Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

Artificial Intelligence and Smart Sensing for Real-Time Soil Health Monitoring: Advancing Sustainable Watershed Management in India

Dr. Thallapally Sameera Pallavi, Anjali Adhikari, Gargi Shekhar, Akanksha Soni, Dr. Somnath G. Kolgiri, Dr. Sushmita Konwar

PHD Scholar, Department of Computer Science, Kakatiya University, Warangal, Telangana,506009, India, ORCID: https://orcid.org/0000-0003-3972-0411, Email Id: thallapally.sameerapallavi@gmail.com
Assistant Professor, Department of Agriculture, School of Agriculture, Dev Bhoomi Uttarakhand University, Uttarakhand, India. ORCID: https://orcid.org/0009-0007-3516-3079
Email: adhikariannu7@gmail.com
Assistant Professor, Department of Agriculture, School of Agriculture, Dev Bhoomi Uttarakhand University, Uttarakhand, India. ORCID: https://orcid.org/0000-0001-9716-9010 Email: drgargi.shekhar@gmail.com
Research Scholar, Civil Engineering (HWRE), Indian Institute of Technology Madras, Chennai–600036, Tamil Nadu, India. ORCID: https://orcid.org/0009-0002-2890-6288 Email: akankshac.e.07@gmail.com
Associate Professor, Department of Mechanical Engineering, Parvatibai Genba Moze College of Engineering, Pune, Maharashtra, India. ORCID: https://orcid.org/0000-0003-0432-0370 Email: sgkolgiri@gamil.com
Assistant Professor, Department of Soil Science, Faculty of Agricultural Sciences and Technology, Assam down town University, Panikhaiti, Guwahati–781026, Assam, India. ORCID: https://orcid.org/0009-0005-7660-0891 Email: sushmita.konwar@adtu.in

Key Words
soil health; smart sensing; Internet of Things; artificial intelligence; machine learning; watershed management; India; PRISMA 2020

Abstract

Healthy soil largely determines how a watershed holds, cleans and releases water, yet most Indian catchments are still judged from a handful of laboratory samples that arrive late and describe little of the landscape. This review, reported according to PRISMA 2020, draws on 29 studies identified through a structured search, supported by wider background literature, to examine how artificial intelligence (AI) and smart sensing can enable real-time soil health monitoring for sustainable watershed management in India. We consider the soil indicators that matter at catchment scale, the in situ, proximal and remote platforms that measure them, ways of fusing their outputs, machine learning and deep learning methods, and decision support tools. No single sensor proves adequate. In situ networks supply ground truth, proximal spectroscopy and electromagnetic induction add spatial detail, and satellite and airborne data provide regional context. AI can reconcile these layers, but only when data are co-registered, models are calibrated locally and uncertainty is reported openly. In India, fragmented landholdings, monsoon variability, sensor drift, poor connectivity, recurring costs and weak institutional capacity are the principal obstacles. A hybrid design, combining few permanent nodes with periodic mobile sampling, funded maintenance and shared data standards, appears most workable. Research priorities follow.

INTRODUCTION

1.1 Why soil matters at the watershed scale

To a surprising degree, a watershed acts the way its soils let it. Whether rain soaks in or runs off, how much nutrient the root zone retains, and how clean the water leaving a farmed landscape turns out to be all depend on the physical, chemical and biological condition of the soil (Hu et al., 2026). These processes unfold over very different spatial and time scales, so trouble in one part of a catchment rarely stays put. Sediment, nutrients and pesticide residues travel downstream, and for that reason soil condition is now treated as a core indicator in catchment planning (Jana et al., 2024; Zeng et al., 2025).

India makes the challenge sharper. Its watersheds span many agro-climatic zones, and intensive cultivation, heavy fertiliser use and monsoon runoff interact in fast-changing ways. Planners need up-to-date knowledge of soil condition, yet conventional approaches have found it hard to supply (Bharti et al., 2025).

1.2 Why conventional assessment falls short

Laboratory analysis remains the norm. It takes time, costs money and demands labour, and because it relies on isolated samples it misses the continuous variation

*Corresponding Author:

Received: 25th July, 2026 | 25th May, 2026; Revised: 6th July, 2026; Accepted: 28th July, 2026; Available Online: 29th August, 2026
(DOI): 10.70102/AEJ.2026.18.8s.41

in soil properties that shapes catchment-scale processes (Fan et al., 2022). Artificial intelligence and Internet of Things (IoT) sensing offer a way past these limits. Together they make continuous, data-driven monitoring possible, with results that can flow straight into watershed management decisions (Ahmad et al., 2025).

1.3 Aim and scope

This review gathers current evidence on AI-enabled smart sensing for real-time soil health monitoring, concentrating on Indian watersheds. Four questions guide it: (i) which soil health indicators matter most for watershed function; (ii) which sensing platforms can record them continuously, and how can their outputs be combined; (iii) which AI methods can turn sensor streams into dependable, uncertainty-aware information; and (iv) what technical and institutional conditions decide whether such systems last in practice.

2. Review Methodology (PRISMA 2020)

The review was planned and reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021).

2.1 Eligibility criteria

We included records that (a) dealt with soil health, soil quality or soil moisture monitoring through in situ, proximal, airborne or satellite sensing; (b) applied or discussed artificial intelligence, machine learning or data fusion for soil or watershed information; or (c) examined deployment, cost, calibration or institutional issues for sensor networks in agricultural or watershed settings, giving particular attention to India and to comparable low- and middle-income contexts. Peer-reviewed articles, reviews, technical reports and book chapters were all considered. We excluded records that lacked enough methodological detail or had no real connection to soils or watersheds.

2.2 Information sources and search strategy

We searched Scopus, Web of Science, Google Scholar and ScienceDirect between June 2025 and 2026. A representative search string was: ("soil health" OR "soil quality" OR "soil moisture") AND (sensor* OR IoT OR "remote sensing" OR spectroscopy) AND ("machine learning" OR "artificial intelligence" OR "deep learning") AND (watershed OR catchment OR India). We also scanned the reference lists of key reviews for further sources.

2.3 Selection, data collection and synthesis

Six reviewers shared the work by theme: soil health indicators, sensing technologies, sensor integration, AI methods, Indian applications, and challenges and institutional barriers. Each reviewer screened records and extracted data for their own theme, and a second reviewer independently checked a 20% sample of those decisions. Disagreements were settled by discussion, and any case that remained unresolved went to an arbitrating author. For each study we recorded the soil variable, sensing platform, analytical method, setting and reported limitations. The studies differ too much in design and outcome measures for a meta-analysis, so we combined them in a structured narrative synthesis organised by theme. The 29 included studies form the core evidence base; other sources were cited selectively to supply conceptual and methodological background.

