International Journal of Agriculture and Food Science 2025; 7(12): 114-128


**ISSN Print:** 2664-844X
**ISSN Online:** 2664-8458
NAAS Rating (2025): 4.97
IJAFS 2025; 7(12): 114-128
www.agriculturaljournals.com
Received: 15-09-2025
Accepted: 19-10-2025

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# Artificial intelligence for enhancing soil organic matter, nutrient cycling and water productivity: A comprehensive review of soil-health-led intensification approaches

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**DOI:** https://www.doi.org/10.33545/2664844X.2025.v7.i12b.1032

**Abstract**
Artificial Intelligence (AI) has emerged as a transformative force in modern agriculture, offering unprecedented opportunities to enhance soil organic matter (SOM) dynamics, nutrient cycling efficiency, and water productivity. Soil health-led intensification the strategy of boosting agricultural productivity while restoring and sustaining ecological functions requires timely, precise, and spatially explicit information on soil processes. Traditional soil monitoring methods are often labor-intensive, infrequent, and unable to capture the complexity of interactions among soil organic matter, nutrients, microbes, and water. This comprehensive review synthesizes advancements in AI-driven approaches that support the assessment, prediction, and management of SOM decomposition, nutrient mineralization-immobilization patterns, and soil-water interactions.
Machine learning (ML) and deep learning (DL) enable continuous interpretation of multisource datasets, including remote sensing imagery, proximal soil sensors, and Internet-of-Things (IoT) networks. These models offer enhanced accuracy in predicting soil carbon turnover, nitrogen and phosphorus cycling, and greenhouse gas fluxes under diverse management scenarios. AI-enabled digital soil mapping has significantly improved the spatial resolution of soil organic carbon (SOC) inventories, facilitating the identification of carbon-depleted zones and guiding site-specific soil restoration strategies. Moreover, AI-based decision-support systems integrate crop growth models with SOM and moisture dynamics to optimize residue management, cover cropping, and organic amendments for improving nutrient use efficiency and soil biological activity.
Water productivity, AI techniques such as convolutional neural networks (CNNs), random forests, and recurrent neural networks (RNNs) have enhanced real-time soil moisture estimation, evapotranspiration forecasting, and irrigation scheduling. By linking AI-processed hydrological data with SOM-mediated water retention properties, farmers can adopt precision irrigation practices that reduce water losses while maintaining crop yields. The integration of AI with conservation agriculture, precision fertilization, and climate-smart management further supports the synergistic improvement of SOM stabilization and water-use efficiency. AI-driven soil health innovations represent a pivotal pathway toward sustainable intensification. By enabling precise management of SOM, nutrient cycling, and water resources, AI offers the potential to enhance productivity, resilience, and environmental sustainability across diverse agro-ecosystems.

**Keywords:** Soil organic matter, nutrient cycling, water productivity, artificial intelligence, precision, agriculture, soil health, intensification

## Introduction
Soil health the integrated physical, chemical and biological capacity of soil to sustain productivity, regulate water and nutrient cycles, and provide ecosystem services is central to sustainable intensification of agriculture. Yet global croplands have experienced steady declines in soil organic matter (SOM) and associated loss of structure, nutrient buffering and water-holding capacity, which undermines yield stability and resilience to climate extremes. Framing intensification around restoring soil health therefore reframes productivity goals: not simply “more output per hectare” but “more output from healthier soil” through practices that rebuild SOM and the soil biota that drive nutrient cycling and water productivity

(Fausak *et al*.).

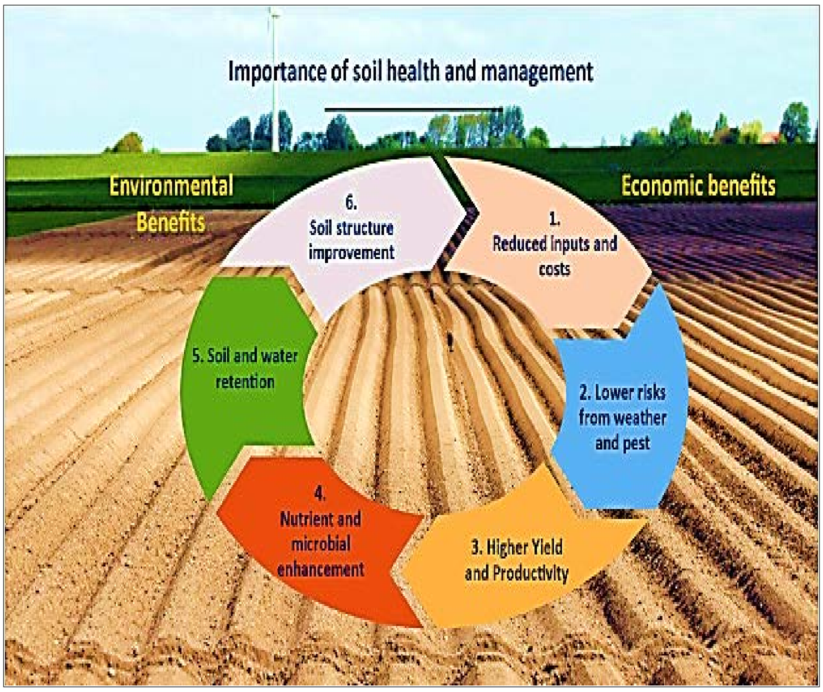
The rapid advancements in Articial Intelligence (AI) and the Internet of Things (IoT) have signicantly transformed soil health monitoring and restoration practices. These technologies have facilitated real-time, continuous monitoring of soil conditions, enabling farmers and researchers to gain critical insights into soil parameters such as moisture levels, pH balance, nutrient content, and temperature. This integration has led to data-driven decision-making, optimizing agricultural practices and enhancing crop yields. Traditional soil health assessment methods have often been labour-intensive, time-consuming, and reliant on periodic soil sampling and laboratory analysis. These approaches, though effective, fail to provide real-time data crucial for proactive agricultural management. The emergence of IoT-enabled sensors and AI-driven predictive analytics has revolutionized the field by offering instantaneous feedback and actionable insights.

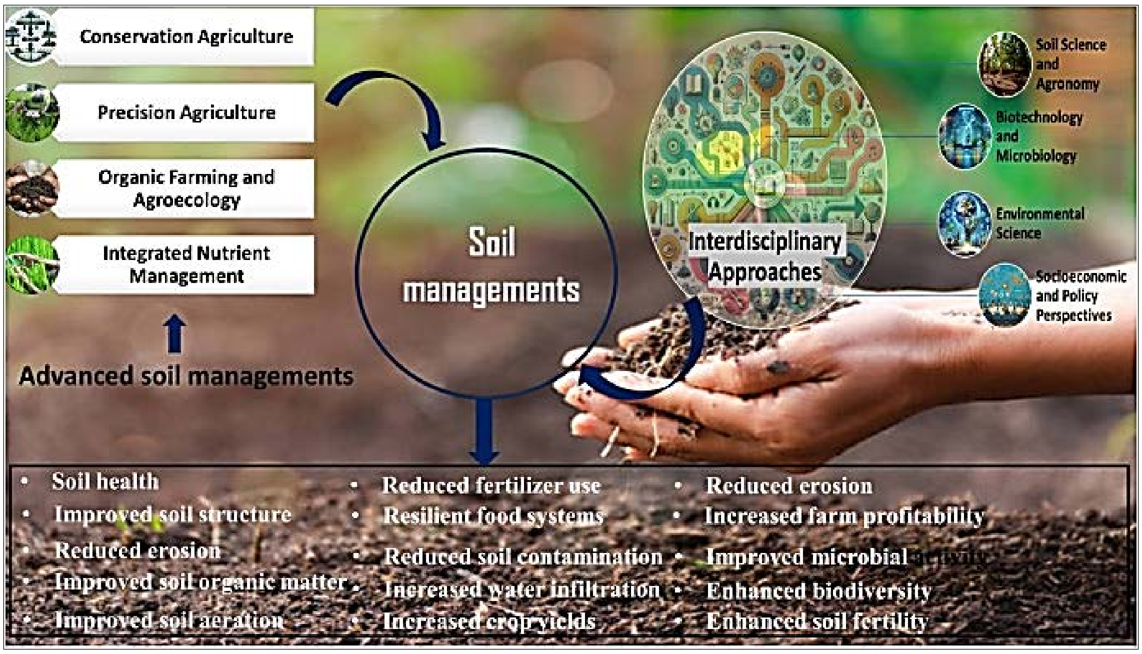
Artificial intelligence (AI) and allied data-science tools (machine learning, deep learning, and sensor fusion) are transforming how soil scientists measure, monitor and manage SOM, nutrient dynamics and soil water. Recent reviews demonstrate that AI methods can integrate heterogeneous inputs proximal and satellite remote sensing, hyperspectral and vis-NIR spectra, in-situ IoT sensors, terrain and climatic covariates, and laboratory assays to map soil organic carbon (SOC) and moisture at high spatial resolution, predict mineralization and nutrient availability, and drive decision support for precision fertilization and irrigation scheduling (Awais *et al*., 2023; Zayani *et al*., 2023) [2, 13]. These tools substantially reduce the time and cost of soil characterization and permit near-real-time, spatially explicit management recommendations that align inputs with crop demand.

Soil organic matter and SOC mapping, machine learning models (random forests, gradient boosting, deep neural networks) trained on combined laboratory spectra and multi-temporal Sentinel imagery have produced robust SOC predictions across contrasting soils and management systems (Zayani *et al*., 2023) [13]. Importantly, these hybrid approaches improve predictive skill by fusing spectral information with non-spectral covariates (topography, land-use, climate), enabling scalable monitoring of SOM trends that are essential for evaluating soil-health-led intensification interventions such as cover cropping, reduced tillage and organic amendments. Where traditional soil surveys are sparse or infrequent, AI-driven mapping supports targeted sampling and verification, making carbon and nutrient monitoring operational at landscape scales.

