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REVIEW ARTICLE

Satellite remote sensing applications for surface soil moisture monitoring: A review

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Abstract Surface soil moisture is one of the crucial variables in hydrological processes, which influences the exchange of water and energy fluxes at the land surface/atmosphere interface. Accurate estimate of the spatial and temporal variations of soil moisture is critical for numerous 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. This paper presents a comprehensive review of the progress in remote sensing of soil moisture, with focus on technique approaches for soil moisture estimation from optical, thermal, passive microwave, and active microwave measurements. The physical principles and the status of current retrieval methods are summarized. Limitations existing in current soil moisture estimation algorithms and key issues that have to be addressed in the near future are also discussed.

Keywords surface soil moisture, monitoring, satellite, remote sensing

1 Introduction

Surface soil moisture is the water that is in the upper 10 cm of soil, whereas root zone soil moisture is the water that is available to plants, which is generally considered to be in the upper 200 cm of soil (http://www.ghcc.msfc.nasa.gov/landprocess/lp_home.html). Compared with the total amount of water on the global scale, this thin layer of soil water may seem insignificant; nonetheless, it is of fundamental importance to many hydrological, biological, and biogeochemical processes. The role of soil moisture in the top 1 to 2 m of the Earth's surface has been widely recognized as a key variable in numerous environmental studies (Walker, 1999), including meteorology, hydrology, agriculture, and climate change (Topp et al., 1980; Jackson et al., 1987; Fast and McCorcle, 1991; Engman, 1992; Entekhabi et al., 1993; Betts et al., 1994; Saha, 1995; Su et al., 1995;). Therefore, it is important to accurately monitor and estimate spatial and temporal variations of soil moisture.

Direct observations of soil moisture are currently restricted to discrete measurements at specific locations, and such point-based measurements do not represent the spatial distribution because soil moisture is highly variable both spatially and temporally (Engman, 1991; Wood et al., 1992) and are therefore inadequate to carry out regional and global studies (http://www.geotimes.org/may02/WebExtra0503.html). Technological advances in satellite remote sensing have offered a variety of techniques for measuring soil moisture across a wide area continuously over time (Engman, 1990). Researches in soil moisture remote sensing began in the mid 1970's shortly after the surge in satellite development. Subsequent research effort has occurred along many diverse paths, spanning most of the electromagnetic spectrum from optical to microwave region. Numerous researchers have shown that near-surface soil moisture content can be measured by optical and thermal infrared remote sensing, as well as passive and active microwave remote sensing techniques (Walker, 1999). The primary difference among these techniques are the wavelength region of the electromagnetic spectrum used, the source of the electromagnetic energy (Walker, 1999), the response measured by the sensor, and the physical relation between the response and the soil moisture content. Table 1 summarizes the relative merits of the different remote sensing techniques for surface soil moisture estumation.

As remote sensors do not measure soil moisture content

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Table 1 Summary of remote sensing techniques for near-surface soil moisture estimation (after Engman, 1991; Moran et al., 2004).

spectrum domain		properties observed	advantages	limitations
optical		soil reflection	fine spatial resolution broad coverage	limited surface penetration cloud contamination many other noise sources
thermal infrared		surface temperature	fine spatial resolution broad coverage physical well understood	limited surface penetration cloud contamination perturbed by meteorological conditions and vegetation
microwave	passive	brightness temperature dielectric properties soil temperature	low atmospheric noise moderate surface penetration physical well understood	low spatial resolution perturbed by surface roughness and vegetation
	active	backscatter coefficient dielectric properties	low atmospheric noise moderate surface penetration high spatial resolution physical well understood	limited swath width perturbed by surface roughness and vegetation

directly, mathematical models that describe the connection between the measured signal and soil moisture content must be derived (de Troch et al., 1996). Usually, the forward model simulates the instrument's response on the basis of relevant land surface parameters (Walker, 1999). A method is then developed for inverting the model by minimizing the residual error between the model simulated and sensor-measured values.

This review presents a comprehensive overview of the commonly used methodologies for soil moisture estimation, including their physical principles, advantages, and constraints from optical, thermal infrared, passive microwave, and active microwave measurements. Since the basic ideas inherent in the model inversion are similar no matter which spectrum domain the sensor uses, the overview of the model inversion approaches is only given in the passive microwave section.

