

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2026): 4.97
IJAFS 2026; 8(11): 92-99
www.agriculturaljournals.com
Received: 23-09-2026
Accepted: 25-10-2026
Published: 04-11-2026

Ravi Shankar
Rural Agriculture Extension Officer, Govt. of Chhattisgarh, India

Sudha Kiran Tigga
Ph.D. Scholar, Department of Plant Pathology, IGKV Raipur, Chhattisgarh, India

Kishan Kumar Sharma
Guest Teacher, Department of Plant Pathology, Mahatma Gandhi Udyanikee Evam Vanikee Vishwavidyalaya, Sankra-Patan, Chhattisgarh, India

Corresponding Author:
Kishan Kumar Sharma
Guest Teacher, Department of Plant Pathology, Mahatma Gandhi Udyanikee Evam Vanikee Vishwavidyalaya, Sankra-Patan, Chhattisgarh, India

Precision nutrient management using artificial intelligence, remote sensing, and smart sensors: A review

Ravi Shankar[1], Sudha Kiran Tigga[2], Kishan Kumar Sharma[3]

DOI: https://www.doi.org/10.33545/2664844X.2026.v8.i11b.89817

Abstract
The goal of precision nutrient management is to apply the right amount of fertilizer at the right place and right time to meet the crop's spatially and temporally varying demands. Avoiding losses of nutrients is also part of this strategy. The variability of soil fertility, soil moisture, crop development, and the availability of nutrients at the field scale is not typically taken into account in conventional uniform-rate nutrient management practices. This narrative review examines how artificial intelligence (AI), satellite remote sensing and/or UAV remote sensing and smart sensors, are used for diagnosis and/or decision support. Published works from 2020 to 2025 have shown that these technologies provide complementary information and are not interchangeable. Imagery depicts canopy patterns and proximal sensors capture microclimates. Advances in machine learning and deep learning have enabled estimation of nutrients using integrated models. Optical indicators of nitrogen still suffer from the presence of other confounding variables. It is estimated that the majority of low-cost (electronic) sensors will not measure nutrients and therefore will serve more as environmental proxies. An integrated approach to nutrient management, taking agronomic constraints into account, is proposed. This approach combines calibrated observations, geospatial data integration, and uncertainty-aware estimation. The integration of variable-rate delivery and post-application feedback is also part of this approach. Easier access to improved diagnostic technologies does not guarantee that there will be a reduction in actual fertilizer losses or an improvement in farm profits. These outcomes will be determined by the results of other field studies.

Keywords: Precision nutrient management, Artificial intelligence, Remote sensing, IoT, Fertilizer optimization, Soil sensors, UAV, Sustainable agriculture

1. Introduction

Sustainable crop intensification is reliant on management of crop nutrients. Crop growth is dependent on the availability of multiple nutrients, and weather and soil conditions affect availability differently for each nutrient. A fixed recommendation leads to some areas being undersupplied, while others are over-supplied. Excess reactive nitrogen leads to nitrate leaching and N_2O emissions. Phosphorus run-off can exacerbate eutrophication. These issues can be addressed by managing inputs based on the demand for smaller zones. This includes the timing, source, placement and rate of inputs.

Observations are increasingly replacing periodic inspections to inform management decisions. Satellite and drone images can be combined with soil and weather measurements. These data, along with an understanding of crop growth, can help inform decisions regarding crop nutrient management. Reviews on site-specific nutrient management and diagnosis of N focus on the need to integrate sensing scales (Vullaganti *et al.*, 2025; Zhou *et al.*, 2025; Li *et al.*, 2024) [2, 3, 1].

Artificial intelligence has been marketed as a tool that facilitates the transformation of observations into recommendations. However, predictions have biases associated with the sampling strategy, soil type, crop stage, and management history. What is accurate in one context may not be accurate in a different context. Also, the response of canopy reflectance to nutrient stress can occur through multiple pathways, e.g. indirectly through the loss of chlorophyll, through changes in leaf area and architecture. Therefore, the use of reflectance data for the interpretation of nutrient stress in crops must consider the uncertainty in the field and be physically interpretable. (Silva *et al.*, 2023; Zhang *et al.*, 2024).

This review examines the synergies between artificial intelligence (AI), remote sensing, intelligent sensors, and closed-loop systems. It explores and evaluates the trade-offs between the technologies, and identifies the most critical research gaps in this field. This review is a narrative synthesis, and therefore will not evaluate the methodological quality of individual primary studies. It will not synthesize findings from unpublished, or other hard-to-access studies.

