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Prashant K. Srivastava

Dawei Han

Miguel A. Rico-Ramirez

Peggy O'Neil

Tanvir Islam

See next page for additional authors

Authors
Prashant K. Srivastava, Dawei Han, Miguel A. Rico-Ramirez, Peggy O'Neil, Tanvir Islam, and Manika Gupta

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PERFORMANCE EVALUATION OF SMOS SOIL MOISTURE RETRIEVAL PARAMETERS FOR HYDROLOGICAL APPLICATION

PRASHANT K. SRIVASTAVA (1,2,3), DAWEI HAN (3), MIGUEL A. RICO RAMIREZ (3), PEGGY O'NEIL (2), TANVIR ISLAM (3,4,5), MANIKA GUPTA (6)

(1): Earth System Science Interdisciplinary Center, University of Maryland, Maryland, USA

(2): NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

(3): Department of Civil Engineering, University of Bristol, Bristol, United Kingdom

(4): NOAA/NESDIS Center for Satellite Applications and Research, College Park, USA

(5): Cooperative Institute for Research in the Atmosphere, Colorado State University, USA

(6): Department of Civil Engineering, IIT Delhi, Hauz Khas, India.

ABSTRACT

Microwave remote sensing has high potential for soil moisture retrieval. However, the efficient retrieval of soil moisture depends on optimally choosing the soil moisture retrieval parameters. In this study first the initial evaluation of SMOS L2 product is performed and then four approaches regarding soil moisture retrieval from SMOS brightness temperature are reported. The radiative transfer equation based tau-omega rationale is used in this study for the soil moisture retrievals. The single channel algorithms (*SCA*) using *H* polarization is implemented with modifications, which includes the effective Land Surface Temperatures (LSTs) simulated from ECMWF (downscaled using WRF-NOAH Land Surface Model (LSM)) and MODIS satellite. The retrieved soil moisture is then utilized for soil moisture deficit (SMD) estimation using empirical relationships with Probability Distributed Model based SMD as a benchmark. The square of correlation during the calibration indicates a value of R^2 =0.359 for approach 4 (WRF-NOAH LSM based LST with optimized roughness parameters) followed by the approach 2 (optimized roughness parameters and MODIS based LST) (R^2 =0.293), approach 3 (WRF-NOAH LSM based LST with no optimization) (R^2 =0.267) and approach 1 (MODIS based LST with no optimization) (R^2 =0.163). Similarly, during the validation a highest performance is reported by approach 4. The other approaches are also following a similar trend as calibration. All the performances are depicted through Taylor diagram which indicates that the *H* polarization using ECMWF based LST is giving a better performance for SMD estimation than the original SMOS L2 products at a catchment scale.

Keywords: SMOS, tau-omega, soil moisture deficit, WRF-NOAH Land Surface Model, MODIS, Hydrological model

1. INTRODUCTION

Soil moisture plays an important role in the Earth's water cycle; it is a key variable in the water and energy exchanges that occur at the land-surface/atmosphere interface and conditions the evolution of weather and climate over continental regions [1]. However, the science of understanding and predicting soil moisture variability is extremely challenging and thus complicating most of the flood and drought monitoring strategies [2, 3]. Several researchers have also shown that near surface soil moisture content can be measured by optical and thermal infrared remote sensing [4, 5]. For decades microwave remote sensing has proven its capability over optical remote sensing for soil moisture retrieval especially from L band [6].

The L band soil moisture can be retrieved by utilizing a radiative transfer model to convert brightness temperature from microwave radiometers to soil moisture using single/dual channel algorithms [7]. Most of the methods for L band soil moisture retrieval from passive radiometers are based on tau-omega rationale [8, 9]. One key factor which is missing at the moment for any flood/drought forecast is the level of soil moisture saturation and/or deficit [10]. In this study, attempts have been made to synergistically combine the SMOS brightness temperature with the MODIS and Weather Research & Forecasting (WRF)-NOAH Land Surface Model downscaled European Center for Medium-Range Weather Forecasts (ECMWF) LST and optimized roughness parameters for the soil moisture retrieval. To see the usefulness of the simulated products for hydrological applications, the retrieved soil moisture from algorithms is then utilized for the SMD prediction using the empirical relationships.

