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SOIL MOISTURE ESTIMATION USING MICROWAVE REMOTE SENSING - A LITERATURE REVIEW

Kumari Snehlata*

*Centre for Climate Change and Water Research, Suresh Gyan Vihar University, Jaipur

*Email id – snehlata.k.sinha@gmail.com

ABSTRACT

Soil moisture plays an important role in recent and numerous environmental studies by controlling the exchange of water and energy at the consolidate between the land surface and atmosphere. Soil moisture information can be utilized for crop yield forecasting, drought management, irrigation scheduling, and reservoir management. Microwave remote sensing has emerged as an important tool for soil moisture estimation due to its high sensitivity to dielectric properties of the target. Passive sensors such as radiometers provide high temporal resolution and larger ground coverage at the cost of coarse spatial resolution, whereas, active sensors such as a SAR provides fine spatial resolution with smaller ground coverage and coarser temporal resolution. Microwave remote sensing is used for monitoring earth resources due to its unique sensitivity to the physical properties and the dielectric of the target that is to be sensed. This paper aims at reviewing the different approaches of microwave remote sensing for soil moisture estimation.

Keywords: Soil moisture, Microwave remote sensing, SAR, Active sensors, passive sensors, etc.

INTRODUCTION

Soil moisture is a key variable in controlling the exchange of heat energy and water between the atmosphere and land surface through plant transpiration and evaporation. Soil moisture information can be utilized for crop yield forecasting, drought management, irrigation scheduling, and reservoir management (Meraj *et al.*, 2021 a, b). It allows the need for irrigation to be quantified in advance of a crop showing signs of distress. Knowing the soil moisture status enables highly efficient irrigation, providing the water as and when required, and eliminating the wasteful use of water when irrigation is not needed. Soil moisture levels affect air content, salinity, and the presence of toxic substances (Pandey et al., 2010; Pandey et al., 2013; Singh and Pandey, 2014; Bhatt et al., 2017; Sharma and Kanga 2020). It regulates soil structure, ductility, and density. Soil moisture is an important parameter for radiation models, as it affects the amount of energy used in latent versus sensible heat flux (Rind 1984; Singh et al., 2017b; Kanga et al. 2020a, b). The measurements of soil moisture are not only important for forest growth, agriculture yield but also used for monitoring flood and drought conditions. The soil moisture content has influence on the infiltration rate, due to which, it is also an important factor in hazard mitigation, as soil moisture content controls the speed at which a contaminant will seep into the ground. Soil moisture is one of the important parameters for monitoring various agricultural applications like crop growth and the development of a drought or a flood in an area (Ross 1999; Kanga et al., 2017a, b; Rather et al., 2018; Hassanin et al., 2020; Kanga et al., 2021). Soil moisture works as a land surface parameter that has an important control over several hydrological and atmospheric processes (Ranga et al., 2020 a, b; Meraj et al., 2020 a, b; Kanga et al., 2020a, b). The exchange of latent heat and sensible heat is controlled due to the changes of evapotranspiration (ET) processes and latent heat between land surface and atmosphere interface (Gujree et al., 2017; Pall et al., 2019; Romshoo et al., 2020). Soil moisture is an essential parameter at different spatial scales for many applications; for example, flood forecasting.(P.K.Srivastava 2016; Bera et al., 2021; Tomar et al., 2021; Joy et al., 2021; Chandel et al., 2021; Kanga et al., 2021).

Microwave remote sensing has widely demonstrated its potential in the continuous monitoring of our rapidly changing planet. This review provides an overview of state-of-the-art methodologies for multi-temporal synthetic aperture radar change detection and its applications to biosphere and hydrosphere monitoring, with special focus on topics like forestry, water resources management in semi-arid environments and floods (Farooq and Muslim, 2014; Nathawat et al., 2010; Kumar et al., 2018; Joy et al 2019).The objective of this review is to highlight the importance of SAR observations in the environmental monitoring activities through a discussion on the latest research exploiting multi-temporal concepts for adding value to data in some selected applications. SAR data can enable several applications, especially in near-real time, or give fundamental contribution through data assimilation in geophysical/hydrological/weather models and/or integration with multisource information. (Donato Amitrano 2021).

Soil moisture observations contribute in improvement of forecasting of air humidity, precipitation and air temperature. Though till date, the record of soil moisture observations was available over a confined number of regional soil moisture networks. On the record of availability of a free available universal soil moisture datasets is procured from the back scatter measurements that is obtained by the Advanced Scatterometer (ASCAT) which is a C-band microwave remote sensing instrument available in the Meteorological Operational (METOP) satellite series.(Wolfgang Wagner 2013).

