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Towards including Dynamic Vegetation Parameters in the ASCAT soil moisture products
FINAL REPORT

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1 Introduction

The TU Wien Soil Moisture Retrieval algorithm has been used to generate several satellite-derived soil moisture products from ASCAT backscatter observations. This change detection approach was first developed for ERS-1/2 data [17, 17, 19, 20], and later iterations were applied to ASCAT data [2, 10]. The WARP (WAter Retrieval Package) software implementation of TUW SMR forms the basis of the operationally used algorithm to produce the soil moisture products generated, distributed by and archived by the EUMETSAT Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF). These are derived from the Advanced Scatterometer (ASCAT) onboard the series of Metop satellites and use the TU Wien soil moisture retrieval algorithm (TUW SMR) to derive surface soil moisture information from backscatter observations. The Metop ASCAT Surface Soil Moisture (SSM) Climate Data Record (CDR) products (H25, H109 and H111) and the Near Real-Time (NRT) Surface Soil Moisture products (H101, H102, H16, H103) are direct applications of the TU Wien change detection approach using Metop ASCAT backscatter observations. The Disaggregated Surface Soil Moisture product at 1 km product (H08) is obtained by downscaling the Metop ASCAT NRT SSM (i.e. H16) using higher resolution SAR data. Root zone soil moisture products (SM DAS 2-H14, SM DAS 3-H27) are obtained by ECMWF by assimilating the Metop ASCAT NRT SSM products into a land surface model. These operational soil moisture products are essential for numerical weather prediction, natural hazard monitoring and mitigation, water management and agricultural applications [21, 4, 12].

The relationship between backscattering coefficient and incidence angle is an essential part of the TU Wien soil moisture retrieval algorithm and described by a second order

Taylor polynomial. Given the coefficients of this polynomial (i.e. slope and curvature), the backscatter observations can be normalized to a common reference incidence angle chosen to be 40°. Relative soil moisture is derived by scaling the normalized backscattering coefficients between the driest and wettest soil conditions respectively.

The slope and curvature coefficients of the Taylor polynomial are estimated from the relation between the backscatter triplet (fore, mid and aft beam) provided by Metop ASCAT. The simultaneous backscatter observations of the three beams allow us to compute an instantaneous backscatter slope, also called "local slope". These very noisy local slope values are used to estimate the slope and curvature coefficients. The current suite of operational ASCAT-derived soil moisture products use several years of local slope data to produce a seasonal climatology of slope and curvature coefficients [21]. This approach was essential for ERS-1/2 scatterometer data to ensure robust parameter estimates. However, the second set of three fan-beam antennas on ASCAT increased the number of backscatter observations available for the determination of the local slope values. This increased data density makes it possible to determine the slope and curvature dynamically, and hence to account for interannual variations. Recently, Melzer [8] proposed a Kernal Smoother (KS) approach to determine the slope and curvature dynamically using the local slope values within some prescribed temporal window. Hahn et al. [7] performed a cross-comparison of the dynamic slope and curvature values estimated separately from Metop-A and Metop-B to confirm the consistency of the estimated parameters from the two satellites. In addition to demonstrating the robustness of the new KS approach, this study also highlighted the insight to be gained in vegetation dynamics from the interannual variability in slope and curvature coefficients. Subsequent studies by Steele-Dunne et al. [13] and Pfeil et al. [11] related variations in slope and curvature to vegetation dynamics in grasslands and broadleaf dediciduous forests.

In this study, we will examine the impact of using the dynamic vegetation parameters in the TU Wien Soil Moisture Retrieval (TUW SMR) algorithm. Intuitively, one would expect that an improved ability to capture interannual variability in the slope and curvature, and hence the dry reference, should translate to an improved soil moisture. Here, we will compare the performance of the soil moisture retrieval algorithm based on Dynamic Vegetation Parameters (DVP) to the current implementation using climatological values, identify limitations of the new approach, and suggest measures to be taken in order to implement it in the operational soil moisture retrieval algorithm.

2 TU Wien Soil Moisture Retrieval (TUW SMR) Approach

The backscattering coefficient from the land surface is influenced by factors such as soil composition, surface roughness and land cover type which are assumed to be temporally stable at the scatterometer measurement scale (25-50 km), as well as the combined influence of vegetation and soil moisture dynamics.

In the TUW SMR, the backscattering coefficient σ° in decibels [dB] is assumed to be linearly related to surface soil moisture. Soil moisture in the surface layer at time t is given by:

$$\Theta_s(t) = \frac{\sigma^\circ(\theta_r, t) - \sigma^\circ_d(\theta_r, t)}{\sigma^\circ_w(\theta_r, t) - \sigma^\circ_d(\theta_r, t)} \tag{1}$$

where σ°_w, σ°_d, and σ° are the wet and dry references, and backscattering coefficients (in dB) at the reference incidence angle θ_r at that time t. The so-called "dry reference" , on a given date, represents the lower limit of the range within which the backscattering coefficient varies due to soil moisture. The upper limit ("wet reference") reflects the highest value of backscattering coefficient observed at a certain location.

The dependence of backscattering coefficient on incidence angle is at the core of the TUW SMR approach. It is used to normalize the ASCAT backscatter measurements to the reference angle θ_r, and to account for the influence of vegetation on the sensitivity of normalized backscatter to soil moisture.

Data from ERS have been used to demonstrate that the slope (σ') depends linearly on incidence angle (θ) [17]:

$$\sigma'(\theta) = \sigma'(\theta_r) + \sigma''(\theta_r) \cdot (\theta - \theta_r) \qquad [dB/deg] \tag{2}$$

where θ_r is a reference incidence angle, set to 40° here. The dependence of backscattering coefficient on incidence angle can therefore be described as a second order polynomial:

$$\sigma^\circ(\theta) = \sigma^\circ(\theta_r) + \sigma'(\theta_r) \cdot (\theta - \theta_r) + \frac{1}{2}\sigma''(\theta_r) \cdot (\theta - \theta_r)^2 \qquad [dB] \tag{3}$$

Given the slope ($\sigma'(\theta_r)$) and curvature ($\sigma''(\theta_r)$), the scatterometer measurements at any incidence angle can be extrapolated to the reference angle of θ_r:

$$\sigma^\circ(\theta_r) = \sigma^\circ(\theta) - \sigma'(\theta_r) \cdot (\theta - \theta_r) - \frac{1}{2}\sigma''(\theta_r) \cdot (\theta - \theta_r)^2 \tag{4}$$

Re-arranging this expression provides a means to extrapolate the backscatter at any incidence angle if the slope, curvature and $\sigma^\circ(\theta_r)$ are known.