2.4 Study selection

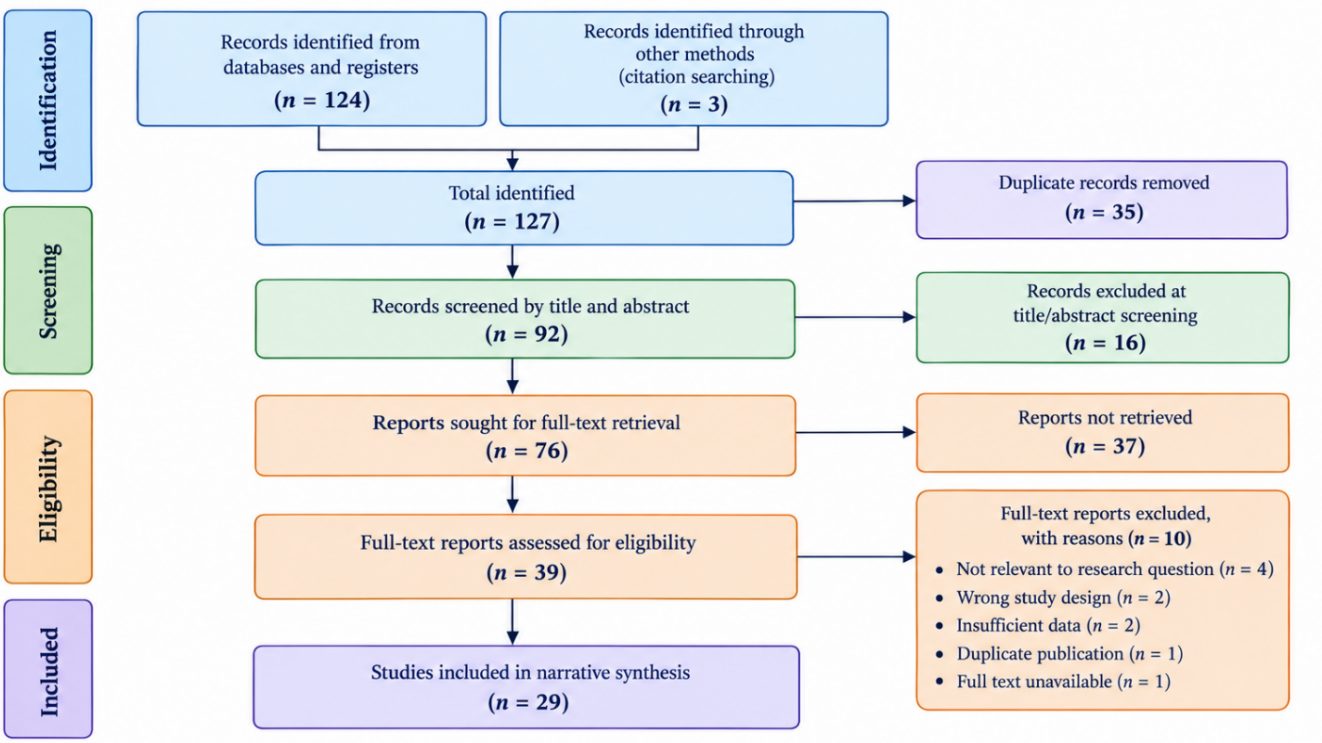


Figure 1. PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in the review. Source: Prepared by the authors based on the PRISMA 2020 reporting framework.

3. Soil Health Concepts and Indicators in a Watershed Setting

3.1 A working definition

Soil health describes a soil's capacity to keep supporting plant and microbial life, to control how water and dissolved substances move, and to absorb environmental shocks. Across a watershed, that capacity is unevenly distributed (Fortuna et al., 2022; Smith et al., 2024). Bedrock, land use and management history leave their mark on every parcel, so a parcel's importance depends on where it lies in the drainage network. Take compaction or lost organic matter: on level ground far from a stream the effect may be modest, while on a headwater slope or next to a channel the same damage can set off heavy runoff and sediment delivery.

It follows that field readings cannot be treated as stand-alone point estimates. A sound watershed assessment links variation in physical, chemical and biological properties to the hydrological and ecological connections between places (Christensen et al., 2025; Kibblewhite et al., 2007).

3.2 Physical, chemical and biological indicators

Physical. Bulk density, aggregate stability, infiltration rate and available water capacity show how well soil lets roots grow, passes water through and withstands erosion. They tie closely to plant growth, water behaviour and the capacity to trap nonpoint source pollutants (Nunes et al., 2021).

Chemical. Soil organic carbon, pH, electrical conductivity and available nutrients point to how well nutrients cycle and how likely dissolved contaminants are to move. Reading them requires local knowledge, since a pH that limits one crop can suit another kind of vegetation perfectly well (Fierer et al., 2020).

Biological. Microbial biomass carbon, respiration, enzyme activity and the abundance of helpful microbes capture the living dimension of soil. They react to changes in management more quickly than total organic carbon, which is why integrated assessments lean on them increasingly (Joshi et al., 2026).

Indicators are interpreted as a group. Composite tools such as the Comprehensive Assessment of Soil Health convert raw measurements into standardised scores, so that soils under different land uses can be compared on common terms (Fausak et al., 2024).

3.3 From indicators to watershed management

What counts at catchment level is how many management units together produce flows of water, sediment and nutrients, so monitoring should be organised around hydrological connectivity and landscape position, not around isolated plots (Lehman et al., 2015). Once point measurements are linked to flow paths, managers can find the critical source areas where degraded soils contribute far more than their share of runoff and sediment. Minimum indicator sets built on biophysical function, rather than on what is easy to sample, keep such diagnoses repeatable between catchments (Bagnall et al., 2023).

Standard diagnostics also give real-time sensor data a yardstick. Five commonly adopted soil quality indicators (organic matter, pH, available phosphorus, water storage and bulk density) line up well with the functions that govern watershed hydrology and nutrient export (Feeney et al., 2023).

4. Smart Sensing Technologies

Tracking soil condition around the clock and across many sites requires equipment that can stay in the field for long periods. Several technology families now fit that need: proximal spectroscopic probes and electrochemical sensors, wireless sensor arrays, vehicle-towed induction instruments, and remote sensing systems that carry point measurements out across a catchment.

4.1 Proximal and networked sensing

Proximal near-infrared (NIR) spectroscopy is appealing because a single scan can estimate several properties together, among them clay content, pH, soil organic carbon, nitrogen, phosphorus and potassium (Kok et al., 2024). Those are the very properties behind the physical, chemical and biological functions that steer watershed behaviour. The catch is depth. The signal reflects only the top few millimetres of soil, so spectra have to be calibrated against laboratory reference data before anyone relies on them for watershed-scale inference (Bünemann et al., 2018). One probe also cannot represent the variation that controls runoff across a catchment, which is why spectral sensing gains much more value as part of a distributed network.

Wireless sensor networks help close that gap. Small, low-power nodes record soil moisture, temperature and electrical conductivity at several depths and send the readings on continuously, giving watershed models hydrological input through data assimilation or data-driven methods (Vereecken et al., 2022). Electromagnetic induction instruments towed across a field add a spatially continuous layer, delivering georeferenced estimates of apparent electrical conductivity that follow changes in texture, moisture, salinity and mineralogy over entire fields and hillslopes (Obade & Gaya, 2021).

4.2 In situ sensors

In situ sensors are buried at set depths in the root zone, where they log volumetric water content, temperature and electrical conductivity at short intervals. For watershed management their strength is catching the rapid shifts in soil moisture that start runoff and release nutrients (Bogena et al., 2015). When installed as dense multi-depth networks they also expose spatial patchiness that single probes miss, laying the groundwork for distributed monitoring (Stegen et al., 2019).

