CHAPTER 7

Radar Remote Sensing for Estimation of Surface Soil Moisture at the Watershed Scale

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CONTENTS

INTRODUCTION

Knowledge of surface soil moisture at the watershed scale would be useful for such critical applications as regional resource management during times of drought or flooding. Surface soil moisture information is also a critical forcing variable in many Soil Vegetation Atmosphere Transfer (SVAT) models to estimate profile soil moisture at daily time steps. Such applications to watershed management have a common set of requirements that define the desired soil moisture product. The spatial distribution is generally required at a very fine resolution (from 10 to 100 m); the required coverage of distributed soil moisture information is on the order of 1000 to 25,000 km^2; and, in most cases, the soil moisture quantization can be coarse, such as three to four levels ranging from dry to very wet.

A great deal of progress has been made in the use of spectral images from satellite sensors for surface soil moisture mapping, where surface soil moisture (m_s) is the average moisture ($cm^3\ cm^{-3}$)

Table 7-1. RADARSAT, ERS, ENVISAT, and JERS configurations.

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	RADARSAT	ERS SAR	ERS ENVISAT ASAR	JERS ALOS PALSAR (planned)
Incidence Angle	**20-50°**	**23°**	**15-45°**	**10-51°**
Wavelength (cm)	**5.7**	**5.7**	**5.7**	**23**
SAR band	**C**	**C**	**C**	**L**
Polarization	**HH**	**VV**	**HH, VV, VH, HV**	**HH,VV,HH,HV,VV&VH**
Resolution (m)	**10-100**	**30**	**10-100**	**10-100**

in the top few centimeters of soil over a heterogeneous volume. The greatest progress has been made with passive microwave sensors. These sensors measure the intensity of microwave emission (at wavelengths λ =1-30 cm) from the soil, which is related to its moisture content because of the large differences in dielectric constant of dry soil (~3.5) and water (~80). This emission is proportional to the product of surface temperature and surface emissivity, which is commonly referred to as the microwave brightness temperature (T_B). The relation between T_B and m_s varies with differences in surface roughness and vegetation biomass and is further affected by the changes in dielectric constant related to soil texture. The efficacy of the measurement is a function of wavelength, where longer wavelengths (λ >10 cm) probe deeper into the soil and have the ability to penetrate a vegetated canopy (see review by Njoku and Entekhabi, 1996).

However, the use of passive microwave measurements for soil moisture mapping at watershed scales is limited for many reasons. First, the spatial resolution is inherently coarse, on the order of tens of kilometers. Second, until just recently, the information was available only from aircraft-based sensors, resulting in limited coverage, infrequent repeat visits, and delays in product delivery. On the other hand, two satellite-based passive microwave sensors will be providing imagery later this decade. The Advanced Microwave Scanning Radiometer (AMSR-E) was successfully deployed on the NASA Aqua platform in 2003 (Njoku et al., 2003), and the Soil Moisture and Ocean Salinity (SMOS) mission is planned for launch by the European Space Agency (ESA) in 2007 (Kerr, 2001). The spatial resolution of these sensors is estimated to be 56 and 37 km, respectively.

The only satellite systems that currently meet the spatial resolution and coverage required for watershed management are active microwave sensors (see review by Moran et al., 2004). 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. Then, these pulses are processed together to simulate a very long aperture capable of high surface resolution (Ulaby et al., 1996). There are three operational SAR satellite systems with frequencies suitable for soil moisture: ESA ERS-1/2 C-band SAR, ESA ENVISAT C-band ASAR, and Canadian C-band RADARSAT-1/2 (Table 7-1). These SAR systems can provide resolutions from 10 to 100 m over a swath width of 50 to 500 km, thus meeting most spatial requirements for watershed management. As with passive microwave sensing, the magnitude of the SAR backscatter coefficient (σ^o) is related to m_s through the contrast of the dielectric constants of bare soil and water. Similarly, the perturbing factors affecting the accuracy of m_s estimation are soil surface roughness and vegetation biomass. Studies, particularly in the past decade, have resulted in a multitude of methods, algorithms, and models relating satellite-based images of SAR backscatter to surface soil moisture. However, no operational algorithm exists using SAR data acquired by existing spaceborne sensors (Borgeaud and Saich, 1999).

