

SOIL MOISTURE ESTIMATION USING REMOTE SENSING

[Jeffrey Walker](#)¹ and [Paul Houser](#)²

¹Lecturer, [Dept. of Civil and Env. Engineering, The University of Melbourne](#), Victoria, Australia

²Head, [Hydrological Sciences Branch, NASA Goddard Space Flight Center](#), Maryland, USA

Abstract

Knowledge of soil moisture content in the root zone is important throughout a wide range of environmental applications, yet adequate monitoring or modelling of this parameter, particularly at larger spatial scales, is difficult due to its high spatial and temporal variability. To overcome the land surface model limits on soil moisture estimation accuracy, point measurement spatial coverage limits, and microwave remote sensing spatial-temporal sampling limits, we reduce uncertainties through a combination of these approaches. The land surface model, forced with observation constrained European Centre for Medium-range Weather Forecasts (ECMWF) reanalysis data, is used to estimate the spatial and temporal variation of soil moisture content. Near-surface soil moisture measurements from the 6.6 GHz (C-band) channels of the Scanning Multi-channel Microwave Radiometer (SMMR) are then assimilated using a Kalman filter to correct for soil moisture estimation errors. Comparison with the limited ground-based point measurements of soil moisture content found a net improvement when near-surface soil moisture observations were assimilated.

Key Words: soil moisture, remote sensing, land surface modelling, data assimilation

Introduction

Soil moisture spatial and temporal variability is a key land surface parameter in many applications, from weather and climate prediction to early warning systems (e.g. flood forecasting), climate-sensitive socio-economic activities (e.g. agriculture and water management) and policy planning (e.g. drought relief and global warming). However, accurate regional soil moisture knowledge is elusive, due to an inability to economically monitor the spatial variation in soil moisture from traditional point measurement techniques. As a result, land surface models have been relied upon to provide an estimate of the spatial and temporal variation in land surface soil moisture. However, due to uncertainties in atmospheric forcing, land surface model parameters and land surface model physics, there is significant variation in soil moisture estimates from different land surface models.

Microwave remote sensing provides an all-weather capability for measuring the spatial distribution of soil moisture content for regions with low to moderate levels of vegetation cover, but is limited to the top few centimetres of soil and to a revisit interval of once every few days. Point measurements of soil moisture, remote sensing, and land surface modelling each have significant limits in estimating soil moisture content for use in critical applications. Therefore, a soil moisture

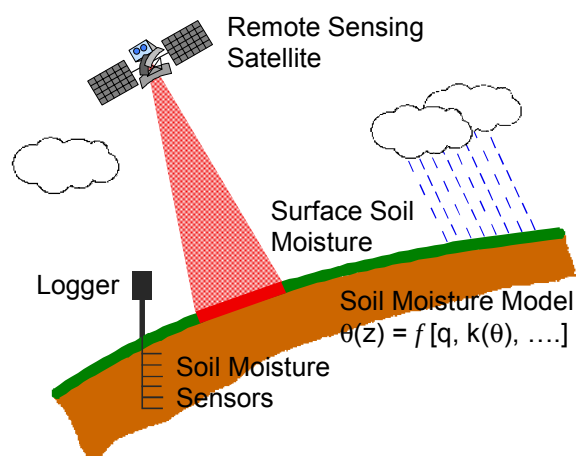


Figure 1 Illustration of the soil moisture estimation problem.

monitoring system that combines these soil moisture information sources in a strategy that minimises their individual limitations must be used, as illustrated in Figure 1.

Despite the first remote sensing satellite having been launched more than two decades ago, remote sensing measurements of near-surface soil moisture content have not found wide spread use. This is largely a result of not having a dedicated space-borne remote sensing mission for soil moisture measurement. However, soil moisture remote sensing information is available from the 6.6 GHz (C-band) channel of the

Scanning Multi-channel Microwave Radiometer (SMMR), flown on board the Nimbus-7 satellite from 1979 to 1987, and the 10.6 GHz (X-band) channel of the Tropical Rainfall Measuring Mission (TRMM), which is significantly affected by vegetation and is only available between 38.5°N and 38.5°S. The Advanced Microwave Scanning Radiometer for the Earth observing system (AMSR-E) is scheduled for launch on the Aqua satellite in mid 2002, once again providing global space-borne radiometer measurements at C-band. It is highly unlikely that there will be dedicated L-band (1-2 GHz) soil moisture sensor in space before 2005. Since C-band data is the best that we can hope for over the next several years, the historic SMMR data set provides an excellent data source in preparation for using AMSR-E observations.

