The Impact of Radar Incidence Angle on Soil-Moisture-Retrieval Skill

Wade T. Crow, *Member, IEEE*, Wolfgang Wagner, *Senior Member, IEEE*, and Vahid Naeimi

***Abstract*—The impact of measurement incidence angle (θ) on the accuracy of radar-based surface soil-moisture (Θ_s) retrievals is largely unknown due to discrepancies in theoretical backscatter models as well as limitations in the availability of sufficiently extensive ground-based Θ_s observations for validation. Here, we apply a data-assimilation-based evaluation technique for remotely sensed Θ_s retrievals that does not require ground-based soil-moisture observations to examine the sensitivity of skill in surface Θ_s retrievals to variations in θ. Past results with the evaluation approach have shown that it is capable of detecting relative variations in the anomaly correlation coefficient between remotely sensed Θ_s retrievals and ground-truth soil-moisture measurements. Application of the evaluation approach to the Vienna University of Technology (TU Wien) European Remote Sensing (ERS) scatterometer Θ_s data set over regional-scale ($\sim 1000^2$ km^2) domains in the Southern Great Plains and southeastern (SE) regions of the U.S. indicate a relative reduction in correlation-based skill of 23% to 30% for Θ_s retrievals obtained from far-field $(\theta > 50^\circ)$ ERS observations relative to Θ_s estimates obtained at $\theta < 26^\circ$. Such relatively modest sensitivity to θ is consistent with Θ_s retrieval noise predictions made using the TU-Wien ERS Water Retrieval Package 5 backscatter model. However, over moderate vegetation cover in the SE domain, the coupling of a bare soil backscatter model with a "vegetation water cloud" canopy model is shown to overestimate the impact of θ on Θ_s retrieval skill.**

***Index Terms*—Data assimilation, radar, remote sensing, soil moisture.**

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 a key design consideration for satellite-based radars tasked with the remote estimation of Θ_s. The work by Dobson and Ulaby demonstrated that low incidence angles (10°–20°) are generally preferred [8], [17], yet larger θ values are typically required in order to achieve good spatiotemporal ground coverage. Side-looking radars, such as the scatterometer on board European Remote Sensing (ERS) satellites, cover the θ range between 20° and 60° (approximately), while the conical-scanning Soil Moisture Active Passive mission will acquire backscatter measurements at a fixed midrange 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 the 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 is the 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 Vienna University of Technology (TU Wien) for retrieving Θ_s from ERS scatterometer and meteorological operational (METOP) Advanced Scatterometer (ASCAT) observations implicitly assumes the presence of a large interaction term [15] and predicts that the sensitivity term $\delta\sigma^\circ(\text{in decibels})/\delta\Theta_s$ is constant across all θ. Since the noise of radar measurements is given in decibels [18], this assumption implies that the signal-to-noise ratio of the Θ_s retrievals, and therefore their skill, do not decrease with increasing θ even at far range $(> 50^\circ)$ 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 has provided 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 water cloud model representation of vegetation is based on decomposing total backscatter (in linear units) into

Manuscript received October 1, 2009; revised December 2, 2009. Date of publication February 22, 2010; date of current version April 29, 2010.

W. T. Crow is with the U. S. Department of Agriculture, Agricultural Research Services, Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705 USA (e-mail: wade.crow@ars.usda.gov).

W. Wagner and V. Naeimi are with the Institute for Photogrammetry and Remote Sensing, Vienna University of Technology, 1040 Vienna, Austria (e-mail: ww@ipf.tuwien.ac.at; vnaeimi@ipf.tuwien.ac.at).

