Surface Soil Moisture Estimation Using Passive Microwave Radiometer Data

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15.	**Abstract:** A methodology to retrieve surface soil moisture using Level-3 brightness temperature data from Advanced Microwave Scanning Radiometer 2 (AMSR2) aboard the Global Change Observation Mission 1st-Water “SHIZUKU” (GCOM-W1) is presented. The retrievals are made with a Land Parameter Retrieval Model (LPRM) that uses a radiative transfer model to solve for surface soil moisture using an iterative forward modelling approach. LPRM depends only on brightness temperature data from AMSR2 to get information on surface temperature and vegetation cover apart from static parameters like soil texture. The procedure assumes known values for surface roughness and single scattering albedo. The vegetation optical depth is derived from the microwave polarization difference index (MPDI). Surface temperature is derived by using 37 GHz V-polarized brightness temperature data. Matlab tools are used to compute and map surface soil moisture in standard format with 25 km resolution. **Key Words:** AMSR-2, Radiometer and Soil Moisture			

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Abstract

A methodology to retrieve surface soil moisture using Level-3 brightness temperature data from Advanced Microwave Scanning Radiometer 2 (AMSR2) aboard the Global Change Observation Mission 1st-Water "SHIZUKU" (GCOM-W1) is presented. The retrievals are made with a Land Parameter Retrieval Model (LPRM) that uses a radiative transfer model to solve for surface soil moisture using an iterative forward modelling approach. LPRM depends only on brightness temperature data from AMSR2 to get information on surface temperature and vegetation cover apart from static parameters like soil texture. The procedure assumes known constant values for surface roughness and single scattering albedo. The vegetation optical depth is derived from the microwave polarization difference index (MPDI). Surface temperature is derived by using 37 GHz V-polarized brightness temperature. Matlab tools are used to compute and map surface soil moisture in standard format with 25 km resolution.

The soil moisture product has been validated with in-situ data from a ground station of International Soil Moisture Network (ISMN) located at IIT Kanpur Airstrip. The LPRM estimated soil moisture coincides quite well with the in-situ measurements and the correlation coefficient is 0.7909.

This document explains the basics of land parameter retrieval model, procedure and tools used to obtain surface soil moisture product using brightness temperature data from AMSR2. The procedure can easily be extended to other space-borne microwave radiometers including Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), Tropical Rainfall Measuring Mission's (TRMM) Microwave Imager (TMI) and Special Sensor Microwave Imager (SSM/I).

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We express our sincere thanks to all concerned who have contributed either directly or indirectly for the successful completion of Surface Soil Moisture computation and product generation using Advance Microwave Scanning Radiometer -2 (AMSR-2) data.

We thankfully acknowledge the providers of AMSR-2 data (GCOM-W1 Data Providing Service) that was used in the current study. The Rainfall data from IMD is acknowledged.

MATLAB tools have been used for developing the necessary algorithms to obtain the data product.

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1. Introduction

Surface soil moisture is an important state variable in land surface hydrology and a key link between the land and the atmosphere. It is an important parameter for many weather forecasting and prediction models. Changes in soil moisture have a severe impact on agricultural productivity, forestry and ecosystem health. So, regular measurements of soil moisture are essential for effective water resources management, drought forecast and management and understanding ecological processes etc.

Soil moisture exhibits high temporal and spatial variability due to heterogeneous soil properties and variability of precipitation. Due to this accurate estimation of soil moisture at larger scales is difficult. In-situ methods can accurately estimate soil moisture throughout the profile but the information is point specific or localized. These point measurements restricts utility for the repetitive measurements over a large spatial coverage. In this regard space based remote sensing of soil moisture assessment has an advantage and being used across the world over three decades. Soil moisture estimation by means of remote sensing depends upon the measurements of electromagnetic energy that has either been reflected (active) or emitted (passive) from the soil surface.

The passive microwave signal offers several advantages over other methods for remote sensing soil moisture; it can penetrate cloud, it has a direct relationship with soil moisture through the soil dielectric constant, and it has a reduced sensitivity to land surface roughness and vegetation cover. Within the microwave spectrum, lower frequencies respond to a deeper soil layer and are less attenuated by vegetation, and are best suited for soil moisture remote sensing. Fig. 1 shows they microwave bands along with their corresponding frequencies and wavelengths.

Band	*Frequency (GHz)*	*Wavelength (cm)*
P	0.255 - 0.390	133 - 76.9
L	0.390 - 1.550	76.9 - 19.3
S	1.550 - 4.20	19.3 - 7.1
C	4.20 - 5.75	7.1 - 5.2
X	5.75 - 10.90	5.2 - 2.7
K	10.90 - 36.0	2.7 - 0.83
K_u	10.90 - 22.0	2.7 - 1.36
K_a	22.0 - 36.0	1.36 - 0.83
Q	36.0 - 46.0	0.83 - 0.65
V	46.0 - 56.0	0.65 - 0.53
W	56.0 - 100.0	0.53 - 0.30

Figure 1: Microwave Spectrum

The Land Parameter Retrieval Model (LPRM) has been developed by researchers from the NASA Goddard Space Flight Center (GSFC) and the Vrije Universiteit Amsterdam [*Owe et al.*, 2001; *De Jeu and Owe*, 2003; *Meesters et al.*, 2005]. This model is based on microwave radiative transfer that links soil moisture to the observed brightness temperatures. LPRM requires no ground observations of soil moisture or vegetation biophysical parameters for calibration purposes.

