



ASCAT Soil Moisture Estimation using Dynamic Regularised Slope and Curvature

Paco Frantzen¹, Susan Steele-Dunne¹, Roland Lindorfer², Sebastian Hahn², Mariette Vreugdenhil², and Wolfgang Wagner²

¹Department of Geoscience and Remote Sensing, Delft University of Technology, Delft

²Department of Geodesy and Geo-Information, Vienna University of Technology, Vienna

Correspondence: Paco Frantzen (p.frantzen@tudelft.nl)

Abstract. Soil moisture content is an essential climate variable driving processes in the hydrosphere, atmosphere and biosphere. Global and multi-decadal records of soil moisture measurements can be realised through spaceborne microwave instruments. The C-band Advanced Scatterometer (ASCAT) provides a global record of backscatter measurements fit for soil moisture retrieval, spanning nearly 20 years. The TU Wien Soil Moisture Retrieval algorithm uses an estimated backscatter-incidence relation to (i) normalise ASCAT backscatter observations from multiple incidence angles, and (ii) to determine reference values for backscatter under dry and wet conditions. A novel method for estimating the backscatter-incidence relation using regularisation was recently developed, resulting in improved short-term dynamics in the estimated time series of the backscatter-incidence relation. In this study, the impact of the regularised estimation backscatter-incidence angle relation on soil moisture retrieval is assessed separately for the backscatter normalisation, and the dry and wet reference calculation. The performance of different configurations in this study are assessed using the Quality Assurance Service for Satellite Soil Moisture Data to validate retrieved soil moisture time series with in-situ measurements provided by the International Soil Moisture Network. Soil moisture retrieval improves over most land cover and climate types when a dynamic regularised backscatter-incidence angle relation is used for backscatter normalisation and the dry wet reference calculation. In particular, short term dynamics of retrieved soil moisture time series are found to improve significantly over most land covers and climate types. Future studies should investigate the use of the dynamic regularised backscatter-incidence angle relation for near real-time soil moisture retrieval, as well as soil moisture retrieval from the ESCAT scatterometer.

1 Introduction

Soil moisture is a key geophysical variable that influences the processes of vegetation transpiration and soil evaporation (Miralles et al., 2025), runoff (Brocca et al., 2010), and heat waves (Fischer et al., 2007). Hence, soil moisture has been identified as an Essential Climate Variable (ECV), which should be monitored globally, with data records covering more than 30 years to allow studies of climate variability and change (Mason et al., 2010).

Global soil moisture data products derived from spaceborne microwave instruments have been available for more than two decades (Bartalis et al., 2007; Kerr et al., 2012; Entekhabi et al., 2010) and have been used to generate climate data



archives (H SAF, 2022; Dorigo et al., 2017), and near real-time products (Hahn et al., 2026; HSAF; O'Neill et al.). Benefits of these products include near-daily global coverage, though their spatial resolution is generally coarse at scales ranging from 12.5 (Hahn et al., 2026) to 40 kilometres (Kerr et al., 2012). These characteristics make the data products fit for real-time applications including drought monitoring (Massart et al., 2025), run-off prediction (Brocca et al., 2010), numerical weather prediction (de Rosnay et al., 2022), as well as for climatological applications such as data assimilation in reanalysis products (ECMWF, 2018), or climatological studies (Bauer-Marschallinger et al., 2013).

One of the longest records of microwave-based soil moisture measurements is provided by the Advanced Scatterometer (ASCAT) onboard the Metop A, B, and C satellites. ASCAT measurements started in 2007 with Metop A, and Metop B and C are still currently operational. This record can be further extended into the past and future by combining the observations from the ESCAT and SCA scatterometers onboard the European Remote Sensing Satellites and Metop Second Generation B satellites respectively. This results in a record starting in 1991 (Dorigo et al., 2017), with observations planned until beyond 2047. These scatterometers all measure microwave backscatter at C-Band from multiple incidence angles per overpass, observing from a large range of incidence angles throughout their repeat cycle.

The foundation of the methodology to retrieve soil moisture measurements from the microwave backscatter observations of these instruments was developed by Wagner et al. (1999a) for ESCAT, relying on the relation between surface soil moisture, and backscatter coefficient (σ°). Central to this methodology is the use of the backscatter-incidence angle relation to normalise σ° observations from multiple incidence angles to a prescribed reference angle, and to account for the effect of vegetation reducing the sensitivity of backscatter coefficient to soil moisture. The backscatter-incidence angle relation is modelled as a second degree Taylor expansion at the reference angle of 40° , with a linear term (slope (σ')), and quadratic term (curvature (σ'')). Initially, the temporal variation of these two variables was empirically modelled as a sinusoidal function with a yearly period and monthly steps, and estimated using all available backscatter observations per grid point. The representation of σ' and σ'' was advanced by Naeimi et al. (2009), using a Monte Carlo simulation and a cubic spline to derive a yearly cycle of σ' and σ'' . The kernel smoothing method later proposed by Melzer (2013) reduced computational cost, enabling the transition from a climatological representation of σ' and σ'' to a time series, supporting inter-annual variation. Hahn et al. (2017) found that this kernel smoother could be used to robustly estimate σ' and σ'' dynamically, although further research was required before the dynamic σ' and σ'' could be included in the TUW SMR. Steele-Dunne et al. (2021) estimated soil moisture using both the climatological and dynamic σ' and σ'' , and compared the resulting soil moisture estimates to *in situ* observations from the USCRN (Bell et al., 2013). Interestingly, the agreement between *in situ* observations and the estimated surface soil moisture did not improve with the inclusion of short-term variations in σ' and σ'' , which Greimeister-Pfeil et al. (2022) attributed to variation in soil moisture. Greimeister-Pfeil et al. (2022) thus recommended that a more suitable smoothing of σ' could reduce influence of soil moisture on σ' .

Recently, a new method for estimating σ' and σ'' was developed by Frantzen et al. (2025). In this method, the two parameters are estimated dynamically using regularised least squares estimation, yielding a time series of σ' and σ'' with improved timing of short-term variation compared to the kernel smoother method. The improved dynamics in σ' and σ'' likely improve the representation of instantaneous $\sigma^\circ - \theta$ relation, and could reduce the fluctuations in σ' and σ'' caused by soil moisture variation



as these variations are temporally more confined. Thus, σ' and σ'' estimated using the regularisation method could benefit both the normalisation of σ° to θ_{ref} , and estimation of the vegetation impact on $\sigma^\circ(40^\circ)$, consequently improving the estimation of soil moisture.

In this study, we revisit the analysis of Steele-Dunne et al. (2021) using the novel slope and curvature dataset computed using the regularisation method (Frantzen et al., 2025). We expect that regularised dynamic slope and curvature lead to an improved estimate of the instantaneous backscatter-incidence angle relation, and thus improve the backscatter normalisation and consequently the retrieved surface soil moisture. Additionally, the improved timing and confined influence of soil moisture-induced fluctuations in regularised slope and curvature are expected to improve the estimates of the dry and wet reference, further benefitting the retrieval of surface soil moisture. A key difference from the analysis of Steele-Dunne et al. (2021) is that the impact of the new slope and curvature estimates is evaluated separately at the two stages of the TUW SMR. First, we test if the TUW SMR improves when a regularised, dynamic estimate of slope and curvature is used for the normalisation of backscatter to a constant reference angle. Second, we test the benefit of utilising the regularised, dynamic estimate of slope and curvature for the computation of the dry and wet backscatter reference in the TUW SMR. The improvements of the TUW SMR are assessed through a validation against the International Soil Moisture Network (ISMN) utilising the Quality Assurance Service for Satellite Soil Moisture Data (QA4SM) (Angewandte Wissenschaft, 2026) validation framework.

2 Data

2.1 ASCAT

Backscatter observations from ASCAT onboard the Metop-A, -B, and -C satellites are used, sampled at a 6.25km spatial interval corresponding to the Fibonacci grid (Hahn et al., 2026). Backscatter observations and their corresponding incidence angles are provided per antenna (fore, mid, or aft) at the satellite overpass epochs, for each grid point. Data from 2007-01-01 to 2024-12-31 are considered, and a large majority of the spatial and temporal domain of the data set contain daily observations. Backscatter dependence on azimuth angle is corrected using the empirical model described by Hahn et al. (2026).

2.2 International Soil Moisture Network (ISMN)

in situ soil moisture measurements from the International Soil Moisture Network (ISMN) (Dorigo et al., 2013) are used for validation. The ISMN comprises many soil moisture monitoring networks, enabling the validation of satellite soil moisture measurements against *in situ* observations across diverse climate- and land cover types.

The ISMN observations from sensors with a 0m to 0.05m depth are used for validating the ASCAT soil moisture estimates as these are assumed to correspond to the sensing depth of C-band microwave sensors such as ASCAT Pfeil et al. (2018). The QA4SM is used to access the ISMN data. Only stations considered “representative” in the Fiducial Reference Measurements classification (Angewandte Wissenschaft, 2026) are considered, ensuring that the *in situ* measurements correspond well with



coarse resolution soil moisture data products. Per station, the time series are filtered such that only observations in the valid
90 geophysical range, and with a “good” quality flag remain.

2.3 Ancillary Data

Land cover and climate type information for each validation location are provided through QA4SM. The Köppen-Geiger climate classification from Peel et al. (2007) is used to define the following classes, presented in Table 1:

Abbreviation	Description
B	Arid
C	Temperate
D	Cold
BSk	Arid, steppe, cold
Csa	Temperate, dry summer, hot summer
Cfa	Temperate, no dry season, hot summer
Cfb	Temperate, no dry season, warm summer
Dfb	Cold, no dry season, warm summer

Table 1. Köppen-Geiger climate class abbreviations and their description.

The ESA Climate Change Initiative (CCI) Land Cover Classes (team and Defourny, 2016) corresponding to the year 2010
95 are used to indicate land cover types, as presented in Table 2.

3 Methods

3.1 Slope and curvature in TUW soil moisture retrieval

The slope (σ') and curvature (σ'') are the linear and quadratic term of a second order Taylor polynomial relating backscatter
($\sigma^\circ(\theta)$) to observation incidence angle (θ) at a prescribed reference angle (θ_{ref}). σ' and σ'' are used in two key steps of the
100 WARP soil moisture retrieval.

First, in the normalisation step, $\sigma^\circ(\theta)$ observations from varying incidence angles are normalised to represent backscatter at
a fixed reference incidence angle $\sigma^\circ(\theta_{ref})$:

$$\sigma^\circ(\theta_{ref}) = \sigma^\circ(\theta) + \sigma'(\theta_{ref} - \theta) + \frac{1}{2}\sigma''(\theta_{ref} - \theta)^2 \quad (1)$$

In Equation 1, the normalised backscatter ($\sigma^\circ(\theta_{ref})$) is computed by extrapolating the backscatter observation $\sigma^\circ(\theta)$ at inci-
105 dence angle θ to the reference incidence angle θ_{ref} using the σ' and σ'' values corresponding to the observation date.

In this step, it is assumed that the σ' and σ'' represent the first and second derivative of the instantaneous $\sigma^\circ - \theta$ relation at
the epoch of each σ° observation. However, in reality, σ' and σ'' do not perfectly represent the derivatives of the instantaneous



ID	Description
10	Cropland, rainfed
11	Cropland, rainfed, herbaceous
12	Cropland, rainfed, tree/shrub
20	Cropland, irrigated or post-flooding
30	Mosaic cropland / natural vegetation (tree, shrub, herbaceous cover)
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) / cropland
50	Tree cover, broadleaved, evergreen, closed to open (>15%)
60	Tree cover, broadleaved, deciduous, closed to open (>15%)
61	Tree cover, broadleaved, deciduous, closed (>40%)
62	Tree cover, broadleaved, deciduous, open (40%>15%)
70	Tree cover, needleleaved, evergreen, closed to open (>15%)
80	Tree cover, needleleaved, deciduous, closed to open (>15%)
90	Tree cover, mixed leaf type (broadleaved and needleleaved)
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
120	Shrubland
130	Grassland

Table 2. ESA CCI Land cover Classes (team and Defourny, 2016) considered in this study.

$\sigma^\circ - \theta$ due to observation errors and the need to aggregate data over time to estimate σ' and σ'' . Therefore, the estimated $\sigma^\circ(\theta_{ref})$ includes an error. A consistent error in σ' and σ'' (e.g. a positive error in σ' throughout a week) in the normalisation
110 step contributes to both over- and underestimation of $\sigma^\circ(\theta_{ref})$, depending on the incidence angle of each $\sigma^\circ(\theta)$. This is illustrated in Figure 1. In the left panel, σ_L° is observed at a reference angle θ_L lower than the reference angle θ_{ref} , while in the right panel, σ_R° is observed at a reference angle θ_R that is higher than θ_{ref} . When Equation 1 is used to compute $\sigma^\circ(\theta_{ref})$ with the true σ' and σ'' (perfectly representing the instantaneous $\sigma^\circ - \theta$ relation), this will yield the true $\sigma^\circ(\theta_{ref})$. When an erroneous σ' and σ'' are used to compute $\sigma^\circ(\theta_{ref})$ using Equation 1, an overestimation occurs in the left panel while an
115 underestimation occurs in the right panel.

