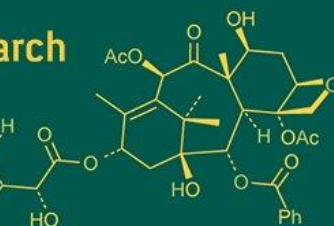
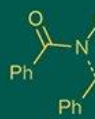


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Remote Sensing, GIS and Artificial Intelligence for Precision Nutrient Management: Advances, Challenges and Future Perspectives

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Abstract

The increasing demand for food, declining soil fertility, rising fertilizer costs and environmental concerns have accelerated the adoption of precision nutrient management (PNM) in digital agriculture. Conventional fertilizer practices often ignore spatial and temporal field variability, resulting in low nutrient use efficiency and environmental degradation. This review synthesizes recent advances in Remote Sensing (RS), Geographic Information Systems (GIS), Artificial Intelligence (AI) and related digital technologies for precision nutrient management. It highlights the applications of satellite, unmanned aerial vehicle (UAV) and proximal sensing, vegetation indices, digital soil mapping, machine learning, variable-rate technology and intelligent decision-support systems for site-specific nutrient management. The review also discusses applications across major cropping systems, recent technological developments and challenges including data integration, affordability and technical constraints. Emerging opportunities, current limitations and future priorities are highlighted. Overall, the integration of geospatial and AI-based technologies provides an effective framework for improving nutrient use efficiency, crop productivity, environmental sustainability and global food security.

Keywords: Precision Nutrient Management; Remote Sensing; Geographic Information Systems; Artificial Intelligence; Digital Soil Mapping; Variable Rate Technology

1. Introduction

Global agriculture faces the challenge of meeting rising food demand while ensuring environmental sustainability amid population growth, climate change, declining soil fertility, water scarcity and land degradation (FAO, 2023; Getahun *et al.*, 2024) [18, 23]. Conventional fertilizer management applies nitrogen (N), phosphorus (P) and potassium (K) uniformly, overlooking spatial and temporal field variability. This reduces nutrient use efficiency, increases nutrient losses, production costs and environmental pollution through leaching, runoff, volatilization and greenhouse gas emissions (Nakachew *et al.*, 2024; Adewusi *et al.*, 2024) [46, 1]. These challenges highlight the urgent need for efficient, site-specific and environmentally sustainable nutrient management strategies.

Precision agriculture (PA) optimizes fertilizer, irrigation, pesticides and other inputs by accounting for within-field spatial and temporal variability. This site-specific approach enhances crop productivity, improves nutrient use efficiency, reduces input costs, minimizes environmental impacts and promotes sustainable agricultural intensification (Sishodia *et al.*, 2020; Getahun *et al.*, 2024) [58, 23]. Digital agriculture has advanced precision nutrient management by integrating *Remote Sensing* (RS), Geographic Information Systems (GIS), Global Positioning Systems (GPS), Artificial Intelligence (AI), Machine Learning (ML) and Variable Rate Technology (VRT). *Remote sensing* platforms provide high-resolution data for monitoring crop health, nutrient status and environmental conditions (Lu *et al.*, 2020; Khanal *et al.*, 2017) [6, 31]. When integrated with GIS, these datasets enable spatial variability analysis, digital soil mapping, management-zone delineation and prescription-map generation for site-specific fertilizer application, thereby improving nutrient management and reducing environmental risks (Sangeetha *et al.*, 2024) [55].

Recent advances in artificial intelligence (AI) and machine learning (ML) have enhanced

precision nutrient management through predictive modelling, nutrient deficiency detection, digital soil mapping, yield forecasting and intelligent decision-support systems, enabling accurate fertilizer recommendations from large geospatial and sensor-derived datasets (Adewusi *et al.*, 2024; Folorunso *et al.*, 2025) ^[1, 21]. Supporting technologies such as IoT-enabled sensing networks, cloud-based data management and edge computing further facilitate real-time data acquisition and processing, enabling adaptive nutrient management under diverse agroecosystems. Despite these advances, widespread adoption remains constrained by high implementation costs, limited digital infrastructure, inadequate technical expertise, interoperability issues among heterogeneous datasets, sensor calibration requirements and data privacy concerns, particularly in developing countries and smallholder farming systems (Kumar *et al.*, 2024; Getahun *et al.*, 2024) ^[23, 2]. Although Remote Sensing (RS), Geographic Information Systems (GIS) and Artificial Intelligence (AI) have been widely reviewed individually, their integrated application for precision nutrient management remains insufficiently explored. Recent advances in machine learning, UAV-based sensing, digital soil mapping and intelligent decision-support systems have also not been comprehensively synthesized. Current challenges and future research priorities are critically discussed within an integrated framework. This review aims to summarize recent advances in Remote Sensing (RS), Geographic Information Systems (GIS) and Artificial Intelligence (AI) for precision nutrient management; compare sensing technologies, GIS applications and AI-based approaches for nutrient assessment and fertilizer recommendation; discuss current challenges, limitations and emerging opportunities; and identify future research directions for developing climate-smart, sustainable and data-driven nutrient management systems.

2. Literature Search Methodology

This review was conducted using a structured narrative literature review approach to synthesize recent advances in Remote Sensing (RS), Geographic Information Systems (GIS), Artificial Intelligence (AI) and related digital technologies for precision nutrient management. Relevant literature published between 2015 and 2025, with emphasis on 2020-2025, was retrieved from Web of Science, Scopus, Science Direct, Springer Link, IEEE Xplore, Wiley Online Library, MDPI and Google Scholar. The search employed Boolean operators (AND, OR) with keywords including “Precision Nutrient Management,” “Remote Sensing,” “GIS,” “Artificial Intelligence,” “Machine Learning,” “Digital Soil Mapping,” “Variable Rate Technology,” “UAV,” “Vegetation Indices,” and “Decision Support Systems.” Peer-reviewed research articles, review papers, conference proceedings and technical reports relevant to precision nutrient management were included, whereas duplicate, non-English and unrelated publications were excluded. The selected studies were critically evaluated and thematically synthesized to identify technological advances, applications, current challenges and future research directions.

3. Precision Nutrient Management

3.1 Precision Nutrient Management: Concept and Principles

Precision Nutrient Management (PNM) is a site-specific approach that optimizes fertilizer source, rate, timing and placement according to crop nutrient requirements and field variability. It integrates soil testing, crop monitoring, Remote

Sensing (RS), Geographic Information Systems (GIS), GPS, Variable Rate Technology (VRT) and Artificial Intelligence (AI) to improve nutrient-use efficiency and support sustainable agriculture (Koley *et al.*, 2024; Liu *et al.*, 2025) ^[12, 13]. Its major components include soil nutrient assessment, crop nutrient diagnostics, spatial variability mapping, decision-support systems, variable-rate fertilizer application and continuous crop monitoring. Site-Specific Nutrient Management (SSNM) synchronizes nutrient supply with crop demand by considering within-field variability. Based on the 4R Nutrient Stewardship framework, it integrates soil fertility, crop growth, weather and yield data to improve nutrient-use efficiency and reduce nutrient losses (Koley *et al.*, 2024) ^[12]. Recent advances in UAV-based remote sensing, hyperspectral imaging, GIS, artificial intelligence (AI), machine learning and real-time sensor networks have improved nutrient deficiency detection, fertilizer recommendations and adaptive nutrient management, while digital advisory platforms support wider adoption of precision nutrient management (Sangeetha *et al.*, 2024; Howari, 2025; Liu *et al.*, 2025) ^[55, 14, 13].

