TECHNICAL MEMORANDUM

403

# Soil moisture analysis combining screen-level parameters and microwave brightness temperature: A test with field data

G. Seuffert, H.Wilker[1], P. Viterbo, J.-F. Mahfouf[2], M. Drusch, J.-C. Calvet[3]

Research Department

[1] MIUB, Germany, [2]SMC, Canada, [3] Meteo France

submitted to Geophys. Res. Letters

March 2003



European Centre for Medium-Range Weather Forecasts
Europäisches Zentrum für mittelfristige Wettervorhersage
Centre européen pour les prévisions météorologiques à moyen terme

For additional copies please contact

The Library
ECMWF
Shinfield Park
Reading
RG2 9AX
library@ecmwf.int

Series: ECMWF Technical Memoranda

A full list of ECMWF Publications can be found on our web site under:
http://www.ecmwf.int/publications/

**Abstract**

To improve the soil moisture initial conditions for numerical weather prediction models the potential of assimilating both screen-level parameters (2m-temperature $T_{2m}$, 2m-relative humidity $RH_{2m}$) and 1.4 GHz microwave brightness temperature $T_B$ is investigated. A soil moisture analysis system based on the Extended Kalman Filter theory is applied to the single column version of the ECMWF numerical weather prediction model for 130 summer days during the MUREX field experiment. A comparison with independent observations shows that the prediction of sensible heat flux, root zone and especially near-surface soil moisture benefits from the assimilation of all three observation types ($T_{2m}$, $RH_{2m}$, $T_B$).

# 1 Introduction

As a lower boundary condition for numerical weather prediction (NWP) models soil moisture is a crucial variable. It strongly influences the partitioning of available energy into sensible and latent heat flux and hence the evolution of the lower atmospheric conditions. But imperfect parameterization of land surface and soil processes and failures in simulating precipitation and cloud cover can lead to considerable drifts of soil moisture. In cases of strong land and atmosphere coupling, screen level parameters are considerably influenced by the underlying soil moisture. This indirect signal contained in measured screen level parameters can be used to adjust modeled root zone soil moisture. Remotely sensed 1.4 GHz microwave brightness temperatures $T_B$ provide a more direct signal of the near-surface soil moisture. In an assimilation framework this soil moisture information has to be transported from the near-surface to the deeper soil layers to have an impact on modeled atmospheric parameters. Many studies using different assimilation techniques show that either the use of screen level parameters (e.g. Mahfouf, 1991; Rhodin et al., 1999; Hess, 2001) or remotely sensed data (e.g. Reichle et al., 2001; Margulis et al., 2003; Crow and Wood, 2003) lead to more realistic root zone and near-surface soil moisture values.

This paper explores the potential of assimilating both data sources, screen-level parameters and remotely sensed observations, to improve the prediction of soil moisture. A simplified Extended Kalman filter is used to assimilate measured 2m-temperature $T_{2m}$, 2m-relative humidity $RH_{2m}$ and synthetic 1.4 GHz $T_B$ acquired during the MUREX (Monitoring the Usable Soil Reservoir EXperimentally) field experiment close to Toulouse, France (Calvet and Noilhan, 2000), into a single column version (SCM) of the European Centre for Medium-Range Weather Forecasts (ECMWF) NWP model. A control run and data assimilation model runs with different configurations of assimilated observations are applied for 130 days during one summer season. Simulated root zone and near-surface soil moisture and sensible heat flux are compared with corresponding observations.

# 2 Soil moisture Analysis System

The assimilation technique used here is based on the operational version implemented at the German Weather Service (Hess, 2001) and has a number of similarities with an Extended Kalman Filter (EKF). The basic idea of the algorithm is that for quasi-linear problems the minimum of the classical cost-function defined in the variational context (Rhodin et al., 1999) can be directly obtained rather than applying an iterative method. The tangent-linear of the observation operator is approximated by a one side finite difference assuming that close to the forecast state the dependencies of the state parameters (soil moisture in three root zone layers) and observation variables ($T_{2m}$, $RH_{2m}$, $T_B$) are linear. Hence, for each soil layer one additional forecast run with slightly perturbed soil moisture content is needed. In this way nor adjoint or tangent linear coding are required. The forecast error covariances evolve temporally with a 24-hour cycling. In contrast to the original algorithm, described in Hess (2001), we account for the soil water transfer between the soil layers for calculating the forecast error covariance.