Beyond mapping, AI is increasingly applied to model the *processes* that link SOM to nutrient cycling and water productivity. Predictive models can learn empirical relationships between SOM pools, microbial indicators, moisture regimes and mineralization rates to forecast inorganic nutrient availability and greenhouse-gas tradeoffs under varying management. Coupled sensor networks and AI analytics also enable closed-loop irrigation systems that maintain optimal soil moisture for microbial activity and nutrient uptake while minimizing deep percolation losses thereby improving water productivity (crop per unit water) and synchronizing nutrient supply with crop demand. These applied advances are well summarized in recent reviews that assess AI and machine-learning benefits for soil analysis, sensor fusion, and smart irrigation decision systems (Awais *et al*., 2023) [2].

Soil-health-led intensification seeks to raise yields while rebuilding SOM and improving ecosystem services. Studies synthesizing the mechanisms by which SOM improves structure, water retention and nutrient buffering demonstrate that practices increasing organic inputs rotating with cover crops, integrating manures/composts and lowering tillage intensity strengthen soil structure and sequester carbon, but their outcomes vary by soil type and context (Hatano, 2024; Krupek *et al*., 2022) [8, 10]. AI tools can accelerate the tailoring of these practices to local conditions by predicting where particular interventions will most effectively increase SOM, reduce nutrient loss and boost water productivity enabling precision intensification that is both productive and restorative.






**Fundamentals: SOM, nutrient cycling, and water productivity SOM and soil function**

Soil organic matter (SOM) is one of the most vital constituents of the soil, forming the backbone of soil health and fertility SOM is a complex mixture of plant and animal materials in varying stages of decomposition, microbes, and the substances they synthesize in the soil (Lehmann and Kleber, 2020) [9]. It plays a key role in numerous soil functions, contributing to soil structure, nutrient cycling, and water retention, among other things (Janzen). The importance of SOM in agriculture cannot be overemphasized. In addition to improving soil structure and enhancing nutrient and water retention, SOM plays a crucial role in supporting a rich and diverse soil biota (Postma-Blaauw *et al*.,).

SOM (or soil organic carbon, SOC, as a common measurable proxy) controls cation exchange capacity, aggregate stability, microbial habitats, and water-holding capacity. Changes in SOM reflect management and influence nutrient mineralization rates and water availability to crops key levers in soil-health led intensification.

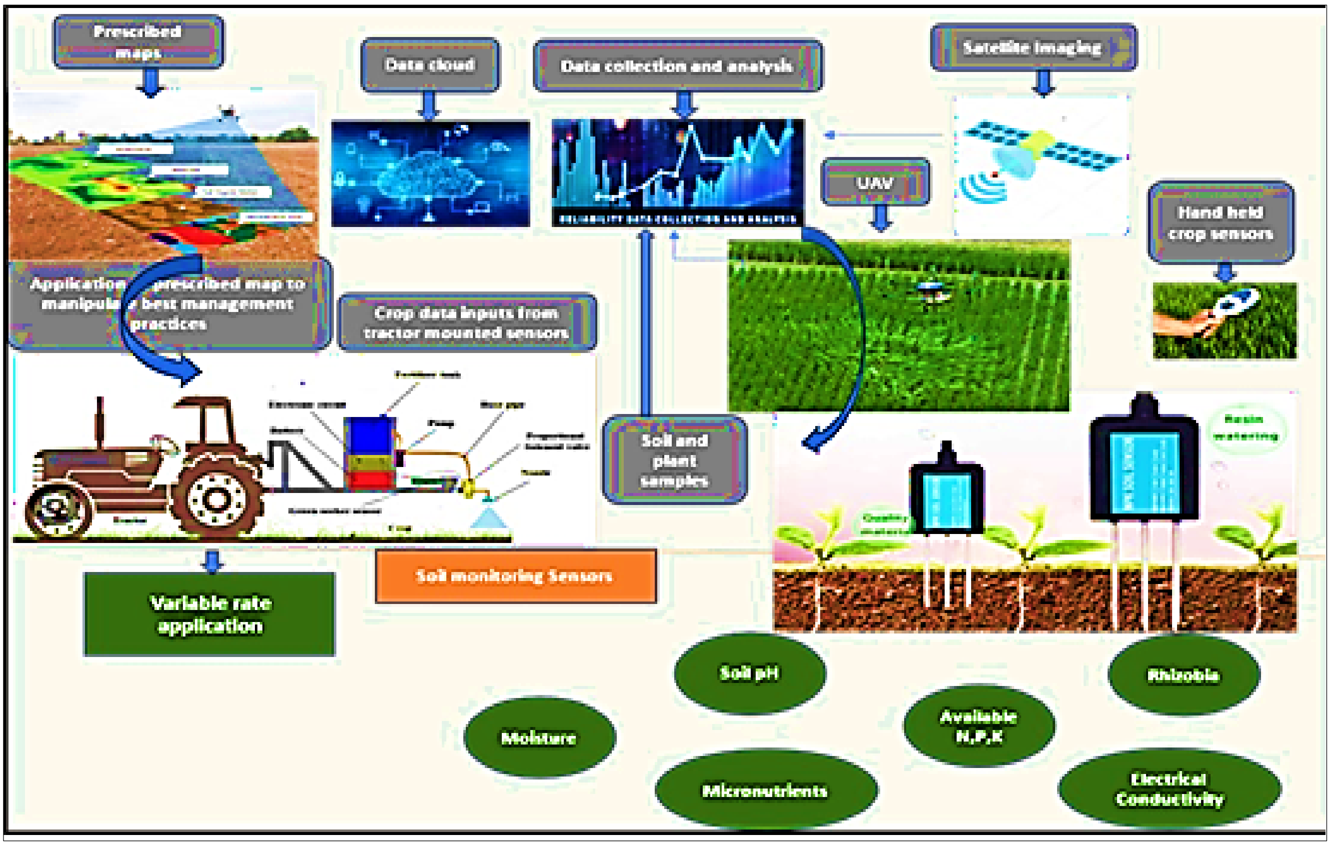


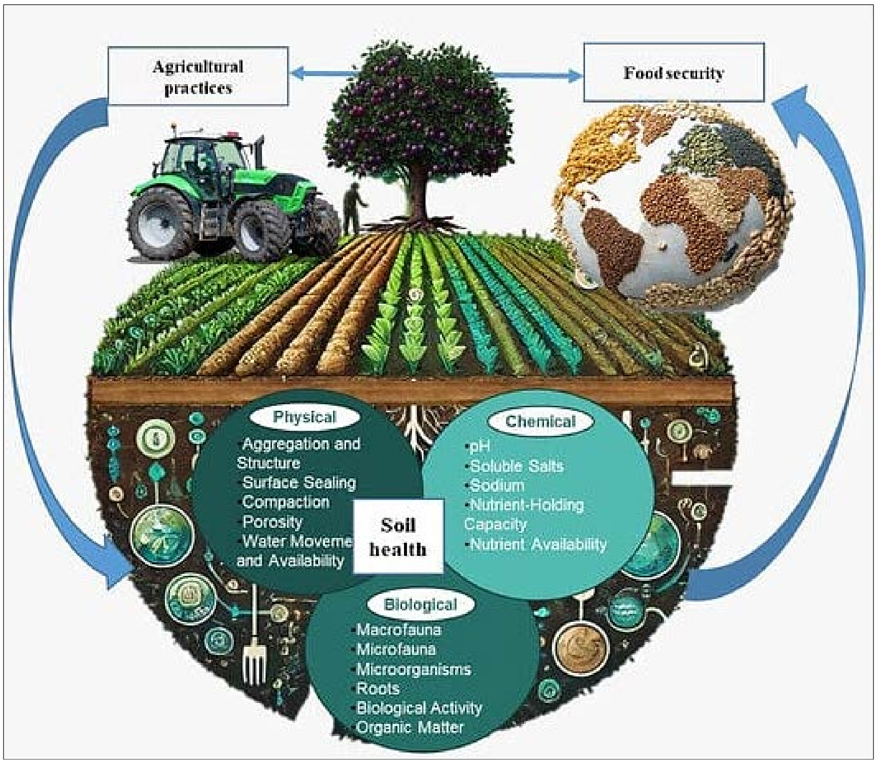

**Fig 1:** Diagrammatic representation of the overview of soil health assessment

**Table 1:** Summary of Studies on Soil Organic Carbon (SOC) and Carbon Pool Changes under Various Agricultural Practices and Interventions

