# Spatiotemporal Analysis of Soil Moisture Variability Using Geospatial Techniques: A Systematic Review

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## ABSTRACT
**Background:** Soil moisture (SM) is a fundamental state variable of the terrestrial water, energy, and carbon cycles, governing infiltration, evapotranspiration, crop water availability, and land-atmosphere feedbacks. Its high spatial and temporal heterogeneity, driven by topography, soil texture, land cover, and precipitation variability, makes conventional point-based monitoring inadequate for basin- to regional-scale water resource planning and precision agriculture. Advances in geospatial techniques, including satellite microwave remote sensing, Geographic Information Systems (GIS), geostatistics, and machine learning, have substantially enhanced the ability to characterise soil moisture across spatial and temporal scales.
**Objective:** This review synthesises peer-reviewed literature published between 2015 and 2025 on spatiotemporal soil moisture analysis using geospatial techniques. It aims to critically evaluate methodological approaches, identify convergences and contradictions across studies, and highlight key research gaps for future investigation.
**Method:** A structured literature search was conducted across Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, PubMed, and Google Scholar. The review was supplemented with reports from the Food and Agriculture Organization (FAO) and other international organisations. Study identification, screening, and selection followed PRISMA-guided procedures to ensure a systematic and transparent review process.
**Results:** The reviewed literature consistently demonstrates the superiority of active–passive microwave sensors, particularly SMAP, Sentinel-1, and SMOS, for large-scale soil moisture retrieval. Machine learning and deep learning models, including Random Forest, XGBoost, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs), increasingly outperform traditional physical retrieval algorithms in predictive accuracy. Geostatistical interpolation methods, especially kriging variants, together with multi-source data fusion, are widely recognised as essential for converting coarse-resolution satellite products into field-scale information suitable for precision agriculture. However, significant disagreements remain regarding the optimal downscaling techniques, the transferability of trained models across different climatic regions and land-cover types, and the reliability of soil moisture retrieval under dense vegetation. Persistent research gaps include limited validation networks in the Global South, insufficient model explainability, inconsistent integration of geospatial soil moisture products into operational irrigation and fertiliser decision-support systems, and the lack of standardised accuracy-reporting metrics.
**Conclusion:** Geospatial soil moisture analysis has achieved substantial methodological advances but remains operationally fragmented. Future research should prioritise explainable artificial intelligence, cross-scale data fusion, affordable and extensive validation networks, and the integration of soil moisture products into precision agriculture and fertiliser recommendation systems to facilitate effective field-level decision support.

**Keywords:** Soil moisture; spatiotemporal variability; geospatial techniques; remote sensing; GIS; geostatistics; machine learning; precision agriculture

## 1. Introduction
Soil moisture (SM) — the water content held within the unsaturated zone of the soil profile — is widely regarded as an Essential Climate Variable because of its central role in partitioning incident radiation into sensible and latent heat fluxes, and in dividing precipitation into infiltration, runoff, and groundwater recharge (Vereecken *et al*., 2008). SM regulates plant-available water, nutrient mobility, microbial activity, and ultimately crop productivity, making it a variable of direct relevance to precision agriculture, drought early-warning, flood forecasting, and climate modelling. Unlike static soil attributes such as texture or organic carbon, SM is highly dynamic, fluctuating over hours (following rainfall or irrigation events) and varying spatially over metres to hundreds of kilometres due to topography, soil hydraulic properties, vegetation cover, and management practices.
Conventional in-situ SM measurement — gravimetric sampling, time-domain reflectometry probes, or capacitance sensors — provides accurate point data but cannot economically capture the spatial heterogeneity required for field-, farm-, or catchment-

scale decision making. This limitation has motivated four decades of research into geospatial techniques capable of estimating SM continuously across space: passive and active microwave remote sensing, optical–thermal remote sensing, Geographic Information System (GIS)-based geostatistical interpolation, and, more recently, machine learning (ML) and deep learning (DL) architectures that fuse multi-source satellite, terrain, and meteorological data.