We hypothesise that the σ' and σ'' estimated dynamically, are more representative of the instantaneous $\sigma^\circ - \theta$ relation than those estimated as a climatology, resulting in a reduced magnitude of the over- and underestimation of $\sigma^\circ(\theta_{ref})$. Additionally, we hypothesise that the regularised σ' and σ'' yield better estimates of the instantaneous $\sigma^\circ - \theta$ relation than those computed using the Epanechnikov kernel, again resulting in reduced errors when estimating $\sigma^\circ(\theta_{ref})$.

120 The second step in which the slope and curvature are used in the TUW SMR is in the determination of the so-called Wet and Dry References, the difference in which is an indication of the backscatter sensitivity to surface soil moisture. For this step, it is assumed that slope and curvature are driven by vegetation growth, and that two incidence angles (so-called crossover angles) exist where under (i) dry and (ii) wet conditions, backscatter sensitivity to soil moisture is independent of vegetation cover,

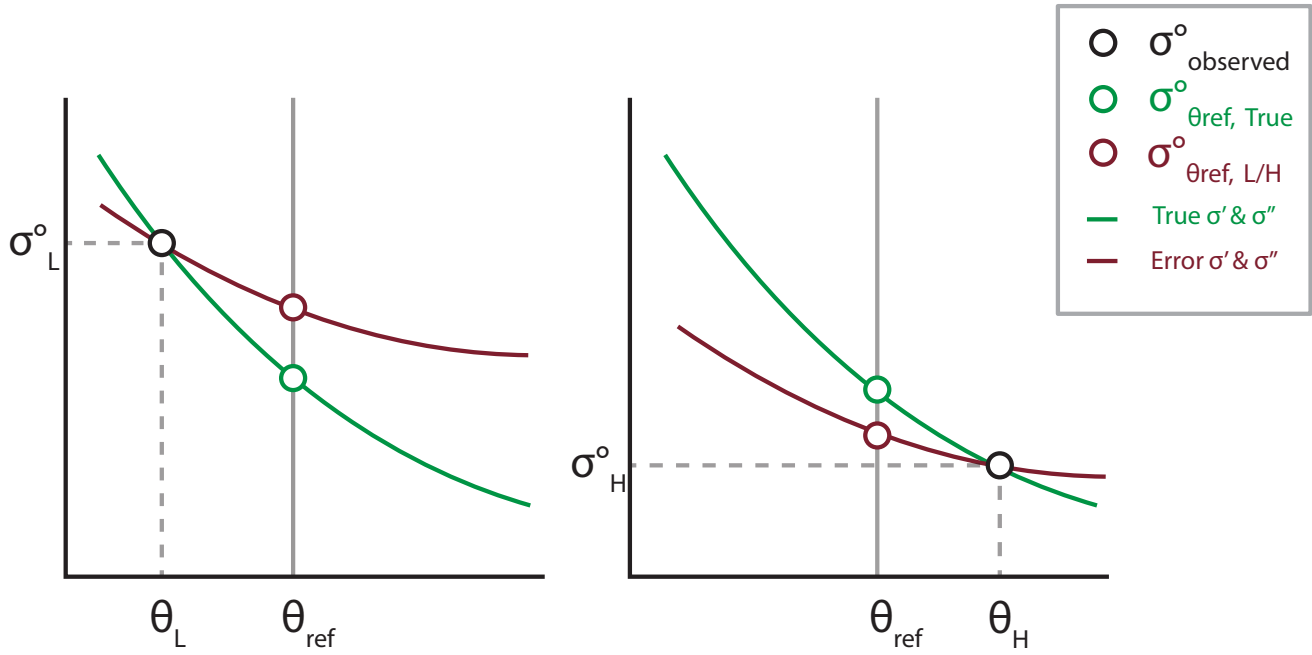


Figure 1. Demonstration of the effect of a (positive) error in σ' when normalising a backscatter observation at an angle lower than θ_{ref} (left), and higher than θ_{ref} (right)

as explained in (Wagner et al., 1999b). Following this assumption, normalised backscatter time series are extrapolated to the dry and wet crossover angle to determine a constant reference backscatter value under dry and wet conditions, respectively.

Next, the sensitivity of normalised backscatter to soil moisture is determined by using the slope and curvature time series to interpolate the constant dry and wet reference backscatter at the crossover angles to the 40° reference angle for each day, resulting in two backscatter values at the reference angle, one representing backscatter under the driest conditions, and one under wettest conditions. The surface soil moisture is then estimated by scaling the normalised backscatter between the dry and wet backscatter values. A more extensive description of this step is provided by Hahn et al. (2020).

We hypothesise that improved timing in the regularised σ' and σ'' will also improve the timing of the dynamics in the dry and wet reference, such that they more accurately represent the dynamics of backscatter sensitivity to soil moisture. Consequently, soil moisture retrieval should improve using the regularisation approach compared to the kernel approach, using both dynamic, and climatological estimates.



135 3.2 Slope and curvature computation

Time series (or climatologies) of σ' and σ'' are derived separately for each ASCAT grid point, using the (azimuth-corrected) backscatter observations and their corresponding incidence angles. First, linear approximations of the $\sigma^\circ - \theta$ relation, so-called local slopes (σ'_{loc}), are computed for each ASCAT overpass using the backscatter observations from the fore (σ_f°), mid (σ_m°), and aft (σ_a°) antenna and their respective incidence angles $\theta_{f/m/a}$. A local slope is computed using the mid and fore beams, as well as the mid and aft beams:

$$\sigma'_{m,f/m,a} = \frac{\sigma_m^\circ - \sigma_{f/a}^\circ}{\theta_m - \theta_{f/a}} \quad (2)$$

By computing the mean of $\sigma'_{m,f}$ and $\sigma'_{m,a}$, a single estimate of the local slope is obtained per overpass:

$$\sigma'_{loc} = \frac{\sigma'_{m,f} + \sigma'_{m,a}}{2} \quad (3)$$

The estimated σ'_{loc} is representative of the σ' only at its corresponding incidence angle since it is a linear approximation, while the modelled relation between θ and σ° is quadratic. The corresponding incidence angle (θ_{loc}) is the weighted mean of θ_f , θ_a and θ_m :

$$\theta_{loc} = \frac{2\theta_m + \theta_f + \theta_a}{4} \quad (4)$$

A time series of σ'_{loc} and their respective θ_{ref} is obtained for each grid point. Next, the time series of σ' and σ'' are estimated from the σ'_{loc} and θ_{ref} time series. Two separate methods are considered for estimating σ' and σ'' : the current approach using an Epanechnikov kernel, and a regularisation approach proposed by Frantzen et al. (2025). Regardless of the method considered, the following observation equation is used to link σ'_{loc} observations and θ_{loc} to the unknowns σ' and σ'' :

$$\sigma'_{loc} = \sigma' + \sigma''(\theta_{loc} - \theta_{ref}) \quad (5)$$

For the current operational ASCAT soil moisture products and previous studies, slope and curvature time series and climatologies are computed using an Epanechnikov kernel with a 21 day half-width (Melzer, 2013; Hahn et al., 2017). In this approach, the slope and curvature are estimated using weighted least squares with weights decreasing with temporal distance of each observation, corresponding to a 21 day half-width Epanechnikov kernel as defined in Equation 6.

$$w(d_i) = \begin{cases} \frac{3}{4} \left(1 - (d_i - d_n)^2 \right), & \text{if } |d_i - d_n| \leq 21 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

Observations within a 42-day window are used to estimate the slope and curvature for each date in the time series. A separate weighted least squares estimation is conducted to estimate slope and curvature for each date d_n :



$$\begin{bmatrix} \sigma'_{d_n} & \sigma''_{d_n} \end{bmatrix} = (\mathbf{A}^T \mathbf{W}_{d_n} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{W}_{d_n} \mathbf{y} \quad (7)$$

with the weight matrix $\mathbf{W}_{d_n}$ computed using Equation 6, $\mathbf{A}$ being the design matrix corresponding to Equation 5, and $\mathbf{y}$ containing the local slopes. For the climatology estimation, the same equations are used, but observations from all years within 21 days of the day of interest are used to estimate the slope and curvature for each day of the year, with d_i and d_n being the i 'th and n 'th day of year, respectively.

In the regularised estimation method for slope and curvature (Frantzen et al., 2025), again the observation equation Equation 5 is used to derive slope and curvature from local slope observations. A single regularised estimation is performed for each time series, where all available σ'_{loc} are the observations, and the design matrix maps the observations to a vector representing the daily values of slope, augmented by the daily values of curvature. This system is underdetermined, and hence, does not yield a robust estimate of slope and curvature. To regularise the underdetermined system of equations, a first-difference matrix introduced that promotes a smoother estimated slope and curvature time series by minimising the squared sum of the first order temporal derivative for the estimated σ' and σ'' time series. The following equation is used to compute regularised time series of σ' and σ'' :

$$\hat{\mathbf{x}} = (\mathbf{A}^T \mathbf{A} + \gamma^2 \mathbf{B}^T \mathbf{B})^{-1} \mathbf{A}^T \mathbf{y} \quad (8)$$

In this equation, $\hat{\mathbf{x}}$ is the vector containing σ' values for each date in the time series, augmented by σ'' values for each date. $\mathbf{y}$ are the local slopes for each overpass at the respective grid point, and $\mathbf{A}$ is the design matrix linking $\mathbf{y}$ to $\hat{\mathbf{x}}$ using Equation 5. $\mathbf{B}$ is the first-difference matrix, and γ is a scalar driving the strength of the applied first-difference penalty. A γ value of 6 is used following the recommendations from Frantzen et al. (2025), yielding a robust estimate of σ' and σ'' time series with improved temporal dynamics compared to the Epanechnikov method.

3.3 Considered slope and curvature configurations

Four methods for estimating slope and curvature are considered, using either an Epanechnikov kernel (indicated with E) or regularisation (indicated with R) to produce either a climatology (indicated with C) or a dynamic time series (indicated with D). For example, CE indicates that an Epanechnikov kernel is used to estimate the slope and curvature and that a climatology is produced. These four methods can be applied at two different steps in the TUW SMR: the normalisation step and the dry/wet reference calculation. Therefore, eight different configurations exist for slope and curvature use in TUW SMR. Given the hypotheses presented in Section 3.1 the five relevant configurations presented in Table 3 are used.

The first configuration in Table 3, CECE, is the configuration currently used in TUW SMR. The second configuration, DECE, differs from the first by using dynamic estimates of slope and curvature for backscatter normalisation. Next, DRCE differs from DECE because the dynamic slope and curvature for the backscatter normalisation are computed using regularisation instead of the Epanechnikov kernel. The DRCR differs from DRCE because this configuration uses the regularised climatologies of slope



Abbreviation	Slope/Curvature for backscatter normalisation to 40°	Slope/curvature for dry/wet reference calculation
CECE	Climatology of Epanechnikov slope and curvature	Climatology of Epanechnikov slope and curvature
DECE	Dynamic Epanechnikov slope and curvature	Climatology of Epanechnikov slope and curvature
DRCE	Dynamic Regularised slope and curvature	Climatology of Epanechnikov slope and curvature
DRCR	Dynamic, Regularised slope and curvature	Climatology of Regularised slope and curvature
DRDR	Dynamic, regularised slope and curvature	Dynamic, regularised slope and curvature

Table 3. Abbreviations and descriptions of the considered configurations of slope and curvature for the two steps in the TUW SMR.

190 and curvature in the dry/wet reference calculation. Finally, the DRDR configuration differs from DRCR by using dynamic regularised slope and curvature instead of a climatology for the dry/wet reference calculation.