2 Optical remote sensing for soil moisture estimation

Remote sensing of soil moisture content using the solar domain with wavelengths between 0.4 and 2.5 μm measures the reflected radiation of the sun from the Earth's surface, known as reflectance (Sadeghi et al., 1984). Compared with microwave and thermal infrared domains that have been most commonly used for soil moisture estimation (Price, 1980; Wuthrich, 1994, Engman and Chauhan 1995, Jackson et al., 1995), little attention has been paid to the use of the solar domain (Liu et al., 2003). However, many investigations have shown that the solar domain also provides the capability for soil moisture estimation (Dalal and Henry, 1986; Schlesinger et al., 1996; Sommer et al., 1998; Leone and Sommer, 2000).

The effect of soil moisture on its reflectance has long been recognized by many scientists. Early in 1925, Angstrom found a decrease in reflectance when soil moisture increases in his measurements (Angstrom, 1925). Thereafter, familiar darkening of soil on wetting has been reported by other researchers (Curcio and Petty, 1951; Bowers and Hanks, 1965; Stoner and Baumgardner, 1980; Ishida et al., 1991). Several empirical approaches have been proposed to describe the connection between soil surface reflectance and moisture contents. Bowers and Smith (1972) observed a linear relationship between the absorption in a water absorption band and soil water content. A factor of about 2 for all soils except sands was employed by Jackson et al. (1976) to account for the reflectance reduction due to the increase of soil moisture content. By using absorbance values measured in the near-infrared, Dalal and Henry (1986) estimated soil moisture with accurate results over a range of soil samples. These empirical approaches, however, provide only a poor indication of soil moisture content, since the spectral characteristic of a soil also depends on numerous other factors, such as mineral composition, organic matter, soil texture, and surface roughness (Asner, 1998; Ben-Dor et al., 1999), causing wide variations when they are applied to other localities outside the calibration conditions.

Lobell and Asner (2002) developed a physical model to explain the soil reflectance variations due to moisture change based on their analysis of the reflectance for four different soils at various moisture contents. The soil reflectance at a particular wavelength is modeled as an exponential function of the volumetric soil moisture. Such nonlinear equations are representative of the physical processes underlying the relationship, i.e., Beer's Law for absorption in random homogenous media (Liu et al., 2002). Since experiments performed by Lobell and Asner involved measuring soil reflectance under various moisture conditions, their model captures both the absorption and scattering effects of soil moisture (Dasgupta, 2007). Similar exponential models were proposed by Liu et al. (2002) to obtain a robust estimate of soil moisture.

Liu et al. (2003) analyzed 18 different soils that represent a large range of permanent soil characteristics and investigated the potential of estimating soil moisture from reflectance measurements in the solar domain. Different approaches were compared, including relative reflectance approach, which normalized the reflectance by the reflectance of the corresponding soil under dry conditions, and derivative/difference approaches, which were based on either reflectance derivatives or absorbance derivatives. The derivative/difference of absorbance approach revealed the highest overall performance and provided the best estimates for soil moisture, as well as minimized the effects of confounding factors.

Most recently, Wang and Qu (2007) designed the normalized multiband drought index (NMDI) for remotely sensing both soil and vegetation water content from space based on the soil and vegetation spectral signatures. Similar to traditional normalized difference water index (NDWI), NMDI uses the channel centered at 0.86 μm, which is insensitive to leaf water content changes as the reference; however, instead of using a single liquid water absorption band, it uses the difference between two liquid water absorption bands (1.64 and 2.13 μm), as the soil and vegetation water sensitive band. Strong differences between these two water absorption bands in response to soil and leaf water content change give this combination potential to estimate the water content for both soil and vegetations. The successful application of NMDI for forest fire detection demonstrated its quick response to the moisture changes through the fire (Wang et al., 2008).

Abovementioned approaches explored a new direction in the use of remote sensing science toward soil moisture estimation and demonstrated the potential for monitoring moisture conditions from solar domain. However, the shallow soil penetration, cloud contamination, and the fact that the contribution of other factors that influence the soil reflectance may not be effectively minimized, limits the utility of solar reflectance measurements for soil moisture content determination.

