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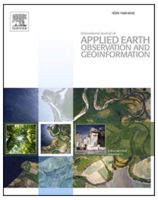

A critical review on the applications of Sentinel satellite datasets for soil moisture assessment in crop production

Anela Mkhwenkwana[a,*], Trylee Nyasha Matongera[c], Ciara Blaauw[b], Onisimo Mutanga[a]

[a] Discipline of Geography and Environmental Science, School of Agricultural Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3201, South Africa
[b] Council for Scientific and Industrial Research (CSIR), Meiring Naudé Rd, Brummeria, Pretoria 0184, South Africa
[c] School of Biosciences, University of Nottingham Malaysia, 43500, Malaysia

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ABSTRACT

Understanding soil moisture dynamics in crop production is critical for optimising water resource management. The Sentinel satellite missions have significantly contributed to soil moisture monitoring by providing high-resolution, multi-sensor data. This review examines advancements in soil moisture assessment using Sentinel datasets, particularly in crop production. It highlights key challenges, evaluates their impact on monitoring accuracy, and explores potential methodological improvements. Findings indicate that Sentinel-1′s synthetic aperture radar (SAR) data, particularly VV and VH polarizations, and Sentinel-2′s multispectral indices, such as NDVI and NDMI, are widely integrated with machine learning algorithms to enhance soil moisture estimation. However, dense vegetation and complex topography reduce retrieval accuracy, necessitating sensor fusion and calibration for improved reliability. Sentinel-3 provides valuable surface temperature and land condition data for indirect soil moisture estimation, but its application remains limited due to higher uncertainty compared to SAR and multispectral approaches. Emerging trends suggest that machine and deep learning techniques, such as RF, SVR, and CNN, can enhance data fusion across Sentinel missions. Additionally, preprocessing steps such as RTC, speckle filtering, and the integration of multipolar and polarimetric data with physical backscattering models show promise in mitigating radar backscatter interference. Further development of robust retrieval models that incorporate topography, soil roughness, and texture are essential for improving soil moisture accuracy in diverse agricultural landscapes. This review underscores the need for continued methodological advancements to maximise the potential of Sentinel datasets for soil moisture monitoring in precision agriculture and water resource management.

1. Introduction

Effective monitoring of soil moisture is crucial not only for optimising crop productivity but also for tackling the growing challenges of water scarcity, food security, and climate change (Ahmed et al., 2023; Ray & Majumder, 2024). Soil moisture is an essential variable in agriculture, directly affecting crop growth, development, and yield (Hillel, 2003). Monitoring soil moisture content is essential to optimise water use, ensure crop health, and prevent severe challenges such as waterlogging and stress (Bwambale et al., 2022; Dubois, 2011). Understanding soil moisture variations is essential to optimise crop production and meet the growing food demand by bridging the gap between potential and actual yield (Müller & Robertson, 2014). A study by Lobell et al. (2014) discovered that inadequate soil moisture can reduce wheat and corn yields by 10–30 % in major agricultural regions.

Similarly, Fischer et al. (2015) found that water stress leads to reduced grain production in cereals during critical growth stages such as ontogenesis. Therefore, monitoring temporal and spatial variations in soil moisture is essential for both optimal crop yield and food security (Lloret et al., 2021; Mukwada et al., 2021). Monitoring soil moisture is becoming increasingly vital for addressing climate change challenges, including severe climatic conditions such as floods, droughts, and water scarcity (Cordovil et al., 2020; Srivastav et al., 2021).

Extreme weather events, such as floods and droughts, pose significant challenges to crop productivity and food security (Lobell et al., 2011). Drought stress reduces crop growth and has led to a 10 % global

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* Corresponding author at: Discipline of Geography and Environmental Science, University of KwaZulu-Natal, Private Bag X01, Scottsville 3209, South Africa.
E-mail address: 224193498@stu.ukzn.ac.za (A. Mkhwenkwana).

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decline in crop yields between 1964 and 2007 (Lesk et al., 2016). The world is currently falling short of achieving critical nutrition targets, including the UN Sustainable Development Goal (SDG) 2 of ending hunger by 2030 (Allahyari & Sadeghzadeh, 2020), with drought being a key obstacle (Enomoto et al., 2023). Monitoring soil moisture enables farmers to optimise planting schedules. This supports SDG 1 (No Poverty) and SDG 2 (Zero Hunger) by promoting food security. Understanding soil moisture dynamics also improves irrigation efficiency by ensuring water is applied only when needed, preventing overuse (Shaxson & Barber, 2003; Wolka et al., 2018). Various methods, including traditional in-situ techniques and remote sensing approaches, are available for reliable soil moisture monitoring (Adeyemi et al., 2018; Babaeian, Sadeghi, et al., 2019; Mohanty et al., 2017).

Traditional soil moisture measurement methods, such as neutron probes, time-domain reflectometry, and gravimetric techniques, provide precise point-based data but are labour-intensive, time-consuming, and limited in spatial coverage (Mukhlisin et al., 2021; Sharma et al., 2018). The gravimetric technique directly measures soil moisture by weighing soil samples before and after drying, offering high accuracy at a low cost, but requiring significant manual effort (Reynolds, 1970; Sharma et al., 2018). Neutron probes measure soil moisture by lowering a probe containing a detector and source into an access hole, and are easier to use (O'Leary & Incerti, 1993). Despite their accuracy, these methods cannot effectively scale to regional or global levels due to soil moisture's spatial and temporal variability, making extrapolation difficult (Petropoulos et al., 2013; Srivastava, 2017).

To overcome these limitations, proximal remote sensing techniques using ground-based multispectral and hyperspectral sensors have become an important bridge between satellite observations and field measurements (Finn et al., 2011; Nasta et al., 2019). These instruments allow researchers to directly capture soil spectral signatures in both controlled laboratory and field conditions, enabling non-invasive estimation of soil moisture and related properties at high spectral resolution (Abdulraheem et al., 2023; Franceschelli et al., 2020). Studies such as that of Xu et al. (2016) and Dhawale et al. (2022) have demonstrated the potential of hyperspectral laboratory and handheld field data to predict soil moisture, having achieved R^2 values higher than 0.933, thereby highlighting the importance of these sensors, as they capture subtle differences in spectral soil properties. Building on these advances, spaceborne missions have extended soil moisture monitoring to regional and global scales. Dedicated satellites such as Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS) provide valuable large-scale soil moisture datasets, however, their spatial resolution, typically 9 to 40 km, remains too coarse for many agricultural, hydrological, and land management applications (Entekhabi et al., 2010; Mohanty et al., 2017). This trade-off between global coverage and spatial detail has prompted increasing use of Sentinel satellites. The European Space Agency's (ESA) Sentinel missions, particularly Sentinel-1 and Sentinel-2, have significantly advanced soil moisture monitoring by integrating synthetic aperture radar and multispectral data, improving accuracy and coverage (Chakhar et al., 2021; Gao et al., 2017).

The open-access policy of Sentinel-1 Synthetic Aperture Radar (SAR) data has revolutionised soil moisture monitoring by providing continuous global observations without financial constraints (Gao et al., 2017; Mastrorosa et al., 2023). With a high temporal resolution of approximately 6 to 12 days, Sentinel-1 effectively captures local soil moisture variations with high predictive accuracy (Gruber et al., 2013; Mengen et al., 2023). Its ability to penetrate clouds and operate day and night makes it particularly valuable in areas with frequent cloud cover, where optical sensors are less effective. However, retrieval accuracy can be affected by vegetation cover and surface roughness. Studies suggest that integrating multipolar and polarimetric data with backscattering models and surface roughness parameters can mitigate these limitations (Lievens et al., 2017; Sun et al., 2018). Additionally, combining SAR with optical data enables vegetation index calculations, improving soil moisture estimation accuracy by correcting or masking vegetation-affected areas (Amazirh et al., 2018; Brunelli et al., 2024; Han et al., 2020).