The incidence angle behaviour of σ° depends on whether total backscatter is dominated by volume scattering from the vegetation, surface scattering from the soil, or multiple scattering between the vegetation and soil. Over bare natural soils, σ° generally decreases sharply with increasing incidence angle due to the dominance of surface scattering. An increase in soil moisture results in an increase in σ° for all incidence angles, i.e. a vertical offset in the $\sigma^\circ - \theta$ curve. A change in vegetation moisture content or structure influences the dominant scattering mechanisms and results in a rotation of this curve.

The slope and curvature coefficients of the Taylor polynomial are estimated by exploiting ASCAT's unique viewing geometry. ASCAT is a fixed fan-beam scatterometer, with two sets of three sideways-looking antennas each illuminating a 550 km wide swath on either side of the satellite track. The three antennas on each side are oriented at 45° (fore), 90° (mid) and 135° (aft) to the satellite track. The incidence angle range of the fore and aft antennas is $34-65°$, while the mid antenna covers $25-55°$. Each location on the surface is observed with three slightly asynchronous, independent backscatter measurements with three independent viewing directions. These "backscatter triplets" are used to compute an instantaneous backscatter slope, also called the "local slope":

$$\sigma'\Big(\frac{\theta_{mid}-\theta_{a/f}}{2}\Big) = \frac{\sigma^{\circ}_{mid}(\theta_{mid}) - \sigma^{\circ}_{a/f}(\theta_{a/f})}{\theta_{mid}-\theta_{a/f}} \qquad [dB/deg] \tag{5}$$

where *mid* indicates the mid beam antenna and the subscript $a/$ indicates the aft beam or fore beam antenna.

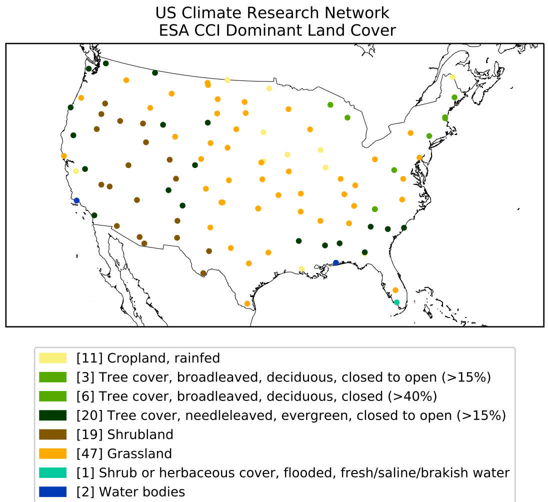
A large number of local slope values must be combined to account for the substantial noise in individual values [18] and to ensure that the slope is sampled across a wide range of incidence angles. The method used to combine many local slope values has evolved to exploit the growing data record and the improved data density of ASCAT observations [7].

Operational ASCAT-derived soil moisture products currently distributed by EUMETSAT H SAF combine several years of local slope data to produce a seasonal climatology of slope and curvature coefficients [19, 10]. This approach was particularly important in the ERS-1/2 era to ensure robust parameter estimates. The increase in data density due to the second set of three fan-beam antennas on ASCAT means that it is now possible to determine the slope and curvature dynamically using a Kernel smoother (KS) approach proposed by Melzer [8]. An Epanechnikov kernel with a half-width λ=21 (days) is used to weight the local slope estimates by distance (in time) from a given day, i.e. the estimate of slope and curvature for a given day is based on all local slope values within a 42-day window. Data points close in time to the date of interest are assigned higher weights. The kernel half-width λ=21 was considered by Melzer et al. [8] to provide a reasonable balance between bias and variance in the estimate. In a subsequent global analysis, Hahn et al. [7] estimated the dynamic slope and curvature separately from Metop-A and Metop-B. Consistency of the independent estimates in a cross-comparison suggests that the estimation approach is robust. Furthermore, time series plots at several locations as well as Hövmoller diagrams were used to demonstrate that this approach captured plausible seasonal and interannual variations in vegetated areas.

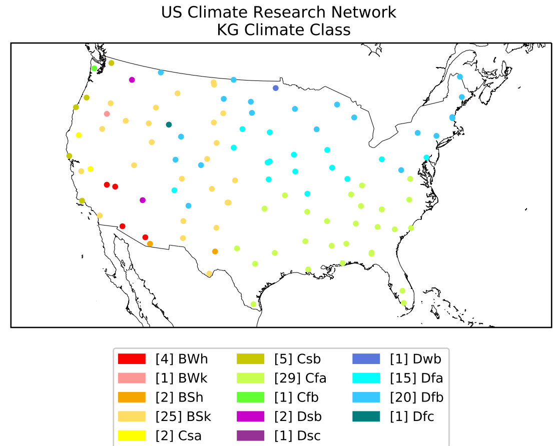
3 Data and Methods

3.1 Study Domain

In-situ soil moisture observations from the United States Climate Research Network (USCRN) were used in this study to ensure some diversity in terms of climate type and land cover. Data for the 109 USCRN stations were accessed through the ISMN. The ASCAT grid points associated with these stations span eight ESA CCI Land Cover Climate Classes and fourteen Koeppen Geiger Climate classes. Almost half of the stations are in grassland areas, with the remainder in footprints dominated by shrubland, tree cover and rainfed cropland. There are four main KG climate classes; humid subtropical climate (Cfa), cold semi-arid climate (BSk), continental climate with a hot summer (Dfa) and continental climate with a warm summer (Dfb).



(a)



(b)

Figure 1: USCRN Soil Moisture Stations, colored by ESA CCI Land Cover class (a) and Koeppen Geiger Climate class (b). The numbers in square brackets indicate the number of occurences of each type.

3.2 ASCAT processing

Ten years of Metop-A ASCAT SZR Level 1b Fundamental Climate Data Record backscatter data, using the 12.5 km swath grid sampling, were obtained from the EUMETSAT Data Centre. Standard pre-processing steps were performed: (1) the backscatter observations were resampled to a fixed Earth grid using a Hamming window function and the procedure described by Naeimi et al. [10]; (2) the empirical approach of Bartalis et al. [1] was used to account for azimuthal effects. Backscatter triplets were used to calculate the local slope using equation (5).

In the climatology case, the vegetation parameters are determined using the current operational approach of [10]. For the dynamic vegetation parameters, the methodology proposed by Melzer [8] was used to estimate the vegetation parameters from these local slopes. In all cases, a kernel λ=11 days was used to estimate the slope and curvature required to normalize the backscatter. For the wet and dry reference calculation, the default value of the kernel λ=21 days is based on the analysis of Melzer [8]. To investigate the influence of the kernel half-width on the estimated soil moisture, the vegetation parameters were also determined using a shorter (λ=11 days) and longer (λ=31 days) window size.

