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Review

Soil moisture retrieval from Sentinel-1: Lessons learned after more than a decade in orbit

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A R T I C L E I N F O

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A B S T R A C T

Soil moisture is a critical variable for hydrology, agriculture and climate. However, large-scale soil moisture observation remains difficult due to sparse in situ networks and the inability of optical sensors to capture it under cloud cover. Synthetic aperture radar (SAR) missions, e.g., Sentinel-1, yield unique all-weather, day and night observations with a fine spatial and temporal resolution that makes them of interest for development of global soil moisture monitoring. Consequently, this review discusses the application of C-band SAR observations from the Sentinel-1 satellite mission to estimate high-resolution near-surface soil moisture. First, the importance of SAR backscatter monitoring from Sentinel-1 is emphasized. Next, the current state-of-the-art in soil moisture retrieval from Sentinel-1 is presented. Although considerable progress has been made in near-surface soil moisture retrieval, several limitations remain. Factors such as the effects of vegetation and surface roughness on the signal, sensor and scattering model limitations, spatial and temporal constraints, and uncertainties, e.g. in data assimilation, pose challenges to its usage. While Artificial Intelligence (AI)-based retrieval methods have shown promise, their interpretability, dependence on large datasets, vulnerability to data quality, and computational burden have been major challenges. Beyond methods that rely on backscatter, there have been recent works indicating that SAR interferometric observables have the potential to estimate soil moisture, especially in arid and semi-arid regions where these are particularly sensitive to moisture changes. To address these challenges, this paper recommends integrating Sentinel-1 with other satellite mission data for a multi-sensor data integration approach (e.g., Sentinel-2 and Soil Moisture Active Passive - SMAP data), refining physical and semi-empirical models, developing advanced AI techniques able to consider physical principles, and combining with emerging data from other high temporal resolution SAR missions (e.g., NASA-ISRO SAR). The review concludes with identification of key research priorities, including standardization of retrieval frameworks, improved validation efforts on standardized reference sets, and cloud processing for real-time user cases. Overall, the review provides a thorough foundation for understanding, refining, and advancing Sentinel-1 based soil moisture retrieval methods.

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1. Introduction

Soil moisture is a key variable in many Earth system processes, such as the hydrological cycle, agricultural productivity, and weather prediction (Rahmati et al., 2024; Mkhwenkwana et al., 2025). From drought monitoring and flood prediction to refining crop yield model predictions and climate change implications, accurate and timely soil moisture information is needed across diverse applications (Robock, 2003; Orth and Seneviratne, 2012; Good et al., 2015). With its operational focus on Earth Observation, the Copernicus program of the European Space Agency (ESA) has carefully deployed satellites to meet these needs, with the Sentinel-1 series of satellites providing a critical piece of the observing system (Potin et al., 2016).

Sentinel-1 has made a substantial contribution to the global record of land surface variables enabled by synthetic aperture radar (SAR), specifically, monitoring and quantifying near-surface soil moisture. Equipped with dual polarization (VH and VV) and dual baseline interferometric capabilities, Sentinel-1 has revolutionized Earth observation. This constellation of satellites provides an independent and powerful tool for monitoring the Earth's surface, especially over regions where optical sensors cannot be used due to adverse weather conditions such as persistent cloud cover.

The Sentinel-1 mission consists of a constellation of polar-orbiting satellites designed for radar-based Earth Observation (Torres et al., 2012). The mission is primarily equipped with a C-band SAR, which provides all-weather, day-and-night imaging capabilities, enabling consistent monitoring of the Earth's surface. Sentinel-1A was launched on 3 April 2014 from the European Spaceport in Kourou, French Guiana, followed by Sentinel-1B, launched on 25 April 2016. However, the mission encountered a significant setback with Sentinel-1B. On 23 December 2021, the Sentinel-1B satellite experienced an anomaly in its power system, leading to the suspension of its operations. Despite efforts to recover the satellite, ESA officially declared the failure of Sentinel-1B on 3 August 2022. Sentinel-1A continues to operate nominally, while Sentinel-1C was launched successfully on 5 December 2024 to take the place of Sentinel-1B. With Sentinel-1D to be launched in November 2025, long-term continuity of the Sentinel-1 series is secured. This stresses its importance for the European and global EO community. Both currently operational satellites are in a sun-synchronous, near-polar orbit at ~693 km altitude with a 12-day orbital repeat cycle for each satellite. The combination of Sentinel-1A and Sentinel-1B (or now Sentinel-1C), decreases the revisit time in exact orbit to 6 days at the equator, greatly improving the temporal coverage. When considering ascending and descending nodes, this reduces further to potentially 3 days. However, actual revisit time depends on location due to orbital overlaps, acquisition priorities, and observation modes (Fig. 1). At higher latitudes (e.g. in Europe or polar regions) the effective revisit period is reduced even more where the orbital coverage is good (Fig. 1). Conversely, in some lower-priority regions including over oceans or unmonitored regions, the revisit time can be longer than 6 days.

The Sentinel-1 mission operates in four distinct imaging modes: Interferometric Wide Swath (IW), Extra-Wide Swath (EW), Stripmap (SM), and Wave (WV) mode, each offering varying resolutions and coverage to address different scientific and operational needs. In IW mode, Sentinel-1 offers a ground range detected (GRD) resolution of 20 m × 22 m (Bauer-Marschallinger et al., 2018). Capabilities include interferometry (Yagüe-Martínez et al., 2016), where the interferometric coherence as a direct measure of the quality of the associated interferometric phase can be exploited to monitor Earth system dynamics (Villarroya-Carpio et al., 2022). Besides soil moisture (Balenzano et al., 2021b), multiple monitoring applications have been reported, such as flood (Twele et al., 2016) and land use mapping (Dahhani et al., 2023), peatland water level dynamics (Asmuß et al., 2019), vegetation dynamics (Vreugdenhil et al., 2018) and crop growth (Mandal et al., 2020). Sentinel-1 data have also been used in forestry (Zhao et al., 2022), oceanography (Martin et al., 2022), cryospheric science (Nagler et al., 2015; Lievens et al., 2022) and geology (Salvi et al., 2012). For easy access, pre-processed data has been provided on multiple platforms (see Table 1) (Mullissa et al., 2021; Wagner et al., 2021). In particular, the consideration of Level 1 GRD or Level 1 Single Look Complex (SLC) products, which address different use cases in terms of analysis, should be highlighted.

For near-surface soil moisture monitoring, Sentinel-1 has been used to provide reasonable spatial and temporal SAR coverage. This importance stems from the efficient combination of fine spatial and temporal resolution, accuracy, and the overall operational goal of the Sentinel-1 program (Hornacek et al., 2012; Bauer-Marschallinger et al., 2018; Pulvirenti et al., 2018; Balenzano et al., 2021b; Benninga et al., 2022). The fine spatial resolution (up to 5 m), high temporal resolution (better than 12 days revisit time) compared to earlier coarse-resolution microwave missions such as ASCAT, AMSR-E, WindSat, or SMOS, and its all-weather capabilities offer a major advantage for near-surface soil moisture monitoring (Wagner et al., 2009). This has inspired many soil moisture retrieval algorithms with noticeable differences among the

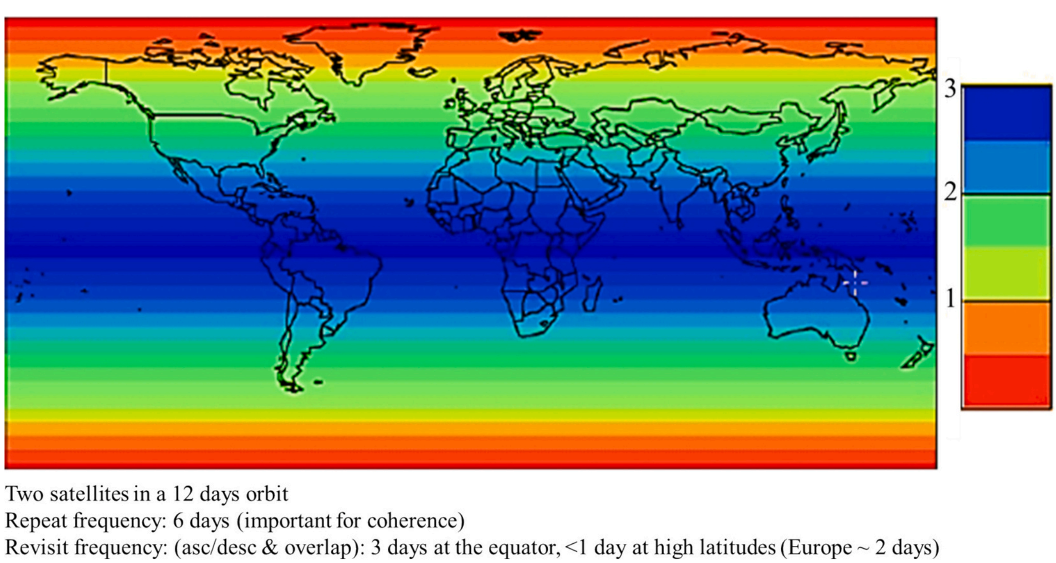

Fig. 1. Conceptual overview of the effective revisit time of Sentinel-1 as a function of latitude. At higher latitudes, orbit overlaps lead to shorter revisit times of 1–3 days near the poles compared with 6–12 days at the equator. Source from ESA Copernicus documentation at https://sentiwiki.copernicus.eu/web/s1-mission.

Table 1
Examples of platforms providing easy access to pre-processed Sentinel-1 Synthetic Aperture Radar (SAR) data.

Platform Category	Platform Name	URL	Key Features/Notes
ESA Platform	ESA Copernicus Open Access Hub	https://scihub.copernicus.eu/	Official ESA archive for Copernicus data, including Sentinel-1. Offers various processing levels.
	ESA Copernicus Browser	https://browser.dataspace.copernicus.eu/	Web-based interface for exploring and downloading Copernicus data.
Cloud-Based Platforms	Google Earth Engine	https://earthengine.google.com/	Cloud-based platform for geospatial analysis, with a vast catalog of Sentinel-1 data pre-processed and ready for computation.
	Sentinel Hub	https://www.sentinel-hub.com/	Provides access to Sentinel-1 data with on-the-fly processing and various APIs for integration into applications.
	AWS Open Data Registry	https://registry.opendata.aws/	Hosts a large collection of publicly available datasets on AWS, including Sentinel-1. Requires using AWS services for access and processing.
	Microsoft Planetary Computer	https://planetarycomputer.microsoft.com/	Provides access to environmental datasets, including Sentinel-1, on Azure with tools for analysis.
DAAC (US)	Alaska Satellite Facility (ASF) DAAC	https://www.asf.alaska.edu/	Provides access to SAR data, including Sentinel-1. Offers various data products and processing options.

numerous methods (Zhu et al., 2020), including various physics-based models and advanced machine learning methods.

The number of studies using Sentinel-1 for near-surface soil moisture retrieval is growing rapidly, and most studies focus on short-term experiments, local case studies, or algorithm development. Although some previous reviews have dealt with the retrieval of soil moisture from SAR (e.g., Kornelsen and Coulibaly, 2013; Akash et al., 2024), these studies have adopted a more general approach with regard to SAR missions in general, or have concentrated on methodological aspects without placing a particular focus on Sentinel-1. As Sentinel-1 is approaching the end of its first decade in orbit and having delivered a global, high-resolution record of SAR observations unlike any sensor before it, a full review on the performance and utility of Sentinel-1 for near-surface soil moisture retrieval has become timely. This review therefore had the following three objectives: (i) to synthesize the various methods developed for Sentinel-1 near-surface soil moisture retrieval, including physically based, (semi-)empirical, change detection, AI-based, InSAR coherence, and closure phase methods; (ii) to provide insights to near-surface soil moisture validation strategies, retrieval uncertainties, and its integration into hydrological and agricultural applications; and finally (iii) to delineate gaps in the current knowledge on near-surface soil moisture retrievals which will help tailor future science priorities towards next-generation operational near-surface soil moisture products. This review hereby delivers the first long-term, Sentinel-1 specific compendium of lessons-learned in terms of what works and what does not when it comes to making use of Sentinel-1 data for near-surface soil moisture retrieval.

This paper provides an overview of the current state of near-surface soil moisture retrieval methods using Sentinel-1 data and the evolution of these techniques over the first decade of mission activity. First, the basic interaction of microwave backscatter with the near-surface soil moisture content is discussed in section 2. Next, the strengths and weaknesses of the various near-surface soil moisture retrieval methods are examined in section 3, including the inversion of physics-based scattering models, semi-empirical models, change detection methods, AI-based techniques, hybrid methods, and estimation from SAR interferometry. Then, section 4 discusses validation strategies, while section 5 discusses the sources of uncertainty in near-surface soil moisture retrieval from Sentinel-1 data. Subsequently the combination of Sentinel-1 data with other sensors, such as passive microwave sensors and *in situ* measurements, which aim to improve retrieval accuracy and broaden the scope of applications, is addressed in section 6. The importance of data assimilation in the use of Sentinel-1 derived near-surface soil moisture in hydrological models is then presented in section 7, the use of Sentinel-1 soil moisture data for root-zone soil moisture estimation in section 8, and the contribution of Sentinel-1 soil moisture to hydrology explored in section 9. Future perspectives and challenges related to Sentinel-1 near-surface soil moisture retrieval are presented in section 10, including open questions regarding model calibration, how vegetation and surface roughness can affect near-surface soil moisture retrieval, and how to improve operational near-surface soil moisture retrieval systems. Finally, the conclusion of the paper is presented in section 11.

2. Basic principles

Soil moisture, which is strongly influenced by soil texture (Babaeian et al., 2019), can be expressed either gravimetrically (grams of water per grams of soil) or volumetrically (cubic centimeters of water per cubic centimeter of undisturbed soil). Another commonly used soil moisture metric is (relative) saturation (dimensionless; cubic centimeters of water per cubic centimeter of soil voids), which can be converted to volumetric soil moisture by multiplying with the porosity of the soil (Lekshmi et al., 2014; Bauer-Marschallinger et al., 2018). While the soil moisture content cannot be directly measured using a microwave sensor, the soil dielectric constant (or relative permittivity) can be measured. This variable reflects the ability of a material to store potential electrical energy in response to an electromagnetic field (Seyfried and Murdock, 2004). It exploits the large permittivity differences between dry soil ($\sim$4), air ($\sim$1), and water ($\sim$80). Dielectric mixing models, such as those proposed by Dobson et al. (1985), Mironov et al. (2009), and Topp et al. (1980), describe the nonlinear relationship between permittivity and soil moisture by incorporating the dielectric contribution from different soil components. Further dielectric mixing models were developed to better account for soil organic matter content (Park et al., 2019), freeze-thaw transitions (Wu et al., 2022), and soil salinity (Gao et al., 2024). For further details, refer to Babaeian et al. (2019), Montzka et al. (2020), and Szypłowska et al. (2021).

Understanding the basics of Maxwell's equations, which underpin classical electromagnetism (Jackson, 2021), is essential for interpreting features such as the near-surface soil moisture retrieved from Sentinel-1 SAR data. These equations describe the propagation of electromagnetic waves, such as those emitted by the Sentinel-1 satellite, and their interaction with the Earth's surface. In fact, the dielectric properties of the soil are very sensitive to the moisture content, which affects the efficiency with which radar signals are scattered. Maxwell's equations predict how the emitted radar waves interact with the terrain to produce the backscatter that is detected by the receiver, thus facilitating the development of models that convert SAR observations into near-surface soil moisture estimates.

In addition to dielectric properties, surface roughness, typically characterized by the standard deviation of surface elevation (vertical Root Mean Square height; RMS height) and horizontal correlation length, impact on the scattering regime from a soil surface. Here, smooth surfaces produce specular reflection, while rough surfaces cause diffuse scattering (Ullmann and Stauch, 2020). Frozen conditions strongly alter the dielectric properties of the soil, and therefore freeze-thaw cycles can be detected by SAR (Baghdadi et al., 2018). The interaction of vegetation with radar signals is influenced by factors such as canopy structure, biomass density, and the dielectric properties of the vegetation (mainly related to the vegetation water content). For C-band, which operates at 5.405 GHz with a wavelength of approximately 5.55 cm, microwaves typically penetrate the first centimeter of the soil when it is covered with low vegetation (such as grassland, crops, and steppe), whereas for denser vegetation the backscattering signal fully originates from within the upper canopy without any direct signal contribution from the soil. Thus, no direct soil moisture retrieval is possible for the latter.

The physical quantity measured by a SAR sensor is the amount of radar energy scattered back from a given target, in the form of the ratio of incident to reflected power. The magnitude of the energy and the phase of the signal depend on type, size, shape, and orientation of the scatterers in the target area; moisture content in the target area; frequency and polarization of the radar pulses; and the incidence angle (see θ in Fig. 2) of the radar beam. The backscattering coefficient is the ratio per given area on the ground. There are three conventions to report the coefficient: beta nought (β^0), sigma nought (σ^0), and gamma nought (γ^0) (Clapp, 1946; Cosgriff et al., 1960; Small, 2011). β^0 is the native quantity of SAR imagery because its computation does not require projection to the Earth. σ^0 represents the radar backscatter normalized by the projected ground area, making it the most widely used measure for geophysical applications such as near-surface soil moisture retrieval. In contrast, γ^0 normalizes the observed backscatter by the plane perpendicular to the radar line of sight, reducing sensitivity to local incidence angle variations and so is often preferred for removing the effects of topography (slope, aspect, and local incidence angle). σ^0 and γ^0 are geocoded and thus suitable for soil moisture retrieval. For a surface with no topography, σ^0 and γ^0 are related simply by a cosine function of incidence angle. σ^0 decreases more rapidly than γ^0 with increasing incidence angle because of the expansion of the ground area (see Fig. 3 of Kim et al., 2015). γ^0 still varies by incidence angle following the Fresnel reflectivity in the case of specular surface for example, but not by the projected area on the ground. With topography, σ^0 shows strong features of terrain, thus confusing SAR responses to near-surface soil moisture variation. Such confusion was not obvious in early soil moisture studies because they utilized coarse resolution spaceborne data (~km) or flat areas. Consequently, near-surface soil moisture algorithms have predominantly used σ^0 until now. With high-resolution spaceborne data such as from Sentinel-1 in areas with steep topography, such as near-surface soil moisture estimation for landslide analyses (Liao et al., 2021), γ^0 may be preferred for near-surface soil moisture retrieval in the future. Spatial integration of elevation is required to convert between

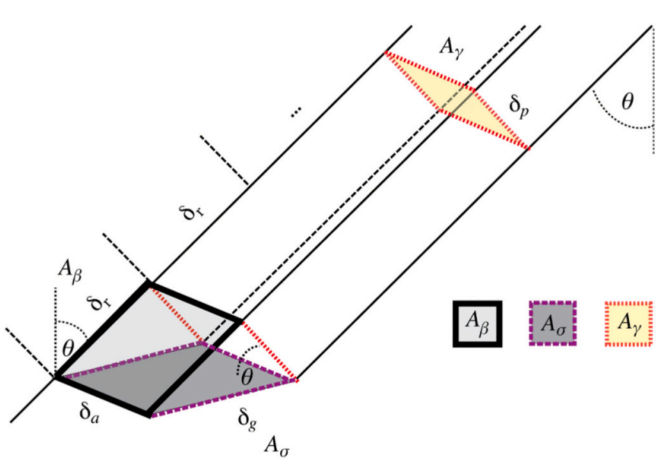

Fig. 2. Backscatter coefficient conventions: β^0, σ^0, and γ^0 (Small, 2011). A_β is the area on the slant range plane, $A\sigma$ and A_γ are the area on the ground plane without and with topography, respectively. The delta δ is the spatial resolution associated with each convention.

σ^0 and γ^0 (radiometric terrain correction).

3. Soil moisture retrieval: state of the art

Generally, retrieval refers to the inversion of a forward scattering process from near-surface soil moisture to received back-scattered power. The retrieval algorithms reviewed in this paper exploit varying degrees of forward model complexity either explicitly (physical, change detection, semi-empirical, and interferometric observables) or implicitly (AI). A flowchart of near-surface soil moisture retrieval based on Sentinel-1 backscatter is given in Fig. 3 and Table 2, showing the main advantages and drawbacks of these methods together with representative references.

3.1. Inversion of physics-based scattering models

This section provides a brief overview of forward models, first, which is warranted because retrieval intrinsically inverts a forward model. At C-band and adjacent frequencies where soil moisture can be estimated (e.g., P-, L-, S-, and X-band), the same governing physics apply, and therefore the summary below applies to these wavelengths. The models of forward scattering from soil and vegetation can be categorized into semi-empirical and theoretical models, which include analytical and numerical models.

I. Semi-empirical models are primarily data-driven but retain some physical basis: soil moisture and σ^0 were found to be linearly related for bare soil (Dubois et al., 1995) at 1 to 11 GHz, and also when plants are treated as temporally static for vegetated surfaces (Kim and van Zyl, 2009). Semi-empirical models incorporate scattering physics with simplified parameterization: e.g., over bare surface (Oh et al., 1992) and vegetated surfaces (Attema and Ulaby, 1978), known e.g. as the water cloud model, WCM.
II. Analytical models also incorporate scattering physics but with considerable sophistication of analytical formulation. For bare soil, the small perturbation model (SPM) (Rice, 1951) was first used, followed by the Integral Equation Model (IEM) (Fung et al., 1992). For vegetated cases, the radiative transfer theory (Tsang et al., 1985; Ulaby et al., 1990) that was tested for 0.5 to 10 GHz using a discrete scattering approach (Durden et al., 1989; Ferrazzoli and Guerriero, 1996) has evolved over the past decades. The latter is implemented more commonly because of the ability to address individual scatterers. Multiple scattering becomes increasingly important at C-band and higher frequencies, which the radiative transfer method can easily simulate through iteration (Liao et al., 2016). Successful analytical models with 1-2 dB discrepancy have been feasible at C-, L-, and P-band for grassland (Dente et al., 2014; Kim et al., 2014; Liao et al., 2021), shrubland (Tabatabaeenejad et al., 2015; Kim et al., 2017), crops (Huang et al., 2016; Liao et al., 2016; Huang et al., 2021; Kim and Liao, 2021; Benninga et al., 2022), and forest (Burgin et al., 2011; Kurum et al., 2021; Jeong et al., 2023; Quast et al., 2023).
III. Numerical solution of the Maxwell equations has brought the latest advancements over bare soil (Duan and Moghaddam, 2012; Huang and Tsang, 2012) and vegetated mediums such as corn (Niknam et al., 2024) and forest (Jeong et al., 2025) at L- and P-bands. Since numerical solutions do not involve parameterization or analytical formulation, the solutions are exact and would intrinsically simulate the strong multiple scattering that occurs at C-band.

The inversion of these forward models is now described (see Fig. 4 for an example flowchart). Retrieval using the Tor Vergara discrete forward model over Tibetan grassland with Sentinel-1 VV as input showed an unbiased root mean square error of ~0.14 m^3/m^3 (Benninga

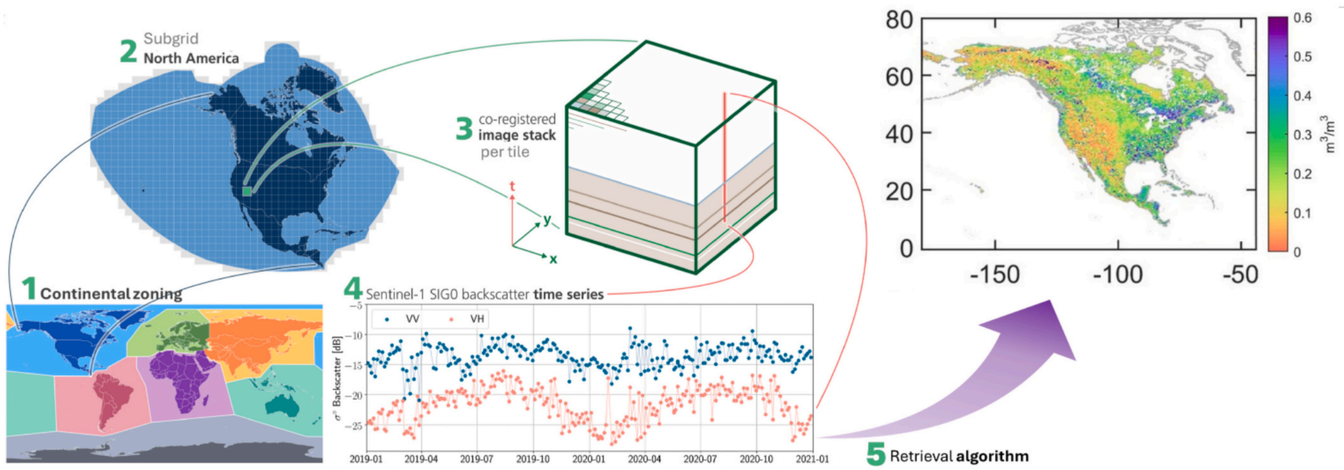

Fig. 3. The overall flowchart of soil moisture retrieval using Sentinel-1 backscatter data (adopted from Wagner et al., 2021).

