# Assessment of soil moisture retrieval with numerical weather prediction model temperatures

**THOMAS R. H. HOLMES[1], WADE T. CROW[1], THOMAS J. JACKSON[1], RICHARD A. M. DE JEU[2], ROLF H. REICHLE[3] & MICHAEL H. COSH[1]**

1 *USDA-ARS Hydrology and Remote Sensing Laboratory, 10300 Baltimore Ave., Beltsville, Maryland 20705, USA*
thomas.holmes@ars.usda.gov

2 *Department of Hydrology and Geo-Environmental Sciences, Faculty of Earth and Life Sciences, VU University Amsterdam, De Boelelaan 1085, Amsterdam 1082 HV, The Netherlands*

3 *NASA GSFC, Hydrological Science Branch, Greenbelt, Maryland 20771, USA*

**Abstract** The effect of using a Numerical Weather Prediction (NWP) soil temperature product instead of estimates provided by concurrent 37 GHz data on satellite-based passive microwave retrieval of soil moisture was evaluated. This was prompted by the change in system configuration of preceding multi-frequency satellites to new single frequency L-band missions. *In situ* soil moisture data from four watershed sites in the USA were used to assess this change with one soil moisture retrieval algorithm. The temperature product substitution resulted in a large decrease in sensitivity to *in situ* soil moisture changes, and illustrates the complications of moving from a coincident source to interpolation of modelled temperature.

**Key words** land surface temperature; soil moisture retrieval; WindSat; LPRM

## INTRODUCTION

Passive microwave soil moisture retrieval algorithms must account for the physical temperature of the emitting surface. In recent years, the configuration of the available satellite instruments (SMMR, TMI, AMSR-E, and WindSat) has provided a suite of microwave frequencies that supported soil moisture retrieval as well as surface temperature estimation. Surface temperature has been estimated from vertical polarized Ka-band (37 GHz) brightness temperature, e.g. Owe *et al.* (2001). The two L-band soil moisture missions, Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP), do not include higher frequencies and as a result must use alternative approaches to provide the temperature information. Both missions are considering the use of ancillary data sets from numerical weather prediction (NWP) models. In this study we evaluate the implications of using NWP data to obtain the effective temperature, as opposed to using a coincident observation as implemented with multi-frequency sensors.

Holmes *et al.* (2012) evaluated the accuracy of NWP land surface temperature products using *in situ* data. Of the NWP sources considered in that study, the Modern Era Retrospective-analysis for Research and Applications (MERRA: http://gmao.gsfc.nasa.gov/research/merra), was found to have the best performance with an absolute accuracy of 1.8 K (RMS error) with a bias removed error of 1.5 K for the morning hours. The relationship between the error in soil temperature data and the requirements of a soil moisture retrieval algorithm are assessed in Holmes & Jackson (2010). For a single channel algorithm soil moisture retrieval, a 1 K error in temperature results in an error of 0.01 to 0.03 $m^3 m^{-3}$ in soil moisture, with the error increasing with vegetation density.

In order to evaluate the potential impact of this change in accounting for surface temperature in passive microwave soil moisture retrieval using SMOS and SMAP, we used data from WindSat. The primary reason for choosing WindSat is that its morning overpass time is the same as SMOS and SMAP. WindSat is a multi-frequency passive microwave instrument on the Coriolis satellite, launched in January 2003. The lowest frequency radiometer on this platform that is not affected by RFI over the US is X-band (10.65 GHz), and it also includes a Ka-band radiometer.

For this preliminary phase of the evaluation we used data for two years (2003 and 2004) for the following elements: NWP product MERRA, soil moisture products from the Land Parameter Retrieval Model (LPRM) (Owe *et al.*, 2008), and *in situ* soil moisture from a set of watershed validation sites (Jackson *et al.*, 2010). Soil moisture was retrieved using the two alternative temperature approaches and compared to the *in situ* data.

# MATERIALS

## Watershed validation networks

The validation resource for this investigation is the set of four soil moisture networks established for AMSR-E. These are all located in the USA: Little Washita, Oklahoma; Walnut Gulch, Arizona; Reynolds Creek, Idaho; and Little River, Georgia. Soil moisture is measured at 5 cm depth, with a replication of 15 to 30 across an area of 150–600 $km^2$. In addition, soil temperature is measured at 5 cm at the same locations. A detailed description of each individual site and its use as ground truth for AMSR-E soil moisture retrievals is given in Jackson *et al.* (2010).