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2. Fundamentals of precision nutrient management

It is vital to understand the crop requirements to optimally manage nutrient availability to the crop. This understanding is particularly important to establish site-specific management recommendations that maximize crop productivity while safeguarding the integrity of soil and sustainability of other environmental services. Site-specific nutrient management should be based on the integration of available soil nutrients, crop demand, expected yield, indigenous sources of nutrients and fertilizers, and the constraint on their application. Soil testing is used to determine the chemical composition of the soil, but the methods of extraction and sampling depth affect the interpretation of the test results. Therefore, soil tests may not be an accurate representation of the nutrient availability in the soil.

Spatial Heterogeneity includes topography, varying parent material, irrigation, previous crop residue and management history. Sampling of soil, elevation and crop conditions, as well as imagery, can predict crop demand and help determine zone delineation. The best resolution of zone delineation is constrained by the density of sampling and the resolution of the equipment. As described by Li *et al.* (2024) [1], sampling density affects nutrient mapping and coarse interpolations often conceal local irregularities.

Indicators for nutrient use efficiency such as partial factor productivity (PFP), agronomic efficiency (AE), recovery efficiency (RE), and nutrient balance (NB) should be evaluated in the context of a well-defined reference frame. A treatment could increase apparent efficiency, for example, by reducing the application rate, or increasing the application rate of another nutrient. This could result in a negative impact on crop yield and soil nutrient levels. In order to substantiate such claims, a range of (environmental) indicators needs to be incorporated to complement the improvement in crop yield and nutrient use.

The final factor in the chain, from sensing to decision, is the utilization of variability-based recommendations to adjust application rate and volume. Success of variable-rate application is based on scientifically plausible nutrient maps and recommendations which are agronomically and economically justified.

Table 1. Comparison of conventional and site-specific nutrient management

Dimension	Conventional	Precision approach
Spatial resolution	Uniform management unit	Zones / mapped rates
Inputs	Periodic tests, experience	Georeferenced tests + crop observations
Decision timing	Fixed schedule	Crop- and weather-responsive updates
Main challenge	Within-field mismatch	Data, calibration and machinery cost

3. Artificial intelligence and machine learning applications

3.1. Machine-learning algorithms

Random forests can capture nonlinear relationships and interactions among spectral, soil, climatic, and management variables without restricting them to a predefined functional form. Support vector regression can be effective with smaller training sets but is sensitive to feature scaling and choice of kernel. Gradient boosting and XGBoost can use structured datasets in agriculture effectively but, with extensive hyperparameter tuning, may mask overfitting. Neural networks can be effective to model nonlinear relationships but require an adequate number of independent observations to capture field variability and adequate regularization. There are opportunities for significant improvement in the area of prediction of crop nutrients management using machine learning (Machine learning in nutrient management, 2023) [4].

3.2. Deep learning

There is potential to use convolutional neural networks to extract spatial textures, architecture, and other patterns from images, and to use long-short term memory networks to model sequencing across dates of acquisitions. Attention based models can fuse phenological sequences and soil and spectral information. Neural networks can be used to predict total soil N and other spectral soil properties (Liu *et al.*, 2024; Liu *et al.*, 2024) [5, 6]. However, in the absence of numerous independent fields, more complex architectures should not be presumed superior to simpler, well-calibrated models.

3.3 Nutrient diagnosis and recommendations

Models can proxy laboratory measured nutrients, leaf nutrient concentrations, crop N status and/or deficiency levels. However, these diagnostic estimates may not be aligned with the agronomic meaning of target crops. Targets may indicate crop N deficiency; however, they do not always describe the needed N fertilizer amount. Recommendation models should account for diagnostic estimates along with crop response, costs of nutrients, soil residual fertility, weather and other environmental conditions, as well as regulatory constraints. Objectives should be clearly stated (i.e., profit, target yield, avoidance of N surplus, etc.). A trade-off may need to be made in the event that two or more of these objectives need to be met simultaneously.

3.4 Explainability and trustworthy decisions

While some ML models may be able to explain certain mechanisms that influence a system, agronomists should independently assess unexpected effects and compare models suggestions to independent nutrient budgets. Explanations should guide the review of sampling strategies, model audits and farmer decisions.

Table 2. AI methods and key technical caveats

Technique	Typical data / target	Main limitation
Random forest	Soil, spectral, weather → nutrient estimate	Transferability and extrapolation
SVR	Sparse reference assays + indices	Scaling and kernel tuning
Gradient boosting	Mixed tabular predictors	Overfitting if weak field independence
CNN / attention	Multiband images and sequences	High data and annotation requirements

Note. Entries summarize technical characteristics; no cross-study performance ranking is implied.

