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Comparison of Two Methods for Extracting Surface Soil Moisture from C-band Radar Imagery

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Abstract – The Integral Equation Method (IEM) model and a newly defined delta index were used to estimate near surface soil moisture from C-band radar satellite imagery in a semi-arid rangeland in southern Arizona, USA. Model results were validated against soil moisture measurements made in the field at the time of satellite overpass. The IEM model performed poorly in this environment possibly due to abundant near-surface rock fragments which were not considered in the model. The delta index performed better than the IEM model and was shown to work with both ERS and Radarsat imagery. Additionally the index was simple to implement and implicitly accounted for both rock fragments and surface roughness.

Keywords – radar; soil moisture; rock fragments; IEM

I. INTRODUCTION

Near surface soil moisture conditions are primary determinants of cross-country mobility, irrigation scheduling, pest management, biomass production, and watershed modeling. Remote sensing has several advantages for monitoring surface soil moisture, such as synoptic, timely coverage with repeat passes, and efficiencies of scale that cannot be matched by ground methods. For these reasons, there is much interest in developing remote sensing techniques for monitoring surface soil moisture over large areas.

A. Background

Currently orbiting radar satellites may offer the best opportunity for near surface soil moisture assessment due to the strong response of radar backscatter to changes in soil moisture, day or night operational capability, and deeper sensing depths than optical sensors. The basis for soil moisture measurements using radar is the difference in dielectric constant, $\acute{\varepsilon}$, for dry soil ($\acute{\varepsilon} = 2$) and water ($\acute{\varepsilon} = 80$). As the water content of a dry soil increases, so does the dielectric constant, which directly affects microwave backscatter, σ^{o} [1]. Microwave energy penetration of soil is on the order of several centimeters [2], but surface roughness and vegetation affect backscatter as much or more than soil moisture [3], [2]. Different methods of accounting for vegetation and roughness have resulted in numerous approaches to extracting soil moisture from radar imagery.

B. Approaches

Researchers have shown it is possible to determine soil moisture from C-band radar imagery using physical, semi-empirical and empirical models. A unique category of empirical approaches used in this research is image differencing.

The most general and commonly used physical model covering a wide range of microwave and surface parameters is the Integral Equation Method (IEM) model of [4]. The IEM model has been used successfully at multiple scales by [5] and [6]. Other models exist but have a limited validity domain.

The semi-empirical models show improved results over purely physical models and ease the difficulty of obtaining surface roughness measurements, but again are limited by the range in conditions for which they have been validated. For these reasons radar models for a wide range in surface properties have been only moderately successful [7].

Empirical models are generally limited to the range in surface conditions and viewing geometry for which they were developed. The predictive capability of single polarization or single incidence angle radar for soil moisture is generally positive, but weak due to influence of highly variable surface roughness [8],[9],[10], and [11].

Another type of empirical approach is the image difference technique that can be used to advantage in landscapes where surface roughness and vegetation is time-invariant, thus optimizing the potential to observe backscatter differences due solely to changes in near-surface soil moisture [8] and [12]. Like empirical approaches, difference techniques require calibration and may only apply to regions and ranges in surface conditions where they have been validated. Additionally, careful image to image registration is critical for meaningful results.

II. OBJECTIVES

Objectives of this research were to: 1) investigate the relative accuracy of methods for determining surface soil moisture from radar backscatter using the IEM model and a difference index, 2) identify the primary factors affecting accuracy in each method.

III. METHODS

A. *Study area*

The study area was the 150 km^2 Walnut Gulch Experimental Watershed (31°.43'N, 110°.41'W) in southern Arizona (Fig. 1). The watershed is a semi-arid rangeland supporting grass and shrub vegetation. Soils, composed primarily of alluvium, are sandy loams, and gravelly loamy sands with approximately 30% rock fragment content. Topography is rolling to mountainous [13] and [14].

