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Review / Synthèse

Estimating soil moisture at the watershed scale with satellite-based radar and land surface models

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Abstract. Spatially distributed soil moisture profiles are required for watershed applications such as drought and flood prediction, crop irrigation scheduling, pest management, and determining mobility with lightweight vehicles. Satellite-based soil moisture can be obtained from passive microwave, active microwave, and optical sensors, although the coarse spatial resolution of passive microwave and the inability to obtain vertically resolved information from optical sensors limit their usefulness for watershed-scale applications. Active microwave sensors such as synthetic aperture radar (SAR) currently represent the best approach for obtaining spatially distributed surface soil moisture at scales of 10–100 m for watersheds ranging from 1 000 to 25 000 km^2. Although SAR provides surface soil moisture, the applications listed above require vertically resolved soil moisture profiles. To obtain distributed soil moisture profiles, a combined approach of calibration and data assimilation in soil vegetation atmosphere transfer (SVAT) models based on recent advances in soil physics is the most promising avenue of research. This review summarizes the state of the science using current satellite-based sensors to determine watershed-scale surface soil moisture distribution and the state of combining SVAT models with data assimilation and calibration approaches for the estimation of profile soil moisture. The basic conclusion of this review is that currently orbiting SAR sensors combined with available SVAT models could provide distributed profile soil moisture information with known accuracy at the watershed scale. The priority areas for future research should include image-based approaches for mapping surface roughness, determination of soil moisture in densely vegetated sites, active and passive microwave data fusion, and joint calibration and data assimilation approaches for a combined remote sensing – modeling system. For validation, a worldwide in situ soil moisture monitoring program should be implemented. Finally, to realize the full potential of satellite-based soil moisture estimation for watershed applications, it will be necessary to continue sensor development, improve image availability and timely delivery, and reduce image cost.

Résumé. Les profils d'humidité du sol spatialement distribués sont nécessaires dans le cadre des applications liées aux bassins versants telles que la prévision des sécheresses et des inondations, la planification des cédules d'irrigation des cultures, la gestion des infestations et la détermination de la mobilité des véhicules légers. L'humidité du sol peut être dérivée des données satellitaires au moyen des capteurs micro-ondes passifs, micro-ondes actifs et des capteurs optiques, bien que la résolution spatiale grossière des capteurs micro-ondes passifs et l'impossibilité d'obtenir une information intégrée verticalement avec les capteurs optiques limitent leur utilité pour les applications à l'échelle du bassin versant. Les capteurs micro-ondes actifs comme le radar à synthèse d'ouverture (RSO) représentent à l'heure actuelle la meilleure alternative pour l'obtention d'information sur l'humidité de surface qui est spatialement distribuée aux échelles de 10–100 m pour les bassins variant en superficie de 1 000 à 25 000 km^2. Quoique le capteur RSO permette d'obtenir de l'information sur l'humidité de surface, les applications énumérées ci-dessus font appel à des profils d'humidité du sol intégrés verticalement. L'avenue la plus prometteuse permettant d'obtenir des profils d'humidité du sol distribués verticalement consiste à utiliser une approche combinée d'étalonnage et d'assimilation des données basée sur l'utilisation des modèles SVAT (« soil vegetation atmosphere transfer models ») basés sur les plus récents développements en physique des sols. Cet article de synthèse résume l'état actuel de la science dans le domaine de l'utilisation des capteurs satellitaires actuels pour la détermination de la répartition de l'humidité de surface à l'échelle du bassin versant, et fait le bilan de l'utilisation conjointe des modèles SVAT et des approches d'assimilation et d'étalonnage des données pour l'estimation des profils d'humidité du sol. La conclusion de base de cette synthèse est à l'effet que les données des capteurs RSO

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présentement en orbite utilisées en combinaison avec les modèles SVAT disponibles peuvent fournir une information sur les profils d'humidité du sol distribués avec une précision déterminée à l'échelle du bassin versant. Les secteurs prioritaires de recherche pour le futur devraient inclure des approches basées sur les images pour la cartographie de la rugosité de surface, la détermination de l'humidité de surface dans les zones de végétation dense, la fusion des données des capteurs micro-ondes actifs et passifs et des approches conjointes d'étalonnage et d'assimilation des données dans l'optique d'un système combiné télédétection–modélisation. Pour fins de validation, on devrait mettre sur pied un programme in situ de suivi de l'humidité du sol à l'échelle du monde. Enfin, pour réaliser pleinement le potentiel de l'estimation de l'humidité du sol à partir de l'information satellitaire dans le contexte des applications au niveau des bassins versants, il sera nécessaire de poursuivre le développement des capteurs, d'améliorer la disponibilité des images et la livraison des données en temps opportun et de réduire le coût des images.
[Traduit par la Rédaction]

Introduction

Information about the distribution of soil moisture has proven useful for watershed management to determine the allocation of limited resources during times of drought and help coordinate relief efforts in times of flooding. Soil moisture distribution also plays a key role in the prediction of erosion and sediment loads in watershed streams and ponds. In cultivated watersheds, soil moisture information has been used for irrigation scheduling, site-specific management of diseases and pests, and improving crop yield prediction. In arid and semiarid watersheds, soil moisture content has been used as a surrogate indicator of general plant health. A practical application of soil moisture information is the determination of mobility with lightweight vehicles.

Such watershed-scale applications have a common set of requirements that define the desired soil moisture product (**Table 1**). The spatial distribution is generally required at a very fine resolution, from 10 to 100 m. The desired soil moisture depth includes the subsurface to the entire root zone, from 15 cm to >1 m, but the uncertainty requirements vary with application. In most cases, the product accuracy requirement is moderate (~75%) because such accuracies are acceptable when the alternative is decision making without any soil moisture information. On the other hand, the requirement for product delivery is very restrictive because watershed managers are often making day-to-day decisions in response to natural and human-induced influences. Thus, product delivery should be upon request of the manager and within 3–4 days of the request. The vast majority of managed *watersheds* in the United States have drainage areas of less than 10 000 km^2, where the term *river basin* is reserved for larger areas (Committee on Watershed Management, 1999). Thus, the required coverage of distributed soil moisture information is 1 000 to 25 000 km^2. These requirements lend themselves well to the use of planned and currently orbiting earth-observation sensors, particularly synthetic aperture radar (SAR) and optical sensors. In fact, a great deal of progress has been made in the use of spectral images from satellite sensors for soil moisture mapping, where surface soil moisture (m_s) is the average moisture (cm^3 cm^{-3}) in the top few centimetres of soil over a heterogeneous volume.

Table 1. Soil moisture product requirements for application to watershed management.

Mapping parameter	Requirement
Spatial resolution	10–100 m
Spatial coverage	1 000 to 25 000 km^2
Vertical resolution	Root zone, 15 cm to >1 m
Quantization	3–4 levels, ranging from dry to very wet
Accuracy	Moderate, ~75%
Product delivery	Upon request, within 3–4 days of request

For all orbiting sensors, remote sensing alone can only provide m_s. Most studies agree that the penetration depth for microwave sensing is between 0.1 and 0.2 times the wavelength, where the longest wavelengths (L-band) are about 21 cm (Oh, 2000; Ulaby et al., 1996). To fully meet the requirements for soil moisture information for the watershed-scale applications described above, it is 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) models. The advantage of SVAT models is that profile soil moisture (m_p) is estimated to several metres depth on hourly, daily, or monthly timesteps. The accuracy depends on the model physics, the number and configuration of soil layers, the accuracy and nature of the input data, and the climate conditions and biophysical and geophysical characteristics of the site. One disadvantage of SVAT models for monitoring watershed soil moisture condition is that the models are typically one-dimensional and, without remotely sensed inputs, are rarely capable of producing a distributed map of soil moisture. Most models have been designed for existing point data and do not account for the spatial variability that is known to exist.

The importance of accounting for soil moisture distribution at the watershed scale cannot be overstated. Soil moisture distribution is a complex function of not only soil physical properties and topography, but also vegetation type, land use, season, time of day, weather conditions, and initial soil moisture. The results of some studies have shown that the coefficient of variation decreases with increasing soil water content (Archer et al., 1999), and the parametric form of the soil moisture distribution deviates from the common gamma or normal distributions with variations in scale (Kothari and Islam, 1999; Beldring et al., 1999). Consequently, management decisions made at the watershed scale with an assumption of uniform soil moisture conditions may result in wasted or insufficient resources.

In this review, we will concentrate on the approaches that have the most promise for operational soil moisture mapping at the scale of managed watersheds (**Table 1**). First, we offer a short review of m_s estimation using optical and microwave sensors to make the case that a system based primarily on SAR sensors represents the best approach for obtaining spatially distributed surface soil moisture at watershed scales. Based on that assertion, we then provide a review of approaches for m_s and m_p estimation, which includes

(1) Approaches for m_s estimation using SAR, with particular emphasis on the use of microwave scattering model, SAR for m_s change detection, and SAR data fusion

(2) Profile soil moisture (m_p) estimation based on a combination of remote sensing (RS) and SVAT models through model calibration and data assimilation, including a short overview of SVAT modeling at the watershed scale

A key theme is that remote sensing can only measure m_s, and SVAT models are best suited to estimate m_p. Consequently, a combined approach using remotely sensed data for calibration and data assimilation in SVAT models is the most promising research direction for satellite-based estimation of soil moisture profiles at the watershed scale.

The review will finish with a synthesis of the most important research and development issues related to a truly operational system for watershed management. Introductory material on spectral measurements for m_s estimation is summarized in **Table 2**.

Overview of optical and microwave soil moisture sensing

This section provides an overview of the progress and constraints of optical and microwave sensing of m_s. The objective of this overview is to provide sufficient information to assess the potential of current orbiting systems to map m_s at the watershed scale. As mentioned in the introduction, the coarse spatial resolution of passive microwave and the inability to obtain vertically resolved information from optical sensors limit their usefulness for watershed-scale applications. Thus, the following sections will focus on the state of the science

Table 2. Summary of spectral measurements for m_s estimation.

Physics	Advantages	Limitations
Visible, NIR, SWIR reflectance		
Spectral information in visible, NIR, and SWIR wavelengths is related to m_s as a function of spectral absorption features; for bare soils, increase in m_s generally leads to a decrease in soil reflectance	Fine spatial resolution Broad coverage Multiple satellite sensors available Hyperspectral sensors show promise	Weak relation to m_s Minimal surface penetration (~1 mm) Limited ability to penetrate clouds and vegetation; attenuated by earth's atmosphere Infrequent repeat coverage Strongly perturbed by vegetation biomass
TIR emittance		
Soil moisture directly influences soil temperatures by increasing both specific heat and thermal conductivity, thus thermal inertia of soils; for bare soil, variations in surface T_R primarily due to varying m_s	Fine spatial resolution Broad coverage Multiple satellite sensors available Strong relation to m_s T_R/VI approaches show promise	Minimal surface penetration (~1 mm) Limited ability to penetrate clouds and vegetation; attenuated by earth's atmosphere Infrequent repeat coverage Strongly perturbed by vegetation biomass
Microwave T_B		
Intensity of microwave emission (at σ^0 = 1–30 cm) from soil is related to m_s because of large differences in dielectric constant of dry soil (~3.5) and water (~80); for bare soils, increase in m_s generally leads to increase in T_B	Broad coverage Satellite sensor recently available Strong relation to m_s Surface penetration up to ~5 cm Insensitive to clouds and earth's atmosphere	Perturbed primarily by surface roughness and vegetation biomass Coarse spatial resolution (~30 km)
Radar σ^0		
As with passive microwave sensing, magnitude of σ^0 is related to m_s through contrast of dielectric constants of bare soil and water; for bare soils, increase in m_s generally leads to increase in σ^0	Fine spatial resolution Multiple satellite sensors available Strong relation to m_s Surface penetration up to ~5 cm Insensitive to clouds and earth's atmosphere	Infrequent repeat coverage Perturbed primarily by surface roughness and vegetation biomass

using SAR sensors combined with available SVAT models to provide distributed, profile soil moisture information with known accuracy at the watershed scale.

Optical sensing of surface soil moisture

Despite the multitude of optical sensors currently in orbit (Kustas et al., 2003), a limited body of literature exists on the use of visible, near-infrared (NIR), shortwave infrared (SWIR) wide-band and (or) hyperspectral sensors for soil moisture assessment (Muller and Décamps, 2000). This is due partly to the fact that optical remote sensing measures the reflectance or emittance from only the top millimetre(s) of the surface. Furthermore, unlike the longer microwave wavelengths, the optical signal has limited ability to penetrate clouds and vegetation canopy, and is highly attenuated by the earth's atmosphere. In addition to moisture content, soil reflectance measurements are also strongly affected by the soil composition, physical structure, and observation conditions, resulting in poor predictors of soil moisture on combined soil-type samples (e.g., Musick and Pelletier, 1988). Because of these controls, efforts to directly relate soil reflectance to moisture have achieved success only when models are fit for specific soil types in the absence of vegetation cover (e.g., Muller and Décamps, 2000).