Table 2
Overview of Sentinel-1-based soil moisture retrieval methods and their key strengths, limitations, and exemplary work

Method	Main Advantages	Main Drawbacks / Limitations	Key References
Physics-based scattering models	● Physically interpretable ● Transferable across frequencies ● Capable of simulating multiple scattering and topography effects	● Reliable ancillary (vegetation) ● Ill-posed inversion with VV ● Fidelity of forward model	Kim et al. (2017) Benninga et al. (2022) Jeong et al. (2025)
Semi-empirical models	● Less input data needed ● Simpler to implement ● Widely used (Oh, Dubois, WCM)	● Limited transferability ● Poor performance under dense vegetation ● Roughness often misrepresented	Oh et al. (1992) Baghdadi et al. (2016) Fan et al. (2025)
Change detection methods	● Conceptually simple ● Robust to static roughness ● Effective at the regional scale ● Operational (e.g., SWI)	● Assumes vegetation/roughness stability ● Needs a long time-series or frequent revisits ● Biased by porosity calibration (e.g., SWI)	Wagner et al. (1999a) Bauer-Marschallinger et al. (2018) Balenzano et al. (2021b) Mengen et al. (2023)
AI-based techniques	● High accuracy in complex environments ● Efficient prediction ● Flexible integration of multi-source data	● Data-hungry ● Limited interpretability ● Costly training ● Sensitive to input quality ● Risk of overfitting	Paloscia et al. (2013) Liu et al. (2021) Zhu et al. (2025)
Hybrid methods	● Combines physics with AI ● Better generalization and interpretability ● Leverage limited ground truth	● Still experimental ● Requires harmonized training/validation ● Higher complexity	Santi et al. (2021) Arab et al. (2024) Yu et al. (2025a)
InSAR coherence & phase closure	● High sensitivity to dielectric changes ● Independent of backscatter magnitude ● Potential in arid zones	● Ambiguity in moisture direction (wetting/drying) ● Temporal decorrelation ● Vegetation interference ● Limited maturity at C-band	De Zan and Gomba (2018) Karamvasis and Karathanassi (2023) Wig et al. (2024)

et al., 2022). The retrieval error using the Tor Vergara model was substantially larger than for the semi-empirical WCM result: over grassland, the weak double bounce allowed the WCM to perform well (Wang et al., 2023b). Benninga et al. (2022) attributed the large error to vegetation modeling performance (since a similar error level was found when inverting the forward model without the vegetation component) and to the uncertainties in vegetation input data.

Fundamentally, retrieval is an ill-posed process with one VV Sentinel-1 input being used to resolve two unknowns (soil moisture and roughness). Time-series inversion using dual co-pol input constrains the ill-posed problem assuming temporally static unknown roughness (2N input with N+1 unknown, where N is the number of time sequences and 1 represents the unknown roughness) (Kim et al., 2012b). With only single co-pol (VV) the constraint based on the time-series would not be feasible, but the roughness constraint was sufficient to improve accuracy to~0.06 m^3/m^3 (Kim and Liao, 2021). The retrieved roughness was physically plausible with ~50% uncertainty (Kim et al., 2018). Alternatively, sophisticated constraints such as annealing were found to be effective without the need for time-series operation (Tabatabaeenejad et al., 2012). The use of a more accurate model for bare soil than the IEM could be another cause of the larger errors in Benninga et al. (2022). For example, numerical exact solutions exhibit 2 dB improvements over the advanced IEM (Huang et al., 2010).

Potential and remaining issues of the physical model inversion are as follows. Though most of the advances were made at L-band, they are also applicable to C-band because the scattering physics are similar, with explicit correction of the vegetation improving retrieval accuracy. However, accurate modeling of the vegetation effects is challenging, and the input data, such as from leaf-area index (LAI), may not capture the effects well (Benninga et al., 2022). The difficulty of undertaking accurate modeling can be mitigated by constructing the inversion as a well-conditioned problem and revising the vegetation correction during retrieval (Kim et al., 2018).

The topography effect is another case where physical model inversion can improve retrieval accuracy. However, the geometry of double-bounce scattering is particularly complicated by topography (Burgin et al., 2016) because the angles of reflection by the soil and plant trunk are no longer the same, unlike on a flat surface. When double-bounce is

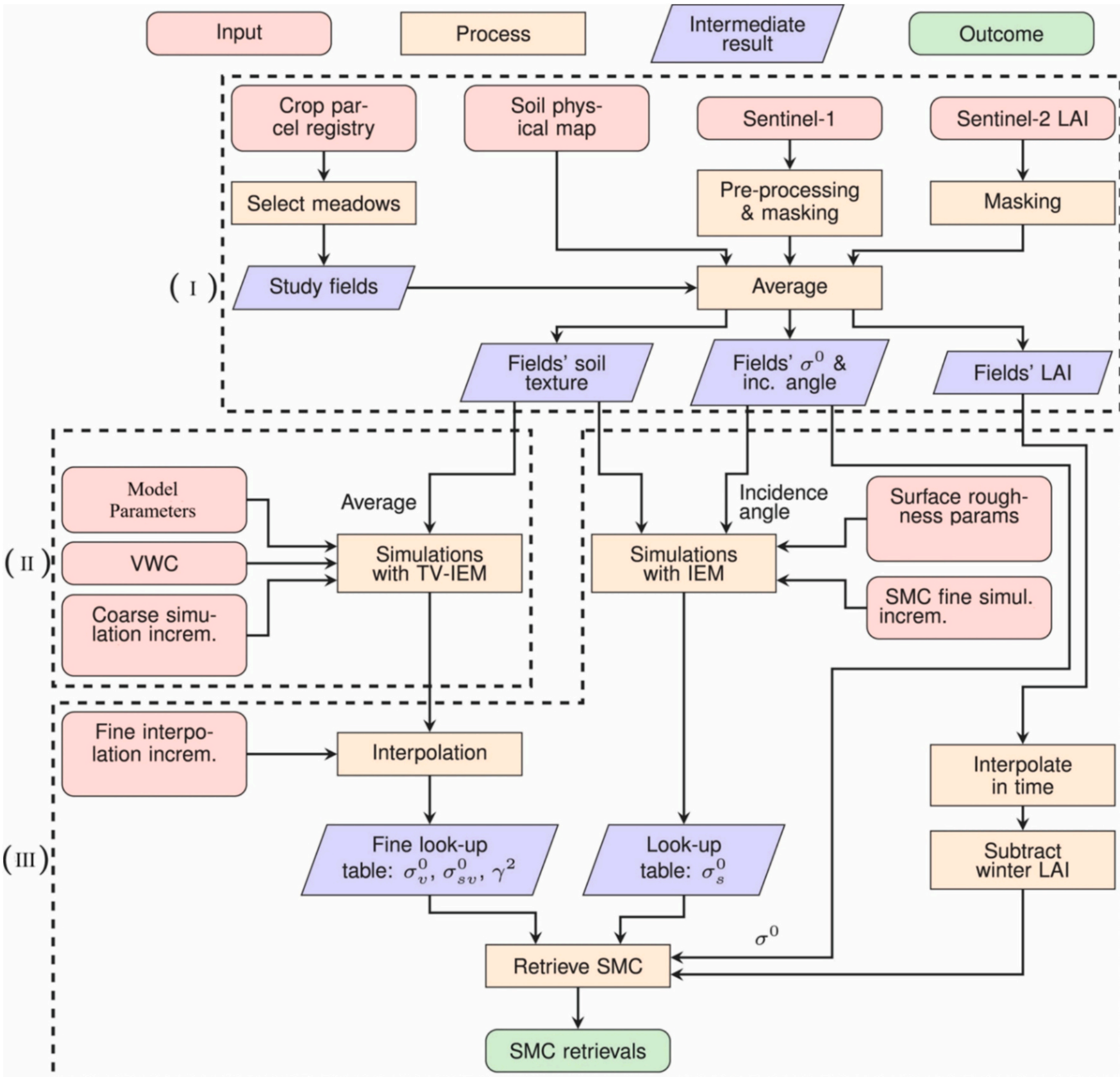

Fig. 4. Inversion of physics-based scattering models (Tor Vergata University of Rome, TV, and the integral equation method, IEM), separated in the preparation of the input data (I), the parameterization of the TV-IEM model (II), and the retrieval of SMC from observations (III) (adopted from Benninga et al., 2022).

weak, the topography effect can be successfully corrected by treating it as the variation in sensor look angle (Liao et al., 2021).

The same value of σ^0 can be associated with geometric or dielectric properties of vegetation in multiple ways. For example, height, diameter, leaf density, and dielectric property can increase vegetation backscatter for crops (e.g., Huang et al., 2016). For trees, density is often the dominant driver determining vegetation amount and σ^0 (Tabatabaeenejad et al., 2012). For plants in arid land, neither geometry nor density vary significantly in time, although the dielectric constant changes seasonally and determines σ^0 (Kim et al., 2017). These conditions lead to more than one way to simulate vegetation effects (e.g., by dielectric or geometry changes), with the retrieval performance depending on whether the vegetation characterization correctly represented the physical reality.

3.2. Semi-Empirical models

The advantage of semi-empirical models compared to physics-based models (sec. 3.1.) is the reduced amount of specific input information and knowledge on scattering mechanisms. Several semi-empirical models have been proposed in the last decades, suitable for near-surface soil moisture retrieval using Sentinel-1 SAR data. The main objective of designing semi-empirical models is to simulate backscattering in an uncomplicated way at different polarizations based on soil and electromagnetic wave characteristics, such as moisture content, roughness, incidence angle, and frequency (Baghdadi et al., 2011). In this way, near-surface soil moisture can be estimated by comparing the simulated backscatter coefficients based on variable input for, e.g., soil moisture, to actual observed backscatter coefficients from, e.g., Sentinel-1 (see Fig. 5). Moreover, limitations of semi-empirical near-surface soil moisture retrieval approaches are their limited generality in representing different or other scattering scenarios, beyond the ones for which they have been built and established. Hence, they often lack transferability to other regions, meaning differing types of soils with different surface roughness conditions and moisture content ranges.

3.2.1. Bare surfaces

For bare soil conditions (no vegetation influencing the Sentinel-1 SAR signal), the most employed semi-empirical soil backscatter models are the Oh and the Dubois near-surface soil moisture inversion methods (e.g., Mirsoleimani et al., 2019; Li et al., 2020; Murugesan et al., 2023; Roy et al., 2025). The Oh model was originally proposed by Oh et al. (1992), which uses the ratio of measured co- and cross-polarized backscatter coefficients to estimate near-surface soil moisture and roughness. The analytical expressions of the backscatter ratios

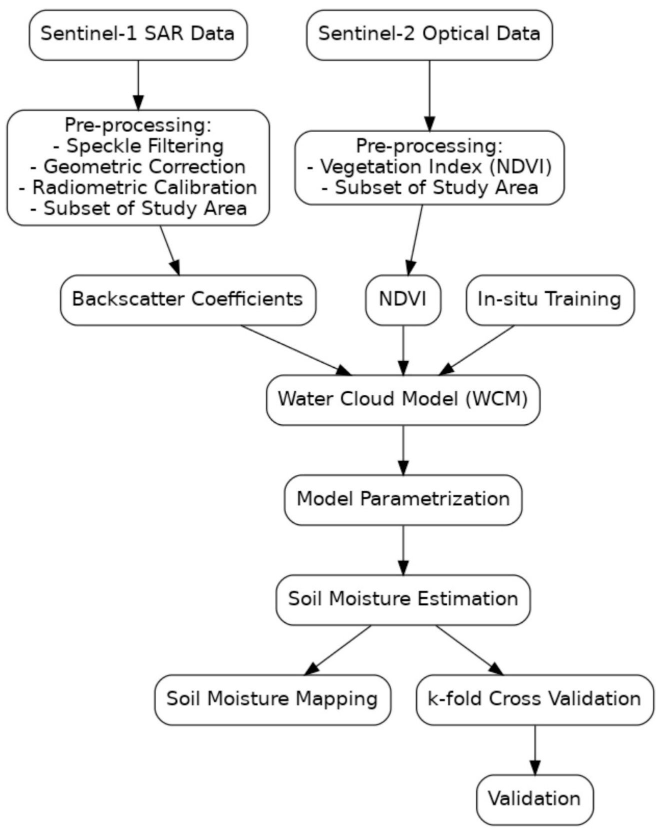

Fig. 5. Inversion of semi-empirical water cloud model (WCM) (adopted from Khellouk et al., 2021).

were then adapted to account additionally for the incidence angle (Oh et al., 1994). New definitions were later proposed for analytical expressions and formulation of the cross-polarized backscatter (Oh et al., 2002). These were again adapted, ignoring the horizontal roughness component (correlation length) within calculations (Oh, 2004; Baghdadi et al., 2016). Conversely, the Dubois model describes the co-polarized backscatter coefficients as a function of near-surface soil moisture, vertical surface roughness (e.g., RMS height), incidence angle, and frequency (Dubois et al., 1995).

The most common shortcoming of these semi-empirical models is the discrepancy between simulated and measured backscatters, because of factors such as inaccurate surface roughness representation in the model. Hence, several modifications to these models have been proposed, e.g., improving the description of surface roughness simulations or extending the validity range (e.g., Baghdadi et al., 2016). Besides these two well-known and well-established models, there is the semi-empirical model of Shi et al. (1997), which is based on the single-scattering component of the analytical physics-based IEM, and hence has taken into account the surface power spectrum (related to surface roughness parameters) (Shi et al., 1997). The surface power spectrum gives “the amplitude of each Fourier component scattered by a rough surface” (Ogilvy and Foster, 1989), and hence describes the assumed surface type for the roughness correlation function (the degree of correlation between two RMS heights). As shown by Fluhrer et al. (2020), the type of assumed correlation function (Gaussian, exponential or n^{th} power) determines the contribution of roughness and hence influences the simulation of radar backscatter. For local near-surface soil moisture estimation, *in situ* measurements along with Sentinel-1 backscatter can be used to build semi-empirical models. Here, the final near-surface soil moisture value results from the linear fit between backscatter coefficients, near-surface soil moisture and surface roughness. This was accomplished by Hoskera et al. (2020) across bare rice agricultural soils in India, who demonstrated the advantage of using both VV and VH polarizations instead of single-polarization retrievals. The disadvantage of these linearly built and *in situ* informed semi-empirical equations is their lack of transferability to other test sites or different soil and vegetation types. Nevertheless, semi-empirical models prove the potential of near-surface soil moisture estimation from Sentinel-1 SAR observations.

3.2.2. *Vegetated surfaces*

In the case of vegetated surfaces, the vegetation contribution as well as the canopy and ground interactions must be modeled in addition to the soil contribution to capture the entire backscatter scenario within a SAR resolution cell. One of the most well-known semi-empirical models for estimating near-surface soil moisture by eliminating vegetation effects on simulated backscatters is the WCM proposed by Attema and Ulaby (1978), and the Single Scattering Radiative Transfer (SSRT) model proposed by De Roo et al. (2001). The WCM is a highly parameterized model for simulating backscatter coefficients as a function of soil and vegetation moisture as well as vegetation height by assuming the vegetation canopy as a cloud of identical and randomly distributed water droplets (Attema and Ulaby, 1978), which has been adapted in various studies to improve, for example, the vegetation description (Yahia et al., 2022; Kanmani et al., 2023; Nijaguna et al., 2023). SSRT is the semi-empirical adaptation of the physics-based Michigan microwave canopy scattering (MIMICS) model, proposed by Ulaby et al. (1990).

To estimate near-surface soil moisture under vegetated soils, two semi-empirical models can be used together to describe the combined bare soil and vegetation backscattering contributions. Among others, Yang et al. (2021) employed the Oh model (Oh, 2004) coupled with the WCM (Attema and Ulaby, 1978) to retrieve near-surface soil moisture within the Tibetan plateau using only the VV polarization of Sentinel-1 observations (Yang et al., 2021). Weiß et al. (2024) employed the SSRT along with the soil scattering model of Oh et al. (1992) to retrieve large-scale near-surface soil moisture from Sentinel-1 SAR data at 1 km × 1 km spatial resolution across southern Germany. Recently, Fan et al. (2025) employed the Oh model Oh et al. (1992) and the WCM (Attema and Ulaby, 1978) for simultaneous retrievals of global near-surface soil moisture and surface roughness from Sentinel-1 SAR data at 1 km spatial resolution. To solve near-surface soil moisture and surface roughness simultaneously, a dual-polarization algorithm (DPA) was proposed, which can be used to retrieve both variables in a snapshot approach from Sentinel-1 VV and VH polarizations.

Recently, Roy et al. (2025) also proposed a novel approach involving model-based decomposition that does not require in situ plant descriptors to reduce the volume contribution of vegetation. When applied to different crop fields, this method led to a root mean square error that was 25–52% lower than that predicted by the Oh model (Oh et al., 2002) and 10–17% lower than that predicted by the Chang model (Chang et al., 2018).

3.3. *Change detection methods*

The change detection approach for near-surface soil moisture retrieval relies on the inversion of temporal variations in σ^0, rather than a single-date backscatter measurement (see Fig. 6). This method assumes that changes in surface parameters that influence radar backscatters such as soil roughness, canopy structure, and vegetation water content — generally occur over longer periods (weeks) compared to changes in near-surface soil moisture (which can happen in hours). Therefore, taking the ratio or difference between two or more frequent repeat-pass radar images can help disentangle the effects of near-surface soil moisture on radar response from other confounding surface variables (Rignot and Van Zyl, 1993). Establishing a strong relationship between backscatter and near-surface soil moisture while using conceptual simplicity, many researchers have advocated for this method (e.g., Shoshany et al., 2000; Wickel et al., 2001; Thoma et al., 2006; Yang

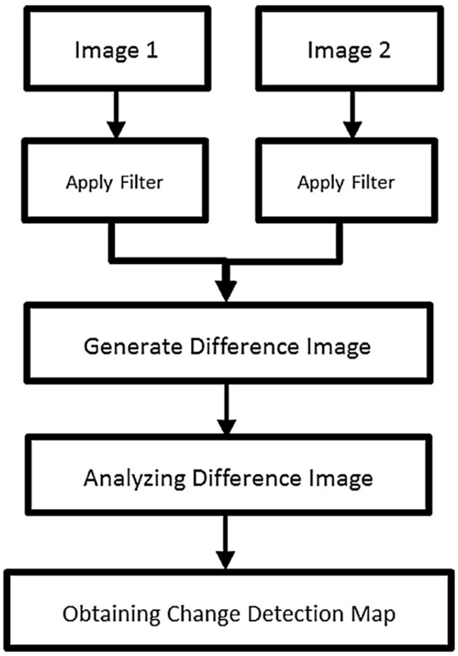

Fig. 6. Flowchart of change-detection algorithm (Keshk and Yin, 2020).

et al., 2006; Zribi et al., 2008).

Due to the lack of spaceborne SAR missions with sufficiently short revisit time in the past, this approach has been adapted by requiring a rather long than temporally dense time series. The Vienna University of Technology (TU-Wien) change detection method (Wagner et al., 1999a) is a snapshot retrieval technique in which the near-surface soil moisture at each time step is estimated based on the backscattering value normalized by the minimum and maximum backscatter observed over a long time series. Across the entire time series of observed backscatter coefficients, the minimum backscatter is associated with the lowest soil moisture content (no liquid water present), and the maximum backscatter is associated with the highest soil moisture content (soil is saturated). The TU-Wien method is currently used to operationally retrieve near-surface soil moisture at low spatial resolution (25 km) and high temporal sampling (1-2 days) from the Advanced SCATterometer (ASCAT) (Bartalis et al., 2007). The soil roughness is assumed to be stable in time while the effect of vegetation at the seasonal scale is accounted for by multi-angular scatterometry measurements. It is supposed that the relationship between σ^0 and radar incidence angle is affected only by vegetation density and not by changes in near-surface soil moisture. Subsequently, the slope and curvature obtained from σ^0 observations under different incidence angles are used to parameterize and correct the vegetation effect. In this regard, Vreugdenhil et al. (2016) highlighted the importance of a dynamic correction for regions with high interannual variability in vegetation and proposed an improved estimation of the incidence angle dependency of backscatter.

Subsequently, the TU-Wien change detection method has been adapted to SAR data, including ENVISAT Advanced Synthetic Aperture Radar (ASAR) data (Pathe et al., 2009), and more recently to Sentinel-1 observations (Bauer-Marschallinger et al., 2018). An operational soil water index (SWI) product derived from Sentinel-1 at 1km spatial resolution is currently distributed through the Copernicus Land Monitoring Service (European Commission Directorate-General Joint Research Centre, 2018). The main limitations of the method are that i) it does not include a dynamic vegetation correction, due to Sentinel-1 lack of simultaneous multi-angle backscatter observations, ii) the assumptions of vegetation and soil roughness long term stability are limited at high spatial resolution, iii) the retrieved quantity is a degree of saturation, which can be converted to volumetric near-surface soil moisture content using the soil porosity. Namely, while the local backscatter fluctuations due to vegetation and soil roughness variability are expected to be suppressed by averaging at the scale of the scatterometry measurements (25-50 km) (Macelloni et al., 1999), at high spatial resolution (< 1 km) the assumption that these quantities are quasi-static in the time window necessary to estimate the backscatter extreme values is questionable and can cause underperformance in detecting localized phenomena such as irrigation, fire, and precipitation events (Brocca et al., 2024). Additionally, inaccuracy associated with the porosity value may lead to a bias in the near-surface soil moisture estimates (Wagner et al., 2013).

A method, known as short-term change detection, was introduced by Balenzano et al. (2011) and applied to the Sentinel-1 observations (Balenzano et al., 2021b) to produce a near-surface soil moisture product at 1 km resolution (Balenzano et al., 2021a). This method utilizes a dense time series of SAR data to retrieve near-surface soil moisture based on the original principles of the change detection framework. Specifically, it examines variations in temporal backscatter between closely timed SAR observations and linking these changes to fluctuations in soil moisture while soil roughness and vegetation remain constant during the time interval between two SAR observations. Additionally, dynamic vegetation masking is employed using cross-polarized backscatter as a threshold index, particularly in areas with dense and branched vegetation that may impede the sensitivity of Sentinel-1 data to near-surface soil moisture, as described in Satalino et al. (2013). This approximation, initially proposed by Balenzano et al. (2011) and referred to as the “alpha approximation”, is expected to improve as the time lag between the SAR acquisitions is decreased.

To address the key limitations of the method — namely the requirement of short time gaps between consecutive Sentinel-1 acquisitions, misleading effect of abrupt changes in vegetation and soil roughness during the observation period, and the need for external information to derive absolute soil moisture values — further refinements have been proposed.

One strategy to reduce the time gap between Sentinel-1 acquisitions is to use multi-orbit time series data (Mengen et al., 2023; Wang et al., 2023b). By using all possible overlapping orbits, the period between consecutive Sentinel-1 acquisitions can be reduced to 2 to 5 days, depending on the latitude of the respective study areas. Due to the alternating incidence angles in a dense Sentinel-1 time series, the backscatter signals need to be angle corrected in advance. Wang et al. (2023b) normalized the backscatter signal using a pixel-wise angle correction based on reference orbits while Mengen et al. (2023) accounted for temporal change in backscatter by excluding repeat intervals of less than 15 days from the backscatter time series and applying harmonic regression.

To account for vegetation influence in periods of high plant dynamics, the correction of backscatter signal ratios by estimating the vegetation attenuation using either radar-based or optical-derived estimators has been implemented (Bhogapurapu et al., 2022; Zhu et al., 2022b; Graldi et al., 2023; Mengen et al., 2023). For example, Zhu et al. (2022b) approximated the effect of changing vegetation on the backscatter time series as the change of vegetation attenuation, which was estimated using the Normalized Difference Vegetation Index (NDVI) from optical images as a bulk vegetation descriptor. By integrating the change of corresponding NDVI values from three consecutive images into the short-term change detection, the effect could be reduced. Similarly, Du et al. (2024) employed an empirical relationship between NDVI and backscatter differences to estimate near-surface soil moisture at 100 m resolution based on an adapted change-detection method using Sentinel-1 and Sentinel-2 data. Mengen et al. (2023) used a vegetation-related detrending of the corresponding backscatter ratios by regression with the corresponding absolute backscatter values on a pixel basis. Assuming that the difference between bare soil and vegetated conditions is directly reflected in the strength of the backscatter signal in agricultural land, while the changes in soil moisture are similar under both conditions, the linear trend between the change in backscatter and absolute backscatter was removed from the time series before applying the short-term change detection method.

