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Review Article

Advances in remote sensing techniques for surface soil moisture estimation: A systematic review of recent developments (2019–2024)

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ABSTRACT

Surface soil moisture (SSM) is a vital variable for irrigation management, estimation of crop water stress, and agricultural drought management. This systematic review integrates recent progress (2019–2024) in remote sensing-based SSM estimation, based on 116 peer-reviewed articles selected using PRISMA guidelines. The review indicates that multi-sensor techniques, integrating optical, radar, and climate information coupled with machine learning (ML) and data assimilation methods, have immensely enhanced the spatial and temporal resolution of SSM products. These developments have brought SSM retrieval within the realm of useful, field-scale application for agricultural water management. Hybrid models and AI-downscaled approaches, in particular, have a very high potential for operational decision-making across varying agro-ecologies. Trends in performance, regional research gaps, and areas for improvement in terms of data coverage, especially for semi-arid and smallholder-dominated landscapes, are also addressed in this review. SWOT analysis of prominent retrieval algorithms identifies their advantages and limitations in application, revealing the compromises between complexity, scalability, and accuracy. Although there has been increasing technical development, with few exceptions, there is no large-scale application in actual irrigation systems. The article ends by placing greater emphasis on enhancing stronger validation protocols, improved application within crop and hydrological models, and region-tailored modifications of retrieval workflows. In the future, new satellite missions and enhanced ground data infrastructure offer opportunities to enhance the contribution of SSM to climate-resilient agriculture. This review offers a timely basis to advance SM monitoring systems that are not only scientifically valid but operationally pertinent to sustainable water management in agriculture.

1. Introduction

Soil moisture (SM) is a crucial variable to understand land-surface-atmosphere exchanges, which ultimately impact meteorological patterns and hydrological cycles (Ahmed et al., 2011; Hirschi et al., 2006). As a result, growers and researchers across the globe rely on this information to make critical water management decisions and research assessments. However, monitoring SM is a major challenge as it is highly variable in space and time, ranging from centimetres to kilometres spatially and from minutes to years temporally (Robinson et al., 2008; Skøien et al., 2003; Vereecken et al., 2008). In this review, SM refers broadly to the water content in the soil. We distinguish *surface soil moisture (SSM)*, the near-surface layer typically represented by satellite retrieval sensitivity (often the upper 0–5 cm), from *root-zone soil moisture (RZSM)*, which integrates moisture over the plant-active rooting depth and is more directly linked to crop water availability and hydrological processes. Because satellites sense SSM more directly than RZSM, a key research challenge is translating SSM into decision-relevant RZSM using modelling, data assimilation, and data-driven approaches.

Three main approaches are commonly used for estimating SM, including in-situ measurements, remote sensing observations, and model-based simulations. In-situ techniques such as gravimetric sampling, neutron probes, time-domain reflectometry (TDR), frequency-domain reflectometry (FDR), and other electromagnetic sensors provides point and subsurface measurements but might not be ideal due to resource intensiveness and soil heterogeneity across larger areas (Dubois

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et al., 1995). These ground-based methods formed the methodological foundation for SM monitoring before the widespread adoption of remote sensing-based passive and active microwave retrievals. Remote sensing helps overcome the spatial limitations of point-based measurements by providing repeated spatio-temporal observations, particularly in areas where ground monitoring networks are sparse or unavailable. At the same time, model-based simulations can integrate satellite retrieval information to improve representation of soil–water processes in the soil profile. Although models provide an essential process framework, their performance can be constrained by data availability, which influences calibration and validation credibility (Ranatunga et al., 2008). As a result, approaches that integrate ML with remote sensing, in-situ observations, and model-based simulations are increasingly viewed as practical pathways for producing frequent and spatially extensive SM information (Duarte and Hernandez, 2024).

Recent methodological progress has reduced several limitations in SM estimation, such as undulated topography, vegetation structure, and water content on the backscattering coefficients, are gradually being addressed using terrain correction methods, improved SAR sensors, and polarization based approaches (Koster et al., 2000). In addition, ML estimated SSM was limited to topsoil and was unable to obtain root-zone SM (RZSM), but using multiple regression, data assimilation, and data-driven techniques help to fill this gap (Yinglan et al., 2022). Emerging real-time and low-cost technologies, such as Global Navigation Satellite Systems Reflectometry (GNSS-R), offer additional potential to complement conventional remote sensing and ML approaches, although factors such as signal behaviour and vegetation interference still restrict broader application (Edokossi et al., 2020; Jin et al., 2020; Wu et al., 2021). Likewise, unmanned aerial vehicles (UAVs) or drones can provide high temporal and spatial resolution imagery for analysing SM variability and supporting precision agriculture (Babaeian et al., 2019; Hardie, 2020).

From 2019 to 2024, SSM research has accelerated through rapid advances in ML and data integration. ML-based SSM estimation has increasingly popular due to its ability to model complex non-linear relationships and combine coarse-resolution SM products with higher-resolution predictors such as land surface temperature (LST), normalized difference vegetation index (NDVI), and topographic wetness indices to generate finer-scale SSM estimates (Duarte and Hernandez, 2024; Senanayake et al., 2024; Zhang et al., 2023b). At the same time, stronger integration of ML, in-situ observations, and data assimilation has expanded the range of achievable spatio-temporal resolutions and enabled broader comparison across platforms and study designs. However, these approaches can remain sensitive to data availability and may perform poorly in data-scarce situations where training data are limited, and representativeness is weak (Singh and Gaurav, 2023). This has driven continued interest in multi-source fusion, robust validation, and approaches designed to improve transferability across regions and conditions.

Several review studies have attempted to consolidate progress, evaluate techniques, and chart future directions. Early reviews primarily compared direct and indirect measurement methods. Ground-based tools such as neutron probes, gravimetric sampling, and electromagnetic sensors offer point-level accuracy but are often expensive, invasive, and limited in spatial coverage (Babaeian et al., 2019; Rasheed et al., 2022). In contrast, passive and active microwave sensors such as SMAP, SMOS, AMSR2, and Sentinel-1 enable large-scale data acquisition and can operate under diverse weather conditions (Abdulraheem et al., 2023; Akash et al., 2024; Edokossi et al., 2020). Despite these advantages, satellite products still face challenges related to spatial resolution, vegetation interference, and the complexity of modelling soil dielectric behaviour (Jackson et al., 2010).

However, existing reviews commonly exhibit three limitations. First, many remain focused either on technology or on application, with inadequate integration of multiple data sources and limited synthesis of full fusion-to-validation workflows. Second, practical challenges such as data harmonization, accessibility, and usability, especially in resource-scarce areas are not consistently addressed (Badaluddin et al., 2021; Myeni et al., 2019). Third, global research efforts show regional imbalance, with stronger representation from North America, Europe, and China and relatively limited local validation in regions with sparse monitoring infrastructure (Badaluddin et al., 2021). Systematic reviews are valuable in this context because they provide a structured synthesis across sensing, modelling, and validation practices, and can identify recurring gaps such as inconsistencies in validation protocols and resolution mismatches that hinder standardization (Dorigo et al., 2011; Peng et al., 2021).

This review synthesizes 2019 and 2024 literature on SSM retrieval and monitoring, emphasising ML-enabled remote sensing, proximal sensing, modelling approaches, and multi-source data fusion. It evaluates methodological innovations, validation practices, and applications in agriculture, hydrology, and climate studies, while also considering pathways that link SSM information to deeper SM conditions, including RZSM where applicable. By identifying persistent limitations and highlighting emerging opportunities, this review provides evidence-based priorities for developing high-resolution, context-specific, and operationally usable SSM monitoring systems. Further, this review is needed because recent SSM research has rapidly shifted from sensor-specific retrieval toward integrated workflows combining multi-sensor fusion, data assimilation and downscaling, machine learning (ML), and decision-support applications. Finally, the review incorporates a SWOT analysis to assess the roles of sensors in SSM estimation and their practical relevance for agriculture, water resources, and climate science, and it outlines future directions including upcoming missions and technological developments.

2. Methodology

2.1. Systematic review protocol and database search strategy

In this review, a robust and reproducible systematic literature review (SLR) technique was followed to search and categorize the literature (Pickering and Byrne, 2014; Pickering et al., 2015). Scopus and Web of Science (WoS) online publication databases were chosen to obtain relevant studies published in the last six years (Jan 2019 – Dec 2024). This specific timeframe was selected to ensure a manageable number of peer-reviewed publications while keeping track of the latest advancements in the field of study. Hence, a search query was formulated to find relevant articles, following the approach by Singh et al. (2023). The term "surface soil moisture" remained constant, while sensor name/satellite mission were systematically substituted. The final database search was conducted on 15 January 2025.The database-specific Boolean search strings were recorded to support reproducibility. An example of the Scopus search string used to identify SMOS-related SSM studies was: TITLE-ABS-KEY(("surface soil moisture") AND ("European Soil Moisture and Ocean Salinity" OR "SMOS")) AND PUBYEAR > 2018 AND PUBYEAR < 2025 AND (LIMIT-TO(DOCTYPE, "ar")) AND (LIMIT-TO(LANGUAGE, "English")). Equivalent Web of Science search strings were adapted using the Topic field and the same year, language, and document-type restrictions. This query was repeated for all the sensors/satellite missions. Only peer-reviewed research articles published in English were included in the search. Review papers, conference papers, proceedings, editorials, book chapters, and other non-research article document types were excluded.

Key terms associated with SSM, such as prominent satellite missions, ML technologies, and analytical methods, were used to quantify the research outputs. These terms included AMSR-2, AMSR-E, ASCAT, ESA-CCI, GNSS-R, LiDAR, ML, Sentinel, SMAP, SMOPS, SMOS and UAV.

