Comparison of four models to determine surface soil moisture from C-band radar imagery in a sparsely vegetated semiarid landscape

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[1] Four approaches for deriving estimates of near-surface soil moisture from radar imagery in a semiarid, sparsely vegetated rangeland were evaluated against in situ measurements of soil moisture. The approaches were based on empirical, physical, semiempirical, and image difference techniques. The empirical approach involved simple linear regression of radar backscatter on soil moisture, while the integral equation method (IEM) model was used in both the physical and semiempirical approaches. The image difference or delta index approach is a new technique presented here for the first time. In all cases, spatial averaging to the watershed scale improved agreement with observed soil moisture. In the empirical approach, variation in radar backscatter explained 85% of the variation in observed soil moisture at the watershed scale. For the physical and best semiempirical adjustment to the physical model, the root-mean-square errors (RMSE) between modeled and observed soil moisture were 0.13 and 0.04, respectively. Practical limitations to obtaining surface roughness measurements limit IEM utility for large areas. The purely image-based delta index has significant operational advantage in soil moisture estimates for broad areas. Additionally, satellite observations of backscatter used in the delta index indicated an approximate 1:1 relationship with soil moisture that explained 91% of the variability, with RMSE = 0.03. Results showed that the delta index is scaled to the range in observed soil moisture and may provide a purely image based model. It should be tested in other watersheds to determine if it implicitly accounts for surface roughness, topography, and vegetation. These are parameters that are difficult to measure over large areas, and may influence the delta index.

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1. Introduction

[2] Near-surface soil moisture conditions are primary determinants of cross-country mobility, irrigation scheduling, pest management, biomass production, and watershed modeling, and are also an important factor related to climate, floods, and drought. Radar remote sensing presents advantages for monitoring near-surface soil moisture (0–5 cm), including synoptic, timely coverage with repeat passes, and day or night operational capability. For these reasons, there is much interest in developing radar-based remote sensing techniques for monitoring surface soil moisture.

[3] Currently orbiting radar satellites offer an opportunity for near-surface soil moisture assessment at high resolution due to the response of radar backscatter to changes in soil moisture resulting from the difference in real dielectric constant, $\acute{\varepsilon}$, for dry soil ($\acute{\varepsilon}$ = 2) and water ($\acute{\varepsilon}$ = 80) [*Henderson and Lewis*, 1998]. Microwave energy penetration in the C-band used in this study is 1–5 cm depending on the soil moisture [*Nolan and Fatland*, 2003; *van Oevelen and Hoekman*, 1999]. Surface roughness and vegetation affect backscatter as much or more than soil moisture [*Zribi and Dechambre*, 2002; *van Oevelen and Hoekman*, 1999]; thus different methods of accounting for vegetation and roughness have resulted in numerous models to determine soil moisture from radar imagery.

[4] Research has shown it is possible to determine soil moisture from C-band radar imagery using empirical, physical, and semiempirical models. Image differencing is a fourth model used in this research. A brief discussion of the

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advantages and disadvantages of each type is presented beginning with empirical models.

[5] Many empirical or regression-based models exist for determining soil moisture directly from radar backscatter. Although regression models using only single polarization and single incidence angle radar are generally positive, they range from weak (R^2 = 0.09) for shrub-dominated sites [*Sano et al.*, 1998] in Arizona and winter wheat in Oklahoma (R^2 = 0.15) [*Oldak et al.*, 2003] to moderate (R^2 = 0.58) for a dry lake bed in Nevada and an agricultural field in England (R^2 = 0.44) [*Kelly et al.*, 2003], to strong (R^2 = 0.92) for herbaceous vegetation and shrubs in Israel [*Shoshany et al.*, 2000]. Leconte used the *Dubois et al.* [1995] model to estimate surface roughness from a uniformly wet radar scene that was then used to account for roughness in derivation of soil moisture estimates for new images. This model worked well at the watershed scale (r = 0.96) when radar signal and measured water content were averaged, but performed poorly at the field scale. Disadvantages of empirical models are that numerous measurements of in situ soil moisture are required at one site over time and results are generally site specific, with varying predictive capability as evidenced by studies conducted around the world.

[6] Physical methods use a radar scattering model to predict backscatter from inputs including radar frequency, incidence angle, surface roughness, and dielectric constant. The most commonly used radar scattering model covering a wide range of microwave and surface parameters is the integral equation method (IEM) model of *Fung et al.* [1992]. IEM has been validated at fine scales in a laboratory setting [*Hsieh et al.*, 1997; *Licheri et al.*, 2001; *Macelloni et al.*, 2000] using uniform media but has not been shown to consistently predict radar backscatter at broad scales. Some of the more successful broad-scale studies include those by *Bindlish and Barros* [2000], who obtained maximum error in estimates of soil moisture less than 10% for a large agricultural watershed in Oklahoma, and *Colpitts* [1998], who found the IEM model predicted soil moisture values 1.8% below measured soil moisture with a standard deviation of 5.8% in plowed fields. The IEM model is difficult to apply for soil moisture retrieval over large areas because natural surface roughness is not well described by statistical representations used in the models and it is difficult to measure over large areas. Additional information such as topography and soil type may also be required to optimize the performance of IEM.

[7] Semiempirical adjustments to physical models have been proposed as practical solutions to the problem of obtaining accurate input parameters to physical models over widely distributed and highly variable geographic surfaces [*Verhoest et al.*, 2000; *Baghdadi et al.*, 2004]. Using a water cloud model in Kansas grasslands, *Hutchinson* [2003] found single date correlations between soil moisture and radar backscatter were r = 0.62 and 0.67 for burned and unburned areas, respectively. *Baghdadi et al.* [2004] optimized correlation lengths for the IEM model and showed a reduction in standard deviation in the difference between modeled and observed backscatter from 2.6 to 1.8 dB that would presumably improve inversion results. Optimization such as this is data intensive and limited in scope by the number and variety of fields where roughness measurements can be made.

[8] All models described to this point are based on soil moisture retrieval from a single image. Image differencing on the other hand requires two images obtained with identical radar wavelength, viewing geometry, and beam mode. Image differencing is an empirical model used by several researchers with much improved results over moisture retrieval using single date imagery [*Sano et al.*, 1998; *Moran et al.*, 2000; *Shoshany et al.*, 2000]. They demonstrated this technique in landscapes where surface roughness is time-invariant, thus optimizing the potential to observe backscatter differences due solely to changes in near-surface soil moisture. Coefficients of determination for soil moisture and backscatter greatly improved when related to the difference between a reference (dry) image and changed (wetter) image (R^2 = 0.93) [*Moran et al.*, 2000]. However, the difference still required a site-specific calibration to soil moisture. The newly developed delta index, presented here for the first time, is similar to image differencing except that the difference is divided by the dry reference backscatter which scales the index to the range of soil moisture. A significant advantage of difference models such as the delta index is that variability in surface properties, which must be parameterized in single-image models, may be accounted for implicitly in the image pair.