The model error covariance matrix is assumed to be diagonal and has been estimated by performing a number of sensitivity studies with varied model errors. For all three soil layers a standard deviation of 0.005 $m^3/m^3$ for a 24h-cycling has been chosen so that the analysis is closest to optimality with reasonably small soil moisture increments. The standard deviation of the observation error have been set to 2K for $T_{2m}$, 10% for $RH_{2m}$ and 2K for $T_B$. The impact of the different types of observations on the soil moisture analysis is partly determined by the corresponding observation errors and model errors. Since this experiment is based on quality controlled forcing data and synthetic $T_B$ observations, errors in the model and $T_B$ can be assumed to be rather low. Prelaunch studies also suggest that a 1 K noise level for the L-band SMOS instrument is achievable (Pellarin et al., 2003). Consequently, the error for L-band $T_B$ was set to 2 K. When the model error is increased, e.g. through erroneous rainfall data, results similar to the ones presented in Section 4 are obtained for brightness temperatures characterized by larger errors.

The advantage of this soil moisture analysis system is the dependence of the forecast errors on the synoptic situation rather than being fixed to statistical derived values as in Optimal Interpolation operational at ECMWF, Météo-France and Canadian Meteorological Centre, for instance. This makes atmospheric criteria for the applicability of the method no longer necessary and allows for an easier implementation of new observation types.

# 3 Application during MUREX experiment 1997

## 3.1 Observations

The soil moisture analysis scheme is applied for data from the MUREX experiment (Calvet and Noilhan, 2000). From June 1994 to May 1998 a meteorological station was operated on a fallow land in Southern France (43°24'N, 1°10'E, altitude 240m). In this study data from 1.6-9.10.1997 are used. During this period the following atmospheric parameters were measured on a 30 min basis: $T_{2m}$, $RH_{2m}$, wind speed and direction, precipitation, surface temperature, solar downward radiation, upward and downward total radiation, sensible heat flux and ground heat flux. A time dependent bias correction was applied to the downward longwave radiation. Latent heat flux was not measured directly. Since errors tend to accumulate in the residual of the energy balance, the latent heat flux given in the MUREX data set was not used for evaluating the data assimilation experiment. The soil condition was monitored by weekly profiles of soil moisture and daily near-surface soil moisture. Soil and vegetation characteristics are given in Table 1 (see Calvet and Noilhan, 2000). Synthetic $T_B$ for 1.4 GHz (L-Band, $\approx$ 21cm) at nadir were estimated using measured near-surface soil moisture and soil temperature as an input for a radiative transfer model described in Pellarin et al. (2003). In this study, to account for the soil temperature profile in the LSMEM calculations (see section 3.2), an effective soil temperature $T_{eff}$ is parameterized using C=0.246 (Choudhury et al., 1982):

$$T_{eff} = T_\infty + (T_{skin} - T_\infty)C \tag{1}$$

For comparison, an observed $T_{eff}$ is calculated using measured surface temperature $T_{skin}$ and measured deep soil temperature $T_\infty$ at 0.5m.

| Parameter | Value | | Parameter | Value | |
|---|---|---|---|---|---|
| Vegetation coverage fraction | 0.95 | meas. | Salinity of soil water | 0.65 psu | Lit. |
| Vegetation water content | 0.7 kg/m$^3$ | Lit. | Soil dry bulk density | 1.45 g/cm$^3$ | meas. |
| Salinity of vegetation water | 6 psu | Lit. | Soil clay fraction | 28 % | meas. |
| Vegetation single scattering albedo | 0.05 | Lit. | Soil sand fraction | 14 % | meas. |
| Vegetation structure coefficient | 0.003 | Lit. | Wilting point | 0.18 m$^3$/m$^3$ | meas. |
| Surface roughness | 1.2 cm | tuned | Field capacity | 0.34 m$^3$/m$^3$ | meas. |