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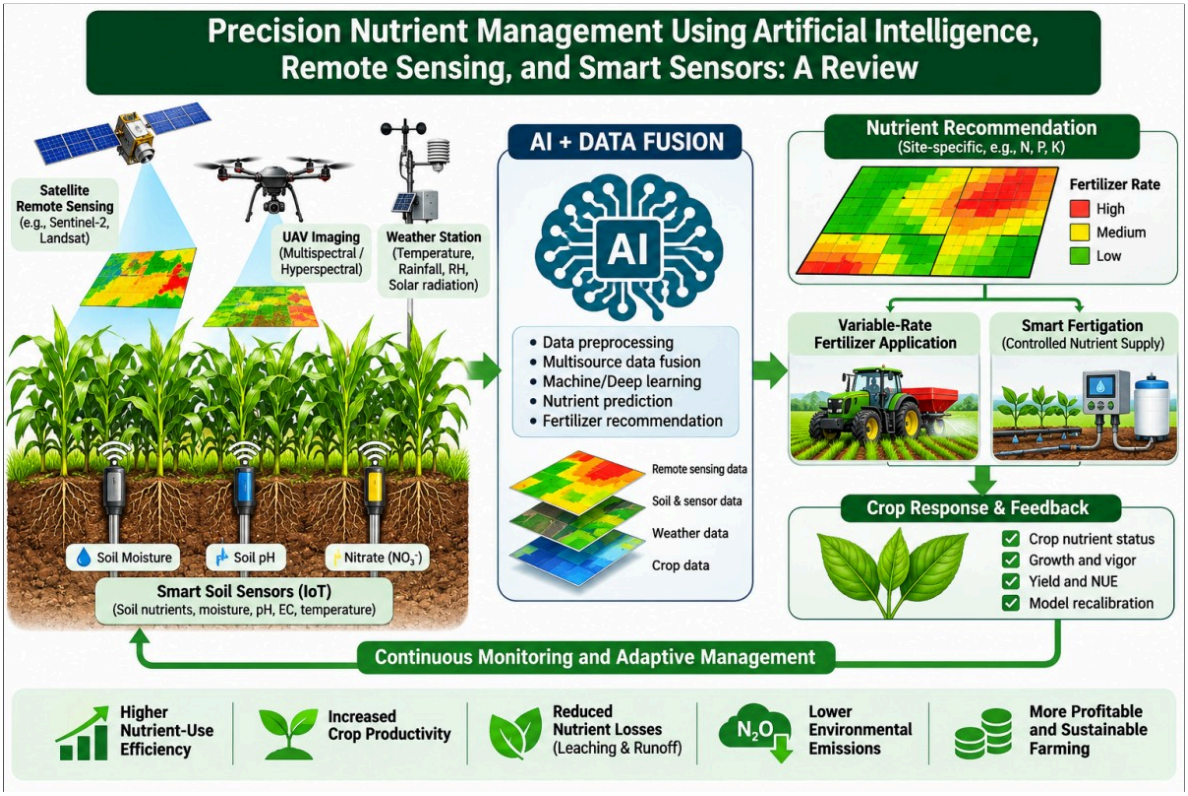


Figure 1. AI-enabled nutrient management overview (original AI-generated conceptual illustration; not field-validated)

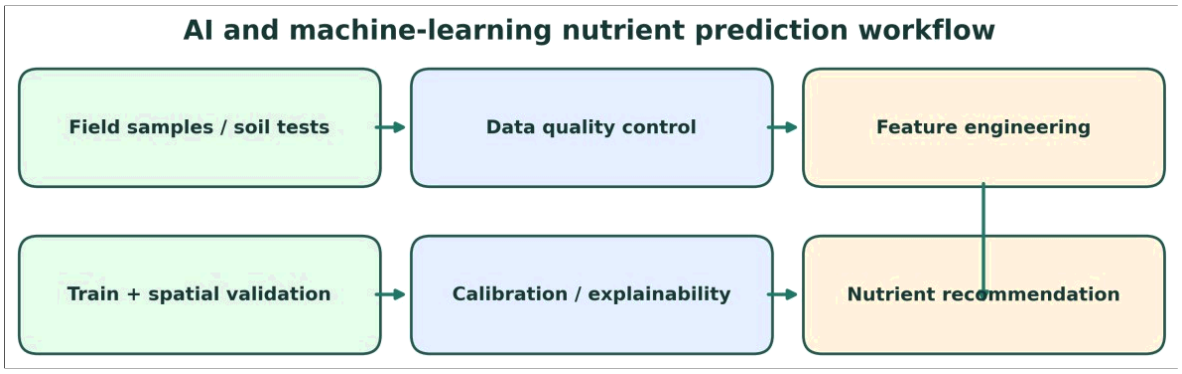


Figure 2. AI and machine-learning nutrient prediction workflow (original conceptual technical diagram; not experimental findings)