3 Thermal infrared remote sensing for soil moisture estimation

Thermal infrared remote sensing measures the thermal emission of the Earth with an electromagnetic wavelength region between 3.5 and 14 μm (Curran, 1985). The estimation of surface soil moisture using remotely sensed thermal wavebands primarily relies on the use of soil surface temperature measurements, either singly like the thermal inertia method or in combination with vegetation indexes as the temperature/vegetation index method.

3.1 Thermal inertia method

Variations in soil moisture have a strong influence on the thermal properties of the soil, which is an intrinsic factor of soil surface temperature change. The amplitude of the diurnal range of soil surface temperature has been found to be highly correlated with the surface soil moisture content (Schmugge, 1978; Friedl and Davis, 1994). Areas having higher soil moisture content are cooler during the day and warmer at night (van de Griend and Engman, 1985).

The thermal properties that control the soil daily range of temperature are the soil thermal conductivity λ and the soil heat capacity C_T. The soil thermal inertia TI can be expressed as:

$$TI = \sqrt{(\lambda C_T)}, \tag{1}$$

where TI is a body property of materials, which describes their resistance to temperature variations (Verstraeten et al., 2006). When soil water content increases, TI proportionally increases as well, thereby reducing the diurnal temperature fluctuation range.

A simple surrogate of TI is the apparent thermal inertia (ATI), which can be derived directly from multispectral remote sensing imagery (Tramutoli et al., 2000; Claps and Laguardia, 2004; Verstraeten et al., 2006), by measurements of spectral surface albedo α and the diurnal temperature range ΔT:

$$ATI = \frac{1-\alpha}{\Delta T}. \tag{2}$$

Then, the volumetric soil moisture W_s can be calculated using the linear empirical equation:

$$W_s = a_0 \cdot ATI + a_1, \tag{3}$$

where a_0 and a_1 are empirical parameters.

The thermal inertia method, simple and easy to use, has clear physical meaning and can achieve high accuracy in estimating soil moisture conditions. However, it is only applicable in the regions with no or little vegetation cover (Xue and Ni, 2006).

3.2 Temperature/vegetation index method

Vegetation and land surface temperature (LST) have a complicated dependence on soil moisture. An earlier description of the vegetation and atmosphere relationship is from the vegetation index/temperature (VIT) trapezoid (Moran et al., 1994). Careful analyses of data by Carlson et al. (1994) and Gillies et al. (1997) showed that there is a unique relationship sometimes referred to as the "Universal Triangle" among soil moisture W_s ,the normalized difference vegetation index (NDVI), and the LST for a given region. The results were later confirmed by theoretical studies using a soil-vegetation-atmosphere-transfer (SVAT) model, which was first named by Gillies and Carlson (1995) and designed to describe the basic evaporation processes at the surface, together with the water partitioning between vegetation transpiration, drainage, surface runoff, and soil moisture variations.

Figure 1 represents a schematic description of the relationship referred to as the "Universal Triangle." The

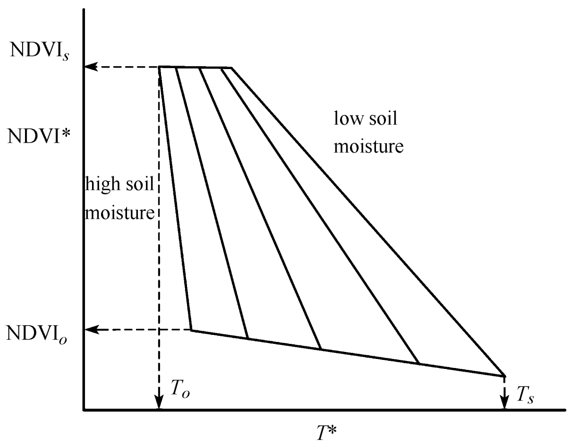

Fig. 1 Universal triangle relationship between soil moisture, temperature, and NDVI (Chauhan, 2003)

abscissa and the ordinate are scaled temperature and NDVI, respectively, such that:

$$T^* = \frac{T - T_o}{T_s - T_o}, \tag{4}$$

$$\mathrm{NDVI}^* = \frac{\mathrm{NDVI} - \mathrm{NDVI}_o}{\mathrm{NDVI}_s - \mathrm{NDVI}_o}, \tag{5}$$

where, T and NDVI are observed LST and NDVI, respectively, and the subscripts o and s stand for minimum and maximum values.