For all orbiting sensors, including the AMSR-E and SMOS missions, remote sensing alone can only provide surface soil moisture m_s, with stated depths varying from 1 to 5 cm (Ulaby et al., 1996; Oh, 2000). Most studies agree that the penetration depth for microwave sensing is between 0.1 to 0.2 times the wavelength, where the longest wavelengths (L-band) are about 21 cm. To fully meet the requirements for soil moisture information for watershed management, it will be necessary to combine the horizontal coverage and spatial resolution of remote sensing with the vertical coverage and temporal continuity of a soil moisture simulation model. Such models are generally called Soil Vegetation Atmosphere Transfer (SVAT). The advantage of SVAT models is that profile soil moisture (m_p) is estimated to several meters depth on hourly, daily or monthly timesteps. One disadvantage of SVAT models for monitoring regional soil moisture condition is that they are one-dimensional, and without remotely sensed inputs, they are rarely capable of producing a distributed map of soil moisture.

In this review, we will concentrate on approaches for estimating m_s at the scale of managed watersheds ranging in size from 1000 to 25,000 km^2. These include physically based approaches for m_s estimation using SAR, with particular emphasis on use of radar backscatter models and brief mention of SAR for m_s change detection and SAR data fusion. The review will finish with a synthesis of the most important research and development issues related to watershed management. For convenience, all acronyms and scientific notation are summarized in Tables 7-2 and 7-3, respectively.

Table 7-2. Summary of Acronyms.

ALOS	**Advanced Land Observation Satellite**
AMSR-E	**Advanced Microwave Scanning Radiometer on the NASA Aqua satellite**
ASAR	**Advanced Synthetic Aperture Radar**
ENVISAT	**ENVIronment SATellite**
ERS SAR	**European Remote Sensing SAR**
ESA	**European Space Agency**
GIS	**Geographic Information System**
HAPEX-Sahel	**Hydrologic Atmospheric Pilot Experiment in the Sahel (Prince et al., 1995)**
HH, VV, HV, VH	**Horizontal and Vertical co-polarization**
HYDROS	**NASA HYDROsphere State mission**
IEM	**Integral Equation Model (Fung and Chen, 1992)**
JERS SAR	**Japanese Earth Resources Satellite SAR**
LAI	**Leaf area index**
NASA	**National Aeronautics and Space Administration**
NBMI	**Normalized Radar Backscatter soil Moisture Index (Shoshany et al., 2000)**
NDVI	**Normalized Difference Vegetation Index**
PALSAR	**Phased Array type L-band Synthetic Aperture Radar**
RADAR	**Radio Detection and Ranging**
RADARSAT	**RADAR SATellite**
RS	**Remote Sensing**
SAR	**Synthetic Aperture Radar**
SGP	**Southern Great Plains**
SMOS	**Soil Moisture and Ocean Salinity**
SSM/I	**Special Sensor Microwave/Imager**
SVAT	**Soil Vegetation Atmosphere Transfer**
WCM	**Water Cloud Model (Attema and Ulaby, 1978)**

SEMI-EMPIRICAL APPROACHES

The radar backscatter, σ^o, from a vegetated surface is composed of three contributions

$$\sigma^o = \tau^2 \sigma_s^o + \sigma_{dv}^o + \sigma_{\text{int}}^o ,$$
[1]

where σ_s^o is the backscatter contribution of the bare soil surface, τ^2 is the two-way attenuation of the vegetation layer, σ_{dv}^o is the direct backscatter contribution of the vegetation layer, and σ_{int}^o represents multiple scattering involving the vegetation elements and the ground surface (Ulaby et al., 1996). For densely vegetated targets, $\tau^2 \approx 0$ and σ^o are determined largely by volumetric scattering from the vegetation canopy. For sparsely vegetated targets, $\tau^2 \approx 1$ and the second and third terms in Eq. [1] are negligible; in that case, σ^o is determined by the soil roughness and moisture content. For bare soil, σ_s^o has a functional relation with m_s, where

$$\sigma_s^o = f(R, m_s)$$
[2]

Table 7-3. Summary of scientific notation.