Fig. 1 shows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram, illustrating the identification and selection of studies. A total of 1,642 studies were initially retrieved from Scopus and Web of Science databases. All records were imported into

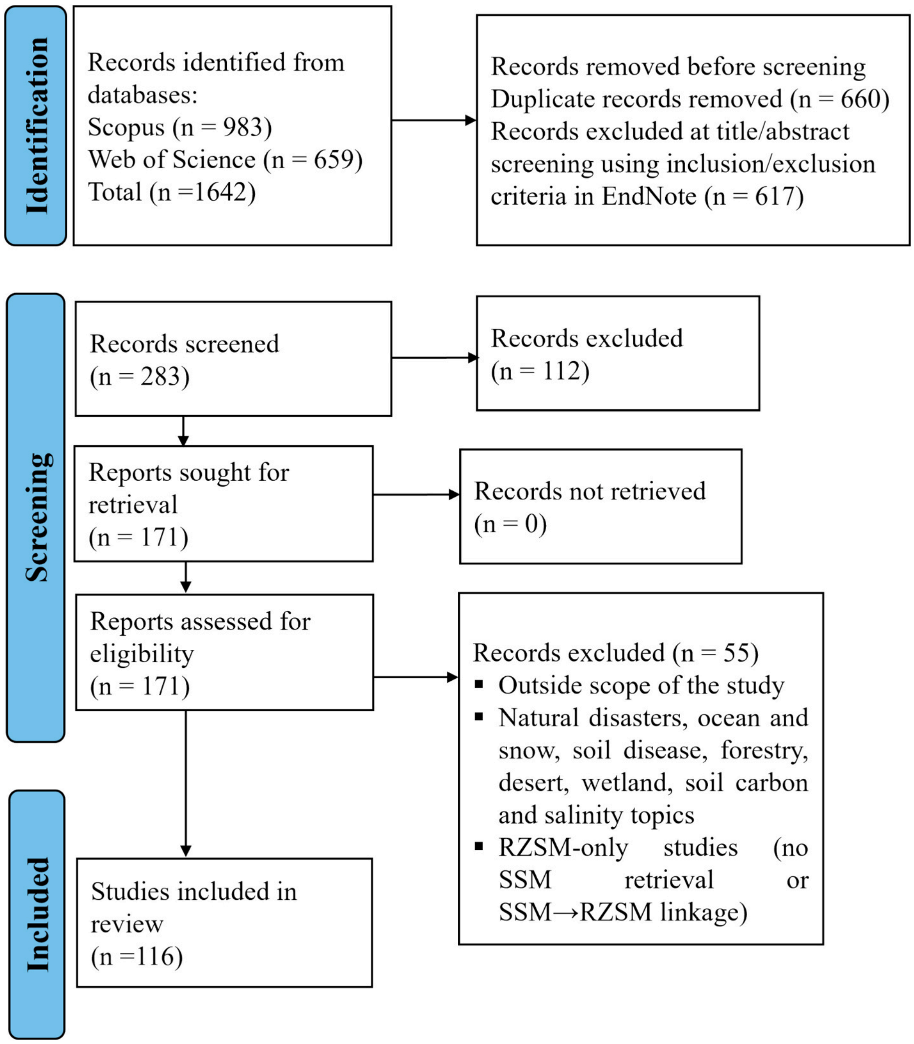

Fig. 1. Steps taken for the systematic quantitative literature review following the PRISMA framework (adapted from Moher et al. (2009)).

Endnote for reference management and screening. Using Endnotes's duplicate detection tool 660 duplicate records were removed. After a rigorous manual screening 617 records were excluded because they did not meet the eligibility criteria (e.g., not focused on SSM retrieval, no ML component, non-agricultural focus, or addressing unrelated variables such as soil salinity/soil organic carbon, or subsurface/RZSM-only studies without an SSM retrieval or SSM-to-RZSM linkage). Further, screening was conducted in two stages: title/abstract screening followed by full-text eligibility assessment. Ultimately, 116 studies were identified as relevant and included in the final analysis.

Furthermore, VOSviewer was used to systematically analyse the scope and research trends in SSM through keyword co-occurrence analysis. Following screening and duplicate removal in EndNote, metadata from eligible records were exported in RIS format and imported into VOSviewer. The keyword co-occurrence analysis was initially performed using the default VOSviewer settings. To improve consistency in the keyword network, a thesaurus file was prepared and edited to merge duplicate, synonymous, and variant keyword forms before re-running the analysis. This process reduced redundancy among keywords and improved the interpretability of the thematic clusters. In addition, SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats) was carried out to provide a strategic-level evaluation of current SM research.

In this study, no formal *meta*-analysis or *meta*-regression was conducted due to substantial heterogeneity among the included studies in sensors, spatial–temporal resolution, soil depth, validation design, study region, modelling approach, and reported metrics. Therefore, pooled effect sizes, P-values, and 95% confidence intervals were not calculated. Instead, reported metrics such as R2, RMSE, and NSE were extracted as presented in the original studies and interpreted through descriptive evidence synthesis, supported by bibliometric keyword analysis and SWOT synthesis.

2.2. Systematic evidence synthesis and review questions

To move beyond descriptive aggregation, this review adopts an explicit evidence-synthesis framework to systematically evaluate how different remote sensing approaches perform under varying spatial scales, agro-climatic conditions, and application contexts.

Based on the screened literature (n = 116), the review addresses the following research questions: (i) what evidence indicates a shift of SSM estimation from experimental retrieval toward operational applicability; (ii) which methodological approaches have most consistently contributed to this shift; (iii) why a disconnect persists between SSM products and root-zone or decision-relevant applications; and (iv) what methodological priorities emerge for bridging SSM retrieval with agricultural and hydrological decision support.

Evidence from individual studies was synthesized across common dimensions, including sensor type, modelling approach, spatial–temporal resolution, validation strategy, and reported performance metrics (R^2, RMSE, NSE). This enabled cross-study comparison and identification of consistent performance patterns and gaps.

3. Recent advances and challenges in remote sensing techniques for SSM estimation

3.1. Sensor platforms and data sources

A diverse range of sensor platforms and data sources has been developed to estimate SSM. Table 1 summarises five major sensor platforms and data sources used for SSM estimation, each offering unique strengths and facing distinct limitations. Passive microwave missions such as AMSR2, SMAP, and SMOS remain the cornerstone for global-scale monitoring due to their frequent revisit times and long, continuous records. However, their coarse spatial resolution restricts use in heterogeneous agricultural landscapes, necessitating downscaling or fusion with higher-resolution sensors. Active microwave systems, including ASCAT and Sentinel-1 SAR, provide finer spatial detail and all-weather capability, making them particularly valuable for regional and agricultural applications. Yet, their performance is hampered by surface roughness, vegetation cover, and high computational demands, while revisit constraints limit temporal continuity. Optical and thermal sensors (e.g., MODIS, Landsat, Sentinel-2) contribute indirectly by capturing vegetation and land surface temperature proxies, offering high spatial detail and synergy with ML approaches for downscaling. Nevertheless, their dependence on clear-sky conditions, susceptibility to vegetation masking, and shallow depth sensitivity restrict their reliability as standalone methods.

To address these challenges, multisensory and data fusion approaches are increasingly employed to integrate complementary strengths, leveraging the high temporal resolution of passive microwave, the spatial detail of SAR and optical imagery, and the process-based insights from thermal data. While fusion products significantly improve coverage and retrieval accuracy, they also introduce additional complexity, including harmonizing spatial and temporal resolutions, propagating uncertainties across sensors, and requiring extensive ground-truth calibration. While multi-sensor fusion generally improves spatial coverage and retrieval accuracy, the stability of fused SSM products depends on how uncertainties from each input source accumulate through the workflow. Key uncertainty sources include: (i) sensor-specific measurement noise and retrieval-model assumptions (e.g., dielectric models, roughness/vegetation effects for SAR; cloud/

Table 1
Summary of major sensor platforms and data sources used for SSM estimation.

Sensor / Data Source	Main principle	Strengths / Capabilities	Limitations / Constraints	References
Passive microwave sensors (e.g., AMSR2, SMAP, SMOS)	Detect naturally emitted microwave radiation to estimate SM	Global coverage All-weather capability Frequent revisits (1–3 days) Long time series for climate/hydro models	Coarse spatial resolution (~25–50 km) Poor performance in heterogeneous/agricultural landscapes Low sensitivity under dense vegetation Requires downscaling/fusion for field-scale use	Entekhabi et al. (2010); Kerr et al. (2012); Yao et al. (2021)
Active microwave sensors (e.g., ASCAT, Sentinel-1 SAR)	Actively transmit and receive radar signals to infer SM	All-weather, day/night imaging High spatial resolution (10–20 m for Sentinel-1) Suitable for regional/agricultural mapping Penetrates vegetation better than optical ASCAT offers stable long-term time series	Sensitive to surface roughness & vegetation Shallow sensing depth (0–5 cm) Saturation at high SM Requires dielectric/roughness knowledge Speckle noise & revisit constraints (6–12 days) Large data & high processing cost	Hahn et al. (2020); Mattia et al. (2020); Parida et al. (2024); Su et al. (2020)
Optical & thermal sensors (e.g., MODIS, Landsat, Sentinel-2)	Use reflectance (VIs like NDVI, EVI, NDWI) and LST to infer SM indirectly	High spatial resolution (10–30 m) Rich vegetation & land surface info Effective for ML and downscaling	Affected by cloud cover & atmosphere Sensitive only to surface mm Strongly masked by vegetation Thermal data affected by diurnal cycle and required complex modelling Indirect estimates via LST/ET Coarse TIR resolution Limited revisit frequency	Geng et al. (2023); Khurshed et al. (2023); Le Page et al. (2023); Xu et al. (2020)
Multisensory / fusion products (e.g., SMAP + Sentinel-1, MODIS + SAR)	Combine multiple sensors (microwave, optical, thermal) to improve SM retrievals	Enhanced accuracy & coverage Leverage spatial & temporal strengths Mitigates individual sensor limitations Mitigates individual sensor limitations Better performance across land cover types Enables high-resolution SM mapping	Spatial/temporal/depth mismatches Complex models & data harmonization Error propagation from each sensor Requires dense in-situ data Region-specific tuning limits global use High computational demands	Paciolla et al. (2020); Wang et al. (2023a); Xu et al. (2020)
Ground-based / in-situ measurements (e.g., USCRN, AmeriFlux)	Directly measure SM at fixed points and multiple depths; used for calibration & validation	Provide benchmark "truth" data Critical for validation & ML training Supports triple collocation analysis	Sparse and uneven global distribution Limited availability in developing regions Hard to scale to landscape or global levels	Elkharrouba et al. (2022); Fan et al. (2022); Geng et al. (2023); Settu and Ramaiah (2024)

atmospheric contamination for optical/thermal), (ii) representativeness and scale mismatch between coarse microwave footprints and finer ancillary predictors (e.g., NDVI/LST/terrain), (iii) temporal mismatch among sensors (different overpass times and revisit intervals), and (iv) preprocessing/resampling choices (gap-filling, interpolation, compositing) that can introduce additional bias.

In ML-driven fusion/downscaling, these errors can compound with model uncertainty (training-data scarcity, overfitting, non-stationarity), producing spatially varying bias and performance degradation when transferred across regions/seasons. As a result, fused products may show high accuracy in-site but reduced robustness under new land-cover, climate, or extreme wet/dry conditions. Therefore, studies should interpret fusion performance alongside stability indicators (cross-region/season tests), and where possible report uncertainty (e.g., ensemble spread/CI or error budgets) and apply scale-aware validation to reduce error accumulation.

Accordingly, in-situ measurements from networks such as USCRN and AmeriFlux remain indispensable for validation and model training. However, their uneven global distribution, especially across developing regions, represents a persistent bottleneck to producing globally consistent and locally accurate SSM products. Overall, the integration of multi-platform data, supported by robust ground-based validation, emerges as the most promising pathway for advancing SM monitoring, though challenges in scalability, uncertainty quantification, and regional transferability remain critical areas for ongoing research.

While numerous satellite and proximal sensing platforms are currently used for SSM estimation, their suitability varies substantially with respect to spatial scale, sensing depth, revisit frequency, and operational constraints. A structured comparison is therefore necessary to clarify how different sensor classes align with agricultural and hydrological applications. To address this, Table 1 provides a consolidated overview of the major sensor platforms used in SSM studies between 2019 and 2024, highlighting their physical principles, strengths, and limitations.