Finally, the method lies in its reliance on relative dynamics, such as ratios, rather than absolute signal level. This requires an absolute reference value to obtain absolute soil moisture levels. This is typically achieved through the calibration of Sentinel-1 data at low resolution (Balenzano et al., 2021b) or by using external sources, which may include field capacity data from hydrological models (Mengen et al., 2023), soil moisture from *in situ* measurements (Palmisano et al., 2020) or the SMAP mission (Ouellette et al., 2017; Zhu et al., 2022b). Uncertainty in the chosen reference value, for example due to spatial mismatch of the external input data, can lead to under- or over-estimation of the soil moisture estimates.

3.4. AI-based techniques

The use of AI techniques to retrieve near-surface soil moisture from Sentinel-1 products dates back to almost the same era when the Sentinel-1 satellites were launched in 2014 and 2016 (Potin et al., 2016), as AI techniques had already proven to be excellent solutions to challenges comparable to soil moisture retrieval from Sentinel-1 products by that time. The strength of AI techniques lies in their ability to recognize data-driven relationships between different variables within the Earth system without the need for *priori* assumptions or process formulations. In other words: unlike the previously mentioned near-surface soil moisture retrieval methods, AI techniques are data-driven, i.e., they learn soil moisture dynamics solely from the input data as they combine various relevant input features, e.g., brightness temperature, SAR backscatter, sensor characteristics, geographic information, and meteorological variables (Singh and Gaurav, 2023) to map the output, namely near-surface soil moisture here. Fig. 7 provides an example flowchart of using AI technique for near-surface soil moisture mapping using back-scatter data. Initial AI applications for near-surface soil moisture extraction from Sentinel-1 data focus on adapting existing machine learning algorithms (e.g., support vector machines, SVMs, random forests, RFs, and artificial neural networks, ANNs) to specifics of SAR data (Singh and Gaurav, 2023). The ability of AI to improve retrieval accuracy has been demonstrated through studies in complex environments where vegetation and surface conditions remain a challenge (Cho et al., 2024; Rahmati and Montzka, 2024; Lakra et al., 2025; Xie et al., 2025). This is because AI techniques, especially deep learning and machine learning, have a great capacity to efficiently handle large and complex data sets. Among machine learning methods, ANNs, particularly multi-layer perceptrons (MLPs), stand out for their ability to model the nonlinear relationships among various input variables such as SAR data, topography, soil, and climate (El Hajj et al., 2016; Santi et al., 2016; Santi et al., 2020; Chung et al., 2022). These models utilize a layered architecture where neurons learn the weighted representation of input

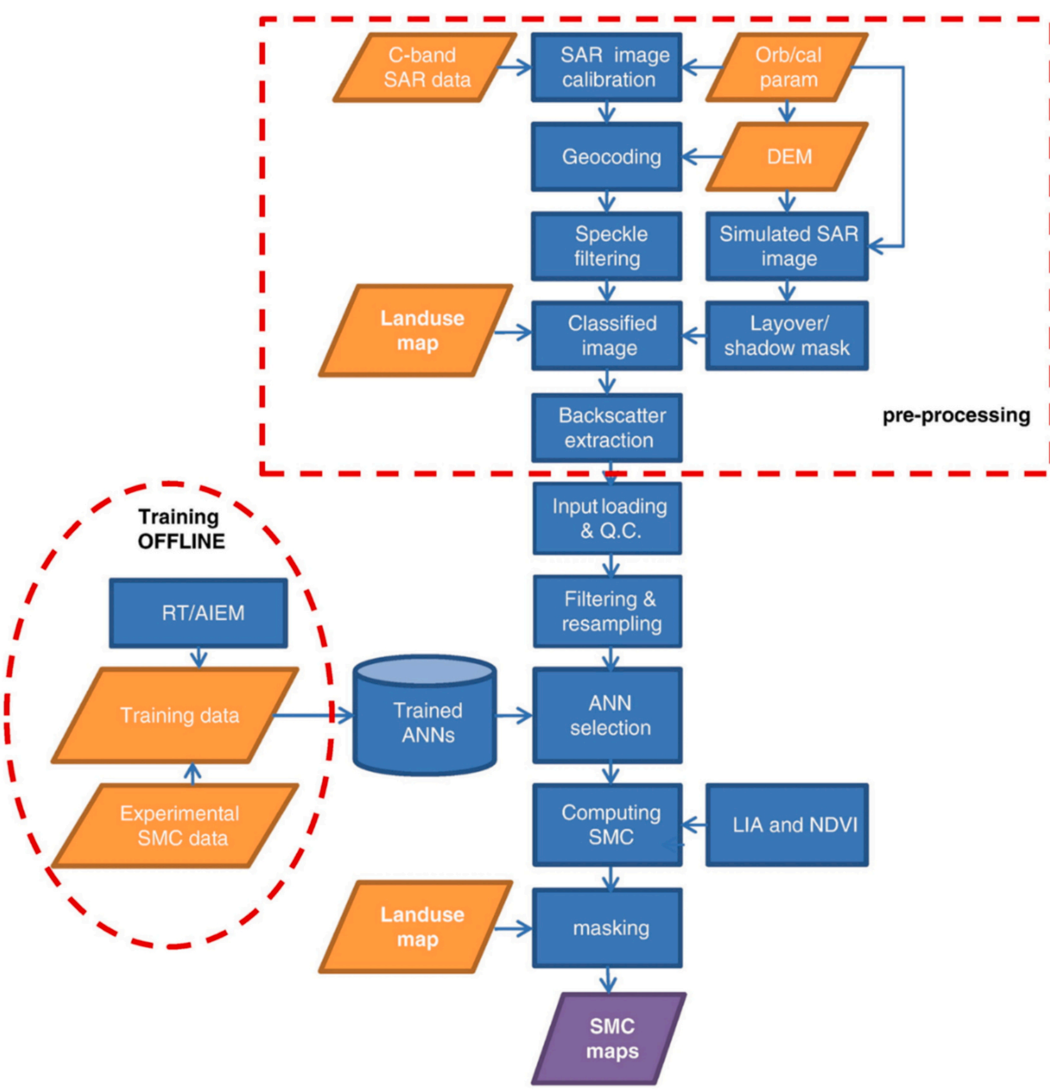

Fig. 7. An example of AI-based retrieval (e.g., ANN algorithm) for soil moisture retrieval.

variables, thus capturing those complex interactions that may not be captured by conventional statistical approaches.

The most important advantage of AI techniques (e.g., ANNs) compared to the other methods mentioned above for retrieving near-surface soil moisture from space observations (e.g., Sentinel-1) is the substantially lower computing time required during the prediction phase (Paloscia et al., 2013). This is of relative importance insofar as the AI technique is particularly suitable for deriving near-real-time and operational near-surface soil moisture products, which can be obtained from a sufficiently robust and representative set of samples in the training phase, due to the lower computing time (Paloscia et al., 2013). The effectiveness of the AI techniques with extremely promising performances (Paloscia et al., 2013) was also proven in challenging operating conditions such as near-surface soil moisture retrieval from remote sensing data in a mountainous area like in the Italian Alps (Paloscia et al., 2010).

Recent developments in deep learning have further expanded the predictive capability of AI techniques. Deep learning models are particularly innovative for advanced automatic feature extraction from raw data, handling problems related to high-dimensional data, and finding complex nonlinear relationships. It is already observed that, for example, convolutional neural networks (CNNs) are very efficient in predicting spatial patterns of soil moisture from Sentinel-1 data (Hegazi et al., 2021). Liu et al. (2021), as another example, examined the fusion of Sentinel-1 SAR and Sentinel-2 optical data via methods such as SVMs, generalized regression neural network, and CNNs and showed that CNNs, when optimized with suitable feature combinations, substantially improved the retrieval accuracy of near-surface soil moisture. Similarly, Wang et al. (2023a) showed that the performance of CNNs on integrated Sentinel-1 and Sentinel-2 data for application in agricultural soil moisture retrieval was highly accurate.

Long short-term memory (LSTM) neural networks, as the state-of-the-art of the deep learning models, have also seen great success in the analysis of temporal datasets. These models leverage time-series dependencies to capture the dynamic behavior of soil moisture as a function of time. For instance, Wu et al. (2024) used LSTMs to forecast the soil moisture at varied depths in one large-scale citrus orchard and demonstrated exceptional performance on various multi-temporal data. In another study, Celik et al. (2022) combined Sentinel-1 SAR with SMAP data and climate features, including soil texture and topographic features, to develop an LSTM-based model for daily near-surface soil moisture prediction, highlighting its potential application in agricultural and hydrological applications.

Various use cases of AI techniques on the topic of soil moisture retrieval from Sentinel-1 products could be demonstrated here. For example, several attempts have already been made to use the capabilities of AI techniques to convert surface reflectance into usable near-surface soil moisture data. As a successful showcase, Rabiei et al. (2021) applied three different machine learning algorithms — an MLP, a CNN, and linear regression — to extrapolate near-surface soil moisture estimates from Sentinel-1 and Sentinel-2 products. The results underlined the superiority of CNN and attributed its superior performance to its skillful understanding of spatial relationships and its improved representation of two-dimensional images.

Another use case for AI techniques in this area is the inversion of analytical and semi-empirical forward models and the subsequent determination of near-surface soil moisture. As an example of this type of application, Paloscia et al. (2013) proposed an algorithm based on the inversion of an analytical electromagnetic model by an ANN — feed-forward MLP — to derive estimates of near-operational near-surface soil moisture at a spatial resolution of 1 km or less from the Sentinel-1 mission. To this end, they trained the ANN using the backscatter data simulated by the Advanced IEM (Wu and Chen, 2004) and Oh models (Fung, 1994; Oh et al., 2002) at different polarizations and incidence angles to predict soil parameters (including near-surface soil moisture) as outputs. Finally, they used the trained ANN together with SAR data collected by the Sentinel-1 mission to map near-surface soil moisture. As another example, Mirsoleimani et al. (2019) used Sentinel-1 SAR data and the modified Dubois model in a neural network for near-surface soil moisture inversion across agricultural fields in Iran and found during analyses that the accuracy between simulated and Sentinel-1 backscatter was highest for VV polarization (compared to VH polarization). Li et al. (2020) employed Sentinel-1 SAR data to evaluate the performance of the modified Dubois model, proposed by Baghdadi et al. (2016), and a multiple linear regression model in comparison to a neural network model and proved the ability of all three models to reproduce Sentinel-1 SAR backscatter sufficiently enough for near-surface soil moisture inversion. Further, Santi et al. (2018) employed Sentinel-1 SAR data together with passive SMAP and AMSR2 radiometer observations in an artificial neural network, that includes the Oh and the WCM models, for estimating near-surface soil moisture across the Po Valley, Italy (Santi et al., 2018).

To mitigate the effects of inherent model and measurement inaccuracies, the ensemble machine learning paradigm was also integrated into the domain of near-surface soil moisture retrieval in multi-SAR missions (Zhu et al., 2020). In ensemble learning, a repertoire of alternative models is systematically developed to accomplish the same task, with the fusion of their outputs - consisting of classifiers and predictors - representing the result (Zhu et al., 2020). There are a variety of ensemble methods for different applications, differing primarily in the methods used to create diversity between models. Such diversity can be created by using different subsets of input data, such as bootstrap aggregation (Breiman, 1996), or by injecting variability into model parameters or structures, such as in the random forest approach (Breiman, 2001).

Despite their apparent success, AI-based algorithms for near-surface soil moisture estimation from Sentinal-1 data encounter some limitations. First, they typically need large, diverse, and high-quality training sets, which are not always available, particularly in data-sparse regions (Hemmati and Sahebi, 2024; Zhu et al., 2025). This may result in overfitting and bad generalization of models to other application domains, especially when applied to regions with sparse training data. More specifically, Zhu et al. (2025) argue that current expectations of SAR near-surface soil moisture estimates via machine learning, while promising, might be overstating the performance and so will need more robust approaches for scenarios where only a few ground measurements are available. Second, they are black boxes, making it unclear how retrieval results are connected to underlying physical scattering processes, and reducing the confidence that users can have in operation (Abbes et al., 2024). Third, while AI models can be computationally efficient in prediction, they are costly in terms of computational resources for training, thus limiting the application of AI models in any closed-loop near-real-time applications. Fourth, input data quality and representativeness (e.g., errors in backscatter calibration, influence of vegetation or ancillary data sets) can be propagated through the models, leading to uncertain estimates. Taken together, these issues demonstrate the necessity for hybrid approaches that combine physical knowledge with data-driven learning, relying on well-defined training and validation datasets, and developments in explainable AI to simultaneously enhance robustness and transparency of AI-based retrieval methods. In this regard, most recently, To handle the data sparsity problem, Zhu et al. (2024) and Hemmati and Sahebi (2024) introduced the concept of transfer learning, pretraining the deep learning model on global datasets with subsequent fine-tuning using local field data. This strategy increased the accuracy of retrieving soil moisture on the local scale when comparing it to the usual methods. This is an innovative approach showing the power of transfer learning to expand the applications of deep learning in data-sparse regions, enabling further investigation into how to overcome data limitations without sacrificing effectiveness in models.

The above shows the great potential of AI-based approaches for the advancement of soil moisture retrieval from Sentinel-1. The present review of literature shows that significant advances have already been made. However, continued research on algorithms, data assimilation, and operational implementation will further enhance the quality and applicability of Sentinel-1 soil moisture products. These state-of-the-art methodological advancements are therefore summarized as follows, and will be discussed further in section 10 where possible strategies for future research and exploration include:

I. **From shallow to deep architecture**: The transition from shallow machine learning models to deep learning with architecture such as CNNs has greatly improved the extraction of complex features from SAR data.
II. **Development of specialized architecture**: The unique characteristics of the data acquired by Sentinel-1 and soil moisture retrieval have led researchers to identify and develop various specialized deep learning architectures suitable for this task.
III. **Integration of multi-source data**: AI-based frameworks are mature enough to integrate data from multiple sources (e.g., Sentinel-1, Sentinel-2, weather data, and *in situ* measurements) to provide robust and accurate estimates of near-surface soil moisture.
IV. **Focus on interpretability**: Although deep learning methods tend to have high accuracy, the black-box nature of deep learning makes it difficult to interpret the results. Technically sophisticated methods to explain deep learning-driven models would be beneficial to better identify how SAR reflects near-surface soil moisture properties in terms of the underlying relationships.
V. **Leveraging transfer learning**: Transfer learning methods, using models that have already been trained on large datasets and can be adapted for retrieving near-surface soil moisture, are powerful techniques to enhance model performance, especially in regions where no training data is available.

3.5. Hybrid methods

Hybridization of traditional near-surface soil moisture retrieval methods, including physics-based, semi-empirical, change detection and AI approaches, is sometimes used to take advantage of their complementarity. Currently, hybridization is limited to AI models trained on the outputs of physical or semi-empirical forward models, e.g., neural networks training on backscatter of simulated physical models, such as IEM or Dubois (Paloscia et al., 2013; Mirsoleimani et al., 2019), or data fusion approaches, e.g., integrating Sentinel-1 retrievals with SMAP data in ANN frameworks (Santi et al., 2021; Arab et al., 2024), or Sentinel-1 with Sentinel-2 or SMAP in deep learning models (Liu et al., 2021; Singh and Gaurav, 2023). A promising approach is the development of a knowledge-guided deep learning method that integrates physical or semi-empirical models into data-driven models to estimate near-surface soil moisture using Sentinel-1 SAR data. These physics-informed, data-driven models (also known as knowledge-guided data-driven approaches) typically modify the dual-component loss function to leverage the capacity of the data-driven model to capture spatiotemporal dependencies, while maintaining physical consistency by including an additional penalty component for physical- or semi-physical model error in the loss function (Yu et al., 2025a). Since hybridization is not a fundamentally novel approach, but rather a combination of existing methods, like those discussed above, and each form of hybridization is indirectly covered in other sections, this review does not delve deeper into this methodology for the sake of brevity. However, in short, although hybrid methods should enhance robustness, generalization, and exploitation of multi-sensor data, they are still complex in design, data hungry, and mostly validated on case studies, sparking questions about scalability and operational exploitation.

3.6. Beyond Backscattering intensity: Sentinel-1 InSAR Coherence and Phase Closure

Interferometric observables such as InSAR coherence and closure phase have recently emerged as alternative means of estimating near-surface soil moisture due to their high sensitivity to dielectric properties influenced by water content (Brake et al., 2013; Zwieback et al., 2015; De Zan and Gomba, 2018). Specifically, InSAR coherence is a measure of the similarity in the reflective ground properties between two SAR acquisitions, which can change due to variations in near-surface soil moisture (De Zan et al., 2013). Phase closure refers to the phase resulting from the circular combination of three multi-looked interferograms derived from three SAR acquisitions (e.g., the sum of phase triplet φ_{12}, φ_{23}, and φ_{31}) (De Zan et al., 2015; Wig et al., 2024).

InSAR coherence is a similarity-metric between the amplitude and interferometric phase of two SAR acquisitions and describes the quality of the InSAR phase information. InSAR coherence can be affected by several factors, such as ground displacements, soil roughness changes, vegetation growth, permanent landscape changes and near-surface soil moisture variations (Zwieback et al., 2017). Numerous studies have demonstrated the connection between InSAR coherence from Sentinel-1 and near-surface soil moisture in various environments including arid (Karamvasis and Karathanassi, 2023), hyper-arid and post-wildfire peatland regions (Hrysiewicz et al., 2023).

Scott et al. (2017) were able to calculate the InSAR coherence component due to near-surface soil moisture change by examining the temporal evolution of InSAR coherence before and after major rain events in hyper-arid regions in Chile and Argentina with little to no vegetation. Bürgi and Lohman (2021) compared the InSAR coherence-based near-surface soil moisture proxies with other soil moisture datasets and highlighted the advantage of the higher spatial resolution that InSAR coherence can offer compared to other near-surface soil moisture products, over hyper-arid regions. Jordan et al. (2020) effectively distinguished the InSAR coherence component due to near-surface soil moisture changes from the other components (e.g. permanent coherence loss due to material movement) at a similar non-vegetated region in the Atacama Desert of Chile. Additionally, Lohman and Bürgi (2023) demonstrated that establishing a relationship between InSAR coherence and near-surface soil moisture can be used to improve the performance of other methods that exploit interferometric observations (e.g. ground deformation studies).

Phase closure is also a promising interferometric observable that can be exploited in near-surface soil moisture estimation approaches. Initially, (non-zero) phase closure was identified as an error source causing systematic bias in multi-looked SAR interferometry for ground deformation estimation (De Zan et al., 2015; Ansari et al., 2020). Later, non-zero phase closure has been associated with physical processes such as near-surface soil moisture changes, vegetation growth, and vegetation moisture changes (De Zan et al., 2013; De Zan et al., 2015; De Zan and Gomba, 2018; Zheng et al., 2022; Wig et al., 2024). The main advantage of using phase closure is that it is invariant to atmospheric, topographic effects, and ground displacements (Zwieback et al., 2017; De Zan and Gomba, 2018; Michaelides, 2020) and contains information about soil/vegetation moisture and scattering mechanism changes (e.g. vegetation growth).

One of the most important models that has been developed for near-surface soil moisture estimation from phase closure and InSAR coherence is the analytical scattering model introduced by (De Zan et al., 2013). This model was designed for bare lands and assumes a uniform soil moisture profile and scattering density with depth. Even though this model was initially designed and validated for L-band SAR data (De Zan et al., 2013; De Zan and Gomba, 2018), there are studies that have applied this model to C-band Sentinel-1 data (Palmisano et al., 2022; Karamvasis and Karathanassi, 2023). Moreover, other more sophisticated models accounting for variations in the refraction angle of the microwave radiation (Michaelides, 2020) and for variability in near-surface soil moisture across multiple discrete soil layers (Zheng and Fattahi, 2024) have been introduced.

Despite the promising results of near-surface soil moisture estimates using InSAR observables, an inherent ambiguity in estimating near-surface soil moisture persists due to the nature of the InSAR observables (Zwieback et al., 2017; De Zan and Gomba, 2018). For instance, identical coherence losses can be caused by either increasing or decreasing near-surface soil moisture. To overcome this limitation, De Zan and Gomba (2018) proposed a method, using L-band SAR data, based on their previously introduced scattering model able to resolve this ambiguity and estimate relative moisture levels. They provided early evidence of phase closure effectiveness in improving the accuracy of near-surface soil moisture estimation. Karamvasis and Karathanassi (2023) adapted this approach for Sentinel-1 data, by incorporating external meteorological information and backscatter information, accompanied by open-source software that can help the community to explore the potential of InSAR observables for soil moisture studies (Murphy et al., 2025).

Wig et al. (2024) proposed an alternative near-surface soil moisture estimation model based on a detrended time series of cumulative sum of phase closure over time. By exploiting Sentinel-1 data, they discovered good anticorrelation between time series of near-surface soil moisture and detrended cumulative phase closure over sites in Oklahoma. Similarly, Zheng and Fattahi (2024) observed that positive near-surface soil moisture anomalies over arid regions produced positive step-changes in cumulative closure phase time series, and negative near-surface soil moisture anomalies over agricultural regions produced negative step-changes in cumulative closure phase time series.

Patterns of phase closure can vary over different land uses, land covers and soil types (Yuan et al., 2024; Zheng and Fattahi, 2024). For example, in vegetated regions, the contribution from vegetation may dominate the near-surface soil moisture contribution to the closure phase, especially using C-band Sentinel-1 data due to its limited penetration. Conversely, in regions with no or low vegetation, the near-surface soil moisture signal may dominate. Even though characteristics of phase closure vary over terrain (Zheng et al., 2022) better performance has been reported in highly vegetated regions (e.g. forests) using L-band (De Zan and Gomba, 2018) as well as C-band Sentinel-1 data (Wig et al., 2024), compared to grasslands and agricultural fields, indicating a high sensitivity of closure phases to tree moisture. Given that vegetation moisture is correlated with soil moisture, additional L-band InSAR data from recent and upcoming L-band SAR missions — e.g. NASA-ISRO SAR (NISAR; Lal et al., 2023) (NISAR; Lal et al., 2023), Radar Observing System for Europe in L-band (ROSE-L; Pierdicca et al., 2019) — will contribute to improving the understanding of a vegetation contribution to phase closure.

Overall, the main advantage of using InSAR coherence and phase closure for near-surface soil moisture estimation is the high sensitivity of interferometric measurements to water content variations (De Zan, 2024). InSAR observables can contribute to near-surface soil moisture monitoring over dry soils where backscattering approaches may struggle due to anomalies caused by subsurface scattering (Ullmann et al., 2023). This is because dry near-surface soil conditions have high InSAR coherence, indicating high-quality interferometric observables (e.g. phase closure).

Conversely, approaches based on interferometric observables also have several limitations. First, temporal changes related to vegetation growth, vegetation moisture and varying scattering properties (due to material movement) significantly affect interferometric observables making it challenging to estimate the contribution from the near-surface soil moisture variations. Second, these approaches cannot provide any estimations in case of loss of coherence (e.g. rapid terrain changes caused by heavy rain/wind events or by anthropogenic activity). Lastly, interferometric (and backscattering) observables provide estimates corresponding to different soil depths, depending on the soil moisture level and the associated penetration ability of the SAR signal.

4. Validation strategies

Validating Sentinel-1-derived near-surface soil moisture retrievals remains a significant challenge due to the differences in scale between ground measurements and SAR footprints, and the variety of retrieval methods. Various strategies have been employed for this purpose thus far, including:

- **In situ networks and field campaigns**: Dense ground-based networks such as the International Soil Moisture Network (ISMN; Dorigo et al., 2021) and cosmic-ray neutron probes (Zreda et al., 2012), as well as Integrated Carbon Observation System (ICOS; Heiskanen et al., 2022) yield high-quality reference data, which can be used to validate Sentinel 1 soil moisture estimation (e.g., Bulut et al., 2024). However, they often have sparse coverage, either are at point scale (e.g., ISMN) or have a typical footprint radius of between 150 and 250 meters (e.g., cosmic-ray probes; Montzka et al., 2017), so extensive field experiments such as the Soil Moisture Active Passive Experiments (SMAPEx; Panciera et al., 2013) in southeastern Australia and the SMAP validation experiment (SMAPVEX; Colliander et al., 2014; Chan et al., 2016) in the USA are essential for planned validation.
- **Cross-sensor comparisons**: Retrievals from Sentinel-1 have been often compared with those from coarse-scale passive microwave missions (e.g., SMAP, Entekhabi et al., 2010; and SMOS, Kerr et al., 2010) and active missions (e.g., ASCAT, Bartalis et al., 2007; Wagner et al., 2013). While these comparisons provide a useful spatial benchmark, differences in sensor frequency, penetration depth, and resolution can hinder meaningful interpretation.
- **Triple collocation and model-based validation**: Statistical methods such as triple collocation (Scipal et al., 2008; Gruber et al., 2016) allow random uncertainties to be estimated without truth data and have been used extensively for passive microwave data (SMAP, SMOS, ASCAT) assessment (Xie et al., 2022; Zhu et al., 2022a); the approach can also be applied for Sentinel-1 assessments. Data assimilation studies (e.g., Cenci et al., 2017b; Rojas-Munoz et al., 2023) serve as an indirect validation method that assesses consistency with land surface models.