In this paper, a land surface model is forced with observation constrained European Center for Medium-range Weather Forecasts (ECMWF) reanalysis data to estimate the spatial and temporal variation of soil moisture content. To correct for errors in modelled soil moisture estimates, near-surface soil moisture measurements derived from the 6.6 GHz channels of SMMR are assimilated using a Kalman filter. The soil moisture estimates, both with and without assimilation, are compared with ground-based point measurements of soil moisture. This paper presents the first known use of space-borne near-surface soil moisture observations within an assimilation framework.

Models

Land Surface Model

The land surface model used in this study is the catchment-based land surface model of Koster *et al.* (2000), illustrated schematically in Figure 2. It uses a non-traditional land surface model framework that includes an explicit treatment of sub-grid soil moisture variability and its effect on runoff and evaporation. A key innovation in this model is the shape of the land surface element; the hydrologic watershed as defined by the topography, rather than an arbitrary grid.

This land surface model uses TOPMODEL (Beven and Kirkby, 1979) concepts to relate the water table distribution to the topography. The consideration of both the water table distribution and non-equilibrium conditions in the root zone leads to the definition of three bulk moisture prognostic variables (catchment deficit, root zone excess and surface excess) and a special treatment of moisture transfer between them.

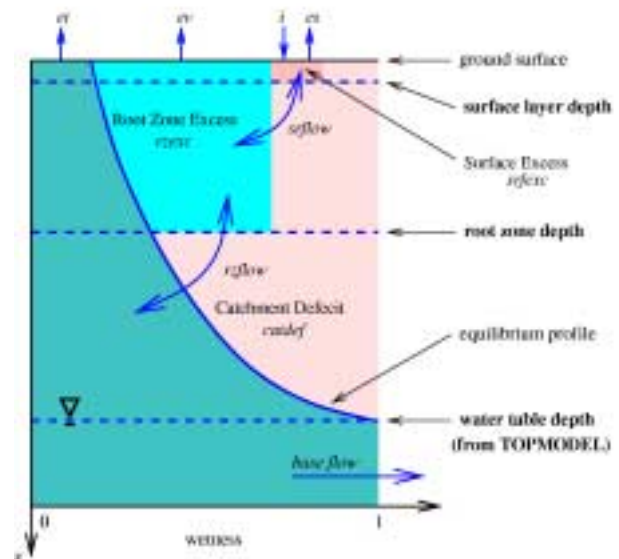


Figure 2 Schematic of the catchment-based land surface model.

Using these three prognostic variables, the catchment may be divided into regions of stressed, unstressed and saturated soil moisture regimes, and the soil moisture content of the surface (top 2 cm), root zone (top 1 m) and complete soil profile (from 1 to 3.5 m) calculated. A complete description of this land surface model is given by Koster *et al.* (2000) and Ducharme *et al.* (2000), and is summarised further by Walker and Houser (2001).

Kalman Filter

The Kalman filter is a common approach used for finding the model representation that is most consistent with observations, a process known as data assimilation. Using this approach, the conditional mean of a statistically optimal estimate of a state vector (ie. the soil moisture content from the land surface model) and its covariance matrix are tracked through a series of forecasting and update steps.

Using a linear set of model forecasting equations, estimates of the model states (i.e. soil moisture) and their covariances (standard deviation and correlation with other states) are made through time. At times when observations are made, the estimates of the model states and their associated covariances may be corrected through a Kalman filter update, so as to reflect the new information provided by the observation. The Kalman filter correction added to the state estimate is the difference between the observation and predicted observation, weighted by their relative uncertainties (Kalman filtering is essentially just an application of Bayes theorem). Corrections are made to unobserved states (i.e. deep soil

moisture) through the estimate of correlation between state values. The reader is referred to Walker and Houser (2001) for a more detailed discussion of the Kalman filter, the Kalman filter equations and their application to the catchment-based land surface model.

In this study, we have used a one-dimensional Kalman filter for updating the soil moisture prognostic state variables of the land surface model. A one-dimensional Kalman filter was used because of its computational efficiency and the fact that at the scale of catchments used, correlation between the soil moisture prognostic states of adjacent catchments is only through the large-scale correlation of atmospheric forcing, soil parameters and topography. Moreover, all calculations for soil moisture in the land surface model are performed independent of the soil moisture in adjacent catchments.