With respect to hyperspectral sensors in the visible, NIR, and SWIR spectrum, analysis performed by Liu et al. (2002) showed that while at low moisture levels, increasing moisture content led to a decrease in soil reflectance, the opposite was true at higher moisture levels. That is, increasing moisture content led to an increase in soil reflectance, determined albeit by much poorer regression results. Ben-Dor et al. (2002) performed a field study of mapping multiple soil properties (including soil moisture) using DAIS-7915 hyperspectral scanner data. The hyperspectral premise is that narrow-band spectral information in the visible, NIR, and SWIR wavelengths allows material identification as a function of their spectral absorption features. Their results were mixed. In all, the use of optical reflectance as a *direct* measure of watershed-level soil moisture is greatly constrained, though reflectance information has an important *indirect* role in soil moisture estimation through data fusion and assimilation in SVAT models (which is discussed later in this paper). Far better success in direct measurement of surface soil moisture is achievable when thermal and microwave measurements are employed.

The estimation of m_s using remotely sensed thermal wavebands is primarily related to the use of radiative temperature (T_R) measurements, either singularly or in combination with vegetation indexes derived from visible and NIR wavebands. Variations in T_R of bare soils have been found to be highly correlated with variations in m_s (Friedl and Davis, 1994; Schmugge, 1978). Recent studies have explored the added value of view angle variation on T_R measurements to estimate m_s. Chehbouni et al. (2001) found that for a semiarid grassland site with static vegetation conditions, multidirectional T_R data from field infrared thermometers could be used to estimate m_s. In a study of coupled SVAT-infrared thermal radiative transfer models, François (2002) could not determine a universal relationship between surface wetness and soil temperature, even when using differences between directional T_R, because of the influence of rapidly varying factors (wind speed, soil texture, incoming solar radiation, vegetation condition, leaf area index). However, he did report that directional T_R measurements dramatically improved soil moisture detection. Although the dual view design of the along track scanning radiometer (ATSR) aboard the European Remote Sensing (ERS) satellites provides multidirectional T_R measurements, few studies have been published using such data to estimate surface water fluxes over heterogeneous surfaces (Chehbouni et al., 2001).

Advanced applications of the dual use of thermal imagery and spectral vegetation indices employ thermodynamic principles embodied in surface energy balance models to estimate surface evapotranspiration rates, and thus improve soil moisture estimation (Kustas et al., 2003). Such approaches have the potential to estimate m_p by using the transpiration of vegetation as a surrogate measure of m_p. Many such approaches are based on the consistent negative correlation between T_R and spectral vegetation indices, such as the normalized difference vegetation index (NDVI). Numerous labels have been given to variations of this technique including the triangle method (Carlson et al., 1995), temperature-vegetation contextual approach (TVX) (Prihodko and Goward, 1997; Czajkowski et al., 2000), surface temperature-vegetation index (T_s/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).

Gilles et al. (1997) used the triangle method on airborne multispectral radiometer data and achieved standard error estimates of 0.16 for m_s relative to field measurements for sites in Kansas and Arizona. A simpler approach was employed by Bosworth et al. (1998) in which linear and equally spaced isopleths of soil moisture were computed under the assumption that m_s varies within the triangle from completely dry to completely saturated. Sandholt et al. (2002) defined TVDI, where corners and moisture isolines were completely image-derived under the assumption that an entire range of surface moisture contents and vegetation cover was included in the scene. They reported regression coefficients of 0.70 when comparing TVDI results for a study site in Senegal to those from a distributed hydrological model. Goward et al. (2002) found in a simulation study that while the slope of the T_R/NDVI line was only weakly correlated to m_s, the relation endpoints (closed canopy temperature and bare ground temperature) along with incident radiation measurements could predict m_s with a residual standard error of 0.04. At continental scales, the slope of the T_R/NDVI relation was strongly correlated with considerable scatter (regression coefficient of 0.83, standard error of 0.06) to crop-moisture-index values, and thus by implication, to surface moisture conditions (Nemani et al., 1993).

Approaches based on either the directional T_R or the complimentary T_R-vegetation index are powerful but have limitations in addition to those common to all optical techniques (shallow soil penetration, cloud contamination, infrequent coverage at spatial resolutions suitable for watershed management). They are often empirical and thus vary across time and land cover types (Smith and Choudhury, 1991; Czajkowski et al., 2000) and are a function of local meteorological conditions such as wind speed, air temperature, and humidity (Nemani et al., 1993), and local relief (Gillies and Carlson, 1995).

Passive microwave sensing of surface soil moisture

Great progress has been made in mapping regional soil moisture 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 the 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 relationship between T_B and m_s varies with the 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 Njoku and Entekhabi, 1996). Simplified retrieval methods for the estimation of m_s from observations of microwave emissivity have been validated through ground-based and aircraft experiments (Schmugge, 1996). Results from these experiments have led to the development of microwave radiative transfer models that are designed to retrieve m_s from the microwave signal based on assumptions of scattering albedo, roughness, polarization response, and surface temperature (e.g., Owe et al., 2001; Oh et al., 1992). 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. 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, three satellite-based passive microwave sensors will be providing imagery this decade. The advanced microwave scanning radiometer (AMSR-E) was successfully deployed on the NASA Aqua platform in 2003, the soil moisture and ocean salinity (SMOS) mission is planned for launch by the European Space Agency (ESA) in 2007, and the NASA hydrospheric states (HYDROS) mission is planned for launch in 2009.

The AMSR-E sensor measures microwave emissivity in six frequencies along a sun-synchronous orbit with an equator crossing at 1330 hours (Njoku et al., 2003). One objective of AMSR-E is to produce soil moisture products and associated estimates of vegetation water content and surface temperature at a spatial resolution of approximately 56 km over a swath width of thousands of kilometres. The accuracy of the retrieved AMSR-E soil moisture will be limited by vegetation biomass since vegetation significantly affects microwave emission from the soil surface. Nonetheless, the expected accuracy of the AMSR-E soil moisture product (0.06 g cm^{-3}) will meet the requirements for watershed management, and the expected product delivery of 48 h and revisit of 2–4 days should be timely. Similarly, the SMOS sensor is designed to monitor soil moisture, vegetation biomass, and surface temperature, using microwave radiometry at low frequencies (L-band: 1.4 GHz) with dual polarization. Again the spatial resolution is coarse, estimated to be 37 km from a low polar orbit platform. The NASA HYDROS will be an integrated passive and active L-band system with spatial resolutions of soil moisture products ranging from 10 to 40 km and a revisit of 2–3 days (http://hydros.gsfc.nasa.gov/). Consequently, AMSR-E, SMOS, and HYDROS products will face significant challenges of mixed pixels over heterogeneous watersheds (Kerr, 2001).

Active microwave sensing of surface soil moisture

The only satellites that can currently meet the spatial resolution and coverage required for watershed management are active microwave sensors. 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. These pulses are then processed together to simulate a very long aperture capable of high surface resolution (Ulaby et al., 1996). Currently, 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 the Canadian C-band RADARSAT-1/2. These SAR systems can provide resolutions from 10 to 100 m over a swath width of 50–500 km, thus meeting most spatial requirements for watershed-scale applications (**Table 1**). As with passive microwave sensing, the magnitude of the SAR backscatter coefficient (σ^0) 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). A significant limitation of SAR for watershed-scale applications is that the sun-synchronous satellites can provide only weekly repeat coverage and even longer for the same orbital path (e.g., ERS-1 has a scheduled repeat pass every 35 days for the same orbital path).

Surface soil moisture estimation using SAR

There are numerous examples of the use of multiwavelength and multipolarization SAR data for soil moisture estimation (e.g., Dubois et al., 1995; Wever and Henkel, 1995). However, current satellite-based SAR sensors are configured with only a single wavelength (C- or L-bands) and, in some cases (ERS SAR), with a single incidence angle θ_i. Furthermore, RADARSAT and ERS SAR sensors offer only single polarization (either HH or VV). Consequently, this review will focus, though not exclusively, on approaches suitable for application with RADARSAT, ERS SAR, ERS ENVISAT ASAR, and the planned ALOS PALSAR sensors (**Table 3**).

Semiempirical approaches

The radar backscatter from a vegetated surface is composed of three contributions.

$$\sigma^0 = \tau^2\sigma_s^0 + \sigma_{\mathrm{dv}}^0 + \sigma_{\mathrm{int}}^0, \tag{1}$$

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

$$\sigma_s^0 = f(R, m_s) \tag{2}$$

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 owing to backscatter from the vegetation canopy, and thus $\sigma^0 \cong \sigma_s^0$. The second step is to determine the relation between σ_s^0 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

$$m_s = a + b\sigma_s^0, \tag{3}$$

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, Equation (3) is only valid for a given sensor, land use, and soil type, and for targets when τ^2, σ_{dv}^0, and σ_{int}^0 are known or negligible.

Quesney et al. (2000) resolved Equations (1)–(3) to derive surface 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, Quesney et al. selected sensitive targets where soil moisture retrieval was possible largely owing 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^0 and corresponding in situ measurements of m_s were determined for each class and applied to all sensitive targets in the SAR image. Quesney et al. concluded that the same relation between σ^0 and m_s could be used from November to August (except for the months of May and June) for wheat fields in an agricultural watershed in France.

Similarly, for a semiarid watershed in Arizona, Moran et al. (2000) utilized the difference between dry- and wet-season SAR σ^0 ($\Delta\sigma^0$) 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. (2004) improved upon this approach to minimize empiricism and used a quantitative form of $\Delta\sigma^0$ to map m_s for an entire watershed with RADARSAT for three dates in 2003 (**Figure 1**). In these studies, the effects of sparse vegetation were found to be negligible and could be ignored, supporting similar findings by Lin and Wood (1993), Chanzy et al. (1997), Demircan et al. (1993), Dobson et al. (1992), and Dubois et al. (1995). But for

Table 3. RADARSAT, ERS, ENVISAT, and JERS configurations.

	RADARSAT	ERS SAR	ERS ENVISAT ASAR	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
Repeat pass (days)	24	35	35	unknown

many other study sites, the vegetation has been reported to be too dense to monitor soil moisture with only a single-wavelength dataset (Wang et al., 1997; Wever and Henkel, 1995).

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^0 data were nearly insensitive to soil moisture because of 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.

Surface soil moisture (m_s) change detection

An approach that may have potential for operational application is the use of single-wavelength, multipass 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^0 between repeat passes results from the change in m_s. Thus, a multitemporal SAR dataset could be used to minimize the influence of R and V, and maximize the sensitivity of σ^0 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^0 measurements at two times (t_1 and t_2) over one location, where

$$\mathrm{NBMI} = \frac{\sigma^0_{t_1} + \sigma^0_{t_2}}{\sigma^0_{t_1} - \sigma^0_{t_2}} \tag{4}$$

(Shoshany et al., 2000). By normalizing the effects of R, soil type, and topography on SAR σ^0, 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^0 with changes in m_s over large areas. For example, Wickel et al. (2001) used 10 RADARSAT scenes over a 1-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^0 and m_s with a strong correlation of r^2 = 0.89.