Digital Object Identifier 10.1109/LGRS.2010.2040134

1545-598X/$26.00

components from transparent (tr) and nontransparent (nt) vegetation canopies within a single scatterometer footprint

$$\sigma^\circ = (1 - C_{\rm nt})\sigma^\circ_{\rm tr} + C_{\rm nt}\sigma^\circ_{\rm nt} \tag{1}$$

where $C_{\rm nt}$ represents the areal fraction of the footprint covered by nontransparent canopy. Here, $\sigma^\circ_{\rm nt}$ is assumed to be

$$\sigma^\circ_{\rm nt} = \frac{\omega_{\rm nt}\cos\theta}{2} \tag{2}$$

$$\sigma^\circ_{\rm tr} = \frac{\omega_{\rm tr}\cos\theta}{2}\left(1 - e^{\frac{-2\tau}{\cos\theta}}\right) + \sigma^\circ_s e^{\frac{-2\tau}{\cos\theta}} \tag{3}$$

where ω is the single scattering albedo of the vegetation canopy (both transparent and nontransparent) and $\tau_{\rm tr}$ is the optical depth of the transparent canopy. The backscatter from the bare soil surface (σ°_s) in (3) is modeled using the integral empirical model (IEM) [10] with an exponential model for surface-roughness autocorrelation. The IEM predicts σ°_s as a function of surface-roughness s, surface reflectivity, and the surface-roughness correlation length l. Surface reflectivity can then be related to volumetric soil moisture (Θ_s) through the Fresnel equations and the Dobson soil-moisture mixing model [9] based on knowledge of soil sand (Sa) and clay (Cl) fractions. Here, the imaginary part of the soil dielectric constant is neglected, and the vegetation dielectric constant is assumed to be one. We will refer to the combination of (1)–(3) with the exponential IEM as the "IEM/Cloud" backscatter model for vegetated surfaces

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 decibel units) across the entire θ range. At a reference angle of 40°, backscatter is given by

$$\sigma^\circ(40^\circ) = \Theta_s({\rm wet}_{\rm ref} - {\rm dry}_{\rm ref}) + {\rm dry}_{\rm ref} \tag{4}$$

and can be related to backscatter at any θ through

$$\sigma^\circ(\theta) = \sigma^\circ(40^\circ) + \sigma'(\theta)(\theta - 40^\circ) + \frac{1}{2}\sigma''(\theta)(\theta - 40^\circ)^2. \tag{5}$$

The backscatter bounding parameters ${\rm wet}_{\rm ref}$ and ${\rm dry}_{\rm ref}$ 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, ${\rm wet}_{\rm ref}$, ${\rm dry}_{\rm ref}$, σ', and σ'' 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 decibel units and a vertically transmitting and receiving (VV) backscatter polarization.

III. $R_{\rm value}$ 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 $R_{\rm value}$ metric for remotely sensed Θ_s retrievals 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 $(P^{\rm sat})$ to derive the antecedent precipitation index (API)

$$\text{API}_i = \gamma_i \text{API}_{i-1} + P^{\rm sat}_i \tag{6}$$

where γ is the unitless API coefficient, i is a daily time index, and $P^{\rm sat}$ has units in millimeters. In the interest of simplicity, γ is assumed equal to a constant value of 0.85. Past work also used a slightly more complex parameterization where γ varies seasonally [6], but verification results presented in [7] suggest that assuming a constant γ is adequate. Higher quality daily rainfall accumulations derived from the retrospective correction of $P^{\rm sat}$ using ground-based rain gauges $(P^{\rm gauge})$ must also be available but are held in reserve for later evaluation.

Following [7], we decompose both precipitation products and Θ_s derived from a remotely sensing source $(\Theta_{\rm RS})$ into their climatology and anomaly components

$$\widehat{\Theta}_{{\rm RS}_i} = \Theta_{{\rm RS}_i} - \overline{\Theta}_{{\rm RS}_{\rm DOY}} \tag{7}$$

$$\widehat{P}^{\rm sat}_i = P^{\rm sat}_i - \overline{P}^{\rm sat}_{\rm DOY} \tag{8}$$

$$\widehat{P}^{\rm gauge}_i = P^{\rm gauge}_i - \overline{P}^{\rm gauge}_{\rm DOY} \tag{9}$$

where $\overline{\Theta}_{{\rm RS}_{\rm DOY}}$, $\overline{P}^{\rm sat}_{\rm DOY}$, and $\overline{P}^{\rm gauge}_{\rm DOY}$ are climatological expectations for a given day of the year (DOY), and $\widehat{\Theta}_{{\rm RS}_i}$, $\widehat{P}^{\rm sat}_i$, and $\widehat{P}^{\rm gauge}_i$ are anomalies relative to these expectations experienced on day i. Climatological expectations are calculated by simple linear averaging within a 31-day moving window centered on the particular DOY corresponding to i and the entire (multiyear) historical data set for each variable.