Carlson et al. (1994) found that the relationship between soil moisture, NDVI*, and T^* can be expressed through a regression formula such as:

$$W_s = \sum_{i=0}^{i=n} \sum_{j=0}^{j=n} \mathrm{a}_{ij} \mathrm{NDVI}^{*(i)} T^{*(j)}, \tag{6}$$

where a_{ij} are regression coefficients.

In terms of a second order polynomial, the above equation can be expanded as (Chauhan, 2003):

$$\begin{aligned} W_\mathrm{s} = a_{00} &+ a_{10}\mathrm{NDVI}^* + a_{20}\mathrm{NDVI}^{*2} \\ &+ a_{01}T^* + a_{02}T^{*2} \\ &+ a_{11}\mathrm{NDVI}^* T^* + a_{22}\mathrm{NDVI}^{*2} T^{*2} \\ &+ a_{12}\mathrm{NDVI}^* T^{*2} + a_{21}\mathrm{NDVI}^{*2} T^*. \end{aligned} \tag{7}$$

Such an approach can be applied in a combination of ground observations and satellite remote sensing measurements. Wang et al. (2007) demonstrated the potential of soil moisture estimation by combining in-situ soil moisture measurements and MODIS land parameters (LST and NDVI) to achieve daily soil moisture products with 1 km resolution.

Numerous variations have been given to this triangle technique including the temperature-vegetation contextual approach (TVX) (Prihodko and Goward, 1997; Czajkowski et al., 2000), surface temperature-vegetation index (*T*/NDVI) space (Lambin and Ehrlich, 1996), temperature-vegetation dryness index (TVDI) (Sandholt et al., 2002), moisture index (Dupigny-Giroux and Lewis, 1999), and the VI/*T*rad relation (Kustas et al., 2003).

Approaches based on either the surface temperature or the complimentary temperature-vegetation index are powerful and have clear physical meaning but have limitations in addition to those common to all optical techniques such as shallow soil penetration and cloud contamination (Moran et al., 2004). They are often empirical and depend on local meteorological conditions, such as wind speed, air temperature, and humidity (Nemani et al., 1993), and thus vary across time and land cover types (Smith and Choudhury, 1991; Czajkowski et al., 2000).

4 Microwave remote sensing for soil moisture estimation

Microwave remote sensing provides a unique capability for soil moisture estimation by measuring the electromagnetic radiation in the microwave region between 0.5 and 100 cm. The fundamental basis of microwave remote sensing for soil moisture is the large contrast between the dielectric properties of water (~80) and soil particles (< 4). As the moisture increases, the dielectric constant of the soil-water mixture increases, and this change is detectable by microwave sensors (Njoku and Kong, 1977; Dobson et al., 1985). Both passive and active microwave remote sensing techniques have demonstrated the most promising ability for globally monitoring soil moisture variations.

4.1 Passive microwave remote sensing

Previous research has shown that passive microwave remote sensors can be used to monitor surface soil moisture over land surfaces (Eagleman and Lin, 1976; Ulaby et al., 1986; Schmugge and Jackson, 1994; Jackson et al., 1995; Wigneron et al., 2004). These sensors measure the intensity of microwave emission from the soil, which is proportional to the brightness temperature, a product of the surface temperature and emissivity. This observed emission is related to its moisture content because of the large differences in the dielectric constant of dry soil and water (Moran et al., 2004). Current and near future spaceborne passive microwave sensors for soil moisture measurements include the Scanning Multichannel Microwave Radiometer (SMMR) on Nimbus-7, the Special Sensor Microwave/Imager (SSM/I) on Defense Meteorological Satellite Program (DMSP), the Tropical Rainfall Measuring Mission Microwave Imager (TRMM-TMI), the Advanced Microwave Scanning Radiometer-EOS (AMSR-E) on Aqua, and the upcoming soil moisture and ocean salinity

(SMOS) mission by the European Space Agency (ESA), NASA hydrospheric states (HYDROS) mission, and Soil Moisture Active and Passive (SMAP) mission.