σ^o	**Radar backscatter coefficient**
σ_{int}^o	**Multiple scattering involving the vegetation elements and the ground surface**
σ_s^o	**Backscatter contribution of the bare soil surface**
σ_{dv}^o	**Direct backscatter contribution of the vegetation layer**
σ_{dry}^o	**Backscatter from vegetated terrain under completely dry soil surface conditions**
σ_{wet}^o	**Backscatter when the soil surface is saturated with water**
$\Delta\sigma^o$	**Difference between dry- and wet-season σ^o**
I_{m_s}	**Relative measure of surface soil moisture**
θ_i	**Incidence angle**
K_{sat}	**Soil hydraulic conductivity**
m_p	**Profile soil moisture**
m_s	**Surface soil moisture.**
ρ_λ	**Surface spectral reflectance in optical wavelengths**
R	**Surface roughness term**
T_B	**Microwave brightness temperature**
T_R	**Infrared radiative temperature**
τ^2	**Two-way attenuation of the vegetation layer**
V	**Vegetation biomass**
λ	**Wavelength**

and *R* is a surface roughness term (Engman and Chauhan, 1995). Considering this, many algorithms using single-wavelength, single-polarization SAR for estimating m_s follow a standard two-step approach, where the first step is to estimate and remove the signal due to backscatter from the vegetation canopy. Thus, $\sigma^o \cong \sigma_s^o$. The second step is to determine the relation between σ_s^o and m_s, based on the assumption that the surface roughness adds a signal to the backscatter intensity that can be treated as an offset (Schneider and Oppelt, 1998). Thus, for a target of uniform *R*,

$$m_s = a + b\sigma_s^o \quad , \tag{3}$$

where *a* and *b* are regression coefficients determined primarily from field experiments, which encompass the target-invariant *R* and the scene-invariant SAR λ, θ_i, polarization, and calibration. Therefore, Eq. [3] is only valid for a given sensor, landuse, and soil type, and for targets when τ^2, σ_{dv}^o and σ_{int}^o are known or negligible. Nonetheless, in some cases, it is a reasonable approach and provides an operational method for regional estimation of m_s.

For example, Quesney et al. (2000) resolved Eq.[1] to [3] to derive soil moisture information with accuracies of ±0.04-0.05 (cm^3 cm^{-3}) from ERS SAR measurements over an agricultural watershed in France. Based on an *a priori* vegetation classification of the site and some in-situ measurements, they selected sensitive targets where soil moisture retrieval was possible due largely to the low vegetation biomass. For these targets, a first-order radiative transfer model was used to correct the radar response for the effect of the vegetation canopy. Then, sensitive targets were classified into roughness classes based on their furrow direction as viewed by the radar beam. These classes were assumed to be homogeneous in terms of large-scale roughness contributions. Empirical relations between σ^o and corresponding in-situ measurements of m_s were determined for each class and applied to all sensitive targets in the SAR image. They concluded that the same relation between σ^o and m_s could be used from November to August (excepting the months of May and June) for wheat fields in an agricultural watershed in France.

Similarly, for a semi-arid watershed in Arizona, Moran et al. (2000) utilized the difference between dry- and wet-season SAR σ^o ($\Delta\sigma^o$) to normalize the effects of surface roughness and topography on ERS SAR measurements. This required that the images be acquired with exactly the same sensor configuration, particularly the same incidence angle. Thoma et al. (2005) improved upon this approach to minimize empiricism and used a quantitative form of $\Delta\sigma^o$ to map m_s for an entire watershed with RADARSAT for three dates in 2003. In these studies, the effects of vegetation were found to be negligible and could be ignored, supporting similar findings by Dobson et al. (1992), Lin and Wood (1993), Demircan et al. (1993), Dubois et al. (1995), and Chanzy et al. (1997). But for many locations, the vegetation was simply too dense to monitor soil moisture with only a single-wavelength data set (Wever and Henkel, 1995; Wang et al., 1996).