Despite these developments, there is currently no universally adopted standardized validation protocol, although good practice guidelines do exist (e.g., see Soil Moisture LPV Focus Area at https://lpvs.gsfc.nasa.gov/). Therefore, there is still a need for standardization of reference datasets, metrics and reporting.

5. Sources of uncertainty

Sources of uncertainty in Sentinel-1 near-surface soil moisture retrievals are diverse and depend on the retrieval scheme and environmental setting, including:

- **Algorithmic uncertainties**: Inverting the physical models is intrinsically ill-posed, particularly with single polarization Sentinel-1 data (Kim et al., 2012a; Benninga et al., 2022). Semi-empirical approaches are faced with a lack of data transferability between field locations (Baghdadi et al., 2016). The AI methods are accurate but not interpretable and can easily be overfit when data for training is limited (Zhu et al., 2025).
- **Uncertainties in measurements**: Errors are incurred from sensor calibration, the array of incidence angles, and speckle noise. The differences between ascending and descending passes also make consistency challenging (Kim et al., 2025).
- **Environmental drivers**: The dynamics in vegetation coverage, the freeze–thaw transition status, and the topography also affect backscatter irrespective of near-surface soil moisture conditions (Lievens et al., 2017a; Liao et al., 2021). InSAR coherence and phase

unwrapping approaches suffer from ambiguity in identifying degradation of coherence due to the increase or decrease of near-surface soil moisture (De Zan and Gomba, 2018).

Quantifying such uncertainties and their impact on downstream applications (hydrological modelling, agricultural monitoring) is still an open area of research.

6. Combination of Sentinel-1 with other sensors

The ill-posed nature of near-surface soil moisture inversion from Sentinel-1 data can be addressed by integrating data from additional sensors to improve both the accuracy and the stability of the retrievals. The most straightforward method is the integration of SAR data from multiple missions operating at different frequencies, incidence angles, and polarizations (Zhu et al., 2019). The varying radar configurations provide more information in relation to the surface roughness and vegetation parameters (Zribi et al., 2014), and so the number of independent observations can be larger than that of the unknowns required by a scattering model or model combination (Ulaby et al., 2014), especially for bare soil surfaces. Near-surface soil moisture and other surface parameters can thus be retrieved using multi-SAR data directly (Bindlish and Barros, 2000; Zhu et al., 2019). However, few studies have used Sentinel-1 in combination with other SAR missions in real-world applications (Zhang et al., 2018), as it is challenging to collect near-coincident multi-SAR data due to the lack of historical multi-frequency SAR missions. For overpass data collected with time gaps, an assumption of time-invariant surface conditions, or at least time-invariant roughness and vegetation, is required to avoid having fewer SAR observations than unknowns. Fortunately, an increase in open-access SAR observations is expected soon, e.g., NISAR and ROSE-L. Importantly, multi-frequency SAR datasets collected from world-wide airborne campaigns (Ye et al., 2020; Mengen et al., 2021) have provided ample data to support the development and validation of multi-frequency algorithms.

Another challenge for the direct inversion of multi-SAR data is the imbalance of scattering model uncertainty for different radar configurations (Mancini et al., 1999; Choker et al., 2017), along with the observation biases observed among different satellites of similar radar configurations (Pettinato et al., 2013). For example, the biases of the IEM measured in a laboratory experiment ranged from 1 to 5 dB (Mancini et al., 1999), while backscatter measured by COSMO-SkyMed was 2-5 dB lower than that of TerraSAR-X from similar observation geometries (Baghdadi et al., 2014). A global calibration of scattering models is thus required for all potential radar configurations to achieve an acceptable near-surface soil moisture estimation (Zhu et al., 2019). Alternatively, the effect of uncertainties can be partly removed using a stochastic ensemble framework, such as bootstrapping where the multi-SAR dataset is divided into different subsets, and corresponding multiple moderate retrievals are made using noisy data and poorly calibrated scattering models, followed by an ensemble average that is less vulnerable to random noise, calibration errors and individual-model biases (Zhu et al., 2020). A comprehensive evaluation using both local and global datasets has demonstrated that ensemble retrievals generally outperform non-ensemble approaches, with reductions in RMSE ranging from 0.004 to 0.014 m^3/m^3, and improvements in correlation coefficients from 0.01 to 0.16 m^3/m^3 (Zhu et al., 2023). Compared to direct inversion of multi-SAR data, sequential (or stepwise) inversion enables more flexibility. For example, Hamze et al. (2021) estimated surface RMS height from L-band ALOS PALSAR-2, which was then combined with Sentinel-1 observations for soil moisture estimation. This approach enables a more flexible integration of SAR data with different configurations and leverages the strengths of each sensor type.

The integration of Sentinel-1 and optical/thermal data has gained more acceptance than the multi-SAR retrieval approach, because optical data provide a more direct description of vegetation and because it is much easier to collect coincident SAR and optical data. In most cases, optical and thermal data serve as auxiliary inputs to provide parameters for scattering models or vegetation correction, as discussed in earlier sections.

Machine learning, especially deep learning, provides a promising alternative of combining Sentinel-1 with other data sources, because of its capability for dealing with multimodal data without requiring a physical scattering model. Various multi-sensor data have been used together with Sentinel-1 in soil moisture retrieval (Paloscia et al., 2013; Santi et al., 2018; Madelon et al., 2023), such as Sentinel-2, AMSR2 and SMAP. Feature selection was found to be a crucial pre-step for the combination of multi-sensor data (Liu et al., 2020; Efremova et al., 2021). Additionally, more recent studies have proposed cross-resolution (Zhu et al., 2024) and multi-resolution (Liu et al., 2022) deep learning methods to fully utilize the multi-sensor data from different scales and regions. As discussed, the main limitation of such methods is the heavy dependence on training data, with poor generalization capabilities over areas with few observations.

Downscaling of passive microwave derived soil moisture such as from SMAP or SMOS through the fusion with Sentinel-1 is a promising integration method for global soil moisture mapping with high spatial and temporal resolution. For example, NASA disseminates an operational, 3-km resolution, global SMAP/Sentinel-1 soil moisture product (Das et al., 2019; Das et al., 2020). The spatial resolution of SMAP/Sentinel-1 soil moisture products has been further enhanced to beyond 1 km (Moghaddas and Tajrishy, 2025) and their performance evaluated under various surface conditions (Schmidt et al., 2024). Moreover, Azimi et al. (2020) proposed a fusion method to combine ASCAT soil moisture at 25 km and the 1 km Sentinel-1 soil moisture to a daily global product, with the spatial details being mainly from the Sentinel-1 soil moisture product. Refer to Sabaghy et al. (2018) and Peng et al. (2017) for comprehensive reviews about the downscaling of SMAP and/or SMOS using radar and other data.

7. Sentinel-1 soil moisture data assimilation

Data assimilation techniques, such as particle or Kalman filtering, can fuse surface soil moisture retrievals (or microwave backscatter observations) from Sentinel-1 with estimates from hydrological or land surface models while accounting for uncertainties in the observed and simulated data (Reichle, 2008; De Lannoy et al., 2022; Kumar et al., 2022). In the assimilation system, the observations provide information that can correct errors in the hydrological or land surface models' meteorological forcing, parameters, or parameterizations; conversely, the model offers a spatiotemporally continuous framework that complements the sparse or noisy nature of the observations. The result is a superior near-surface soil moisture estimate that better represents the true soil moisture state.

The assimilation of near-surface soil moisture retrievals at high spatial resolution (1 km or finer) into hydrological or land surface models, as provided by Sentinel-1, offers numerous potential advantages (Peng et al., 2021). High-resolution soil moisture estimates provide detailed spatial information, which is crucial for enhancing flood forecasts in smaller catchments (Pauwels et al., 2001), weather forecasts through coupled land-atmosphere models at convection-permitting scales (Prein et al., 2015), and crop growth and irrigation modeling (Modanesi et al., 2022).

Like near-surface soil moisture retrievals from ASCAT or SMAP, retrievals from Sentinel-1 are subject to systematic differences with the corresponding land surface model estimates, thus requiring bias correction techniques that align the observations with the land surface model space before assimilation (Reichle et al., 2004; Koster et al., 2009). Consequently, Sentinel-1 soil moisture assimilation studies have employed cumulative density function (CDF) matching (Cenci et al., 2017b), triple colocation-based matching (Azimi et al., 2020), seasonal matching (Lievens et al., 2017b), or calibrated observation operators

(Rains et al., 2021; Bechtold et al., 2023) to overcome these systematic differences. However, several data assimilation studies have indicated that bias correction becomes more complex at high spatial resolution because the retrieval biases exhibit greater variation over time, particularly in cases such as crop rotation at the scale of individual fields (Modanesi et al., 2022; Bechtold et al., 2023).

Data assimilation studies using near-surface soil moisture retrievals derived from, or enhanced by, Sentinel-1 have highlighted notable advantages over coarser-scale retrievals but also underscore significant challenges. For example, Azimi et al. (2020) pointed out that assimilating higher spatial resolution near-surface soil moisture retrievals obtained by merging ASCAT and Sentinel-1 observations provided relatively little benefit compared to only assimilating the coarser-resolution ASCAT retrievals. This limitation was partly attributed to the noise in Sentinel-1 retrievals, particularly in complex and vegetated terrains.

The critical role of mitigating vegetation effects in near-surface soil moisture retrievals and addressing biases between observations and models was demonstrated by Cenci et al. (2017b), who assimilated synthetic SAR near-surface soil moisture retrievals after CDF matching to the model climatology with and without vegetation correction, together with an ancillary vegetation descriptor from optical remote sensing.

Rojas-Munoz et al. (2023) showed that the assimilation of Sentinel-1 soil moisture retrievals after seasonal bias removal into the Interactions between Soil, Biosphere, and Atmosphere (ISBA) land surface model mainly improved soil moisture estimates over croplands; additional improvements were obtained through additional assimilation of LAI observations from optical satellite data.

Removing the systematic differences between the observed and modeled soil moisture can inadvertently eliminate valuable signals such as irrigation, which may be present in the observations, when the process is not represented in the model (Kumar et al., 2015). Motivated by this concern, Laluet et al. (2024) opted to forgo bias correction during Sentinel-1 assimilation, which resulted in improved irrigation simulation compared to model-only simulations.

Addressing the inconsistencies between retrieved and modeled near-surface soil moisture in data assimilation poses significant challenges. Alternatively, directly assimilating Sentinel-1 backscatter observations via a calibrated observation operator might allow for better disentangling of the combined soil moisture and vegetation information, either by updating soil moisture alone (De Lannoy et al., 2024) or by simultaneously updating soil moisture and vegetation (Modanesi et al., 2022; Bechtold et al., 2023; de Roos et al., 2024); so far, positive impacts have only been reported for soil moisture. In these studies, the WCM (section 3) was employed as the observation operator, calibrated for each grid cell using modeled soil moisture and vegetation data as inputs. However, vegetation structure violates the "water cloud" assumption of the WCM (Schlund and Erasmi, 2020), which prompted the exploration of machine learning-based observation operators such as Support Vector Regression (SVR). Using SVR as the observation operator achieved closer fits between the simulated and observed backscatter but ultimately did not yield more accurate soil moisture assimilation estimates (Rains et al., 2021; de Roos et al., 2023).

Finally, another key limitation affecting the impact of Sentinel-1 observations in data assimilation studies is their relatively low temporal resolution compared to coarse-scale alternatives like ASCAT. A potential solution is to jointly assimilate observations from, say, Sentinel-1, ASCAT, and NISAR. Such multi-sensor assimilation will allow more frequent updates and thus benefit applications that critically depend on high-frequency observations like irrigation modeling (Rabiei et al., 2021; Jalilvand et al., 2023; Busschaert et al., 2024) and flood forecasting for small, fast-responding basins (Azimi et al., 2020).

8. Estimating root-zone soil moisture from Sentinel-1 observations

A key objective in many soil moisture assimilation applications, including most of the aforementioned Sentinel-1 assimilation studies (see section 7), is to improve knowledge of soil moisture in the top ~100 cm of the soil, which is often referred to as "root-zone" soil moisture. Knowledge of root-zone soil moisture is critical for applications such as estimating evapotranspiration and irrigation, for predicting crop growth, and for monitoring and forecasting runoff generation and subsequent flooding hazards (Mao et al., 2019).

Root-zone soil moisture estimates have been obtained from Sentinel-1 near-surface soil moisture in different ways. Applying an exponential filter to near-surface soil moisture (Wagner et al., 1999b; Albergel et al., 2008) can yield a crude estimate of root-zone soil moisture, given an appropriate filtering time scale. In fact, Cenci et al. (2017b) have applied such an exponential filter before assimilating the Sentinel-1 observations into their hydrological model, whose only soil moisture prognostic variable is a "root-zone saturation degree".

Several of the aforementioned Sentinel-1 near-surface soil moisture assimilation studies have used land surface models with multiple soil moisture layers, including the NASA Catchment model (Lievens et al., 2017a), Noah-MP (e.g., Bechtold et al., 2023), the Variable Infiltration Capacity (VIC) model (Jalilvand et al., 2023), and ISBA (Rojas-Munoz et al., 2023). In these studies, an observation operator relates the assimilated Sentinel-1 near-surface soil moisture or backscatter to the simulated near-surface soil moisture for computation of the observation-minus-forecast differences that drive the soil moisture analysis. The analyzed state vector can then consist of just the model near-surface soil moisture variable (e.g., De Lannoy et al., 2024; de Roos et al., 2024), along with other variables such as vegetation. In this case, information from the assimilated Sentinel-1 observations gets propagated to the deeper soil moisture layers via the model physics in subsequent model time steps. More commonly, several of the soil moisture layers of the model are included in the analysis update (e.g., Lievens et al., 2017a; Modanesi et al., 2022; Bechtold et al., 2023; Rojas-Munoz et al., 2023). In this case, the analysis increments are proportional to diagnosed or prescribed error cross-correlations between the near-surface and deeper-layer soil moisture. In both cases, the success of propagating the observational information from the near-surface to deeper layers depends on the strength of the coupling between the near-surface and deeper layers in nature and in the land surface model (Kumar et al., 2009; Chen et al., 2011).

While the assimilation of Sentinel-1 observations generally improves the simulated near-surface soil moisture (section 7), results for the root-zone soil moisture have been mixed. For instance, Lievens et al. (2017a) and Rojas-Munoz et al. (2023) report that the assimilation of Sentinel-1 backscatter observations alone had a mostly neutral or small impact on root-zone soil moisture estimates. These results stand in contrast with the improvements in root-zone soil moisture from the assimilation of SMAP brightness temperature observations (e.g., Reichle et al., 2021), and from the joint assimilation of Sentinel-1 observations and SMAP brightness temperature observations (Lievens et al., 2017a) or LAI observations (Rojas-Munoz et al., 2023).

9. Sentinel-1 soil moisture in action: contribution to hydrology

Soil moisture is a key variable in the partitioning of water fluxes (e.g., precipitation, evaporation and infiltration) between the atmosphere and the land surface, making it essential for hydrological applications such as flood forecasting, drought monitoring and water resources management. The Sentinel-1 satellite mission has provided the first comprehensive dataset of near-surface soil moisture at high resolution in both time and space, enabling a wide range of new applications in hydrology, agriculture, and disaster risk management (e.g., Brocca et al., 2023a). Table 3 offers a summary of existing Sentinel-1-derived soil

Table 3
Sentinel-1-based near-surface soil moisture products

Product Name	Description	Spatial Resolution	Temporal Coverage	Reference
Copernicus Global Soil Moisture	Provides global soil moisture data derived from Sentinel-1 SAR data, offering information on the relative water content in the soil.	1 km for Europe and 12.5 km for globe	2007 to present	Copernicus Land Monitoring Service
SMAP/Sentinel-1 Soil Moisture	Combines SMAP radiometer observations with Sentinel-1 radar backscatter data to produce global soil moisture maps at higher spatial resolutions.	1 km and 3 km	March 2015 to present	(Das et al., 2020)
Sentinel-1 Surface Soil Moisture	Demonstrates Sentinel-1's capability to support systematic surface soil moisture product generation at high resolution.	1km	2015-2018	(Balenzano et al., 2021b)

Table 4
Open access tools for retrieving near-surface soil moisture from Sentinel-1 data

Tool name	Description	Access link
INSAR4SM	A tool leveraging InSAR coherence for soil moisture estimation using Sentinel-1 data.	GitHub - INSAR4SM
Soil_Moisture	A Python-based tool for estimating soil moisture using Sentinel-1 data.	GitHub - Soil_Moisture
PySMM	A Python package for soil moisture mapping from Sentinel-1 data.	PySMM Documentation
ESA SNAP software	The official and freely available ESA SNAP software providing multiple toolboxes, one specifically for Sentinel, where processing chains for soil moisture estimation are implemented.	STEP - SCIENTIFIC TOOLBOX EXPLOITATION PLATFORM
SNAPISTA	A GPT wrapper for Python to use SNAP in Python.	GitHub - Soil_Moisture
mlhrsm	An open-sourced R package, which can be used to generate Machine Learning-based high-resolution (30 to 500 m, daily to monthly) soil moisture maps across the contiguous USA at 0–5 cm and 0–1 m using Sentinel-1 SAR data as input	GitHub - MLHRSM (Peng et al., 2024)
S2MP (Sentinel-1/Sentinel-2-Derived Soil Moisture Product) algorithm	An algorithm to retrieve SM at the surface at the agricultural plot scale using the Sentinel-1 backscattering coefficients and Sentinel-2 NDVI, as input variables of a neural classifier trained on simulations of the Water Cloud Model.	Available upon request from authors (Madelon et al., 2023)

moisture products and their spatial resolution, temporal extent, and notable references. The open-source tools provided in Table 4 also utilize Sentinel-1's SAR capabilities to provide valuable soil moisture information for various applications, including hydrological modeling, agriculture, and climate studies.

One of the potential key emerging applications of Sentinel-1 near-surface soil moisture data is (flash) flood forecasting for small basins (Cenci et al., 2017a). Although this field is still developing, early studies have demonstrated the potential of Sentinel-1 near-surface soil moisture to improve hydrological modelling and flood predictions. Azimi et al. (2020) found that the relatively high spatial resolution of Sentinel-1 is not enough on its own for improving flood forecasting in small basins, as the temporal resolution is even more important than spatial resolution to track the fast changes in precipitation and runoff for these basins. Bechtold et al. (2023) demonstrated that the assimilation of Sentinel-1 near-surface soil moisture is beneficial in catchments with strong soil moisture–runoff coupling, as also obtained in earlier assimilation studies with coarse resolution soil moisture data (e.g., Brocca et al., 2010). Alfieri et al. (2021) used several high-resolution satellite products for improving flood prediction in a large river basin in Italy (Po River, 70000 km^2). The use of Sentinel-1 near-surface soil moisture was found to have a limited impact on the simulations with a slight reduction in the modelling performance— Kling Gupta Efficiency (KGE) reduction of 6%—while precipitation was found to be the variable with the greatest impact on flood prediction with changes in the KGE performance of up to 30%. Therefore, the use of Sentinel-1 near-surface soil moisture for improving precipitation (e.g., Filippucci et al., 2022) may be the best solution to maximize the impact of such observations for flood prediction (see e.g., Massari et al., 2018).

Another major area of application is the detection and quantification of irrigation. Numerous studies have leveraged Sentinel-1 near-surface soil moisture data to map irrigation activities (e.g., Dari et al., 2022; Elwan et al., 2022) and to estimate irrigation water use (e.g., Modanesi et al., 2022; Dari et al., 2023a; Zappa et al., 2024), providing valuable insights for water resource management. For instance, Dari et al. (2023a) developed the first high-resolution irrigation water use dataset for three regions, being in Italy, Spain and Australia, by inverting the soil water balance equation; the dataset is available (Dari et al., 2023b) and is being developed for other regions. Modanesi et al. (2022) and Busschaert et al. (2024) developed data assimilation frameworks to assess the value of Sentinel-1 near-surface soil moisture for improving the land surface modelling capabilities to estimating irrigation water use. These studies have demonstrated the effectiveness of satellite-derived near-surface soil moisture in tracking irrigation dynamics, and the scientific community around this topic is growing rapidly with new results and applications (see McDermid et al., 2023 for a review).

Beyond these well-established applications, researchers are also exploring innovative uses of Sentinel-1 soil moisture data. For instance, recent studies have investigated its role in groundwater recharge estimation (Dari et al., 2025), landslide susceptibility assessment (Brocca et al., 2023b), and post-fire landscape analysis (Brocca et al., 2024). These novel applications highlight the expanding utility of Sentinel-1 near-surface soil moisture data in environmental and geophysical research. As the scientific community continues to explore and refine the use of Sentinel-1 soil moisture data, its contributions to hydrology, agriculture, and disaster risk management are expected to grow, making it an invaluable resource for both research and operational applications.

Despite the encouraging advances mentioned above, the global scalability of Sentinel-1 near-surface soil moisture applications is still impeded for several reasons. In arid and sandy environments, the low dielectric contrast between dry soil and surface roughness reduces the sensitivity of backscattering, which complicates near-surface soil moisture retrieval (El Hajj et al., 2018). In dense forests or situations involving strong vegetation dynamics, canopy scattering typically dominates the SAR signal, obscuring the contribution of the soil and causing significant uncertainty (Lievens et al., 2017a). Variations in acquisition modes, incidence angles, and data gaps due to priority acquisitions further complicate the generation of consistent global products. These limitations highlight the importance of regional calibration, assimilation of multiple sensors, and ongoing methodological development to improve the robustness of Sentinel-1 near-surface soil moisture retrievals in different environmental contexts.

10. Soil moisture retrieval: shortcomings and way forward

Near-surface soil moisture retrieval from Sentinel-1 data has made tremendous progress in the decade since the Sentinel-1 launch, but challenges remain that warrant further investigation and innovation. This section highlights some of the important limitations and suggests several ways to improve the accuracy, robustness, and applicability of near-surface soil moisture retrieval methods.

10.1. Vegetation- and surface roughness-related challenges and opportunities

Vegetation (biomass, moisture & structure) and surface roughness are the main factors that complicate near-surface soil moisture retrieval (Kim et al., 2012b; Kim et al., 2018; Benninga et al., 2022). While retrieval methods, including physically based scattering models, change detection, and even AI methods, attempt to compensate for this, their efficacy is often insufficient. Vegetation water content, canopy structure, and biomass density alter the radar backscatter, making it difficult to decouple the near-surface soil moisture signal from these other signals (Kim et al., 2018). In addition, seasonal changes and intermittent growth cycles make it difficult to recover the soil moisture signal (Vreugdenhil et al., 2016), especially in agricultural areas (Rojas-Munoz et al., 2023).

Prevailing vegetation conditions play a central role in the accuracy of soil moisture determination (Bao et al., 2018; Benninga et al., 2019; Ma et al., 2020), thus requiring further exploration in future research initiatives, ideally focused on single biomes. State-of-the-art research recognizes the difficulties posed by the uncertainties associated with vegetation, particularly in the context of physically based models. Future research efforts should focus on fine-tuning parameterizations and model structures to better capture the intricate scattering interactions between vegetation and soil dynamics. Recent advances on exact modeling of scattering from vegetation will provide a guide (Jeong et al., 2025). More specifically, diversity in vegetation type, density, and structure may contribute to differences in scattering model performance and soil moisture retrievals. However, exploring how the variability across each region contributes to differences in land cover is likely to be beneficial in increasing model accuracy in heterogeneous areas. Other confounding factors, such as intercepted water on leaves (rain & dew), are important to understand and incorporate to avoid misinterpretation and spurious artifacts in the retrieval of near-surface soil moisture and vegetation parameters (Vermunt et al., 2022). Researching innovative remote sensing methods capable of deciphering the diverse influences of different vegetation types on soil moisture measurement is very promising. Polarimetric SAR, especially compact polarimetry, can provide extra information about vegetation structure and water content and help to improve accuracy in near-surface soil moisture retrieval by differentiating between soil and vegetation signals more clearly. By carefully elucidating the subtleties of the influence of vegetation, future research will be able to drive the development of more refined correction mechanisms and thus improve the reliability of the retrieval. Moreover, the integration of optical, SAR and passive microwave data (e.g., SMAP, SMOS) may allow for a more thorough evaluation of the effect of vegetation versus near-surface soil moisture by allowing for better partitioning of the effects in heterogeneous landscapes.

Another long-standing difficulty with C-band SAR near-surface soil moisture retrieval is disentangling the contributions of soil moisture and surface roughness, since it is difficult to determine which aspect of surface backscatter is more sensitive. The classical monostatic radar observations, such as those from Sentinel-1, have a poor capacity to resolve this ambiguity. Previous research found that bistatic radar configurations, such as forward scattering observations, could weaken the impact of surface roughness and enhance the influence of soil moisture on the backscattering signal (Zeng et al., 2016; Zeng and Chen, 2018). These results indicate that new observation modes (e.g., bistatic radar) could be a viable approach for improving the retrieval accuracy of soil moisture at C-band.

