Present status of soil moisture estimation by microwave remote sensing

Kousik Das and Prabir Kumar Paul

Cogent Geoscience (2015), 1: 1084669
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Kousik Das1* and Prabir Kumar Paul1

Abstract: The spatiotemporal distribution of soil moisture is a key variable for hydrological and meteorological applications that influences the exchange of water and energy fluxes at the land surface/atmosphere interface. Accurate estimate of the spatiotemporal variations of soil moisture is critical for numerous large-scale environmental studies. Recent technological advances in satellite remote sensing have shown that soil moisture can be measured by a variety of remote sensing techniques, each with its own strengths and weaknesses which minimizes the ill-posed conventional problems. Technical and methodological advances such as multi-configuration radar and forthcoming SAR constellations are increasingly mitigating the shortcomings of SAR with respect to soil moisture estimation at the field and catchment scale. This paper presents a comprehensive review of few selected inversion methods of soil moisture, with focus on technique in passive microwave and active microwave measurements, in addition to the factors which affect the microwave return. The theoretical and physical principles and the status of current basic retrieval methods are summarized. Limitations existing in current soil moisture estimation algorithms and the major influencing factors including radar configurations (polarization, incidence angle and frequency of bands) and soil surface characteristics on backscattering coefficient have been addressed and also discussed.

Keywords: soil moisture; radar; SAR; microwave; remote sensing

1. Introduction

Soil moisture is a quantity of water contained in soil on a volumetric or gravimetric basis (Al-Yaari et al., 2014; Zhao & Li, 2013). Soil moisture participates in the distribution of precipitation between run-off and evapotranspiration. More recently, the influence of water vapor on the global climate system has become evident. Remote sensing of soil moisture, therefore, becomes a key variable for improving the accuracy of regional weather forecasting models and global climate models. Thereupon, a variety of active and passive microwave remote sensing systems are being utilized to measure and map soil moisture at the field, catchment, or regional scales. In general, soil moisture retrieval from passive microwave measurements involves solving an inverse scattering problem.

ABOUT THE AUTHOR

The author has been working for a decade on Remote Sensing and Geographical Information System. The major thrust is focused on Remote Sensing and GIS application on natural resources and mining. To name a few we had been working on landslide zoning, location of sites for small hydel and ground water. Presently we are working on various applications of SAR data specifically on town planning, soil moisture etc.

PUBLIC INTEREST STATEMENT

This review paper is addressed towards the scientific community those are working or try to working on that field of soil moisture retrieval by microwave remote sensing. This review paper is used to describe the fundamentals of active and passive microwave remote sensing technology there models and algorithms to retrieve soil moisture. Basically it depicts limitations existing in current soil moisture estimation algorithms and the major influencing factors that affect radar configurations. New readers will be benefitted from this paper by the information of very beginning of this technology of soil moisture estimation to till date.
and infiltration (Petropoulos, Ireland, & Barrett, in press; Seneviratne et al., 2010). Soil moisture influences meteorological and climatic processes (Álvarez-Mozos, Casali, González-Audicana, & Verhoest, 2005; Wagner et al., 2007), though surface soil moisture only constitutes 0.0012% of all water available on Earth (Chow, Maidment, & Mays, 1988). Soil moisture was recognized as an essential climate variable (ECV) in 2010 because it plays a crucial role in various processes occurring on the soil-atmosphere interface (European Space Agency [ESA], Soil moisture network, http://www.esa-soilmoisture-cci.org/node) (Al-Yaari et al., 2014; Zhao & Li, 2013). The representative ground-based measurements of soil moisture are an unsolved problem because the only soil moisture data available are from point measurements (Laguardia & Niemeyer, 2008). Considering the high variability and the low degree of observed autocorrelation, it is difficult to obtain reliable estimates at the larger scale from point measurements (Engman & Gurney, 1991; Giacomelli, Bacchiega, Troch, & Mancini, 1995; Kornelsen & Coulibaly, 2013; Ulaby, Moore, & Fung, 1986). Possibility of retrieving soil moisture has been investigated using satellites, space shuttles and airborne synthetic aperture radars (Baghdadi, Holoh, & Zribi, 2006a; Baghdadi, King, Chanzy, & Wigneron, 2002). Microwave remote sensing is the most effective technique for soil moisture estimation, with advantages for all-weather observations and solid physics (Engman, 1990; Kornelsen & Coulibaly, 2013; Petropoulos et al., in press). Since microwave measurements of the soil surface are affected by the water content (Engman & Gurney, 1991; Petropoulos et al., in press; Seneviratne et al., 2010; Shi et al., 2012; Ulaby et al., 1986), it is easy to see the potentiality of remote sensing in soil moisture mapping and other related applications (Batlivala & Ulaby, 1977; Giacomelli et al., 1995; Petropoulos et al., in press; Seneviratne et al., 2010).

The use of radar data to retrieve soil moisture is of considerable importance in many domains, including agriculture, hydrology and meteorology (Baghdadi, King, Chanzy, et al., 2002; Petropoulos et al., in press; Seneviratne et al., 2010). Despite many advantages that can be derived from the knowledge of soil moisture distribution, measurement of soil moisture has few limitations. However, the measurement of soil moisture is not only depended on target characteristics such as surface roughness, vegetation cover, dielectric constant and topography (Ulaby, Batlivala, & Dobson, 1978) but also depends on various combinations of the radar sensor parameters including frequency, polarization and angle of incidence ($\theta$) with respect to nadir (Anguela, Zribi, Baghdadi, & Loumagne, 2010; Bertoldi et al., 2014; Dobson & Ulaby, 1981, 1986; Kornelsen & Coulibaly, 2013; Ulaby et al., 1978).

2. Microwave remote sensing

2.1. Active microwave remote sensing

Active microwave remote sensing uses the radar antenna in terms of either real or synthetic aperture, which transmits wave pulses of known energy and receives a return signal whose intensity depends on target characteristics (Kornelsen & Coulibaly, 2013). The returned signal which has been recorded by the sensor is usually expressed as backscattering coefficient ($\sigma^0$). The $\sigma^0$ is mostly dependent on soil moisture content mainly due to the dielectric constant ($\varepsilon$) of the soil (Prakash, Singh, & Pathak, 2012; Schmugge, Jackson, & McKim, 1980), and thus provides a method of retrieving soil water content. Therefore, microwave is the most suitable for the purpose of soil moisture because it is free from atmospheric attenuation. Number of factors like vegetation, surface roughness, measurement depth and topography affect the backscattering signal detected by the antenna (Bertoldi et al., 2014; Kornelsen & Coulibaly, 2013; Petropoulos et al., in press; Schmugge et al., 1980; Ulaby et al., 1986).