2. General Background

People have developed a variety of modeling techniques to estimate soil moisture from microwave brightness temperature observations. Results from initial field and aircraft experiments revealed strong regression-based relationships between surface moisture and both brightness temperature and surface emissivity [*Schmugge*, 1976, 1977; *Jackson et al*., 1984]. Models have subsequently become more complex by accounting for vegetation effects [*Mo et al*., 1982; *Jackson et al*., 1982; *Jackson and Schmugge*, 1991], surface roughness [*Choudhury et al*., 1979], polarization mixing [*Wang and Choudhury*, 1981], and other perturbing factors [*Jackson and O'Neill*, 1987; *Jackson et al*., 1992, 1997; *O'Neill and Jackson*, 1990]. While many of these models are based on radiative transfer theory, an element of empiricism often remains because of difficulty in parameterizing some components from other measurable biophysical properties and at more meaningful spatial scales.

Experiments have shown good correlation between soil moisture derived from microwave-based models and field observations [*Owe et al*., 1992; *Jackson*, 1997; *Drusch et al*., 2001; *Jackson and Hsu*, 2001]. However, a characteristic problem with ground measurements has been the issue of scaling point observations to sensor footprint-sized averages, especially at satellite scales. This task becomes even more difficult with increasing land cover heterogeneity. The lack of large-scale surface moisture observations, has often forced researchers to calculate soil wetness indices (e.g., Antecedent Precipitation Index) from more readily available meteorological data, for comparison to satellite observations [*McFarland*, 1976; *Wilke and McFarland*, 1986; *Owe et al*., 1988, *Ahmed*, 1995; *Achutuni and Schofield*, 1997]. Fig. 2 shows some of the space-borne passive microwave radiometers. *McFarland and Neale* [1991] developed a regression technique that used brightness temperatures from several Special Sensor Microwave Imager (SSM/I) channels in a series of three empirical equations that accounted for different vegetation density classes. However, this approach calculated a soil wetness index, and was calibrated to regional Antecedent Precipitation Index calculations for test sites in the U.S. Southern Great Plains region. Errors associated with this method were found to be quite high and its application to other locations and at global scales may therefore be less useful, especially in data-poor regions where validation and recalibration may be more difficult. These approaches have successfully demonstrated the spatial and temporal sensitivity of satellite sensors, and have also been extremely useful for studying long-term seasonal and interannual climatologies. However, wetness indices do not necessarily relate directly to actual surface moisture quantities, and therefore their value is limited for use in many environmental monitoring and modeling applications.

Only a few modeling approaches can be considered for soil moisture retrieval. These techniques are, for the most part, physically based and account for most of the major components in radiative transfer theory. They typically solve for the soil emissivity, from which volumetric soil moisture is subsequently derived by inverting the Fresnel relationships and a dielectric mixing model [*Schmugge*, 1985]. The model developed by *Jackson* [1993] has compared well with aircraft data from several large field experiments [*Jackson et al*., 1995, 1999]. The model has also performed well with Tropical Rainfall Measuring Mission

(TRMM) Microwave Imager (TMI) and SSM/I measurements over these same experimental sites [*Jackson and Hsu*, 2001; *Jackson et al.*, 2002]. However, this approach requires a parameterization of the vegetation water content (VWC) in order to calculate the canopy optical depth [*Jackson et al.*, 1982; *Jackson and Schmugge*, 1991]. While extensive biophysical measurements were made during field experiments from which VWC was calculated, it may be more difficult to obtain this information on a regular basis for application at the global scale.

The method developed by *Njoku and Li* [1999] and *Njoku et al*. [2003] is the official Advanced Microwave Scanning Radiometer (AMSR-E) soil moisture science team contribution [*Njoku*, 2004]. This approach is based on polarization ratios, which effectively eliminate or minimize the effects of surface temperature. The original approach used six microwave channels (three frequencies, each at two polarizations) to solve for three land surface parameters (soil moisture, vegetation water content, and surface temperature). It was expected to provide surface soil moisture with an accuracy of 6% absolute moisture content (0.06 cm^3 cm^{-3}) in areas with low vegetation biomass (< 1.5 kg m^{-2}). However, unanticipated radio frequency interference (RFI) problems were encountered at the 6.9 GHz frequency, requiring modification of this approach [*Njoku*, 2004].

Another recently developed retrieval approach is based on the microwave polarization difference index [*Owe et al*., 2001; *De Jeu and Owe*, 2003; *Meesters et al*., 2005]. This method uses a forward modeling optimization procedure to solve a radiative transfer equation for both soil moisture and vegetation optical depth, and requires no calibration or fitting parameters, or other biophysical measurements during the retrieval process. A unique feature of this approach is that it may be applied at any relevant microwave frequency, and it was used in the retrieval of the data sets described in this paper. A more detailed description of this model is provided in Section 4 and 5.

Space-borne Passive Microwave Radiometers

Sensors	Frequency (GHz)	Parameters
SMMR (1981- 1987)	6.6, 10.7, 18, 21, 37	Ocean wind speed, cloud liquid water, Integrated water vapor, sea ice, Snow depth, Soil Moisture
SSM/I (1987-present)	19.35, 22.2, 37, 85.5	Ocean wind speed, cloud liquid water, Integrated water vapor, Precipitation, Snow depth, Soil Moisture
TRMM (1997-present)	10.7, 19.35,23.8, 37, 85	Ocean wind speed, cloud liquid water, Integrated water vapor, Precipitation, Snow depth, Soil Moisture
AMSR-E (2002- 2012)	6.9, 10.7,18.6, 23.8, 36.5, 89	SST, Ocean wind speed, cloud liquid water, Integrated water vapor, Precipitation, Soil Moisture, Snow depth
SMOS (2009-present)	1.4	Soil Moisture, Ocean Salinity
AMSR-2 (2012-present)	6.9,7,10.7,18.6, 23.8, 36.5, 89	SST, Ocean wind speed, cloud liquid water, Integrated water vapor, Precipitation, Snow depth ,Soil Moisture