Since the API equation is linear, (1) can also be trivially modified into its anomaly-based form

$$\widehat{\text{API}}_i = \gamma_i \widehat{\text{API}}_{i-1} + \widehat{P}^{\rm sat}_i. \tag{10}$$

Values of $\widehat{\Theta}_{{\rm RS}_i}$ are then assimilated into (10) using a Rauch–Tung–Strebel smoother that has been optimized to produce uncorrelated filtering innovations. Details of the assimilation procedure are given in [7]. The end result of this assimilation is a time series of daily analysis increments (δ) which reflect modifications made to (10) by the smoother in response to comparisons with $\widehat{\Theta}_{{\rm RS}_i}$. Our approach is based on summing these increments into a series of nonoverlapping windows of length m

$$[\delta]_k = \sum_{j=mk+1}^{j=mk+m} \delta_j \tag{11}$$

where k indexes individual m-day windows. In parallel, a comparable aggregation of rainfall errors is performed, i.e.,

$$[\varepsilon^{\rm rain}]_k = \sum_{j=mk+1}^{j=mk+m} \left(\widehat{P}^{\rm gauge}_i - \widehat{P}^{\rm sat}_i\right). \tag{12}$$

Here, m will be set equal to 15 days, and only 15-day windows in which at least two $\Theta_{\rm RS}$ retrievals are available will be included into the eventual $R_{\rm value}$ calculation. This window size is slightly larger than the five- to seven-day windows used in [5]–[7] to account for the reduced frequency of ERS scatterometer measurements at a given point relative to products obtained from scanning radiometers (i.e., the primary focus of past work).

Given a sufficiently long time series of data, the Pearson's correlation coefficient (R) between $[\delta]$ and $[\varepsilon^{\text{rain}}]$ 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}. Comparisons with extensive ground-based Θ_s observations at isolated test-bed sites reveal a strong linear relationship between R_{value} and 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 such 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 goal 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} data set 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. The WARP5 model is now also used to operationally generate the European Meteorological Satellite Organization METOP ASCAT Θ_s product [4]. It includes several improvements to the earlier algorithm developed by [23] but leaves the general functionality of the algorithm unchanged. One improvement is a module for correcting azimuthal anisotropy as observed over some land surface types [3]. WARP5 also includes a comprehensive error model to estimate Θ_s retrieval noise for each grid point. This retrieval noise varies in space and time primarily reflecting changes in sensitivity due to different land cover and phenological states [15].

P^{gauge} is obtained from the gauge-based National Center for Environmental Prediction Climate Prediction Center (CPC) retrospective contiguous United States rainfall product [12]. Following the convention used in CPC processing, daily rainfall accumulations are defined as total observed precipitation between 12 and 12 coordinated universal time. Because daily satellite-based rainfall products do not extend back for the entire length of the ERS data set, P^{sat} is generated through the artificial degradation of P^{gauge}. Here, this degradation is performed via

$$P_i^{\text{sat}} = \alpha P_i^{\text{gauge}} + \beta \tag{13}$$

where the unitless random variable α is log-normally distributed with mean one and standard deviation σ_α, and β is normally distributed with mean zero and standard deviation σ_β. To roughly match previous R_{value} results in the southern U.S. derived from actual satellite-based precipitation measurements [6], σ_α and σ_β are set to values of 3 (unitless) and 10 mm, respectively.