The surface emission model is one of the essential components in the applications of microwave remote sensing of soil moisture in the bare or vegetated surfaces (Wang et al., 1983; Mo and Schmugge, 1987; Jackson and Schmugge, 1991; Jackson et al., 1999; Njoku and Li, 1999; Prigent et al., 2000; Wigneron et al., 2001; Shi et al., 2002; Njoku et al., 2003). A number of models have been developed for the computation of microwave emission from land surface (Ulaby et al., 1986; Wang and Choudhury, 1995; Njoku and Entekhabi, 1996), with different approximations and parameterizations of the key processes in radiative transfer equation, depending on the specific application and frequency range.

4.1.1 Surface emission model

4.1.1.1 Soil emission model

The most commonly used model that describes the bare soil surface emission as a function of the surface roughness and dielectric properties is the so-called Q/H model (Choudhury et al., 1979; Wang and Choudhury, 1981; Shi et al., 2003):

$$R_p^e = 1-\varepsilon_p = \left[(1-Q)\cdot r_p + Q\cdot r_q\right]\cdot H, \tag{8}$$

where R_p^e and ε_p are the surface effective reflectivity and emissivity at polarization of p, respectively. The subscript p or q describes the polarization state v or h; r is the surface reflectivity for flat surface. The roughness parameter Q describes the energy emitted in orthogonal polarization due to the surface roughness effects. The roughness parameter H is a measure of the surface roughness effect on surface effective reflectivity. The surface roughness parameters Q and H are usually determined empirically from the experimental data (Wang et al., 1983; Mo and Schmugge, 1987; Shi et al., 2005).

The other semiempirical models are basically developed by modifying the Q/H model. They all assumed Q with the different functional forms of H parameter (Shi et al., 2005).

4.1.1.2 Emission model for vegetation-covered areas

When a vegetation layer is present over the soil surface, it attenuates soil emission and adds its own contribution to the emitted radiation. These effects can be well approximated by a simple radiative transfer model, commonly referred to as the τ~ω model (Wigneron et al., 2003). This model is based on two parameters, the optical depth τ and the single scattering albedo ω, which are used to parameterize, respectively, the vegetation attenuation properties and the scattering effects within the canopy layer (Mo et al., 1982; Wigneron et al., 2003). Using the τ~ω model, the brightness temperature, T_{Bp}, of a soil and vegetation layer is the sum of three terms: the canopy-attenuated soil emission, the direct vegetation emission, and the vegetation emission reflected by the soil and attenuated by the canopy:

$$\begin{aligned} T_{Bp} =& T_s\cdot\varepsilon_p\cdot\exp(-\tau_c) + T_c\cdot(1-\omega)\cdot[1-\exp(-\tau_c)] \\ &+ T_c\cdot\left(1-\varepsilon_p\right)\cdot(1-\omega)\cdot[1-\exp(-\tau_c)]\cdot\exp(-\tau_c), \end{aligned} \tag{9}$$

where T_s and T_c are the physical temperatures (K) of the soil and vegetation canopy, ε_p is the surface emissivity, τ_c is the vegetation optical depth, and ω is the single scattering albedo.

Several studies found that τ_c can be estimated through its relationship to the total vegetation water content W_c (kg/m^2) given by (Jackson and Schmugge, 1991):

$$\tau_c = b\cdot W_c/\cos\theta, \tag{10}$$

where b is a coefficient that depends on vegetation type (Jackson and Schmugge, 1991; van de Griend and Wigneron, 2004), and θ is the incident angle.

The τ-ω model can be applied successfully if other factors that influence the brightness temperature, such as instrument configuration and target characteristics, are invariant for a particular locality (Schmugge et al., 1980; Schmugge, 1983; Engman and Chauhan, 1995). The spatial variability of the soil texture and temperature, surface roughness, and vegetation, from one locality to another and even within a single instrument footprint, complicates the application of this technique (http://weather.msfc.nasa.gov/omega/scienceAssessment.html).

More recently, polarization indices have been proposed to monitor soil moisture and vegetation development, as the microwave signatures of soil and vegetation exhibit distinct response to polarization effects. The most common index is the microwave polarization difference index (MPDI) (Owe et al., 2001; Meesters et al., 2005) defined as:

$$\text{MPDI} = (T_{BV}-T_{BH})/(T_{BV}+T_{BH}), \tag{11}$$

where T_{BV} and T_{BH} are brightness temperature at V and H polarization, respectively. As the MPDI is a normalized calculation of brightness temperature, it primarily depends on the polarization difference, thereby minimizing the variable surface temperature effects.

