Scientific Advances on the Use of ASCAT Soil Moisture Observations for Rainfall and Drought Monitoring



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https://www.tuwien.at/mg/geo

My Previous Webinars

EO AFRICA

Date	Title
15 Oct 2025	Combining Optical and SAR Data for Mapping Water Bodies and Floods
16 Apr 2025	Using the new H SAF 6.25km ASCAT soil moisture data for drought monitoring
13 Jun 2023	Surface Soil Moisture products at continental scale
14 Feb 2023	Global flood monitoring and Surface Soil Moisture anomalies

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Aim of this Webinar

- Give an update on the **status and use of ASCAT soil moisture** products
  - focus is on rainfall and drought monitoring over Africa
- ASCAT soil moisture data are freely distributed by:

Product	Programme
Surface Soil Moisture (SSM)	EUMETSAT Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF)
Soil Water Index (SWI)	Copernicus Land Monitoring Service (CLMS)
Long-term multi-sensor soil moisture (ACTIVE)	ESA Climate Change Initiative (CCI) & Copernicus Climate Change Service (C3S)

European C-Band Scatterometer Series







ERS Scatterometer

Frequency: 5.3 GHz
Polarisation: VV
Resolution: 50 km
Daily coverage: 40%

Satellites

ERS-1: 1991-2000
ERS-2: 1995-2011

METOP ASCAT

Frequency: 5.255 GHz
Polarisation: VV
Resolution: 25 km
Daily coverage: 82%

Satellites

METOP-A: 2006-2021
METOP-B: 2012 ongoing
METOP-C: 2018 ongoing

METOP-SG SCA

Frequency: 5.355 GHz
Polarisation: VV + VH + HH
Resolution: 12.5 km
Daily coverage: 88%

Satellites

METOP-SG-B1: 2026
METOP-SG-B2: 2032
METOP-SG-B3: 2039

Daily Global Coverage

- With two satellites, one obtains two ASCAT measurements per day for most of the global land surface areas

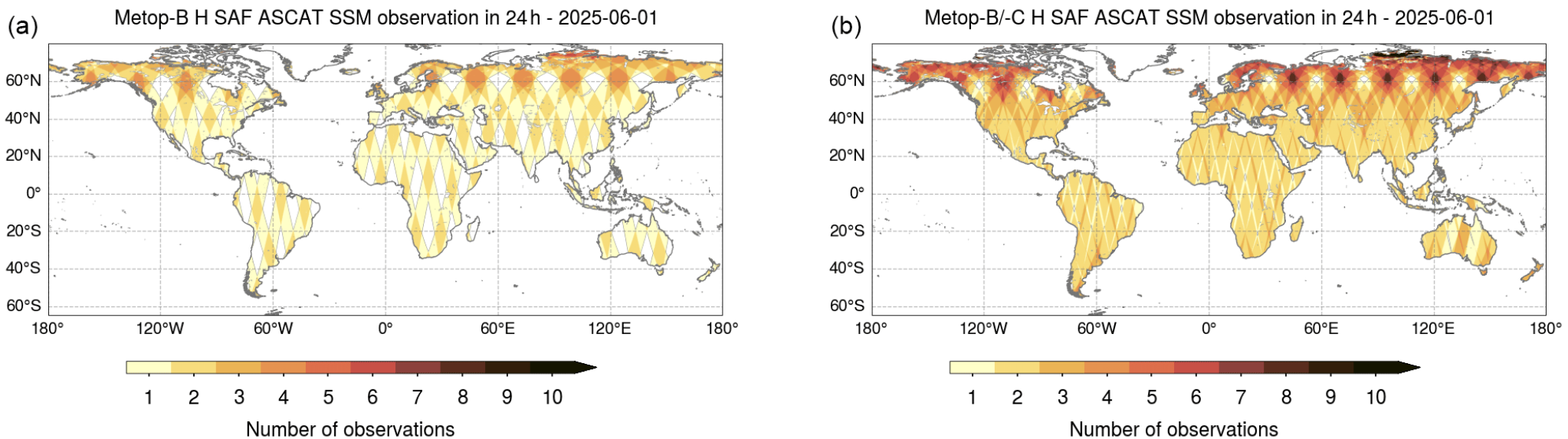
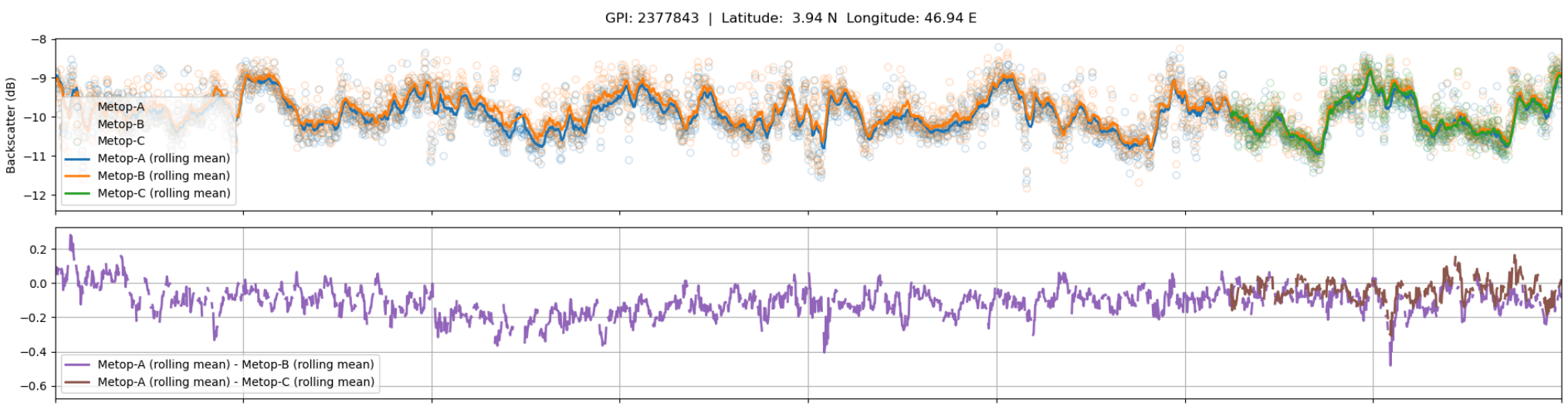


Figure 9 from Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

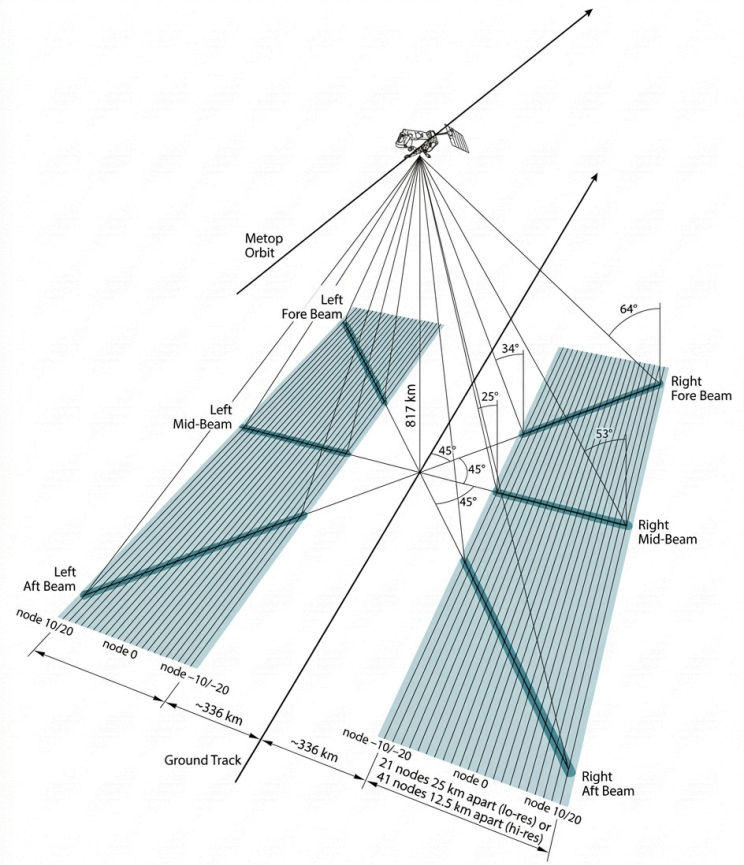
Best-Calibrated Radar Sensor Series

- Backscatter measurements are extremely well calibrated across sensors
  - Active transponders
  - Tropical forests as stable reference targets
  - Vicarious calibration strategies, e.g., by winds community



Intercalibration of ASCAT backscatter from METOP-A/B/C (extracted from H119)

Measurement Principle



- Scatterometers are side-looking radars that measure the backscattering coefficient from different viewing directions

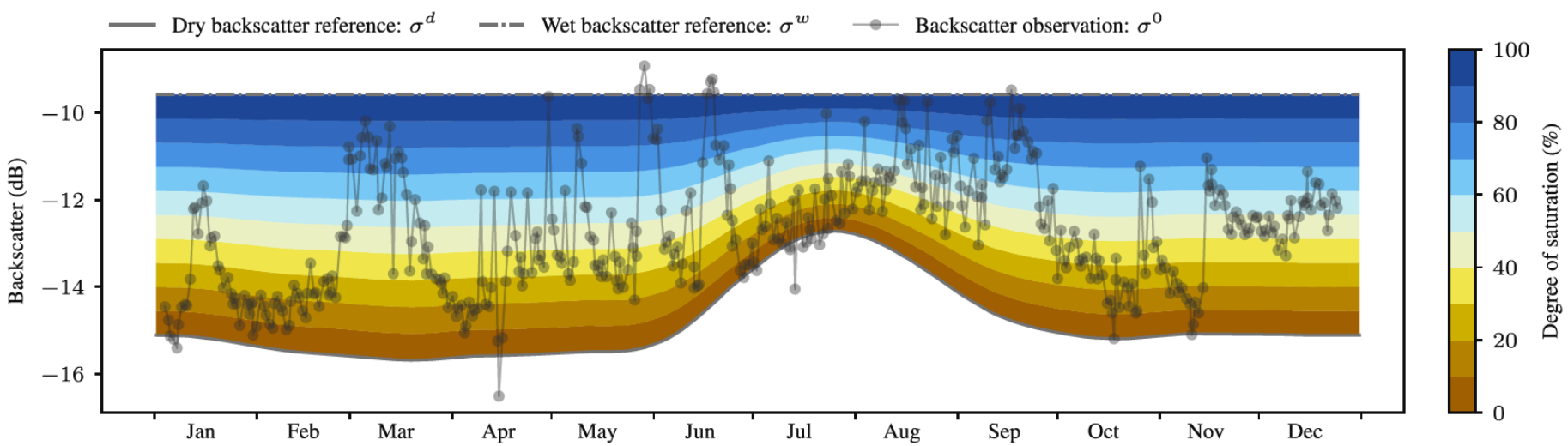
- Advanced Scatterometer (ASCAT)
  - 6 antennas to cover two 550 km-wide swaths
    - Three quasi-instantaneous measurements with the fore-, mid-, and aft-beams
    - Incidence angle range from 25° to 65°

Figa-Saldaña et al. (2002) The advanced scatterometer (ASCAT) on the meteorological operational (MetOp) platform: A follow on for European wind scatterometers, Canadian Journal of Remote Sensing, 28(3), 404–412.