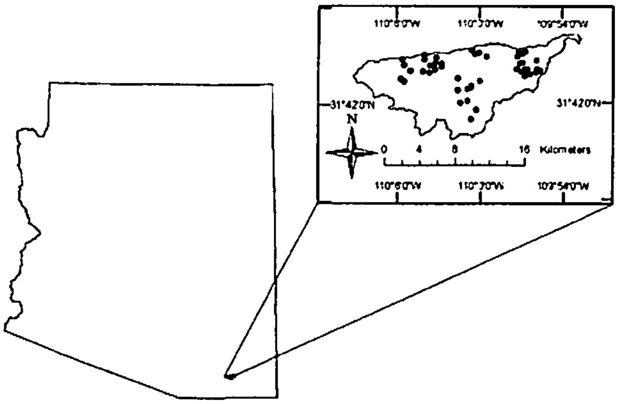

Figure 1. Location of Walnut Gulch Experimental Watershed in southern Arizona, USA and 46 sites where ground measurements of soil moisture were collected at times of satellite overpass.

B. *Imagery*

Both 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 field campaigns conducted in 1997 at three sparsely vegetated grass and shrub sites that were sampled repeatedly over time [12].

Three Radarsat-1 images were acquired coincident with field measures of soil moisture in 2003 on 30 July, 31 August, and 16 September. Geometry for these images was selected to match an historic image acquired 04 January 2002. The ERS-2 and Radarsat-1 backscatter coefficients were computed as the average of a 7 x 7 pixel window representing 8100 m^2 and 1225 m^2 respectively due to differences in spatial resolution. Additionally, all Radarsat-1 images were median filtered with a 5 x 5 moving window prior to averaging in order to reduce speckle.

C. *Soil moisture measurements*

Soil moisture measurements were made either gravimetrically or with factory calibrated capacitance probes within a few hours of 11:00am and 6:30pm for ERS-2 and Radarsat overpass times respectively. Soil moisture for the January 2003 image was assumed to be a uniform 3% at all sites.

TABLE I. CHARACTERISTICS OF RADAR IMAGERY AND NUMBER OF FIELD SITES SAMPLED AT TIME OF SATELLITE OVERPASS.

	ERS-2 All dates	RADARSAT-1 04 Aug 2002	RADARSAT-1 All other dates
n	10	18	44
pixel resolution	12.5	8	8
polarization	V V	H H	H H
incidence angle	23°	46°	46°
frequency	C-band (5.3 GHz)	C-band (5.3 GHz)	C-band (5.3 GHz)
wavelength	5.6 cm	5.6 cm	5.6 cm

D. *Roughness*

Surface roughness was obtained from previous research [8]. It was measured with a pin meter at all of the sites used with the IEM model. Both root mean square error (rms) of surface heights and correlation length (L) were computed for 30 one-meter roughness transects at each site. Results were averaged by site for use in simulations using the IEM model.

E. *Models*

A pseudo inversion of the Integral Equation Method (IEM) model was created with a Look-Up-Table (LUT) to estimate soil moisture from backscatter and roughness input variables. The LUT was used to predict soil dielectric from Radarsat pixel values and roughness at field sites. Soil dielectric was converted to soil moisture using the relationship of Hallikainen et al. [15].

An image difference technique proposed by Moran et al. [12] was modified by normalizing the difference of pixel values to the dry scene value. The delta index was defined as,

$$\Delta\text{-index} = \text{abs}[(\sigma^{o}_{wet} - \sigma^{o}_{dry})/\ \sigma^{o}_{dry})*100], \qquad (1)$$

where σ^{o}_{dry} = average radar backscatter of dry soil, and σ^{o}_{wet} = average radar backscatter of wet soil.

Results from both IEM inversion and Δ-index methods were validated against in situ measurements of surface soil moisture determined at the time of satellite overpass.

IV. RESULTS

A. *Backscatter - Soil Moisture Relationship*

On a site by site basis the relationship between 5 x 5 pixel averaged backscatter and soil moisture was weak (r^2 = 0.11). However, the relationship between watershed averaged backscatter and corresponding field measured soil moisture when averaged by date was strong (r^2 = 0.97) (Fig. 2). These findings agreed with other researchers [10], [12], [16], and [17]. Spatial averaging reduced the effect of residual speckle, while temporal grouping maintained a large range of soil moistures that induced a response greater than the noise level of the sensor.