Our analysis is based on 1° simulations run within two separate regions of the U.S.: a Southern Great Plains (SGP) regional domain between 32.5° N and 40.5° N, and 94.5° W and 103.5° W, and a southeastern (SE) regional domain covering 30.5° N–38.5° N and 79.5° W–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 that each contains an approximately equal fraction of all ERS WARP5 retrievals. Here, θ is assumed to be the average of the fore-beam, aft-beam, and midbeam incidence angles for ERS measurements within a single 1° grid box on a given day. The R_{value} is then individually estimated for ERS WARP5 Θ_s retrievals falling within each θ range. Hereinafter, these results will be referred to as the "real ERS" data case. Relative variations in R_{value} for this case reveal the manner in which θ changes impact Θ_s retrieval skill.

A secondary goal is comparing real ERS results with synthetic cases in which the variation of R_{value} with θ is predicted from a radar backscatter model. To this end, a synthetic baseline truth Θ_{RS} time series is generated by driving (1) with P^{gauge}. These "truth" soil-moisture values (API^*) are then artificially perturbed following

$$\Theta_{\text{RS}_i} = \text{API}_i^* + \lambda \cdot \varepsilon_{\Theta_s} \cdot \eta_i \tag{14}$$

where ε_{Θ_s} is the standard error in volumetric Θ_s retrievals and η is a normalized Gaussian random variable with no temporal or spatial autocorrelation. The constant scaling factor λ [in millimeters] is required to translate between volumetric and water-depth units and is used as a tuning parameter. Note that an additional scaling factor could be used to convert the entire right-hand side of (14) back into volumetric soil-moisture units; however, it is unnecessary since R_{value} results are insensitive to any linear transformation of Θ_{RS} [5].

Here, ε_{Θ_s} is estimated from

$$\varepsilon_{\Theta_s}^2 \approx \sum_{j=1}^{n} \left(\frac{\delta \Theta_s}{\delta x_j} \right)^2 \varepsilon_{x_j}^2 \tag{15}$$

where the length-n vector $\mathbf{x}$ consists of various parameter inputs into the backscatter model. For the WARP5 model, values of ε_{Θ_s} are already provided by [15]. For the IEM/Cloud model, $\mathbf{x}$ is defined as

$$\mathbf{x} = [\sigma^\circ, \tau_{\text{tr}}, \omega_{\text{tr}}, \omega_{\text{nt}}, C_{\text{nt}}, l, s, Sa, Cl]. \tag{16}$$

Values for $\delta\Theta_s/\delta x_j$ are then derived from tangent linear calculations of (1)–(3). Parameter values for the application of the IEM/Cloud model to both domains are given in Table I. The 1σ magnitude of input errors (ε_{x_j}) are based on assuming

TABLE I
IEM/CLOUD MODEL PARAMETERS FOR THE SGP AND SE U.S. DOMAINS

	$\tau_{\rm tr}$	s	l	$C_{\rm nt}$	$\omega_{\rm tr}$	$\omega_{\rm nt}$	Sa	Cl
	[-]	[cm]	[cm]	[-]	[-]	[-]	[%]	[%]
SGP	0.30	0.5	10.0	0.10	0.10	0.45	30	20
SE	0.75	0.5	10.0	0.25	0.10	0.45	30	20

a 20% relative uncertainty in $\tau_{\rm tr}$ and $\omega_{\rm tr}$ and 10% relative uncertainty in s and l. Biases in time-constant parameters (i.e., Sa, Cl, and $C_{\rm nt}$) are neglected since $R_{\rm value}$ captures skill with regard to relative change detection only. In addition, $\varepsilon_{\sigma^\circ}$ is set equal to 0.50 dB. The values of θ required for the calculation of $\delta\Theta_s/\delta x_j$ are taken from the actual time-series of ERS overpasses within each domain, and the soil-moisture values required to calculate $\delta\Theta_s/\delta x_j$ are derived from API$^*/15$ mm to reflect an expected 30-mm measurement depth and 50% soil porosity.