2.2. Passive microwave remote sensing

For soil moisture retrieval, passive microwave remote sensing has been considered to be superior and more reliable in terms of lower frequencies than active microwave remote sensing (Petropoulos et al., in press). A series of operational satellite-based passive microwave sensors have been available since 1978 and are represented in (Table 1) (Basist et al., 1998; Liu et al., 2011; Oza, Singh, Dadhwal, & Desai, 2006; Singh, Mishra, Sahoo, & Dey, 2005). Among all passive microwave sensors, more recently, the Advanced Microwave Scanning Radiometer—Earth observing system (AMSR-E)
on-board the Aqua satellite (since 2002), Soil moisture and ocean salinity satellite (SMOS since 2009), Multi-frequency Scanning Microwave Radiometer (MSMR since 1999) and Soil Moisture Active Passive (SMAP) (since January 2015) are presently operational, providing satellite data for the globe on a daily basis. Passive microwave remote sensing provides the temporal data of earth daily which are applicable to models like numerical weather predictions (NWP) model (Anudeep, 2013). Passive microwave instruments are typically characterized by wide swath and high temporal resolution, but also coarse spatial resolutions around 10–30 km at L-band and C-band, respectively (Anudeep, 2013; Moran, Peters-Lidard, Watts, & McElroy, 2004; Wigneron et al., 2003). The microwave ranges within 10–30 cm are not affected largely by the surface roughness, vegetation cover and soil texture rather it is highly sensitive to the soil moisture (Chai et al., 2010).

The ESA launched SMOS mission on 2 November 2009. It is also the first-ever L-band passive microwave sensor dedicated to the global measurement of the Earth’s near-surface (up to 10 cm) soil moisture (Petropoulos et al., in press). The spatial resolution of SMOS is sufficient enough to retrieve soil moisture for many global applications. Combination of SMOS data with other sensors’ higher resolution data can provide a potential solution for global soil moisture estimates (Petropoulos et al., in press).

SMAP mission was launched in January 2015. The SMAP sensor is designed in such a way to produce active (radar: VV, HH and HV polarizations) and passive (radiometer; V, H and high register and 4th Stokes parameter polarizations) soil moisture data simultaneously. Multiple polarizations help in accurate soil moisture estimates with corrections for vegetation, surface roughness, Faraday rotation and other perturbing factors in the 1.2–1.4 GHz range (L-band) from a sun-synchronous low Earth orbit (Petropoulos et al., in press). The SMAP project is managed for NASA by the Jet Propulsion Laboratory, with participation by the Goddard Space Flight Centre (Entekhabi et al., 2010).

### 3. Factors influencing microwave remote sensing
Surface characteristics, such as roughness and vegetation cover, have significant influence on the backscattering coefficient; thus, it is very difficult to retrieve the soil moisture without detailed knowledge of it (Altese, Bolognani, Mancini, & Troch, 1996; Anguela et al., 2010; Bertoldi et al., 2014; Kornelsen & Coulibaly, 2013; Petropoulos et al., in press). In addition, number of radar sensor parameters, such as frequency, \( \epsilon \) polarization and \( \theta \) with respect to nadir, influence the microwave backscatter in several ways which are described as follows (Anguela et al., 2010; Bertoldi et al., 2014; Dobson & Ulaby, 1981, 1986; Kornelsen & Coulibaly, 2013; Petropoulos et al., in press; Ulaby et al., 1978):

### Table 1. Passive microwave sensors used for the generation of the soil moisture data sets from 1978 to 2015

| Parameter                  | SMMR            | SSM/I           | TRMM            | MSMR            | AMSR-E          | SMOS            | SMAP            |
|----------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Launch date                | 1978–1987       | 1987/92/95     | 1997–2001       | 1999–2001       | 2002–2011       | 2009            | 2015            |
| Frequency (GHz)            | 6.6, 10.7, 18.0, 21 and 37 | 19.3, 22.2 (V), 38.0 and 85.5 | 10.65, 19.35, 22.24, 37.0 and 85.5 | 6.6, 10.65, 18.21 | 6.6, 10.65, 18.723.8, 36.5, 89 | 1.4       | 1.41            |
| Polarization               | H and V         | H and V (except 22.2 GHz) | H and V (except 22.23 GHz) | H and V         | H and V         | H and V         | H, V and HV or VH |
| IFOV (km)                  | 148 x 95, 91 x 59, 55 x 41, 46 x 30, 27 x 18 | 69 x 43, 60 x 40, 17 x 28, 15 x 13 | 11 x 8 | 150 x 144, 75 x 72, 50 x 36, 50 x 36 | 76 x 44, 49 x 28, 28 x 16, 31 x 18, 14 x 8, 6 x 4 | 43 x 43 | 40 x 40 |
| Swath width (km)           | 822             | 1400            | 880             | 1,360           | 1445            | –               | 1,000           |
| Revisit coverage (days)    | –               | 1               | 2               | 2               | 3               | 3               | 3               |
| Incidence angle (deg.)     | 50.3 (at the surface) | 53.3 (at the surface) | 35.0           | 43.13           | 54 (at the surface) | 0–55            | 35–50           |
3.1. Dielectric constant (ε)

ε of moist soils is proportional to the number of water dipoles per unit volume (Dobson & Ulaby, 1986). Estimation of soil moisture with the use of microwave instruments is the perspective of sensitivity of ε to water content for such instances (Chen et al., 2012; Hallikainen, Ulaby, Dobson, El-Rayes, & Wu, 1985). Real part of dielectric constant (ε'), which can vary from 2.5 for very dry soil to 25 for very moist soil, is a function of both the composition of the soil and the microwave frequency (Singh & Kathpalia, 2007; Ulaby, Moore, & Fung, 1982). Several investigations have been initiated in laboratory conditions to find out the effect of soil moisture, bulk density and soil texture on the net dielectric behaviour of the soil medium using either guided-wave or free-space transmission techniques (Dobson, Ulaby, Hallikainen, & El-Rayes, 1985; Gharechelou, Tateishi, & Sumantyo, 2015; Hallikainen et al., 1985; Li, Zhao, Ren, Ding, & Wu, 2014; Wang & Schmugge, 1980). Grain size of soil is another operating factor of ε due to their interstice water content (Hallikainen et al., 1985; Mironov, Dobson, Kaupp, Komarov, & Kleshchenko, 2004; Srivastava, Patel, & Navalgund, 2006). Hallikainen et al. (1985) generated empirical expressions for ε as a function of the volumetric moisture content (Mv) and soil textural (sand (s) and clay (c) percent of weight) configuration (1).

\[ \varepsilon' = (a_0 + a_1s + a_2c) + (b_0 + b_1s + b_2c)M_v + (c_0 + c_1s + c_2c)M_v^2 \]  
\[ \varepsilon'' \]

where, s and c are the percentage of sand and clay by weight, and a1, b1, and c1 are the frequency dependent coefficients. ε' and ε'' are the real and imaginary parts of the dielectric constant.

Several models have been developed to correlate ε and soil moisture content. For soil moisture retrieval studies, the polynomial expressions fitted by Hallikainen et al. (1985) and the semi-empirical four-component mixing model developed by Dobson et al. (1985) are general-purpose models of ε. The latter model is valid for frequencies larger than 4 GHz and smaller than 18 GHz, which was further extended for 0.3–1.3 GHz range by Peplinski, Ulaby, and Dobson (1995a, 1995b). Generalized refractive mixing dielectric model (GRMDM) was developed by Mironov, Dobson, Kaupp, Komarov, and Kleshchenko (2002) and is used to retrieve the soil complex ε, which is a function of frequency for both free and bound soil water (Mironov et al., 2002, 2004). But, most common methods found in the literature to relate the soil moisture and the ε without direct field measurement are done using empirical curves of Hallikainen et al. (1985), which was extensively used by a number of researchers (Rao et al., 2013). A site-specific calibration procedure was developed by D’Urso and Minaecapilli (2006) for Oh, Sarabandi, and Ulaby (1992) model to derive soil ε without prior soil surface related information.

