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

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Abstract—The impact of measurement incidence angle (θ) on the accuracy of radar-based surface soil-moisture (Θs) retrievals is largely unknown due to discrepancies in theoretical backscatter models as well as limitations in the availability of sufficiently extensive ground-based Θs observations for validation. Here, we apply a data-assimilation-based evaluation technique for remotely sensed Θs retrievals that does not require ground-based soil-moisture observations to examine the sensitivity of skill in surface Θs 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 Θs 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 Θs data set over regional-scale (~1000 km²) 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 Θs retrievals obtained from far-field (θ > 50°) ERS observations relative to Θs estimates obtained at θ < 26°. Such relative modest sensitivity to θ is consistent with Θs 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 Θs 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 (Θs) retrieval skill is a key design consideration for satellite-based radars tasked with the remote estimation of Θs. 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 Θs 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 Θs 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 Θs at large θ. Conversely, the Water Retrieval Package 5 (WARP5) backscatter model developed by Vienna University of Technology (TU Wien) for retrieving Θs 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 δσ°/δΘs 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 Θs retrievals, and therefore their skill, do 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 Θs observations are sufficiently dense for direct comparisons with coarse-scale (> 10 km) satellite retrievals. For example, a validation study of several remotely sensed Θs products over Western Africa using sparse ground-based Θs 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 Θs observations [5]–[7]. Here, we apply this technique in an attempt to clarify the impact of θ on radar-based Θs retrieval skill.

II. BACKSCATTER MODELING

The water cloud model representation of vegetation is based on decomposing total backscatter (in linear units) into

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

\[
\sigma^o = (1 - C_{nt})\sigma^o_{tr} + C_{nt}\sigma^o_{nt}
\]  

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

\[
\sigma^o_{nt} = \frac{\omega_{nt} \cos \theta}{2} \left( 1 - e^{-2\theta mR} \right) + \sigma^o_s e^{-2\theta mR}
\]

where \( \omega \) is the single scattering albedo of the vegetation canopy (both transparent and nontransparent) and \( \tau_{tr} \) is the optical depth of the transparent canopy. The backscatter from the bare soil surface \( (\sigma^o_s) \) in (3) is modeled using the integral empirical model (IEM) [10] with an exponential model for across the entire depth of the transparent canopy. The backscatter from the surface-roughness function of surface-roughness autocorrelation. The IEM predicts \( \sigma^o_s \) 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 \( (\Theta_s) \) 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 \( \Theta_s \) at far range by assuming a linear relationship between \( \Theta_s \) and \( \sigma^o \) (now in decibel units) across the entire \( \theta \) range. At a reference angle of 40°, backscatter is given by

\[
\sigma^o(40^\circ) = \Theta_s (\text{wet}_ref - \text{dry}_ref) + \text{dry}_ref
\]

and can be related to backscatter at any \( \theta \) through

\[
\sigma^o(\theta) = \sigma^o(40^\circ) + \sigma'(\theta)(\theta - 40^\circ) + \frac{1}{2}\sigma''(\theta)(\theta - 40^\circ)^2.
\]

The backscatter bounding parameters \( \text{wet}_ref \) and \( \text{dry}_ref \) in (4) are calculated from extremely high and low backscatter values within a sufficiently long time series of \( \sigma^o \) observations at a single point. In addition, \( \text{wet}_ref, \text{dry}_ref, \sigma', \) 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 \( \sigma^o \) assume decibel units and a vertically transmitting and receiving (VV) backscatter polarization.

III. \( R_{value} \) METRIC

Directly inferring the impact of \( \theta \) on \( \Theta_s \) retrieval skill requires the availability of large-scale \( \Theta_s \) 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 \( \Theta_s \) retrievals is based on sampling the Pearson’s correlation coefficient between data assimilation analysis increments, realized upon the assimilation of a remotely sensed \( \Theta_s \) 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)

\[
API_i = \gamma_i API_{i-1} + P_{sat}
\]

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

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

\[
\Theta_{RS} = \Theta_{RS} \pm \Theta_{RS-DAY}
\]

where \( \Theta_{RS-DAY}, P_{rain-DAY}, \) and \( P_{gauge-DAY} \) are climatological expectations for a given day of the year (DOY), and \( \Theta_{RS} \), \( P_{sat} \), and \( P_{gauge} \) 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

\[
\hat{API}_i = \gamma_i \hat{API}_{i-1} + \hat{P}_{sat}
\]

Values of \( \Theta_{RS} \) 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 \( (\delta) \) which reflect modifications made to (10) by the smoother in response to comparisons with \( \Theta_{RS} \). Our approach is based on summing these increments into a series of nonoverlapping windows of length \( m \)

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

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

\[
[\epsilon]_k = \sum_{j=mk+1}^{j=mk+m} \left( \hat{P}_{gauge} \pm \hat{P}_{sat} \right).
\]