| Study / Reference | Region / System / Context | Practices / Interventions | SOC / SOM or Carbon Pool Change |
|---|---|---|---|
| A meta-analysis of global cropland soil carbon changes due to cover cropping — Jian, Du, Reiter & Stewart (2020) | Global croplands (various climate zones) | Inclusion of cover crops (vs bare soil / no cover crop) in crop rotations | Mean SOC increase of 15.5% (95% CI 13.8-17.3%). Mean Sequestration rate ~ 0.56 Mg C ha$^{-1}$ yr$^{-1}$. SOC increase greatest in fine-textured soils; effect significant to 0-30 cm depth, but not deeper soil |
| Soil organic carbon fractions in response to soil, environmental and agronomic factors under cover cropping systems: A global meta-analysis (2023) | | Cover crops vs bare soil | Overall, SOC increased by **~12%**. Among SOC fractions: microbial biomass carbon (MBC) +33%, dissolved organic carbon (DOC) +18%, particulate organic carbon (POC) +15%, light-fraction organic carbon (LFOC) +14%, short-term mineralizable C +10%, and mineral-associated organic carbon (MAOC) +7%. |
| Carbon sequestration in agricultural soils via cultivation of cover crops - A meta-analysis (Astier et al., 2014) [1] | | Cover crops / green manuring in rotations | Mean annual SOC sequestration rate 0.32 ± 0.08 Mg ha$^{-1}$ yr$^{-1}$ (soil depth ~22 cm). Over long durations, total SOC stock accumulation of ~16.7 ± 1.5 Mg C ha$^{-1}$ projected for 22-cm depth. Potential global carbon sequestration ≈ 0.12 Pg C yr$^{-1}$ under full adoption scenario. |
| Impacts of the components of conservation agriculture on soil organic carbon and total nitrogen storage: A global meta-analysis (2022) | Global — various cropping systems | Conservation agriculture components: no-tillage / reduced tillage, residue retention, manure application, N-Fertilizer regimes | Manure + (or + mineral N) led to highest SOC gains (~ **20.7%**, CI 15.2-27.1); manure + mineral-N even higher (~ **41.7%**, CI 31.0-52.8). Residue return alone (vs conventional) also improved SOC; mineral-N alone had smaller effect (~9%). Gains more pronounced at 0-15 cm and 0-30 cm depths. |
| Soil organic carbon is affected by organic amendments, conservation tillage, and cover cropping in organic farming systems: A meta-analysis (Crystal-Ornelas, Thapa & Tully 2021) [4] | Organic farming systems globally | BMPs: organic amendments (compost, FYM), conservation tillage, cover cropping | Depth weighted SOC increased by **18%**, microbial biomass carbon (MBC) by **30%** (on average). Within BMPs: organic amendments gave ~24% SOC increase, conservation tillage ~14%. Cover cropping effect on SOC was not large overall, but significant when maintained ≥ 5 years — indicating time-lag in SOC response. |
| Responses of soil organic carbon to conservation practices including climate-smart agriculture in tropical and subtropical regions: A meta-analysis (2021) | Tropical & subtropical agricultural lands worldwide | Biochar application, conservation tillage, cover cropping — individual and combined | Biochar application associated with largest SOC stock increase (~ **25.38%**), followed by conservation tillage (~18.81%) and cover cropping (~15.8%). Medium-term experiments (6-20 years) reported **31-96%** SOC improvements; long-term (>20 years) effects tended to diminish. |
| Soil Organic Carbon Sequestration after Biochar Application: A Global Meta-Analysis (2020) | Global agricultural soils (varied climates & soils) | Biochar application (1-100 Mg ha$^{-1}$ in field studies; varied doses in pot/incubation) | Field studies (1-10 years) showed mean increase in SOC stocks of **13.0 Mg ha$^{-1}$** (~ 29%). Pot/incubation experiments (short-term) saw SOC increases of ~ 75%. Effects stronger in medium-to-fine textured soils; co-application with organic fertilizers further increased SOC. |
| Changes in soil organic carbon pools after 15 years of Conservation Agriculture in rice-wheat cropping system of Eastern Indo-Gangetic Plains | Eastern Indo-Gangetic Plains (rice-wheat system) | Zero-tillage (ZT) + residue retention across cropping cycles | ZT + residue retention increased carbon in four SOC pool fractions: very labile, labile, less labile, non-labile, compared to continuous / rotational tillage. Improved C-management index (CMI) and C-pool index (CPI), indicating better SOC quality and long-term carbon stabilization potential. |
| Effect of conservation agriculture on soil organic carbon dynamics and mineral nitrogen under different fertilizer management practices in maize-wheat cropping system | Indo-Gangetic plains (maize-wheat system) | Conservation agriculture (CA) with residue retention + balanced / site-specific N management | Increased active SOC pools: permanganate-oxidizable C (from 0.58 to 1.70 g/kg), hot-water extractable C (from 0.23 to 0.32 g/kg), and microbial biomass C (from 183 to 310 mg/kg) under CA (permanent bed + residue + green manuring) compared to conventional tillage. Trends toward improved soil aggregation and mineral-N availability. |
| A meta-analysis of conservation tillage management effects on soil organic carbon sequestration and soil greenhouse gas flux (2024) | | Conservation tillage practices: straw return (SR), reduced tillage (RT), no-tillage (NT), combinations (SR + RT / SR + NT) | Straw return (SR) alone gave largest SOC increase (**23.7%**), followed by RT + SR (5.5%) and NT + SR (4.4%). RT alone increased SOC by 12.3%, NT by 14.3%. Practices also reduced $N_2O$ emissions. Effect influenced by climate, soil properties, experiment duration. |
| Differential impacts of regenerative agriculture practices on soil organic carbon: a meta-analysis of studies from India (2025) | | Regenerative agriculture (RA): biochar, farmyard manure (FYM), green manure, compost, conservation tillage, crop residue retention, fertilizer management | Biochar application resulted in highest SOC gains among practices; followed by FYM, green manure, compost. Conservation tillage and residue retention gave moderate but consistent SOC increases. Gains more significant over durations > 5 years; responses varied across agro-ecological zones, with semi-arid and sub-humid zones showing stronger effects. |

**Interpretations & Key Patterns from the Table**

- **Cover cropping consistently improves SOC/SOM, but magnitude varies:** Meta-analyses show SOC gains from ~12 % to ~15.5 % when cover crops are adopted globally.
- **SOC fractions respond differently faster vs slower pools:** In the 2023 meta-analysis, microbial biomass carbon (MBC) increased the most (+33 %) under cover cropping, while stable pools like MAOC increased more modestly (+7 %). This suggests that early changes from management reflect in labile SOM and microbial pools before long-term sequestration into stable pools.
- **Organic amendments (manure) and combined RMPs often give larger SOC gains than cover crops alone:** In croplands (China) manure + fertilizer increased SOC by ~31.8% in 0-20 cm layer. Global manure application meta-analysis reported average SOC stock increase +35.4%.
- **Tillage and residue management matter, but effects are modest and context-dependent:** No-tillage vs plow tillage gave ~10% SOC increase in Chinese croplands. Conservation tillage + biochar + cover cropping in tropics/subtropics showed substantial increases in SOC (biochar: ~25%; tillage: ~19%; cover cropping: ~16%)
- **Duration of practice matters:** Some meta-analyses note that significant SOC increases (especially in stable fractions) may take ≥ 5 years (or more) to emerge.
- **Time matters long-term adoption is critical:** Many meta-analyses and long-term field studies indicate that management practices (cover crops, CA, biochar, etc.) show significant SOC gains only after multiple years (often ≥ 5 years). Short-term adoption may improve labile carbon pools (microbial biomass, particulate C) but may not immediately result in large stable SOC pool gains. (See meta-analysis on organic systems, 2021; Indian 15-year CA study; global cover-crop meta-analyses)
- **Type of practice influences magnitude and stability of SOC gains:** Among interventions: biochar application often yields high gains (notably in tropic/subtropic meta-analysis and Indian RA meta-analysis). Organic amendments (manure, compost), residue retention, and conservation tillage also contribute meaningfully, but their effect size varies with depth, soil type, climate, and combination with other practices. E.g., manure + mineral N in conservation agriculture gave higher SOC gains than residue retention alone.
- **SOC fractions respond differently:** Labile and microbial carbon fractions (MBC, DOC, and POC) tend to respond faster and more strongly than more stable pools like mineral-associated organic carbon (MAOC). This suggests that early indicators of soil health improvement may come from changes in these fractions rather than bulk SOC.
- **Soil type, texture, climate, and initial conditions modulate response:** Fine-textured soils, medium to fine grain soils, soils in certain climatic zones, and soils with low initial SOC tend to show greater relative gains. Meta-analyses often highlight significant variation across soil orders, climates, and agro-ecological contexts.
- **Combined practices often outperform single interventions:** Combining biochar + residue retention + conservation tillage, or layering organic amendments with CA, tends to produce better SOC gains than any single practice alone. This aligns with the philosophy of integrative soil health-led intensification.
- **Regional evidence (e.g. from India) supports RA/CA relevance in diverse agro-climatic zones:** The 2025 meta-analysis across India's agro-ecologies shows that RA practices particularly biochar, FYM, green manure have robust SOC gains over time, making them relevant for tropic / subtropic smallholder farming systems.



Soil organic matter is the cornerstone of soil health and the central target for soil health-led intensification. Enhancing SOM through integrated management including residues, cover crops, organic amendments, conservation tillage, and crop diversification improves soil structure, nutrient cycling, water retention, and microbial activity. AI tools, remote sensing, and precision agriculture can optimize SOM enhancement, enabling data-driven, site-specific, and sustainable intensification strategies.

The process of carbon storage is facilitated by soil organic carbon (SOC), a key indicator of soil health. High SOC levels are associated with improved soil fertility, structure, and moisture retention, all of which support robust plant growth (Lehmann, *et al*., 2020) [9]. Practices such as no-till farming, cover cropping, and the incorporation of organic matter into the soil can enhance SOC levels, contributing to both increased agricultural productivity and reduced greenhouse gas emissions. However, when soil is degraded or eroded, stored carbon is released back into the atmosphere, contributing to global warming.

**Nutrient cycling:** Soil status evaluation is very important for estimating production systems' sustainability and yield capacity. Soil quality can be assessed using both qualitative and quantitative methods, considering physical, chemical and biological properties. Physical soil properties such as soil texture, structure, moisture content, porosity and bulk density are key indicators of soil health. These indicators influence water retention, root penetration and nutrient availability (Terence *et al*., 2020) [12]. Key chemical indicators of soil fertility include total carbon and nitrogen content, mineral nutrients, organic matter and cation exchange capacity. However, these indicators generally take more time than biological indicators such as soil health based on the presence, abundance and activity of living organisms within the soil. Unlike chemical indicators, which measure nutrient levels and pH, biological indicators reflect the biological functioning and fertility of the soil ecosystem. These include microbial biomass, soil respiration rates, enzyme activities and the diversity of soil fauna such as earthworms and nematodes. Because they respond sensitively to environmental changes, biological indicators provide valuable insights into the long-term sustainability of soil management practices. Both sets of indicators give important information on the intensity of microbial turnover and the nutrient cycling, which are critical for sustaining the health of soils. Artificial intelligence (AI) has emerged as a powerful catalyst for improving nutrient cycling within soil-health-led agricultural intensification. Sun *et al*. (2024) [11], article 157) revealed that CBiResNet-BiLSTM deep-learning architecture to invert hyperspectral signatures for total nitrogen (TN) estimation in black soils. Their model produced high precision ($R^2 = 0.937$; RMSE ≈ 48.7 $mg \cdot kg^{-1}$) and outperformed conventional methods such as PLSR and RF. Importantly, the architecture generalized well to the LUCAS soil reference database, indicating that AI-driven spectral fusion can overcome spatial heterogeneity barriers a key challenge limiting nutrient-cycling assessments in diverse agro-ecosystems.