3.4 Validation against *in situ* observations

To validate the ASCAT observations against *in situ* observations from the ISMN, stations considered in Section 2.2 are used as a spatial reference, and are compared to the nearest ASCAT grid point. Per location, the ASCAT overpasses with valid
195 backscatter observations are used as a temporal reference, and the temporally closest observation from the corresponding *in situ* station is matched, a search window of 12 hours is used, such that ASCAT observations without *in situ* observations available within 12 hours proximity are not considered in the validation. While the *in situ* measurements are reported as volumetric soil moisture, the ASCAT retrieved surface soil moisture is represented as a degree of saturation (0 to 100%). Therefore, prior to the computation of validation metrics, the ASCAT surface soil moisture time series are scaled such that the temporal mean and
200 standard deviation of the *in situ* measurements are equal for ASCAT surface soil moisture and *in situ* measured soil moisture. For each pair of *in situ* and ASCAT time series, the Pearson correlation (R), Spearman's ρ , and the unbiased root mean squared deviation (ubRMSD) are computed. To assess the ability to resolve the soil moisture response to precipitation events, the performance statistics are additionally computed for short term anomalies. The anomalies are computed by subtracting the respective 35 day moving averages from the ASCAT and *in situ* soil moisture data sets. Next, Pearson's R, Spearman's ρ , and
205 ubRMSD are computed as described above.

Results are aggregated over land cover and climate classes, where table 4 provides the number of stations considered in each case.

Following the validation against *in situ* soil moisture measurements, a time series of ASCAT-derived surface soil moisture from the CECE and DRCR configuration are compared along with the respective slope, curvature, normalised backscatter, and
210 the dry and wet backscatter at reference angles for the, to highlight the impact of the choice of slope and curvature time series. The time series are plotted for the grid point closest to the *Stillwater-5-WNW* station for comparison with *in situ* soil moisture measurements.



LC	10	12	20	30	40	60	61	62	70	100	110	120	130
climate													
A	1	-	-	-	-	-	-	2	-	-	-	1	-
B	21	1	3	4	2	-	-	-	3	-	-	43	12
C	46	4	-	-	1	-	1	-	14	-	1	5	175
D	95	-	-	1	1	3	1	-	17	7	4	3	71
E	-	-	-	-	-	-	-	-	-	-	-	-	29

Table 4. Number of ISMN stations used for validation per climate and land cover (LC) type.

4 Results

4.1 Baseline configuration

Here, the performance of the current operational configuration (CECE) is evaluated using QA4SM. Figure 2 shows the Pearson correlation, Spearman ρ , and ubRMSD between *in situ* and ASCAT-derived soil moisture measurements for the CONUS, Western Europe, and Eastern Texas. Areas with poor agreement between *in situ* and ASCAT soil moisture time series include the Southern Pyrenees with low correlations in Figure 2(b) and (e), the South-Western US, with negative ρ in Figure 2(d), and the Rocky Mountains. Agreement with *in situ* observations is generally good at most stations in Eastern Texas Figure 2(c), (f), and (i).

The median Pearson correlation, Spearman ρ , and ubRMSD at various combinations of land cover and climate type are shown in Table 5 for the CECE configuration. The best agreement between ASCAT and *in situ* measurements occurs in tropical climates, although the number of stations in this climate class is limited (Table 4). Low correlations occur in arid croplands, shrublands, and evergreen needleleaf forests, likely due to frequent subsurface scattering in arid conditions, causing negative correlation between soil moisture and backscatter (Wagner et al., 2022), and reduced backscatter sensitivity to soil moisture. The anomaly validation performance of the CECE configuration is shown in Table 6. The CECE configuration best captures anomalies over grasslands and in temperate climates, while over arid shrublands and arid evergreen needleleaf forests, the anomalies correlate less with the anomalies from *in situ* measurements.

4.2 Influence of dynamic estimation and regularisation on soil moisture retrieval

In this section, the median performance of the various configurations are presented for a selection of land cover classes and climate types that are well represented in the validation dataset. First, the general performance across land covers and climate types are discussed for both the standard and anomaly validation. Then the differences between the configurations are analysed.

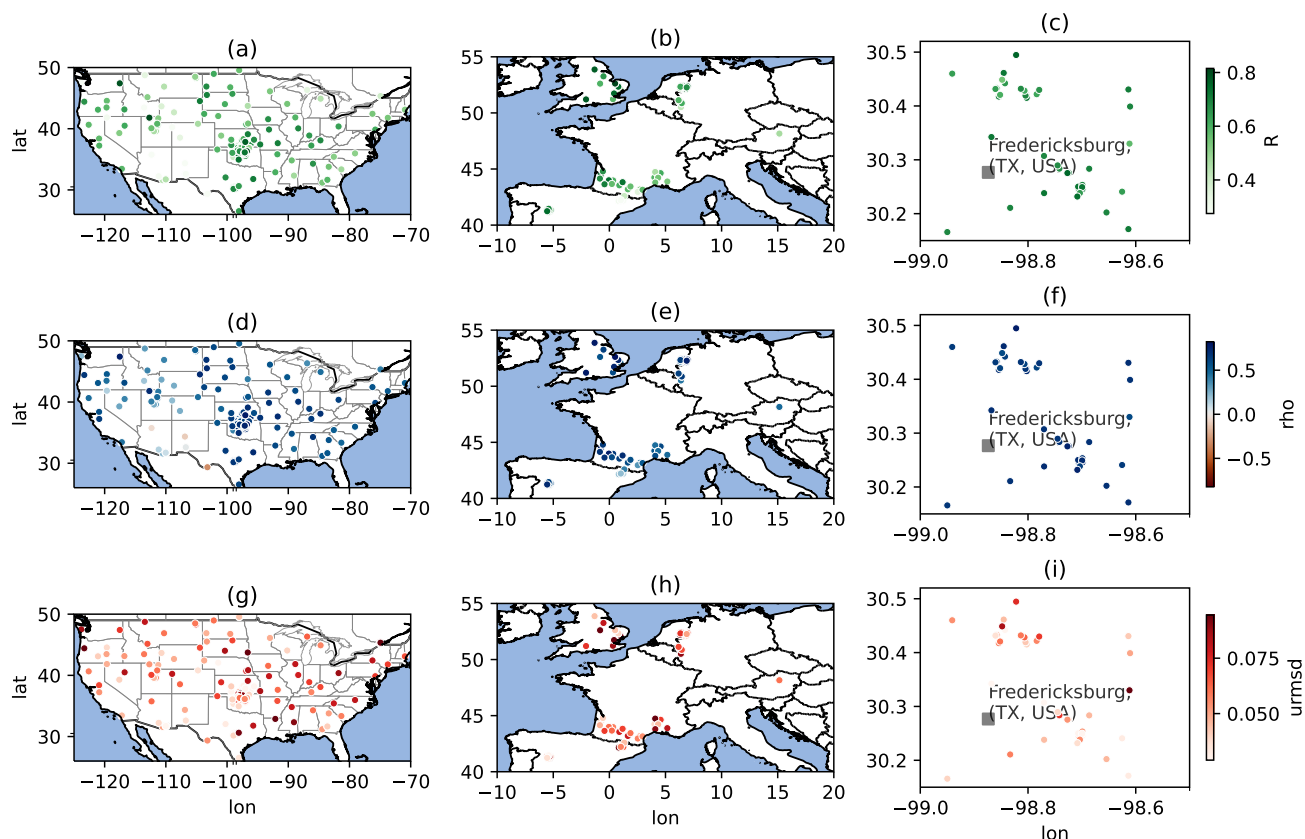


Figure 2. Median Pearson R (a,b,c), Spearman's ρ (d,e,f) and ubRMSD (g,h,i) at ISMN stations over the continental US (a,d,g) Western Europe (b,e,h) and Eastern Texas (c,f,i) for the soil moisture retrieved using the currently used CECE configuration.

Figure 3 The median R (a), ρ (b), and ubRMSD (c) vary across the configurations and land covers. The impact due to choice of configuration is largest for shrublands, while the performance of the different configurations changes less for the croplands and
235 needle leaf forests. Interestingly, performance metrics for these two land covers are similar even though theory would suggest that soil moisture retrieval over croplands should be better than that over needleleaf forests. This similarity could be due to heterogeneous land cover in the vicinity of the ISMN stations. The DRCR configuration performs best for all land covers except for shrublands and croplands, where the dynamic regularised slope and curvature (DRDR) improves the dry wet reference and hence the estimated soil moisture.

240 Figure Figure 3(d), (e), and (f) shows that within grasslands, the optimal configuration depends on climate type. Most configurations perform best in temperate climates with dry summer, while the DRDR configuration performs significantly worse in this climate type. In Arid cold steppe (Bsk), and cold and temperate wet with warm summer (Dfb) climates, all configurations perform worse than in temperate climates.



LC	10	12	20	30	40	60	61	62	70	100	110	120	130
KG													
A	0.918	-	-	-	-	-	-	0.919	-	-	-	0.900	-
B	0.609	0.659	0.646	0.656	0.648	-	-	-	0.583	-	-	0.284	0.561
C	0.605	0.580	-	-	0.557	-	0.637	-	0.628	-	0.509	0.719	0.693
D	0.566	-	-	0.441	0.592	0.517	0.540	-	0.547	0.475	0.492	0.519	0.593
E	-	-	-	-	-	-	-	-	-	-	-	-	0.816
A	0.887	-	-	-	-	-	-	0.913	-	-	-	0.892	-
B	0.555	0.491	0.605	0.639	0.671	-	-	-	0.455	-	-	0.099	0.548
C	0.618	0.609	-	-	0.570	-	0.654	-	0.666	-	0.545	0.724	0.691
D	0.573	-	-	0.458	0.553	0.513	0.536	-	0.551	0.456	0.498	0.427	0.598
E	-	-	-	-	-	-	-	-	-	-	-	-	0.824
A	0.032	-	-	-	-	-	-	0.033	-	-	-	0.024	-
B	0.040	0.024	0.058	0.077	0.060	-	-	-	0.062	-	-	0.052	0.053
C	0.067	0.077	-	-	0.079	-	0.056	-	0.059	-	0.081	0.066	0.056
D	0.060	-	-	0.056	0.092	0.066	0.070	-	0.053	0.060	0.052	0.046	0.064
E	-	-	-	-	-	-	-	-	-	-	-	-	0.045

Table 5. CECE median Pearson R (green), Spearman ρ (blue), and unbiased root mean squared deviation (red) per combination of climate and land cover types. Land cover (LC) ID's correspond to those presented in Table 2, and climate types are described in Table 1.

Figure 3(g), (h) and (i) show the performance of the configurations over rainfed croplands in the main climate classes. The DRDR and DRDR configurations yield the best performance metrics for croplands in all considered climates. Similar to grasslands, configurations perform worst in cropland areas with a polar climate where the dynamic DRDR configuration performs best. In contrast to the grasslands, the performance of all configurations is high in rainfed croplands in an arid climate.

Figure 4(a), (b) and (c) show the median performance metrics computed over anomalies from a 35 day moving average for different land covers and configurations. Similar to the standard validation in Figure 3, all configurations perform best in grasslands and worst in shrublands. While for the nominal validation metrics, the DRDR configuration performed best for nearly all land covers, the DRDR configuration performs best for most land cover classes in the anomaly validation.

The statistics of the anomaly validation for grasslands are shown in Figure 4(d), (e) and (f). The different configurations perform similarly in Cfa grasslands. In grasslands with arid BSk climates, performance metrics improve going from a climatological to a dynamic slope and curvature, and improve further when regularised dynamic slope and curvature are used for both normalisation and the calculation of the dry and wet reference. The DRDR configuration performs slightly better than other configurations in Csa grasslands, where performance of DRDR is poor in absolute validation metrics compared to other configurations (Figure 3(d) and (e)). Furthermore, over grasslands in arid climates (BSk) anomaly R and ρ are significantly higher for DRDR than for other configurations.



lc_2010	10	12	20	30	40	60	61	62	70	100	110	120	130
climate_KG													
A	0.557	-	-	-	-	-	-	0.606	-	-	-	0.582	-
B	0.483	0.410	0.475	0.574	0.526	-	-	-	0.387	-	-	0.309	0.552
C	0.500	0.387	-	-	0.306	-	0.452	-	0.469	-	0.367	0.594	0.583
D	0.419	-	-	0.345	0.505	0.253	0.397	-	0.313	0.399	0.410	0.385	0.439
E	-	-	-	-	-	-	-	-	-	-	-	-	0.779
A	0.438	-	-	-	-	-	-	0.538	-	-	-	0.529	-
B	0.372	0.349	0.463	0.537	0.514	-	-	-	0.310	-	-	0.137	0.541
C	0.497	0.376	-	-	0.269	-	0.412	-	0.468	-	0.320	0.584	0.561
D	0.426	-	-	0.306	0.461	0.239	0.361	-	0.314	0.384	0.396	0.215	0.447
E	-	-	-	-	-	-	-	-	-	-	-	-	0.788
A	0.034	-	-	-	-	-	-	0.035	-	-	-	0.025	-
B	0.040	0.022	0.047	0.077	0.060	-	-	-	0.055	-	-	0.040	0.051
C	0.060	0.069	-	-	0.077	-	0.057	-	0.058	-	0.073	0.063	0.051
D	0.055	-	-	0.049	0.089	0.064	0.067	-	0.054	0.060	0.049	0.047	0.060
E	-	-	-	-	-	-	-	-	-	-	-	-	0.042

Table 6. CECE anomaly validation median Pearson R (green), Spearman ρ (blue), and unbiased root mean squared deviation (red) per combination of climate and land cover types. Land cover (LC) ID's correspond to those presented in Table 2, and climate types are described in Table 1.