A great limitation of all these approaches is that the sensitivity of radar backscatter to *R* can be much greater than the sensitivity to m_s. For example, Herold et al. (2001) reported that the backscatter range from different roughness conditions was about 17 dB, whereas the variations caused by soil moisture were about 6 dB. Sano et al. (1998) found that SAR σ^o data were nearly insensitive to soil moisture due to the stronger influence of soil roughness. Oh et al. (1992) stated that the primary cause of backscatter variation in radar image scenes was surface roughness, and secondarily, moisture content. Thus, it is imperative that surface roughness and topography be accounted for in any operational approach.

m_s CHANGE DETECTION

An approach that may have potential for operational application is the use of single-wavelength, multi-pass SAR images for change detection, rather than absolute m_s estimation (Engman 1994). This approach is based on the assumption that the temporal variability of *R* and vegetation biomass (*V*) is generally at a much longer time scale than that of m_s, and therefore, the change in SAR σ^o between repeat passes results from the change in m_s. Thus, a multi-temporal SAR data set could be used to minimize the influence of *R* and *V*, and maximize the sensitivity of σ^o to changes in m_s. Though useful for many applications, it is notable that the assumptions do not hold for cultivated crops where *R* and *V* change dramatically over short time periods. Furthermore, images must be acquired with the same sensor configuration to avoid the need for topographic corrections due to variations in θ_i and image orientation.

Simply applied, a Normalized Radar Backscatter soil Moisture Index (NBMI) was derived from σ^o measurements at two times (t_1 and t_2) over one location where,

$$NBMI = \frac{\sigma^o_{t_1} + \sigma^o_{t_2}}{\sigma^o_{t_1} - \sigma^o_{t_2}}$$

[4]

(Shoshany et al., 2000). By normalizing the effects of *R*, soil type, and topography on SAR σ^o, such ratio techniques offer a relative soil moisture index varying from 0 to 1 related to distributed m_s variations.

Using a long backscatter series, it is possible to correlate changes in σ^o with changes in m_s over large areas. For example, Wickel et al. (2001) used 10 RADARSAT scenes over a one-month period to monitor m_s change in fields of wheat stubble in Oklahoma. They corrected all images for the difference in θ_i using an empirical approach and a modeling approach (Ulaby and Dobson, 1989), and then eliminated wheat fields with “major” temporal roughness changes. They computed a multitemporal regression of day-to-day differences in σ^o and m_s with a strong correlation of r^2=0.89.

Wagner and Scipal (2000) offered a variation on this approach that has been tested with some success in Canadian prairies, the Iberian Peninsula, the Ukraine, and savanna and grasslands in western Africa. Based on a multi-year series of ERS scatterometer images with spatial resolution of 50 km, a “knowledge base” about the backscatter behavior of each pixel was constructed. The behavior of σ^o related to θ_i over time was used to determine relative *R* and *V*, and to normalize σ^o to a reference θ_i of 40° at time t. For pixels of similar *R* and *V*, a relative measure of surface soil moisture (I_{m_s}) was estimated as

$$I_{m_x} = \frac{\sigma^o(40°,t) - \sigma^o_{dry}(40°,t)}{\sigma^o_{wet}(40°,t) - \sigma^o_{dry}(40°,t)}$$

[5]

where $\sigma^o_{dry}(40°,t)$ represents σ^o from vegetated terrain under completely dry soil surface conditions and $\sigma^o_{wet}(40°,t)$ represents σ^o when the soil surface is saturated with water. The values $\sigma^o_{dry}(40°,t)$ and $\sigma^o_{wet}(40°,t)$ were derived from the lowest and highest values of σ^o (40°,t) from six years of data. Thus, in this approach, the normalization of variations in θ_i , R and V and the estimation of I_{m_s} are all accomplished with a frequent-repeat, multi-year backscatter data series. With SAR data, Lu and Meyer (2002) suggested a similar change detection approach with a significant variation. That is, they incorporated information from both SAR backscatter intensity and phase to perform an initial discrimination of changes in soil moisture from changes in surface roughness. With that preprocessing and an image-based estimate of σ^o_{dry} , they were able to detect changes in m_s ranging from 0.05 to 0.20 $cm^3\ cm^{-3}$.