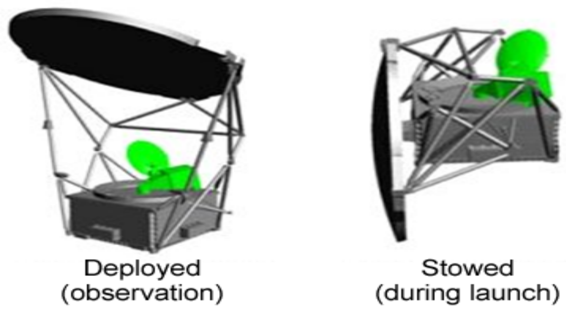
Figure 2: Space-borne passive microwave radiometers along with their standard products

3. Datasets

The passive microwave data used in the methodology are from the Advanced Microwave Scanning Radiometer 2 (AMSR2) aboard of the Global Change Observation Mission 1st-Water “SHIZUKU” (GCOM-W1). AMSR2 is multi-frequency, total-power microwave radiometer system with dual polarization channels for all frequency bands. The instrument measures the microwave radiation emitted by the Earth’s surface in vertical and horizontal polarization which is expressed in terms of brightness temperature. The instrument is a successor of AMSR on the ADEOS-II satellite and AMSR-E on the Aqua satellite. The instrument employs a conical scanning mechanism at a rotation speed of 40 rpm to observe the Earth’s surface with a constant incidence angle of 55 degrees. It provides brightness temperatures at six different frequency bands ranging from 7 GHz to 89 GHz. It scans the surface in an ascending node (1:30 pm) and descending node (1:30 am). The ground resolution of AMSR2 is 35×62 km at C band, 24×42 km at X band and 7×12 km at Ka band (Fig. 3). The instrument began transmitting data in July 2012 and is currently active.

AMSR2 Level 3 brightness temperatures at 0.25 degree grid are obtained from the GCOM-W1 Data Providing Service. Information on soil texture is obtained from Harmonized World Soil Database (version 1.2).

Rainfall in-situ data is obtained from Indian Meteorological Department (IMD).



GCOM-W/Main Specifications of AMSR2

Scan and rate	Conical scan at 40 rpm
Antenna	Offset parabola with 2.0m dia.
Swath width	1450km
Incidence angle	Nominal 55 degrees
Digitization	12bits
Dynamic range	2.7-340K
Polarization	Vertical and horizontal

AMSR2 Channel Set

Center Freq.	Band width	Pol.	Beam width	Ground res.	Sampling interval
GHz	MHz		degree	km	km
6.925/7.3	350	V/H	1.8	35 x 62	10
10.65	100		1.2	24 x 42	
18.7	200		0.65	14 x 22	
23.8	400		0.75	15 x 26	
36.5	1000		0.35	7 x 12	
89.0	3000		0.15	3 x 5	5

Figure 3: AMSR2 satellite and sensor characteristics

The land use land cover data is taken from National LULC mapping project for year 2011-12. National LULC mapping project was taken up during 2004-05 with an objective to undertake rapid assessment of national LULC on 1:250,000 scale using multi temporal IRSP6 AWiFS data sets (Resolution: 56m) as part of natural resources repository activity under NNRMS [NRC LULC, 2005].

4. Microwave Radiative Transfer Theory

The radiation from the land surface as observed from above the canopy may be expressed in terms of the radiative brightness temperature, $T_{b,p}$, and is given as a zero-order radiative transfer equation [*Mo et al*., 1982].

$$T_{b,p} = T_s e_p \Gamma_C \; + \; (1 - \Gamma_C) T_C (1\text{-}\omega) \quad + \quad (1\text{-}\, e_p)\,(1 - \Gamma_C) T_C (1\text{-}\omega)\, \Gamma_C \qquad (1)$$

Where T_s and T_C are the thermodynamic temperatures of the soil and the canopy respectively, Γ_C is the canopy transmissivity, $e_{r,p}$ is the rough surface emissivity and ω is the single scattering albedo. The subscript p denotes either horizontal (H) or vertical (V) polarization. The first term of the above equation represents the radiation from the soil dissipated by the overlying vegetation layer. The second term represents the upward radiation directly from the vegetation and the third term accounts for the downward radiation from the vegetation, reflected upward by the soil and again attenuated by the vegetation [*Owe et al*., 2001].

The canopy transmissivity is expressed in terms of the canopy optical depth, τ_C, and satellite look angle, u, such that

$$\Gamma_C = \exp\left(-\frac{\tau_C}{cos\, u}\right) \qquad (2)$$

The single scattering albedo, *ω*, describes the scattering of the soil emissivity by the vegetation. It depends on the geometrical characteristics of each of the components that make up the vegetation. There is very limited information available regarding single scattering albedo. Existing experimental research reported values of 0.02 to 0.13 [*Brunfeldt and Ulaby*, 1984].

The emissivity of the surface increases with the roughness of the surface. So, the empirical model of *Wang and Choudhury* [1981] is used to calculate rough surface emissivity,$e_{r,p}$ such that

$$e_{r,p} = 1 - Q\left(r_{s,p} + (1 - Q) r_{s,q}\right) \exp(-h' cos^2 u) \qquad (3)$$

Where Q is the polarization mixing ratio, h' is the roughness height, r_s is smooth surface reflectivity and the subscripts p and q denotes opposite polarizations (H or V). Q and h' are constants and depend on the surface roughness.