They are not without drawbacks. Sensors drift, each soil needs its own calibration, and keeping networks running across varied catchments is costly. Many programmes therefore add proximal surveys that fill the spatial gaps between fixed installations (Stavi et al.,

2021). Dielectric moisture probes, whether time-domain or frequency-domain, can act as the ground-truth layer against which proximal and remote estimates are calibrated and validated (Fares et al., 2013).

4.3 Remote sensing platforms

Satellite microwave and optical sensors extend these measurements to the catchment scale. Active and passive microwave instruments retrieve surface soil moisture at revisit frequencies that suit drought monitoring and runoff forecasting (Ochsner et al., 2013). Their weakness is that they see only the top few centimetres and are strongly affected by vegetation and surface roughness, so they must be read together with in situ and proximal data before feeding root-zone models (Babaeian et al., 2019; Vereecken et al., 2016). Drones carrying ground-penetrating radar occupy the middle ground. By combining permittivity and electrical conductivity, they can estimate soil moisture and salinity within a field at a resolution between proximal and satellite data (Cheng et al., 2025). Overall, airborne and satellite products work best as partners: aircraft and drones deliver detailed local pictures, and satellites place those pictures in the wider catchment (Bouanani et al., 2025).

4.4 Platform comparison

Platform	Typical measurements	Main strength	Main limitation	Key sources
Proximal NIR spectroscopy	Clay, pH, SOC, N, P, K	Several properties from one scan	Top few millimetres only; needs lab calibration	Kok et al. (2024); Bünemann et al. (2018)
Wireless sensor networks	Moisture, temperature, EC at several depths	Continuous, distributed time series	Drift, calibration, upkeep cost	Vereecken et al. (2022); Stavi et al. (2021)
Electromagnetic induction	Apparent EC (texture, salinity, moisture)	Spatially continuous field mapping	Indirect; needs interpretation	Obade & Gaya (2021)
UAV ground-penetrating radar	Permittivity, EC, moisture, salinity	Bridges proximal and satellite scales	Localised coverage	Cheng et al. (2025)
Satellite microwave/optical	Surface soil moisture	Regional coverage, regular revisits	Shallow depth; vegetation and roughness effects	Ochsner et al. (2013); Babaeian et al. (2019)

5. Sensor Integration and Uncertainty

Bringing in situ, proximal and remote data together begins with placing them in one geospatial framework. A moisture or conductivity value means little until we know precisely where it sits relative to the terrain, land cover and soil maps that determine how representative it is (Lemenkova, 2026). Without that step, a sensor network can appear to match satellite or airborne products merely because their support volumes differ, not because they capture the same soil variability. Point probes, network arrays and footprint-scale proxies must therefore be reconciled deliberately before being fused (Grosse et al., 2026; McCabe et al., 2017).

After reconciliation, the fused product can be compared with independent in situ observations to check that its spatial and vertical soil moisture estimates agree across scales before they steer catchment decisions (Peng et al., 2017). Every fused product also carries forward the uncertainty of each input. To be trusted for management, it needs those errors tracked through the whole workflow instead of being presented as one authoritative figure (Huang et al., 2025; Wang et al., 2025).

For real-time monitoring in Indian watersheds, the practical implication is clear. Uncertainty from each data stream, whether the drift of cheap probes or the mismatch between a point and a satellite pixel, should travel with the data into the decision layer, so that managers can tell how far a fused soil health indicator deserves their confidence.

6. Artificial Intelligence Methods for Soil Monitoring

6.1 What AI adds

AI earns its place by finding nonlinear relationships between sensor readings, spectral signatures and soil attributes, relationships that conventional regression often cannot capture. That advantage is greatest when networks, proximal surveys and satellite products each bring their own biases and support volumes (Howari, 2025). Supervised learners such as random forests and gradient-boosted trees can be trained on paired in situ moisture and salinity observations, then used to map fused sensor and remote sensing features onto root-zone properties. The result is a calibrated, spatially explicit estimate that can be refreshed whenever new readings come in (Roach-Krajewski et al., 2026).

Deep learning goes a step further. Convolutional neural networks can extract spatial patterns from fused imagery and have beaten traditional methods at representing nonlinear soil–environment relationships (Kikis & Antoniadis, 2026). They do demand large amounts of data, though. With so few co-located soil measurements across Indian watersheds, transfer learning and automated model selection are frequently needed to make such methods workable at catchment scale (Parra-López et al., 2025).

6.2 Machine learning approaches

Supervised regression and classification are the workhorses of the soil monitoring literature. Random forest, support vector regression and gradient-boosted ensembles are widely used to predict soil organic carbon, aggregate stability and moisture from

combined sensor, weather and terrain inputs (Benos et al., 2021). Accuracy, however, is uneven. Studies that compare several algorithms keep finding that the best performer for one soil indicator is not the best for another (Wadoux, 2025).

For Indian watersheds the lesson is to select models separately for each target property and to test candidates against independent in situ data, rather than assuming a model will carry over between indicators (Sun et al., 2026). Where labelled data are thin, unsupervised techniques such as k-means and self-organising maps can sort observations into condition classes, although specialists need to interpret those classes before they can inform management.

6.3 Data fusion and uncertainty quantification

Fusion pipelines merge mixed spectral and environmental inputs inside a single learning framework. Deep architectures suit the job because convolution can combine several spectral sources without hand-built index predictors (Tziolas et al., 2024), and they can handle heterogeneous data with intricate spatiotemporal links between sensor readings and landscape covariates (Ding et al., 2025). Their outputs are best regarded as calibrated estimates, with spatial reliability confirmed against independent ground observations through the same cross-scale checks used on the sensor streams.

A fused model can be no more trustworthy than its training labels, so catchment soil health maps should carry explicit uncertainty estimates, something many popular algorithms do not offer by default (Barrena-González et al., 2023). Quantile regression forests, Bayesian model averaging and ensemble spread can all produce prediction intervals, which let managers judge how far a soil organic carbon or moisture estimate can be relied upon before acting on it.

7. Decision Support Systems

Remote sensing and big Earth data products are frequently too specialised for operational use as they stand. Decision support systems close that gap by converting reconciled, uncertainty-tagged soil indicators into charts and statistical maps that officials and watershed managers can act on (Wang et al., 2023). They serve as the link between sensor evidence and catchment planning, showing soil health trends, confidence bounds and threshold alerts alongside rainfall, land use and irrigation records.

That combination lets managers pose practical questions. Does falling soil moisture, or rising salinity, in a sub-watershed coincide with certain cropping patterns or rainfall shortfalls? Answers of that kind turn monitoring output into targeted decisions rather than stray diagnostic readings.

8. Applications in Indian Watersheds

8.1 Opportunities

In India the opening lies in combining inexpensive, distributed sensor nodes with machine learning models tuned to local soils, cropping systems and monsoon-driven moisture patterns. Such a combination could deliver real-time soil health indicators for sub-watersheds that today have no dense network of ground observations (Manono et al., 2026; Pasut et al., 2026). Early deployments would also show whether locally calibrated indicators, for example root-zone moisture and salinity trends, hold steady across the different soils and monsoon regimes inside one catchment before the network is expanded (Ma et al., 2025).