SAR DATA FUSION

The problem associated with discriminating the multiple influences of surface properties and sensor characteristics (e.g., R, V, θ_i, λ) on the relation between SAR σ^o and m_s has prompted a number of SAR data fusion studies. The majority of studies have addressed the complementarity and interchangeability of 1) active (SAR) microwave σ^o and passive microwave T_B, and 2) SAR σ^o and optical measurements, such as infrared radiative temperature (T_R) and surface spectral reflectance in visible and near-infrared wavelengths (ρ_λ).

As mentioned earlier, the greatest advantage of active over passive microwave sensing for watershed applications is the fine spatial resolution, where SAR resolution is on the order of tens of meters and passive microwave resolution is tens of kilometers. Similar passive and active microwave configurations appear to have similar sensitivities to soil moisture (Chauhan et al., 1999) and near-similar sensitivities to roughness (Du et al., 2000). Data fusion of passive and active microwave sensing has generally taken the form of using SAR σ^o for determining fine-resolution vegetation and roughness parameters and then combining these with coarse-resolution passive microwave T_B for estimation of regional soil moisture (e.g., Chauhan, 1997; Lakshmi et al., 2000). In other approaches, complementary passive microwave emissivity and SAR backscatter were fused through Bayesian logic to improve estimates of soil moisture condition (Notarnicola and Posa, 2001). Huang and Jin (1995) used passive and active microwave data to construct a mesh graph, where any point on the graph could be used to estimate soil moisture and roughness of bare soil separately.

There is great potential to determine subpixel variability of passive-derived soil moisture with the finer resolution active microwave data. In a recent study, Bindlish and Barros (2002) downscaled soil moisture estimates from a passive microwave sensor from 200 m to 40 m using a single polarization, single wavelength L-band SAR system. They concluded that integration of active and passive microwave technologies to monitor watershed scale soil moisture is an alternative worth exploring. This approach will likely receive more attention when the soil moisture products from AMSR-E and SMOS become available. Further support will be provided by the NASA HYDROsphere State (HYDROS) mission with a satellite-based, integrated passive and active L-band system with spatial resolutions of 3 to 40 km.

Microwave and optical remote sensing have been used separately for estimation of surface properties, and both measurements have distinct advantages. Several studies have focused on definition of the complementarity (independent information) and interchangeability (similar information) of optical and SAR data. Basically, the longer λ SAR bands (λ >6 cm) have been related to thermal T_R measurements through the physical relation between surface evaporation and surface soil moisture content (e.g., Moran et al., 1997). For vegetated targets, shorter λ SAR bands (e.g. $\lambda \approx 2$ cm) have been related to optical vegetation indices (e.g., Normalized Difference Vegetation Index, NDVI) because visible, near-IR, and short- λ SAR signals are largely influenced by the crown layer of branches and foliage in the canopy (e.g., Prevot et al., 1993; Moran et al., 1997). Other studies have taken advantage of both the complementarity and interchangeability of optical and SAR data to improve simulation model parameterization and inversion. Theoretical studies have shown that the inverse problem for m_s estimation could be achieved with an optical/SAR data set, but a unique solution would not be possible with either observation alone (Entekhabi et al., 1994; Chanzy et al., 1995). This work has been supported by field experiments with crops in France and Poland (Taconet et al., 1996; Olioso et al., 1998; and Dabrowska-Zielinska et al., 2001) and rangelands in Arizona (Wang et al., 2003).

SAR PLUS RADAR BACKSCATTER MODELS

The continuing efforts to disentangle the relative influences of *R*, *V*, and m_s on SAR σ^o have ultimately led to the use of physically based backscatter models. These models generally predict σ^o as a function of sensor configuration and surface conditions, and can thus be inverted to estimate m_s. Empirical, semi-empirical, and theoretical models have been developed for this purpose. Empirical models are generally derived from experiments to fit their data and may only apply to surface conditions and radar parameters at the time of the experiment (Dobson et al., 1985; Oh et al., 1992; Dubois et al., 1995; Wang et al., 1996).

