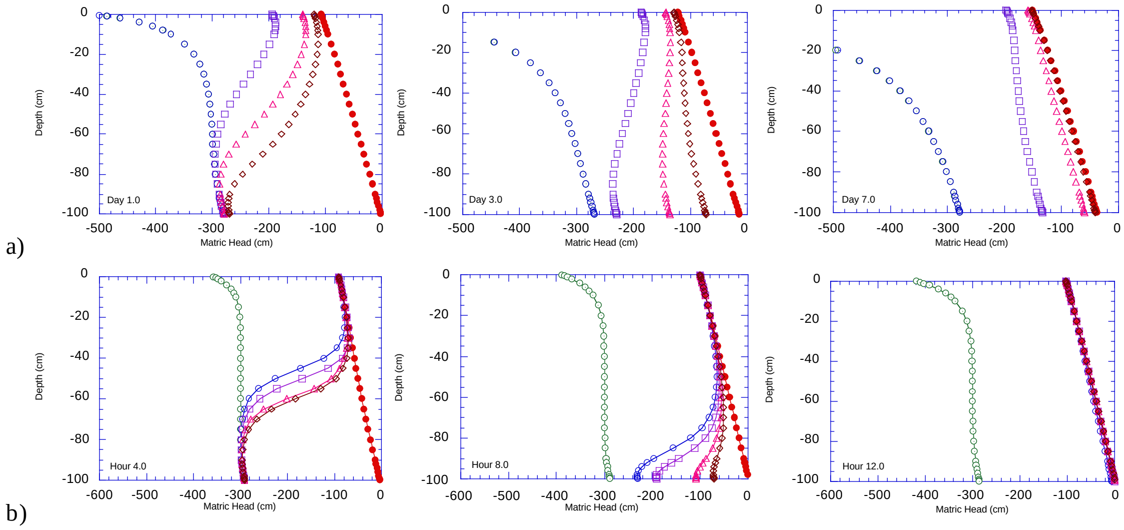

Figure 4: Comparison of retrieved soil moisture profiles for observation depths of 0 (open circle), 1 (open square), 4 (open triangle) and 10 (open diamond) cm with the true soil moisture profile (solid circle) and the open loop soil moisture profile (open circle with dot) for observations each hour. a) Direct-insertion assimilation technique; and b) Kalman-filter assimilation technique.

Dirichlet (fixed value) boundary condition over the observation depth, profile soil moisture retrieval required between 5 (10 cm observation depth) and 8 (surface node observation) days, while profile temperature retrieval required greater than 20 days. This indicates that for very shallow observations, the direct-insertion assimilation technique requires a Dirichlet boundary condition for some proportion of the time. The direct-insertion assimilation technique treats observations as being instantaneous, with the extra mass added (or subtracted) over the observation depth being rapidly redistributed throughout the profile. As surface observations are applicable for some finite period of time, applying the surface observations for some period of time allows for extra mass to be added (or subtracted).

The direct-insertion results are compared with those from the Kalman-filter assimilation technique in Figure 4, where soil moisture profiles were retrieved for all observation depths (including the surface node) after only 12 hours. These results show the obvious advantage of using the Kalman-filter assimilation technique over the direct-insertion assimilation technique. In this instance, an increased observation depth had only a minor effect on the rate of profile retrieval, indicating that an increased observation depth is unimportant for the Kalman-filter assimilation technique.

Whilst updating with surface observations once every hour shows that the Kalman-filter assimilation technique is superior to the direct-insertion assimilation technique for profile soil moisture retrieval, an observation frequency of once every hour is totally unrealistic for any practical application of profile retrieval from remote sensing observations. At best, we may expect a repeat coverage of once every day. However, a repeat coverage of once every 5 days or greater is more probable, at least for the near future. What updating once every hour does show is that near surface observations with a single Time Domain Reflectometry (TDR) probe may be used to improve profile soil moisture estimates.

With an update interval of 5 days, the Kalman-filter yielded poor estimates of the soil moisture profile. Rather than perform an update that would lie between the model estimate and "true" profiles, the updated profile was equal to the "true" profile at the surface, followed by an oscillation between the two profiles before shooting off to a very large matric suction. In subsequent updates there was only slight improvement in the retrieved profile. This instability was not observed for more frequent updating, and is believed to be a result of the linearisation of an extremely non-linear model and the large difference between the "observations" and the model estimate after 5 days.

In view of these stability problems, a more robust application of the Kalman filter retrieval algorithm was sought. Surface observations of soil moisture are indicative of the soil moisture at depth [11]. Thus, it was proposed that actual observations would be applied over the observation depth, and "quasi" observations to the remainder of the moisture profile. This is illustrated in Figure 5. The quasi observations could either be: (i) the observed soil moisture at the observation depth; or (ii) an extrapolation of the soil moisture observation at the observation depth by the steady state assumption [11]. It was chosen to apply the steady state assumption, as

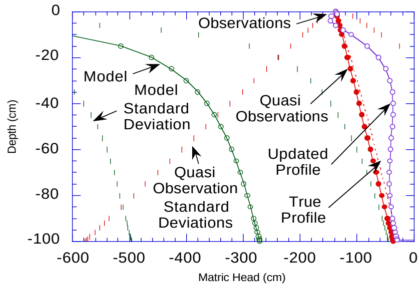

Figure 5: Illustration of Kalman-filter profile retrieval algorithm using quasi observations.

this has been shown to be a reasonable approximation under low flux conditions [11]. In addition, when there is a large matric suction gradient under exfiltration conditions, this would have the effect of making the quasi observations slightly closer to reality.