Finally, Figure 4(g), (h) and (i) shows the anomaly validation statistics over croplands. The correlations over temperate climates with a hot summer (Cfa) is best for nearly all configurations, in contrast to Figure 3(g) and (h). In all four climate classes, the DRDR configuration has a significantly higher anomaly ρ compared to other configurations (Figure 4(h)). Interestingly, this is not reflected in the Pearson R for Cfa and Cfb climates (Figure 4(g)). This may be due to non-linearity in the relation between the *in situ* anomaly and scaled soil moisture estimate anomalies from the DRDR configuration.

Comparing the changes in performance going from CECE to DECE, the median of performance metrics of DECE improves slightly for all land cover classes (Figure 3(a) (b) and (c)), compared to CECE. The most notable improvement is the reduction in the ubRMSD over evergreen needleleaf forests. Over grasslands, DECE again performs slightly better than CECE, except in temperate climates with a dry, hot summer (Csa). This could be explained by a strong seasonal pattern in the slope and curvature due to the dry summers, yielding a better soil moisture retrieval when the robust climatological slope and curvature are used for backscatter normalisation. Over croplands (Figure 3(g) (h) and (i)), DECE generally performs better than CECE, with the largest improvement for arid and polar climates. The anomaly validation metrics in Figure 4 show that DECE performs similarly to CECE across all combinations of land cover and climate types.

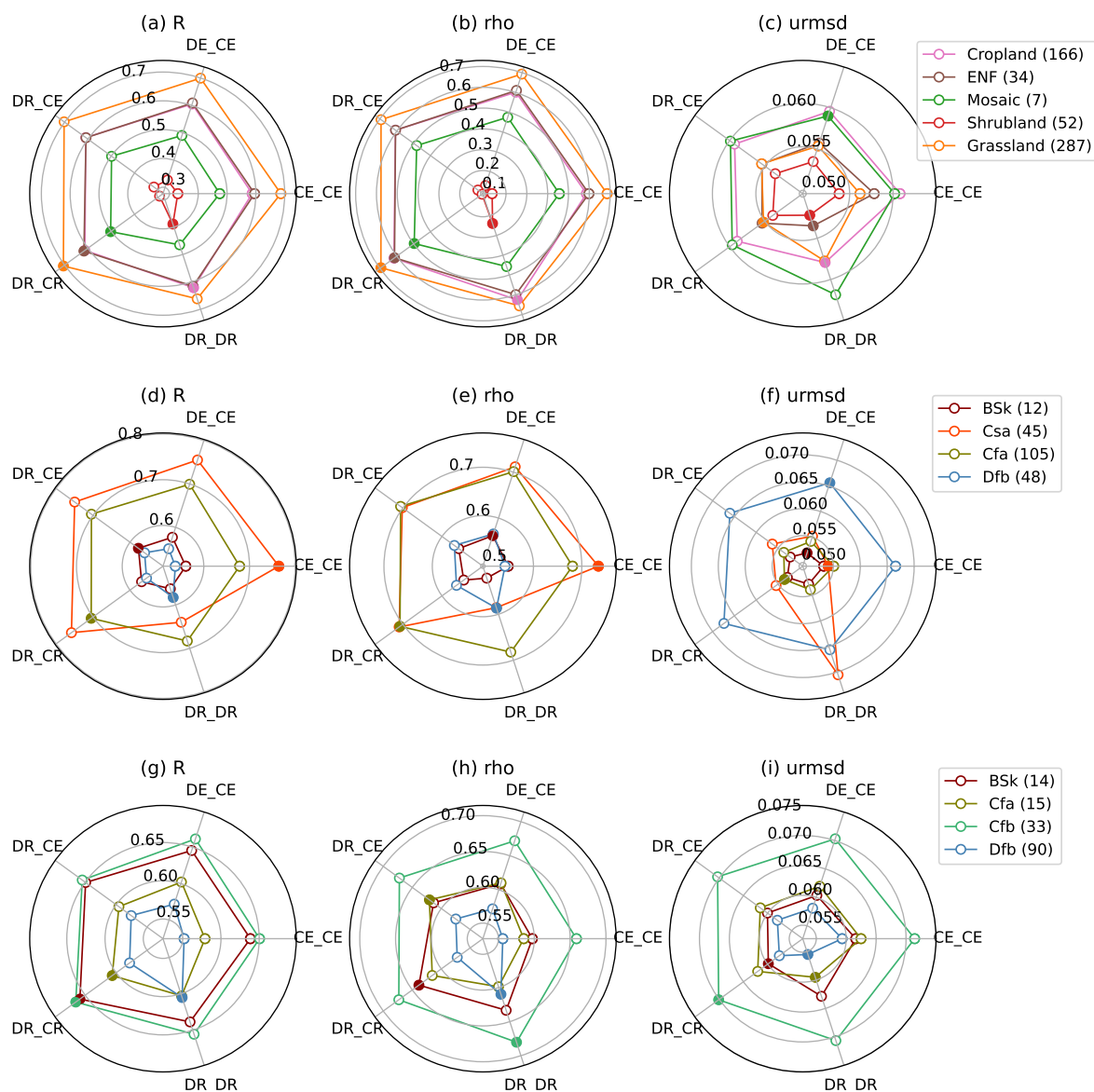


Figure 3. Median pearson R (a,d,g), Spearman's ρ (b,e,h) and ubRMSD (c,f,i) per land cover (a,b,c), and for four climate types in grasslands (c,d,e) and rainfed croplands (f,g,h), for the five configurations. A coloured dot indicates the best performing configuration per land cover or climate type. Box plots showing the distribution of performance metrics per land cover alongside the median are provided in Figure A1.

Going from DECE to DRCE, slight improvements occur over all land cover classes except shrublands. Zooming into grasslands and croplands, it can be seen that no significant differences in performance occur in temperate climates. The anomaly

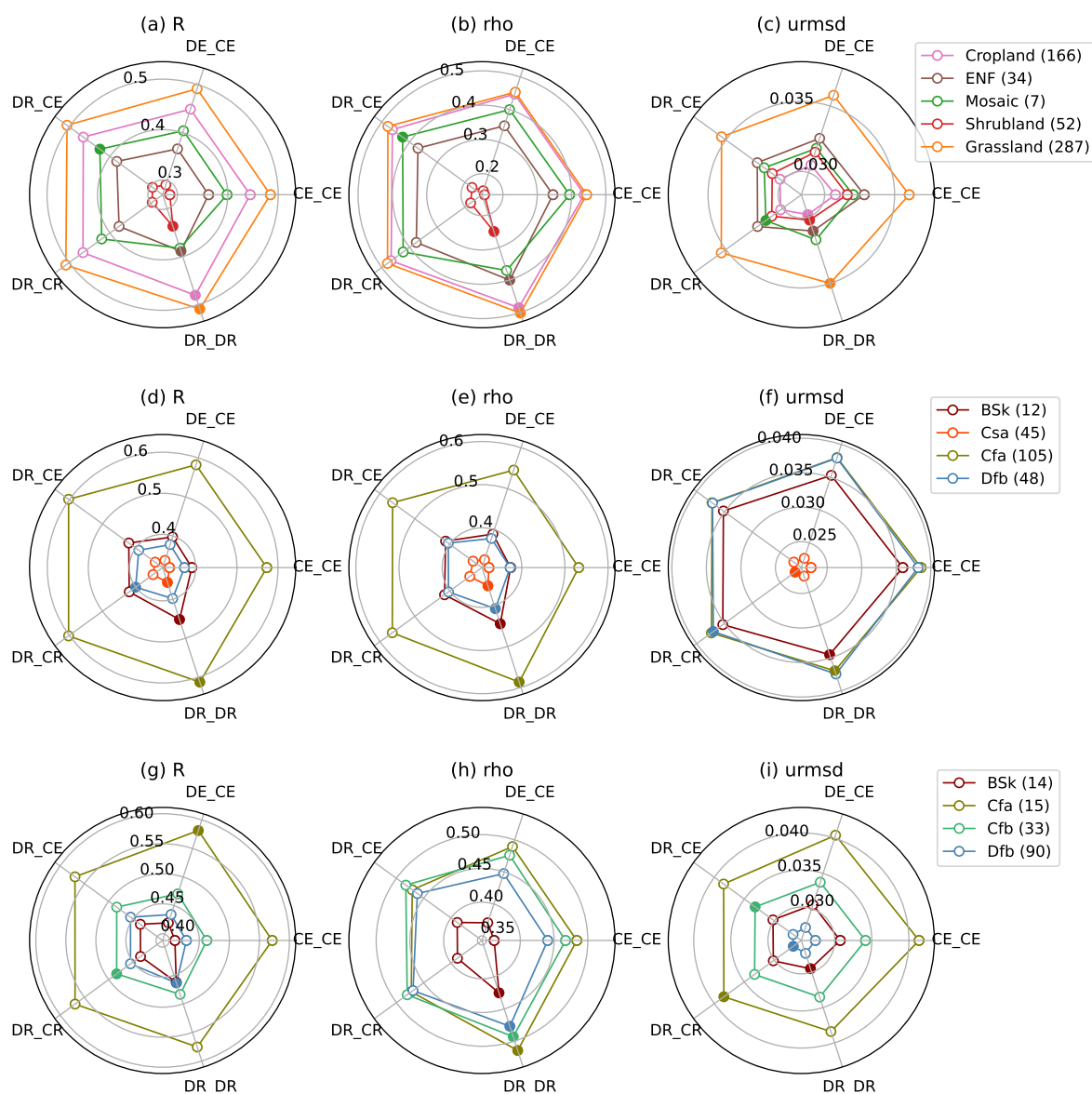


Figure 4. Anomaly validation median Pearson's R (a,d,g), Spearman's ρ (b,e,h) and ubRMSD (c,f,i) per land cover (a,b,c), and for four climate types in grasslands (c,d,e) and rainfed croplands (f,g,h), for the five configurations. A coloured dot indicates the best performing configuration per land cover or climate type.

performance metrics for all land covers (Figure 4(a), (b) and (c)) benefit from the regularised slope/curvature for backscatter
 275 normalisation, as most anomaly performance metrics slightly improve, except over Cfa croplands (Figure 4(g) and (h)).



Replacing the Epanchnikov climatology with the regularised climatology in the dry wet reference step (i.e. replacing DRCE with DRCR) further improves the performance metrics, with the exception of arid grasslands and shrublands, which mostly occur in arid climates (Table 4). This indicates that the dry/wet reference step benefits from the improved timing of the regularised slope/curvature when used as a climatology. Short-term dynamics of soil moisture do not benefit from this change as the performance metrics in Figure 4 are nearly identical for DRCE and DRCR.

Finally, using the dynamic regularised slope/curvature in the dry/wet reference calculation improves soil moisture estimation for shrublands, arid grasslands, and cold croplands. In the remaining climate and land cover classes, the metrics are similar or impaired. For example, a significant decrease in R in Csa grasslands occurs, compared to other configurations in Figure 3(d). The anomaly validation presented in Figure 4 shows favourable metrics for DRDR compared to DRCR, with DRDR yielding the best median performance for all considered land covers except for grasslands. This suggests that short-term estimation of soil moisture can benefit significantly from a dynamic slope and curvature in the dry/wet reference calculation, although the benefits vary significantly per land cover.

4.3 Detailed comparison between DRCR and the baseline configuration

Following the results presented in Section 4.1, the DRCR configuration is considered to perform best of all configurations considering the favourable validation metrics across land covers and climate types in both the nominal, and anomaly validation for this configuration. In this section the validation results from the DRCR configuration are further compared to those of the CECE configuration that is currently used.

A map of the changes in validation metrics between DRCR and CECE per station is shown in Figure 5 for the CONUS, Western Europe, and Central US. The large majority of the stations show a slight improvement in the three considered metrics when DRCR is used instead of CECE. Notable improvements occur in the Cfb (Temperate, humid, warm summer) climates of the Central US, and Southern France, while validation metrics worsen for stations in the arid Western US and a few stations in Europe.