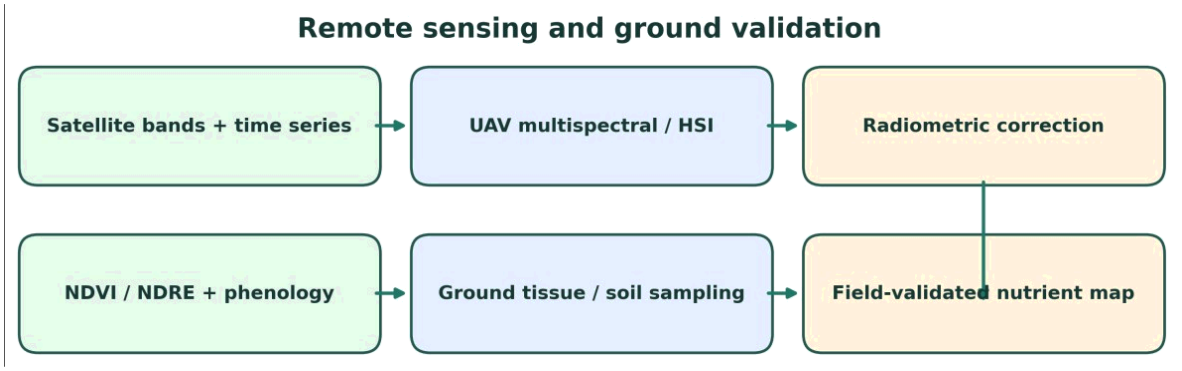


Figure 3. Remote sensing and ground validation (original conceptual technical diagram; not experimental findings)

4. Remote sensing technologies

4.1 Satellites

Sentinel-2 and Landsat data allow for repetitive observation of crop growth over larger agricultural areas. Strengths of satellites include large coverage and long-term data archives. Limitations include mixed pixels, cloud contamination, varying illumination, and off-target acquisition timing. Satellite data coupled with field boundaries and crop calendar data along with atmospheric correction improve the precision of crop growth assessments.

4.2 UAV platforms

Compared to satellites, UAV-based sensing allows for improved spacial resolution and more flexible flight schedules. While UAV data has the potential to detect variability within fields not visible in coarser satellite data, it requires careful control of variables such as flight planning, radiometric calibration, and georeferencing and compliance with aviation laws. In the case of making nitrogen diagnosis,

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the variables relating to the crop growth stage and the target variable to be measured as well as cost constraints must also be taken into account (Li *et al.*, 2024; Guebsi *et al.*, 2024) [1].

4.3 Vegetation indices

NDVI is inverted from what is expected (high values from dense canopies) and can saturate in dense canopies. Related metrics using the red edge can be useful in situations where NDVI loses sensitivity. Neither index can be used to identify/measure N, P or K. Overlapping spectral responses from different factors, such as N deficiency or drought, can yield similar spectra and therefore make indices less useful.

4.4. Hyperspectral analysis

Narrow bands of the electromagnetic spectrum allow detection of biophysical features and/or subtle canopy changes related to nutrition. However, higher dimensionality increases the risk of overfitting, noise, and correlated features. Before definitive statements can be made on nutrient specificity, cross-site laboratory and field validation would be beneficial. Machine learning and hyperspectral reflectance have been used to predict N accumulation in legumes (Flynn *et al.*, 2023) [7].

4.5. From diagnosis to action

Remote sensing should not be used to replace agronomic field truth. It should be used to identify and demonstrate spatial patterns and variation, and justify the need for field sampling. The best approaches integrate multiple observing scales and hierarchies and describe and quantify the residual uncertainty (Zhou *et al.*, 2025; Silva *et al.*, 2023; Zhang *et al.*, 2024) [3].

Table 3. Observation platforms and spectral measures

Method	Measurement strength	Limitation
Satellite multispectral	Time series / regional coverage	Clouds / mixed pixels
UAV multispectral	Sub-field heterogeneity	Flight and calibration demands
NDVI	General canopy vigor	Saturation and nonspecificity
NDRE	Red-edge chlorophyll sensitivity	Still requires reference validation
Hyperspectral	Narrowband feature extraction	Dimensionality and expense

Note. Entries summarize technical characteristics; no cross-study performance ranking is implied.