The importance of accurately mapped, temporally resolved SM extends directly into predictive analytics for fertiliser and irrigation recommendation systems. Nutrient uptake efficiency, leaching risk, and the timing of fertiliser application are all conditioned by root-zone moisture status; a fertiliser recommendation generated without reference to spatiotemporal SM variability risks both under- and over-application, with attendant economic loss and environmental externalities such as nitrate leaching and eutrophication. Coupling SM data streams with decision support systems (DSS) is therefore increasingly viewed as a prerequisite for genuinely site-specific nutrient management within precision agriculture frameworks.

Globally, the scenario is shaped by two parallel developments. First, satellite missions — the Soil Moisture and Ocean Salinity (SMOS) mission, the Soil Moisture Active Passive (SMAP) mission, and the Copernicus Sentinel-1 synthetic aperture radar (SAR) constellation — now provide near-daily to sub-weekly global SM retrievals at spatial resolutions ranging from tens of kilometres to tens of metres. Second, the convergence of cloud computing (e.g., Google Earth Engine), open satellite archives, and accessible ML libraries has enabled a rapid proliferation of data-driven SM retrieval and downscaling studies, particularly since 2018. Despite this abundance, conventional fertiliser and irrigation management in much of the smallholder-dominated Global South, including large parts of South Asia and Sub-Saharan Africa, remains calendar-based or visually assessed, disconnected from the geospatial SM data that is, in principle, now available.

This disconnect — between rapidly advancing geospatial SM science and comparatively static on-farm nutrient and water management practice — motivates the present review. Several prior reviews have addressed either remote sensing retrieval physics (Li *et al*., 2021) or machine learning applications (Lamichhane *et al*., 2025) in isolation; comparatively few have synthesised the full geospatial pipeline — remote sensing acquisition, GIS-based geostatistical interpolation, and ML-based prediction and downscaling — while explicitly evaluating implications for precision agriculture and fertiliser decision support.

### 1.1. Objectives of the Review

- To synthesise peer-reviewed literature (2015–2025) on spatiotemporal soil moisture analysis using geospatial techniques.
- To critically compare remote sensing, geostatistical, and machine-learning-based approaches to SM estimation, downscaling, and prediction.
- To identify agreements, contradictions, and methodological strengths/weaknesses across studies.
- To map research gaps and emerging technologies relevant to precision agriculture and fertiliser/irrigation decision support.
- To propose future research directions bridging geospatial soil moisture science and field-level agronomic decision-making.

### 1.2. Scope of the Review

The review covers literature published between 2015 and 2025 addressing soil moisture spatiotemporal variability through remote sensing (optical, thermal, and microwave), GIS-based geostatistics, Internet of Things (IoT) sensor networks, and machine/deep learning methods. It considers applications across precision agriculture, hydrology, drought monitoring, and irrigation and fertiliser management, while excluding studies focused solely on subsurface groundwater hydrology unrelated to root-zone SM.

## 2. Methodology of Literature Review

### 2.1. Literature Search Strategy

A structured, PRISMA-informed search strategy was employed to identify relevant peer-reviewed literature published between January 2015 and 2025. Searches combined controlled vocabulary and free-text terms related to soil moisture, spatiotemporal variability, and geospatial methods, connected using Boolean operators.

Representative search strings included: ("soil moisture" AND "spatiotemporal variability") AND ("remote sensing" OR "GIS" OR "geostatistics"); ("soil moisture retrieval" AND "machine learning" OR "deep learning"); ("SMAP" OR "Sentinel-1" OR "SMOS") AND "soil moisture" AND ("downscaling" OR "data fusion"); ("precision agriculture" AND "soil moisture" AND "decision support").