An algorithm for retrieving soil moisture content (SMC) from synergic use of both active and passive microwave acquisitions is presented. The algorithm takes advantage of the integration of microwave data from SMAP, Sentinel-1 and AMSR2 for overcoming the SMAP radar failure and obtaining a SMC product at enhanced resolution (0.1° × 0.1°) and improved accuracy with respect to the original SMAP radiometric SMC product. A disaggregation technique based on the Smoothing filter based intensity modulation (SFIM) allows combining the radiometric and SAR data (Santia et al 2018).

Soil moisture is determined using two methods:

i) Direct methods –In direct method the soil moisture is calculated relating to he difference between the weight of soil sample before and after drying.

ii) Indirect method- soil moisture determined by sensor.

Microwave approach for soil moisture estimation:

The role of soil moisture is important along with other components in crop yield forecasting models (Dubois, et. al., 1995). Surface soil moisture information is a critical parameter required for daily profile soil moisture estimation using many Soil Vegetation Atmosphere Transfer (SVAT) models. Soil moisture estimation can be done using point measurement (gravimetric method) and from hydrological models.

SAR return signal is affected by sensor parameters like wavelength, polarization and the incidence angle at which the sensor is being operated and target dielectric and geometrical properties in general.Some useful thumb rule for using SAR data for soil moisture estimation:

- Higher or brighter the backscatter of the image, rougher the surface being imaged.
- Flat surfaces that reflect little or no microwave energy back towards the radar will always appear dark in radar images.
- Vegetation is usually moderately rough on scale of most radar wavelengths and appears as grey or light grey in radar images.
- Surfaces inclined towards radar will have a stronger backscatter than surface, which slope away from radar, will tend to appear brighter.
- Backscatter is sensitive to target electrical property including water content, watery object will appear bright and dried object will appear dark.
- Backscatter varies depending upon the use of different polarisation.
- Backscatter is affected by different observation angles , low incidence angles result in high scatter, backscatter decreases with increasing incidence angle.

The responsiveness of microwave scattering to geometrical structure of the soil surface and the dielectric properties has made radar remote sensing an attractive technique to address a wide range of environmental problems related to the natural surface condition. Two parameters of particular interest that have been the subject of intensive studies for many decades are surface soil moisture and surface roughness. A major cause of quantitative estimation of soil moisture and surface roughness from SAR is the separation of their individual scattering effects that contribute to the backscattered signal.(Brian W. Barrett et al 2009).

ASCAT is one of the major satellite EO missions utilized today for global soil moisture estimation. This study evaluated ASCAT data for the years 2010 and 2011 in comparison to in situ observations from the FLUXNET network, aiming to appraise the accuracy of ASCAT data in a variety of ecosystem types across different continents. The direct comparison of ASCAT operational product with in situ SSM observations indicated a moderate performance of the product at the studied sites. The results of the study emphasize how essential it is to validate the magnitude and spatial structure of the uncertainties of any new satellite-based remote sensing product before its use in operational applications.(Khidir Abdalla Kwal Deng et al 2019).

Microwave remote sensing techniques have been used in agricultural applications like irrigation management, early warning of disasters as well as in crop yield forecasting. A significant progress has been observed in the vegetation classification and monitoring from hyperspectral visible/infrared remote sensing. The parameters that affects soil moisture retrievals are wavelength ,incidence angle, polarization, surface roughness, soil texture, topography, observation depth and vegetation characteristics. Since there are considerable limitations in the hyperspectral remote sensing techniques under cloud cover, it is combined with the microwave techniques for soil moisture retrieval that gives positive results. The goal of this research is vast and requires the validation and calibration of vegetation and soil moisture retrieval methodologies corresponding to present (AMSR-E, SMOS) and future (SMAP) soil moisture missions in addition to a better theoretical understanding of microwave radiative transfer particularly in dense vegetation.(Tarendra Lakhankar et al 2009).

Passive microwave has more possibility for large-scale soil moisture monitoring, but it has a low spatial resolution. Active microwave has very high spatial resolution, though it has a very low revisit frequency and is more sensitive to vegetation and soil roughness. SAR has a great significance in retrieval of soil moisture maps at regional scales. (Kousik Das et al 2015)

Models for Soil moisture Estimation:

Empirical models are established for predicting surface soil moisture (SSM, 0–0.05 m) in 2018 based on historical (2016–2017) Sentinel-1 and ancillary data at the

U.S. Climate Reference Network soil moisture. Multiple linear regressions (MLR), Cubist, and Random Forest models are compared to fit the models using 30-m Sentinel-1 data, a 10-m digital elevation model, 30-m Polaris soil property maps, and 30-m land cover maps of the USA. The success of SSM retrieval was mostly attributed to soil properties, followed by Sentinel-1 backscatter data, terrain parameters, and land cover. The approach shows the potential for retrieving SSM using Sentinel-1 data in a combination of high-resolution ancillary data across the conterminous United States (CONUS).(Sumanta Chatterjee et al 2020).