Wagner and Scipal (2000) offered a variation of this approach that has been tested with some success in the Canadian prairies, the Iberian Peninsula, the Ukraine, and savanna and grasslands in western Africa. Based on a multiyear series of ERS scatterometer images with a spatial resolution of 50 km, a "knowledge base" about the backscatter behavior of each pixel was constructed. The behavior of σ^0 related to θ_i over

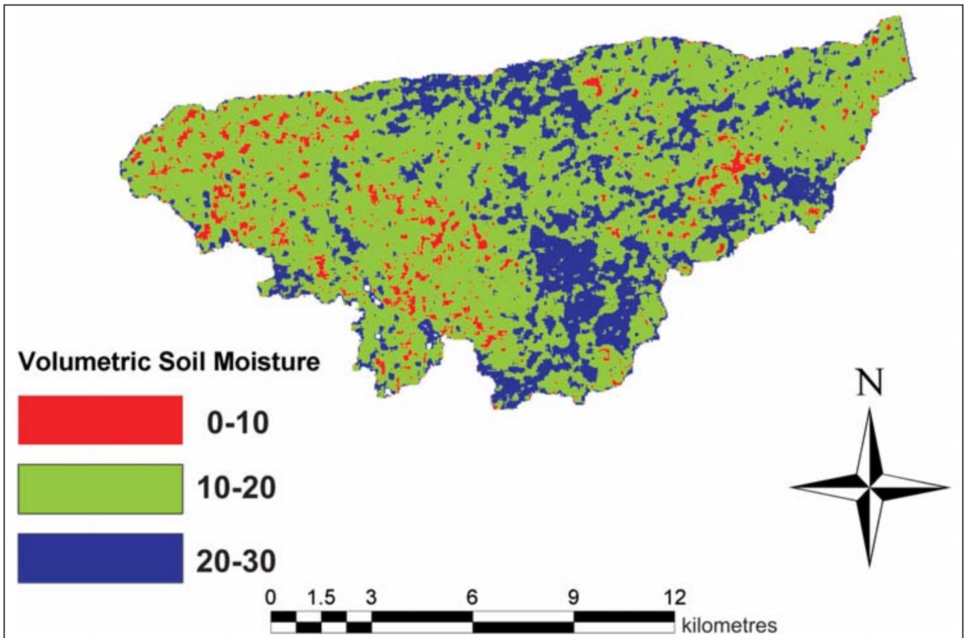

Figure 1. A surface soil moisture map of Walnut Gulch Experimental Watershed near Tucson, Arizona, derived from the time series differences in RADARSAT radar backscatter signals from wet and dry soils. Reproduced with permission from Thoma et al. (2004).

time was used to determine relative R and V, and to normalize σ^0 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

$$I_{m_s} = \frac{\sigma^0(40°, t) - \sigma^0_{\mathrm{dry}}(40°, t)}{\sigma^0_{\mathrm{wet}}(40°, t) - \sigma^0_{\mathrm{dry}}(40°, t)} \tag{5}$$

where $\sigma^0_{\mathrm{dry}}(40°, t)$ represents σ^0 from vegetated terrain under completely dry soil surface conditions and $\sigma^0_{\mathrm{wet}}(40°, t)$ represents σ^0 when the soil surface is saturated with water. The values $\sigma^0_{\mathrm{dry}}(40°, t)$ and $\sigma^0_{\mathrm{wet}}(40°, t)$ were derived from the lowest and highest values of $\sigma^0(40°, t)$ from 6 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 only a frequent-repeat, multiyear 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^0_{dry}, they were able to detect changes in m_s ranging from 0.05 to 0.20.

Such estimates of temporally and spatially continuous m_s have been used for the estimation of the spatial distribution of other critical soil properties, including surface and profile soil hydraulic conductivity (K_{sat}). Mattikalli et al. (1998) reported that a 2-day change in soil moisture derived from SAR imagery was related to surface K_{sat}, and with a hydrologic model and geographic information system (GIS), they were able to estimate profile K_{sat}. Furthermore, Mattikalli et al. found that it was possible to estimate the spatial distribution of soil texture from multiday, SAR-derived images of soil moisture. That is, soil moisture decreased at different magnitudes and rates that were related to soil texture.

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^0 and m_s has prompted a number of SAR data fusion studies. The majority of studies have addressed the complementarity (independent information) and interchangeability (similar information) of (1) active (SAR) microwave σ^0 and passive microwave T_B, and (2) SAR σ^0 and optical measurements, such as infrared radiative temperature (T_R) and surface spectral reflectance ($\rho\lambda$) in visible and near-infrared wavelengths.

As mentioned earlier, the greatest advantage of active over passive microwave sensing for watershed applications is the fine spatial resolution, where SAR resolution is tens of metres and passive microwave resolution is tens of kilometres. Similar passive and active microwave configurations appear to have similar sensitivities to soil moisture (see Chauhan et al., 1999) and near-similar sensitivities to roughness (see Du et al., 2000). Data fusion of passive and active microwave sensing has generally taken the form of using SAR σ^0 for determining fine-resolution vegetation and roughness parameters and then combining these with coarse-resolution passive microwave T_B for the estimation of regional soil moisture (e.g., Chauhan, 1997; Lakshmi et al., 2000; 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 recent studies, soil moisture maps at coarse resolutions have been downscaled to finer resolutions by incorporating information on the spatial structure of soil texture and vegetation water content (Bindlish and Barros, 2002; Kim and Barros, 2002a; 2002b). The basic conclusion was that the 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, SMOS, and HYDROS become available.

Microwave and optical remote sensing have been used separately for the estimation of surface properties, and both measurements have distinct advantages. Several studies have focused on the definition of the similarities between optical and SAR data. Basically, the longer λ SAR bands (λ > 6 cm) have been related to thermal T_R measurements through the physical relationship between surface evaporation and surface soil moisture content (e.g., Moran et al., 1997). For vegetated targets, shorter λ SAR bands (e.g., λ ~ 2 cm) have been related to optical vegetation indices (e.g., 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., Moran et al., 1997; Prevot et al., 1993). Other studies have taken advantage of both the differences between 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 dataset, 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 (Olioso et al., 1998; Taconet et al., 1996; and Dabrowska-Zielinska et al., 2001) and rangelands in Arizona (Wang et al., 2003).

SAR plus microwave scattering models

The continuing efforts to disentangle the relative influences of R, V, and m_s on SAR σ^0 have ultimately led to the use of physically based scattering models. These models generally predict σ^0 as a function of sensor configuration and surface conditions, and can thus be inverted to estimate m_s. Empirical, semiempirical, 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

(Wang et al., 1986; Oh et al., 1992; Dobson et al., 1985; Dubois et al., 1995).

To avoid this limitation, semiempirical 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 (σ^0) is represented by Equation (1), which is simplified to $\sigma^0 = \tau^2\sigma_s^0 + \sigma_{\mathrm{dv}}^0$ based on the assumption that σ_{int}^0 is negligible. The attenuation of the vegetation layer (τ^2) and direct backscatter from the vegetation layer (σ_{dv}^0) are determined empirically by

$$\tau^2 = \exp(-2BV\sec\theta) \tag{6}$$

$$\sigma_{\mathrm{dv}}^0 = AV\cos\theta(1-\tau^2) \tag{7}$$

$$\sigma_s^0 = C + Dm_s \tag{8}$$

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 microwave scattering 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 $R \ll \lambda$ (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 scattering 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^0. 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) and Baghdadi et al. (2002a) 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, but also that this approach was preferable to direct ground measurements owing 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 multitemporal data rather than multiangular data to determine an effective roughness parameter. Thus, multitemporal ERS-1 SAR σ^0 was used to invert the IEM model to retrieve m_s from bare soil with reasonable accuracy.

Despite these successes, there are numerous reports that IEM and other existing models do not provide consistently good agreement with the data from satellite-based radar sensors even with excellent in situ measurements of R (e.g., Leconte et al., 2004; Baghdadi et al., 2002b; Bryant et al., 2003). It has therefore been suggested that these models be calibrated to compensate for discrepancies and improve accuracy. For example, Baghdadi et al. (2004) proposed empirical relations between several IEM parameters that improved the IEM inversion to retrieve surface roughness and soil moisture values from radar images.

There have been numerous other 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 (Shi et al., 1997; Chen et al., 1995; van Oevelen and Hoekman, 1999). The results are a look-up table of IEM simulations that serve to directly relate SAR σ^0 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 (Equations (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 because of an increase in the penetration depth of the incident wave when the soil moisture was low (e.g., Weimann, 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 (Weimann, 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^0 with microwave scattering 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 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.

Modeling watershed soil moisture

Modeling m_p from the surface to 1 m or more over a watershed requires the solution of a form of the Richards' equation (as reviewed by Sposito, 1995), including representation of parameters and processes controlling the evolution of soil moisture such as infiltration, evapotranspiration, percolation, and drainage. Models for simulating these processes are generally called soil vegetation atmosphere transfer (SVAT), land surface models (LSM), or unsaturated zone models (for convenience, all will be referred to as SVAT models in this discussion). SVAT models have been developed for the distinct applications of weather and climate modeling, and hydrological, agricultural, watershed management, and soils modeling.

Examples of SVAT models developed for weather and climate modeling applications (all of which are 1-d vertical) include the biosphere-atmosphere transfer scheme (BATS) (Dickinson et al., 1986; 1993), the simple biosphere model (SiB1 and SiB2) (Sellers et al., 1986; 1996a; 1996b), and its successor the simplified simple biosphere model (SSiB) (Xue et al., 1991), the coupled atmosphere-plant soil model (CAPS) (Mahrt and Pan, 1984; Pan and Mahrt, 1987), and its successor NOAH (Chen et al., 1996; 1997), TOPMODEL-based land atmosphere land surface transfer scheme (TOPLATS) (Famiglietti and Wood, 1994a; 1994b; Peters-Lidard et al., 1997), soil-water-atmosphere-plant systems (SWAPS) (Ashby, 1999), and the variable infiltration capacity model (VIC) (Liang et al., 1994; 1996). Some SVAT models in this community do not solve the 1-d Richards' equation, but instead use a bulk (or bucket) representation of m_p, e.g., the simple SVAT (Boulet et al., 2000). Many models in this category have been involved in large international comparison projects, including the project for intercomparison of land-surface parameterization schemes (PILPS) (Henderson-Sellers et al., 1993; 1995), and the global soil wetness project (GSWP) (Dirmeyer et al., 1999). Excellent overviews of SVAT performance and behavior with respect to the estimation of m_p are given by Shao and Henderson-Sellers (1996) and Koster and Milly (1997).

NASA's collaborative land data assimilation systems (LDAS), including the North American NLDAS (Mitchell et al., 2004), global GLDAS (Rodell et al., 2004), and new land information system (LIS) (Peters-Lidard et al., 2004) have provided more recent soil moisture intercomparison opportunities from pseudo-operational systems that could serve as prototypes for watershed management applications. Results from an ensemble of SVAT models in NLDAS (including NOAH and VIC) suggest that simulated and observed total water storage at 17 sites in Illinois are highly correlated and that simulated values from the NOAH model compare well with the measured values (Schaake et al., 2004). Further, these results reinforce the earlier conclusions of the PILPS and GSWP studies that various SVAT models respond differently to the same input data owing to differences in physics and the meaning of parameters in a particular model.

Examples of models developed for hydrological, agricultural, watershed management, and soils modeling applications include the HYDRUS 1D and 2D models (Simunek et al., 1998; Simunek and van Genuchten, 1999), MIKE-SHE (Refsgaard and Storm, 1995; Christiaens and Feyen, 2002), fast all-seasons soil state model (FASST) (Albert et al., 2000), crop SVAT (Sharma et al., 1997), soil and water assessment tool (SWAT) (Srinivasan and Arnold, 1994; Arnold et al., 1998), and WASH123D model (Yeh et al., 1998). Although most of these models are based on the theory of soil moisture and heat transport and have been extensively tested with detailed observational data, they have generally had limited use for operational applications because of the great difficulties associated with the specification of parameters, initial and boundary conditions. A notable exception to this is the SWAT model, which has been integrated with a GIS interface for use in watershed management applications. Scanlon et al. (2002) provided a recent review of the abilities of seven different codes, including the HYDRUS 1D model, to predict the near-surface water balance in warm (Texas) and cold (Idaho) semiarid regions. Their results indicated that the predicted soil water profiles down to 3 m from most codes were similar and reasonably approximated measured water balance components. Simulation of infiltration-excess runoff was a problem for all codes, and differences in results (for those that solve Richards' equation) are attributed primarily to infiltration formulation and soil water retention formulation.

Profile soil moisture estimation by combining RS and SVAT models

Many investigators have demonstrated the feasibility of estimating soil moisture profiles by assimilating remote sensing data into SVAT models. Most examples have focused on passive microwave T_B in synthetic and data-based studies from local to global scales (Entekhabi et al., 1994; Houser et al., 1998; Calvet et al., 1998; Galantowicz et al., 1999; Calvet and Noilhan, 2000; Walker and Houser, 2001; Walker et al., 2001a; 2001b; Reichle et al., 2001a; 2002a; 2002b; Reichle and Koster, 2002; Crow and Wood, 2002a; 2002b; 2003; Margulis et al., 2002). Hoeben and Troch (2000) provided the first comparable study based on SAR. Other projects have used soil temperature assimilation for the estimation of surface energy balance components or soil wetness indices (Boni et al., 2001a; 2001b; Castelli et al., 1999; Lakshmi et al., 2000), while others have combined thermal imagery and spectral vegetation indices with a SVAT-type model to estimate soil moisture, including Bastiaanssen et al. (1997), Diak et al. (1995), and Gillies and Carlson (1995). Some of these approaches have been evaluated by Kustas et al. (2003) in a recent review of coupled modeling – remote sensing approaches for evaluating the spatial distribution of evapotranspiration.

