Inferring the impact of radar incidence angle on soil moisture retrieval skill using data assimilation

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I. Introduction

The sensitivity of radar backscatter signals to vegetation and surface properties is expected to vary significantly as a function of radar incidence angle (θ). Consequently, the impact of θ on surface soil moisture (Θ_s) retrieval skill is an key design consideration for satellite-based radars tasked with the remote estimation of Θ_s. Work by Ulaby and colleagues demonstrated that low incidence angles (10-20°) are generally preferred [8], [17], yet larger θ values are typically required in order to achieve good spatio-temporal ground coverage. Side-looking radars such as the scatterometer on board European Remote Sensing (ERS) satellites cover the θ range between 20 to 60° (approximately), while the conical scanning Soil Moisture Active Passive (SMAP) mission will acquire backscatter measurements at a fixed mid-range incidence angle of 40° [13]. Unfortunately, the impact of θ on retrieval skill is difficult to quantify because of significant uncertainties in existing backscatter (σ°) models [2]. Even over bare soil surfaces, σ° models exhibit markedly different sensitivities to θ because of difficulties describing the roughness of natural surfaces [20]. This uncertainty is compounded over vegetated surfaces where variations in Θ_s uncertainty with θ depend on the assumed strength of so-called "canopy interaction" and/or "double-bounce" backscatter terms [21].

Theoretical models exist for capturing such terms [19], however they cannot be properly inverted due to their complexity. Therefore, simpler model functions trained by either theoretical models and/or derived from empirical observations are required for operational Θ_s retrieval. One possibility are so-called "vegetation water cloud" models which explicitly ignore canopy interaction terms [1]. In general, backscatter models lacking such terms attribute changes in far-range backscatter almost exclusively to vegetation [14] and predict little or no sensitivity to Θ_s at large θ. Conversely, the Water Retrieval Package 5 (WARP5) backscatter model developed by TU-Wien for retrieving Θ_s from ERS scatterometer and METOP Advanced Scatterometer (ASCAT) observations implicitly assumes the presence of a large interaction term [15] and predicts the sensitivity term $\delta\sigma^\circ[\mathrm{dB}]/\delta\Theta_s$ is constant across all θ. Since the noise of radar measurements is given in dB [18], this assumption implies that the signal to noise ratio of the Θ_s retrievals, and therefore their skill, does not decrease with increasing θ, even at far-range (>50°) and in the presence of dense vegetation.

Attempts to resolve this discrepancy over realistic landscapes are typically hampered by a lack of sites where ground-based Θ_s observations are sufficiently dense for direct comparisons with coarse-scale (>10 km) satellite retrievals. For example, a validation study of several remotely-sensed Θ_s products over Western Africa using sparse ground-based Θ_s measurements yielded very similar results for scatterometer soil moisture products retrieved with WARP5 and a second backscatter model developed by [24], even though the two models treat the vegetation component quite differently [11]. However, a recently-developed evaluation technique provides a method of evaluating large-scale soil moisture products in the absence of ground-based Θ_s observations [5]–[7]. Here, we apply this technique in an attempt to clarify the impact of θ on radar-based Θ_s retrieval skill.

II. Backscatter Modeling

The ERS WARP5 backscatter model is similar in functionality to the cloud model, with the important exception that it exhibits an increased sensitivity to Θ_s at far-range by assuming a linear relationship between Θ_s and σ° (now in dB units) across the entire θ range. At a reference angle of 40°, backscatter is given by

$$\sigma^\circ(40^\circ) = \Theta_s(\mathrm{wet}_{\mathrm{ref}} - \mathrm{dry}_{\mathrm{ref}}) + \mathrm{dry}_{\mathrm{ref}} \tag{1}$$

and can be related to backscatter at any θ through

$$\sigma^{\circ}(\theta)=\sigma^{\circ}(40^{\circ})+\sigma^{'}(\theta)(\theta-40^{\circ})+\frac{1}{2}\sigma^{''}(\theta)(\theta-40^{\circ})^{2} \tag{2}$$

Backscatter bounding parameters $\mathrm{wet}_{\mathrm{ref}}$ and $\mathrm{dry}_{\mathrm{ref}}$ in (4) are calculated from extremely high and low backscatter values within a sufficiently long time series of σ° observations at a single point. In addition, $\mathrm{wet}_{\mathrm{ref}}$, $\mathrm{dry}_{\mathrm{ref}}$, $\sigma^{'}$, and $\sigma^{''}$ all vary seasonally due to patterns of vegetation growth and decay. Full WARP5 details and exact parameterizations are given in [15]. Note that, starting with (4), all references to σ° assume dB units and a vertically transmitting and receiving (VV) backscatter polarization.

