International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I10P116

Volume 73 Issue 10, 192-202, October 2025

Original Article

Soil Health Monitoring Through Computer-Based Systems: Techniques, Applications, and Future Trends

Girija Shankar Joshi[1], Sumit Chaudhary[2], Geetanjali Shukla[3], Rahul Mahala[4], Anurag Kumar[5]

[1,2,5]*Uttaranchal Institute of Technology, Uttaranchal University, Dehradun, Uttarakhand, India.*
[3]*School of Applied and Life Sciences, Uttaranchal University, Dehradun, Uttarakhand, India.*
[4]*Law College Dehradun, Uttaranchal University, Uttarakhand, India.*

[4]*Corresponding Author : rahulmahala98@gmail.com*

Received: 03 July 2025 Revised: 27 August 2025 Accepted: 23 October 2025 Published: 31 October 2025

Abstract *- Soil health monitoring is crucial in sustainable agricultural and environmental management strategies due to soil degradation caused by chemical fertilizers, industrial agriculture, deforestation, and climate change. Traditional methods are slow, expensive, and laborious, leading to spatial and temporally variable soil health. The agricultural industry is transitioning to digital solutions using IoT sensors, remote sensing, AI, machine learning, GIS, and mobile-based applications. These technologies provide real-time data collection, analysis, and visualization, allowing farmers, researchers, and policymakers to understand soil variability, reduce input use, and develop long-term land management plans. The article reviews computer-based techniques for soil health monitoring, including IoT, remote sensing, and AI, and analyzes their applications in agriculture, sustainability, and soil management. It also identifies future trends, challenges, and research directions for precision soil health monitoring. Computer-aided soil health assessment offers real-time, affordable solutions for agriculture, replacing traditional methods. Technologies like IoT sensors, artificial intelligence, and machine learning improve accuracy and efficiency. These systems provide site-specific data, enabling farmers to make informed decisions about irrigation, fertilization, and crop management. However, barriers like investment cost, human capital, and data privacy need to be addressed.*

Keywords *- Soil health, Computer-based monitoring, Artificial Intelligence, Machine Learning, IoT, Precision agriculture.*

1. Introduction

In recent decades, drastic pressure to understand soil degradation processes caused by excessive chemical fertilizers, industrial agriculture, deforestation, and climate change has propelled soil health monitoring to centre-stage in sustainable agricultural and environmental management strategies [1]. The health of soil systems' physical, chemical, and biological components affects plant development, water filtration, carbon storage, and nutrient cycling [2].

Conventional soil health monitoring typically involves sampling and either measuring or analyzing samples in laboratory settings. While this is technically sound, conventional methods of laboratory analysis tend to be slow, expensive, laborious, and location-restricted. Traditional methods such as manual, lab-based, and observational techniques usually also lack the responsiveness and resolution volume that precision agriculture demands, requiring timely and practical high-resolution, site-specific data to maximize yield or minimize resource inputs, which leads to serious agricultural, economic and environmental problems that leads soil health tremendously spatially and temporally variable, traditional scales of soil health measurement [3]. In the face of these challenges, the agricultural industry is working to transition to a digital world marked by the introduction of computer-based solutions. Agricultural solutions using the Internet of Things (IoT) sensors, remote sensing, using satellites and drones, Artificial Intelligence (AI), Machine Learning (ML), Geographic Information Systems (GIS), and mobile-based applications were increasingly adopted in soil monitoring systems [4]. Databases are now able to continuously, accurately, and relatively quickly assess conditions over large quantities of land. Capable of real-time data collection, analysis, and visualization, this technology provides potential to take the guesswork out, allowing farmers, researchers, and policymakers to understand the variability in soil, reduce input use, lessen their environmental footprints, and develop plans to manage the land over the long term [5]. The objectives of the article are as follows:

- To review computer-based techniques for soil health monitoring, including IoT, remote sensing, and AI.
- To analyze applications of these systems in agriculture, sustainability, and soil management.
- To identify future trends, challenges, and research directions for precision soil health monitoring.

2. Methodology

For this review, we systematically collected research articles related to soil health monitoring using computer-based systems, including IoT, AI, ML, and remote sensing technologies. A total of approximately 180 articles were initially retrieved from trusted publishers and reputed databases such as ScienceDirect, Springer, Wiley, Taylor & Francis, Elsevier, and IEEE Xplore. Following a rigorous screening process based on relevance, quality, and contribution to the field, we shortlisted 56 of the most suitable articles that provided significant insights into techniques, applications, challenges, and future directions. These selected studies form the foundation of our analysis and critical discussions, ensuring that the review reflects both the breadth of existing research and the depth of the most impactful contributions in the domain.

3. Soil Health Parameters

Soil health is a complex topic that represents the capacity of soils to work as a living, dynamic system that supports plant growth, regulates water, cycles nutrients, and provides habitat for numerous organisms [6].

It is a concise description that highlights several key parameters. Different aspects of soil health measure the physical, chemical, and biological properties of soil that contribute to soil health and productivity in their own specific manner [7]. The physical properties of soil are essential indicators of soil structure, porosity, and ability to hold and transmit air and water (which directly impact root growth and microbial activity). The moisture content of soils has a significant impact on growth and is one of the most important parameters because moisture content determines water availability for plant uptake, solubility of nutrients, and microbial functioning [8].

Either soils being too dry or too wet can produce crops showing moisture stress, reductions in effective microbial action, and reduced yield [9]. The soil texture, or the proportions of coarse sand, fine sand, silt, and clay, impacts soil permeability, water holding capacity, and ability to tolerate root systems. Sandy soils often drain quickly, but retain fewer nutrients [10].

Clayey soils retain more water but will often prohibit root expansion and aeration. Soil temperature is critical for seed germination, enzyme activity, and microbial activity. Soil temperature is also important to note as fluctuations can have a substantial impact on nutrient mineralization and rates of microbial respiration, and hence will change soil fertility, as shown in Figure 1 [11].