Soil Moisture Retrieval

Soil moisture is retrieved using a **change detection model** that accounts for seasonal vegetation phenology:

$$m_s(t) = \frac{\sigma^0(t) - \sigma^0_{\text{dry}}(t)}{\sigma^0_{\text{wet}}(t) - \sigma^0_{\text{dry}}(t)}$$



Hahn et al. (2021) Improving ASCAT soil moisture retrievals with an enhanced spatially-variable vegetation parameterisation, IEEE Transactions on Geoscience and Remote Sensing, 10, 8241-8256.

Soil Moisture Retrieval Workflow

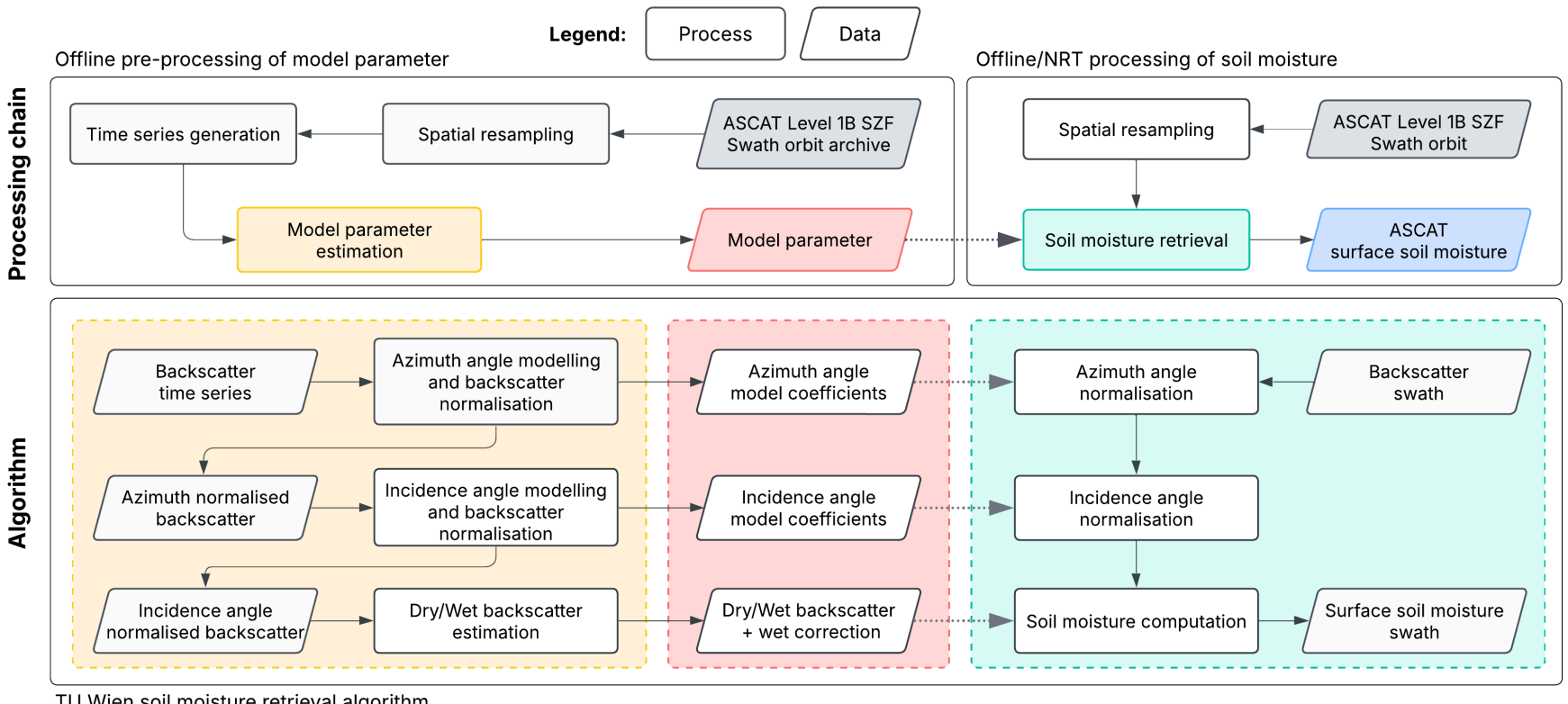
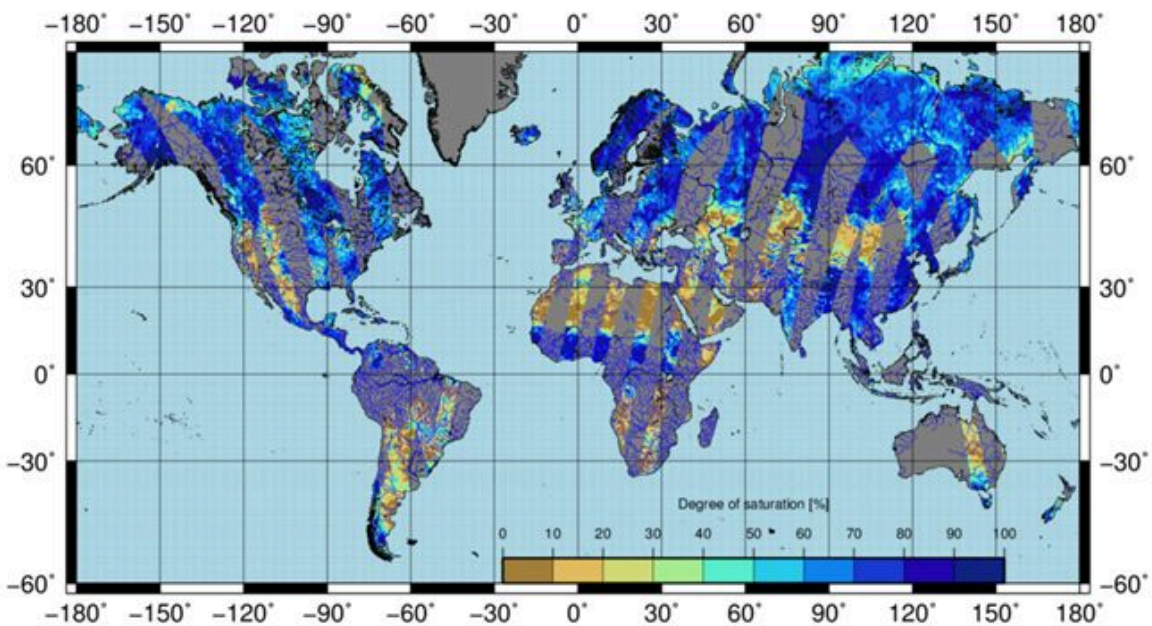


Figure 1 from Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

ASCAT Surface Soil Moisture Service

- Near-real-time (NRT) services started in 2008



- „as close as possible to the satellite measurements“
- within 3 hours after sensing
- Surface soil moisture (SSM)
  - degree of saturation (%)
- Spatial sampling (resolution)
  - 6.25 km (15 km)
  - 12.5 km (25 km)
- Masks and quality flags

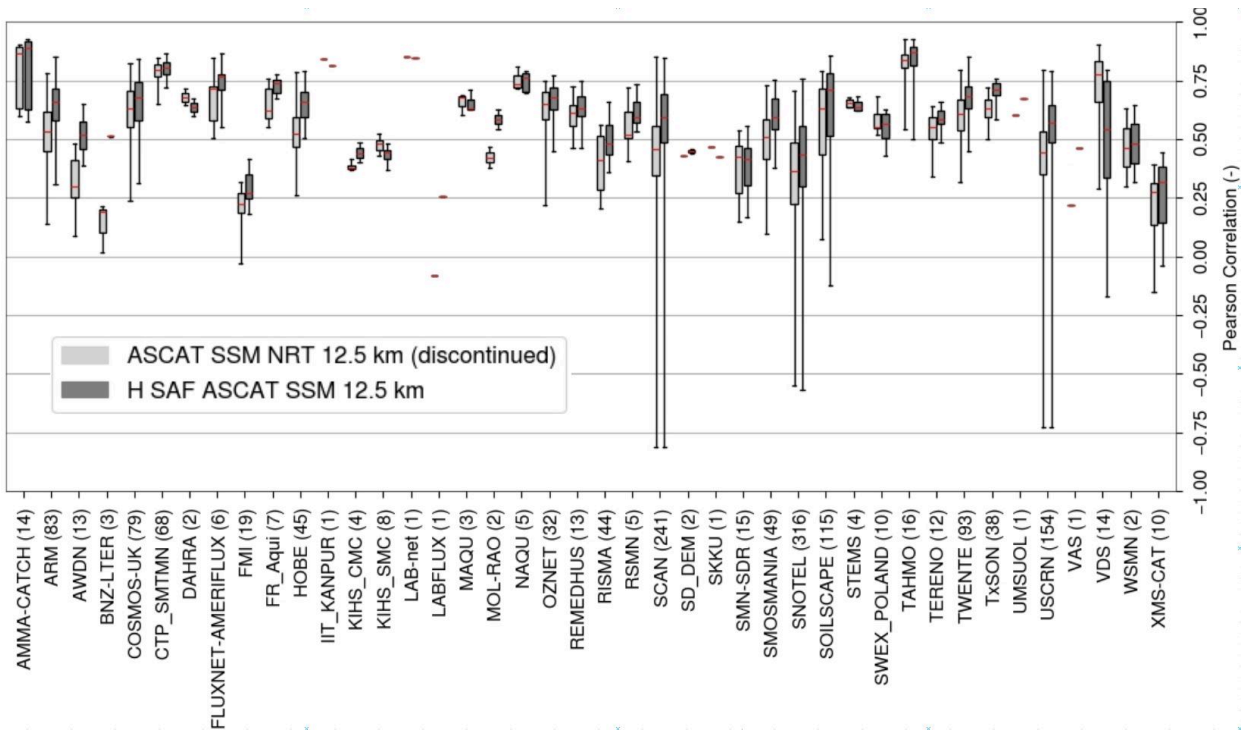
Bartalis et al. (2007) Initial soil moisture retrievals from the METOP-A Advanced Scatterometer (ASCAT), Geophysical Research Letters, 34(20), L20401.