3.2. Backscattering coefficient (σ0)

Backscattering coefficient is linearly dependent upon soil moisture at moisture levels below saturation. Near saturation, the backscattering levels off, apparently becoming less sensitive to added increments of water (Dobson et al., 1985). Soil moisture influences the backscattered quantity due to the dielectric properties of the soil (Altese et al., 1996; Callens, Verhoest, & Davidson, 2006). When the ε of a soil increases linearly, σ0 also increases, i.e. σ0 and soil moisture content become positively correlated (Champion, 1996). Unit of σ0 is m2 m−2, but in general, it is expressed in dB (Wagner, 1998). σ0 increases with an increase in soil moisture until the moisture content reaches 35 volumetric % when the radar signal becomes insensitive to the soil moisture (Dobson & Ulaby, 1981; Gorraz, Zribi, Baghdadi, Lili-Chabaane, & Mougenot, 2014; Ulaby et al., 1986; Zribi, Baghdadi, Holah, & Fafin, 2005). From the numerous field experiments, the linear relationship between σ0 and Mv content is empirically expressed in Equation (2) (e.g. Champion, 1996):

\[ \sigma^0 = A + B.\varepsilon \]  
\[ (2) \]

where A is the backscattering coefficient of a completely dry soil surface and B is the sensitivity of σ0 to change with the surface soil moisture content. A and B are regression coefficients dependent on soil surface roughness, incidence angle and soil texture (Autret, Bernard, & Vidal-Madjar, 1989; Bertuzzi, Chaœnzy, Vidal-Madjar, & Autret, 1992; Champion & Faivre, 1997; Dobson & Ulaby, 1986;
Ulaby & Batlivala, 1976; Wagner, 1998). A is primarily controlled by surface roughness and the incidence angle (Dobson & Ulaby, 1986; Wagner, 1998).

However, field measurements have shown that the saturation effect at high moisture contents and the supersaturated and flooded soils behave as specular surfaces, which yield lower backscattering at off-nadir angles than non-saturated (but wet) soils (Dobson & Ulaby, 1981; Dobson et al., 1985).

Theoretical research on scattering of electromagnetic waves by rough surfaces has been done extensively and studies show that backscatter is very sensitive on the r.m.s (route mean square surface height) and the autocorrelation function of the surface height variations (Fung, 1994; Tsang, Kong, & Shin, 1985). However, in case of retrieval of $\sigma^0$ from Integral Equation Method (IEM) in well-defined situations shows good agreement with experimental results (Baghdadi, King, & Bonnifait, 2002; Baghdadi, King, Chanzy, et al., 2002).

### 3.3. Surface roughness

Soil surface roughness is one of the main indicators for mapping potential run-off surfaces because it triggers the infiltration processes (Baghdadi, King, & Bonnifait, 2002). Surface roughness intensely affects radar return and it is much more than the presence of surface soil moisture (Srivastava, Patel, Manchanda, & Adiga, 2003; Srivastava et al., 2006; Srivastava, Yogarajan, Jayaraman, Rao, & Chandrasekhar, 1997). Incident radar beam is scattered in specular direction, rather it is directly reflected back to the sensor depending on the magnitude of surface roughness, and thus the radar image is constructed by part of reflected radar beam received by the antenna (Callens et al., 2006).

Numerous studies have proved that radar signal is more sensitive to surface roughness at high incidence angles than at low incidence angles (Baghdadi, King, & Bonnifait, 2002; Baghdadi, Cerdan, et al., 2008; Fung & Chan, 1992; Ulaby et al., 1986; Zribi & Dechambre, 2002). However, in case of retrieval of $\sigma^0$, radar return is sensitive to soil surface roughness parameter, especially dependent on correlation length ($L$), whereas other surface parameters are not too much sensitive (Baghdadi, King, & Bonnifait, 2002; Baghdadi, King, Chanzy, et al., 2002). Furthermore, measuring the $L$ is problematic due to substantial instability of agricultural soils. Baghdadi, Paillou, Grandjean, Dubois, and Davidson (2000) have shown that roughness parameters estimated from field measurements are very sensitive to the length of the roughness profile, and also shown that the root mean square surface height (r.m.s) and the $L$ increase with profile length (Baghdadi et al., 2004).

Bryant et al. (2007) reported that the main source of retrieval errors is due to the differences in soil roughness parameters resulting from different measurement techniques and roughness transects (Baghdadi et al., 2000, 2006a). The discrepancies found are mainly related to the uncertainty in the measured roughness parameters, especially with respect to the $L$ (Baghdadi et al., 2000; Le Toan et al., 1999). $L$ was removed from the practical implementation in Oh (2004) due to measurement uncertainty. To minimize the effect of $L$, Oh (2004) used r.m.s as a model parameter (13). But the $L$ was retrieved empirically and applied further explicitly by Baghdadi and Zribi. Dubois, Van Zyl, and Engman (1995a) derived a backscattering model (16–17) which does not require any $L$ as well as ERS Scatterometer data (19, 21).

$$\text{r.m.s} = \sqrt{\frac{\sum_{i=0}^{n} (Z_i - \bar{Z})^2}{n-1}}$$

where $Z_i$ denotes the height of the point, $\bar{Z}$ is the mean height and $n$ is the total number of points taken under consideration.

### 2.4. Bulk density

Soil bulk density ($\rho_b$) has a significant inverse relationship with microwave emission (Mattikalli, Engman, Jackson, & Ahuja, 1998). The increasing bulk density of soil affects the dielectric properties

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of dry and moist soil (Hallikainen et al., 1985; Singh & Kathpalia, 2007; Ulaby et al., 1982). It has been
evident that dielectric parameters of soil at microwave frequencies are mainly the function of vari-
ous properties of soil such as texture, moisture, bulk density, temperature and soil type (Gupta &
Jangid, 2011a, 2011b).

3.5. Soil texture
Determination of direct soil texture through SAR images is a very difficult task. Soil texture affects
the backscattering coefficient by change in soil dielectric properties through its textural configura-
tion in terms of its water-holding capacity (Hallikainen et al., 1985). Sandy soils contain higher
amount of free water than clay soils (Kong & Dorling, 2008; Srivastava et al., 2006); thus, the Pearson
correlation between backscatter and soil moisture is higher in sandy soils (Blumberg et al., 2000).
Jackson and Schmugge (1989) found that water molecules are adsorbed onto the soil particles and
effectively immobilize their dipoles, disallowing bound water to interact with the radar signal.
Difference in texture explains the difference in surface drying rate. For this reason, difficulties can be
encountered in the interpretation of radar signals in cases where the vertical moisture profile varies
strongly in the first centimeters (Anguela et al., 2010). In the C-band, decreasing soil clay content
increases the sensitivity of the radar signal to soil moisture (Aubert et al., 2011; Ulaby et al., 1978).
Because the distribution of grain sizes controls the amount of free water that interacts with the inci-
dent microwave, the amount of free water gives significant contribution to SAR backscatter (Aubert
et al., 2011; Srivastava et al., 2006; Srivastava, Patel, Sharma, & Navalgund, 2009).