3.3 Performance assessment

Each implementation of the TUW SMR approach was applied at the grid points co-located with the in-situ soil moisture stations of the USCRN network [3]. Data for these stations were obtained from the ISMN [5], and temporal matching was applied at a daily level. The estimated soil moisture values were compared to those reported for surface soil moisture

(0-5cm) at each station. Local slopes obtained over frozen or snow-covered soil introduce artefacts into the dry reference that are unrelated to vegetation, resulting in an error in soil moisture. Dates upon which the the soil was frozen or snow-covered were identified using ERA5 soil temperature and snow depth data. To ensure that a consistent number of data points were considered in each scenario, the snow/frozen soil mask was determined for the longest half-width (λ=31 days) and applied to all time series prior to the calculation of the performance metrics. Results were evaluated using the Pearson Correlation Coefficient, unbiased Root Mean Squared Difference and bias [6].

4 Results

4.1 Climatology

Figure 2 shows the performance metrics using the current operational approach for all 109 USCRN stations. Statistics, including the box plots (e.g. Figure 3) are based on 85 stations. All stations for which R is negative are excluded from further analysis. (In Appendix A, it is argued that enhanced subsurface scattering occurs at desert shrubland locations in the western US, explaining the negative correlation coefficients). In addition, climate or land cover classes with fewer than five stations are omitted. For example, this excludes stations within an ASCAT footprint classed as water, or flooded with brackish water (e.g. Everglades, Florida). For the remaining stations, the median Pearson correlation coefficient is 0.58 with 90% of values between 0.29 and 0.79 respectively. Values are generally higher in the central US and lower at the more arid stations in the West. The median ubRMSD is 0.09 %, with 90% of values between 0.06 and 0.13. The median bias is 0.01% with 90% of values between -0.13% and 0.10%. Negative values are more common in the West, positive in the East, particularly the Northeast.

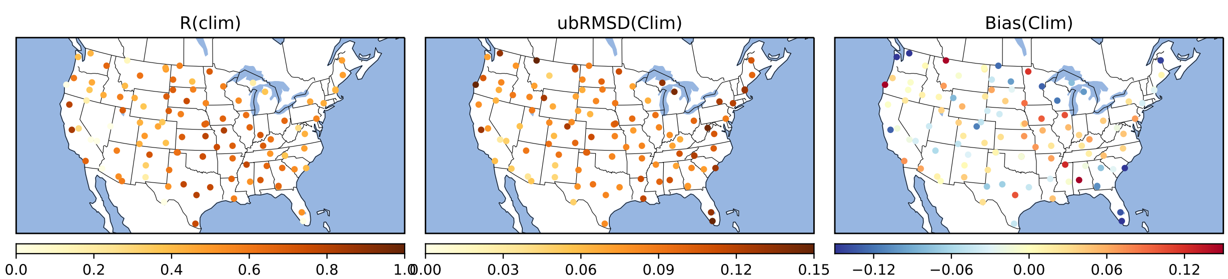


Figure 2: Pearson Correlation Coefficient (R), unbiased RMSD and bias between in-situ soil moisture and soil moisture retrieved using vegetation parameters derived from climatological values.

Figure 3 shows how the performance metrics relate to the dominant land cover (a - c), and climate classes (d - f). The best and most consistent performance is in grasslands in which R is generally greater than 0.5, ubRMSD is at the lower end of the range observed and the median bias is close to zero. The same is true for rainfed cropland (LC = 10), though it is noteworthy that the range in bias is large. Performance is notably good over

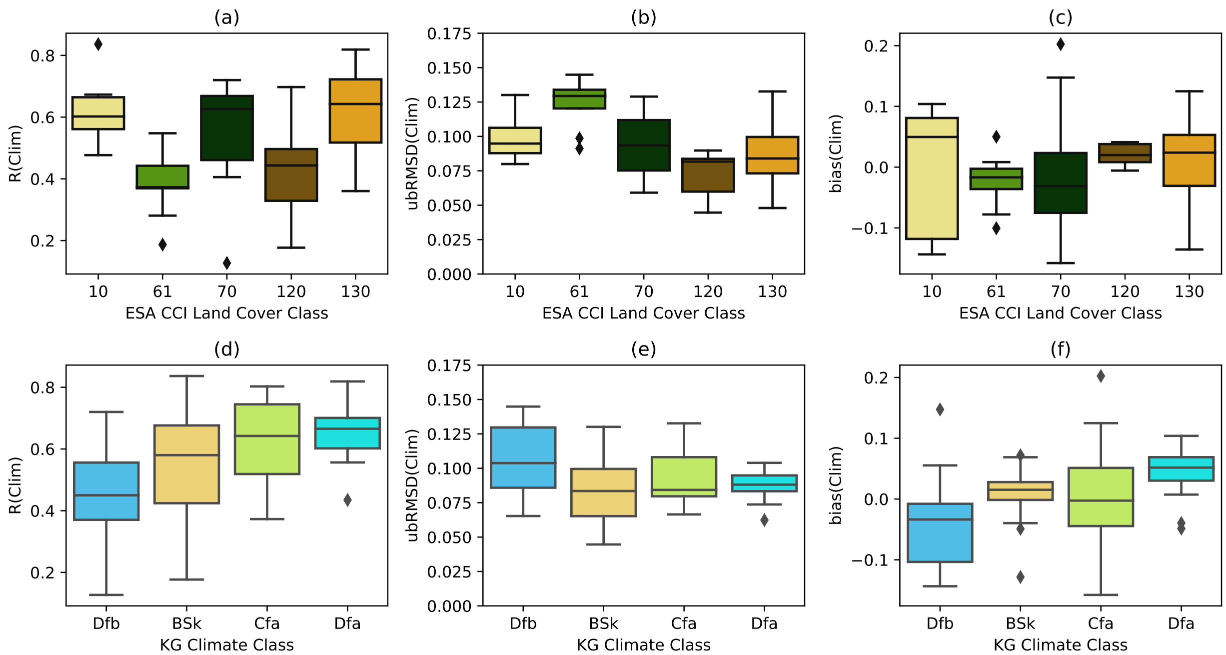


Figure 3: Box plots of the Pearson Correlation Coefficient (R), unbiased RMSD and bias between in-situ soil moisture and soil moisture retrieved using vegetation parameters derived from climatological values, sorted by ESA CCI Land Cover Class (top row) and Koeppen Geiger Climate Class (bottom row).

evergreen forests: R and ubRMSD are comparable to those observed in grassland and rainfed cropland, and the median bias is close to zero. Performance is relatively poor in Broadleaf Deciduous Forest where R is low and ubRMSD is higher than in the other land classes. In terms of climate class, it seems that performance is best in Dfa (the humid continental climate with hot summers). This corresponds to a mixture of land cover types in the Central to Northeastern US. The worst performance is in the Dfb (humid continental climate with warm summers). The stark difference between these two climate subtypes is due to the fact that many of the stations in the Dfb climate class are broadleaf deciduous forest.