[9] Objectives of this research were to (1) evaluate empirical models, the physically based IEM model, semiempirical adjustments to IEM, and the newly defined delta index, (2) identify the primary factors affecting accuracy in each method, and (3) make recommendations to improve results.

2. Methods

2.1. Study Area

[10] The study area was the 150-km^2 Walnut Gulch Experimental Watershed (31°43′N, 110°41′W) in southern Arizona (Figure 1) operated by the U.S. Department of Agriculture Agricultural Research Service. The watershed is a semiarid rangeland supporting low-density grass and shrub vegetation that has negligible effect on radar backscatter [*Moran et al.*, 2000]. Soils are composed primarily of alluvium and contain 0–60% rock fragments by volume in the top 5 cm of soil profiles. The diameter of most rock fragments falls between 2 and 75 mm. Rock fragment volume averaged 47% at the sites selected for study in this experiment [*U.S. Department of Agriculture*, 2002]. Common near-surface soils are very gravelly sandy loams, and very gravelly loamy sands. Elevation ranges from 1220 to 1960 m across rolling and heavily dissected terrain.

2.2. Imagery and Image Processing

[11] ERS-2 and RADARSAT-1 imagery were used in this study (Table 1). The ERS-2 imagery and associated soil moisture data were obtained from *Moran et al.* [2000] for the Walnut Gulch study area from field campaigns conducted in 1997 at three sites that were sampled repeatedly over time. Three RADARSAT-1 images were acquired coincident with field measures of soil moisture at 44 sites in 2003 on 30 July, 31 August, and 16 September.

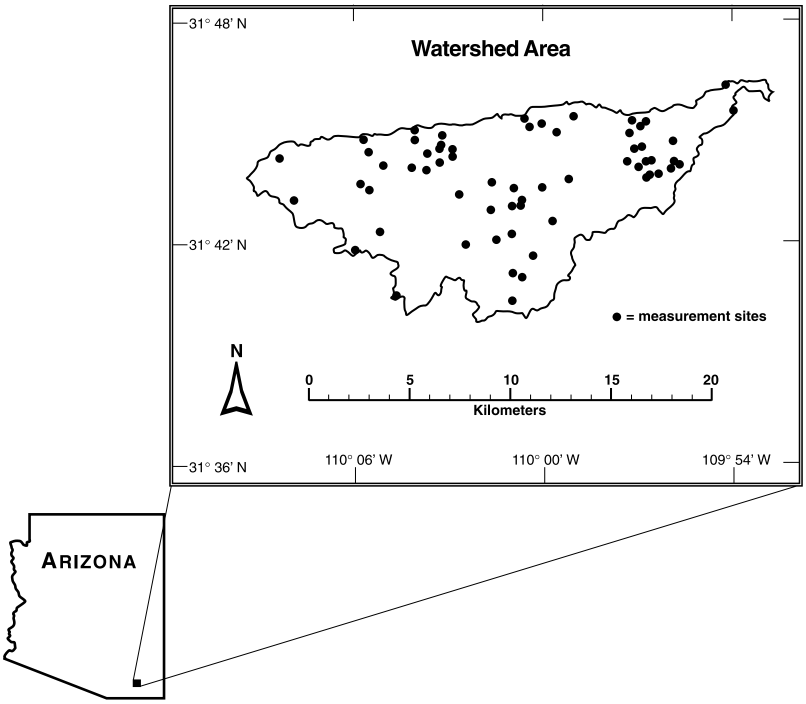

Figure 1. Location of Walnut Gulch Experimental Watershed in southern Arizona, and sites where ground measurements of soil moisture and surface roughness were made.

[12] Careful registration was necessary for meaningful results in the image difference approach. Some registration error was unavoidable but was minimized by averaging pixels over a homogenous land surface that encompassed areas of field work. RADARSAT imagery was georeferenced by matching clearly visible buildings and road intersections with 1-m resolution U.S. Geological Survey (USGS) digital orthophotographs. Registration error (root-mean-square error (RMSE)) was kept below 4 m using between 26 and 44 ground control points. No quantitative information on registration accuracy was available for the 1997 ERS imagery, but similar registration procedures were used.

2.3. RADARSAT Speckle Analysis

[13] A potential advantage of radar remote sensing over passive microwave is the possibility to make observations at higher spatial resolution. However, the interaction of radar and rough surface features results in addition and cancellation of waves, causing random return intensities for similar adjacent surfaces, which is termed speckle [*Henderson and Lewis*, 1998]. Speckle removal is necessary for quantitative analysis, yet there exists a tradeoff between speckle removal and resolution.

[14] The best size for a speckle-reducing median filter window was determined for RADARSAT images by examining the change in backscatter statistics at 44 field sites after passing moving window filters ranging in size from 3×3 to 49×49 pixels across the images. The pixel resolution was retained at 7 m after all levels of median filtering. The 7-m filtered output pixel resolution resulted in pixels that contained information from surrounding pixels in the input imagery and thus represented a ground area greater than 7 m^2. The relationship used to determine the ground area represented by a square pixel cluster after passing a moving window median filter is

$$a = \left(\left(\sqrt{c} + 2 \times \left(\sqrt{n} - 1\right)\right) * r\right)^2, \tag{1}$$

where
a ground area after median filtering (m^2);
c square pixel cluster size of interest (pixels^2);
n moving window median filter size (pixels^2);
r pixel resolution (m).

[15] We determined an appropriate median filter size that reduced speckle yet retained the highest possible ground resolution by examining trends in backscatter statistics

Table 1. Characteristics of Radar Imagery and Number of Field Sites Sampled at Time of Satellite Overpass

	ERS-2 All Dates	RADARSAT-1 19 Jan 2003	RADARSAT-1 All Other Dates
Number of images	8	1	3
Field sites	10	18	44
Pixel resolution	12.5	7	7
Polarization	VV	HH	HH
Incidence angle, deg	23	46	46
Frequency, GHz	C-band, 5.3	C-band, 5.3	C-band, 5.3
Wavelength, cm	5.6	5.6	5.6