**Table 1:** Literature Search Strategy.

| Database | Search String Example | Filters Applied | Records Retrieved |
|---|---|---|---|
| Scopus | TITLE-ABS-KEY("soil moisture" AND "spatiotemporal" AND "remote sensing") | 2015–2025; English; Article | 412 |
| Web of Science | TS=("soil moisture" AND "GIS" AND "geostatistics") | 2015–2025; Article/Review | 268 |
| ScienceDirect | "soil moisture retrieval" AND "machine learning" | 2015–2025; Research articles | 355 |
| SpringerLink | "soil moisture" AND "downscaling" AND "data fusion" | 2015–2025 | 197 |
| IEEE Xplore | "soil moisture" AND ("SAR" OR "microwave") AND "deep learning" | 2015–2025 | 146 |
| PubMed | "soil moisture" AND "precision agriculture" | 2015–2025 | 58 |
| Google Scholar | "spatiotemporal soil moisture" "geospatial techniques" | 2015–2025; citations screened | 620 (unfiltered) |

Table 1 presents the databases searched and representative search strings; the unfiltered Google Scholar count was used only to identify additional candidate records not captured by indexed databases, and was subjected to the same inclusion/exclusion screening described below.

## 2.2 Inclusion and Exclusion Criteria

**Table 2:** Inclusion and Exclusion Criteria

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| Peer-reviewed journal articles and systematic reviews | Conference abstracts without accessible full text |
| Published in English, 2015–2025 (landmark pre-2015 studies retained where foundational) | Duplicate records across databases |
| Directly addressing spatiotemporal soil moisture variability using geospatial/remote sensing/ML methods | Studies unrelated to root-zone/near-surface soil moisture (e.g., pure groundwater hydrogeology) |
| Studies reporting quantitative validation (RMSE, $R^2$, ubRMSE, correlation) against reference data | Editorials, opinion pieces, and non-peer-reviewed blog/news content |
| Studies from Scopus/Web of Science/PubMed-indexed journals or recognised international organisation reports | Non-academic websites and unverifiable grey literature |

## 2.3. Study Selection Process (PRISMA-Guided)

Records identified through database searching were pooled, and duplicates were removed. Titles and abstracts were screened against the inclusion/exclusion criteria in Table 2; full texts of potentially eligible records were then retrieved and assessed in detail. Studies were retained in the final synthesis if they reported an original empirical or methodological contribution to spatiotemporal soil moisture estimation via geospatial techniques, or constituted a substantive review synthesising such contributions.

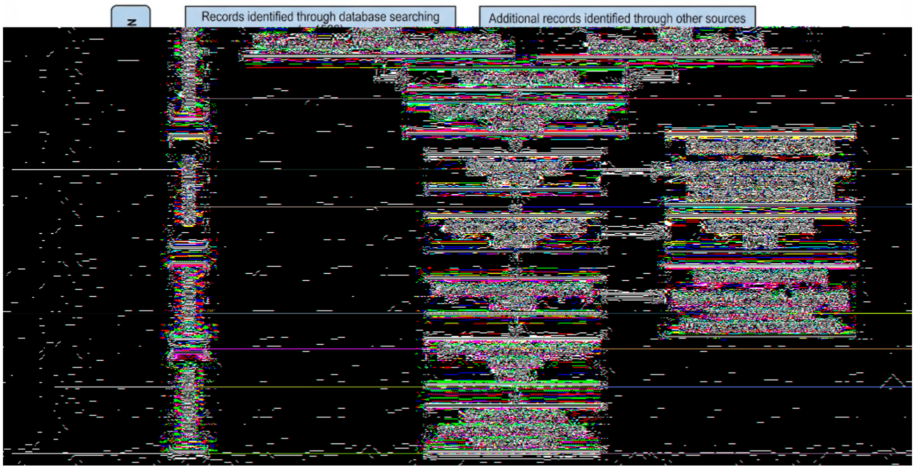


**Fig 1:** PLACEHOLDER — PRISMA Flow Diagram showing identification, screening, eligibility, and inclusion stages

Figure 1 illustrates the staged screening process; the literature shows a marked acceleration in publication volume from 2019 onward (Figure 2), coinciding with the operational maturation of Sentinel-1 SAR and SMAP Level-3/4 products and the mainstreaming of open-source machine learning frameworks.