The depth through which energy is emitted and sensed by microwave radiometers has been the subject of research and discussion. Microwave energy originates from within the soil, and the contribution of any one soil layer decreases with the depth. The surface layer provides most of the measurable energy contribution and is termed as the thermal sensing depth or skin depth [*Schmugge*, 1983]. This layer has been established as a few tenths of a wavelength thick [*Wiheit et al*, 1978; *Newton*, 1983; *Wang*, 1987]. However, the actual thickness depends on the moisture content, wavelength, polarization, and incidence angle [*Owe et al*., 2001]. As the average moisture content of this layer increases, its thickness decreases as shown in Fig. 4 [*Ulaby*, 1982; *Njoku et al*., 1999]. So, in the retrieval process it is assumed that the surface temperature and surface soil moisture vertical distributions are uniform in this layer.

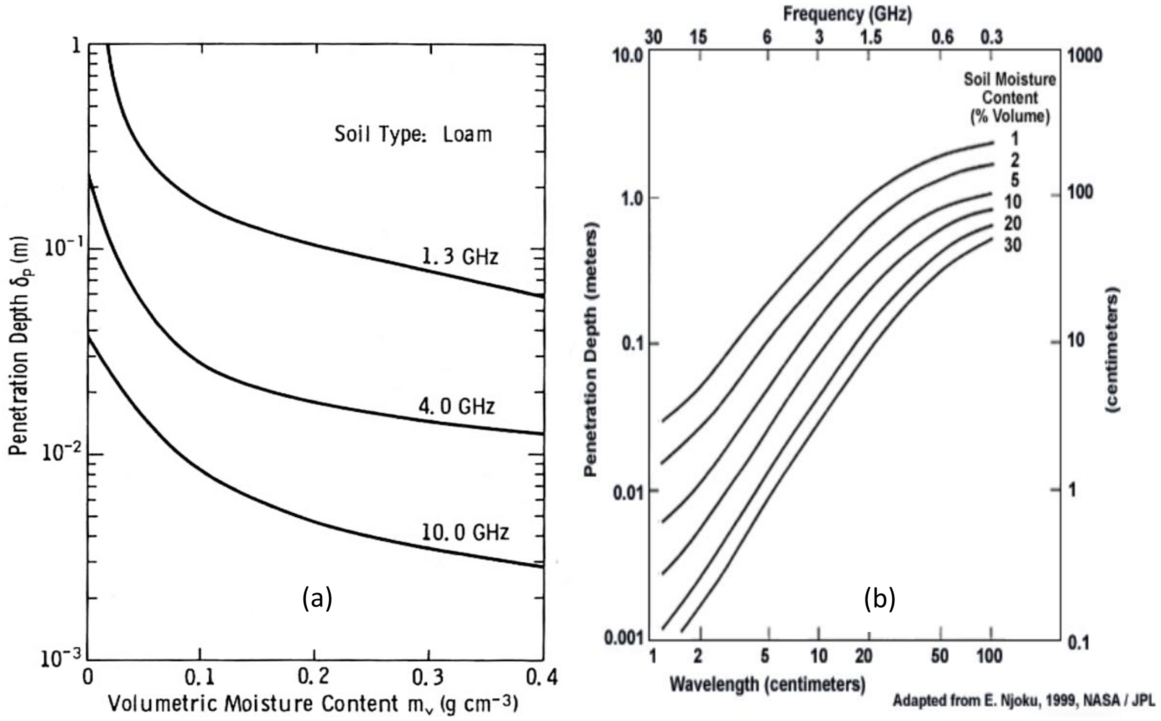


Figure 4: Microwave soil penetration depth at different (a) Frequencies (b) Soil moisture content

The smooth surface reflectivity ($r_{s,H}$ and $r_{s,V}$) are calculated using the Fresnel equations such that

$$r_{s,H} = \left| \frac{cos\,u - \sqrt{k - sin^2\,u}}{cos\,u + \sqrt{k - sin^2\,u}} \right|^2 \tag{4}$$

$$r_{s,V} = \left| \frac{k\cos u - \sqrt{k - \sin^2 u}}{k\cos u + \sqrt{k - \sin^2 u}} \right|^2 \tag{5}$$

Where k ($|k' + ik''|$) is the absolute value of the complex dielectric constant of the soil and subscripts H and V refer to the vertical and horizontal polarization of the emitted radiation. The dielectric constant is an electrical property of matter and is a measure of the response of a medium to an applied electric field. The dielectric constant of soil is a function of several ground parameters (Soil moisture, Soil texture, Bulk density, Temperature, Salinity) and sensor parameters (frequency). It is a complex number, containing a real (*k'*) and imaginary (*k''*) part. The real part determines the propagation characteristics of the energy as it passes upward through the soil, while the imaginary part determines the energy losses [*Schmugge et al*., 1986]. Microwave remote sensing of soil moisture is possible due to the large contrast between the dielectric properties of water (~80) and dry soil (~3) at these frequencies. The change in water content induces change in the dielectric properties, which in turn affects the emissivity and therefore the brightness temperature [*Njoku and Kong*, 1977]. Fig. 5 shows the variation of dielectric constant of soil with soil moisture at different frequencies. Dielectric models, which are commonly used in theoretical calculations are the Dobson Model [*Dobson et al*., 1985], a modified version of this model developed by *Peplinski et al*. [1995] and the Wang-Schmugge Model [*Wang and Schmugge*, 1980].