In this paper the experiments described have demonstrated that it is possible to observe brightness temperature variations produced by changes in soil moisture with airborne micro- wave radiometers flying over unvegetated terrain. The response is a function of the wavelength of the radiometer and the distribution of the moisture in the soil. In spite of the thinness of the layer to which the 1.55-cm radiometer is sensitive, this radiometer is nevertheless useful for monitoring the moisture content in a field from the standpoint 'of both agriculture and meteorology. (T.Schmug et al 1974)

In this paper, results on estimation of soil moisture from an ERS-2 SAR image in the catchment of the Solani River (a tributary to the River Ganga) in and around the town of Roorkee, India, have been presented. The radar backscatter coefficient for each pixel of the image has been modeled from the digital numbers of the SAR image. Gravimetric measurements have been made simultaneously during the satellite pass to determine the concurrent value of volumetric soil moisture at a large number of sample points within the satellite sweep area. The backscatter coefficient is found to vary from –30 dB to –42 dB for a variation in soil moisture from 30 to 75%. Regression analyses between volumetric soil moisture and both the digital numbers and backscatter coefficients were performed. Strong correlations between volumetric soil moisture and digital number were observed with R2 values of 0.84, 0.75 and 0.83 for bare soil, vegetative and combined surfaces, respectively. A similar trend was observed with the relationship between backscatter and volumetric soil moisture with R2 values of 0.60, 0.89 and 0.67 for bare soil, vegetative and combined surfaces, respectively.(S. S. Haider et al 2004)

Brian W. Barrett (2009) analyzed in this paper that there are certain obstacles in the SAR technique of soil moisture retrieval. Despite these obstacles, the current generation of space borne SAR sensors, (e.g., ALOS PALSAR, TerraSAR-X and Radarsat-2) operating in fully polarimetric mode in three respective frequencies (L-, X-, and C-bands) along with future planned sensors (see table 1) offer a potential to gain a more in-depth knowledge of soil surface dynamics and ultimately improve soil moisture estimates in the future. The use of InSAR and also differential techniques has produced positive results in soil moisture determination using a range of interferometric products, from simply using the coherence to identify areas of unchanged geometry, i.e., constant surface roughness, whereby the changes in backscattering for those places can be related solely to soil moisture variations; to using the temporal decorrelation and also the signal-to-noise decorrelation of the phase shifts to determine soil moisture content.

Khidir Abdalla Kwal Deng et al (2019) in this paper provide the results of an extensive investigation of the Advanced Scaterometter (ASCAT) surface soil moisture global operational product accuracy across three continents (United States of America (USA), Europe, and Australia). ASCAT predictions of surface soil moisture were compared against near concurrent in situ measurements from the FLUXNET observational network. A total of nine experimental sites were used to assess the accuracy of ASCAT Surface Soil Moisture (ASCAT SSM) predictions for two complete years of observations (2010, 2011). Results indicate a reasonable validity between the ASCAT product and the in situ soil moisture measurements in the 0–5 cm soil moisture layer.

N. Baghdadi et al (2012) in this study develop an inversion technique based on neural networks to estimate soil surface parameters (moisture content and roughness) over bare agricultural areas from fully polarimetric RADARSAT-2 C-band SAR data. The training of the Neural Network is performed by using simulated radar backscattering coefficients through the IEM. First, soil parameters retrieval from polarimetric data is accomplished by using NN applied to a simulated dataset from the IEM model. In order to make the IEM simulation realistic, SAR measurement errors are added to the simulated backscattering coefficients. Next, the approach is validated using RADARSAT-2 data. The viability of the inversion technique is used in introducing a priori information on the surface roughness and the soil moisture. This work enables evaluating the potential of polarimetric SAR sensors at C-band for retrieving surface soil parameters. Section 2 gives a review of datasets, and presents the NN and the inversion methodology. The purpose of this study is to estimate soil surface parameters from C-band polarimetric SAR data in the case of bare agricultural soils.

M. Aubert et al (2011) analyzed in this paper the potential of high-spatial-resolution data from the TerraSAR-X sensor to monitor the soil-surface characteristics of bare agricultural soils (roughness, moisture, composition and structure) at plot and within-plot scales. The backscattering coefficients obtained from multi-temporal SAR acquisitions at HH polarization and two incidence angles (25° and 50°) were compared to ground observations and measurements. Our results are promising for retrieving soil moisture information from TerraSAR-X data and for monitoring the dynamics of slaking crust hydric states within plots.