Improvements of July 2025 Release

Latest Implementation	Previous Implementation	Improvement/Physical Impact
Model parameters estimated over 2007–2024 using Metop-A, -B and -C ASCAT backscatter	Model parameters calibrated over 2007–2014 using Metop-A only	More representative parameter calibration across time
Spatial resampling based on ASCAT Level 1B full-resolution (SZF) backscatter with filtering of echoes over open water and urban areas	Spatial resampling based on ASCAT Level 1B SZR (Sigma Zero Research) product	Fine-grained control over spatial resampling and echo selection, development of ASCAT SSM 6.25 km
Spatially-variable vegetation correction parameters (Hahn et al., 2021)	Globally uniform vegetation correction parameters	More accurate vegetation correction across diverse land cover
Moving-window approach for dry and wet backscatter reference computation	Dry and wet backscatter reference derived from the full time series	Prevents long-term backscatter trends from leaking into soil moisture retrievals
Dry/wet backscatter bounds estimated via percentiles; scaling range narrowed to 5 %–95%	Scaling range 0 %–100% with bounds from lower/upper 10 % of observations	More robust and stable estimation of backscatter bounds
Monthly subsurface scattering probability flag included (Lindorfer et al., 2023)	No subsurface scattering information available	Enables identification and filtering of subsurface scattering effects

Table 3 from Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

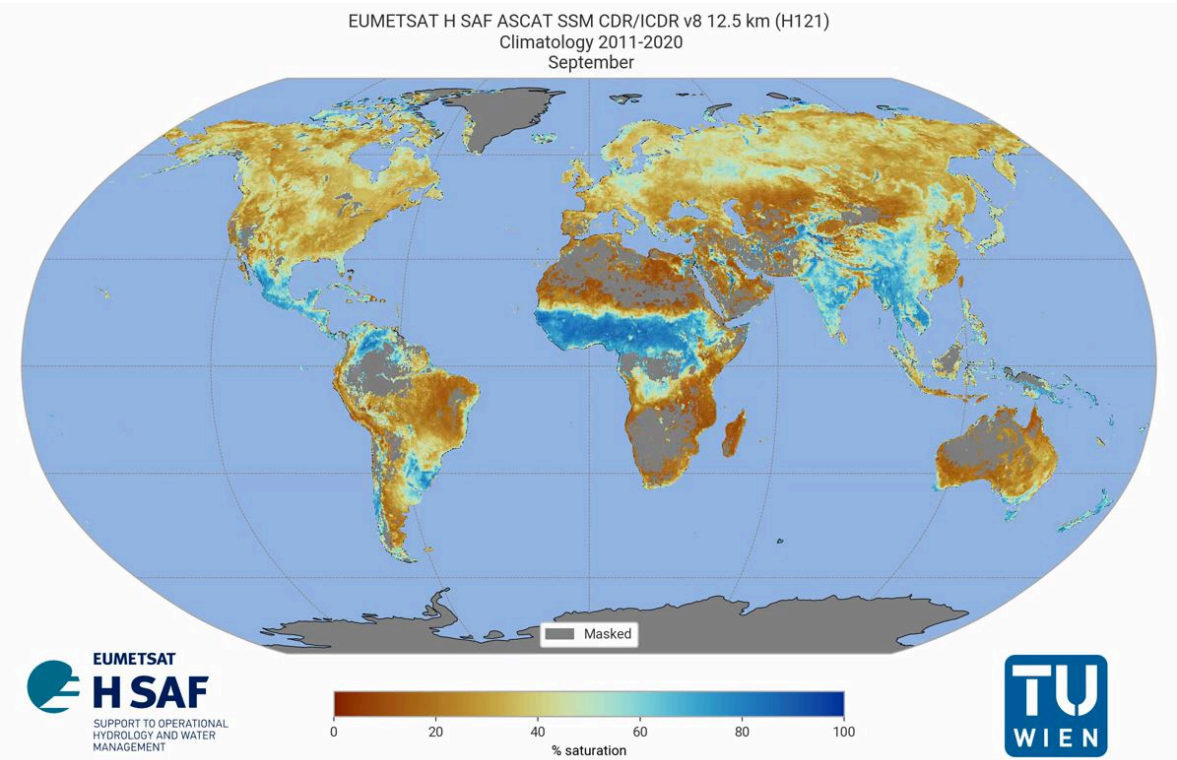
Correlation against in situ Data



- ASCAT surface soil moisture (SSM) validated against in situ measurements from the **International Soil Moisture Network** (ismn.earth)
- New dataset version correlates better with in situ data than the previous one in most regions, but not everywhere

Figure 15 (modified) from Hahn et al. (2026): Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

ASCAT Soil Moisture Animation

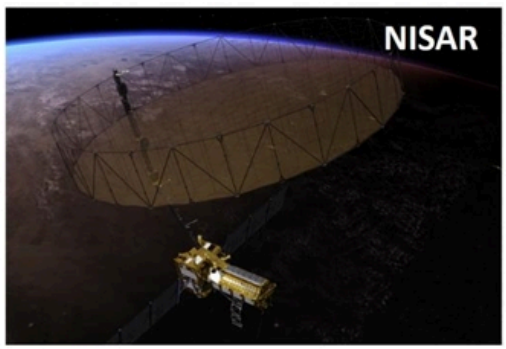


Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

Putting ASCAT Soil Moisture Data in Context

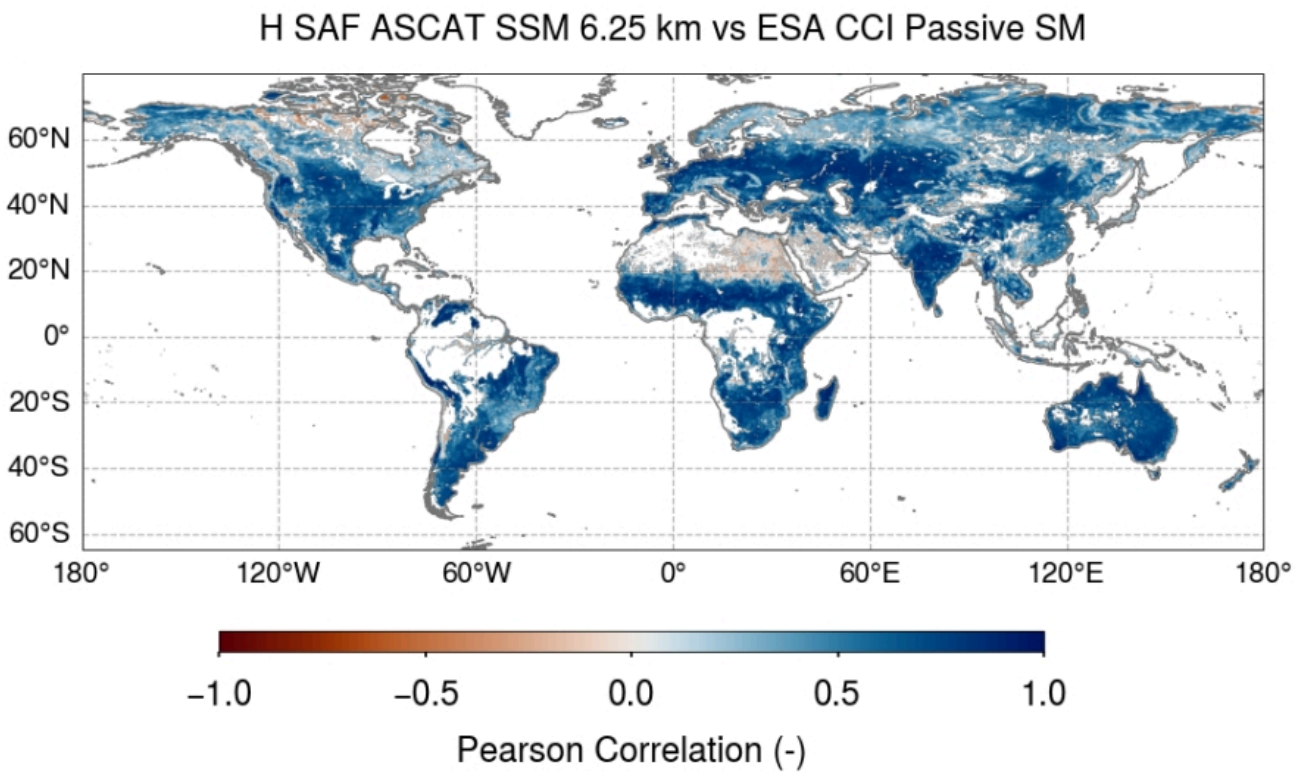
ASCAT is one of many Soil Moisture Products

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	Radiometers	Active/Passive	Synthetic Aperture Radar
L-Band			
C-Band			
	10-50 km Resolution		0.1-1 km Resolution

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Correlation between ASCAT and CCI Passive



- ESA CCI Passive soil moisture product
  - Merges multiple passive microwave soil moisture products
  - Merging weights depend on data quality
  - L-band sensors (SMAP, SMOS) receive high weights

Figure 11a from Hahn et al. (2026): Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393-4423.

Spatial Resolution and Sampling

- According to the **Nyquist–Shannon sampling theorem**, spatial sampling (=digital representation) should be half the spatial resolution (=physical footprint)
- Sampling is always precisely known; resolution is only an estimate

Dataset name	Spatial sampling	Spatial resolution	Availability	Soil moisture unit
H SAF ASCAT SSM NRT 6.25 km (H122)	6.25 km	15 km	June 2025–present	% saturation
H SAF ASCAT SSM CDR 6.25 km (H129)	6.25 km	15 km	Jan 2007–Dec 2024	% saturation
H SAF ASCAT SSM ICDR v1 6.25 km (H130)	6.25 km	15 km	Jan 2025–present	% saturation
H SAF ASCAT SSM NRT 12.5 km (H29)	12.5 km	25 km	June 2025–present	% saturation
H SAF ASCAT SSM CDR v8 12.5 km (H121)	12.5 km	25 km	Jan 2007–Dec 2024	% saturation
H SAF ASCAT SSM ICDR v8 12.5 km (H139)	12.5 km	25 km	Jan 2025–present	% saturation
SMOS L2 SM V700	15 km	35–50 km	Jan 2010–present	$m^3\ m^{-3}$
SMOS NRT L2	15 km	35–50 km	Jan 2015–present	$m^3\ m^{-3}$
SMAP L2 SM V9	36 km	36 km	Mar 2015–present	$m^3\ m^{-3}$
SMAP Enhanced L2 SM V6	9 km	36 km	Mar 2015–present	$m^3\ m^{-3}$
LPRM AMSR-E	25 km	44–70 km	Jul 2002–Oct 2011	$m^3\ m^{-3}$

Table 2 from Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

Degree of Saturation vs Volumetric Soil Moisture

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- Soil moisture can be expressed in several different physical units
  - The absolute-level estimate depends on the quality of available soil property data

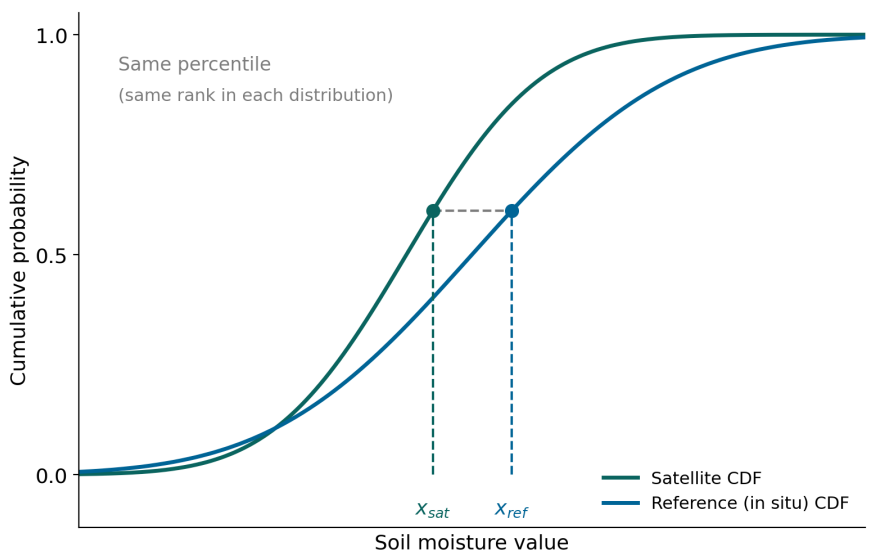
- **Volumetric soil moisture** m_v — volume of water per unit volume of soil
  - Units: $m^3 m^{-3}$ (often given as %)
  - Ranges from 0 up to the soil's porosity (typically 0.4–0.6 $m^3 m^{-3}$)
- **Degree of saturation** m_s — how full the pore space is
  - Units: % (0–100%)
  - $m_s = 100\%$ means all pores are water-filled (fully saturated)