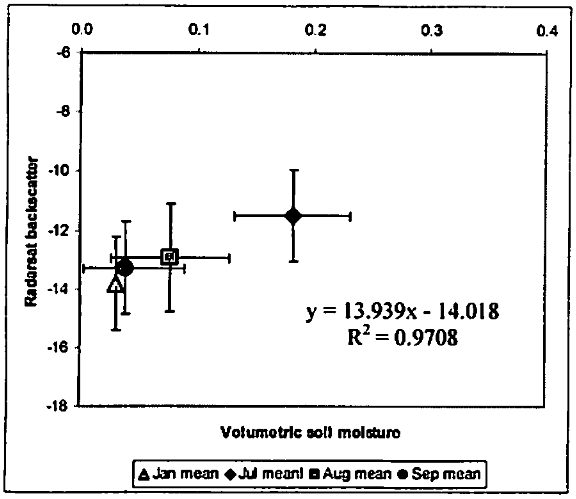

Figure 2. Relationship between mean volumetric soil moisture and mean Radarsat backscatter at the watershed scale. Backscatter and soil moisture were averaged by date for the 44 field sites. Soil moisture for the January image was not measured, but assumed to be 3% at all sites.

B. *IEM*

There was a strong relationship between Radarsat backscatter and IEM modeled backscatter for 44 sites when grouped by date and averaged spatially across the study area (Fig. 3), but the LUT was a poor predictor of volumetric soil moisture at the study area scale (Fig. 4). This was because there was only 1.7 dB range in Radarsat backscatter for the 14% range in average watershed volumetric soil water content during the study (Fig. 2). The narrow range in observed Radarsat backscatter for the range of moisture conditions in the watershed resulted in a correspondingly narrow range in predicted soil moisture (2.6%) using the LUT (Fig. 4).

The primary reason for poor predictive capability of the IEM generated LUT in this environment was likely due to the abundance of rock fragments near the soil surface. Rock fragments occupied significant bulk volume in the research watershed, but held no water and maintained a constant dielectric near that of dry soil regardless of the moisture status of the surrounding soil matrix. Thus, rock fragments effectively reduced the sensitivity of backscatter even for large changes in volumetric water content. For C-band scatterometer data a 90% reduction in the range of observed emmisivity was attributed to 35% rock volume in wet and dry soils [18].

A dielectric vs. soil moisture relationship was required in forward iteration of the IEM model for LUT construction, and for inversion to estimate soil moisture. In this study an empirical dielectric vs. soil moisture relationship for non-rocky soils was used [15]. Results would likely improve if the dielectric vs. soil moisture relationship was modified as a function of volumetric rock fragment content as proposed by Jackson et al. [18].

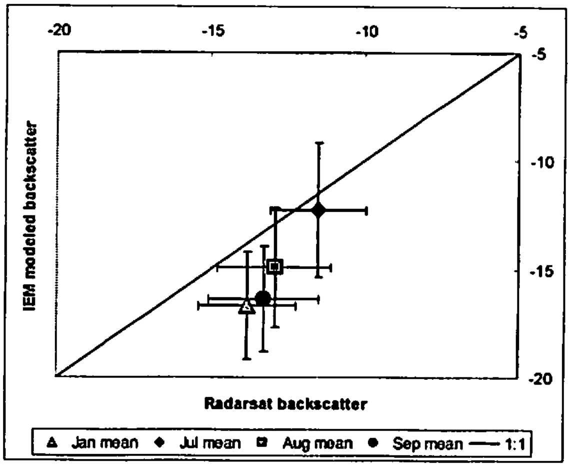

Figure 3. Observed radar backscatter versus modeled radar backscatter for 35 x 35 m^2 areas in 2003. Each point is an average of 44 sites.