*Table 1: Vegetation and soil parameters at the MUREX- site. Parameters were either measured (meas.), adopted from the literature (Lit.)(Dobson et al., 1985; Kerr and Njoku, 1990; Ulaby et al., 1983) or were tuned for the field site.*

### 3.2 SCM and LSMEM Modeling

The soil moisture assimilation algorithms are tested with the SCM of the ECMWF NWP model. Its land surface model TESSEL (Tiled ECMWF Scheme for Surface Exchanges over Land)(van den Hurk et al., 2000; Viterbo and Beljaars, 1995) employs four soil layers (0.07m, 0.21m, 0.72m, 1.89m), where the top three layers cover most of the root zone for all vegetation types. For six different tiles the land energy balance is solved with regard to skin temperature. In this study the weighted average skin temperature is used. Sensible and latent heat flux are parameterized by resistance based formulations. Soil heat budget is calculated based on Fourier diffusion law. The vertical water transport follows Darcy's law and free drainage is assumed at the bottom. For the stomatal resistance a value of 90 s/m is used which was determined by accounting for the measured time dependent leaf area index, measured stomatal resistance and the constant leaf area index of 3 m$^3$/m$^3$ in TESSEL.

To simulate microwave brightness temperatures the SCM is coupled to a land surface microwave emissivity model (LSMEM), which is different from the one used to create the synthetic $T_B$ for MUREX (see section 3.1). The LSMEM takes vegetation, rough surface and atmospheric contributions into account dealing with frequencies between 1.4-20 GHz. The model has been used and tested in various studies with coupled hydrologic models. For details the reader is referred to Drusch et al. (2001). LSMEM vegetation and soil parameters used for the MUREX experiment are listed in Table 1. For the LSMEM calculations $T_{eff}$ is used according to equation (1) with $T_\infty$ from layer 3 (0.64m deep).

### 3.3 Experiment design

To test and compare the performance of assimilating a combination of screen-level and remotely sensed observations the following model runs are conducted: a) a control run with free running of soil moisture and soil temperature (Ctrl), b) a model run in which $T_{2m}$ and $RH_{2m}$ are assimilated (KTR) c) a model run in which $T_B$ are assimilated and d) a model run in which all three types of observations are assimilated (KTRB). All model runs are started at local midnight and are initialized every 24 hours with atmospheric ERA40 re-analysis data. ERA40 soil moisture and soil temperature values are never used in any of the simulations. Precipitation, incoming shortwave and longwave radiation are prescribed every 20 min (equals model time step) from observations to avoid errors in the forcing which are crucial for soil moisture simulation. The initial soil conditions at the 1$^{st}$ of June are derived from the observations.