3.2 Nutrient Variability in Agricultural Fields

Spatial variability in soil texture, organic matter, topography, moisture and management practices creates uneven nutrient distribution within fields. Consequently, uniform fertilizer application often causes nutrient deficiencies or excesses, reducing fertilizer-use efficiency and increasing environmental and economic risks (Sangeetha *et al.*, 2024) ^[8]. Remote sensing, UAVs, hyperspectral imaging, GIS and artificial intelligence improve assessment of spatial nutrient variability by integrating multisource datasets. These technologies enable accurate soil nutrient mapping, management-zone delineation and dynamic fertilizer recommendations for site-specific nutrient management (Howari, 2025; Liu *et al.*, 2025) ^[14, 13].

3.3 Benefits of Precision Nutrient Management

Precision Nutrient Management (PNM) improves nutrient-use efficiency, crop productivity and profitability through site-specific fertilizer application. Variable-rate technology reduces nutrient losses and environmental pollution, while integrating Artificial Intelligence (AI), Remote Sensing (RS), GIS and decision-support systems enables efficient, sustainable nutrient management (Liu *et al.*, 2025) ^[13]. Recent evidence demonstrates that AI-enabled precision nutrient management can reduce fertilizer consumption while improving crop yield and overall resource-use efficiency under variable field conditions, making PNM an important component of climate-smart and sustainable agriculture (Sangeetha *et al.*, 2024; Howari, 2025) ^[8, 14].

4. Remote Sensing Technologies in Precision Nutrient Management

Remote Sensing (RS) provides rapid, non-destructive and spatially explicit information on crop and soil conditions. By monitoring crop growth, biomass, chlorophyll content and nutrient stress through canopy reflectance, RS enables early nutrient deficiency detection and supports timely, site-specific fertilizer management (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) ^[8, 15]. Recent advances in satellite imagery, unmanned aerial vehicles (UAVs), hyperspectral imaging, proximal sensing and artificial intelligence (AI) have improved nutrient assessment by enabling spatial variability analysis, nutrient deficiency detection, prescription-map generation and variable-rate fertilizer application for efficient nutrient management (Ioja *et al.*, 2023) ^[16]. Consequently, RS has

become an essential component of climate-smart and data-driven agriculture.

4.1 Fundamentals of Remote Sensing

Remote sensing acquires information on crops and soils without direct contact by measuring reflected or emitted electromagnetic radiation. Sensors operating in the visible, near-infrared (NIR) and thermal regions assess crop health, biomass, soil moisture and nutrient status. Variations in spectral reflectance enable multispectral, hyperspectral, thermal and LiDAR sensors to identify nutrient-deficient areas and support site-specific fertilizer management (Yang *et al.*, 2025; Sangeetha *et al.*, 2024) ^[15, 8].

4.2 Remote Sensing Platforms

Remote sensing platforms differ in spatial resolution, temporal frequency, operational flexibility and acquisition cost, making

them suitable for different scales of precision nutrient management. Platform selection depends on field size, crop type, monitoring objectives and resource availability. Satellite systems provide regular and cost-effective observations for regional and large-scale crop monitoring, whereas unmanned aerial vehicles (UAVs) deliver ultra-high resolution imagery for field-level nutrient assessment. Aircraft-based platforms are mainly employed for specialized surveys and research applications, while ground-based (proximal) sensors provide real-time measurements for crop diagnosis, sensor calibration and variable-rate fertilizer application. Together, these complementary platforms enable accurate monitoring of crop nutrient status, spatial variability and management zones, thereby supporting site-specific fertilizer recommendations and improving nutrient use efficiency (Sangeetha *et al.*, 2024; Gomes *et al.*, 2025; Kuunya *et al.*, 2026) ^[8, 17, 18].

Table 1: Comparison of Remote Sensing Platforms for Precision Nutrient Management

Platform	Typical Spatial Resolution	Major Advantages	Limitations	Major Applications	References
Satellite-based (Landsat, Sentinel-2, WorldView)	0.3–30 m	Large-area coverage, regular revisit frequency, cost-effective, long-term monitoring	Cloud interference, lower spatial resolution (except commercial satellites)	Regional crop monitoring, vegetation mapping, nutrient status assessment, prescription mapping	(Chaves <i>et al.</i> , 2020; Segarra <i>et al.</i> , 2020) ^[19, 20] ; (Sishodia <i>et al.</i> , 2020; Gomes <i>et al.</i> , 2025) ^[58, 17]
UAV (Drone)-based	1–10 cm	Ultra-high spatial resolution, flexible deployment, on-demand data acquisition, high accuracy	Limited flight duration, weather dependency, higher operational cost	Crop nutrient assessment, vegetation indices, variable-rate fertilizer application, field-scale monitoring	(Lu <i>et al.</i> , 2020; Eskandari <i>et al.</i> , 2020; Choosumrong <i>et al.</i> , 2023; Yang <i>et al.</i> , 2025) ^[6, 21, 22, 15]
Aircraft-based	Sub-meter to several meters	Covers larger areas than UAVs with higher resolution than satellites; accommodates advanced sensors	Expensive operation, limited accessibility	Regional agricultural surveys, hyperspectral mapping, research applications	(Gomes <i>et al.</i> , 2025) ^[17]
Ground-based (Proximal) Sensors	Very high (plant level)	Real-time measurements, unaffected by cloud cover, high accuracy, ideal for calibration	Limited spatial coverage, manual operation	Nitrogen diagnosis, crop vigor assessment, calibration of satellite/UAV observations, variable-rate fertilization	(Sangeetha <i>et al.</i> , 2024; Tagarakis <i>et al.</i> , 2022; Cummings <i>et al.</i> , 2021) ^[8, 23, 24]

4.3 Types of Sensors

Multispectral sensors are widely used for routine nutrient monitoring, whereas hyperspectral, thermal and LiDAR sensors enhance nutrient deficiency detection, stress assessment and biomass estimation. Their integration with Geographic Information Systems (GIS), Artificial Intelligence (AI) and machine learning improves site-specific nutrient management (Gomes *et al.*, 2025; Yang *et al.*, 2025) ^[17, 15]. Remote sensing employs a variety of sensor technologies to assess crop physiology, nutrient status and environmental conditions for precision nutrient management. Optical (RGB) sensors provide cost-effective information on crop colour, canopy cover and overall plant health but are less sensitive to early nutrient stress (Eskandari *et al.*, 2020) ^[21]. Multispectral sensors, operating in the blue, green, red, red-edge and near-infrared (NIR) regions, are widely used for estimating vegetation indices such as NDVI, GNDVI and NDRE to evaluate crop vigor and nitrogen status (Choosumrong *et al.*, 2023; Gomes *et al.*, 2025) ^[22, 17]. Hyperspectral sensors capture hundreds of narrow spectral bands, enabling highly sensitive detection of macro- and micronutrient deficiencies, although they require sophisticated processing and are relatively

expensive (Lu *et al.*, 2020; Yang *et al.*, 2025) ^[6, 15]. Thermal sensors assess canopy temperature to detect physiological stress associated with water and potassium deficiencies, while LiDAR provides accurate three-dimensional information on crop architecture, biomass and plant height for precision nutrient management (Eskandari *et al.*, 2020; Yang *et al.*, 2025) ^[21, 15].