2. MATERIALS AND METHODOLOGY

2.1 Study area

The Brue catchment (135.5 Km^2) chosen as the study area, located in the south-west of England, at central coordinates 51.11 °N and 2.47 °W (**Figure 1**). It is a good experimental site with low vegetation cover (mainly grass), a maintained meteorological and flow station, moderate topography, and availability of nearly all required datasets. The Probability Distributed Model (PDM) model is implemented over this catchment to estimate the SMD using a two-year calibration period (1^{st} February 2009 to 31^{st} January 2011) and one-year for validation (1^{st} February 2011 to 31^{st} January 2012). SMD from the validation (2011-12) is taken into account for comparison with the SMOS retrieved soil moisture. The detailed information on PDM calibration, validation, sensitivity and uncertainty analysis over the Brue are mentioned in the research by [11, 12].

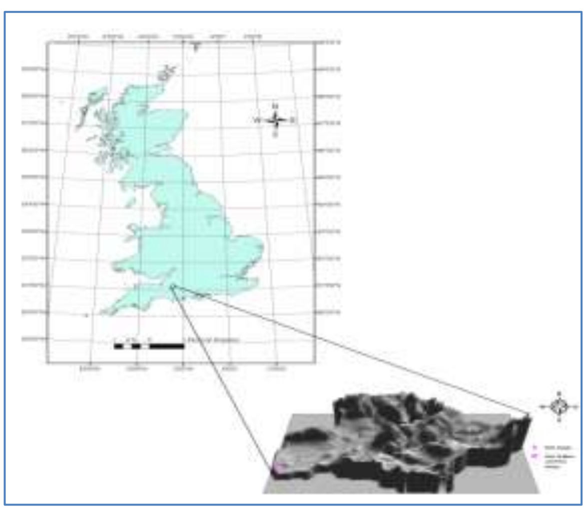


Fig.1 Location of the Brue catchment with meteorological station, rain and flow gauges over the DEM (Digital Elevation Model)

2.2 Datasets used

The latest Weather Research and Forecasting model coupled with NOAH Land Surface Model (LSM) is used in this study with the Advanced Research WRF (ARW) dynamic core version 3.1 [13] for LST data extraction from ECMWF global reanalysis datasets. The MODIS satellite products are used in this study for estimating soil moisture retrieval parameters such as vegetation optical depth (VOD) and LST. The other important dynamic dataset very important in soil moisture retrieval is Leaf Area Index (LAI) which has been derived from MODIS (MOD15) product and subsequently used for VOD estimation. The MIRAS instrument in the SMOS satellite acquiring data at the frequency of 1.4 GHz is used for L band brightness temperature extraction which includes SMOS Level 2 product and Level 1C SMOS Brightness temperature retrieved at 42.5° incidence angle.

2.3 Rationale tau-omega

The τ–ω model is based on two parameters i.e. the vegetation optical depth τ and the vegetation scattering albedo ω that are used to parameterize the vegetation attenuation properties and the scattering effects within the vegetation layer. The low vegetation $\tau - \omega$ model can be expressed as Eq. (1):

$$TB_P = (1-\omega_p)(1-\gamma_p)(1+\gamma_p r_{gp})T_c + (1-r_{gp})\gamma_p T_g \quad (1)$$

where T_g and T_c are the effective soil and vegetation temperatures, r_{gp} is the soil reflectivity, ω_p the single scattering albedo, γ_p the vegetation attenuation factor. The last term can be computed from the optical depth τ_p as Eq. (2):

$$\gamma_p = \exp(-\tau_p / \cos\theta) \quad (2)$$

For surface temperature, it is assumed that effective soil (T_g) and vegetation (T_c) temperatures are approximately equal to a single value $T_{gc} \approx T_c \approx T_g$.