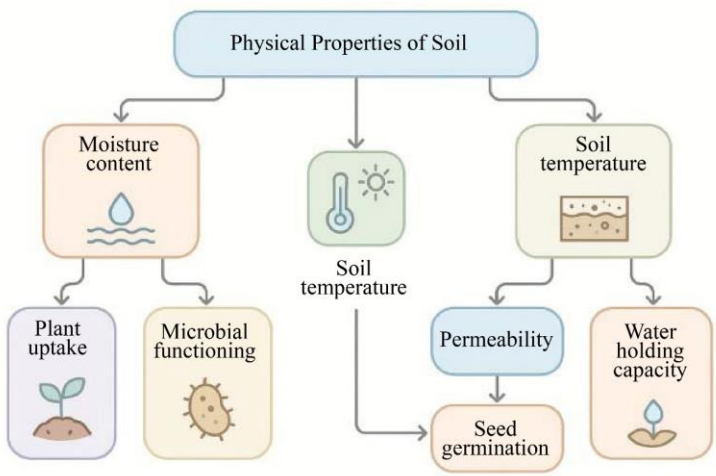

Fig. 1 Physical properties affect soil

Bulk density refers to soil density and is a measurement of soil compaction or porosity. Like soil texture, high bulk density relates to heavy compaction and can inhibit root expansion, reduce air and water infiltration, and phosphate-limited microbials [12]. Low bulk density indicates lots of air passage and room for root expansion, but too little density can show poor structure of soil if it is too loose. Soil physical parameters can be measured to promote better management of irrigation, tillage, and crop rotations [13]. Soil chemical health relates to the nutrients contained in the soil as well as salinity and pH levels of the soil, all of which directly affect plant nutrition and soil biota, as shown in Figure 2. [14]. Soil pH is an important technical indicator of soil chemistry as it influences nutrient availability, microbial diversity, and soil chemistry overall [15]. Most crops like soils that have an optimum pH slightly acidic to moderately neutral (6.0 to 7.5), ionized cations (toxicity/deficiency) can occur at both the extremes of acidity and alkalinity, which can limit or completely stop plant growth and affect microbial activity [16]. Electrical Conductivity (EC) indicates the concentration of soluble salts in the soil, which is usually considered a measurement of soil salinity [17]. High-EC soils can cause osmotic stress to plants, which can induce physiological drought even when the surrounding soils are wet. This becomes more problematic in arid and semi-arid regions of the world if soils are salinized by natural processes or by irrigation [18]. Micronutrients, for example, zinc (Zn) and iron (Fe), are often taken up in smaller amounts but are vital to enzymatic function, chlorophyll formation, and reproductive production [20]. Figure 3 elaborates on how soil properties are affected by different components. Any discrepancy or deficiency of the two can result in debilitating physiological disorders in crops. Chemical analyses of soils can support the development of targeted nutrient management strategies and fertilization management strategies, which allow for improved productivity and deal with environmental stewardship [21].

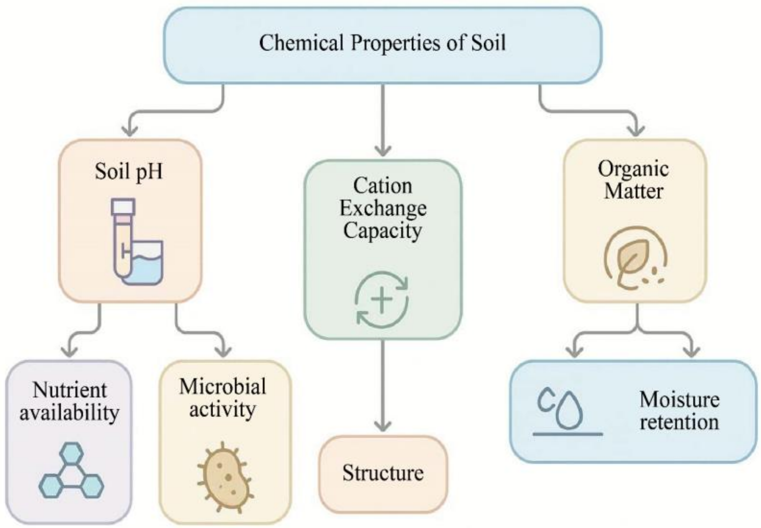

Fig. 2 Chemical properties affect soil

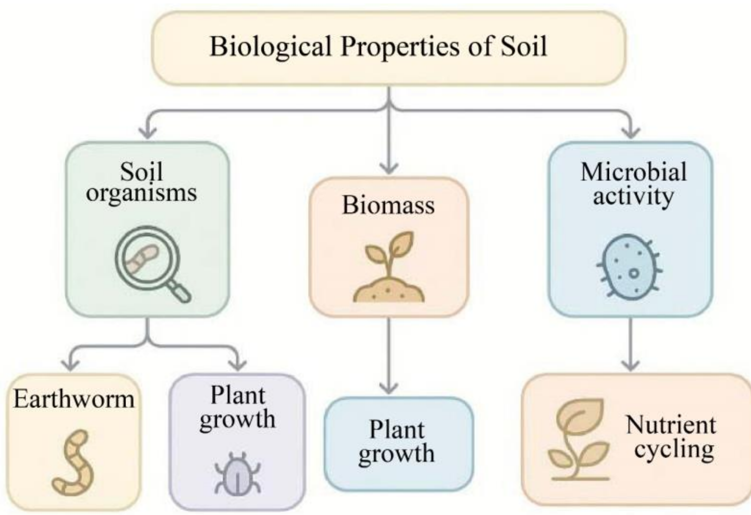

Fig. 3 Biological properties affect soil

Biological indicators embody the living component of the soil, their microbial diversity, their biogeochemical function, and organic matter status, all of which help with nutrient cycling, organic matter decomposition, and ecological recovery [22]. Soil respiration, which measures the CO_2 given off by microbial and root metabolism, provides an indication of the biological activity and turnover of organic matter. High respiration rates, regardless of their condition, indicate similar microbial communities and healthy soil. Low respiration rates can indicate diseased biological health or soil degradation [23]. Microbial biomass is defined as the total mass of the microorganisms (bacteria, fungi, actinomycetes) in the soil, which can be considered a reservoir of nutrients (nitrogen and phosphorus) [24]. Microbial biomass is also important for the soil structural stability because it also exudes glues or binders that help hold soil aggregates together, and a diverse and active microbial population can also provide resistance to pathogens and supplement nutrient availability through nitrogen fixation or through mycorrhizal relationships. The ideal quantity for a healthy soil is approximately 300mg C/kg soil [25]. Enzyme activities (dehydrogenases, ureases, and phosphatases) can be possible indicators of microbial activity and biochemical potential in the soil. Enzymes are important for the transformation and mineralization of organic matter and specifically are important for the release of nutrients in a bioavailable form for plant use [26]. Enzyme activity can also be used as an indicator of soil stress or pollution and to record information about how well organic amendments or conservation practices are working. From the perspective of soil assessments, indicators of physical, chemical, and biological properties contribute to a holistic and integrative assessment of soil health that can also support land managers in making informed soil management decisions that align with sustainability principles [27]. Regularly monitoring the indicators and interpreting them can help make better decisions for improving and sustaining soil resources over the long term for the potential future plant production, ecological balance, and resilience to climate change and anthropogenic influences.

