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# Synergistic integration of remote sensing and soil metagenomics data: advancing precision agriculture through interdisciplinary approaches

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## Introduction

The global demand for food is driving the need for high-performance, sustainable agricultural systems that incorporate advanced technologies for monitoring, control, and decision-making. With the population expected to reach 9.7 billion by 2050, agriculture must boost productivity while maintaining sustainability. Precision agriculture (PA) addresses this challenge by using advanced technologies to increase yields, reduce resource waste, and minimize environmental impacts (Gebbers and Adamchuk, 2010; Delgado et al., 2020; El-Kader and El-Basioni, 2020). This "fourth agricultural revolution" is reshaping farming through innovations in data analytics, communication, and technology (Mohindru et al., 2021; Abdel-Basset et al., 2024).

A key aspect of sustainable agriculture is the soil microbiome, especially the rhizosphere, which promotes soil health and crop resilience while reducing environmental harm. Next-generation sequencing (NGS) techniques, such as amplicon sequencing and shotgun metagenomics, provide deep insights into microbial communities, their diversity, and functional roles. These tools are vital for monitoring agricultural interventions, identifying beneficial microbes, and detecting pathogens early to prevent crop diseases (Elnahal et al., 2022).

Understanding the physical, biological, and chemical characteristics of soil is crucial for optimizing crop management practices such as irrigation, drainage, and nutrient management—key components of PA. The integration of advanced technologies like artificial intelligence (AI), remote sensing, unmanned aerial vehicles (UAVs), big data analytics, the Internet of Things (IoT), Global Positioning system (GPS), and Geographic Information Systems (GIS) enables the precise management of spatial variability in fields. UAVs, with their high spatial resolution and flexibility, have revolutionized soil and crop monitoring, offering real-time data collection from difficult-to-reach areas (Boursianis et al., 2022).

Integrating UAV-based remote sensing with soil metagenomics represents a transformative step forward for PA and ecosystem restoration. The fusion of these advanced tools not only enhances farming by improving resource efficiency but also aligns with the broader objectives of sustainable agriculture, reducing the environmental impact of farming by minimizing chemical inputs and fostering healthier, more resilient ecosystems. As these technologies evolve and become more cost-effective and accessible, their integration will likely become a standard practice in modern agriculture, driving widespread adoption and promoting a sustainable future for global food production. We review the current advancements in both fields, propose methods for integrating remote sensing data with soil microbiome profiles, and present a framework for implementing this integrated approach to optimize precision farming.

## Soil metagenomics

Soil is a diverse environment, home to billions of microorganisms. Enhancing soil health can boost crop productivity by 10–50%, and with plant growth-promoting microbes, productivity can rise by 50–60% (Abram, 2015; O'Callaghan et al., 2022). This reduces reliance on chemical fertilizers, supporting sustainable agriculture. Metagenomics, which sequences and analyzes environmental DNA, reveals microbial diversity and aids in discovering therapeutic molecules, biotechnological innovations, and sustainable practices (Abram, 2015; Garrido-Oter et al., 2018). It offers insights into microbial community structures, including bacteria, archaea, and eukaryotes, based on functional gene composition (Philippot et al., 2013; Martínez-Porchas and Vargas-Albores, 2017). The workflow of soil metagenomics will be discussed in detail further.

### Soil sampling, library preparation, and sequencing

Metagenomic studies involve collecting soil samples, particularly from the rhizosphere, where soil microbes and root secretions interact (Weaver, 1994; Brooks, 2015). Total DNA is extracted from the samples using kits like Genejet Soil DNA Kit (Thermo Fisher) or Fast DNA SPIN Kit (MP Biochemicals). DNA is then enzymatically fragmented using library preparation kits such as Nextera Tagmentation (Illumina) or Fragmentase (New England Biolabs), with alternative methods including acoustic shearing, sonication, and others (Sabale et al., 2020). DNA concentration and purity are measured using Qubit and Nanodrop, while integrity is assessed via agarose gel electrophoresis or Agilent TapeStation. The DNA fragments are cloned into bacterial plasmids, featuring elements like an origin of replication, restriction sites, selective markers, and cloning sites (Granjou and Phillips, 2019). Fragments are analyzed using a fragment analyzer for quality and quantity. Sequencing is conducted on platforms like Illumina, Pyrosequencing, Nanopore, and PacBio. Post-sequencing, data are de-multiplexed and analyzed (Martin, 2011; Oulas et al., 2015; Mahmoud et al., 2019; Zhang et al., 2021).