Figure 6 shows the difference in Spearman's ρ between DRCR and CECE and the corresponding CECE Spearman's ρ for stations in the most common land cover and climate types. Most stations show an increase in correlation for the DRCR configuration, compared to the CECE configuration. Stations with low CECE correlations generally see a larger difference in correlation between DRCR and CECE than stations with high CECE correlations. Figure 6(a) shows that rainfed croplands and needleleaf forests (land cover 10 and 70, respectively) benefit most from using a regularised dynamic slope and curvature. Over grasslands, the changes in performance when using a dynamic slope and curvature can be negative, especially at stations where initial performance was already good. Figure 6(b) shows that the large majority of the grassland stations with a better correlation for CECE than for DRCR, are in a Csa climate (Temperate climate with dry and hot summer). The DRCR configuration performs better than CECE in the other climates that are common in the validation (Dfb, Cfb, Cfa).

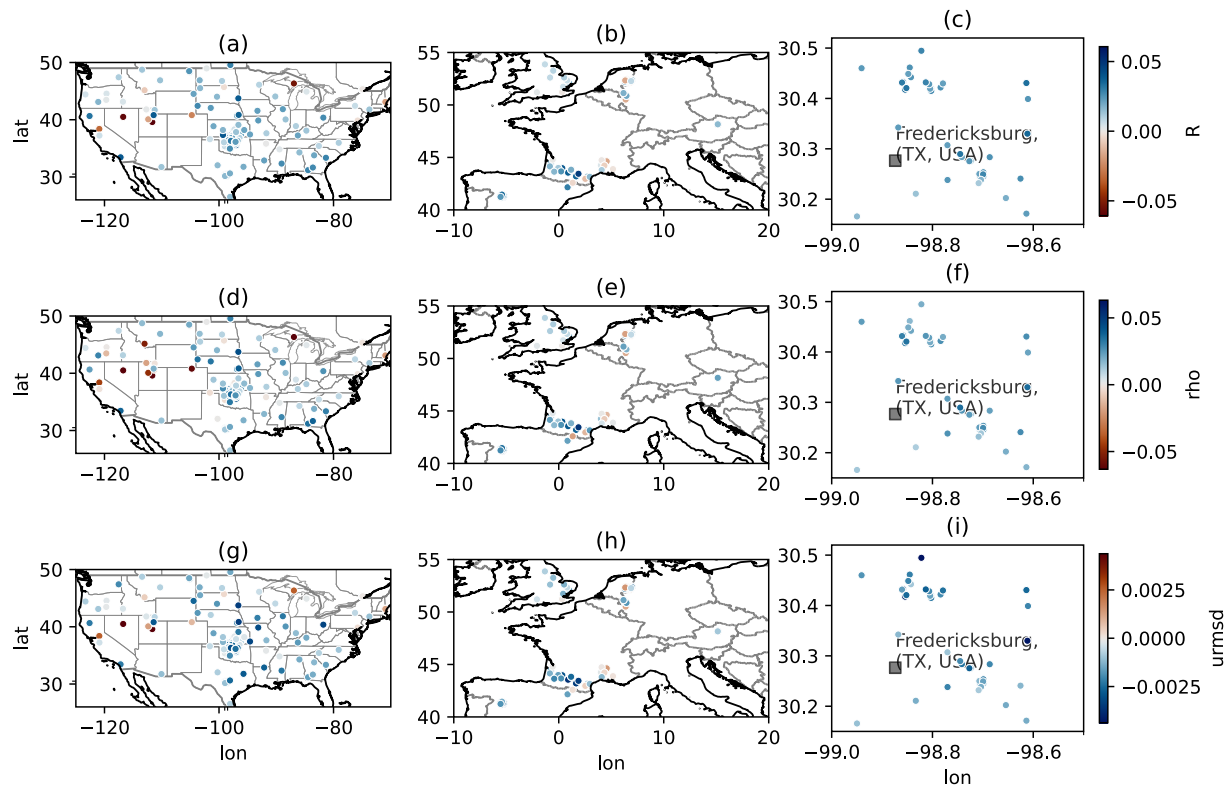


Figure 5. DRDR-CECE difference in nominal validation metrics: Pearson R (a,b,c), Spearman's ρ (d,e,f) and unbiased root mean squared deviation (g,h,i), at ISMN stations over the continental US (a,d,g) Western Europe (b,e,h) and Eastern Texas (c,f,i) for the soil moisture retrieved using the proposed DRDR, and the current CECE configuration.

4.4 Detailed anomaly comparison between DRDR and DRDR

Figure 7 Shows the change in anomaly performance metrics going from DRDR to DRDR in the CONUS, Europe, and Eastern Texas. In the central CONUS, around the 100° longitude, the anomaly correlations generally improve for DRDR, compared to DRDR. In the Western US, the DRDR anomaly correlations are lower for stations in the Rocky Mountains, where nominal correlations are also lower for DRDR than for CECE (Figure 5). In Europe, the anomaly correlations for DRDR are higher than for DRDR at most stations, with a big increase in correlations for stations in Spain and South East France. Around Frederiksburg ((Figure 7(c), (f) and (i)) the anomaly performance is equal for DRDR and DRDR in the southern stations (below 30.35°N), while DRDR performs significantly better for staions at northern stations. Comparing the Copernicus land cover classification over this region, presented in Figure A2, it can be seen that the similar performance for DRDR compared to DRDR occurs mostly in managed agricultural lands and grasslands, while improved performance occurs over open forested areas.

Figure 8 shows the difference in anomaly Spearman's ρ between DRDR and DRDR and the corresponding anomaly DRDR ρ for stations in the most common land cover and climate types. In Figure 8(a) the DRDR anomaly correlations increase

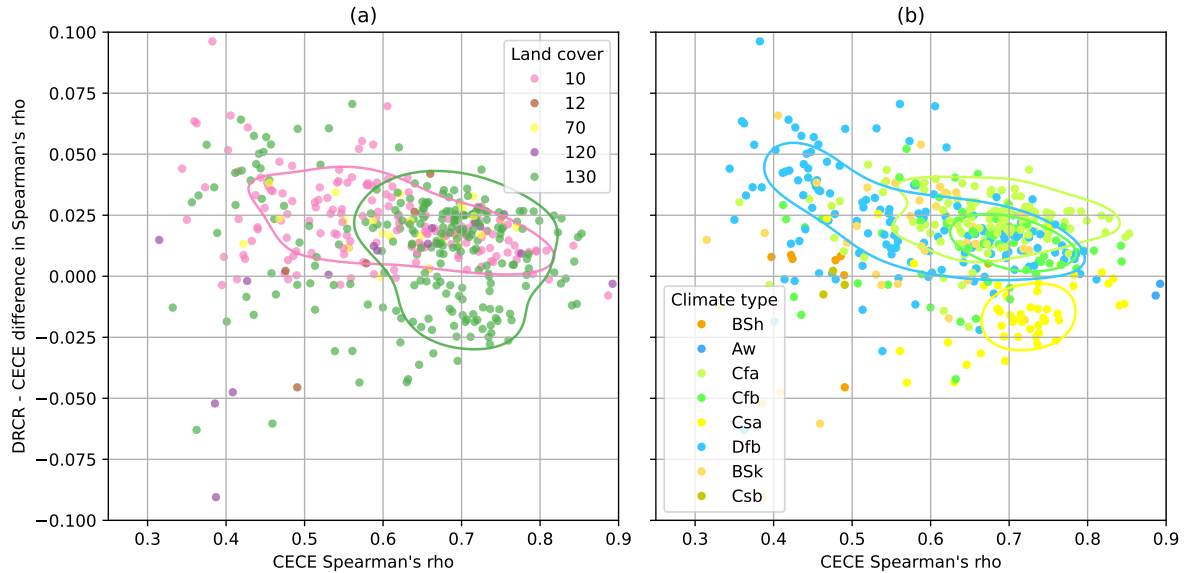


Figure 6. Nominal Spearman's ρ difference between DRCR and CECE, and CECE Spearman's ρ per land cover (a), and climate type (b) For the 8 most common climate types and 5 most occurring land covers in the validation. The 50% contour of the estimated kernel density are provided in (a) for Croplands (pink) and Grasslands (green), and in (b) for Climate types Dfb, Cfa, Cfb and Csa. An additional data point in a BSk shrublands at (0.385, -0.186) clipped out.

compared to DRCR for most croplands and grasslands. Grassland stations with a very high DRCR anomaly ρ see a small
 320 decrease in anomaly ρ when dynamic slope and curvature are used for the dry and wet reference calculation, while grassland
 stations with a median DRCR anomaly ρ are positively impacted. For nearly all stations in Evergreen needleleaf forests and
 shrublands (land cover 70 and 120, respectively), the DRDR anomaly ρ is higher than for DRCR. The anomaly ρ is higher for
 DRDR than for DRCR for the majority of the stations in each climate type in Figure 8(b). For Csa, Cfb, Cfa and Dfb climates,
 this is also reflected in the 50% contours of the estimated kernel densities, which mainly span the region corresponding to an
 325 increase of anomaly ρ following a dynamic regularised slope and curvature for the dry and wet reference calculation.

4.5 Demonstrating the impact of regularised dynamic slope and curvature on time series of retrieved soil moisture

Time series from a grid point near the the USCRN Stillwater-5-WNW station are plotted in Figure Figure 9 to illustrate the
 impact of the choice of configuration on the various steps in soil moisture retrieval. Figure 9(a) and Figure 9(b) respectively
 show the σ' and σ'' used to normalise backscatter observations to the 40° reference angle, resulting in the σ_{40}° time series
 330 shown in Figure 9(c), and their difference provided in Figure 9(d). The dry/wet range resulting from the DRCR and CECE σ'
 and σ'' are shown in Figure 9(c), and the estimated surface soil moisture is provided in Figure 9(e), together with the *in situ*
 measured volumetric soil moisture at 5 cm depth.

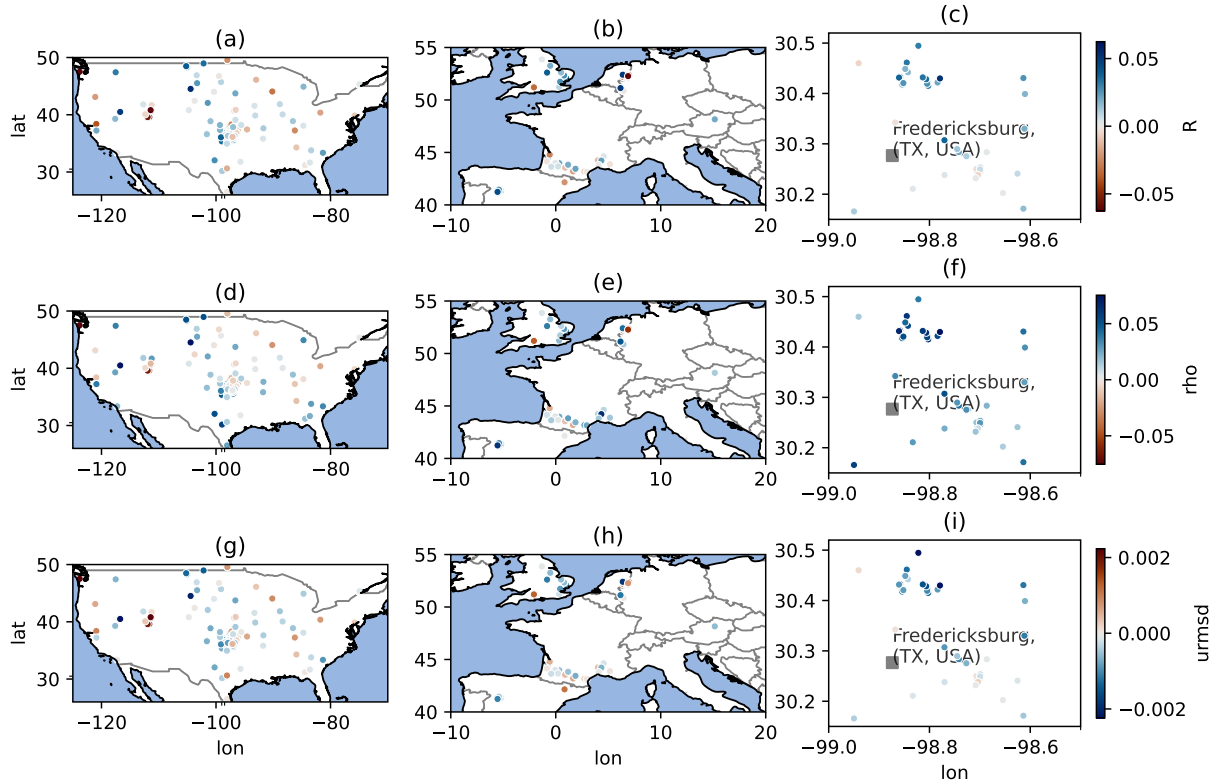


Figure 7. DRDR-DRCR difference in anomaly validation metrics: Pearson R (a,b,c), Spearman's ρ (d,e,f) and unbiased root mean squared deviation (g,h,i), at ISMN stations over the continental US (a,d,g) Western Europe (b,e,h) and Eastern Texas (c,f,i) for the soil moisture retrieved using the proposed DRCR, and the current CECE configuration.

