Special Section: Remote Sensing for Vadose Zone Hydrology

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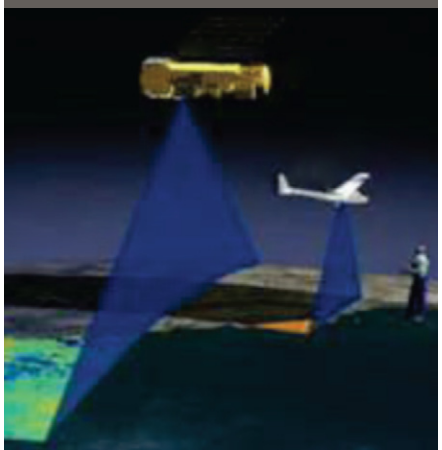

The guest editors introduce the special section, highlighting the latest remote sensing techniques for characterizing the vadose zone.

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Remote Sensing for Vadose Zone Hydrology—A Synthesis from the Vantage Point

Ground-based, air-borne, and space-borne remote sensing techniques have evolved over the past several decades and provided many new techniques for estimating various land surface attributes at multiple scales related to mass and energy dynamics. The vadose zone, encompassing land surface, root zone, and the deeper soil profile down to the groundwater table, is a complex domain, particularly related to various hydrologic and biological processes across different scales. In this zone, spatial distributions and temporal dynamics of soil moisture and evapotranspiration (ET), including their interdependence, are critical to climate feedback, hydrology, and plant canopy health. Their temporal and spatial variability across catchments affect surface and subsurface runoff, modulates evaporation and transpiration, determines the extent of groundwater recharge and contaminant transport, and initiates or sustains feedback between the land surface and the atmosphere. With the recent development and deployment of various remote sensing platforms working with different techniques such as optical, microwave, gravitational, infrared, and other sensors, improved temporal and spatial measurement or estimates of soil moisture, evapotranspiration, soil hydraulic parameters, soil salinity, and vegetation attributes are possible. In this special section "Remote Sensing for Vadose Zone Hydrology," 14 contributions on fundamental and applied studies using different remote sensing platforms, including satellite retrieval algorithm development, data assimilation techniques, scaling issues, ground validation, and field applications in the context of vadose zone hydrology are presented. The foci of these papers range across root zone soil moisture retrieval and variability, evapotranspiration dynamics and distribution, agricultural water management, soil hydraulic and mechanical property estimation, ecosystems assessment, land–atmosphere interaction, and land surface hazard assessment. Here we organized the summary of these papers in four overlapping sections including (i) estimation, variability, scaling, and data assimilation of soil moisture by microwave remote sensing; (ii) estimating evapotranspiration by remote sensing and water management applications; (iii) estimating vadose zone properties by remote sensing; and (iv) ground-based soil moisture for calibration and validation of microwave remote sensing.

Estimation, Variability, Scaling, and Data Assimilation of Soil Moisture by Microwave Remote Sensing

Soil moisture in the vadose zone (typically the top few meters) is the natural state variable of the land surface and subsurface, critical to climate feedback, hydrology, and agriculture, and a key component of the global water cycle. Its temporal and spatial variability over catchment areas affects surface and subsurface runoff, modulates evaporation and transpiration, determines the extent of groundwater recharge, and initiates or sustains

Abbreviations: AMSR-E, Advanced Microwave Scanning Radiometer; ASCAT, Advanced SCATterometer; AVHRR, Advanced Very High Resolution Radiometer; CLM, Community Land Model; ET, evapotranspiration; InSAR, Interferometric Synthetic Aperture Radar; ISMN, International Soil Moisture Network; LETKF, Local Ensemble Transformed Kalman Filter; L-MEB, L-band Microwave Emission of the Biosphere; METRIC, Mapping Evapotranspiration at high Resolution and with Internalized Calibration; MODIS, Moderate Resolution Imaging Spectroradiometer; NARR, North American Regional Reanalysis; NLDAS, North American Land Data Assimilation System; QC, quality control; SCAN, Soil Climate Analysis Network; SEBAL, Surface Energy Balance Algorithm for Land; SEBS, Surface Energy Balance System; SMAP, Soil Moisture Active Passive; SMOS, Soil Moisture and Ocean Salinity; S-SEBI, Simplified Surface Energy Balance Index; SWB, Soil Water Balance; SVAT, soil–vegetation–atmosphere transfer; TSM, Two Source Model.

feedback between the land surface and the atmosphere (National Research Council, 1991). At a particular point in time, soil moisture content is influenced by (i) precipitation history; (ii) soil texture, which determines the water-holding capacity; (iii) slope of the land surface, which affects runoff and infiltration; and (iv) vegetation and land cover, which influences evapotranspiration and deep percolation. In other terms, partitioning soil moisture into groundwater recharge, ET to the atmosphere, and surface/subsurface runoff to the streams at different spatiotemporal scales and under different hydro-climatic conditions, pose one of the greatest challenges to weather and climate prediction, water resources availability, sustainability, quality, and variability in agricultural, range and forested watersheds.

