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REVIEW ARTICLE

Emerging trends in soil and crop sensing for enhanced data-driven decision making in precision agriculture

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Abstract

The integration of advanced soil and crop sensing technologies with data-driven strategies is revolutionising precision agriculture, addressing urgent global challenges such as increasing food demand and sustainability. Recent advancements in both proximal and remote sensing methods, including electromagnetic, optical, thermal and LiDAR systems, are enhancing the ability to assess soil status, moisture levels, nutrient availability and crop development. Moreover, the innovative application of artificial intelligence (AI), machine learning (ML) and the Internet of Things (IoT) is transforming raw sensor data into actionable insights, enabling more efficient irrigation, optimised nutrient management and improved yield prediction. These technologies are improving operational efficiency considerably by limiting the wastage of resources, lowering labour needs and allowing for timely interventions. Notably, multispectral and hyperspectral imaging are being applied for crop health monitoring, AI-driven pest detection and biomass estimation using 3D modelling advancing sustainable, data-driven precision agriculture. However, despite these promising developments, challenges remain, including difficulties in calibration, system interoperability and the high costs associated with implementation. Therefore, this review addresses the need for standardized methodologies, user-friendly tools for farmers and scalable AI solutions to enhance adoption. Ultimately, by aligning cutting-edge technology with practical agricultural needs, these innovations pave the way for more climate-resilient, productive and sustainable smart farming practices.

Keywords: artificial intelligence, crop monitoring; crop sensing, precision agriculture; soil and crop monitoring; smart farming; sensor technology

Introduction

At present, agriculture faces several critical challenges related to soil and crop management. These include soil degradation due to intensive cultivation, the excessive and improper use of chemical pesticides and fertilizers that diminish soil fertility and biodiversity and the rising problems of soil salinity and erosion. These issues are further expected to worsen under the impacts of climate change. Poor irrigation leads to waterlogging and loss of nutrients; while cultivating the same crops every season drains the soil and weakens the plants to diseases and pests. Most of farmers are reluctant to embrace sustainable methods like crop rotation, cover crops and precision agriculture, resulting in productivity problems. Emerging pest threats and unpredictable weather patterns further complicate crop management.

Integrating advanced sensor technologies into agriculture has become essential due to increasing global food demands and environmental concerns. In this context, Precision agriculture emerges as a pivotal approach, as it combines advanced hardware and software technologies to enable data-driven decision-making. This facilitates optimised and targeted practices in planting, fertilisation, pest management and harvesting. By leveraging real-time data and analytics, the approach not only maximises resource use but also enhances productivity and strengthens overall farm management for sustainable agriculture (1).

Furthermore, modern agriculture increasingly relies on precision farming because it offers multiple advantages not just for productivity and sustainability, but also for profitability and food security. Its implementation allows farmers to reduce expenses while improving operational efficiency, often yielding rapid financial returns (2). At the core of this approach lies data-driven decision-making, which enables farmers to act promptly, accurately and effectively. By Combining real-time analysis with historical data through AI-driven insights offers farmers valuable decision support during the production cycle.

Although the potential of precision farming remains strong, challenges such as high implementation costs, connectivity limitations and complex data management persist. Nonetheless, by integrating data from sources like satellite imagery, drones, soil sensors and weather stations, farmers can monitor field conditions in real time. Moreover, historical data enhances crop planning, risk analysis and yield forecasting. Wider adoption will ultimately depend on supportive policies including financial incentives, standardized data protocols and comprehensive farmer training programs (3).

Soil and crop sensing technologies serve as the foundation of precision crop management, offering essential insights into soil health, crop conditions, growth dynamics and environmental variables. As a fundamental component of agriculture, soil directly influences nutrient availability, water retention and overall plant productivity. Understanding soil conditions is therefore essential for effective crop management and sustainable land use. Soil sensing technology has emerged as a core element of modern precision farming. It utilizes advanced sensors to measure key soil parameters such as moisture, temperature, pH, salinity and nutrient levels (4). These sensors, operate based on physical and chemical principle including electrical conductivity, dielectric behaviour and thermal response deliver accurate, real-time information on soil conditions.

Crops are central to agricultural systems, serving as key sources of food, animal feed and raw materials for industry. To ensure optimal yields and maintain food security, it is essential to monitor crop health, growth stages and stress responses. Rising global demand-driven by population growth, urbanization and changing dietary patterns-has made enhancing crop productivity more urgent than ever (5). Consequently, crop sensing technology has gained prominence in modern agriculture, enabling more precise crop monitoring and control. This technology employs multispectral and hyperspectral sensors, thermal imaging and LiDAR mounted on drones, satellites, or ground platforms to assess chlorophyll content, canopy temperature, biomass and nutrient status (6). By analysing light reflectance and thermal emissions, these tools detect subtle changes in plant health. As agriculture becomes more climate-smart and data-driven, crop sensing continues to play an increasingly central role in achieving sustainable and resilient farming systems (7).

Conventional soil and crop surveillance has traditionally relied on manual labour, visual inspections and basic equipment. These methods typically involve collecting soil samples for laboratory testing (e.g., phosphorus, nitrogen, potassium content, pH), visually examining crops for pests or nutrient deficiencies and traversing fields using tools such as hand lenses. Weather stations, while useful for recording temperature, humidity and precipitation, often lack real-time updates and broad spatial coverage (8). Although these traditional practices remain applicable, they are labour-intensive, time-consuming and less precise compared to modern alternatives. Their reliance on human observation introduces inconsistency and limits the amount and frequency of actionable data, potentially delaying critical interventions.

Conversely, sensing technologies are transforming agriculture by allowing real-time monitoring, predictive analytics and site-specific management enabling a transition away from traditional to more precise, efficient and sustainable practices. Technologies such as soil sensors, crop sensors, weather sensors and remote sensing devices now collect real-time data on soil moisture, nutrient levels, crop health and environmental conditions (9). This supports site-specific management, allowing targeted application of water, fertilizers and pesticides, which reduces input costs and environmental impact. Additionally, early detection of crop stress, disease and pests enables timely interventions. When combined with GPS, IoT and analytics, these technologies enhance decision-making, resource use and yield forecasting, aligning with the goals of climate-smart, data-driven agriculture.

This review aims to provide a concise and up-to-date overview of recent advancements in soil and crop sensing technologies that support data-driven decision-making in precision agriculture. It explores how various sensing instruments, including both proximal and remote sensors, are employed to monitor soil and crop health. Furthermore, it examines how these sensing technologies are increasingly integrated with data analytics and machine learning to improve input efficiency, enhance crop health monitoring and enable accurate yield forecasting. In addition, the review consolidates findings from recent studies, technological advancements and real-world applications to inform researchers, policymakers and farmers alike. It highlights a wide range of sensing technologies from electromagnetic and optical systems to thermal and LiDAR tools while also emphasizing the role of intelligent technologies such as Artificial Intelligence (AI), the Internet of Things (IoT) and decision-support systems in transforming raw sensor data into actionable insights. Finally, the review addresses practical challenges like data quality and adoption barriers and outlines future research directions for building more climate-smart and efficient agricultural systems.

Methodology

Literature search strategy

Systematic review was performed according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to find studies on recent trends in soil and crop sensing technologies applicable to precision agriculture. The literature search aimed at peer-reviewed research articles published between 2021 to 2025, involving soil and crop sensing using new technologies like proximal, remote and in-situ sensing and integrating with Artificial Intelligence (AI) and Machine Learning (ML) for data-driven decision support in agriculture.

The search accessed three leading academic databases Scopus, Web of Science and Google Scholar to provide the most extensive coverage of recent progress. The review also pinpointed gaps among soil and crop sensing streams of research, potential integration possibilities in the future and constraints of existing practices.

Search queries

The literature search utilized Boolean operators, keyword searches in the Title, Abstract and Keywords fields and backward citation tracing.

Scopus search query

(TITLE-ABS-KEY ("soil sensing" OR "crop sensing" OR "proximal sensing" OR "remote sensing" OR "in-situ sensing") AND TITLE-ABS-KEY ("emerging technology" OR "AI" OR "machine learning" OR "precision agriculture") AND PUBYEAR > 2020 AND PUBYEAR < 2026) AND (LIMIT-TO (DOCTYPE, "ar") AND (LIMIT-TO (LANGUAGE, "English")))

Web of Science search query

TS= ("soil sensing" OR "crop sensing" OR "remote sensing" OR "proximal sensing") AND

TS= ("AI" OR "machine learning" OR "data-driven" OR "precision agriculture") AND

PY= (2021-2025) AND DT= ("Article") AND LA= ("English")

Google scholar keywords: *"soil sensing; crop monitoring; precision agriculture; smart farming; hyperspectral imaging"*

Study selection and screening

The preliminary search resulted in 437 papers, which were screened for relevance using the following criteria:

The inclusion criteria were as follows: i) Studies focused on emerging soil and crop sensing technologies, ii) Research integrating sensing data with AI/ML algorithms for decision-making. iii)Peer-reviewed empirical articles published in English from 2021 to 2025.