The time series of synthetic $\Theta_{\rm RS}$ calculated from (14) are then substituted into (7)–(12) and are used to calculate $R_{\rm value}$ for the θ ranges described earlier. Since noise in synthetically generated $\Theta_{\rm RS}$ is based solely on sensitivities present in each backscatter model, the calculated $R_{\rm value}$ reflects the predicted variation (for each backscatter model) of retrieval skill with θ. Because our goal is to examine only the relative variation of $R_{\rm value}$ with θ, a single-domain-scale value of λ in (14) is tuned so that the $R_{\rm value}$ results for the central θ range of 35°–43° match those sampled for the real ERS case. The error bars for the sampled $R_{\rm value}$ estimates are based on the application of Fisher's z-transformation to ensure normality (see [16, p. 148]) and an assumption of spatial and temporal independence in $\overline{\delta_i}$ and $\overline{\varepsilon_i^{\rm rain}}$ values. The likelihood of such independence is maximized by the large spatial and temporal scales of the analysis (1° latitude/longitude and 15 days).

V. RESULTS

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

In order to compare the results in Fig. 1 with uncertainty predictions based on existing backscatter models, Fig. 2 shows the plot of $R_{\rm value}$ results for the real ERS data case alongside synthetic results based on noise calculations derived from the ERS WARP5 and IEM/Cloud backscatter models. As described earlier, these synthetic cases are generated by adding noise values (derived from [15] for WARP5 and (15) for the IEM/Cloud model) to API* via (14). For each synthetic case, a domain-constant value of λ in (14) is tuned to ensure that $R_{\rm value}$ results match the real ERS data case for the 35°–43° θ range. Within

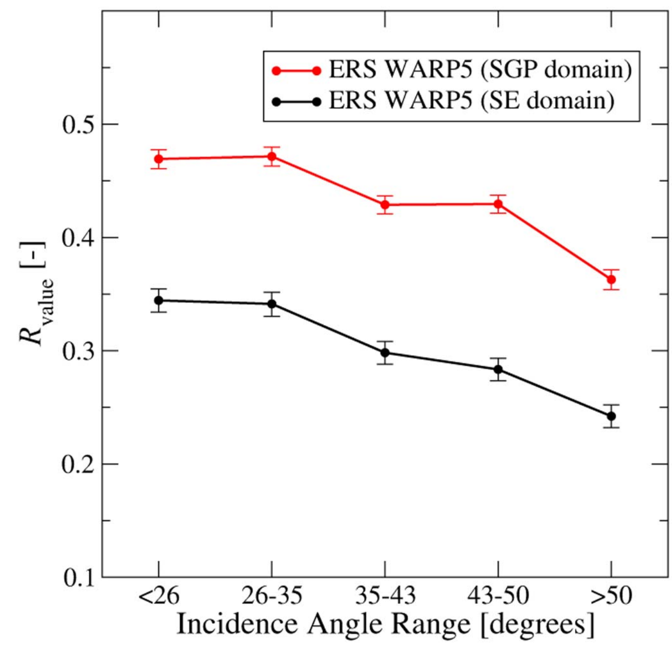

Fig. 1. Observed variation of domain-averaged $R_{\rm value}$ with θ for the real ERS data case over the lightly vegetated SGP and the moderately vegetated SE U.S. domains. Error bars represent the 2σ sampling uncertainty range of domain-averaged $R_{\rm value}$.