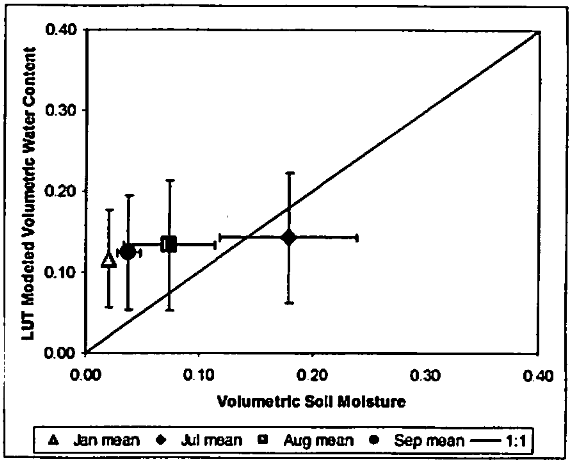

Figure 4. Predicted volumetric water content obtained through IEM generated LUT versus field volumetric water content on four dates in 2003. Soil moisture for the January period was not measured, but assumed to be 3%.

C. *Delta index*

The Δ-index approach was a better predictor of field volumetric water content than the IEM generated LUT approach (Fig. 5) as indicated by a nearly 1:1 relationship with volumetric soil moisture. Unlike the IEM, the Δ-index required two images, a dry reference image and a wetter image, to generate a relative change in water content that implicitly accounted for both roughness and volume scatter caused by rock fragments. This method provided meaningful results as long as surface roughness and vegetation density did not change significantly between image acquisition dates. Precise image registration was required to avoid erroneous change detection.

It follows that the Δ-index should increase as soil moisture increases due to a lager numerator in equation (1) for wet conditions. However, there is not a clear physical explanation for the 1:1 relationship between volumetric water content and the Δ-index. The relationship may hold in other sparsely vegetated environments because it is independent of surface roughness conditions, rock fragments and vegetation and depends primarily on the relationship between volumetric water content and real dielectric which is relatively consistent for most non-clayey mineral soils, and is robust to differences in bulk density [15].

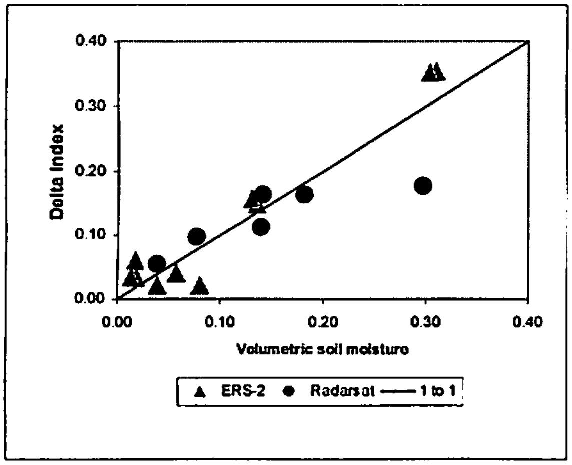

Figure 5. Delta index and volumetric soil moisture for field conditions sensed by both ERS and Radarsat satellites.

An additional advantage of the Δ-index approach is the convenience of using data from multiple sensors as long as a reference image for each sensor is available. A prominent disadvantage is its limitation to areas of un-changing surface roughness. The Δ-index is easier to implement than IEM model inversion but it should be tested in other environments.

V. Conclusions

The relationship between radar backscatter and site specific soil moisture was poor but improved dramatically when sites were spatially averaged. This indicated that radar backscatter was sensitive to large changes in soil moisture and may be useful for predicting soil moisture over large areas or across spans of time that include large changes in soil moisture.

The IEM generated LUT approach to estimating soil moisture was negatively affected by the abundance of rock fragments in the near surface soil in the study area as indicated by a narrow range in observed backscatter for a large range in observed soil moisture content. It should be re-examined by modifying the dielectric vs. soil moisture relationship to account for volumetric rock fraction in the near surface soil.

The Δ-index was a better predictor of soil moisture as indicated by its approximation of the 1:1 line with soil moisture, and it was shown to be useful with both ERS and Radarsat imagery. It accounted for sparse vegetation, rock fragments and surface roughness implicitly by using a reference image that contained that 'information' in a spatial context. It was easier to implement than the IEM generated LUT but required careful image registration and would only be useful in environments where surface roughness and vegetation do not change between image acquisitions. It should be tested in other environments to determine if this relationship is universal for sparsely vegetated areas.

VI. References

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