Mathematical approaches to data assimilation range from simplistic weighting schemes to filtering and variational approaches, as reviewed by McLaughlin (1995; 2002) and van Loon and Troch (2001). One of the earliest examples of watershed-scale soil moisture estimation was presented by Houser et al. (1998), who applied five different suboptimal estimation algorithms, from simple to more complex using the SVAT model TOPLATS and 6 days of passive microwave-based m_s products. Houser et al. found that all methods, with the exception of direct insertion, significantly improved the estimation of m_s as compared to the TOPLATS simulations without data assimilation. They also found that Newtonian nudging produced the most desirable results in terms of the spatial and temporal propagation of information. As shown in **Figure 2**, Walker et al. (2001a) found that Kalman filter assimilation is superior to direct insertion for retrieving m_p from hourly m_s observations, with the Kalman filter taking 12 h compared with 8 days or more for direct insertion, depending on observation depth. The extended Kalman filter (EKF) has been applied by many investigators (e.g., Entekhabi et al., 1994; Galantowicz et al., 1999; Hoeben and Troch, 2000), although its application to watershed scales is somewhat difficult because of the high computational demand associated with the error covariance integration. An alternative approach, called the ensemble Kalman filter (EnKF) reduces the computational demand relative to the EKF by integrating an

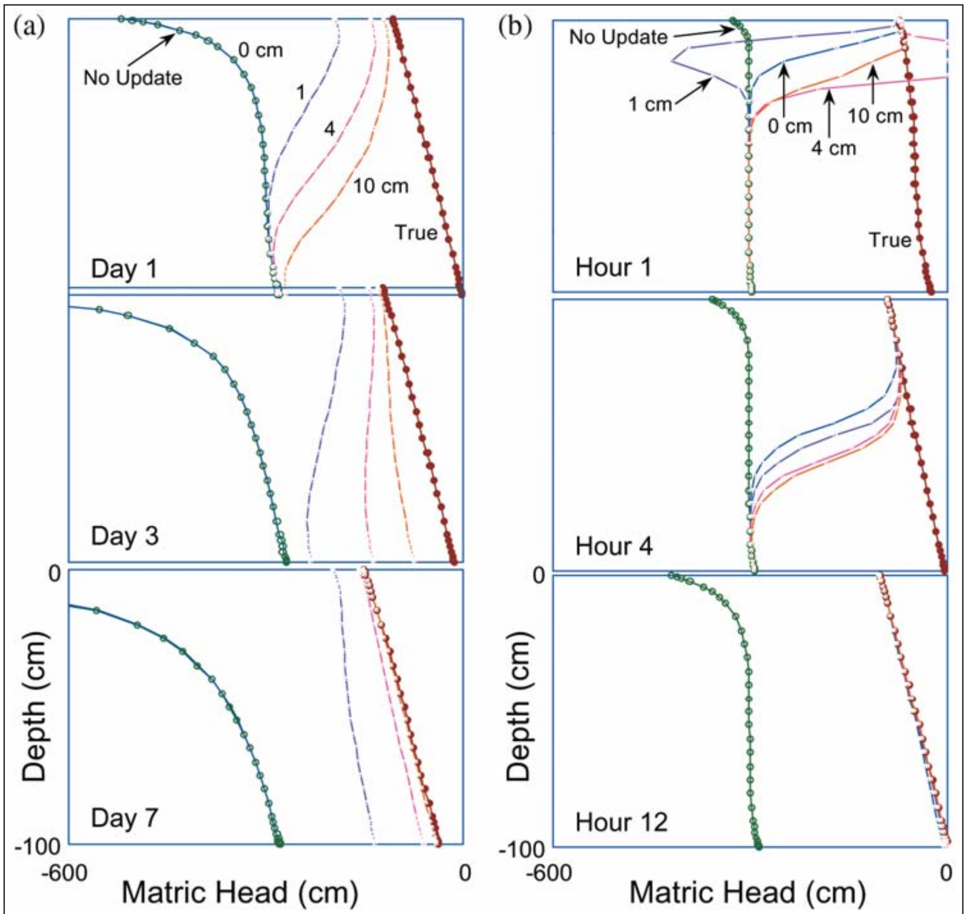

Figure 2. Intercomparison of approaches to map retrieval from hourly observations of m_s at different effective depths. (a) Hourly direct insertion of m_s observations into a SVAT model takes a week or more to retrieve the true m_p compared with (b) the Kalman filter approach, which takes less than 12 h. Curves with open circles represent modeled soil moisture profiles without assimilation; curves with closed circles represent the “true” soil moisture profiles. Dashed curves represent the modeled m_p with assimilation of m_s at various effective depths (0, 1, 4, and 10 cm). The deeper the effective depth of the observed m_s, the faster the profile reaches the true profile, although for the Kalman filter, all cases reach the true profile within 12 h. Reproduced with permission from Walker et al. (2001a).

ensemble of states from which the covariances are obtained at each update, thereby avoiding the need to linearize. Work by Reichle et al. (2002b) indicates that the EnKF approach can be marginally superior to the EKF for soil moisture data assimilation, owing to the EnKF's ability to represent nonadditive model errors with fewer members, as well to its flexibility in covariance modeling (including horizontal error correlations). However, the EnKF converges to the solution of a linear problem, and therefore does not fully represent the nonlinear soil physics in a SVAT model. The nonrecursive optimal estimation algorithm is often called the variational approach (e.g., Reichle et al., 2000; 2001a; 2001b). Variational approaches for modeling m_p at the watershed scale are generally not available, as they require the adjoint of the SVAT model, which is extremely difficult to derive.

In addition to the assimilation approach, it is important to note that the ability to retrieve m_p, given observations of m_s, is a strong function of the SVAT model physics and parameters, and the model-observation error specifications. For example, Houser et al. (1998) found that nudging and statistical interpolation resulted in more significant root zone moisture changes than statistical correction and direct insertion. Hoeben and Troch (2000) found that the initial error covariance matrix and the presence of off-diagonal elements in this matrix strongly control the magnitude and speed with which m_s information is propagated vertically. If the observation error is too high, then the limiting behavior of filter techniques is such that m_p will converge to the case where the model is run without data assimilation. Recently, Reichle and Koster (2003) compared 1D- and 3D-EnKFs and found that the 3D-EnKF produces more accurate soil moisture estimates than the 1D-EnKF, because of the 3D filter's ability to propagate observation information from observed to unobserved locations. Their study suggests that if measurements of m_s could be obtained in only part of a watershed, then a 3D-filter approach would be preferable to a 1D approach to obtain the best possible estimate of m_p everywhere in the watershed. However, their study also shows that the 3D versus 1D filter are essentially equivalent if observations of m_s are available throughout the watershed.

As discussed by Peters-Lidard et al. (2001), the ability of a model to produce a spatially distributed map of soil moisture over time is strongly related to the physical parameterizations of the model in addition to the parameters of that model. Errors caused by imperfect physics and parameters will adversely impact the ability of a model to estimate m_p even with perfect information about m_s. Therefore, a promising avenue of research is to explore simultaneously calibrating SVAT model parameters and assimilation of RS data. Earlier attempts at this approach have focused on adjusting soil moisture initial conditions and sensitive input parameters via standard calibration methodologies (e.g., Giacomelli et al., 1995; Nouvellon et al., 2001). There has been a large body of work devoted to automatic calibration of hydrologic model parameters, including the shuffled complex evolution algorithm (SCE-UA) (Duan et al., 1992) and the multi-objective complex evolution algorithm (MOCOM-UA) (Yapo et al., 1998). Recent work by Liu et al. (2004) has shown that optimal SVAT parameters estimated in uncoupled (i.e., with prescribed atmospheric meteorological inputs) versus coupled (i.e., with an interactive atmospheric meteorological model) differ substantially, particularly for vegetation-related parameters. However, their study did not consider m_s or m_p as calibration variables, so a future area of research would be to explore the coupled system behavior in the context of soil moisture profile estimation. A major contribution to the area of joint calibration–estimation is the work of Moradkhani et al. (2004), who have formulated a dual state-parameter estimation approach that unifies data assimilation and calibration using an EnKF approach described previously. Although this work is applied to the problem of streamflow forecasting, their approach represents an exciting future direction for soil moisture profile estimation.

Combining RS and SVAT modeling using data assimilation enables m_p estimation at watershed management scales by using RS data from a variety of methods outlined previously in this paper. The ability to retrieve the profile through the root zone is determined largely by the specifications of the error covariances in the data assimilation framework, and the errors in both the observations and the model must be sufficiently small for the combination approach to be successful.

Synthesis

Soil moisture distribution at the watershed scale is a highly nonlinear function of soil, topography, vegetation, land use, and weather. Despite this complexity, there are a multitude of opportunities for satellite-based estimation of soil moisture for critical watershed applications (see summary in **Tables 4** and **5**). The basic conclusion of this review is that currently orbiting sensors combined with available SVAT models could provide distributed, profile soil moisture information with known accuracy at the watershed scale. The most robust, adaptable system will likely be based primarily on SAR images. It may include optical, thermal, or passive microwave data for ancillary information, and it will require a radar backscatter model for determining m_s, a SVAT model for determining m_p, and ground information for validation. Ideally, such a system could provide distributed soil moisture data on a daily timestep, at a variety of depths with known accuracy, all-weather capability, and global applicability. Given that, there are particular opportunities for research, validation, and development to support a truly operational application for watershed management.

Research

The primary perturbing factors affecting the accuracy of SAR-derived m_s estimations are soil surface roughness and vegetation biomass. 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. Furthermore, vegetation biomass significantly influences surface reflectance, thermal emission, microwave emission, and radar backscatter from the soil

Table 4. Promising approaches using SAR and optical sensors for m_s estimation.

Approach	Examples
Multi-angle TIR Multidirectional T_R measurements now available from satellite; results for m_s estimation promising, but mixed	Chehbouni et al. (2001); François (2002)
TIR-vegetation index Both empirical and analytical approaches are used; promising site-specific results; many limitations related to site heterogeneity, meteorological conditions, and image processing	Bosworth et al. (1998); Gilles et al. (1997); Goward et al. (2002); Nemani et al. (1993); Sandholt et al. (2002)
Semiempirical SAR 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); Thoma et al. (2004)
SAR for m_s change detection Requires multiple identical 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^0 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^0	Bindlish and Barros (2002); Kim and Barros (2002a; 2002b); Chauhan (1997); Huang and Jin (1995); Lakshmi et al. (2000); Notarnicola and Posa (2001)
SAR data fusion – microwave and optical Based on complementarity (independent information) and interchangeability (similar information) of optical and SAR data; simplifies the inverse modeling problem for m_s estimation	Chanzy et al. (1995); Dabrowska-Zielinska 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, semiempirical, and theoretical models available; models are inverted to estimate m_s from σ^0; advantage — high accuracy; disadvantage — difficult model parameterization	Baghdadi et al. (2004); Colpitts (1998); Fung et al. (1996); Pasquariello et al. (1997); Tansey and Millington (2001); Verhoest et al. (2000); Weimann (1998)

surface. This review presents several approaches to derive roughness from satellite imagery and to minimize the effects of vegetation. Despite these attempts, there is no operational algorithm or model using existing spaceborne sensors to map roughness or determine the soil moisture of densely vegetated sites. These should be considered priority research areas.

Another area of research that could greatly increase the accuracy of estimated soil properties (i.e., both soil moisture and texture) is the normalization of differences in SAR scattering due to sensor configuration. The SAR backscatter signal from a given target is highly sensitive to the multitude of wavelengths, incidence angles, polarizations, resolutions and overpass times described in **Table 3**. This sensitivity has proven advantageous for studies based on the multidimensional information resulting from multi-λ, multi-θ_i, and (or) multipolarization data; however, variations in sensor configuration can be devastating to studies based on the assumption that a change in σ^0 is due exclusively to a change in surface condition. The most promising approach for this normalization is through further development of theoretical backscattering models.

There is great potential to determine subpixel variability of passive-derived soil moisture with the finer resolution active microwave data. This approach will likely receive more attention when the soil moisture products from AMSR-E, SMOS, and HYDROS become available.

Further research could have great impact on data assimilation of remote sensing information in SVAT models for the estimation of m_p at watershed scale. First, the computational demand of modeling soil moisture profiles at hillslope scales requires simplifications of the governing equations, as exemplified by the 1-d SVAT models discussed in this review. Second, the accuracy of m_p is affected by the complexity (e.g., weighting versus filtering) and dimensionality (e.g., 1D- versus 3D-EnKF) of the data assimilation approach. The third issue is the representation of errors in the model, including its parameters, observations, and the relationships between model and observation errors. A major opportunity in this area is to jointly optimize the parameters of the model in addition to assimilating the observations.

Validation

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 (e.g., 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 interdisciplinary field

Table 5. Promising approaches using models and remote sensing for m_p estimation.