4.2 Including Dynamic Vegetation Parameters (DVP)

Figure 4 maps the difference in the performance metrics when the dynamic vegetion parameters (λ=21 days) are used to estimate the dry reference, compared to using climatological values. For the 85 stations considered, the median change in R was 0.00. While some increase in R was observed in the West, R is consistently lower in the Central US. Furthermore, introducing DVP led to a median increase in both ubRMSD and bias of 0.02% (volumetric soil moisture). The bias is generally lower in the West, but higher in the East and North.

Figure 5 provides some insight into the impact of the dynamic vegetation parameters as a function of land cover and climate class. The median improvement in R is close to zero in all land cover types apart from shrublands. Both the ubRMSD and bias are higher using DVP than climatology in all cover types. The impact on bias is particularly large in rainfed

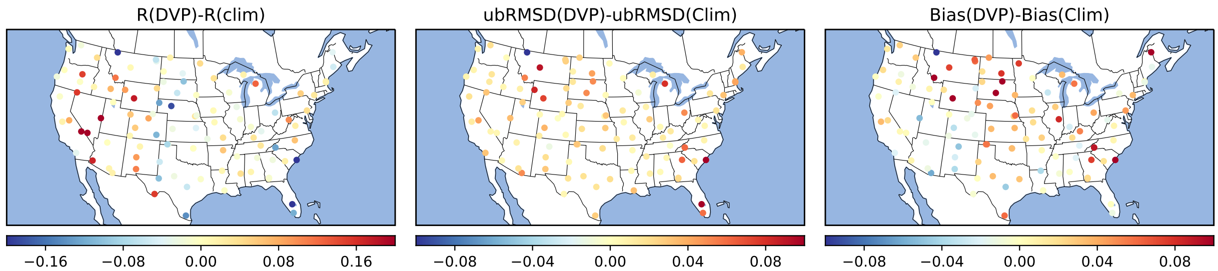


Figure 4: Difference in Pearson Correlation Coefficient (R), unbiased RMSD and bias between in-situ soil moisture and soil moisture retrieved using vegetation parameters derived using Dynamic Vegetation Parameters (hw=21), and those derived from climatological values.

cropland and grasslands. The range of impact, in the sense of change in performance metric is consistently largest for the grasslands. The degree to which high frequency variations are introduced by DVP, clearly varies considerably among grassland sites. From Figure 5 (d - f), the results mostly indicate that the widest variation in terms of impact is in the BSk (cold semi-arid climates), i.e. in the West, which includes grasslands and shrublands. The impact is also highly variable in the Dfb class, which contains many of the forest cover types.

Figure 6 shows the dry reference for three stations to illustrate the impact of implementing DVP compared to using the climatological values. At Chillicothe (Figure 6 (a)), the seasonal cycle in dry reference is strong, and there is little interannual variability. The Pearson correlation coefficient using climatological vegetation parameters is already 0.82. Accounting for interannual variability in the slope and curvature has barely any effect on the dry reference, so implementing DVP has a limited effect on the soil moisture retrieval performance. At Bowling Green (Figure 6 (b)), implementing DVP reveals a decreasing trend in the maximum dry reference which is obviously not taken into account in the climatological values. Implementation of DVP results in an increase of 0.04 in R. Data from Lander (Figure 6 (c)) show that the implementation of DVP sometimes yields an apparently substantial increase in R. While there certainly does appear to be interannual variability in the dry reference, it is important to note that there are relatively few days without snow/frozen soil. Hence, the statistics at this station are based on too few data to be reliable.

4.3 Influence of kernel half-width (λ)

Figure 7 shows a single year of data from Stillwater, Oklahoma for each of the TUW SMR implementations to illustrate the influence of the the kernel smoother and the kernel half-width λ on the vegetation parameters and dry reference. Stillwater is a grassland site with a humid, subtropical climate (Cfa). The seasonal cycle in vegetation cover is reflected in the variations of slope and curvature [13]. The dry reference estimated using the climatological vegetation parameters has a smooth seasonal cycle with a maximum during the northern hemisphere summer. The sensitivity to soil moisture is greatest during the winter; note that the normalized backscatter (σ°_{40}) is much higher than the dry reference when the in-situ soil