III. The R_{value} Metric

Directly inferring the impact of θ on Θ_s retrieval skill requires the availability of large-scale Θ_s measurements derived from ground-based sampling. Since such observations are rarely available, we will explore the application of an alternative strategy based solely on ground-based precipitation measurements. The R_{value} metric for remotely-sensed Θ_s retrieval is based on sampling the Pearson's correlation coefficient between data assimilation analysis increments, realized upon the assimilation of a remotely-sensed Θ_s product into a water balance model, and known rainfall errors [5]–[7]. The typical model implementation is using daily, satellite-based precipitation accumulation estimates (P^{sat}) to derive the Antecedent Precipitation Index (API)

$$\mathrm{API}_i=\gamma_i\mathrm{API}_{i-1}+P_i^{\mathrm{sat}} \tag{3}$$

where γ is the unit-less API coefficient, i is a daily time index and P^{sat} has units of mm. In the interest of simplicity, γ is assumed equal to a constant value of 0.85.

Using a Rauch-Tung-Strebel smoother (RTS), Θ_{RS} retrievals are assimilated into (6). At each retrieval time, the RTS smoother either removes or adds water to (6) in response to information contained in Θ_{RS}. The time-series of these changes are referred to as analysis increments. Given a sufficiently long time series of data, the Pearson's correlation coefficient (R) between 5-day sums of analysis increments and precipitation errors can be sampled for a particular geographic location. Following [5], the negative of this sampled coefficient is referred to as the R_{value} coefficient for a particular soil moisture product. The magnitude of R_{value} reflects the efficiency with which the assimilation of Θ_{RS} can compensate (6) for stochastic error in P^{sat}. Higher R_{value} corresponds greater amount of added value in Θ_{RS} estimates. In fact, comparisons with extensive ground-based Θ_s observations at isolated test-bed sites reveal a linear relationship between R_{value} and the R between anomalies in Θ_{RS} and ground-based Θ_s observations [7]. Therefore, the R_{value} metric is a robust proxy for relative variations in soil moisture retrieval skill. While alternative R_{value} approaches could be designed with more complex water balance models, a statistical analysis of verification results in [7] implies that more complex models are unlikely to improve its reliability as a skill metric. In practical terms, the current R_{value} approach also has the added benefit of not requiring the availability of ground-based Θ_s observations or any other ancillary information and is thus broadly applicable at continental and global scales. Our specific purpose here is to use the R_{value} approach to provide supporting evidence regarding the appropriate relationship between soil moisture retrieval skill and θ.

IV. Methodology

A. Soil Moisture and Precipitation Data

The ERS scatterometer Θ_{RS} dataset is derived using the WARP5 model presented by [15] and 5.3 GHz VV-polarization σ° measurements obtained from the ERS-1 and -2 satellites between August 1991 and May 2007. P^{gauge} is obtained from the gauge-based National Center for Environmental Prediction (NCEP) Climate Prediction Center (CPC) retrospective CONUS rainfall product [12]. Following the convention used in CPC processing, daily rainfall accumulations are defined as total observed precipitation between 12 and 12 UTC. Because daily satellite-based rainfall products do not extend back for the entire length of the ERS dataset, P^{sat} is generated through the artificial degradation of P^{gauge}.

Our analysis is based on 1° simulations run within two separate regions of the United States: a Southern Great Plains (SGP) regional domain between 32.5-40.5°N and 94.5-103.5°W and a Southeastern (SE) regional domain