3.6. Vegetation cover
Presence of vegetation over the soil surface reduces the backscattering sensitivity of soil, even if in
agricultural fields, soil moisture gradients near the surface can change rapidly (D’Urso & Minaecapilli,
2006). Vegetation cover also affects the soil moisture retrieval by microwave due to various factors
which are vegetation biomass, canopy type and configuration and crop condition (Bertoldi et al.,
2014; Kornelsen & Coulibaly, 2013; Petropoulos et al., in press). Vegetation effects become stronger in
case of dense vegetation as well as with the increase in microwave frequency. Among all microwave
bands, L-band measurements still yield good results under various canopy types because it has a
higher penetration power to vegetation canopy or vegetation cover to reach the soil surface, whereas
for C-band which is highly sensitive to vegetation cover may lead to a distorted measurement
(Jagdhuber, Hajnsek, Bronstert, & Papathanassiou, 2013; Vereecken et al., 2014; Western et al., 2004).
However, for X-band SAR signals of this wavelength (λ ~ 3 cm) are not able to penetrate vegetation
cover due to the way that dielectric permittivity of the biomass affects radar response (Baghdadi,
Aubert, & Zribi, 2012; Jagdhuber et al., 2013; Vereecken et al., 2014). The effect of vegetation cover is
also dependent upon the incidence angle and polarization of the instrument (Ulaby et al., 1986).

3.7. Incident angle (θ)
Local incidence angle has an important role to inversion of soil moisture with respect to surface
roughness condition of soil (Aubert et al., 2011; Baghdadi, Cerdan, et al., 2008). Numerous experi-
mental results and simulated data showed that sensitivity of radar signal is more sensitive to sur-
face roughness at high incidence angles than at low incidence angles. Though low incidence angles
are optimal for soil moisture estimation (Autret et al., 1989; Baghdadi, King, Chanzy, et al., 2002;
Holoh, Baghdadi, Zribi, Bruand, & King, 2005; Ulaby et al., 1978). Baghdadi, King, Chanzy, et al., 2002
have reported that high incidence angles (>45°) are suitable for the discrimination between smooth
and rough areas, under this conditions the backscattered signal has an exponential dependence on
surface roughness (e.g. Baghdadi, Cerdan, et al., 2008; Baghdadi, Zribi, et al., 2008; Zribi & Dechambre,
2002). The Frauenhofer criterion proposed in Ulaby et al. (1982) considers a soil surface as rough
when the phase difference between two rays scattered from separate points on the surface
(Δφ = 2·k·r·m.s·cos(θ)) exceeds π/8 (r.m.s* /λ(32·cos(θ))), where, Δφ is phase difference, k is wave number,
k·r·m.s is electromagnetic surface roughness and λ is a wave length (Baghdadi, Zribi, et al., 2008).
They also observed that the dependence of the radar signal on surface roughness in agricultural
area is mainly significant for low levels of roughness and it is difficult to discriminate between rough-
ness greater than around 0.015 m with C-band SAR sensors (Baghdadi, Zribi, et al., 2008).
3.8. Bands

The ability of radar sensor to measure soil moisture is very much hampered in the areas with high vegetation dominance such as forest, because the lower microwave bands are inefficient to escape from vegetation attenuation (Jagdhuber et al., 2013; Ulaby & El-Rayes, 1987; Vereecken et al., 2014; Western et al., 2004). The crop canopies can also influence the $\sigma_0$; because plants also affect the $\sigma_0$ by their leaves dielectric behaviour. Dielectric behaviour of leaves was determined by direct measurements of oven-dried various types of vegetation material to find out the influence on radar return on complete dry condition and presence of water. Leaves have real part of the dielectric constant ($\varepsilon'$) between 1.5 and 2, and imaginary part of the dielectric constant ($\varepsilon''$) is below 0.1 (Ulaby & El-Rayes, 1987).

On the other hand soil moisture estimation by shorter wavelength than C-band is hydrologically inefficient due to the small surface penetration power (Ulaby, Dubois, & van Zyl, 1996), where as L-band measurements still yield good results under various canopy types (Jagdhuber et al., 2013; Vereecken et al., 2014; Western et al., 2004) (Figure 1). To retrieve soil moisture using C- and lower bands (Table 2) requires more accurate roughness information for retrieval studies (Mattia et al., 1997). Longer wavelength (> L-band) contains more soil profile information in the backscattered signal (Ulaby et al., 1996). Thus, to minimize the influence of vegetation cover on radar images, long wave bands and steep incident angles are preferred (Álvarez-Mozos et al., 2005).

![Figure 1. Behaviour of three different wave lengths due to vegetation cover.](image)

Note: The shorter microwave signal (X-band, ~3 cm) interacts mainly with the top of the canopy cover, while C-band (~8 cm) travel more than X-band at vegetation canopy while longer wavelengths (L-band, ~24 cm) are able to penetrate further into the canopy and reflect from the soil surface.

| S. No. | Band | Frequency range      |
|--------|------|----------------------|
| 1      | HF   | 3–30 MHz             |
| 2      | VHF  | 30–300 MHz           |
| 3      | UHF  | 300–1,000 MHz        |
| 4      | L    | 1–2 GHz              |
| 5      | S    | 2–4 GHz              |
| 6      | C    | 4–8 GHz              |
| 7      | X    | 8–12 GHz             |
| 8      | Ku   | 12–18 GHz            |
| 9      | K    | 18–27 GHz            |
| 10     | Ka   | 27–40 GHz            |
| 11     | V    | 40–75 GHz            |
| 12     | VV   | 75–110 GHz           |
| 13     | Mm   | 110–300 GHz          |
3.9. Polarization

Retrieval of soil moisture by radar return is highly dependent on surface geometry. This kind of problems could be minimized using multi-polarized and/or multi-frequency sensors systems (Baghdadi, Cerdan, et al., 2008; Zribi & Dechambre, 2002). Hirosawa, Komiyama, and Matsuzaka (1978) in his work used 9-GHz and his observations of Kanto loam confirmed that the cross-polarized sensitivity to near-surface volumetric soil moisture was four times better than that of the like-polarized back-scattering. The HH and HV polarizations are more sensitive to soil roughness than the VV polarization (Holah et al., 2005), but Baghdadi, Cerdan, et al. (2008) found that retrieval of soil moisture by radar signal was not influenced by polarization, using an assembled database of ERS-2, RADARSAT-1 and ENVISAT data.