Conversion: $m_s = \frac{m_v}{\text{Soil porosity}} \times 100\%$

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Matching of Soil Moisture Biases

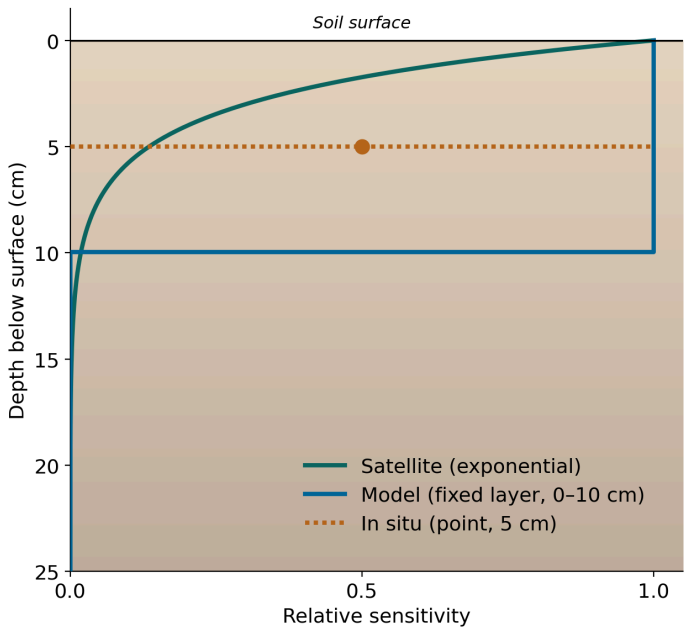
- Absolute soil moisture data are uncertain for many reasons
  - Measurement or model biases
  - Spatial scale and representativity issues
  - Different soil layers
- In practice, some kind of matching of soil moisture data is always needed
  - Linear regression
  - Cumulative distribution function (CDF) matching →
  - Linear rescaling
  - Min/max correction



Brocca, Melone, et al. (2013) Scaling and Filtering Approaches for the Use of Satellite Soil Moisture Observations. In G. P. Petropoulos (Ed.), Remote Sensing of Energy Fluxes and Soil Moisture Content (pp. 411–424). CRC Press, Taylor & Francis Group.

Sensing Depth and Soil Moisture Dynamics

- Different techniques are sensitive to different soil layers
  - Satellites are most sensitive to the surface, with sensitivity decaying exponentially with depth
    - Longer wavelength penetrate deeper
  - In situ sensors typically measure a small soil volume at a fixed depth
  - Models represent a fixed, predefined layer depth



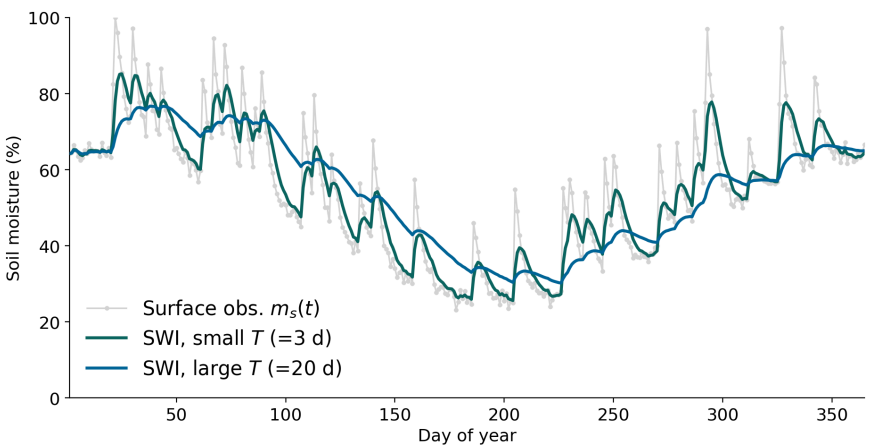
- As a result, each technique captures different soil moisture dynamics
  - Higher dynamics for near-surface shallow layers
  - Lower dynamics in deeper, thicker layers

Matching of Soil Moisture Dynamics

- Soil moisture dynamics can be matched using the **exponential filter**, which is the solution of a simple water balance model relating a profile soil water index $\mathrm{SWI}(t)$ to the surface observations $m_s(t)$

$$\mathrm{SWI}(t) = \frac{1}{T} \int_{-\infty}^{t} m_s(t') \exp\left(-\frac{t-t'}{T}\right) dt'$$

T ... characteristic time length

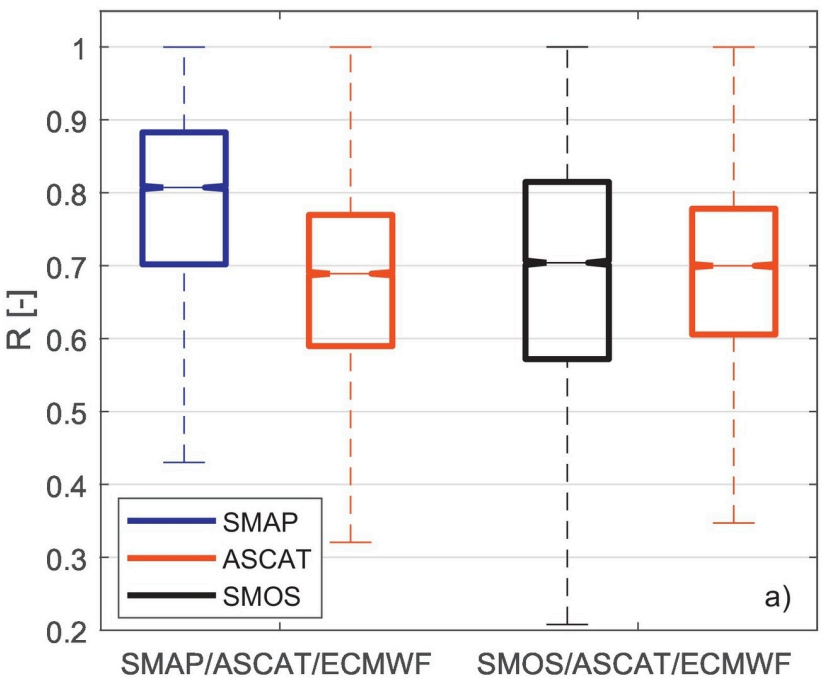


- Besides estimating profile soil moisture (down to depths of about 0.5–1 m), the exponential filter also suppresses short-term observational noise
- ASCAT SWI data are distributed by the Copernicus Land Monitoring Service

Wagner et al. (1999) A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, Remote Sensing of Environment, 70(2), 191–207.

How does ASCAT compare to SMAP?

- SMAP is currently considered the “gold standard” for satellite soil moisture



- ASCAT correlations are generally somewhat lower than for SMAP due to
  - Seasonal soil moisture biases
  - Subsurface scattering
  - Shallower sensing depth

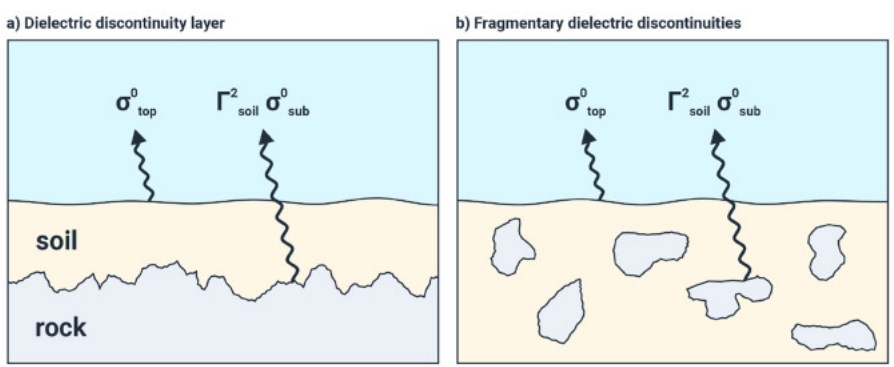
Correlations for SMAP, SMOS, and ASCAT estimated using triple collocation (Chen et al., 2018)

Figure 8a from Chen et al. (2018) Global-scale evaluation of SMAP, SMOS and ASCAT soil moisture products using triple collocation, Remote Sensing of Environment, 214, 1-13.

Subsurface Scattering

- When soils are dry then the radar pulses penetrate deeper
- When there are strong subsurface scatterers then total backscatter is the sum of a surface term plus an attenuated subsurface term:

$$\sigma^0_{\text{soil}} = \alpha e^{\beta m_s} + \psi e^{-\xi m_s}$$



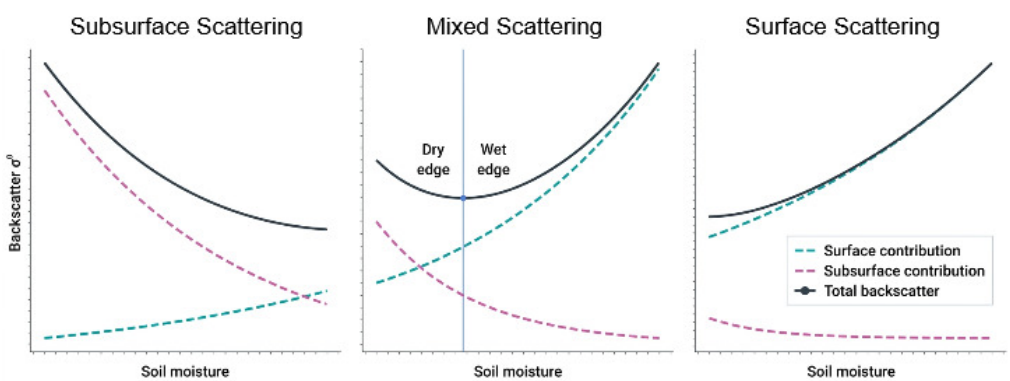
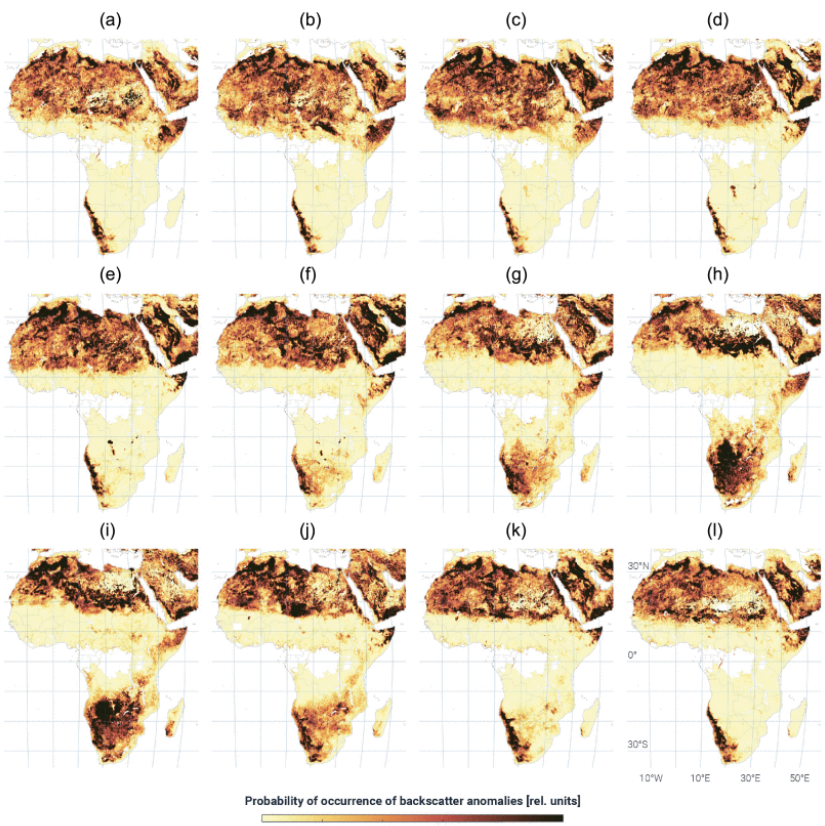


Figure 2 (left) and Figure 3 (right, modified) from Wagner et al. (2022) Widespread occurrence of anomalous C-band backscatter signals in arid environments caused by subsurface scattering. Remote Sensing of Environment, 276, 113025.