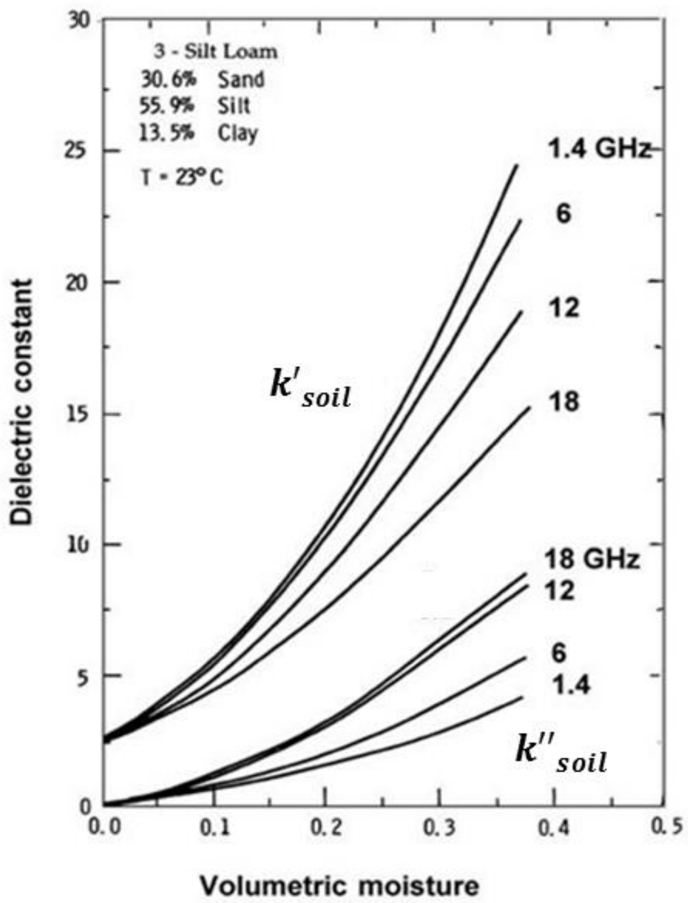


Figure 5: Variation of dielectric constant of soil with soil moisture at different frequencies

The canopy optical depth is derived using the Microwave Polarization Difference Index (MPDI), the single scattering albedo and the dielectric constant of the soil [*Meesters et al*., 2005]. The MPDI is defined as:

$$MPDI = \frac{T_{b,V} - T_{b,H}}{T_{b,V} + T_{b,H}} \quad (6)$$

It is widely accepted that both τ_C and ω have minimum polarization dependence at satellite scales [*Njoku and li*, 1999; *Owe et al*., 2001]. The analytical solution to canopy optical depth can be described as:

$$\tau_C = \cos u \ln(ad + \sqrt{(ad)^2 + a + 1}) \tag{7}$$

Where *a* and *d* are defined as

$$a = \frac{1}{2}\left[\frac{e_{r,V} - e_{r,H}}{MPDI} - e_{r,V} - e_{r,H}\right]$$

And,

$$d = \frac{1}{2}\left(\frac{\omega}{1-\omega}\right)$$

The 37 GHz vertical polarized brightness temperature is used to derive surface temperature (T_s) as it is considered the most appropriate microwave frequency for temperature retrieval [*Holmes et al*., 2009].

5. Methodology

Land Parameter Retrieval Model (LPRM) is used to retrieve surface soil moisture using H and V polarized brightness temperature at X band (10.65 GHz) to avoid error due to Radio Frequency Interference (RFI). It has been determined that RFI has a significant impact on both H and V polarization brightness temperatures at C band (6.95 GHz). RFI is usually caused by communications and broadcast signals, and frequently results in abnormally high brightness temperatures. While the existence of RFI has been known for some time, rigorous studies of this phenomenon in Earth observation data (AMSR-E) have only recently been reported [*Li et al*., 2004; *Njoku et al*., 2005]. The presence of RFI in radiometer data can be identified from original brightness temperature values [*Li et al*., 2004]. Radio frequency contamination in 6–7 GHz range is seen to be highly dominant over large highly populated urban areas. *Li et al*. [2004] developed a spectral difference method to quantify the magnitude and extent of RFI observed over urban areas. The difference obtained by subtracting the 6.9-GHz brightness temperatures from the 10-GHz brightness temperatures (positive spectral gradients) is known as RFI Index (RI) and it can be used to separate RFI at 6.9 GHz from the natural emission background. RI is used not only to identify the location of RFI but also to quantify its intensity. The larger the RI, the stronger the RFI. Fig. 6 shows the magnitude and extent of RFI over India in AMSR-2 channels (C band).

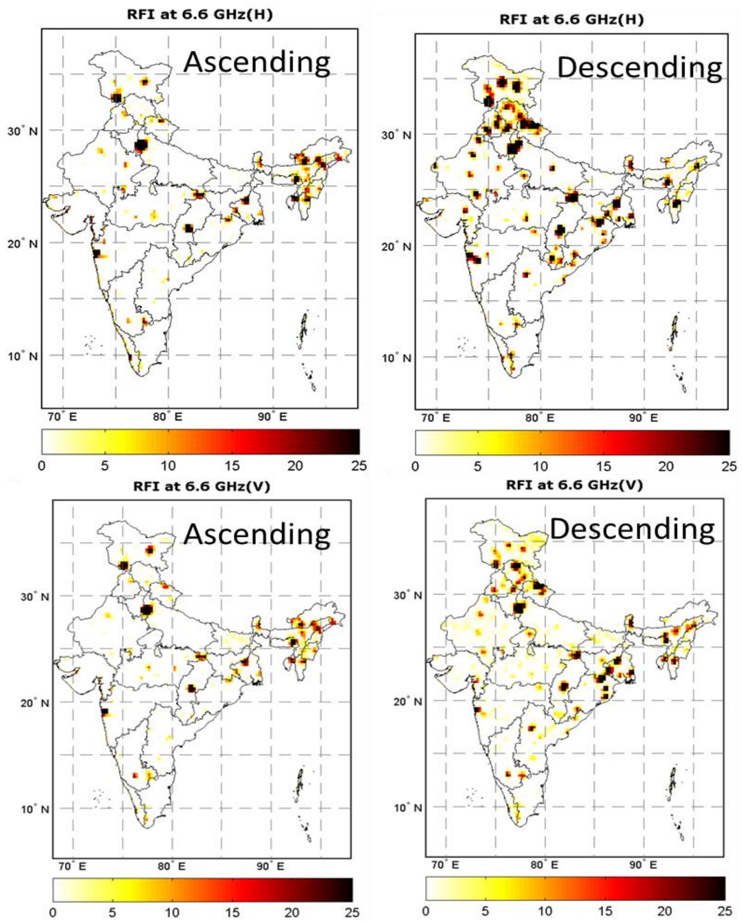


Figure 6: RI survey maps over India using AMSR2 ascending and descending passes (H-V polarization)