4. Models for retrieval of backscattering coefficient and soil moisture

Numerous theoretical, empirical and semi-empirical methods have been developed since the beginning of SAR studies to relate the SAR backscatter coefficient to soil moisture (Baghdadi, El Hajj, et al., 2006; Bryant et al., 2007; Dubois et al., 1995a; Fung, Li, & Chen, 1992; Haider, Said, Kothyari, & Arora, 2004; Oh et al., 1992; Sanli, Kurucu, Esetlili, & Abdikan, 2008; Srivastava et al., 2009; Wang & Qu, 2009). These theoretical models were derived from the electromagnetic theory. These theories are dependent on the site and surface type on which they were developed and tested by considering the incidence angle, \( \lambda \) and soil parameters (Baghdadi et al., 2004; D’Urso and Minaecapilli, 2006; Wang & Qu, 2009). Some of the most used models have been described below.

4.1. Most used theoretical models for active imaging microwave data

Theoretical models are used to derive the general trend of \( \sigma^0 \) in respect to soil moisture content and surface roughness (Dubois & van Zyl, 1994; Wang & Qu, 2009). Number of factors, surface roughness, \( \varepsilon \), polarization and problem of electromagnetic wave scattering from random surfaces, influence the retrieval of \( \sigma^0 \), which has long been studied because of its complexity (Wang & Qu, 2009).

Numerous currently used surface scattering models have been developed from the small perturbation method (SPM) (Rice, 1951) and the Kirchhoff model (Beckmann & Spizzichino, 1963), which limits the range of roughness conditions (Wang & Qu, 2009). Perturbation solutions can be used whenever the soil surface slightly deviates from smooth to rough surfaces, and in SPM (Rice, 1951; Tsang et al., 1985), the r.m.s height must be much smaller than the wavelength and the r.m.s slope should be of the same order of magnitude as the wave number times the r.m.s height (Rice, 1951). A perturbation method based on perturbation expansion of the phase of the surface field (PPM) was developed which extends the region of validity of SPM to higher values of the r.m.s height, providing the slope remains relatively small (Winebrenner & Ishimaru, 1985). The other limiting case is when surface irregularities are large compared to the wavelength, which is equivalent to having a large radius of curvature at each point on the surface. In this type of limiting conditions, the Kirchhoff approximation (KA) is applicable (Boisvert et al., 1997; Ulaby et al., 1986). Various types of modifications and improvements to this model can be found in the literature. Extended validity of the KA solution was considered by Oh et al. (1992) but in limited extent.

Oh et al. (1992) developed an empirical model for retrieving soil moisture using the multi-polarized radar signal (HH, VV, HV and VH), and tried to find out the extended validity of KA and SPM model to measure surface roughness (Oh et al., 1992). Using the multi-polarized radar signal and considering the co-polarized \( (p = \sigma_{HH}^0 / \sigma_{VV}^0) \) and cross-polarized \( (q = \sigma_{HH}^0 / \sigma_{VV}^0) \) ratio, this model could predict the r.m.s height of the surface and soil \( \varepsilon \). Oh, Sarabandi, and Ulaby (1993) modified and developed an empirical relation between the co-polarized phase parameters and roughness and \( \varepsilon \) of rough surfaces, where \( \alpha \) is the degree of correlation, which is a measure of width of probability density function of a co-polarized phase angle. Oh, Sarabandi, and Ulaby (1994) modified the expression of cross-polarized ratio \( (q) \) in respect to Oh et al. (1992) for the same purpose. The expressions for \( p \) and \( q \) were further modified in 2002, and a new expression was proposed for the cross-polarized backscatter coefficient (Oh et al., 2002). Oh (2004) further updated semi-empirical polarimetric
backscattering model to retrieve both \( M_v \) and \( k.r.m.s \) (electromagnetic surface roughness) height by subsequent modification of \( q \) in respect of Oh et al. (2002).

A site-specific calibration procedure was developed by D'Urso and Minaecapilli (2006) for Oh et al.'s model (1992) to derive soil moisture content without prior information of surface roughness and soil water content.

The initial version of the Oh's model was presented by Oh et al. (1992) in Equations (4–6).

\[
p = \frac{\sigma_{HH}^0}{\sigma_{VV}^0} = \left[ 1 - \left( \frac{\theta}{90} \right)^{1/3} \right]^{2} e^{-k.r.m.s}
\]

\[
q = \frac{\sigma_{HV}^0}{\sigma_{VV}^0} = 0.23 \sqrt{\Gamma_0} \left( 1 - e^{-k.r.m.s} \right)
\]

\[
\Gamma_0 = \frac{1 - \sqrt{\ell}}{1 + \sqrt{\ell}}
\]

where co-polarized ratio \( p \) \( (p = \sigma_{HH}^0/\sigma_{VV}^0) \) and the cross-polarized ratio \( q \) \( (q = \sigma_{HV}^0/\sigma_{VV}^0) \) to incident angle \( (\theta) \), wave number \( (k) \) and Fresnel reflectivity of the surface at nadir \( (\Gamma_0) \). The parameters \( p \) and \( q \) are derived by empirical fitting to the ground-based measurements of \( \sigma_{HH}^0, \sigma_{VV}^0 \) and \( \sigma_{HV}^0 \).

A new expression for \( q \) was proposed by Oh et al. (1994) to incorporate the effect of the incidence angle in Equation (7).

\[
q = 0.25 \sqrt{\Gamma_0 (0.1 + \sin^{0.9} \theta)} \left( 1 - e^{-[1.4 - 1.6 \Gamma_0] k.r.m.s} \right)
\]

The expressions for \( p \) and \( q \) were again modified in 2002, and an expression was proposed for the cross-polarized backscatter coefficient, expressed in Equations (8–10) (Oh, Sarabandi, & Ulaby, 2002):

\[
p = 1 - \left( \frac{\theta}{90} \right)^{0.35} M_v^{0.6} \cos^{0.4} (k.r.m.s)^{1.4}
\]

\[
q = 0.1 \left( \frac{f.r.m.s}{L} + \sin 1.3 \theta \right)^{1.2} \left( 1 - e^{-0.9 (k.r.m.s)^{0.8}} \right)
\]

\[
\sigma_{HV}^0 = 0.11 M_v^{0.7} \cos^{2.2} \theta \left( 1 - e^{-0.32 (k.r.m.s)^{1.8}} \right)
\]

Given that the measurement of the correlation length may not be exact (Baghdadi et al., 2000; Oh & Kay, 1998) and that the ratio \( q \) is insensitive to the roughness parameter, Oh (2004) proposed a new formulation for \( q \) that ignores the correlation length (11).

\[
q = 0.095 (0.13 + \sin 1.5 \theta)^{1.4} \left( 1 - e^{-1.3 (k.r.m.s)^{0.3}} \right)
\]

The general formula to retrieve backscattering coefficient is expressed in Equation (12).

\[
\sigma_{VV}^0 = \frac{\sigma_{HV}^0}{q}
\]
where $\sigma_{HH}^0$ was derived from Equation (10).

$$\sigma_{HH}^0 = p \sigma_{VV}^0 = \frac{p}{q} \sigma_{HV}^0$$  \hspace{1cm} (13)

The estimates of r.m.s. and $M_v$ can also be obtained from the measurements of $\sigma_{HH}^0$ and $p$ by the simple computation in Equation (10). Solving Equation (10) for the estimate of $k.r.m.s$ yields Equation (14).

$$k.r.m.s(\theta, M_v, \sigma_{VHM}^0) = \left[ -3.125 \ln \left( 1 - \frac{\alpha_{VHM}^0}{0.11 M_v^{0.7} (\cos \theta)^{2.2}} \right) \right]^{0.006}$$  \hspace{1cm} (14)

where $\alpha_{VHM}^0$ is the measurement of the VH-polarized scattering coefficient.

$$1 - \left( \frac{\theta}{90^\circ} \right)^{0.35 M_v^{\cos \theta}} \cdot e^{-0.4 \left( k.r.m.s(\theta, M_v, \sigma_{VHM}^0) \right)^{1.4}} - p_m = 0$$  \hspace{1cm} (15)

From the above Equation (15), $M_v$ can be estimated, where $p_m$ denotes the measured co-polarized ratio of $p$ and $k.r.m.s(\theta, M_v, \sigma_{VHM}^0)$ given in Equation (14) and $k.r.m.s$ can computed from Equation (14) and r.m.s. height can also be obtained subsequently (Oh, 2004).