In the past three decades, estimating soil moisture from remote sensing platforms (ground-based, air-, and space-borne) has progressed significantly (Fig. 1). Active and passive microwave remote sensing on satellite platforms provides a unique capability to obtain observations of land surface (approximately top ∼0–5 cm) soil moisture at global and regional scales that help satisfy the science and application needs for hydrology (Njoku and Entekhabi, 1996; Ulaby et al., 1996; Kerr et al., 2001; Schmugge et al., 2002). The emissive and scattering characteristics of the soil surface primarily depend on soil moisture content, and other attributes such as land surface temperature, roughness, and vegetation characteristics. The electromagnetic response of the land surface is modified by the soil moisture status and dynamics, and modulated by surface roughness, vegetation opacity and interaction with the atmosphere, before being received by a remote sensor. These ancillary (i.e., "non-soil-moisture") effects increase at higher frequencies, thus making low-frequency observations desirable for observation of soil moisture (Choudhury et al., 1979; Ulaby et al., 1983). Longer wavelengths also sense deeper soil layers (2–5 cm at the L band, 1–2 GHz frequency), the penetration depth being of the order of one-tenth of the wavelength (Ulaby et al., 1986). Retrieving soil moisture using a ground-based or aircraft-mounted radiometer, operating at the L band, has been demonstrated in several prior studies (Wang and Schmugge, 1980; Schmugge et al., 1992; O'Neill et al., 1996; Jackson and Le Vine, 1996; Njoku et al., 2002; Bolten et al., 2003; Narayan et al., 2004).

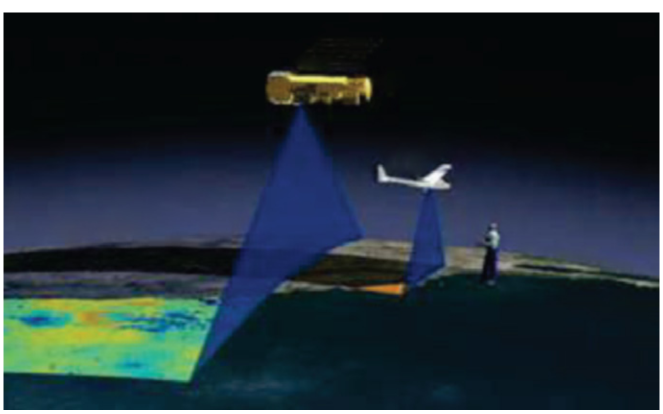

Fig. 1. Schematics of multi-scale remote sensing. Space-borne, air-borne, and ground-based sensing for vadose zone hydrology has grown over the past decades, in particular for near surface soil moisture.

Recent work using radiative transfer models, along with brightness temperatures from satellite platforms, have greatly improved soil moisture retrieval from space. In this special issue, Montzka et al. (2013) improved the estimation of parameters for retrieval of soil moisture from L-band passive microwave observations by simulating the soil moisture and soil temperature using a one-dimensional soil hydrology model (HYDRUS_1D) along with radiative transfer model (L-band Microwave Emission of the Biosphere, L-MEB) to estimate the brightness temperature. Brightness temperature observations were assimilated by a particle filter to estimate the radiative transfer parameters that are then used for the estimation of soil moisture state. Three synthetic scenarios (Scenario 1: temporally constant vegetation and surface roughness parameters; Scenario 2: temporally variable parameters; and Scenario 3: systematic difference between simulated brightness temperature and observation) were investigated. The integrated approach considerably improved the estimation of soil moisture under these scenarios and performed well with Soil Moisture and Ocean Salinity (SMOS) satellite data and insitu observations at a Soil Climate Analysis Network (SCAN) site.