The exclusion criteria were as follows: i) Duplicate or irrelevant studies, ii) Review articles without original data or methodology, iii) Studies not focused on agricultural applications.

After screening, 111 articles were selected for in-depth review. Among them, 37 articles are concerned with soil sensing, including instruments that quantify moisture, nutrients, pH and organic matter. 20 articles address crop sensing, including the imaging methods multispectral, hyperspectral, thermal and LiDAR. 10 articles address data analysis and machine learning, demonstrating how AI facilitates the interpretation of sensor data. 27 papers emphasize applications in real life, including fertilizer application, irrigation, crop tracking and yield estimation. The final 8 papers emphasize emerging trends like sensor fusion, sharing of data and future prospects in smart agriculture.

Soil sensing technologies

Soil sensing technologies have undergone remarkable advancements in recent years, significantly transforming how farmers monitor and manage soil health. These innovations provide critical insights into various soil parameters, including moisture levels, nutrient content, compaction and other factors essential for crop growth and productivity (10). Different sensors operate based on diverse scientific principles: electromagnetic wave-based sensors measure moisture via dielectric permittivity, electrochemical sensors evaluate pH and nutrient concentrations through ion-selective membranes, optical spectroscopy detects organic matter composition and mechanical resistance tools assess soil compaction (11-14). As a result, they enable real-time, accurate monitoring of soil conditions, supporting optimized decisions while minimizing environmental impact.

Soil sensing technologies are a foundational component of precision agriculture, enabling a shift from traditional practices toward data-driven and sustainable approaches. By providing precise information, it helps avoid over- or under-application of water and agrochemicals, thereby reducing input costs and mitigating environmental harm. Additionally, real-time monitoring facilitates early detection of soil degradation, allowing timely interventions to preserve soil health. Fig. 1 illustrates key categories of advanced soil sensing technologies for precision agriculture. Advanced soil sensing technologies include proximal, remote and moisture sensing. Proximal tools like EC sensors and pH

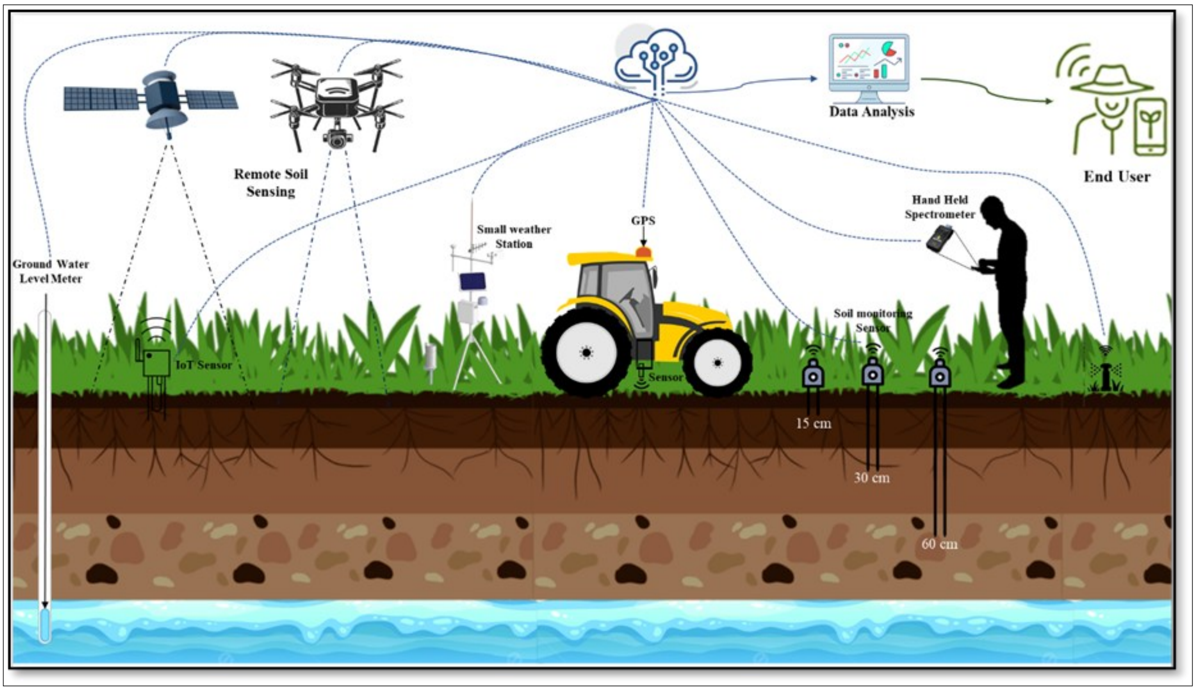

Fig. 1. Overview of advanced soil sensing technologies for precision agriculture.

probes give accurate soil data in the field. Remote sensing uses satellites and drones to monitor large areas. Moisture sensors track soil water levels in real time, helping to improve irrigation efficiency. When integrated with AI, IoT and drone technologies (15), these systems further enhance water and nutrient use efficiency, improve field-level insights and supports sustainable farm management. However, challenges such as soil-specific calibration and high implementation costs remain barriers to widespread adoption.

Proximal soil sensing

Proximal soil sensing (PSS) refers to the direct field measurement of soil properties using ground-deployed sensors that either make physical contact with the soil or operate in close proximity to it (16). Common technologies include electrical methods such as Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR) and capacitance sensors, as well as optical spectroscopy (Visible-Near Infrared [Vis-NIR], Laser-Induced Breakdown Spectroscopy [LIBS]), electrochemical analysis and mechanical resistance probes (17-19). As a result, PSS serves as a powerful tool for precision agriculture and sustainable land use management by offering detailed on-site soil characterization. Facilitating site-specific management that minimizes input overuse, enhances soil health and increases crop productivity.

TDR, FDR and capacitance sensors are commonly used to measure soil moisture, salinity and texture based on the soil's electrical conductivity. Optical sensing methods such as Vis-NIR and Mid-Infrared (MIR) spectroscopy, along with LIBS, provide non-destructive analysis of organic matter and macronutrients (N, P, K). Electrochemical sensors equipped with ion-selective electrodes monitor soil pH and nutrient ions (e.g., NO^{3-}, K^{+}), aiding in precise fertilization (13, 20, 21). Mechanical sensors like penetrometers evaluate soil structure, while acoustic and thermal sensors assess porosity and water flow patterns through sound and heat transfer (22). Integrated with wireless IoT platforms, these technologies support real-time, autonomous monitoring systems, offering instant, minimally invasive measurements though they still require precise calibration for varying soil types and conditions and although initial expense may be considerable, the ease of availability of portable versions as well as government subsidy makes them progressively more viable for smallholder farmers.

Remote soil sensing

Remote soil sensing refers to the application of satellite, airborne and drone-based technologies to monitor and assess soil conditions from a distance, without requiring direct physical contact. This method offers the advantage of rapid, large-scale data acquisition, which is particularly valuable for modern, data-driven agricultural practices. Fig. 2 illustrates how remote sensing aids in measuring soil characteristics such as texture, moisture and erosion. It begins with data acquisition and analysis, followed by providing the information for maps, decision-support tools and research. The process enables intelligent, sustainable farming through precise real-time soil measurement and enlightened decision-making, enabling timely diagnosis of issues such as nutrient deficiencies and water stress, as well as enhanced timing and accuracy of interventions. One prominent technique involves hyperspectral imaging via