Complementary strategies are also being developed through the integration of multiple C- and L-band SAR orbital missions. L-band has a greater ability to penetrate vegetation for near-surface soil moisture retrieval. Consequently, future missions like ROSE-L, in combination with Sentinel-1, will enhance near-surface soil moisture monitoring by extending its coverage both temporally and spatially to vegetated regions.

Further research may consider complementary aspects in observation geometries (e.g., mono and bistatic) and SAR frequencies to retrieve a suite of surface variables, such as near-surface soil moisture, roughness and vegetation water content products.

10.2. Multi-sensor and multi-SAR fusion and benchmarking

Near-surface soil moisture effects are also difficult to separate from other effects due to the limited single-frequency nature of Sentinel-1 SAR observations (Baghdadi et al., 2011). Retrieval accuracy can be improved by a multi-frequency SAR data set (Zhang et al., 2018), e.g. by combining Sentinel-1 observations with those from recent and upcoming SAR missions such as NISAR and ROSE-L (L-band) or BIOMASS (P-band). In addition, existing retrieval models are based on assumptions that do not always hold in real-world conditions, which can lead to false positives. Consequently, many models assume homogeneous soil roughness over large areas, whereas roughness is actually quite heterogeneous in space, and varies significantly in intensity and distribution, because of agricultural activity or natural surface heterogeneity. Such misrepresentation can lead to retrieval algorithms ascribing the variations in backscatter as a change in near-surface soil moisture content instead of surface roughness effects (Oh et al., 1992). Furthermore, physics-based models rely on accurate surface parameter inputs, e.g. for soil roughness and vegetation amount (Zhu et al., 2020), which are not necessarily available at fine spatial resolutions, though they could be estimated (Zribi et al., 2008; Kim et al., 2018).

Despite the progress made with Sentinel-1C, the ~6-day revisit interval of Sentinel-1 observations is still too infrequent to capture rapid changes in soil moisture (McNairn et al., 2015; Benninga et al., 2022), especially due to highly variable processes such as irrigation or extreme weather events. High-resolution retrievals (~1 km or finer) are critical for local applications, but noise and inconsistencies also become apparent at these finer scales, especially over heterogeneous landscapes (Mengen et al., 2023). To overcome these limitations, new ideas such as Medium Earth Orbit SAR (MEO-SAR) missions (Matar et al., 2019), e.g. HydroTerra+, have been proposed. This system will allow more frequent observations to be made with high spatial resolution, potentially covering the globe on a daily basis (Fischer et al., 2024). This high temporal sampling can play a key role in facilitating the retrieval of rapid moisture dynamics and thus contribute significantly to near-surface soil moisture retrieval performance.

Building on the advantages of combining near-surface soil observations to overcome the limitations of using a single sensor to retrieve near-surface soil moisture, future research should further develop previous initiatives to jointly analyze Sentinel-1 data with data from other sensors. These include passive microwave missions (e.g., SMAP, SMOS, and CIMR), optical sensors (e.g., Sentinel-2, MODIS, and EnMAP), and thermal infrared sensors (e.g., Sentinel-3, ECOSTRESS, Constellation, and the future LSTM mission) (Ojha et al., 2021; Li et al., 2023; Rahmati and Montzka, 2024). Multi-sensor fusion allows for vegetation correction and more accurate retrieval under different environmental conditions (Kumar et al., 2015). For example, Cui et al. (2022) pointed out the challenge of retrieving near-surface soil moisture in agroforestry areas based on Sentinel-1 observations alone and found an increased accuracy by utilizing both L-band (ALOS-2) and C-band (Sentinel-1) data in vegetation-dense landscapes. The integration of optical vegetation phenology observations with information on changing vegetation type (e.g., due to crop rotation) should be explored as a tool to reduce errors in the observation predictions. This should be accompanied by research on alternative observation operators to optimally balance between input data quality and observation operator complexity. With the development of technology and increasingly mature machine learning algorithms, there is potential to use multi-sensor data in conjunction with machine learning frameworks for improved near-surface soil moisture estimation.

Focusing on multi-SAR missions would open important research avenues, including optimization of ensemble methods tailored to the broader context of multi-SAR missions and improved interpolation methods that are more precise and allow higher scalability. Multi-frequency SAR approaches are clearly effective for improving -retrieved near-surface soil moisture products and are beneficial for improving spatial resolution and vegetation characterization. In perspective on the future of operational SAR-based soil moisture monitoring, the benefits are from the Copernicus SAR strategy, which covers the Sentinel-1 Next Generation (S1-NG) missions and the innovative potential of upcoming bistatic observations (ESA Harmony missions). Additionally, synergistic multi-frequency capabilities are becoming available through the ongoing Sentinel-1 (C-band) and future ROSE-L (L-band) missions that complement the past (ALOS PALSAR) and present (SAOCOM and ALOS-2) L-band missions.

10.3. Standardisation, uncertainty, and new missions

In the future, three paths seem particularly crucial: 1) Standardisation and benchmarking: Community adoption of common reference datasets (e.g., ISMN, ESA CCI Soil Moisture) to validate algorithms against harmonised metrics offers potential for more stringent intercomparison of retrieval systems; 2) Uncertainty-aware retrievals: Ensemble-based methods (Zhu et al., 2022a) as well as probabilistic frameworks can provide uncertainty bounds rather than a single deterministic estimate; and 3) Integration with new missions and cloud-based platforms: The emergence of L-band missions such as NISAR and ROSE-L will allow merging multi-frequency data, while cloud-based backend providers (e.g., Google Earth Engine, Copernicus Data Space Ecosystem) provide opportunities of scalable and near-real-time validation workflows. Together, this will improve the robustness and readiness of Sentinel-1 near-surface soil moisture products for ingestion into hydrological, agricultural, and climate applications.

10.4. Retrievals and data assimilation convergence

Although data assimilation of Sentinel-1 near-surface soil moisture retrievals appears advantageous, bias correction and observation-model discrepancies are of concern (Modanesi et al., 2022; Bechtold et al., 2023). Methods to remove bias, such as CDF matching (Cenci et al., 2017b) or seasonal adjustment (Lievens et al., 2017a), sometimes result in the loss of useful information, particularly for identifying irrigation effects. The incorporation of Sentinel-1 backscatter rather than a derived near-surface soil moisture into land surface models requires a well calibrated observation operator, which poses challenges when modeled input data, such as soil moisture and vegetation properties, are erroneous and underlying assumptions of the observation operator (e.g., simplified model of scattering process, no interannual variation of vegetation type) are violated. Moreover, with the sparse temporal coverage of Sentinel-1, an efficient assimilation of its data into continuously running (operational) models requires varying update strategies. Temporal smoothing strategies, like for the particle batch smoother (Jalilvand et al., 2023), could assist, as using a temporal window to optimize, rather than just assimilation through time, has been demonstrated to lower/mitigate long-term errors (Dunne and Entekhabi, 2006; Margulis et al., 2015) and thus improve soil moisture estimates.

At some level, multi-sensor near-surface soil moisture retrieval algorithms and data assimilation methods converge. Retrieval algorithms are generally considered as stand-alone inversion methods of scattering or radiative transfer model for individual satellite images, while data assimilation embeds a dynamic land surface or hydrological model with a data assimilation framework to correlate satellite observations across time. Both approaches benefit from the combined use of multiple sensors: retrieval algorithms profit from added constraints and additional environmental corrections, while data assimilation benefits from more informative and complementary observational inputs, removing uncertainty in near-surface soil moisture estimates over time.

In addition to multi-sensor data fusion, future investigations should also focus on the synergistic use of different near-surface soil moisture retrieval algorithms applied to identical Sentinel-1 data. A better approach would be to implement multi-model (e.g., combination of physical-based, semi-empirical, and AI-driven models) averaging or developing ensemble approaches that build on the strengths and weaknesses of different physics-based, empirical or AI-based inversion models that are more robust and accurate. Current developments indicate that machine and deep learning algorithms such as RF, SVR, and CNN can improve data fusion between Sentinel missions (Mkhwenkwana et al., 2025). Further investigation is needed to find optimal strategies for combining the outputs from diverse retrieval methods across different scenarios.

10.5. Advances in data assimilation methods

New missions (e.g., NASA–ISRO SAR, ROSE-L, RADARSAT Constellation Mission, SIASGE constellation, among others) with shorter revisit intervals (either considered individually or in combination) will provide a unique opportunity to improve soil moisture monitoring (Cenci et al., 2018). New missions also provide new opportunities for comparing a broader range of data merging algorithms, such as improved data assimilation approaches, including ensemble-based filtering approaches or machine learning-based observational operators, which can improve model estimates and reduce prediction uncertainty. A recent review by De Lannoy et al. (2022) provides an overview of using data assimilation as a tool to merge observations from multiple missions, including soil moisture retrievals from Sentinel-1, via multi-variate and multi-sensor data assimilation approaches.

Direct assimilation of backscatter data, as opposed to near-surface soil moisture retrievals, could provide further benefits by better accounting for vegetation and surface roughness effects (Sun et al., 2021). To mitigate issues related to the high level of noise in near-surface soil moisture retrievals, as well as low temporal repeat, assimilation strategies based on data smoothing (Dunne and Entekhabi, 2006; Margulis et al., 2015) can be beneficial, by digesting multiple observations over a moving window to obtain optimal estimates. Moreover, more sophisticated multi-sensor data assimilation methods (e.g., multi-source Kalman filtering, four-dimensional variational assimilation methods, etc.) could be applied to improve the temporal evolution and spatial coherence of the soil moisture estimates. Whether these approaches are harnessed for retrieval or assimilation, they will be crucial for the generation of accurate, high-resolution soil moisture datasets for hydrological and environmental applications. While the Gravity Recovery and Climate Experiment (GRACE) satellite mission (Tapley et al., 2004) data has not yet been directly combined with Sentinel-1 soil moisture retrievals (to our knowledge), the combination of GRACE and Sentinel-1 observations could be beneficial for soil moisture estimation at large scales and for hydrologic modelling in the future. This is because GRACE provides a mean estimate for total terrestrial water storage (including root-zone soil moisture and groundwater) over hundreds of kilometers, while Sentinel-1 supplies an instantaneous high-resolution near-surface soil moisture observation. Their integration could bridge the temporal and spatial scales from local near-surface processes to basin-scale storage, and thus increase the constraints in hydrological modelling, drought monitoring and groundwater monitoring by jointly observing both near-surface dynamics and sub-surface water storage.

10.6. Validation frameworks and operational readiness

For Sentinel-1 near-surface soil moisture retrieval to be widely adopted in operational hydrological, agricultural and/or climate models, a rigorous validation process is required. A key challenge in this context is the spatial scale mismatch between Sentinel-1 retrievals and ground-based measurements. Although SAR-derived soil moisture generally has a spatial resolution of tens to hundreds of meters, point-based ground measurements represent only a few centimeters. This difference can lead to large representativeness errors, most notably in complex landscapes. Recent investigations have revealed that land cover heterogeneity contributes significantly to these errors. Peng et al. (2025) introduced a novel representativeness measurement for identifying the more appropriate sites for validation, thus guaranteeing robustness in evaluation frameworks. In parallel, Yu et al. (2025b) provided upscaling methods that would enable adding in situ data to footprint scales closer to what is used by Sentinel-1, hence lowering the mismatch and leading to consequent credible validation results.

The development and expansion of ground-based validation networks, such as the Global Climate Observing System (GCOS) sites (Houghton et al., 2012), citizen science programs (MacPhail and Colla, 2020), and the ISMN (Dorigo et al., 2021) for *in situ* data collection can further facilitate large-scale validation efforts following CEOS validation good practices (Gruber et al., 2020; Montzka et al., 2020). In addition, near real-time soil moisture monitoring for decision making can be supported by automated cloud-based processing pipelines. Prospectively, a set of site representativeness indicators and a reproducible upscaling methodology on harmonized protocols among networks would be pivotal to having Sentinel-1 near-surface soil moisture products validated in a consistent and reliable way. Advances in the validation of techniques are a requirement for their applicability to broader hydrological, agricultural and climatic applications.

10.7. Incidence angle dependence and correction methods

A usual requirement when using multi-orbit Sentinel-1 data for near-surface soil moisture retrieval is to address both the presence of different incidence angles and how they affect the backscattering signal, as a traditional incidence angle correction to a reference incidence angle (mostly at 40 degree) is not sufficient (Mengen et al., 2023). While several attempts have been made to overcome these issues, including application of Fourier Series transformation used by Mengen et al. (2023), application of AI would be a good compromise here. Accordingly, Navacchi et al. (2025) recently presented a probabilistic method based on machine learning to estimate the slope of the backscatter–incidence angle relationship using multiple backscatter statistics, providing a promising approach to be followed in the future. However, this method needs radiometric terrain-corrected gamma nought time series and so may surpass the constraints of limited orbital coverage as shown from a case of the Sentinel-1 constellation.

10.8. Accounting for Radio Frequency Interference (RFI)

Radio Frequency Interference (RFI) has been well recognized as a critical issue for C-band microwave remote sensing (Njoku et al., 2005). Although passive radiometers are the most affected, even active missions like Sentinel-1 can be at risk of performance degradation, as localized interference can also affect backscatter signals. Recent studies have shown that operational RFI monitoring, and suppression is already addressed in the Sentinel-1 ground segment (Monti-Guarnieri et al., 2017; Franceschi et al., 2021; Franceschi et al., 2022). However, the residual effect of RFI on near-surface soil moisture retrieval still needs to be quantitatively measured with methodological studies for a systematic evaluation in data-driven frameworks where even weak noise can propagate into model outputs. Integration of RFI into retrieval uncertainty frameworks, standardized reporting of RFI mitigation in data products, and the opportunity for using AI-based detection algorithms are part of a joint effort to further increase the reliability of future soil moisture products based on Sentinel-1and upcoming C-band and L-band mission potential.

10.9. AI-driven retrievals and hybrid modeling

While AI soil moisture estimation has some advantages, it also has certain drawbacks including:

I. **Interpretability**: Deep learning models are "black box" models, making it difficult to understand how the estimates/results are generated compared to physics-based models (Camps-Valls et al., 2020; Harani et al., 2025). This affects reliability, especially when it comes to decision-making. While the 'black box' nature of deep learning models is acknowledged, recent developments in explainable AI (XAI), such as SHAP or LIME, may help mitigate this issue by interpreting the influence of input features (e.g., Mallik et al., 2025).
II. **Data-dependence**: Large high-quality training data sets are required. Geographical particularities and specialties can bias these models (Hachani et al., 2019), resulting in inaccurate predictions in locations not included in the training stage. Errors in the training data (mismatch in resolution, time gaps, etc.) can also lead to errors.
III. **Sensitivity**: Performance is affected by the design inputs (SAR backscatter, vegetation indices, meteorological data). Performance can also be degraded with noise, cloud contamination, or inconsistencies.
IV. **Computation**: AI is a processor- as well as current-hungry technique and so is not applicable in real-time use or resource-constrained environments, which requires a need for efficient AI and cloud solutions.
V. **Generalization**: AI models need to consider soil types, vegetation, topography, and climate. Models are often built and established locally and do not transfer well, although significant progress has been made with transfer learning techniques.

Research into sophisticated machine learning algorithms that are precisely tuned to detect and correct vegetation-related biases could also prove to be a fruitful avenue. The integration of high-resolution satellite datasets, such as the Sentinel-2 imagery, in conjunction with advanced spectral indices, offers the opportunity to decipher the nuanced relationships between vegetation and soil moisture (Ma et al., 2020; Nega et al., 2022). Although traditional statistical methods work well for soil moisture retrieval, deep learning approaches, especially CNN and LSTM networks (Hegazi et al., 2021; Liu et al., 2021; Rabiei et al., 2021; Wang et al., 2023a; Wu et al., 2024), can better capture the complexity of the non-linear relationships that exist between SAR backscatter, vegetation dynamics, and soil properties. Machine-learning models (e.g. neural networks or deep learning) may be capable of disentangling non-linear and complex vegetation and soil interactions, whilst also utilizing large, multi-sensor datasets for high precision soil moisture retrievals that are tailored to specific regions.

The transfer learning approaches, which involve pre-training on large global datasets and then fine-tuning for a more regional application, could mitigate the challenges of data scarcity (Hemmati and Sahebi, 2024). Therefore, further development of these techniques is a promising path forward. Conversely, retrieval errors can potentially be reduced by using improved scattering models that explicitly account for the effects of vegetation and surface roughness. Here, the combination of numerical solutions of Maxwell's equations and AI-based methods can lead to a hybrid (physics-based AI) modeling framework that retains some of the computational efficiency of the latter while maintaining the physical interpretability of the former. Hybrid (physics-based AI) modeling frameworks play an important role in enhancing both the accuracy and interpretability of near-surface soil moisture retrieval and have great potential for near real-time availability. AI-based method possesses computational efficiency and, when merged properly with the complexity of physical models, could establish faster processing chains capable of managing the large volumes of Sentinel-1 data with a reduced time-lag. This development is essential for operational applications where timely information about soil moisture is needed, such as flood forecasting, agricultural monitoring, and drought assessment. This is because the rapid availability of data is crucial. In addition, adaptive semi-empirical models that are dynamically updated by AI based on environmental conditions can better support retrieval performance. Furthermore, in developing an approach for advancing near-surface soil moisture retrieval from Sentinel-1, exploring synergistic pathways that leverage the strengths of existing methods while overcoming their inherent limitations is imperative. The complicated nature of soil moisture dynamics requires a comprehensive paradigm that integrates the effectiveness of short-term change detection, physics-based scattering models, and AI-based methods. By merging these different approaches, a more comprehensive understanding of soil moisture variability can be achieved, leading to higher precision and reliability of results. Additionally, linking retrieval approaches with hydrological modeling may offer helpful physical parameters that constrain retrievals to reasonable hydrological ranges, improving overall accuracy and robustness. However, careful consideration is required not to let model-based constraints overwhelm the advantages of retrievals driven entirely by observations, especially where processes such as irrigation or human management actions are absent or poorly represented in the model.

10.10. Large Language Models for soil moisture retrieval

Soil moisture retrieval using Large Language Models (LLMs) is an interesting approach to AI-based algorithms that should be explored; however, the challenges associated with training data availability and physics-based relationships should also be considered. Although the use of LLMs may improve the processing of data, interpretation and modeling accuracy through aggregating varied geospatial, meteorological, and historical datasets to enable automated information extraction and model improvement (Miao et al., 2024), the most relevant limitation centers on the availability of suitable large language-based training datasets for establishing direct connections between soil moisture and optical-based or other remotely sensed observations or auxiliary variables. However, since Sentinel-1 has provided a decade of SAR observations, the synergy between LLMs and microwave-based retrieval models might be a promising pathway to better account for uncertainties, integrate auxiliary data sources (e.g., Sentinel-2, *in situ* sensors), and refine soil moisture predictions in diverse environmental conditions. Beyond their use for static data aggregation and integration across heterogeneous datasets, LLMs are poised to revolutionize active learning-based near-surface soil moisture retrieval by dynamically adjusting the model's parameters based on real-time data assimilation. As AI-driven soil moisture inversion models evolve, integrating LLMs with ensemble learning, physically based inversion methods, and geospatial data fusion techniques will play a pivotal role in enhancing near-surface soil moisture retrieval accuracy, scalability, and real-world applicability.

11. Conclusion

A decade of Sentinel-1-based retrieval of near-surface soil moisture has established a solid foundation for application maturity, fostered by Copernicus' open data policy. However, substantial research requirements remain, particularly the need to overcome challenges associated with vegetation effects, model errors, and data assimilation inconsistencies. Future SAR-based near-surface soil moisture retrievals should focus on multi-sensor integration, AI-assisted near-surface retrieval algorithms, and higher temporal resolution. These products would not only supersede current capabilities by virtue of their detail and resolution, but with improved retrieval methods and the evolving capabilities of remote sensing, would also be verified, operationally useful and beneficial for a variety of global applications.

Lessons from past research emphasize the importance of accounting for vegetation-induced retrieval errors, enhancing model parameterization, and optimizing inter-sensor synergy. Vegetation also complicates backscatter interpretation, requiring future retrieval efforts to focus on dynamic correction mechanisms such as using optical indices, polarimetric SAR and AI-enhanced models which may evolve based on seasonal vegetative patterns. Additionally, enhancing the representation of soil roughness and multi-frequency SAR approaches are vital for improving the accuracy of the retrieval, especially in non-homogeneous landscapes. While SAR-based near-surface soil moisture monitoring is a valuable measure, to reach its full potential, development efforts must at least be directed towards integrative frameworks encompassing various environments, guarantee robust retrievals in difficult environments. Beyond traditional backscatter-based approaches, novel methods exploiting InSAR-derived coherence and phase closure offer further opportunities for near-surface soil moisture retrieval, especially in arid and semi-arid areas where those interferometric observables exhibit significant sensitivity to moisture changes.

New advancements in AI, specifically deep learning and LLMs, provide a disruptive paradigm shift for near-surface soil moisture retrieval. AI-based methods, although allowing complex, non-linear relationships between soil properties, vegetation, and meteorological conditions to be captured, are also subject to interpretability, computational efficiency, and data dependency challenges/issues. A hybrid modeling framework that balances the strengths of physics-based models and AI-driven retrieval techniques should be explored further in future research. Transfer learning and self-supervised learning approaches could also help reduce regional biases by allowing retrieval models to generalize across different attributes and regions.

Besides methodological improvements, the operationalization of near-surface soil moisture retrieval will demand deeper investigations into data assimilation strategies and validation frameworks. In missions like NISAR, ROSE-L, or Hydroterra+, the temporal resolution of SAR observations will improve, allowing better tracking of rapid moisture dynamics due to extreme weather and agricultural practices (e.g., irrigation). Additionally, AI-defined assimilation methods and hybrid retrieval methods that combine physics-based methods with deep learning solutions may dispense exciting potentials for propelling retrieval data uncertainty. This will further facilitate the integration of Sentinel-1-based soil moisture products into hydrological forecasting, agricultural management, and climate monitoring through methods such as standardized validation networks, citizen science approaches, and real-time processing pipelines. Reinforcing research with close cooperation among space agencies, academic researchers and industry stakeholders is necessary to bring SAR-based near-surface soil moisture retrieval as close to operational implementation as possible. The use of SAR interferometric techniques, in conjunction with backscatter methods, may improve retrievals by reducing ambiguities in near-surface soil moisture estimation, particularly with the growing availability of L-band SAR data from future missions.