3.2. SSM estimation approaches

A number of SM estimation approaches have been developed, which can broadly be categorized into three groups: (i) ML and data-driven methods, (ii) hybrid approaches that integrate physical models with statistical or geostatistical techniques, and (iii) emerging technologies such as GNSS-Reflectometry and UAV-based sensing. Table 2 provides a consolidated summary of these approaches, outlining their underlying principles, strengths, and limitations. In this review, approaches are grouped by their primary inversion logic (i.e., how SSM is estimated), while downscaling, disaggregation, and data fusion are treated as implementation strategies that can be executed within either ML-only or hybrid frameworks. ML/data-driven methods refer to models that learn statistical relationships between predictors (e.g., SAR backscatter, VI/LST, terrain variables) and SSM without explicitly enforcing physical water-energy constraints. Hybrid approaches integrate a physics-based component (e.g., land-surface/hydrological models, water-energy balance constraints) and/or data assimilation with ML/statistical/geostatistical methods to improve physical consistency and temporal continuity. Emerging technologies describe new observation platforms (e.g., GNSS-R, UAV/proximal sensing) that provide novel inputs and may be paired with either ML or hybrid inversion. Accordingly, when a study combines multiple components, it is classified based on the dominant inversion component (ML vs hybrid), with fusion/downscaling described as supporting strategies.

ML and hybrid approaches have become central to advancing SSM estimation, offering clear advantages over traditional statistical and physically based retrievals (Taheri et al., 2025), particularly in data-scarce or heterogeneous environments. Classical ML models such as Random Forest, SVR, and ANN have proven effective in handling non-linear relationships between diverse input variables. Generally, RF often shows strong performance due to its robustness and low sensitivity to overfitting, whereas SVR and ANN models may perform better in settings with less noise and more consistent ground truth data (Elkharrouba et al., 2022; Xu et al., 2024a). Their capacity to integrate diverse datasets makes them powerful tools for regional-scale applications. However, they remain constrained by data quality, risk of overfitting, and limited transferability across heterogeneous environments (Wang et al., 2023b), underscoring the importance of regional calibration and feature selection.

Enhancements to these ML frameworks increasingly involve the integration of vegetation indices (VIs) and terrain attributes. VIs act as proxies for evapotranspiration and canopy water content, while terrain features, such as slope, aspect, and elevation, facilitate capture hydrologically-driven microclimate and runoff dynamics, especially in complex landscapes (Araya et al., 2020; Lamichhane et al., 2025; Nguyen et al., 2022).

While no single ML algorithm universally outperforms others, recent ensembles and hybrid frameworks tend to deliver more consistent results across different agro-ecological zones. Hybrid approaches represent a convergence of strengths, where physics-based models infused with ML (e.g., water-energy balance constraints) enhance interpretability and robustness, while ML coupled with geostatistics leverages both spatial autocorrelation and data-driven flexibility. Both avenues, however, demand reliable input data and face questions of uncertainty propagation and regional generalizability (Han et al., 2023; Lv et al., 2024). Ensemble and DL techniques, such as CNNs, LSTMs, and boosted tree models, have demonstrated superior performance in capturing spatiotemporal dynamics of SSM, contingent on large datasets and powerful computation. Yet, their “black-box” nature underscores a growing need for explainable AI (XAI) methods to improve transparency and trust in environmental applications (Han et al., 2023; Wang et al., 2023b).

AI-driven downscaling serves as a practical bridge between coarse-resolution satellite products (e.g., SMAP) and field-scale applications. These ML approaches deliver finer-grained SSM maps critical to hydrological and agricultural applications, though dependence on multi-source ancillary data and the potential lack of physical plausibility remain ongoing concerns (Senanayake et al., 2024; Srivastava et al., 2013). Further, data assimilation frameworks that incorporate satellite-derived SSM into hydrological or climate models yield enhanced real-time forecasting and monitoring capabilities (De Lannoy et al., 2015; Ni-Meister, 2008). However, their effectiveness depends heavily on the temporal alignment with model dynamics and the reliability of the input satellite data.

In parallel, disaggregation algorithms and data fusion frameworks are increasingly important for refining SM products. Disaggregation methods exploit ancillary datasets such as LST, NDVI, and topography or combine SMAP, MODIS, Landsat, and Sentinel-1 to enhance spatial resolution (Merlin et al., 2009; Ojha et al., 2021). On the other hand, data fusion methods integrate multiple sources, satellite products, reanalysis, land surface models, and in-situ data to improve completeness and consistency (Peraza et al., 2025). Fusion of microwave, optical, and thermal datasets also improves accuracy (Van der Schalie et al., 2018). Despite their value, both approaches depend heavily on high-quality ancillary data, are sensitive to cloud-related gaps in optical inputs and face persistent challenges in scaling and uncertainty quantification.

Beyond these established frameworks, emerging technologies are expanding the SM monitoring landscape. GNSS-Reflectometry (GNSS-R) provides compelling advantages, including passive sensing, all-weather capability, rapid revisits, and potential global coverage. Yet its practical use is restrained by roughness and vegetation interference, calibration complexities, and immature operational methods (Roberts et al., 2022; Setti Jr and Tabibi, 2023; Yang et al., 2024). UAV-based sensing, including multispectral, thermal, and hyperspectral imaging, offers unprecedented field-scale resolution and temporal flexibility. Combined

Table 2
Summary of major approaches for SSM estimation.

Approaches	Main principle	Strengths / Capabilities	Limitations / Constraints	References
ML and hybrid				
ML models (RF, SVR, ANN, Decision Trees)	Use flexible algorithms to model non-linear relationships between backscatter, vegetation indices, terrain, and climate variables	Handle complex, non-linear relationships Integrate diverse datasets Improve retrieval accuracy at regional scales	Risk of overfitting Require large, labelled datasets Limited transferability across regions	Khurshed et al. (2023); Nativel et al. (2022); (Souissi et al., 2022)
Integration of VIs & terrain features	Incorporates VIs (e.g., NDVI, EVI, NDWI) and terrain attributes (elevation, slope, aspect) into ML models to capture canopy and topographic effects	Improves retrieval accuracy in complex land cover/ topography VIs as proxies for evapotranspiration & root-zone moisture Terrain features capture microclimate, runoff, drainage	Requires high-quality ancillary datasets Vegetation/terrain effects may vary seasonally Limited transferability in heterogeneous landscapes	Khurshed et al. (2023); Nguyen et al. (2022); Xu et al. (2020)
Hybrid ML + physical models	Combines physically-based models with ML to maintain physical plausibility while enhancing predictive power	Improves interpretability Ensures physical consistency (e.g., water/energy balance) Effective for operational use	Complex to implement Requires high-quality multi-sensor inputs	Elkharrouba et al. (2022); Le Page et al. (2023); Li et al. (2024); Settu and Ramaiah (2024); Stefan et al. (2021)
Ensemble & DL (LightGBM, XGBoost, CNN, LSTM)	Advanced ML methods that improve robustness and exploit high-dimensional data	High predictive accuracy Handle large datasets Capture spatio-temporal variability	Computationally demanding Overfitting and lack of interpretability Data-hungry	Li and Yan (2024); Wang et al. (2023c); Zhang et al. (2022b)
AI-driven downscaling	Use ML/DL to refine coarse-resolution products (e.g., SMAP 36 km to 1 km)	Enhances field-scale utility Supports agricultural and hydrological applications More flexible than physics-only downscaling	Requires multi-source high-quality inputs Limited transferability across regions May lack physical constraints	Şahin and Gündüz (2024); Wang et al. (2024); Xu et al. (2022)
Data assimilation and downscaling				
Data assimilation in hydrological models	Integrates satellite-derived SM into models (SWAT, VIC, Noah-MP, SURFEX)	Reduces parameter/forcing uncertainties Improves near-real-time predictions Enhances drought and water resource monitoring	Dependent on satellite input quality Synchronization with model timesteps required	Azimi et al. (2020); Blyverket et al. (2019); Le et al. (2022); Mao et al. (2020)
Climate model integration	Uses SM data to initialize and improve land–atmosphere interactions in climate forecasts	Improves seasonal/long-term predictions Reduces uncertainties in rainfall/drought forecasts Supports impact assessments	Climate outputs are coarse (~50–100 km) Limited direct local applications	Busschaert et al. (2022); Kumar et al. (2019); Reichle et al. (2021); Zuo et al. (2019)
Hybrid ML + geostatistics downscaling	Combines kriging with ML to integrate spatial autocorrelation and non-linear modelling	Exploits both spatial structure & non-linear relationships Improves interpolation in dense networks	Data sparsity reduces performance Uncertainty propagation Poor generalization in complex terrains	Jin et al. (2020); Karamouz et al. (2022)
Disaggregation algorithms	Use ancillary data (LST, NDVI, topography) to refine coarse SM estimates	Provides higher-resolution SM maps Suitable for environmental applications	Dependence on quality of ancillary data Transferability issues Uncertainty quantification needed	Gao et al. (2024); Song et al. (2019); Tong et al. (2024)
Data fusion for gap-filling & resolution enhancement	Combines satellite, reanalysis, LSM outputs, and in-situ data for complete SM products	Enhances spatial/temporal completeness Useful for hydrology, agriculture, climate studies	Same issues as disaggregation (data dependency, uncertainty) Requires extensive multi-source integration	Batchu et al. (2023); Huang et al. (2022); Liu et al. (2023); Zhu et al. (2024)
Emerging				
GNSS-Reflectometry (GNSS-R)	Uses reflected GNSS signals (GPS, Galileo) for passive microwave SM retrieval	Works under vegetation/ clouds Sensitive to dielectric properties Potential at both global & field scales	Early stage of operational use Coarse resolution Noise under dense vegetation Requires calibration & algorithm development	Edokossi et al. (2020); Jin et al. (2022); Santi et al. (2024); Wu et al. (2023)
UAV-based optical, thermal & hyperspectral sensors	UAVs equipped with multispectral, hyperspectral, and thermal sensors for high-resolution mapping	Very high spatial detail Flexible, low-cost, on-demand Effective for agriculture & local hydrology	Shallow sensing depth Vegetation & roughness effects Operational/logistical constraints	Acharya et al. (2021); Ge et al. (2021); Khose and Mailapalli (2024); Nur and Bachmann (2023); Ye et al. (2023)
UAV + ML integration	Combines UAV imagery with ML for field-scale SSM estimation	Models complex, non-linear relationships Near-real-time monitoring Valuable for precision agriculture	Limited penetration depth Calibration needed Smallholder heterogeneity challenges	Cheng et al. (2022); Shokati et al. (2023); Zhang et al. (2023a)

with ML, UAV platforms facilitate high-resolution SSM mapping, although logistical constrains, shallow penetration depth, and data processing challenges limit scalability (Aboutalebi et al., 2019; Cheng et al., 2023; Shokati et al., 2023).