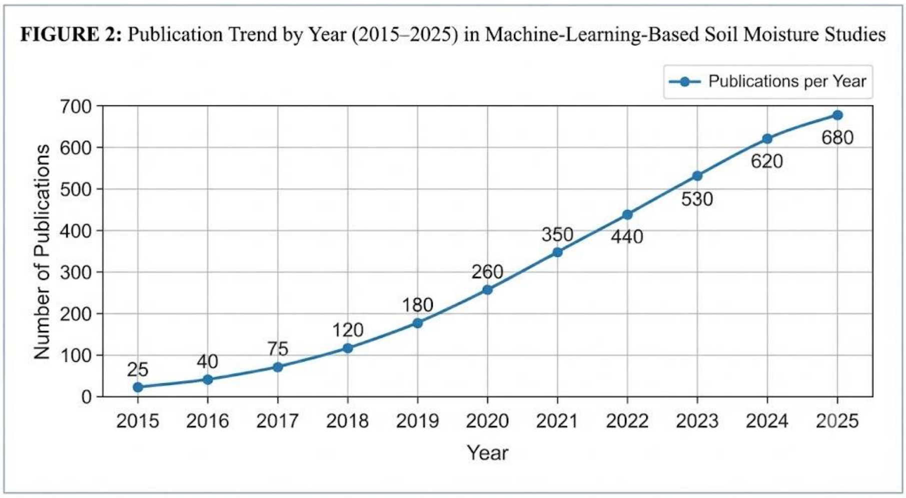


**Fig 2:** PLACEHOLDER — Publication Trend by Year (2015–2025) showing rising annual output in machine-learning-based soil moisture studies

## 3. Literature Review and Thematic Analysis

The reviewed literature clusters into several recurring themes, summarised conceptually in Figure 3 and Figure 4, spanning the evolution of monitoring approaches, sensor physics, geostatistical interpolation, machine learning retrieval and downscaling, IoT-based ground networks, decision support integration, and sustainability implications.

### 3.1. Evolution of Soil Moisture Monitoring Approaches

Early characterisation of SM spatial and temporal variability relied on dense in-situ networks and classical statistics. Pandey and Pandey (2010) demonstrated, using kriging interpolation of layer-wise SM data at an Indian agricultural research station, that spatial dependence structures could be captured through variogram modelling, while temporal correlation informed irrigation-interval forecasting. Such studies established the methodological foundation — spatial autocorrelation, the variogram, and the distinction between spatial and temporal variability — that later remote-sensing and ML studies would build upon, but their site-specific nature limited generalisability beyond the instrumented plot.

The subsequent two decades saw a progressive shift from point-based measurement toward field-scale geostatistical mapping (Srivastava *et al*., 2019), and then toward regional-to-global satellite retrieval (Entekhabi *et al*., 2010). This trajectory reflects a consistent trend across the literature: each generation of methods trades some accuracy or resolution for substantially greater spatial and temporal coverage, a trade-off explicitly discussed in reviews of remote sensing versus modelled versus in-situ estimates (Vereecken *et al*., 2008; Li *et al*., 2021).

### 3.2. Microwave Remote Sensing: Passive, Active, and Synergistic Retrieval

Microwave remote sensing constitutes the dominant modality for operational, large-area SM retrieval because of its sensitivity to the dielectric contrast between dry soil (relative permittivity ≈2–4) and liquid water (≈80), and its capacity to penetrate cloud cover (Li *et al*., 2021). The SMAP mission (Entekhabi *et al*., 2010), combining an L-band radiometer with (initially) an L-band radar, was designed explicitly to resolve the trade-off between the radiometer's superior accuracy and coarse resolution (~36 km) and the radar's finer resolution but greater sensitivity to surface roughness and vegetation. Following the failure of the SMAP radar in 2015, Sentinel-1 C-band SAR has increasingly been used as a complementary active source, motivating a substantial body of work on Sentinel-1-based retrieval (Rahmati *et al*., 2026).