4.4 Vegetation Indices for Nutrient Assessment

Vegetation indices (VIs) are mathematical combinations of spectral reflectance values used to assess crop health, chlorophyll content, biomass, canopy vigor and nutrient status. Commonly used indices include the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), Normalized Difference Red Edge Index (NDRE), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and Canopy Chlorophyll Content Index (CCCI), each providing specific advantages for nutrient assessment under different crop and environmental conditions. Integration with UAV imagery and artificial intelligence (AI) further improves nutrient diagnosis and variable-rate fertilizer recommendations (Peticilă *et al.*, 2025; Yang *et al.*, 2025) ^[48, 15].

Table 2: Major Vegetation Indices Used for Precision Nutrient Management

Vegetation Index	Formula	Primary Application	Major Advantages	References
NDVI (Normalized Difference Vegetation Index)	$NDVI = \frac{NIR - Red}{NIR + Red}$	Biomass estimation, crop vigor, nitrogen assessment	Simple, widely used, suitable for large-scale monitoring	(Peticila <i>et al.</i> , 2025) ^[48]
EVI (Enhanced Vegetation Index)	$EVI = \frac{2.5 \times (NIR - Red)}{(NIR + 6 \times Red - 7.5 \times Blue + 1)}$	Dense vegetation monitoring	Reduces atmospheric and soil background effects	(Peticila <i>et al.</i> , 2025) ^[48]
NDRE (Normalized Difference Red Edge Index)	$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$	Chlorophyll estimation, nitrogen management	Highly sensitive under dense crop canopies	(Yang <i>et al.</i> , 2025) ^[15]
GRVI (Green-Red Vegetation Index)	$GRVI = \frac{Green - Red}{Green + Red}$	Chlorophyll monitoring	Simple indicator of chlorophyll variation	(Haque <i>et al.</i> , 2024) ^[25]
GNDVI (Green Normalized Difference Vegetation Index)	$GNDVI = \frac{NIR - Green}{NIR + Green}$	Nitrogen status, chlorophyll estimation	More sensitive than NDVI for nitrogen assessment	(Yang <i>et al.</i> , 2025) ^[15]
SAVI (Soil Adjusted Vegetation Index)	$SAVI = \frac{(NIR - Red)(1 + L)}{NIR + Red + L}$	Early crop growth assessment	Reduces soil brightness effects	(Haque <i>et al.</i> , 2024) ^[25]
SR (Simple Ratio)	$SR = \frac{NIR}{Red}$	Vegetation density estimation	Easy to calculate and interpret	(Haque <i>et al.</i> , 2024) ^[25]
CCCI (Canopy Chlorophyll Content Index)	$CCCI = \frac{NDRE}{NDVI}$	Chlorophyll and nutrient stress detection	Highly effective for nutrient deficiency assessment	(Yang <i>et al.</i> , 2025; Peticila <i>et al.</i> , 2025) ^[15, 48]

4.5 Remote Sensing for Nutrient Deficiency Detection

Remote sensing enables early, non-destructive detection of nutrient deficiencies by identifying changes in crop spectral responses before visible symptoms appear. The integration of multispectral, hyperspectral, thermal and proximal sensing with Artificial Intelligence (AI) and machine learning (ML) improves the accuracy of nutrient diagnosis and supports site-specific fertilizer recommendations (Gomes *et al.*, 2025; Yang

et al., 2025)^[17, 15]. Nitrogen deficiency is commonly assessed using vegetation indices such as NDVI, GNDVI, NDRE and CCCI, whereas phosphorus, potassium and micronutrient deficiencies are detected through canopy characteristics, thermal responses and hyperspectral signatures. AI-driven multisensor data fusion further enhances nutrient assessment and adaptive precision nutrient management (Peticilă *et al.*, 2025; Yang *et al.*, 2025)^[48, 15].

Table 3: Remote Sensing Approaches for Nutrient Deficiency Detection

Nutrient	Major Physiological Response	Typical Spectral Response	Preferred Sensor	Common Vegetation Index / Technique	References
Nitrogen (N)	Reduced chlorophyll synthesis and photosynthetic activity	Increased red reflectance; decreased NIR reflectance	Multispectral, Hyperspectral	NDVI, GNDVI, NDRE, CCCI	(Gomes <i>et al.</i> , 2025; Yang <i>et al.</i> , 2025) ^[17, 15]
Phosphorus (P)	Reduced root growth, biomass accumulation and chlorophyll content	Lower canopy reflectance and vegetation index values	Multispectral	NDVI, GNDVI with AI-assisted analysis	(Yang <i>et al.</i> , 2025) ^[15]
Potassium (K)	Reduced stomatal conductance and transpiration	Increased canopy temperature	Thermal + Multispectral	Thermal imaging integrated with vegetation indices	(Yang <i>et al.</i> , 2025) ^[15]
Micronutrients (Fe, Zn, Mn, Mg, S)	Changes in pigment composition and leaf biochemistry	Subtle spectral changes across narrow wavelengths	Hyperspectral	Hyperspectral analysis with AI and multisensor data fusion	(Yang <i>et al.</i> , 2025; Peticila <i>et al.</i> , 2025) ^[15, 48]

5. Geographic Information Systems (GIS) in Precision Nutrient Management

Geographic Information Systems (GIS) integrate geo-referenced soil, crop, remote sensing and GPS data to analyze spatial variability in soil fertility and crop nutrient status, enabling site-specific fertilizer management and improving nutrient-use efficiency in precision agriculture (Sangeetha *et al.*, 2024)^[8]. Recent integration of GIS with remote sensing, unmanned aerial vehicles (UAVs), artificial intelligence (AI), cloud computing and the Internet of Things (IoT) has further strengthened real-time nutrient monitoring and precision decision-making, making GIS a central technology in digital agriculture (Yang *et al.*, 2025)^[15].

5.1 Fundamentals of GIS

A Geographic Information System (GIS) is a computer-based platform for capturing, managing, analyzing and displaying geographically referenced data. In precision agriculture, GIS integrates multiple spatial datasets, including soil properties,

topography, climate, crop growth, irrigation and yield information, to evaluate field variability and support site-specific nutrient management. Using raster and vector data together with spatial analysis techniques such as overlay, buffering, interpolation and map generation, GIS identifies nutrient-deficient zones and provides decision-support information for precision fertilizer management (Longley *et al.*, 2015; Kumar *et al.*, 2025; Kumar *et al.*, 2026; Sangeetha *et al.*, 2024)^[11, 27, 8, 28].

5.2 Spatial Variability Analysis

Spatial variability in soil nutrients results from differences in soil texture, organic matter, moisture, topography, cropping history and management practices. GIS analyzes geo-referenced soil and crop data to delineate management zones with similar nutrient characteristics, enabling variable-rate fertilizer application according to local crop requirements. Integration with remote sensing, historical yield records and machine learning further improves the assessment of field

variability and supports adaptive nutrient management throughout the growing season (Mulla, 2013; Yang *et al.*, 2025; Nawar *et al.*, 2017) ^[29, 15, 30].