Model plus remote sensing	Examples
Data assimilation: forward approaches Assimilation focuses on merging RS-derived estimates of m_s with m_s predicted by SVAT model	Margulis et al. (2002); Houser et al. (1998); Calvet et al. (1998); Calvet and Noilhan (2000); Walker and Houser (2001); Walker et al. (2001a; 2001b); Reichle et al. (2001a; 2002b); Reichle and Koster (2002; 2003); Crow and Wood (2002a; 2002b; 2003)
Data assimilation: inverse approaches Satellite observable quantities (e.g., σ^0, ρ_λ, T_B) assimilated and m_p derived as a byproduct	Entekhabi et al. (1994); Galantowicz et al. (1999); Hoeben and Troch (2000)
Model calibration SVAT model initial conditions and sensitive input parameters calibrated by minimizing difference between modeled m_s and m_s retrieved from RS measurements	Giacomelli et al. (1995); Nouvellon et al. (2001); Liu et al. (2004)
Dual state-parameter estimation SVAT model states and sensitive input parameters jointly estimated using data assimilation approach	Moradkhani et al. (2004)

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 km^2 (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; Jackson, 1999; O'Neill et al., 1998; Jackson and Hsu, 2001). Microwave images were acquired with aircraft- and satellite-based systems, as well as with the Priroda sensors on the Mir Space Station. Information regarding these remote sensing soil moisture experiments including data, images, and reports is 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.

The US has several soil moisture networks currently available, including the USDA–NRCS Soil Climate Analysis Network (SCAN) (http://www.wcc.nrcs.usda.gov/scan/), the DOE Atmospheric Radiation Measurement (ARM) – Cloud and Radiation Testbed (CART) facility in Oklahoma and Kansas (http://www.arm.gov/docs/sites/sgp/sgp.html), the Illinois State Water Survey soil moisture network (Hollinger and Isard, 1994), the Oklahoma Mesonet (http://www.mesonet. ou.edu/), and the High Plains Regional Climate Center network in Nebraska (http://hprcc.unl.edu/soilm/home.html). Recent satellite soil moisture campaigns, such as the soil moisture experiments (SMEX 2002, 2003, 2004) associated with AMSR-E validation, have provided a variety of gravimetric and in situ (Vitel) networks at several USDA/ARS watersheds (http://www.nsidc.org/data/amsr_validation/soil_moisture/). Currently, there is no coordinated global soil moisture network, but the Global Soil Moisture Data Bank at Rutgers University (Robock et al., 2000; http://climate.envsci.rutgers.edu/soil_moisture/) is gathering and distributing worldwide soil moisture data. The design of in situ networks to validate satellite-based estimates of soil moisture is problematic, because many authors have shown that soil moisture varies over multiple scales (e.g., Peters-Lidard et al., 2001). Moreover, recent work by Krajewski et al. (2003) suggests that rain gauge networks should be designed or augmented to include a cluster of two or more stations to characterize small-scale (<5 km^2) variability in rainfall. Given that soil moisture variability results from the superposition of rainfall variability and soil variability, soil moisture networks should similarly be designed or augmented to include a cluster of more collocated stations.

Development

The most promising approaches described in this review are based on multiple, single-wavelength, multipass SAR images for m_s estimation. It should be recognized and emphasized that these will not be reasonable at the watershed scale until the price of SAR imagery decreases from current levels.

On the other hand, three passive microwave satellite systems are now in development 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, would 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 (**Table 1**), the technology development and demonstration will certainly benefit the science of soil moisture mapping at all scales.

Once all the pieces are in place, a primary obstacle to operational application will be the sheer technological complexity involved in the implementation of a remote sensing/backscatter model/SVAT system by hydrologists, geospatial analysts, and watershed managers. This could be accomplished by a commercial venture or government space agency dedicated to providing information of the resolution, coverage, and frequency required by watershed managers, though no such operation currently exists. If decentralized, a given watershed manager would need to employ computer-savvy personnel who could make the high-technology, high-science components work smoothly with minimal technical support. This is not currently the profile of most watershed management units.

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References

Albert, M., Koening, G., and Mason, G. 2000. Development of a fast all-seasons model for the state of the ground. In *Proceedings of the 2000 Winter Simulation Conference*, 10–13 December 2000, Orlando, Fla. Edited by J.A. Joines, R.R. Barton, K. Kang, and P.A. Fishwick. IEEE, Piscataway, N.J. pp. 1010–1019.

Archer, F., Manu, A., Laymon, C.A., Senwo, Z.N., and Coleman, T.L. 1999. Soil moisture variability on the landscape as a function of land use: implications for remote sensing of surface soil moisture. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '99*, 28 June – 2 July 1999, Hamburg, Germany. IEEE, Piscataway, N.J. pp. 1102–1104.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., and Williams, J.R. 1998. Large area hydrologic modeling and assessment: Part I. Model development. *Journal of the American Water Resources Association*, Vol. 34, No. 1, pp. 73–89.

Ashby, M. 1999. Modelling the water and energy balances of Amazonian rainforest and pasture using Anglo-Brazilian Amazonian climate observation study data. *Agricultural and Forest Meteorology*, Vol. 94, pp. 79–101.

Attema, E., and Ulaby, F. 1978. Vegetation modeled as a water cloud. *Radio Science*, Vol. 13, pp. 357–364.

Baghdadi, N., Gaultier, S., and King, C. 2002a. Retrieving surface roughness and soil moisture from synthetic aperture radar (SAR) data using neural networks. *Canadian Journal of Remote Sensing*, Vol. 28, pp. 701–711.

Baghdadi, N., King, C., Chanzy, A., and Wingneron, J.P. 2002b. An empirical calibration of IEM model based on SAR data and measurements of soil moisture and surface roughness over bare soils. *International Journal of Remote Sensing*, Vol. 23, pp. 4325–4340.

Baghdadi, N., Gherboudj, I., Zribi, M., Sahebi, M., King, C., and Bonn, F. 2004. Semi-empirical calibration of the IEM backscattering model using radar images and moisture and roughness field measurements. *International Journal of Remote Sensing*, Vol. 25, No. 18, pp. 3593–3623.

Bastiaanssen, W.G.M., Pelgrum, H., Droogers, P., de Bruin, H.A.R., and Menenti, M. 1997. Area-average estimates of evaporation, wetness indicators and top soil moisture during two golden days in EFEDA. *Agricultural and Forest Meteorology*, Vol. 87, pp. 119–137.

Beldring, S., Gottschalk, L.,Seibert, J., and Tallaksen, L.M. 1999. Distribution of soil moisture and groundwater levels at patch and catchment scales. *Agricultural and Forest Meteorology*, Vol. 98–99, pp. 305–324.

Ben-Dor, E., Patkin, K., Banin, A., and Kernieli, A. 2002. Mapping of several soil properties using DAIS-7915 hyperspectral scanner data – a case study over clayey soils in Israel. *International Journal of Remote Sensing*, Vol. 23, No. 6, pp. 1043–1062,

Bindlish, R., and Barros, A.P. 2001. Parameterization of vegetation backscatter in radar-based soil moisture estimation. *Remote Sensing of Environment*, Vol. 76, pp. 130–137.

Bindlish, R., and Barros, A.P. 2002. Subpixel variability of remotely sensed soil moisture: an inter-comparison study of SAR and ESTAR. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 40, pp. 326–337.

Boisvert, J.B., Gwyn, Q.H.J., Chanzy, A., Major, D.J., Brisco, B., and Brown, R.J. 1997. Effect of surface soil moisture gradients on modeling radar backscattering from bare fields. *International Journal of Remote Sensing*, Vol. 18, pp. 153–170.

Boni, G., Castelli, F., and Entekhabi, D. 2001a. Sampling strategies and assimilation of ground temperature for the estimation of surface energy balance components. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 39, pp. 165–172.

Boni, G., Entekhabi, D., and Castelli, F. 2001b. Land data assimilation with satellite measurements for the estimation of surface energy balance components and surface control on evaporation. *Water Resources Research*, Vol. 37, pp. 1713–1722,

Borgeaud, M., and Floury, N. 2000. On the soil moisture retrieval of bare soils with ERS SAR data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS '00*, 24–28 July 2000, Honolulu, Hawaii. IEEE, New York. pp. 1687–1689.

Borgeaud, M., and Saich, P. 1999. Status of the retrieval of bio- and geo-physical parameters from SAR data for land applications. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '99*, 28 June – 2 July 1999, Hamburg, Germany. IEEE, Piscataway, N.J. pp. 1901–1903.

Bosworth, J., Koshimizu, T., and Acton, S.T. 1998. Automated segmentation of surface soil moisture from Landsat TM data. In *IEEE Southwest Symposium on Image Analysis and Interpretation*, 5–7 April 1998, Tucson, Ariz. IEEE, Piscataway, N.J. pp. 70–74.

Boulet, G., Chehbouni, A., Braud, I., Vauclin, M., Haverkamp, R., and Zammit, C. 2000. A simple water and energy balance model designed for regionalization and remote sensing data utilization. *Agricultural and Forest Meteorology*, Vol. 105, pp. 117–132.

Bryant, R., Thoma, D., Moran, M.S., Holifield, C.D., Goodrich, D.C., Keefer, T., Paige, G., Williams, D., and Skirvin, S. 2003. Evaluation of hyperspectral, infrared temperature and radar measurements for monitoring surface soil moisture. In *Proceedings of the First Interagency Conference on Research in the Watersheds*, 27–30 October 2003, Benson, Ariz. USDA-ARS, Beltsville, Md. pp. 528–533.

Calvet, J.-C., and Noilhan, J. 2000. From near-surface to root-zone soil moisture using year-round data. *Journal of Hydrometeorology*, Vol. 1, pp. 393–411.

Calvet, J.-C., Noilhan, J., and Bessemoulin, P. 1998. Retrieving the root-zone soil moisture from surface soil moisture or temperature estimates: A feasibility study based on field measurements. *Journal of Applied Meteorology*, Vol. 37, No. 4, pp. 371–386.

Carlson, T.N., Gillies, R.R., and Schmugge, T.J. 1995. An interpretation of methodologies for indirect measurement of soil water content. *Agricultural and Forest Meteorology*, Vol. 77, pp. 191–205,

Castelli, F., Entekhabi, D., and Caporali, E. 1999. Estimation of surface heat flux and an index of soil moisture using adjoint-state surface energy balance. *Water Resources Research*, Vol. 35, No. 10, pp. 3115–3125.

Chanzy, A., Bruckler, L., and Perrier, A. 1995. Soil evaporation monitoring: a possible synergism of microwave and infrared remote sensing. *Journal of Hydrology*, Vol. 165, pp. 235–259.

Chanzy, A., Kerr, Y., Wigneron, J.P., and Calvet, J.C. 1997. Soil moisture estimation under sparse vegetation using microwave radiometry at C-band. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '97*, 3–8 August 1997, Singapore. IEEE, Piscataway, N.J. pp. 1090–1092.

Chauhan, N.S. 1997. Soil moisture estimation under a vegetation cover: combined active and passive microwave remote sensing approach. *International Journal of Remote Sensing*, Vol. 18, pp. 1079–1097.

Chauhan, N., Le Vine, D., and Lang, R. 1999. Passive and active microwave remote sensing of soil moisture under a forest canopy. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '99*, 28 June – 2 July 1999, Hamburg, Germany. IEEE, Piscataway, N.J. pp. 1914–1916.

Chehbouni, A., Nouvellon, Y., Kerr, Y.H., Moran, M.S., Watts, C., Prevot, L., Goodrich, D.C., and Rambal, S. 2001. Directional effect on radiative surface temperature measurements over a semi-arid grassland site. *Remote Sensing of Environment*, Vol. 76, pp. 360–372.

Chen, K.S., Yen, S.K., and Huang, W.P. 1995. A simple model for retrieving bare soil moisture from radar scattering coefficients. *Remote Sensing of Environment*, Vol. 54, pp. 121–126.

Chen, F., Mitchell, K., Schaake, J., Xue, Y., Pan, H.-L., Koren, V., Duan, Q.Y., Ek, M., and Betts, A. 1996. Modeling of Land-Surface Evaporation by Four Schemes and Comparison with FIFE Observations. *Journal of Geophysical Research*, Vol. 101, pp. 7251–7268.

Chen, F., Janjic, Z., and Mitchell, K. 1997. Parameterizations in the new land-surface scheme of the NCEP mesoscale Eta model. *Bound-Layer Meteorology*, Vol. 85, pp. 391–421.

Christiaens, K., and Feyen, J. 2002. Use of sensitivity and uncertainty measures in distributed hydrological modeling with an application to the MIKE SHE model. *Water Resources Research*, Vol. 38, No. 9, pp. 1–15.

Colpitts, B.G. 1998. The integral equation model and surface roughness signatures in soil moisture and tillage type determination. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 36, pp. 833–837.

Committee on Watershed Management. 1999. Spatial and temporal scales for watersheds. In *New Strategies for America's Watersheds*. Commission on Geosciences, Environment, and Resources, National Research Council. National Academic Press, Washington, D.C. pp. 37–55.