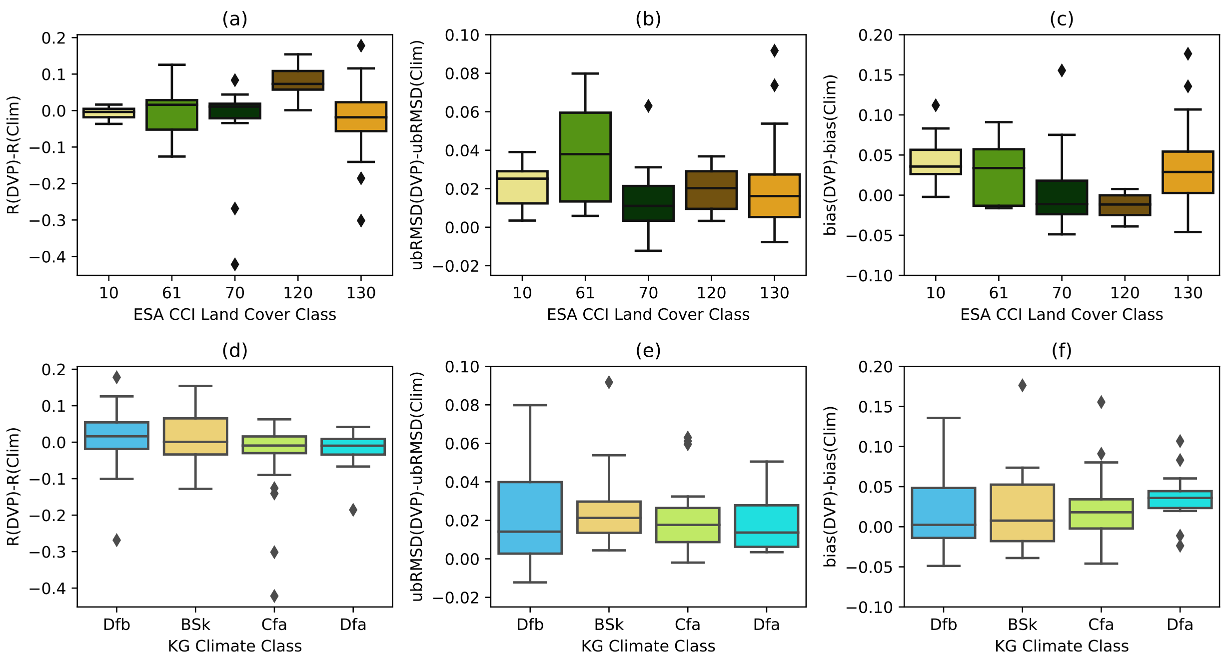


Figure 5: Box plot of the difference in Pearson Correlation Coefficient (R), unbiased RMSD and bias between in-situ soil moisture and soil moisture retrieved using vegetation parameters derived using Dynamic Vegetation Parameters (λ=21 days), and those derived from climatological values. Data are binned by ESA CCI Land Cover Class (top row) and Koeppen Geiger Climate Class (bottom row).

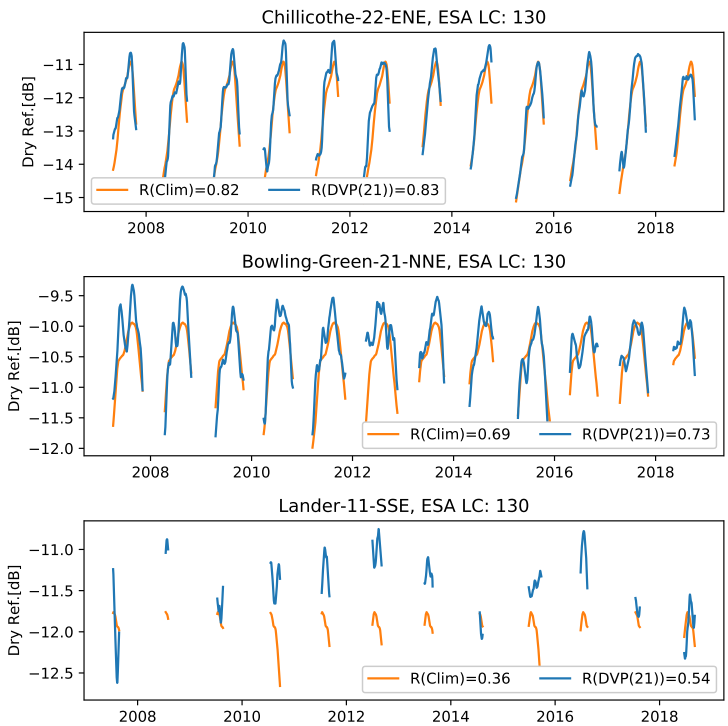


Figure 6: Comparison of the Dry Reference estimated using vegetation parameters from climatology, and dynamic vegetation parameters at three stations that indicate modest to significant improvement in R when DVP are used.

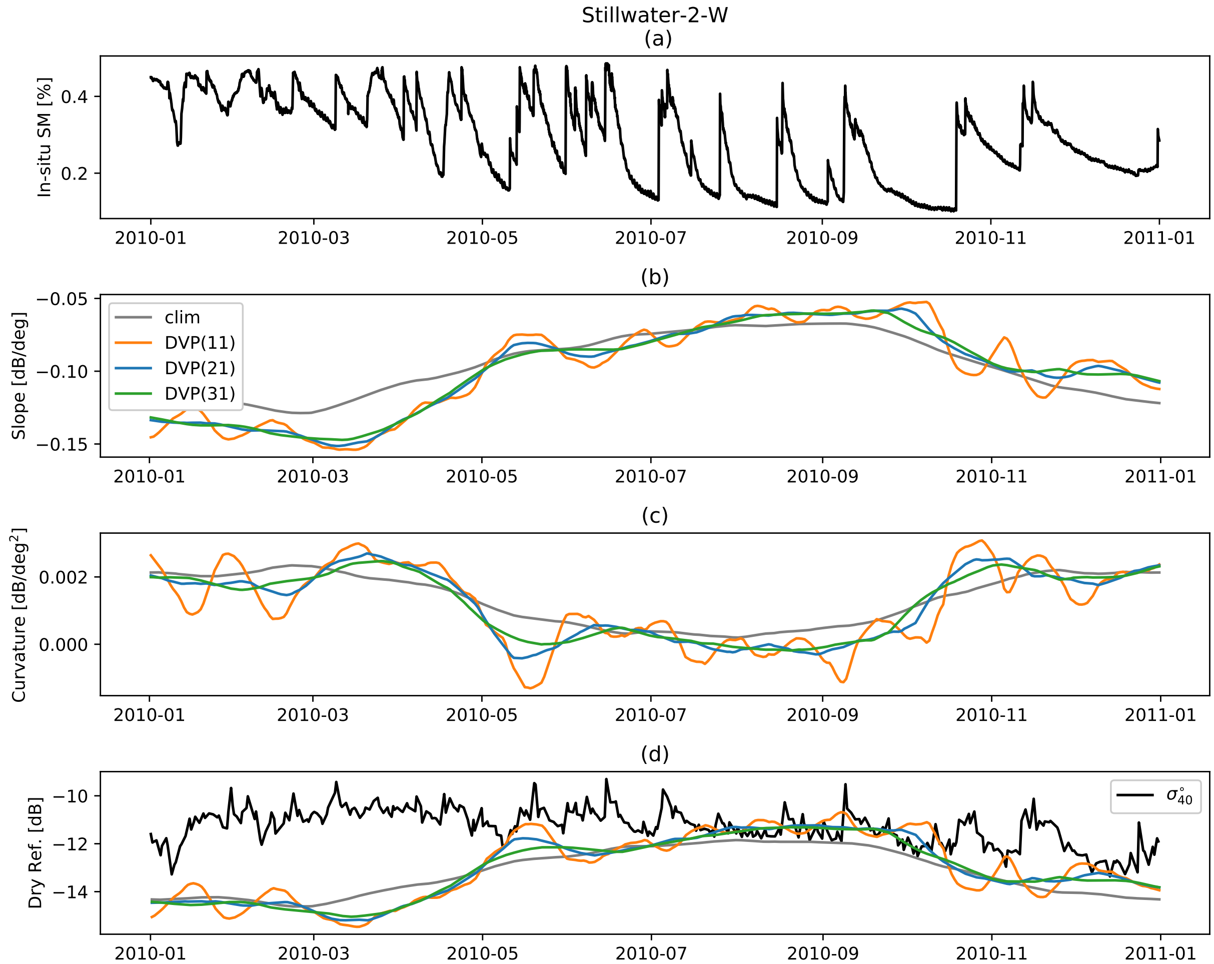


Figure 7: The influence of kernel half-width (in days 11: orange, 21: blue or 31: green) on the dynamic vegetation parameters and estimated dry reference at Stillwater, Oklahoma in 2010.