## WindSat

The WindSat multi-frequency radiometer (Gaiser *et al.*, 2004) is part of the Coriolis satellite with equatorial overpass times at 6 am and 6 pm, similar to those of SMOS and SMAP. The centre frequency of its X-band radiometer is 10.65 GHz, with an incidence angle of 49.9 degrees. The Ka band radiometer is centred at 37 GHz, and has an incidence angle of 53 degrees. A time series of observations is extracted for each watershed from the high resolution set (Version 2). For each observation time, the data that fall in the 0.25 grid box with its centre in the watershed were averaged. There are a total of ±140 ascending and descending overpasses per year, of which ±10 are not used due to a high standard deviation of the Ka-band channel, which is indicative of rain events.

## Reanalysis temperature data

The Modern Era Retrospective-analysis for Research and Applications (MERRA) is generated by the NASA Global Modeling and Assimilation Office (http://gmao.gsfc.nasa.gov/research/merra). The MERRA products are generated using Version 5.2.0 of the GEOS-5 DAS (Goddard Earth Observing System (GEOS) Data Assimilation System (DAS)) with the model and analysis each at 0.5 by 0.67 degrees resolution in latitude and longitude, respectively. Hourly land surface output is available. The land surface processes are described by the NASA catchment land surface model (Ducharne *et al.*, 2000; Koster *et al.*, 2000). Each MERRA grid cell contains several irregularly shaped tiles. For each tile, surface exchange processes and “surface” temperatures are represented separately for sub-tiles that are characterized by one of three unique hydrological states: saturated, unsaturated, and wilting. The sub-tile fractions of each catchment are modelled dynamically based on the total amount of water in the catchment. The “surface” temperature of a grid cell is then obtained by area-weighted averaging of the surface temperatures of all sub-tiles within the grid cell. The above-mentioned surface temperatures are prognostic variables of the model and represent a bulk layer that includes the vegetation canopy and the top 5 cm of the soil column. In this study, we analyse the area-weighted surface temperatures that describe the temperature of this composite of the canopy and the top 5 cm of soil, here referred to as $T_{ME}$.

## LPRM

The soil moisture retrieval algorithm used here is the Land Parameter Retrieval Model (LPRM). It is one of several algorithms that have been used with AMSR-E, as well as other passive microwave satellites. Ultimately, the analyses presented here should be performed using several alternative algorithms because a recent study (Jackson *et al.*, 2010) revealed some issues with LPRM in terms of absolute accuracy. However, for this preliminary investigation it is an adequate tool for the proposed analysis of the temperature product impacts.

LPRM is a tau-omega based passive microwave soil moisture retrieval algorithm that utilizes the polarization difference to parameterize the optical depth (Owe *et al.*, 2008). It uses the soil temperature as an explicit input and is therefore suitable to test different temperature inputs. LPRM has previously been applied on a range of satellites, most recently on on WindSat

(Parinussa *et al.*, 2011). Here, LPRM is applied with the same parameters as used previously for AMSR-E X-band observations, with the roughness parameterized according to Choudhury *et al.* (1979) with $h = 0.18$ and $Q = 0.127$, a single scattering albedo of 0.06, and an atmospheric opacity of 0.011.

The soil and canopy temperature are assumed equal ($T = T_s = T_c$), and the temperature sensing depth is assumed to be 1.2 cm. As in the case of AMSR-E, a linear relationship between the Ka-band channel ($T_{B37V}$) and the soil temperature at this depth was established for the overpass times of WindSat:

$$T_{KA} = 0.99 T_{B37V} + 16.1 \qquad (1)$$

## TEMPERATURE DEPTH CONSIDERATIONS

It is difficult to validate shallow soil temperature measurements with *in situ* data within the first 5 cm of the soil layer because it is difficult to maintain stable sensor depths for long time periods. At the watershed sites, soil temperature sensors are installed at a nominal depth of 5 cm, but the exact depth for the period under consideration must be regarded with an uncertainty of ±2 cm. Given a continuous soil temperature record, such as recorded at the watershed sites, it is possible to model the temperature at a second depth by applying basic heat flow principles (Van Wijk & de Vries, 1963). Considering a given phase lag between two temperature records, these can then be synchronized by shifting one record in time and adjusting the amplitude in proportion to that phase shift (*dt*).

For the purpose of validating the soil temperature inputs, the *dt* between *in situ* measurements and $T_{KA}$ (as estimated from the 37 GHz V-pol data according to equation (1) is determined by optimizing the coefficient of determination ($R^2$) between the Ka-band and the synchronized *in situ* temperature. The optimal *dt* for each watershed is then applied to synchronize the *in situ* temperature record.