Subsurface Scattering over Africa



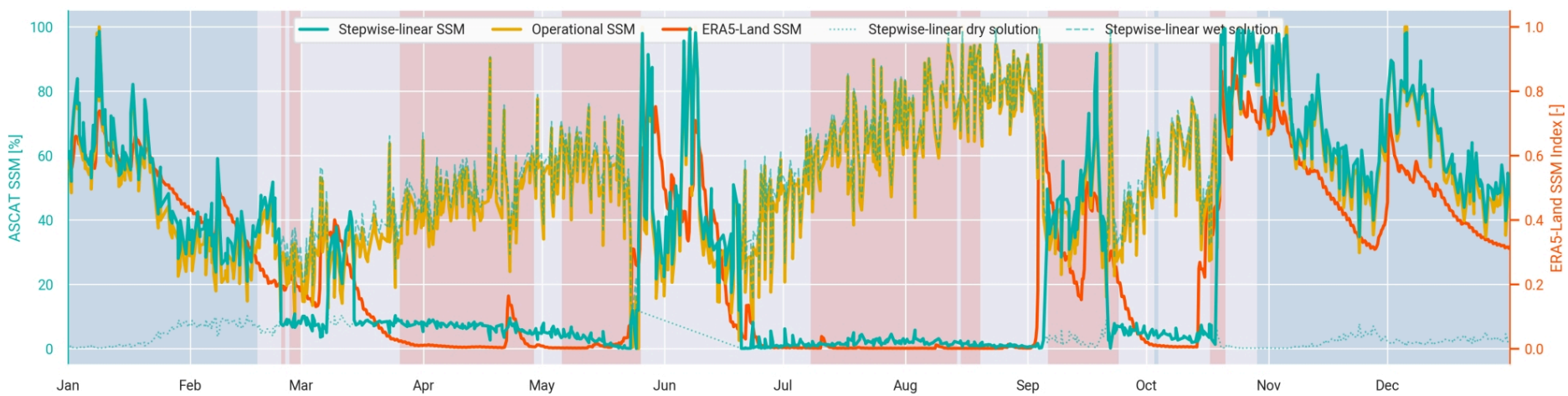
- Subsurface scattering is pronounced for
  - Thin layer of sand on bedrock
  - Distinct soil horizons
  - Soils with large fraction of coarse fragments



Wagner et al. (2024) Global scale mapping of subsurface scattering signals impacting ASCAT soil moisture retrievals, IEEE Trans. Geosci. Remote Sensing, 62, 1–20.

Retrieval Model with Subsurface Scattering

- Also in case of subsurface scattering, backscatter is sensitive to m_s : $\psi e^{-\xi m_s}$
- **Idea:** Compute two candidate soil moisture solutions — a **dry** and a **wet** solution — and select the best estimate at each time step



ASCAT and ERA5-Land soil moisture time series for a grid point near Ciudad Real, Spain. Red shading = periods of active subsurface scattering; blue shading = periods without subsurface-scattering contribution.

Main Strengths of New ASCAT Soil Moisture Data

Long-term stability $\rightarrow$ Drought monitoring

High spatio-temporal coverage $\rightarrow$ Rainfall detection

ASCAT Soil Moisture Time Series

EUMETSAT H SAF
SUPPORT TO OPERATIONAL HYDROLOGY AND WATER MANAGEMENT

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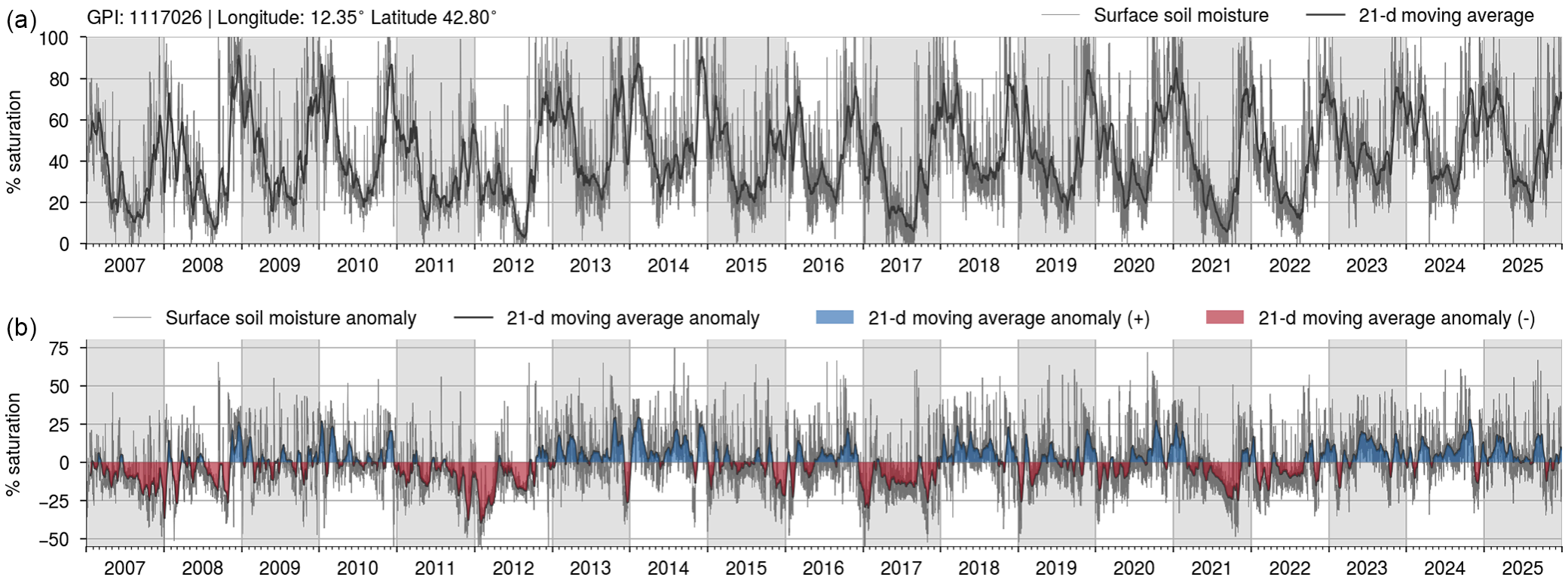


Figure 10 from Hahn et al. (2026) Next-generation METOP ASCAT surface soil moisture datasets from EUMETSAT H SAF, Earth System Science Data, 18(6), 4393–4423.

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Drought Monitoring

Drought Monitoring Studies over Eastern Africa

DrySat

Mozambique

Austrian Development Agency

ROSSHINI

Eastern Africa

FFG

Massart et al. (2025) High-resolution drought monitoring with Sentinel-1 and ASCAT: A case-study over Mozambique. Agricultural Water Management, 318.

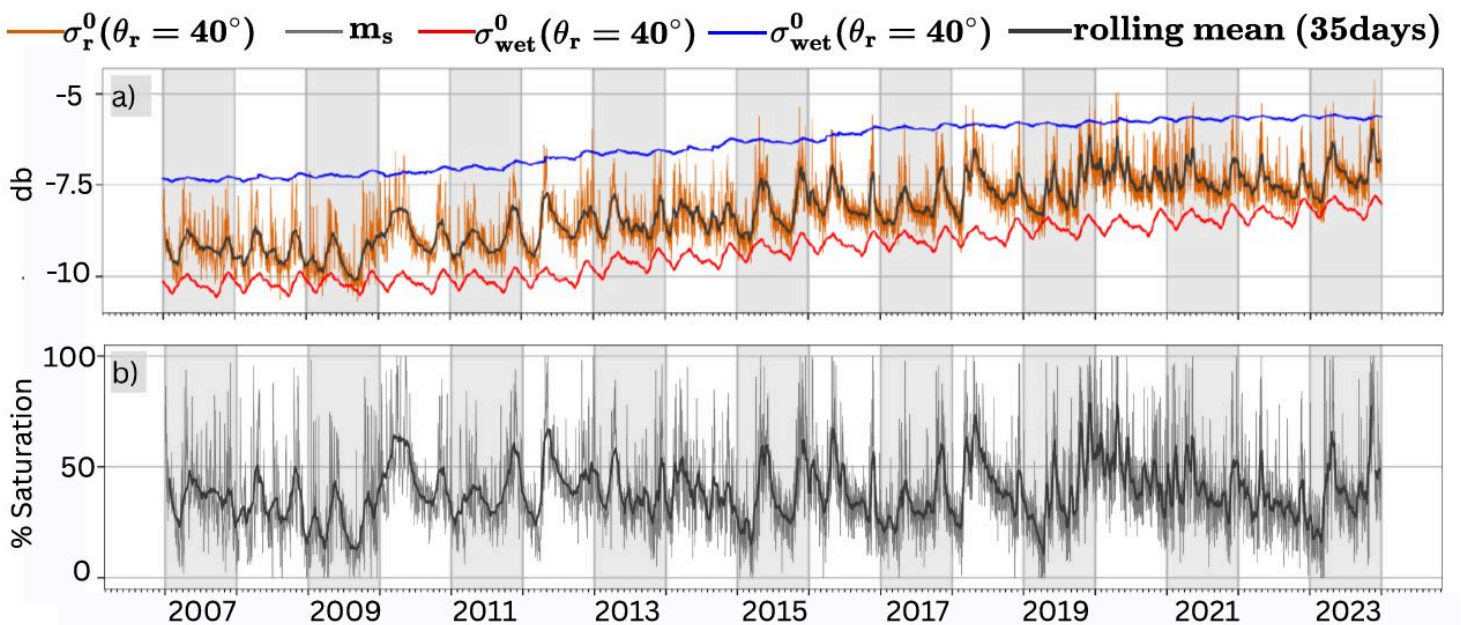
Villegas-Lituma et al. (2026) Agricultural drought monitoring with Sentinel-1 cross-ratio in heterogeneous tropical agriculture: A Mozambique case study. International Journal of Remote Sensing, 1–31.