There is much greater uncertainty associated with the quasi observations than for the actual observations, even for a layer of soil directly below the observation depth. With increasing depth from the lowest observation, the uncertainty in the quasi observation increases dramatically. To account for this, a quantile jump in the variance of the quasi observation was applied immediately below the observation depth, relative to the variance of the actual observations. An increasing quasi observation variance with depth was then applied (see Figure 5).

Results from updating once every 5 days with quasi observations for the soil moisture updating are given in Figure 6a for soil moisture and Figure 6b for soil temperature. These results show that full retrieval of profile soil moisture is achieved for all observation depths after only 10 days (2 updates), whilst there has been significant profile temperature retrieval after only 10 days. Complete soil temperature profile retrieval was achieved after an additional update at day 15. The necessity for quasi observations with soil moisture updating once every 5 days illustrates the difficulties which may be encountered when applying the Kalman filter to highly non-linear problems. A summary of simulation results is given in Table 2.

Conclusions

This work has shown that the Kalman-filter assimilation technique is by far superior to the direct-insertion technique, and that profile retrieval cannot be realised for direct-insertion of the surface nodes alone. However, difficulties may be encountered when applying the Kalman-filter to highly non-linear problems. It has also been

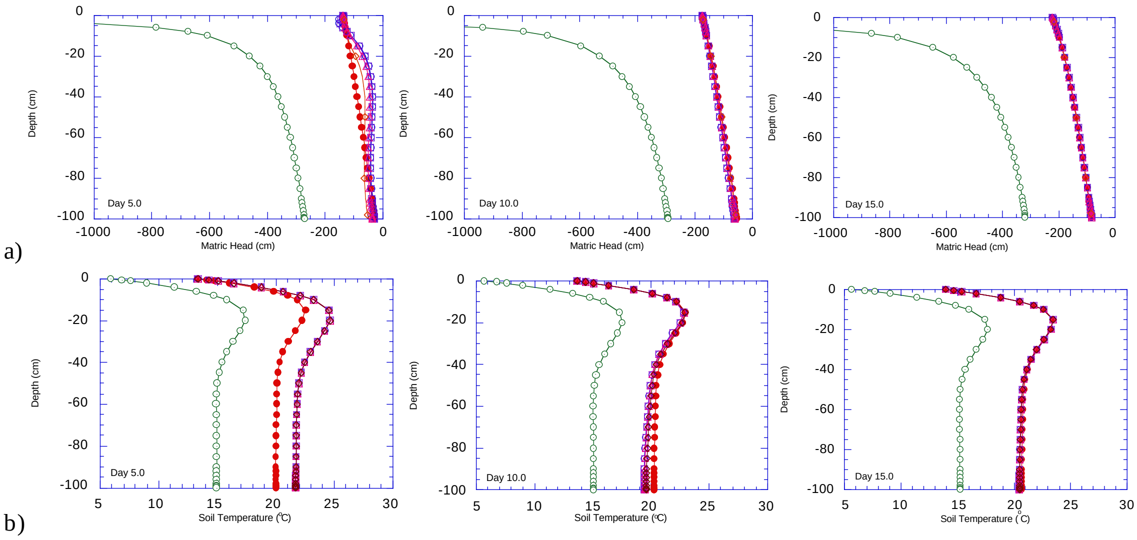

Figure 6: a) Comparison of retrieved soil moisture profiles for observation depths of 0 (open circle), 1 (open square), 4 (open triangle) and 10 (open diamond) cm with the true soil moisture profile (solid circle) and the open loop soil moisture profile (open circle with dot) for observations each 5 days. b) Comparison of retrieved soil temperature profile for observations of the surface node with the true soil temperature profile (solid circle) and the open loop soil temperature profile (open circle with dot) for observations each 5 days. Retrieved soil temperature profiles correspond with retrieved soil moisture profiles for observation depths of 0 (open circle), 1 (open square), 4 (open triangle) and 10 (open diamond) cm.

Table 2: Summary of results.

Update Interval	*Direct-Insertion (days)*		*Kalman-Filter (days)*	
	Moisture[1]	*Temperature*	*Moisture*	*Temperature*
continuous	5	>20		
1 hour	7	-	0.5	2
1 day	>20[2]	>20[2]	3	6
5 days	>40[3]	>40[3]	10[4]	15

1. 10 cm observation depth
2. Dirichlet boundary condition for 1 hour
3. Dirichlet boundary condition for 1 day
4. Quasi observations

shown that observation depth does not have a significant effect on the number of observations required for profile retrieval with the Kalman-filter retrieval algorithm.

Acknowledgments

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