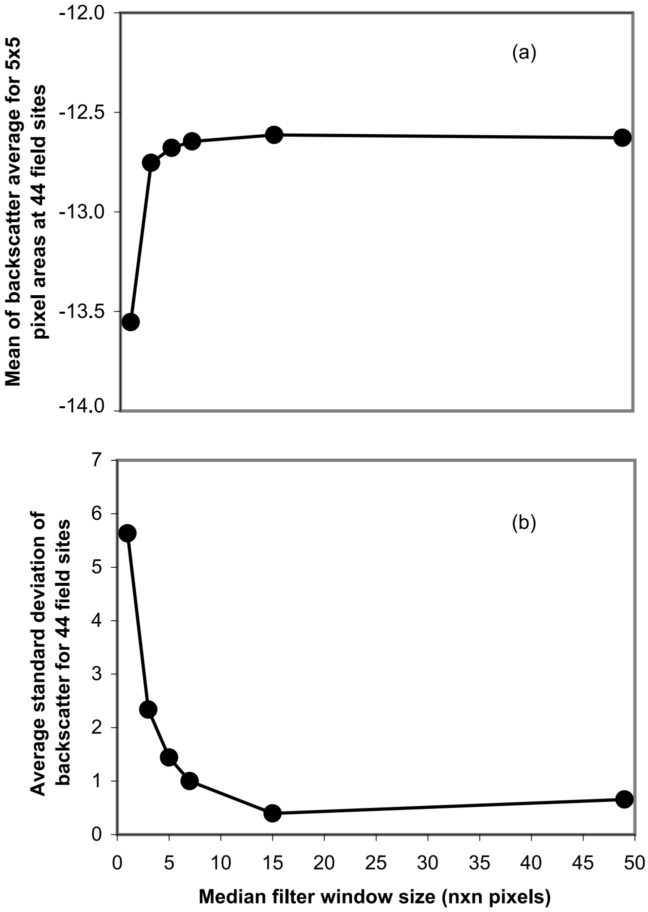

Figure 2. Effect of median filter window size on RADARSAT backscatter. (a) Mean backscatter from 44 field sites on three image dates in Walnut Gulch, Arizona. (b) Mean of standard deviations of backscatter from 44 field sites on three image dates. The area used to calculate standard deviation and mean for each of 44 sites was five by five pixels (91 × 91 m) nested over the 35 × 35 m ground area sampled for soil moisture at time of satellite overpass.

according to moving window filter size. Averaging the mean and standard deviation at each filter level across all 44 sites provided a way to determine the best filter level for the watershed as a whole, which was determined as the moving window size where further increases in window size did not appreciably change the watershed backscatter statistics. The filter size where curves flattened indicated the finest spatial scale where speckle influence was minimized (Figures 2a and 2b). For the mean curve this occurred with a 7 × 7 pixel moving window which represented a ground area of 119 × 119 m, and for the standard deviation curve this occurred with a 15 × 15 pixel moving window which represented a ground area of 231 × 231 m. Standard deviation continued to decrease even as the mean stabilized beyond the 7 × 7 pixel median filter window (Figure 2b), indicating that outlying backscatter values continued to be removed with larger filter sizes. At the same time, the mean backscatter became more positive (Figure 2a), indicating that a skewed negative distribution of backscatter in unfiltered imagery became less important on computation of the mean as filter size increased. Although larger window sizes improved aesthetic image quality at broader scales, the difference between mean backscatter of field sites using a 5 × 5 pixel window and any filter larger than 5 × 5 pixels was no more than 0.07 dB (Figure 2a). For this reason, the 5 × 5 filter size was selected as the optimum filter window size that balanced resolution with a consistent measure of backscatter central tendency. From this point forward, when making reference to the RADARSAT image data, only the 5 × 5 pixel median filtered imagery is discussed.

[16] Distribution and abundance of scatterers on the ground including surface roughness and near-surface rock fragments affect the spatial scale of speckle. Thus it is expected that the magnitude and distribution of speckle will vary by study area and the optimum median filter chosen for this study area may be unique.

[17] Because some residual speckle effect may have still been present after filtering, the backscatter at each of 44 field sites was averaged over 5 × 5 pixels, representing an effective ground area of 91 × 91 m to obtain backscatter values used in subsequent analysis. The 12.5-m resolution ERS-2 imagery was not median filtered because it was lower resolution and three-look, which had the effect of reducing speckle. However, backscatter for the ERS-2 field sites (different from those used with RADARSAT) was also determined by averaging pixels, in this case a 7 × 7 pixel area (87.5 × 87.5 m) that further reduced speckle effects. In both ERS and RADARSAT imagery the number of pixels averaged to determine backscatter at field sites represented approximately the same geographic extent.

[18] No topographic correction was applied to ERS imagery because the associated field sites were flat. However, because some of the field sites associated with the RADARSAT imagery were not flat, a local incident angle correction was applied [*Henderson and Lewis*, 1998]. The correction involved multiplying backscatter values by the ratio of backscatter received from a sloping surface to that received from a horizontal surface, where

$$\beta_s^o/\beta_h^o = \sin\Theta_i/\sin(\Theta_i - \alpha_{loc}), \tag{2}$$

β_s^o backscatter from sloping surface;
β_h^o backscatter from a horizontal surface;
Θ_i average radar incident angle;
α_{loc} local incident angle determined from 7-m digital elevation model.

The correction effect was minor in most cases because slopes at the field sites were mostly level.

2.4. Soil Moisture Measurements

[19] Soil moisture measurements at field sites were made in one of three ways over an integrated 0- to 5-cm depth, or at 5-cm depth for the in situ sensors. (1) For each ERS-2 image, 49 soil moisture measurements were made gravimetrically over a 90 × 90 m area at three sites. (2) For RADARSAT image acquisition dates, 30 July, 31 August, and 16 September 2003, volumetric soil moisture was measured using capacitance-based Dynamax TH_2O Theta probes at 30 to 50 locations on a grid within a 35 × 35 m area at each of 44 sites. The number of measurements made was based on sampling intensity needed to obtain a stable measure of mean soil moisture. (3) For the RADARSAT image acquisition date 19 January 2003, soil moistures were retrieved from continuously recording Stevens/Vitel Hydra

soil moisture probes installed at 5-cm depth in 18 widely distributed locations within the study area. All field measurements of soil moisture were made within a few hours of 1100 LT and 1830 LT overpass times for ERS-2 and RADARSAT, respectively. A factory calibration for mineral soil was used for Theta probes, and factory calibration for sand type soil was used with the in situ Vitel probe in all but one location where the clay calibration was used.

[20] Rock fragment content has been shown to affect radar backscatter through its effect on water holding capacity [*Jackson et al.*, 1992] because rocks do not absorb appreciable amounts of water. This coupled with the fact that portable probes could only be inserted where rocks were absent caused an overestimation of bulk volumetric soil moisture. Thus a rock fragment correction was made by subtracting rock fragment volume from volumetric soil moisture in the following manner:

$$\Theta_r = \Theta_v - (f_r \times \Theta_v), \tag{3}$$

where Θ_r = rock fragment adjusted volumetric soil moisture, Θ_v = field measured volumetric soil moisture, and f_r = fraction of bulk soil occupied by rock fragments >15 mm.

[21] Rocks up to 15 mm diameter could fit between the measuring rods of the portable Theta probes, and therefore this size fraction was not considered in the soil moisture adjustments. Subtracting the fraction that could fit between the sensing rods from the average study site rock fragment content provided the best average estimate for rock fragment correction (f_r = 0.376). After rock fragment correction, volumetric soil moisture for the sites used in this study ranged from 0.02 to 0.35.