### Data processing

Pre-processing of soil metagenomics data begins with quality control to filter out low-quality reads and remove adapter sequences. Tools such as UCHIME, MG-RAST, RDP tools (Bolger et al., 2014), KTrim, Trim Galore, and Trimmomatic (Sun, 2020) are utilized for these tasks, ensuring sequences are trimmed for uniform length and quality. Following trimming, reads are further filtered to exclude sequences below specified length thresholds, and errors are corrected while polymerase chain reaction (PCR) duplicates are removed to enhance accuracy. Denoising of metagenomic data is achieved using platforms like MOTHUR and QIIME 2, with UCHIME used for detecting and eliminating chimeric sequences (Santamaria et al., 2018). Post-processing involves grouping reads by unique barcodes, removing primers, and employing tools such as Taxator-tk (Dröge et al., 2015) and MEGAHIT (Liu et al., 2015) for further taxonomic and functional classification. Recent advancements in *de novo* assemblers like Meta-IDBA, metaSPAdes, Ray Meta, and Contig Extender allow for assembly of metagenomic reads into contigs, particularly beneficial for sequencing novel microbial genomes without prior reference sequences (Peng et al., 2011; Boisvert et al., 2012; Kumar et al., 2018; Deng and Delwart, 2021). Subsequently, reads are aligned to reference databases or assembled into contigs for comprehensive taxonomic and functional analysis, facilitating robust interpretation of soil microbial community data.

### Data Analysis and interpretation

Metagenomic data processing forms the basis for taxonomic and functional profiling, essential for understanding microbial communities in soil. Tools like Krona, MEGAN, and phyloseq in R visualize taxonomic diversity and abundance (Huson et al., 2007; Ondov et al., 2011; McMurdie and Holmes, 2013). Functional analysis begins with gene prediction using tools such as Prodigal and MetaGeneMark, followed by annotation via KEGG, COG, and Pfam databases using eggNOG-mapper and InterProScan (Hyatt et al., 2010; Zhu et al., 2010). Pathway reconstruction is achieved using KEGG and MetaCyc databases with HUMAnN2 (Franzosa et al., 2018) and PathoScope (Hong et al., 2014), while functional capabilities are predicted by tools like PICRUSt, and Tax4Fun (Langille et al., 2013; Sun et al., 2020). Statistical

Abbreviations: AI, Artificial Intelligence; AREF, Auto-Regressive Error Function; CNN, Convolutional Neural Networks; DESeq2, Differential gene expression analysis based on the negative binomial distribution; DL, Deep learning; DNA, Deoxyribonucleic Acid; ELM, Extreme Learning Machine; GIS, Geographic Information Systems; GPS, Global Positioning System; IoT, Internet of Things; KEGG, Kyoto Encyclopedia of Genes and Genomes; k-NN, k-Nearest Neighbors; LAI, Leaf Area Index; LIDAR, Light Detection and Ranging; LoRaWAN, Long Range Wide Area Network; MC, Moisture Content; MG-RAST, Metagenomic Rapid Annotations using Subsystems Technology; ML, Machine Learning; MLR, Multiple linear Regression; NB-IoT, Narrowband Internet of Things; NDVI, Normalized Difference Vegetation Index; NGS, Next-generation sequencing; NMDS, Non-metric multidimensional scaling; PA, Precision Agriculture; PCA, Principal Component Analysis; PCR, Polymerase Chain Reaction; PICRUSt, Phylogenetic Investigation of Communities by Reconstruction of Unobserved States; PLSR, Partial Least Squares Regression; QIIME, Quantitative Insights Into Microbial Ecology; RDP, Ribosomal Database Project; SaE, Self-Adaptive Evolutionary Agents; SOC, Soil Organic carbon; SOM, Soil Organic Matter; SVM, Support Vector Machines; SVR, Support Vector Regression; TN, Total Nitrogen; UAV, Unmanned Aerial Vehicle; UN, United Nations; 5G, Fifth generation of wireless cellular technology.