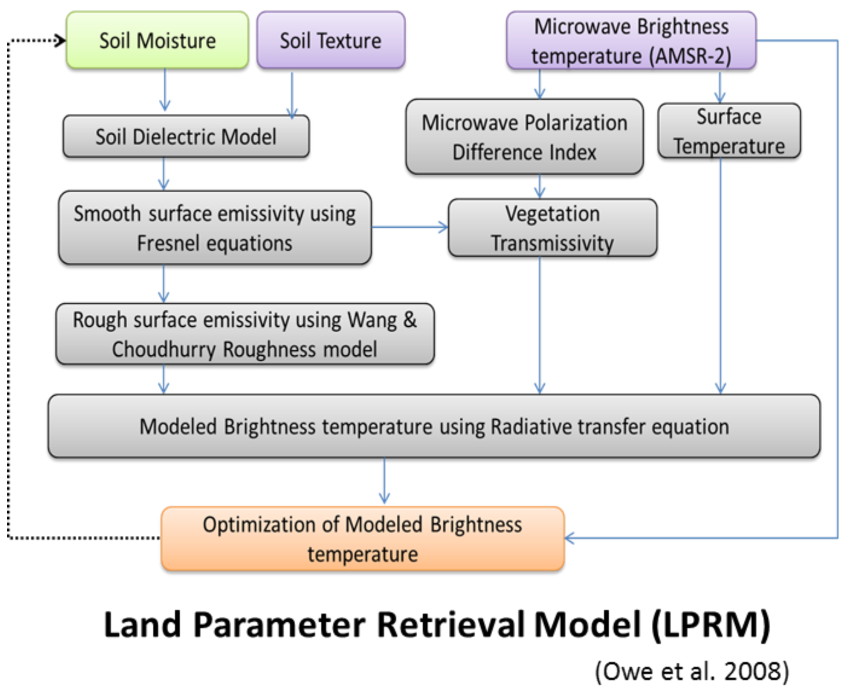


Figure 7: Flow chart of soil moisture retrieval from AMSR-2 data

The retrieval methodology uses the radiative transfer model [Equation 1] to solve for surface soil moisture using an iterative forward modeling approach. Fig. 7 shows the scheme of the adopted procedure to model brightness temperature and estimate soil moisture using AMSR-2 data.

It is assumed in the current version of implementation that the atmosphere has no influence on the H and V polarized brightness temperature at 10.65 GHz [*Ulaby et al.*, 1982]. An average value for the single scattering albedo of 0.06 is used [*Brunfeldt and Ulaby*, 1984]. An assumption of surface temperature (T_s) being equal to canopy temperature (T_C) is also made. So to meet this assumption we have limited our retrieval process to the nighttime observations only as nighttime soil and canopy temperatures are more stable and comparable. This is a reasonable assumption and is used by many other microwave based retrieval models [*Njoku and li,* 1999; *Njoku et al.,* 2003].

The values for roughness parameters *Q* and *h'* at 10.65 GHz are taken as constants [*Fujii et al*., 2009].

The canopy transmissivity (Γ_C) is expressed as a function of MPDI and dielectric constant (*k*) by substituting Eq. 1 into Eq. 6. As horizontal polarization has greater sensitivity to soil moisture [*Ulaby et al*., 1982], the rough surface emissivity ($e_{r,p}$) at horizontal polarization is expressed as a function of dielectric constant using the Fresnel equations (Eq. 4). MPDI is calculated using satellite observed brightness temperatures at 10.65 GHz (H and V) using Eq. 6. Surface temperature (T_s) is calculated directly using 37 GHz V polarized brightness temperature as described in *Holmes et al*., 2009. Now the only variable in the Eq. 1 is the dielectric constant (*k*) as all the other parameters (*h', Q, ω*) are given a fixed value.

The model now uses a nonlinear iterative procedure [*Brent*, 1973; *Forsythe*, 1976] to solve Eq. 1 in horizontal polarization by adjusting the dielectric constant (*k*). The Brent Method finds the roots of the Eq. 1 without calculating the derivatives. This improves both speed and precision of the retrieval process. The algorithm of this procedure uses golden section search and parabolic interpolation to achieve convergence. Once convergence between the simulated and observed brightness temperatures at H polarization is attained, the model uses the Dobson soil dielectric model [*Dobson et al*., 1985] along with the soil texture information to solve for the surface soil moisture. Global dataset of soil texture information is available at a resolution of about 1 km (30 arc seconds by 30 arc seconds). It is rebinned to 0.25 degree grid to match the grid size of brightness temperatures.

6. Results

The LPRM has been applied to data set of AMSR2 brightness temperatures (Descending nodes) for the period July 2012 through December 2013 over the Indian subcontinent. The retrieved datasets of surface soil moisture have been written and stored in Network Common Data Form (NetCDF), which is accepted worldwide. Fig. 8 shows soil moisture for 1st June 2013 representing pre monsoon and 15th June 2013 representing onset of monsoon.