For the initial covariance matrix, diagonal terms were specified to have a standard deviation of the maximum difference between the initial prognostic state value and the upper and lower limits, with off-diagonal terms specified as zero. The diagonal terms of the forecast model error covariance matrix were taken to be the predefined values of 0.00025, 0.0025 and 0.025 mm/min for surface excess, root zone excess and catchment deficit respectively, with the off-diagonal terms taken to be zero. The assumption of independence for errors in the three soil moisture prognostic variables due to errors in the model physics is valid, as the physics used for forecasting these three prognostic variables are independent. This is unlike typical land surface models that vertically discretise the soil and apply the same physics to the soil moisture prognostic variables for each of the soil layers.

Data Sets

Model Parameters

The catchment-based land surface model requires topographic, soil and vegetation parameters. The topographic parameters are the mean, standard deviation and skewness of the compound topographic index. The catchment delineations and topographic index statistics were taken from the HYDRO1K (HYDROlogically correct 1 km) data set (<http://edcdaac.usgs.gov/gtopo30/hydro/>), which is based on the GTOPO30 digital elevation model. Scaling of the 1 km topographic index data to the equivalent of 100 km data was performed as suggested by Wolock and McCabe (2000). The catchments used in this application are at level 5

in the Pfafstetter system (Verdin & Verdin, 1999) with an average catchment area of 4400 km².

Soil parameters include porosity, wilting point, saturated hydraulic conductivity, the Clapp and Hornberger (1978) soil texture parameter, saturated matric potential and total soil depth. Apart from soil depth, soil parameters were inferred from dominant soil texture information given by the 5' × 5' resolution Food and Agriculture Organisation (FAO) digital soil map of the world, using the suggested values in Cosby *et al.* (1984). Total soil depth was taken from the first International Satellite Land Surface Climatology Project (ISLSCP) initiative (Sellers *et al.*, 1996a) 1° × 1° resolution global data set. Catchment partitioning and timescale parameters required by the catchment-based land surface model were pre-processed using the topographic and soil parameters by the methodology of Ducharme *et al.* (2000).

Vegetation parameters included vegetation type, greenness fraction and leaf area index. The Leaf Area Index (LAI) is defined as the ratio of leaf area to soil area while the greenness fraction is defined as the fraction of leaf area index that is photosynthetically active. A simplified version of the SiB vegetation classification (Sellers *et al.*, 1986) was used, with raw vegetation type information taken from the ISLSCP Initiative 1 data set. Many of the land surface model's vegetation-dependent parameters are taken directly from the SiB framework. Climatologies for monthly values of greenness fraction and LAI were derived from Advanced Very High Resolution Radiometer (AVHRR) measurements of Normalised Difference Vegetation Index (NDVI) at 1° × 1° resolution using the relationships of Sellers *et al.* (1996b), by averaging the parameter estimates over the time period of 1982 to 1990. The AVHRR data are adjusted for sensor degradation, volcanic aerosol effects, cloud contamination and solar zenith angle variations (Los *et al.*, 2000). The snow free albedo was calculated from the LAI, greenness fraction, vegetation type and a look-up table (Koster and Suarez, 1991), while zero plane displacement height and momentum roughness length was calculated from the month of year, vegetation type and a look up table (Koster and Suarez, 1996).

Forcing Data

Atmospheric forcing data were from the observation constrained 15-year (1979-1993) ECMWF Re-Analysis (ERA-15) data set (Berg *et al.*, 2001). The original ERA-15 data set is on a Gaussian grid with an equatorial resolution of approximately 1.125° and a temporal resolution of

6 hours. The atmospheric data fields used included: air temperature and humidity at 2 m, wind speed at 10 m, total and convective precipitation, downward solar and longwave radiation and atmospheric pressure.

The atmospheric data fields from reanalysis are subject to significant model bias, so we constrained the reanalysis fields to monthly average observations using a bias correction technique. The ERA-15 reanalysis, constraining observations, and land surface model fields were on a number of different projections, so the data sets were interpolated directly to the catchment grid for bias correction and use by the land surface model. In this way, the number of interpolations was kept to a minimum and the interpolation error minimised. After interpolation of both the ERA-15 data fields and the observational data fields, observation constraints were imposed using a difference or ratio correction, depending on the field. The reader is referred to Berg *et al.* (2001) for a complete description of the observation constrained forcing data set development.