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analyses, including DESeq2, edgeR, PCA, and NMDS, identify and visualize differential taxa or functions. Integration of taxonomic and functional data, along with network and ecological models, further explores microbial interactions and their ecological roles (Robinson et al., 2010).

### Nutrient management plan

Common microbial species isolated from rhizosphere soil using metagenomic approaches include Firmicutes, Bacteroidetes, Proteobacteria, Actinobacteria, and others (Babalola, 2010; Santos et al., 2019; Prasad and Zhang, 2022). Table 1 highlights microbial species and their impact on soil quality. By promoting beneficial microbes that fix nitrogen or solubilize phosphorus, farmers can reduce reliance on synthetic fertilizers, enhancing crop productivity, profits, and sustainability (Mendes et al., 2013). Enzymes like sulfatases, dehydrogenases, and phosphatases improve soil fertility, crop growth, and yield, reducing pesticide use (Peng et al., 2018). Metagenomics also supports the development of biofertilizers and microbial inoculants for agriculture and offers cost-effective alternatives to traditional soil remediation methods (Philippot et al., 2013, 2024). Several studies have demonstrated the economic advantages of microbial inoculants in agriculture. For instance, recurrent pre-sowing applications of *Pseudomonas fluorescens* have significantly boosted maize growth, reducing reliance on costly chemical fertilizers (Papin et al., 2024). Investigations into microbiota responses to nitric oxide regulation in *Arabidopsis thaliana* highlight the potential for enhancing crop productivity through optimized plant-microbe interactions (Berger et al., 2024). Moreover, trials using affordable microbial nutrient solutions have underscored their role in improving food security while offering cost-effective alternatives to conventional agricultural practices (van der Velde et al., 2013).

## Remote sensing

The appropriate spatio-temporal resolution required for PA depends on various factors, including management objectives, field size, and the capability of farm equipment to vary input (irrigation, fertilizer, pesticide, etc.) application rates. While PA can use a variety of sensors, this paper limits itself to those studies that primarily used UAV image data (Shafi et al., 2019). UAVs are transforming agriculture by offering precise, efficient, and sustainable solutions for various farming practices. They help in enhancing productivity, conserving resources, and promoting eco-friendly practices. Recent studies predict that by 2025, the global UAV industry for agriculture would increase at a compound annual growth rate of 35.9% and reach $5.7 billion (*Agriculture Drones Market*).

### Drones and cameras

Aerial platforms such as UAVs or drones generally provide higher spatial resolution (<5 meters) images compared to satellites (Bochtis et al., 2023). Thus, UAVs and other ground-based platforms offer greater flexibility in providing images at fine spatial and temporal resolutions (more frequently) or as needed. The hydrologic and climatic parameters—such as soil organic carbon, soil moisture, soil characteristics, the normalized Difference Vegetation Index (NDVI), leaf area index (LAI), groundwater, and rainfall—as well as the health of the vegetation and soil are monitored using unmanned aerial vehicles (UAVs) (Zhang et al., 2022).

Equipped with various sensors, UAVs perform specialized tasks: multispectral sensors capture plant health data in specific light wavelengths, thermal cameras detect temperature changes to identify irrigation or pest issues, and LIDAR creates detailed topographic maps for land and water management (Maddikunta et al., 2021; Tahir et al., 2023). However, global adoption of drone technology varies due to differing legal, financial, and physical conditions across countries. Supplementary Table S1 lists the various drones that are recognized for their capabilities in precision farming and improved crop management, ensuring compliance with safety and operational standards of respective aviation authorities.

