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SMAP soil moisture retrieval using Single Channel algorithm over agricultural area

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Abstract

Passive microwave remote sensing approaches have demonstrated eminence potential in mapping and monitoring global soil moisture. The National Aeronautics and Space Administration's (NASA) Soil Moisture Active Passive (SMAP) has made significant contribution towards this cause. To assess the accuracy of SMAP brightness temperature for soil moisture retrieval over agricultural landscape in India, in this investigation, the most widely used Single Channel Algorithm using horizontal (H) polarization (SCA-H) has been attempted with Mironov dielectric mixing model, roughness parameter and the estimated Vegetation Optical Depth (VOD) derived from the Copernicus Global Land Operation (CGLS) Leaf Area Index (LAI) over an agricultural landscape in Northern India. The SCA-H retrieved and ground collected soil moisture showed a good correlation of 0.73, RMSE = 0.12, Degree of Agreement(d) = 0.73, Standard Deviation = 0.84, PBIAS = -40.8 over the study area.

Key words: SMAP, Single Channel Algorithm, Soil Moisture, Performance Assessment, Agriculture

1. Introduction

Soil moisture (SM) is an important descriptor of hydrological cycle [1]. It regulates the evolution of climate and weather and control the exchange of water and energy at the earth/surface- atmosphere interface [1]. Recognizing the importance of SM in significant environmental and hydrological processes through modelling and decision procedure led to the advancement of satellite-based SM products using remote sensing techniques, specially the microwave approaches [2]. The continuous monitoring of global SM change has been playing a crucial role in climate prediction, weather forecast, water resource management and prediction and mitigation of hydrological hazards such flood and drought [2]. Microwave Remote sensing techniques both, Active (Radar/ backscatter) and Passive (Radiometer/ Brightness Temperature) offer unique way for measuring SM with each having their distinct advantages over a range of topographic and vegetation cover conditions and up to an effective depth [1]

Kerr et al.,[3] [1], Mladenova et al., [4] and Srivastava in [5] explains that the retrieval algorithms comprise of two major steps. Step 1, modelling the thermal radiation from the earth surface using the Radiative Transfer Theory and Step 2, applying the dielectric mixing model to estimate SM. The two elements are linked with the Fresnel's reflectivity model [4].

Therefore, in this study the performance of SCA-H, based on the tau-omega model in retrieving SM against the ground collected SM has been performed to understand results over agricultural area.

2. Materials and methods

2.1 Study Area

The Varanasi district (25.310N, 82.970E) of Uttar Pradesh, located in Northern part of India has been chosen as the study area for this investigation. This is a good experimental site for the validation of satellite-derived SM data products due a well-maintained automatic SM and temperature sensors installed at various locations, supported by Design and Innovation Centre-BHU (funded by MHRD), ISRO and other International agencies. Varanasi has a humid subtropical climate with very hot and wet summers while winters are fairly dry and cold but the temperature rarely falls below the freezing.

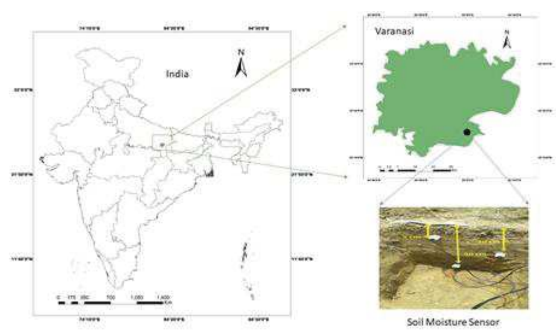

Figure 1 Study Site.

2.2 Soil Moisture Active Passive (SMAP) L1C dataset

The Soil Moisture Active Passive (SMAP) L1C product is the time-ordered brightness temperature measurements at the surface of earth at Vertical (V) and Horizontal (H) polarization along with the third and fourth Stokes parameter of the microwave radiation at 40 km spatial resolution. All the SMAP products are provided in the

Hierarchical Data Format Version 5 (HDF5), the format with a general-purpose file purpose file format and programming library for storing files. The brightness temperature measurements over Varanasi were extracted using the MATLAB 2016a Version, over the time period June, 2017 to May, 2018.