5.3 Soil Fertility and Nutrient Distribution Mapping

Soil fertility and nutrient distribution mapping are among the most important applications of GIS in precision nutrient management. GPS-referenced soil samples, laboratory analyses and remote sensing observations are integrated to generate digital maps of soil properties and the spatial distribution of macro- and micronutrients. These maps identify nutrient-deficient areas, delineate management zones and support site-specific fertilizer recommendations. The incorporation of UAV-derived vegetation indices further enhances mapping accuracy and enables continuous monitoring of nutrient status for sustainable soil fertility management (Sangeetha *et al.*, 2024; Mulla, 2013; Yang *et al.*, 2025) ^[8, 29, 15].

5.4 Geostatistical Techniques

Geostatistical techniques are widely used to transform point-based soil observations into continuous spatial nutrient maps, enabling accurate assessment of within-field variability. Among these methods, Kriging is preferred because it incorporates spatial autocorrelation and provides reliable estimates of soil properties, while Inverse Distance Weighting (IDW) offers a simpler and computationally efficient interpolation approach for dense sampling datasets. These techniques improve soil nutrient mapping, support

management-zone delineation and enhance site-specific fertilizer recommendations for precision nutrient management (Kumar *et al.*, 2026; Kumar *et al.*, 2025) ^[28, 27].

5.5 Variable-Rate Fertilizer Application

GIS-based nutrient management generates prescription maps for variable-rate fertilizer application by integrating soil fertility, nutrient distribution, yield history, remote sensing and crop nutrient requirements. These maps guide GPS-enabled applicators, optimizing fertilizer rates, reducing input costs and nutrient losses, while cloud-based GIS and decision-support systems support dynamic fertilizer recommendations (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) ^[8, 15].

5.6 Integration of GIS with GPS and Remote Sensing

The integration of GIS with GPS and remote sensing has transformed precision agriculture into a comprehensive spatial decision-support system. GPS provides accurate geo-referencing for soil sampling, field operations and yield monitoring, whereas satellite, UAV and ground-based sensors continuously monitor crop growth, vegetation indices and nutrient status. GIS integrates these datasets to generate soil fertility maps, management zones and variable-rate fertilizer prescriptions. Furthermore, the incorporation of AI, cloud computing and IoT technologies enables real-time monitoring and predictive nutrient management, improving crop productivity while reducing environmental impacts (Sangeetha *et al.*, 2024; Yang *et al.*, 2025; Bhamini *et al.*, 2025) ^[8, 15, 31].

Table 4: GIS Applications in Precision Nutrient Management

Application Area	GIS Role	Benefits	References
Soil Mapping	Analysis of spatial variability in soil properties (pH, organic carbon, N, P, K, micronutrients)	Supports site-specific nutrient management and fertilizer recommendations	(Raihan 2024; Sangeetha <i>et al.</i> , 2024) ^[32, 8]
Crop Health Monitoring	Integration of remote sensing imagery, vegetation indices and field observations	Early detection of crop stress and nutrient deficiencies, enabling timely interventions	(Raihan, 2024; Yang <i>et al.</i> , 2025) ^[32, 15]
Variable Rate Technology (VRT)	Development of geo-referenced prescription maps for fertilizer application	Optimizes fertilizer use, improves nutrient use efficiency, reduces production costs and minimizes environmental pollution	(Raihan, 2024) ^[32]
Irrigation Management	Spatial analysis of soil moisture, crop water requirements and field variability	Enhances irrigation efficiency, improves nutrient uptake and conserves water resources	(Raihan, 2024; Yang <i>et al.</i> , 2025) ^[32, 15]

6. Artificial Intelligence in Precision Nutrient Management

Artificial Intelligence (AI) enables data-driven precision nutrient management by analyzing satellite, UAV, soil, weather and Internet of Things (IoT) data to diagnose nutrient deficiencies, predict crop requirements, optimize fertilizer recommendations and support variable-rate application (Sangeetha *et al.*, 2024; Bustami *et al.*, 2025) ^[8, 33]. The integration of AI with remote sensing, Geographic Information Systems (GIS), cloud computing and IoT has further enhanced real-time nutrient monitoring and precision decision-making (Yang *et al.*, 2025) ^[15].

6.1 Overview of Artificial Intelligence in Agriculture

Artificial Intelligence refers to computer systems capable of learning, reasoning, pattern recognition, prediction and decision-making. In agriculture, AI integrates machine learning, deep learning, computer vision, remote sensing and sensor technologies to improve crop productivity while reducing production costs and environmental impacts (Liakos *et al.*, 2018) ^[34]. By analyzing data from satellites, UAVs, soil sensors, weather stations and GPS-enabled equipment, AI supports nutrient deficiency detection, crop growth monitoring, yield prediction, irrigation scheduling and site-

specific fertilizer recommendations. Recent advances in cloud computing, IoT and digital agriculture have further strengthened AI-driven decision-support systems for sustainable nutrient management (Sangeetha *et al.*, 2024; Bustami *et al.*, 2025) ^[8, 33].

6.2 Machine Learning Algorithms

Machine learning (ML) enables computer systems to learn patterns from historical data and generate accurate predictions without explicit programming. In precision nutrient management, ML algorithms analyze soil properties, climatic conditions, crop characteristics, remote sensing observations and fertilizer inputs to predict nutrient status and support management decisions. Compared with conventional statistical approaches, ML models effectively capture complex nonlinear relationships, improving nutrient prediction and fertilizer recommendations (Liakos *et al.*, 2018; Bustami *et al.*, 2025) ^[34, 33]. Commonly used ML algorithms include Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB) and Extreme Gradient Boosting (XGBoost), each offering specific advantages for soil fertility assessment, nutrient deficiency detection, yield prediction and fertilizer optimization. Among these, Random Forest and

XGBoost are widely preferred because of their high prediction accuracy, robustness and ability to process large and complex

agricultural datasets (Bustami *et al.*, 2025; Yang *et al.*, 2025) [33, 15].

Table 5: Machine Learning Algorithms Used in Precision Nutrient Management

Algorithm	Working Principle	Agricultural Application	Advantages	References
Decision Tree (DT)	Tree-based classification and regression	Soil fertility classification, nutrient prediction	Simple, interpretable, low computational cost	(Bustami <i>et al.</i> , 2025; Liakos <i>et al.</i> , 2018) [33, 34]
Random Forest (RF)	Ensemble of multiple decision trees	Nutrient deficiency detection, yield prediction, soil fertility assessment	High accuracy, robust to noise and nonlinear data	(Bustami <i>et al.</i> , 2025; Chlingaryan <i>et al.</i> , 2018) [33, 35]
Support Vector Machine (SVM)	Hyperplane-based supervised classification	Crop stress detection, nutrient classification, disease diagnosis	Effective for small and high-dimensional datasets	(Liakos <i>et al.</i> , 2018; Bustami <i>et al.</i> , 2025) [34, 33]
Gradient Boosting (GB)	Sequential ensemble learning using weak learners	Fertilizer recommendation, yield prediction	Excellent predictive performance and flexibility	(Bustami <i>et al.</i> , 2025) [33]
XGBoost	Optimized gradient boosting with regularization	Soil nutrient prediction, crop yield estimation, fertilizer optimization	Fast, accurate, scalable, handles missing values	(Bustami <i>et al.</i> , 2025; Yang <i>et al.</i> , 2025) [33, 15]

Machine learning continues to evolve through advances in ensemble learning and automated machine learning (AutoML). Its integration with remote sensing, GIS, IoT and cloud-based decision-support systems has significantly improved nutrient prediction, fertilizer management and sustainable crop production (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) [8, 15].