For the scattering effects at L-Band, the value of the single scattering albedo ω is found to be rather low and hence neglected in most of the cases. To model the optical depth τ_p, several studies found that $\tau_p = b_p \times VWC$ where VWC is the vegetation water content and b_p is factor which is mainly dependent on the frequency, the canopy type, and the vegetation dielectric constant (Jackson and Schmugge, 1991). At 1.4 GHz, a value of $b_p = 0.12 \pm 0.03$ was found to be representative of low vegetation and also, recent studies found good correlations between τ_p and LAI [14]. Hence in this study LAI based τ_p is taken into account.

2.4 Performance statistics

Over here we compared the performances of the retrieved SMOS soil moisture using the abovementioned approaches with the PDM SMD. The Square of correlation (R^2) and Taylor diagram [15] are used for evaluating the model performances.

3. RESULTS AND DISCUSSION

3.1 Performance of tau-omega algorithm

The scatter plots representing the performances of different approaches in terms of correlations are shown in **Figure 2**. The results are presented for single channel using *H* polarization. All the retrieved soil moisture values indicate an inverse relation with the SMOS SMD; hence a negative correlation is expected between the estimated soil moisture and SMD in figure 2. From the performance analysis, it can be revealed that the results are sensitive to the selection of the *h* and *Q* parameters. By using the optimized *h* and *Q* datasets the results are highly improved. The notable things observed in this work are the some lower performance SCA-H using MODIS LST datasets. The best correlation statistics are given by the approaches such as approach 4 (*r*= -0.55) followed by approach 2 (*r*= -0.52), approach 3 (*r*= -0.47) and approach 1 (*r*= -0.41) with SMD. The SMOS L2 correlation performance (*r*= -0.42) is similar to approach 1 which indicates the LST conditions used in SMOS Algorithm Theoretical Basis Document (ATBD) are similar to MODIS measurements.