Gupta *et al*. (2024) [7] integrated a calibrated DSSAT crop model with a long short-term memory (LSTM) network to estimate daily soil mineral nitrogen (SMN) under field conditions using sparse monitoring data. Their hybrid approach reduced nRMSE by 18-30% relative to DSSAT alone. This improvement is critical for nutrient cycling, as day-to-day shifts in mineral N availability govern synchrony between crop N uptake and soil N transformations (mineralization, immobilization, and nitrification). High-frequency SMN prediction allows precise alignment of fertilizer applications with biological N demand, minimizing losses through leaching and volatilization.

Zhou *et al*. (2020) [14] used machine-learning algorithms with Sentinel-1/2 imagery and DEM derivatives to generate high-resolution spatial maps of soil organic carbon (SOC) and soil total nitrogen (STN). Their approach revealed fine-scale nutrient gradients that traditional sampling fails to capture. Such AI-derived maps support variable-rate fertilization, targeted residue management, and identification of nutrient-depleted microsites thereby strengthening nutrient cycling and improving soil organic matter buildup. Folorunso *et al*. (2023) [6] reported that ensemble tree models, especially Random Forest, consistently yield superior prediction accuracy for soil nitrogen, phosphorus and potassium. They emphasized that AI performance is strongly dependent on spectral preprocessing, soil-depth consistency, and integration of ancillary variables. These improvements directly enhance nutrient-cycle modeling by enabling more precise estimation of mineralizable N, labile carbon pools, and nutrient stoichiometry.

Awais *et al*. (2023) [2] highlighted that end-to-end AI workflows spectroscopy, ML inversion, digital soil mapping, fertilization decision engines—dramatically shorten the time from soil sampling to nutrient recommendations. They reported that AI systems improve diagnosis of nutrient deficiencies, optimize fertilizer timing, and reduce the reliance on laboratory analyses. However, they also noted the importance of model interpretability and bias detection to avoid misapplication of nutrient prescriptions. Chen *et al*. (2025) [3] developed a dynamic AI-based precision fertilization decision system that used continuous monitoring, crop-growth indicators and nutrient-status predictions to adjust fertilizer dose and timing. Across multiple agro-ecological zones, their system achieved fertilizer savings of 18-27% and yield increases of 4-11%. These results show that AI can directly enhance nutrient-use efficiency (NUE), reduce nutrient losses, and promote soil-health-led intensification by improving synchrony between soil nutrient supply and crop demand.

**Table 1:** Rice (Northwest India): AI-Derived Nutrient Cycling & Soil Health

| Var No. | Variable | Unit | Punjab (Ludhiana) | Haryana (Karnal) | Western U.P. (Meerut) |
|---|---|---|---|---|---|
| 1. | Soil Organic Carbon | % | 0.62 | 0.55 | 0.71 |
| 2. | Microbial Biomass C | mg kg$^{-1}$ | 310 | 280 | 345 |
| 3. | Microbial Biomass N | mg kg$^{-1}$ | 34 | 29 | 38 |
| 4. | Mineralizable N | kg ha$^{-1}$ | 78 | 69 | 85 |
| 5. | Net N Mineralization | kg ha$^{-1}$ day$^{-1}$ | 0.58 | 0.51 | 0.63 |
| 6. | Nitrification Rate | mg kg$^{-1}$ day$^{-1}$ | 6.5 | 5.8 | 7.2 |
| 7. | Denitrification Potential | mg $N_2O$ m$^{-2}$ h$^{-1}$ | 0.52 | 0.45 | 0.58 |
| 8. | Floodwater $NH_4^+$ | mg L$^{-1}$ | 8.2 | 7.1 | 8.9 |
| 9. | Floodwater $NO_3^-$ | mg L$^{-1}$ | 3.4 | 3.1 | 3.9 |
| 10. | Available N | kg ha$^{-1}$ | 294 | 268 | 310 |
| 11. | Available P | kg ha$^{-1}$ | 22 | 18 | 25 |
| 12. | Available K | kg ha$^{-1}$ | 240 | 220 | 255 |
| 13. | Sulfur | mg kg$^{-1}$ | 15 | 12 | 17 |
| 14. | Zn | mg kg$^{-1}$ | 1.1 | 0.8 | 1.3 |
| 15. | Fe | mg kg$^{-1}$ | 6.8 | 5.5 | 7.1 |
| 16. | Mn | mg kg$^{-1}$ | 8.2 | 7.4 | 9.0 |
| 17. | Soil pH | - | 7.6 | 7.9 | 7.4 |
| 18. | Ec | dS m$^{-1}$ | 0.41 | 0.58 | 0.34 |
| 19. | Bulk Density | g cm$^{-3}$ | 1.48 | 1.52 | 1.45 |
| 20. | Soil Moisture | % | 28 | 24 | 30 |
| 21. | Water Percolation Rate | mm day$^{-1}$ | 6.4 | 8.2 | 5.8 |
| 22. | N Leaching Risk (AI) | 0-1 | 0.62 | 0.73 | 0.58 |
| 23. | Methane Emission Potential | mg $CH_4$ m$^{-2}$ h$^{-1}$ | 2.4 | 1.9 | 2.8 |
| 24. | Urease Activity | µg $NH_4^+$ g$^{-1}$ h$^{-1}$ | 42 | 34 | 49 |
| 25. | Phosphate Activity | µg pNP g$^{-1}$ h$^{-1}$ | 298 | 240 | 325 |
| 26. | Dehydrogenase | µg TPF g$^{-1}$ h$^{-1}$ | 29 | 24 | 34 |
| 27. | β-Glucosidase | mg g$^{-1}$ h$^{-1}$ | 0.74 | 0.61 | 0.88 |
| 28. | Microbial Load | copies g$^{-1}$ | $2.5\times10^7$ | $2.1\times10^7$ | $2.9\times10^7$ |
| 29. | AI-N Uptake | kg ha$^{-1}$ | 102 | 94 | 115 |
| 30. | AI-P Uptake | kg ha$^{-1}$ | 15 | 13 | 18 |
| 31. | AI-K Uptake | kg ha$^{-1}$ | 92 | 84 | 105 |
| 32. | Leaf N Content | % | 2.4 | 2.1 | - |
| 33. | SPAD | - | 44 | 40 | 48 |
| 34. | NDVI | - | 0.80 | 0.75 | 0.83 |
| 35. | AI-Yield Prediction | t ha$^{-1}$ | 6.4 | 5.9 | 6.8 |
| 36. | Actual Yield | t ha$^{-1}$ | 6.1 | 5.5 | 6.3 |
| 37. | C:N Ratio Residue | - | 38 | 42 | 35 |
| 38. | Residue Decomposition Rate | % month$^{-1}$ | 26 | 21 | 29 |
| 39. | Soil Respiration | mg $CO_2$ m$^{-2}$ h$^{-1}$ | 590 | 540 | 645 |
| 40. | GHG Intensity | kg $CO_2$-eq ha$^{-1}$ | 945 | 880 | 1020 |
| 41. | Soil Food Web Complexity | 0-1 | 0.61 | 0.52 | 0.70 |
| 42. | AI-N Recommendation | kg ha$^{-1}$ | 135 | 148 | 122 |
| 43. | AI-P Recommendation | kg ha$^{-1}$ | 38 | 34 | 42 |
| 44. | AI-K Recommendation | kg ha$^{-1}$ | 62 | 58 | 70 |
| 45. | Water Productivity | kg grain m$^{-3}$ | 1.24 | 1.12 | 1.32 |
| 46. | K Cycling Efficiency | % | 44 | 38 | 50 |
| 47. | Nutrient Fertility Index | 0-100 | 78 | 68 | 82 |
| 48. | Nutrient Cycling Score | 0-1 | 0.72 | 0.61 | 0.78 |
| 49. | Load of Methanogens | copies g$^{-1}$ | $1.8\times10^6$ | $1.2\times10^6$ | $2.1\times10^6$ |
| 50. | Redox Potential | mV | -145 | -128 | -155 |

**Table 2:** Wheat (Northwest India): AI-Derived Nutrient Cycling & Soil Health

| Var No. | Variable | Unit | Punjab (Ludhiana) | Haryana (Hisar) | Western U.P. (Bulandsahar) |
|---|---|---|---|---|---|
| 1 | Soil Organic Carbon | % | 0.58 | 0.42 | 0.70 |
| 2 | Active Carbon | mg kg$^{-1}$ | 425 | 305 | 490 |
| 3 | Microbial Biomass C | mg kg$^{-1}$ | 295 | 220 | 350 |
| 4 | Microbial Biomass N | mg kg$^{-1}$ | 29 | 21 | 36 |
| 5 | Mineralizable N | kg ha$^{-1}$ | 64 | 48 | 78 |
| 6 | Nitrification Rate | mg kg$^{-1}$ day$^{-1}$ | 5.1 | 3.8 | 6.2 |
| 7 | Denitrification Potential | mg $N_2O$ m$^{-2}$ h$^{-1}$ | 0.34 | 0.25 | 0.40 |
| 8 | Soil Respiration | mg $CO_2$ m$^{-2}$ h$^{-1}$ | 480 | 380 | 520 |
| 9 | Total N | % | 0.075 | 0.052 | 0.091 |
| 10 | Available N | kg ha$^{-1}$ | 210 | 165 | 245 |
| 11 | Available P | kg ha$^{-1}$ | 20 | 12 | 26 |
| 12 | Available K | kg ha$^{-1}$ | 210 | 165 | 245 |