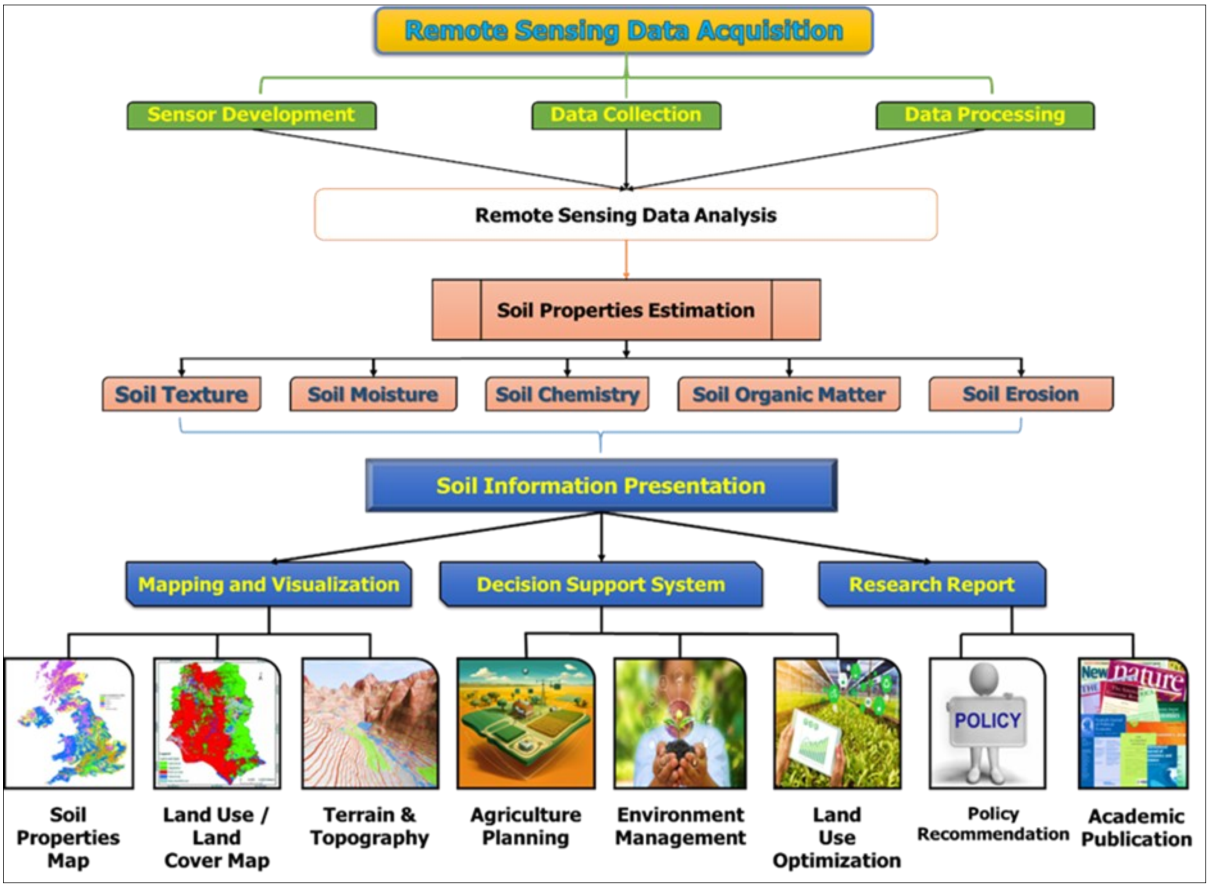

Fig. 2. The schematic framework encompasses the use of remote sensing techniques, the interpretation of data and their applications in soil measurements.

satellites or aircraft, which captures detailed spectral reflectance data in the visible and near-infrared (VIS-NIR) spectrum. This spectral data is analysed to estimate vital soil properties such as organic carbon, moisture content and mineral composition, facilitating the creation of detailed soil maps and improving land-use planning and crop management (23).

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution optical sensors provides localized, high-frequency monitoring of soil and crop condition. These sensors detect subtle changes in soil and plant conditions, allowing for the early identification of nutrient deficiencies, moisture stress, or pest issues (24). Additionally, electromagnetic induction (EMI), which measures soil electrical conductivity, is highly effective in mapping soil salinity and texture. When combined with digital soil models (DSM), EMI enhances predictive soil mapping and supports precise agricultural interventions (25). Thermal infrared (TIR) sensors also play a key role, measuring surface temperature variations that correlate with evaporation rates and soil moisture levels, thus aiding irrigation planning and drought detection (26).

Furthermore, remote sensing supports time-series analysis, enabling continuous monitoring of soil condition changes throughout the growing season. This temporal data assists in the early detection of land degradation, compaction and fertility shifts, facilitating timely corrective actions (27). The integration of machine learning algorithms significantly improves the interpretation of complex spectral and geospatial datasets, enhancing soil classification, nutrient forecasting and anomaly detection accuracy. When linked with geographic information systems (GIS), these platforms visualize spatial variability and inform site-specific strategies (28). Satellite imagery systems such as Sentinel-2 and Planet Scope are important for real-time monitoring of farm irregularities through regular high-resolution images that assist in recognizing initial indications of crop stress, disease epidemics, nutrient shortages and waterlogging (29) and with satellite imaging freely available, low-cost drones and mobile apps, remote sensing has been democratized for farmers, particularly through service-based models that do away with the requirement to invest in costly equipment.

Soil moisture sensing

Soil moisture sensing employs a range of techniques to determine the quantity and availability of water in the soil, serving as a cornerstone of precision farming. This technology enables continuous and accurate monitoring of soil water content, which is crucial for guiding irrigation practices and supporting optimized plant growth, water conservation and enhanced yields (30). By using real-time data from soil moisture sensors, farmers can make informed decisions on when and how much to irrigate, leading to cost savings and reduced environmental impact key goals of sustainable agriculture. Moreover, advancements in sensor miniaturization, wireless communication and IoT integration now allow these sensors to transmit real-time data to mobile devices or cloud-based systems. An insights soil and crop sensing technologies and their roles in precision agriculture is presented in Table 1. As a result, automated irrigation systems can adjust water application dynamically, thereby transforming traditional irrigation into site-specific, efficient and climate-resilient water management.

Soil water content monitoring incorporates several innovative methods to measure water availability in both crops and environmental systems. Among these, dielectric techniques such as Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR) and capacitance sensors operate by detecting changes in soil dielectric permittivity, which closely correlates with water content (31). These contact-based sensors deliver precise, real-time data, making them essential for efficient irrigation scheduling. Furthermore, electrical resistivity tomography builds on this by generating detailed 2D and 3D moisture maps through subsurface conductivity measurements, making it ideal for root zone analysis. At larger scales, microwave remote sensing via satellites like SMAP and Sentinel-1 measures surface soil moisture (0-5 cm depth) using radar backscatter analysis, thereby supporting global drought monitoring and climate modelling efforts (32). Although neutron probes offer accurate water content estimation through hydrogen density detection, their use has declined due to radiation safety concerns. Meanwhile, tensiometers remain valuable for assessing soil water potential. With recent advances, these technologies are increasingly integrated with IoT and machine learning, forming a powerful, multi-scale toolkit that supports precision agriculture, hydrological forecasting and sustainable water resource management (33). These technologies enhance irrigation by minimizing water loss and increasing yields. Accessible sensors such as TDR and tensiometers, along with IoT, enable accurate irrigation to be simple and affordable for most farmers.

Crop sensing technologies

Crop sensing technologies have increasingly emerged as indispensable tools for modern agriculture, as they offer farmers unprecedented insights into crop health, growth dynamics and environmental conditions. Fig. 3 presents advancements in these technologies, showcasing various tools that enhance crop management. By integrating advanced sensors, imaging techniques and data analytics, these systems allow for precise crop monitoring and informed decision-making to optimize yields and resource efficiency (10).

Multispectral imaging

Multispectral imaging is an integral part of contemporary crop sensing technology, allowing for precise and non-destructive monitoring of plant health. It allows for high-level plant condition detail to be provided in a form useful for optimizing the use of inputs such as fertilizers and water while maximizing decision support for sustainable agriculture. The technology records reflectance information in several broad spectral bands, commonly red, green, blue, near-infrared (NIR) and red-edge. Because it is economical and easy to integrate, multispectral imaging has found extensive application on various platforms like drones, satellites (e.g., Sentinel-2, Landsat 8) and handheld platforms (47). It also facilitates calculation of vegetation indices such as NDVI, NDWI, SAVI and GNDVI, which are critical for assessing crop health and performance. The indices enable detection of early warning signs of pest, disease, or drought stress, enable site-specific irrigation and fertilization and aid in biomass and yield estimation. Consequently, multispectral imaging has

Table 1. Comparative overview of advanced soil and crop sensing technologies and their applications in precision agriculture