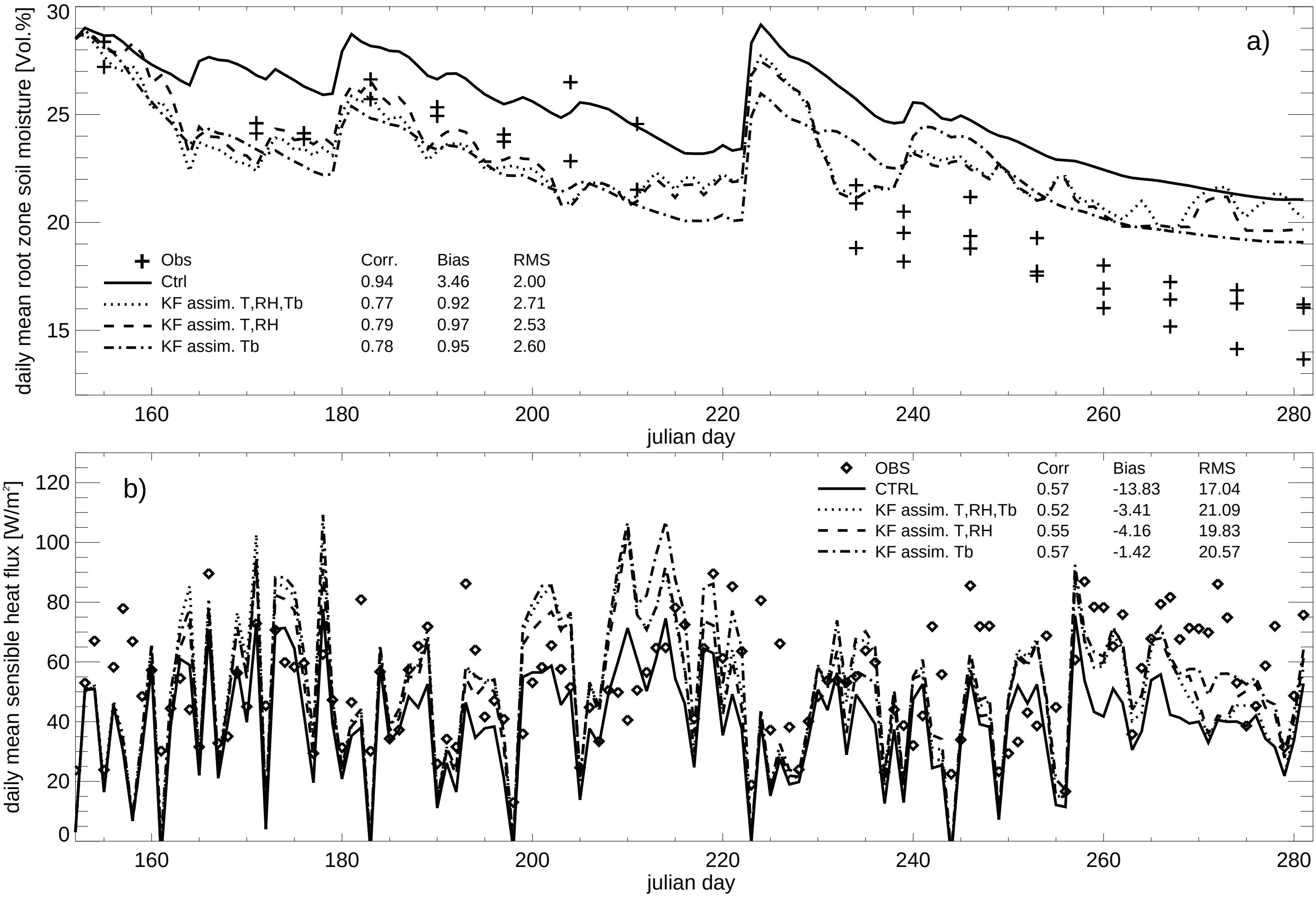


*Figure 1: Evolution of the daily mean a) root-zone soil moisture and b) sensible heat flux for 1.6-9.10.1997. Soil moisture profiles were measured at three different locations and are marked with +.*

## 4 Results

The temporal evolution of root zone soil moisture shows that the Ctrl-run simulates too large soil moisture values for the whole period compared with the observations (Fig.1a). All three assimilation runs improve the simulated root zone soil moisture. Assimilating only $T_B$ results in the lowest soil moisture values underestimating soil moisture in early summer. The best agreement with the measurements are obtained with the KTR- and KTRB-runs whose simulated root zone soil moisture differ only slightly. In general, drying periods are considerably better captured by the assimilation runs. However, none of the four model runs simulates the strong soil drying in late summer (days 245-280).

Analysing simulated $T_{2m}$ and $RH_{2m}$ for the four model runs, it is found that the cold bias of the Ctrl-run is reduced in the KTR-, KB- and KTRB-runs whereas the wet bias of the Ctrl-run becomes a dry bias in the KTR-, KB- and KTRB-runs (Tab. 2a+b). Additionally, Tables 2a+b show that correlation coefficient and root mean square errors (RMS) are similar in all four model runs. For the assimilation runs, with $T_{2m}$ and $RH_{2m}$ only, in most cases the system is dominated by the cold bias at 9, 12, 15 UTC and the wet bias at 15 UTC, whereas at 9, 12 UTC a dry bias exists. This means that at certain times $T_{2m}$ and $RH_{2m}$ departures from observations