2.3 Copernicus Global Land Operation (CGLS) Leaf Area Index (LAI) dataset

The Copernicus Global Land Operation (CGLS) Leaf Area Index (LAI) Version 1 product has been used in this study to estimate soil moisture retrieval parameter, vegetation optical depth (τ). The product is derived from PROBA- V daily data as 30-day composite updated at every 10 days using moving the moving window technique. The product is projected on a regular latitude/longitude with a resolution of 1/1120 by using the INRA (Institute National de Recherche Agronomique) defined algorithm. The PROBA- V instrument is composed of 3 cameras and each camera containing 2 sensors, one in Visible and near-infrared (VNIR) and another in Short- wave infrared (SWIR) range. The LAI products were downloaded from the Copernicus Global Land Services web portal (http://land.copernicus.eu/global/products).

2.4 Single Channel Algorithm

Single Channel Algorithm (SCA) is an Inverse- based, single parameter model [4]. Based on the Jackson et al., [6] SCA utilizes a single frequency/ polarization instrument which is considered most sensitive to the surface soil moisture. The algorithm depends on ancillary data (Normalized Vegetation Difference Index, NDVI; Leaf Area Index; LAI) for the correction of factors such as Vegetation Water Content (VWC) that affects the soil moisture retrieval. SCA assumes the single scattering albedo, ῳ = 0 and atmospheric contribution to be minimal and therefore the equation for the Brightness temperature (TB) can be written as

(1).

$$TB(f,p) = T_S\left\{1-\left(1-e_{s,rough}\right)\left(e\left[\frac{-\tau}{\cos\theta}\right]\right)\right\}^2 \quad (1).$$

Where TB is the brightness temperature, p is polarization, Ts is surface physical temperature, es,rough is rough surface emissivity, τ is vegetation optical depth and θ is the angel of incidence.

Taking all the assumption, the equation for the smooth surface reflectivity can represented as

$$R^{smooth}_{(f,p)} = \left\{\left(1-\left(\frac{T_{B(f,p)}}{T^S}\right)\right)e^{\left[h\cos^2\theta+2b*\frac{VWC}{\cos\theta}\right]}\right\} \quad (2).$$

In the above equation $R^{s,smooth}_{(f,p)}$ is the smooth surface reflectivity, TB is the brightness temperature, Ts is the surface physical temperature, VWC is the Vegetation Water Content and θ is the angel of incidence.

2.5 Performance Analysis

In this study, the SMAP derived SM estimates using the algorithm and datasets discussed in previous sections of this article for the test locations, is compared against the in-situ, Hydra probe measured SM values. The performance of algorithm derived, Simulated SM values is compared with Hydra probe measured Observed SM, using five statistical scores; square of correlation (r), Root Mean Square Error (RMSE), Standard Deviation (SD), Percentage Bias (%BIAS) and degree of Agreement (d).

3. Results and discussion

The comparisons between retrieved SM using SMAP and ground-based sensor time series exhibit a high temporal variability during the period under investigation and follow a strong seasonal cycle, peaking normally in June and July; typically, a very high soil moisture occurs during the monsoon period in the months of June – September. The soil moisture increases in the monsoon season and it follows an exponential decay as expected. When SM content slacken in the Summer season, during month of March - May, rainfall wets-up the soil profile– and hence a surging graph can be seen in Figure 2. The SM pattern shows that June- September are the relatively wettest periods during the analysis, conversely, March to May are slightly drier than other months. Generally, maximum SM content are also higher in June and are associated with moderately short-duration storms.

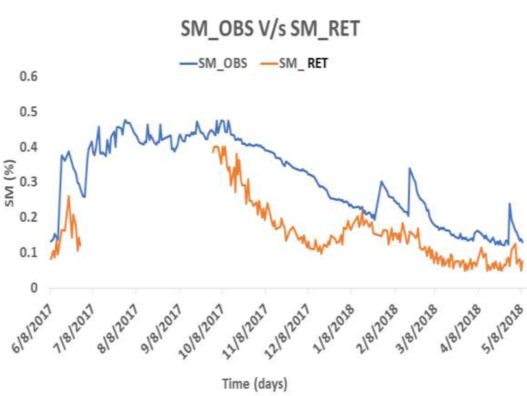

Figure 2 Time Series plot for Observed SM (SM_OBS) and Retrieved SM (SM_RET) over the study period.