A phased rollout would give programmes evidence for choosing which sub-watersheds to prioritise: those where sensor-derived indicators depart most from conventional survey estimates. Limited monitoring resources would then go where real-time information is most likely to change decisions. Where agencies have already trialled networks, the time series they hold can sharpen sensor calibration too, because repeated comparison with field sampling reveals which indicators drift and which remain stable season after season.

8.2 Agricultural watersheds

Benchmark watersheds in India, Thailand and Vietnam (five on-farm and three on-station sites) differ sharply in agroecology and socio-economic conditions, so monitoring needs for cropped catchments cannot be standardised (Kijne et al., 2004). Protocols have to be tailored to each landscape, with sensor placement, sampling depth and revisit frequency chosen to match its dominant soils and production systems (Peng et al., 2020).

This is especially relevant in India, where smallholdings are fragmented and soil moisture and nutrient patterns can vary at finer scales than conventional sampling captures (Gaab et al., 2025). Networks must pick up within-field variation that a few composite samples would smooth over, notably where cropping intensity and inputs change within short distances. A pragmatic answer is a hybrid design in which a small set of permanent nodes is backed by periodic mobile or manual sampling, so that the time resolution of real-time data is matched by spatial coverage across the field mosaic.

Hybrid designs also leave room for high-frequency sensing, which has been shown to reduce the cost and labour of routine manual sampling, a real advantage for programmes on tight budgets (Juncal et al., 2023). Permanent reference stations can serve as calibration anchors for neighbouring fields and for nearby ungauged catchments (Dimitrova-Petrova et al., 2021). Regular comparison of sensor-derived moisture and salinity with independent field measurements exposes drift in low-cost sensors before the data are used to guide irrigation or fertiliser choices (Rode et al., 2016).

8.3 Management applications

Real-time soil information is most valuable when tied to the conservation and restoration structures that control how water is stored and infiltrates across a catchment. Central India's Bundelkhand region shows how: traditional rainwater harvesting structures, check dams and field bunds were renovated there as part of climate-resilience work (Garg et al., 2020). Local soil moisture readings could flag when infiltration capacity has fallen below what these structures were built to provide, prompting maintenance or relocation before runoff and erosion get worse. The same feedback would allow planners to test, over several monsoon

seasons, whether sensor-informed interventions measurably improve infiltration and moisture retention, rather than depending on post-project surveys alone.

9. Challenges and Barriers to Deployment

9.1 Cost, connectivity and reliability

Rolling out these systems across Indian watersheds runs into practical limits: sensors must be replaced at recurring cost, rural catchments often lack reliable data connectivity, and trained people are scarce for maintaining networks and making sense of the output (Abdelmoneim et al., 2025; Miller et al., 2025). Reliability is a further concern. Low-cost sensors can last anywhere from a few months to several years depending on build quality and exposure (Dorigo et al., 2021), and manufacturer calibration equations are usually less accurate than relationships developed in the field (Hendrickx et al., 2026).

The economics of hardware set the boundaries. Prices per unit must remain low enough to allow dense networks in remote areas, while lifetimes should be as long as possible (Torresan et al., 2021). Watershed monitoring programmes are often underfunded, leaving little money to install and maintain equipment and producing records with gaps in space and time (Bremer et al., 2020). Sensor readings then have to be interpreted against sparse reference data, which restricts how far real-time information can be validated and scaled up across a watershed (Gregory et al., 2024).

9.2 People and inclusion

Smallholder farmers and citizen scientists are central to many Indian watershed programmes, but they often lack training to run and interpret handheld or networked sensors. Designing around users and building local capacity are therefore essential if use is to last (Chan et al., 2020; Mao et al., 2020). That means nodes cheap enough for dense deployment yet rugged enough to be installed, waterproofed and calibrated by non-specialists without losing scientific credibility (Brown et al., 2024).

Low-cost sensing is better seen as a continuing process of adaptation than a one-time technology transfer, since readings from low-tech systems are only as good as the calibration and maintenance behind them (Daudin et al., 2025). If such routines are not written into budgets and institutional duties, data quality usually declines once the pilot ends. Governance arrangements that bring community-validated data into official frameworks therefore remain a priority for Indian watershed programmes (Goff et al., 2026).

9.3 Technical and institutional barriers

Three linked barriers determine whether sensor-based soil monitoring endures: data quality, infrastructure cost and institutional capacity. Sensors used straight from the vendor, without site-specific testing and calibration, can give readings too unreliable for operational decisions (Bayih et al., 2022). Data quality problems typically arise from uncalibrated drift, gaps in telemetry that leave records incomplete, and the absence of reference measurements against which readings can be checked (Hamel et al., 2024; Mane et al., 2025). Without such references, field visits are costly and technicians are few, so drift and telemetry faults often pass unnoticed until the data have already shaped decisions (Veness et al., 2022, 2025).

Infrastructure costs add to the strain. Hardware, gateways and cloud subscriptions, along with calibration, battery replacement and sensor renewal, must be funded across a network lifespan of three to five years, a burden that has so far proved economically viable mainly in better-resourced settings (Sellami et al., 2026). Institutional capacity worsens matters. Most watershed agencies in India lack dedicated data management units, standard maintenance procedures and budget lines for recurring calibration, so networks set up through pilot projects often lapse when external funding ends (Swan et al., 2024).

Barrier	How it shows up	Response suggested by the literature
Sensor drift and weak calibration	Unreliable readings; manufacturer equations less accurate than field calibration	Soil-specific calibration; regular checks against field samples (Hendrickx et al., 2026; Rode et al., 2016)
Telemetry gaps and sparse reference data	Incomplete records; faults found late	Reference stations; routine validation (Hamel et al., 2024; Veness et al., 2022)
Recurring cost	Replacement, batteries, subscriptions over 3–5 years	Low-cost nodes; budgeted maintenance (Sellami et al., 2026; Torresan et al., 2021)
Limited technical capacity	Farmers and staff unable to operate or interpret sensors	User-centred design; local training (Chan et al., 2020; Mao et al., 2020)
Institutional gaps	Pilots lapse when funding ends	Named owner, standard procedures, funded upkeep (Swan et al., 2024; Goff et al., 2026)

10. Research Priorities and Future Directions

Watershed agencies, research institutions and local communities should set priorities for validation, interoperability and long-term monitoring together. Calibration protocols, shared data standards and recurring funding need to be agreed before networks are scaled up, not after pilot money has run out.

Until then, each new network risks repeating the same story of installation, drift and abandonment, and the soil information it was meant to deliver will be missing when planners need it. Breaking that pattern means designing every network from day one with a funded maintenance schedule, a named institutional owner and a shared data standard. Only then will soil moisture and infiltration records stay continuous enough to support multi-season evaluation of watershed interventions.

The evidence points to three further needs: region-specific training datasets, so that deep learning and transfer learning can be applied dependably under Indian conditions; routine reporting of prediction

uncertainty with every fused indicator; and field trials comparing sensor-informed management with conventional practice over several monsoon seasons.

11. Conclusion

Real-time soil health monitoring is shifting from research ambition to practical option for Indian watersheds, though the studies reviewed here show that results depend more on how a system is designed than on any one technology. Soil health matters at catchment scale because it controls infiltration, nutrient retention and sediment delivery, and these functions change with landscape position. Laboratory sampling cannot follow that variation; continuous sensing can.