6.3 Deep Learning Methods

Deep learning (DL), a subset of artificial intelligence, has significantly advanced precision nutrient management by automatically extracting complex features from multispectral, hyperspectral, UAV, soil sensor and weather datasets without manual feature engineering. Its ability to process high-dimensional agricultural data has improved nutrient deficiency detection, crop health assessment, yield prediction and fertilizer recommendation (Kamilaris and Prenafeta-Boldú,

2018; Bustami *et al.*, 2025) [36, 33]. Among DL architectures, Convolutional Neural Networks (CNNs) are widely used for image-based nutrient assessment, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks effectively analyze temporal data such as crop growth and weather patterns. More recently, Vision Transformers (ViTs) have demonstrated superior performance for high-resolution UAV and hyperspectral imagery by capturing long-range spatial relationships, improving nutrient deficiency detection and crop stress analysis (Liakos *et al.*, 2018; Bustami *et al.*, 2025; Yang *et al.*, 2025) [34, 33, 15]. The integration of deep learning with remote sensing, cloud computing and IoT technologies has enabled real-time nutrient monitoring and intelligent fertilizer management, enhancing the efficiency and sustainability of precision agriculture.

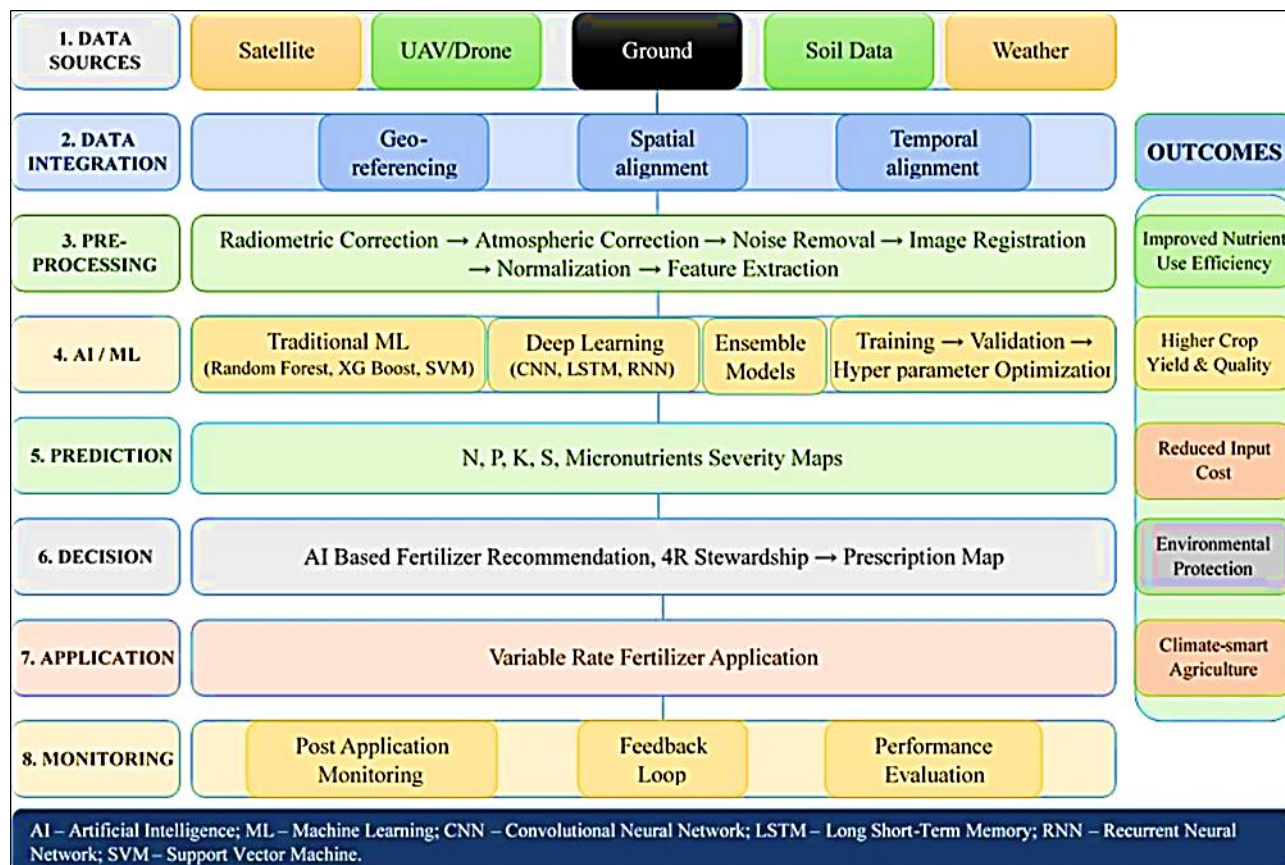


Fig 1: AI-Based Workflow for Precision Nutrient Management

6.4 AI for Nutrient Deficiency Detection

Artificial intelligence has significantly improved early nutrient deficiency detection by integrating remote sensing, proximal sensing, laboratory analyses and environmental data into predictive models. Machine learning and deep learning algorithms process multispectral, hyperspectral, thermal and soil sensor data to identify nutrient stress before visible symptoms appear, enabling timely nutrient management (Bustami *et al.*, 2025) ^[33]. Among AI models, CNNs are highly effective for image-based nutrient deficiency detection, while Random Forest, XGBoost and Vision Transformers (ViTs) improve prediction accuracy by integrating spectral and soil information. These approaches enhance the detection of nitrogen, phosphorus, potassium and micronutrient deficiencies across diverse cropping systems, supporting accurate and site-specific fertilizer recommendations (Chlingaryan *et al.*, 2018; Bustami *et al.*, 2025; Yang *et al.*, 2025) ^[35, 33, 15].

6.5 AI-Based Fertilizer Recommendation Systems

Artificial intelligence has transformed fertilizer recommendation from conventional advisory approaches to intelligent, site-specific decision-support systems. AI models integrate soil nutrient status, crop growth stage, weather conditions, historical yield records, remote sensing observations and management practices to determine optimal fertilizer rates and support variable-rate fertilizer application (Sangeetha *et al.*, 2024) ^[8]. Among the available algorithms, Random Forest, XGBoost, CNN and LSTM are widely used because of their high prediction accuracy and ability to analyze complex spatial and temporal datasets. Their integration with remote sensing, IoT and cloud-based platforms enables adaptive fertilizer recommendations that improve nutrient use efficiency while reducing fertilizer costs and environmental impacts (Yang *et al.*, 2025) ^[15].

Table 6: AI-Based Fertilizer Recommendation Systems

Input Data	AI Technique	Output	Primary Application	References
Soil nutrient analysis	Random Forest	Fertilizer dose recommendation	Site-specific nutrient management	(Bustami <i>et al.</i> , 2025) ^[33]
UAV and satellite imagery	CNN	Nitrogen status and fertilizer recommendation	Crop nutrient monitoring	(Yang <i>et al.</i> , 2025) ^[15]
Weather + soil + crop data	XGBoost	Variable-rate fertilizer prescription	Precision nutrient optimization	(Bustami <i>et al.</i> , 2025) ^[33]
IoT sensor networks	LSTM	Real-time nutrient scheduling	Dynamic nutrient management	(Bustami <i>et al.</i> , 2025) ^[33]
Historical yield and remote sensing	Gradient Boosting	Nutrient optimization and yield prediction	Decision-support systems	(Liakos <i>et al.</i> , 2018) ^[34]

AI-driven fertilizer recommendation systems continue to evolve through advances in machine learning, deep learning and geospatial technologies, providing accurate and sustainable nutrient management for precision agriculture (Liakos *et al.*, 2018; Bustami *et al.*, 2025) ^[34, 33].