The reanalysis temperature represents the average temperature of the canopy and 0–5 cm surface soil layer. To account for the possible difference in temperature depth between $T_{ME}$ and the $T$ needed for the retrieval, the *dt* between $T_{ME}$ and $T$ is determined by optimizing the $R^2$ of the retrieved soil moisture. This *dt* is then applied to calculate the $T_{ME,1}$ for each watershed.

## RESULTS

Two alternative sets of soil moisture are retrieved from WindSat X-band observations over the four watersheds by applying LPRM with either $T = T_{KA}$ as input, or with $T = T_{ME,1}$. Both sets are validated against the *in situ* data and the results are discussed in terms of $R^2$, the standard error of estimate (root mean square error of predictions with regression), and the watershed bias-removed RMS error (RMSb). The results are shown in Table 1, both for the input temperature and for the retrieved soil moisture.

The validation of the input temperature shows a clear advantage for $T_{ME,1}$, both in terms of correlation coefficient and standard error. This is despite the fact that the reference temperature was optimized on the $T_{Ka}$. Based on this, it could be expected that $T_{ME,1}$ would also be a better input for the soil moisture retrieval. This appears not to be true: the Ka-band is clearly a better input to the LPRM soil moisture algorithm than $T_{ME,1}$. The substitution results in a large decrease in correlation, and an increased standard error and bias-removed RMS. This, even though $T_{ME,1}$ was optimized to retrieve soil moisture with the lowest RMSb, something that may be difficult to do in practice.

**Table 1** Validation of input temperature and retrieved soil moisture from WindSat X-band data from February 2003 to December 2004. The four validation sites are indicated by their state, and bold indicates best result.

| | T-Input | Statistic | WindSat 6 AM OK | AZ | ID | GA | WindSat 6 PM OK | AZ | ID | GA |
|---|---|---|---|---|---|---|---|---|---|---|
| Temp-erature | $T_{KA}$ | $R^2$ | 0.87 | 0.93 | 0.85 | 0.91 | 0.96 | **0.95** | 0.93 | 0.93 |
| | **$T_{ME,1}$** | | **0.96** | 0.93 | **0.95** | **0.96** | 0.96 | 0.94 | **0.95** | **0.94** |
| | $T_{KA}$ | SE (K) | 2.6 | 2.5 | 2.7 | 2.1 | **2.0** | 3.3 | 3.0 | 2.1 |
| | **$T_{ME,1}$** | | **1.8** | **2.4** | **1.7** | **1.5** | 2.1 | **3.2** | **2.6** | **1.8** |
| Soil Moisture | **$T_{KA}$** | $R^2$ | **0.49** | **0.67** | **0.41** | 0.38 | **0.58** | **0.68** | **0.54** | **0.55** |
| | $T_{ME,1}$ | | 0.44 | 0.40 | 0.13 | **0.40** | 0.37 | 0.34 | 0.25 | 0.41 |
| | **$T_{KA}$** | SE | **0.041** | **0.016** | **0.053** | **0.032** | **0.035** | **0.015** | **0.050** | **0.028** |
| | $T_{ME,1}$ | ($m^3m^{-3}$) | 0.043 | 0.021 | 0.064 | 0.032 | 0.043 | 0.022 | 0.064 | 0.032 |
| | **$T_{KA}$** | RMSb | **0.048** | 0.052 | **0.060** | **0.045** | **0.044** | **0.043** | **0.076** | **0.047** |
| | $T_{ME,1}$ | ($m^3m^{-3}$) | 0.086 | **0.045** | 0.089 | 0.067 | 0.074 | 0.050 | 0.111 | 0.072 |

## DISCUSSION AND CONCLUSIONS

This paper illustrates the effect of using a NWP soil temperature product instead of estimates provided by concurrent 37 GHz data on satellite-based passive microwave retrieval of soil moisture retrieval. A validation of the temperature products using *in situ* temperature data showed better performance for MERRA, both in terms of correlation coefficient and standard error. However, the opposite was observed for the retrieved soil moisture; the Ka-band is clearly a better input to this soil moisture algorithm than the MERRA surface temperature. The substitution results in a large decrease in sensitivity to *in situ* soil moisture changes, and demonstrates the complications of moving from a coincident source to a modelled interpolation.

It has to be noted that these results apply specifically to X-band and may be less apparent at L-band. This is because the effect of temperature errors increases exponentially with increasing vegetation optical depth (as used in the retrieval model), and the vegetation opacity is higher at X-band than it is at L-band. Also, the temperature sensing depth of L-band is deeper which reduces the weight of the highly dynamic surface temperature in the weighted effective temperature. Furthermore, only one soil moisture algorithm was evaluated. The algorithm structure can influence the sensitivity of the retrieval to the temperature source.

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