Initial Conditions

While the assimilation of near-surface soil moisture has the potential to correct for poor initial conditions (Walker & Houser, 2001), it was desired to have as accurate initial conditions as possible. In this way, the impact of near-surface soil moisture assimilation on improving the soil moisture estimation could be observed directly. The initial land surface model states for 1 January 1979 were derived from driving the catchment-based land surface model to equilibrium. The spin-up equilibrium states were obtained by cycling the land surface model with the 1979 atmospheric forcing data for 10 years.

Evaluation Data

So far as the authors are aware, continuously measured in-situ point soil moisture data is publicly available for only three locations throughout the entire North American continent during the SMMR period of 1979 to 1987 (Robock *et al.*, 2000). These locations are all within the United States and consist of 6 stations across two small catchments in southwestern Iowa (1972 to 1994), an 18-station network in Illinois (1981 to 1986) and an 89-point transect in New Mexico (1982 to present). Many more North American soil moisture observation networks were developed in the 1990's, but these are not directly applicable to the SMMR era focus of this study.

In this paper, we analyse the simulation results from 1979, thus limiting ourselves to the Iowa data

set (41.2°N, 95.6°W) for evaluation purposes. While both catchments were planted with a summer corn crop, two different techniques were used to prepare the soil. The soil moisture data were measured in layers using both thermogravimetric and neutron probe techniques; the top four layers were 7.8 cm thick, the next four were 15.2 cm thick, and the last five were 30.5 cm thick. The soil moisture was measured from April through October approximately once a fortnight (Entin *et al.*, 2000).

Observation Data

Near-surface soil moisture observation data were derived from the 6.6 GHz vertically and horizontally polarised brightness temperature measurements from the space-borne SMMR instrument on board the Nimbus-7 satellite. The radiative transfer model of Mo *et al.* (1982) was used to solve for the near-surface soil moisture content and vegetation optical depth simultaneously using the microwave polarisation difference index non-linear iterative optimisation procedure of Owe *et al.* (2001). Constant values for single scattering albedo and roughness, and equal horizontal and vertical polarisation optical depth values were assumed. Soil temperature was estimated from the 37 GHz vertically polarised brightness temperature measurements, soil properties were from the FAO soil map, and dielectric constant was related to soil moisture content by the Wang and Schmugge (1980) dielectric mixing model.

Due to power constraints onboard the Nimbus-7 satellite, the SMMR instrument was only turned on for alternate days. The satellite orbited the Earth approximately 14 times per day, with local noon (ascending) and local midnight (descending) equator crossings. With a 780 km swath width and 150 km footprint at 6.6 GHz (25 km at 37 GHz), complete coverage of the Earth required about six days, with repeat coverage in the mid-latitudes about every three to four days. The SMMR brightness temperature swath data (Njoku *et al.*, 1998) were provided as daily $0.25^\circ \times 0.25^\circ$ resolution global maps. If the footprint centre fell within a grid then the grid was assigned that brightness value, while multiple brightness values within a grid were averaged.

In the analysis of SMMR data for near-surface soil moisture, brightness temperature values affected by water bodies (i.e. along the coastline and surrounding the Great Lakes) and brightness temperature values with a surface temperature value of less than 1°C were excluded due to the possibility of frost, ice, frozen soil or snow. Likewise, brightness temperature values for areas with a large optical depth value were excluded, as