4. Technologies in Computer-Based Soil Monitoring

Improvements in agricultural technology have brought to the market several computer-based tools that help address some issues of classical soil monitoring practices, as shown in Figure 4. Remote Sensing (RS) provides information about specific soil properties at the surface level across large agricultural sites and uses reflectance data to model measurable parameters such as surface moisture and the variability in texture over space and time [28]. The strength of RS is that it is able to provide information at the scale of the region, but its dependence on satellite calibration at arbitrary times and potential interference from clouds may restrict data application [29]. In contrast, IoT sensors used in the field are designed to improve data collection of sub-surface real-time measurements of dynamic soil variables for production, which can deliver time-stamped measurement data that inform immediate agronomic decision-making to maximize crop production [30]. However, challenges to deploying IoT sensors in the field include an inconsistent electric supply for maintenance and poor internet connectivity for locations that are largely off-grid. ML uses past data and sensor data to develop smart systems that detect changes in soil behavior and classify soil types and nutrient requirements. ML also works with high-dimensional datasets and changing decision rules, but ultimately, the quality of the predictions depends on the availability of current and diverse training data [31]. With GIS, soil and geospatial coordinates can be produced to create layered maps that show spatial trends [32]. An example of this is having erosion-prone areas or nutrient-depleted areas visible on a single map. However, using GIS also requires certain technical capabilities, which make it specially designed for experts rather than non-experts. Mobile applications such as Plantix, Krishi Network, Cropln SmartFarm, AgriApp, etc., are designed to close the information gap for end users, most notably smallholder farmers, by offering actionable recommendations, alerts, and making information easier to consume [33]. However, there may be limited access to soil intelligence in areas of low technological access or digital literacy, as clearly elaborated in Table 1. Each tool shown in this paper approaches the monitoring of soil health from a stand-alone perspective, and together they offer a complete and scalable digital agriculture ecosystem.

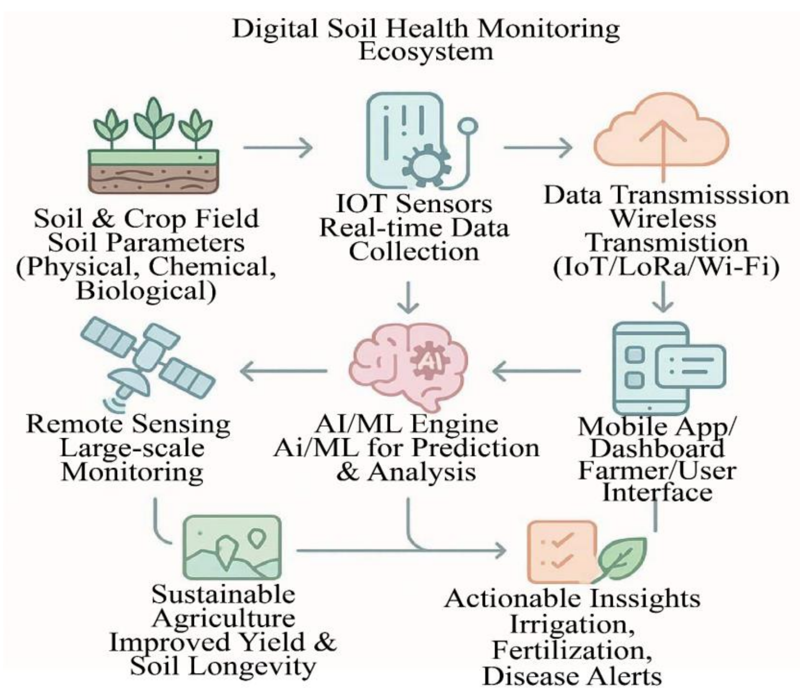

Fig. 4 Digital soil health monitoring ecosystem

Table 1. Various technologies, applications, advantages, and limitations

Technology	Application	Advantages	Limitations
Remote Sensing [34]	Satellite-based spatial assessment of soil moisture, texture, and temperature	Covers up to 90% of agricultural land in large-scale mapping; enables temporal monitoring with 5–15-day revisit cycles	Limited spatial resolution (~10–60 m); ±7% moisture accuracy due to cloud cover and aerosols
IoT Sensors [35]	In-situ monitoring of moisture, pH, EC, and temperature using embedded sensors	Provides real-time data with ±3% moisture accuracy; allows 24/7 monitoring; supports up to 95% decision accuracy when integrated with AI	Data transmission issues in >35% of rural regions due to poor connectivity
Machine Learning [36]	Predictive modeling of soil pH, nutrient status, and yield forecasting	Achieves pH prediction accuracy of 92% (SVM) and 94% (Random Forest); handles large multidimensional datasets	Requires >70% clean, labelled data for optimal model training; computationally intensive
Geographic Information System (GIS) [37]	Geospatial visualization, soil health mapping, spatial-temporal correlation	Integrates 100+ spatial layers; enables multispectral data fusion and predictive zoning.	Requires specialized skill sets in GIS software and spatial analysis; subjective interpretation risk
Mobile Applications [38]	Front-end interface for farmers to receive soil health insights, alerts, and decision support	Used by 60–70% of digitally literate farmers; cost-effective with ₹50–₹100/month operation	Limited usability in regions with <40% smartphone penetration and low literacy

5. Quantitative Analysis of Techniques

The quantitative analysis of the different computer-based soil monitoring approaches shows interesting differences in accuracy, effectiveness, and overall cost [39]. For the determination and estimation of moisture, IoT sensors, being in the ground and immersed in a soil environment, have higher overall occurrences of accuracy with a margin of ±3% [40]. Satellite remote sensing has a somewhat broader range of estimating moisture (larger spatial dimensions to cover soil monitoring) but is less accurate (/- 7%) against baseline estimates, depending on atmospheric issues such as aerosols and clouds, and the associated spatial resolution limits of satellite observation [41]. In terms of predictions of pH, there are good, clear advantages of utilising machine learning approaches. The predictions of pH from SVM models were roughly at an accuracy of 92% and Random Forest models were about 94% (a small improvement due to ensemble learning and their ability to fit non-linear relationships in their associated datasets-based soil response observations) [42]. When examined for cost-effectiveness using classical laboratory-based methods of analysis and predictions, the costs generally range from ₹500 per soil sample, which can accumulate quickly with many soil samples being examined in frequency or bulk [43].