6.6 Predictive Modeling of Crop Nutrient Requirements

Predictive modeling is an important application of artificial intelligence in precision nutrient management, enabling proactive estimation of crop nutrient requirements throughout the growing season. AI models integrate soil fertility, historical crop performance, weather conditions, topography, remote sensing observations and management practices to predict nutrient demand and optimize fertilizer application (Bustami *et al.*, 2025; Yang *et al.*, 2025) ^[33, 15]. Machine learning algorithms, including Random Forest, Gradient Boosting, XGBoost and Artificial Neural Networks (ANNs), effectively capture complex interactions among soil, climate and crop variables, providing more accurate nutrient predictions than conventional statistical approaches (Liakos *et al.*, 2018) ^[34]. The integration of real-time geospatial and sensor data further enables adaptive fertilizer management, improving nutrient use efficiency while reducing fertilizer losses and environmental impacts (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) ^[8, 15].

6.7 Explainable AI for Agricultural Decision Making

Although artificial intelligence models provide highly accurate predictions, many operate as "black-box" systems with limited interpretability. Explainable Artificial Intelligence (XAI) improves model transparency by identifying the factors influencing AI predictions, thereby increasing user confidence and supporting informed agricultural decision-making (Lundberg and Lee, 2017; Arrieta *et al.*, 2020) ^[37, 38].

Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) help explain fertilizer recommendations by quantifying the contribution of variables such as soil nutrient status, vegetation indices, weather conditions and crop growth stages. Improved model interpretability enhances the reliability and adoption of AI-based decision-support systems, making XAI an essential component of future precision nutrient management (Bustami *et al.*, 2025) ^[33].

7. Integration of Remote Sensing, GIS and Artificial Intelligence for Precision Nutrient Management

The integration of *Remote Sensing* (RS), Geographic Information Systems (GIS) and Artificial Intelligence (AI) has transformed precision nutrient management into an intelligent, data-driven approach. *Remote sensing* monitors crop and nutrient status, GIS analyzes spatial variability and management zones and AI predicts nutrient requirements and fertilizer recommendations. Together, these technologies enable real-time decision-making, improve nutrient-use efficiency, reduce fertilizer losses and support climate-smart, sustainable agriculture (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) ^[8, 15].

7.1 Data Integration and Decision Support Systems

Precision nutrient management integrates satellite and UAV imagery, Geographic Information Systems (GIS), soil, weather, Internet of Things (IoT) and historical crop data through data fusion techniques, improving nutrient assessment accuracy and enabling reliable, site-specific fertilizer recommendations and decision support (Bustami *et al.*, 2025) ^[33]. Integrated Decision Support Systems (DSS) combine agricultural datasets, machine learning and crop simulation models to generate site-specific nutrient recommendations.

Cloud-based platforms and mobile applications provide real-time decision support, enabling nutrient deficiency detection, fertilizer optimization and variable-rate fertilizer application (Sangeetha *et al.*, 2024; Bustami *et al.*, 2025; Yang *et al.*, 2025) [8, 33, 15].

7.2 Digital Soil Mapping and Precision Fertilizer Recommendation

Digital Soil Mapping (DSM) combines GIS, remote sensing, geostatistics and AI to generate higher-resolution maps of soil properties and nutrient distribution. Geo-referenced soil samples are integrated with environmental variables such as topography, vegetation indices, climate and satellite imagery to predict soil pH, organic carbon, soil moisture, texture and macro- and micronutrient status. Machine learning approaches, including Random Forest, Gradient Boosting, XGBoost and Artificial Neural Networks (ANNs), have substantially improved the accuracy of soil fertility mapping and nutrient prediction (Bustami *et al.*, 2025; Yang *et al.*, 2025) [33, 15]. AI integrates soil fertility maps, vegetation indices, weather, crop growth and yield data to generate site-specific fertilizer recommendations, enabling GPS-guided variable-rate application, improved nutrient-use efficiency and reduced production costs and environmental impacts (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) [8, 15].

7.3 Smart Digital Agriculture Platforms

The integration of cloud computing, big data analytics and the Internet of Things (IoT) has further strengthened precision nutrient management by enabling continuous monitoring and real-time decision-making. Cloud platforms provide scalable infrastructure for storing and processing large datasets collected from satellites, UAVs, weather stations, farm

machinery and IoT sensors. Big data analytics identifies complex relationships among soil, crop and environmental variables, improving nutrient prediction and fertilizer optimization (Sangeetha *et al.*, 2024; Bustami *et al.*, 2025) [8, 33]. IoT-enabled sensors continuously monitor soil moisture, nutrient availability, temperature and weather conditions, transmitting real-time data to cloud-based Artificial Intelligence (AI) [8, 33] systems. These platforms enable adaptive fertilizer recommendations, early nutrient stress detection, improved fertilizer-use efficiency and sustainable crop production (Yang *et al.*, 2025) [15].

7.4 Emerging Technologies and Future Integration

Recent advances in Digital Twin technology have enhanced intelligent nutrient management by creating dynamic virtual models of agricultural systems using *Remote Sensing* (RS), Geographic Information Systems (GIS), the Internet of Things (IoT) and Artificial Intelligence (AI). These models simulate nutrient management scenarios, predict crop responses and optimize fertilizer strategies before field implementation (Purcell *et al.*, 2023; Yang *et al.*, 2025) [39, 15].

Future precision nutrient management will increasingly rely on the seamless integration of RS, GIS, AI, cloud computing, IoT and digital twins into comprehensive decision-support systems. These technologies will facilitate autonomous nutrient monitoring, predictive fertilizer management and intelligent resource optimization, enhance crop productivity while minimize environmental impacts. Their continued development is expected to play a central role in achieving climate-smart and sustainable agricultural production (Sangeetha *et al.*, 2024; Bustami *et al.*, 2025; Yang *et al.*, 2025) [8, 33, 15].

Table 7: Integration of Digital Technologies for Precision Nutrient Management

Technology	Primary Function	Key Data Sources	Major Benefits	References
Remote Sensing	Crop health and nutrient monitoring	Satellite, UAV, multispectral and hyperspectral imagery	Early nutrient stress detection and crop monitoring	(Yang <i>et al.</i> , 2025; Sangeetha <i>et al.</i> , 2024) [15, 8]
GIS	Spatial analysis, mapping and management zone delineation	Soil samples, GPS, remote sensing, topographic data	Site-specific nutrient management and prescription mapping	(Sangeetha <i>et al.</i> , 2024) [8]
Artificial Intelligence	Prediction, classification and decision support	Soil, weather, crop, yield and image datasets	Nutrient prediction, fertilizer optimization and yield forecasting	(Bustami <i>et al.</i> , 2025) [33]
Cloud Computing	Centralized data storage and real-time analytics	Multi-source agricultural databases	Scalable processing, data sharing and decision support	(Yang <i>et al.</i> , 2025) [15]
Internet of Things (IoT)	Continuous monitoring through connected sensors	Soil moisture, nutrient, weather and environmental sensors	Real-time field monitoring and automated management	
Digital Twin	Virtual representation of agricultural systems	Integrated GIS, AI, sensor and remote sensing data	Scenario simulation, predictive nutrient management and resource optimization	(Purcell <i>et al.</i> , 2023; Yang <i>et al.</i> , 2025) [39, 15]

8. Applications in Major Crops

Precision nutrient management (PNM) improves nutrient use efficiency, crop productivity and environmental sustainability through site-specific fertilizer management. By integrating remote sensing, Geographic Information Systems (GIS), artificial intelligence (AI) and variable-rate technologies, PNM optimizes nutrient application across cereals, oilseeds, pulses, horticultural and plantation crops according to crop requirements and field variability (Sangeetha *et al.*, 2024; Yang *et al.*, 2025) [8, 15].