In Figure 9(a) and (b), the differences in σ' and σ'' between the DRCR and CECE configurations are characterised by smoother time series for the CECE configuration, and a higher σ' for the DRCR configuration starting mid October. In this period, the resulting $\sigma_{(40)}^\circ$ estimates for DRCR are lower than for CECE. This bias is explained by the fact that observations more frequently occur at incidence angles higher than the reference incidence angle. Thus following Figure 1, an increase in slope will generally decrease the estimated $\sigma_{(40)}^\circ$.

The dry/wet range in Figure 9c, resulting from the Epanechnikov and regularisation configurations are very similar. Hence, the differences in estimated soil moisture from the two configurations mostly result from the normalisation step. In a period with limited expected variation in soil moisture (12 November to 3 December), the soil moisture estimated from DRCR is lower, and has a lower standard deviation (0.085 %) than the soil moisture estimated using CECE (0.11%). Again, this could be explained by the effects described in Figure 1. In mid December, gaps can be seen in the slope and curvature time series,

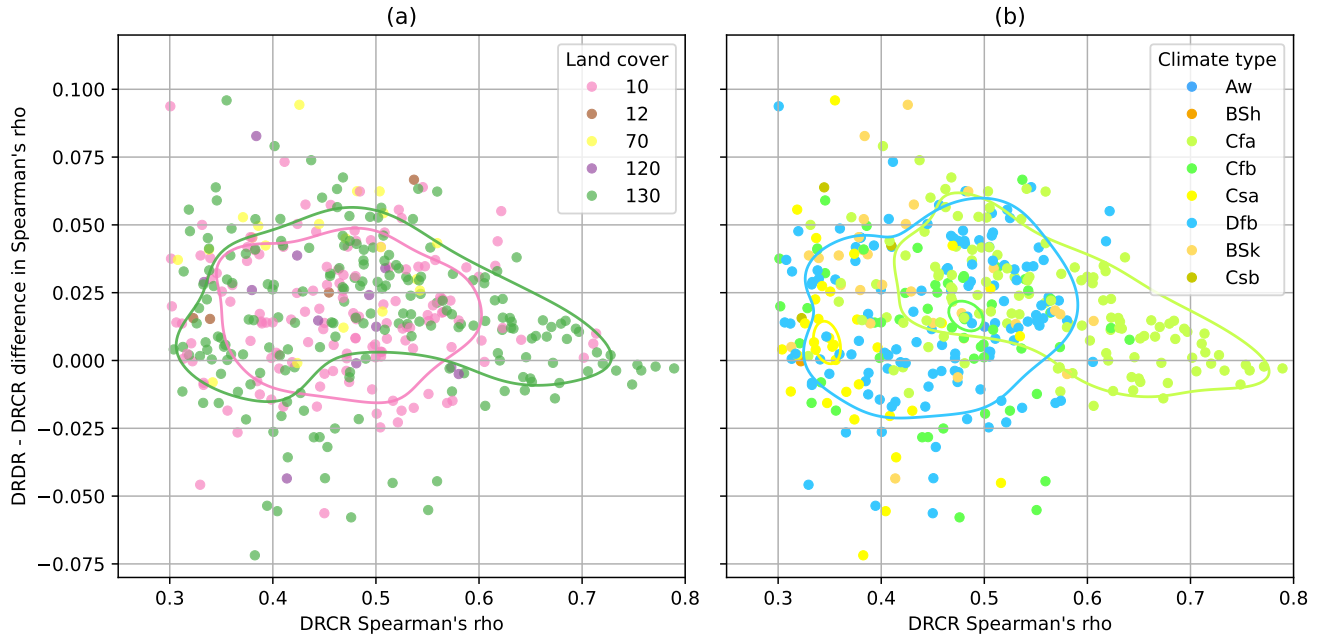


Figure 8. DRDR-DRCR Anomaly Spearman's ρ difference per land cover (a), and climate type (b) For the 8 most common climate types and 5 most occurring land covers in the validation. The 50% contour of the estimated kernel density are provided in (a) for Croplands (pink) and Grasslands (green), and in (b) for Climate types Dfb, Cfa, Cfb and Csa.

which are masked during snow covered or frozen soil conditions. Around these masked periods, the unmasked σ' and σ'' remain higher for DRCR than for CECE, again resulting in lower estimates of $\sigma_{(40)}^\circ$ and surface soil moisture.

345 5 Discussion

5.1 Improvements in the normalisation step

Changes in the slope and curvature affect the estimates of normalised backscatter, with an increased slope leading to lower estimates of normalised backscatter and vice-versa, as demonstrated in Section 4.5. Differences between the slope and curvature computed from the Epanechnikov climatology, and those computed using the dynamic regularisation method result in different
 350 time series of normalised backscatter, affecting the time series of estimated soil moisture. This is reflected in the validation against *in situ* soil moisture measurements in Section 4.3.

The improved (anomaly) validation metrics for most land covers and climate types in Section 4.3 suggest that the dynamic regularised slope and curvature are more suitable for normalising backscatter. The dynamic regularised slope and curvature more accurately represent the instantaneous $\sigma^\circ - \theta$ -relation at each epoch.

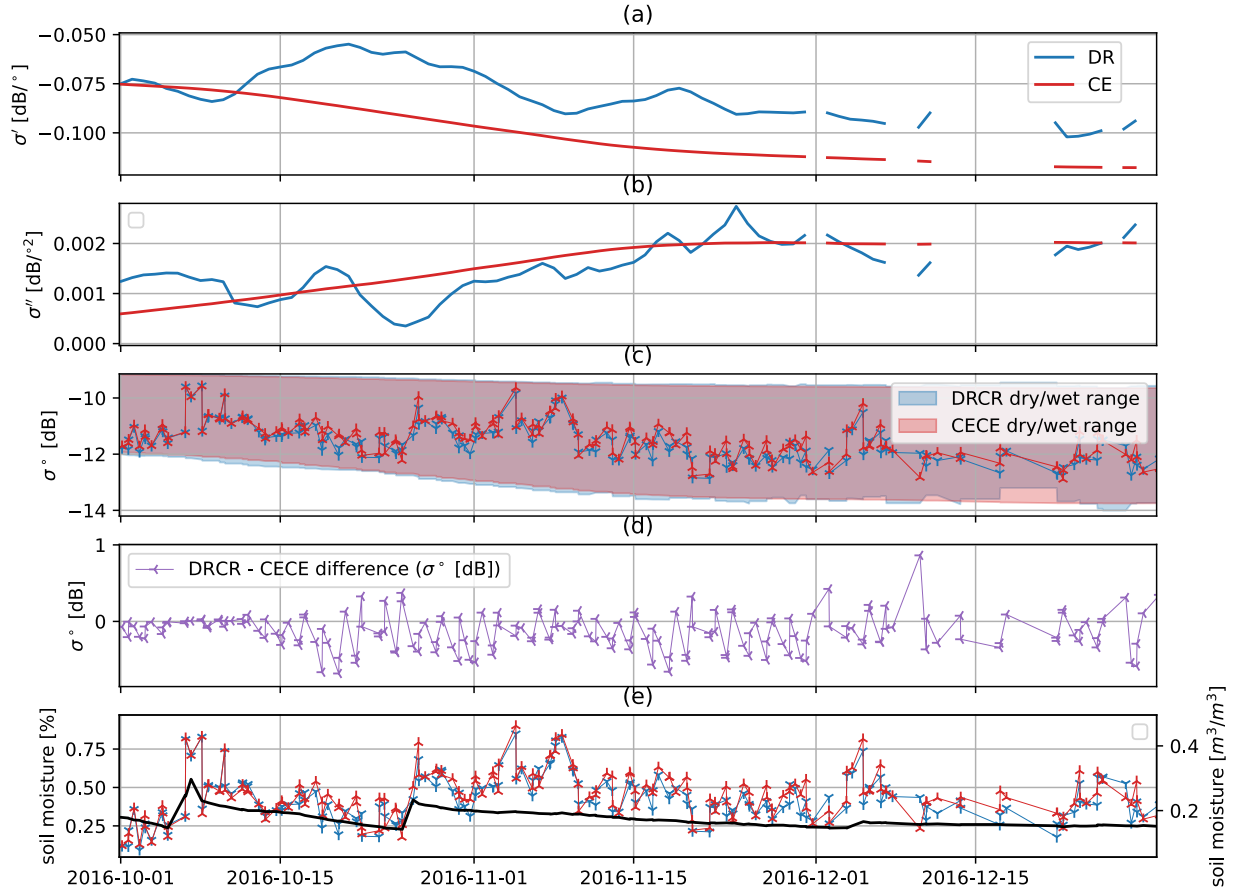


Figure 9. Time series of DRCR and CECE σ' (a), σ'' (b), σ°_{40} (c), σ°_{40} difference (DRCR-CECE) (d) and surface soil moisture (e), with *in situ* soil moisture (USCRN station Stillwater-5-WNW) at 5cm depth presented in black in (e) for grid point 3875822.

355 5.2 Impact of dynamic slope and curvature in the Dry/wet reference calculation

The impact of replacing slope and curvature in the dry/wet reference calculation is more nuanced compared to the normalisation step. Utilising regularised climatology as opposed to the Epanechnikov climatology does not yield a real benefit, as the slope and curvature time series are very similar (Section 4.5). Consequently, validation metrics are very similar for regularised and Epanechnikov climatology. However, clear differences in validation metrics exist when comparing dynamic against climatological slope and curvature time series. Nominal validation statistics suggest that a dynamic slope and curvature works best



for the dry/wet reference calculation in Shrublands and arid and cold climates, while retrievals are worse for other land cover and climate classes.

The generally worsened performance in the nominal validation using a dynamic slope and curvature for the dry/wet reference calculation could be explained by the geophysical processes driving variation in the slope and curvature. In the dry/wet reference calculation, it is assumed that variations in the slope and curvature are solely due to varying attenuation and direct scattering by vegetation (Wagner et al., 1999b), while additional processes including interception and variations in surface soil moisture content may also influence short-term dynamics of slope and curvature (Greimeister-Pfeil et al., 2022). These additional processes are smoothed out in the climatological slope and curvature due to their irregular timing and short time scales, while their influence remain in the dynamic slope and curvature. Hence, the assumption in the dry/wet reference calculation that solely vegetation drives slope and curvature is valid for climatological slope and curvature, but could be problematic when a dynamic slope and curvature are used. Change in performance in soil moisture retrieval with a dynamic slope and curvature in the dry/wet reference calculation are thus a balance between improved representation of inter-annual variation in phenology, and less suppression of confounding factors influencing slope and curvature. The contrast in performance increases around Fredericksburg in Figure 7(f) and (i) possibly demonstrates two sides of this balance, where in the Northern region, unmanaged open forests could have stronger inter-annual variability and lower influence of confounding factors on σ' , compared to the managed croplands and grasslands in the Southern region, leading to a larger improvement for the Northern region when the dry/wet reference is calculated using a dynamic σ' and σ'' . Short-term confounding factors could possibly be suppressed while allowing inter-annual variation if the slope and curvature are computed dynamically, but only considering observations with incidence angles above a certain threshold, as the sensitivity to surface soil moisture decreases for higher incidence angles.

Contrary to the absolute validation metrics, the anomaly validation metrics show a clear benefit from using a dynamic slope and curvature for all land cover classes except grasslands, suggesting that the surface soil moisture response to precipitation events is better captured when a dynamic slope and curvature are used in the dry/wet reference computation. For applications that benefit from improved short-term dynamics in estimated soil moisture, the soil moisture estimated using the DRDR configuration could be a useful product. For example, the HSAF near real time soil moisture data product could benefit from a dynamic regularised slope and curvature as short-term variations in soil moisture are better represented than when a climatological slope and curvature are used for the backscatter normalisation and dry and wet reference calculation.

5.3 Towards dynamic normalisation

From the considered configurations, most performed better in the validation than the currently used CECE configuration. While the biggest improvements occur when a climatic σ' and σ'' are replaced by a dynamic variant in the normalisation step, the DRDR configuration was the best performing for most land covers and climate types in the absolute validation, while DRDR performed best in the anomaly validation. Therefore, it is worth considering the use of both DRDR and DRDR as an alternative to the current CECE configuration in the TUW SMR.