### Data collection and pre-processing

Data collection and preprocessing in precision agriculture (PA) involve drones and IoT sensors, creating a comprehensive dataset. IoT sensors, such as Decagon EC-5 for soil, Davis Vantage Pro2 for weather, and GreenSeeker for crops, gather key data on moisture, temperature, pH, nutrients, climate, and crop health (García et al., 2020; Fuentes and Chang, 2022). Supplementary Table S2 highlights IoT sensors employed in precision agriculture, emphasizing their importance in enabling real-time, data-driven farming solutions.Connectivity networks like LoRaWAN, NB-IoT, and 5G transmit this data through gateways like Kerlink Wirnet Station. Flight planning software like DJI Ground Station Pro and drones like DJI Phantom 4 RTK capture aerial images (KriŽanović et al., 2023), followed by georeferencing and image stitching using tools like Agisoft Metashape. Noise reduction in software like Pix4Dmapper enhances image quality, while cloud computing supports secure data storage and real-time analysis (Debauche et al., 2022).

### Data analytics and AI

Precision farming is widely adopted due to the power of AI, driven by machine learning (ML) and deep learning (DL) (Khan et al., 2022; Ojo and Zahid, 2022; Hashmi and Kesakr, 2023). ML models analyze UAV-captured images, and AI-enabled farm management systems use sensor data to provide real-time recommendations for farmers. Machine learning (ML) approaches like Support Vector Machines (SVM) and Random Forests were applied for soil management to analyze soil temperature, moisture, and drying patterns (Liakos et al., 2018; Sharma et al., 2021). Models utilizing Decision Trees and Neural Networks were created to predict soil pH and fertility (Suchithra and Pai, 2020), while Multiple Linear Regression (MLR) and Support Vector Regression

TABLE 1 Microbial community and its potential impact on soil quality.

| Microorganism | Type | Function/role in soil | Implications for soil quality | References |
|---|---|---|---|---|
| *Azospirillum brasilense* | Bacteria | Nitrogen fixation | Enhances soil fertility and plant growth | Bashan et al., 2004 |
| *Pseudomonas fluorescens and other Pseudomonas* spp | Bacteria | Plant growth promotion, biocontrol; phosphate solubilization | Suppresses soil-borne pathogens, improves plant health, bioremediation | Weller et al., 2002; Hariprasad et al., 2014 |
| *Rhizobium leguminosarum and other Rhizobium* spp | Bacteria | Symbiotic nitrogen fixation | Crucial for legume growth, improves nitrogen content; soil restoration | Shameem et al., 2023 |
| *Bacillus subtilis* | Bacteria | Decomposition, plant growth promotion | Enhances nutrient cycling, plant disease resistance | Earl et al., 2008; Mahapatra et al., 2022 |
| *Streptomyces griseus* | Bacteria | Antibiotic production, decomposition | Suppresses pathogens, contributes to organic matter breakdown | (Chen Y. et al., 2017; Hong et al., 2019) |
| *Methylobacterium* spp. | Bacteria | Oxidation of methane, plant growth promotion | Bioremediation, derine energy and carbon for biomass | Kang et al., 2022 |
| *Clostridium thermocellum* | Bacteria | Cellulose degradation | Enhances organic matter decomposition, nutrient cycling | Lynd et al., 2002 |
| *Mycobacterium smegmatis* | Bacteria | Organic matter degradation; fixing atmospheric hydrogen | Contributes to nutrient cycling and soil health | Greening et al., 2014; Walsh et al., 2019 |
| *Nitrosomonas europaea* | Bacteria | Nitrification | Converts ammonia to nitrate, important for nitrogen cycling | Chain et al., 2003; Sedlacek et al., 2016 |
| *Nitrobacter winogradskyi* | Bacteria | Nitrification | Converts nitrite to nitrate, important for nitrogen cycling | Starkenburg et al., 2006 |
| *Trichoderma harzianum* | Fungi | Biocontrol, decomposition | Controls soil pathogens, enhances organic matter decomposition | Harman et al., 2004; Jamil, 2021 |
| *Penicillium chrysogenum* | Fungi | Decomposition, antibiotic production | Improves nutrient availability, suppresses pathogens | Galeano et al., 2023 |
| *Aspergillus niger* | Fungi | Decomposition | Enhances release of potassium, nutrient cycling | Ashrafi-Saiedlou et al., 2024 |
| *Glomus intraradices* | Fungi | Mycorrhizal symbiosis | Improves plant nutrient uptake, soil structure | Chen M. et al., 2017 |
| *Arbuscularmycorrhizal fungi* | Fungi | Nutrient uptake, plant growth promotion | Erosion control, bioremediation | El-Sawah et al., 2021 |
| *Fusarium oxysporum* | Fungi | Pathogen | Can reduce soil health and plant productivity | van Bruggen et al., 2015 |
| *Alternaria alternata* | Fungi | Plant pathogen | Can negatively affect plant health | DeMers, 2022 |