2.5. Roughness Measurements

[22] *Sano et al.* [1998] measured surface roughness along thirty 1-m transects with a pin meter at each of the 44 field sites sampled for soil moisture on RADARSAT overpass dates. Surface heights were measured at 1 cm horizontal increments aligned with the local contour. Both root-mean-square error of surface heights (h_{rms}) and correlation length (L_c) were computed for each 1-m transect [*Henderson and Lewis*, 1998]. Results were averaged by site for use in model simulations.

$$\mathrm{h_{rms}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_i - \bar{z})^2} \tag{4}$$

where n = number of height measurements, z_i = a single measurement, and $\bar{z}$ = mean of all measurements.

[23] Correlation length is derived from the autocorrelation function:

$$r_j = \frac{\sum_{i=1}^{n-j}(z_i - \bar{z})(z_{i+j} - \bar{z})}{\sum_{i=1}^{n}(z_i - \bar{z})^2} \tag{5}$$

for j = 1, 2, 3, 4 … n/4 where

- n number of measurements of height;
- z_i a single measurement;
- $\bar{z}$ mean of all measurements;
- j distance between measurements;
- L_c is where $\mathrm{r_j} = 1/e$.

2.6. Models

[24] The first three models described below have been used by previous researchers and are presented here for comparison with the newly proposed delta index model. Each model was used at site and watershed scales and with the same soil moisture data for validation so that they could be compared directly.

[25] Empirical regression relationships between observed backscatter and soil moisture were determined at site and watershed scales and also for areas of homogenous vegetation. The regression relationships were condition-specific, meaning they were developed for unique radar systems and scales.

[26] The IEM model of *Fung et al.* [1992] determines backscatter as a function (*f*) of radar-specific parameters and surface properties for bare soil surfaces, where

$$\sigma^o = f(F, I, h_{\mathrm{rms}}, L_c, \acute{\varepsilon}_{\mathrm{r}}, \acute{\varepsilon}_{\mathrm{i}}, \text{ and } acf) \tag{6}$$

- σ^o dual polarized backscatter response (dB);
- F radar frequency (GHz);
- I incident angle (degrees);
- $\acute{\varepsilon}_{\mathrm{r}}$ real part of dielectric constant of scattering medium;
- $\acute{\varepsilon}_{\mathrm{i}}$ imaginary part of dielectric constant of scattering medium;
- acf autocorrelation function shape.

For all simulations in this study, F = 5.3 GHz, I = 46.5°, and acf = exponential. Field-measured values of h_{rms} and L_c were used in IEM simulations while dielectric constant was determined from field measured soil moisture using the relationship of *Hallikainen et al.* [1985]. Inversion of the IEM model was made with a look-up-table (LUT) that was created by running forward iterations of the IEM model for the expected range in dielectric constant and roughness characteristics in the study area (Table 2). The LUT was used to predict soil dielectric constant from RADARSAT pixel values and measured roughness at field sites. Soil dielectric constant was converted to soil moisture using the relationship of *Hallikainen et al.* [1985].

[27] A semiempirical model was used to adjust measured surface roughness inputs to IEM to account for discrepancies between simulated and observed backscatter that resulted either from inadequacies in the IEM model for this study area or inaccurate model inputs. The most likely factor resulting in discrepancies has been identified by *Callens and Verhoest* [2004] and others [*Oh and Kay*, 1998; *Davidson et al.*, 2000] as inaccurate measurements of L_c. They have shown that while h_{rms} can be measured to within 10% accuracy using traditional 1-m profilers, impractically long profile lengths are required to achieve the same level of accuracy for L_c. Because of the difficulty of physically measuring L_c accurately in the field, *Baghdadi et al.* [2002] proposed calibrating L_c based on the much more easily measured and accurate h_{rms}. The calibration was determined by iterative adjustment of L_c inputs to the IEM model so that RMSE between observed and IEM modeled backscatter was minimized. The calibration for this watershed took the form

$$L_{opt} = 2 \text{ if } h_{\mathrm{rms}} < 1.25, \qquad \text{otherwise } 1.25 \times (h_{\mathrm{rms}})^{0.25} \tag{7}$$

where L_{opt} = optimum calibrated correlation length for surface conditions and radar geometry determined by min-

Table 2. Parameters Used in Forward Iterations of IEM Model to Generate the Look-up-Table (LUT) of Expected Backscatter for Known Surface Parameters and Viewing Geometry[a]

Parameter	Value
Frequency, GHz	5.3
Incidence angle, deg	46
L_c correlation length, cm	0.1–50.1
$h_{\rm rms}$ height, cm	0.1–5.1
Real dielectric constant[b], unitless	0.2–80
Imaginary dielectric constant[b], unitless	0.00–23.83
Autocorrelation function	exponential

[a]The LUT was used with measurements and adjusted measurements of surface roughness to determine soil moisture from RADARSAT imagery.
[b]Real and imaginary dielectric constants were computed via *Hallikainen et al.* [1985].

imizing RMSE between observed and IEM simulated backscatter (cm), and $h_{\rm rms}$ = field-measured root-mean-square error of surface heights from equation (4) (centimeters).

[28] First we focused on adjustments to field measured L_c to derive L_{opt} as suggested by *Baghdadi et al.* [2002], then moved on to iterative adjustments of $h_{\rm rms}$ to account for inaccuracies in $h_{\rm rms}$ measured in the field with a pin meter profiler. Multiple iterations indicated that the best calibration for $h_{\rm rms}$ in this watershed occurred when $h_{\rm rms}$ was multiplied by a factor of 2. Then,

$$L_{opt} = 0.25 \text{ if } h_{\rm rms} < 1.5, \text{ otherwise } 1.5 \times (h_{\rm rms})^2. \tag{8}$$

[29] An image difference technique proposed by *Sano et al.* [1998] was modified to evaluate backscatter from a dry reference scene and a wetter scene of interest by normalizing the difference of pixel values to the dry scene value. The delta index represents a change relative to dry scene backscatter, and thus the delta index should be interpreted in light of dry scene soil moisture. This is because any "dry" scene backscatter is likely to be affected by at least a small amount of residual soil moisture. For two carefully coregistered images representing dry conditions in one image and wetter conditions in the other obtained at a different time, the delta index is defined on a per pixel basis as

$$\text{delta index} = \left| \frac{\sigma^o_{wet} - \sigma^o_{dry}}{\sigma^o_{dry}} \right| \tag{9}$$

where σ^o_{dry} = backscatter (decibels) from a pixel in a radar image representing dry soil conditions, and σ^o_{wet} = radar backscatter (decibels) from a pixel in the same geographic location representing wet soil conditions at a different time.

[30] The delta index quantifies the change from a more negative backscatter (dry image) to a more positive backscatter (wet image). In terms of soil moisture this is a change in the positive direction. Because backscatter values are always negative, the absolute value is necessary to scale the delta index to a positive range that reflects the positive change in soil moisture status. The delta index can be calculated for spatial extents greater than the pixel resolution by averaging backscatter from blocks of pixels to further minimize the influence of speckle if both images are filtered in the same way and if the arithmetic average of pixel values for coincident areas in the two images are used in the computation.