Here, \( m \) will be set equal to 15 days, and only 15-day windows in which at least two \( \Theta_{RS} \) retrievals are available will be included into the eventual \( R_{value} \) 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 $R_{\text{value}}$ coefficient for a particular soil-moisture product. The magnitude of $R_{\text{value}}$ reflects the efficiency with which the assimilation of $\Theta_{\text{RS}}$ can compensate (6) for stochastic error in $P_{\text{sat}}$. Comparisons with extensive ground-based $\Theta_s$ observations at isolated test-bed sites reveal a strong linear relationship between $R_{\text{value}}$ and $R$ between anomalies in $\Theta_{\text{RS}}$ and ground-based $\Theta_s$ observations [7]. Therefore, the $R_{\text{value}}$ metric is a robust proxy for relative variations in soil-moisture-retrieval skill. While alternative $R_{\text{value}}$ 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 $R_{\text{value}}$ approach also has the added benefit of not requiring the availability of ground-based $\Theta_s$ observations or any other ancillary information and is thus broadly applicable at continental and global scales. Our goal here is to use the $R_{\text{value}}$ approach to provide supporting evidence regarding the appropriate relationship between soil-moisture-retrieval skill and $\theta$.

IV. METHODOLOGY

A. Soil-Moisture and Precipitation Data

The ERS scatterometer $\Theta_{\text{RS}}$ data set is derived using the WARP5 model presented by [15] and 5.3-GHz VV-polarization $\sigma^0$ 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 $\Theta_s$ 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 $\Theta_s$ 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].

$P_{\text{gauge}}$ 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, $P_{\text{sat}}$ is generated through the artificial degradation of $P_{\text{gauge}}$. Here, this degradation is performed via

$$P_{\text{sat}} = \alpha P_{\text{gauge}} + \beta$$  \hspace{1cm} (13)

where the unitless random variable $\alpha$ is log-normally distributed with mean one and standard deviation $\sigma_\alpha$, and $\beta$ is normally distributed with mean zero and standard deviation $\sigma_\beta$. To roughly match previous $R_{\text{value}}$ results in the southern U.S. derived from actual satellite-based precipitation measurements [6], $\sigma_\alpha$ and $\sigma_\beta$ 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 upland forested areas and valley-based cropland. Prior to the analysis, all data is processed onto a daily 1° latitude/longitude grid, and the subsequent $R_{\text{value}}$ analysis is applied separately to each 1° box.

B. $R_{\text{value}}$ Approach

In order to examine the relative variation of $R_{\text{value}}$ with $\theta$, all ERS soil-moisture retrievals are divided into five separate $\theta$ 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, $\theta$ 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 $R_{\text{value}}$ is then individually estimated for ERS WARP5 $\Theta_s$ retrievals falling within each $\theta$ range. Hereinafter, these results will be referred to as the “real ERS” data case. Relative variations in $R_{\text{value}}$ for this case reveal the manner in which $\theta$ changes impact $\Theta_s$ retrieval skill.

A secondary goal is comparing real ERS results with synthetic cases in which the variation of $R_{\text{value}}$ with $\theta$ is predicted from a radar backscatter model. To this end, a synthetic baseline $\Theta_{\text{RS}}$ time series is generated by driving (1) with $P_{\text{gauge}}$. These “truth” soil-moisture values (API) are then artificially perturbed following

$$\Theta_{\text{RS},i} = \text{API}^\text{t} \cdot \varepsilon_{\Theta_s} \cdot \eta_i$$  \hspace{1cm} (14)

where $\varepsilon_{\Theta_s}$ is the standard error in volumetric $\Theta_s$ retrievals and $\eta$ is a normalized Gaussian random variable with no temporal or spatial autocorrelation. The constant scaling factor $\lambda$ [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 $R_{\text{value}}$ results are insensitive to any linear transformation of $\Theta_{\text{RS}}$ [5].

Here, $\varepsilon_{\Theta_s}$ is estimated from

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

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

$$x = [\sigma^0, \tau_{tr}, \omega_{tr}, \omega_{in}, C_{nt}, l, s, S_a, Cl]$$  \hspace{1cm} (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 ($\varepsilon_{x_j}$) are based on assuming
TABLE I

<table>
<thead>
<tr>
<th>IEM/CLOUD MODEL PARAMETERS FOR THE SGP AND SE U.S. DOMAINS</th>
<th>( \tau_{tr} )</th>
<th>( s )</th>
<th>( l )</th>
<th>( C_{int} )</th>
<th>( \theta_{tr} )</th>
<th>( \theta_{int} )</th>
<th>( S_{\theta} )</th>
<th>( C_{\theta} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>SGP</td>
<td>0.30</td>
<td>0.5</td>
<td>10.0</td>
<td>0.10</td>
<td>0.10</td>
<td>0.45</td>
<td>30</td>
<td>20</td>
</tr>
<tr>
<td>SE</td>
<td>0.75</td>
<td>0.5</td>
<td>10.0</td>
<td>0.25</td>
<td>0.10</td>
<td>0.45</td>
<td>30</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 1: IEM/Cloud Model Parameters for the SGP and SE U.S. Domains