Sentinel-2 optical data has been widely utilised and shown effective for estimating soil moisture, particularly in vegetated areas, due to its high spatial resolution, a temporal resolution of 5 days, and its multispectral bands that are sensitive to changes in vegetation water content and surface reflectance influenced by soil moisture (Liu et al., 2021; Wang et al., 2024). Results by Gangat et al. (2020) demonstrated that employing the Random Forest (RF) regression algorithm obtained a high coefficient of determination with Sentinel-2 bands compared to individual bands. Sentinel-2 provides high-resolution mapping of soil moisture, making it suitable for landscapes such as smallholder agricultural plots (Karlson et al., 2020; Timmermans, 2018). However, unlike SAR sensors, optical sensors are affected by cloud cover, surface texture, and vegetation density when detecting soil moisture (Prakash et al., 2011; Qiu et al., 2019). The incorporation of multitemporal phenological stages, vegetation indices, and different incident angles has been employed to minimise the impacts that vegetation has on soil moisture assessment (Holzman et al., 2014; Jagdhuber et al., 2012). Holzman et al. (2014) applied time-series Normalized Difference Vegetation Index (NDVI) and multitemporal SAR observations to separate vegetation and soil signals, improving moisture retrieval under dynamic canopy conditions. Jagdhuber et al. (2012) further demonstrated that combining multi-incidence angle SAR data with polarimetric decomposition techniques helped distinguish surface scattering from volume scattering in vegetated landscapes. Studies utilising Sentinel datasets have contributed to improving soil moisture monitoring, predicting crop yield, and enhancing irrigation management (El Hajj et al., 2017; Zhuo et al., 2019).

Several reviews, such as that of Wang and Qu (2007), Petropoulos et al. (2015), and Babaeian, Sidike, et al. (2019) have explored soil moisture retrieval using satellite observations, with a strong focus on microwave remote sensing products and retrieval algorithms. Z.-L. Li et al. (2021) summarised current knowledge and future directions, while Bauer-Marschallinger et al. (2018) examined the use of Sentinel-1 for global soil moisture monitoring. However, a comprehensive review specifically addressing Sentinel datasets for soil moisture assessment remains lacking. Existing reviews generally cover remote sensing broadly, overlooking Sentinel's unique advantages, such as its high temporal frequency, spatial resolution, and the integration of radar and optical data (Z.-L. Li et al., 2021; Zhang & Zhou, 2016). This study aims to fill the gap by providing an in-depth analysis of Sentinel-based soil moisture monitoring, evaluating recent algorithms, and emphasising the combined use of Sentinel-1 and Sentinel-2 for improved accuracy. Additionally, it offers recommendations for future research on optimising Sentinel datasets for soil moisture assessment.

2. Literature search and selection of sources

The Web of Science, Google Scholar, and ScienceDirect databases were used to compile relevant literature due to their strong coverage of peer-reviewed journals, interdisciplinary reach, and focus on remote sensing, agricultural, and environmental sciences. Although Scopus and Scielo were considered, these databases were prioritised for their citation capabilities and access to recent publications. The search terms used were "Soil Moisture", "Remote Sensing", "Geospatial technologies", "Vegetation indices", "Crop production", "Crop water stress", "Precision farming", and only peer-reviewed soil moisture literature that focused on crop production was considered. The search was restricted to the publication's title, abstract, and keywords using the following string: ("Sentinel-1" OR "SAR") AND ("Sentinel-2" OR "Optical" OR "Multispectral") AND ("Soil moisture" OR "Soil water content" OR "Water stress" OR "Water logging") AND ("Estimation" OR "Assessment" OR "Monitoring"). The selection and structure of keywords were based on previous similar literature reviews.

The geographic extent and year of publication were not restricted, while non-English written articles were excluded. Non-English articles were excluded because most scientific journals publish in English, and the process of translating non-English articles is time-consuming and costly. A total of 356 publications were initially retrieved, and this number was refined through the inclusion criteria of the search terms and strings; the search can be extended; the chosen scope ensures the analysis remains focused and reflects the most directly relevant studies for the objectives of this review. From the 356 publications, 102 duplicates, 30 non-full-text articles, and 5 non-English articles were excluded. Subsequently, 60 publications were identified as suitable for inclusion in the review. Thereafter, by examining the reference lists of these 60 publications, 8 more relevant articles were added, resulting in a final total of 68 publications included in this review. The final 68 publications included in this review were critically read through the different sections, and the results of this review reflect the analysis of the content in these publications.

3. Remote sensing techniques for assessing soil moisture content

Remote sensing offers a practical and efficient approach for large-scale soil moisture monitoring, providing enhanced spatial coverage, near real-time tracking, frequent temporal acquisition, and cost-effective data accessibility (Khanal et al., 2020; Liu et al., 2023). Remote sensing techniques for soil moisture assessment are generally classified into microwave, optical, thermal infrared (TIR), and integrated approaches, with microwave-based methods (active and passive) being especially valuable due to their sensitivity to surface roughness, dielectric properties, and soil water content (Z.-L. Li et al., 2021; Petropoulos et al., 2015). Earlier studies, such as those of Le Hégarat-Mascle et al. (2002) using active sensors, laid important groundwork by applying a change detection algorithm to European Remote Sensing (ERS) data, successfully capturing soil moisture dynamics over agricultural fields. Das et al. (2023) used the SMAP mission initially combined L-band radar and radiometer measurements, achieving soil moisture retrievals with Root Mean Square Error (RMSE) values of 0.04 m^3/m^3. Additionally, Gorrab et al. (2015) applied a semi-empirical model using TerraSAR-X data and achieved an R^2 value of 0.75, particularly under bare or sparsely vegetated conditions. However, performance declined with increased vegetation density, therefore, lower-frequency L-band SAR systems such as ALOS PALSAR have demonstrated superior capabilities for penetrating vegetation and retrieving soil moisture beneath canopy cover (Gao et al., 2021; Ottinger & Kuenzer, 2020). Shashikant et al. (2021) used ALOS PALSAR data to develop a linear model between backscatter and ground soil moisture, achieving R^2 values between 0.6 and 0.8 across mixed agricultural landscapes. These findings reinforce the advantages of L-band sensors for soil moisture monitoring in vegetated areas.

Active sensors often face trade-offs between spatial and temporal resolution, where higher spatial resolution typically comes at the cost of less frequent revisits, therefore, the use of passive systems that offer broad spatial coverage at coarse spatial resolutions is of importance as well (Q. Li et al., 2021; Petropoulos et al., 2015). Recent studies such as that of Albergel et al. (2009) and Gruhier et al. (2008) showed that soil moisture products derived from C and/or X-band satellite passive microwave observations correlate well with in situ observations and model estimates of the soil moisture, over agricultural regions characterised by dense crop fields. As such, Calvet et al. (2010) utilised the PALS for soil moisture retrieval, achieving R^2 values between 0.5 and 0.7, while Han et al. (2015) achieved an RMSE value lower than 0.04 m^3/m^3 in dense vegetated areas, and these results indicate a good correlation between soil moisture retrievals and in situ measurements. Compared to optical sensors and TIR, microwave systems offer deeper soil penetration and all-weather observation capabilities, which are crucial advantages for improving the reliability of soil moisture estimation (Abdulraheem et al., 2023; Gruber et al., 2013; Hussain et al., 2025).