4.1.2 Soil moisture retrieval methods

Many approaches have been developed to retrieve soil moisture from microwave radiometric measurements, which can be grouped into two main categories: statistical techniques and forward model inversion.

4.1.2.1 Statistical approaches

Statistical approaches are generally based on the regression analysis between measured brightness temperature and surface soil moisture. For each group of spaceborne observations, regression relationships are established between measured brightness temperature and physical parameters. The regression relations are then analyzed in terms of physical variables and parameters, which can be estimated from ancillary data (Wigneron et al., 2003).

Statistical approaches are simple and efficient, which have demonstrated the capabilities of passive microwave remote sensing techniques for monitoring soil moisture. However, these methods are "these methods site-specific," as they can only be used for the similar conditions during which they were calibrated, while are not applicable for monitoring events or trends out of the domain of calibration.

4.1.2.2 Forward model inversion

In this approach, a radiative transfer model is first selected to simulate the microwave radiometric measurements on the basis of relevant land surface parameters, and a method is then developed for inverting the model by minimizing the residual error between the model-simulated and microwave-measured brightness temperature values.

Corresponding to different kinds of surface emission models, numerous inversion methods have been developed, among which, the statistical inversion approach is the most common algorithm.

Most of the studies using semiempirical and empirical forward models are based on statistical regression analysis. For example, the simple linear relationship between soil moisture and emissivity, $\varepsilon_p = a_0 - a_1 \cdot w_s$, proves to be valid under a large range conditions for bare soils, provided that sufficient ground data are available to calibrate the coefficients a_0 and a_1. Thus, soil moisture can be retrieved by inverting the above linear equation (Wigneron et al., 2003).

Over vegetation-covered areas, the statistical techniques for soil moisture retrieval differ primarily in the way of approximating the vegetation effects on the relationship between brightness temperature and soil moisture. Usually, the surface soil moisture is statistically related to a combination of microwave emissivity and vegetation indices, which are used to correct for the soil roughness and vegetation effects (Wigneron et al., 2003). In the statistical retrieval approaches developed by Jackson et al. (1982) and Theis et al. (1984), the vegetation indices, such as MPDI and NDVI, have been used in the regression function to relate the microwave emissivity to soil moisture. Based on this principle, Choudhury et al. (1987) and Choudhury and Golus (1988) carried out retrievals of soil wetness from spaceborne radiometer observations (Wigneron et al., 2003).

Compared with conventional statistical algorithms, relatively satisfactory retrieval results have been found for statistical approaches based on forward model inversion by accounting for the vegetation effects (Pulliainen et al., 1993).

Soil moisture retrieval from space-based passive microwave instruments has solid physical basis, as well as the advantage of all-weather observations and better vegetation penetration especially at the lower frequencies between 1 and 3 GHz (L band) (Njoku and Li, 1999; Njoku et al., 2002). However, the use of passive microwave measurements for the global estimation is limited for many reasons. First, the spatial resolution is inherently coarse, which is usually in the range of 10–20 km. Further, the available wavelengths from satellites do not provide adequate soil moisture sensitivity for all types and levels of vegetation cover. Current algorithms are mainly valid for weakly vegetated regions and relatively flat surface. Lower frequencies in the L band are recognized to be of the greatest utility in measuring soil moisture content because they provide adequate sensitivity to soil moisture for most ranges of vegetation cover (Njoku et al., 2002). However, long wavelengths require large antennas in orbit, which amounts to a challenge for engineering within operational cost constraints (Zhan et al., 2002; Crosson et al., 2005).

4.2 Active microwave sensing

Great progress has been made in mapping regional soil moisture with active microwave sensors. In active microwave methods, a microwave pulse is sent and received. The power of the received signal is compared with which was sent to determine the backsca-ttering coefficient of the surface (http://envisat.esa.int/envschool_2006/lectures/su2.pdf), which has been shown to be sensitive to soil moisture. The most common imaging active microwave configuration is the synthetic aperture radar (SAR), which transmits a series of pulses as the radar antenna traverses the scene (Moran et al., 2004). These SAR systems can provide resolutions in the order of tens of meters over a swath width of 50–500 km. Currently, there are five operational SAR satellite systems with frequencies suitable for soil moisture retrieval: ESA ERS-1/2 C-band SAR, ESA ENVISAT (ERS-3) C-band ASAR (Advanced SAR), the Canadian C-band RADARSAT-1/2, the Japanese L-band ALOS-PALSAR (Advanced Land Observing Satellite- Phased Array type L-band SAR, JERS-2), as well as the recent successful launches of German X-band TerraSAT.