IoT-based systems for soil health based upon continuous monitoring represent a recurring cost of roughly ₹100 per month for each device, making a significant impact on maintaining soil health in a sustainable method for long-term continuous monitoring, as well as impactful soil health and agricultural sustainability [44]. Overall, these numbers help to summarize the economic, technical, and computational possibilities and opportunities when considering modern computer-based tools in precision agricultural practice.

5.1. Case Studies

Such a real-world computer-driven soil health monitoring application stands as testimony to the existence of practical advantages and adaptability of newer technology over varied agricultural lands. One example of application technology was the Soil Project in India, which combined IoT sensors. Ahmad et al. (2025) mentioned in their studies that India's Soil Health Project has effectively deployed IoT sensor devices and mobile-enabled platforms to monitor pH, moisture, nutrients, and other soil-related characteristics in real time, as shown in Figure 5. This approach was used in smallholder farming communities with the aim of providing localized soil intelligence accessible to smallholder farmers' mobile devices, which have the complete capability to irrigate and fertilize their farms based on the technology. The results showed improved yields and improved use of resources, demonstrating a feasible, affordable, and scalable precision agriculture system in developing economies [45]. Pascoal et al., 2024, "Practical Applications and Recommendations for IoT-based Sensors in Precision Agriculture and Viticulture." An IoT-based soil sensor network was developed in Italy and France to measure soil temperature and moisture at multiple depths on a continuous basis. This continuous or real-time data flow provides vineyard managers with better opportunities to adjust irrigation schedules and manage canopy conditions to improve grapes and reduce water use. The system enables optimization of high-value crops while maintaining low environmental impact. The working mechanism is well defined in Figure 6 [46]. Barathkumar et al elaborated that experimental farms in Europe and Asia have used machine learning models--Random Forest and Support Vector Machines (SVM)--that were trained on soil lab and multispectral data to predict nutrient deficiencies. The prediction accuracies were 92% (SVM) and 94% (RF) for pH, as shown in Figure 7. Such AI tools can deliver precision nutrient application strategies that can improve yield while conserving soil health [31].