[31] In semiarid regions, long dry periods up to several months duration are common and generally are the best times to obtain a reference image representing dry soil conditions across broad areas. Obtaining dry reference imagery for more humid regions may be difficult, but if soil moisture measurements are made on the ground at times of image acquisition it may be possible to account for that level of soil moisture through subtraction, or interpret the delta index as a relative change from the reference soil moisture, rather than an absolute measure of soil moisture. In this study the watershed average volumetric soil moisture associated with imagery used for the reference pixel values was between 0.01 and 0.05 at the time of dry reference image acquisition on 19 January 2003 and 7 July 1997 for RADARSAT and ERS, respectively.

3. Results and Discussion

3.1. Scale Effects on Model Accuracy

[32] A general finding related to scale pertinent to all models used in this study is that site-specific relationships between model predictions and observed soil moisture were poor. A representative example is that obtained for the site-based empirical relationship for all RADARSAT image sites on four dates (Figure 3a). The same observation is presented in later sections for the other models. The most likely reason for poor results at high spatial resolution is due to the insensitivity of the radar to changes in soil moisture, effects of residual speckle, and natural variability of surface characteristics that interact to affect backscatter that confound relationships. This is even true for physical models that can account for complex interactions, because variability in surface characteristics that serve as model inputs is difficult to measure accurately over large areas of natural surfaces. Some residual speckle influence is expected to affect site-specific relationships because the speckle-reducing technique was based on the best filter for the watershed as a whole. Natural variability in surface features would imply the chosen filter technique may "over" filter or "under" filter in different areas. By averaging spatially across the watershed and temporally across a large range in soil moisture conditions, the variability of surface factors is minimized while the range in observations is maximized. Only when central tendencies in soil moisture and backscatter become apparent through the noise of variability do useful broad-scale relationships appear (Figure 3b). This study indicated that accurate soil moisture relationships obtained with radar may not provide improved spatial resolution over that achievable with passive sensors. This does not mean radar imagery used in this study is only useful for broad-scale observations, but that the highest resolution achievable must be broader than the scale represented by individual sites used in this study.

3.2. Empirical Model

[33] On a site by site basis, the relationship between 5 × 5 pixel average backscatter and soil moisture was weak. Backscatter and soil moisture, grouped by date and then spatially averaged across the watershed, showed a dramatic improvement over site-specific relationships (Figure 3a) by

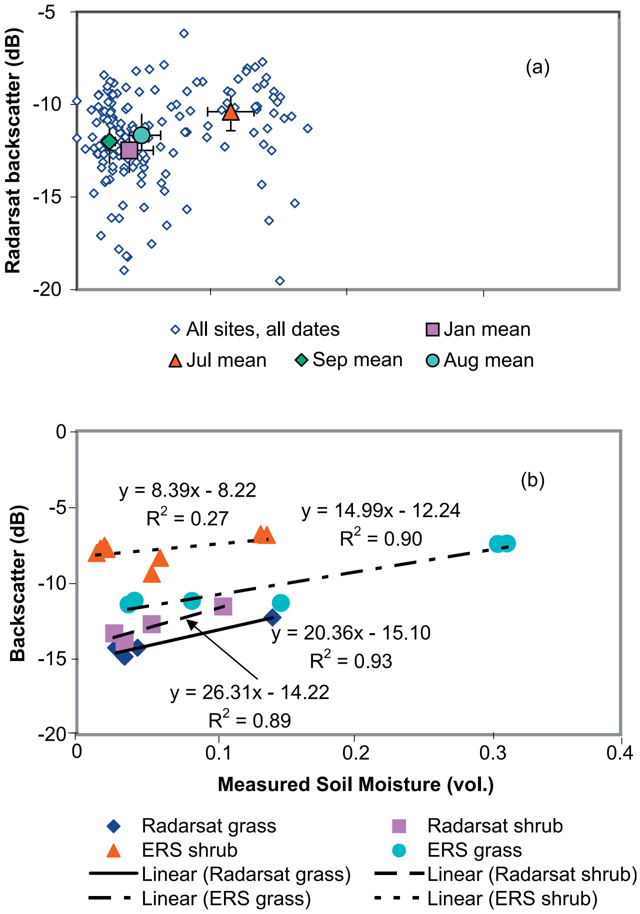

Figure 3. (a) Backscatter versus measured soil moisture by site and averaged for the watershed on four dates in 2003 using only RADARSAT observations. (b) Empirical relationships derived for homogenous areas of vegetation with both RADARSAT and ERS radar sensors across multiple dates.

reducing the effect of variation in surface roughness, soil moisture, and residual speckle. Spatial and temporal aggregation highlighted a range of soil moistures that induced a backscatter response outside the variability caused by confounding factors. This in part explained better correlation between backscatter and multidate imagery when the temporal range of soil moisture was greater than that generally found in a single image. Useful relationships might be possible at scales intermediate between "site" and "watershed," as indicated by a weakly defined scale based on areas of homogenous vegetation type (Figure 3b).

[34] Although several of the condition-specific relationships were strong, they have limited predictive capability due to subtle changes in backscatter response across large ranges in soil moisture indicated by flat regression line slopes. The need to spatially average backscatter at some scale agreed with *LeConte et al.* [2004], *Kelly et al.* [2003], *Hutchinson* [2003], and *Moran et al.* [2000], who also found poor relationships at field scales but better relationships when sites or fields were spatially averaged.

[35] Aside from predictive capability, another interesting observation can be made related to vegetation and its influence on backscatter. In general, backscatter from shrub-dominated portions of the watershed is greater than that from grass-dominated portions of the watershed regardless of moisture status (Figure 3b). This difference, presumably due to vegetation type, is only apparent when data are averaged across the watershed.

3.3. Physical Model

[36] The geographic limitations imposed by empirical techniques do not apply to physical models such as IEM, but physical models present other challenges. The IEM model is point based and has been validated with scatterometers at lab and plot scales with well-defined media of known dielectric constant and well-characterized roughness. However, when the IEM model was extended to highly variable landscapes using space-based imagery, it performed poorly (Figure 4a). IEM backscatter was less than observed RADARSAT backscatter for all dates, which contradicts *Baghdadi et al.* [2002], who found IEM generally overestimated observed backscatter. This difference may be in part explained by the presence of minor amounts of vegetation in this study area as pointed out earlier. *Bindlish and Barros* [2001] showed a weak positive relationship (R^2 = 0.23) between radar backscatter and rangeland biomass. The lack of fit between measured and observed backscatter could be caused by not accounting for vegetation in the IEM model or due to difficulty measuring L_c and h_{rms} of rangeland surfaces used for model inputs. Also, the inability of the pin meter to measure subsurface rock fragments that affect volume scatter may have resulted in underestimation of IEM backscatter relative to observed radar backscatter. The speculation that the problem is largely due to roughness is echoed by the findings of *Moran et al.* [2000], who showed vegetation had no effect on backscatter in this watershed, and others who have noted difficulty characterizing surface roughness at field scales [*Verhoest et al.*, 2000; *Baghdadi et al.*, 2004], and results presented next for the semiempirical model.