The literature consistently favours layers. In situ probes give dependable ground truth, proximal spectroscopy and electromagnetic induction contribute spatial continuity, and satellite and airborne products set local readings in a regional frame. AI ties these layers together, with random forests, gradient boosting and deep learning able to capture nonlinear relationships that standard regression overlooks. Yet models are only as credible as their training labels, and no algorithm is best for every soil property. Target-specific benchmarking, careful co-registration and transparent uncertainty estimates are therefore essential before fused indicators guide decisions.

In India, the main constraints are practical, not conceptual. Fragmented landholdings, monsoon variability, sensor drift, patchy connectivity, recurring costs and thin institutional capacity all endanger networks once pilot funding ends. Hybrid designs that pair a small number of permanent nodes with periodic mobile sampling, backed by funded maintenance, a named institutional owner and shared data standards, offer the most realistic path. Decision support tools showing trends, confidence bounds and alerts can then turn data into action, for example timely maintenance of check dams and bunds.

Some limitations qualify these conclusions. We did not appraise risk of bias formally, much of the evidence comes from outside India, long-term field performance is seldom reported, and the studies are heterogeneous. Future work should prioritise region-specific calibration, open and interoperable data, and rigorous multi-season testing of whether sensor-informed interventions improve infiltration and soil moisture retention.

References

1. Abdelmoneim, A. A. A., Kimaita, H. N., Kalaany, C. M. A., Derardja, B., Dragonetti, G., & Khadra, R. (2025). IoT Sensing for Advanced Irrigation Management: A Systematic Review of Trends, Challenges, and Future Prospects. Sensors, 25(7), 2291. https://doi.org/10.3390/s25072291
2. Ahmad, S., Kaushik, R., Ghatuary, R., Kotiyal, A., Jarial, S., & Kumar, R. (2025). Utilizing IoT and AI for Soil Health Monitoring and Enhancement in Sustainable Agriculture (pp. 110–125). https://doi.org/10.1201/9781003527664-7
3. Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., & Tuller, M. (2019). Ground, Proximal, and Satellite Remote Sensing of Soil Moisture. Reviews of Geophysics, 57(2), 530–616. https://doi.org/10.1029/2018rg000618
4. Bagnall, D. K., Rieke, E. L., Morgan, C. L. S., Liptzin, D., Cappellazzi, S. B., & Honeycutt, C. W. (2023). A minimum suite of soil health indicators for North American agriculture. Soil Security, 10, 100084. https://doi.org/10.1016/j.soisec.2023.100084
5. Barrena-González, J., Gabourel-Landaverde, V. A., Mora, J., Contador, J. F. L., & Fernández, M. P. (2023). Exploring soil property spatial patterns in a small grazed catchment using machine learning. Earth Science Informatics, 16(4), 3811–3838. https://doi.org/10.1007/s12145-023-01125-1
6. Bayih, A. Z., Morales, J., Assabie, Y., & By, R. A. de. (2022). Utilization of Internet of Things and Wireless Sensor Networks for Sustainable Smallholder Agriculture. Sensors, 22(9), 3273. https://doi.org/10.3390/s22093273
7. Benos, L. Th., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine Learning in Agriculture: A Comprehensive Updated Review. Sensors, 21(11), 3758. https://doi.org/10.3390/s21113758
8. Bharti, B., Bharti, V., Negi, N., Mohan, J., Arya, R., & Kumar, A. (2025). Role of AI technologies in soil health monitoring system. International Journal of Advanced Biochemistry Research, 9(4), 1158–1162. https://doi.org/10.33545/26174693.2025.v9.i4n.4262
9. Bogena, H., Huisman, J. A., Güntner, A., Hübner, C., Kusche, J., Jonard, F., Vey, S., & Vereecken, H. (2015). Emerging methods for noninvasive sensing of soil moisture dynamics from field to catchment scale: a review. Wiley Interdisciplinary Reviews Water, 2(6), 635–647. https://doi.org/10.1002/wat2.1097
10. Bouanani, N. E., Laamrani, A., Hajji, H., Bourriz, M., Bourzeix, F., Abdelali, H. A., El-Battay, A., Amazirh, A., & Chehbouni, A. (2025). Estimating Soil Attributes for Yield Gap Reduction in Africa Using Hyperspectral Remote Sensing Data with Artificial Intelligence Methods: An Extensive Review and Synthesis. Remote Sensing, 17(9), 1597. https://doi.org/10.3390/rs17091597
11. Bremer, L. L., Hamel, P., Ponette-González, A. G., Pompeu, P. V., Saad, S. I., & Brauman, K. A. (2020). Who Are we Measuring and Modeling for? Supporting Multilevel Decision-Making in Watershed Management. Water Resources Research, 56(1). https://doi.org/10.1029/2019wr026011