Crow, W.T., and Wood, E.F. 2002a Impact of soil moisture aggregation on surface energy flux prediction during SGP '97. *Geophysical Research Letters*, Vol. 29, No. 1, pp. 1008.

Crow, W.T., and Wood, E.F. 2002b The value of coarse-scale soil moisture observations for regional surface energy balance modeling. *Journal of Hydrometeorology*, Vol. 3 No. 4, pp. 467–482.

Crow, W.T., and Wood, E.F. 2003. The assimilation of remotely sensed soil brightness temperature imagery into a land surface model using ensemble Kalman filtering: a case study based on ESTAR measurements during SGP97. *Advances in Water Resources*, Vol. 26, No. 2, pp. 137–149.

Czajkowski, K., Goward, S.N., Stadler, S.J., and Waltz, A. 2000. Thermal remote sensing of near surface environmental variables: application over the Oklahoma Mesonet. *Professional Geographer*, Vol. 52, pp. 345–357.

Dabrowska-Zielinska, K., Inoue, Y., Gruszczynska, M., Kowalik, W., and Stankiewicz, K. 2001. Various approaches for soil moisture estimates using remote sensing. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS '01*, 9–13 July 2001, Sydney, Australia. IEEE Inc., Piscataway, N.J. pp. 261–263.

Demircan, A., Rombach, M., and Mauser, W. 1993. Extraction of soil moisture from multitemporal ERS-1 SLC data of the Freiburg test site. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '93*, 18–21 August 1993, Tokyo, Japan. Vol. 4, IEEE, Piscataway, N.J. pp. 1794–1796.

Diak, G.R., Rabin, R.M., Gallo, K.P., and Neale, C.M. 1995. Regional-scale comparisons of vegetation and soil wetness with surface energy budget properties from satellite and in situ observations. *Remote Sensing Reviews*, Vol. 12, pp. 94–128.

Dickinson, R.E., Henderson-Sellers, A., Kennedy, P.J., and Wilson, M.F. 1986. *Biosphere Atmosphere Transfer Scheme (BATS) for the NCAR Community Climate Model.* National Center for Atmospheric Research, Boulder, Colo. 69 pp.

Dickinson, R.E., Henderson-Sellers, A., and Kennedy, P.J. 1993. *Biosphere Atmosphere Transfer Scheme (BATS) Version 1e as Coupled to the NCAR Community Climate Model*. National Center for Atmospheric Research, Boulder, Colo. 72 pp.

Dirmeyer, P.A., Dolman, A.J., and Sato, N. 1999. The Global Soil Wetness Project: a pilot project for global land surface modeling and validation. *Bulletin of the American Meteorological Society*, Vol. 80, pp. 851–878.

Dobson, M.C., Ulaby, F.T., Hallikainen, M.T., and El-Rayes, M.S. 1985. Microwave dielectric behavior of wet soil: II. Dielectric mixing models. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 23, pp. 35–46.

Dobson, M.C., Pierce, L., Arabandi, K., Ulaby, F.T., and Sharik, T. 1992. Preliminary analysis of ERS-1 SAR for forest ecosystem studies. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 30, pp. 203–211.

Du, Y., Ulaby, F.T., and Dobson, M.C. 2000. Sensitivity to soil moisture by active and passive microwave sensors. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 38, pp. 105–114.

Duan, Q.Y., Gupta, V.K., and Sorooshian, S. 1992. Effective and efficient global optimization for conceptual rainfall-runoff models. *Water Resources Research*, Vol. 28, No. 4, pp. 1015–1031.

Dubois, P.C., van Zyl, J., and Engman, E.T. 1995. Measuring soil moisture with imaging radars. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 33, pp. 915–926.

Dupigny-Giroux, L., and Lewis, J.E. 1999. A moisture index for surface characterization over a semiarid area. *Photogrammetric Engineering & Remote Sensing*, Vol. 65, pp. 937–946.

Engman, E.T. 1994. The potential of SAR in hydrology. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '94*, 8–12 August 1994, Pasadena, Calif. IEEE, Piscataway, N.J. pp. 283–285.

Engman, E.T., and Chauhan, N. 1995. Status of microwave soil moisture measurements with remote sensing. *Remote Sensing of Environment*, Vol. 51, pp. 189–198.

Entekhabi, D., Nakamura, H., and Njoku, E.G. 1994. Solving the inverse problem for soil moisture and temperature profiles by the sequential assimilation of multifrequency remotely sensed observations. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 32, pp. 438–448.

Famiglietti, J.S., and Wood, E.F. 1994a. Multiscale modeling of spatially variable water and energy balance processes. Water *Resources Research*, Vol. 30, No. 11, pp. 3079–3093.

Famiglietti, J.S., and Wood, E.F. 1994b. Application of Multiscale water and energy balance models on a tallgrass prairie. *Water Resources Research*, Vol. 30, No. 11, pp. 3061–3078.

François, C. 2002. The potential of directional radiometric temperatures for monitoring soil and leaf temperature and soil moisture status. *Remote Sensing of Environment*, Vol. 80, pp. 122–133.

Friedl, M.A., and Davis, F.W. 1994. Sources of variation in radiometric surface temperature over a tallgrass prairie. *Remote Sensing of Environment*, Vol. 48, pp. 1–17.

Fung, A.K., and Chen, K.S. 1992. Dependence of the surface backscattering coefficients on roughness, frequency and polarization states. *International Journal of Remote Sensing*, Vol. 13, pp. 1663–1680.

Fung, A.K., Li, Z., and Chen, K.S. 1992. Backscattering from a randomly rough dielectric surface. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 30, pp. 356–369.

Fung, A.K., Dawson, M.S., Chen, K.S., Hsu, A.Y., Engman, S.T., O'Neill, P.O., and Wang, J. 1996. A modified IEM model for scattering from soil surfaces with application to soil moisture sensing. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '96*, 27–31 May 1996, Lincoln, Nebr. IEEE, Piscataway, N.J. pp. 1297–1299.

Galantowicz, J.F., Entekhabi, D., and Njoku, E.G. 1999. Tests of sequential data assimilation for retrieving profile soil moisture and temperature from observed L-band radiobrightness. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 37, No. 4, pp. 1860–1870.

Giacomelli, A., Bacchiega, U., Troch, P.A., and Mancini, M. 1995. Evaluation of surface soil moisture distribution by means of SAR remote sensing techniques and conceptual hydrological modelling. *Journal of Hydrology*, Vol. 166, pp. 445–459.

Gillies, R.R., and Carlson, T.N. 1995. Thermal remote sensing of surface soil water content with partial vegetation cover for incorporation into climate models. *Journal of Applied Meteorology*, Vol. 34, pp. 745–756.

Gillies, R.R., Carlson, T.N., Cui, J., Kustas, W.P., and Humes, K.P. 1997. Verification of the triangle method for obtaining surface soil water content and energy fluxes from remote measurements of Normalized Difference Vegetation Index (NDVI) and surface radiant temperature. *International Journal of Remote Sensing*, Vol. 18, pp. 3145–3166.

Goward, S.N., Xue, Y., and Czajkowski, K.P. 2002. Evaluating land surface moisture conditions from the remotely sensed temperature/vegetation index measurements: an exploration with the simplified simple biosphere model. *Remote Sensing of Environment*, Vol. 79, pp. 225–242.

Henderson-Sellers, A.,Yang, Z.-L., and Dickinson, R.E. 1993. The project for intercomparison of land-surface parameterization schemes. *Bulletin of the American Meteorological Society*, Vol. 74, pp. 1335–1349.

Henderson-Sellers, A., Pitman, A.J., Love, P.K., Irannejad, P., and Chen, T.H. 1995. The project for intercomparison of land surface parameterization schemes PILPS: Phases 2 and 3. *Bulletin of the American Meteorological Society*, Vol. 76, pp. 489–503.

Herold, M., Shi, J., and Schmullius, C.C. 2001. Multi-parameter airborne SAR remote sensing of soil moisture in agricultural areas. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '01*, 9–13 July 2001, Sydney, Australia. IEEE Inc., Piscataway, N.J. pp. 2103–2105.

Hoeben, R., and Troch, P.A. 2000. Assimilation of active microwave observation data for soil moisture profile estimation. *Water Resources Research*, Vol. 36, No. 10, pp. 2805–2920.

Hollinger, S.E., and Isard, S.A. 1994. A soil moisture climatology of Illinois. *Journal of Climate*, Vol. 7, pp. 822–833.

Houser, P.R., Shuttleworth, W.J., Famiglietti, J.S., Gupta, H.V., Syed, K.H., and Goodrich, D.C. 1998. Integration of soil moisture remote sensing and hydrologic modeling using data assimilation. *Water Resources Research*, Vol. 34, No. 12, pp. 3405–3420.

Huang, X., and Jin, Y.-Q. 1995. A simple method to estimate the soil wetness and surface roughness by using active/passive microwave data. *Remote Sensing of Environment*, Vol. 53, pp. 212–214.

Jackson, T.J. 1999. Remote sensing of soil moisture in the southern great plains hydrology experiment. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '99*, 28 June – 2 July 1999, Hamburg, Germany. IEEE, Piscataway, N.J. pp. 1158–1160.

Jackson, T.J. and Hsu, A.Y. 2001. Soil moisture and TRMM microwave imager relationships in the Southern Great Plains 1999 (SGP99) experiment. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 39, pp. 1632–1642.

Jackson, T., Gasiewski, A., Oldak, A., Klein, M., Njoku, E., Yevgrafov, A., Christiani, S., and Bindlish, R. 2002a. Soil moisture retrieval using the C-band polarimetric scanning radiometer during the Southern Great Plains 1999 experiment. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 40, pp. 2151–2161.

Jackson, T.J., Hsu, A.Y., Shutko, A.M., Tishchenko, Y., Petrenko, B., Kutuza, B., and Armand, N. 2002b. Priroda microwave radiometer observations in the SGP97 hydrology experiment. *International Journal of Remote Sensing*, Vol. 23, pp. 231–248.

Jackson, T.J., Le Vine, D.M., Swift, C.T., Schmugge, T.J., and Schiebe, F.R. 1995. Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita '92. *Remote Sensing of Environment*, Vol. 53, pp. 27–37.

Kerr, Y.H. 2001. The objectives and rationale of the soil moisture and ocean salinity (SMOS) mission. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '01*, 9–13 July 2001, Sydney, Australia. IEEE, Piscataway, N.J. pp. 1004–1006.

Kim, G., and Barros, A.P. 2002a. Space-time characterization of soil moisture from passive microwave remotely sensed imagery and ancillary data. *Remote Sensing of Environment*, Vol. 81, pp. 393–403.

Kim, G., and Barros, A.P. 2002b. Downscaling of remotely sensed soil moisture with a modified fractal interpolation method using contraction mapping and ancillary data. *Remote Sensing of Environment,* Vol. 83, pp. 400–413.

Koster, R.D., and Milly, P.C.D. 1997. The interplay between transpiration and runoff formulations in land surface schemes used with atmospheric models. *Journal of Climate*, Vol. 10, pp. 1578–1591.

Kothari, R., and Islam, S. 1999. Spatial characterization of remotely sensed soil moisture data using self organizing feature maps. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 37, pp. 1162–1165.

Krajewski,W.F., Ciach,G.J., and Habib, E. 2003. An analysis of small-scale rainfall variability in different climatic regimes. *Hydrological Sciences Journal*, Vol. 48, No. 2, pp. 151–162.

Kustas, W.P., Moran, M.S., and Norman, J.M. 2003. Evaluating the spatial distribution of evaporation. Chap. 26. In *Handbook of Weather, Climate and Water: Atmospheric Chemistry, Hydrology and Societal Impacts*. Edited by T.D. Potter and B.R. Colman. John Wiley & Sons, Inc., Hoboken, N.J. pp. 461–492.

Lakshmi, V., Bolten, J., Njoku, E., and Yueh, S. 2000. Monitoring of large scale soil moisture from airborne PALS sensor observations during SGP99. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS '00*, 24–28 July 2000, Honolulu, Hawaii. IEEE, New York. pp. 1069–1071.

Lambin, E.F., and Ehrlich, D. 1996. The surface temperature -vegetation index space for land cover and land-cover change analysis. *International Journal of Remote Sensing*, Vol. 17, pp. 463–487.

Leconte, R., Brissette, F., Galarneau, M., and Rousselle, J. 2004. Mapping near-surface soil moisture with RADARSAT-1 synthetic aperture radar data. *Water Resources Research*, Vol. 40, pp. 1–13.

Le Vine, D.M., Jackson, T., Kao, M., Griffis, A., and Swift, C.T. 1994. Status of ESTAR validation: results from Washita-92. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '94*, 8–12 August 1994, Pasadena, Calif. IEEE, Piscataway, N.J. pp. 1320–1322.