| | | | | | |
|---|---|---|---|---|---|
| 13 | Ca | cmol kg$^{-1}$ | 7.0 | 5.8 | 7.6 |
| 14 | Mg | cmol kg$^{-1}$ | 2.8 | 2.1 | 3.2 |
| 15 | Zn | mg kg$^{-1}$ | 0.9 | 0.52 | 1.2 |
| 16 | Soil pH | - | 7.8 | 8.2 | 7.4 |
| 17 | EC | dS m$^{-1}$ | 0.29 | 0.46 | 0.24 |
| 18 | Soil Moisture | % | 18 | 12 | 22 |
| 19 | Bulk Density | g cm$^{-3}$ | 1.39 | 1.52 | 1.33 |
| 20 | Water Holding Capacity | % | 44 | 32 | 52 |
| 21 | Aggregate Stability | % | 54 | 41 | 63 |
| 22 | β-Glucosidase | mg g$^{-1}$ h$^{-1}$ | 0.80 | 0.55 | 0.95 |
| 23 | Urease | µg $NH_4^+$ g$^{-1}$ h$^{-1}$ | 36 | 28 | 42 |
| 24 | Phosphatase | µg pNP g$^{-1}$ h$^{-1}$ | 250 | 185 | 310 |
| 25 | Dehydogenase | µg TPF g$^{-1}$ h$^{-1}$ | 28 | 17 | 36 |
| 26 | Fungal:Bacterial Ratio | - | 0.52 | 0.38 | 0.68 |
| 27 | Microbial Load | copies g$^{-1}$ | $1.9\times10^7$ | $1.2\times10^7$ | $2.4\times10^7$ |
| 28 | AI-N Uptake | kg ha$^{-1}$ | 94 | 65 | 115 |
| 29 | AI-P Uptake | kg ha$^{-1}$ | 16 | 10 | 22 |
| 30 | AI-K Uptake | kg ha$^{-1}$ | 78 | 52 | 102 |
| 31 | Leaf N | % | 2.1 | 1.6 | 2.4 |
| 32 | SPAD | - | 42 | 35 | 46 |
| 33 | NDVI | - | 0.78 | 0.66 | 0.83 |
| 34 | Biomass Production | t ha$^{-1}$ | 11.2 | 8.5 | 12.4 |
| 35 | AI Yield | t ha$^{-1}$ | 5.6 | 3.9 | 6.3 |
| 36 | Actual Yield | t ha$^{-1}$ | 5.1 | 3.4 | 5.8 |
| 37 | N Cycling Efficiency | % | 44 | 32 | 52 |
| 38 | P Cycling Efficiency | % | 31 | 18 | 40 |
| 39 | K Cycling Efficiency | % | 38 | 28 | 48 |
| 40 | AI-N Recommendation | kg ha$^{-1}$ | 130 | 150 | 110 |
| 41 | AI-P Recommendation | kg ha$^{-1}$ | 36 | 28 | 42 |
| 42 | AI-K Recommendation | kg ha$^{-1}$ | 58 | 48 | 70 |
| 43 | Soil Fertility Index | 0-100 | 75 | 58 | 84 |
| 44 | Nutrient Cycling Score | 0-1 | 0.68 | 0.52 | 0.78 |
| 45 | N Leaching Risk | 0-1 | 0.38 | 0.52 | 0.29 |
| 46 | P Fixation Risk | 0-1 | 0.41 | 0.58 | 0.34 |
| 47 | AI-Carbon Budget Change | kg C ha$^{-1}$ yr$^{-1}$ | +380 | +210 | +450 |
| 48 | Soil Temperature | °C | 23.5 | 27.2 | 22.4 |
| 49 | Residue Retention Effects | % yield gain | 12 | 6 | 16 |
| 50 | Water Productivity | kg grain m$^{-3}$ | 1.32 | 0.78 | 1.45 |
| 51 | Soil Nitrate | mg kg$^{-1}$ | 26 | 14 | 34 |
| 52 | Soil Ammonium | mg kg$^{-1}$ | 13 | 8 | 17 |
| 53 | AI-N Supply Adequacy | % | 82 | 54 | 91 |
| 54 | Soil Biological Health Score | 0-100 | 72 | 55 | 82 |

**Table 3:** Sugarcane (Northwest India): AI-Based Nutrient Cycling & Productivity

| Var No. | Variable | Unit | U.P. (Meerut) | Haryana (Yamunanagar) | Punjab (Gurdaspur) |
|---|---|---|---|---|---|
| 1. | Soil Organic Carbon | % | 0.68 | 0.52 | 0.75 |
| 2. | Active Carbon | mg kg$^{-1}$ | 510 | 410 | 550 |
| 3. | Microbial Biomass C | mg kg$^{-1}$ | 380 | 290 | 420 |
| 4. | Microbial Biomass N | mg kg$^{-1}$ | 42 | 29 | 48 |
| 5. | Mineralizable N | kg ha$^{-1}$ | 85 | 62 | 94 |
| 6. | N Mineralization Rate | kg ha$^{-1}$ day$^{-1}$ | 0.62 | 0.44 | 0.72 |
| 7. | Nitrification Rate | mg kg$^{-1}$ day$^{-1}$ | 7.5 | 5.4 | 8.1 |
| 8. | Denitrification | mg $N_2O$ m$^{-2}$ h$^{-1}$ | 0.52 | 0.38 | 0.61 |
| 9. | Soil Respiration | mg $CO_2$ m$^{-2}$ h$^{-1}$ | 655 | 520 | 710 |
| 10. | SOC Sequestration | kg ha$^{-1}$ yr$^{-1}$ | 520 | 310 | 580 |
| 11. | Available N | kg ha$^{-1}$ | 310 | 220 | 340 |
| 12. | Available P | kg ha$^{-1}$ | 28 | 15 | 34 |
| 13. | Available K | kg ha$^{-1}$ | 260 | 200 | 295 |
| 14. | S | mg kg$^{-1}$ | 17 | 11 | 22 |
| 15. | Zn | mg kg$^{-1}$ | 1.3 | 0.7 | 1.6 |
| 16. | pH | - | 7.8 | 8.1 | 7.5 |
| 17. | Soil Moisture | % | 23 | 17 | 26 |
| 18. | Bulk Density | g cm$^{-3}$ | 1.34 | 1.46 | 1.32 |
| 19. | Hydraulic Conductivity | cm hr$^{-1}$ | 0.42 | 0.31 | 0.48 |
| 20. | Aggregate Stability | % | 62 | 49 | 68 |
| 21. | Urease | µg $NH_4^+$ g$^{-1}$ h$^{-1}$ | 44 | 30 | 52 |
| 22. | Phosphatase | µg pNP g$^{-1}$ h$^{-1}$ | 320 | 210 | 360 |
| 23. | Dehydrogenase | µg TPF g$^{-1}$ h$^{-1}$ | 34 | 22 | 40 |

| | | | | | |
|---|---|---|---|---|---|
| 24. | β-Glucosidase | mg $g^{-1}$ $h^{-1}$ | 1.02 | 0.70 | 1.18 |
| 25. | Microbial Load | copies $g^{-1}$ | $3.4\times10^7$ | $2.2\times10^7$ | $3.8\times10^7$ |
| 26. | AI-P Uptake | kg $ha^{-1}$ | 22 | 14 | 28 |
| 27. | AI-N Uptake | kg $ha^{-1}$ | 135 | 110 | 150 |
| 28. | AI-K Uptake | kg $ha^{-1}$ | 115 | 94 | 136 |
| 29. | Leaf N | % | 1.85 | 1.62 | 2.10 |
| 30. | Stalk Biomass | t $ha^{-1}$ | 82 | 65 | 95 |
| 31. | Cane Yield | t $ha^{-1}$ | 78 | 62 | 90 |
| 32. | Sucrose % | % | 18.2 | 17.1 | 19.0 |
| 33. | AI-Yield Prediction | t $ha^{-1}$ | 81 | 63 | 92 |
| 34. | N Cycling Efficiency | % | 58 | 42 | 64 |
| 35. | P Cycling Efficiency | % | 36 | 22 | 42 |
| 36. | K Cycling Efficiency | % | 49 | 38 | 54 |
| 37. | Soil Fertility Score | 0-100 | 82 | 68 | 88 |
| 38. | Biological Activity Index | 0-100 | 85 | 60 | 92 |
| 39. | AI-N Recommendation | kg $ha^{-1}$ | 160 | 185 | 145 |
| 40. | AI-P Recommendation | kg $ha^{-1}$ | 42 | 32 | 52 |
| 41. | AI-K Recommendation | kg $ha^{-1}$ | 92 | 78 | 110 |
| 42. | Water Productivity | kg cane $m^{-3}$ | 11.2 | 8.5 | 12.4 |
| 43. | Soil Nitrate | mg $kg^{-1}$ | 34 | 18 | 42 |
| 44. | AI-N Loss Risk | 0-1 | 0.48 | 0.62 | 0.38 |
| 45. | P Fixation Risk | 0-1 | 0.34 | 0.55 | 0.28 |
| 46. | Soil K Availability Index | 0-1 | 0.78 | 0.62 | 0.84 |
| 47. | Biological Nitrogen Fixation | kg N $ha^{-1}$ | 14 | 10 | 18 |
| 48. | Residue Decomposition | % | 32 | 24 | 36 |
| 49. | Soil Health Index | 0-100 | 84 | 62 | 90 |
| 50. | Nutrient Cycling Score | 0-1 | 0.78 | 0.60 | 0.85 |