Dubois et al. (1995a) developed an empirical algorithm for the retrieval of soil moisture content and r.m.s. from remotely sensed scatterometer data. The algorithm was optimized for bare surfaces and developed with data for frequencies varying between 1.5 ($\lambda = 0.205$ m) and 11 GHz ($\lambda = 0.28$ m), roughness ranging from 0.003 to 0.03 m and incidence angles between 30 and 45°. Using two co-polarized signals and omitting the usually weaker HV-polarized returns made the algorithm less sensitive to system noise. Dubois et al. (1995a) chose to use only the co-polarized backscatter signal instead of cross-polarized signals because they are less sensitive to vegetation, easy to calibrate and less susceptible to system noise. The empirical model of Dubois et al. (1995a) was widely used in retrieval of soil moisture (Rao et al., 2013) (16, 17). Even this model could be used in sparsely vegetated surfaces but limiting towards normalized difference vegetation index (NDVI) up to 0.4 (Neusch & Sties, 1999; Sikdar & Cumming, 2004). Dubois model is not valid for P-band (Western et al., 2004). To increase the domain of applicability of this model, Dubois et al. (1995a) found that vegetation effects could be minimized by excluding areas where the L-band $\sigma_{HH}^0 / \sigma_{VV}^0$ ratio (an index of vegetation cover) exceeds −11 dB.

$$\sigma_{HH}^0 = 10^{-2.75} \left( \frac{\cos^3 \theta}{\sin^2 \theta} \right) 10^{0.028 \times \tan \theta (k.r.m.s \sin \theta)^{1.4} \lambda^{0.7}}$$  \hspace{1cm} (16)

$$\sigma_{VV}^0 = 10^{-2.35} \left( \frac{\cos^3 \theta}{\sin^2 \theta} \right) 10^{0.046 \times \tan \theta (k.r.m.s \sin \theta)^{1.1} \lambda^{0.7}}$$  \hspace{1cm} (17)

4.2. Physical model for active imaging microwave data

The physical models evolved to predict the radar $\sigma^0$ and soil characteristics using the theoretical approaches of radar return. Physical models have site-specific dependencies and are limited to the range of roughness (Baghdadi, El Hajj, et al., 2006; Paloscia, Pampaloni, Pettinato, & Santi, 2008). The integral equation model (IEM) (Fung et al., 1992) is a widely used physical model to retrieve $\sigma^0$ by considering roughness parameters. IEM’s validity domain covers wide range of surface roughness values encountered on agricultural soils. IEM model (Fung, 1994) provided a good result in laboratory experiments (Mancini, Hoeben, & Troch, 1999) but was unable to shown a good retrieval capability in field base measurement (Altese et al., 1996; Baghdadi, Holah, & Zribi, 2006b; Paloscia et al., 2008). The major difficulty associated with this model was that it was highly sensitive to surface roughness in terms of $L$ and r.m.s height (Davidson et al., 2000). To minimize the retrieval error, Baghdadi, King, Chanzy, et al. (2002), Baghdadi, King, and Bonnifait (2002) developed a calibration...
method to retrieve soil moisture with low retrieval error by IEM. As IEM is dependent on surface roughness, L, Baghdadi, King, Chanzy, et al. (2002), Baghdadi, King, and Bonnifait (2002) developed an optical correlation length (Lopt) to derive σ₀ with minimum error.

4.3. Topp model

Topp model (Topp, Davis, & Annan, 1980) has been effectively used to derive soil moisture from soil ε (Song et al., 2010) (18). Topp model is used to create a comparative study with retrieved soil moisture and σ₀ for each of the theoretical and physical models (Aqil & Schmitt, 2010; Rao et al., 2013). To derive soil moisture, this model does not require any prior knowledge of soil texture and surface roughness and Mᵥ can be retrieved by algorithm (18).

\[
Mᵥ = -5.3 \times 10^{-2} + 2.92 \times 10^{-2} \varepsilon' - 5.5 \times 10^{-4} \varepsilon'^2 + 4.3 \times 10^{-6} \varepsilon'^3
\]  

(18)

4.4. Relative (mₛ) and profile (W(t)) soil moisture content

Soil moisture retrieval method for ERS Scatterometer data was presented by Magagi and Kerr (1997), Pulliainen, Manninen, and Hallikainen (1998), Wagner, Noll, Borgeaud, and Rott (1999) and Wagner, Lemoine, Borgeaud, and Rott (1999). This method of profile soil moisture content (W) retrieval was explicitly described by Wagner, Lemoine, et al. (1999). This experiment required auxiliary information on soil type, soil texture, bulk density (kg m⁻³), wilting level of both gravimetric and volumetric units, field capacity (FC) in mm and porosity/total water capacity (TWC) in mm. FC is the saturation level of soil with water when deep percolation nearly stops, and porosity is relative pore volume of the soil and is equal to the TWC of the soil. To retrieve soil moisture, the method compared time series data of σ₀ with standard reference incident angle 40° of ERS Scatterometer data. From this time series data, highest and lowest σ₀ were determined and denoted as σ₀ wet (40, t) and σ₀ dry (40, t), where 40° is the reference incident angle. σ₀ wet is considered to be the lowest σ₀ when no liquid water is present in the soil surface layer and σ₀ dry (40, t) is the highest σ₀ of the soil surface layer when it is saturated with water. σ₀ wet (40, t) and σ₀ dry (40, t) were calculated according to Wagner, Noll, et al. (1999).

The relative soil moisture content (mₛ) was calculated according to Wagner, Lemoine, et al. (1999) (19).

\[
mₛ(t) = \frac{σ₀ (40, t) - σ₀ dry (40, t)}{σ₀ wet (40, t) - σ₀ dry (40, t)}
\]

(19)

Mᵥ of surface layer can be estimated by multiplying the mₛ with the soil porosity or TWC and this mₛ is considered to be the degree of saturation (Wagner, Lemoine, & Rott, 1999).