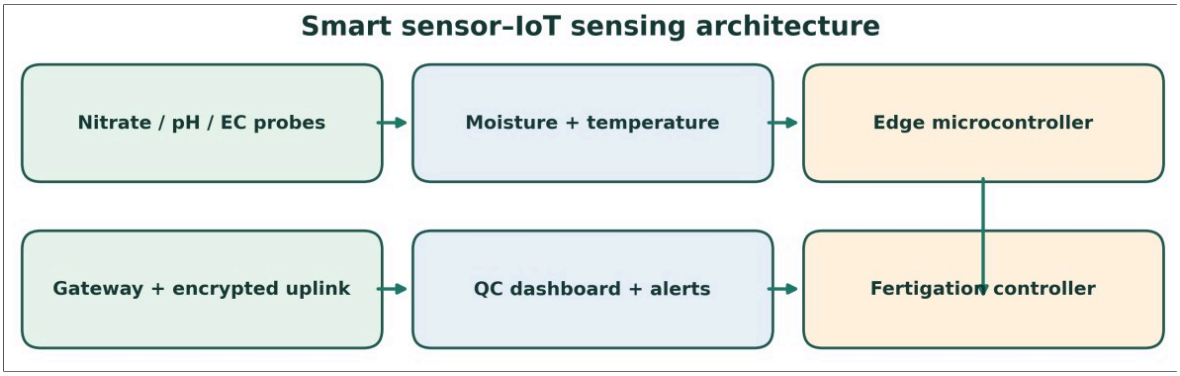


Figure 4. Smart sensor–IoT sensing architecture (original conceptual technical diagram; not experimental findings)

5. Smart sensors and IoT-based monitoring

Smart sensing integrates spatial imagery with soil and solution measurements at strategically selected locations. *Ion-selective electrodes* (ISEs) are sensors for measuring dissolved ions, e.g. nitrate. Other options include optical and spectroscopic sensors, which are used to determine material properties by a calibrated response. Soil moisture, temperature, pH, and electrical-conductivity sensors, are among environmental conditions measured, which are relevant to the transport and uptake of nutrients by crops. However, these sensor measurements do not quantify the availability of N–P–K. The ability to make recommendations for crop fertilization hinges on the direct measurement of plant nutrients using chemical sensors (Postolache *et al.*, 2023; Reza *et al.*, 2025) [8, 9].

Integrated systems composed of sensor nodes, local processing, and low-power wireless communication are enabled by edge and cloud computing. Edge computing may enable measurement plausibility checks and suppress noise in the absence of connectivity. Historical data may be retained and visualized at the edge, whereas machine learning (ML) models may be updated over the cloud. Even though data is sent to a central location, bias may remain due to several factors including sensor fouling, drift of ion-selective electrodes, and salinity and water content of the soil. Calibration of sensors against reference methods is needed, particularly in the absence of evidence for their permanent compliance.

Soil insertion of ISEs does not guarantee they measure the nutrient supply that is available to the crop. Commercial 'NPK' sensors deserve similar scrutiny, particularly if they are used to make decision in agronomy, and evidence regarding their analytical validation and operability is not made public.

Operationally, smart fertigation systems can link nutrient solution measurement and irrigation control. However, there should be safety limits to prevent over-application when measurements fail. Siting of sensors is another major issue. One point monitoring may not represent the entire field. Sampling strategies should consider soil zones, irrigation topology, topography and crop management. Also, there are practical design requirements, such as the security of the data network, battery life, availability of spare parts and ownership of the data.

Innovations in use of the Internet of Things (IoT) in nutrient monitoring show progress but many of the same problems identified in previous research, such as cost, field reliability, interoperability and farmer acceptance (Fauziah *et al.*, 2024; Aarif *et al.*, 2025) [11, 10], remain. Developments should focus on affordable maintenance and documented performance, as opposed to increasing the number of connected devices.

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From the perspective of value-added by a measurement, a smart fertilizer decision is only valuable if it results in an agronomic decision that justifies its cost. For example, if sensors show that soil in different parts of a field has different levels of nutrients, a fertilizer decision may be made to apply different rates of fertilizer to those zones. Conversely, a small number of calibrated sensors may enable crop zones to be managed differently. Different sensors should be chosen based on decisions to be made and response of the crop to fertilizer as opposed to the volume of data produced by the sensors.

Adaptive management and decision making may give better results compared to fixed schedules. The data produced by sensors may support decision making in some cases, but the presence of unmanageable variability indicates fixed schedules are justified. Prescribing flexibly based on a diversity of surrounding management and weather conditions is likely to provide better results.