12. Brown, L. E., Maavara, T., Zhang, J., Chen, X., Klaar, M. J., Moshe, F. O. R., Ben-Zur, E., Stein, S., Grayson, R. P., Carter, L., Levintal, E., Gal, G., Ziv, P., Tarkowski, F., Pathak, D., Khamis, K., Barquín, J., Philamore, H., Hernandez, M. S. G., & Arnon, S. (2024). Integrating sensor data and machine learning to advance the science and management of river carbon emissions. Critical Reviews in Environmental Science and Technology, 55(9), 600–623. https://doi.org/10.1080/10643389.2024.2429912
13. Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R., Deyn, G. B. D., Goede, R. G. M. de, Fleskens, L., Geissen, V., Kuyper, T. W., Mader, P. M., Pulleman, M., Sukkel, W., Groenigen, J. W. van, & Brussaard, L. (2018). Soil quality – A critical review. Soil Biology and Biochemistry, 120, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030
14. Chan, K., Schillereff, D., Baas, A. C. W., Chadwick, M. A., Main, B., Mulligan, M. P., O'Shea, F. T., Pearce, R. H., Smith, T. E. L., Soesbergen, A. van, Tebbs, E. J., & Thompson, J. (2020). Low-cost electronic sensors for environmental research: Pitfalls and opportunities. Progress in Physical Geography Earth and Environment, 45(3), 305–338. https://doi.org/10.1177/0309133320956567
15. Cheng, Q., Cheng, Y. S., Ma, Z., Binley, A. M., Liu, J., Zhang, Z., Huang, F., & Chen, X. (2025). Combined Measurement of Soil Permittivity and Electrical Conductivity Using UAV-Based Ground Penetrating Radar. Water Resources Research, 61(10). https://doi.org/10.1029/2024wr039519
16. Christensen, S., Nicolaisen, M. H., Winding, A., Hestbjerg, H., Walter, M., Jensen, R. E., Ling, M., Morgan, C., & Hansen, V. (2025). Towards a unified framework for integrating plant biologicals into soil health management. Plant and Soil, 518(1), 777–788. https://doi.org/10.1007/s11104-025-08035-9
17. Daudin, K., Bouzidi, Z., & Lejars, C. (2025). Adaptive practices of researchers involved in low-tech co-innovation processes: Feedbacks from a multi-site experience with ICTs for irrigation systems. Agricultural Water Management, 319, 109786. https://doi.org/10.1016/j.agwat.2025.109786
18. Dimitrova-Petrova, K., Rosolem, R., Soulsby, C., Wilkinson, M., Lilly, A., & Geris, J. (2021). Combining static and portable Cosmic ray neutron sensor data to assess catchment scale heterogeneity in soil water storage and their integrated role in catchment runoff response. Journal of Hydrology, 601, 126659. https://doi.org/10.1016/j.jhydrol.2021.126659
19. Ding, Z., Liu, K., Grunwald, S., Smith, P., Ciais, P., Wang, B., Wadoux, A. M. J.-C., Ferreira, C., Karunaratne, S. B., Shurpali, N., Yin, X., Roberts, D., Madgett, O., Duncan, S., Zhou, M., Liu, Z., & Harrison, M. T. (2025). Advancing Soil Organic Carbon Prediction: A Comprehensive Review of Technologies, AI, Process-Based and Hybrid Modelling Approaches. Advanced Science, 12(31). https://doi.org/10.1002/advs.202504152
20. Dorigo, W., Himmelbauer, I., Aberer, D., Schremmer, L., Petrakovic, I., Zappa, L., Preimesberger, W., Xaver, A., Annor, F., Ardö, J., Baldocchi, D., Bitelli, M., Blöschl, G., Bogena, H., Brocca, L., Calvet, J., Camarero, J. J., Capello, G., Choi, M., … Sabia, R. (2021). The International Soil Moisture Network: serving Earth system science for over a decade. Hydrology and Earth System Sciences, 25(11), 5749–5804. https://doi.org/10.5194/hess-25-5749-2021
21. Fan, Y., Wang, X., Funk, T., Rashid, I., Herman, B., Bompoti, N., Mahmud, M. S., Chrysochoou, M., Yang, M., Vadas, T. M., Lei, Y., & Li, B. (2022). A Critical Review for Real-Time Continuous Soil Monitoring: Advantages, Challenges, and Perspectives. Environmental Science & Technology, 56(19), 13546–13564. https://doi.org/10.1021/acs.est.2c03562
22. Fares, A., Temimi, M., Morgan, K. T., & Kelleners, T. J. (2013). In-Situ and Remote Soil Moisture Sensing Technologies for Vadose Zone Hydrology. Vadose Zone Journal, 12(2), 1–3. https://doi.org/10.2136/vzj2013.03.0058
23. Fausak, L. K., Bridson, N., Diaz-Osorio, F., Jassal, R. S., & Lavkulich, L. M. (2024). Soil health – a perspective. Frontiers in Soil Science, 4. https://doi.org/10.3389/fsoil.2024.1462428
24. Feeney, C. J., Robinson, D. A., Keith, A. M., Vigier, A., Bentley, L., Smith, R. P., Garbutt, A., Maskell, L. C., Norton, L., Wood, C. M., Cosby, B. J., & Emmett, B. A. (2023). Development of soil health benchmarks for managed and semi-natural landscapes. The Science of The Total Environment, 886, 163973. https://doi.org/10.1016/j.scitotenv.2023.163973
25. Fierer, N., Wood, S. A., & Mesquita, C. P. B. de. (2020). How microbes can, and cannot, be used to assess soil health. Soil Biology and Biochemistry, 153, 108111. https://doi.org/10.1016/j.soilbio.2020.108111
26. Fortuna, A., Lewandowski, A., & Osterholz, W. R. (2022). Enhancing the Soil Health–Watershed Health Nexus: Introduction. Journal of Environmental Quality, 52(3), 407–411. https://doi.org/10.1002/jeq2.20420

27. Gaab, J., Ruiz, L., Sekhar, M., Dharumarajan, S., Jethro, M. T., Okoto, M. E., & A, C. G. (2025). Detection of short-term changes in soil clay content at field scale with Sentinel-2 enables mapping of the reservoir sediment reuse in cropland. Geoderma, 464, 117630. https://doi.org/10.1016/j.geoderma.2025.117630
28. Garg, K. K., Singh, R., Anantha, K. H., Singh, A. K., Akuraju, V. R., Barron, J., Dev, I., Tewari, R. K., Wani, S. P., Dhyani, S. K., & Dixit, S. (2020). Building climate resilience in degraded agricultural landscapes through water management: A case study of Bundelkhand region, Central India. Journal of Hydrology, 591, 125592. https://doi.org/10.1016/j.jhydrol.2020.125592
29. Goff, L. L., Fuentes, N., Soto-Alvarez, M., Hervé-Fernández, P., & Ayala, R. A. (2026). A review of autonomous and low cost sensor systems for surface water quality monitoring with implications for local decision making. Discover Water, 6(1). https://doi.org/10.1007/s43832-026-00446-8
30. Gregory, A., Kelly, E., Landa, S., Muthike, D. M., Samo, J., Lopez, J., Burrows, G., McManus, C., Sobsey, M. D., Salzberg, A. A., & Cronk, R. (2024). Challenges and opportunities for enhancing groundwater data access and usability in low- and middle-income countries: insights and recommendations from WaSH researchers and practitioners. Journal of Water Sanitation and Hygiene for Development, 14(10), 929–937. https://doi.org/10.2166/washdev.2024.066
31. Grosse, P. M., Marret-Sicard, E., Scheiffele, L. M., Dimitrova-Petrova, K., Francke, T., Altdorff, D., Heistermann, M., Schiel, M., Neumann, C., Scheffler, D., Saberioon, M., Kunz, M., Marach, J., Reginatto, M., Zbořil, M., Balenzano, A., Rasche, D., Stumpp, C., Trost, B., & Oswald, S. E. (2026). The Potsdam Soil Moisture Observatory: high-coverage reference observations at kilometer scale. Earth System Science Data, 18(3), 1703–1727. https://doi.org/10.5194/essd-18-1703-2026
32. Hamel, P., Ding, N., Cherqui, F., Zhu, Q., Walcker, N., Bertrand-Krajewski, J.-L., Champrasert, P., Fletcher, T. D., McCarthy, D., Navrátil, O., & Shi, B. (2024). Low-cost monitoring systems for urban water management: Lessons from the field. Water Research X, 22, 100212. https://doi.org/10.1016/j.wroa.2024.100212
33. Hendrickx, M., Vanderborght, J., Janssens, P., Laloy, E., Bombeke, S., Matthyssen, E., Waverijn, A., & Diels, J. (2026). Field-Scale Soil Moisture Predictions in Real Time Using In Situ Sensor Measurements in an Inverse Modeling Framework: SWIM 2. Water Resources Research, 62(2). https://doi.org/10.1029/2025wr041324
34. Howari, F. M. (2025). AI–Remote Sensing for Soil Variability Mapping and Precision Agrochemical Management: A Comprehensive Review of Methods, Limitations, and Climate-Smart Applications. Agrochemicals, 5(1), 1. https://doi.org/10.3390/agrochemicals5010001
35. Hu, Y., Cross, A. T., Shen, Z., Bouma, J., & Rossel, R. A. V. (2026). On soil health and the pivotal role of sensing. SOIL, 12(1), 227–252. https://doi.org/10.5194/soil-12-227-2026
36. Huang, J., Sehgal, V., Alvarez, L. V., Brocca, L., Cai, S., Cheng, R., Cheng, X., Du, J., Masri, B. E., Endsley, K. A., Fang, Y., Hu, J., Jampani, M., Kibria, M. G., Koren, G., Li, L., Liu, L., Mao, J., Moreno, H. A., … Fisher, J. B. (2025). Remotely Sensed High-Resolution Soil Moisture and Evapotranspiration: Bridging the Gap Between Science and Society. Water Resources Research, 61(5). https://doi.org/10.1029/2024wr037929
37. Jana, S., Chatterjee, D., Pal, N., Pal, K., Roy, K., & Bashak, S. (2024). AI in Soil Health Monitoring: A Data-Driven Approach. International Journal for Research in Applied Science and Engineering Technology, 12(10), 1327–1335. https://doi.org/10.22214/ijraset.2024.64871
38. Joshi, N., Jinger, D., Joshi, S., Joshi, E., Sharma, J. K., Paramesha, V., Meena, V. S., Kumar, S., Verma, M., Singh, S., Yadav, D., Lakaria, B. L., Jat, R. A., N, N. K., Kumar, M., & Madhu, M. (2026). Soil health management strategies for climate-resilient agriculture. Discover Soil, 3(1). https://doi.org/10.1007/s44378-026-00194-0
39. Juncal, M. J. L., Masino, P., Bertone, E., & Stewart, R. A. (2023). Towards nutrient neutrality: A review of agricultural runoff mitigation strategies and the development of a decision-making framework. The Science of The Total Environment, 874, 162408. https://doi.org/10.1016/j.scitotenv.2023.162408
40. Kibblewhite, M., Ritz, K., & Swift, M. J. (2007). Soil health in agricultural systems. Philosophical Transactions of the Royal Society B Biological Sciences, 363(1492), 685–701. https://doi.org/10.1098/rstb.2007.2178
41. Kijne, J. W., Barker, R., & Molden, D. (2004). Water productivity in agriculture: limits and opportunities for improvement. RePEc: Research Papers in Economics, 42(2), 42–937. https://doi.org/10.5860/choice.42-0937
42. Kikis, C., & Antoniadis, V. (2026). Benefits and Challenges of Artificial Intelligence in