Sensor Name	Sensor Type	Principle Mechanism	Power/ Energy	Working Mechanism	Specifications	Limitations	Evaluation Technique	Target Application	Platform	Accuracy	Deployment Time	Reference
Teralytic Wireless Soil Sensor	In-situ (IoT-based)	Electrochemical, dielectric	Battery (3–5 years)	Probes measure NPK, moisture, salinity	Depth: 30 cm, LoRaWAN	Limited to 3 major nutrients	±5 % deviation	Soil fertility, irrigation	Wireless IoT node	±5 % moisture	<30 min	(34)
Veris P4000 EC Sensor	Proximal (on-the-go)	Electrical Conductivity (EC)	Vehicle-powered	Electrodes measure EC on-the-go	Depth: 0–90 cm, 10 Hz rate	No direct nutrient detection	EC map accuracy >90 %	Soil salinity, texture profiling	Tractor-mounted	High	1–2 hrs	(35)
Hyperscout 2 (H2)	Remote (satellite/UAV)	Hyperspectral imaging	Solar-powered	Reflectance-based imaging	40+ bands, 5–30 m spatial res	High cost, data processing complexity	RMSE <10 % for OM estimation	Organic matter, soil moisture	Satellite or drone	High	N/A	(36)
ThetaProbe ML3	In-situ	Dielectric permittivity	Low power	Time Domain Reflectometry (TDR)	Depth: 6 cm, ±1 % VWC	Measures only moisture/temp	±1 % VWC accuracy	Soil moisture monitoring	Stationary probe	±1 % VWC	<30 min	(37)
AgriFlect SpectraVue	Proximal (on-the-go)	VIS-NIR-SWIR spectroscopy	Battery-powered	Spectral reflectance	1 nm resolution, 1–5 cm spot size	Sensitive to surface condition	$R^2 > 0.9$ for organic carbon	Organic carbon, pH mapping	Tractor-mounted	High	1 hr	(38)
Sentek Drill & Drop	In-situ (profile probe)	Capacitance (dielectric)	Solar/ Battery	Multi-depth capacitance sensing	Depths: 10–100 cm, modular design	Soil-specific calibration	±2 % VWC accuracy	Soil moisture, temp profile	IoT probe	±2 % VWC	1–2 hrs	(39)
MicaSense Altum-PT	Remote (drone-based)	Multispectral + thermal radiometry	UAV battery	Radiometric capture + thermal overlay	5 cm/pixel (flying height dependent)	Limited to surface-only data	NDVI accuracy >95 %	Crop stress, thermal profile	UAV (drone)	High	Flight-based	(40)
SoilOptix γ-ray Sensor	Proximal (gamma sensor)	Natural gamma-ray spectroscopy	Vehicle-powered	Detects gamma rays from soil elements	20 m spatial resolution	Requires slow movement	Lab correlation >90 %	Mapping K, Th, U, soil texture	Tractor or ATV	High	~2 hrs	(41)
Arable Mark 3	In-situ (multi-sensor)	Multispectral + environmental	Solar-powered	Combines reflectance + climate/weather	5–10 min sampling interval	Shallow soil coverage	Combines crop & soil accuracy	Irrigation scheduling, crop health	IoT weather-station style	Moderate	<30 min	(42)
CropX Soil Sensor	In-situ (wireless IoT)	Capacitance + EC	Battery (replaceable)	Moisture + salinity monitoring	Depth: 10–30 cm, auto-calibrating	Limited to upper soil horizon	$R^2 > 0.85$ for moisture/ salinity	Moisture, salinity	Wireless probe	Moderate	<30 min	(43)
PNT SoilCheck	Proximal (handheld)	Ion-selective electrodes	Rechargeable battery	Ion sensors for N, P, K	3–5 minute reading per point	Sensitive to probe fouling	±10 % accuracy	Instant nutrient measurement	Handheld	Moderate	Instant	(44)
Trimble Soil Information System (SIS)	Proximal (vehicle-based)	EC, GPR, soil resistivity	Vehicle-powered	Array of sensors for profiling	Multi-sensor platform	Expensive, heavy equipment	>90 % EC/GPR correlation	Full soil profiling	Tractor-mounted	High	~4 hrs	(45)
Terras entia Rover	Remote (ground robot)	RGB, LiDAR, multispectral	Battery-operated	Ground scanning for traits & soil/ plant data	2–5 cm spatial resolution	Best for structured rows	Variable, trait-specific	Soil & plant interaction	Ground robot	High	Depends on route	(46)

IoT	Internet of Things	VIS	Visible Spectrum
NPK	Nitrogen, Phosphorus, Potassium	SWIR	Short-Wave Infrared
LoRaWAN	Long Range Wide Area Network	UAV	Unmanned Aerial Vehicle
EC	Electrical Conductivity	NDVI	Normalized Difference Vegetation Index
OM	Organic Matter	K, Th, U	Potassium (K), Thorium (Th), Uranium (U)
RMSE	Root Mean Square Error	GPR	Ground Penetrating Radar
NIR	Near-Infrared	RGB	Red, Green, Blue (color channels in imaging)
R^2	Coefficient of Determination	LiDAR	Light Detection and Ranging
TDR	Time Domain Reflectometry	SIS	Soil Information System
VWC	Volumetric Water Content		

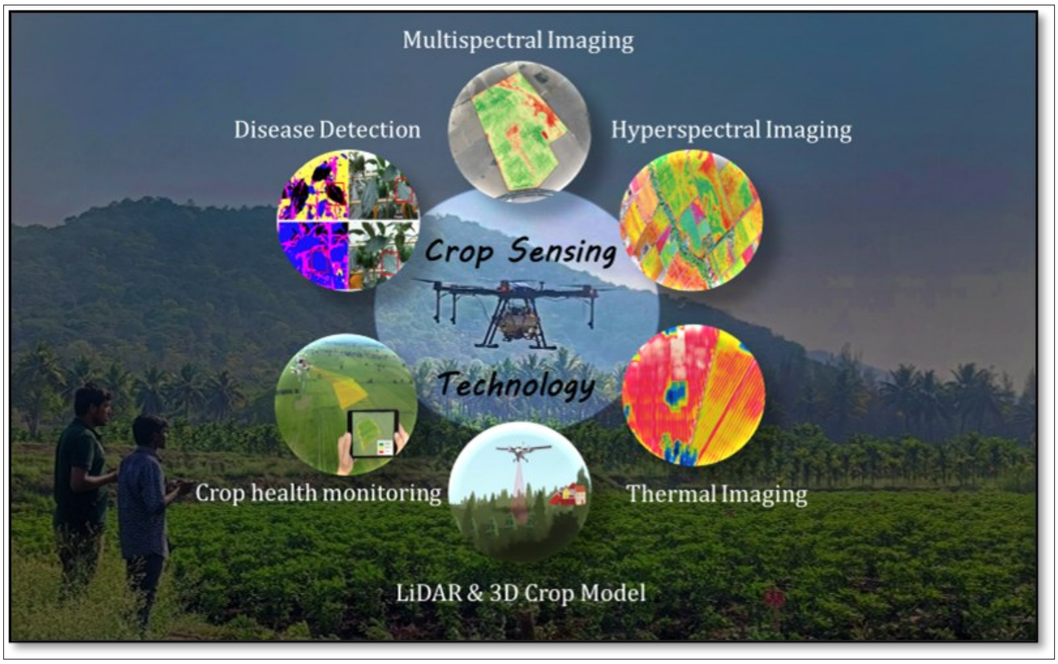

Fig. 3. Emerging trends in crop sensing technologies.

become core to data-driven agriculture by enabling timely, accurate information for enhanced productivity and sustainability (48).

Hyperspectral imaging

Conversely, hyperspectral imaging collects reflectance information in hundreds of contiguous, narrow spectral bands, with much greater spectral resolution. This facilitates the identification of subtle plant physiological and biochemical changes that are frequently beyond the range of multispectral sensors (49). In comparison to multispectral imaging, it provides finer detail, making it highly suitable for advanced agricultural applications. Through this technology, accurate analysis of leaf pigments such as chlorophyll and carotenoids, as well as precise measurement of nutrient levels like nitrogen and phosphorus, becomes possible along with the early detection of diseases and pest infestations, often before visible symptoms appear (50). Although more complex and costly, hyperspectral imaging significantly enhances precision agriculture by enabling highly targeted, timely interventions that support sustainable practices, optimize inputs and strengthen crop resilience under climate and environmental stress.

Thermal imaging

The continuous deployment of fixed or UAV-borne sensors of air and soil temperature e.g., ATMOS 41, TEROS 12 and CropX System has increasingly proved their importance in simulating crop evapotranspiration (ET), a combined process of water evaporation from the soil and plant transpiration. These continuous sensors also aid disease forecasting by making it possible to continuously monitor microclimatic factors that affect pathogen development (51). In this context, thermal imaging, which measures infrared radiation emitted by objects based on temperature, becomes especially valuable. Since healthy plants generally exhibit cooler leaf temperatures than stressed ones, thermal patterns reveal water stress, nutrient deficiencies, or pest infestations (52), enabling farmers to optimise irrigation and implement precise pest management strategies (53).