(SVR) were used to estimate pH and Soil Organic Matter (SOM) in paddy soils (Yang et al., 2019). Partial Least Squares Regression (PLSR) was used to predict moisture content (MC), total nitrogen (TN), and soil organic carbon (SOC) (Morellos et al., 2016). Soil moisture was estimated by combining the Auto-Regressive Error Function (AREF) with Gradient Boosting and k-Nearest Neighbors (k-NN) (Johann et al., 2016). Extreme Learning Machine (ELM) integrated with a Self-Adaptive Evolutionary agent (SaE) was used to assess soil temperature (Nahvi et al., 2016), while ELM was employed to forecast surface humidity (Acar et al., 2019). Lastly, Random Forests and SVM were used to estimate SOC and TN in Moroccan soils (Reda et al., 2019). Several studies also advanced ML and image recognition techniques for seed sorting and counting (Li et al., 2021; Nehoshtan et al., 2021; Laudari et al., 2022; Ekramirad et al., 2024). Deep Learning, especially Convolutional Neural Networks (CNNs), revolutionized plant disease and pest detection, allowing rapid and accurate diagnosis, which is crucial for minimizing crop loss (Mohanty et al., 2016; Ramcharan et al., 2017; Too et al., 2019; Argüeso et al., 2020). These methods optimize agricultural processes like planting, irrigation, and fertilization, enhancing productivity. Table 2 highlights key soil parameters detected using UAV technologies across various crops, showcasing advancements in PA research. AI models further refine resource use by recommending precise amounts of water, fertilizer, and pesticides, reducing waste and minimizing environmental impact. These models also simulate different farming scenarios, helping farmers assess and select the most effective strategies (Marvuglia et al., 2022).

## Actionable insights

Complex data is simplified into actionable insights for farmers, delivered to farmers via mobile apps and dashboards, providing real-time updates, visualizations, and alerts. For instance, farmers receive notifications about pest outbreaks with suggested treatments or alerts about sudden soil moisture drops with actionable irrigation advice. Farmers implement these

TABLE 2 Optimum soil parameter ranges detected by UAV technologies in diverse crops.

| Soil parameter | Optimum range | Detection method | Crop | Source |
|---|---|---|---|---|
| Soil moisture | 50–75% field capacity | UAV thermal and multispectral imaging | Wheat, Maize | Hunt et al., 2019; Zhang et al., 2023 |
| Soil pH | 6.0–7.5 | UAV spectral analysis | Rice, Soyabean | Yang et al., 2020; Alabi et al., 2022 |
| Organic matter content | 2–4% | UAV hyperspectral imaging | Rapeseed | Guo et al., 2020 |
| Nitrogen content (N) | 0.2–0.5% | UAV multispectral analysis | Potato, Wheat | Liu et al., 2022; Fan et al., 2023 |
| Phosphorus content (P) | 10–30 ppm | UAV hyperspectral imaging | Wheat, Barley | Kefauver et al., 2017; Mazur et al., 2023 |
| Potassium content (K) | 100–300 ppm | UAV multispectral analysis | Wheat, Potato | Ma et al., 2023; Mazur et al., 2023 |
| Soil texture | Loam | UAV digital terrain modeling | Various fields | Song et al., 2023 |
| Electrical conductivity (EC) | 0.2–0.6 dS/m | UAV electromagnetic induction | Corn, Soybeans, Alfalfa | Guan et al., 2022 |
| Soil compaction | $<1.2$ g/cm$^3$ | UAV LiDAR scanning | Sugarbeet, Corn | Lindenstruth, 2020; Killeen et al., 2024 |
| Soil temperature | 18–25°C | UAV thermal imaging | Various fields | Basurto-Lozada et al., 2020 |