Han et al. (2013) in this issue characterized the soil moisture and soil temperature profiles, using a joint data assimilation scheme with land surface temperature and L-band microwave brightness temperature. By using land surface temperature from Moderate Resolution Imaging Spectroradiometer (MODIS) platform and brightness temperature from a radiative transfer model, in conjunction with Community Land Model (CLM) and Local Ensemble Transformed Kalman Filter (LETKF), Han et al. (2013) estimated soil moisture, surface temperature, sensible heat flux, and latent heat flux. The impact of surface temperature assimilation on profile soil moisture was significant under dry conditions and less under wet conditions. Joint data assimilation using surface temperature and brightness temperature further improved the latent heat and sensible heat fluxes under dry condition. This synthetic study focused on the Rur catchment in Germany. These data assimilation studies signify the importance of global soil moisture remote sensing missions, such as SMOS and the upcoming Soil Moisture Active Passive (SMAP) mission. As these products are being assimilated into various models, evaluating the value of that assimilation in the modeling community is necessary.

Along the line of estimating soil moisture from satellite platforms, Chaouch et al. (2013) in this issue proposed an improved technique to estimate soil moisture from Advanced Microwave Scanning Radiometer (AMSR-E) C-band (6.9 GHz) passive microwave observations. The study was conducted in the Mackenzie River Basin, in northwestern Canada, during the summer months of 2002 through 2004, as part of the Canadian Mackenzie GEWEX

(Global Energy and Water Cycle Experiment) study. They inverted a simplified radiative transfer model (Mo et al., 1982) using a two-stage approach for retrieving soil and vegetation parameters. In a first calibration step, soil surface roughness, vegetation opacity, and single scattering albedo were adjusted iteratively. Data recorded at relatively dry conditions were used to infer soil surface roughness and a relatively wet condition dataset was used to infer vegetation opacity and single scattering albedo. In a second retrieval step, soil moisture was estimated using the previously defined parameters and iteratively minimizing the objective function. The resulting soil moisture was compared to soil moisture data from the NASA AMSR-E products, as well as to daily soil moisture data from the North American Regional Reanalysis (NARR) database. Using in situ soil moisture observations, Chaouch et al. (2013) discussed the advantage of their new approach over AMSR-E and NARR products and suggested it as a viable approach for data gap filling in data scarce remote regions.

A current limitation of soil moisture, estimated by satellite passive microwave sensors is their low spatial resolution. In their contribution, Fang et al. (2013) used the vegetation and land surface temperature data from MODIS to disaggregate the soil moisture retrieved from the AMSR-E using the lookup curves derived using the North American Land Data Assimilation System (NLDAS). The algorithm was applied to the 1-km MODIS land surface temperature to obtain 1-km soil moisture estimates. They validated the results against soil moisture data collected from the Oklahoma Mesonet and the Little Washita Micronet for several summer months, suggesting that downscaled soil moisture provides better spatial variability and accuracy than the AMSR-E and NLDAS estimates, when compared to in situ data.

Another limitation of satellite microwave observations of land surface soil moisture is the confounding effects of complex topography, and snow and ice cover in mountainous regions. To investigate the potential of assimilating soil hydrologic modeling and satellite observations to estimate soil moisture in an Alpine catchment in northern Italy, Brocca et al. (2013) in this issue evaluated data retrieved by the Advanced SCATterometer (ASCAT) sensor on board MetOp satellite and by the Soil Water Balance (SWB) model. Top soil moisture and root zone soil moisture index at 25-km scale was retrieved from ASCAT backscatter by the time series change detection approach of Wagner et al. (1999). To apply this technique in the mountainous region of the Valle d'Aosta, the SWB model was extended by a snowmelt module for estimating snow water equivalent. Using in situ observations at multiple ground stations, Brocca et al. (2013) showed better performance of SWB with snowmelt feature in conjunction with satellite based soil moisture products. The proposed scheme will be valuable in ungauged mountainous regions to improve flood and landslide prediction and prevention. On the basis of the findings in the above-mentioned articles in this special section, we suggest that the optimal combination of a model and satellite observations, through data assimilation and scaling schemes, may reduce uncertainties in soil moisture predictions.

Estimating Evapotranspiration by Remote Sensing and Water Management Applications

Evapotranspiration is another critical variable in the hydrological cycle and grounded to vadose zone. Over the past decades, several energy balance algorithms have been developed for estimating spatially distributed ET using pixel-based remote sensing data, including the Two Source Model (TSM) (Norman et al., 1995), Surface Energy Balance Algorithm for Land, SEBAL (Bastiaanssen et al., 1998, 2005), Mapping Evapotranspiration at high Resolution and with Internalized Calibration, METRIC (Allen et al., 2007), Simplified Surface Energy Balance Index, S-SEBI (Roerink et al., 2000), and Surface Energy Balance System, SEBS (Su, 2002). While challenges (e.g., aerodynamic complexity in the boundary layer, selection of hot and cold pixels) persist related to accuracy of ET estimates using remote sensing data at the footprint scale, progress has been incremental in specific land surface conditions and on a regional basis.