Beyond sensor selection, the accuracy and applicability of SSM products depend critically on the modelling frameworks used to translate raw observations into SM estimates. These frameworks range from purely data-driven ML models to hybrid approaches that embed physical constraints or exploit spatial autocorrelation. Given the rapid methodological diversification in recent years, a systematic classification is required to distinguish their relative strengths, limitations, and operational maturity. Table 2 synthesizes the major SSM estimation approaches reported in the literature, grouped by modelling philosophy and implementation strategy.

It can be seen that the most compelling SM retrieval methods now lie at the intersections of ML, physical modelling, multi-source data fusion, and emerging sensing technologies. Furthermore, research on addressing critical challenges, such as uncertainty quantification, generalization, interpretability, and operational scalability, will be essential for advancing towards reliable, high-resolution, and globally applicable SSM estimation frameworks.

3.3. Cross-study evidence synthesis and operational relevance

Although numerous studies report promising performance metrics for SSM estimation, direct comparison across approaches is often hindered by differences in spatial scale, validation strategy, and study design. Performance in the reviewed studies is most commonly reported using R^2 and RMSE, which capture different aspects of model skill. R^2 (dimensionless) reflects how well the model explains variability in observed SSM, whereas RMSE (SM units) quantifies the typical magnitude of prediction error and is sensitive to bias and scale. Because these metrics are not directly comparable in magnitude and RMSE is unit-dependent, they are interpreted separately as complementary indicators, rather than combined into a ratio. Where available, NSE is also reported as a hydrology-oriented efficiency metric that reflects relative predictive skill against a mean benchmark.

To move beyond individual case studies, this review synthesizes evidence across the full body of screened literature (n = 116), focusing on consistency, validation robustness, and readiness for operational deployment. Table 3 presents a cross-study evidence synthesis that contrasts major SSM estimation pathways in terms of reported performance, validation depth, and practical applicability. Across all evidence categories, hybrid ML-physics models consistently demonstrate the best balance between accuracy, stability, and operational readiness. Pure ML approaches show high performance in controlled or data-rich environments but exhibit reduced robustness under regional transfer. SAR-optical fusion emerges as the most reliable pathway for field-scale agricultural applications, while passive microwave products remain indispensable for large-scale monitoring but insufficient as standalone tools. These findings suggest that future SSM systems should adopt tiered architectures, combining global passive products with regional SAR-based refinement.

3.4. Main factors affecting SSM retrieval accuracy

In this manuscript, the reviewed studies used different sensors, spatial resolutions, validation datasets, soil depths, and reporting units, the performance metrics were not statistically pooled. R^2, RMSE, and NSE were therefore interpreted as complementary indicators of model performance rather than as directly comparable effect sizes. R^2 was used to indicate the proportion of observed variability explained by the model, RMSE represented the typical prediction error, and NSE provided a hydrological efficiency measure where available. Hence, R^2/RMSE values were used only as indicative descriptors of reported model efficiency and were not treated as formal statistical effect sizes.

The comparative analysis indicates that model performance, spatiotemporal resolutions, and satellite products are the three main factors affecting SSM retrieval accuracy (Figs. 2-4). Generally, ML-based models exhibit superior performance, particularly those integrating multiple ML datasets. For example, the ML models such as GA-BP, SVR, and RF demonstrated the highest ratio of R^2/RMSE ≈ 60.04 (Xu et al., 2024a). The study utilized Sentinel-1 (C-band), TerraSAR (X-band), and Sentinel-2 data at 10–30 m resolution and 6–12-day revisit.

Hybrid models such as the Modified Water Cloud Model (WCM) combined with SVR and VIs achieved moderate accuracy (R^2/RMSE ≈ 30.96) using Sentinel-1 and Sentinel-2 data at 10 m spatial resolution and 5-day temporal resolution (Li et al., 2021; Lin et al., 2022). At coarser resolutions, feature-space approaches like Triangular Feature Space (Tri) with RF performed promisingly (R^2/RMSE ≈ 47.5) for gap-filling missing SM values from ECV data at 25 km and daily frequency (Liu et al., 2020). Terrain-integrated RF models with Sentinel-1 at ~ 17 m resolution and a 6-day temporal resolution also improved field-scale estimates, achieving R^2/RMSE ≈ 33.02 (Schönbrodt-Stitt et al., 2021).

By contrast, ensemble learning (LightGBM, RF, XGBoost, ERT) applied to SMAP, MODIS, and ERA5-Land at 1 km resolution and daily observations produced showed lower R^2/RMSE efficiency despite achieving R^2/RMSE ≈ 9.77 at large scales (Yang et al., 2023). CatBoost using Sentinel-1 and Sentinel-2 produced competitive results with R^2/RMSE ≈ 16.24 (Ya'Nan et al., 2024). Common ML models (RF, SVR,

Table 3
Systematic evidence synthesis of surface soil moisture (SSM) estimation approaches reported between 2019 and 2024.

Approach category	Primary sensors	Modelling techniques	Typical spatial scale	Reported performance (RMSE / R^2)	Validation strategy	Evidence consistency	Operational readiness
Passive microwave retrieval	SMAP, SMOS, AMSR2	RF, ANN, CNN	25–36 km	RMSE ≈ 0.05–0.08; R^2 ≈ 0.50–0.70	Sparse in-situ networks, triple collocation	Moderate (global consistency, coarse scale)	Low
Active microwave (SAR)	Sentinel-1, Radarsat-2, TerraSAR-X	SVR, RF, ANN	10–30 m	RMSE ≈ 0.02–0.05; R^2 ≈ 0.65–0.85	Field-scale in-situ validation	High (regional studies)	Medium
SAR-optical fusion	Sentinel-1 + Sentinel-2 / Landsat	RF, ANN, hybrid WCM	10–20 m	RMSE ≈ 0.02–0.04; R^2 ≈ 0.70–0.88	Multi-site agricultural experiments	High	Medium-High
Hybrid ML-physics models	Multi-sensor (SAR + optical + climate)	ML constrained by water/energy balance	100 m-1 km	RMSE ≈ 0.02–0.03; R^2 ≈ 0.75–0.90	Model-observation integration	Very high	High
AI-driven downscaling	SMAP + MODIS / ERA5	CNN, XGBoost, LightGBM	1 km	RMSE ≈ 0.03–0.06; R^2 ≈ 0.60–0.80	Cross-scale validation	Moderate	Medium
GNSS-Reflectometry	CYGNSS	Empirical, ML-based	1–5 km	RMSE ≈ 0.06–0.09; R^2 ≈ 0.40–0.60	Limited field experiments	Low	Experimental
UAV-based sensing + ML	UAV multispectral / thermal	CNN, RF	cm-m	RMSE ≈ 0.01–0.03; R^2 > 0.85	Field campaigns	High (local)	Local-scale only

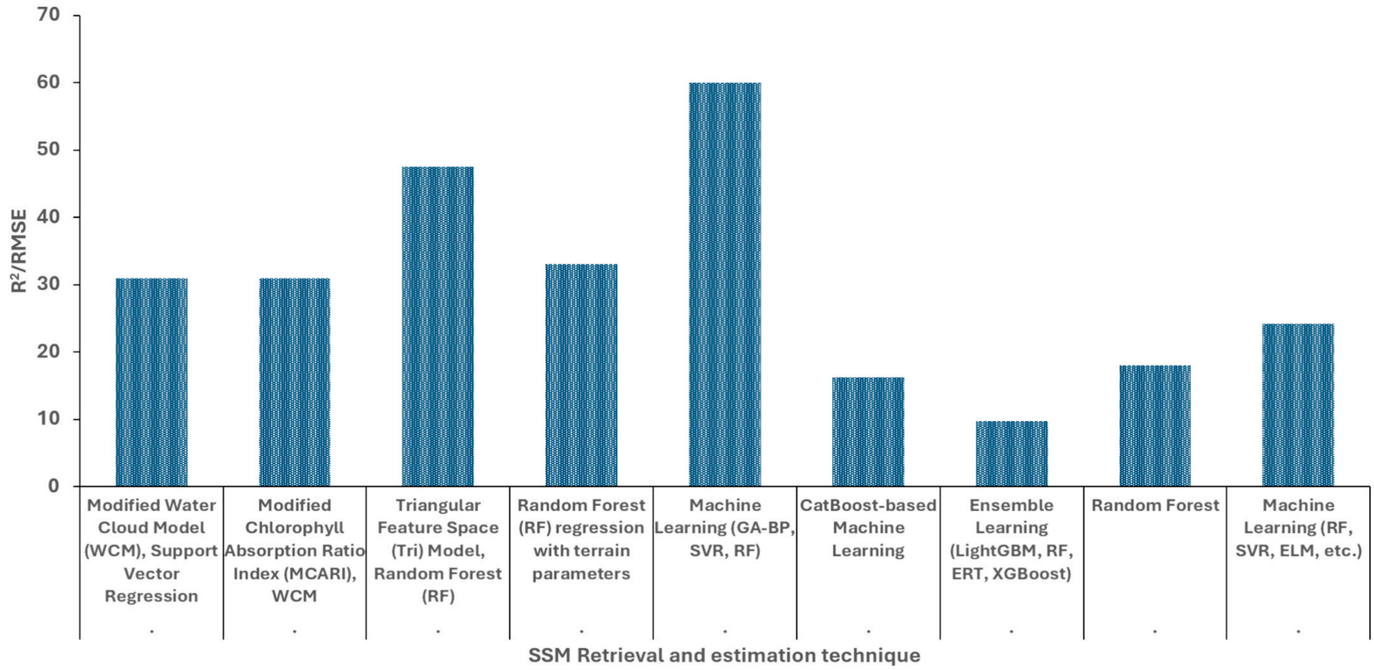

Fig. 2. Performance of SSM retrieval and estimation techniques as represented the R^2/RMSE ratio.

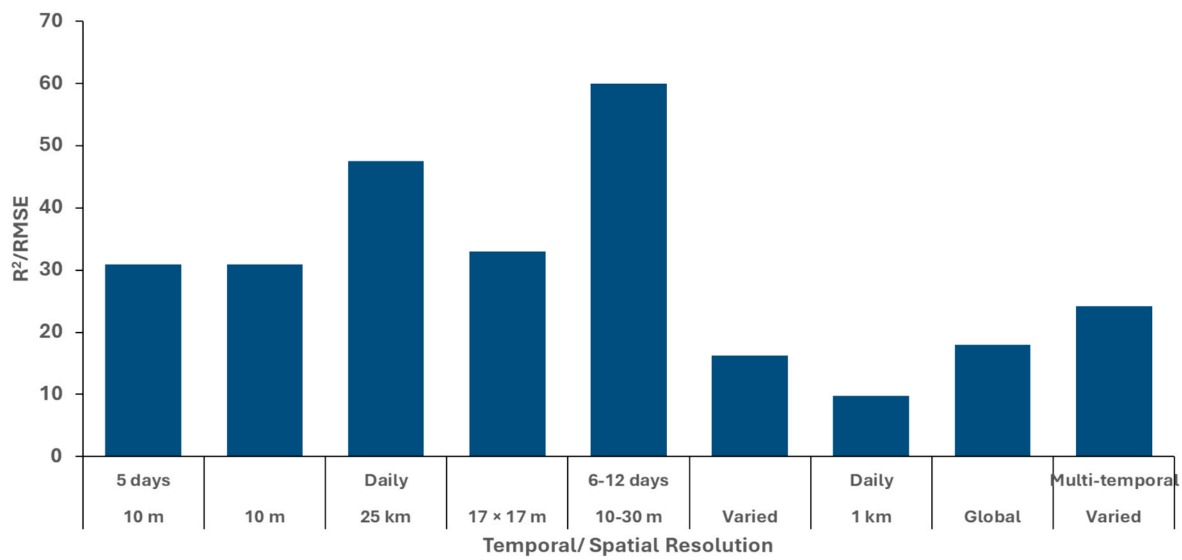

Fig. 3. Performance of SSM retrieval and estimation at various combinations of spatial and temporal resolution, as represented statistically by R^2/RMSE ratio.