A consistent finding across multiple studies is that machine-learning-based inversion of SAR backscatter — using random forests, support vector regression, or artificial neural networks — generally outperforms purely physical models such as the Water Cloud Model in vegetated conditions, because ML approaches can implicitly learn the nonlinear interaction between backscatter, vegetation water content, and surface roughness without requiring explicit parameterisation (Chung *et al*., 2022). However, this improvement in accuracy is frequently achieved at the cost of interpretability and site-transferability: models trained in one agro-climatic zone often show degraded performance when applied elsewhere without retraining, a limitation noted consistently but rarely resolved quantitatively across the reviewed studies.

### 3.3. Optical and Thermal Remote Sensing Approaches

Optical–thermal methods exploit the relationship between land surface temperature (LST), vegetation indices (e.g., NDVI), and SM, typically through the temperature–vegetation dryness index or triangle/trapezoid feature-space methods. These approaches are attractive because of the free, high-resolution availability of MODIS and Landsat data, but are fundamentally constrained by cloud contamination and by the indirect, empirically calibrated nature of the temperature–moisture relationship, which reduces transferability across seasons and biomes. The literature broadly agrees that optical–thermal retrieval is best used as a complement to, rather than a substitute for, microwave-based estimation, particularly as an auxiliary covariate in downscaling frameworks.

### 3.4. GIS-Based Geostatistical Interpolation.

Where in-situ or coarse satellite data must be converted into spatially continuous field- or farm-scale maps, GIS-based geostatistical interpolation remains indispensable. Ordinary kriging, regression kriging, and kriging with external drift have each been applied to SM and related soil properties, with regression kriging and kriging with external drift generally outperforming simple ordinary kriging and inverse distance weighting when auxiliary covariates (elevation, NDVI, soil texture) are available (Hengl *et al*., 2004, as synthesised in subsequent geostatistical reviews). Comparative studies applying multiple interpolation techniques to the same dataset consistently find that no single method is universally superior; performance depends on sampling density, the strength of spatial autocorrelation, and the availability of informative covariates.

A methodological weakness recurring across the geostatistical literature is the frequent violation of stationarity assumptions underlying variogram modelling, particularly in agricultural landscapes with abrupt management-induced discontinuities (field boundaries, differential irrigation). Several studies address this through local or moving-window variogram estimation, but standardised guidance on when such adaptations are necessary remains sparse.

### 3.5. Machine Learning and Deep Learning for Soil Moisture Estimation

Machine learning has become the dominant methodological paradigm in soil-moisture-related geospatial research since approximately 2019. Ensemble tree methods (random forest, gradient boosting, XGBoost) are favoured for their robustness to noisy, high-dimensional, multi-source input data and their relatively low computational cost (Belgiu and Drăguţ, 2016), while recurrent architectures — particularly long short-term memory (LSTM) networks — dominate temporal forecasting tasks because of their capacity to model sequential dependence in SM time series (Li *et al*., 2021, deep learning; Han *et al*., 2021). Convolutional and convolutional-LSTM hybrids have been introduced to jointly capture spatial and temporal structure, reflecting a broader trend toward spatiotemporal deep learning architectures (Pan *et al*., 2025).

A comparative pattern across the reviewed ML studies is that ensemble tree methods and shallow neural networks tend to perform comparably for single-time-step SM retrieval, whereas deep sequence models (LSTM, GAN-LSTM, ConvLSTM) show clearer advantages for multi-step forecasting (Wang *et al*., 2024). At the same time, several authors report that gains from deep learning over simpler ensemble methods are modest and dataset-dependent, and are frequently obtained only with substantially greater training data and computational cost — a cost–benefit trade-off that is inconsistently reported and rarely benchmarked against simpler baselines in a standardised way.