Optical and TIR methods infer soil moisture indirectly by tracking vegetation vigor, surface reflectance changes, and land-surface temperature (Sadeghi et al., 2015; Zhang & Zhou, 2016). Data from Sentinel-2, particularly vegetation indices and red-edge bands, have been widely used for soil moisture assessment, with Sadeghi et al. (2015) demonstrating that Sentinel-2 NDVI and red-edge indices correlate with soil moisture deficits in semi-arid rangelands ($R = 0.65$). Liu et al. (2021) further improved retrievals by integrating a red-edge chlorophyll index, cutting RMSE by roughly 10 % under moderate canopy cover. Yet cloud cover, penetration depth, and atmospheric interference remain critical constraints. Prudente et al. (2020) observed up to 30 % data loss during monsoon seasons when using Landsat 8 surface reflectance, and Wu et al. (2023) reported similar gaps in tropical agroecosystems. In the thermal domain, sensors such as Sentinel-3′s Sea and Land Surface Temperature Radiometer (SLSTR) can complement soil moisture assessments by highlighting thermal anomalies related to soil evaporation and plant transpiration (Frezza et al., 2024; Gomarasca et al., 2019). Zhuang and Wu (2015) combined Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) TIR land-surface temperatures with an energy-balance model to retrieve soil moisture ($R^2 = 0.91$) over irrigation zones, building on foundational work by Kustas and Anderson (2009), who employed SEBAL-derived evaporative fraction from TIR as a proxy for surface wetness in sparse vegetation. However, like optical sensors, TIR systems are constrained by cloud cover and have lower spatial resolution compared to SAR data. Given each sensor's individual limitations, synergistic approaches, which integrate multi-sensor data, have gained prominence (Samadzadegan et al., 2025; Zhang et al., 2024). Recognising that no single sensor meets all requirements, recent studies have embraced synergistic frameworks that fuse microwave, optical, and TIR data. Samadzadegan et al. (2025) integrated Sentinel-1 backscatter with Sentinel-2 red-edge indices in a machine-learning model, achieving a 20 % error reduction compared to SAR-only retrievals. Zhang et al. (2024) further enhanced this by incorporating SLSTR-derived thermal anomalies from Sentinel-3, producing an ensemble soil moisture product with RMSE below 0.03 m^3/m^3 across mixed forest–grassland sites. Complementary investigations by Sinha et al. (2018) and Wardlow et al. (2024) confirm that multi-sensor integration offers the best compromise between spatial detail, temporal frequency, and penetration depth, particularly in landscapes characterised by heterogeneous land cover. Overall, these advances underscore a clear trajectory in the literature that, while substantial progress has been achieved through single-sensor approaches, no individual technique sufficiently addresses the full range of challenges associated with soil moisture retrieval. Therefore, the transition from single-sensor soil moisture retrievals toward integrated, data-fusion approaches that harness the strengths of each sensor type delivers more accurate, reliable soil moisture products.

4. Sentinel datasets for soil moisture assessment

The Sentinel missions are a set of Earth observation satellites developed and operated by the European Space Agency (ESA) under the Copernicus Programme, a joint initiative of the European Union (EU) and ESA (Showstack, 2014). Launched in 2014 as part of the Copernicus Programme, the Sentinel missions provide continuous, accurate, and timely data to support environmental monitoring, climate change research, and disaster management (Jutz & Milagro-Perez, 2020). The Sentinel constellation comprises a variety of satellites, each equipped with different sensor technologies to monitor various aspects of the Earth's surface (Berger et al., 2012) (Table 2). The series includes Sentinel-1, which carries a SAR for all-weather, day-and-night imaging; Sentinel-2, which has a multispectral optical sensor for high-resolution imagery of Land Use and Land Cover (LULC) (Addabbo et al., 2016). The constellation also includes Sentinel-3, which focuses on land surface temperatures and colour, as well as sea surface topography and colour

(Löscher et al., 2020; Main-Knorn et al., 2017). Since its inception, the Sentinel missions have provided a wealth of open-access data, enabling scientists, researchers, and policymakers to make well-informed decisions across various sectors (Mathieu et al., 2017).

4.1. Sentinel 1

While studies have increasingly utilised Sentinel 1 due to its C-band radar's all-weather, day-and-night data collection capabilities (Balenzano et al., 2021; Hachani et al., 2019), there is an ongoing discourse about the sensor's limitations, including how the penetration depth restricts measurements to surface moisture, posing challenges for subsurface moisture assessment (Baghdadi et al., 2018; Bazzi et al., 2024). Polarization configurations also impact retrieval accuracy, with studies indicating that VV polarization correlates more strongly with field-based measurements than VH (Datta et al., 2021), though this varies based on vegetation cover and surface roughness (Yang et al., 2021). While univariate regression models achieve reasonable accuracy ($R^2 = 0.75$ for VV polarization) as employed by Datta et al. (2021), their effectiveness declines in heterogeneous landscapes (Baghdadi et al., 2018). Zribi et al. (2011) reported similar results, R^2 values between 0.65 and 0.78, over a semi-arid region depending on vegetation density, while Ballester-Berman et al. (2013) observed performance drops in mixed land covers. Consequently, there is growing interest in machine learning techniques to better account for soil moisture dynamics, vegetation effects, and surface roughness variations (Bauer-Marschallinger et al., 2018). Despite the spatial resolution of Sentinel-1 being celebrated for enabling detailed moisture mapping at field and landscape scales, there are contrasting views on its adequacy for fine-scale agricultural management (Dube et al., 2023; Mohseni et al., 2022). Research such as that of Gao et al. (2017) and Elwan et al. (2022) argues that, despite its relatively high spatial resolution, Sentinel-1 alone may be insufficient to capture small-scale moisture variations critical to precision agriculture and suggests fusing Sentinel-1 with optical data to achieve more nuanced insights. While Sentinel-1 has become instrumental in soil moisture assessment, the latest studies (e.g., Jia et al., 2025; Lee et al., 2023; Liu et al., 2024) advocate for more sophisticated methods that integrate polarization, scale, and multi-source data to address its limitations and enhance its effectiveness in soil moisture monitoring. (See Fig. 1 and Table 1.).

Studies consistently emphasise Sentinel-1′s high temporal resolution as pivotal for advancing soil moisture research (Bauer-Marschallinger et al., 2018; Gao et al., 2018). This capability has proven instrumental in addressing challenges such as precision irrigation and drought mitigation, as shown in applications outlined by Amazirh et al. (2018) and Wagner et al. (2008). The argument for Sentinel-1 as a tool for timely data is compelling, with many researchers such as Rinaldi and He (2014) and Adeyemi et al. (2017) citing its contributions to effective decision-making in agriculture. However, Gu et al. (2020) and Kelly et al. (2021) argued that soil texture and type can affect the accuracy of retrieving soil moisture, introducing uncertainty and complicating the decision-making process. As highlighted by Yin et al. (2013) and Huang et al. (2022), finer-textured soils, such as clay, exhibit stronger moisture-induced changes in reflectance compared to coarser soils like sand. This is due to clay's higher water retention capacity, which prolongs the influence of moisture on reflectance behaviour. For instance, Gao et al. (2018), utilised data from Sentinel-1 to map irrigated farmland, and while their study validated the utility of SAR data for capturing spatiotemporal variations in soil moisture, it also underscored how variability in soil texture affects water retention, thus influencing the accuracy of moisture estimates.