LiDAR (Light Detection and Ranging)

LiDAR is a remote sensing technology that determines distances by emitting laser pulses and calculating the time taken for their return. As a result, LiDAR sensors generate three-dimensional point clouds, which enable highly precise measurements of crop height, canopy structure and biomass (54). This data can be employed to estimate biomass, monitor canopy architecture and evaluate plant height variability within fields. By analysing these LiDAR-derived metrics, farmers can make informed decisions to optimise planting density, assess crop growth patterns and predict yield potential (55).

3D crop model

Building on the detailed spatial data provided by LiDAR, 3D crops models represent a cutting-edge advancement in crop sensing, offering high structural detail by reconstructing crops in three dimensions. These models are developed using data from LiDAR sensors, RGB or multispectral cameras and photogrammetry or Structure-from-Motion (SfM) techniques mounted on drones or ground platforms. Unlike traditional 2D imagery, 3D models provide accurate representations of canopy height, volume and plant architecture, which are critical for determining biomass, crop growth stages and spatial variability. Furthermore, when integrated with spectral data, they support early detection of crop stress, disease, or lodging by identifying physical abnormalities (56). Ultimately, 3D crop modelling significantly enhances yield prediction and enables precise, variable-rate input application, making it a cornerstone of digital and sustainable agriculture (57).

Crop health monitoring

Crop monitoring through sensing technologies plays a pivotal role in precision agriculture by enabling real-time, accurate and non-destructive evaluation of crop growth and health. Through remote platforms such as satellites, drones (UAVs) and ground-based sensors, spectral and spatial data from agricultural fields are continuously collected and processed. This information is crucial for assessing crop development, detecting stress factors such as drought, nutrient deficiency, or disease and facilitating informed, site-specific management decisions. Among the key analytical tools used in remote crop monitoring are vegetation indices, which provide critical insights into plant vitality and environmental conditions.

Commonly used indices include:

- NDVI (Normalized Difference Vegetation Index) is widely employed to assess plant greenness and vigor by comparing reflectance in red and near-infrared wavelengths; higher NDVI values typically indicate healthier vegetation (58).
- NDWI (Normalized Difference Water Index) helps evaluate plant water content, offering an effective tool for identifying drought stress and guiding irrigation strategies (59).
- GNDVI (Green Normalized Difference Vegetation Index), a variant of NDVI using the green spectral band, enhances the detection of chlorophyll levels and nutrient deficiencies.
- SAVI (Soil Adjusted Vegetation Index) improves accuracy in regions with sparse vegetation by compensating for soil brightness.

Together, these indices contribute significantly to data -driven crop management. In addition, fluorescence imaging, which measures light re-emitted by plants during photosynthesis, serves as another powerful technique. Healthy plants exhibit strong fluorescence signals, whereas reduced intensity may indicate stress. Consequently, fluorescence imaging enables early detection of nutrient imbalances, pathogen presence, or water stress, supporting timely corrective actions (60, 61).

Disease and pest detection using AI-integrated imaging

Disease and pest identification through AI-aided imaging marks a transformative advancement in smart agriculture, aiming to enhance crop yields and promote sustainability. This approach seamlessly integrates the capabilities of artificial intelligence (AI), remote sensing and image processing to accurately identify plant stress caused by pathogens or pest infestations (33). High-resolution imagery is captured via platforms such as drones, satellites and stationary ground cameras, providing broad spatial and temporal monitoring of agricultural landscapes (62). Such images are examined through AI-based methods, specifically machine learning (ML) and deep learning (DL) algorithms that have been trained using large datasets containing labelled examples of healthy and infected crops.

Through this training, AI systems learn to detect subtle visual cues such as discoloration, wilting, spotting, deformation, or unusual growth patterns that often precede visible symptoms of disease or pest activity. Consequently, early detection becomes possible, even before symptoms are apparent to the human eye. Moreover, AI-powered imaging systems go beyond detection by enabling disease and pest classification and severity quantification (63). This technology lessens the requirement for manual scouting, which is time-consuming, labour-intensive and prone to errors. It delivers interactive field maps and real-time views to farmers and agronomists, enabling accurate interventions.

Some of the most important advantages of AI-based imaging are:

- Early detection of plant stress
- Accurate classification of disease or pest type
- Quantification of severity
- Real-time field mapping for targeted treatment

As a result, pesticide or biocontrol application is localized, reducing input costs and mitigating environmental impact (64).

Growth and yield prediction

Growth and yield forecasting is a critical application of crop sensing technologies in precision agriculture. Devices such as drones, satellites and ground sensors collect real-time data on parameters like canopy cover, plant height and chlorophyll content. Vegetation indices (e.g., NDVI, GNDVI, SAVI) reflect biomass and vigour, which correlate with yield potential (65).

These indicators reflect crop health, vigour and biomass, which correlate closely with growth stages and yield potential. Moreover, by applying machine learning and artificial intelligence algorithms to this data, it becomes possible to simulate and forecast crop growth patterns. Consequently, analysing temporal and spatial crop variations helps detect stress factors like nutrient deficiencies, water stress, or disease effects, allowing timely interventions (66). Furthermore, combining historical climate and soil data with real-time sensing inputs significantly enhances yield prediction accuracy. The performance of different crop phenotyping and sensing technologies is assessed and thoroughly outlined in Table 2.

Data analytics and machine learning

Data pre-processing and feature extraction

In crop and soil sensing, feature extraction and data pre-processing are essential steps, where automated data cleaning removes noise and outliers from spectral, LiDAR and IoT sensor data. Moreover, multisensory fusion integrates inputs from drones, satellites and ground sensors to enhance accuracy, while dimensionality reduction techniques like Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) simplify complex data by selecting the most important features for effective modelling (67). Additionally, edge computing processes data locally on devices near the sensors, enabling faster, real-time decisions compared to cloud computing, which relies on remote servers. This thorough pre-processing and integration lead to more accurate detection of crop stress or precise soil mapping, supporting timely and targeted interventions in the field.

Machine learning algorithms for soil and crop classification

Machine learning algorithms are revolutionizing soil and crop categorization through a variety of advanced methods. For instance, supervised learning techniques such as Support Vector Machines (SVM) (68) and Random Forest (69) utilize hyperspectral data to accurately classify soils and assess crop health. For instance, SVMs have already been employed to classify the various forms of soil pollution or to identify

Table 2. Performance evaluation of different crop phenotyping and sensing technologies

Sensor Name	Sensor Type	Principle Mechanism	Power	Spectrum/Data	Working Mechanism	Specifications	Limitations	Evaluation	Target Crop Parameter	Accuracy
FluorPen FP110	In-situ	Chlorophyll Fluorescence	Battery-operated	Chlorophyll index (Fv/Fm)	Measures fluorescence to detect stress	Handheld, <1 min read time	Point-based, small area coverage	Visual + stress mapping	Plant stress, photosynthetic activity	>90 % for stress detection
CropCircle ACS-470	Proximal (on-the-go)	Active spectral reflectance (VIS-NIR)	Vehicle-powered	Red, Red-edge, NIR	Measures vegetation indices from moving vehicle	1–3 m canopy height, 3 bands	Sensitive to canopy uniformity	NDVI, NDRE	Nitrogen status, chlorophyll	$R^2 = 0.88$ for LCC
FieldScan 3D	Stationary scanner	3D LiDAR + Multispectral	AC-powered	LiDAR + VIS/NIR	Scans crop rows for volume, height, leaf area index	Millimeter accuracy, multi-row	Expensive, fixed station	Height and LAI comparison	Biomass, canopy structure	RMSE < 5 % for height estimation
PhenoCam Network	Remote (camera)	RGB time-lapse imaging	Solar/Battery	RGB	Timelapse captures crop greenness changes	Daily/Hourly capture, web-enabled	Influenced by lighting/ clouds	Gcc (Greenness Index)	Vegetative index, senescence	Seasonal trends validated
Matrice 300 + RedEdge-MX	UAV (drone)	Multispectral Imaging (5 bands)	Drone battery	Blue, Green, Red, RE, NIR	UAV flights collect reflectance data at high resolution	5 cm/pixel @ 100 m, 16-bit radiometry	Limited by battery & weather	NDVI, NDRE, VARI	Plant health, variability	$R^2 > 0.9$ for vegetation indices
FluorCam FC 800-C	Controlled lab/ greenhouse	Chlorophyll kinetic imaging	AC-powered	Fluorescence (PSII)	Visualizes chlorophyll fluorescence dynamically	Camera + LED panels	Not field-portable	FV/FM, NPQ analysis	Stress response, photosynthesis	Subcellular resolution accuracy
SpectroSense2+ GPS	Handheld Proximal	Sunlight reflectance + GPS	Rechargeable	VIS-NIR (4–6 bands)	Measures canopy indices along transect	1 Hz sampling, GPS -integrated	Operator variation risk	NDVI, PRI	LAI, chlorophyll, N-content	$R^2 \sim 0.85$ with SPAD
CropQuant Platform	IoT + Imaging	RGB + Env. sensors + AI	Solar-powered	RGB, humidity, temp	Time-series images + sensors + ML for trait analysis	Raspberry Pi-based, cloud connected	Requires strong connectivity	DL/ML trait detection	Crop growth rate, flowering	80–90 % for stage classification
Agremo AI Analysis	SaaS (Drone Imaging)	AI on multispectral/NDVI maps	N/A	VIS-NIR/NDVI	Upload aerial maps, AI counts plant, detects issues	Platform agnostic	Needs drone input, subscription	ML-based validation	Plant count, vigor, stress	>90 % plant count accuracy
TerraSentia Phenotyping Robot	Autonomous Ground Robot	RGB + LiDAR + AI	Battery-powered	3D + RGB	Travels between rows collecting plant height, width, greenness	Field-navigable, multi-sensor	Large row spacing needed	Manual validation + ML	Plant traits, vigor	RMSE < 5 cm in canopy metrics