For radar, the total copolarized backscatter σ^{τ}_{pp} from the surface is the sum of three components:

$$\sigma^{\tau}_{pp} = \sigma^{s}_{pp} \cdot \exp(-2 \cdot \tau_c) + \sigma^{\mathrm{vol}}_{pp} + \sigma^{\mathrm{int}}_{pp}, \tag{12}$$

the first term is the soil surface backscatterer, σ^{s}_{pp}, modified by the two-way attenuation through a vegetation layer of opacity τ_c. The second and third terms represent the backscatter from the vegetation volume $\sigma_{pp}^{\mathrm{vol}}$ and the interaction between the vegetation and soil surface $\sigma_{pp}^{\mathrm{int}}$, respectively (Ulaby et al., 1996). For bare or surfaces with little vegetation, the σ_{pp}^{s} contribution dominates the received signal and is influenced primarily by the soil moisture and surface roughness. For densely vegetated areas, the backscatter is determined largely by volumetric scattering from the vegetation canopy.

Many theoretical, empirical, and semiempirical models have been developed since the beginning of SAR studies to relate the SAR backscatter coefficient to soil moisture through the contrast of the dielectric constants of bare soil and water (Fung et al., 1992; Oh et al., 1992; Dubois et al., 1995; Shi et al., 1995).

4.2.1 Theoretical approaches

Some effort has been made to describe the microwave backscattering from surfaces with known roughness characteristics by means of different theoretical models on a strictly theoretical basis. Theoretical approaches are usually derived from the diffraction theory of electromagnetic waves and have different ranges of validity, depending on the wavelength and the range of surface roughness (Fung et al., 1992; D'Ursoa and Minacapillib, 2006).

Most of the current frequently used surface scattering models originated from the small perturbation method (SPM) (Rice, 1951) and the Kirchhoff model (Beckmann and Spizzichino, 1963), which are both restricted to a limited range of roughness conditions (http://envisat.esa.int/envschool_2006/lectures/su2.pdf). In the integral equation model (IEM) (Fung et al., 1992; Fung, 1994), these two theories are combined to a method applicable to a wider range of roughness conditions than that from conventional models such as physical optical model and geometric optical model (Fung, 1994; Shi et al., 2005). Recently, Chen et al. (2003) extended the original IEM and developed the advanced integral equation model (AIEM).

Theoretical models can predict reasonably well the general trend of backscattering coefficient in response to changes in roughness or soil moisture content (Dubois and van Zyl, 1994). However, their complexity and the restrictive requirement for the parameterization of the vegetation and soil surface layer hamper their effective applicability for the soil moisture retrieval (Ulaby et al., 1986).

4.2.2 Empirical approaches

Empirical models are generally derived from experimental measurements to establish useful empirical relationships for inversion of soil moisture from backscattering observations (Walker et al., 2004). The main advantage of empirical backscattering models over theoretical backscattering models is that many natural surfaces do not fall into the validity regions of the theoretical backscattering models, and even when they do, the available backscattering models fail to provide results in good agreement with experimental observations (Oh et al., 1992; Walker et al., 2004).

An example of an empirical method has been proposed by Shoshany et al. (2000), who used the normalized backscatter moisture index (NBMI) as a basis for their soil moisture retrieval algorithm:

$$\mathrm{NBMI} = \frac{\sigma_{t1}^0 - \sigma_{t2}^0}{\sigma_{t1}^0 + \sigma_{t2}^0}, \tag{13}$$

$$W_s = a_{\mathrm{r}} \cdot \mathrm{NBMI} + b_{\mathrm{r}}, \tag{14}$$

where σ_{t1}^0 and σ_{t2}^0 are the backscatter coefficients at different time steps and a_{r} and b_{r} are empirical parameters fitted from in situ soil moisture observations. Rather than finding an exact relationship between active microwave observations and surface soil moisture content, this approach estimates soil moisture through change detection (Engman, 1990; Kite and Pietroniro, 1996) by using the normalized calculation of NBMI, which minimizes the impact of other factors such as soil texture, surface roughness, and vegetation because they usually change slowly with time (Engman and Chauhan, 1995). Thus, the change in the target is assumed from a change in soil moisture content (Engman, 1990).