The utility of Sentinel-1 for soil moisture monitoring raises a concern regarding the balance between frequent monitoring and the need for additional contextual data for accurate assessment. While some studies, Beriaux et al. (2021) argue that near real-time data allows farmers to make timely irrigation decisions, other studies by Bassine et al. (2023) and Attri et al. (2024) contend that integrating Sentinel-1 with additional datasets such as those detailing soil type and crop characteristics

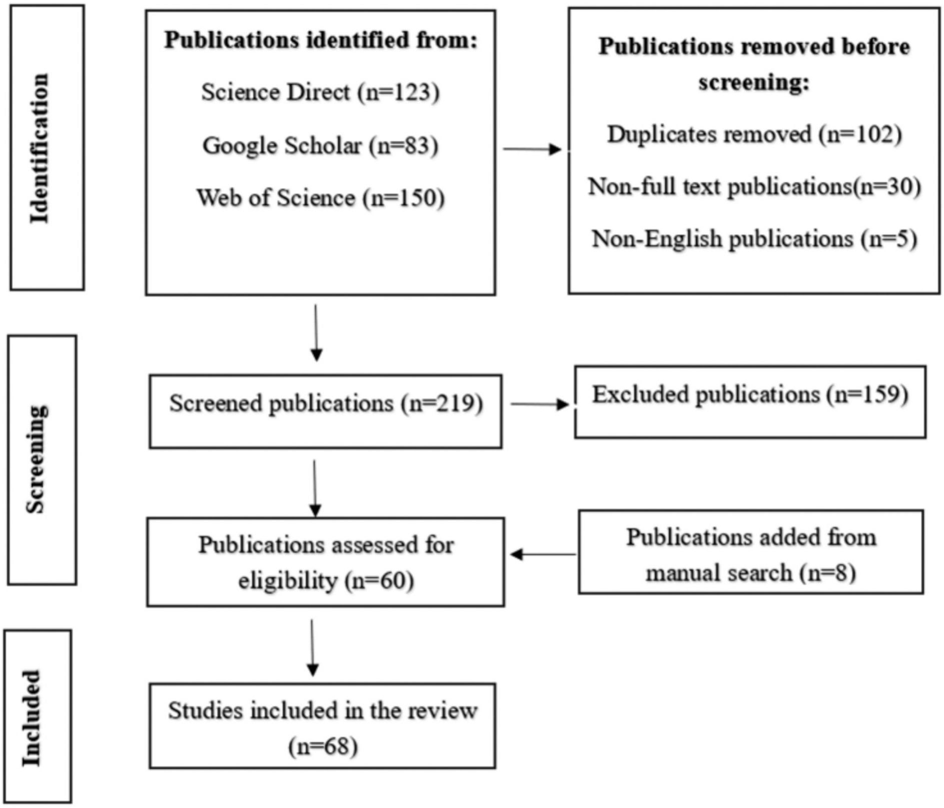

Fig. 1. Literature search, exclusion, and inclusion flow diagram.

Table 1

A comparison of the remote sensing techniques that are utilised for monitoring soil moisture content availability.

Group	Advantages	Disadvantages	Benefits	Limitations	References
Microwave Passive	Directly sensitive to soil moisture, all weather observations, and unaffected by cloud cover.	Coarse spatial resolution (25–50 km); accuracy decreases in dense vegetation and rough terrain areas.	Provides volumetric soil moisture estimates essential for global hydrological and drought models.	Limited application for field- or plot-scale precision agriculture due to low spatial resolution.	(Liu et al., 2016; Zheng et al., 2020; Zhu et al., 2024)
Microwave Active (SAR)	High spatial resolution (10–100 m); sensitive to surface roughness, vegetation, and moisture; weather-independent.	Retrieval affected by vegetation cover and soil surface roughness; requires complex calibration and modeling.	Enables soil moisture estimation in partially vegetated areas and under various weather conditions.	Accuracy declines in dense vegetation; advanced algorithm development is needed.	(Akash et al., 2024; Hussain et al., 2025)
Optical	High spatial resolution (up to 10 m with Sentinel-2); vegetation indices enable indirect soil moisture assessment.	Strongly limited by cloud cover and atmospheric conditions; primarily sensitive to surface moisture of bare soils.	Useful for monitoring soil surface moisture and vegetation water stress during early crop growth stages.	Ineffective under persistent cloud cover or dense vegetation.	(Babaeian, Sidike, et al., 2019; Ma et al., 2022; Mardan & Ahmadi, 2021)
Thermal Infrared	Useful in arid and semi-arid climates and surface temperature-based soil moisture estimation using thermal inertia.	Affected by atmospheric interference and cloud cover. Shallow sensing depth limits subsurface moisture detection.	Complements microwave and optical data for surface moisture estimation and energy balance modeling.	Primarily limited to clear-sky conditions and surface-level soil moisture; requires ancillary data.	(Imtiaz et al., 2024; Zhou et al., 2021)
Synergistic Methods	Combines multi-sensor data (microwave, optical, thermal); compensates for single-sensor limitations; enhances accuracy.	Computationally intensive; requires reliable multi-source data availability and advanced fusion techniques.	Increases the robustness and accuracy of soil moisture estimates for precision agriculture and drought monitoring.	Dependent on multi-sensor availability and sophisticated retrieval algorithms.	(Bousbih et al., 2018; El Hajj et al., 2017; Liang et al., 2021)

Table 2

Sentinel datasets characteristics.

Sentinel mission	Spectral bands	Temporal resolution	Spectral resolution	Spatial resolution	References
Sentinel 1	C-band (~5GHz)	6–12 days	N/A	5–40 *m*	(Small & Schubert, 2019)
Sentinel 2	13 bands (VNIR and SWIR)	5 days	15–180 nm (varies by band)	10 m, 20 m, 60 *m*	(Handbook & Tools, 2015)
Sentinel 3	21 bands (Ocean and Land Colour Instrument)	1–2 days	10–20 nm (OLCI), 0.2–1.0 K (SLSTR radiance)	300 m, 500 m, 1.2 km	(Nieke et al., 2015)

is essential to achieving applicable insights. Such integration would potentially mitigate the challenges of variability highlighted by Gao et al. (2018) and improve the reliability of moisture data for targeted irrigation strategies. While there is broad agreement on the advantages of Sentinel-1, such as the high temporal resolution for near-real-time soil moisture monitoring, debates persist about its stand-alone efficacy in agriculture. There is a need for further refinement, potentially through integrating Sentinel-1 data with other sources, which can enhance the practical utility of these soil moisture estimates, supporting more precise water-saving irrigation schedules and higher crop yields (Chauhdary et al., 2023; Erazo-Mesa et al., 2022; Lakhiar et al., 2024).

One of the main limitations of using Sentinel-1 for estimating soil moisture is the sensitivity of the signal of backscattering to vegetation and surface roughness, which introduces uncertainties in scattering models and, consequently, in retrieving soil moisture (Moran et al., 2000; Thoma et al., 2006). Park et al. (2009) and Schuler et al. (2002) argue that Sentinel-1′s signal alone is insufficiently robust for accurate soil moisture assessment, particularly in complex landscapes. The complex landscapes include regions with significant topographic relief and heterogeneous land-cover mosaics (mountainous vineyards, forest–crop interfaces, and *peri*-urban agricultural zones). In such areas, geometric distortions (e.g., foreshortening, layover) and mixed-pixel scattering introduce significant biases (Park et al., 2009; Schuler et al., 2002). To address these issues, preprocessing steps such as radiometric terrain correction (RTC) (Lee & Kim, 2024), speckle filtering (Sebastianelli et al., 2022) and the integration of multipolar and polarimetric data with physical backscattering models is commonly applied (Dave et al., 2023; Zhang et al., 2023). Without these corrections, classification accuracy can decrease by 20–30 % in steep and heterogeneous regions (Ma et al., 2020; Schönbrodt-Stitt et al., 2021). For instance, Jagdhuber et al. (2012) demonstrated that using model-based polarimetric decomposition significantly enhances soil moisture estimation by minimising vegetation-induced scattering effects in agricultural landscapes. Wang et al. (2016), applied a simplified polarimetric decomposition to differentiate soil moisture signals from vegetation cover, with an RMSE of 0.06–0.12 m^3/m^3 and Wang et al. (2017) reported similar results with an RMSE of 0.06–0.11 m^3/m^3 in cropland regions with varying phenology. These approaches highlight the growing importance of polarimetric analysis in overcoming surface roughness and vegetation uncertainties in radar-based soil moisture studies.