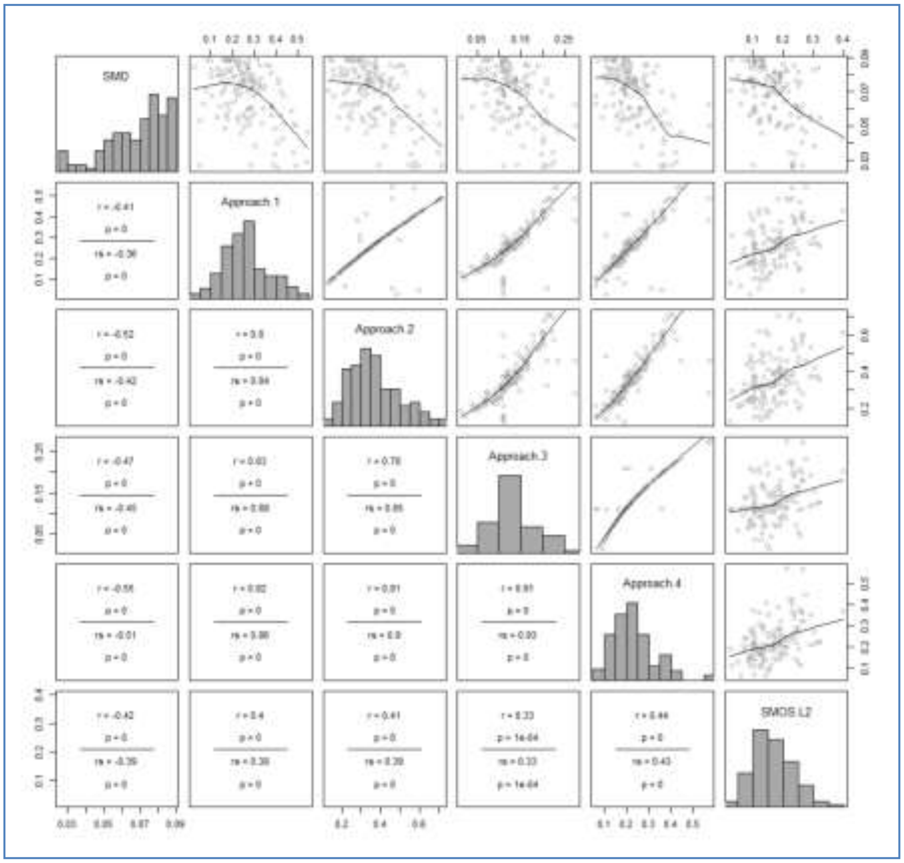
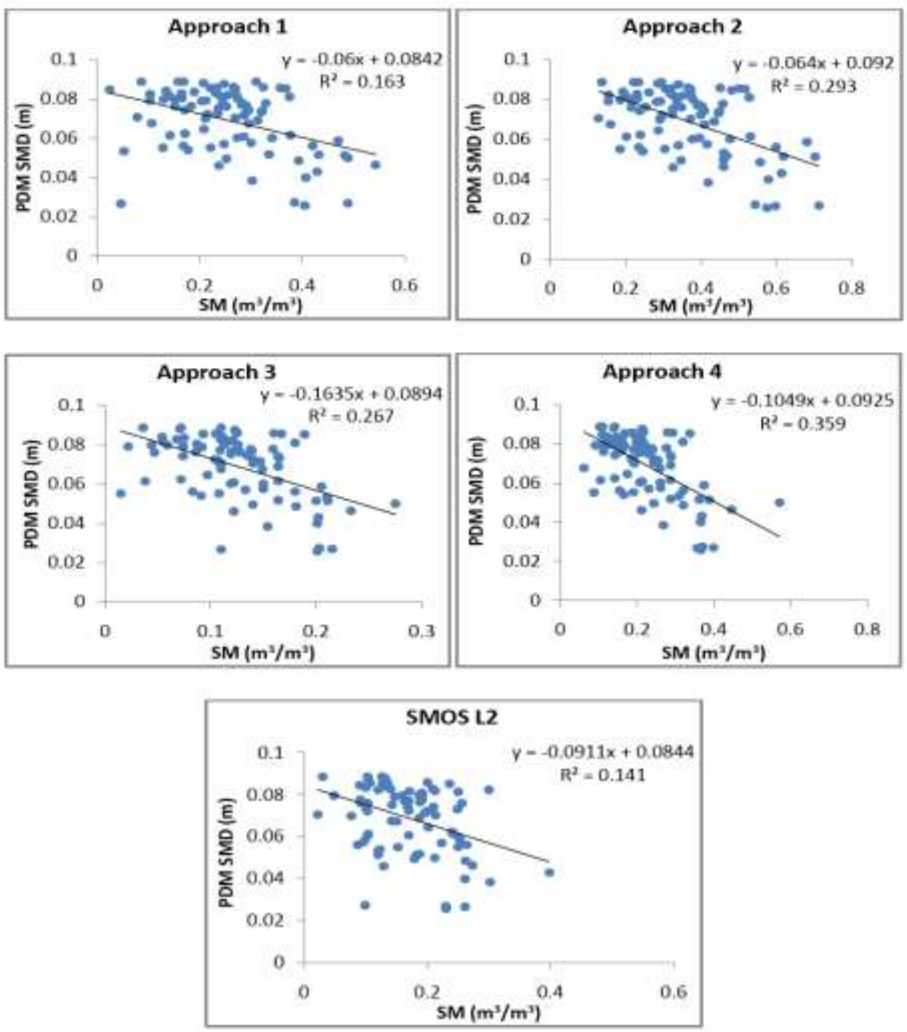


Fig. 2 Performance of SCA-H approaches: Approach 1 (MODIS based LST with no optimization); Approach 2 (optimized roughness parameters and MODIS based LST); Approach 3 (WRF-NOAH LSM based LST with no optimization); Approach 4 (WRF-NOAH LSM based LST with optimized roughness parameters)