Gowda et al. (2013) in this issue evaluated ET estimates based on SEBS algorithm using lysimetric measurements. Primarily using Landsat 5 Thematic Mapper scenes, they evaluated the ability of SEBS algorithm to estimate hourly ET in the Southern High Plains region in the south-central United States. In addition, authors developed a locally derived, surface albedo-based, soil heat flux regression model that further improved the energy balance. Results of the local evaluation study showed good promise for applying SEBS algorithm to estimate ET in extensively irrigated semiarid regions where crop water demand far exceeds rainfall. However, Gowda et al. (2013) cautioned that extrapolating the approach to larger-scale applications for water management of the major crops in the region should be undertaken only after more detailed sensitivity analysis is conducted under different agroclimatological conditions.

In the contribution of Teluguntla et al. (2013) in this issue, authors took a long-term view and evaluated the multi-decadal trend of ET in a river basin scale encompassing landscape heterogeneities and temporal evolution of irrigated agriculture. They used a combination of modified Penman–Monteith model with data from the Advanced Very High Resolution Radiometer (AVHRR) for estimating ET over the Krishna basin in India for the time period of 1983 through 2001. The ET estimates were validated using lysimeter data as well as Landsat and MODIS-based ET estimates, aggregated to match the footprint (8-km) scale. They found that the ET over this area increased in recent decades, due to increased irrigation development in 1980s. The AVHRR ET estimates of this study showed that the basin average ET increased at a rate of 4.97 mm yr^{-1} in the Krishna River Basin during the period of the study. Another important finding from this study was the increase in biomass represented by an increase in NDVI. The authors linked the cause and effect relationship—increased irrigation, increased crop biomass, increased ET. Their findings further explained the drastic reduction of the Krishna River discharge because of developed irrigation and storage structures in the past decades.

Zhang and Wang (2013) in this issue used remotely sensed infrared temperature for estimating plant water stress in peach trees in the San Joaquin Valley, California. In their study, the authors used an experimental setup on a farm to measure soil moisture, stem water potential, and amount of water used for irrigation. They also measured canopy temperature using a network of above-canopy infrared thermometers. Using midday differences (ΔT) between infrared canopy to air temperature, deficit irrigation (for furrow and surface drip) was scheduled and consequential fruit yield, fruit size, and water productivity were measured for two crop growing seasons. They found consistent linear relations for various deficit irrigation treatments for canopy to air temperature difference, soil water content, and stem water potential. The results of this study indicate that the adopted deficit irrigation practice results in considerable water savings without affecting fruit yield. Although significant benefits are apparent for water management practices, further research is necessary to generalize these findings to other regions and/or other crops.

Estimating Vadose Zone Properties by Remote Sensing

Beyond estimating soil moisture and evapotranspiration using remote sensing platforms, algorithms have been developed in the past decades for estimating more complex vadose zone parameters. Soil hydraulic parameters, important attributes for land surface and vadose zone hydrology models, are being estimated using time series of soil moisture and ET. In particular microwave remote sensing of near-surface soil moisture has played a key role in this respect. Inverse modeling, regression techniques, data assimilation methods using remotely sensed data with soil–vegetation–atmosphere transfer (SVAT) models, genetic algorithm based optimization, and uncertainty quantification using ensemble based approaches under synthetic and field conditions have been developed and adapted over the years for effectively estimating soil hydraulic properties at the remote sensing footprint scale. In this special issue, Shin et al. (2013) outlined a method for estimating effective soil hydraulic properties, at the footprint scale, using soil moisture and SEBAL-based ET from remote sensing. Adopting a number of input scenarios, including soil moisture only, ET only, and a combination of soil moisture and ET, along with a genetic algorithm based optimization technique and a SVAT model under various hydrologic scenarios, Shin et al. (2013) evaluated the efficacy of the approach at multiple spatial (point, air-borne, and satellite footprint) scales. The results showed that combining soil moisture and ET has a much lower uncertainty in the estimated soil hydraulic properties than other scenarios. Results were further validated with field data in Iowa, Illinois, and Texas.

In another innovative application of remote sensing for vadose zone hydrology, te Brake et al. (2013) in this issue established a method for estimating soil water depletion from clay shrinkage at large scale. They used satellite-based Interferometric Synthetic Aperture Radar (InSAR) to detect small elevation changes based on interferometry phase differences between multiple satellite passes and relating that to clay shrinkage. In the Netherlands, using in situ measurements of soil water storage and remotely sensed elevation change from TerraSAR-X satellite over clayey areas in polders with limited vegetation, these authors developed a relationship between soil water storage depletion and soil (top 100 cm) layer shrinkage. The finding opens new avenues for applying remote sensing platforms in vadose zone hydrology and geomechanics, particularly for clay-rich regions.