moisture is high during the winter. During the summer months, in-situ soil moisture varies considerably, but σ°_{40} varies within a more limited range as the dry reference is higher due to the seasonal cycle of vegetation. The slope, curvature, and dry reference estimated using the DVP with λ=11 days exhibit high-frequency variations superimposed on the background seasonal cycle. Increasing the half-width means averaging over more local slope values, mitigating the influence of individual events. Smoothing these features out yields a seasonal cycle in the dry reference more similar to that from the climatological values. Increasing the kernel length smooths out most of the features during the winter months. However, there are some features (e.g. in May and October) for which increasing the half-width to λ=31 days results in further smoothing, bringing the dry reference estimate closer to the estimate from climatology. The degree to which additional smoothing should be applied is discussed in the next section.

Figure 8 shows the impact of changing the kernel half-width for all stations. In general, using a shorter kernel leads to a decrease in R, an increase in ubRMSD and an increase in

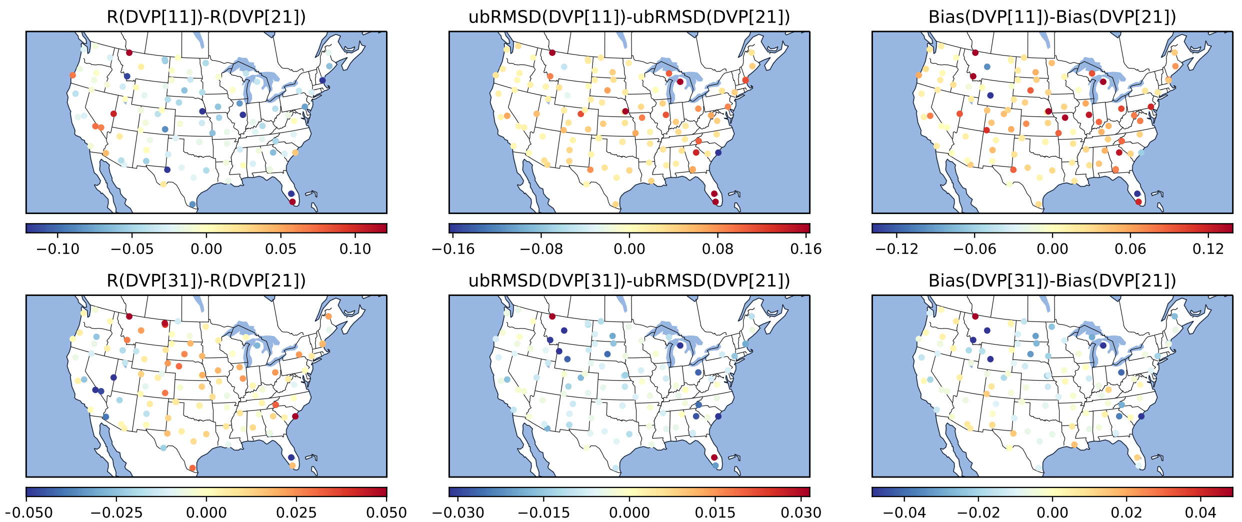


Figure 8: Impact of the kernel half-width (λ) on the R, ubRMSD and bias between in-situ and soil moisture retrieved using dynamic vegetation parameters. Half-widths of λ=11 and λ=31 are compared to the default value of λ=21 in the top and bottom rows respectively

bias, i.e. a detrimental effect on performance. As shown in Figure 7, this can be attributed to the introduction of high frequency variations when few local slope values are averaged. A small number of stations in the Western USA seem to have a higher R, but these are stations for which R(clim) was very low or even negative in Figure 2. Increasing the kernel length generally leads to a lower Pearson correlation coefficient in the dry western areas, but an increase across the Central and Eastern USA. It also reduces the ubRMSD and bias. It seems that a short kernel length is adequate in the dry, shrubland areas in the West. In the more humid areas with more vegetation, a longer kernel generally leads to an improved performance.

Regardless of kernel length, DVP still often fails to perform as well as estimating vegetation parameters from climatology. This is shown in Figure 9 where the Pearson correlation coefficient for each kernel length is compared to that from climatology for the five most prevalent cover types. A value of zero indicates performance equivalent to that obtained from climatology. Positive/negative values indicate that dynamic vegetation parameters are better/worse than climatology. In rainfed cropland (LC = 10), using a short window has a very detrimental effect compared to using climatological values. Increasing the kernel half-width generally improves performance. However, the results remain mixed, with the DVP yielding a modest improvement at about half of the stations. Similarly mixed results are observed in the other cover types. In grasslands (LC = 130), the results are also mixed, though increasing λ generally results in an improvement. In addition to the R values from climatology already being high in needleleaf forest areas (LC = 70), it is noteworthy that introducing DVP often improves the estimate further. The influence of increasing λ beyond 21 days in this cover type seems limited for the stations with R ¿ 0.5. Results in the broadleaf forest areas are less consistent, but R is generally lower in this cover type. Using DVP generally leads to an improvement in shrubland areas. Although large improvements are observed at the stations where R is negative, even using DVP is not enough to make retrieval meaningful at these sites. At sites where R is closer to 0.5, using DVP generally results in an improvement regardless of the size of λ .

5 Discussion

Estimating dynamic vegetation parameters using a kernel smoother or similar approach can be beneficial in areas where there is interannual variation in the vegetation cover. Interannual variability may include the presence of a long-term trend, a variation in terms of the timing of the growing season, or a change in the vegetation moisture content or structure. By capturing interannual variation in the slope and curvature estimates, and hence the dry references, the dynamic vegetation parameters are capable of accounting for this interannual variability in the soil moisture retrieval algorithm. However, the results presented here suggest that the vegetation parameters estimated using the current "climatology" approach often produce a better estimate of soil moisture than the dynamic parameters.