Table 4. Smart sensing modalities and interpretation

Sensor	Direct or proxy variable	Validation priority
Ion-selective electrode	Selected dissolved ion	Selectivity, reference extraction
pH / EC probe	Acidity / bulk ionic conductivity	Temperature and salinity effects
Moisture probe	Volumetric water content	Soil-specific calibration
Optical spectrometer	Reflectance / indirect chemistry	Ground truth and drift
Meteorological station	Atmospheric drivers	Exposure and sensor maintenance

Note. Entries summarize technical characteristics; no cross-study performance ranking is implied.

6. Integrated AI–remote sensing–IoT framework

In a robust platform, six linked layers of precision nutrient management can be identified. At the base is the observation layer, which consists of georeferenced samples from laboratory and field analyses, supplemented with data from UAVs and satellites, field weather conditions, crop variety, and field operations. The next quality-assurance layer identifies incomplete, inconsistent, or erroneous information. The next layer is the fusion layer, whereby dates and/or times, georeferencing and/or spatial supports, are aligned.

The next layer is the inference layer, whereby a nutrient-status target is defined, uncertainty is estimated, and results are validated against a reference measurement. The next layer is the prescriptive layer, whereby soil balance, expected yield response, the cost of nutrients and crop protection, and environmental and crop management constraints are integrated. The final layer is the application layer, where the prescriptive layer is translated into action by machinery and/or controlled fertigation. Fertilizers and/or crop protection products are delivered according to a prescription, and/or a fertigation schedule, and feedback is collected.

The proposed architecture illustrated in Figures 1 and 5-7 is a conceptual design, not a field-tested product. An uncertainty threshold triggers sampling, and in most cases, fertilizer is not applied in an autonomous manner. Recommendations are based on data provenance, i.e. data age, sensor calibration, confidence intervals, rationale, assumptions, model version, and operator override.

Potential performance benefits of a multimodal integration approach are plausible, because different sources observe different complementary processes. As the number of integrated sensors increases, total error and/or uncertainty may not always increase. Therefore, comparative case studies must evaluate true agronomic outcomes and/or impacts. Total operational costs must be considered. Improvements in prediction accuracy alone do not necessarily result in improvements in agronomic outcomes. For example, a model may over-predict nutrients, under-predict nutrients, or be correct, but inaccurate.

Distinguishing accuracy and other levels of evidence remains a major challenge in research reporting. Reporting measurements is critical to demonstrate accuracy of lab or field studies. Reporting different levels of evidence requires rigor and precision in differentiating predictions and effects of causal interventions. Research reporting should include instances where the management strategy was ineffective, that is, where controlled field outcomes were lacking. These represent important and valuable learning opportunities for the research community. Examples of negative research findings should be published, including spectral signals that are ambiguous, inconclusive, or nonspecific, sensor drifts that exceed tolerances, and instances where a complex machine learning model is unable to improve a baseline model. Researchers should make their data and code available to the research community in order to promote trust and confidence in research findings, as well as improve reproducibility and validation.

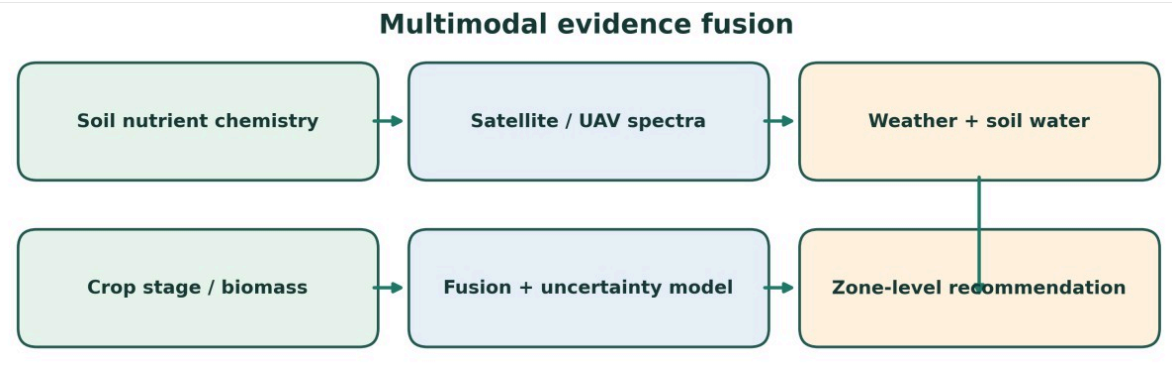


Figure 5. Multimodal evidence fusion (original conceptual technical diagram; not experimental findings).