To avoid this limitation, semi-empirical models have been developed based on a theoretical foundation with model parameters derived from (i.e., fitted to) experimental data. An example is the widely used Water Cloud Model (WCM) that represents the canopy as a uniform cloud of spherical droplets that are held in place structurally by dry matter (Attema and Ulaby, 1978). In WCM, the canopy can be represented by bulk variables such as leaf area index (LAI) or vegetation water content, and the model can be easily inverted. Simply, the backscatter coefficient is represented by Eq. [1], which is simplified to $\sigma^o = \tau^2 \sigma_s^o + \sigma_{dv}^o$ based on the assumption that σ_{int}^o is negligible. The attenuation of the vegetation layer (τ^2) and direct backscatter from the vegetation layer (σ_{dv}^o) are determined empirically by

$$\tau^2 = \exp(-2BV\sec\theta) \quad , \qquad [6]$$

$$\sigma_{dv}^o = AV\cos\theta(1-\tau^2) \quad , \text{ and} \qquad [7]$$

$$\sigma_s^o = C + Dm_s \quad , \qquad [8]$$

where *V* could be green LAI, and *A*, *B*, *C*, and *D* are empirical parameters dependent upon canopy type and soil roughness (Prevot et al., 1993; Taconet et al., 1996; Moran et al., 1998).

Some effort has been made to examine radar backscatter on a strictly theoretical basis, though theoretical models are difficult to implement using computers, and their validity range is often limited. For instance, models based on the Kirchoff formulation are known to be applicable only to gently undulating surfaces within restrictive R/λ conditions, and those based on the small perturbation theory were developed for only slightly rough surfaces where $R<\lambda$ (Ulaby et al., 1982). The Integral Equation Model (IEM) combines the Kirchoff and small perturbation theories to address a wide range of roughness for bare soil surfaces, with an expression that is simpler to calculate and invert (Fung and Chen, 1992; Fung et al., 1992). For this reason, it has become the most widely used radar backscatter model and will be the focus of this section.

The IEM model has been found to be particularly suitable for retrieving m_s from single-wavelength, single-pass SAR σ^o. However, in all cases, an *a priori* measure of R was required (e.g., Tansey and Millington, 2001). This has led to a number of suggestions for determining distributed R information from orbiting SAR sensors. Considering that RADARSAT images can be acquired at a variety of θ_i, Colpitts (1998) combined two or more images of different θ_i with the IEM model to separate effects of m_s and R for several tillage types. Similarly, Pasquariello et al. (1997) found that IEM-retrieved estimates of m_s were greatly improved through inversion with multi-θ_i SAR imagery. Based on a theoretical analysis, Fung et al. (1996) reported that not only could angular SAR measurements be used to determine roughness parameters for IEM, this approach was preferable to direct ground measurements due to considerations of scale, heterogeneity and resolution. However, approaches based on multi-θ_i SAR imagery are limited because pixel information is integrated over different spatial domains with variations in θ_i. In a different approach, Verhoest et al. (2000) used multi-temporal data rather than multi-angular data to determine an effective roughness parameter. Thus, multi-temporal ERS-1 SAR σ^o was used to invert the IEM model to retrieve m_s from bare soil with reasonable accuracy.

As a result of these successes, there have been numerous refinements, improvements, and additions to the IEM that will certainly encourage more use of the model for m_s retrieval. To reduce the complexity of IEM application, algorithms have been developed based on fitting of IEM numerical simulations for a wide range of R and m_s conditions (Chen et al., 1995; Shi et al., 1997). The results are a look-up table of IEM simulations that serve to directly relate SAR σ^o to theoretical model predictions over bare and sparsely vegetated surfaces with known radar parameters. These simplified IEM-based algorithms require fewer parameters and are much easier to use with remotely sensed data.

Another critical refinement of IEM was the incorporation of vegetation backscatter effects into the m_s inversion algorithm. The original IEM was developed for bare soil conditions only, although the retrieval algorithm performed well for sparsely vegetated areas. Bindlish and Barros (2001) formulated an IEM vegetation scattering parameterization in the framework of the WCM (Eq. [6]-[8]). They reported that the application of the modified IEM led to an improvement in the correlation coefficients between ground-measured and SAR-derived m_s estimates from 0.84 to 0.95. The incorporation of vegetation scattering will expand IEM applications to moderately vegetated sites and improve applications in arid and semiarid regions where m_s is so low that the soil contribution may be equal to the magnitude of the vegetation contribution.