ELM) using Sentinel-1/2 and Radarsat-2 showed mid-range performance (R^2/RMSE ≈ 24.22) (Zhao et al., 2022).

Fig. 4 presents the RMSE values for SSM retrieval across various satellite products. The x-axis lists different satellite sensors and data fusion approaches, including optical (e.g., MODIS, Landsat-8), radar-based (e.g., Sentinel-1, Radarsat-2, TerraSAR-X), passive microwave (e.g., SMOS, SMAP, AMSR2), and reanalysis or multi-source datasets (e.g., ERA5, ESA CCI).

The RMSE values vary significantly depending on the satellite product used. Generally, multi-sensor approaches, such as combinations of Sentinel-1 and Sentinel-2, or integrations with climate models and in-situ data, show moderate to low RMSE, indicating improved retrieval accuracy due to data synergy. Passive microwave sensors like SMAP and SMOS exhibit higher RMSE values, likely due to their coarse spatial resolution and atmospheric influences, whereas SAR-based products (e.g., Sentinel-1, Radarsat-2) generally provide lower RMSE values due to their high spatial resolution and sensitivity to SM changes.

Notably, some datasets combining multiple sources, including reanalysis products (e.g., ERA5, ESA CCI), display higher RMSE, which may be attributed to model uncertainties or the blending of datasets with different spatial and temporal characteristics. The variations in RMSE bring into focus the balance between spatial resolution, sensor characteristics, and retrieval frequency in SSM, illustrating the importance of choosing satellite products based on specific application requirements, ranging from field-level monitoring to global-level evaluations.

The abovementioned evidence suggests that the combination of multiple SAR bands with moderate temporal frequency (Xu et al., 2024b) or multi-temporal SAR-optical approaches (Zhao et al., 2022) can enhance SM retrieval accuracy. However, there are trade-offs between complexity and local precision. A combination of 10–30 m spatial resolution and 6–12-day revisit datasets offer the best balance between

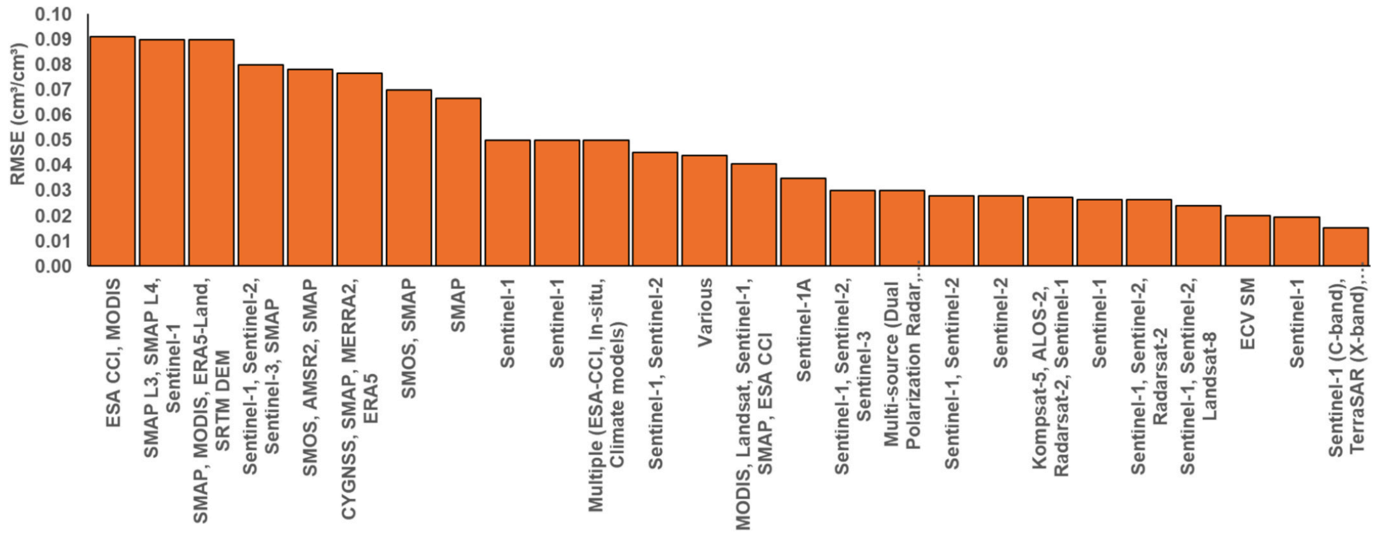

Fig. 4. Root mean square error (RMSE) values for SSM retrieval across various satellite products.

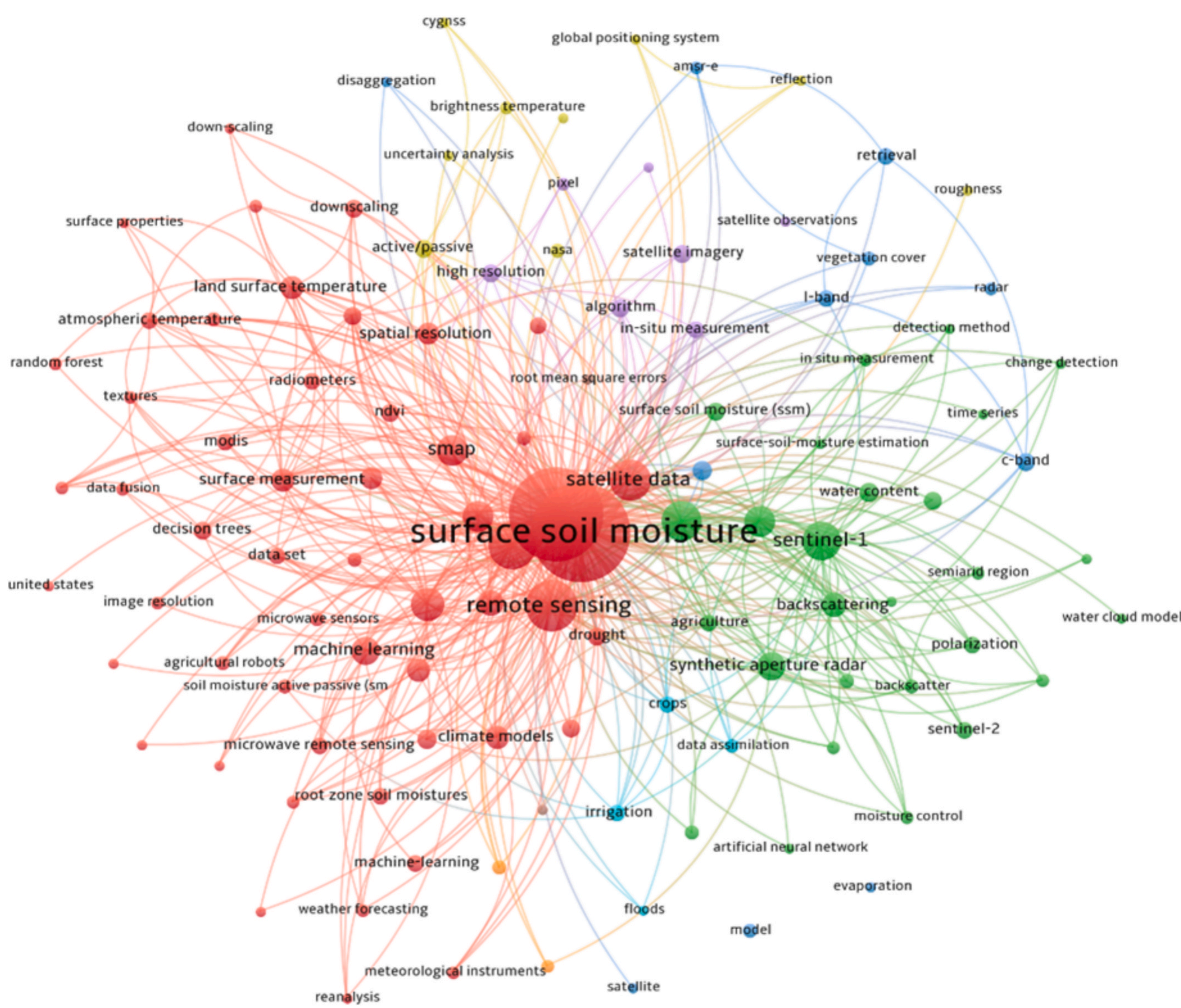

Fig. 5. The figure shows keyword network analysis from research articles published from January 2019 – December 2024.

precision and efficiency. Further, multi-source ML models provide the highest accuracy, while hybrid, feature-space, and terrain-based approaches offer valuable improvements in specific contexts such as vegetated or topographically complex regions. Ensemble methods remain more effective for large-scale daily mapping, though they may not be as accurate as region-specific ML models. Ultimately, the analysing results also indicate that integrating terrain parameters, feature-space models, and optimized ML techniques can enhances SM retrieval across diverse agricultural and environmental settings.

4. Keyword network analysis and thematic classification

To systematically understand the scope and research trends in SSM, a popular tool called VOSviewer (Van Eck and Waltman, 2011) was used. A total of 116 English peer-review articles published between 2019 and 2024 were compiled, and a keyword co-occurrence network was generated. The map produced (Fig. 5) shows the conceptual framework of the collected literature, where "*surface soil moisture*" becomes the primary connector.

Further, the network map highlights other important thematic clusters. The *red cluster* comprises terms related to ML platforms, SMAP, ML, NDVI, and data fusion, showing a clear focus on the use of sensor-based estimation and computational modeling. On the other hand, the *green cluster* includes keywords such as Sentinel-1, synthetic aperture radar (SAR), polarization, and agriculture, emphasizing radar-based methods and field-level applications. The *blue cluster* groups terms associated with retrieval techniques and validation, such as backscatter, in-situ measurement, and roughness, drawing attention in the area of physical modeling and error assessment. Smaller clusters (*yellow, purple, orange*) address niche but significant areas like uncertainty analysis, brightness temperature, algorithm evaluation, irrigation, and floods.