However, several simple models are used in soil moisture estimation, but with the increase in time lag, the potentiality of measurement decreased simultaneously. Thus, to improve the retrieval potentiality, temporal variations in terms of characteristic time length (T) were taken into consideration in soil water index (SWI) as given by Equation (20).

\[
SWI(t) = \sum mₛ(t_i) e^{-\frac{(t-t_i)'}{T}} \text{ for } t_i \leq t
\]

(20)

where mₛ is the surface soil moisture estimated from the ERS Scatterometer at time t. The SWI is calculated if there is at least one ERS Scatterometer measurement in the time interval [t-T, t] and at least three measurements in the interval [t-5T, t]. Parameter T is the characteristic time length (Wagner, Lemoine, & Rott, 1999).

The profile soil moisture content W at time t can be estimated from SWI (21).
\[ W(t) = W_{\text{min}} + SWI(t)(W_{\text{max}} - W_{\text{min}}) \]  \hspace{1cm} (21)

SWI is the trend indicator which ranges between 0 and 1. \( W_{\text{min}} \) and \( W_{\text{max}} \) are the minimum and maximum wetness values.

### 4.5. Passive radiometric models

#### 4.5.1. Radiative transfer model

Radiative transfer model (Njoku, 1999) is used to retrieve \( M_v \). The algorithm requires the values of \( T_e \) (physical temperature) and \( W \) (vegetation columnar water content). The baseline algorithm (Njoku, 1999) uses two lowest AMSR frequencies (6.9 and 10.7 GHz), because above ~10 GHz frequency, surface roughness and vegetation scattering effects produce complexity and uncertainty in derived products. These frequencies have better vegetation penetration and soil moisture sensitivity, although with decreased spatial resolution (Njoku, 1999). In general parameter retrieval algorithms, the land surface is modelled as absorbing vegetation layer above soil in Figure 2.

The brightness temperature (\( T_{bp} \)) observed at the top of the atmosphere at a given incidence angle and at a given frequency can be expressed by the radiative transfer Equation (22) (Njoku, 1999).

\[
T_{bp} = T_u + \exp (-\tau_v) \left\{ T_d r_{sp} \exp (-2\tau_v) \right\} + \left\{ e_{sp} T_e \exp (-\tau_v) + T_c \left( 1 - \omega_p \right) \left[ 1 - \exp (-\tau_v) \right] \left[ 1 + r_{sp} \exp (-\tau_v) \right] \right\} \]

where, \( T_u \) is the upwelling atmospheric temperature (K), \( T_d \) is the downwelling atmospheric temperature (K), \( T_e \) is the atmospheric opacity, \( T_c \) is the vegetation temperature (K), \( r_v \) is the vegetation opacity, \( r_{sp} \) is the soil reflectivity, \( T_e \) is the effective soil temperature (K) (the effective temperature is the weighted-average temperature over the microwave penetration depth in the medium) and \( \omega_p \) is the vegetation single-scattering albedo.

A simplified approximation is that the vegetation and underlying soil are close to the same physical temperature \( T_e \). This approximation does not degrade the moisture retrieval accuracy, but will result in the retrieval of a mean or “effective” radiating temperature of the composite soil/vegetation medium.

Substituting \( T_v \approx T_c \approx T_e \) in Equation (22), we obtain Equation (23).

\[
T_{bp} = T_u + \exp (-\tau_v) \left\{ T_d r_{sp} \exp (-2\tau_v) \right\} + T_e \left\{ (1 - r_{sp}) \exp (-\tau_v) + (1 - \omega_p) \left[ 1 - \exp (-\tau_v) \right] \left[ 1 + r_{sp} \exp (-\tau_v) \right] \right\} \]

#### 4.5.1.1. Atmosphere

Standard expression for \( T_u \) and \( T_d \) can be obtained from the literature (Hofer & Njoku, 1981; Njoku, 1999; Njoku & Li, 1999). At atmospheric window frequencies \( T_u \) and \( T_d \), it can be expressed using the effective radiating temperature approximation as Equation (24) (ignoring the space contribution to \( T_d \)).
where $T_{aw}$ is the mean temperature of the microwave-emitting region of the atmosphere. This expression is valid for most atmospheric water vapour and cloud conditions. $T_{aw}$ is frequency dependent and also depends on the distributions of temperature, humidity and liquid water. $T_{aw}$ may be expressed simply as a function of the surface air temperature $T_{as}$ and a frequency-dependent offset $\delta_T$ in Equation (25).

$$T_{ae} \approx T_{as} - \delta_T$$

The effect of uncertainty in $T_{aw}$ on the observed $T_B$ is sufficiently small. The opacity $\tau_a$ along the atmospheric path is dependent on the viewing angle $\theta$ and the precipitable/vertical-column amounts of water $q_v$ and vertical-column cloud liquid water $q_l$. It can be expressed (for a plane parallel atmosphere) in Equation (26).

$$\tau_a = (t_0 + a_v q_v + a_l q_l) / \cos \theta$$

where $t_0$ is the oxygen opacity at nadir and $a_v$ and $a_l$ are frequency-dependent coefficients and viewing angle $\theta$.

4.5.1.2. Surface. The dependence of $\tau_c$ on vegetation columnar water content follows an approximately linear relationship, depicted in Equation (27) (Njoku, 1999).

$$\tau_c = b w_e / \cos \theta$$

where $\cos \theta$ accounts for the slant path through the vegetation. The coefficient $b$ depends on canopy structure and frequency. Theory and experimental data suggest that for a given vegetation type ($b$), is approximately proportional to frequencies below ~10 GHz (Jackson & Schmugge, 1991; Levine & Karam, 1996).

This indicates that at higher frequencies, the frequency dependence of $b$ decreases and its dependence on canopy structure eventually increases. This provides rationale for restricting the physically based retrieval algorithm to be in between 6.9 and 10.7 GHz.

The reflectivity of rough soil, $r_{sv}$, is related to that of smooth soil; $r_{sh}$ is computed by Equations (28) and (29) (Njoku & Li, 1999):

$$r_{sv} = [(1 - Q)rov + Qroh] \exp(-h)$$

$$r_{sh} = [(1 - Q)roh + Qrov] \exp(-h)$$

where $r_{sv}$ and $r_{sh}$ denoted the reflectivity of soil for both polarizations horizontal and vertical. Expression for $h$ and $Q$ is expressed in Equations (30) and (31).

$$Q = 0.35 \left[ 1 - \exp \left( -0.6 \sigma^2 \lambda \right) \right]$$

$$h = \left( \frac{4 \pi \sigma \cos \theta}{\lambda} \right)^2$$

where $\lambda$ is the wavelength of the radiometer and $\sigma$ is the surface r.m.s height.
The Fresnel expressions relate the reflectivities $r_{ov}$ and $r_{oh}$ of a smooth, homogeneous soil to the complex dielectric constant of the soil $\varepsilon_r$. In the above equation, $\theta$ is the incidence angle relative to the surface normal. For a given frequency, the dielectric constant depends on the $M_v$ and to a lesser extent on the soil type. This relationship can be expressed in Equation (34).

$$\varepsilon_r = f(M_v; \rho_b, s, c)$$ (34)

where $M_v$ is the volumetric moisture content, $\rho_b$ is the soil bulk density and $s$ and $c$ are soil and clay fraction.