3.2 Assessment of SMOS Soil Moisture for SMD estimation

The Spearman ($r_{spearman}$) and Pearson ($r_{pearson}$) correlation statistics between SMOS soil moisture and PDM SMD yields nearly similar values, indicate that there is no strong nonlinearity existed between the datasets and linear curve fitting could be a useful choice because of its simplicity [16]. The linear model between PDM SMD and retrieved soil moisture from various approaches during the calibration are used for developing linear regression models. The linear curve fitting used for calculation of the empirical relationships are shown in **Figure 3**. The square of correlation during the calibration indicates a value of R^2 =0.359 for approach 4 (WRF-NOAH LSM based LST with optimized roughness parameters) followed by the approach 2 (optimized roughness parameters and MODIS based LST) (R^2 =0.293), approach 3 (WRF-NOAH LSM based LST with no optimization) (R^2 =0.267) and approach 1 (MODIS based LST with no optimization) (R^2 =0.163). The Taylor plot (**Figure 4)** is used here to show the ability of the performance of all the approaches in comparison to the PDM SMD during the validation. The circle mark in the *x*-axis in the Taylor plot, called the reference point, closer to this point represents the perfect fit between algorithm results and data. The statistics obtained are evident for a better performance in the case of WRF LST with optimized solution of roughness parameters. It shows that the *SCA-H* algorithm with WRF LST and roughness modification has a higher performance than the SMOS level 2 products for SMD estimation and could be a suitable choice for soil moisture retrieval for hydrological applications. The higher performance of WRF LST can be attributed to more accurate representation of surface temperature because of sophisticated numerical prediction and parameterization schemes.