Liang, X., Lettenmaier, D.P., Wood, E.F., and Burges, S.J. 1994. A simple hydrologically based model of land surface water and energy fluxes for GSMs. *Journal of Geophysical Research*, Vol. 99, No. D7, pp. 14 415 – 14 428.

Liang, X., Wood, E.F., and Lettenmaier, D.P. 1996. Surface soil moisture parameterization of the VIC-2L model: Evaluation and modifications. *Global and Planetary Change*, Vol. 13, pp. 195–206.

Lin, D.-S., and Wood, E.F. 1993. Behavior of AirSAR signals during MAC-Europe '91. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '93*, 18–21 August 1993, Tokyo, Japan. Vol. 4. IEEE, Piscataway, N.J. pp. 1800–1802.

Liu, W., Baret, F., Gu, X., Tong, Q., Zheng, L., and Zhang, B. 2002. Relating soil surface moisture to reflectance. *Remote Sensing of Environment*, Vol. 81, pp. 238–246.

Liu, Y., Gupta, H.V., Sorooshian, S., Bastidas, L.A., and Shuttleworth, W.J. 2004. Constraining land surface and atmospheric parameters of a locally coupled model using observational data. *Journal of Hydrometeorology.* In preparation.

Lu, Z., and Meyer, D.J. 2002. Study of high SAR backscattering caused by an increase of soil moisture over a sparsely vegetated area: implications for characteristics of backscatter. *International Journal of Remote Sensing*, Vol. 23, pp. 1063–1074.

Mahrt, L., and Pan, H.L. 1984. A two-layer model of soil hydrology. *Boundary-Layer Meteorology*, Vol. 29, pp. 1–20.

Mattikalli, N.M., Engman, E.T., Ahuja, L.R., and Jackson, T.J. 1998. Microwave remote sensing of soil moisture for estimation of profile soil property. *International Journal of Remote Sensing*, Vol. 19, pp. 1751–1767.

Margulis, S., McLaughlin, D., Entekhabi, D., and Dunne, S. 2002. Land data assimilation and soil moisture estimation using measurements from the Southern Great Plains 1997 field experiment. *Water Resources Research*, Vol. 38, No. 12, pp. 1–18.

McLaughlin, D. 1995. Recent developments in hydrologic data assimilation. *Reviews of Geophysics*, Vol. 33, pp. 977–984.

McLaughlin, D. 2002. An integrated approach to hydrologic data assimilation: interpolation, smoothing, and filtering. *Advances in Water Resources*, Vol. 25, No. 8–12, pp. 1275–1286.

Mitchell, K.E., Lohmann, D., Houser, P.R., Wood, E.F., Schaake, J.C., Robock, A., et al. 2004. The multi-institution North American Land Data Assimilation System (NLDAS): utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. *Journal of Geophysical Research*, Vol. 109, No. D07S90, pp. 1–32.

Moradkhani, H., Sorooshian, S., Gupta, H.V., and Houser, P.R. 2004. Dual state-parameter estimation of hydrological models using ensemble Kalman filter. *Advances in Water Resources*. In preparation.

Moran, M.S., Vidal, A., Troufleau, D., Inoue, Y., Qi, J., Clarke, T.R., Pinter, P.J. Jr., Mitchell, T., and Neale, C.M.U. 1997. Combining multi-frequency microwave and optical data for farm management. *Remote Sensing of Environment*, Vol. 61, pp. 96–109.

Moran, M.S., Vidal, A., Troufleau, D., Inoue, Y., and Mitchell, T. 1998. Ku- and C-band SAR for discriminating agricultural crop and soil conditions. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 36, pp. 265–272.

Moran, M.S., Hymer, D.C., Qi, J., and Sano, E.E. 2000. Soil moisture evaluation using multi-temporal synthetic aperture radar SAR in semiarid rangeland. *Agricultural and Forest Meteorology*, Vol. 105, pp. 69–80.

Muller, E., and Décamps, H. 2000. Modeling soil moisture-reflectance. *Remote Sensing of Environment*, Vol. 76, pp. 173–180.

Musick, H.B., and Pelletier, R.E. 1988. Response to soil moisture of spectral indexes derived from bidirectional reflectance in thematic mapper wavebands. *Remote Sensing of Environment*, Vol. 25, pp. 167–184.

Nemani, R., Pierce, L., Running, S.N., and Goward, S.N. 1993. Developing satellite-derived estimates of surface moisture status. *Journal of Applied Meteorology*, Vol. 32, pp. 548–557.

Njoku, E.G., and Entekhabi, D. 1996. Passive microwave remote sensing of soil moisture. *Journal of Hydrology*, Vol. 184, pp. 101–129.

Njoku, E., Jackson, E., Lakshmi, V., Chan, T., and Nghiem, S. 2003. Soil moisture retrieval from AMSR-E. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 41, pp. 215–229.

Notarnicola, C., and Posa, F. 2001. Bayesian fusion of active and passive microwave data for estimating bare soil water content. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS '01*, 9–13 July 2001, Sydney, Australia. IEEE, Piscataway, N.J. pp. 1167–1169.

Nouvellon, Y., Moran, M.S., Lo Seen, D., Bryant, R.B., Ni, W., Begue, A., Chehbouni, A.G., Emmerich, W.E., Heilman, P., and Qi, J. 2001. Coupling a grassland ecosystem model with Landsat imagery for a 10-year simulation of carbon and water budgets. *Remote Sensing of Environment*, Vol. 78, pp. 131–149.

Oh, Y., 2000. Retrieval of the effective soil moisture contents as a ground truth from natural soil surfaces. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '00*, 24–28 July 2000, Honolulu, Hawaii. IEEE, New York. pp. 1702–1704.

Oh, Y., Sarabandi, F.T., and Ulaby, F. 1992. An empirical model and an inversion technique for radar scattering from bare soil surfaces. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 30, pp. 370–381.

Olioso, A., Chauki, H., and Wigneron, J.-P. 1998. Estimation of energy fluxes and photosynthesis from thermal infrared spectral reflectances, microwave data and SVAT modeling. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '98*, 6–10 July 1998, Seattle, Wash. IEEE, New York. pp. 1493–1495.

O'Neill, P.E., Hsu, A.Y., Jackson, T.J., and Swift, C.T. 1998. Ground-based microwave radiometer measurements during the southern great plains '97 experiment. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '98*, 6–10 July 1998, Seattle, Wash. Geoscience and Remote Sensing Society, IEEE, New York. pp. 1843–1845.

Owe, M., De Jeu, R., and Walker, J. 2001. A methodology for surface soil moisture and vegetation optical depth retrieval using microwave polarization difference index. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 39, pp. 1643–1653.

Pan, H.-L., and Mahrt, L. 1987. Interaction between soil hydrology and boundary layer developments. *Boundary-Layer Meteorology*, Vol. 38, pp. 185–202.

Pasquariello, G., Satalino, G., Mattia, F., Casarano, D., Posa, F., Souyris, J.C., and Le Toan, T. 1997. On the retrieval of soil moisture from SAR data over bare soils. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '97*, 3–8 August 1997, Singapore. IEEE, Piscataway, N.J. pp. 1272–1274.

Peters-Lidard, C.D., Zion, M.S., and Wood, E.F. 1997. A soil-vegetation-atmosphere transfer scheme for modeling spatially variable water and energy balance processes. *Journal of Geophysical Research*, Vol. 102, No. D4, pp. 4303–4324.

Peters-Lidard, C.D., Pan, F., and Wood, E.F. 2001. A re-examination of modeled and measured soil moisture spatial variability and its implications for land surface modeling. *Advances in Water Resources*, Vol. 24, No. 9–10, 1069–1083.

Peters-Lidard, C.D., Kumar, S., Tian, Y., Eastman, J.L., and Houser, P. 2004. Global urban-scale land-atmosphere modeling with the land information system. In *Proceedings of the 84th AMS Annual Meeting, Symposium on Planning, Nowcasting, and Forecasting in the Urban Zone*, 11–15 January 2004, Seattle, Wash. pp. 1–5.

Prevot, L., Dechambre, M., Taconet, O., Vidal-Madjar, D., Normand, M., and Galle, S. 1993. Estimating the characteristics of vegetation canopies with airborne radar measurements. *International Journal of Remote Sensing*, Vol. 14, pp. 2803–2818.

Prihodko, L., and Goward, S.N. 1997. Estimation of air temperature from remotely sensed surface observations. *Remote Sensing of Environment*, Vol. 60, pp. 335–346.

Prince, S.D., Engman, E.T., Sellers, P., Kerr, Y.H., Goutorbe, J.-P., Lebel, T., Tinga, A., Bessemoulin, P., Brouwer, J., Dolman, A.J., Gash, J.H.C., Hoepffner, M., Kabat, P., Monteny, B., Said, F., and Wallace, J. 1995. Geographical, biological and remote sensing aspects of the hydrologic atmospheric pilot experiment in the Sahel HAPEX-Sahel. *Remote Sensing of Environment*, Vol. 51, pp. 215–234.

Quesney, A., Le Hégarat-Mascle, S., Taconet, O., Vidal-Madjar, D., Wigneron, J.P., Loumagne, C., and Normand, M. 2000. Estimation of watershed soil moisture index from ERS/SAR data. *Remote Sensing of Environment*, Vol. 72, pp. 290–303.

Refsgaard, J.C., and Storm, B. 1995. MIKE SHE. In *Computer Models of Watershed Hydrology*. Edited by V.P. Singh. Water Resources Publications, Highlands Ranch, Colo. pp. 809–846.

Reichle, R., and Koster, R.D. 2002. Land data assimilation with the ensemble Kalman filter: assessing model error parameters using innovations. In *Computational Methods in Water Resources*. Vol. 1 and 2. Edited by S.M. Hassanizadeh, R.J. Schotting, W.G. Gray, and G.F. Pinder. Elsevier Science, Delft, Netherlands. pp. 1387–1394.

Reichle, R.H., and Koster, R.D. 2003. Assessing the impact of horizontal error correlations in background fields on soil moisture estimation. *Journal of Hydrometeorology*, Vol. 4, No. 6, pp. 1229–1242.

Reichle, R., McLaughlin, D., and Entekhabi, D. 2000. Variational data assimilation of soil moisture and temperature from remote sensing observations. In *Proceedings of the ModelCARE 99 Conference, IAHS Red Book on Calibration and Reliability in Groundwater Modelling- Coping with Uncertainty*. Edited by W.K.F. Stauffer, K. Kovar, and E. Hoehn. AHS Press, Zurich, Switzerland. pp. 353–359.

Reichle, R.H., Entekhabi, D., and McLaughlin, D. 2001a. Downscaling of radiobrightness measurements for soil moisture estimation: A four-dimensional variational data assimilation approach. *Water Resources Research*, Vol. 37, No. 9, pp. 2353–2364.

Reichle, R.H., McLaughlin, D., and Entekhabi, D. 2001b. Variational data assimilation of microwave radiobrightness observations for land surface hydrologic applications. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 39, No. 8, pp. 1708–1718,

Reichle, R., McLaughlin, D., and Entekhabi, D. 2002a. Hydrologic data assimilation with the Ensemble Kalman filter. *Monthly Weather Review*, Vol. 130, No. 1, pp. 103–114.

Reichle, R., Walker, J.P., Koster, R.D., and Houser, P.R. 2002b. Extended vs. Ensemble Kalman filtering for land data assimilation. *Journal of Hydrometeorology*, Vol. 3, 728–740.

Robock, A., Vinnikov, K.Y., Srinivasan, G., Entin, J.K., Hollinger, S.E., Speranskaya, N.A., Liu, S., and Namkhai, A. 2000. The global soil moisture data bank. *Bulletin of American Meteorological Society*, Vol. 81, pp. 1281–1299.

Rodell, M., Houser, P.R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J.K., Walker, J.P., Lohmann, D., and Toll, D. 2004. The global land data assimilation system. *Bulletin of the American Meteorological Society*, Vol. 85, No. 3, pp. 381–394.

Sandholt, I., Rasmussen, K., and Andersen, J. 2002. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment*, Vol. 79, pp. 213–224.

Sano, E.E., Huete, A.R., Troufleau, D., Moran, M.S., and Vidal, A. 1998. Sensitivity analysis of ERS-1 synthetic aperture radar data to the surface moisture content of rocky soils in a semiarid rangeland. *Water Resources Research*, Vol. 34, pp. 1491–1498.

Scanlon, B.R., Christman, M., Reedy, R.C., Porro, I., Simunek, J., and Flerchinger, G.N. 2002. Intercode comparisons for simulating water balance of surficial sediments in semiarid regions. *Water Resources Research*, Vol. 38, No. 12, pp. 1–16.