Muguda Sanjeevamurthy et al. (2026) Analysis of the new 6.25 km ASCAT soil moisture data record for improved anomaly detection over eastern Africa, SSRN, preprint.

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Improved Long-term Anomaly Detection

- Old ASCAT SSM workflow did not account for long-term land cover changes
  - A dynamic parameterisation has solved that issue



Sample grid point in Kenya

Extract from Figure 2 from Muguda Sanjeevamurthy et al. (2026) Analysis of the new 6.25 km ASCAT soil moisture data record for improved anomaly detection over eastern Africa, SSRN, preprint.

Correlation ASCAT vs SMAP and ERA5-Land

Horn of Africa

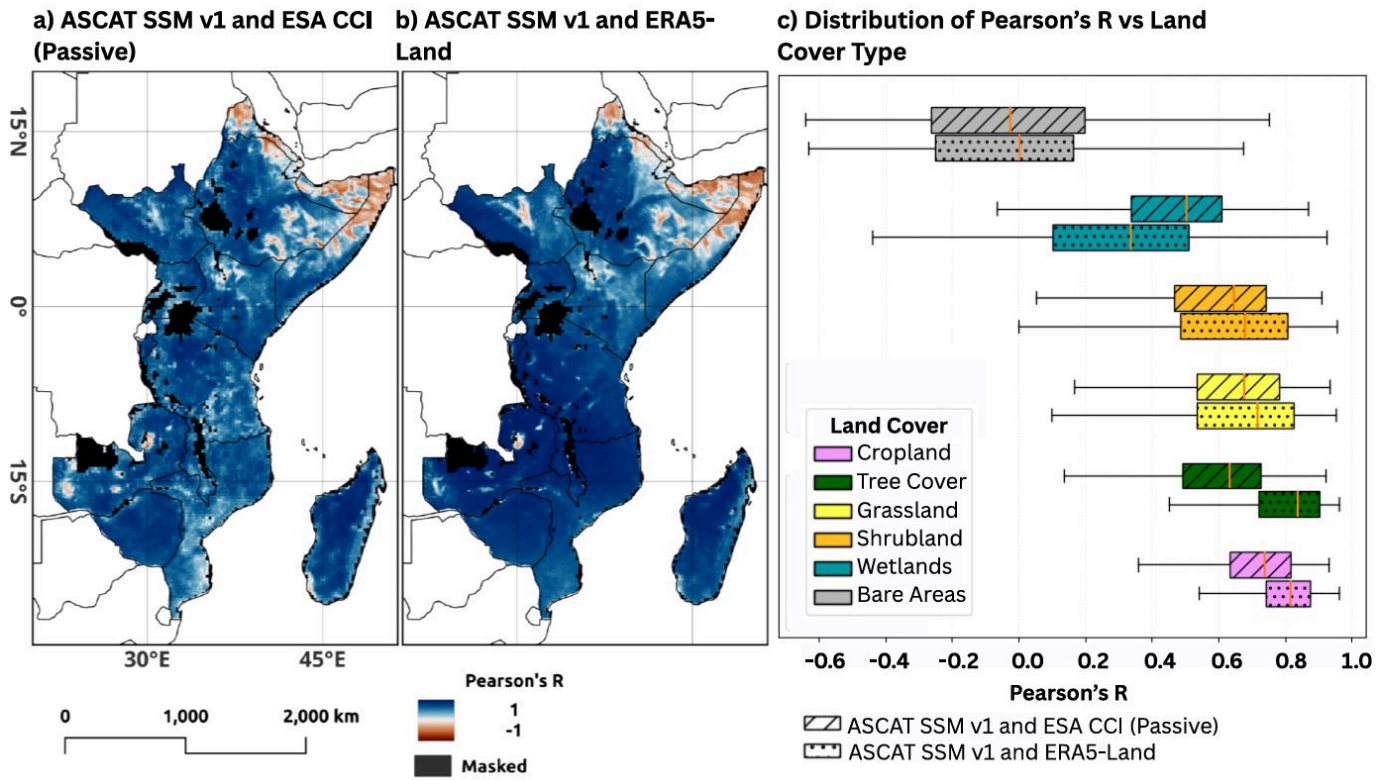
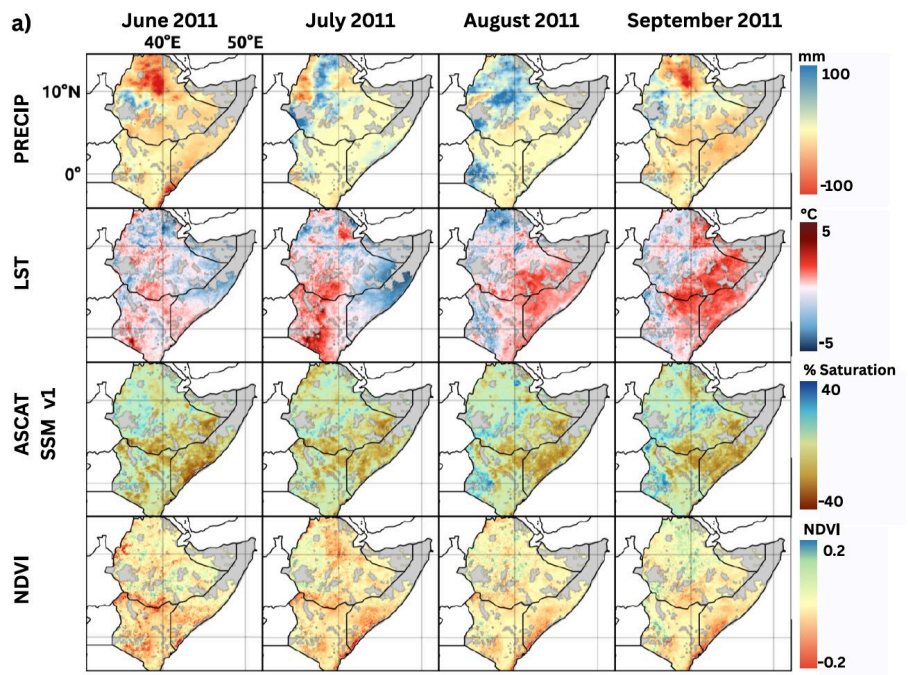


Figure 10 from Muguda Sanjeevamurthy et al. (2026) Analysis of the new 6.25 km ASCAT soil moisture data record for improved anomaly detection over eastern Africa, SSRN, preprint.

Horn of Africa June-September 2011

Monthly anomalies (left) and ASCAT-SSM-based drought indicators (right)



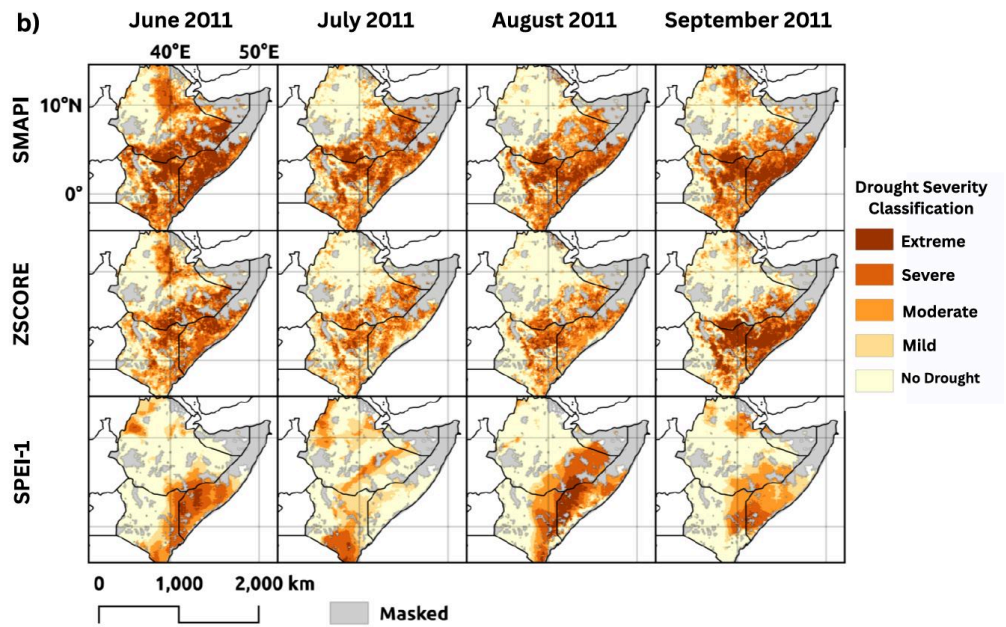


Figure 13 from Muguda Sanjeevamurthy et al. (2026) Analysis of the new 6.25 km ASCAT soil moisture data record for improved anomaly detection over eastern Africa, SSRN, preprint.