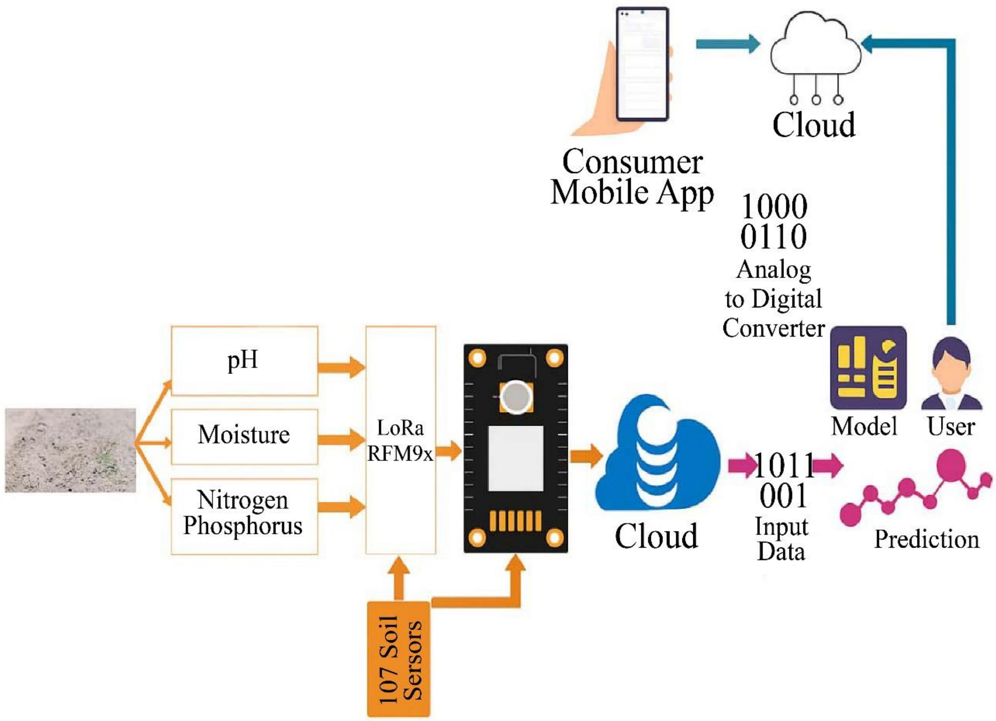

Fig. 5 Soil health monitoring through IoT sensor

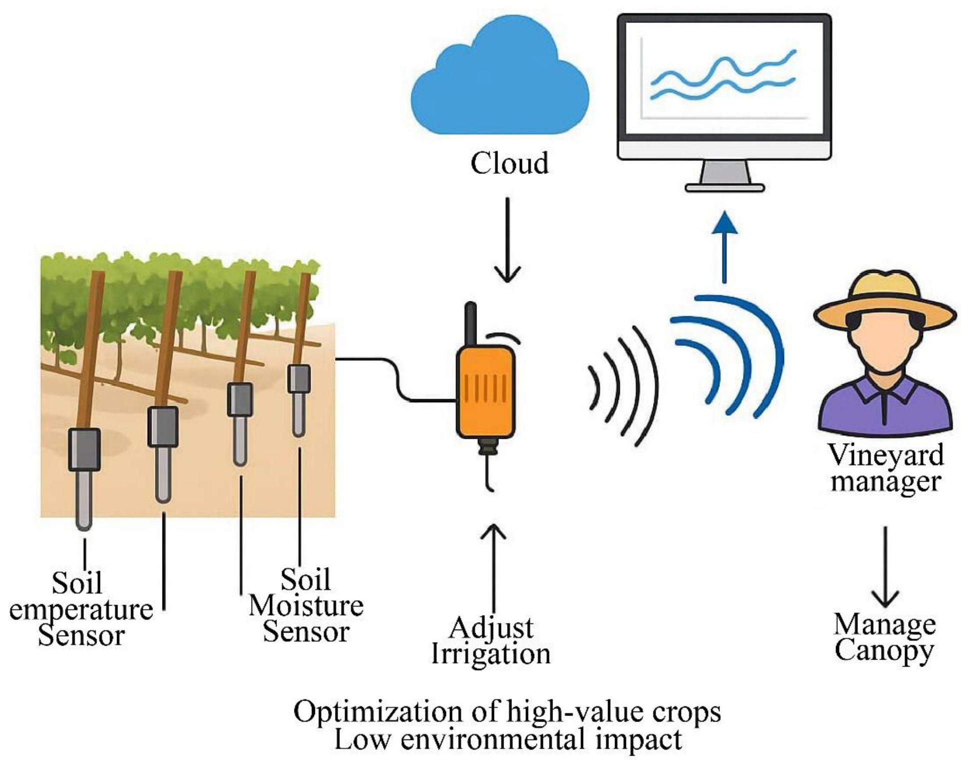

Fig. 6 Optimization of high-value crops with low environmental impact

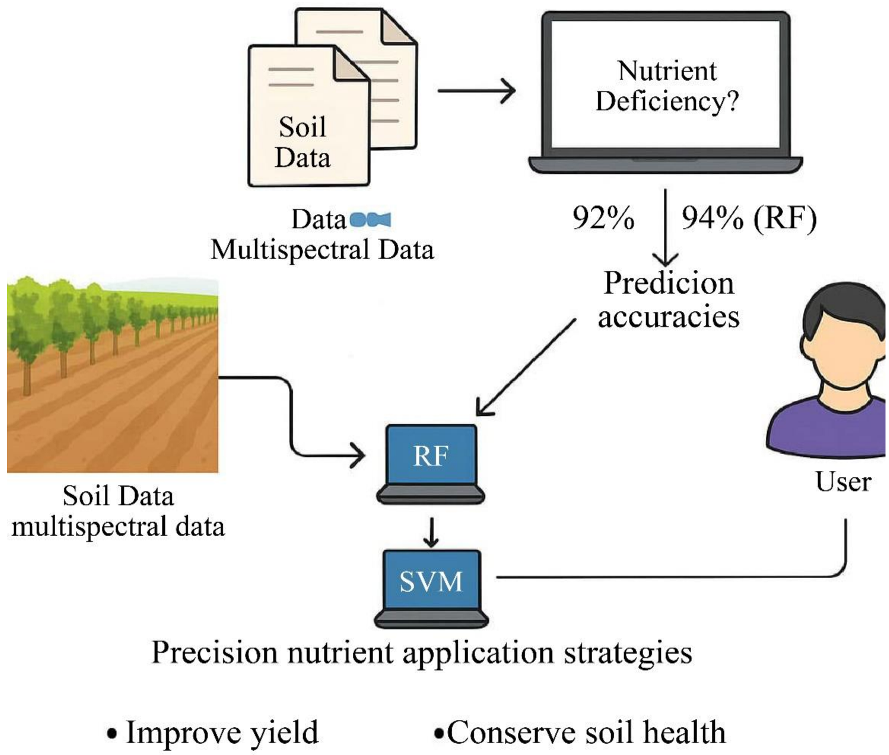

Fig. 7 Precision nutrient application strategies

UAV-based remote sensing has offered new opportunities to measure soil moisture variability at high spatial resolution across semi-arid regions in Australia, as shown in Figure 8. By combining UAV data with GIS-based systems, maps of drought stress can be produced and used to assist in adaptive cropping or irrigation. Using UAV data enhances the spatial resolution of the data, whilst also overcoming limitations of satellite-based systems by providing more frequent intervals for collecting new data [47].

Applications such as Plantix and Krishi Network are closing the knowledge gap for smallholder farmers in Sub-Saharan Africa, as shown in Figure 9. The applications deliver real-time decision support by combining soil test data, remote sensing, and local weather forecasting data. Although barriers related to literacy still exist, their simple and mostly intuitive design allows digitally literate smallholder farmers to manage fertilizer application risks, predict pest outbreaks, and improve [48].