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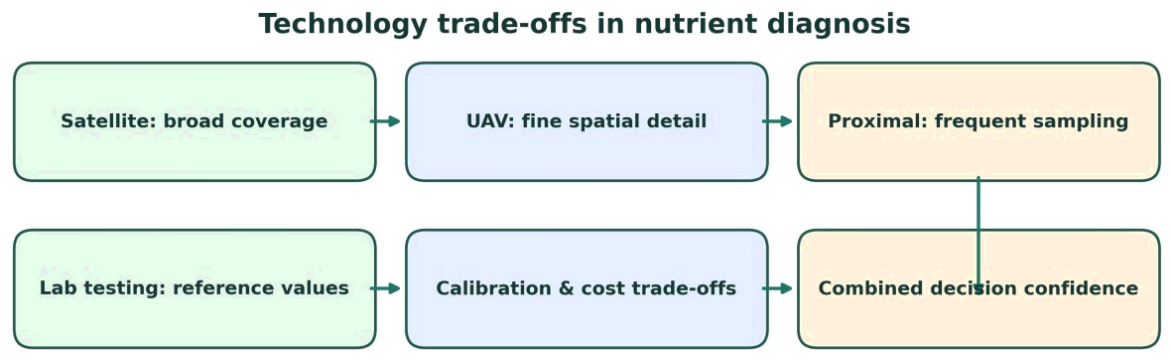


Figure 6. Technology trade-offs in nutrient diagnosis (original conceptual technical diagram; not experimental findings).

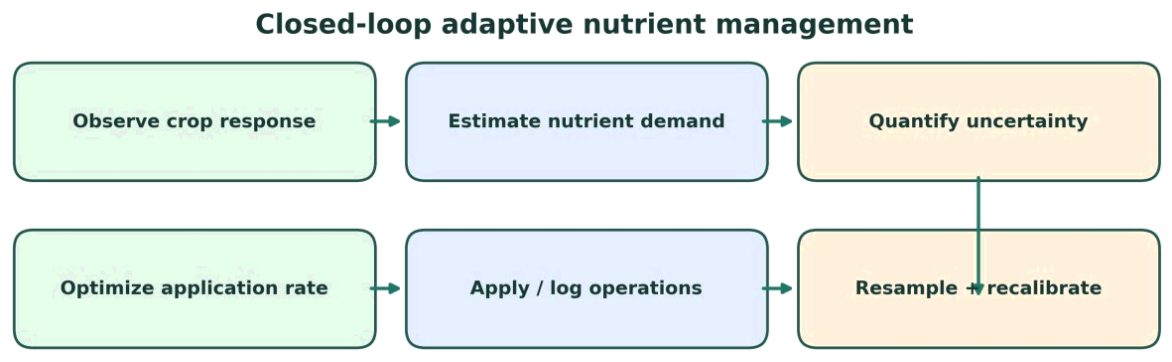


Figure 7. Closed-loop adaptive nutrient management (original conceptual technical diagram; not experimental findings).

7. Challenges, research gaps, and future prospects

Data representativeness is still the major limitation. Published data sets often contain only a few independent farms, a short period, and/or a limited number of fertilizer treatments. Models trained on a particular crop genotype or irrigation practice may contain site-specific patterns that are not transferred to other sites. It is important to make multi-season, cross-region tests and to publish information on the sampling depth, the crop growth stage, the method of soil extraction, spectral calibration, and the target variable.

A second gap is the disconnection of nutrient diagnosis and economic and agronomic benefit. In addition, the prediction of leaf N status does not imply that the recommended fertilizer increase economic and/or agronomic benefit or reduce nitrate loss. Nutrient and field trials should compare the integrated system with the local best practices, and report the nutrient balance, yield, input, and energy costs as well as pertinent environmental indicators.

Challenges related to the uptake of integrated systems are substantial. Interoperability between different suppliers of sensors, farm management systems, and machine controls, is still limited. Connectivity gaps, costs of calibration, and variability in UAV operations due to weather, disproportionately affect smallholders. Equipment share, open architectures, offline-capable systems, and greater transparency in models could alleviate the situation in a more cost effective manner.

Novel approaches require evaluation within limits. Physics-informed modeling can add constraints to nutrient cycling and crop growth models. Digital Twins may integrate these models with sensors. Federated learning may mitigate the transfer of sensitive farm records, and non-identical local datasets may destabilize training. Edge inference may also be used to model systems with low-connectivity, however it requires versioning and safe updates. Foundation models may also facilitate better representation learning. In the absence of independent, nutrient-specific evidence, it is uncertain how reliable these models may be.

Some priority questions include: What is the minimum sampling density for calibration to generate a dependable nutrient map? When does multisource sensing improve net farm returns compared with soil testing? How should prediction intervals be interpreted for crop growth modeling? Which sensor maintenance schedules ensure the most accurate readings? How reliable are these models across varying soil conditions and farm locations? And can a model be built for precision across various seasons? Answering these questions would determine the potential for digital tools to revolutionize agricultural decision making.