[37] Inversion of the IEM model with the LUT to generate predictions of soil moisture performed poorly on a site by site basis, but had a near linear fit when data were spatially averaged (Figure 4b). Nevertheless, soil moisture modeled this way overestimated measured soil moisture on all image dates.

3.4. Semiempirical Model

[38] Semiempirical adjustments can be made in light of potential weaknesses in field measurement of model parameters. The physics behind IEM theory have been carefully evaluated and shown to work at fine scales, but it is not clear if weaknesses in the model result in poor results at broad scales or, if more likely, the lack of fit between observed and modeled backscatter is due to uncertainty in observed radar backscatter, uncertainty in field measured surface roughness, or uncertainty in field measured soil moisture.

[39] Uncertainty in radar backscatter for the duration of this study was expected at worst to be within 2 dB [*Staples and Branson*, 1998], and although this level of error could result in modeled error greater than plus or minus 0.10 cm^3 cm^{-3}, it was not considered for adjustment beyond the median filter step because radiometric calibration was performed by the data provider.

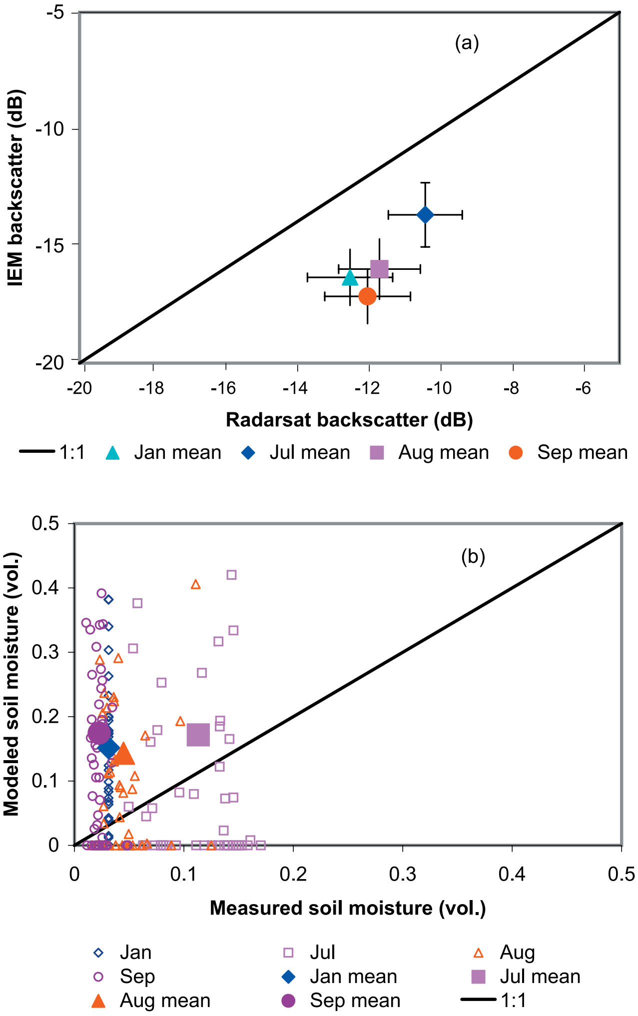

Figure 4. (a) Site-averaged IEM versus RADARSAT backscatter for 44 field sites sampled on four dates. The error bars represent backscatter standard deviation. (b) Site-specific modeled versus measured soil moisture and average modeled versus measured soil moisture. Only RADARSAT results are presented because surface roughness data were not available for IEM simulation at the ERS-2 field sites.

[40] Uncertainty in field-measured soil moisture was addressed by confidence interval testing at 95% with one sample t-test. This indicated that sample sizes of field soil moisture measurements (30–50 measurements at each field site) were sufficient to ensure mean soil moisture estimates were within 1 and 2% of true soil moisture for dry and moist field conditions, respectively. Additional measurements did not change the mean value more than 1%. Therefore adjustment of soil moisture used to compute dielectric constant was not considered. The discrepancy in field area sampled (35 $\times$ 35 m) for RADARSAT image dates and the area used to determine mean backscatter (91 $\times$ 91 m) may have influenced model results. However, the pixels used to determine the mean backscatter were centered over the field sites, and the field sites on the scale of 100 m were relatively homogenous. In two field trials at 13 representative field sites we obtained mean soil moisture values in nested blocks of 35 $\times$ 35 m and 100 $\times$ 100 m that differed by less than 0.018 $cm^3\ cm^{-3}$. This provided some assurance that the measurements made at 35 $\times$ 35 m adequately represented the soil moisture status of larger 100 $\times$ 100 m areas.

[41] This left uncertainty in surface roughness as an important factor that could affect model performance. Surface roughness parameters, L_c and h_{rms}, have strong influence on IEM-generated backscatter and thus, through adjustment, have much potential to improve fit between observed and modeled soil moisture. Furthermore, others have had difficulty accurately measuring surface roughness [*Baghdadi et al.*, 2002; *Verhoest et al.*, 2000]. Coefficients were calibrated using equations (7) and (8) to achieve adjustments to field-measured L_c and h_{rms} that minimized the difference between modeled and measured backscatter. Evaluation of roughness calibration was made by comparing LUT modeled soil moisture to field measured soil moisture (Figure 5).

[42] Simulations using adjusted surface roughness parameters showed improvement when L_c was decreased and when h_{rms} was increased. Shorter correlation lengths and larger h_{rms} values effectively increased roughness in the IEM model and its inversion which improved the fit between modeled and observed soil moisture. Poor agreement between modeled and observed backscatter resulted when field measures of surface roughness, L_c and h_{rms}, were used (RMSE = 0.13). Considerable improvement occurred by adjusting L_c only (RMSE = 0.05), but little additional improvement could be achieved for all dates by adjusting h_{rms} and L_c simultaneously (RMSE = 0.04). However, adjusting h_{rms} and L_c simultaneously had a large influence on accuracy of soil moisture prediction for the wettest month. This difference may be due to inability of the surface-based pin meter to account for volume scattering caused by subsurface rock fragments that have a greater proportional effect on volumetric soil moisture in wetter conditions (equation (3)). Although the fit between modeled

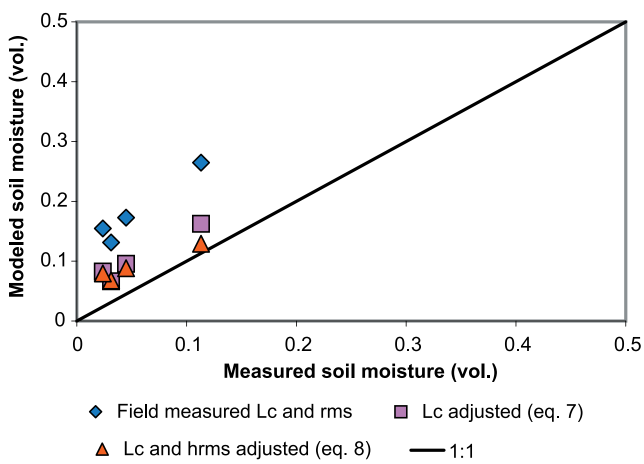

Figure 5. Modeled versus measured soil moisture for simulations at the watershed scale. The shift in data grouped by symbol represents L_c calibration suggested by *Baghdadi et al.* [2004] or L_c calibration plus h_{rms} adjustment. Only RADARSAT results are shown here because surface roughness data were not available for IEM simulation at the ERS-2 field sites.