VIS	Visible Spectrum	PSII	Photosystem II
NIR	Near-Infrared	FV/FM	Maximum Quantum Efficiency of
RE	Red Edge	NPQ	Non-Photochemical Quenching
NDVI	Normalized Difference Vegetation Index	PRI	Photochemical Reflectance Index
NDRE	Normalized Difference Red Edge	SPAD	Soil Plant Analysis Development
VARI	Visible Atmospherically Resistant Index	AI	Artificial Intelligence
LCC	Leaf Chlorophyll Content	DL	Deep Learning
LAI	Leaf Area Index	ML	Machine Learning
Gcc	Green Chromatic Coordinate (Greenness Index)	SaaS	Software as a Service
UAV	Unmanned Aerial Vehicle	GPS	Global Positioning System
RGB	Red, Green, Blue	RMSE	Root Mean Square Error

certain diseases in crops such as wheat rust using spectral data. In contrast, unsupervised methods like K-means and DBSCAN (70) clustering analyse unlabelled data to uncover hidden patterns in soil moisture and fertility, generating insights without prior labelling. Furthermore, transfer learning (a method where one models trained on one task are re-purposed to execute a similar task by minimizing the amount of large, labelled data) improves model performance by adapting pre-trained networks (e.g., ResNet) to new agricultural datasets, even with limited labelled samples, thereby saving training time and boosting accuracy. Additionally, Explainable AI tools like SHAP values (71) (SHAP: Shapley Additive explanations, an interpretation and explanation method for the contribution of every feature to predictions made by the model) offer transparent model interpretations, empowering agronomists to trust and act on AI-driven recommendations.

Regression analysis for yield prediction and nutrient management

Regression analysis plays a central role in yield estimation and nutrient application by enabling informed agricultural decision -making. Forecasting models such as linear regression, XGBoost and Gaussian Processes analyse soil properties and weather patterns to predict yields with high accuracy (72). For example, XGBoost was utilized to make predictions on rice output using multisource data such as soil nutrients and rain, typically with over 90 % accuracy. Additionally, geospatial regression models support precision fertilizer mapping by identifying optimal application zones, thereby enhancing efficiency and reducing environmental risks. Time series prediction using LSTM networks, which are optimized to work with sequential information, has been employed to predict maize yields according to long-term weather and soil patterns to enable farmers to better plan ahead for forthcoming seasons (73). Moreover, IoT-based recommendation systems utilize real -time sensor data to provide instant nutrient adjustment suggestions (74). These tools can trigger automated alerts when nutrient levels fall below thresholds, ensuring timely interventions. Together, these regression-based strategies enhance productivity, ensure precise nutrient management and promote sustainable farming through advanced analytics and machine learning.

Deep learning application in soil and crop sensing

Deep learning is significantly transforming soil and crop sensing by offering advanced analytical capabilities. For instance, Convolutional Neural Networks (CNNs) analyse high -resolution satellite and drone imagery to detect crop diseases, weeds and nutrient deficiencies with remarkable precision. For instance, CNNs have been employed to detect early blight in potato fields from aerial photos using drones, facilitating timely intervention and minimizing yield loss. Additionally, Generative AI methodologies, such as Generative Adversarial Networks (GANs), composed of two competing neural networks working on generating realistic fake data, solve the problem of sparse data by creating synthetic examples for underrepresented crop conditions, thus improving the robustness of the model (75). In parallel, 3D crop modelling utilizes LiDAR-derived point cloud data to assess plant structure, growth patterns and biomass with unprecedented detail. Additionally, AutoML techniques like neural architecture search (NAS), which automatically design and optimize deep learning models without manual tuning, streamline the development of optimized deep learning models for agriculture (76). Collectively, these innovations elevate monitoring accuracy, enable early threat detection and support smarter, resource-efficient precision farming.

Application of soil and crop sensing

Soil health and conservation tillage

Current agriculture increasingly depends on soil and crop sensing technologies to enhance both productivity and sustainability. Airborne and satellite hyperspectral sensors (e.g., NASA's Hyperion) allow for discrimination of crop residue cover (CRC) based on indices such as the Cellulose Absorption Index (CAI), which is aimed at lignin and cellulose signatures around 2100 nm. The technique attains >90 % accuracy in tillage intensity classification (77). For instance, hyperspectral reflectance spectroscopy enables non-invasive detection of heavy metals such as Cu, Zn and Cd, as well as soil organic matter, thereby facilitating real-time soil health evaluation (78). These capabilities help assess elemental composition (C, N, heavy metals), aiding precision nutrient management, particularly in reduced-tillage systems.

Machine learning models process this spectral data to predict contamination levels, effectively informing remediation strategies. Simultaneously, soil sensors monitor pH, moisture and nutrient levels, allowing precision nutrient management and minimizing fertilizer losses (79). These advancements also promote the application of organic amendments like compost and biochar, which improve soil structure, boost microbial populations and increase carbon storage (80). Furthermore, conservation tillage practices such as no-till and strip-till reduce soil disturbance, conserve moisture and enhance organic matter retention. Conservation tillage methods such as no-till and strip-till minimize disturbance, conserve moisture and retain organic matter. When paired with cover cropping, they reduce erosion, support nitrogen fixation and promote microbial health (81).

In addition, remote sensing and UAV imagery enable real-time monitoring of soil and crop conditions, while variable-rate technology (VRT) ensures site-specific tillage and residue management (82). Technologies like FieldScan 3D combine LiDAR with multispectral data to assess residue cover and soil roughness, critical for erosion control in conservation tillage systems (83). Drones (e.g., Matrice 300 + RedEdge-MX) capture 5 cm/pixel data to map residue cover and tillage impacts on soil health. AI platforms like Agremo analyse these datasets for plant vigour and residue retention. Long-term research confirms that conservation tillage in diversified cropping systems enhances yield stability and soil resilience (84). Altogether, integrating sensor data with precision agriculture empowers farmers to make informed decisions that reduce input costs, curb soil degradation and ensure long-term agricultural sustainability.

Nutrient management and fertilizer application

The use of soil and crop sensing technologies has become essential for precision nutrient management in agriculture by providing data-driven insights that optimize fertilizer application. Proximal soil sensors measuring parameters such as electrical conductivity (EC), pH and organic matter content allow for detailed mapping of soil nutrient variability. For instance, previous studies demonstrated that EC and NIR -based sensors improved nitrogen prediction accuracy by up to 87 % compared to traditional sampling methods (85). Furthermore, crop sensing through indices like NDVI and NDRE has proven effective in assessing nitrogen status. In NDRE from UAV imagery strongly correlated with rice leaf nitrogen content, enabling accurate mid-season nitrogen recommendations (86) . Similarly, UAV hyperspectral imagery and CNNs to detect nitrogen stress in wheat, achieving 92.6 % classification accuracy (87). Additionally, integrated satellite-derived indices with machine learning to deliver real-time nitrogen advice, boosting yield by 12 % and reducing nitrogen use by 18 % (88) . Moreover, a 25 % reduction in fertilizer costs using sensor-based VRA on cotton farms in Gujarat, India was reported (89).