The use of machine learning algorithms such as RF, Support Vector Regression (SVR), and Artificial Neural Network (ANN) has also been adopted by other studies to adaptively address signal interference from vegetation and surface roughness, potentially offering a more flexible approach (Dong et al., 2022; Ezzahar et al., 2023; Liu et al., 2020). These models can learn complex non-linear relationships between radar backscatter or optical reflectance and soil moisture under varying surface conditions (Ali et al., 2015; Dong et al., 2022). For instance, Zeng et al. (2021) applied an RF model that fused Sentinel-1 SAR backscatter with Sentinel-2 indices, reporting an R^2 of 0.82 for soil moisture estimation in agricultural regions. Similarly, Singh and Gaurav (2023) employed an ANN model trained on multi-temporal datasets, achieving an R^2 of 0.80 across diverse land covers. The results underline the capacity of machine learning.

to reduce the effects of vegetation and surface roughness, without requiring explicit parameter calibration. However, machine learning techniques are computationally demanding, as highlighted by Wang et al. (2023) that demonstrated that a Convolutional Neural Network (CNN) based soil moisture retrieval model using Sentinel datasets time series achieved an R^2 of 0.80, but the training process required significant computational resources and long processing times, raising concerns about scalability for operational use in resource-constrained regions.

The advancement of machine learning models is essential for extracting reliable soil moisture information in heterogeneous environments, but the computational and data requirements of both physical and machine learning methods often limit their widespread adoption, particularly in regions with limited computational resources, such as in Africa is questioned (Castrignanò et al., 2020; Grunwald et al., 2015; Verrelst et al., 2015). Hybrid approaches that blend physical models with machine learning post-processing have shown promising results in the literature. For instance, Tahmouresi et al. (2024) used an ensemble strategy where outputs from physical models were refined using RF, improving R^2 from 0.68 to 0.82 across test sites. Lee et al. (2017) highlighted a similar fusion strategy, combining satellite-derived soil moisture retrievals with statistical correction models, leading to reduced bias and enhanced temporal stability. Consequently, soil moisture retrieval methods must be refined, ideally by integrating physical models with data-driven techniques, to ensure both accuracy and scalability. (Liu et al., 2024; Rajeswari & Rathika, 2024; Sheffield et al., 2018).

4.2. Sentinel 2

There is a growing consensus on Sentinel-2′s transformative potential for soil moisture and crop monitoring due to its advanced red-edge bands (Buthelezi et al., 2023; ISHOLA, 2021). Several authors, including Sadeghi et al. (2015), argue that the unique characteristics of the red edge bands make Sentinel-2 a powerful tool for soil moisture estimation, citing its capability to capture phenological and physiological shifts in crops that correspond to water availability. However, it is also important to acknowledge that these bands can be affected by spectral saturation, particularly during advanced phenological stages or under dense vegetation cover, which can reduce their sensitivity to subtle moisture variations (Gong et al., 2024; Mutanga et al., 2023). This is also reinforced by Clevers and Gitelson (2013) and Frampton et al. (2013), who find that the resolution of Sentinel-2 imagery, both spatial and spectral, enhances the accuracy of moisture-related indices in complex agricultural landscapes. While some studies highlight Sentinel-2′s ability to aid timely irrigation decisions by detecting moisture stress (Ramoelo et al., 2015; Sadeghi et al., 2017), other studies (Abdelbaki & Udelhoven, 2022; Gutman et al., 2021) question the robustness of red-edge indices under varying environmental conditions, such as mixed crop types or high vegetation density, suggesting that further refinement may be needed for universal application. Despite these points of contention, the overarching trend in recent studies supports Sentinel-2 as a valuable tool in agriculture, with the red-edge bands exhibiting a crucial role in advancing soil moisture assessment (Hegazi et al., 2023; Liu et al., 2021; Segarra et al., 2020).

A key application of Sentinel-2′s capabilities in field monitoring is the ESA Sen2-Agri system, which generates modules of time series of vegetation status indicators to assess crop changes throughout the growing season (Defourny et al., 2019; Vijayasekaran, 2019). These various products include monthly cloud-free surface reflectance and dynamic cropland masks of spatial resolution provided from agricultural mid-season and time series of vegetation condition indicators, including indices (Jiao et al., 2022; Solano-Correa et al., 2019). While the system's high spatial resolution can capture fine-scale soil moisture heterogeneity essential in agricultural contexts, other studies (Deng et al., 2019; Dobriyal et al., 2012) caution that this level of detail may come with trade-offs, suggesting that while high-resolution data provides detail, it also demands careful calibration and interpretation. Another advantage is Sentinel-2′s frequent revisit time, which enhances agricultural monitoring by capturing seasonal trends, droughts, and weather impacts, with tools such as Sen2-Agri advancing soil moisture assessments and crop management (Van Leeuwen et al., 2020; Xi et al., 2021). However, challenges such as data overload and the complexity of data interpretation highlight the need for improved processing and adaptive strategies (Bontemps et al., 2015; Nelson, 2019).

Measuring soil moisture in vegetated areas remains challenging due to vegetation interference with surface moisture signals (Barrett and Petropoulos, 2013; Li et al., 2017). Sentinel-2′s multispectral bands, particularly Shortwave Infrared (SWIR) and Near-Infrared (NIR), help capture vegetation moisture content, enabling corrections for vegetation effects on soil moisture assessment (Brown, 2008; Liu et al., 2021). For instance Liu et al. (2021) employed the Normalized Difference Water Index (NDWI) and Modified Soil Moisture Monitoring Index (SMMI) derived from Sentinel-2′s NIR/SWIR bands to estimate moisture, reporting an R2 = 0.85. Additionally, Jopia et al. (2020) used a set of Sentinel-2 bands to predict the water potential of the stem in cotton through RF, finding that the most important bands correspond to SWIR and red edge. Therefore, integrating Sentinel-2′s optical data with Sentinel-1′s radar backscatter, which is sensitive to moisture and surface roughness, enhances soil moisture assessment in vegetated regions (Wang et al., 2018). Studies have demonstrated that this fusion improves accuracy, with Balenzano et al. (2021) reporting a low RMSE of 0.04 m^3/m^3 in agricultural fields, an accuracy level difficult to achieve with either sensor alone. This supports the growing trend of multi-sensor approaches for overcoming vegetation interference in soil moisture monitoring. Bauer-Marschallinger et al. (2018), however, highlight concerns about the complexity of data fusion techniques and their computational demands, particularly when applied on a global scale.

There is also an emphasis on the transformative impact of free, open access to Sentinel-2 data, which has democratised remote sensing by lowering financial barriers, allowing more researchers, especially in developing countries, to engage in soil moisture long-term studies (Segarra et al., 2020; Upadhyay et al., 2022). This accessibility has expanded soil moisture research to previously underrepresented regions and ecosystems (Brown, 2008; Camps-Valls et al., 2021). However, despite these positive trends, there are potential limitations to relying exclusively on open-access data for critical environmental monitoring. Atzberger (2013) and Hank et al. (2019) suggest that while freely available Sentinel data have expanded research scope, they may lack the precision of commercial datasets in specific applications. Moreover, Hritz (2014) points to challenges in data processing and quality control, which can vary widely in different geographic and environmental contexts, indicating that accessibility alone does not always equate to operational efficacy. The open access model of Sentinel data has reshaped soil moisture research, particularly by removing access barriers and encouraging studies across diverse landscapes and ecosystems (Monteiro et al., 2024; Suter, 2024).