CRediT authorship contribution statement

Mehdi Rahmati: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Anna Balenzano:** Writing – review & editing, Writing – original draft, Validation. **Michel Bechtold:** Writing – review & editing, Writing – original draft, Validation. **Luca Brocca:** Writing – review & editing, Writing – original draft, Validation. **Anke Fluhrer:** Writing – review & editing, Writing – original draft, Validation. **Thomas Jagdhuber:** Writing – review & editing, Writing – original draft, Validation. **Kleanthis Karamvasis:** Writing – review & editing, Writing – original draft, Validation. **David Mengen:** Writing – review & editing, Writing – original draft, Validation. **Rolf H. Reichle:** Writing – review & editing, Writing – original draft, Validation. **Seung-bum Kim:** Writing – review & editing, Writing – original draft, Validation. **Ruhollah Taghizadeh-Mehrjardi:** Writing – review & editing, Writing – original draft, Validation. **Jeffrey Walker:** Writing – review & editing, Writing – original draft, Validation. **Liujun Zhu:** Writing – review & editing, Writing – original draft, Validation. **Carsten Montzka:** Writing – review & editing, Writing – original draft, Validation, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could appear to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

Abbes, A.B., Jarray, N., Farah, I.R., 2024. Advances in remote sensing based soil moisture retrieval: applications, techniques, scales and challenges for combining machine learning and physical models. Artif. Intell. Rev. 57, 224.
Akash, M., Kumar, P.M., Bhaskar, P., Deepthi, P., Sukhdev, A., 2024. Review of estimation of soil moisture using active microwave remote sensing technique. Remote Sensing Applications: Society and Environment 33, 101118.
Albergel, C., Rüdiger, C., Pellarin, T., Calvet, J.-C., Fritz, N., Froissard, F., Suquia, D., Petitpa, A., Piguet, B., Martin, E., 2008. From near-surface to root-zone soil moisture using an exponential filter: an assessment of the method based on in-situ observations and model simulations. Hydrol. Earth Syst. Sci. 12, 1323–1337.
Alfieri, L., Avanzi, F., Delogu, F., Gabellani, S., Bruno, G., Campo, L., Libertino, A., Massari, C., Tarpanelli, A., Rains, D., 2021. High resolution satellite products improve hydrological modeling in northern Italy. Hydrol. Earth Syst. Sci. Discuss. 2021, 1–29.
Ansari, H., De Zan, F., Parizzi, A., 2020. Study of systematic bias in measuring surface deformation with SAR interferometry. IEEE Trans. Geosci. Remote Sens. 59, 1285–1301.
Arab, S., Easson, G., Ghaffari, Z., 2024. Integration of sentinel-1a radar and SMAP radiometer for soil moisture retrieval over vegetated areas. Sensors 24, 2217.
Asmuß, T., Bechtold, M., Tiemeyer, B., 2019. On the Potential of Sentinel-1 for High Resolution Monitoring of Water Table Dynamics in Grasslands on Organic Soils. Remote Sens 11, 1659.
Attema, E., Ulaby, F.T., 1978. Vegetation modeled as a water cloud. Radio Sci. 13, 357–364.
Azimi, S., Dariane, A.B., Modanesi, S., Bauer-Marschallinger, B., Bindlish, R., Wagner, W., Massari, C., 2020. Assimilation of Sentinel 1 and SMAP–based satellite soil moisture retrievals into SWAT hydrological model: the impact of satellite revisit time and product spatial resolution on flood simulations in small basins. J. Hydrol. 581, 124367.
Babaeian, E., Sadeghi, M., Jones, S.B., Montzka, C., Vereecken, H., Tuller, M., 2019. Ground, Proximal, and Satellite Remote Sensing of Soil Moisture. Rev. Geophys. 57, 530–616.
Baghdadi, N., Saba, E., Aubert, M., Zribi, M., Baup, F., 2011. Evaluation of radar backscattering models IEM, Oh, and Dubois for SAR data in X-band over bare soils. IEEE Geosci. Remote Sens. Lett. 8, 1160–1164.
Baghdadi, N., El Hajj, M., Dubois-Fernandez, P., Zribi, M., Belaud, G., Cheviron, B., 2014. Signal level comparison between TerraSAR-X and COSMO-SkyMed SAR sensors. IEEE Geosci. Remote Sens. Lett. 12, 448–452.
Baghdadi, N., Choker, M., Zribi, M., Hajj, M.E., Paloscia, S., Verhoest, N.E., Lievens, H., Baup, F., Mattia, F., 2016. A new empirical model for radar scattering from bare soil surfaces. Remote Sens 8, 920.
Baghdadi, N., Bazzi, H., El Hajj, M., Zribi, M., 2018. Detection of Frozen Soil Using Sentinel-1 SAR Data. Remote Sens 10, 1182.
Balenzano, A., Satalino, G., Pauwels, V., Mattia, F., 2011. Soil moisture retrieval from dense temporal series of C-band SAR data over agricultural sites. In: 2011 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp. 3136–3139.
Balenzano, A., Mattia, F., Satalino, G., Lovergine, F.P., Palmisano, D., Davidson, M.W., 2021a. Dataset of Sentinel-1 surface soil moisture time series at 1 km resolution over Southern Italy. Data in Brief 38, 107345.
Balenzano, A., Mattia, F., Satalino, G., Lovergine, F.P., Palmisano, D., Peng, J., Marzahn, P., Wegmüller, U., Cartus, O., Dąbrowska-Zielińska, K., 2021b. Sentinel-1 soil moisture at 1 km resolution: a validation study. Remote Sens. Environ. 263, 112554.
Bao, Y., Lin, L.-J., Wu, S., Deng, K.A.K., Petropoulos, G.P., 2018. Surface soil moisture retrievals over partially vegetated areas from the synergy of Sentinel-1 and Landsat 8 data using a modified water-cloud model. Int. J. Appl. Earth Obs. Geoinf. 72, 76–85.
Bartalis, Z., Wagner, W., Naeimi, V., Hasenauer, S., Scipal, K., Bonekamp, H., Figa, J., Anderson, C., 2007. Initial soil moisture retrievals from the METOP-A Advanced Scatterometer (ASCAT). Geophys. Res. Lett. 34.
Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufler, S., Stachl, T., Modanesi, S., Massari, C., Ciabatta, L., Brocca, L., 2018. Toward global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles. IEEE Trans. Geosci. Remote Sens. 57, 520–539.
Bechtold, M., Modanesi, S., Lievens, H., Baguis, P., Brangers, I., Carrassi, A., Getirana, A., Gruber, A., Heyvaert, Z., Massari, C., 2023. Assimilation of Sentinel-1 backscatter into a land surface model with river routing and its impact on streamflow simulations in two Belgian catchments. J. Hydrometeorol. 24, 2389–2408.
Benninga, H.-J.F., Velde, R.V.D., Su, Z., 2019. Impacts of Radiometric Uncertainty and Weather-Related Surface Conditions on Soil Moisture Retrievals with Sentinel-1. Remote Sens 11, 2025.
Benninga, H.-J.F., Van Der Velde, R., Su, Z., 2022. Soil moisture content retrieval over meadows from Sentinel-1 and Sentinel-2 data using physically based scattering models. Remote Sens. Environ. 280.
Bhogapurapu, N., Dey, S., Homayouni, S., Bhattacharya, A., Rao, Y.S., 2022. Field-scale soil moisture estimation using sentinel-1 GRD SAR data. Adv. Space Res. 70, 3845–3858.
Bindlish, R., Barros, A.P., 2000. Multifrequency soil moisture inversion from SAR measurements with the use of IEM. Remote Sens. Environ. 71, 67–88.
Brake, B.T., Hanssen, R.F., van der Ploeg, M.J., de Rooij, G.H., 2013. Satellite-based radar interferometry to estimate large-scale soil water depletion from clay shrinkage: possibilities and limitations. Vadose Zone J. 12 (vzj2012), 0098.
Breiman, L., 1996. Bagging predictors. Mach. Learn. 24, 123–140.
Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.
Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., Hasenauer, S., 2010. Improving runoff prediction through the assimilation of the ASCAT soil moisture product. Hydrol. Earth Syst. Sci. 14, 1881–1893.
Brocca, L., Barbetta, S., Camici, S., Ciabatta, L., Dari, J., Filippucci, P., Massari, C., Modanesi, S., Tarpanelli, A., Bonaccorsi, B., 2023a. A Digital Twin of the terrestrial water cycle: a glimpse into the future through high-resolution Earth observations. Frontiers in Science 1. In.
Brocca, L., Zhao, W., Lu, H., 2023b. High-resolution observations from space to address new applications in hydrology. Innovation 4.
Brocca, L., Gaona, J., Bavera, D., Fioravanti, G., Puca, S., Ciabatta, L., Filippucci, P., Mosaffa, H., Esposito, G., Roberto, N., 2024. Exploring the actual spatial resolution of 1 km satellite soil moisture products. Sci. Total Environ. 945, 174087.
Bulut, Ü., Mohammadi, B., Duan, Z., 2024. Estimation of surface soil moisture from Sentinel-1 synthetic aperture radar imagery using machine learning method. Remote Sensing Applications: Society and Environment 36, 101369.
Bürgi, P., Lohman, R., 2021. High-resolution soil moisture evolution in hyper-arid regions: A comparison of InSAR, SAR, microwave, optical, and data assimilation

systems in the southern Arabian Peninsula. J. Geophys. Res. Earth Surf. 126, e2021JF006158.
Burgin, M., Clewley, D., Lucas, R., Moghaddam, M., 2011. A generalized radar backscattering model based on wave theory for multilayer multispecies vegetation. IEEE Trans. Geosci. Remote Sens. 49, 4832–4845.
Burgin, M., Khankhoje, U.K., Duan, X., Moghaddam, M., 2016. Generalized Terrain Topography in Radar Scattering Models. IEEE Trans. Geosci. Remote Sens. 54, 3944–3952.
Busschaert, L., Bechtold, M., Modanesi, S., Massari, C., Brocca, L., De Lannoy, G., 2024. Irrigation quantification through backscatter data assimilation with a buddy check approach. J. Adv. Model. Earth Syst. 16, e2023MS003661.
Camps-Valls, G., Reichstein, M., Zhu, X., Tuia, D., 2020. Advancing deep learning for earth sciences: from hybrid modeling to interpretability. In: IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, pp. 3979–3982.
Celik, M.F., Isik, M.S., Yuzugullu, O., Fajraoui, N., Erten, E., 2022. Soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning. Remote Sens 14, 5584.
Cenci, L., Pulvirenti, L., Boni, G., Chini, M., Matgen, P., Gabellani, S., Squicciarino, G., Basso, V., Pignone, F., Pierdicca, N., 2017a. Exploiting Sentinel 1 data for improving (flash) flood modelling via data assimilation techniques. In: 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, pp. 4939–4942.
Cenci, L., Pulvirenti, L., Boni, G., Chini, M., Matgen, P., Gabellani, S., Squicciarino, G., Pierdicca, N., 2017b. An evaluation of the potential of Sentinel 1 for improving flash flood predictions via soil moisture–data assimilation. Adv. Geosci. 44, 89–100.
Cenci, L., Pulvirenti, L., Boni, G., Pierdicca, N., 2018. Defining a Trade-off Between Spatial and Temporal Resolution of a Geosynchronous SAR Mission for Soil Moisture Monitoring. Remote Sens 10, 1950.
Centre, E.C.D.-G.J.R., 2018. Surface Soil Moisture 2014-present (raster 1 km), Europe, daily - version 1. In: Chan, S.K., Bindlish, R., O'Neill, P.E., Njoku, E., Jackson, T., Colliander, A., Chen, F., Burgin, M., Dunbar, S., Piepmeier, J., Yueh, S., Entekhabi, D., Cosh, M.H., Caldwell, T., Walker, J., Wu, X.L., Berg, A., Rowlandson, T., Pacheco, A., McNairn, H., Thibeault, M., Martínez-Fernández, J., González-Zamora, A., Seyfried, M., Bosch, D., Starks, P., Goodrich, D., Prueger, J., Palecki, M., Small, E.E., Zreda, M., Calvet, J.C., Crow, W.T., Kerr, Y. (Eds.), Assessment of the SMAP Passive Soil Moisture Product, 54. IEEE Transactions on Geoscience and Remote Sensing, pp. 4994–5007.
Chan, S.K., Bindlish, R., O'Neill, P.E., Njoku, E., Jackson, T., Colliander, A., Chen, F., Burgin, M., Dunbar, S., Piepmeier, J., Yueh, S., 2016. Assessment of the SMAP passive soil moisture product. IEEE Trans. Geosci. Remote Sens. 54 (8), 4994–5007.
Chang, J.G., Shoshany, M., Oh, Y., 2018. Polarimetric radar vegetation index for biomass estimation in desert fringe ecosystems. IEEE Trans. Geosci. Remote Sens. 56, 7102–7108.
Chen, F., Crow, W.T., Starks, P.J., Moriasi, D.N., 2011. Improving hydrologic predictions of a catchment model via assimilation of surface soil moisture. Adv. Water Resour. 34, 526–536.
Cho, S., Lee, S., Jeon, H., Choi, M., 2024. SAR Soil Moisture Retrieval Using Physically Based AI Model. In: IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, pp. 5134–5138.
Choker, M., Baghdadi, N., Zribi, M., El Hajj, M., Paloscia, S., Verhoest, N.E., Lievens, H., Mattia, F., 2017. Evaluation of the Oh, Dubois and IEM backscatter models using a large dataset of SAR data and experimental soil measurements. Water 9, 38.
Chung, J., Lee, Y., Kim, J., Jung, C., Kim, S., 2022. Soil moisture content estimation based on Sentinel-1 SAR imagery using an artificial neural network and hydrological components. Remote Sens 14, 465.
Clapp, R.E., 1946. A theoretical and experimental study of radar ground return. Radiation Laboratory, Massachusetts Institute of Technology.
Colliander, A., Jackson, T., McNairn, H., Chazanoff, S., Dinardo, S., Latham, B., O'Dwyer, I., Chun, W., Yueh, S., Njoku, E., 2014. Comparison of airborne passive and active L-band system (PALS) brightness temperature measurements to SMOS observations during the SMAP validation experiment 2012 (SMAPVEX12). IEEE Geosci. Remote Sens. Lett. 12, 801–805.
Cosgriff, R., Peake, W., Taylor, R., 1960. Terrain scattering properties for sensor system design (Terrain Handbook II). Engineering Expt, Station Bull, p. 181.
Cui, H., Jiang, L., Paloscia, S., Santi, E., Pettinato, S., Wang, J., Fang, X., Liao, W., 2022. The Potential of ALOS-2 and Sentinel-1 Radar Data for Soil Moisture Retrieval With High Spatial Resolution Over Agroforestry Areas, China. IEEE Trans. Geosci. Remote Sens. 60, 1–17.
Dahhani, S., Raji, M., Hakdaoui, M., Lhissou, R., 2023. Land Cover Mapping Using Sentinel-1 Time-Series Data and Machine-Learning Classifiers in Agricultural Sub-Saharan Landscape. Remote Sens 15, 65.
Dari, J., Brocca, L., Quintana-Seguí, P., Casadei, S., Escorihuela, M.J., Stefan, V., Morbidelli, R., 2022. Double-scale analysis on the detectability of irrigation signals from remote sensing soil moisture over an area with complex topography in central Italy. Adv. Water Resour. 161, 104130.
Dari, J., Brocca, L., Modanesi, S., Massari, C., Tarpanelli, A., Barbetta, S., Quast, R., Vreugdenhil, M., Freeman, V., Barella-Ortiz, A., 2023a. Regional data sets of high-resolution (1 and 6 km) irrigation estimates from space. Earth System Science Data 15, 1555–1575.
Dari, J., Brocca, L., Modanesi, S., Massari, C., Tarpanelli, A., Barbetta, S., Quast, R., Vreugdenhil, M., Freeman, V., Barella-Ortiz, A., Quintana-Seguí, P., Bretreger, D., Volden, E., 2023b. Regional data sets of high-resolution (1 and 6 km) irrigation estimates from space. Zenodo.
Dari, J., Filippucci, P., Brocca, L., Quast, R., Vreugdenhil, M., Miralles, D.G., Morbidelli, R., Saltalippi, C., Flammini, A., 2025. A novel approach for estimating groundwater recharge leveraging high-resolution satellite soil moisture. J. Hydrol. 652, 132678.
Das, N.N., Entekhabi, D., Dunbar, R.S., Chaubell, M.J., Colliander, A., Yueh, S., Jagdhuber, T., Chen, F., Crow, W., O'Neill, P.E., 2019. The SMAP and Copernicus Sentinel 1A/B microwave active-passive high resolution surface soil moisture product. Remote Sens. Environ. 233, 111380.
Das, N., Entekhabi, D., Dunbar, R.S., Kim, S., Yueh, S.C., Olliander, A., O'Neill, P.E., Jackson, T., Jagdhuber, T., Chen, F., Crow, W.T., Walker, J., Berg, A., Bosch, D., Caldwell, T., Cosh, M., 2020. SMAP/Sentinel-1 L2 Radiometer/Radar 30-Second Scene 3 km EASE-Grid Soil Moisture. In: Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center.
De Lannoy, G.J., Bechtold, M., Albergel, C., Brocca, L., Calvet, J.-C., Carrassi, A., Crow, W.T., De Rosnay, P., Durand, M., Forman, B., 2022. Perspective on satellite-based land data assimilation to estimate water cycle components in an era of advanced data availability and model sophistication. Frontiers in Water 4, 981745.
De Lannoy, G.J., Bechtold, M., Busschaert, L., Heyvaert, Z., Modanesi, S., Dunmire, D., Lievens, H., Getirana, A., Massari, C., 2024. Contributions of irrigation modeling, soil moisture and snow data assimilation to high-resolution water budget estimates over the Po basin: Progress towards digital replicas. J. Adv. Model. Earth Syst. 16, e2024MS004433.
De Roo, R.D., Du, Y., Ulaby, F.T., Dobson, M.C., 2001. A semi-empirical backscattering model at L-band and C-band for a soybean canopy with soil moisture inversion. IEEE Trans. Geosci. Remote Sens. 39, 864–872.
de Roos, S., Busschaert, L., Lievens, H., Bechtold, M., De Lannoy, G.J., 2023. Optimisation of AquaCrop backscatter simulations using Sentinel-1 observations. Remote Sens. Environ. 294, 113621.
de Roos, S., Bechtold, M., Busschaert, L., Lievens, H., De Lannoy, G.J., 2024. Assimilation of Sentinel-1 backscatter to update AquaCrop estimates of soil moisture and crop biomass. J. Geophys. Res. Biogeosci. 129, e2024JG008231.
De Zan, F., 2024. InSAR contributions to water status retrieval. In: EUSAR 2024; 15th European Conference on Synthetic Aperture Radar. VDE, pp. 15–17.
De Zan, F., Gomba, G., 2018. Vegetation and soil moisture inversion from SAR closure phases: First experiments and results. Remote Sens. Environ. 217, 562–572.
De Zan, F., Parizzi, A., Prats-Iraola, P., López-Dekker, P., 2013. A SAR interferometric model for soil moisture. IEEE Trans. Geosci. Remote Sens. 52, 418–425.
De Zan, F., Zonno, M., Lopez-Dekker, P., 2015. Phase inconsistencies and multiple scattering in SAR interferometry. IEEE Trans. Geosci. Remote Sens. 53, 6608–6616.
Dente, L., Ferrazzoli, P., Su, Z., van der Velde, R., Guerriero, L., 2014. Combined use of active and passive microwave satellite data to constrain a discrete scattering model. Remote Sens. Environ. 155, 222–238.
Dobson, M.C., Ulaby, F.T., Hallikainen, M.T., El-Rayes, M.A., 1985. Microwave dielectric behavior of wet soil-Part II: Dielectric mixing models. IEEE Trans. Geosci. Remote Sens. 35–46.
Dorigo, W., Himmelbauer, I., Aberer, D., Schremmer, L., Petrakovic, I., Zappa, L., Preimesberger, W., Xaver, A., Annor, F., Ardö, J., 2021. The International Soil Moisture Network: serving Earth system science for over a decade. Hydrol. Earth Syst. Sci. Discuss. 2021, 1–83.
Du, S., Duan, P., Zhao, T., Wang, Z., Niu, S., Ma, C., Zou, D., Yao, P., Guo, P., Fan, D., 2024. An improved change detection method for high-resolution soil moisture mapping in permafrost regions. GIScience & Remote Sensing 61, 2310898.
Duan, X., Moghaddam, M., 2012. Electromagnetic scattering from arbitrary random rough surfaces using stabilized extended boundary condition method (SEBCM) for remote sensing of soil moisture. IEEE Trans. Geosci. Remote Sens. 50, 87–103.
Dubois, P.C., van Zyl, J.J., Engman, E.T., 1995. Measuring soil moisture with imaging radars. IEEE Trans. Geosci. Remote Sens. 33, 915–926.
Dunne, S., Entekhabi, D., 2006. Land surface state and flux estimation using the ensemble Kalman smoother during the Southern Great Plains 1997 field experiment. Water Resour. Res. 42.
Durden, S.L., van Zyl, J.J., Zebker, H.A., 1989. Modeling and observation of the radar polarization signature of forested areas. IEEE Trans. Geosci. Remote Sens. 27, 290–301.
Efremova, N., Seddik, M.E.A., Erten, E., 2021. Soil moisture estimation using Sentinel-1/-2 imagery coupled with cycleGAN for time-series gap filing. IEEE Trans. Geosci. Remote Sens. 60, 1–11.
El Hajj, M., Baghdadi, N., Zribi, M., Belaud, G., Cheviron, B., Courault, D., Charron, F., 2016. Soil moisture retrieval over irrigated grassland using X-band SAR data. Remote Sens. Environ. 176, 202–218.
El Hajj, M., Baghdadi, N., Zribi, M., Rodríguez-Fernández, N., Wigneron, J.P., Al-Yaari, A., Al Bitar, A., Albergel, C., Calvet, J.-C., 2018. Evaluation of SMOS, SMAP, ASCAT and Sentinel-1 Soil Moisture Products at Sites in Southwestern France. Remote Sens 10, 569.
Elwan, E., Le Page, M., Jarlan, L., Baghdadi, N., Brocca, L., Modanesi, S., Dari, J., Quintana Seguí, P., Zribi, M., 2022. Irrigation mapping on two contrasted climatic contexts using Sentinel-1 and Sentinel-2 data. Water 14, 804.
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., 2010. The soil moisture active passive (SMAP) mission. Proc. IEEE 98, 704–716.
Fan, D., Zhao, T., Jiang, X., García-García, A., Schmidt, T., Samaniego, L., Attinger, S., Wu, H., Jiang, Y., Shi, J., 2025. A Sentinel-1 SAR-based global 1-km resolution soil moisture data product: Algorithm and preliminary assessment. Remote Sens. Environ. 318, 114579.
Ferrazzoli, P., Guerriero, L., 1996. Passive microwave remote sensing of forests: a model investigation. IEEE Trans. Geosci. Remote Sens. 34, 433–443.
Filippucci, P., Brocca, L., Quast, R., Ciabatta, L., Saltalippi, C., Wagner, W., Tarpanelli, A., 2022. High-resolution (1 km) satellite rainfall estimation from SM2RAIN applied to Sentinel-1: Po River basin as a case study. Hydrol. Earth Syst. Sci. 26, 2481–2497.

Fischer, J., Scheiber, R., Kubanek, J., 2024. First Comparative Analysis of Simulated Low and High Resolution Hydroterra and Conventional SAR Data. In: In, *EUSAR 2024; 15th European Conference on Synthetic Aperture Radar*. VDE, pp. 260–265.

Fluhrer, A., Jagdhuber, T., Akbar, R., O'Neill, P.E., Entekhabi, D., 2020. Simultaneous retrieval of surface roughness parameters for bare soils from combined active–passive microwave SMAP observations. IEEE Trans. Geosci. Remote Sens. 59, 8182–8194.

Franceschi, N., Recchia, A., Piantanida, R., Giudici, D., Albinet, C., Miranda, N., 2021. A Global C-Band RFI Monitoring System Based on Sentinel-1 Data. In: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, pp. 1658–1661.

Franceschi, N., Recchia, A., Piantanida, R., Hajduch, G., Vincent, P., Pinheiro, M., Miranda, N., Albinet, C., 2022. Operational RFI Mitigation Approach in Sentinel-1 IPF. In: EUSAR 2022; 14th European Conference on Synthetic Aperture Radar, pp. 1–5.

Fung, A.K., 1994. Microwave scattering and emission models and their applications (No Title).

Fung, A.K., Li, Z., Chen, K.S., 1992. Backscattering from a randomly rough dielectric surface. IEEE Trans. Geosci. Remote Sens. 30, 356–369.

Gao, L., Song, X., Li, X., Ma, J., Leng, P., Wang, W., Zhu, X., 2024. An enhanced saline soil dielectric constant model used for remote sensing soil moisture and salinity retrieval. Remote Sens 16, 452.

Good, S.P., Noone, D., Bowen, G., 2015. WATER RESOURCES. Hydrologic connectivity constrains partitioning of global terrestrial water fluxes. Science 349, 175–177.

Graldi, G., Zardi, D., Vitti, A., 2023. Retrieving Soil Moisture at the Field Scale from Sentinel-1 Data over a Semi-Arid Mediterranean Agricultural Area. Remote Sens 15, 2997.

Gruber, A., Su, C.-H., Zwieback, S., Crow, W., Dorigo, W., Wagner, W., 2016. Recent advances in (soil moisture) triple collocation analysis. Int. J. Appl. Earth Obs. Geoinf. 45, 200–211.

Gruber, A., De Lannoy, G., Albergel, C., Al-Yaari, A., Brocca, L., Calvet, J.-C., Colliander, A., Cosh, M., Crow, W., Dorigo, W., 2020. Validation practices for satellite soil moisture retrievals: What are (the) errors? Remote Sens. Environ. 244, 111806.

Hachani, A., Ouessar, M., Paloscia, S., Santi, E., Pettinato, S., 2019. Soil moisture retrieval from Sentinel-1 acquisitions in an arid environment in Tunisia: application of Artificial Neural Networks techniques. Int. J. Remote Sens. 40, 9159–9180.

Hamze, M., Baghdadi, N., El Hajj, M.M., Zribi, M., Bazzi, H., Cheviron, B., Faour, G., 2021. Integration of L-Band derived soil roughness into a bare soil moisture retrieval approach from C-Band SAR data. Remote Sens 13, 2102.

Harani, P., Gautam, S., Joshi, S.K., Asirvatham, L.G., Rakshith, B.L., 2025. Advancements in soil moisture estimation through integration of remote sensing and artificial intelligence techniques. Sci. Total Environ. 1001, 180503.

Hegazi, E.H., Yang, L., Huang, J., 2021. A convolutional neural network algorithm for soil moisture prediction from Sentinel-1 SAR images. Remote Sens 13, 4964.

Heiskanen, J., Brümmer, C., Buchmann, N., Calfapietra, C., Chen, H., Gielen, B., Gkritzalis, T., Hammer, S., Hartman, S., Herbst, M., 2022. The integrated carbon observation system in Europe. Bull. Am. Meteorol. Soc. 103, E855–E872.

Hemmati, E., Sahebi, M.R., 2024. Surface soil moisture retrieval based on transfer learning using SAR data on a local scale. Int. J. Remote Sens. 45, 2374–2406.