A combined time series plot of Simulated and Observed SM over the time period from June.2017 to May 2018 is also presented in Figure 1, depicting the daily variation in both the datasets. A scatter plot showing performance of SCA algorithm in terms of different performance statistics are shown in Figure 3. The comparison between simulated and observed SM reveals a satisfactory performance with square of correlation (0.73), RMSE (0.12), Degree of Agreement(d) (0.73), Standard Deviation (0.84) PBIAS (-

40.8). Results of other statistical scores are presented in **Table 1**.

Table 1 Results of Statistical tests

Statistical test	Values
Square of Correlation (R^2)	0.73
Root Mean Square Error (RMSE)	0.12
Degree of Agreement (d)	0.73
Standard Deviation (SD)	0.84
%BIAS	-40.8

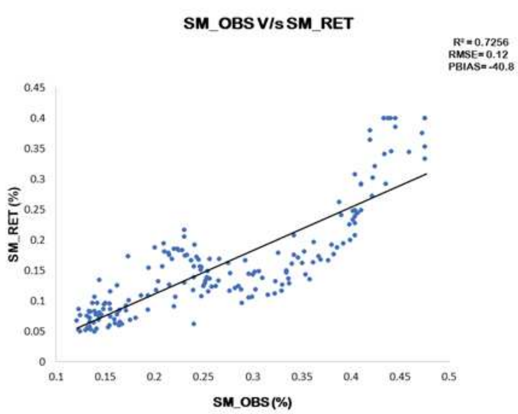

Figure 3 Scatter plot between Observed SM (SM_OBS) and Retrieved Soil Moisture (SM_RET).

ground based or in-situ measurements, despite their limitation in representing the SM condition over large spatial coverage, in mapping and monitoring of SM over larger domains [7]. The overall analysis indicates that SCA-H is performing well in sub-tropical climate like India and can be used for soil moisture retrieval from SMAP.

4. Conclusion

SMAP satellite is new and its algorithm performances over different landscape are needed to understand the product utility. This study offers a promising approach towards developing SM retrieval algorithm and role of

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6. References

[1] E. T. Engman and N. Chauhan, "Status of microwave soil moisture measurements with remote sensing," Remote Sensing of Environment, vol. 51, pp. 189-198, 1995.

[2] P. K. Srivastava, D. Han, M. A. Rico-Ramirez, P. O'Neill, T. Islam, and M. Gupta, "Assessment of SMOS soil moisture retrieval parameters using tau–omega algorithms for soil moisture deficit estimation," Journal of Hydrology, vol. 519, pp. 574-587, 2014.

[3] Y. H. Kerr, P. Waldteufel, J.-P. Wigneron, J. Martinuzzi, J. Font, and M. Berger, "Soil moisture retrieval from space: The Soil Moisture and Ocean Salinity (SMOS) mission," IEEE transactions on Geoscience and remote sensing, vol. 39, pp. 1729-1735, 2001.

[4] I. Mladenova, T. Jackson, E. Njoku, R. Bindlish, S. Chan, M. Cosh, 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.

[5] P. K. Srivastava, D. Han, M. A. Rico-Ramirez, P. O'Neill, T. Islam, M. Gupta, et al., "Performance evaluation of WRF-Noah Land surface model estimated soil moisture for hydrological application: Synergistic evaluation using SMOS retrieved soil moisture," Journal of Hydrology, vol. 529, pp. 200-212, 2015.

[6] T. J. Jackson, "III. Measuring surface soil moisture using passive microwave remote sensing," Hydrological processes, vol. 7, pp. 139-152, 1993.

[7] P. Srivastava, V. Pandey, S. Suman, M. Gupta, and T. Islam, "Available Data Sets and Satellites for Terrestrial Soil Moisture Estimation," in Satellite Soil Moisture Retrieval, ed: Elsevier, 2016, pp. 29-44.