Nicolas Baghdadi et al (2011) in this paper presents different models for backscattering in different bare fields. The semi-empirical models of Oh and Dubois as well as the IEM physical backscattering model were evaluated by using TerraSAR-X data and ground measurements on bare soils in agricultural environments. The objective of this article is to evaluate the errors of these models and to propose a semi empirical calibration of the IEM model in X-band. Oh's model correctly simulates the radar signal for HH and VV polarizations (bias<1dB and RMSE<3dB). The Dubois model stimulations show a very poor correlation between TerraSAR data and model simulations (RMSE between 2.2 and 4.4 dB, bias can reach 3.4 dB according to incidence and polarization).

Peter J. van Oevelen (1999) in this paper, presented a general framework to estimate soil moisture from microwave backscatter measurements. This framework consists of five different steps, each describing a different relationship. The first three steps are necessary to obtain a soil moisture estimate from microwave backscatter measurements. These steps describe the relationship between surface parameters and backscatter coefficient, the influence of vegetation on this relationship, and the relationship between dielectric properties and retrieval of effective water content. The last two steps are necessary for a correct interpretation and application of the soil moisture estimates. These steps describe the soil moisture profile and sensing depth and the role of soil moisture in hydrological models.

D.K.Gupta et al (2014) in this paper introduces a technique of ANN .The artificial neural network (ANN) approach has been found more potential in retrieving soil moisture from microwave sensors as compared to traditional techniques. For this purpose, a back propagation artificial neural network (BPANN) based on Levenberg Marquardt (TRAINLM) algorithm was developed. The measurement of scattering coefficient was carried out over a range of incidence angle from 20° to 70° at 5° steps for both the HH- and VV- polarizations. The BPANN was trained and tested with the experimentally obtained data by using bistatic X-band scatterometer for different values of soil moistures (12%, 16%, 21% and 25%) at 300 incidence angle. The scattering coefficient and soil moisture data were interpolated into 20 data sets and these data sets were divided into training data sets (70%) and testing data sets (30%). The performance of the trained BPANN was evaluated by comparing the observed soil moisture and estimated soil moisture by developed BPANN using a linear regression analysis (least square fitting) and performance factor Adj_R2. The values of Adj_R2 were found 0.93 and 0.94 for HH- and VV- polarization at 300 incidence angle respectively. The estimation of soil moisture by BPANN with Levenberg Marquardt training algorithm was found better at both HH- and VV- polarizations.

Sat Kumar Tomer et al (2016) in this paper develops an algorithm for Merging Active and Passive microwave Soil Moisture (MAPSM). The algorithm merges the soil moisture retrieved from active (fine spatial scale and coarse temporal resolution) and passive (coarse spatial scale and fine temporal resolution) microwave satellites. The algorithm relies on temporally transforming the fine scale information based on the innovative concept of water change capacity. This concept expresses the magnitude at which the soil at fine scale is impacted by a soil moisture change at the coarser scale. A case study using MAPSM is presented in this paper by using the RADARSAT-2 and SMOS retrieved soil moisture data products over Berambadi watershed, Karnataka, India. The algorithm parameters show scalability from the spatial resolution of 20 m to 2000 m.. The algorithm developed can also be used to merge SMOS / SMAP and Sentinel-1data.

Gayane Faye el al (2018) in this paper used a RTM (Roughness Transfer Model) for estimating the surface roughness of the Ferlo region, Snenegal. The above model was designed for leaf orientation distribution, branch orientation distribution and the branch size distribution for each size. In this study, the RTM has been standardized with ESCAT (European Radar Satellite Scatterometer) data, and has been used for soil moisture retrieval. The results obtained have allowed to track the spatial and temporal dynamics of soil as well as the influence of geology and morphopedology on the spatial dynamics of the soil moisture variability. These results are accepted despite the fact that the inversed RTM usually faces difficulties to interpret the signal for saturated soils, though giving deviating values of soil moisture more often than not.

Luca Pasolli et al (2016) in this paper presents an experimental analysis in which two non-linear machine learning techniques, the well known and commonly adopted Multi Layer Perceptron neural network and the more recent Support Vector Regression, are applied to solve the problem of soil moisture retrieval from active and passive microwave data.

CONCLUSION

Soil moisture is the key variable in managing the exchange of heat energy and water between the atmosphere and land surface. SM plays an important role in recent and numerous environmental studies by influencing the exchange of water and energy at the interface between the land surface and atmosphere. For the study of soil moisture different remotely sensors are available such as RADARSAT-1,RADARSAT-2, SMOS, SMAP, Landsat, Sentinel-1,ASMR-E (Source:-MDPI). Despite remote sensing offers a powerful tool for spatial and temporal monitoring of soil moisture information over a large agricultural area, it has some disadvantages. Generally, active microwave remote sensing of soil moisture using Synthetic Aperture Radar (SAR) data is considered to be the best tool for soil moisture information at field level, but it also has severe problems like presence of surface roughness, crop cover and variation in soil texture over a large agricultural area. So different approaches has to be taken for the study of these three target parameters that mainly affects the SAR sensitivity to soil moisture using different models.

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