In another study how hyperspectral imaging combined with machine learning can accurately predict soil nitrogen levels, enabling variable-rate fertilizer application that reduced nitrogen use by 15-20 % while maintaining crop yields (90). Additionally, on-the-go sensor system that monitors soil properties in real-time to support site-specific nutrient decisions. These technologies minimize environmental impact while maximizing nutrient efficiency though challenges such as calibration, data overload and affordability persist (4)

Precision irrigation management

Precision irrigation solutions are transforming agricultural water management through the integration of smart technologies such as Smart Electricity Meters (SEMs), Model Predictive Control (MPC) and IoT-based automation. For example, SEMs, combined with the Electricity-to-Water Conversion Coefficient (E-Wc), enable accurate soil moisture prediction and irrigation control, achieving high prediction accuracy (RMSE: 0.0139-0.0204) while preventing groundwater overextraction in the North China Plain (91). Similarly, data-driven MPC can optimize real-time irrigation scheduling using soil and weather data, improving water distribution efficiency and reducing almond tree water use by 7.9 % without yield loss (92) . The drip irrigation systems cut water use by 35-65 % and when paired with IoT automation, improve water-use efficiency by 20-40 % and increase yields by up to 40 % (93). Fig. 4 provides a visual representation of the interconnected components within an IoT and Machine Learning-driven smart irrigation system

For instance, the previous study created an IoT-based intelligent irrigation system that integrates soil moisture sensors with weather forecasting models to schedule irrigation automatically (94). Their work showed that machine learning-based optimizations based on soil moisture and evapotranspiration could lower water consumption by 30 % compared to traditional methods. In complement to this, former researchers investigated hyperspectral and thermal imaging for the detection of barley crop water stress (95). Through examination of spectral signatures and canopy temperature differences, they mapped drought-stressed regions, allowing for site-specific irrigation that saved 20-25 % of water without affecting yield. Technologies like these are particularly vital in water-deficient areas, where irrigation efficiency needs to be maximized in order to maintain sustainable agriculture.

Despite these advancements, challenges such as high initial costs, data complexity and limited farmer adoption continue to hinder widespread use. Nevertheless, these innovations collectively emphasize the transformative impact of precision irrigation on sustainable agriculture. The previous research demonstrates that machine learning algorithms, including decision trees, random forests and support vector machines, can achieve high accuracy (up to 97.86 %) in estimating irrigation needs, thereby optimizing water use and reducing energy costs (96). Furthermore, the study emphasize the role of AI in real-time soil moisture and weather forecasting, leading to up to 30 % water savings without yield loss (97). Additionally, reinforcement and deep learning methods enhance adaptive irrigation, crop health monitoring and remote management via digital platforms.

Crop

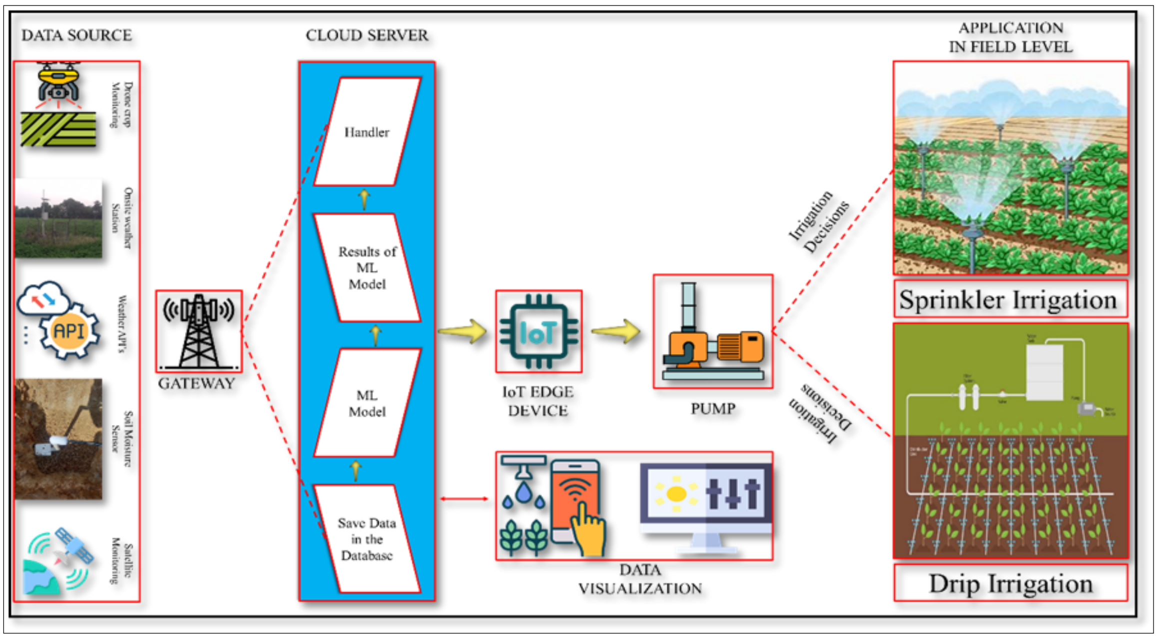

Fig. 4. IoT and machine learning-based smart irrigation system architecture.

monitoring and yield prediction

To boost crop productivity, early and regular disease monitoring is essential; thus, tools like RGB cameras, multispectral sensors, thermography and 3D scanning enable accurate, non-destructive detection at both field and plant levels. Moreover, combining optical and molecular techniques enhances detection efficiency. These sensor-based technologies support precision farming and research (98). Additionally, integrating machine learning with remote sensing improves crop observation and yield prediction, addressing complexities from soil, weather and crop variability. These technologies aim to grow more food, enhance quality and safeguard the environment. By leveraging data from sensors, field observations and historical records, farmers gain insights into how water, fertilizers, pests and diseases impact crops, enabling smarter, more efficient farm management (99).

Furthermore, the previous study demonstrated that integrating the Temperature-Vegetation Index into ML models like XGBR, RFR and SVR improved soil moisture and winter oilseed rape yield predictions, with R^2 reaching 0.773 (100). Similarly, achieved 50-99 % accuracy using Random Forest and CNN, highlighting the value of multi-source data despite challenges in data access and model complexity (101). The application of data-driven methods such as soil analysis, GIS, GPS and variable rate application (VRA) has shown notable success in maximizing crop yields, with case studies from North Dakota and Iowa reporting improved yields and resource conservation (102).

Additionally, the integration of computer vision and AI enables real-time analysis of soil nutrients, disease detection and yield prediction using drones and multispectral imaging, achieving high accuracy rates like 98 % for lettuce yield prediction (103). Moreover, remote sensing, ML models like CNNs and SVMs and multi-modal data fusion significantly boost monitoring precision and predictive capability. Table 3 provides a comprehensive overview of the emerging soil and crop sensing technologies, highlighting their application in yield prediction and management and showcasing their potential to enhance precision agriculture practices. Together, these technologies support anticipatory decisions, reduce input waste and foster sustainable agriculture, although challenges like cost and adoption remain, underscoring the need for further research and accessible solutions.

Emerging trends and technologies

Data quality and calibration

Maintaining accurate and reliable soil and crop sensor data remains a critical challenge in precision agriculture, as inconsistencies in sensor calibration, environmental factors and soil heterogeneity can affect decision-making reliability. Therefore, highlights the importance of calibrating low-cost moisture sensors in biochar-amended soils with varying salinity to ensure data accuracy (104). Similarly previous study showed that drone-based LiDAR and multispectral data, when calibrated with ground-truth soil samples, improved spatial resolution for variable-rate fertilization by 30 % (105). For example, calibrating inexpensive capacitance-type soil moisture sensors has been found to greatly enhance the performance of crop models such as Aqua Crop, resulting in improved water productivity and crop yield estimation (30). Advanced calibration techniques, including data assimilation methods that combine models such as Hydrus 1D with particle filters, have shown significant improvements in sensor accuracy, closely matching readings to high-precision references (37).