Ground-Based Soil Moisture for Calibration and Validation of Microwave Remote Sensing

An important requirement for all remotely sensed land surface attributes is their ground validation. In addition, products developed by land surface models need to be calibrated and validated using independent measurements. Soil moisture content estimated by space-borne or air-borne microwave sensors are typically calibrated and validated by spatially intense field campaigns in study watersheds or regions over weeks to months (e.g., Mohanty et al., 2000; Joshi and Mohanty, 2010; Joshi et al., 2011) and/or by spatially distributed long-term monitoring networks. Thus, availability and quality (accuracy) of in situ soil moisture data are of prime importance to many of the microwave remote sensing missions and hydrologic modeling studies.

Several publications of this special issue (e.g., Adams et al., 2013; te Brake et al., 2013; Bramer et al., 2013; Brocca et al., 2013; Chaouch et al., 2013; Han et al., 2013; Montzka et al., 2013; Shin et al.. 2013) require for their studies in situ soil moisture records, either as model input or for validation purposes. The International Soil Moisture Network (ISMN) (Dorigo et al., 2011) collects in situ soil moisture data from operational networks and measurement campaigns to make the data easily accessible to the public. However, different datasets need to be harmonized in terms of measurement units, structure, precision, etc. for proper interpretation and usage. In this issue, Dorigo et al. (2013) developed an operational quality control (QC) system for soil moisture data hosted in the ISMN database. This system was designed with an objective to be applicable to a large variety of networks and stations around the globe differing strongly in nature and available metadata. Two types of soil moisture QC procedures were embedded in the system, including (i) geophysical (natural phenomena and surrogates) dynamic range and measurement consistency and (ii) random noise, spikes, breaks, constant high or low values, and instrument breakdowns. Although future work is warranted to make the data QC approach more comprehensive, the goal of this initial method is to identify and flag spurious observations automatically without manipulating or removing data values by the operators themselves.

Microwaves at L- (1–2 GHz), C- (4–8 GHz), and X- (8–12.5 GHz) band wavelengths are most suitable for retrieval of soil moisture from active (e.g., ENVISAT ASAR, ERS-1/2, RADARSAT-1/2, Terra SAR-X) and passive (e.g., SMOS, AMSR-E) sensors. However, at wavelengths of interest, microwave interactions with soils are physically complex, and thus the depth of interaction is estimated to vary within the top 5 cm or less of the soil surface, due to soil and sensor characteristics (e.g., soil wetness, incidence angle). Using 3400 impedance probe measurements across 72 agricultural fields at two different depths (3 and 6 cm), Adams et al. (2013) in this issue evaluated the appropriateness of ground-based soil moisture and the penetration depth for calibration and validation of L-band microwave remote sensors. A statistically significant average difference in soil moisture content of 0.016 m^3 m^{-3} was discovered between the two sampling depths, suggesting the importance of recognizing near-surface volumetric soil moisture spatial and depth variability effects during ground calibration and validation of soil moisture microwave sensors. In a similar context of ground-based calibration and validation studies, Bramer et al. (2013) investigated the number of point measurements required to account for the spatial variability of soil moisture within the footprint of a ground-based (tractor-mounted) microwave radiometer. They inferred that sampling design (lattice, stratified, or random) may hold the key to this question. Using a random sampling design in a field experiment in Iowa, they found that approximately 20 measurements within a 7- by 9-m sensor footprint would be sufficient for that purpose.

Satellite derived soil moisture products may incur systematic biases and need to be corrected. Sridhar et al. (2013) in this issue have implemented a statistical bias correction method based on matching cumulative probability distributions of soil moisture derived using satellite data and in situ data. Using the AMSR-E over the state of Nebraska and in situ data from 37 stations in an automated weather data network, the proposed approach improved the satellite-based soil moisture estimates.

In summary, the suite of papers published in this special issue provides a good cross section of recent development in remote sensing science, modeling, and data analyses algorithms related to vadose zone hydrology at large scale. While their findings show progress and potential for applying remote sensing techniques in land–atmosphere interaction, hydrology, agricultural water management, and geohazard assessment, many key gaps persist, warranting further development. As new satellites are being launched for earth systems observation in the current decade, opening new opportunities, scientists should explore creative venues to take advantage of new generation technologies for further advancing vadose zone hydrology at multiple scales and applications.

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