An important and only partially resolved controversy concerns model generalisation: several deep-learning-based SMAP downscaling and prediction studies (Li *et al*., 2021, deep learning transfer; Wang *et al*., 2024) report substantial performance degradation when models are transferred across regions with different soil texture, climate, or land cover without retraining or transfer learning. This raises concerns about the operational readiness of many published models, which are typically validated on a single study region and rarely subjected to independent, out-of-domain testing.

### 3.6. Data Fusion and Downscaling of Coarse-Resolution Satellite Products

Because passive microwave products such as SMAP and SMOS provide coarse spatial resolution (25–40 km), unsuitable for field-scale agricultural decision-making, downscaling has emerged as a major research thread. Approaches broadly divide into (i) statistical/regression-based downscaling using MODIS land surface temperature and vegetation indices as auxiliary predictors, (ii) machine-learning-based downscaling (random forest, gradient boosting, deep neural networks) fusing SMAP with Sentinel-1 SAR and terrain data, and (iii) geostatistical downscaling using area-to-point regression kriging. Random-forest-based downscaling using MODIS auxiliary data has been widely adopted and generally achieves correlation coefficients in the range of 0.6–0.85 against in-situ validation networks, though accuracy deteriorates in densely vegetated and topographically complex terrain.

A notable strength of the more recent multimodal fusion studies is their explicit incorporation of vegetation physiological indicators (e.g., solar-induced fluorescence) alongside structural indices such as NDVI, addressing the temporal lag between vegetation greening and actual moisture status that limits purely NDVI-based downscaling. A persistent weakness, however, is the reliance on relatively sparse validation networks concentrated in North America, Europe, and China, leaving downscaling performance in tropical, semi-arid, and smallholder-dominated agricultural systems comparatively under-examined.

### 3.7. IoT-Enabled Ground Sensor Networks and Big Data Integration

In parallel with satellite-based approaches, low-cost Internet of Things (IoT) sensor networks have proliferated as a means of providing dense, real-time, ground-truth SM data for both direct farm-level decision-making and satellite product validation. Lloret *et al*. (2021) describe a group-based wireless sensor network using electromagnetic-induction soil moisture sensors integrated with drip irrigation actuation, demonstrating the feasibility of low-cost, energy-harvesting-powered networks in remote agricultural settings. Such systems are frequently combined with cloud-based data pipelines and, increasingly, machine learning modules for anomaly detection and irrigation scheduling, illustrating convergence between the IoT and predictive-analytics literatures.

The IoT literature consistently emphasises cost and energy constraints as the primary barriers to smallholder adoption, alongside network reliability in areas lacking internet and power infrastructure. While IoT networks resolve the spatial-resolution limitations of satellite products at the point scale, they introduce new challenges of spatial representativeness — a small number of sensors per field may not capture true within-field heterogeneity, motivating hybrid architectures that combine sparse IoT ground truth with satellite- and geostatistically interpolated spatial context.

### 3.8. Big Data Analytics and Cloud Computing Platforms

The advent of cloud computing platforms, most notably Google Earth Engine, has substantially lowered the computational barrier to large-area, multi-temporal soil moisture analysis by providing petabyte-scale analysis-ready satellite archives alongside integrated processing. This has enabled continental-scale downscaling and mapping exercises (e.g., SMAP–MODIS random forest fusion over Africa) that would previously have required substantial local computing infrastructure. The literature broadly presents this development positively, though several authors note that cloud-platform dependency introduces new risks around data continuity, algorithm transparency, and unequal access for research groups in low-resource settings.