Yearly Anomalies over Mozambique 2019-2024

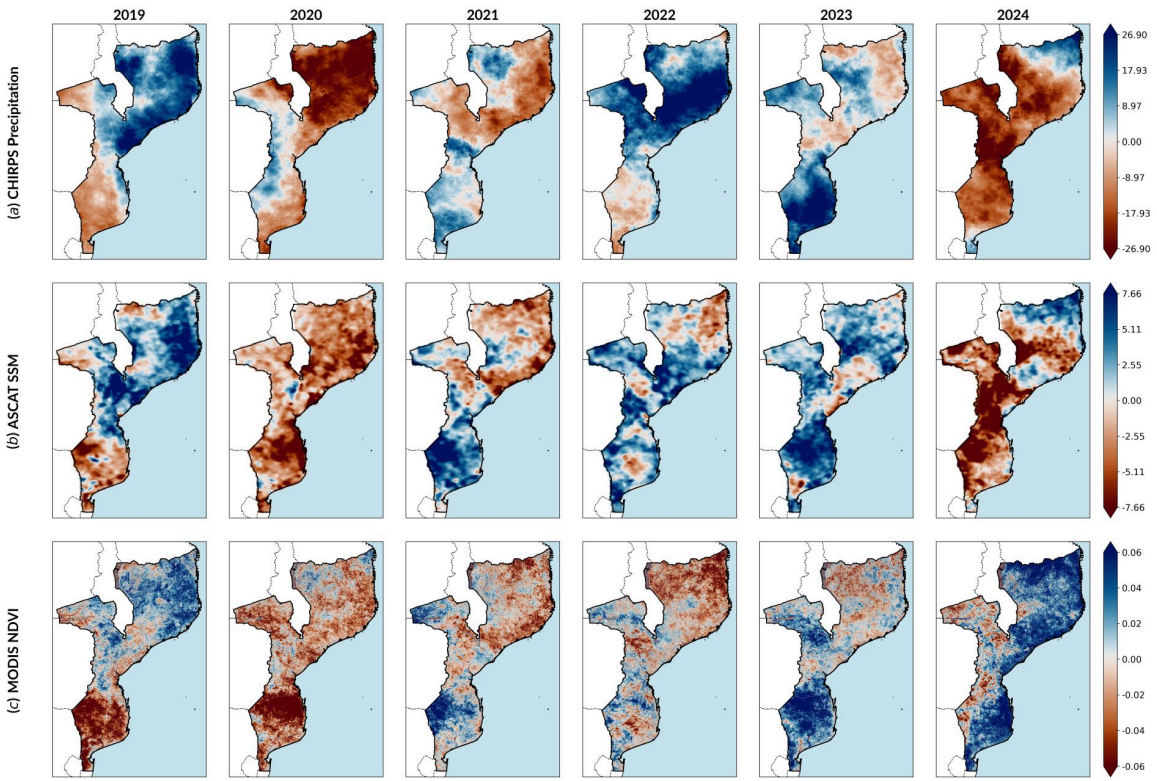
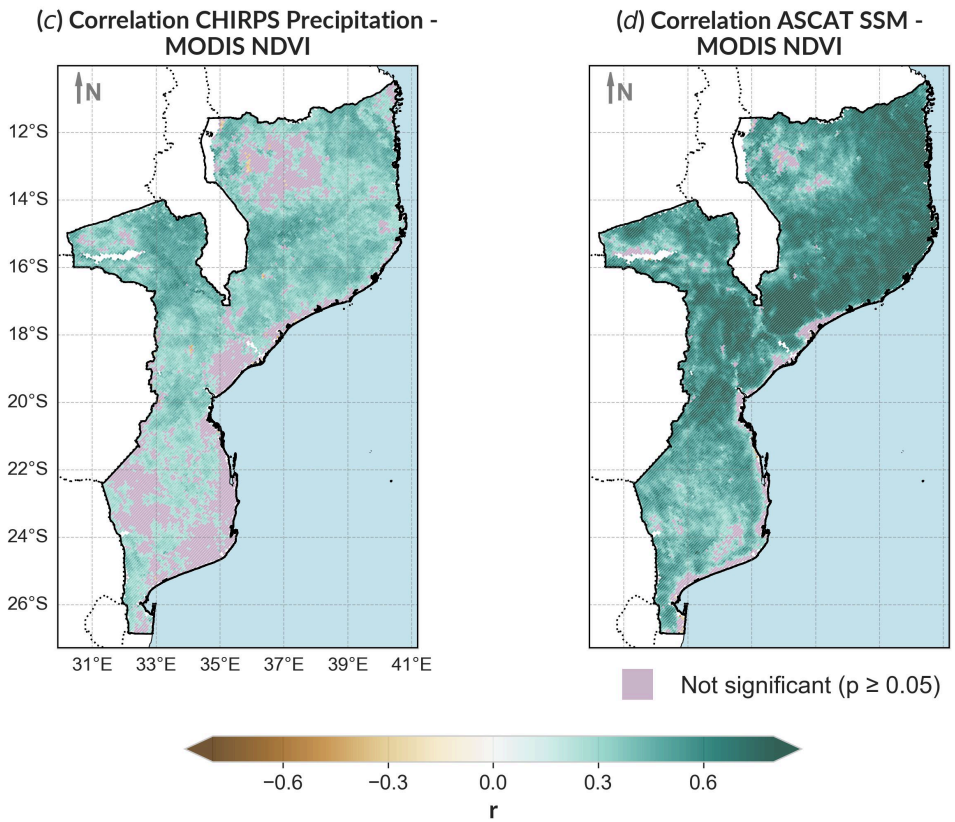


Figure 6 (modified) from Villegas-Lituma et al. (2026) Agricultural drought monitoring with Sentinel-1 cross-ratio in heterogeneous tropical agriculture: A Mozambique case study. International Journal of Remote Sensing, 1–31.

Correlation Rainfall and Soil Moisture vs Vegetation

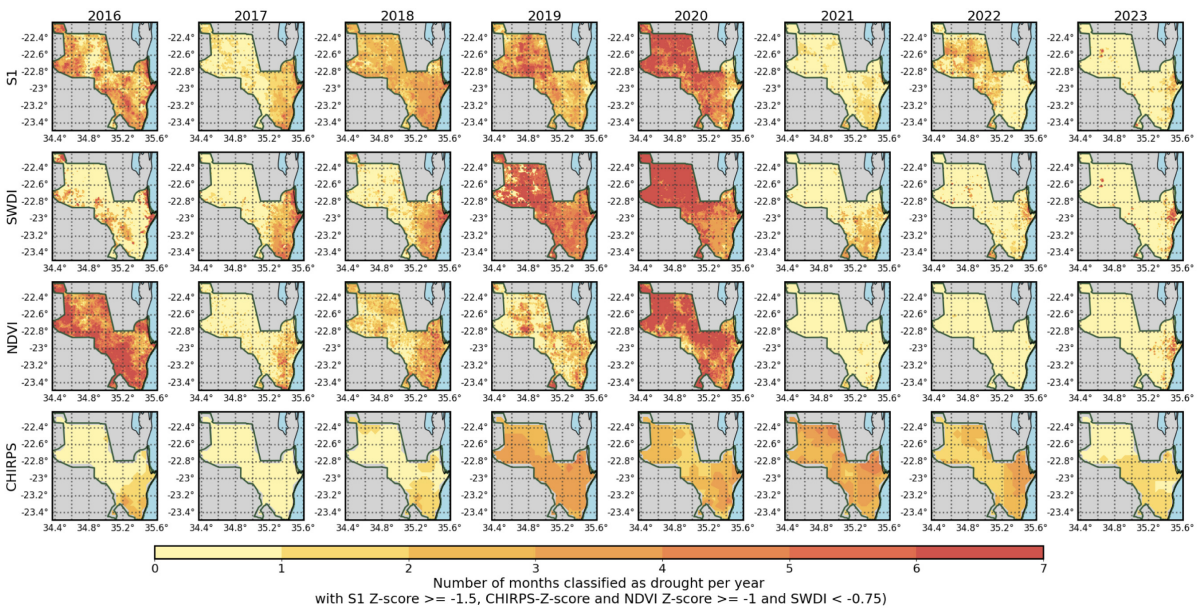


Mozambique

Figure 5ab from Villegas-Lituma et al. (2026) Agricultural drought monitoring with Sentinel-1 cross-ratio in heterogeneous tropical agriculture: A Mozambique case study. International Journal of Remote Sensing, 1–31.

Drought Monitoring with 1 km Sentinel-1 Data

- ASCAT and Sentinel-1 soil moisture data can be combined to monitor drought at much higher spatial resolution (e.g., at the level of districts).

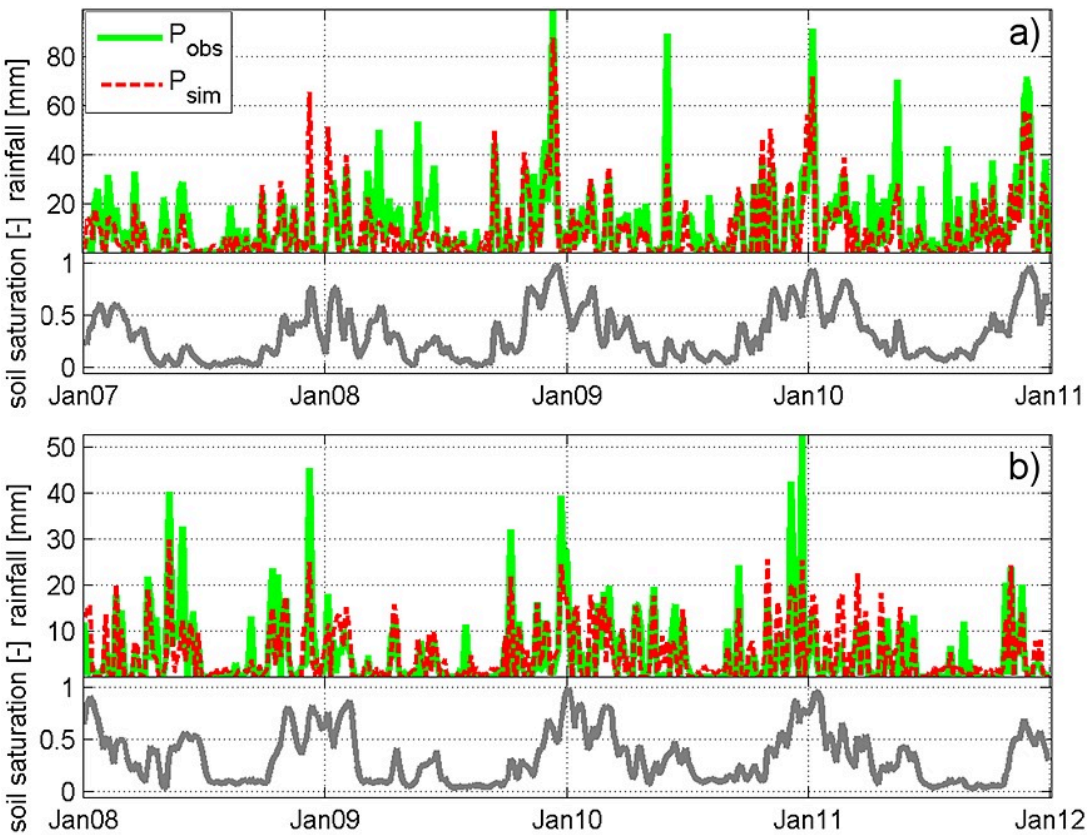


Annual number of months classified as drought based on different drought monitoring approaches in the Massinga district in Mozambique. 1 km Sentinel-1 soil moisture data are used to compute the Z-score (top) and the soil water deficiency index (second row).

Figure 9 from Massart et al. (2025) Agricultural drought monitoring with Sentinel-1 cross-ratio in heterogeneous tropical agriculture: A Mozambique case study. International Journal of Remote Sensing, 1–31.

Rainfall Detection

SM2RAIN - Estimating Rainfall from Soil Moisture



- A bottom-up approach to estimate rainfall from soil moisture
- Inversion of a soil water balance equation:

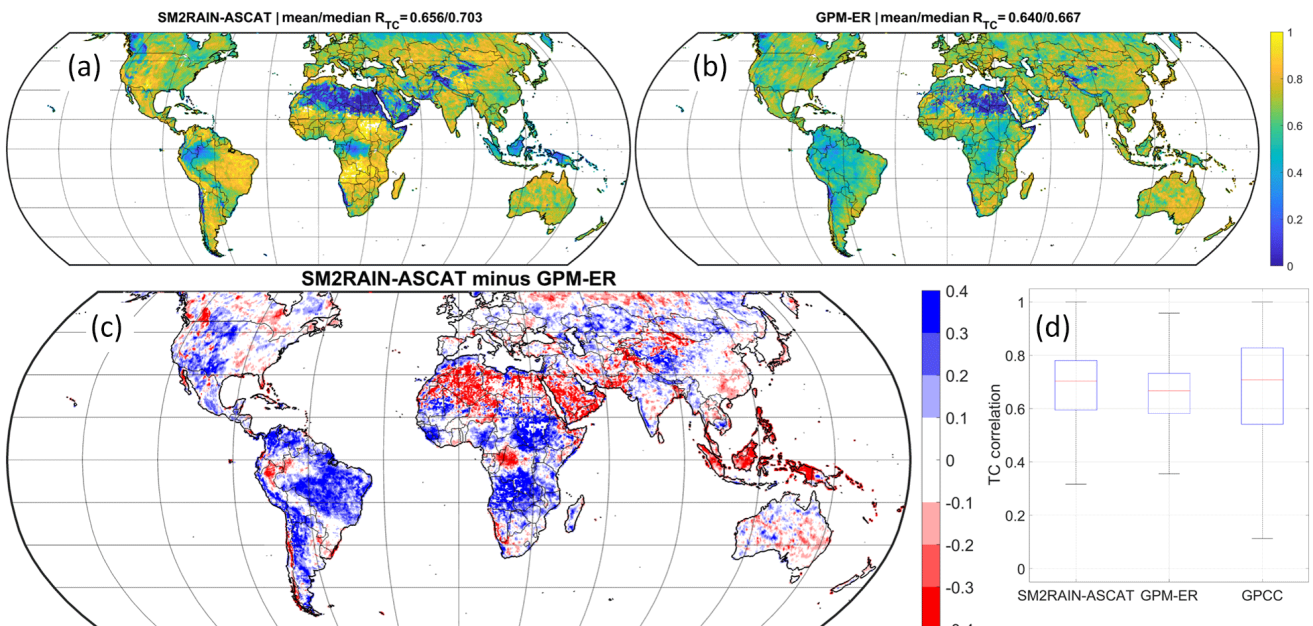
$$P(t) \approx Z\frac{dm_s(t)}{dt} + am_s(t)^b$$

Rainfall estimated from ASCAT SWI data for two sites in (a) Italy and (b) Spain

Figure 3 from Brocca, Moramarco, et al. (2013) A new method for rainfall estimation through soil moisture observations. Geophysical Research Letters, 40(5), 853–858.