Accordingly, based on the keyword network analysis, this review literature was classified into seven research themes based on methodological focus and application domain (Fig. 6a). These categories were selected to capture the critical aspects of SM research, reflecting the emerging trends in the study. Many studies contribute to more than one category, highlighting the interdisciplinary nature of SM research. Techniques such as AI/ML, downscaling, and forecasting are frequently combined into evaluation and retrieval-based studies, collectively providing a structured understanding of research directions, technological advancements, and knowledge gaps in SM modelling.

The most common category was Evaluation (68 occurrences) (Fig. 6b), which shows the importance of model performance assessment and validation, ensuring the accuracy and reliability of SM estimations for both hydrological and agricultural applications. Downscaling (57 occurrences) was selected due to the growing need for finer-resolution SM data, especially for localized decision-making, with studies employing statistical and ML techniques to enhance spatial resolution. SSM Retrieval (41 occurrences) is core to ML applications, especially in hydrology, as research in this category focuses on developing and refining methods for extracting SM information from satellite, airborne, and in-situ sources.

The recent trends in increasing integration of AI/ML (31 occurrences) in SM studies justify its inclusion because AI combined with ML techniques is popular to use for predictions, recognize patterns, and optimize model efficiency. Forecasting (24 occurrences) is essential in prediction research such as drought, water resource management, and agricultural planning, and hence makes it a basic category for the prediction of SM changes using statistical, ML, and process-based models. Assimilation (14 occurrences) was included due to its significance in integrating observational SM data into models to improve their accuracy and realism by including real-world observations. Lastly, Proximal Sensing (17 occurrences) was selected because of its role in complementing ML efforts, utilizing ground-based sensors and field surveys to validate model outputs and improve SM monitoring.

4.1. Citation trends in SM estimation research

Between 2019 and 2024, the global research landscape on SSM has evolved significantly in terms of both quantity and focus, though it remains unevenly distributed across countries. The total number of citations across all studies during this period reached 1,465, with a notable peak in 2020 (499 citations), followed by a steady decline through 2021 (471), 2022 (191), 2023 (65), and only 13 citations recorded so far in 2024 (Fig. 7). This sharp decline after 2021 could reflect a publication lag or narrowing of research focus post-COVID research surge.

China has emerged as the most dominant contributor to SSM research, accounting for 614 citations, which is over 40% of the total. The country's research focus is wide-ranging and technically advanced, with substantial outputs in spatiotemporally continuous SSM estimation, soil salinity mapping, high-resolution SSM products, and the use of multi-band SAR and optical data for inversion models. Noteworthy is China's early leadership in 2019 and 2020, with a shift toward more refined applications like L-band assessments and improved SM retrieval in the later years. In contrast, the United States showed a different trajectory-its research output peaked in 2020 and 2021, with major contributions to error assessments, high-resolution RZSM mapping, UAV-assisted retrieval, sub-kilometric modeling, and validation

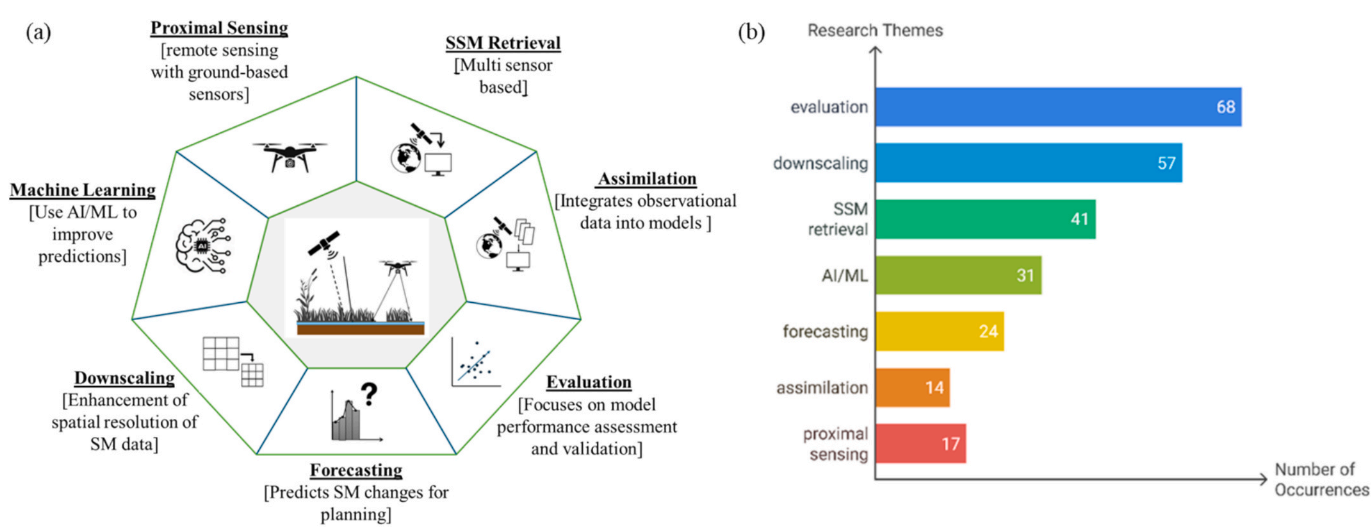

Fig. 6. Categorisation of literature into different categories followed in this study and their frequency.

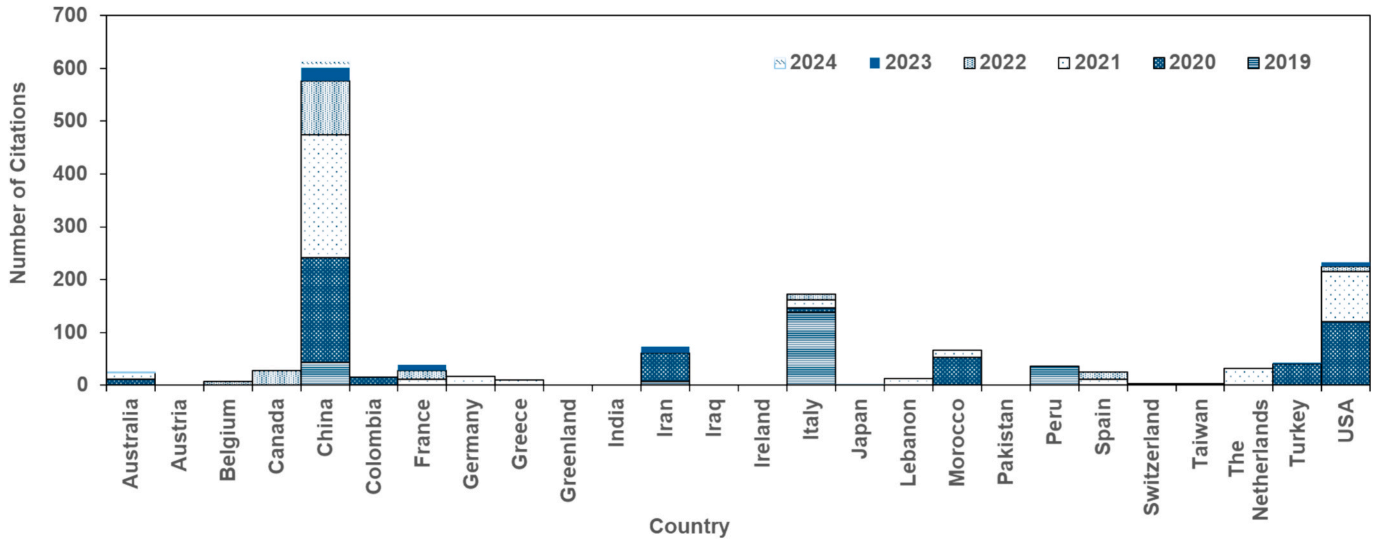

Fig. 7. Country-wise and year-wise distribution of citations in surface SM research (2019–2024).

frameworks. However, its contributions drastically dropped after 2021, with minimal new themes emerging in 2023 and 2024.

Italy ranked third in overall contributions (173 citations), with a concentrated output in 2019 focused on global rainfall datasets for SM retrieval. Later years saw more specific themes emerge, such as irrigation event detection and hybrid change detection for SSM retrieval. Countries like Iran (74 citations) and Morocco (67 citations) have shown notable bursts in activity, particularly between 2020 and 2021, focusing on high-resolution SSM maps, discharge simulation, and SSM retrievals over wheat fields and irrigated areas.

France (35 citations), Spain (16), and Germany (17) have contributed moderately, often focusing on airborne SSM mapping, hydrological integration, and retrieval evaluation. Other countries such as Australia, Canada, Turkey, and Lebanon made limited but focused contributions, often targeting themes like water balance prediction, climate attribution, or irrigation support. Meanwhile, countries like India, Pakistan, and several from Africa and Southeast Asia have minimal to no representation, despite their high vulnerability to climate-induced SM variability. This highlights a critical regional disparity in global SM research.

Thematically, the research has matured from general mapping and validation toward finer-resolution retrievals, model coupling, and data assimilation. Emerging keywords include “Seamless Downscaled SSM,” “Spatiotemporally Continuous Estimates,” “High-Resolution Surface Soil Moisture,” and “Enhanced Estimation via Data Assimilation,” reflecting a trend toward dynamic, high-accuracy, and operationally relevant outputs. These outputs are increasingly being integrated into agricultural decision support, hydrological forecasting, and climate risk management.

4.2. *Geographical and temporal distribution of current operational SM products*

Examining the distribution of studies across various countries from 2019 to 2024 (Fig. 8) reveals that certain nations have consistently spearheaded research efforts in SSM. China emerges as a prominent

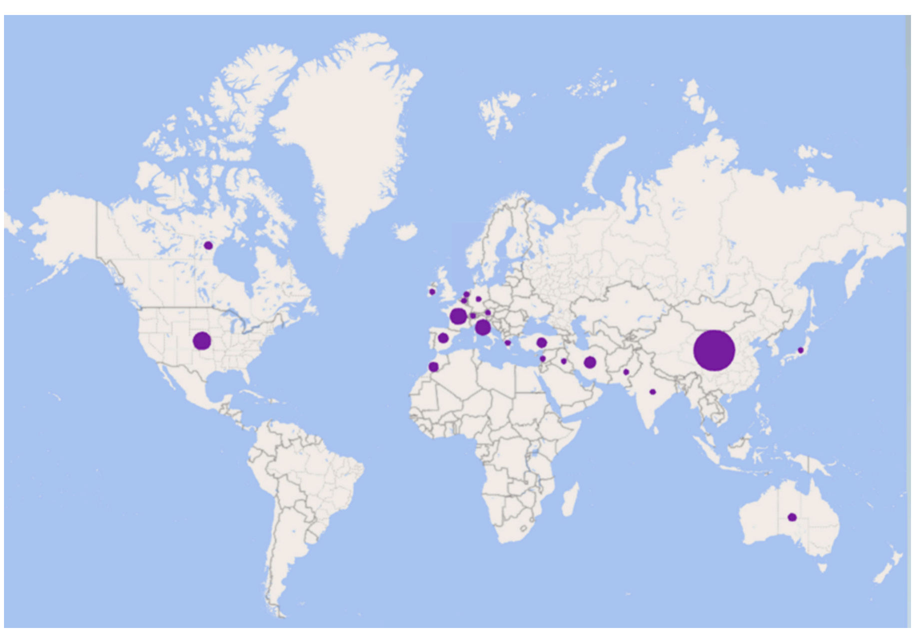

Fig. 8. Illustration of the contribution of countries in soil moisture studies globally from January 2019 –December 2024.

leader, conducting 53 studies with a peak of 16 in 2022. The United States follows with 24 studies, demonstrating steady contribution, particularly in 2022, and France shows an increasing trend culminating in 2023. Italy and Spain also maintain steady contributions, while 2022 stands out as a peak year of global research, suggesting a possible co-ordinated response to emerging challenges. This pattern highlights both the responsive nature of these regions and a concentration of research in certain geographic areas, indicating gaps in SSM studies likely linked to limited validation data and uneven research capacity, highlighting priorities for future SSM studies.