recommendations and provide feedback, which helps refine the system's accuracy and relevance over time. This feedback loop, combined with adaptive learning, enhances the system's predictive capabilities for future growing seasons. The benefits include optimized operations through precise irrigation, fertilization, and pest control, increased yields from timely interventions, and sustainable practices by reducing chemical use and promoting efficient resource allocation. This practice empowers farmers to make informed decisions, boosting productivity, profitability, and sustainability in agriculture.

## Integrating metagenomic and UAV data for precision agriculture

Various studies highlight the power of integrating advanced technologies for sustainable agriculture. Remote sensing and metagenomics have been used to monitor biodiversity and microbial diversity in agricultural landscapes (Herzog and Franklin, 2016; Lewin et al., 2024). The combination of exascale computing, AI, and multi-omics data supports plant biology research and the UN's Sustainable Development Goals (Streich et al., 2020; Cembrowska-Lech et al., 2023). Integrating microbiome analysis, metagenomics, and imaging links microbial dynamics to broader ecological processes and plant root health (Beatty et al., 2021; Singer et al., 2021). Soil-plant-microbiota interactions, crucial for ecosystem health, are emphasized for improved sustainability (Giovannetti et al., 2022; Dlamini et al., 2023). UAVs, metagenomics, and environmental sensors optimize real-time soil health management (Meena et al., 2024; Zeng et al., 2024), while AI-driven studies advance forest management, nutrient cycling, and drought tolerance in crops (Chaudhury et al., 2024; Jamil et al., 2024). Additionally, omics and AI applications enhance phytoremediation and environmental outcomes (Mohan et al., 2024). As demonstrated by these studies and illustrated in Figure 1, it is clear that these integrated techniques can significantly promote sustainable farming practices. While integrating diverse datasets within an interdisciplinary framework offers a promising pathway forward, it poses significant challenges due to the complexity and variability of harmonizing data with differing scales, structures, and complexities, requiring solutions such as multivariate statistical and network-based methods (Streich et al., 2020; Cembrowska-Lech et al., 2023). Ensuring model interpretability is another hurdle, as many AI/ML models function as "black boxes," complicating biological interpretation and limiting trust in predictions. Overfitting, a common issue in ML, further undermines model generalizability and predictive accuracy. Additionally, automating analysis, uncovering non-linear interactions, and fostering interdisciplinary collaboration are essential but demanding tasks that require significant expertise and innovation. Addressing these challenges is crucial for leveraging the full potential of UAV and metagenomics data integration in sustainable agriculture.

## Future direction

The future of sustainable agriculture hinges on an interdisciplinary approach that integrates remote sensing data with Omics data, all grounded in the One Health concept, which emphasizes the interconnectedness of human, plant, and environmental health. Collaboration among experts in molecular biology, microbiology, ecology, bioinformatics, and computer science is key to managing complex datasets, enhancing resource efficiency, and improving precision farming. In-field technologies like drones, sensors, and real-time sequencing (e.g., using Oxford Nanopore's MinION) enable immediate analysis of microbial communities, soil health, and crop conditions, delivering actionable insights directly to farmers through mobile-friendly, easy-to-understand reports. These advances promise a low-intervention, automated agricultural system where sophisticated algorithms process data instantly, enabling farmers to optimize resource use, respond to challenges in real time, and improve yields. Despite challenges around data complexity, technical expertise, integration, privacy, security, and cost limitations, this integrated technology-driven approach holds the potential to boost soil health, crop productivity, and