The slope and curvature describe how the normalized backscatter coefficient varies with incidence angle, which is an indication of the relative importance of different scattering mechanisms to the total backscatter. The relative importance of surface, volumetric and multiple scattering depends on many parameters describing the state of the soil and vegetation including the dielectric properties, roughness and texture of the soil, the vegetation water content, its distribution within the vegetation, the structure and geometry of the vegetation as well as the presence of surface canopy water. Individual local slope values reflect the instantaneous state of the vegetation and soil. It is essential to aggregate the local slope values due to their inherently noisy nature, and to ensure that range of incidence angles is sampled. However, aggregating local slope values in time also combines observations affected by different states of the soil and vegetation. Using the climatology approach, the local slope values are aggregated over several years, so that short-term fluctuations are averaged out. As a result, the climatological vegetation parameters are smooth, as they primarily reflect longer-term variations due to the seasonal cycle in vegetation biomass and structure. The dynamic vegetation parameters, on the other hand, are more sensitive to short term fluctuations. Results in Figure 7 show that increasing the kernel window length could smooth out short term fluctuations, but is that the right thing to do?

Using a short window, the estimated slope, curvature and dry reference are a superposition of a seasonal signal due to vegetation, and higher-frequency variations. These fluctuations are due to physical changes in the soil and vegetation state, particularly the vegetation state. The fundamental question is whether or not the dry reference, as it is currently defined, should contain these short-term fluctuations. The detrimental impact of the DVP on the performance of the soil moisture retrieval suggests not. Recall that the dry reference, or more specifically the difference between the dry and wet references, is a measure of the sensitivity to soil moisture. Variations in this sensitivity are intended to represent the

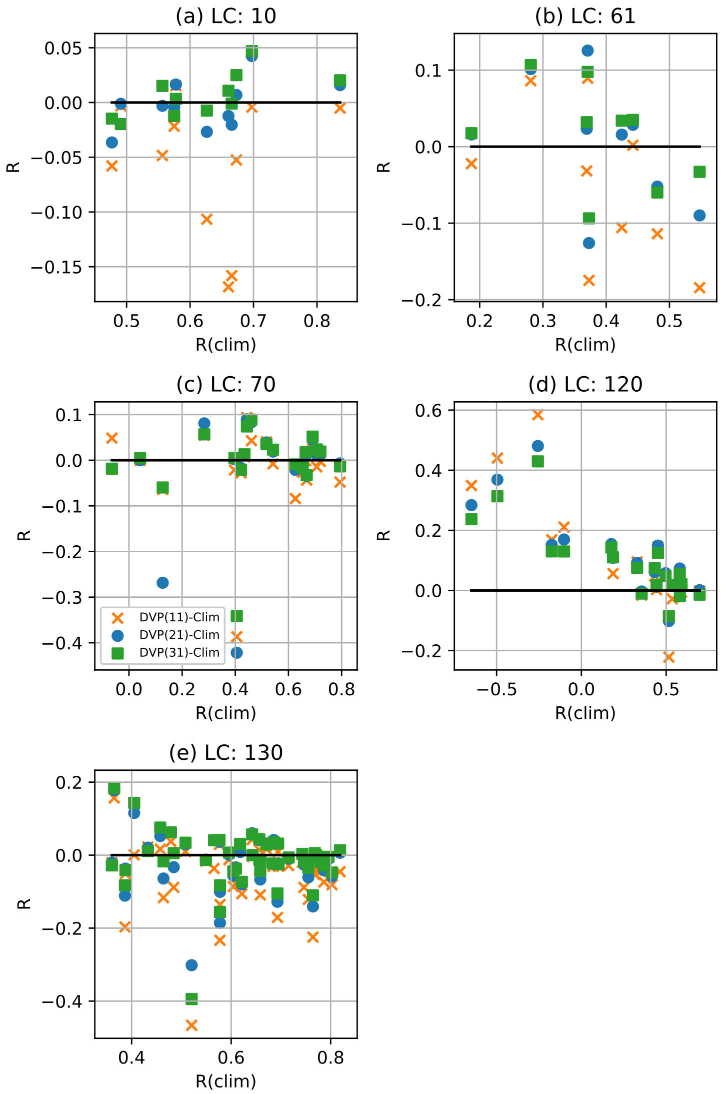


Figure 9: The influence of kernel half-width (λ) on the Pearson correlation coefficient (R) at rainfed cropland (a), broadleaf forest (b), needleleaf forest (c), shrubland (d) and grassland (e) sites. Differences are shown with respect to the R based on vegetation parameters from climatology.

attenuating effect of the vegetation on the signal backscattered from the soil.

Recall that the linear relationship between slope and incidence angle is at the core of the TUW SMR. Wagner et al. [17] demonstrated this relationship using several years of ERS data, and argued that averaging over several years ensured that measurement noise was suppressed to yield average slope values that represent vegetation phenology. This explains why early iterations of the TUW SMR representing the seasonal cycle with empirical trigonometric functions were successful, and why the climatological vegetation parameters continue to provide a robust soil moisture retrieval. Employing a kernel to dynamically estimate vegetation parameters implicitly assumes that the relationship at shorter time scales is also primarily governed by phenology. The short-term fluctuations introduced in the slope and curvature introduced in the slope and curvature at short kernel lengths suggest that the slope of the linear fit may vary in response response to short term variations in vegetation structure and water content changes.

To use dynamic vegetation parameters effectively, there is an urgent need for an improved understanding of the factors underlying short-term variations in the relationship between slope and incidence angle. From a physical perspective, this translates to a need to understand factors that influence backscatter variations at scales finer than the seasonal cycle. Examples include the influence of water availability and atmospheric demand on internal water content, and the influence of surface water on the vegetation due to interception and dew. Tower-based L-band observations have demonstrated that short-term variations in these quantities affect total backscatter [15], though their impact on the contribution of various scattering mechanisms to total backscatter still needs to be quantified.

In terms of the TUW SMR approach, their impact on the sensitivity of total backscatter to soil moisture is of primary importance. From a physical perspective, the definition of the dry reference could eventually be revisited to account for the influence of these short-term confounding influences on soil moisture sensitivity. However, a more pragmatic approach would be to retain the current definition of the dry reference and adapt the kernel smoother implementation to ensure that the dynamic vegetation parameters used in soil moisture retrieval capture only phenology-related variations. This could be achieved by increasing the kernel length to smooth out the fluctuations, though this incurs a risk of smoothing out real phenological features such as those identified by Pfeil et al. [11]. Alternatively, a data-driven approach could be used to identify local slope values that deviate from the assumed linear relationship within a kernel window and filter them out prior to the application of the kernel smoother. This would ensure that the kernel smoother captures only the seasonal variations considered in the current implementation of the TUW SMR approach, but also captures any interannual variability therein.