a) 2m-Temperature

| | Corr. | Bias | RMS |
|---|---|---|---|
| Ctrl | 0.92 | -1.80 | 1.81 |
| KTRB | 0.92 | -1.52 | 1.82 |
| KTR | 0.92 | -1.28 | 1.82 |
| KB | 0.92 | -1.15 | 1.88 |

b) 2m-Relative Humidity

| | Corr. | Bias | RMS |
|---|---|---|---|
| Ctrl | 0.79 | 0.44 | 11.86 |
| KTRB | 0.79 | -1.98 | 11.75 |
| KTR | 0.82 | -4.01 | 11.34 |
| KB | 0.80 | -4.94 | 12.04 |

*Table 2: Daytime (6-18 UTC) correlation coefficient, mean bias (simulated minus observed) and rms error (bias corrected) for a) $T_{2m}$ [K] and b) $RH_{2m}$ [%]*

are positively correlated. The assimilation tends to reduce soil moisture in accordance with the cold and wet bias at 15 UTC. This leads to a deterioration of the dry bias, which predominates in between the assimilation times. This partly explains the improvement and deterioration of simulated daytime bias of $T_{2m}$ and $RH_{2m}$, respectively, in the KTR- and KTRB-runs. In contrast, for the KB-run, the changes in the biases are the result of a considerable reduction of simulated root zone soil moisture caused by the $T_B$ signal (Fig. 1a). In conclusion, the separate assimilation of the two different observation types leads to similar results for $T_{2m}$ and $RH_{2m}$. This suggests that part of the $T_{2m}$ and $RH_{2m}$ bias is not soil moisture controlled but by the atmosphere e.g. advection or by the parameterization of vegetation which might not capture the particular characteristics of this site.

The changes in simulated soil moisture of the assimilation runs result in higher values of daily mean sensible heat flux when compared to the Ctrl-run (Fig. 1b). Although all four model runs underestimate sensible heat flux the bias is reduced by approx. 10 W/m$^2$ due to the assimilation.

Observed surface soil moisture is best captured when only $T_B$ or additionally $T_{2m}$ and $RH_{2m}$ are assimilated, (Fig. 2a). Especially, in drying periods the soil moisture is in better agreement with the observations compared with the Ctrl- and KTR-run. However, in late summer the additional assimilation of $T_B$ does not result in a further improvement because the modeled surface soil moisture already has reached the wilting point.

Although in early summer (days 155-180) the simulated soil moisture minima are well captured by the KB- and KTRB-runs, the simulated brightness temperature underestimates the observations (Fig. 2b). In mid summer period (days 180-190) observed soil moisture is underestimated by the simulations but $T_B$ is in good agreement with the measurements. This might be partly explained by an underestimation of observed $T_{eff}$ in the simulations in this period (not shown). On the other hand, in late summer (days 250-280) measured and observed $T_{eff}$ are in better agreement (not shown) and the differences in measured and observed $T_B$ result from the observed and simulated soil moisture differences. It is also important to indicate that the soil roughness effects are parameterized differently in the LSMEMs used to derive the synthetic $T_B$ and the one used for the assimilation experiments. This might partly explain a bias between simulated and observed $T_B$.

## 5 Discussion and conclusions

This study shows that the assimilation of screen-level parameters combined with 1.4 GHz $T_B$ into a SCM using a simplified EKF algorithm gives promising results. Compared with observations, the simulation of sensible