Hornacek, M., Wagner, W., Sabel, D., Truong, H.-L., Snoeij, P., Hahmann, T., Diedrich, E., Doubková, M., 2012. Potential for high resolution systematic global surface soil moisture retrieval via change detection using Sentinel-1. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 5, 1303–1311.

Hoskera, A.K., Nico, G., Irshad Ahmed, M., Whitbread, A., 2020. Accuracies of soil moisture estimations using a semi-empirical model over bare soil agricultural croplands from sentinel-1 SAR data. Remote Sens 12, 1664.

Houghton, J., Townshend, J., Dawson, K., Mason, P., Zillman, J., Simmons, A., 2012. The GCOS at 20 years: The origin, achievement and future development of the Global Climate Observing System. Weather 67, 227–235.

Hrysiewicz, A., Holohan, E.P., Donohue, S., Cushnan, H., 2023. SAR and InSAR data linked to soil moisture changes on a temperate raised peatland subjected to a wildfire. Remote Sens. Environ. 291, 113516.

Huang, S., Tsang, L., 2012. Electromagnetic scattering of randomly rough soil surfaces based on numerical solutions of Maxwell equations in 3 dimensional simulations using a hybrid UV/PBTG/SMCG method. IEEE Trans. Geosci. Remote Sens. 50, 4025–4035.

Huang, S., Tsang, L., Njoku, E.G., Chen, K.S., 2010. Backscattering coefficients, coherent reflectivities, emissivities of randomly rough soil surfaces at L-band for SMAP applications based on numerical solutions of Maxwell equations in three-dimensional simulations. IEEE Trans. Geosci. Remote Sens. 48, 2557–2567.

Huang, H.T., Kim, S.B., Tsang, S., Xu, X.L., Liao, T.H., Jackson, T.J., Yueh, S.H., 2016. Coherent model of L-band radar scattering by soybean plants: model development, validation and retrieval. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 9, 272–284.

Huang, H.T., Liao, T.H., Kim, S.B., Xu, X.L., Tsang, S., Jackson, T.J., Yueh, S.H., 2021. L-Band Radar Scattering and Soil Moisture Retrieval of Wheat, Canola and Pasture Fields for SMAP Active Algorithm. Prog. Electromagn. Res. su170, 129–152.

Jackson, J.D., 2021. Classical electrodynamics. John Wiley & Sons.

Jalilvand, E., Abolafia-Rosenzweig, R., Tajrishy, M., Kumar, S.V., Mohammadi, M.R., Das, N.N., 2023. Is it possible to quantify irrigation water-use by assimilating a high-resolution satellite soil moisture product? Water Resour. Res. 59, e2022WR033342.

Jeong, J., Tsang, L., Gu, W., Colliander, A., Yueh, S.H., 2023. Wave Propagation in Vegetation Field by Combining Fast Multiple Scattering Theory and Numerical Electromagnetics in the Hybrid Method. IEEE Trans. Antenn, Propag. 71 (4), 3598–3610.

Jeong, J.L., Tsang, L., Kurum, K., Ghosh, A., Colliander, A., Yueh, S.H., McDonald, K., Steiner, N., Cosh, M.C., 2025. Full-wave Simulations of Forest at L-band with Fast Hybrid Method and Comparison with GNSS Signals. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 18, 5395–5405.

Jordan, T.E., Lohman, R.B., Tapia, L., Pfeiffer, M., Scott, C.P., Amundson, R., Godfrey, L., Riquelme, R., 2020. Surface materials and landforms as controls on InSAR permanent and transient responses to precipitation events in a hyperarid desert, Chile. Remote Sens. Environ. 237, 111544.

Kanmani, K., Vasanthi, P., Pari, P., Shafeer Ahamed, N., 2023. Estimation of soil moisture for different crops using SAR polarimetric data. Civ Eng J 9, 1402–1411.

Karamvasis, K., Karathanassi, V., 2023. Soil moisture estimation from Sentinel-1 interferometric observations over arid regions. Comput. Geosci. 178, 105410.

Kerr, Y.H., Waldteufel, P., Wigneron, J.-P., Delwart, S., Cabot, F., Boutin, J., Escorihuela, M.-J., Font, J., Reul, N., Gruhier, C., 2010. The SMOS mission: New tool for monitoring key elements ofthe global water cycle. Proc. IEEE 98, 666–687.

Keshk, H.M., Yin, X.-C., 2020. Change detection in SAR images based on deep learning. Int. J. Aeronaut. Space Sci. 21, 549–559.

Khellouk, R., Barakat, A., El Jazouli, A., Lionboui, H., Benabdelouahab, T., 2021. Assessment of Water Cloud Model based on SAR and optical satellite data for surface soil moisture retrievals over agricultural area. Eur. J. Soil Sci. 10, 243–250.

Kim, S.B., Liao, T.H., 2021. Robust retrieval of soil moisture and roughness at field scale across wide-ranging SAR incidence angles for soybean, wheat, forage and grass. Remote Sens. Environ. 266, 112712.

Kim, Y., van Zyl, J.J., 2009. A time-series approach to estimate soil moisture using polarimetric radar data. IEEE Trans. Geosci. Remote Sens. 47, 2519–2527.

Kim, S.-B., Tsang, L., Johnson, J.T., Huang, S., van Zyl, J.J., Njoku, E.G., 2012a. Soil moisture retrieval using time-series radar observations over bare surfaces. IEEE Trans. Geosci. Remote Sens. 50, 1853–1863.

Kim, S.B., Tsang, L., Johnson, J.T., Huang, S., van Zyl, J.J., Njoku, E.G., 2012b. Soil moisture retrieval using time-series radar observations over bare surfaces. IEEE Trans. Geosci. Remote Sens. 50, 1853–1863.

Kim, S.B., Huang, H.T., Tsang, S., Jackson, T.J., McNairn, H., van Zyl, J.J., 2014. Soil moisture retrieval using L-band time-series SAR data from the SMAPVEX12 experiment. In: Proc. of 10th European Conference on Synthetic Aperture Radar. Berlin, Germany.

Kim, S.B., Jackson, T.J., Yueh, S.H., Xu, X., Hensley, S., 2015. Feasibility of inter-comparing airborne and spaceborne observations of radar backscattering coefficients for soil moisture retrieval. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 8, 3507–3519.

Kim, S.B., Arii, M., Jackson, T.J., 2017. Modeling L-band synthetic aperture radar observations through dielectric changes in soil moisture and vegetation over shrublands. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. https://doi.org/10.1109/JSTARS.2017.2741497.

Kim, S.B., Huang, H.T., Liao, T.H., Colliander, A., 2018. Estimating vegetation water content and soil surface roughness using physical models of L-band radar scattering for soil moisture retrieval. Remote Sens 10, 556.

Kim, S.B., Xu, X.L., Kraatz, S., Colliander, A., Cosh, M., Kelly, V.R., Siqueira, P., 2025. Airborne SAR soil moisture estimates over forests replicating NISAR observations. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 18, 7364–7373.

Kornelsen, K.C., Coulibaly, P., 2013. Advances in soil moisture retrieval from synthetic aperture radar and hydrological applications. J. Hydrol. 476, 460–489.

Koster, R.D., Guo, Z.C., Yang, R.Q., Dirmeyer, P.A., Mitchell, K., Puma, M.J., 2009. On the Nature of Soil Moisture in Land Surface Models. J. Clim. 22, 4322–4335.

Kumar, S.V., Reichle, R.H., Koster, R.D., Crow, W.T., Peters-Lidard, C.D., 2009. Role of subsurface physics in the assimilation of surface soil moisture observations. J. Hydrometeorol. 10, 1534–1547.

Kumar, S., Peters-Lidard, C., Santanello, J., Reichle, R., Draper, C., Koster, R., Nearing, G., Jasinski, M., 2015. Evaluating the utility of satellite soil moisture retrievals over irrigated areas and the ability of land data assimilation methods to correct for unmodeled processes. Hydrol. Earth Syst. Sci. 19, 4463–4478.

Kumar, S., Kolassa, J., Reichle, R., Crow, W., de Lannoy, G., de Rosnay, P., MacBean, N., Girotto, M., Fox, A., Quaife, T., 2022. An agenda for land data assimilation priorities: Realizing the promise of terrestrial water, energy, and vegetation observations from space. J. Adv. Model. Earth Syst. 14, e2022MS003259.

Kurum, M., Kim, S.B., Akbar, R., Cosh, M., 2021. Surface Soil Moisture Retrievals Under Forest Canopy For L- band SAR Observations Observations Across A Wide Range of Incidence Angles By Inverting A Physical Scattering Model. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 14, 1741–1753.

Lakra, D., Pipil, S., Srivastava, P.K., Singh, S.K., Gupta, M., Prasad, R., 2025. Soil moisture retrieval over agricultural region through machine learning and sentinel 1 observations. Frontiers in Remote Sensing 5, 1513620.

Lal, P., Singh, G., Das, N.N., Entekhabi, D., 2023. Multi-scale algorithm for high-resolution soil moisture retrievals with uncertainty estimation for the upcoming NISAR mission. In: AGU Fall Meeting Abstracts (pp. H14C-03).

Laluet, P., Olivera-Guerra, L.E., Altés, V., Paolini, G., Ouaadi, N., Rivalland, V., Jarlan, L., Villar, J.M., Merlin, O., 2024. Retrieving the irrigation actually applied at district scale: assimilating high-resolution Sentinel-1-derived soil moisture data into a FAO-56-based model. Agric. Water Manag. 293, 108704.

Lekshmi, S.U., Singh, S.D.N., Baghini, M.S., 2014. A critical review of soil moisture measurement. Measurement 54, 92–105.

Li, Y., Yan, S., Chen, N., Gong, J., 2020. Performance evaluation of a neural network model and two empirical models for estimating soil moisture based on Sentinel-1 SAR data. Progress In Electromagnetics Research C 105, 85–99.

Li, J., Leng, G., Peng, J., 2023. The Merit of Estimating High-Resolution Soil Moisture Using Combined Optical, Thermal, and Microwave Data. IEEE Geosci. Remote Sens. Lett. 20, 1–5.

Liao, T.H., Kim, S.B., Tan, S., Tsang, S., Su, C.X., Jackson, T.J., 2016. Multiple scattering effects with cyclical terms in active remote sensing of vegetated surface using vector radiative transfer theory. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 9, 1414–1429.
Liao, T.H., Kim, S.B., Handwerger, A., Fielding, E.J., Cosh, M.C., Schultz, W.S., 2021. High Resolution Soil Moisture Maps Over Landslide Regions in Northern California Grassland. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 14, 4547–4560.
Lievens, H., Reichle, R.H., Liu, Q., Lannoy, G.D., Dunbar, R.S., Kim, S., Das, N.N., Cosh, M.H., Walker, J.P., Wagner, W., 2017a. Joint Sentinel-1 and SMAP data assimilation to improve soil moisture estimates. Geophys. Res. Lett. 44, 6145–6153.
Lievens, H., Reichle, R.H., Liu, Q., Lannoy, G.D., Dunbar, R.S., Kim, S., Das, N.N., Cosh, M.H., Walker, J.P., Wagner, W., 2017b. Joint Sentinel-1 and SMAP data assimilation to improve soil moisture estimates. Geophys. Res. Lett. 44, 6145–6153.
Lievens, H., Brangers, I., Marshall, H.P., Jonas, T., Olefs, M., De Lannoy, G., 2022. Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps. Cryosphere 16, 159–177.
Liu, Y., Qian, J., Yue, H., 2020. Combined Sentinel-1A with Sentinel-2A to estimate soil moisture in farmland. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 14, 1292–1310.
Liu, J., Xu, Y., Li, H., Guo, J., 2021. Soil moisture retrieval in farmland areas with sentinel multi-source data based on regression convolutional neural networks. Sensors 21, 877.
Liu, J., Rahmani, F., Lawson, K., Shen, C., 2022. A Multiscale Deep Learning Model for Soil Moisture Integrating Satellite and In Situ Data. Geophys. Res. Lett. 49, e2021GL096847.
Lohman, R., Bürgi, P., 2023. Soil moisture effects on InSAR-a correction approach and example from a hyper-arid region. Remote Sens. Environ. 297, 113766.
Ma, C., Li, X., McCabe, M.F., 2020. Retrieval of High-Resolution Soil Moisture through Combination of Sentinel-1 and Sentinel-2 Data. Remote Sens 12, 2303.
Macelloni, G., Paloscia, S., Pampaloni, P., Sigismondi, S., De Matthaeis, P., Ferrazzoli, P., Schiavon, G., Solimini, D., 1999. The SIR-C/X-SAR experiment on Montespertoli: Sensitivity to hydrological parameters. Int. J. Remote Sens. 20, 2597–2612.
MacPhail, V.J., Colla, S.R., 2020. Power of the people: A review of citizen science programs for conservation. Biol. Conserv. 249, 108739.
Madelon, R., Rodríguez-Fernández, N.J., Bazzi, H., Baghdadi, N., Albergel, C., Dorigo, W., Zribi, M., 2023. Soil moisture estimates at 1 km resolution making a synergistic use of Sentinel data. Hydrol. Earth Syst. Sci. 27, 1221–1242.
Mallik, S., Chakraborty, A., Podder, K., Talukdar, S., Rahman, A., Mishra, U., 2025. Enhancing soil moisture prediction with explainable AI: Integrating IoT and multi-sensor remote sensing data through soft computing. Appl. Soft Comput. 180, 113406.
Mancini, M., Hoeben, R., Troch, P.A., 1999. Multifrequency radar observations of bare surface soil moisture content: A laboratory experiment. Water Resour. Res. 35, 1827–1838.
Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J.M., McNairn, H., Rao, Y.S., 2020. Dual polarimetric radar vegetation index for crop growth monitoring using sentinel-1 SAR data. Remote Sens. Environ. 247, 111954.
Mao, Y., Crow, W.T., Nijssen, B., 2019. A framework for diagnosing factors degrading the streamflow performance of a soil moisture data assimilation system. J. Hydrometeorol. 20, 79–97.
Margulis, S.A., Girotto, M., Cortés, G., Durand, M., 2015. A particle batch smoother approach to snow water equivalent estimation. J. Hydrometeorol. 16, 1752–1772.
Martin, A.C.H., Gommenginger, C.P., Jacob, B., Staneva, J., 2022. First multi-year assessment of Sentinel-1 radial velocity products using HF radar currents in a coastal environment. Remote Sens. Environ. 268, 112758.
Massari, C., Camici, S., Ciabatta, L., Brocca, L., 2018. Exploiting Satellite-Based Surface Soil Moisture for Flood Forecasting in the Mediterranean Area: State Update Versus Rainfall Correction. Remote Sens 10, 292.
Matar, J., Rodriguez-Cassola, M., Krieger, G., López-Dekker, P., Moreira, A., 2019. MEO SAR: System concepts and analysis. IEEE Trans. Geosci. Remote Sens. 58, 1313–1324.
McDermid, S., Nocco, M., Lawston-Parker, P., Keune, J., Pokhrel, Y., Jain, M., Jägermeyr, J., Brocca, L., Massari, C., Jones, A.D., 2023. Irrigation in the Earth system. Nature Reviews Earth & Environment 4, 435–453.
McNairn, H., Jackson, T.J., Wiseman, G., Belair, S., Bullock, P., Colliander, A., Kim, S.B., Magagi, R., Moghaddam, M., Adams, J., Homayouni, S., Ojo, E., Rowlandson, T., Shang, J., Goita, K., Hosseini, M., 2015. The Soil Moisture Active Passive Validation Experiment 2012 (SMAPVEX12): Pre-Launch Calibration and Validation of the SMAP Satellite. IEEE Trans. Geosci. Remote Sens. 53, 2784–2801.
Mengen, D., Montzka, C., Jagdhuber, T., Fluhrer, A., Brogi, C., Baum, S., Schüttemeyer, D., Bayat, B., Bogena, H., Coccia, A., 2021. The SARSense campaign: Air-and space-borne C-and L-band SAR for the analysis of soil and plant parameters in agriculture. Remote Sens 13, 825.
Mengen, D., Jagdhuber, T., Balenzano, A., Mattia, F., Vereecken, H., Montzka, C., 2023. High Spatial and Temporal Soil Moisture Retrieval in Agricultural Areas Using Multi-Orbit and Vegetation Adapted Sentinel-1 SAR Time Series. Remote Sens 15, 2282.
Miao, C., Hu, J., Moradkhani, H., Destouni, G., 2024. Hydrological research evolution: A large language model-based analysis of 310,000 studies published globally between 1980 and 2023. e2024WR038077. Wiley Online Library.
Michaelides, R.J., 2020. Quantifying permafrost processes and soil moisture with interferometric phase and closure phase. Stanford University.
Mironov, V.L., Kosolapova, L.G., Fomin, S.V., 2009. Physically and mineralogically based spectroscopic dielectric model for moist soils. IEEE Trans. Geosci. Remote Sens. 47, 2059–2070.
Mirsoleimani, H.R., Sahebi, M.R., Baghdadi, N., El Hajj, M., 2019. Bare soil surface moisture retrieval from sentinel-1 SAR data based on the calibrated IEM and dubois models using neural networks. Sensors 19, 3209.
Mkhwenkwana, A., Matongera, T.N., Blaauw, C., Mutanga, O., 2025. A critical review on the applications of Sentinel satellite datasets for soil moisture assessment in crop production. Int. J. Appl. Earth Obs. Geoinf. 141, 104647.
Modanesi, S., Massari, C., Bechtold, M., Lievens, H., Tarpanelli, A., Brocca, L., Zappa, L., De Lannoy, G.J., 2022. Challenges and benefits of quantifying irrigation through the assimilation of Sentinel-1 backscatter observations into Noah-MP. Hydrol. Earth Syst. Sci. Discuss. 2022, 1–31.
Moghaddas, M., Tajrishy, M., 2025. A Novel Random Forest Approach to Downscale Smap Soil Moisture Products to 100m Resolution Using Temporally Closest Satellite Observation Data. Remote Sensing Applications: Society and Environment 39, 101710.
Montzka, C., Cosh, M., Bayat, B., Al Bitar, A., Berg, A., Bindlish, R., Bogena, H.R., Bolten, J.D., Cabot, F., Caldwell, T., Chan, S., Colliander, A., Crow, W., Das, N., De Lannoy, G., Dorigo, W., Evett, S.R., Gruber, A., Hahn, S., Jagdhuber, T., Jones, S., Kerr, Y., Kim, S., Koyama, C., Kurum, M., Lopez-Baeza, E., Mattia, F., McColl, K., Mecklenburg, S., Mohanty, B., ONeill, P., Or, D., Pellarin, T., Petropoulos, G.P., Piles, M., Reichle, R.H., Rodriguez-Fernandez, N., Rüdiger, C., Scanlon, T., Schwartz, R.C., Spengler, D., Srivastava, P., Suman, S., van der Schalie, R., Wagner, W., Wegmüller, U., Wigneron, J.-P., Camacho, F., 2020. In: Montzka, C., Cosh, M., Nickeson, J., Camacho, F. (Eds.), Nickeson. Version 1.0., Eds. https://doi.org/10.5067/doc/ceoswgcv/lpv/sm.001
Monti-Guarnieri, A., Giudici, D., Recchia, A., 2017. Identification of C-Band Radio Frequency Interferences from Sentinel-1 Data. Remote Sens 9, 1183.
Montzka, C., Bogena, H.R., Zreda, M., Monerris, A., Morrison, R., Muddu, S., Vereecken, H., 2017. Validation of Spaceborne and Modelled Surface Soil Moisture Products with Cosmic-Ray Neutron Probes. Remote Sens 9, 103.
Mullissa, A., Vollrath, A., Odongo-Braun, C., Slagter, B., Balling, J., Gou, Y., Gorelick, N., Reiche, J., 2021. Sentinel-1 SAR Backscatter Analysis Ready Data Preparation in Google Earth Engine. Remote Sens 13, 1954.
Murphy, P.C., Codyre, P., Geever, M., O'Farrell, J., Fionnagáin, Ó., Spillane, C., Golden, A., 2025. Regional-Scale Analysis of Soil Moisture Content in Malawi Determined by Remote Sensing. Remote Sens 17, 890.
Murugesan, A., Dave, R., Kushwaha, A., Pandey, D.K., Saha, K., 2023. Surface soil moisture estimation in bare agricultural soil using modified Dubois model for Sentinel-1 C-band SAR data. Journal of Agrometeorology 25, 517–524.
Nagler, T., Rott, H., Hetzenecker, M., Wuite, J., Potin, P., 2015. The Sentinel-1 Mission: New Opportunities for Ice Sheet Observations. Remote Sens 7, 9371–9389.
Navacchi, C., Reuß, F., Wagner, W., 2025. Using a Neural Network to Model the Incidence Angle Dependency of Backscatter to Produce Seamless, Analysis-Ready Backscatter Composites over Land. Remote Sens 17, 361.
Nega, W., Nigussie, W., Balew, A., 2022. Investigating spatial relationship between vegetation cover and soil moisture using sentinel satellites: a case study of North Gondar Zone, Ethiopia. J. Spat. Sci. 68, 667–683.
Nijaguna, G., Manjunath, D., Abouhawwash, M., Askar, S.S., Basha, D.K., Sengupta, J., 2023. Deep learning-based improved WCM technique for soil moisture retrieval with satellite images. Remote Sens 15, 2005.
Niknam, K., Judge, J., Roberts, A.K., Monsivais-Huertero, A., Moore, R.C., Sarabandi, K., Wu, J.Y., 2024. A 3-D Full-Wave Model to Study the Impact of Soybean Components and Structure on L-Band Backscatter. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 17, 13089–13107.
Njoku, E.G., Ashcroft, P., Chan, T.K., Li, L., 2005. Global survey and statistics of radio-frequency interference in AMSR-E land observations. IEEE Trans. Geosci. Remote Sens. 43, 938–947.
Ogilvy, J., Foster, J., 1989. Rough surfaces: Gaussian or exponential statistics? J. Phys. D. Appl. Phys. 22, 1243.
Oh, Y., 2004. Quantitative retrieval of soil moisture content and surface roughness from multipolarized radar observations of bare soil surfaces. IEEE Trans. Geosci. Remote Sens. 42, 596–601.
Oh, Y., Sarabandi, K., Ulaby, F.T., 1992. An empirical model and an inversion technique for radar scattering from bare soil surfaces. IEEE Trans. Geosci. Remote Sens. 30, 370–382.
Oh, Y., Sarabandi, K., Ulaby, F.T., 1994. An inversion algorithm for retrieving soil moisture and surface roughness from polarimetric radar observation. In: Proceedings of IGARSS'94-1994 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp. 1582–1584.
Oh, Y., Sarabandi, K., Ulaby, F.T., 2002. Semi-empirical model of the ensemble-averaged differential Mueller matrix for microwave backscattering from bare soil surfaces. IEEE Trans. Geosci. Remote Sens. 40, 1348–1355.
Ojha, N., Merlin, O., Amazirh, A., Ouaadi, N., Rivalland, V., Jarlan, L., Er-raki, S., Escorihuela, M.J., 2021. A Calibration/Disaggregation Coupling Scheme for Retrieving Soil Moisture at High Spatio-Temporal Resolution: Synergy between SMAP Passive Microwave, MODIS/Landsat Optical/Thermal and Sentinel-1 Radar Data. Sensors (Basel, Switzerland) 21, 7406.
Orth, R., Seneviratne, S.I., 2012. Analysis of soil moisture memory from observations in Europe. J. Geophys. Res.-Atmos. 117, D15115.
Ouellette, J.D., Johnson, J.T., Balenzano, A., Mattia, F., Satalino, G., Kim, S.-B., Dunbar, R.S., Colliander, A., Cosh, M.H., Caldwell, T.G., 2017. A time-series approach to estimating soil moisture from vegetated surfaces using L-band radar backscatter. IEEE Trans. Geosci. Remote Sens. 55, 3186–3193.
Palmisano, D., Mattia, F., Balenzano, A., Satalino, G., Pierdicca, N., Guarnieri, A.V.M., 2020. Sentinel-1 sensitivity to soil moisture at high incidence angle and the impact on retrieval over seasonal crops. IEEE Trans. Geosci. Remote Sens. 59, 7308–7321.