8.1 Cereals

Precision nutrient management in cereal crops, including rice, wheat and maize, enhances nutrient use efficiency through remote sensing, Geographic Information Systems (GIS),

unmanned aerial vehicles (UAVs) and artificial intelligence (AI), enabling accurate nutrient deficiency detection, variable-rate fertilizer application, improved grain yield and quality (Liakos *et al.*, 2018; Bustami *et al.*, 2025; Yang *et al.*, 2025; Gomes *et al.*, 2025) [34, 33, 15, 17].

8.2 Oilseed and Pulse Crops

In oilseed and pulse crops, precision nutrient management improves nutrient-use efficiency, seed quality and productivity through site-specific fertilizer recommendations. Geospatial technologies and artificial intelligence (AI) optimize nitrogen, phosphorus, sulfur, potassium and micronutrient management across diverse agroecological conditions (Liakos *et al.*, 2018; Mulla, 2013; Bustami *et al.*, 2025; Sangeetha *et al.*, 2024) [34, 29, 33, 8].

8.3 Horticultural Crops

In high-value horticultural crops, precision nutrient management enables early nutrient deficiency detection, optimized fertigation and balanced nutrient distribution. Integration of Geographic Information Systems (GIS), *Remote Sensing* (RS), the Internet of Things (IoT) and Artificial Intelligence (AI) improve fertilizer-use efficiency, fruit quality and productivity while reducing production costs (Kamilaris and Prenafeta-Boldú, 2018; Bustami *et al.*, 2025) ^[36, 33].

8.4 Plantation Crops

Precision nutrient management is increasingly applied in plantation crops such as tea, coffee, coconut, oil palm, rubber and cocoa. Geospatial technologies combined with AI facilitate continuous monitoring of nutrient status and support site-specific fertilizer management in perennial production systems. These approaches improve nutrient-use efficiency, yield, product quality and environmental sustainability while reducing fertilizer inputs (Yang *et al.*, 2025; Sangeetha *et al.*, 2024) ^[15, 8].

Table 8: Applications of Precision Nutrient Management in Major Crops

Crop Group	Major Crops	Key Technologies	Major Nutrients	Major Benefits	References
Cereals	Rice, Wheat and Maize	RS, GIS, AI, UAV, VRT	N, P, K	Higher NUE, yield improvement, reduced fertilizer losses	(Yang <i>et al.</i> , 2025; Bustami <i>et al.</i> , 2025) ^[15, 33]
Oilseeds	Soybean, Canola, Sunflower, Groundnut	GIS, AI, Remote Sensing	N, S	Improved oil quality and nutrient-use efficiency	(Liakos <i>et al.</i> , 2018) ^[34]
Pulses	Chickpea, Lentil, Pigeon pea, Mung bean	GIS, AI, Remote Sensing	P, K, S, Micronutrients	Better nodulation, balanced nutrition, higher productivity	(Mulla, 2013; Sangeetha <i>et al.</i> , 2024) ^[29, 8]
Horticultural Crops	Tomato, Potato, Citrus, Grapevine, Banana	Hyperspectral Imaging, IoT, AI	Macro- and Micronutrients	Improved fruit quality and fertigation efficiency	(Kamilaris and Prenafeta-Boldú, 2018; Bustami <i>et al.</i> , 2025) ^[36, 33]
Plantation Crops	Tea, Coffee, Oil Palm, Coconut, Rubber	Satellite, UAV, GIS, AI	Crop-specific	Sustainable nutrient management and improved yield	(Yang <i>et al.</i> , 2025; Sangeetha <i>et al.</i> , 2024) ^[8, 15]

9. Recent Advances in Precision Nutrient Management

Recent advances in hyperspectral imaging, unmanned aerial vehicles (UAVs), artificial intelligence (AI), robotics, the Internet of Things (IoT), edge computing and cloud computing have transformed precision nutrient management by enabling rapid nutrient diagnosis, real-time monitoring, automated fertilizer application and data-driven decision-making, improving nutrient use efficiency and sustainable agricultural production (Wolfert *et al.*, 2017; Sishodia *et al.*, 2020; Yang *et al.*, 2025) ^[40, 58, 15].

9.2 Intelligent Digital Agriculture

The integration of AI-powered mobile applications, edge computing, IoT and cloud computing has advanced intelligent nutrient management. AI applications enable rapid nutrient diagnosis and fertilizer recommendations, while IoT sensors, edge computing and cloud platforms support realtime monitoring, predictive analytics and data-driven decision-making for precision agriculture (Ferentinos, 2018; Kamilaris and Prenafeta-Boldú, 2018; Shi *et al.*, 2020; Wolfert *et al.*, 2017; Ameen *et al.*, 2025) ^[41, 36, 45, 40, 42].

9.1 Emerging Sensing and Imaging Technologies

Recent advances in hyperspectral imaging and UAV-based sensing have enhanced early nutrient deficiency detection. UAVs equipped with RGB, multispectral, hyperspectral, thermal and LiDAR sensors provide high-resolution crop monitoring, while integration with artificial intelligence (AI) improves nutrient diagnosis, decision-making and variable-rate fertilizer application for precision nutrient management (Sishodia *et al.*, 2020; Wolfert *et al.*, 2017; Yang *et al.*, 2025) ^[58, 40, 15].

9.3 Automation and Smart Nutrient Management

Automation enhances precision nutrient management through agricultural robotics and real-time monitoring. GPS-, AI- and machine vision-enabled fertilizer applicators ensure precise nutrient placement, while integrated sensor networks continuously monitor soil and crop conditions, enabling adaptive fertilizer scheduling, improving operational efficiency, nutrient-use efficiency and environmental sustainability (Khanna and Kaur, 2019; Visser *et al.*, 2023; Yang *et al.*, 2025) ^[43, 15].

Table 9: Emerging Technologies in Precision Nutrient Management.