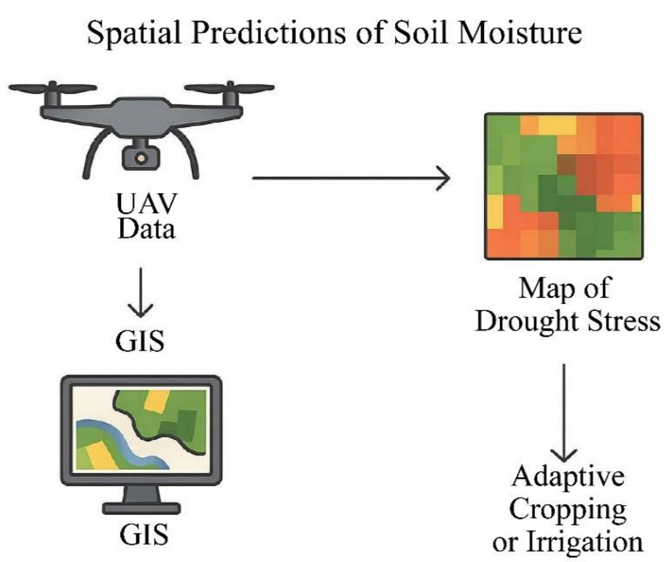

Fig. 8 Spatial prediction of soil moisture

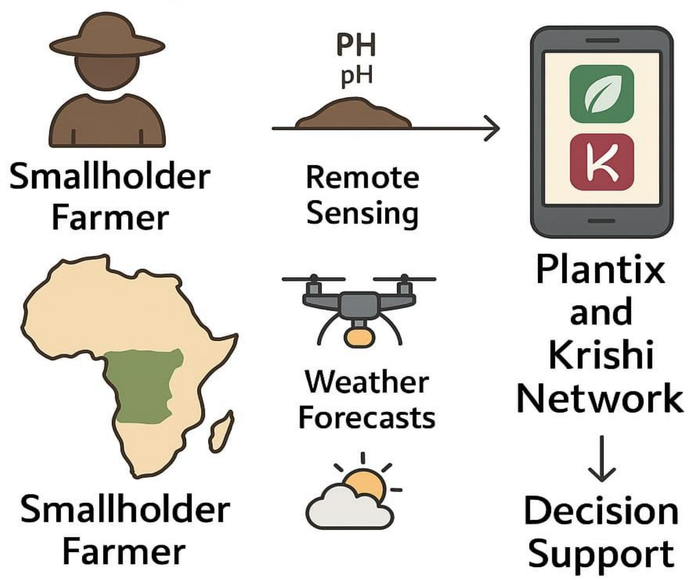

Fig. 9 Enhancing the dissemination of agricultural services

6. Challenges and Limitations

While there are emerging computer-based management tools that can measure soil health and provide clear benefits, there are still obstacles and limitations that exist to fully adopt the technology. A key obstacle to the uptake of the technology is the issue of data contractual rights and privacy [49]. It is common for farm-level data to be collected and shared by a company, leading to concerns around ownership of data and how the data can be used. Data possession, while retainable, varies from data ownership in legal terms: without permits and contracts in place, it is still possible that farmers may be less likely to adopt digital applications without assurance around data privacy and ethical use of the data [50]. Another significant barrier is cost in terms of sensors, which is especially restrictive for smaller and marginal farmers; while costs may be lower in terms of longer-term use, the issue and barrier of initial investment in IoT or sensor technologies can still be moderate in terms of limiting resource-scarce agricultural contexts [51].

Another challenge is the issue of data standardization and interoperability, as sensors, devices, platforms, and software are from many suppliers, compounded by the lack of harmonized data, which makes integration and comparisons of datasets and limits the full optimization of agricultural decision support tools [52]. Finally, the importance of training and simple, intuitive interfaces should not be underestimated. Farmers have less digital literacy than is required to operate and derive insights from these systems. Without training or a user-interface design based on the needs of the farmer team, these systems may only be partially utilized, or even worse, could be misused or misinterpreted. These issues must be addressed to create a technology equivalent, scalable, and eventually useful for every level of farming system.

7. Future Perspectives

The future of soil health monitoring could be more intelligent, transparent, and farmer-centric, with policy and much-needed support, as shown in Figure 10.

Promising avenues towards developing soil health monitoring are through blockchain, AI-powered smart fertilization, deep learning, open-source interoperable digital platforms, user-friendly mobile applications, etc.

- The integration of blockchain technology for traceability of soil data in the agricultural supply chain is tamper-proof, non-repudiable, and transparent. This element builds consumer trust.
- The integration of AI-based real-time soil analytics offers data-driven records of nutrient input, which reduces the opportunity for over-fertilization and increases the lifespan of the soil.
- The integration of deep learning models that can predict soil-climate-crop interactions, pathways of diseases, and nutrient dynamics.
- The development of interoperable digital platforms allows for the integration of a wide range of sensors, applications, and management systems that will work together seamlessly.
- Mobile applications that are user-friendly and localized for those with little or no digital literacy, especially in rural communities.
- Supporting government policy is established (e.g., subsidies, ICT infrastructure, digital literacy training, data privacy laws) to increase the use of technology.
- Scalable, low-cost systems are a priority for smallholder farmers with low upfront investment.

- New digital technologies are integrated into existing patterns of farm practices and decisions.
- Further expansion includes automated irrigation systems and robotics to perform soil sampling based on real-time soil data analysis.
- Provide local farms with data visibility to utilize science-based technologies supporting climate-smart agriculture for better climate resilience, reduced carbon footprints, and sustainable land decisions.

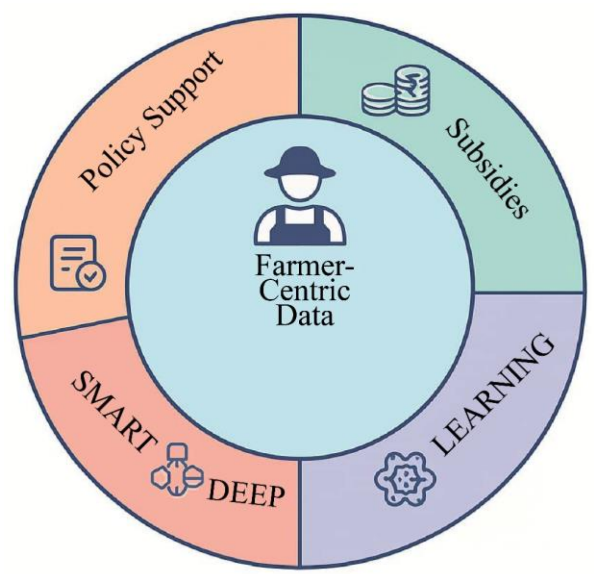

Fig. 10 Future-oriented innovations in soil monitoring

These systems provide the opportunity to collect site-specific data with an applicable recommendation, providing farmers the ease of making informed decisions concerning their irrigation and fertilization, as well as overall crop management. In comparative quantitative terms, digital systems have been shown to provide better precision and improved affordability than traditional laboratory systems, and for large-scale or regular testing, make a solid case for agriculture.

Further, case studies are emerging globally that showcase various agricultural ecosystems and how they develop practices that see these systems in action, from small Indian farms to vineyards in Europe. However, several of these technologies are still under development and depend on scaling up beyond a limited number of case studies; as such, they still face the greater barriers of up-front investment cost, human capital (digital literacy), the attitudes toward, and protocols for, data privacy, and the issue of interoperability (across devices/platforms). Approaches to overcome these barriers will therefore need to be collective and coordinated, including inclusive policy-making, funding based on policy-based subsidy, capacity building, and improvements to digital infrastructure. The future is exciting; using blockchain-based traceability, AI-based nutrient mapping, and smart (sustainable) fertilization will improve not just production productivity but also environmental sustainability and climate-resilient practices at the same time! Ultimately, computer-based soil health monitoring is not simply an improvement upon practices: it is situated in the bigger strategic movement to sustainable, data-full, equitable agricultural systems that meet human needs, and that together also maintain (promote inclusively) ecological health and integrity in the face of climate challenges and resource constraints.