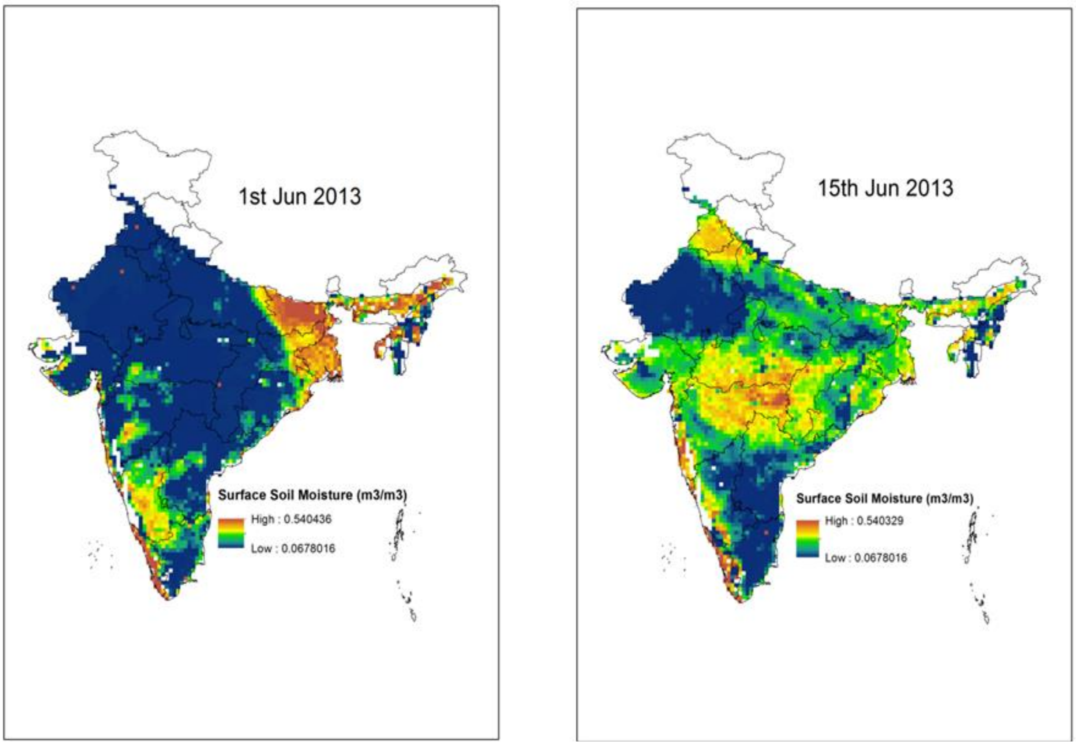


Figure 8: LRRM derived surface soil moisture over India for 1 June 2013 (pre monsoon) and 15 June 2013 (onset of monsoon)

In October 2013, a very severe cyclonic storm Phailin that originated from a remnant cyclonic circulation from the South China Sea progressed westward toward the Indian subcontinent and made its landfall in Gopalpur town of an eastern Indian state of Orissa. The landfall (on October 12, 2013) was followed by very heavy rainfall in the Indian states of Orissa, Andhra Pradesh, Chhattisgarh, Jharkhand, Bihar, and West Bengal, threatening floods in some of these states. So, an attempt has been made to build up a correlation between in situ rainfall and soil moisture using LPRM for the cyclone period (October 10–16, 2013). The study reveals a good agreement between the variations of rainfall (cause) and soil moisture (response) with correlation coefficient greater than 0.6 and the sensitivity of AMSR2 brightness temperature to soil moisture variations. [*Maurya et al.* 2014]

The LPRM algorithm has certain known limitations. In the areas covered with widely distributed dense vegetation, soil moisture retrieval is less accurate because of the attenuation of the signal from the soil surface by the vegetation layer. In such cases canopy transmissivity (Γ_C) becomes very small and uncertain [*Meesters et al*., 2005]. Certain land cover characteristics which includes steep mountainous terrain, snow cover or frozen surface, substantial amount of pixel area covered by water, also increases the error in soil moisture retrieval. Soil moisture around coastline also shows erroneously high value due to water surface effects. The Pixels where the surface temperature is observed equal or below 273 K are flagged as Snow or Frozen surface. The effect of water droplets in clouds and active precipitation on microwave emission is significant, and depends mainly on the phase state of the particles (i.e. ice or liquid) and the size of the particle relative to the wavelength [*Ulaby et al.*, 1982]. In all such cases, pixels are allotted a suitable flag in order to retain their uniqueness.

7. Validation

Validation study has been carried out for a ground station of International Soil Moisture Network (ISMN) located at IIT Kanpur Airstrip (26.51˚N, 80.23˚E). In-situ soil moisture data from this station is available from 16 Jun 2011 to 22 Nov 2012 [*Dorigo et al.,* 2011]. The International Soil Moisture Network is an international cooperation to establish and maintain a global in-situ soil moisture database. This database is an essential means of the geoscientific community for validating and improving global satellite observations and land surface models.

Fig. 9 shows the time series of LPRM derived soil moisture compared against soil moisture observations from ISMN ground station for the period 4 July 2012 to 22 Nov 2012. The LPRM estimated soil moisture coincides quite well with the in-situ measurements. The correlation coefficient between In-situ data and LPRM is 0.7909. But a good one-to-one correspondence is not always observed; it is also not expected. There are several important differences when comparing the satellite derived surface soil moisture with the in-situ measurements.

- Differences in spatial resolution. The LPRM derived soil moisture is a spatial average integrated over the foot print, whereas the in-situ data are point measurements.
- Differences in vertical resolution. The in-situ data from IIT_K station are average soil moisture within the top 10 cm profile, whereas the LPRM retrievals reflect only the soil moisture within top 2 cm at most.