While there is an agreement that these developments mark a significant step forward, there is caution regarding the limitations inherent in open-access datasets, advocating for ongoing improvements in data quality and methodological support to maximise the utility of these resources (Radeloff et al., 2024; Ramachandran et al., 2021). This discourse highlights the transformative yet complex role of open-access remote sensing data, advancing soil moisture monitoring while underscoring the need for balanced approaches in achieving both accessibility and precision. The development of global soil moisture products using Sentinel data, such as those by Bauer-Marschallinger et al. (2018) has advanced drought early warning and hydrological modeling by providing high-resolution, scalable monitoring tools across multiple scales (Ochsner et al., 2013). A notable example is the Copernicus Soil Moisture product (Cover, 2018), which combines Sentinel data with other sources to deliver consistent near-real-time and historical soil moisture maps (RIXEN et al., 2024). This includes the Surface Soil Moisture dataset, reflecting the topsoil water content, and the Soil Water Index, which indicates moisture conditions at various depths which both are essential for agriculture, water management, and weather forecasting (Paciolla et al., 2020; Paulik et al., 2014). As such, fusion of Sentinel datasets has become essential in environmental and agricultural applications, including water resource management, drought monitoring, and precision agriculture (Jędrejek & Pudełko, 2023; Qader et al., 2023).

4.3. Sentinel 3

Compared to Sentinel-1 and Sentinel-2, Sentinel-3 is seldom used for soil moisture assessment because it was designed primarily for oceanographic and atmospheric measurements, land surface monitoring, and vegetation dynamics rather than direct soil moisture retrieval (Donlon et al., 2012; Petropoulos et al., 2020). However, Sentinel-3′s instruments, particularly the SLSTR and the Ocean and Land Colour Instrument (OLCI), offer valuable indirect insights into soil moisture by capturing surface thermal behaviour and vegetation stress responses (González Delgado, 2019; Ojha et al., 2021). These features make it valuable for studying surface energy balance and vegetation water stress, both of which are indirectly linked to soil moisture dynamics (Ojha et al., 2021). Compared to other Sentinel missions, Sentinel-3′s advantage lies in its high temporal resolution and wide swath coverage, which allow for near-daily observations at moderate spatial scales (Olmanson et al., 2011; Xue et al., 2021). However, its spatial resolution of 300 m for OLCI and approximately 1 km for SLSTR is relatively coarse for field-scale soil moisture monitoring, limiting its stand-alone use in precision agriculture, where finer spatial detail is often essential (González Delgado, 2019).

Despite its limitations, several studies have investigated Sentinel-3′s potential for soil moisture assessment, often in combination with other datasets to compensate for its coarse spatial resolution. González Delgado (2019) employed Sentinel-3′s Land Surface Temperature (LST) and vegetation indices to downscale SMOS soil moisture products, achieving improved spatial detail but noting reduced accuracy in areas with complex land cover. Similarly, Stefan et al. (2018) applied Sentinel-3 SLSTR data within the DISPATCH algorithm to generate 1 km soil moisture estimates, demonstrating enhanced spatial refinement in arid zones, though performance was constrained by surface heterogeneity and cloud-induced data gaps. Madelon et al. (2023) further explored Sentinel-3′s synergy with Sentinel-1 and Sentinel-2 in the S2MP algorithm, concluding that while spatial precision was limited by Sentinel-3′s resolution, its frequent temporal coverage improved the consistency of soil moisture estimates, especially under persistent cloud conditions. Additionally, Ojha et al. (2021) integrated Sentinel-3, SMAP, and MODIS using the DISPATCH framework and reported enhanced soil moisture retrieval accuracy in semi-arid regions; however, the study also emphasised that Sentinel-3′s spatial limitations and cloud sensitivity remained significant challenges for agricultural applications.

A study by Petropoulos et al. (2020) also investigated the accuracy of a technique, known as the "simplified triangle", using Sentinel-3 EO data, and the technique was found to be able to predict soil moisture with reasonable accuracy when compared to ground measurements. Comparisons performed relatively good with correlation coefficients R^2 of 0.721. The study consisted of the first detailed assessment of the "simplified triangle", in this case, using Sentinel-3 data and in a Mediterranean setting. Additionally, a study by Hu et al. (2019) also evaluated the Vegetation Temperature Condition Index (VTCI) drought monitoring index derived from Sentinel-3A SLSTR and compared these values against those obtained from the MODIS instrument. The results also revealed that the VTCI was sensitive to rainfall and, therefore, was sensitive to both soil moisture content and variation, and can be used for monitoring agricultural drought in the study area. When combined with the LST and NDVI retrieved from satellite data, VTCI may provide more valuable information – for agricultural drought monitoring, especially in large-scale areas and regions with insufficient ground monitoring stations or infrastructure. Existing studies show that while Sentinel-3 alone cannot achieve the spatial detail needed for detailed soil moisture mapping, its integration through downscaling techniques and multi-sensor fusion enhances both the spatial and temporal quality of soil moisture retrievals (Hu et al., 2019; Madelon et al., 2023; Stefan et al., 2018).

5. Data fusion and advanced techniques for soil moisture monitoring

Recent research has increasingly focused on integrating Sentinel-1 and Sentinel-2 data to address the limitations of individual sensors in soil moisture monitoring (Bazzi et al., 2024; Ma et al., 2020; Valero et al., 2021). Sentinel-1′s C-band radar offers reliable soil moisture estimates under various weather conditions, but its performance declines in densely vegetated areas due to reduced backscatter sensitivity to subsurface moisture (Ayari et al., 2021). To overcome this, Sentinel-2′s vegetation indices have been employed to provide indirect insights into soil moisture, as they reflect vegetation health, which is often linked to soil water availability (Jiao et al., 2022; Van Tricht et al., 2018). Sentinel-2′s red edge spectral bands are effective proxies for plant water stress, enhancing soil moisture assessments in vegetated landscapes (Segarra et al., 2020; Varghese et al., 2021).Studies like Ma et al. (2020) have shown that integrating the red edge bands with Sentinel-1 data significantly improves soil moisture mapping accuracy in such regions. This combined use of multispectral and SAR datasets reflects a growing trend in the literature, which recognises the complementary strengths of these sensors for comprehensive soil moisture assessment (Liang et al., 2021; Liu et al., 2020). Beyond optical indices, SAR-derived indices such as the Radar Vegetation Index (RVI) and the Polarimetric Radar Vegetation Index (DpRVI) have also proven valuable for characterising vegetation, further enriching soil moisture retrieval efforts when used alongside optical data (Hashemi, 2024; Hu et al., 2024).

However, the reliance on vegetation indices for inferring soil moisture has sparked debate. Casamitjana et al. (2020) and West et al. (2022) argue that plant health is influenced by multiple factors beyond soil moisture, such as nutrient availability and pest stress, raising concerns about the accuracy of using vegetation indices alone for deeper moisture estimation. Conversely, Pignotti (2012) and Duckett (2014) further caution that optical data may oversimplify complex soil-vegetation interactions, potentially leading to misleading assumptions about subsurface moisture (Duckett, 2014; Pignotti, 2012). This is particularly relevant for root zone soil moisture, where surface indicators alone may not accurately reflect deeper soil conditions (Sehgal et al., 2024). To address this, recent studies have employed data assimilation and physically based models to estimate moisture at depth better. For instance, Entekhabi et al. (2010), through the SMAP mission, demonstrated that assimilating surface soil moisture observations into land surface models can improve root zone moisture estimates. Similarly, Brocca et al. (2012) showed that blending satellite-derived surface data with water balance models can significantly improve estimates of deeper soil water content. Despite these challenges, there is broad agreement that integrating Sentinel datasets enhances soil moisture estimation in vegetated and heterogeneous environments (Benninga et al., 2022; Urban et al., 2018). These findings collectively suggest that while vegetation indices offer useful surface-level information, more integrated approaches are required to reliably capture root zone soil moisture.