4.5.2. Change detection algorithm

Global SWI is also known as the Basist wetness index (Basist, Grody, Peterson, & Williams, 1998). Surface wetness Index (SWI) is used to retrieve surface soil moisture using multi-temporal data from multi-frequency passive microwave radiometer (SSM/I). A change detection algorithm is used to compute soil moisture (SM) from SWI variations by considering field capacity and air–dry status, pixel by pixel (Oza et al., 2006; Singh, Oza, Chaudhari, & Dadhwal, 2005). Air–dry moisture status is considered to be minimum soil water content when SWI value is lowest and is considered to be maximum soil water content when SWI value is highest. Field-capacity and air–dry moisture status are obtained by considering multi temporal SWI data (Oza et al., 2006). The added advantage was that they have higher sensitivity towards soil moisture and less towards the surface geometry (Basist et al., 1998; Singh, Oza, Chaudhari, & Dhawal, 2005; Oza et al., 2006). By comparing the emissivity and wave frequency, Basist et al. (1998) developed a relation to derive SWI. SWI is proportional to the slope of emissivity as a function of frequency and is defined in Equation (35) (Basist et al., 1998).

$$SWI = \Delta \in T_s$$ (35)

where

$$\Delta \in [\beta_1 \in (f_2) - \in (f_1)] + \beta_2 \in (f_3) - \in (f_2)]$$ (36)

where $T_s$ is the surface temperature, $f_1$, $f_2$, and $f_3$ represent operated vertical channels (frequency) and $\beta_1$ and $\beta_2$ are proportionality constants.

$$SM_i = M_{ad} + \left[ \frac{(M_{fc} - M_{ad})}{SWI_{max} - SWI_{min}} \right] (SWI_i - SWI_{min})$$ (37)

where $SM_i$ is the soil moisture at pixel $i$, $M_{fc}$ is the field capacity of soil at pixel $i$, $M_{ad}$ is air–dry moisture level of soil at pixel $i$, $SWI_{max}$ and $SWI_{min}$ are the maximum and minimum SWI on multi-temporal data-set at pixel $i$ and $SWI_{i}$ is SWI in wetness composite image at pixel $i$.

Singh, Mishra, Shao, and Dey (2005) retrieved the soil moisture using IRS P4 (Oceansat 1) MSMR data. Algorithm of Gohill (1999) has been used to derive soil moisture at 6.6 GHz frequency because that frequency can’t be affected by atmospheric attenuation or vegetation sensitivity. For radiometers working in shorter wavelength ranges, atmospheric attenuation and emission of the signal can be expressed as (Engman, 1991; Schmugge, 1985):
where \( e = (1-r) \) is the emissivity, \( T_B \) is the microwave brightness temperature, \( t(\text{H}) \) is the atmospheric transmission, \( r \) is the surface reflectivity and \( T_{\text{sky}}, T_{\text{soil}}, T_{\text{atm}} \) are temperatures of sky, soil and atmosphere respectively.

The SM has been estimated using 6.6 GHz horizontally polarized MSMR data using Equation (39) (Gohill, 1999):

\[
SM = (-0.284T_{6.6\text{GHz}}) + 76.2
\]

where SM is the soil moisture, total amount of water available (% volume) and \( T_{6.6\text{GHz}} \) is the brightness temperature at 6.6 GHz frequency in horizontal polarization.

4.5.3. Optimization of models

How to invert the moisture, soil texture and roughness from remote sensing data has been one of the most interesting problems to be resolved. Lots of theoretical and empirical models (Dubois et al., 1995a; Fung et al., 1992; Oh, 2004; Oh et al., 1992; Satalino, Mattia, Pasquariello, & Dente, 2005; Ulaby et al., 1982) were developed to retrieve the moisture content and roughness, but limitations of these models are that they can invert a few parameters only depending upon the number of the data-sets. Optimization techniques generally started to retrieve more of the parameters with less number of datasets. Nowadays, commonly used optimization techniques are artificial neural networks (ANN) (Lakhankar, Ghedira, & Khanbilvardi, 2006; Zhao et al., 2003) and genetic algorithms (GA) (Jin & Wang, 2000; Singh & Kathpalia, 2007).

5. Conclusion

The aim of this paper is to provide a systematic review on different basic soil moisture retrieval methods and models since 1978 until 2015 for both active and passive microwave remote sensing. Each of the methods and models has its own limitations of retrieval capacity in terms of their microwave bands (L-, C- and X-) used or in their target surface characteristics. However, the fact is that the contribution of other factors that influences the soil reflectance may not be effectively minimized.

To overcome these problems, SAR has shown its large potential for retrieving soil moisture maps at regional scales. However, since the backscattered signal is determined by several surface characteristics, the retrieval of soil moisture is an ill-posed problem when using single-configuration imagery. The advent of new, high-resolution sensors observing in X- and L-band, and C-band sensors yielding polarimetric data (\( HH, VV, HV \) and \( VH \)) allow for a better characterization of surface parameters. Along with the sensor configuration, different inversion methods have different validity regions. In hydrological perspective, L-band measurements yield good results under various canopy types due to high penetration power (Western et al., 2004). Passive microwave has more potential for large-scale soil moisture monitoring, but has a low spatial resolution. Active microwave can provide high spatial resolution, but has low revisit frequency and is more sensitive to soil roughness and vegetation. At microwave frequencies, many natural surfaces do not fall into the validity regions of the theoretical models, and even when they do, the available models fail to provide results in good agreement with experimental observations due to the following reasons (Oh et al., 1992):

(a) Dubois et al. (1995a), Dubois, VanZyl, and Engman (1995b) could yield good results of an area having normalized difference vegetation index (NDVI) up to 0.4 (Neusch & Sties, 1999; Sikdar & Cumming, 2004), but the range of this NDVI value is not valid for P-band (Western et al., 2004).
(b) The major difficulty associated with Oh model (Oh et al., 1992) is that the model is highly sensitive to surface roughness in terms of correlation length (L) and r.m.s height (Davidson et al., 2000). To minimize the effect of surface roughness, the Oh (2004) model was further modified to remove the effect of correlation length.
(c) However, ERS Scatterometer data have evolved to estimate the soil profile moisture content (W) by considering temporal variations.

(d) Soil moisture can be estimated using passive radiometer; for radiometer brightness temperature \( T_b \), it was shown to be sensitive to soil moisture.

(e) For IRS P4 (Oceansat 1) MSGR data, Gohill (1999) developed an algorithm to retrieve soil moisture at 6.6 GHz frequency.

Beside the active microwave remote sensing, ESA launched SMOS on 2 November 2009 which is the first L-band passive satellite sensor dedicated for global soil moisture estimation. Thereafter SMAP mission is for first-tire mission by NRC launch in January 2015, for estimation of soil moisture in L-band for both active and passive modes with each polarization (HH, VV, HV or VH). Furthermore, ESA is developing to launch Sentinel-1 mission that includes radar and multi-spectral imaging instruments for land, ocean and atmospheric monitoring (ESA, 2014). This mission can be able to provide high spatial (<1 km) and temporal (every 6 days globally) soil moisture data.
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