The IEM model has also been refined to include a penetration depth model. Studies have reported problems in IEM-based m_s retrieval due to an increase in the penetration depth of the incident wave when the soil moisture was low (e.g., Wiemann, 1998). As a result, modeled m_s could not be compared with ground measurements because IEM did not account for the fact that

SAR beam penetration exceeded the layer where the soil moisture was measured (Wiemann, 1998). Boisvert et al. (1997) offered three approaches to refine IEM to account for variations in beam penetration depth. They reported that the correction allowed reliable comparisons among different SAR configurations and took into account the daily variations in the beam penetration with soil moisture.

The general consensus of studies using SAR σ^o with radar backscatter models is that the retrieval of m_s with single-wavelength, single-θ_i, single-pass SAR data is not possible without information about the surface roughness. The results also demonstrate the need for continuous measurement of surface roughness and fine-resolution information about surface topography, if

Table 7-4. Promising approaches using SAR sensors for m_s estimation.

Approach	Examples
Semi-empirical algorithm Generally uses SAR images of single λ, θ_I, and polarization. Requires multiple passes and/or ancillary information. Often scene- or site-dependent.	Moran et al. (2000); Quesney et al. (2000)
SAR for m_s change detection Requires multiple passes. Assumes temporal variability of R and V is at longer time scale than that of m_s. High potential for operational application.	Lu and Meyer (2002); Shoshany et al. (2000); Wagner and Scipal (2000); Wickel et al. (2001)
SAR data fusion – passive and active microwave Generally, uses active σ^o to determine fine resolution V and R, and passive T_B to estimate m_s OR downscales passive-derived m_s with fine resolution σ^o.	Bindlish and Barros (2002); Chauhan (1997); Huang and Jin (1995); Lakshmi et al. (2000); Notarnicola and Posa (2001)
SAR data fusion – microwave and optical Based on complementarity or interchangeability of optical and SAR data. Simplifies the inverse problem for m_s estimation.	Chanzy et al. (1995); Dabrowska-Zielinksa et al. (2001); Entekhabi et al. (1994); Moran et al. (1997); Olioso et al. (1998); Taconet et al. (1996); Wang et al. (2003)
SAR plus microwave scattering model Empirical, semi-empirical and theoretical models available. Models are inverted to estimate m_s from σ^o. Advantage: high accuracy. Disadvantage: difficult model parameterization.	Colpitts (1998); Fung et al. (1996); Pasquariello et al. (1997); Tansey and Millington (2001); Verhoest et al. (2000); Wiemann (1998)

soil moisture is to be monitored accurately with single-wavelength SAR data. When SAR data with consistent ground truth information are available, it will be possible to test the many existing retrieval algorithms.

CONCLUSIONS

The basic conclusion of this review is that currently orbiting SAR sensors can provide surface soil moisture information with known accuracy at the watershed scale. Future research should be dedicated to refining the approaches that meet the requirements for watershed application and have the most potential for operational estimation of m_s (Table 7-4). The most robust, adaptable system will likely be based primarily on SAR images, and it will require a radar backscatter model for determining m_s and ground information for validation. However, there are many obstacles yet to be overcome for a truly operational application for watershed management.

First, the primary perturbing factors affecting the accuracy of SAR-derived m_s estimations are soil surface roughness and vegetation biomass. These, along with soil texture, are also primary inputs to SVAT models. In this review, several promising approaches for estimating these surface properties with satellite imagery were mentioned (e.g., Pasquariello et al., 1997; Colpitts, 1998; Mattikali et al., 1998; Verhoest et al., 2000). Not only are these approaches feasible, they are preferable to direct ground measurements because they offer flexibility of coverage and resolution required at the watershed scale.

Second, the accuracy of m_s retrieved from remote sensing in all wavelengths is limited by the non-linear effects of vegetation change. Vegetation biomass significantly influences surface reflectance, thermal emission, microwave emission, and radar backscatter from the soil surface. This review presents several approaches designed to minimize this effect, for example, limiting analysis to sparsely vegetated sites (Quesney et al., 2000), monitoring signal differences when vegetation is known to be static (Wickel et al., 2001), and by combining optical and SAR data (Chanzy et al., 1995). Alternatively, there are models designed to determine SAR backscatter from vegetation that have the potential to discriminate surface soil moisture (e.g., Ulaby et al., 1990; Bindlish and Barros, 2001). Despite these attempts, there is no operational algorithm or model using existing spaceborne sensors to determine the soil moisture of densely vegetated sites. This should be considered a priority research area.