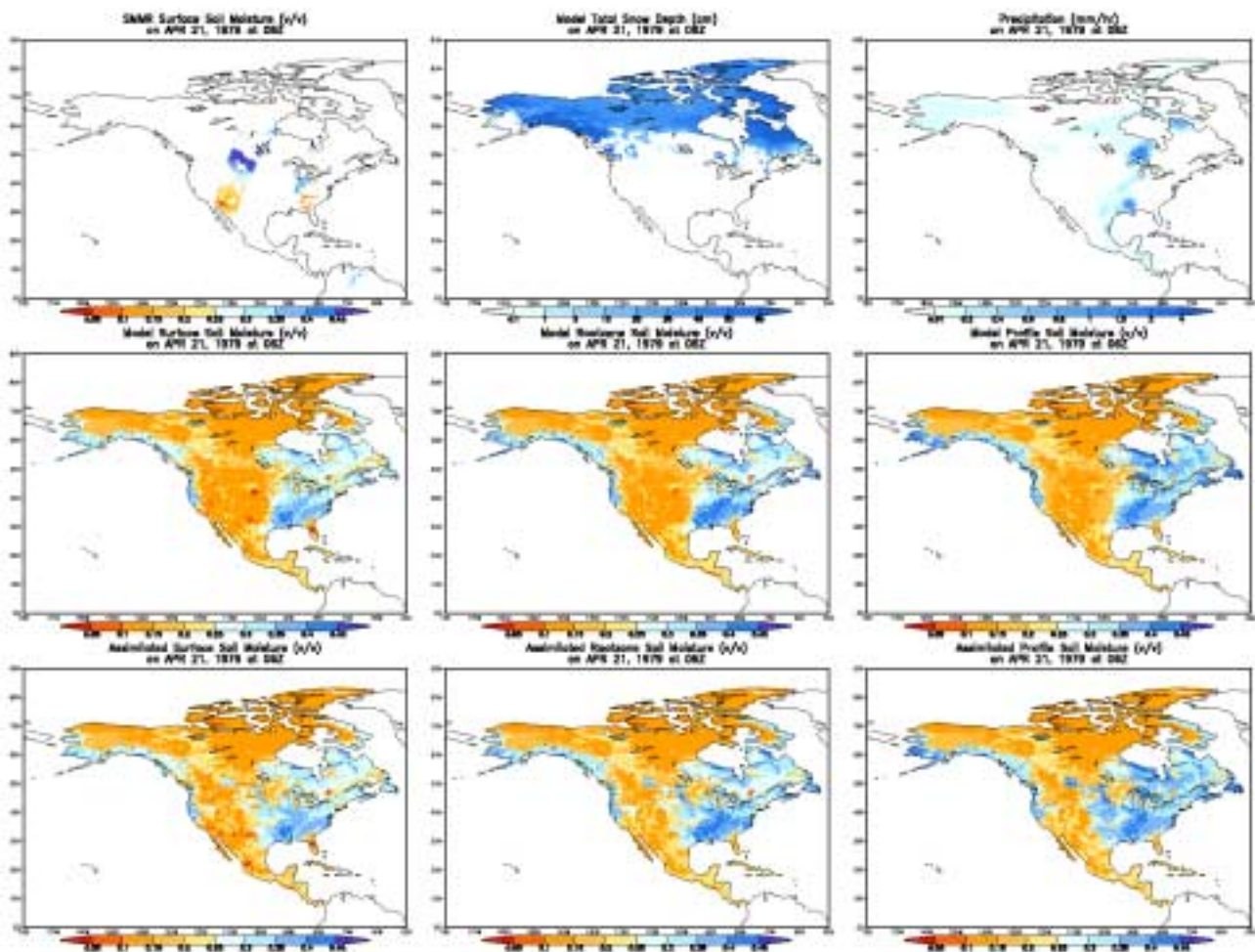


Figure 3 Animation for March, April and May of 1979, showing the impact from assimilation of SMMR near-surface soil moisture observations on the land surface model estimates of near-surface (top 2 cm), root zone (top 1 m) and total profile (up to 3.5 m). Soil moisture fields are updated once every 6 hrs with the exception of the SMMR data, which is shown twice. Click the icon to start.



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vegetation was considered to be too great to permit measurement of the near-surface soil moisture content. Accuracy estimates for the soil moisture observation data were derived from standard error propagation theory (Mikhail and Ackerman, 1976), using prescribed standard deviations for the brightness temperature measurements and soil properties.

While there was no calibration of the near-surface soil moisture retrieval algorithm to ground measured soil moisture data, results compared well with point measurements of soil moisture in the top 10 cm layer and satellite-derived vegetation index data from optical sensors (Owe *et al.*, 2001). The comparisons were for two test sites in Illinois that maximised the number of soil moisture stations in each site. The test sites had a mixture of pasture, cropland and woodland.

Results

The simulations presented in this paper are for 1979; the results for simulations from other years will be forthcoming in future papers. The animation in Figure 3 shows the land surface model response to precipitation in both the snow and soil moisture fields. It also shows how the satellite data comes in swaths and is only available for snow-free areas and areas with low to moderate vegetation cover. Moreover, it shows that after only a very short period of assimilation (from mid March) there are notable differences between the land surface model predictions of soil moisture with and without assimilation for central North America. It is possible that this is due to irrigation not accounted for in the model, but this has not been verified.