Schaake, J.C., Duan, Q., Koren, V., Mitchell, K.E., Houser, P.R., Wood, E.F., Robock, A., Lettenmaier, D.P.,Lohmann, D., Cosgrove, B., Sheffield, J., Luo, L., Higgins, R.W., Pinker, R.T. and Tarpley, J.D. 2004. An intercomparison of soil moisture fields in the North American Land Data Assimilation System (NLDAS). *Journal of Geophysical Research*, Vol. 109, No. D01S90, pp. 1–16.

Schmugge, T.J. 1978. Remote sensing of soil moisture. *Journal of Applied Meteorology*, Vol. 17, pp. 1549–1557.

Schmugge, T.J. 1996. Applications of passive microwave observations of surface soil moisture. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '96*, 27–31 May 1996, Lincoln, Nebr. IEEE, Piscataway, N.J. pp. 1051–1053.

Schneider, K., and Oppelt, N. 1998. The determination of mesoscale soil moisture patterns with ERS data. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '98*, 6–10 July 1998, Seattle, Wash. IEEE, New York. pp. 1831–1833.

Sellers, P.J., Mintz, Y., and Dalcher, A. 1986. A simple biosphere model SiB for use within general circulation models. *Journal of Atmospheric Science*, Vol. 43, pp. 505–531.

Sellers, P.J., Randall, D.A., Collatz, G.J., Berry, J.A., Field, C.B., Dazlich, D.A., Zhang, C., Collelo, G.D., and Bounoua, L. 1996a. A revised land surface parameterization SiB2 for atmospheric GCMs. Part I: Model formulation. *Journal of Climate*, Vol. 9, pp. 676–705.

Sellers, P.J., Los, S.O., Tucker, C.J., Justice, C.O., Dazlich, D.A., Collatz, G.J., and Randall, D.A. 1996b. A revised land surface parameterization SiB2 for atmospheric GCMs. Part II: The generation of global fields of terrestrial biophysical parameters from satellite data. *Journal of Climate*, Vol. 9, pp. 706–737.

Shao, Y., and Henderson-Sellers, A. 1996. Validation of soil moisture simulation in land surface parameterization schemes with HAPEX data. *Global and Planetary Change*, Vol. 13, pp. 11–46.

Sharma, B.D., Kar, S., and Sarkar, S. 1997. Calibration of a water uptake simulation model under varying soil moisture regime and nitrogen level for wheat crop. *Agricultural and Forest Meteorology*, Vol. 83, pp. 135–146.

Shi, J., Wang, J., Hsu, A.Y., O'Neill, P.E., and Engman, E.T. 1997. Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 35, pp. 1254–1266.

Shoshany, M., Svoray, T., Curran, P.J., Foody, G.M., and Perevolotsky, A. 2000. The relationship between ERS-2 SAR backscatter and soil moisture: generalization from a humid to semi-arid transect. *International Journal of Remote Sensing*, Vol. 21, pp. 2337–2343.

Simunek, J., and van Genuchten, M. Th. 1999. Using the HYDRUS-1D and HYDRUS-2D codes for estimating unsaturated soil hydraulic and solute transport parameters. In *Characterization and Measurement of the Hydraulic Properties of Unsaturated Porous Media*. Edited by M.T. van Genuchten, F.J. Leij, and L. Wu. University of California, Riverside, Calif. pp. 1523–1536.

Simunek, J., Huang, K., and van Genuchten, M. Th. 1998. *The HYDRUS code for simulating the one-dimensional movement of water, heat, and multiple solutes in variably saturated media*. Version 6.0. US Salinity Laboratory,Agrocultural Research Service, US Department of Agriculture, Riverside, Calif. 164 pp.

Smith, R.C.G., and Choudhury, B.J. 1991. Analysis of normalized difference and surface temperature observations over southeastern Australia. *International Journal of Remote Sensing*, Vol. 12, pp. 2021–2044.

Sposito, G. 1995. Recent Advances Associated with Soil-Water in the Unsaturated Zone. *Reviews of Geophysics*, Vol. 33 (Part 2 Supplement S), pp. 1059–1065.

Srinivasan, R., and Arnold. J.G. 1994. Integration of a basin-scale water quality model with GIS. *Water Resources Bulletin*, Vol. 30, No. 3, pp. 453–462.

Taconet, O., Vidal-Madjar, D., Emblanch, Ch., and Normand, M. 1996. Taking into account vegetation effects to estimate soil moisture from C-band radar measurements. *Remote Sensing of Environment*, Vol. 56, pp. 52–56.

Tansey, K.J., and Millington, A.C. 2001. Investigating the potential for soil moisture and surface roughness monitoring in drylands using ERS SAR data. *International Journal of Remote Sensing*, Vol. 22, pp. 2129–2149.

Thoma, D., Moran, M.S., Bryant, R., Rahman, M., Holifield-Collins, C.D., Skirvin, S., and Sano, E. 2004. Comparison of two methods for determining surface soil moisture from C-band radar imagery. *Water Resources Research*. In preparation.

Ulaby, F.T., and Dobson, M.C. 1989. *Handbook of radar scattering statistics for terrain*. Artech House, Norwood, Mass. 357 pp.

Ulaby, F.T., Moore, R.K., and Funk, A.K. 1982. Radar remote sensing and surface scattering and emission theory. In *Microwave Remote Sensing: Active and Passive*. Vol. II. Addison-Wesley, Reading, Mass. pp. 457–1064.

Ulaby, F.T., Dubois, P.C., and Van Zyl, J. 1996. Radar mapping of surface soil moisture. *Journal of Hydrology*, Vol. 184, pp. 57–84.

van Loon, E.E., and Troch, P.A. 2001. Directives for 4-D soil moisture data assimilation in hydrological modelling. In *Soil-Vegetation-Atmosphere Transfer Schemes and Large-Scale Hydrological Models*. Vol. IAHS, Publ. 270. Edited by A.J.H. Dolman, M.L. Kavvas, T. Oki, and J.W. Pomeroy. International Association of Hydrological Sciences, Maastricht, Netherlands. pp. 257–267.

van Oevelen, P.J., and Hoekman, D.H. 1999. Radar backscatter inversion techniques for estimation of surface soil moisture: EFEDA-Spain and HAPEX-Sahel case studies. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 37, pp. 113–123.

Verhoest, N.E.C., Hoeben, R., De Troch, F.P., and Troch, P.A. 2000. Soil moisture inversion from ERS and SIR-C imagery at the Zwalm catchment, Belgium. In *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS '00*, 24–28 July 2000, Honolulu, Hawaii. IEEE, New York. pp. 2041–2043.

Wagner, W., and Scipal, K. 2000. Large-scale soil moisture mapping in Western Africa using the ERS scatterometer. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 38, pp. 1777–1782.

Walker, J.P., and Houser, P.R. 2001. A methodology for initializing soil moisture in a global climate model: Assimilation of near-surface soil moisture observations. *Journal of Geophysical Research*, Vol. 106, No. 11, pp. 11 761 – 11 774.

Walker, J.P., Willgoose, G.R., and Kalma, J.D. 2001a. One-dimensional soil moisture profile retrieval by assimilation of near-surface measurements: A comparison of retrieval algorithms. *Advances in Water Resources*, Vol. 24, pp. 631–650.

Walker, J.P., Willgoose, G.R., and Kalma, J.D. 2001b. One-dimensional soil moisture profile retrieval by assimilation of near-surface measurements: A simplified soil moisture model and field application. *Journal of Hydrometeorology*, Vol. 2, pp. 356–373.

Wang, J.R., Engman, E.T., Shiue, J.C., Rusek, M., and Steinmeier, C. 1986. The SIR-B observations of microwave backscatter dependence on soil moisture, surface roughness and vegetation covers. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 24, pp. 510–516.

Wang, J.R., Hsu, A., Shi, J.C., O'Neill, P.E., and Engman, E.T. 1997. A comparison of soil moisture retrieval models using SIR-C measurements over the Little Washita River watershed. *Remote Sensing of Environment*, Vol. 59, pp. 308–320.

Wang, C., Qi, J., Moran, M.S., and Marsett, R. 2003. Soil moisture estimation in a semi-arid rangeland using ERS-2 and TM imagery. *Remote Sensing of Environment*, Vol. 90, No. 2, pp. 178–189.

Weimann, A. 1998. Inverting a microwave backscattering model by the use of a neural network for the estimation of soil moisture. In *Proceedings of the International Geoscience and Remote Sensing Symposium*, *IGARSS'98*, 6–10 July 1998, Seattle, Wash. IEEE, Piscataway, N.J. pp. 1837–1839.

Wever, T., and Henkel, J. 1995. Evaluation of the AIRSAR system for soil moisture analysis. *Remote Sensing of Environment*, Vol. 53, pp. 118–122.

Wickel, A.J., Jackson, T.J., and Wood, E.F. 2001. Multitemporal monitoring of soil moisture with RADARSAT SAR during the 1997 Southern Great Plains hydrology experiment. *International Journal of Remote Sensing*, Vol. 22, pp. 1571–1583.

Xue, Y., Sellers, P.J., Kinter, J.L. III, and Shukla, J. 1991. A simplified biosphere model for global climate studies. *Journal of Climate*, Vol. 4, pp. 345–364.

Yapo, P.O., Gupta, H.V., and Sorooshian, S. 1998. Multi-objective global optimization for hydrological models. *Journal of Hydrology*, Vol. 204, pp. 83–97.

Yeh, G.T., Cheng, H.P., Cheng, J.R., and Lin, J.H. 1998. A numerical model to simulate water flow and contaminant and sediment transport in watershed systems of 1-D stream-river network, 2-D overland regime, and 3-D subsurface media (WASH123D: Version 1.0). Waterway Experiment Station, US Army Corps of Engineering, Vicksburg, Miss. 369 pp.

List of acronyms

ALOS	advanced land observing satellite
AMSR-E	advanced microwave scanning radiometer
ASAR	advanced synthetic aperture radar
ATSR	along track scanning radiometer
BATS	biosphere-atmosphere transfer scheme
CAPS	coupled atmosphere-plant soil model
EKF	extended Kalman filter
EnKF	ensemble Kalman filter
ENVISAT	environment satellite
ERS SAR	European remote sensing SAR
ESA	European Space Agency
FASST	fast all-seasons soil state model
GIS	geographic information system
GSWP	global soil wetness project
HAPEX-Sahel	hydrologic atmospheric pilot experiment in the Sahel
HH, VV, HV, VH	horizontal and vertical copolarizations
HYDROS	hydrospheric states microwave mission
HYDRUS 1D & 2D	hydrology of the unsaturated zone
IEM	integral equation model
JERS SAR	Japanese earth resources satellite SAR
LAI	leaf area index
LDAS	land data assimilation systems
MIKE-SHE	unification of the MIKE river simulation code and the Système hydrologique Européen
NASA	National Aeronautics and Space Administration
NBMI	normalized radar backscatter soil moisture index
NDVI	normalized difference vegetation index
NIR	near infrared
NOAA	National Oceanic and Atmospheric Administration
NOAHSVAT	developed jointly by NOAA NCEP, Oregon State University, Air Force Weather Agency, and NWS Office of Hydrology
PALSAR	phased array type L-band synthetic aperture radar
PILPS	project for intercomparison of land-surface parameterization schemes
RADAR	radio detection and ranging
RADARSAT	radar satellite
RS	remote sensing
SAR	synthetic aperture radar
SGP	southern Great Plains
SiB1, SiB2	simple biosphere model
SMOS	soil moisture and ocean salinity
SSiB	simplified simple biosphere model
SSM/I	special sensor microwave/imager
SVAT	soil vegetation atmosphere transfer
SWAPS	soil-water-atmosphere-plant systems
SWIR	shortwave infrared

TIR	thermal infrared
TOPLATS	TOPMODEL-based land atmosphere land surface transfer scheme
TVDI	temperature-vegetation dryness index
TVX	temperature-vegetation contextual approach
VIC	variable infiltration capacity scheme
WASH123D	watershed modeling system for 1-D stream-river network, 2-D overland regime, and 3-D subsurface media
WCM	water cloud model

List of symbols

σ^0	radar backscatter coefficient
σ^0_{int}	multiple scattering involving the vegetation elements and the ground surface
σ^0_s	backscatter contribution of the bare soil surface
σ^0_{dv}	direct backscatter contribution of the vegetation layer
σ^0_{dry}	backscatter from vegetated terrain under completely dry soil surface conditions
σ^0_{wet}	backscatter when the soil surface is saturated with water
$\Delta\sigma^0$	difference between dry- and wet-season σ^0
I_{m_s}	relative measure of surface soil moisture
ρ_λ	surface spectral reflectance
θ_i	incidence angle
K_{sat}	soil hydraulic conductivity
m_p	profile soil moisture
m_s	surface soil moisture
R	surface roughness term
T_B	microwave brightness temperature
T_R	thermal infrared radiative temperature
τ^2	two-way attenuation of the vegetation layer
V	vegetation biomass
λ	wavelength