The computational cost for regularised estimation of σ' and σ'' is higher than for the kernel smoothing method, so the feasibility of computing regularised estimates of σ' and σ'' in the TUW SMR should be assessed. Additionally, the reliability



395 of regularised estimation of slope and curvature in a near real time context should be assessed, ensuring consistency with
climate data records. Furthermore, this study is limited to a comparison with *in situ* measurements, whereas a comparison to
other satellite products, and land surface models (LSMs) will provide a more comprehensive overview (Gruber et al., 2020)
of the improvements in the soil moisture retrieval when using dynamic regularised estimates of σ' and σ'' . Based on the
results presented here, a trade-off analysis is recommended between DRCR, DRDR, and CECE configurations, regarding their
400 performance in soil moisture retrieval and their computational cost.

In addition to the ASCAT measurements, the proposed configurations could additionally benefit soil moisture from ESCAT
measurements, which also uses the TUW SMR. The regularisation method is especially interesting for ESCAT since the
temporally sparser observations reduce the robustness of DE slope and curvature with kernel-based estimates given the 21
day half-width used for ASCAT. While a larger kernel half-width could increase the robustness, this will come at the cost of
405 suppressed dynamics in the estimated slope and curvature time series. The regularisation method could possibly provide robust
estimates of slope and curvature while avoiding large window sizes or stronger constraints because the slope and curvature
parameters are constrained in the temporal domain.

6 Conclusions and Recommendations

In this study we investigated the impact of using several configurations to estimate slope and curvature for two key steps in
410 the TU Wien ASCAT soil moisture retrieval. The current ASCAT soil moisture data products utilise a climatological slope
and curvature estimated using an Epanechnikov kernel. These variables are used to (i) normalise backscatter observations to a
constant reference incidence angle, and (ii) to quantify backscatter sensitivity to soil moisture. For both steps, we investigated
the impact on soil moisture retrieval when using dynamically estimated slope and curvature instead of a climatology, and when
using regularisation instead of an Epanechnikov kernel.

415 A validation against *in situ* measurements from the ISMN following the QA4SM validation framework showed that ASCAT
soil moisture retrieval improves when a regularised, dynamic estimate of slope and curvature is used for the normalisation of
backscatter to the 40° reference angle. Dynamic estimates of slope and curvature for calculating the dry and wet backscatter
reference did not provide clear benefits, considering absolute validation metrics. However, anomaly validation metrics signif-
icantly improved when using a dynamic slope and curvature in the dry and wet reference calculation, indicating a benefit for
420 estimation of short-term soil moisture dynamics.

Example time series of variables computed throughout the soil moisture retrieval demonstrated how changes in slope and
curvature propagate to changes in the normalised backscatter, with increased slope corresponding to lower estimates of nor-
malised backscatter and vice versa. The effects of slope and curvature in the dry/wet reference calculation were limited in this
example because of the similarity between the Epanechnikov and Regularised climatologies of slope and curvature.

425 The best performing DRCR configuration showed improved performance metrics at a large majority of the *in situ* stations of
the validation, compared to the currently used CECE configuration. Decreased performance mainly occurs at a small number
of *in-situ* stations where climate and land cover provide challenging conditions for ASCAT soil moisture retrieval. The DRDR



configuration performed better than DRCR in the anomaly validation for a majority of stations, with significantly impaired performance mainly limited to stations where surface conditions are not ideal for ASCAT soil moisture retrieval. We therefore
430 recommend considering both the DRCR and DRDR configuration as an alternative to the current CECE configuration used for the TUV SMR.

Future studies should more extensively investigate the implications of the DRCR and DRDR slope and curvature configuration for ASCAT soil moisture retrieval before these configurations are used to generate a soil moisture climate data record or near real time data product. Particularly, a validation against global soil moisture data such as ERA-land, SMAP-, or SMOS-
435 derived soil moisture should highlight possible shortcomings that may not surface in a validation against sparsely spaced *in situ* measurements. While the implementation of the regularisation method in the TUV SMR would require further development and studies regarding computational cost, the current TUV SMR could already be improved with relatively low effort, by using the dynamic Epanechnikov kernel that is already implemented in the TUV SMR to compute slope and curvature time series for backscatter normalisation. Additionally, the use of the regularisation method for near real-time soil moisture retrieval
440 should be studied, with a focus on consistency with climate data records. Finally, the impact of the different configurations on the ESCAT soil moisture retrieval should be investigated.

The positive impact of dynamic and regularised slope and curvature on backscatter normalisation in the ASCAT soil moisture retrieval suggests that the HSAF surface soil moisture products could be further improved. Furthermore, the configurations benefitting ASCAT surface soil moisture retrieval will likely benefit the retrieval from ESCAT. Thus, the surface soil moisture
445 estimates from a record spanning over 35 years could potentially be improved, benefitting products that rely on ASCAT soil moisture estimates, such as the ERA Land climate reanalysis (ECMWF, 2018).

Data availability. The QA4SM validations are available online at <https://doi.org/10.5281/zenodo.22113299> (Frantzen, 2026).

Appendix A

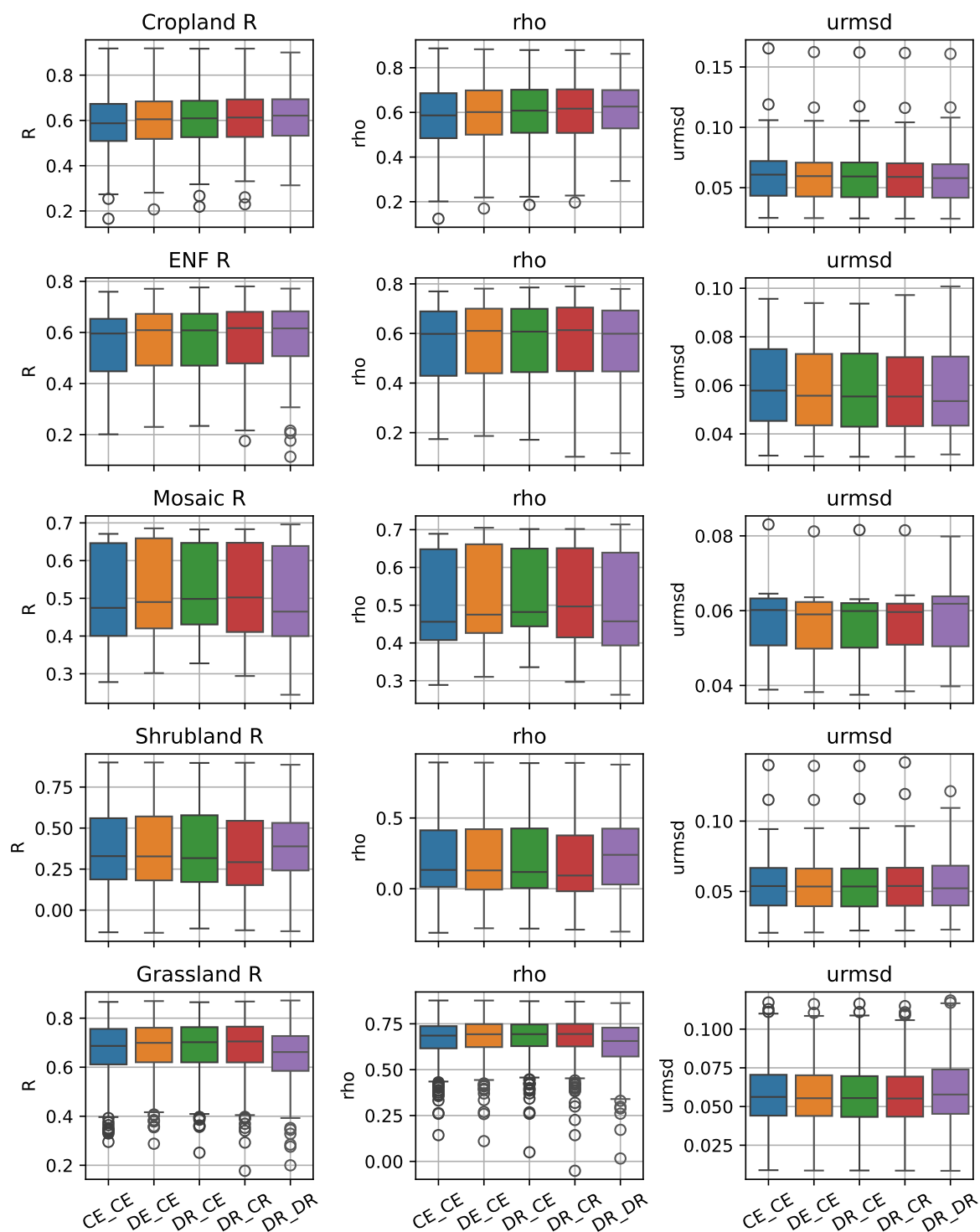


Figure A1. Boxplots of Pearson R , Spearman ρ , and unbiased root mean squared deviation per land cover type for the nominal QA4SM validation.

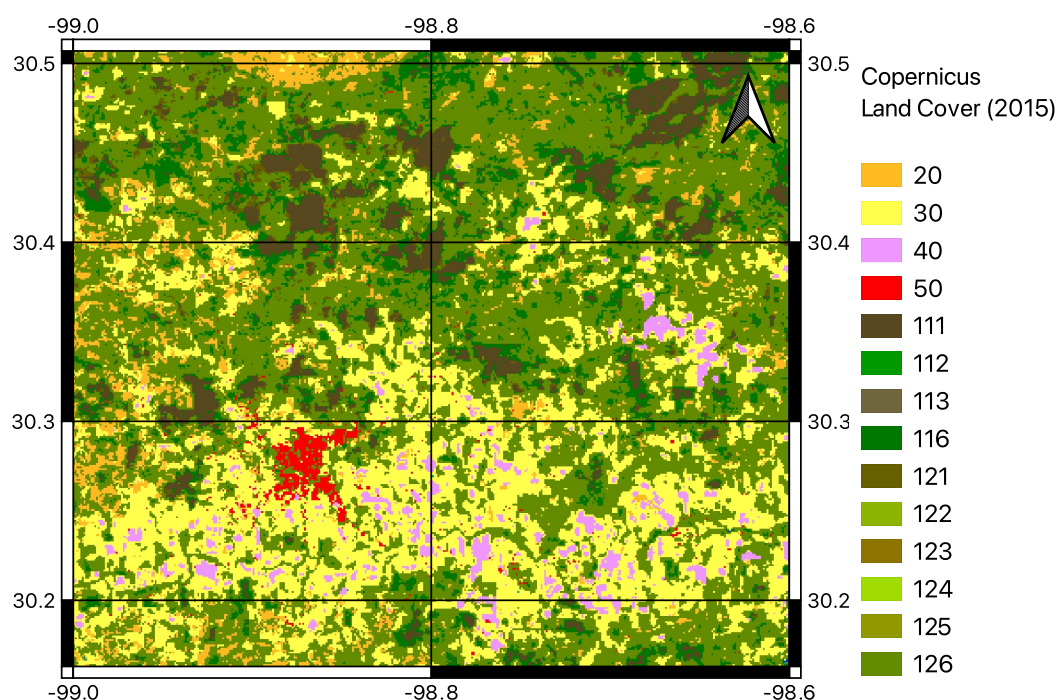


Figure A2. Copernicus land cover (2015) around Frederiksburg, with Land cover ID's: 20 – Shrubs, 30 – Herbaceous vegetation, 40 – Cultivated and managed vegetation/agriculture, 50 – Urban/built up, 111 – Closed forest, evergreen needle leaf, 112 – Closed forest, evergreen broad leaf, 113 – Closed forest, deciduous needle leaf, 114 – Closed forest, deciduous broad leaf, 115 – Closed forest, mixed, 116 – Closed forest, unknown/other, 121 – Open forest, evergreen needle leaf, 122 – Open forest, evergreen broad leaf, 123 – Open forest, deciduous needle leaf, 124 – Open forest, deciduous broad leaf, 125 – Open forest, mixed, 126 – Open forest.



Author contributions. **PF**: conceptualisation, data curation, formal analysis, investigation, methodology, visualisation, writing - original
450 draft. **SSD**: conceptualisation, formal analysis, funding acquisition, methodology, project administration, supervision, Writing - review &
editing. **RL**: data curation, methodology, software. **SH**: conceptualisation, data curation, software, Writing - review & editing. **MV**: concep-
tualisation, **WW**: conceptualisation, supervision, Writing - review & editing.

Competing interests. Some authors are members of the editorial board of Earth Observation.

Acknowledgements. The work of Paco Frantzen and Susan C. Steele-Dunne was additionally supported by NWO under Grant ENW.GO.001.034
455 as part of the “Use of space infrastructure for Earth observation and planetary research” research program. The work of Roland Lindorfer,
Wolfgang Wagner, Sebastian Hahn and Mariette Vreugdenhil was additionally supported by the EUMETSAT Satellite Application Facility
on Support to Operational Hydrology and Water Management (H SAF CDOP4). This work was supported by the European Space Agency
(FDR4LDYN, ESA Co. RFP/3-18440/24/I-DT-1). The results used in this study were generated using the QA4SM service available at:
https://qa4sm.eu. The service was developed by TU Wien GEO and AWST GmbH. The results were generated on 2026-07-23. AI tools were
460 used to obtain suggestions for refined sentence structures and improved readability.