Other empirical models based on the use of horizontal and vertical polarization diversity have also been developed for inversion purposes to retrieve both the roughness and moisture parameters (Wang and Zhang, 2005).

Empirical methods yield often accurate soil moisture results but may not be applicable for datasets that exceed the calibration conditions (Chen et al., 1995; Dubois et al., 1995), since a great number of experimental measurements is a must to derive general statistical laws and establish a useful empirical relationship for inversion of soil moisture from backscattering observations (Oh et al., 1992), while current empirical models generally are derived from a limited number of observations and therefore are site-specific.

4.2.3 Semiempirical approaches

Alternatively, semi-empirical models of backscattering, which represent an acceptable compromise between theoretical and empirical approaches, have been developed based on a theoretical foundation with model parameters derived from experimental data.

Among the semi-empirical models used for soil moisture retrieval with polarimetric radar data, the first was that of

Oh et al. (1992). Oh et al. found that the depolarization ratio ($\sigma^0_{vh}/\sigma^0_{vv}$) is very sensitive to soil moisture and developed the semi-empirical model based on empirical fittings of scatterometer measurements over bare soil surfaces with different roughness conditions. In the semi-empirical method proposed by Dubois et al. (1995), the copolarization backscattering coefficients σ^0_{vv} and σ^0_{hh} are expressed as nonlinear functions of the surface dielectric constant, the incidence angle, the wavelength and the root mean square of surface height.

The main advantage of these backscattering models is that they are not expected to have the site-specific problems commonly associated with empirical models (Walker et al., 2004). In most cases, these types of models are suited for bare soil surface conditions rather than vegetated surfaces.

4.3 Active and passive microwave sensing

Recent advances in remote sensing have demonstrated the ability to measure the spatial variation of surface soil moisture under a variety of topographic and land cover conditions using both active and passive microwave measurements, each with its own strength and weakness. Active sensors, although having the capability to provide high spatial resolution in the order of tens of meters, have a poor resolution in time with repeat time excess of 1 month. On the other hand, the spaceborne passive systems can provide spatial resolutions only in the order of tens of kilometers but with a higher temporal resolution.

Despite the disadvantages of SAR or passive-based soil moisture retrieval, the ALOS-PALSAR and the proposed SMOS and SMAP mission offer the opportunity of retrieving soil moisture in a combined passive/active microwave approach, which is expected to increase the accuracy of the retrievals and can yield high-resolution soil moisture products (http://envisat.esa.int/envschool_2006/lectures/su2.pdf).

5 Summary and discussion

This paper outlines the basic principles of the satellite-based techniques for soil moisture estimation and reviews briefly the status of current retrieval methods. There are a fairly wide variety of approaches, which have been used to retrieve soil moisture from optical, thermal infrared, passive microwave and active microwave satellite measurements.

The basis of the optical technique for soil moisture estimation rests on the connection between soil surface reflectance and moisture contents. Several empirical approaches and physical models have been proposed to describe the soil moisture effects on surface reflectance with satisfactory results. However, the fact that the contribution of other factors that influence the soil reflectance may not be effectively minimized limits the utility of solar reflectance measurements for soil moisture content determination.

Approaches based on either the surface temperature or the complimentary temperature/vegetation index are powerful and have clear physical principles but have limitations in addition to those common to all optical techniques. Such approaches are often empirical and thus vary across time and land cover types and generally cannot be extrapolated from one location to another.

Microwave remote sensing is the most effective technique for soil moisture estimation, with advantages for all-weather observations and solid physics. Soil moisture can be estimated using passive radiometer or active radar measurements. Both radiometer brightness temperature and radar backscattering measurements have been shown to be sensitive to soil moisture. 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.

For future soil moisture retrieval algorithms, it would be more beneficial to synergistically integrate the spaceborne measurements from multiple sensors, physically based model predictions, as well as in situ observations. The priority areas for future research should also include the approaches for mapping soil moisture in densely vegetated areas.

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