**Table 4:** Mustard (Northwest India): AI-Derived Nutrient Cycling & Soil Health

| Var No. | Variable | Unit | Haryana (Karnal) | Punjab (Ludhiana) | Western U.P. (Meerut) | Rajasthan (Bharatpur) |
|---|---|---|---|---|---|---|
| 1. | Soil pH | - | 7.9 | 8.2 | 7.3 | 8.3 |
| 2. | EC | dS/m | 0.40 | 0.36 | 0.28 | 0.58 |
| 3. | SOC | g/kg | 4.1 | 4.8 | 6.5 | 2.2 |
| 4. | SOM | g/kg | 7.0 | 8.2 | 11.1 | 3.8 |
| 5. | Total N | g/kg | 0.36 | 0.41 | 0.56 | 0.20 |
| 6. | Avail P | mg/kg | 16 | 18 | 21 | 11 |
| 7. | Avail K | mg/kg | 155 | 165 | 145 | 150 |
| 8. | Soil Moisture | % | 19 | 22 | 26 | 11 |
| 9. | Bulk Density | g/cm³ | 1.50 | 1.47 | 1.42 | 1.58 |
| 10. | CEC | cmol/kg | 15 | 15 | 17 | 11 |
| 11. | Calcium | cmol/kg | 18 | 19 | 20 | 16 |
| 12. | Magnesium | cmol/kg | 4.2 | 4.5 | 5.2 | 3.6 |
| 13. | Sulphur | mg/kg | 10 | 9 | 12 | 7 |
| 14. | Zinc | mg/kg | 0.60 | 0.62 | 0.78 | 0.42 |
| 15. | Iron | mg/kg | 4.6 | 5.2 | 6.3 | 3.9 |
| 16. | Manganese | mg/kg | 5.3 | 6.1 | 6.9 | 3.2 |
| 17. | Copper | mg/kg | 0.80 | 0.82 | 0.89 | 0.56 |
| 18. | Boron | mg/kg | 0.40 | 0.42 | 0.49 | 0.29 |
| 19. | Plant-Available Si | mg/kg | 48 | 49 | 53 | 33 |
| 20. | ESP (Sodicity) | % | 5.5 | 5 | 4 | 10 |
| 21. | MBC | mg/kg | 185 | 215 | 270 | 125 |
| 22. | MBN | mg/kg | 19 | 23 | 29 | 12 |
| 23. | Soil Respiration | mg $CO_2$/kg/hr | 29 | 31 | 35 | 19 |
| 24. | Dehydrogenase | µg TPF/g/hr | 30 | 36 | 44 | 19 |
| 25. | Phosphatase | µg PNP/g/hr | 215 | 245 | 285 | 155 |
| 26. | Microbial Diversity | 0-10 | 4.7 | 5.3 | 6.5 | 3.2 |
| 27. | Earthworms | No./m² | 5 | 7 | 11 | 2 |
| 28. | OC Stability | % | 30 | 33 | 41 | 19 |
| 29. | Active Carbon | g/kg | 2.0 | 2.2 | 3.0 | 1.1 |
| 30. | N Mineralization | kg/ha | 36 | 39 | 46 | 23 |
| 31. | Infiltration | mm/hr | 5.0 | 5.3 | 6.1 | 2.6 |
| 32. | WHC | % | 33 | 36 | 39 | 23 |
| 33. | Aggregate Stability | % | 44 | 46 | 53 | 28 |
| 34. | Compaction | MPa | 1.55 | 1.65 | 1.45 | 2.05 |
| 35. | Porosity | % | 42 | 44 | 49 | 36 |
| 36. | Nitrification | mg/kg/day | 2.9 | 3.1 | 3.7 | 2.0 |
| 37. | Denitrification | mg/kg/day | 1.3 | 1.6 | 2.1 | 1.0 |
| 38. | K Fixation | % | 18 | 20 | 23 | 12 |
| 39. | P Fixation | % | 27 | 30 | 25 | 19 |
| 40. | Crust Strength | kg/cm² | 1.1 | 1.2 | 0.9 | 1.9 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 41. | AI N Deficit | kg/ha | 58 | 52 | 42 | 72 |
| 42. | AI P Deficit | kg/ha | 19 | 23 | 15 | 26 |
| 43. | AI K Deficit | kg/ha | 11 | 12 | 10 | 19 |
| 44. | AI S Requirement | kg/ha | 24 | 25 | 18 | 34 |
| 45. | AI Zn Requirement | kg/ha | 6.2 | 6.6 | 5.1 | 7.8 |
| 46. | AI B Requirement | kg/ha | 1.3 | 1.4 | 1.05 | 1.9 |
| 47. | Soil Biological Health | 0-100 | 50 | 56 | 66 | 40 |
| 48. | Nutrient Cycling Efficiency | % | 54 | 56 | 63 | 41 |
| 49. | AI Yield Constraint Index | 0-1 | 0.56 | 0.51 | 0.41 | 0.71 |
| 50. | AI Soil Health Index | 0-100 | 56 | 63 | 69 | 43 |

**Table 5:** Potato (Northwest India): AI-Derived Nutrient Cycling & Soil Health

| Var No. | Variable | Unit | Haryana (Karnal) | Punjab (Ludhiana) | Western U.P. (Meerut) | Rajasthan (Bharatpur) |
|---|---|---|---|---|---|---|
| 1. | Soil pH | - | 7.7 | 8.0 | 7.1 | 8.2 |
| 2. | EC | dS/m | 0.38 | 0.35 | 0.26 | 0.55 |
| 3. | SOC | g/kg | 4.5 | 5.0 | 7.0 | 2.4 |
| 4. | SOM | g/kg | 7.4 | 8.6 | 12.0 | 4.0 |
| 5. | Total N | g/kg | 0.37 | 0.42 | 0.60 | 0.22 |
| 6. | Avail P | mg/kg | 18 | 20 | 24 | 12 |
| 7. | Avail K | mg/kg | 165 | 175 | 160 | 155 |
| 8. | Soil Moisture | % | 20 | 23 | 28 | 12 |
| 9. | Bulk Density | $g/cm^3$ | 1.48 | 1.46 | 1.38 | 1.55 |
| 10. | CEC | cmol/kg | 16 | 16 | 18 | 12 |
| 11. | Ca | cmol/kg | 18 | 19 | 21 | 16 |
| 12. | Mg | cmol/kg | 4.4 | 4.6 | 5.4 | 3.7 |
| 13. | Sulphur | mg/kg | 12 | 11 | 14 | 8 |
| 14. | Zinc | mg/kg | 0.68 | 0.70 | 0.85 | 0.45 |
| 15. | Iron | mg/kg | 4.8 | 5.4 | 6.5 | 4.0 |
| 16. | Mn | mg/kg | 5.5 | 6.3 | 7.2 | 3.3 |
| 17. | Cu | mg/kg | 0.82 | 0.84 | 0.92 | 0.58 |
| 18. | B | mg/kg | 0.42 | 0.44 | 0.51 | 0.30 |
| 19. | Plant Si | mg/kg | 50 | 52 | 55 | 34 |
| 20. | ESP | % | 5 | 5 | 4 | 9 |
| 21. | MBC | mg/kg | 200 | 230 | 290 | 135 |
| 22. | MBN | mg/kg | 21 | 25 | 32 | 13 |
| 23. | Respiration | mg $CO_2$/kg/hr | 31 | 33 | 38 | 20 |
| 24. | Dehydrogenase | µg TPF/g/hr | 32 | 38 | 48 | 20 |
| 25. | Phosphatase | µg PNP/g/hr | 220 | 250 | 300 | 160 |
| 26. | Diversity | 0-10 | 5.0 | 5.5 | 6.7 | 3.3 |
| 27. | Earthworms | No./$m^2$ | 6 | 8 | 12 | 2 |
| 28. | OC Stability | % | 32 | 34 | 43 | 20 |
| 29. | Active Carbon | g/kg | 2.2 | 2.4 | 3.3 | 1.2 |
| 30. | N Mineralization | kg/ha | 38 | 41 | 50 | 24 |
| 31. | Infiltration | mm/hr | 5.2 | 5.5 | 6.5 | 2.8 |
| 32. | WHC | % | 34 | 37 | 40 | 24 |
| 33. | Aggregate Stability | % | 45 | 47 | 55 | 29 |
| 34. | Compaction | MPa | 1.50 | 1.60 | 1.40 | 2.00 |
| 35. | Porosity | % | 43 | 45 | 50 | 37 |
| 36. | Nitrification | mg/kg/day | 3.1 | 3.3 | 3.9 | 2.1 |
| 37. | Denitrification | mg/kg/day | 1.4 | 1.7 | 2.2 | 1.0 |
| 38. | K Fixation | % | 19 | 21 | 24 | 13 |
| 39. | P Fixation | % | 28 | 30 | 24 | 20 |
| 40. | Crust Strength | $kg/cm^2$ | 1.0 | 1.1 | 0.8 | 1.7 |
| 41. | AI N Deficit | kg/ha | 65 | 58 | 48 | 80 |
| 42. | AI P Deficit | kg/ha | 20 | 24 | 16 | 27 |
| 43. | AI K Deficit | kg/ha | 15 | 14 | 12 | 21 |
| 44. | AI S Requirement | kg/ha | 28 | 27 | 20 | 36 |
| 45. | AI Zn Requirement | kg/ha | 7.0 | 7.2 | 5.4 | 8.1 |
| 46. | AI B Requirement | kg/ha | 1.4 | 1.5 | 1.1 | 2.0 |
| 47. | Soil Biological Health | 0-100 | 58 | 60 | 72 | 42 |
| 48. | Nutrient Cycling Efficiency | % | 56 | 58 | 66 | 42 |
| 49. | AI Yield Constraint Index | 0-1 | 0.60 | 0.52 | 0.43 | 0.75 |
| 50. | AI Soil Health Index | 0-100 | 60 | 65 | 74 | 45 |