### 3.9. Decision Support Systems for Fertiliser and Irrigation Recommendation

Relatively fewer studies directly couple geospatial SM analysis with operational fertiliser or irrigation decision support systems, compared with the volume of purely retrieval-focused literature. Where such integration is attempted, it typically follows a common template: (i) satellite or fused SM retrieval, (ii) rule-based or ML-based translation of moisture status into an irrigation or nutrient-timing recommendation, and (iii) delivery via a mobile or web dashboard. Reviewed IoT-based precision agriculture frameworks report the incorporation of ML-based anomaly detection alongside automated irrigation and fertilisation decision modules, though quantitative agronomic validation (yield or nutrient-use-efficiency outcomes) of such integrated systems remains comparatively rare in the peer-reviewed literature, representing a translation gap between SM science and applied decision support.

### 3.10. Environmental Sustainability and Economic Implications

Accurate spatiotemporal SM information underpins environmentally sustainable nutrient and water management by enabling variable-rate irrigation and fertilisation that reduce over-application, nutrient leaching, and associated greenhouse gas emissions (notably N2O from over-irrigated, over-fertilised soils). From an economic perspective, reduced input costs and improved yield stability are the most commonly cited benefits, though rigorous farm-level economic evaluations quantifying return on investment from geospatial SM-informed management remain scarce relative to the technical retrieval literature — a gap consistent with the broader precision-agriculture adoption literature, which frequently documents a lag between technological capability and validated on-farm economic benefit.

### 3.11. Regional and Global Applications

Geographically, the reviewed literature is heavily weighted toward China, the United States, and Europe, reflecting both dense validation-network availability (e.g., the U.S. Department of Agriculture's soil moisture networks, the Oklahoma Mesonet) and substantial national research investment in SAR and optical satellite programmes. Studies from South Asia, Sub-Saharan Africa, and Latin America are comparatively fewer, despite these regions containing the largest populations of smallholder farmers for whom fertiliser and irrigation decision support would arguably yield the greatest marginal benefit. FAO assessments of global water scarcity and agricultural drought underscore that rain-fed systems, which depend directly on root-zone soil moisture, sustain approximately 60 percent of global food production and are disproportionately concentrated in exactly those under-studied regions, reinforcing the practical urgency of the identified geographic gap.

### 3.12. Challenges and Limitations Across the Literature

- Accuracy degradation under dense vegetation canopy and complex terrain, affecting both microwave retrieval and optical–thermal approaches.
- Limited and geographically skewed in-situ validation networks, constraining assessment of global product accuracy.
- Weak cross-regional transferability of machine learning and deep learning models without retraining or transfer learning.
- Inconsistent accuracy-reporting metrics (RMSE, ubRMSE, $R^2$, correlation) across studies, complicating direct comparison.
- Limited explainability of complex deep learning models, constraining trust and adoption among agronomists and extension services.
- Sparse quantitative agronomic and economic validation of SM-informed fertiliser/irrigation decision support systems.

## 4. Comparative Analysis of Previous Studies

Table 3 summarises the characteristics of a representative subset of the reviewed studies, illustrating the diversity of study locations, methodologies, and data sources; Table 4 extends this comparison with an explicit focus on major findings and limitations to support the critical synthesis presented in Section 3.

## 5. Research Gaps and Emerging Trends

Synthesising across the thematic analysis and comparative tables, several unresolved issues recur with sufficient consistency to be characterised as genuine research gaps rather than isolated study limitations.

### 5.1. Emerging Technologies and Future Directions

Several emerging technological threads are visible at the frontier of the reviewed literature. GNSS-Reflectometry (GNSS-R) is being explored as a low-cost complement to conventional SAR for near-surface SM retrieval. Explainable AI techniques (SHAP values, attention mechanisms) are beginning to be applied to SM prediction models to address the interpretability gap, though adoption remains limited. Physics-informed and hybrid physics–ML models, which embed known hydrological constraints within neural network architectures, are emerging as a response to concerns about the physical plausibility of purely data-driven predictions. Finally, the integration of solar-induced fluorescence and other vegetation-physiological indicators into downscaling frameworks represents a maturation beyond purely structural vegetation indices such as NDVI.