Figure 3 Calibration plots between SMOS L2, SCA-H approaches with PDM SMD



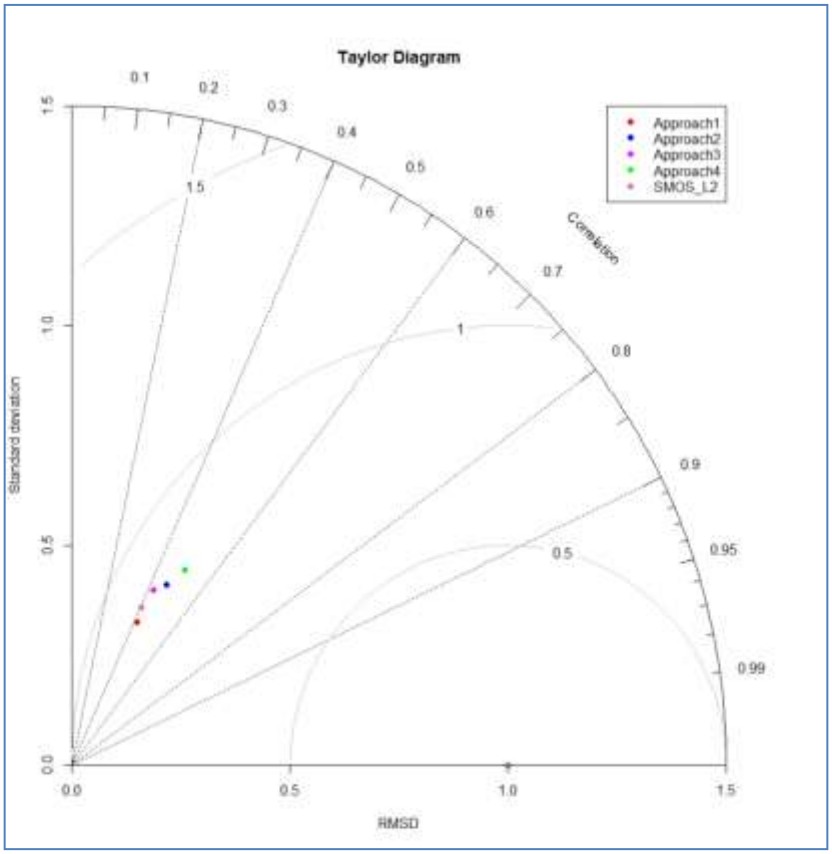


Figure 4 Taylor plots for performance during the validation

4. CONCLUSION

Soil moisture is an important component in Earth's hydrological cycle. The promising solution for large scale soil moisture measurements is satellite based approaches especially microwave using low frequency L band radiometers. SMOS is the latest major earth observation L band satellite for soil moisture measurements. However, before using the data, it is important that SMOS data should be evaluated for different application areas, so that data providers and users could understand the quality and uncertainties of the data and find ways to improve the data. In this study SMOS satellite captured brightness temperature are taken into account for soil moisture retrieval and tested against various soil moisture retrieval parameters for deducing its suitability towards hydrological applications. The initial evaluation of SMOS L2 and *SCA-H* approach using the correlation statistics with PDM SMD indicates that *SCA- H* gives a better performance than the original SMOS L2 product using the WRF-NOAH LSM downscaled LST datasets and optimized roughness parameters.

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6. REFERENCES

[1] T. Carlson, "An overview of the" triangle method" for estimating surface evapotranspiration and soil moisture from satellite imagery," *Sensors,* vol. 7, pp. 1612-1629, 2007.
[2] T. J. Jackson, *et al.*, "Soil moisture mapping at regional scales using microwave radiometry: The Southern Great Plains Hydrology Experiment," *Geoscience and Remote Sensing, IEEE Transactions on,* vol. 37, pp. 2136-2151, 1999.
[3] P. K. Srivastava, *et al.*, "Appraisal of SMOS soil moisture at a catchment scale in a temperate maritime climate," *Journal of Hydrology,* vol. 498, pp. 292-304, 2013.
[4] M. Owe, *et al.*, "A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index," *Geoscience and Remote Sensing, IEEE Transactions on,* vol. 39, pp. 1643-1654, 2001.
[5] T. J. Jackson, "III. Measuring surface soil moisture using passive microwave remote sensing," *Hydrological processes,* vol. 7, pp. 139-152, 1993.
[6] T. Schmugge, *et al.*, "Passive microwave soil moisture research," *Geoscience and Remote Sensing, IEEE Transactions on,* pp. 12-22, 1986.
[7] T. J. Jackson, *et al.*, "Passive microwave observation of diurnal surface soil moisture," *Geoscience and Remote Sensing, IEEE Transactions on,* vol. 35, pp. 1210-1222, 1997.
[8] R. A. de Jeu, *et al.*, "A spatially coherent global soil moisture product with improved temporal resolution," *Journal of Hydrology,* 2014.
[9] I. Mladenova, *et al.*, "Remote monitoring of soil moisture using passive microwave-based techniques—Theoretical basis and overview of selected algorithms for AMSR-E," *Remote sensing of environment*, vol. 144, pp. 197-213, 2014.
[10] P. K. Srivastava, *et al.*, "Data Fusion Techniques for Improving Soil Moisture Deficit Using SMOS Satellite and WRF-NOAH Land Surface Model," *Water Resources Management,* vol. 27, pp. 5069-5087, 2013.
[11] P. K. Srivastava, *et al.*, "Machine Learning Techniques for Downscaling SMOS Satellite Soil Moisture Using MODIS Land Surface Temperature for Hydrological Application," *Water Resources Management,* vol. 27, pp. 3127-3144, 2013/06/01 2013.
[12] P. K. Srivastava, *et al.*, "Sensitivity and uncertainty analysis of mesoscale model downscaled hydro-meteorological variables for discharge prediction," *Hydrological Processes. DOI: 10.1002/hyp.9946,* 2013.
[13] J. G. Powers, "Numerical prediction of an Antarctic severe wind event with the Weather Research and Forecasting (WRF) model," *Monthly Weather Review,* vol. 135, pp. 3134-3157, 2007.
[14] Y. H. Kerr, *et al.*, "The SMOS soil moisture retrieval algorithm," *Geoscience and Remote Sensing, IEEE Transactions on,* vol. 50, pp. 1384-1403, 2012.
[15] K. E. Taylor, "Summarizing multiple aspects of model performance in a single diagram," *J. Geophys. Res,* vol. 106, pp. 7183-7192, 2001.
[16] A. Blumer, *et al.*, "Occam's razor," *Information processing letters,* vol. 24, pp. 377-380, 1987.