Soil Science—A Review. Land, 15(2), 331. https://doi.org/10.3390/land15020331
43. Kok, M., Sarjant, S., Verweij, S. E., Vaessen, S. F. C., & Ros, G. H. (2024). On-site soil analysis: A novel approach combining NIR spectroscopy, remote sensing and deep learning. Geoderma, 446, 116903. https://doi.org/10.1016/j.geoderma.2024.116903
44. Lehman, R. M., Cambardella, C. A., Stott, D. E., Acosta-Martínez, V., Manter, D. K., Buyer, J. S., Maul, J. E., Smith, J. L., Collins, H. P., Halvorson, J. J., Kremer, R. J., Lundgren, J. G., Ducey, T., Jin, V. L., & Karlen, D. L. (2015). Understanding and Enhancing Soil Biological Health: The Solution for Reversing Soil Degradation. Sustainability, 7(1), 988–1027. https://doi.org/10.3390/su7010988
45. Lemenkova, P. (2026). Distributed Deep Learning and Intelligent Soil–Water Analytics in Precision Agriculture: A Comprehensive Review. Land, 15(7), 1125. https://doi.org/10.3390/land15071125
46. Ma, L., Xu, Z., Fan, L., Jia, H., Hu, H., & Li, L. (2025). Multi-Source Data Integration and Model Coupling for Watershed Eco-Assessment Systems: Progress, Challenges, and Prospects. Processes, 13(9), 2998. https://doi.org/10.3390/pr13092998
47. Mane, S., Singh, G., Das, N. N., Kanungo, A., Nagpal, N., Cosh, M. H., & Dong, Y. (2025). Development of low-cost handheld soil moisture sensor for farmers and citizen scientists. Frontiers in Environmental Science, 13. https://doi.org/10.3389/fenvs.2025.1590662
48. Manono, B. O., Mwami, B., K, M. S., & Nzilu, F. M. (2026). Precision Farming with Smart Sensors: Current State, Challenges and Future Outlook. Sensors, 26(3), 882. https://doi.org/10.3390/s26030882
49. Mao, F., Khamis, K., Clark, J. R. A., Krause, S., Buytaert, W., Ochoa-Tocachi, B. F., & Hannah, D. M. (2020). Moving beyond the Technology: A Socio-technical Roadmap for Low-Cost Water Sensor Network Applications. Environmental Science & Technology, 54(15), 9145–9158. https://doi.org/10.1021/acs.est.9b07125
50. McCabe, M. F., Rodell, M., Alsdorf, D., Miralles, D. G., Uijlenhoet, R., Wagner, W., Lucieer, A., Houborg, R., Verhoest, N. E. C., Franz, T. E., Shi, J., Gao, H., & Wood, E. F. (2017). The future of Earth observation in hydrology. Hydrology and Earth System Sciences, 21(7), 3879–3914. https://doi.org/10.5194/hess-21-3879-2017
51. Miller, T. I., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. Sensors, 25(12), 3583. https://doi.org/10.3390/s25123583
52. Nunes, M. R., Veum, K. S., Parker, P. A., Holan, S. H., Karlen, D. L., Amsili, J. P., Es, H. M. van, Wills, S., Seybold, C. A., & Moorman, T. B. (2021). The soil health assessment protocol and evaluation applied to soil organic carbon. Soil Science Society of America Journal, 85(4), 1196–1213. https://doi.org/10.1002/saj2.20244
53. Obade, V. de P., & Gaya, C. (2021). Digital technology dilemma: on unlocking the soil quality index conundrum. Bioresources and Bioprocessing, 8(1), 6. https://doi.org/10.1186/s40643-020-00359-x
54. Ochsner, T. E., Cosh, M. H., Cuenca, R. H., Dorigo, W., Draper, C., Hagimoto, Y., Kerr, Y. H., Larson, K. M., Njoku, E. G., Small, E. E., & Zreda, M. (2013). State of the Art in Large-Scale Soil Moisture Monitoring. Soil Science Society of America Journal, 77(6), 1888–1919. https://doi.org/10.2136/sssaj2013.03.0093
55. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71
56. Parra-López, C., Abdallah, S. B., Garcia-Garcia, G., Hassoun, A., Trollman, H., Jagtap, S., Gupta, S. K., Aït-Kaddour, A., Makmuang, S., & Carmona-Torres, C. (2025). Digital technologies for water use and management in agriculture: Recent applications and future outlook. Agricultural Water Management, 309, 109347. https://doi.org/10.1016/j.agwat.2025.109347
57. Pasut, C., Li, M., Armour, B., Asanopoulos, C. H., Brown, G., Crawford, D., Farrell, M., Garrard, M., Hoyle, F. C., McCaskill, M. R., Migliorati, M. D. A., Moreton, R., O'Keeffe, T., Polain, K., Reeves, S., Schapel, A., Wilson, B., & Karunaratne, S. B. (2026). Integrating soil monitoring and machine learning to map historical tillage and stubble management across Australian cropping systems (2001–2023). Computers and Electronics in Agriculture, 243, 111408. https://doi.org/10.1016/j.compag.2026.111408
58. Peng, J., Albergel, C., Balenzano, A., Brocca, L., Cartus, O., Cosh, M. H., Crow, W. T., Dąbrowska-Zielińska, K., Dadson, S., Davidson, M., Rosnay, P. de, Dorigo, W., Gruber, A., Hagemann, S., Hirschi, M., Kerr, Y. H., Lovergine, F., Mahecha, M. D.,