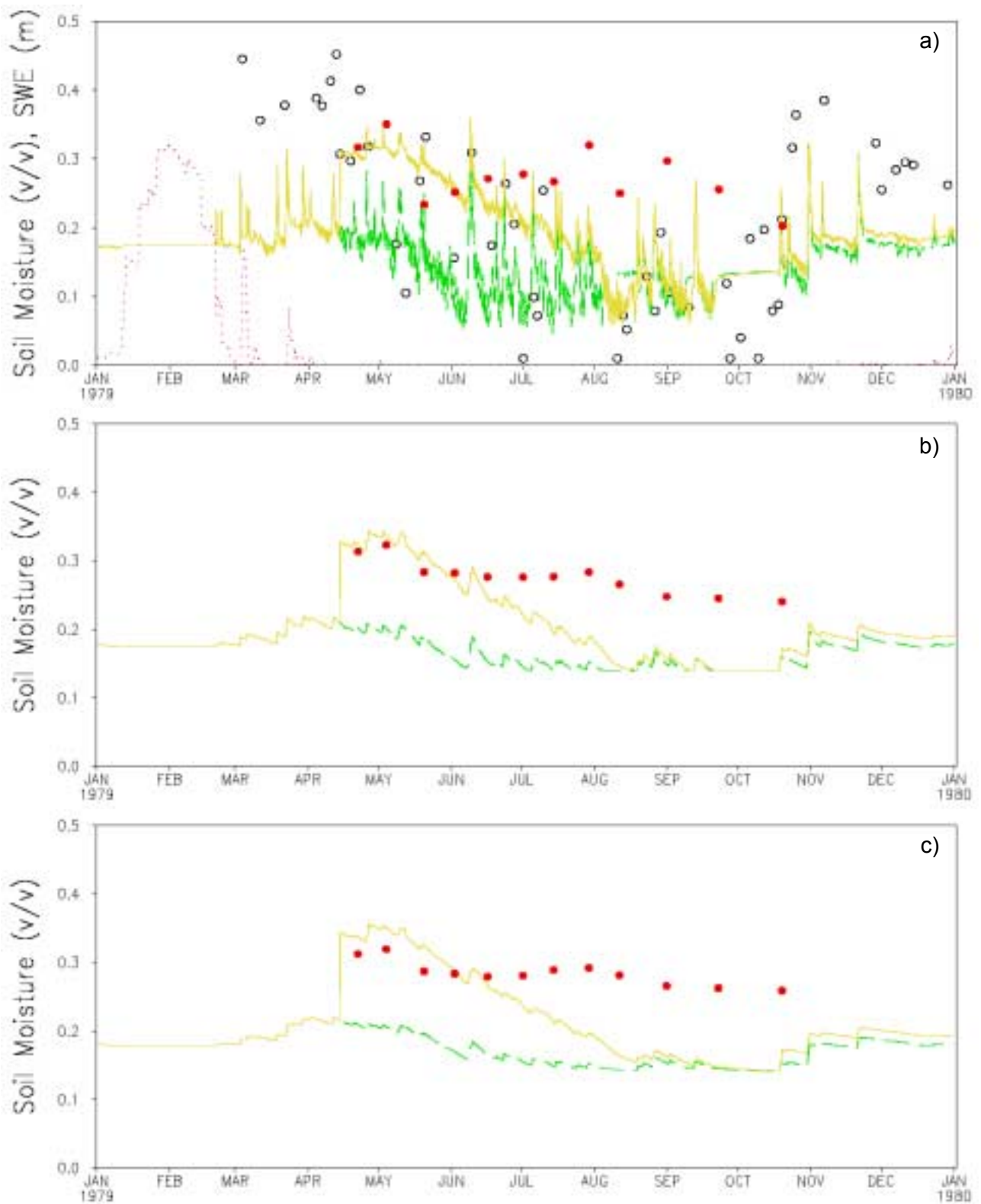


Figure 4 Evaluation of SMMR assimilation in the catchment-based land surface model for a catchment in Iowa, United States of America; a) surface, b) root zone and c) total profile. Assimilation results (solid yellow line) are compared with model simulation without assimilation (dashed green line), point soil moisture measurements (solid red circles) and SMMR surface soil moisture data (open white circles). Satellite observations were not assimilated when the land surface model predicted snow on the ground, as given by the snow water equivalent (SWE; dotted red line). Note that surface soil moisture content is 2 cm from the land surface model, approximately 1 cm from SMMR measurements at C-band, and 7.8 cm from point measurements.