**Table 6:** Pulses (Northwest India): AI-Derived Nutrient Cycling & Soil Health

| Var No. | Variable | Unit | Haryana (Karnal) | Punjab (Ludhiana) | Western U.P. (Meerut) | Rajasthan (Bharatpur) |
|---|---|---|---|---|---|---|
| 1. | Soil pH | - | 7.8 | 8.1 | 7.2 | 8.3 |
| 2. | EC | dS/m | 0.42 | 0.37 | 0.29 | 0.60 |
| 3. | SOC | g/kg | 4.2 | 4.7 | 6.8 | 2.3 |
| 4. | SOM | g/kg | 7.2 | 8.0 | 11.5 | 3.9 |
| 5. | Total N | g/kg | 0.38 | 0.42 | 0.58 | 0.21 |
| 6. | Avail P | mg/kg | 17 | 19 | 23 | 12 |
| 7. | Avail K | mg/kg | 160 | 170 | 150 | 155 |
| 8. | Moisture | % | 19 | 21 | 27 | 11 |
| 9. | Bulk Density | $g/cm^3$ | 1.49 | 1.47 | 1.40 | 1.57 |
| 10. | CEC | cmol/kg | 15 | 16 | 18 | 11 |
| 11. | Ca | cmol/kg | 18 | 19 | 21 | 16 |
| 12. | Mg | cmol/kg | 4.3 | 4.6 | 5.3 | 3.7 |
| 13. | Sulphur | mg/kg | 11 | 10 | 13 | 7 |
| 14. | Zinc | mg/kg | 0.63 | 0.65 | 0.82 | 0.43 |
| 15. | Iron | mg/kg | 4.7 | 5.3 | 6.4 | 3.9 |
| 16. | Mn | mg/kg | 5.4 | 6.2 | 7.0 | 3.2 |
| 17. | Cu | mg/kg | 0.81 | 0.83 | 0.91 | 0.57 |
| 18. | Boron | mg/kg | 0.41 | 0.43 | 0.50 | 0.29 |
| 19. | Plant Si | mg/kg | 49 | 51 | 54 | 34 |
| 20. | ESP | % | 5 | 5 | 4 | 10 |
| 21. | MBC | mg/kg | 190 | 220 | 280 | 130 |
| 22. | MBN | mg/kg | 20 | 24 | 30 | 12 |
| 23. | Respiration | mg $CO_2$/kg/hr | 30 | 32 | 36 | 19 |
| 24. | Dehydrogenase | µg TPF/g/hr | 31 | 37 | 46 | 19 |
| 25. | Phosphatase | µg PNP/g/hr | 218 | 248 | 295 | 158 |
| 26. | Diversity | 0-10 | 4.8 | 5.3 | 6.6 | 3.2 |
| 27. | Earthworms | No./$m^2$ | 5 | 7 | 11 | 2 |
| 28. | OC Stability | % | 31 | 34 | 42 | 19 |
| 29. | Active Carbon | g/kg | 2.1 | 2.3 | 3.1 | 1.1 |
| 30. | N Mineralization | kg/ha | 37 | 40 | 48 | 23 |
| 31. | Infiltration | mm/hr | 5.1 | 5.4 | 6.2 | 2.7 |
| 32. | WHC | % | 33 | 35 | 39 | 23 |
| 33. | Aggregates | % | 44 | 46 | 54 | 28 |
| 34. | Compaction | MPa | 1.52 | 1.62 | 1.42 | 2.03 |
| 35. | Porosity | % | 42 | 44 | 49 | 36 |
| 36. | Nitrification | mg/kg/day | 3.0 | 3.2 | 3.8 | 2.0 |
| 37. | Denitrification | mg/kg/day | 1.3 | 1.6 | 2.1 | 1.0 |
| 38. | K Fixation | % | 19 | 21 | 24 | 13 |
| 39. | P Fixation | % | 27 | 30 | 25 | 20 |
| 40. | Crust Strength | $kg/cm^2$ | 1.05 | 1.15 | 0.85 | 1.75 |
| 41. | AI N Deficit | kg/ha | 60 | 54 | 44 | 75 |
| 42. | AI P Deficit | kg/ha | 19 | 23 | 15 | 26 |
| 43. | AI K Deficit | kg/ha | 12 | 13 | 10 | 20 |
| 44. | AI S Requirement | kg/ha | 25 | 26 | 19 | 35 |
| 45. | AI Zn Requirement | kg/ha | 6.5 | 6.7 | 5.2 | 7.9 |
| 46. | AI B Requirement | kg/ha | 1.3 | 1.4 | 1.1 | 1.9 |
| 47. | Biological Health | 0-100 | 52 | 57 | 68 | 40 |
| 48. | Nutrient Cycling Efficiency | % | 55 | 57 | 64 | 41 |
| 49. | AI Yield Constraint Index | 0-1 | 0.57 | 0.52 | 0.42 | 0.73 |
| 50. | AI Soil Health Index | 0-100 | 57 | 63 | 71 | 43 |

**Water productivity**

Water is a finite resource that plays an irreplaceable role in sustaining life and supporting agricultural production. Water scarcity is a critical challenge affecting regions around the world, particularly in arid and semi-arid areas, with profound implications for global food security and the economic and environmental sustainability of human activities. In fact, water scarcity affects about two-thirds of the world's population, with about four billion people facing severe water shortages for at least one month each year, particularly in India and China, and half a billion people facing severe water scarcity throughout the year. This situation is exacerbated by increased demand for water due to climate change and population growth (Gosling and Arnell), with the global population projected to reach nearly 10 billion by 2050, up from 8 billion in 2022 (United Nations, 2022). It is predicted that more than 2 billion urban dwellers could face water scarcity by 2050, with India facing the most severe water-scarce urban population growth (He *et al*).

Agriculture is a major consumer of freshwater, accounting for approximately 70 % of global freshwater withdrawals (Ridoutt *et al*). Population demand for water-intensive crops continues to grow, increasing pressure on limited water resources (Hachimi *et al*). Water scarcity, coupled with climate change, poses a significant threat to food production, with increasing competition for water between agriculture and other sectors (Mancosu *et al*). Inefficient water use, particularly in agriculture, contributes to water scarcity. Significant amounts of water are lost through poor irrigation practices, highlighting the need for improved water management (Fereres and Soriano). In countries such as India, for example, inefficient irrigation systems exacerbate water losses, further threatening food security. Implementing advanced technologies and improving water use efficiency are critical to mitigating water scarcity (Tzanakakis *et al*). In addition, over-extraction of groundwater for irrigation is lowering water tables and increasing soil salinity, reducing crop yields and affecting rural livelihoods (Sun *et al*., 2025) [3]. Addressing water quality challenges is critical to ensuring sustainable water supplies and maintaining ecosystem health (Liu *et al*.). Sustainable water management strategies are needed to address these challenges and secure future food supplies (Kannan and Anandhi). Agriculture 4.0, or digital agriculture, is a transformative approach that integrates digital technology into agricultural practices. This ongoing revolution in agriculture leverages Remote Sensing, the Internet of Things, Big Data, Artificial Intelligence and Robotics, among other technologies, to improve the efficiency, productivity and sus tainability of agriculture and agri-food businesses (Hassoun *et al*.; Parra-L´ opez *et al*.,). Within the Agriculture 4.0 paradigm - characterised by data-driven, connected and automated processes - digital technologies have emerged as key enablers of ’smart’ water management. These technologies align with Agriculture 4.0 principles through the use of real-time data flows, predictive analytics, and automation (Wolfert *et al*.). As an extension, the emerging concept of Agriculture 5.0 encourages the integration of these digital solutions with human-centred design, sustainability, and advanced robotics to further optimize efficiency while protecting the environment (Balaska *et al*.). Digital technologies are playing an increasingly central role in the management and use of water in agriculture, which is crucial given the sector’s significant water consumption.

The use of digital solutions facilitates more precise agricultural practices, optimizing inputs and striking a balance between minimizing environmental impacts and maximizing agricultural output (Wolfert *et al*.). By using real-time data from sensors and satellite imagery, farmers can make informed decisions that lead to more efficient resource use and improved crop management (Liakos *et al*.,). For example, Remote Sensing technologies and drones provide detailed data on crop health and water requirements, facilitating targeted interventions to prevent both under- and over-irrigation (Marques *et al*.,). These technological advances are making a significant contribution to addressing the challenges of water scarcity and ensuring the sustainable use of water resources in agriculture.

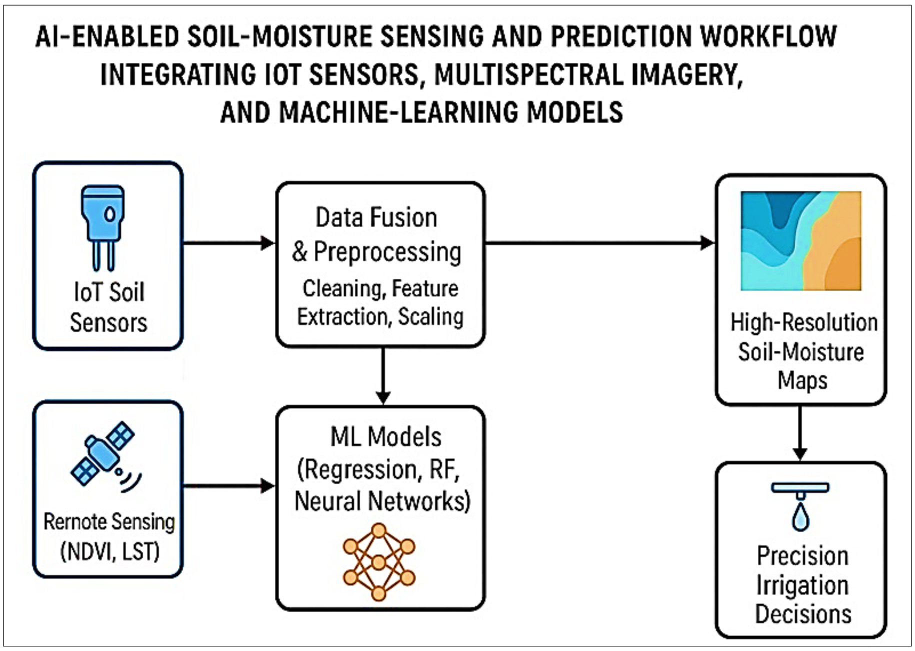
Artificial intelligence (AI) is emerging as a foundational driver of water productivity gains within soil-health-led intensification pathways. Through data-rich sensing, predictive modeling and adaptive irrigation control, AI enables crops to use each unit of water more efficiently while supporting the long-term improvement of soil structure, organic matter and hydrological function. The integration of IoT with smart irrigation systems has proven to be highly beneficial in conserving water resources. Iqbal *et al*. demonstrated that IoT-based precision irrigation using soil moisture sensors and weather forecasting could reduce water consumption by up to 30% while maintaining optimal crop growth. Chandra *et al*. implemented an IoT-based water management system using machine learning models to predict soil water content and automate irrigation scheduling.