Fig. 10 shows Time series of estimated surface soil moisture using LPRM against Rainfall data for two locations (Central India and Indo Gangetic Plans). For both the locations, soil moisture conditions show a very good agreement in terms of response to incident rainfall as a function of time.

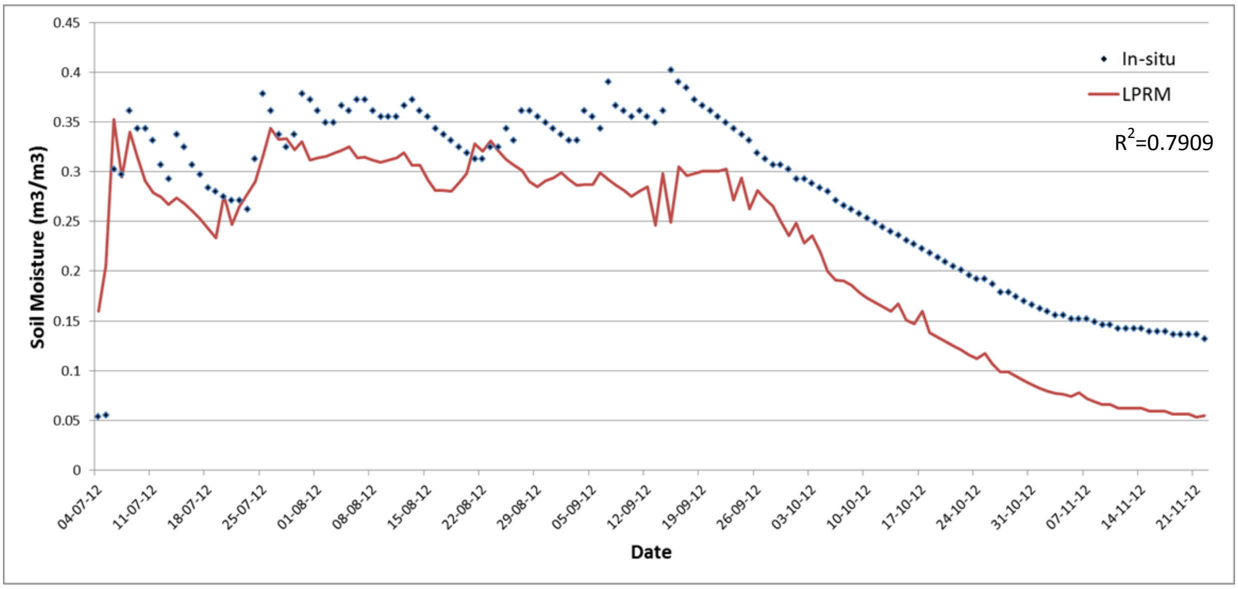


Figure 9: Time series of retrieved soil moisture (m3/m3) using LPRM against in-situ observations from IIT Kanpur station from July 2012 to Nov 2012

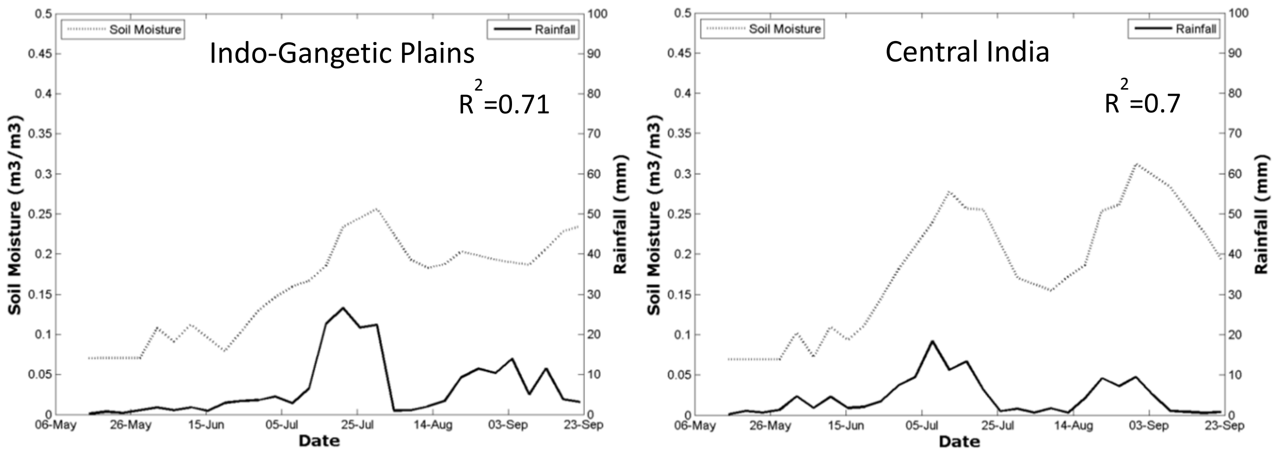


Figure 10: Response of LPRM retrieved Soil moisture to Rainfall (IMD) from May 2013

8. Summary and Conclusions

A methodology for the retrieval of surface soil moisture from dual-polarized microwave brightness temperature data is presented and has been applied to 10.65 GHz AMSR-2 data. The radiative transfer based Land Parameter Retrieval Model does not use ground observations of soil moisture, vegetation biophysical data, or other geophysical data as calibration parameters, and may be applied to any frequency.

The version 1.0 product of surface soil moisture has been successfully generated for the period July 2012 through Dec 2013. The present study was limited to one study site (IIT Kanpur Ground Station) as a demonstration because of the availability of soil moisture in-situ data for comparison. Time series of the satellite derived surface soil moisture compared well with the available ground observations and precipitation data. Validation studies in other regions are currently being conducted. In future, efforts will be made to improve the model performance by addressing some of the assumptions in the current implementation.

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