Various data fusion strategies have been employed to leverage Sentinel-1 and Sentinel-2 data, including machine learning, statistical models, physical models, and hybrid frameworks. For instance, Ma et al. (2020) demonstrated that combining Sentinel-1 radar backscatter with Sentinel-2 vegetation indices via an RF model achieved an R^2 of 0.74 for soil moisture prediction in croplands. Similarly, Bazzi et al. (2020) used regression trees and RF techniques to fuse these datasets, reaching an R^2 of 0.78 in Mediterranean agricultural zones. Urban et al. (2018) reported R^2 values between 0.71 and 0.79 when integrating Sentinel-1 and Sentinel-2 data using machine learning and data assimilation, highlighting improvements in both spatial accuracy and temporal stability over single-sensor models. While integration offers clear benefits, it also introduces computational and methodological demands. Monteiro et al.

(2024) employed SVR on fused Sentinel datasets and achieved an R^2 of 0.81 in Mediterranean drylands, but noted that such methods require significant computational resources, which can limit their use in regions with restricted access to advanced infrastructure or skilled personnel (Grabska & Socha, 2021).

To extend sensor capabilities even further, Lee et al. (2023) and Monteiro et al. (2024) advocate for incorporating Sentinel-3, as it offers complementary information about surface temperatures. However, this multi-sensor approach demands careful spatial and temporal alignment and increases processing complexity, particularly for root zone moisture estimation. Sehgal et al. (2024) emphasised that integrating surface reflectance, thermal infrared, and microwave backscatter from Sentinel-2, Sentinel-3, and Sentinel-1, respectively, can lead to more comprehensive multi-layer soil moisture profiles. Physical modeling techniques, such as the Water Cloud Model (WCM) and radiative transfer models, have also been applied to correct for vegetation effects on SAR signals. Zribi et al. (2019) used WCM with simulated Sentinel-1 data to separate vegetation contributions, achieving R^2 values between 0.65 and 0.75 depending on crop type. Veloso et al. (2017) combined Sentinel-1 and Sentinel-2-derived vegetation parameters within the WCM, reporting an R^2 of 0.68. Beyond physical models, hybrid approaches combining machine learning and physical modeling have gained attention for blending theoretical understanding with empirical flexibility. Montzka et al. (2018) employed a hybrid data assimilation method that integrated Sentinel-1 data with the Community Land Model using Ensemble Kalman Filtering, reducing soil moisture prediction errors by 30–40 % compared to traditional simulations. Additionally, Qiu et al. (2019) combined radiative transfer models with machine learning techniques, achieving R^2 values between 0.70 and 0.82 across varied vegetation scenarios. These advancements highlight the growing potential of combining multi-sensor satellite data, physical models, and machine learning techniques to improve soil moisture retrieval accuracy, offering a more robust and scalable framework for addressing the complexities of soil moisture monitoring across diverse landscapes.

Sentinel-1, 2, and 3 alone cannot comprehensively address the complexities of soil moisture monitoring. The fusion of these satellites, however, represents a transformative approach for achieving higher accuracy and applicability across diverse landscapes. While methodological advancements, such as machine learning integration, physical models, and hybrid frameworks, hold promise for refining soil moisture estimates, challenges related to data fusion, such as aligning spatial and temporal resolution, must be carefully managed (Abbes et al., 2024; Singh & Gaurav, 2023). Machine learning models excel at capturing nonlinear relationships but can risk overfitting, while physical models offer interpretability at the cost of requiring site-specific calibration (Basak et al., 2023; Marquez, 2023). Hybrid frameworks attempt to balance these trade-offs but demand high-quality ground-truth data and advanced computing capabilities (Almalki et al., 2024; Nsoh et al., 2024). For decision-makers, adopting integrated soil moisture monitoring solutions promises clear advantages for precision agriculture and water resource management, particularly in water-scarce regions. However, these benefits come with the need for investment in computational infrastructure and methodological expertise. Overall, there is strong consensus that the combined use of Sentinel-1, Sentinel-2, and Sentinel-3 is crucial for overcoming the limitations of individual sensors, enhancing soil moisture retrievals, and supporting modern agricultural and hydrological practices (Lee et al., 2023; Monteiro et al., 2024).

6. Spectral reflectance and soil moisture

Soil moisture may be measured with high spatiotemporal resolution data, including optical and active remote sensing (Huang et al., 2022). A key point in the literature is that soil reflectance varies based on variables including soil texture, mineral composition, moisture content, and surface roughness (Yin et al., 2013). The vegetation and soil exhibit increased reflectance under water stress, particularly in the optical wavelength spectrum of 0.4–2.5 μm, with notable sensitivity in the SWIR and red regions (Cibula et al., 1992; Maimaitiyiming et al., 2017). The trend highlights that soil moisture levels can be more accurately assessed across varied land cover by monitoring these spectral responses, particularly in red and SWIR bands. However, this approach has also sparked debate, while Maimaitiyiming et al. (2017) endorse using different land-cover types for channel differences for estimating soil moisture, others (Glenn et al., 2008; Toole et al., 2000) argue that such measurements may oversimplify complex interactions between soil characteristics and environmental conditions, which can affect reflectance data accuracy.

The correlation between soil reflectance and soil moisture in the shortwave spectrum is well established, with wet soils appearing darker due to reduced reflectance caused by pore water affecting light scattering and absorption (Kaleita et al., 2005; Lobell & Asner, 2002). Skidmore et al. (1975) discovered an ongoing decrease in soil reflectance as moisture content increased, with the most significant drop occurring in bands with high water absorption. However, at very high soil moisture levels exceeding field capacity, this relationship may become nonlinear, complicating soil moisture estimation in saturated conditions (Haubrock et al., 2008; Liu et al., 2003). Sentinel-2 has been effective in capturing these spectral variations, yet factors such as organic matter, soil texture, and surface conditions introduce uncertainties, making direct soil moisture retrieval from reflectance data complex and debated (Sedaghat et al., 2022; Shokati et al., 2024).

Studies such as that of Bach and Verhoef (2003) found that soil reflectance declines are particularly strong in the red and SWIR regions, aligning with water's natural absorption peaks. The SWIR bands have been observed to show a reflectance decrease proportionally with soil moisture levels until saturation occurs (Whiting et al., 2004). An interesting trend known as the "saturation effect" has been noted in cases of very high soil moisture content, typically beyond field capacity. Liu et al. (2003) revealed that when soils reach near saturation, the decline in reflectance flattens or even reverses in certain bands. This saturation effect arises because fully saturated soils are less affected by further water additions, leading to stabilised reflectance values (Tian & Philpot, 2015; Yong & Ouhadi, 2007). This non-linear response presents difficulties for soil moisture retrieval, as models based solely on reflectance values may underestimate moisture at high levels. The literature also reveals that soil texture, surface roughness, and mineral composition significantly impact the soil moisture reflectance relationship. Clay-rich soils exhibit more significant moisture-induced reflectance variations than sandy soils, owing to their higher water retention capacity, which prolongs the influence of moisture on reflectance behaviour (Huang et al., 2022; Yin et al., 2013). Additionally, Cibula et al. (1992) examined spectral responses in soils under varying surface roughness and found that smooth surfaces with high moisture produced lower reflectance values than rough, dry surfaces. This trend highlights how surface texture mediates the energy interaction with soil, complicating the relationship between reflectance and moisture.