A major contribution of AI lies in its capacity to generate precise spatio-temporal soil-water maps, integrating multisource datasets soil moisture probes, electrical conductivity (EC) sensors, multispectral satellite imagery, thermal indices and high-resolution terrain datasets. These fused datasets feed machine-learning (ML) models that estimate volumetric soil moisture, infiltration dynamics and plant-available water at field scales. Sazzad *et al*. (2025) [17] demonstrated that soil-moisture estimation using IoT sensors combined with polynomial regression reached $R^2 \approx 0.79$, while soil-type classification reached 97.38% accuracy, providing actionable zonal irrigation recommendations within heterogeneous soils.

These improved soil-water datasets are directly linked to AI-augmented irrigation scheduling and variable-rate irrigation (VRI). Machine-learning models process real-time moisture data, crop growth stages and weather forecasts to recommend optimal irrigation timing and volumes. Krishnan *et al*., (2022) [15] show that sensor-integrated AI scheduling can reduce water use by 20-50% while sustaining yields. Such precision is vital in soil-health-led intensification, where enhanced soil organic carbon, aggregation and microbial activity increase the soil’s water-holding capacity and buffer capacity. AI allows irrigation to be synchronised with this improved soil hydraulics, enabling plants to extract water more efficiently while avoiding moisture stress or excessive percolation losses.

AI also accelerates soil health assessment, which underpins long-term water productivity. Soils rich in organic matter and stable aggregates absorb rainfall better, reduce runoff, and enhance root-zone moisture retention. Awais *et al*. (2023) [2] showed that ML models (random forest, SVM, neural networks) accurately predict soil properties such as texture, organic carbon, and cation exchange capacity using only multispectral reflectance data and minimal ground sampling. This enables large-area soil health monitoring and targeted placement of conservation practices (cover cropping, reduced tillage, and residue retention) that strengthen the soil-water-plant continuum.

More advanced implementations use reinforcement learning (RL) and decision-support systems that integrate seasonal soil health trajectories with immediate irrigation needs. These systems evaluate multi-season strategies, recommending combinations of irrigation, mulching, residue retention and nutrient management that maximize cumulative water productivity rather than single-season water-use efficiency. Getahun *et al*., (2024) [16] show that RL-based irrigation and cropping strategies outperform rule-based systems, especially in variable rainfall regimes.




**Internet of things**

The Internet of Things (IoT) is emerging as the ideal solution for implementing smart water management applications and precision agriculture to avoid under- and over-irrigation. However, the seamless integration of the different technologies required for its practical use is still a work in progress (Jagtap *et al.*,). The rise of the IoT is attributed to several converging factors, including affordable devices, low-power wireless technologies, the presence of cloud data centres for storage and processing, management frameworks for handling un structured data from social networks, high-performance computing resources on standard platforms, and computational intelligence algorithms tailored to process vast amounts of data (Ahmed *et al.*, 2025) [17]. In recent years, the application of IoT technologies has emerged as a transformative force in agriculture, providing innovative solutions to improve efficiency, sustainability and productivity in various aspects of agriculture, with a focus on irrigation, water reuse, water pollution monitoring and livestock management.

One of the key challenges in agriculture is efficient water management and water quality monitoring. IoT technologies have revolutionized this aspect by enabling real-time monitoring and decision making (Jagtap *et al.*). For example, studies such as Mezni *et al.* and Bhardwaj *et al.*, present IoT-based frameworks that integrate water quality sensors with cloud platforms for continuous monitoring of water bodies such as rivers or irrigation reservoirs. These systems use sensor nodes such as Waspmote and Raspberry Pi, coupled with cloud computing, to analyze water parameters and detect pollution events in a timely manner (Jan *et al.*). The use of wireless sensor networks (WSNs) and cloud-based analytics enables timely intervention, ensuring water safety and minimizing pollution risks. In addition, the integration of IoT in water reuse provides a sustainable approach to agriculture (Zia). By leveraging edge computing and cloud plat forms such as FIWARE, IoT systems facilitate the recirculation of water within greenhouses, reducing pollution risks and optimising resource use (O'Grady *et al.*). This smart approach not only saves water, but also increases crop yields through precise irrigation control based on real-time data analysis.

Otherwise, IoT-enabled water pipeline monitoring focuses on early leak detection and pipeline integrity (Mohd Yussof and Ho). Innovative sensor technologies, such as force sensitive resistors and flow meters integrated with Arduino or Raspberry Pi boards, enable real-time data collection and transmission to central servers. The use of predictive analytics and machine learning algorithms helps identify anomalies, preventing potential water waste and infrastructure damage. IoT-based irrigation systems also represent a paradigm shift towards precision agriculture (Monteleone *et al.*). These systems use WSNs and cloud platforms to optimise water use based on real-time environ mental data such as soil moisture, temperature and humidity. By auto mating irrigation processes and integrating actuators controlled by microcontrollers, farmers can achieve significant water savings while maximizing crop yields. The development of mobile applications for remote monitoring and control further enhances the accessibility and usability of these systems.

**Robotics**

Robots can be used in agriculture to save a lot of human labour by performing repetitive physical tasks. Although people have traditionally used agricultural machinery to work faster and with less physical effort (for example, tractors, harvesters, planters and sprayers), these machines have relied on human manoeuvring. The main advantage of using robots on farms is that they can monitor and decide what tasks need to be carried out and then carry them out. I n particular, the main applications of robotics for water management in agriculture are in the areas of crop and soil monitoring, and watering/irrigation. An example of these two applications is the work of Wu *et al.*), who developed a robot that can monitor soil temperature and humidity and automatically water crops when needed. Their system also used weather forecasts through Long Short-Term Memory, a type of artificial neural network architecture, to make more accurate irrigation decisions. Other parameters are also useful in deciding when to water crops and can be incorporated into robotic irrigation systems, such as stem

water potential (Dechemi *et al*.) and leaf density (Baltazar *et al*.
There are a number of other robotic systems that support water use and management in agriculture. For example, developed a robotic irrigation system consisting of a moving bridge manipulator and a sensor-based platform to monitor soil water content. Fern´ andez-Novales *et al*. used a ground robot equipped with thermal infrared radiometry to assess water status in vineyards. Robots can also be used to monitor water quality parameters such as pH, turbidity and temperature, and to determine whether a water source should be used for a particular soil (Gupta *et al*., 2024) [7]. A particularly interesting application of robots in agricultural water management is the detection of water leaks. Türkler *et al*. integrated visible light and thermal camera sensors into a robot, enabling the system to detect water leaks in drip irrigation systems.

**Smart Sensors**

In agricultural water management, Smart Sensors (SSs) promote water use efficiency and enable precision irrigation. These advanced sensors provide up-to-date information on key environmental parameters such as soil moisture, temperature, humidity and rainfall. They provide real-time data for informed irrigation scheduling and water application decisions. While IoT typically encompasses large networks of sensors and actuators, we explicitly highlight SSs as a separate technology in this review to emphasize that they can function as standalone solutions with embedded processing capabilities. However, these smart sensors are often integrated into broader IoT architectures to enable data sharing and remote control.
Over the years, many researchers have focused on the application of SSs for agricultural water management (Kumar Kasera *et al*.). Khoa *et al*. used IoT multisensors for water management. The system design includes three main components: sensors for data collection, a Long Range Radio Third-generation Technology transmission module for IoT connectivity over large areas, and a single-chip microprocessor for data processing. The system uses real-time data from sensors installed in farm tunnels and other locations to predict watering needs and recommend watering schedules.
However, it relies on specific applications, such as Blynk, and has challenges with reliability and internet connectivity. To address this, an alternative solution is to develop a SS combined with other advanced open source technologies such as cloud computing, machine learning and data analytics tools. In this context, Tzerakis *et al*. developed an open source IoT platform for water management in agriculture, focusing mainly on optimal irrigation and pest control in olive orchards. The experiment involved the integration of soil and atmospheric monitoring SSs with microcontrollers. These sensors transmit data to a cloud-based IoT platform using the Message Queuing Telemetry Transport protocol. The system immediately alerts farmers when soil moisture falls below critical thresholds or pest risks increase. The platform also calculates the amount of water required for irrigation based on crop needs, helping farmers use water efficiently.

**Conclusions**

Artificial intelligence (AI) is reshaping modern soil management by enabling continuous, high-resolution assessment of soil organic matter (SOM), nutrient cycling efficiency, and water productivity three core pillars of soil-health-led agricultural intensification. Through machine learning, remote sensing, IoT soil sensors, automated soil testing, and predictive modelling, AI provides the analytical power needed to move from uniform, reactive nutrient and water management to highly adaptive, site-specific, and forward-looking decision frameworks.
AI-enhanced SOM monitoring uses spectral sensing, digital soil mapping, and deep-learning algorithms to quantify organic carbon patterns and track changes across seasons and management scenarios. These capabilities support targeted interventions such as precision residue retention, organic amendment placement, cover-crop optimization, and conservation tillage zoning. By linking SOM dynamics with yield and climatic variability, AI models help design strategies that maximize carbon inputs while minimizing losses through erosion and microbial decomposition.
In nutrient cycling, AI-driven nutrient decision support systems integrate soil data, crop models, and weather forecasts to deliver variable-rate fertilizer recommendations that align nutrient release with crop demand. This reduces nitrogen and phosphorus losses, enhances soil biological activity, and strengthens nutrient-use efficiency—key objectives of regenerative intensification pathways. Similarly, AI-powered irrigation tools use real-time soil moisture, evapotranspiration forecasting, and crop water modelling to tailor irrigation schedules that improve water-use efficiency and reduce energy and water waste.
Despite these advances, challenges persist. Gaps in ground-truth soil data, inconsistencies in sensor accuracy, limited representativeness of training datasets, and model transferability issues across agroecological zones constrain the reliability of AI predictions. Integrating mechanistic soil process models with data-driven approaches remains essential for credible and scalable solutions. Moreover, inclusive co-design with farmers, transparent model outputs, and capacity building for extension systems are crucial for field-level adoption. AI holds transformative potential for enhancing SOM, nutrient cycling, and water productivity under soil-health-led intensification frameworks. When supported by robust data ecosystems, hybrid modelling approaches, and farmer-centric implementation, AI can enable productivity gains while restoring ecological functions supporting resilient, climate-smart, and sustainable agricultural systems.

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