A 20% relative uncertainty in \( \tau_{tr} \) and \( \omega_{tr} \) and 10% relative uncertainty in \( s \) and \( l \). Biases in time-constant parameters (i.e., \( S_{\theta}, C_{\theta} \), and \( C_{int} \)) are neglected since \( R_{\text{value}} \) captures skill with regard to relative change detection only. In addition, \( \varepsilon_{\theta} \) is set equal to 0.50 dB. The values of \( \theta \) 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 \( \theta_{RS} \) calculated from (14) are then substituted into (7)–(12) and are used to calculate \( R_{\text{value}} \) for the \( \theta \) ranges described earlier. Since noise in synthetically generated \( \theta_{RS} \) is based solely on sensitivities present in each backscatter model, the calculated \( R_{\text{value}} \) reflects the predicted variation (for each backscatter model) of retrieval skill with \( \theta \). Because our goal is to examine only the relative variation of \( R_{\text{value}} \) with \( \theta \), a single-domain-scale value of \( \lambda \) in (14) is tuned so that the \( R_{\text{value}} \) results for the central \( \theta \) range of 35\(^\circ\)–43\(^\circ\) match those sampled for the real ERS. The error bars for the sampled \( R_{\text{value}} \) 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 \( \delta_{\theta} \) and \( \varepsilon_{\theta} \) values. The likelihood of such independence is maximized by the large spatial and temporal scales of the analysis (1\(^\circ\) latitude/longitude and 15 days).

V. Results

Fig. 1 shows the variation of \( R_{\text{value}} \) with \( \theta \) for the real ERS data case. The \( R_{\text{value}} \) results are presented as spatial averages of all 1\(^\circ\) \( R_{\text{value}} \) results calculated within each domain. For the SGP domain, the calculated \( R_{\text{value}} \) declines slightly with \( \theta \). Since the \( R_{\text{value}} \) metric has a strong linear relationship with the Pearson’s correlation coefficient between retrieved and ground-observed \( \theta_{s} \) anomalies [7], the ratio \( \hat{R}_{\text{value}} = R_{\text{value}}(> 50\%) / R_{\text{value}}(< 26\%) \) approximates the corresponding ratio in correlation-based skill. Based on this reasoning, the highest \( \theta \) range in Fig. 1 (for the SGP domain) retains 77% of the correlation-based anomaly skill found in the lowest \( \theta \) range (i.e., \( \hat{R}_{\text{value}} = 0.77 \)). Reflecting the impact of increased vegetation biomass and thus, lower retrieval skill, relatively lower \( R_{\text{value}} \) results are noted over the SE domain. In addition, slightly more sensitivity to \( \theta \) is found as the \( \hat{R}_{\text{value}} \) 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 \( R_{\text{value}} \) 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 \( \lambda \) (14) is tuned to ensure that \( R_{\text{value}} \) results match the real ERS data case for the 35\(^\circ\)–43\(^\circ\) \( \theta \) range. Within the lightly vegetated SGP domain [Fig. 2(a)], the relationship between retrieval skill and \( \theta \) predicted by the ERS WARP5 model (blue line) presents a good fit to real ERS results (black line). In particular, the WARP5 model predicts \( \hat{R}_{\text{value}} = 0.74 \), which nearly matches the real ERS result of \( \hat{R}_{\text{value}} = 0.77 \). However, the predicted \( \hat{R}_{\text{value}} \) for the IEM/Cloud case (red line) falls to 0.63—indicating a slight overestimation of the actual impact of \( \theta \) 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 \( \theta \) (blue line) and fails to capture the modest decline in \( R_{\text{value}} \) at high
observed in the real ERS case (black line). Conversely, the IEM/Cloud model (red line) sharply overpredicts the impact of \( \theta \) on retrieval skill—leading to a predicted \( R_{\text{value}} \) that significantly understimates the real ERS case (0.31 versus 0.70). Consequently, as parameterized in Table I, the IEM/Cloud model substantially underestimates the skill of \( \Theta_s \) 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 \( \alpha \) and \( \beta \) in (13) to generate \( P_{\text{nat}} \). 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 \( R_{\text{value}} \) predictions exhibit sensitivity to retrieval parameter values listed in Table I. Alternative parameterizations exist (e.g., lower \( \tau \) or higher \( s \)) that could reduce the impact of \( \theta \) variations on IEM/Cloud \( R_{\text{value}} \) predictions.

VI. Conclusion

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

1) Despite a slight reduction in skill with increasing \( \theta \), statistically significant skill is detectable at all \( \theta \) ranges within the TU-Wien WARP5 surface \( \Theta_s \) data product. Specifically, \( \theta \) 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 \( \theta \) range (\( \theta < 26^\circ \)).

2) Over the lightly vegetated SGP domain, this lack of sharp variation in retrieval skill with increasing \( \theta \) 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 \( \theta \) on retrieval skill.

3) The coupling of the IEM bare soil backscatter model with a vegetation cloud model generally overestimates the impact of \( \theta \) on \( \Theta_s \) 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 \( \Theta_s \) retrievals over vegetated landscapes. However, it is also possible that alternative parameterizations of the IEM/Cloud model (e.g., variations in \( s \), \( l \), or \( \tau \)) 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.

REFERENCES