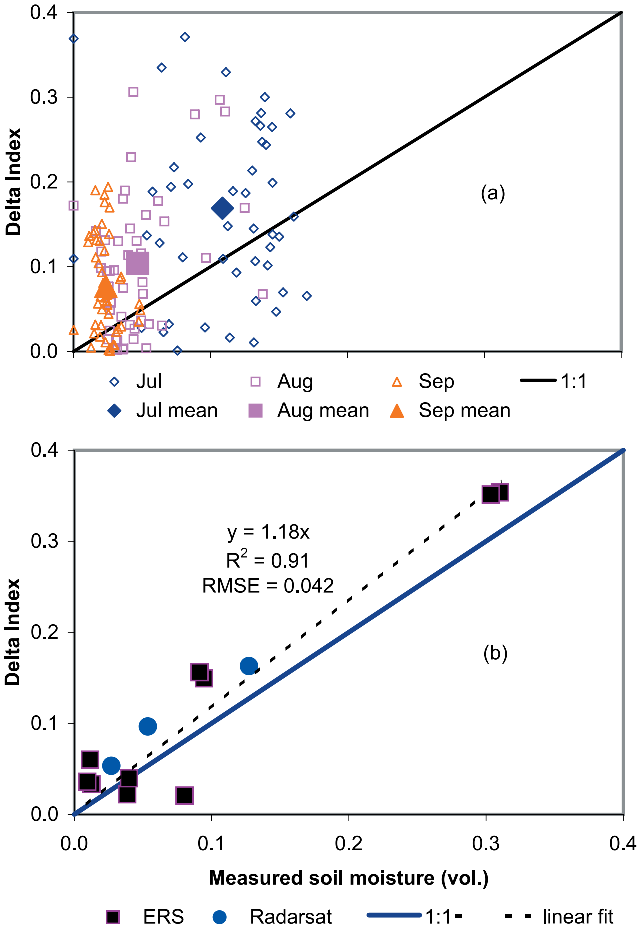

Figure 6. (a) Site-specific relationship between delta index and field measured soil moisture and averages of delta index and measured soil moisture. (b) Average delta index from 44 sites derived from RADARSAT imagery on three dates and delta index from three sites derived from ERS imagery on multiple dates versus soil moisture measured in the field. RMSE was computed as average difference between observed soil moisture and delta index.

and measured backscatter could be optimized by adjusting roughness parameters, inversion to obtain soil moisture still overestimated measured soil moisture.

[43] Others [*Baghdadi et al.*, 2002; *Verhoest et al.*, 2000] have made adjustments to L_c based on the assumption that h_{rms} can be accurately measured in the field and is related to L_c. However, those studies were made in agricultural fields that have periodic row structure and may not have high rock fragment content. Empirical adjustments to both h_{rms} and L_c may complicate handling of roughness in model inversions. Adjustment of h_{rms}, however, may be necessary in rocky environments to account for subsurface volume scattering that cannot be measured using surface-based pin meters.

3.5. Delta Index Model

[44] As with the other models, the site-specific relationship between delta index and measured soil moisture was poor but improved dramatically with spatial and temporal averaging (Figure 6a). A strong relationship through time existed between the delta index and field-measured soil moisture at the watershed scale with delta index explaining 91% of the variability in soil moisture when both RADARSAT and ERS imagery were used to predict soil moisture (Figure 6b). In this study the delta index relationship was a good predictor of soil moisture with pairs of HH and pairs of VV polarized imagery. The key to meaningful results lies in obtaining imagery with the same beam position, precise image to image registration, and speckle filtering and so that differences result primarily from changes in moisture status.

[45] The effect of normalizing with dry reference image pixel values was that delta index values were scaled to the range of observed soil moistures, a marked improvement in the image difference approach first proposed by *Sano et al.* [1998], and the observations, at least in this watershed, approximated a 1:1 relationship. The proximity of observations to the 1:1 line may result from cancellation of time-invariant features that affect backscatter, including view geometry, polarization, topography, soil type, and surface roughness because they are the same in the two images used in the delta index and the only difference in the image backscatter is due to soil moisture. If this holds true in other watersheds, empirical calibration may not be required if reference scene soil moisture is very dry. This presents an important operational advantage if soil moisture could be predicted by imagery alone without the need for ground-based measures of surface roughness. However, if roughness and soil moisture have an interaction effect as suggested by IEM model simulations, then the delta index may be no different from other empirical models that must be reexamined for each new study area.

[46] The delta index may be less affected by surface roughness, rock fragments, and subtle vegetation influences than IEM, as indicated by an examination of site-scale variability in IEM and delta index modeled soil moisture for September (Figures 4b and 6a). For the range in soil moisture measured on the ground for the September image date, there is a larger spread in modeled IEM soil moisture values (0–0.4) than delta index values (0–0.2). We speculate that there are two primary reasons why the delta index outperformed the IEM model at the site scale. First, for the IEM model, it is difficult to accurately characterize surface roughness and other factors such as subsurface rock fragments that may contribute to roughness even over relatively small areas such as the 35 $\times$ 35 m sites used in this study. The second is due to residual speckle influence that may not have been entirely removed or minimized at each field site during the filtering process. All imagery in the study was filtered the same way, but if residual speckle remained it served as error in IEM inversion but "cancelled" in the delta index. The relatively large spread in the delta index results indicates speckle effects did not entirely cancel, which may result from very slight shifts in viewing geometry on successive orbits that cannot be practically taken into account. This is a limitation imposed by the observation system that will limit the scale at which model results will be valid.