Regional inequalities in SSM research should be understood not only by publication counts but also by agro-ecological conditions and resource availability. SAR based with ML supported retrieval may be useful for drought and irrigation monitoring, especially when vegetation descriptors and local field observations are included to represent crop cover and surface variability (Abdikan et al., 2023; Ayari et al., 2023). Also, Ahmad et al. (2022) demonstrated that, microwave-based SM assimilation into land surface models can be useful for regional scale applications in data scarce or climatically variable areas for South Asia. Additionally, heterogeneous agricultural landscapes may benefit from high-resolution Sentinel-1/Sentinel-2 fusion and UAV-assisted field validation, which can improve field-scale SSM mapping where ground observations are limited (Cheng et al., 2022; Gao et al., 2017), while in dense vegetated landscapes, SAR-optical coupling and vegetation correction approaches reduce canopy errors in SSM retrieval (Shi et al., 2025). In low-resource regions, open-access satellite products, multi sensor fusion, transfer learning, and low-cost ground observations may provide practical pathways for adaptive SSM monitoring (Singh et al., 2025; Zhu et al., 2024).

4.3. SWOT analysis of SSM research approaches

A SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis (Table 3), was conducted to provide a comprehensive overview of current SM research, highlighting both the spatial scales and model types across studies (Table 4 and Fig. 3). The SWOT categories were derived from the cross-study evidence synthesis used throughout this review (sensor type, modelling approach, spatial–temporal resolution, validation strategy, and performance metrics such as R^2, RMSE, and NSE). Accordingly, the SWOT is used here as an interpretive framework to translate the evidence base into field-level implications and methodological priorities, rather than a study-by-study summary.

Strengths include a strong focus on global-and regional-scale studies, particularly in SSM retrieval and data assimilation, where AI/ML and physical models dominate. These approaches demonstrate broad applicability and the ability to address large-scale hydrological and climatic challenges. Weaknesses arise from the relatively limited attention to localized, multi-national, or field-scale research, as well as the

Table 4
Strategic-level evaluation of satellite-based SM retrieval techniques based on SWOT analysis.

Strengths	Weaknesses	Opportunities	Threats
High accuracy from data fusion: Fusion of Sentinel-1 and Landsat improved spatiotemporal consistency and reduced RMSE by up to 9.4% (Abowarda et al., 2021)	**TVDI limitations in Arctic**: TVDI fails in cold Arctic soils where soil-vegetation-temperature dynamics are uncoupled (Hollesen et al., 2023)	**Advancements in satellite technology**: New satellites like Sentinel-2 and Landsat-9 provide 10 m spatial resolution, improving SM monitoring at local and regional scales	**Overgeneralization risk**: Overreliance on ML/physical models may ignore region-specific needs (Ramírez Casas et al., 2022)
ANN and RF models' high performance: ANN models achieved R ≈ 0.85 with X-band radar, while RF models delivered NSE ≈ 0.73 in semi-arid areas (Abdikan et al., 2023; Adab et al., 2020)	**Generalization issues**: ML models like RF and SVM face a 20% increase in RMSE when applied to new regions without recalibration (Gao et al., 2022; Liu et al., 2020)	**Improved ML with AI**: Deep learning (e.g., CNNs) can reduce RMSE by 5–10%, offering substantial improvements in complex terrains (e.g., mountainous regions) (Chen et al., 2021; Zhang et al., 2022a)	**Cost of high-resolution commercial data**: High-resolution radar data from commercial satellites (e.g., TerraSAR-X) increases monitoring costs by 20–30%, limiting accessibility for some regions (Abdikan et al., 2023)
Radar-optical synergy: Radar-optical data fusion enhances spatial resolution and retrieval accuracy in diverse land cover settings (Liang et al., 2020; Ouaadi et al., 2024)	**High computational requirements**: Data fusion and ML models, especially ANN and RF, require extensive computational resources, leading to processing time increases of up to 25% (Deng et al., 2024; Yang et al., 2023)	**Expansion to unmonitored regions**: Applying satellite and AI models to unexplored regions (e.g., high-altitude, tropical areas) can improve model accuracy by 10–15% (Chen et al., 2021)	**Algorithm overfitting in ML models**: Without recalibration, ML models (e.g., RF, ANN) show a 25% increase in RMSE when applied outside their training regions (Adab et al., 2020; Gao et al., 2022)
Sensor resolution strength: X-band radar (e.g., Kompsat-5) excels in agricultural monitoring, with RMSE values significantly lower than L-band radar data (Abdikan et al., 2023)	**Limited temporal coverage for high-resolution data**: High-resolution satellite data (e.g., from TerraSAR-X and Landsat) often suffer from limited temporal resolution, impacting real-time SM monitoring (Wang et al., 2020)	**Free satellite data for widespread monitoring**: Programs like Copernicus and SMAP provide free satellite data, enabling widespread SM monitoring at reduced costs (Abdikan et al., 2023; Ayari et al., 2023)	**Uncertainty in data quality for fusion techniques**: Fusion of different satellite sensors (e.g., radar + optical) sometimes leads to inconsistent results, with error margins increasing by up to 15% (Gao et al., 2021; Min et al., 2022)
Localised calibration: Studies show that calibration based on specific land cover types improves model accuracy, with some regions seeing a 10–15% increase in RMSE performance (Chen et al., 2021). Localized model calibration and site-specific parameterization enhance SM retrieval across diverse terrains (Huang et al., 2022; Qian et al., 2024)	**Lack of consistency in data fusion methods**: Some studies report inconsistent results depending on the fusion technique used, resulting in up to 15% variation in performance across different datasets (Min et al., 2022; Xi et al., 2023)	**UAV synergy**: Proximal sensing with UAVs enhances field-level accuracy and complements satellite data (Araya et al., 2020; Hollesen et al., 2023)	**Extreme weather**: Causes up to 20% drop in accuracy, especially in semi-arid/tropical zones (Ahmad et al., 2022; Patel et al., 2022)
Disaggregation Impact: Disaggregation and hybrid methods improve irrigation and drought detection (Ouaadi et al., 2024; Pascal et al., 2023)	**Limited Scale of UAV Surveys**: UAV-based studies, while accurate, are constrained by coverage area and operational feasibility for large-scale monitoring.	**Open-access expansion**: Free satellite data from Copernicus and SMAP expands access and reduces monitoring costs (Abdikan et al., 2023; Ayari et al., 2023)	**Sensor-specific calibration and error propagation:** Calibration issues in hyperspectral UAV sensors and variation across platforms can introduce bias in SM retrieval (Levy and Johnson, 2021; Wigmore et al., 2019)
		Multi-sensor UAV integration: Combining RGB, multispectral, and thermal UAV data enhances archaeological and environmental applications (Hollesen et al., 2023)	**Limited temporal coverage of UAV and proximal method:** UAV missions are restricted to short time windows and specific campaigns, limiting their utility for real-time or long-term SM monitoring (Lu et al., 2020; Wigmore et al., 2019)

underutilization of certain methods such as DL, water accounting, and instrumental techniques. This reflects an under-exploration of context-specific studies and methodological diversity.

Opportunities lie in expanding research at finer spatial scales, including multi-national or field-specific applications, which could better capture regional variability and enhance model precision. Further development of hybrid approaches, deep learning, and process-based assimilation methods also offers potential to diversify modelling frameworks and drive innovation. Threats include the risk of over-reliance on large-scale studies and dominant approaches such as AI/ML and physical models, which may neglect localized dynamics and constrain methodological diversity. This may leave critical gaps in addressing region-specific challenges and alternative pathways, such as energy balance or index-based models.

Synthesizing the SWOT outcomes reveals a clear methodological inflection point in SSM research. Strengths and opportunities overwhelmingly favour hybrid ML-physics and multi-sensor fusion approaches, indicating that future advances are more likely to come from integration rather than algorithmic novelty alone. Conversely, the overlap between weaknesses and threats, particularly model transferability, overfitting, and data scarcity suggests that continued reliance on purely data-driven approaches without physical constraints may exacerbate regional inequities in SSM applicability. These findings imply that future SSM research should prioritize standardization of validation protocols, physically informed learning frameworks, and region-adaptive calibration strategies rather than incremental accuracy gains.

The SWOT synthesis supports the review questions by: (i) consolidating evidence of a shift toward operational applicability; (ii) identifying the approaches most consistently enabling this shift (fusion, hybrid ML-physics, and assimilation); (iii) clarifying why SSM-RZSM/decision-support gaps persist (transferability limits, data scarcity, and inconsistent validation); and (iv) translating these patterns into methodological priorities for agricultural and hydrological decision support (standard benchmarking, uncertainty propagation, and region-adaptive calibration).

Future development pathways include emerging missions, hybrid modelling, and decision-support integration. Recent advancements in SSM estimation have increasingly transcended traditional retrieval and downscaling methodologies, driven by the demand for higher spatial resolution, improved temporal continuity, and enhanced physical realism. This section synthesizes evidence on emerging and next-generation technologies that have gained prominence in the 2019–2024 literature, evaluating their methodological contributions, maturity, and potential for operational deployment.

The future of SSM estimation (Fig. 9) looks promising with the upcoming launch of several sophisticated satellite missions equipped with advanced SAR technology. Notably, the NISAR mission, a collaborative effort between NASA and ISRO, launched on 30 July 2025, offering high-resolution data (3–48 m) with dual L-band/S-band frequencies, enhancing the precision of SM and landscape dynamics assessments (Singh et al., 2023). Similarly, the ROSE-L mission by ESA, planned for 2028, aims to provide detailed regional and global scale observations using L-band SAR at a 25 m^2 to 50 m^2 resolution (Wagner et al., 2024). Germany's TANDEM-L mission, also expected in 2028, will focus on high-frequency data collection (every 8 days) to monitor dynamic changes in SM (Huber et al., 2018). Additionally, NASA's GLOWS, still under consideration, proposes to integrate radar and radiometer technologies to cover broad areas with a focus on L-band measurements (Bindlish et al., 2023; Long et al., 2021). These missions signify a significant advancement in environmental monitoring, promising enhanced capabilities for managing water resources, agricultural planning, and climate research, further solidifying our understanding of Earth's hydrosphere interactions.