Technology	Primary Application	Major Advantages	References
Hyperspectral Imaging	Nutrient deficiency detection	Early detection of biochemical changes	(Sishodia <i>et al.</i> , 2020; Yang <i>et al.</i> , 2025) ^[58, 15]
UAV-Based Monitoring	Crop nutrient assessment	High spatial resolution and rapid monitoring	(Wolfert <i>et al.</i> , 2017; Yang <i>et al.</i> , 2025) ^[40, 15]
AI Mobile Applications	Nutrient diagnosis and fertilizer advisory	Low-cost, field-based decision support	(Ferentinos, 2018; Kamilaris & Prenafeta-Boldú, 2018) ^[41, 36]
Edge Computing	Real-time field analytics	Low latency and rapid decision-making	(Shi <i>et al.</i> , 2020; Wolfert <i>et al.</i> , 2017) ^[45, 40]
Agricultural Robotics	Autonomous fertilizer application	Precision nutrient placement and reduced labor	(Visser <i>et al.</i> , 2023; Khanna & Kaur, 2019) ^[43]
Real-Time Monitoring Systems	Continuous nutrient assessment	Dynamic fertilizer management	
Internet of Things (IoT)	Smart sensor networks	Automated monitoring and data integration	(Ameen <i>et al.</i> , 2025) ^[42]
Cloud Platforms	Data storage and decision support	Scalable analytics and information sharing	(Wolfert <i>et al.</i> , 2017; Yang <i>et al.</i> , 2025) ^[40, 15]

10. Challenges

Despite rapid advances in *Remote Sensing* (RS), Geographic Information Systems (GIS), Artificial Intelligence (AI) and associated digital technologies, several challenges continue to limit the widespread implementation of precision nutrient management (PNM). Addressing these constraints is essential to improve nutrient-use efficiency, technology accessibility and sustainable agricultural production (Finger *et al.*, 2019) [44].

10.1 Data Quality and Integration Challenges

Effective PNM depends on accurate, standardized and interoperable datasets. However, sensor calibration errors, cloud contamination in satellite imagery, missing observations, inconsistent sampling and interoperability issues among RS, GIS, AI and Internet of Things (IoT) platforms reduce prediction accuracy and limit decision-support performance. Advanced geospatial processing and AI models also require substantial computational resources (Shi *et al.*, 2016; Wolfert *et al.*, 2017) [45, 40].

10.2 Economic and Infrastructure Challenges

The adoption of PNM remains constrained by the high cost of UAVs, multispectral sensors, GPS guided machinery, soil sensors and variable-rate applicators. Limited digital infrastructure, fragmented landholdings, inadequate technical expertise and uncertain economic returns further restrict technology adoption, particularly among smallholder farmers (Finger *et al.*, 2019; Lowenberg-DeBoer and Erickson, 2019; Rose *et al.*, 2021) [44, 46, 47, 48].

10.3 AI Model and Validation Challenges

Most AI and machine learning models are developed using region-specific datasets, limiting their applicability across different crops, soils and climatic conditions. Climate variability further influences nutrient dynamics and crop demand, emphasizing the need for standardized datasets, explainable AI, adaptive prediction models and multi-location validation (Van Klompenburg *et al.*, 2020; Calvin *et al.*, 2023) [49, 50].

10.4 Policy and Data Governance Challenges

Data ownership, interoperability, cybersecurity, privacy and technology certification remain major concerns affecting user confidence. Standardized digital agriculture frameworks and secure data governance are needed to facilitate data sharing and technology integration (Wolfert *et al.*, 2017; Khanam *et al.*, 2020) [40, 51].

10.5 Capacity Building and Technology Adoption

Limited digital literacy, insufficient extension support and weak university–industry collaboration continues to hinder PNM adoption. Strengthening farmer training, public–private partnerships and capacity-building initiatives will be essential for expanding sustainable digital agriculture (Finger *et al.*, 2019; Rose *et al.*, 2021; Khanam *et al.*, 2020) [44, 47, 51].

11. Future Perspectives

Future advances in precision nutrient management will be driven by the convergence of Artificial Intelligence (AI), *Remote Sensing* (RS), Geographic Information Systems (GIS), the Internet of Things (IoT), cloud computing, robotics and advanced sensing technologies. These innovations are expected to enable intelligent, predictive and site-specific nutrient management, improving agricultural productivity and

environmental sustainability (FAO, 2022; Ali *et al.*, 2025) [52, 9].

11.1 Intelligent Digital Nutrient Management

Future AI-driven decision-support systems will integrate satellite imagery, UAV observations, IoT sensors, weather information, soil databases and crop growth data to provide real-time fertilizer recommendations. Explainable AI, digital twins, cloud computing, edge computing and autonomous machinery will improve prediction accuracy, transparency and operational efficiency (Duckett *et al.*, 2018; Reichstein *et al.*, 2019; Verdouw *et al.*, 2021; Kairouz *et al.*, 2021) [53, 54, 55, 56].

11.2 Climate-Smart Agriculture

The integration of AI, GIS, RS and climate forecasting will support adaptive nutrient management while reducing nutrient losses and greenhouse gas emissions. Standardized data frameworks, affordable sensing technologies and supportive policies will accelerate climate-smart and sustainable agriculture (Jakku *et al.*, 2019; Kumar *et al.*, 2026; Bossio *et al.*, 2020; DeBoe and Jouanjean, 2019; FAO, 2022) [57, 28, 58, 48, 52].

11.3 Emerging Digital Technologies

Emerging technologies, including digital twins, advanced hyperspectral sensing, robotics, autonomous fertilizer applicators and edge computing, will enhance continuous monitoring, predictive analytics and automated nutrient management, improve resource-use efficiency and reduce production costs (Duckett *et al.*, 2018; Verdouw *et al.*, 2021; Reichstein *et al.*, 2019; Lord, 2024) [53, 55, 54, 59].

11.4 Research and Standardization

Future research should prioritize standardized datasets, interoperable digital platforms, explainable AI and multi-location validation to improve model transparency, reproducibility and global applicability. Interdisciplinary collaboration and open agricultural databases will further strengthen digital agriculture research (Basso and Antle, 2020; Cassman and Grassini, 2020; van Klompenburg *et al.*, 2020; Rolnick *et al.*, 2022; Sabir and Ozkececi, 2025) [60, 61, 49, 62, 63].

11.5 Inclusive and Sustainable Adoption

Affordable technologies designed for smallholder farmers, stronger extension services and public–private partnerships will be essential for the widespread adoption of precision nutrient management. These efforts will enhance nutrient-use efficiency, strengthen climate resilience and contribute to sustainable agricultural development and global food security (FAO, 2022; Cassman and Grassini, 2020; Sabir and Ozkececi, 2025) [52, 61, 63].

12. Conclusion

Precision nutrient management (PNM) has emerged as a key approach for improving crop productivity, nutrient-use efficiency and environmental sustainability through the integration of *Remote Sensing* (RS), Geographic Information Systems (GIS), Artificial Intelligence (AI) and other digital technologies. This review highlights the roles of remote sensing, digital soil mapping, machine learning, variable-rate technology and intelligent decision-support systems in enabling accurate nutrient assessment and site-specific fertilizer management. Emerging technologies, including the Internet of Things (IoT), cloud computing, digital twins and explainable AI, further strengthen real-time monitoring and

predictive nutrient management. Despite challenges related to data integration, affordability and technology adoption, continued innovation, standardized data frameworks and interdisciplinary collaboration will accelerate the development of climate-smart, sustainable and data-driven precision nutrient management systems.

13. Limitations

This review has several limitations. First, it is based on a structured narrative review rather than a quantitative meta-analysis and, therefore, does not estimate overall effect sizes or publication bias. Second, most reviewed studies are region- and crop-specific, limiting the generalizability of findings across diverse agroecological conditions. Third, the performance of Remote Sensing (RS), Geographic Information Systems (GIS) and Artificial Intelligence (AI) depends on data quality, sensor calibration and model validation. Finally, many advanced technologies have been evaluated mainly under research or pilot-scale conditions. Future research should emphasize multi-location validation, standardized protocols and long-term field evaluations to improve the reliability and practical applicability of precision nutrient management.

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