Figure 4 shows a time series comparison of the soil moisture estimates both with and without assimilation, and evaluation with the field measured soil moisture data for three depth intervals in Iowa during 1979. These results show that the assimilation has yielded a vast improvement in the soil moisture estimate for all depths during the months of May and June, with the estimates without assimilation vastly underestimating the soil moisture content. No improvement was made in the soil moisture estimate with assimilation prior to May, due to snow on the ground and an inability to measure the near-surface soil moisture content from space when there is snow cover. During the months following June, the soil moisture estimate with assimilation converged back towards the soil moisture estimate without assimilation, which is drier than the field measured soil moisture content. This appears not to be a limitation of the assimilation algorithm, but rather a limitation of the land surface model and the remotely sensed soil moisture observations, as outlined below.

The near-surface soil moisture estimate with assimilation is in good agreement with the remotely sensed data, as expected, but the remotely sensed data indicates a much drier near-surface soil moisture content than the field measured soil moisture data beginning from around June. While it is difficult to make conclusive comments regarding the accuracy of SMMR derived near-surface soil moisture data from comparison with the field measured soil moisture, due to a disparity in layer depths and the representativeness of averaging a few point measurements to describe the spatial average, it would appear that the SMMR derived soil moisture content is underestimated for this particular site during the summer months. It is possible that the apparent underestimation of SMMR near-surface soil moisture measurements is a result of high vegetation biomass masking the soil once the corn crop approached maturity. However, the greater uncertainty in SMMR near-surface soil moisture measurements during this period is not adequately reflected by the observation error covariance matrix, meaning that when the Kalman filter is used to make an update of the soil moisture profile, it preferentially uses the observed near-surface soil moisture content over the model predicted value. The net result of this is to artificially dry the soil moisture estimate, both in the near-surface layer and at depth. However, assimilation has still yielded a net improvement in the soil moisture estimate when comparing with the limited point data.

These results highlight the need for accurate unbiased near surface soil moisture measure-

ments and an adequate characterisation of their uncertainty by the error estimates if data assimilation is to be a viable tool for soil moisture estimation.

Conclusions

This paper has presented results from the first known study to use space-borne measurements of near-surface soil moisture content to estimate the spatial and temporal variation of soil moisture content at the continent scale by the process of data assimilation. While remotely sensed measurements of near-surface soil moisture content appear to be underestimated for the evaluation site in southwestern Iowa during the summer months of 1979, the soil moisture estimate with assimilation was an improvement over the estimate without assimilation, when compared to the point measurement data, particularly during the months of May and June.

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Author Biographies

Jeffrey P. Walker completed his B. Surv. and B.E. (Civil) degrees at the University of Newcastle, Australia in 1995 and went on to complete his Ph.D. in environmental engineering at the same university in 1999. Dr. Walker then joined the Hydrological Sciences Branch at the NASA Goddard Space Flight Center as a visiting scientist for 2 years, before joining the Department of Civil and Environmental Engineering at the University of Melbourne, Australia. His research has been focussed on the measurement of soil moisture from remote sensing techniques and the assimilation of such information into land surface models.

Postal Address: Jeffrey Walker, Department of Civil and Environmental Engineering, The University of Melbourne, Parkville, Victoria 3010, Australia.

E-mail: j.walker@unimelb.edu.au

Paul R. Houser received his B.S. and Ph.D. in hydrology and water resources at the University of Arizona, USA. He joined the Hydrological Sciences Branch at the NASA Goddard Space Flight Center in 1997 as a hydrometeorologic research scientist, served as a visiting senior scientist at NASA Headquarters during 1999-2000, and became the head of the Hydrological Sciences Branch in April 2000. Dr. Houser's research focuses on multi-scale land surface-atmospheric process observation and numerical simulation, and the development and application of eco-hydrologic data assimilation methods.

Postal Address: Paul Houser, Code 974, NASA Goddard Space Flight Center, Greenbelt, Maryland 20771, United States of America.

E-mail: paul.houser@gsfc.nasa.gov