[47] The delta index is largely determined by two theoretical relationships that are illustrated with a dielectric model [*Hallikainen et al.*, 1985] and IEM [*Fung et al.*, 1992]. These are the dependency of real dielectric constant

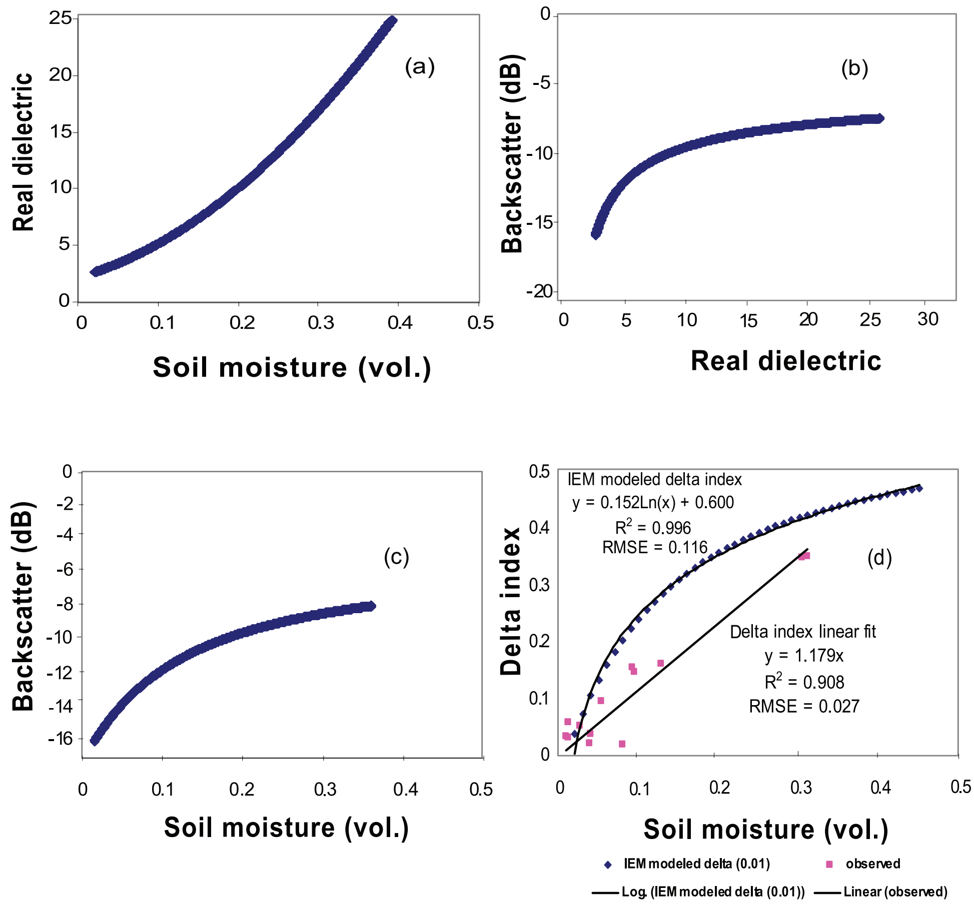

Figure 7. (a) Modeled dependence of real dielectric constant on soil moisture. (b) Modeled dependence of backscatter on dielectric constant. (c) Soil moisture versus backscatter relationship that is exploited by the delta index. (d) Delta index computed using radar image pixel values from Figure 6 and IEM-modeled backscatter versus field-measured soil moisture. A volumetric soil moisture content of 0.05 was used as the dry "reference" soil condition while optimized h_{rms} and L_c (1.13 cm and 1.93 cm, respectively) served as roughness inputs to develop the IEM-simulated delta index. RMSE was computed as average difference between observed soil moisture and modeled fit.

on volumetric soil moisture (Figure 7a), and the dependency of backscatter on real dielectric constant (Figure 7b). Backscatter and soil moisture are linked through these relationships (Figure 7c). Because imaginary dielectric constant changes much less than real dielectric constant with soil moisture, it will not be discussed further. Increasing backscatter with soil moisture presents the opportunity to discriminate levels of soil moisture by exploiting the change in backscatter normalized by the initial, "reference," condition, similar to the way gravimetric soil moisture content is normalized by dry soil mass. Because the relationships between soil moisture, dielectric constant, and backscatter are nonlinear, the delta index as modeled with IEM is also nonlinear (Figure 7d) with a shape similar to the backscatter/soil moisture relationship of Figure 7c. For comparison, a delta index curve derived by generating backscatter values using IEM (dashed blue line in Figure 7d) was made for the specific conditions of surface roughness in the watershed. The RMSE was less around the observed delta index line (0.03) than around the IEM-derived delta index curve (0.12). This indicates that IEM may not be a suitable model for operational broad-scale soil moisture estimates in this watershed. However, more data at higher water contents might indicate a better fit with the IEM-derived curve.

[48] The linearity of the observed delta index may result from factors that cannot be accounted for in the IEM model. It could be related to cumulative effects of surface features and scale that IEM does not model effectively, or it could be the IEM model does not account for rock fragments just below the soil surface that act as roughness elements affecting backscatter and also act as a limit on volumetric soil moisture content. In a dry soil the surrounding matrix is as dry as rocks contained therein. As the soil wets-up the volume occupied by rocks remains dry, thus suppressing the backscatter influence for that volume. This has the effect of compressing the entire backscatter response into a narrower range that may be more linear than what would be observed over a broader range of soil moisture if rocks were absent. If the delta index is capable of handling the cumulative effect of rock fragments and variable surface factors, it may have potential to be extended easily to other study sites. For this

reason, the observed delta index derived from satellite observations should be evaluated across a wide range of surfaces types before definitive conclusions are drawn about its suitability rather than basing its utility on comparison with IEM-modeled delta index behavior.

[49] Although the delta index versus soil moisture relationship does not exactly follow the 1:1 line, it is a close approximation in this watershed and may provide meaningful estimates of soil moisture in some cases even without calibration.

4. Conclusions

[50] A generalization apparent from all model results is that spatial averaging can be used to improve predictive capability regardless of model used by focusing on central tendencies. Wide ranges in backscatter over short distances are caused by high degrees of spatial variability in surface roughness, soil moisture, and speckle. However, at broader scales the central tendency of backscatter due to roughness and speckle tends to stabilize while large differences in soil moisture through time shift the central tendency. For this reason, it is more likely that soil moisture relationships using any of these models will be stronger when evaluated at broader scales and across larger moisture gradients, either spatial or temporal. The minimum spatial scale for meaningful radar-based soil moisture estimates is still undetermined, but clearly estimates near the scale of image resolution are not appropriate. Additional research is now being focused on determining the minimum spatial scale where central tendencies are clearly discernable from noise that confounds backscatter/soil moisture relationships.

[51] Empirical models were strongest when data were averaged across study sites, but finer-scale relationships were possible for specific vegetation types and radar geometry. Inversion of the IEM model using field measures of surface roughness had poor agreement with observed soil moisture even at the watershed scale when all sites were averaged. Considerable improvement was made by empirically adjusting surface roughness inputs to the inversion model. However, the semiempirical model required much field data and limited the inversion of the physical model to a specific geographic area of similar roughness characteristics. The newly proposed delta index was presented in context with other commonly used models for comparison. The delta index model was as good or better than the other models at the watershed scale, indicating it may have much potential as a tool for estimating soil moisture from radar imagery, especially in an operational context where imagery alone could be used to predict soil moisture if the 1:1 relationship found in this study holds for other areas.

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