Marzahn, P., … Loew, A. (2020). A roadmap for high-resolution satellite soil moisture applications – confronting product characteristics with user requirements. Remote Sensing of Environment, 252, 112162. https://doi.org/10.1016/j.rse.2020.112162

59. Peng, J., Loew, A., Merlin, O., & Verhoest, N. E. C. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture. Reviews of Geophysics, 55(2), 341–366. https://doi.org/10.1002/2016rg000543
60. Roach-Krajewski, M., Giroux-Bougard, X., Paré, D., Dallaire, C., Guindon, L., Jordan, F., Norris, C., Webster, K., & Laganière, J. (2026). Post-disturbance soil monitoring in forests using remote sensing: an evidence map. SOIL, 12(2), 885–914. https://doi.org/10.5194/soil-12-885-2026
61. Rode, M., Wade, A. J., Cohen, M. J., Hensley, R. T., Bowes, M. J., Kirchner, J. W., Arhonditsis, G. B., Jordan, P., Kronvang, B., Halliday, S., Skeffington, R. A., Rozemeijer, J. C., Aubert, A. H., Rinke, K., & Jomaa, S. (2016). Sensors in the Stream: The High-Frequency Wave of the Present. Environmental Science & Technology, 50(19), 10297–10307. https://doi.org/10.1021/acs.est.6b02155
62. Sellami, M. H., Saab, M. T. A., & Albrizio, R. (2026). Toward water-smart cereal production: a narrative review of agronomic, genetic, and digital innovations for water productivity and climate resilience. Frontiers in Plant Science, 17, 1826562. https://doi.org/10.3389/fpls.2026.1826562
63. Smith, P., Poch, R. M., Lobb, D. A., Bhattacharyya, R., Alloush, G. A., Eudoxie, G. D., Anjos, L. H. C. dos, Castellano, M. J., Ndzana, G. M., Chenu, C., Naidu, R., Vijayanathan, J., Muscolo, A., Studdert, G. A., Rodríguez, N., Calzolari, M. C., Amuri, N. A., & Hallett, P. D. (2024). Status of the World's Soils. Annual Review of Environment and Resources, 49(1), 73–104. https://doi.org/10.1146/annurev-environ-030323-075629
64. Stavi, I., Thevs, N., & Priori, S. (2021). Soil Salinity and Sodicity in Drylands: A Review of Causes, Effects, Monitoring, and Restoration Measures. Frontiers in Environmental Science, 9. https://doi.org/10.3389/fenvs.2021.712831
65. Stegen, J., Brodie, E., Wrighton, K., Bayer, P., Lesmes, D., Emani, S. R., & Moerman, J. W. (2019). Open Watershed Science by Design: Leveraging Distributed Research Networks to Understand Watershed Systems: Workshop Report. https://doi.org/10.2172/1616528
66. Sun, J., Wang, Q., Li, Q., Xu, G., Liang, B., Ma, C., Tian, S., & Gao, Q. (2026). Artificial Intelligence in Smart Agriculture Across the Production-to-Postharvest Continuum: Progress, Challenges, and Future Directions. Sustainability, 18(10), 4908. https://doi.org/10.3390/su18104908
67. Swan, A., Schiffer, A., Skipworth, P., & Huntingdon, J. (2024). Review of remote monitoring systems for the delivery of sustainable and resilient water infrastructure. Journal of Engineering Design and Technology, 24(2), 516–532. https://doi.org/10.1108/jedt-06-2023-0270
68. Torresan, C., Garzón, M. B., O'Grady, M. J., Robson, T. M., Picchi, G., Panzacchi, P., Tomelleri, E., Smith, M., Marshall, J. D., Wingate, L., Tognetti, R., Rustad, L. E., & Kneeshaw, D. (2021). A new generation of sensors and monitoring tools to support climate-smart forestry practices. Canadian Journal of Forest Research, 51(12), 1751–1765. https://doi.org/10.1139/cjfr-2020-0295
69. Tziolas, N. V., Tsakiridis, N., Heiden, U., & Wesemael, B. van. (2024). Soil organic carbon mapping utilizing convolutional neural networks and Earth observation data, a case study in Bavaria state Germany. Geoderma, 444, 116867. https://doi.org/10.1016/j.geoderma.2024.116867
70. Veness, W., Butler, A. P., Ochoa-Tocachi, B. F., Moulds, S., & Buytaert, W. (2022). Localizing Hydrological Drought Early Warning Using In Situ Groundwater Sensors. Water Resources Research, 58(8). https://doi.org/10.1029/2022wr032165
71. Veness, W., Dussaillant, A., Coxon, G., Stercke, S. D., Old, G. H., Fry, M., Evans, J. G., & Buytaert, W. (2025). User priorities for hydrological monitoring infrastructures supporting research and innovation. Hydrology and Earth System Sciences, 29(21), 6201–6219. https://doi.org/10.5194/hess-29-6201-2025
72. Vereecken, H., Amelung, W., Bauke, S. L., Bogena, H., Brüggemann, N., Montzka, C., Vanderborght, J., Bechtold, M., Blöschl, G., Carminati, A., Javaux, M., Konings, A. G., Kusche, J., Neuweiler, I., Or, D., Dunne, S. C., Verhoef, A., Young, M. H., & Zhang, Y. (2022). Soil hydrology in the Earth system. Nature Reviews Earth & Environment, 3(9), 573–587. https://doi.org/10.1038/s43017-022-00324-6
73. Vereecken, H., Schnepf, A., Hopmans, J. W., Javaux, M., Or, D., Roose, T., Vanderborght, J., Young, M. H., Amelung, W., Aitkenhead, M. J., Allison, S., Assouline, S., Baveye, P. C., Berli, M., Brüggemann, N., Finke, P., Flury, M., Gaiser, T., Govers, G., … Young, I. M. (2016). Modeling Soil Processes: Review, Key Challenges, and New Perspectives. Vadose Zone Journal, 15(5), 1–57. https://doi.org/10.2136/vzj2015.09.0131

74. Wadoux, A. M. J.-C. (2025). Artificial intelligence in soil science. European Journal of Soil Science, 76(2). https://doi.org/10.1111/ejss.70080
75. Wang, J., Zhen, J., Hu, W., Chen, S., Lizaga, I., Zeraatpisheh, M., & Yang, X. (2023). Remote sensing of soil degradation: Progress and perspective. International Soil and Water Conservation Research, 11(3), 429–454. https://doi.org/10.1016/j.iswcr.2023.03.002
76. Wang, L., Warix, S. R., Callahan, R. P., Sullivan, P., & Singha, K. (2025). Data-Model Integration to Unravel Critical Zone Dynamics: Challenges, Successes, and Future Directions. Wiley Interdisciplinary Reviews Water, 12(6). https://doi.org/10.1002/wat2.70040
77. Zeng, Y., Verhoef, A., Vereecken, H., Ben-Dor, E., Veldkamp, A., Shaw, L. J., Ploeg, M. J. van der, Wang, Y., & Su, Z. (2025). Monitoring and Modeling the Soil–Plant System Toward Understanding Soil Health. Reviews of Geophysics, 63(1). https://doi.org/10.1029/2024rg000836