Palmisano, D., Satalino, G., Balenzano, A., Mattia, F., 2022. Coherent and incoherent change detection for soil moisture retrieval from Sentinel-1 data. IEEE Geosci. Remote Sens. Lett. 19, 1–5.
Paloscia, S., Pampaloni, P., Pettinato, S., Santi, E., 2010. Generation of soil moisture maps from ENVISAT/ASAR images in mountainous areas: a case study. Int. J. Remote Sens. 31, 2265–2276.
Paloscia, S., Pettinato, S., Santi, E., Notarnicola, C., Pasolli, L., Reppucci, A., 2013. Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation. Remote Sens. Environ. 134, 234–248.
Panciera, R., Walker, J.P., Jackson, T.J., Gray, D.A., Tanase, M.A., Ryu, D., Monerris, A., Yardley, H., Rüdiger, C., Wu, X., 2013. The soil moisture active passive experiments (SMAPEx): Toward soil moisture retrieval from the SMAP mission. IEEE Trans. Geosci. Remote Sens. 52, 490–507.
Park, C.H., Montzka, C., Jagdhuber, T., Jonard, F., De Lannoy, G., Hong, J., Jackson, T.J., Wulfmeyer, V., 2019. A dielectric mixing model accounting for soil organic matter. Vadose Zone J. 18, 190036.
Pathe, C., Wagner, W., Sabel, D., Doubkova, M., Basara, J.B., 2009. Using ENVISAT ASAR global mode data for surface soil moisture retrieval over Oklahoma, USA. IEEE Trans. Geosci. Remote Sens. 47, 468–480.
Pauwels, V.R., Hoeben, R., Verhoest, N.E., De Troch, F.P., 2001. The importance of the spatial patterns of remotely sensed soil moisture in the improvement of discharge predictions for small-scale basins through data assimilation. J. Hydrol. 251, 88–102.
Peng, J., Loew, A., Merlin, O., Verhoest, N.E., 2017. A review of spatial downscaling of satellite remotely sensed soil moisture. Rev. Geophys. 55, 341–366.
Peng, J., Albergel, C., Balenzano, A., Brocca, L., Cartus, O., Cosh, M.H., Crow, W.T., Dabrowska-Zielinska, K., Dadson, S., Davidson, M.W., 2021. A roadmap for high-resolution satellite soil moisture applications–confronting product characteristics with user requirements. Remote Sens. Environ. 252, 112162.
Peng, Y., Yang, Z., Zhang, Z., Huang, J., 2024. A Machine Learning-Based High-Resolution Soil Moisture Mapping and Spatial–Temporal Analysis: The Mlhrsm Package. Agronomy 14, 421.
Peng, C., Zeng, J., Chen, K.S., Ma, H., Letu, H., Zhang, X., Shi, P., Bi, H., 2025. Spatial Representativeness of Soil Moisture Stations and Its Influential Factors at a Global Scale. IEEE Trans. Geosci. Remote Sens. 63, 1–15.
Pettinato, S., Santi, E., Paloscia, S., Pampaloni, P., Fontanelli, G., 2013. The intercomparison of X-band SAR images from COSMO-SkyMed and TerraSAR-X satellites: Case studies. Remote Sens 5, 2928–2942.
Pierdicca, N., Davidson, M., Chini, M., Dierking, W., Djavidnia, S., Haarpaintner, J., Hajduch, G., Laurin, G.V., Lavalle, M., López-Martínez, C., 2019. The copernicus L-band SAR mission ROSE-L (radar observing system for Europe)(conference presentation). In: Active and Passive Microwave Remote Sensing for Environmental Monitoring III. SPIE, 111540E.
Potin, P., Rosich, B., Grimont, P., Miranda, N., Shurmer, I., O'Connell, A., Torres, R., Krassenburg, M., 2016. Sentinel-1 mission status. In: Proceedings of EUSAR 2016: 11th European conference on synthetic aperture radar. VDE, pp. 1–6.
Prein, A.F., Langhans, W., Fosser, G., Ferrone, A., Ban, N., Goergen, K., Keller, M., Tölle, M., Gutjahr, O., Feser, F., 2015. A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges. Rev. Geophys. 53, 323–361.
Pulvirenti, L., Squicciarino, G., Cenci, L., Boni, G., Pierdicca, N., Chini, M., Versace, C., Campanella, P., 2018. A surface soil moisture mapping service at national (Italian) scale based on Sentinel-1 data. Environ. Model Softw. 102, 13–28.
Quast, R., Wagner, W., Bauer-Marschallinger, B., Vreugdenhil, M., 2023. Soil moisture retrieval from Sentinel-1 using a first-order radiative transfer model—A case-study over the Po-Valley. Remote Sens. Environ. 295, 113651.
Rabiei, S., Jalilvand, E., Tajrishy, M., 2021. A method to estimate surface soil moisture and map the irrigated cropland area using sentinel-1 and sentinel-2 data. Sustainability 13, 11355.
Rahmati, M., Montzka, C., 2024. Advances in Soil Moisture Retrieval From the Sentinel Products. In: IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, pp. 4428–4430.
Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., Brocca, L., Chen, H., Groh, J., Koster, R.D., 2024. Soil Moisture Memory: State-of-the-art and the way forward. Rev. Geophys. 62, e2023RG000828.
Rains, D., Lievens, H., De Lannoy, G.J., McCabe, M.F., de Jeu, R.A., Miralles, D.G., 2021. Sentinel-1 backscatter assimilation using support vector regression or the water cloud model at European soil moisture sites. IEEE Geosci. Remote Sens. Lett. 19, 1–5.
Reichle, R.H., 2008. Data assimilation methods in the Earth sciences. Adv. Water Resour. 31, 1411–1418.
Reichle, R.H., Koster, R.D., Dong, J., Berg, A.A., 2004. Global Soil Moisture from Satellite Observations, Land Surface Models, and Ground Data: Implications for Data Assimilation. J. Hydrometeorol. 5, 430–442.
Reichle, R.H., Liu, Q., Ardizzone, J.V., Crow, W.T., De Lannoy, G.J., Dong, J., Kimball, J. S., Koster, R.D., 2021. The contributions of gauge-based precipitation and SMAP brightness temperature observations to the skill of the SMAP Level-4 soil moisture product. J. Hydrometeorol. 22, 405–424.
Rice, S.O., 1951. Reflection of electromagnetic waves from slghtly rough surfaces. Commun. Pure Appl. Math. 4, 351–378.
Rignot, E.J., Van Zyl, J.J., 1993. Change detection techniques for ERS-1 SAR data. IEEE Trans. Geosci. Remote Sens. 31, 896–906.
Robock, A., 2003. HYDROLOGY | Soil Moisture. In: Holton, J.R. (Ed.), Encyclopedia of Atmospheric Sciences. Academic Press, Oxford, pp. 987–993.
Rojas-Munoz, O., Calvet, J.-C., Bonan, B., Baghdadi, N., Meurey, C., Napoly, A., Wigneron, J.-P., Zribi, M., 2023. Soil moisture monitoring at kilometer scale: assimilation of sentinel-1 products in ISBA. Remote Sens 15, 4329.
Roy, P.D., Dey, S., Bhogapurapu, N., Chakraborty, S., 2025. Retrieval of Surface Soil Moisture at Field Scale Using Sentinel-1 SAR Data. Sensors 25, 3065.
Sabaghy, S., Walker, J.P., Renzullo, L.J., Jackson, T.J., 2018. Spatially enhanced passive microwave derived soil moisture: Capabilities and opportunities. Remote Sens. Environ. 209, 551–580.
Salvi, S., Stramondo, S., Funning, G.J., Ferretti, A., Sarti, F., Mouratidis, A., 2012. The Sentinel-1 mission for the improvement of the scientific understanding and the operational monitoring of the seismic cycle. Remote Sens. Environ. 120, 164–174.
Santi, E., Paloscia, S., Pettinato, S., Fontanelli, G., 2016. Application of artificial neural networks for the soil moisture retrieval from active and passive microwave spaceborne sensors. Int. J. Appl. Earth Obs. Geoinf. 48, 61–73.
Santi, E., Paloscia, S., Pettinato, S., Brocca, L., Ciabatta, L., Entekhabi, D., 2018. On the synergy of SMAP, AMSR2 AND SENTINEL-1 for retrieving soil moisture. Int. J. Appl. Earth Obs. Geoinf. 65, 114–123.
Santi, E., Pettinato, S., Paloscia, S., Clarizia, M.P., Dente, L., Guerriero, L., Comite, D., Pierdicca, N., 2020. Soil moisture and forest biomass retrieval on a global scale by using CyGNSS data and artificial neural networks. In: In, *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, pp. 5905–5908.
Santi, E., Paloscia, S., Pettinato, S., Fontanelli, G., 2021. Neural network integration of SMAP and Sentinel-1 for estimating soil moisture at high spatial resolution. In: In, *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*. IEEE, pp. 6327–6330.
Satalino, G., Balenzano, A., Mattia, F., Davidson, M.W., 2013. C-band SAR data for mapping crops dominated by surface or volume scattering. IEEE Geosci. Remote Sens. Lett. 11, 384–388.
Schlund, M., Erasmi, S., 2020. Sentinel-1 time series data for monitoring the phenology of winter wheat. Remote Sens. Environ. 246, 111814.
Schmidt, S.I., Schröder, T., Kutzner, R.D., Laue, P., Bernert, H., Stelzer, K., Friese, K., Rinke, K., 2024. Evaluating Satellite-Based Water Quality Sensing of Inland Waters on Basis of 100+ German Water Bodies Using 2 Different Processing Chains. Remote Sens 16, 3416.
Scipal, K., Holmes, T., De Jeu, R., Naeimi, V., Wagner, W., 2008. A possible solution for the problem of estimating the error structure of global soil moisture data sets. Geophys. Res. Lett. 35, L24403.
Scott, C., Lohman, R., Jordan, T., 2017. InSAR constraints on soil moisture evolution after the March 2015 extreme precipitation event in Chile. Sci. Rep. 7, 4903.
Seyfried, M.S., Murdock, M.D., 2004. Measurement of soil water content with a 50-MHz soil dielectric sensor. Soil Sci. Soc. Am. J. 68, 394–403.
Shi, J., Wang, J., Hsu, A.Y., O'Neill, P.E., Engman, E.T., 1997. Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. IEEE Trans. Geosci. Remote Sens. 35, 1254–1266.
Shoshany, M., Svoray, T., Curran, P., Foody, G.M., Perevolotsky, A., 2000. The relationship between ERS-2 SAR backscatter and soil moisture: generalization from a humid to semi-arid transect. Int. J. Remote Sens. 21, 2337–2343.
Singh, A., Gaurav, K., 2023. Deep learning and data fusion to estimate surface soil moisture from multi-sensor satellite images. Sci. Rep. 13, 2251.
Small, D., 2011. Flattening gamma: Radiometric terrain correction for SAR imagery. IEEE Trans. Geosci. Remote Sens. 49, 3081–3093.
Sun, L., Bélair, S., Carrera, M.L., Bilodeau, B., Dabboor, M., 2021. Comparing Assimilation of Synthetic Soil Moisture Versus C-Band Backscatter for Hyper-Resolution Land Surface Modeling. Water Resour. Res. 57, e2020WR028921.
Szypłowska, A., Lewandowski, A., Yagihara, S., Saito, H., Furuhata, K., Szerement, J., Kafarski, M., Wilczek, A., Majcher, J., Woszczyk, A., 2021. Dielectric models for moisture determination of soils with variable organic matter content. Geoderma 401, 115288.
Tabatabaeenejad, A., Burgin, M., Moghaddam, M., 2012. Potential of L-Band Radar for Retrieval of Canopy and Subcanopy Parameters of Boreal Forests. IEEE Trans. Geosci. Remote Sens. 50, 2150–2160.
Tabatabaeenejad, A., Burgin, M., Duan, X.Y., Moghaddam, M., 2015. P-Band Radar Retrieval of Subsurface Soil Moisture Profile as a Second-Order Polynomial: First AirMOSS Results. IEEE Trans. Geosci. Remote Sens. 53, 645–658.
Tapley, B.D., Bettadpur, S., Ries, J.C., Thompson, P.F., Watkins, M.M., 2004. GRACE measurements of mass variability in the Earth system. Science 305, 503–505.
Thoma, D., Moran, M., Bryant, R., Rahman, M., Holifield-Collins, C., Skirvin, S., Sano, E., Slocum, K., 2006. Comparison of four models to determine surface soil moisture from C-band radar imagery in a sparsely vegetated semiarid landscape. Water Resour. Res. 42, W01418.
Topp, G.C., Davis, J., Annan, A.P., 1980. Electromagnetic determination of soil water content: Measurements in coaxial transmission lines. Water Resour. Res. 16, 574–582.
Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Traver, I.N., Deghaye, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L'Abbate, M., Croci, R., Pietropaolo, A., Huchler, M., Rostan, F., 2012. GMES Sentinel-1 mission. Remote Sens. Environ. 120, 9–24.
Tsang, L., Kong, J.A., Shin, R.T., 1985. Theory of microwave remote sensing. Wiley, Hoboken.
Twele, A., Cao, W., Plank, S., Martinis, S., 2016. Sentinel-1-based flood mapping: a fully automated processing chain. Int. J. Remote Sens. 37, 2990–3004.
Ulaby, F.T., Sarabandi, K., Mcdonald, K., Whitt, M., Dobson, M.C., 1990. Michigan Microwave Canopy Scattering Models (MIMICS). Int. J. Remote Sens. 11, 1223–1253.
Ulaby, F.T., Long, D.G., Blackwell, W.J., Elachi, C., Fung, A.K., Ruf, C., Sarabandi, K., Zebker, H.A., Van Zyl, J., 2014. Microwave radar and radiometric remote sensing. The University of Michigan Press, Ann Arbor.

Ullmann, T., Stauch, G., 2020. Surface Roughness Estimation in the Orog Nuur Basin (Southern Mongolia) Using Sentinel-1 SAR Time Series and Ground-Based Photogrammetry. Remote Sens 12, 3200.
Ullmann, T., Jagdhuber, T., Hoffmeister, D., May, S.M., Baumhauer, R., Bubenzer, O., 2023. Exploring Sentinel-1 backscatter time series over the Atacama Desert (Chile) for seasonal dynamics of surface soil moisture. Remote Sens. Environ. 285, 113413.
Vermunt, P.C., Steele-Dunne, S.C., Khabbazan, S., Kumar, V., Judge, J., 2022. Towards Understanding the Influence of Vertical Water Distribution on Radar Backscatter from Vegetation Using a Multi-Layer Water Cloud Model. Remote Sens 14, 3867.
Villarroya-Carpio, A., Lopez-Sanchez, J.M., Engdahl, M.E., 2022. Sentinel-1 interferometric coherence as a vegetation index for agriculture. Remote Sens. Environ. 280, 113208.
Vreugdenhil, M., Dorigo, W.A., Wagner, W., De Jeu, R.A., Hahn, S., Van Marle, M.J., 2016. Analyzing the vegetation parameterization in the TU-Wien ASCAT soil moisture retrieval. IEEE Trans. Geosci. Remote Sens. 54, 3513–3531.
Vreugdenhil, M., Wagner, W., Bauer-Marschallinger, B., Pfeil, I., Teubner, I., Rüdiger, C., Strauss, P., 2018. Sensitivity of Sentinel-1 Backscatter to Vegetation Dynamics: An Austrian Case Study. Remote Sens 10, 1396.
Wagner, W., Lemoine, G., Borgeaud, M., Rott, H., 1999a. A study of vegetation cover effects on ERS scatterometer data. IEEE Trans. Geosci. Remote Sens. 37, 938–948.
Wagner, W., Lemoine, G., Rott, H., 1999b. A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sens. Environ. 70, 191–207.
Wagner, W., Sabel, D., Doubkova, M., Bartsch, A., Pathe, C., 2009. The potential of Sentinel-1 for monitoring soil moisture with a high spatial resolution at global scale. In: Symposium of Earth Observation and Water Cycle Science, p. 60.
Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., De Rosnay, P., Jann, A., Schneider, S., 2013. The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications. Meteorol. Z. 22 (1), 5–33.
Wagner, W., Bauer-Marschallinger, B., Navacchi, C., Reuß, F., Cao, S., Reimer, C., Schramm, M., Briese, C., 2021. A Sentinel-1 Backscatter Datacube for Global Land Monitoring Applications. Remote Sens 13, 4622.
Wang, R., Zhao, J., Yang, H., Li, N., 2023a. Inversion of Soil Moisture on Farmland Areas Based on SSA-CNN Using Multi-Source Remote Sensing Data. Remote Sens 15, 2515.
Wang, Z., Zhao, T.J., Shi, J.C., Wang, H.Q., Ji, D.B., Yao, P.P., Zheng, J.Y., Zhao, X.S., Xu, X., 2023b. 1-km soil moisture retrieval using multi-temporal dual-channel SAR data from Sentinel-1 A/B satellites in a semi-arid watershed. Remote Sens. Environ. 284, 113334.
Weiß, T., Jagdhuber, T., Ramsauer, T., Löw, A., Marzahn, P., 2024. RTM-based downscaling of medium resolution soil moisture using Sentinel-1 data over agricultural fields. IEEE J. Select. Top. Appl. Earth Observat. Remote Sens. 17, 15463–15479.
Wickel, A., Jackson, T., Wood, E.F., 2001. Multitemporal monitoring of soil moisture with RADARSAT SAR during the 1997 Southern Great Plains hydrology experiment. Int. J. Remote Sens. 22, 1571–1583.
Wig, E., Michaelides, R., Zebker, H., 2024. Fine-resolution measurement of soil moisture from cumulative InSAR closure phase. IEEE Trans. Geosci. Remote Sens. 62, 1–15.
Wu, T.-D., Chen, K.-S., 2004. A reappraisal of the validity of the IEM model for backscattering from rough surfaces. IEEE Trans. Geosci. Remote Sens. 42, 743–753.
Wu, S., Zhao, T., Pan, J., Xue, H., Zhao, L., Shi, J., 2022. Improvement in modeling soil dielectric properties during freeze-thaw transitions. IEEE Geosci. Remote Sens. Lett. 19, 1–5.
Wu, Z., Cui, N., Zhang, W., Liu, C., Jin, X., Gong, D., Xing, L., Zhao, L., Wen, S., Yang, Y., 2024. Estimating soil moisture content in citrus orchards using multi-temporal sentinel-1A data-based LSTM and PSO-LSTM models. J. Hydrol. 637, 131336.
Xie, Q., Jia, L., Menenti, M., Hu, G., 2022. Global soil moisture data fusion by Triple Collocation Analysis from 2011 to 2018. Sci Data 9, 687.
Xie, Y., Cui, G., Zheng, K., Tang, G., 2025. Integrating Sentinel-1 SAR and Machine Learning Models for Optimal Soil Moisture Sensor Placement at Catchment Scale. Remote Sens 17, 2330.
Yagüe-Martínez, N., Prats-Iraola, P., González, F.R., Brcic, R., Shau, R., Geudtner, D., Eineder, M., Bamler, R., 2016. Interferometric Processing of Sentinel-1 TOPS Data. IEEE Trans. Geosci. Remote Sens. 54, 2220–2234.
Yahia, O., Karoui, M.S., Guida, R., 2022. An Inversion of a Modified Water Cloud Model for Soil Moisture Content Estimation Through Sentinel-1 and Landsat-8 Remote Sensing Data. In: In, *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, pp. 6181–6184.
Yang, H., Shi, J., Li, Z., Guo, H., 2006. Temporal and spatial soil moisture change pattern detection in an agricultural area using multi-temporal Radarsat ScanSAR data. Int. J. Remote Sens. 27, 4199–4212.
Yang, M., Wang, H., Tong, C., Zhu, L., Deng, X., Deng, J., Wang, K., 2021. Soil moisture retrievals using multi-temporal sentinel-1 data over nagqu region of tibetan plateau. Remote Sens 13, 1913.
Ye, N., Walker, J.P., Wu, X., Jeu, R.D., Gao, Y., Jackson, T.J., Jonard, F., Kim, E., Merlin, O., Pauwels, V., Renzullo, L.J., Rüdiger, C., Sabaghy, S.C., Hebel, V., Yueh, S. H., Zhu, L., 2020. The Soil Moisture Active Passive Experiments: Validation of the SMAP Products in Australia. IEEE Trans. Geosci. Remote Sens. 59, 2922–2939.
Yu, Y., Filippi, P., Bishop, T.F., 2025a. Field-scale soil moisture estimated from Sentinel-1 SAR data using a knowledge-guided deep learning approach. arXiv preprint arXiv: 2505.00265.
Yu, Y., Malone, B.P., Renzullo, L.J., Burton, C.A., Tian, S., Searle, R.D., Bishop, T.F.A., Walker, J.P., 2025b. Spatial Soil Moisture Prediction From In Situ Data Upscaled to Landsat Footprint: Assessing Area of Applicability of Machine Learning Models. IEEE Trans. Geosci. Remote Sens. 63, 1–19.
Yuan, Y., Kleinherenbrink, M., López-Dekker, P., 2024. On Crop Growth and InSAR Closure Phases. IEEE Trans. Geosci. Remote Sens. 62, 1–12.
Zappa, L., Dari, J., Modanesi, S., Quast, R., Brocca, L., De Lannoy, G., Massari, C., Quintana-Seguí, P., Barella-Ortiz, A., Dorigo, W., 2024. Benefits and pitfalls of irrigation timing and water amounts derived from satellite soil moisture. Agric. Water Manag. 295, 108773.
Zeng, J., Chen, K.S., 2018. Theoretical Study of Global Sensitivity Analysis of L-Band Radar Bistatic Scattering for Soil Moisture Retrieval. IEEE Geosci. Remote Sens. Lett. 15, 1710–1714.
Zeng, Z.Z., Zhu, Z.C., Lian, X., Li, L.Z.X., Chen, A.P., He, X.G., Piao, S.L., 2016. Responses of land evapotranspiration to Earth's greening in CMIP5 Earth System Models. Environ. Res. Lett. 11, 104006.
Zhang, X., Chen, B., Zhao, H., Li, T., Chen, Q., 2018. Physical-based soil moisture retrieval method over bare agricultural areas by means of multi-sensor SAR data. Int. J. Remote Sens. 39, 3870–3890.
Zhao, F., Sun, R., Zhong, L., Meng, R., Huang, C., Zeng, X., Wang, M., Li, Y., Wang, Z., 2022. Monthly mapping of forest harvesting using dense time series Sentinel-1 SAR imagery and deep learning. Remote Sens. Environ. 269, 112822.
Zheng, Y., Fattahi, H., 2024. Modeling, Prediction and Retrieval of Surface Soil Moisture from Insar Closure Phase. Remote Sens. Environ. 333, 115104.
Zheng, Y., Fattahi, H., Agram, P., Simons, M., Rosen, P., 2022. On closure phase and systematic bias in multilooked SAR interferometry. IEEE Trans. Geosci. Remote Sens. 60, 1–11.
Zhu, L., Walker, J.P., Tsang, L., Huang, H., Ye, N., Rüdiger, C., 2019. A multi-frequency framework for soil moisture retrieval from time series radar data. Remote Sens. Environ. 235, 111433.
Zhu, L., Walker, J.P., Shen, X., 2020. Stochastic ensemble methods for multi-SAR-mission soil moisture retrieval. Remote Sens. Environ. 251, 112099.
Zhu, L., Li, W., Wang, H., Deng, X., Tong, C., He, S., Wang, K., 2022a. Merging microwave, optical, and reanalysis data for 1 km daily soil moisture by triple collocation. Remote Sens 15, 159.
Zhu, L., Si, R., Shen, X., Walker, J.P., 2022b. An advanced change detection method for time-series soil moisture retrieval from Sentinel-1. Remote Sens. Environ. 279, 113137.
Zhu, L., Yuan, S., Liu, Y., Chen, C., Walker, J.P., 2023. Time series soil moisture retrieval from SAR data: Multi-temporal constraints and a global validation. Remote Sens. Environ. 287, 113466.
Zhu, L., Dai, J., Liu, Y., Yuan, S., Qin, T., Walker, J.P., 2024. A cross-resolution transfer learning approach for soil moisture retrieval from Sentinel-1 using limited training samples. Remote Sens. Environ. 301, 113944.
Zhu, L., Dai, J., Jin, J., Yuan, S., Xiong, Z., Walker, J.P., 2025. Are the current expectations for SAR remote sensing of soil moisture using machine learning over-optimistic? IEEE Trans. Geosci. Remote Sens. 63, 1–15.
Zreda, M., Shuttleworth, W., Zeng, X., Zweck, C., Desilets, D., Franz, T., Rosolem, R., 2012. COSMOS: The cosmic-ray soil moisture observing system. Hydrol. Earth Syst. Sci. 16, 4079–4099.
Zribi, M., André, C., Decharme, B., 2008. A method for soil moisture estimation in Western Africa based on the ERS scatterometer. IEEE Trans. Geosci. Remote Sens. 46, 438–448.
Zribi, M., Gorrab, A., Baghdadi, N., Lili-Chabaane, Z., Mougenot, B., 2014. Influence of radar frequency on the relationship between bare surface soil moisture vertical profile and radar backscatter. IEEE Geosci. Remote Sens. Lett. 11, 848–852.
Zwieback, S., Hensley, S., Hajnsek, I., 2015. Assessment of soil moisture effects on L-band radar interferometry. Remote Sens. Environ. 164, 77–89.
Zwieback, S., Hensley, S., Hajnsek, I., 2017. Soil moisture estimation using differential radar interferometry: Toward separating soil moisture and displacements. IEEE Trans. Geosci. Remote Sens. 55, 5069–5083.