8. Conclusion

With computer-aided soil health assessment, agriculture now has the opportunity to replace outdated conventional methods with real-time, wide-scale, very affordable solutions. New technologies involving IoT sensors, artificial intelligence algorithms, machine learning models, remote sensing, GIS, and mobile-based platforms have accelerated the accuracy, availability, and efficiency of soil health diagnostics from conventional soil testing to digital soil assessment.

Acknowledgments

Authors 1, 2, and 3 have written, reviewed, and prepared the methodology. Author 4 reviewed the article, helped prepare the methodology and supervision, and edited it.

References

[1] Yingying Xing, Xiukang Wang, and Adnan Mustafa, "Exploring the Link Between Soil Health and Crop Productivity," *Ecotoxicology and Environmental Safety*, vol. 289, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Imran, and Ibrahim Ortas, "Mechanism in Soil Health Improvement with Soil Microbial Actions and Its Role in Potential Agriculture," *Communications in Soil Science and Plant Analysis*, vol. 56, no. 13, pp. 2066-2087, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] Ritesh Kumar Singh, Rafael Berkvens, and Maarten Weyn, "AgriFusion: An Architecture for IoT and Emerging Technologies Based on a Precision Agriculture Survey, *IEEE Access*, vol. 9, pp. 136253-136283, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Abhishek Patel et al., *Smart Farming: Utilization of Robotics, Drones, Remote Sensing, GIS, AI, and IoT Tools in Agricultural Operations and Water Management*, Integrated Land and Water Resource Management for Sustainable Agriculture Volume 1, Springer, pp. 127-151, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Shabnam Kumari, Gaurav Kumar Pandey, and Shrikant Tiwari, "Data Visualization Techniques in Smart Agriculture Implementation," *AI Applications for Business, Medical, and Agricultural Sustainability*, pp. 122-159, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Manish R. Pandao et al., "Soil Health and Nutrient Management," *International Journal of Plant and Soil Science*, vol. 36, no. 5, pp. 873-883, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Edoardo A.C. Costantini, and Stefano Mocali, "Soil Health, Soil Genetic Horizons and Biodiversity#," *Journal of Plant Nutrition and Soil Science*, vol. 185, no. 1, pp. 24-34, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sahil Sharma et al., "Soil Quality Indicators: A Comprehensive Review," *International Journal of Plant and Soil Science*, vol. 35, no. 22, pp. 315-325, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Kalisa Bogati, and Maciej Walczak, "The Impact of Drought Stress on Soil Microbial Community, Enzyme Activities and Plants," *Agronomy*, vol. 12, no. 1, pp. 1-26, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Brian John Huntley, *Soil, Water and Nutrients*, Ecology of Angola, Springer, Cham, pp. 127-147, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ruosong Qu et al., "Soil Temperature, Microbial Biomass and Enzyme Activity are the Critical Factors Affecting Soil Respiration in Different Soil Layers in Ziwuling Mountains, China," *Frontiers in Microbiology*, vol. 14, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Sunny Goh Eng Giap, and Mohammad Fadhli Ahmad, "Factors Affecting Soil Bulk Density: A Conceptual Model," *Journal of Soil, Environment and Agroecology*, vol. 1, no. 1, pp. 27-45, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Pradeep K. Sharma, and Sandeep Kumar, *Soil Structure and Plant Growth*, Soil Physical Environment and Plant Growth, Springer, Cham, pp. 125-154, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Heena Nisar Pahalvi et al., *Chemical Fertilizers and Their Impact on Soil Health*, Microbiota and Biofertilizers, vol. 2, Springer, Cham, pp. 1-20, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] Shazia Iqbal et al., *Chemical Fertilizers, Formulation, and Their Influence on Soil Health*, Microbiota and Biofertilizers, Springer, Cham, pp. 1-15, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Neeraj Kulshreshtha et al., *Genetic Interventions to Improve Salt and Microelement Toxicity Tolerance in Wheat*, New Horizons in Wheat and Barley Research, Springer, Singapore, pp. 429-483, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Demis Andrade Foronda, and Gilles Colinet, "Prediction of Soil Salinity/Sodicity and Salt-Affected Soil Classes from Soluble Salt Ions Using Machine Learning Algorithms," *Soil Systems*, vol. 7, no. 2, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sharaf M. Al-Tardeh et al., "In Vitro Assessment of Salinity Stress Impact on Early Growth in Ten Certified Palestinian Barley Cultivars (Hordeum Vulgare L.) Potentially Suitable for Cultivation on Former Quarry Substrates," *Water*, vol. 15, no. 6, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Abde Sherefu, and Israel Zewide, "Review Paper on Effect of Micronutrients for Crop Production," *Journal of Nutrition and Food Processing*, vol. 4, no. 7, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Bommireddy Mamatha et al., "Enhancing Soil Health and Fertility Management for Sustainable Agriculture: A Review," *Asian Journal of Soil Science and Plant Nutrition*, vol. 10, no. 3, pp. 182-190, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Debarati Bhaduri et al., "A Review on Effective Soil Health Bio-Indicators for Ecosystem Restoration and Sustainability," *Frontiers in Microbiology*, vol. 13, pp. 1-25, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Chunyang Zhan, "Microbial Decomposition and Soil Health: Mechanisms and Ecological Implications," *Molecular Soil Biology*, vol. 15, no. 2, pp. 59-70, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Zhijian Mou et al., "Nutrient Availability and Stoichiometry Mediate Microbial Effects on Soil Carbon Sequestration in Tropical Forests," *Soil Biology and Biochemistry*, vol. 186, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Nisha Singh et al., "Soil Enzyme Activities as Bioindicators of Soil Health: Implications for Sustainable Agriculture," *Journal of Natural Resource Conservation and Management*, vol. 5, no. 2, pp. 124-136, 2024. [Google Scholar] [Publisher Link]