Third, a common lament in nearly all soil moisture studies at the watershed scale is that consistent ground information about m_s and m_p is rarely available at the scale and frequency required for model calibration and validation. Though it is technologically feasible (Borgeaud and Floury, 2000), no worldwide in situ soil moisture monitoring program is currently in place. Consequently, most studies have been undertaken in conjunction with inter-disciplinary field campaigns coordinated with multiple aircraft and satellite overpasses. For example, the HAPEX-Sahel campaign in 1992 provided multi-scale soil moisture measurements up to a regional area of 12,100 km2 (Prince et al., 1995). Microwave images were acquired by the ERS SAR and SSM/I satellite sensors, and detailed project information can be obtained at http://www.ird.fr/hapex/. The Washita experiment conducted in 1992 and the Southern Great Plains (SGP) experiments undertaken in 1997 and 1999 employed a wide range of microwave instrumentation that provided useful soil moisture measurement techniques at numerous scales appropriate for watershed management (LeVine et al., 1994; Jackson et al., 1995, 2002a, 2002b; O'Neill et al., 1998; Jackson, 1999; Jackson and Hsu, 2001). Microwave images were acquired with aircraft- and satellite-based systems, as well as the Priroda sensors on the Mir Space Station. Links to these remote sensing soil moisture experiments, including data, images, and reports, are available at http://hydrolab.arsusda.gov/rsbarc/RSofSM.htm. Though such place-based campaigns have expanded the science of soil moisture estimation, it will be necessary to have spatially and temporally consistent ground truth information coincident with SAR overpasses to test the many existing retrieval algorithms.

Fourth, as described in Table 7-1, current SAR sensor configurations include a multitude of wavelengths, incidence angles, polarizations, resolutions, and overpass times. The SAR backscatter signal from a given target is highly sensitive to sensor configuration. This sensitivity has proven advantageous for studies based on the multi-dimensional information resulting from multi-λ, multi-θ_i, and/or multi-polarization data (e.g., Dubois et al., 1995; Wever and Henkel, 1995; Pasquariello et al., 1997; Colpitts, 1998). However, variations in sensor configuration can be devastating to studies based on the assumption that a change in σ^o is due exclusively to a change in surface condition (e.g., Mattikalli et al., 1998; Wagner and Scipal, 2000). As a result, most studies of change detection have been limited to the use of a single SAR sensor with a fixed configuration. The accuracy of estimating soil properties (i.e., both soil moisture and texture) could be greatly increased if the differences in scattering due to sensor configuration could be normalized. In some cases, this has been resolved through the use of existing theoretical backscatter models (e.g., Wickel et al., 2001).

Fifth, an approach that has great potential for immediate operational application is the use of single-wavelength, multi-pass SAR images for change detection, rather than absolute m_s estimation. Many multi-pass approaches for estimating m_s were identified in this review (e.g., Shoshany et al., 2000; Wagner and Scipal, 2000; Wickel et al., 2001; Lu and Meyer, 2002). Though useful, these will not be reasonable at the watershed scale until the price of SAR imagery decreases from current levels.

Finally, in this review, three satellite systems were described with the explicit mission of measuring global soil moisture. The AMSR-E sensor, now in orbit aboard the NASA Aqua platform, was designed to provide soil moisture mapping at 56 km and generally demonstrate technology feasibility. The SMOS sensor, to be launched this decade by ESA, will provide improved soil moisture mapping at a spatial resolution of potentially 37 km. The NASA HYDROS will combine passive and active sensors to improve both sensitivity to soil moisture and spatial resolution (estimated to be 10 km). Through international cooperation, these missions have been designed to complement and build upon each other. Though none of these missions meets the spatial resolution requirements for watershed applications (10 to 100 m), the technology development and demonstration will certainly benefit the science of soil moisture mapping at all scales.

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