Despite the strong opportunities identified, several challenges may constrain future progress. Key issues include limited transferability of ML models across regions and seasons, uncertainty propagation and error accumulation in fusion/downscaling workflows, and persistent shortages of ground validation data in data-scarce regions. Operational uptake may also be limited by computational demands, inconsistent preprocessing/benchmarking standards, and constraints on access to high-resolution commercial datasets. Translating improved SSM retrieval into routine agricultural and hydrological decision support will require scalable pipelines, transparent uncertainty reporting, and closer integration with model-based forecasting and end-user requirements. Beyond technical challenges, operational adoption of SSM retrieval technologies depends on access costs, computational capacity, internet connectivity, user training, advisory infrastructure, institutional coordination, and policy support. Large commercial farms may integrate SSM products into precision irrigation platforms and crop modelling systems, whereas smallholder and low-resource systems require open-access satellite data, cloud-based workflows, low-cost validation, and delivery through extension services or government advisory platforms. An end-to-end application pathway should therefore link satellite data

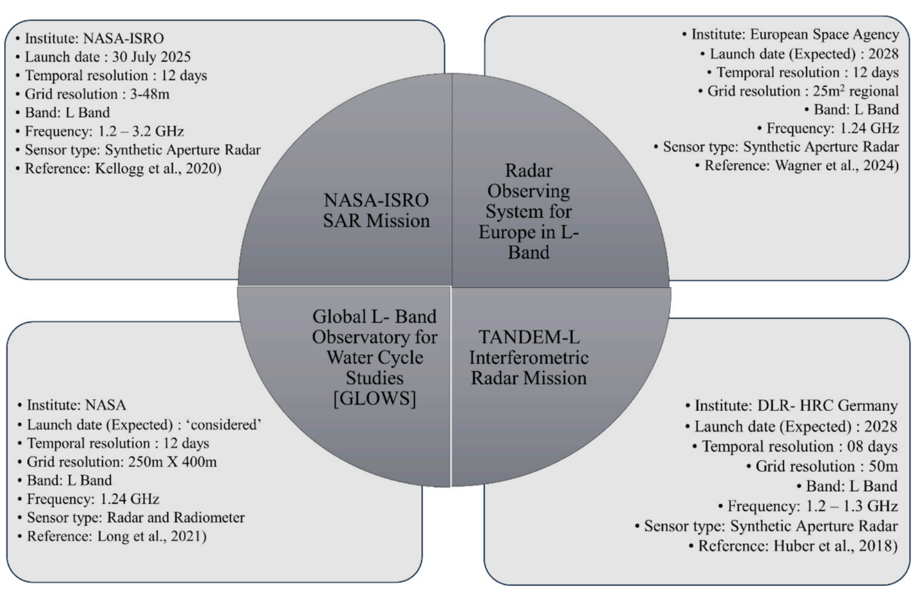

Fig. 9. Emerging future missions of the satellites and sensor technologies.

acquisition, preprocessing, SSM retrieval, local validation, uncertainty reporting, crop/hydrological model integration, and user-oriented decision support.

5. Bridging Surface Soil Moisture (SSM) to Root-Zone Soil Moisture (RZSM)

Remote sensing techniques predominantly provide estimates of SSM, typically representing the upper 0–5 cm of the soil profile. However, most agricultural, hydrological, and climate-impact applications require information on RZSM, which integrates soil water availability across depths relevant to plant root uptake. This mismatch between observable surface signals and decision-relevant subsurface states represents one of the most critical challenges limiting the operational use of satellite-based SM products (Gheybi et al., 2019; Souissi et al., 2022; Stefan et al., 2021).

Despite the growing sophistication of SSM retrieval methods, the transformation of SSM into RZSM remains methodologically fragmented across the literature. Existing studies adopt diverse strategies ranging from empirical time filtering to physically based data assimilation and, more recently, ML and hybrid AI-process approaches. However, these approaches are often evaluated in isolation, using different assumptions regarding soil depth, rooting characteristics, and validation data, making cross-study comparison difficult. To clarify the current state of practice and identify systematic gaps, this review synthesizes the principal methodological pathways used to propagate SSM information into the root zone, highlighting their conceptual basis, data requirements, strengths, and limitations.

5.1. Methodological pathways for SSM-RZSM transformation

Table 5 summarizes the dominant methodological approaches reported in the literature for transforming SSM into RZSM. These approaches can be broadly classified into four categories: (i) time-filtering methods, (ii) data assimilation into land surface or hydrological models, (iii) process-based soil water balance modelling, and (iv) ML or hybrid AI-physics frameworks. The information in Table 5 illustrates that while multiple transformation pathways exist, no single approach currently offers a universally transferable solution for robust SSM-RZSM conversion across agro-ecological regions.

5.2. Implications for agricultural modelling and decision support

The absence of a standardized and validated SSM-RZSM transformation framework has direct implications for agricultural applications. Crop growth models such as APSIM, DSSAT, and AquaCrop rely on RZSM to simulate plant water uptake, transpiration stress, and yield formation. In practice, satellite-derived SSM is used in three main ways: (i) initializing SM profiles at the start of simulations, (ii) periodically correcting simulated soil water states through assimilation or nudging, and (iii) constraining model calibration by providing independent surface moisture information. However, the reviewed literature reveals that few studies explicitly evaluate how uncertainty propagates from SSM into RZSM and subsequently into crop model outputs (Fan et al., 2022; Qian et al., 2024; Qiu et al., 2021). Validation of RZSM estimates is further constrained by the scarcity of deep SM observations, particularly in semi-arid regions and smallholder-dominated agricultural systems (Hong et al., 2024; Xing et al., 2021).

To contextualize the operational implications of this gap, Table 6 aligns commonly used SSM and RZSM products with their practical role in agricultural modelling workflows.

5.3. Synthesis and remaining gaps

Overall, the evidence synthesized in this section indicates that SSM-RZSM transformation is a necessary but insufficiently resolved step in the application chain of remote sensing SM products. While data assimilation and process-based approaches provide physically consistent pathways, their operational uptake remains limited by data availability and computational complexity. ML and hybrid approaches show

Table 6
Practical alignment of SSM and RZSM datasets for agricultural and hydrological applications.

Data source	Primary strength	Role in SSM-RZSM workflow	Key caution
Satellite SSM (SAR, passive MW) (Babaeian et al., 2019; Karthikeyan et al., 2020; Tian et al., 2021)	Surface dynamics and spatial detail	Surface constraint or anomaly detection	Limited penetration depth
Downscaled SSM (AI/fusion) (Babaeian et al., 2019; Qian et al., 2024)	Field-scale surface estimates	Improved spatial relevance	Transferability uncertainty
SMAP Level-4-type products (Fan et al., 2022; Qiu et al., 2021)	Profile soil moisture baseline	Reference RZSM state	Coarse resolution
ERA5-Land / GLDAS (Hong et al., 2024; Xing et al., 2021)	Temporal continuity and climatology	Forcing-consistent RZSM	Model dependency
Crop models (APSIM, DSSAT, AquaCrop) (Fan and Schütze, 2024; Holzworth et al., 2014)	Decision-relevant soil water states	Final integration layer	Sensitive to initialization

Table 5
Systematic synthesis of approaches for transforming surface soil moisture (SSM) into root-zone soil moisture (RZSM).

Approach category	Core principle	Typical inputs	Key strengths	Key limitations	Evidence maturity
Exponential / SWI filtering (Gheybi et al., 2019; Stefan et al., 2021)	Time-lagged smoothing of SSM to approximate deeper moisture dynamics	SSM time series	Simple, low computational cost	Sensitive to soil texture and climate; limited transferability	Moderate
Data assimilation (Fan et al., 2022; Qiu et al., 2021; Xing et al., 2021)	Updating soil profile states in land surface or hydrological models	SSM + meteorological forcing	Physically consistent; depth-resolved	Model-dependent; calibration-intensive	High
Process-based water balance models (Gheybi et al., 2019; Qian et al., 2024)	Simulation of infiltration, redistribution, and root uptake	Climate + soil + vegetation + SSM constraints	Agronomically interpretable; compatible with DSS	Parameter uncertainty; site-specific tuning	High
Machine learning (Babaeian et al., 2019; Souissi et al., 2022)	Empirical mapping from SSM and ancillary variables to RZSM	SSM + NDVI/ET/soil data	High accuracy in data-rich regions	Limited generalization; black-box behavior	Emerging
Hybrid AI-physics models (Qian et al., 2024; Xu et al., 2023)	ML constrained by soil water or energy balance	Multi-sensor + physical constraints	Improved robustness and interpretability	Methodological complexity	Emerging

promise but require more rigorous cross-region validation and uncertainty characterization (Qian et al., 2024; Souissi et al., 2022; Xu et al., 2023). Addressing this gap is essential for translating advances in SSM retrieval into actionable information for irrigation scheduling, crop yield forecasting, and climate-resilient agricultural management (Babaeian et al., 2019; Qiu et al., 2021; Xu et al., 2023).

6. Conclusion

This review provides an up-to-date synthesis of advances in remote sensing-based SSM estimation from 2019 to 2024. Across 116 peer-reviewed studies, ML, multi-sensor fusion, downscaling, retrieval, forecasting, and data assimilation have substantially improved the accuracy, spatial detail, and usability of SSM products for agriculture, hydrology, and climate applications. A consistent trend is the growing use of Sentinel-1 SAR combined with ML, which supports field-to-regional scale mapping, while hybrid physics-AI approaches are increasingly adopted to improve robustness in heterogeneous environments.

The SWOT synthesis highlights that ML models (e.g., RF, SVR, GA-BP) can achieve high accuracy but often depend on large training datasets and show reduced performance when transferred beyond their calibration regions. Physically based and index-driven approaches (e.g., Water Cloud Model coupled with vegetation indices) remain valuable in vegetated conditions but are comparatively underused, and terrain/feature-space methods can support gap-filling and resolution enhancement. UAV-based multispectral/hyperspectral observations offer field-scale detail, but satellite platforms remain essential for scalable, repeatable SSM monitoring.

Despite progress, major gaps persist. Research is concentrated in a limited set of countries, and tropical and desert regions remain underrepresented, constraining the generalizability of current methods. Future work should expand validation in data-scarce regions, strengthen uncertainty-aware fusion and downscaling, and develop open, user-friendly tools that are practical in low-resource settings. Importantly, while SSM retrieval is moving from experimental demonstrations toward operational potential-driven by fusion, ML, and hybrid physics-AI methods the disconnect between surface observations and root-zone, decision-relevant processes remains a central bottleneck. Bridging this gap will require standardized validation, physically informed learning, and explicit coupling of SSM products with crop and hydrological models. Overall, advances in remote sensing and ML for SSM monitoring are pivotal for climate-resilient agriculture and water security, but the next step is ensuring these methods are transferable, uncertainty-aware, and usable for real-world decision support.

CRediT authorship contribution statement

Monika Rawat: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Thong Nguyen-Huy:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **DR Sena:** Writing – review & editing. **Aram Ali:** Writing – review & editing, Supervision.

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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.

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Data availability

Data will be made available on request.

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