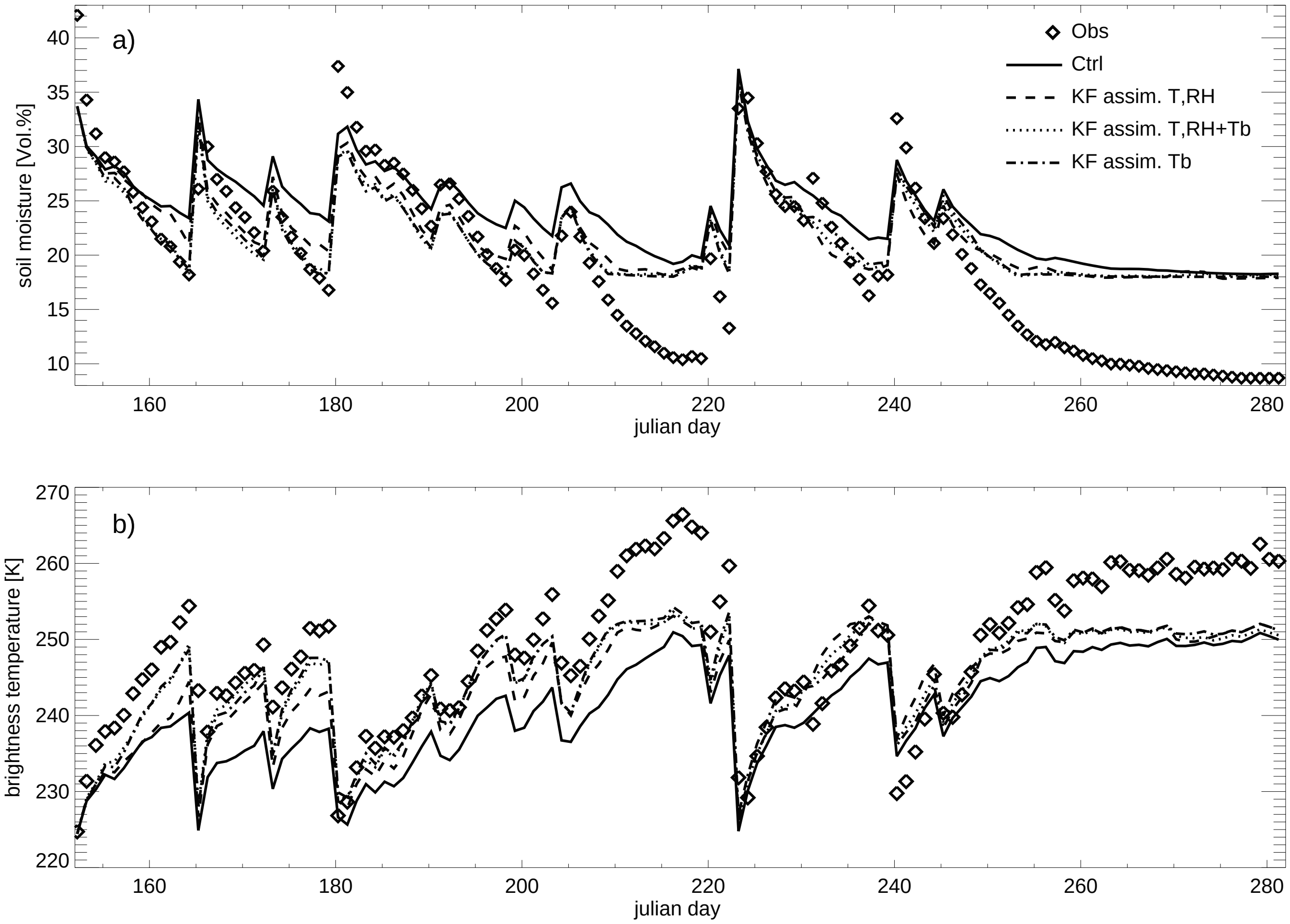


*Figure 2: Evolution of a) the near surface soil moisture and b) 1.4 GHz microwave brightness temperature for 1.6-9.10.1997 at 6 UTC.*

heat flux, root zone and surface soil moisture are improved most by the assimilation of all three variables compared to a control run and model runs, in which $T_{2m}$ and $RH_{2m}$ or $T_B$ are assimilated separately.

In order to not only improve the trend of surface soil moisture but also the absolute value, the impact of differences in simulated and observed skin and soil temperature on $T_B$ can not be neglected. The assimilation of remotely sensed skin temperatures or a temporal bias correction are possible options to account for this problem. Also differences in the soil texture of the near-surface and deeper layers lead to differences in simulated and observed near-surface soil moisture and hence $T_B$. Soil models with better vertical resolution or renormalization of the near-surface soil moisture before using it as input into the LSMEM could lead to improvements (Calvet and Noilhan, 2000), but both methods rely on a good spatial knowledge of either near-surface soil texture or longterm near-surface soil moisture measurements, which for larger scales are not currently available with the required accuracy.