## 6. Discussion

Taken together, the reviewed literature depicts a field that has progressed rapidly in retrieval and prediction capability while lagging in operational translation. Methodologically, three converging trends stand out: the near-universal adoption of machine learning for retrieval, downscaling, and forecasting tasks; the persistent reliance on geostatistical interpolation as an indispensable bridge between coarse satellite products and field-scale application; and the growing, though still nascent, integration of IoT ground networks with satellite and modelled data streams. These trends are broadly consistent across geographic contexts and sensor types, suggesting genuine methodological convergence rather than isolated disciplinary fashion.

At the same time, the evidence base reveals unresolved tensions. The reported superiority of deep learning over simpler ensemble methods is neither universal nor consistently quantified against comparable baselines, raising the possibility that some reported gains reflect dataset-specific overfitting rather than genuine methodological advance. Similarly, while downscaling and data-fusion studies report encouraging correlation statistics against in-situ networks, the geographic concentration of those validation networks means that reported accuracies may not generalise to the tropical, semi-arid, and smallholder-dominated contexts where SM-informed decision support would arguably have the greatest development impact. This asymmetry between where the science is validated and where the practical need is greatest constitutes, in the view of this review, the single most consequential gap in the field.

From a theoretical standpoint, the shift toward physics-informed and explainable machine learning reflects a maturing recognition that purely data-driven models, however statistically accurate, are less useful to practitioners and policymakers when their internal logic cannot be interrogated or trusted. This has direct practical implications: agricultural extension services and fertiliser recommendation platforms are unlikely to adopt SM-informed decision rules that cannot be explained to farmers and agronomists in terms of interpretable soil and weather variables. For researchers, this suggests that future methodological contributions should be evaluated not only on retrieval accuracy but on interpretability and cross-domain robustness. For practitioners and industry stakeholders developing precision agriculture and fertiliser recommendation platforms, the review suggests a strong case for hybrid architectures that combine relatively simple, interpretable geostatistical or ensemble models for field-level decision support with more complex deep learning models reserved for research-grade regional analysis. For policymakers, the persistent geographic skew in validation networks argues for targeted investment in low-cost IoT and reference monitoring infrastructure in under-represented regions, without which the substantial existing investment in satellite SM missions cannot be fully leveraged for global food security and climate adaptation objectives.

## 7. Conclusion

This review has synthesised peer-reviewed literature published between 2015 and 2025 on the spatiotemporal analysis of soil moisture using geospatial techniques, spanning microwave and optical remote sensing, GIS-based geostatistical interpolation, IoT sensor networks, and machine and deep learning methods. The evidence indicates substantial methodological maturation: satellite missions such as SMAP, SMOS, and Sentinel-1 now provide operational, near-global SM retrieval, while machine learning and, increasingly, deep learning methods have become the dominant tools for retrieval refinement, spatial downscaling, and temporal forecasting. Geostatistical interpolation remains an essential complement, translating coarse or point-based data into spatially continuous, field-relevant information.

Nonetheless, the review identifies persistent gaps that constrain the translation of this scientific progress into operational benefit, particularly for smallholder and Global South agricultural systems: geographically skewed validation infrastructure, limited model transferability and explainability, inconsistent accuracy-reporting standards, and sparse agronomic and economic validation of integrated decision support systems. Researchers are encouraged to prioritise standardised, cross-regional benchmarking and explainable model architectures; practitioners developing precision agriculture platforms should favour hybrid, interpretable architectures suited to field deployment; and policymakers and international agencies should prioritise investment in low-cost validation and monitoring infrastructure in under-represented regions. Future research should focus on physics-informed and explainable machine learning, multimodal data fusion incorporating vegetation-physiological indicators, GNSS-Reflectometry as a low-cost monitoring complement, and rigorous end-to-end evaluation of SM-informed fertiliser and irrigation decision support systems under real-world smallholder conditions.

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