In order to distinguish between wet and dry soil surfaces and for mapping vegetation water stress, the SWIR can be used and as such. Le Page et al. (2020) used this band to map soil moisture in arid regions, making it valuable for soil moisture estimation and drought monitoring. Studies confirm that indices derived from SWIR can accurately estimate soil moisture, particularly in arid regions, and contribute to water resource management (Herrera et al., 2017; Transon et al., 2018). Although the visible and NIR bands of Sentinel-2 are not directly sensitive to soil moisture, they provide indirect insights by assessing vegetation health, soil properties, and surface reflectance (Brosinsky et al., 2014; Zhang et al., 2013). Integrating SWIR, visible, and NIR bands enhances soil moisture estimation by combining direct soil observations with vegetation responses, offering a comprehensive approach for drought monitoring and water management.

7. Spectral indices for soil moisture monitoring

A wide range of spectral and backscatter-based indices have been employed in soil moisture estimation, derived from both optical and SAR data. These indices serve various roles, from directly estimating soil moisture content to reflecting vegetation water status, or combining both for improved accuracy (Pôças et al., 2020; Zhang & Zhou, 2016). Table 3 summarises commonly used indices, including their formulas, benefits, and limitations.

8. Challenges and future directions in Sentinel datasets for soil moisture assessment

While Sentinel datasets offer a reliable means for global soil moisture monitoring due to their high resolution and frequent revisit times, several challenges remain. Sentinel-1′s radar backscatter models are generally constrained to soil moisture levels between 5 % and 35 % volumetric water content and are only capable of penetrating the top few centimetres of the soil, limiting their utility for subsurface moisture assessment. Similarly, Sentinel-2′s reliance on vegetation indices and surface reflectance makes it susceptible to inaccuracies, particularly in densely vegetated areas or immediately following short-term rainfall events (Xu et al., 2024). Terrain-related factors such as vegetation cover, surface roughness, and topography further complicate soil moisture retrieval from Sentinel-1, necessitating the use of correction methods such as the WCM, radiative transfer models, and machine learning-based calibration to reduce vegetation and surface roughness effects (Veloso et al., 2017; Zribi et al., 2019). Moreover, Sentinel-2′s dependence on optical data makes it highly sensitive to cloud cover, limiting its applicability in persistently cloudy or rainy regions (Kganyago, 2022).

Another important limitation, often overlooked, is the effect of satellite acquisition time on soil moisture measurements. The timing of image capture varies depending on the satellite's orbit and geographic location, and this temporal variation can significantly affect soil moisture estimations (Kerr et al., 2016; Lei et al., 2015). For instance, Wang et al. (2012) and Verstraeten et al. (2008) highlighted that soil moisture tends to be higher in the early morning due to lower evapotranspiration, while afternoon acquisitions typically reflect drier surface conditions, influenced by increased temperature and evaporation. Therefore, this fluctuation highlights the need for time-of-day consideration in both data interpretation and model calibration (Joiner et al., 2018). To address these challenges, integrating Sentinel-1 and Sentinel-2 datasets can improve soil moisture estimates by combining radar-derived surface structure insights with optical-based vegetation and reflecta-nce data, offering a more comprehensive representation of land surface conditions. Advanced data fusion techniques such as machine learning-based ensemble approaches, data assimilation frameworks (e.g., Ensemble Kalman Filtering), and hybrid physical-statistical models like the integration of the WCM with ANN (Peng et al., 2021) have shown promise in enhancing soil moisture retrieval accuracy. Future research should continue refining these methods while adapting retrieval models across varying climatic zones, soil textures, and topographic complexities. Additionally, integrating deep learning could offer dynamic pathways for adjusting soil moisture predictions in real-time, ultimately supporting more precise and sustainable agricultural and water resource management practices.

9. Conclusion

The present study reviewed the literature on the application of sentinel datasets for the assessment of soil moisture in crop production. Monitoring soil moisture in crop production is important because it improves water use efficiency, crop health, and productivity, making it a key factor in sustainable and climate-resilient agricultural practices. Empirical evidence has revealed that Sentinel datasets offer crucial data sources in soil moisture assessment across regional and global scales, a previously impossible task using ground-based measurements. Additionally, the literature shows that studies that have combined Sentinel-1 and 2 offer great potential and more accuracy for monitoring soil moisture than studies that have utilised them separately. However, challenges remain, therefore, including adopting advanced models such as deep learning algorithms and other machine learning algorithms to account for surface roughness and vegetation cover in estimating soil moisture could enhance the accuracy. Despite these limitations, the applications of Sentinel satellite datasets have laid a strong foundation for future advancements in crop production, offering promising solutions to address food security, water scarcity, and sustainable agricultural development.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Table 3
Summary of commonly used spectral and SAR-based indices for soil moisture assessment, including their formulas, benefits, and limitations.

Index Name	Formula	Benefits	Limitations	References
Normalized Multi-band Drought Index (NMDI)	$\frac{B8A-(B11-B12)}{B8A+(B11-B12)}$	Sensitive to vegetation and soil moisture; effective for drought and soil moisture assessment.	Requires SWIR bands; influenced by surface roughness and atmospheric water vapor.	(Qiu et al., 2018; Wang & Qu, 2007; Zhang et al., 2009)
Normalized Difference Vegetation Index (NDVI)	$\frac{B08-B04}{B08+B04}$	Simple, widely used for vegetation monitoring and soil moisture masking.	It saturates in dense vegetation, influenced by soil background and atmosphere.	(Amani et al., 2017; Holzman et al., 2014; Nie et al., 2020)
Normalized Difference Moisture Index (NDMI)	$\frac{B8A-B11}{B8A+B11}$	Highlights vegetation water content; useful in soil moisture estimation.	Less effective over bare soil; affected by cloud and atmospheric conditions.	(Abdelbaki & Udelhoven, 2022; Imtiaz et al., 2024; Taloor et al., 2021)
Soil Adjusted Vegetation Index (SAVI)	$\frac{B8-B4}{B8+B4+L}*1.5\mathrm{L}=0.5$	Reduces soil brightness influence; improves soil moisture retrieval under sparse vegetation.	Requires L tuning; less effective for dense vegetation.	(Samalca, 2007; Sun et al., 2012; Taloor et al., 2021)
Global Moisture Vegetation Index (GVI)	$\frac{B8+0.1}{B8+B11+0.1}$	Sensitive to drought stress and canopy water content; useful for soil-vegetation moisture dynamics.	Influenced by atmospheric noise and is limited to areas with vegetation cover.	(Ceccato et al., 2002; González-Dugo & Mateos, 2008; Sun et al., 2012)
Vegetation Optical Depth (VOD)	Retrieved via model inversion from SAR or passive microwave backscatter.	Separates vegetation water content from soil moisture signals.	Sensitive to vegetation model accuracy and complex to retrieve.	(De Jeu & Owe, 2003; Meyer et al., 2018; Owe et al., 2001)
Radar Vegetation Index (RVI)	$\frac{\sigma^0\_VV}{\sigma^0\_VH}$	Reflects vegetation scattering and assists with soil moisture estimation refinement.	Sensitive to surface roughness, incidence angle, and canopy structure; calibration is required.	(Huang et al., 2015; Kim et al., 2011; Szigarski et al., 2018)
Polarization Difference Index (PDI)	$\sigma^0\_HH-\sigma o\_HV\mathrm{or}\sigma^0\_VV-\sigma^0\_VV$	Highlights canopy and surface moisture differences; useful for soil moisture correction.	Affected by surface roughness and vegetation volume; requires calibration.	(Ma & Liu, 2025; Owe et al., 2001; Singh & Dadhwal, 2003)

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CRediT authorship contribution statement

Anela Mkhwenkwana: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Trylee Nyasha Matongera:** Writing – review & editing, Supervision, Conceptualization. **Ciara Blaauw:** Writing – review & editing, Supervision, Conceptualization. **Onisimo Mutanga:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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