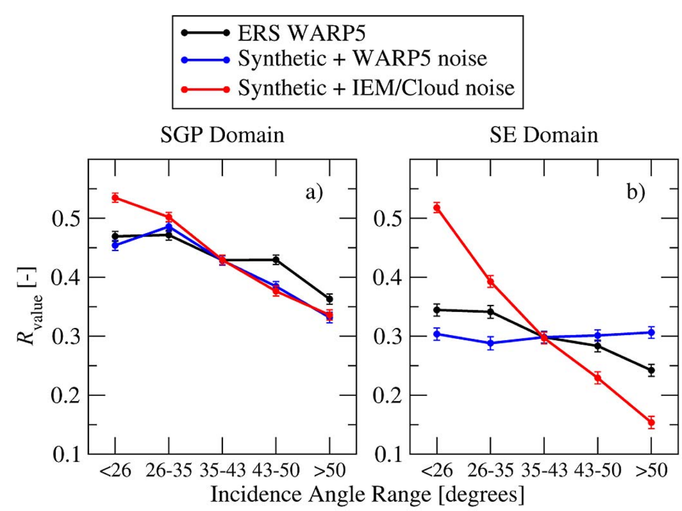

Fig. 2. Variation of domain-averaged $R_{\rm value}$ with θ for the real ERS, synthetic + WARP5.0 noise, and synthetic + IEM/Cloud noise cases within the (a) lightly vegetated SGP and (b) moderately vegetated SE domains. Error bars represent the 2σ sampling uncertainty range of domain-averaged $R_{\rm value}$.

the lightly vegetated SGP domain [Fig. 2(a)], the relationship between retrieval skill and θ predicted by the ERS WARP5 model (blue line) presents a good fit to real ERS results (black line). In particular, the WARP5 model predicts $\widehat{R}_{\rm value} = 0.74$, which nearly matches the real ERS result of $\widehat{R}_{\rm value} = 0.77$. However, the predicted $\widehat{R}_{\rm value}$ for the IEM/Cloud case (red line) falls to 0.63—indicating a slight overestimation of the actual impact of θ on retrieval skill by the IEM/Cloud model.

The performance of both backscatter models degrades over the more densely vegetated SE domain [Fig. 2(b)]. The ERS WARP5 model predicts essentially no variation with θ (blue line) and fails to capture the modest decline in $R_{\rm value}$ at high

θ observed in the real ERS case (black line). Conversely, the IEM/Cloud model (red line) sharply overpredicts the impact of θ on retrieval skill—leading to a predicted $\widehat{R}_{\mathrm{value}}$ that significantly underestimates the real ERS case (0.31 versus 0.70). Consequently, as parameterized in Table I, the IEM/Cloud model substantially underestimates the skill of Θ_s retrievals based on far-field ERS observations.

Several sensitivities should be noted when interpreting Figs. 1 and 2. One arbitrary aspect of the analysis is the selection of α and β in (13) to generate P^{sat}. However, sensitivity analyses (not shown) demonstrate that the presented results are generally robust to variations in these parameters. In contrast, care should be taken in interpreting the IEM/Cloud model synthetic results since the R_{value} predictions exhibit sensitivity to retrieval parameter values listed in Table I. Alternative parameterizations exist (e.g., lower τ or higher s) that could reduce the impact of θ variations on IEM/Cloud R_{value} predictions.

VI. Conclusion

The impact of θ on Θ_s retrieval skill represents an area of significant uncertainty for efforts to apply spaceborne radars to operationally estimate Θ_s over continental-scale regions. Here, we have attempted to clarify this issue by applying a new data-assimilation-based evaluation method for remotely sensed Θ_s products. Our results support three specific conclusions.

1) 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 $(\theta < 26^\circ)$.
2) Over the lightly vegetated SGP domain, this lack of sharp variation in retrieval skill with increasing θ is roughly consistent with uncertainty predictions obtained from the ERS WARP5 backscatter model. However, over the SE domain, noise predictions from the WARP5 model slightly underpredict the observed impact of θ on retrieval skill.
3) The coupling of the IEM bare soil backscatter model with a vegetation cloud model generally overestimates the impact of θ on Θ_s retrieval skill—particularly over the moderately vegetated SE domain. One possible cause for this is the lack of a canopy interaction term in (3) which causes the IEM/Cloud model to underestimate the skill in far-field Θ_s retrievals over vegetated landscapes. However, it is also possible that alternative parameterizations of the IEM/Cloud model (e.g., variations in s, l, or τ) may produce more accurate results without requiring the presence of a canopy interaction term in (3). Clearly differentiating between these two possible causes will likely require the examination of finer scale sites where the IEM/Cloud model parameters can be independently obtained.

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