However, the combined assimilation of screen-level parameters and 1.4 GHz $T_B$ offers the potential of improved coupled soil and atmospheric predictions. In future applications, this potential could be exploited in NWP when the ESA's Soil Moisture and Ocean Salinity Mission (SMOS) provides 1.4 GHz $T_B$ observations with a global coverage.

## Acknowledgments

This work was supported by the European Commissions 5th framework programme on Energy, Environment and Sustainable Development (EVG1-CT-2001-00050) through the European Land Data Assimilation project. It was partly funded by the German Climate Research Program DEKLIM (01LD0006). The work benefited from valuable discussions with A.C.M. Beljaars (ECMWF), M. Fisher (ECMWF) and B.J.J.M. van den Hurk (KNMI).

## References

Calvet J.-C. and J. Noilhan, 2000: From near-surface to root-zone soil moisture using year-round data, J. Hydrometeor. Vol. 1, No. 5, 393-411.

Choudhury, B.J., T.J. Schmugge and T. Mo, 1982: A Parameterization of effective soil temperature for microwave emission. J. Geophys. Res. Lett., 87, C2, 1301-1304.

Crow, W.T., and E.F. Wood, 2003: The assimilation of remotely sensed soil brightness temperature imagery into land surface model using Ensemble Kalman filtering: a case study based on ESTAR measurements during SGP97. Advances in Water Resources, 26, 137-149.

Dobson, M.C., F.T. Ulaby, M.T. Hallilainen and M.A. El-Rayes, 1985: Microwave dielectric behavior of wet soil -Part II: Dielectric Mixing Models. IEEE Trans. Geosci. Remote Sens., GE-23, 1, 35-46.

Drusch, M., E.F. Wood and T.J. Jackson, 2001: Vegetative and atmospheric corrections for the soil moisture retrieval from passive microwave remote sensing data: Results from the Southern Great Plains hydrology Experiment 1997. J. Hydrometeor., 2, 181-192.

Hess, R., Assimilation of screen-level observations by variational soil moisture analysis, 2001: Meteorol. Atmos. Phys., 77, 145-154.

Kerr, Y.H. and E.G. Njoku, 1990: A semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space. IEEE Trans. Geosci. Remote Sens., Ge-28, 3,384-393.

Mahfouf, J.F., 1991: Analysis of soil moisture from near-surface parameters. A feasibility study. J. Appl. Meteorol., 7, 506-526.

Margulis, S.A., D. McLaughlin, D. Entekhabi, and S. Dunne, 2003: Land data assimilation and estimation of soil moisture using measurements from the Southern Great Plains 1997 field experiment. Accepted at Water Resour. Res.

Pellarin, T. and Co-authors, Two-year global simulation of L-band brightness temperatures over land, 2003: submitted to IEEE Trans. Geosci. Remote Sens.

Reichle, R.H., D. Entekhabi, and D.B. McLaughlin, 2001: Downscaling of radiobrightness measurements for soil moisture estimation: A four-dimensional variational data assimilation approach. Water Resour. Res., 31, 2353-2364.

Rhodin, A., F. Kucharski, U. Callies, D.P. Eppel and W. Wergen, 1999: Variational soil moisture analysis from screen-level atmospheric parameters: Application to a shortrange weather forecast model. Q.J.R. Met. Soc., 125, 2427-2448.

Ulaby, F.T., M. Razani, and M. Dobson, 1983: Effects of vegetation cover on the microwave radiometric sensitivity to soil moisture, IEEE Trans. Geosci. Remote Sens., Ge-21, 1, 51-61.

van den Hurk, B.J.J.M., P. Viterbo, A.C.M. Beljaars, and A.K. Betts, 2000: Offline validation of the ERA40 surface scheme. ECMWF Tech. Mem. 295, 42pp.

Viterbo, P. and A.C.M. Beljaars, 1995: An improved land surface parameterization scheme in the ECMWF model and its validation. J. Climate, 8, 2716-2748.