6 Conclusions

Results presented here indicate that accounting for interannual variability in the effect of vegetation on sensitivity of ASCAT normalized backscatter to soil moisture could benefit soil moisture retrievals. However, the proposed approach using a kernel smoother with a kernel half-width of λ=21 days to estimate dynamic vegetation parameters is undermined by its sensitivity to short-term variations in the relationship between slope and incidence angle. These manifest as high-frequency fluctuations in the dry reference superimposed on the seasonal cycle due to phenological development. Comparing results estimated with different kernel half-widths and the climatological values suggests that a smooth dry reference, capturing phenological development produces the best soil moisture retrieval.

The success of the current TUW SMR approach, and its precursors, appears to lie in the robustness of the linear slope incidence angle relationship estimated using a long data record.

The success of the current TUW SMR approach, and its precursors, appears to lie in the robustness of estimating the parameters of the linear relationship between slope and incidence angle using a long data record. This ensures that the relationship effectivevly captures variations due to phenological change. In the DVP approach, the parameters are estimated with fewer data and are more sensitive to confounding factors that vary at finer time scales. A pragmatic approach to resolve this limitation of the proposed dynamic vegetation parameters would be to filter the local slope estimates prior to the use of the kernel smoother to ensure that local slope values influenced by confounding factors other than phenology are excluded from the linear fitting in shorter time windows.

Any improvement in the representation of vegetation in the TUW SMR algorithm will also benefit the ASCAT VOD products which are derived from the wet and dry references estimated in the TUW SMR [16]. In the longer term, the Metop Second Generation SCA instrument is scheduled to launch in October 2024. It builds on the heritage of its predecessor ASCAT, but will also provide VH- and HH-pol data in addition to VV-pol [14]. The temporal density of data will be comparable to that from ASCAT. Additional polarizations provide complementary information on the contributions from soil and vegetation and are expected to benefit soil moisture and vegetation products. To make optimal use of the SCA data, it is essential to improve our understanding of how the incidence angle dependence of backscatter varies over shorter time scales due to soil and vegetation processes at time scales shorter than phenological development.

A Exclusion of dry shrublands

Figure 10 (a) shows the normalized backscatter σ°_{40} and how it varies between the dry and wet references at Stovepipe Wells, California. The in-situ soil moisture at this station is compared to the soil moisture estimated using the vegetation parameters from climatology in Figure 10 (b). The Pearson correlation coefficient was -0.50. At this station in Death Valley, soil moisture is almost always extremely dry, with just two discernible precipitation events (in May and July) in 2011. The soil moisture estimated using the TUW SMR bears little resemblance to that observed. Despite the absence of vegetation, the maximum difference between the wet and dry references is barely 1dB. Recall from Figure 7, that this was almost 4 dB at Stillwater.

Applying the logic of the TUW SMR, this would suggest that the sensitivity of soil moisture is limited. In reality, it is more likely that the wet reference is difficult to estimate as so few precipitation events occur. Furthermore, in Figure 10, σ°_{40} often dips below the dry reference, which would produce negative soil moisture values in the TUW SMR. The data presented in Figure 10 exhibit two unusual features: σ°_{40} appears to drop suddenly when

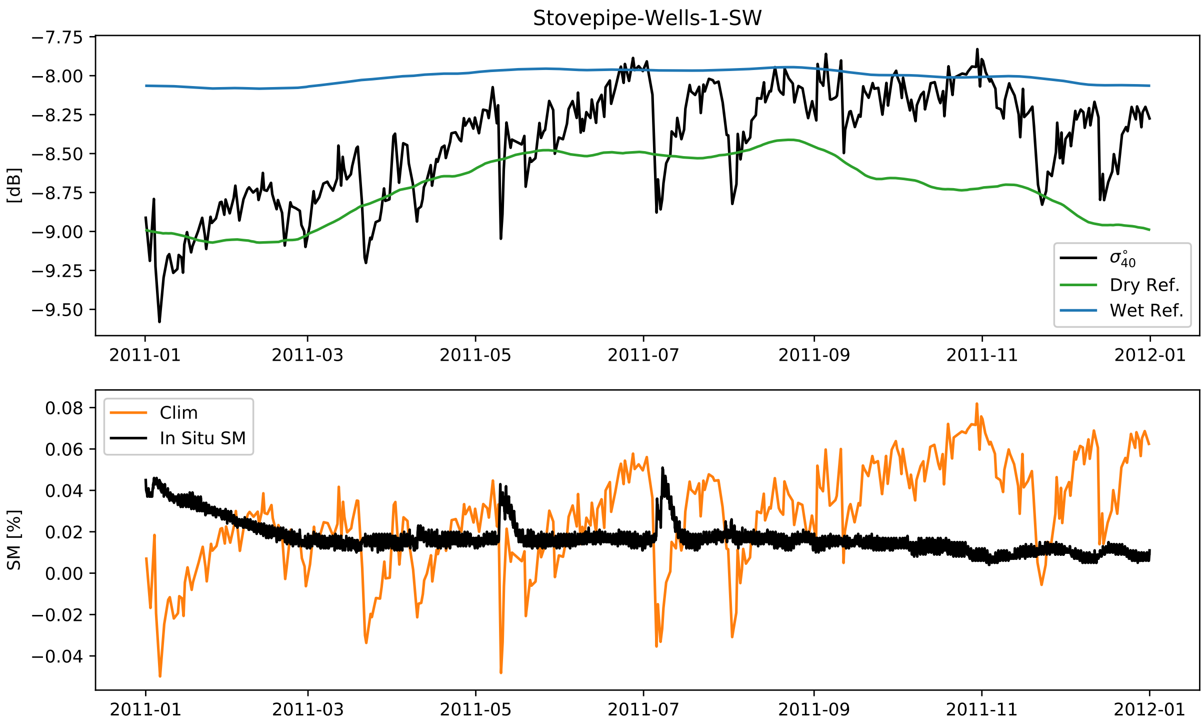


Figure 10: Data to illustrate potential enhanced subsurface scattering at Stovepipe Wells, California: (a) Normalized backscatter σ°_{40}, dry and wet references and (b) in-situ soil moisture compared to retrieved soil moisture derived using climatological vegetation parameters.

there is precipitation, and σ°_{40} (and hence estimated soil moisture) increase as the soil dries down. This behaviour is often observed in bare, extremely dry soil. It is hypothesized that as the soil dries, the penetration depth increases and the amount of backscatter increases due to enhanced volumetric scattering [9]. The occurence of this mechanism violates the assumptions in the TUW SMR. Hence, stations at which it occurs (shrublands with hot desert climates, identifiable by having negative R values) are not considered in the box plots or statistics presented in this study.

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