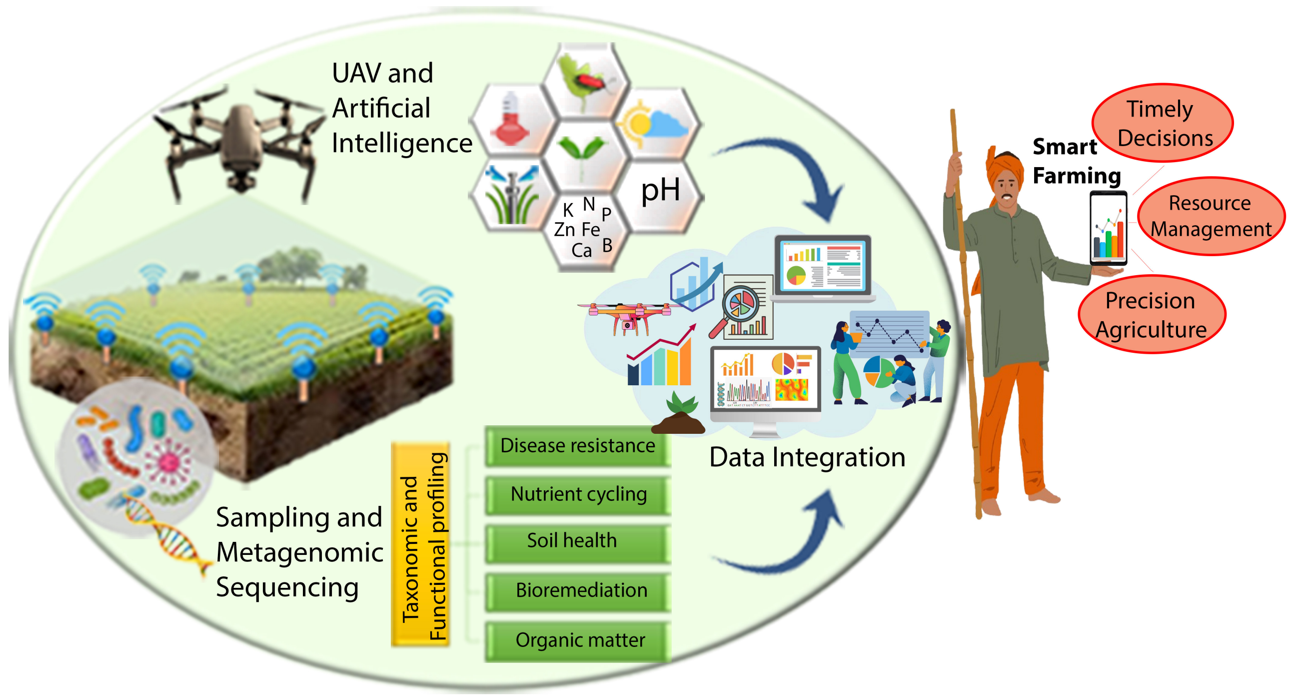


FIGURE 1
Integrated approach to smart farming. Field sensors, data from unmanned aerial vehicles (UAVs), and artificial intelligence (AI) work together to provide real-time insights into key agricultural parameters, such as irrigation needs, soil pH, temperature, weather patterns, pest activity, and nutrient levels. These technologies allow continuous monitoring and real-time adjustments to optimize soil fertility, crop health and productivity. Simultaneously, soil sampling and metagenomic sequencing offer detailed taxonomic and functional profiling of soil microorganisms, revealing the microbial communities involved in nutrient cycling, disease resistance, and soil health. By integrating these datasets, precision agriculture can be enhanced, enabling smarter decision-making and more efficient resource management. This combined approach allows farmers to make timely adjustments in water, fertilizer, and pesticide application while promoting sustainability through reduced resource waste and minimized environmental impact.

sustainability, transforming modern farming into a more resilient and efficient system.

## Author contributions

BA: Conceptualization, Data curation, Writing – original draft, Writing – review & editing. RMan: Data curation, Writing – original draft. RMad: Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2024.1499973/full#supplementary-material

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