Sensor integration and interoperability

For effective overall monitoring in precision agriculture, it is essential to integrate diverse sensor technologies and ensure their interoperability. However, differences in communication protocols and data formats often hinder seamless data

Table 3. Overview of emerging soil and crop sensing technologies for yield prediction and management

Sensor/System	Category	Type	Key parameter	Predictive model (s)	Model inputs	Model output	Model accuracy (R^2 / RMSE)	Platform
Teralytic Wireless	Soil	In-situ	NPK, moisture, salinity	Random Forest, MLR	Soil data, weather	Yield potential	R^2: 0.78–0.85	Fixed probe
Sentek Drill & Drop	Soil	In-situ	Soil moisture, temperature	Hydrus-2D, DSSAT	Soil moisture profiles	Irrigation impact on yield	RMSE: ±5 %	IoT probe
Veris P4000 EC	Soil	Proximal	Electrical Conductivity (EC), texture	Geostatistical Kriging	Soil EC data	Soil variability zones (yield zones)	R^2: 0.82	Tractor-mounted
MicaSense Altum-PT	Crop	UAV	NDVI, LAI, canopy temperature	CNN, PLSR	Multispectral imagery	Biomass yield estimate	RMSE: 8–12 %	Drone
Hyperscout 2 (H2)	Integrated	Satellite	Hyperspectral (400–2500 nm)	Partial Least Squares (PLS)	Spectral bands	Nutrient stress → yield prediction	R^2: 0.88	Satellite/Drone
AgriFlect SpectraVue	Soil/Crop	Proximal	Organic matter (OM), pH, NDVI	XGBoost, ANN	Soil + canopy spectra	Yield prediction	R^2: 0.91	Tractor-mounted
Arable Mark 3	Integrated	In-situ	Soil moisture, NDVI, weather	LSTM, Bayesian Networks	Multi-sensor time series	Dynamic yield forecast	RMSE: ±7 %	IoT weather pole
SoilOptix γ-ray	Soil	Proximal	K, Thorium (Th), Uranium (U)	Linear Mixed Models (LMM)	Gamma-ray data + soil samples	Soil fertility → yield potential	R^2: 0.79	ATV-mounted

NPK	Nitrogen (N), Phosphorus (P), Potassium (K)	ANN	Artificial Neural Network
MLR	Multiple Linear Regression	LSTM	Long Short-Term Memory
EC	Electrical Conductivity	DSSAT	Decision Support System for Agrotechnology Transfer
CNN	Convolutional Neural Network	LMM	Linear Mixed Models
PLSR	Partial Least Squares Regression	IoT	Internet of Things
PLS	Partial Least Squares	R^2	Coefficient of Determination
NDVI	Normalized Difference Vegetation Index	RMSE	Root Mean Square Error
LAI	Leaf Area Index	UAV	Unmanned Aerial Vehicle
OM	Organic Matter	ATV	All-Terrain Vehicle

integration. Consequently, the lack of standardization can delay the development of unified systems and as noted in the former studies, advancing sensor technologies requires IoT and wireless network convergence for smooth communication (106). The proliferation of the various types of sensors and communication protocols tends to create fragmented data systems that make effective data exchange challenging (107). Recent efforts stress the importance of standard frameworks; IoT-based agricultural systems should adopt common communication standards to enable interoperability (108). Furthermore, the design of spatio-temporal semantic data management frameworks has been suggested to further increase interoperability by offering a common structure for various sensor data (109). Despite these advances, high implementation costs and the need for farmer education remain barriers, underscoring the need for collaborative action among stakeholders to promote interoperable sensor adoption in agriculture.

Data interpretation and decision making

Transforming massive amounts of sensor data into actionable information is still a major challenge for precision agriculture, with the analytical intensity and the necessity for real-time processing calling for sophisticated computational tools and experienced experts. In addition, data noise and variability pose challenges to reliable interpretation and prediction. Hence, creating user-friendly decision-support systems with noise filtering and explainability is crucial. Here, former studies suggest causal machine learning for unravelling intricate agroecosystem interactions and optimizing sustainable decision-making (110). Whereas one of researcher introduce a new spatio-temporal semantic data management system that enhances interoperability among disparate agricultural IoT systems by arranging sensor data along spatial, temporal and semantic dimensions thus facilitating seamless integration and real-time decision-making in precision agriculture (109).

Economic factor and adoption barriers

The initial high cost of adopting advanced sensor technologies poses a significant barrier for many farmers, especially in developing countries, as the return on investment may not be immediately apparent. Additionally, limited capital access, lack of technical know-how and resistance to shifting from traditional methods further hinder adoption. To overcome these challenges, funding, education of farmers and demonstration of apparent long-term advantages are critical. The primary barriers include high costs, technological complexity and digital divides, as identified in previous research (106).

Socio psychological barrier

At the socio-psychological level, prior studies have systematically synthesized and meta-analysed published literature to outline principal determinants of the adoption of precision agriculture technologies. All these educational achievement, age and farm size were shown to exert statistically significant impacts on adoption choices. In addition, the research stresses that poor technical literacy and inadequate access to credible information mainly regarding anticipated profitability are important dimensions influencing the willingness of farmers to embrace digital innovations. These results underscore the importance of targeted training and outreach programs for filling the gap between technological innovation and real-world application (111).

Limitations of emerging trends and technologies

- Sensors may provide inaccurate readings due to soil variability and environment. Low-cost sensors require proper calibration, which can be difficult.
- Various sensors are not always compatible with each other since they employ disparate systems. This becomes difficult to utilize all data with ease. Moreover, it is expensive and requires training for farmers.
- Large volumes of data are difficult to analyse rapidly and accurately. Equipment can be complex, making it difficult for farmers to use.
- They are costly initially and therefore most farmers cannot afford them. Farmers might also be hesitant whether it's worth the expenses or would rather go with conventional methods.
- Farmers' education, age and farm size influence whether they utilize these tools. Lack of information and skills discourage them. Increased training and assistance are necessary.

Future directions and research needs

To fully realise the potential of soil and crop sensing in precision agriculture, future advancements must strategically focus on four key areas. First, closer integration with Internet of Things (IoT) networks, autonomous devices and AI-based decision platforms is essential for enabling closed-loop management, wherein real-time sensor data directly guides site-specific applications and robotic operations. Second, the development of scalable algorithms and edge-computing frameworks such as lightweight machine learning models will facilitate real-time analysis of complex datasets, including hyperspectral and thermal imagery, while reducing dependence on cloud infrastructure and minimising processing delays. Third, addressing current compatibility issues requires standardising sensor protocols and promoting interoperable hardware systems, alongside implementing secure data provenance mechanisms like blockchain to ensure traceability and the integrity of agronomic recommendations. Fourth, it is critical to address data privacy and cybersecurity risks, such as sensor tampering and unauthorised data access, to maintain operational reliability.

Furthermore, emerging technologies like quantum sensing for sub-surface imaging and biodegradable sensors for short-term deployment present promising avenues but demand interdisciplinary research among agronomists, engineers and data scientists to ensure scalability and practical deployment. Equally important is designing farmer-centric solutions that emphasise usability and demonstrate clear return-on-investment (ROI) metrics, which will be pivotal for broader adoption. Additionally, the establishment of regulatory frameworks and certification standards for sensor precision and data reliability will help build user confidence. Collectively, these advancements aim to usher in an era of self-managing, adaptive cropping systems that dynamically respond to field variability, while upholding high standards for data security, interoperability and sustainability in global agriculture.

Conclusion

New soil and crop monitoring equipment such as moisture sensors, drones and intelligent computer software assist farmers in better utilization of water and fertilizers. It saves money, increases yields and conserves the soil. Certain tools also assist in maintaining a healthy soil. However, high expenses, complex data and reduced usage in poor nations are challenges. Making these equipment affordable, simpler and providing farmers with training can assist. Despite the challenges, these technologies have the ability to render agriculture more efficient and environmentally friendly.

With sensors and machine learning, farmers are better able to make decisions based on data coming directly from their local area in real-time. This overview demonstrates how to use remote and ground sensors to measure soil and crop health. AI makes it possible to convert this information into actionable guidance. But there are some issues-such as high expense, sensor malfunction and data combination from various sources. To solve this, experts must collaborate to construct improved systems. Above all, these tools must be easy and useful for farmers to apply in the field. New technologies like edge computing, generative AI and combining different types of data are expected to improve prediction and help build more sustainable and eco-friendly farming systems.

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Authors' contributions

EV contributed to the conceptualization, remote sensing data analysis, visualization and drafting of the original manuscript. KP was responsible for supervision, review and editing of the manuscript, particularly in relation to nanotechnology applications in agriculture. MD supported geospatial methodology development and validation of results. Praneetha Subramanyam contributed domain-specific insights on vegetable science and assisted in interpreting agricultural relevance of the findings. PG contributed to agronomic validation and the framing of implications for field -level practices.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interests to disclose.

Ethical Issue: None

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