The practical benchmark is an achievable alternative for farmers that doesn't require a idealized technology stack. Future studies should include soil testing and location-specific nutrient management practices as explicit comparators. More data collected from different farm sizes and climates will be more helpful than a single case study showing predictive accuracy. Digital tools focused on nutrient management will be beneficial only if the information is useful at the field-level.

Extension services play a large role in the adoption of any new technology, as do accurate fertilizer labels and working equipment. Researchers should be responsible and communicate practical limits of their estimates, particularly when an estimate is made but management action is not warranted. This will help advance Nutrient Management and complement the efforts of Extension Services. While field research should be the primary driver for advances in agricultural technology, it's important that Extension Services are adequately trained to help farmers evaluate and utilize advancements in their area.

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Table 5. Research gaps and proposed evaluation

Gap	Recommended research action
Pixel leakage	Cross-field and cross-season testing
Proxy nutrient sensing	Lab calibration and selectivity testing
Lack of field outcomes	Yield, cost, N loss and soil fertility endpoints
Limited smallholder uptake	Affordability and offline field trials
Uncertain prescriptions	Prediction intervals and sampling triggers

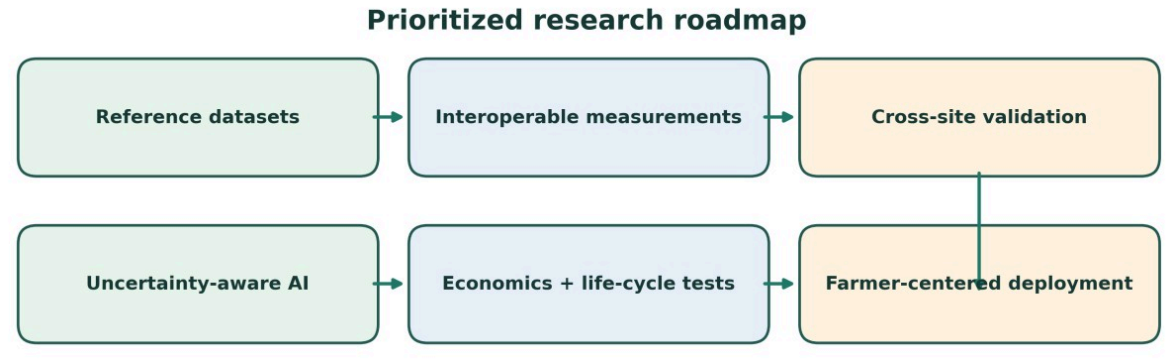


Figure 8. Prioritized research roadmap (original conceptual technical diagram; not experimental findings).

8. Conclusion

Artificial Intelligence (AI), remote sensing, and smart sensors cover different aspects of the precision nutrient management challenge. Each component of the above-mentioned solution brings different characteristics to the solution. For example, artificial satellites provide broad temporal coverage, UAV platforms help capture fine scale crop variation, and soil or environmental sensors provide measurements at the local level. AI connects the dots, integrates the different elements of the solution, and helps identify management zones. The literature demonstrates potential for variable rate recommendations, but practical implementations, reliance on predictive maintenance, and calibration for actionable recommendations remain key challenges.

Improvements in nutrient sensing have primarily been centered around nitrogen. There have been significant advances in the area of nutrient sensing and estimation. There are recurring weaknesses in nutrient monitoring. Proxy measurements are often substituted for direct nutrient assessments. Image-based correlations are often erroneously interpreted to be cause and effect. Data collected from spatially non-independent locations are used to validate models, and diagnostic performance is reported without economic and/or environmental evaluation. These shortcomings can be resolved with the use of clearer definitions and a better measurement framework.

An integrated closed-loop architecture is a novel research direction but should be considered a concept until adequate validation is performed. Comparative experiments should define and measure yield, report recoveries or balance, and provide relevant information about environmental protection over multiple seasons. Particular attention should be given to small and fragmented holdings, as sensor economics and the availability of farming equipment to apply nutrients may determine the feasibility of this research direction.

The most efficient and effective nutrient management systems of the future will rely on a balance of sensors and algorithms to protect long-term soil fertility and provide adequate nutrients for crop growth while ensuring measurement system integrity and economy.

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How to cite this article: Shankar R, Tigga SK, Sharma KK. Precision nutrient management using artificial intelligence, remote sensing, and smart sensors: A review. *International Journal of Agriculture and Food Science*. 2026;8(11):92-99. doi: https://www.doi.org/10.33545/2664844X.2026.v8.i11b.89817

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