[25] Michael T. Löbmann et al., "Systems Knowledge for Sustainable Soil and Land Management," *Science of the Total Environment*, vol. 822, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[26] Alexander Hernandez et al., "Spatial Predictions of Soil Moisture Across a Longitudinal Gradient in Semiarid Ecosystems Using UAV and RGB Sensors," *Geocarto International*, vol. 40, no. 1, pp. 1-27, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[27] Tshanga M. Matthieu, Lindani Ncube, and Elna van Niekerk, "Remote Sensing Insights into Subsurface-Surface Relationships: Land Cover Analysis and Copper Deposits Exploration," *Earth Science Informatics*, vol. 17, no. 5, pp. 3979-4000, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Rohan Le Roux et al., "Slope Stability Monitoring Methods and Technologies for Open-Pit Mining: A Systematic Review," *Mining*, vol. 5, no. 2, pp. 1-35, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[29] Yixin Huang et al., "Data-Driven Soil Analysis and Evaluation for Smart Farming Using Machine Learning Approaches," *Agriculture*, vol. 13, no. 9, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[30] Murali Krishna Senapaty, Abhishek Ray, and Neelamadhab Padhy, "IoT-Enabled Soil Nutrient Analysis and Crop Recommendation Model for Precision Agriculture," *Computers*, vol. 12, no. 3, pp. 1-34, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Obvious Mapiye et al., "Information and Communication Technologies (Icts): The Potential for Enhancing the Dissemination of Agricultural Information and Services to Smallholder Farmers in Sub-Saharan Africa," *Information Development*, vol. 39, no. 3, pp. 638-658, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[32] Mengqi Duan et al., "Mapping the Soil Types Combining Multi-Temporal Remote Sensing Data with Texture Features," *Computers and Electronics in Agriculture*, vol. 200, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] Hammad Shahab et al., "IoT-Driven Smart Agricultural Technology for Real-Time Soil and Crop Optimization," *Smart Agricultural Technology*, vol. 10, pp. 1-9, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[34] Edwin Omol, Lucy Mburu, and Dorcas Onyango, "Anomaly Detection in IoT Sensor Data Using Machine Learning Techniques for Predictive Maintenance in Smart Grids," *International Journal of Science, Technology and Management*, vol. 5, no. 1, pp. 201-210, 2024. [Google Scholar]

[35] Joseph J. Kerski, *Teaching and Learning Geography with a Web GIS Approach*, Re-Visioning Geography, Springer, Cham, pp. 113-135, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[36] Mariette McCampell, *More Than What Meets the Eye: Factors and Processes that Shape the Design and use of Digital Agricultural Advisory and Decision Support in Africa*, Doctoral Thesis, Wageningen University, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[37] Seyed M. Biazar et al., "Artificial Intelligence in Hydrology: Advancements in Soil, Water Resource Management, and Sustainable Development," *Sustainability*, vol. 17, no. 5, pp. 1-27, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[38] Pisana Placidi et al., "Monitoring Soil and Ambient Parameters in the IoT Precision Agriculture Scenario: An Original Modeling Approach Dedicated to Low-Cost Soil Water Content Sensors," *Sensors*, vol. 21, no. 15, pp. 1-28, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[39] I.P. Senanayake et al., "Estimating Catchment Scale Soil Moisture at a High Spatial Resolution: Integrating Remote Sensing and Machine Learning," *Science of The Total Environment*, vol. 776, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[40] E. Syed Mohamed et al., "A Hybrid Mental Health Prediction Model Using Support Vector Machine, Multilayer Perceptron, and Random Forest Algorithms," *Healthcare Analytics*, vol. 3, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[41] Insha Wani et al., "Critical Review of Biochar Applications in Geoengineering Infrastructure: Moving Beyond Agricultural and Environmental Perspectives," *Biomass Conversion and Biorefinery*, vol. 14, no. 5, pp. 5943-5971, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[42] Deepak Kumar et al., *IoT Based Models in Healthy Natural Resource Management: Healthy Soils for Healthy Food Productions*, IoT-Based Models for Sustainable Environmental Management, Springer, pp. 211-242, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[43] Sultan Ahmad et al., *Utilizing IoT and AI for Soil Health Monitoring and Enhancement in Sustainable Agriculture*, 1st ed., IoT and Advanced Intelligence Computation for Smart Agriculture, CRC Press, pp. 110-125, 2025. [Google Scholar] [Publisher Link]

[44] David Pascoal et al., "A Technical Survey on Practical Applications and Guidelines for IoT Sensors in Precision Agriculture and Viticulture," *Scientific Reports*, vol. 14, no. 1, pp. 1-30, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[45] S. Barathkumar et al., "Advancements in Soil Quality Assessment: A Comprehensive Review of Machine Learning and AI-Driven Approaches for Nutrient Deficiency Analysis," *Communications in Soil Science and Plant Analysis*, vol. 56, no. 2, pp. 251-276, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[46] Swee King Phang et al., "From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture," *IEEE Access*, vol. 11, pp. 127057-127076, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[47] Anand K. Gavai et al., "Agricultural Data Privacy: Emerging Platforms and Strategies," *Food and Humanity*, vol. 4, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[48] Umar Daraz, Štefan Bojnec, and Younas Khan, "Energy-Efficient Smart Irrigation Technologies: A Pathway to Water and Energy Sustainability in Agriculture," *Agriculture*, vol. 15, no. 5, pp. 1-27, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[49] Nigel Hughes, and Dipak Kalra, *Data Standards and Platform Interoperability*, Real-World Evidence in Medical Product Development, Springer, Cham, pp. 79-107, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[50] Twinkle Geojini Gurupatham, Yesubai Rubavathi Charles, and Ramnath Muthusamy, "Revolutionizing Agricultural Supply Chain Management with Blockchain-Based IoT: Improving Traceability, Efficiency and Sustainability," *AIP Conference Proceedings: International Conference on Innovative Approaches in Engineering & Technology, (ICIAET-24)*, Proddatur, India, vol. 3237, no. 1, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[51] Mohsen Soori, Behrooz Arezoo, and Roza Dastres, "Artificial Intelligence, Machine Learning and Deep Learning in Advanced Robotics, A Review," *Cognitive Robotics*, vol. 3, pp. 54-70, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[52] Julián F. Becerra-Encinales et al., "Agricultural Extension for Adopting Technological Practices in Developing Countries: A Scoping Review of Barriers and Dimensions," *Sustainability*, vol. 16, no. 9, pp. 1-20, 2024. [CrossRef] [Google Scholar] [Publisher Link]