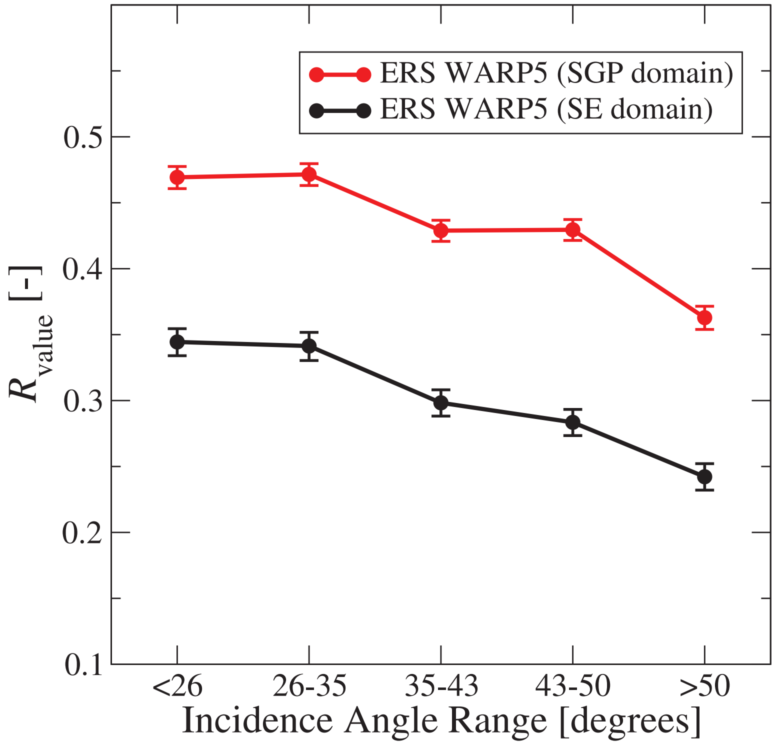

Fig. 1. The observed variation of domain-averaged R_{value} with θ for the real ERS data case over the lightly-vegetated Southern Great Plains (SGP) and moderately-vegetated Southeastern (SE) United States domains. Error bars represent the 2σ sampling uncertainty range of domain-averaged R_{value}.

covering 30.5-38.5°N and 79.5-88.5°W. Landcover in the SGP domain is generally short grassland and rangeland with low levels of vegetation biomass. In contrast, the SE domain is more heavily vegetated with a combination of upload forested areas and valley-based cropland. Prior to the analysis, all data is processed onto a daily, 1° latitude/longitude grid, and the subsequent R_{value} analysis is applied separately to each 1° box.

B. R_{value} Approach

In order to examine the relative variation of R_{value} with θ, all ERS soil moisture retrievals are divided into five separate θ bins: $<26°$, 26-35°, 35-43°, 43-50° and $>50°$. These particular bins are selected so each contains an approximately equal fraction of all ERS WARP5 retrievals. Here, θ is assumed to be the average of the fore-, aft- and mid-beam incidence angles for ERS measurements within a single 1° grid-box on a given day. R_{value} is then individually estimated for ERS WARP5 Θ_s retrievals falling within each θ range. Relative variations in R_{value} for this case reveal the manner in which θ changes impact Θ_s retrieval skill. Error bars for sampled R_{value} estimates are based on the application of Fisher's z-transformation to ensure normality (see [16] p. 148).

V. Results

Figure 1 shows the variation of R_{value} with θ for the real ERS data case. R_{value} results are presented as spatial averages of all 1° R_{value} results calculated within each domain. For the SGP domain, calculated R_{value} declines slightly with θ. Since the R_{value} metric has a strong linear relationship with the Pearson correlation coefficient between retrieved and ground-observed Θ_s anomalies [7], the ratio $\widehat{R}_{\text{value}} = R_{\text{value}}(>50°) \big/ R_{\text{value}}(<26°)$ approximates the corresponding ratio in correlation-based skill. Based on this reasoning, the highest θ range in Figure 1 (for the SGP domain) retains 77% of the correlation-based anomaly skill found in the lowest θ range (i.e. $\widehat{R}_{\text{value}} = 0.77$). Reflecting the impact of increased vegetation biomass and thus lower retrieval skill, relatively lower R_{value} results are noted over the SE domain. In addition, slightly more sensitivity to θ is found as the $\widehat{R}_{\text{value}}$ ratio falls to 0.70.

VI. Conclusions

The impact of θ on Θ_s retrieval skill represents an areas of significant uncertainty for efforts to apply spaceborne radars to operationally estimate Θ_s over continental-scale regions. Here, we attempt to clarify this issue by applying a new data assimilation-based evaluation method for remotely-sensed Θ_s products. Despite a slight reduction in skill with increasing θ, statistically significant skill is detectable at all θ ranges within the TU-Wien WARP5 surface Θ_s data product. Specifically, θ retrievals based on far-field ($\theta > 50^\circ$) ERS observations in the SGP (SE) domain retain 77% (70%) of the correlation-based skill present in retrievals at the lowest available ERS θ range. Additional results presented in our presentation will examine the degree to which observed variations with θ are consistent will assumptions underlying the WARP5 and cloud vegetation backscattering models.

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