Global ASCAT-based SM2RAIN Data

- Quality comparable to other satellite-based rainfall products
  - Particularly valuable over data-scarce regions



Triple-collocation results (correlation to a hypothetic rainfall truth) for
(a) SM2RAIN–ASCAT and
(b) Global Precipitation Measurement (GPM-ER)

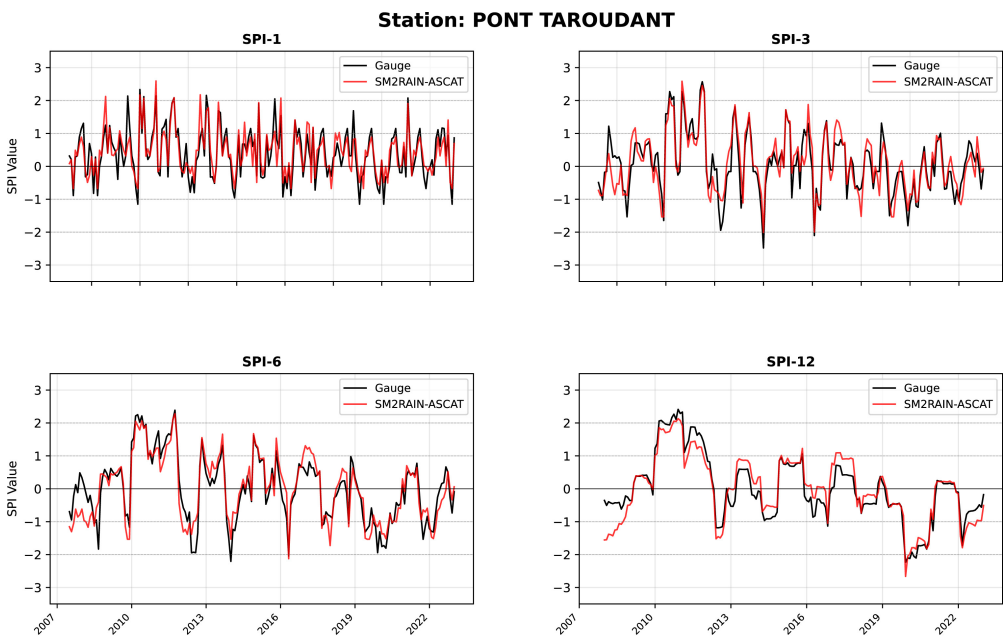
(c) Difference:

- SM2RAIN better
- GPM-ER better

Figure 7 from Brocca et al. (2019) SM2RAIN–ASCAT (2007–2018): Global daily satellite rainfall data from ASCAT soil moisture observations. Earth System Science Data, 11(4), 1583–1601.

Standard Precipitation Index from SM2Rain

- SM2RAIN-ASCAT can be used to compute the Standardised Precipitation Index (SPI) at 1, 3, 6, and 12-month scales



SPI time series from station data and SM2Rain ASCAT over a location in Morocco

- Validation results over Morocco by El Goumi et al. (2026) show that it is a robust, low-cost option for drought monitoring in data-scarce regions

Figure 11 from El Goumi et al. (2026) Assessing the SM2RAIN-ASCAT dataset in Morocco: Accuracy evaluation and drought monitoring application. Atmospheric Research, 332, 108729.

Strong Convective Initiation explained with ASCAT

- Thunderstorm cells tend to grow particularly rapidly and intensely where
  - differences in soil moisture generate near-surface winds
  - while winds at higher altitudes blow in the opposite direction

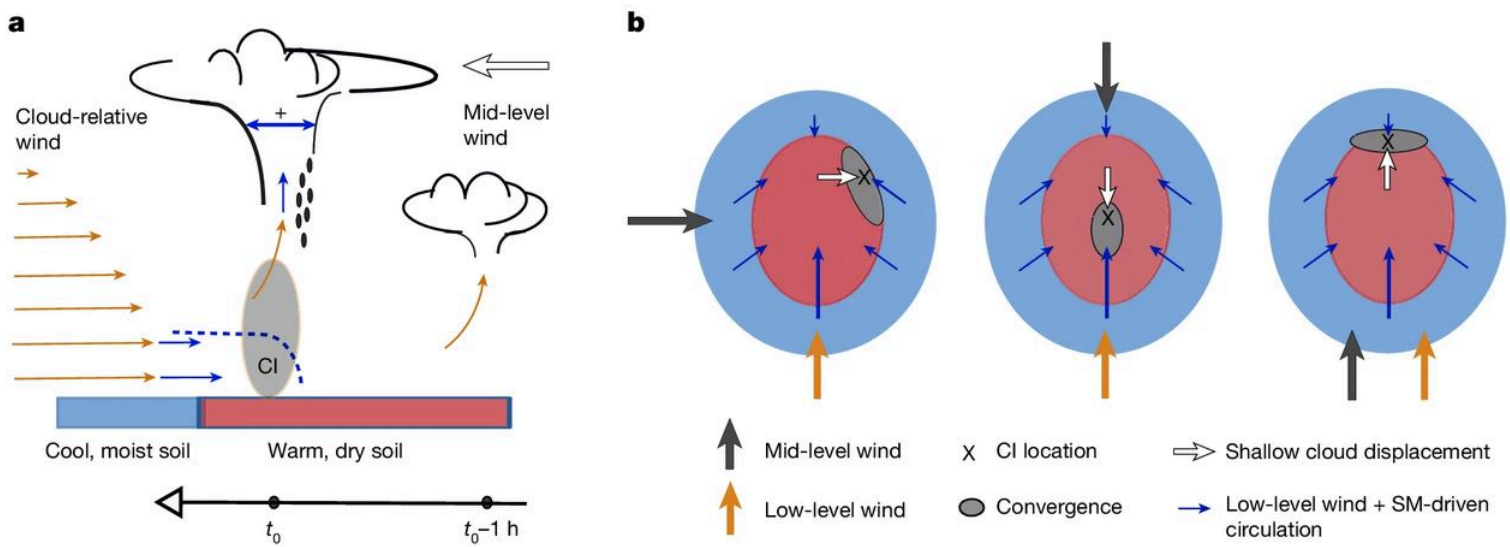
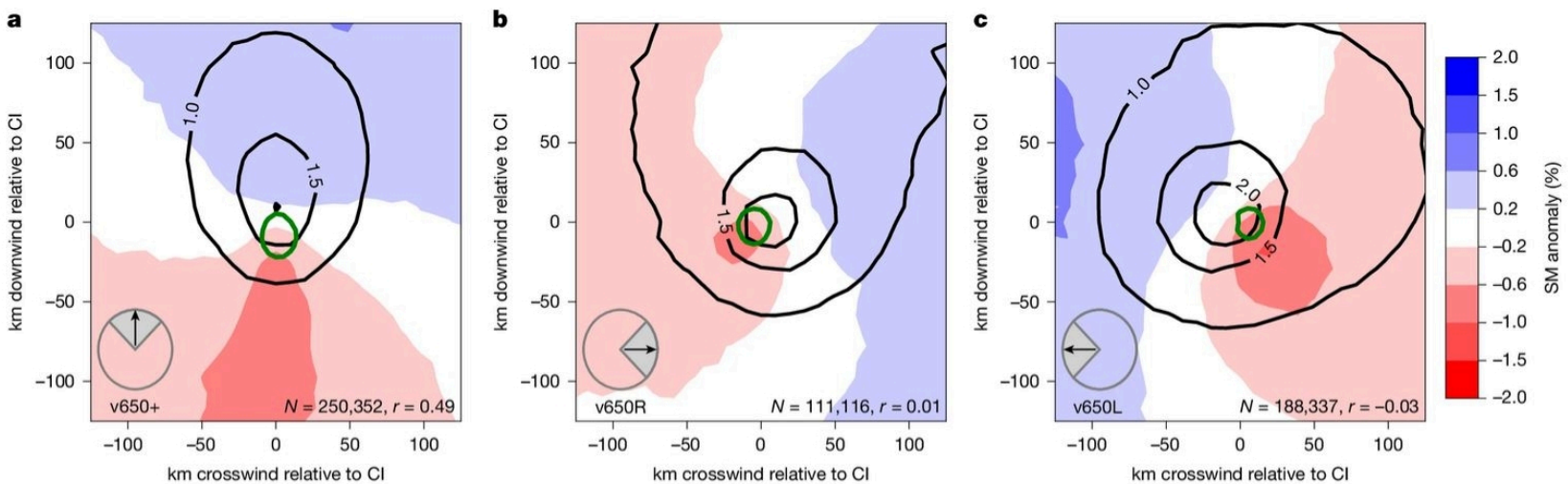


Figure 3 from Taylor et al. (2026) Wind shear enhances soil moisture influence on rapid thunderstorm growth. Nature, 651(8104), 116–121.

Convective Initiation

- The twice-daily and high spatial resolution of the new 6.25 km ASCAT SSM product were key to understand soil moisture patterns before and after thunderstorms



Composite mean SM anomalies around convective initiation events, rotated according to the 100 m wind. Black contours depict 3-h post-initiation P accumulations (mm). The insets show mid-level wind direction relative to the low-level flow.

Figure 2abc from Taylor et al. (2026) Wind shear enhances soil moisture influence on rapid thunderstorm growth. Nature, 651(8104), 116–121.

Summary and Outlook

- The new H SAF 6.25 km ASCAT surface soil moisture (SSM) product is unique among satellite soil moisture products, combining twice-daily sampling with 15 km spatial resolution

  🌧️ Essential for rainfall detection

- The new dynamic parameterisation of the TU Wien change detection model, used to generate the H SAF ASCAT SSM data, has significantly improved long-term anomaly detection

  ☀️ Essential for drought monitoring

Outlook: ASCAT data will be stored in Zarr format, enabling fast, cloud-native access for large-scale analysis

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