References

- Angewandte Wissenschaft, S. u. T. G.: QA4SM Software User Manual Version 4.0, <https://qa4sm.eu/api/user-manual>, 2026.
- Bartalis, Z., Wagner, W., Naeimi, V., Hasenauer, S., Scipal, K., Bonekamp, H., Figa, J., and Anderson, C.: Initial soil moisture retrievals from the METOP-A Advanced Scatterometer (ASCAT), *Geophysical Research Letters*, 34, <https://doi.org/10.1029/2007GL031088>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2007GL031088>, 2007.
- 465 Bauer-Marschallinger, B., Dorigo, W. A., Wagner, W., and Dijk, A. I. J. M. v.: How Oceanic Oscillation Drives Soil Moisture Variations over Mainland Australia: An Analysis of 32 Years of Satellite Observations, *Journal of Climate*, 26, 10159–10173, <https://doi.org/10.1175/JCLI-D-13-00149.1>, 2013.
- Bell, J. E., Palecki, M. A., Baker, C. B., Collins, W. G., Lawrimore, J. H., Leeper, R. D., Hall, M. E., Kochendorfer, J., Meyers, T. P., Wilson, T., and Diamond, H. J.: U.S. Climate Reference Network Soil Moisture and Temperature Observations, *Journal of Hydrometeorology*, 14, 977–988, <https://doi.org/10.1175/JHM-D-12-0146.1>, 2013.
- 470 Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., and Hasenauer, S.: Improving runoff prediction through the assimilation of the ASCAT soil moisture product, *Hydrology and Earth System Sciences*, 14, 1881–1893, <https://doi.org/10.5194/hess-14-1881-2010>, 2010.
- 475 de Rosnay, P., Browne, P., de Boissésion, E., Fairbairn, D., Hirahara, Y., Ochi, K., Schepers, D., Weston, P., Zuo, H., Alonso-Balmaseda, M., Balsamo, G., Bonavita, M., Borman, N., Brown, A., Chrust, M., Dahoui, M., Chiara, G., English, S., Geer, A., Healy, S., Hersbach, H., Laloyaux, P., Magnusson, L., Massart, S., McNally, A., Pappenberger, F., and Rabier, F.: Coupled data assimilation at ECMWF: current status, challenges and future developments, *Quarterly Journal of the Royal Meteorological Society*, 148, 2672–2702, <https://doi.org/10.1002/qj.4330>, _eprint: <https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.4330>, 2022.
- 480 Dorigo, W., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A., Zamojski, D., Cordes, C., Wagner, W., and Drusch, M.: Global Automated Quality Control of In Situ Soil Moisture Data from the International Soil Moisture Network, *Vadose Zone Journal*, 12, vzj2012.0097, <https://doi.org/10.2136/vzj2012.0097>, 2013.
- Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P. D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W., Liu, Y. Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C., van der Schalie, R., Seneviratne, S. I., Smolander, T., and Lecomte, P.: ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions, *Remote Sensing of Environment*, 203, 185–215, <https://doi.org/10.1016/j.rse.2017.07.001>, 2017.
- 485 ECMWF: IFS Documentation CY45R1 - Part II : Data assimilation, <https://doi.org/http://dx.doi.org/10.21957/a3ri44ig4>, 2018.
- Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T. J., Johnson, J., Kimball, J., Piepmeier, J. R., Koster, R. D., Martin, N., McDonald, K. C., Moghaddam, M., Moran, S., Reichle, R., Shi, J. C., Spencer, M. W., Thurman, S. W., Tsang, L., and Van Zyl, J.: The Soil Moisture Active Passive (SMAP) Mission, *Proceedings of the IEEE*, 98, 704–716, <https://doi.org/10.1109/JPROC.2010.2043918>, 2010.
- 490 Fischer, E. M., Seneviratne, S. I., Lüthi, D., and Schär, C.: Contribution of land-atmosphere coupling to recent European summer heat waves, *Geophysical Research Letters*, 34, <https://doi.org/10.1029/2006GL029068>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2006GL029068>, 2007.
- Frantzen, P.: QA4SM validation of ASCAT soil moisture using variations of the backscatter-incidence angle relation., <https://doi.org/10.5281/zenodo.22113299>, 2026.



- Frantzen, P., Steele-Dunne, S. C., Quaife, T., Vreugdenhil, M., Hahn, S., and Wagner, W.: Improved Estimation of Temporal Dynamics in the ASCAT Backscatter-Incidence Angle Relation Using Regularization, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 18, 13 457–13 471, <https://doi.org/10.1109/JSTARS.2025.3572306>, 2025.
- Greimeister-Pfeil, I., Wagner, W., Quast, R., Hahn, S., Steele-Dunne, S., and Vreugdenhil, M.: Analysis of short-term soil moisture effects on the ASCAT backscatter-incidence angle dependence, *Science of Remote Sensing*, 5, 100 053, <https://doi.org/10.1016/j.srs.2022.100053>, 2022.
- Gruber, A., De Lannoy, G., Albergel, C., Al-Yaari, A., Brocca, L., Calvet, J. C., Colliander, A., Cosh, M., Crow, W., Dorigo, W., Draper, C., Hirschi, M., Kerr, Y., Konings, A., Lahoz, W., McColl, K., Montzka, C., Muñoz-Sabater, J., Peng, J., Reichle, R., Richaume, P., Rüdiger, C., Scanlon, T., van der Schalie, R., Wigneron, J. P., and Wagner, W.: Validation practices for satellite soil moisture retrievals: What are (the) errors?, *Remote Sensing of Environment*, 244, 111 806, <https://doi.org/10.1016/j.rse.2020.111806>, 2020.
- H SAF: Product User Manual (PUM) Metop ASCAT Surface Soil Moisture Climate Data Record v7 12.5 km sampling (H119) and Extension (H120), EUMETSAT SAF on Support to Operational Hydrology and Water Management, v0.3 edn., 2022.
- Hahn, S., Reimer, C., Vreugdenhil, M., Melzer, T., and Wagner, W.: Dynamic Characterization of the Incidence Angle Dependence of Backscatter Using Metop ASCAT, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10, 2348–2359, <https://doi.org/10.1109/JSTARS.2016.2628523>, conference Name: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2017.
- Hahn, S., Wagner, W., Steele-Dunne, S. C., Vreugdenhil, M., and Melzer, T.: Improving ASCAT Soil Moisture Retrievals With an Enhanced Spatially Variable Vegetation Parameterization, *IEEE Transactions on Geoscience and Remote Sensing*, 59, 8241 – 8256, <https://doi.org/10.1109/TGRS.2020.3041340>, 2020.
- Hahn, S., Melzer, T., and Wagner, W.: Next-generation Metop ASCAT Surface Soil Moisture datasets, *Earth System Science Data Discussions*, pp. 1–43, <https://doi.org/10.5194/essd-2025-746>, 2026.
- HSAF: SMOS NRT Soil Moisture product, <https://user.eumetsat.int/catalogue/EO:EUM:DAT:SMOS:SM-NRT-NN/overview>.
- Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A., Cabot, F., Gruhier, C., Juglea, S. E., Leroux, D., Mialon, A., and Delwart, S.: The SMOS Soil Moisture Retrieval Algorithm, *IEEE Transactions on Geoscience and Remote Sensing*, 50, 1384–1403, <https://doi.org/10.1109/TGRS.2012.2184548>, 2012.
- Mason, P. J., Zillman, J. W., Simmons, A., Lindstrom, E. J., Harrison, D. E., Dolman, H., Bojinski, S., Fischer, A., Latham, J., Rasmussen, J., Arkin, P., Armstrong, R., Braathen, G., Brouchkov, A., DeWayne Cecil, L., Digiacomio, P. M., Drinkwater, M. R., Goldammer, J. G., Goldberg, M. D., Goodison, B., Haeberli, W., Hilsenrath, E., Jones, P., Kajfez-Bogataj, L., Kent, E. C., Kundzewicz, Z. W., Lafeuille, J., Levelt, P. F., Looser, U., Ogallo, L. A., Ondras, M., Peterson, T. C., Pinty, B., Quegan, S., Saunders, R., Schmetz, J., Song, L., Stammer, D., Steffen, K., Tanner, M., Tansey, K., Trenberth, K. E., Verstraete, M. M., Visbeck, M., Vuglinsky, V., Westermeyer, W., and Wooster, M.: Implementation Plan for the Global Observing System for Climate in Support of the UNFCCC (2010 Update), <https://eprints.soton.ac.uk/162953/>, num Pages: 180, 2010.
- Massart, S., Vreugdenhil, M., Borguete, R. R., Villegas-Lituma, C., Sanjeevamurthy, P. M., Hahn, S., and Wagner, W.: High-resolution drought monitoring with Sentinel-1 and ASCAT: A case-study over Mozambique, *Agricultural Water Management*, 318, 109 638, <https://doi.org/10.1016/j.agwat.2025.109638>, 2025.
- Melzer, T.: Vegetation Modelling in WARP 6.0, in: *Proceedings of the EUMETSAT Meteorological Satellite Conference*, pp. 16–20, Vienna, Austria, 2013.



- 535 Miralles, D. G., Vilà-Guerau de Arellano, J., McVicar, T. R., and Mahecha, M. D.: Vegetation–climate feedbacks across scales, *Annals of the New York Academy of Sciences*, 1544, 27–41, <https://doi.org/10.1111/nyas.15286>, *_eprint: https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/nyas.15286*, 2025.
- Naeimi, V., Scipal, K., Bartalis, Z., Hasenauer, S., and Wagner, W.: An Improved Soil Moisture Retrieval Algorithm for ERS and METOP Scatterometer Observations, *IEEE Transactions on Geoscience and Remote Sensing*, 47, 1999–2013, <https://doi.org/10.1109/TGRS.2008.2011617>, conference Name: IEEE Transactions on Geoscience and Remote Sensing, 2009.
- 540 O'Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., and Chaubell, J.: Near Real-time SMAP L2 Radiometer Half-Orbit 36 km EASE-Grid Soil Moisture, <https://doi.org/10.5067/NCTT8THPWRTL>.
- Peel, M. C., Finlayson, B. L., and McMahon, T. A.: Updated world map of the Köppen-Geiger climate classification, *Hydrology and Earth System Sciences*, 11, 1633–1644, <https://doi.org/10.5194/hess-11-1633-2007>, 2007.
- 545 Pfeil, I., Vreugdenhil, M., Hahn, S., Wagner, W., Strauss, P., and Blöschl, G.: Improving the Seasonal Representation of ASCAT Soil Moisture and Vegetation Dynamics in a Temperate Climate, *Remote Sensing*, 10, 1788, <https://doi.org/10.3390/rs10111788>, number: 11, 2018.
- Steele-Dunne, S. C., Hahn, S., Wagner, W., and Vreugdenhil, M.: Towards Including Dynamic Vegetation Parameters in the EUMETSAT H SAF ASCAT Soil Moisture Products, *Remote Sensing*, 13, 1463, <https://doi.org/10.3390/rs13081463>, number: 8, 2021.
- team, E. L. C. C. p. and Defourny, P.: ESA Land Cover Climate Change Initiative (Land_Cover_cci): Global Land Cover Maps, Version 1.6.1, <https://catalogue.ceda.ac.uk/uuid/4761751d7c844e228ec2f5fe11b2e3b0/>, 2016.
- 550 Wagner, W., Lemoine, G., Borgeaud, M., and Rott, H.: A study of vegetation cover effects on ERS scatterometer data, *IEEE Transactions on Geoscience and Remote Sensing*, 37, 938–948, <https://doi.org/10.1109/36.752212>, conference Name: IEEE Transactions on Geoscience and Remote Sensing, 1999a.
- Wagner, W., Lemoine, G., and Rott, H.: A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, *Remote Sensing of Environment*, 70, 191–207, [https://doi.org/10.1016/S0034-4257\(99\)00036-X](https://doi.org/10.1016/S0034-4257(99)00036-X), 1999b.
- 555 Wagner, W., Lindorfer, R., Melzer, T., Hahn, S., Bauer-Marschallinger, B., Morrison, K., Calvet, J.-C., Hobbs, S., Quast, R., Greimeister-Pfeil, I., and Vreugdenhil, M.: Widespread occurrence of anomalous C-band backscatter signals in arid environments caused by subsurface scattering, *Remote Sensing of Environment*, 276, 113 025, <https://doi.org/10.1016/j.rse.2022.113025>, 2022.