# Precision Agronomic Interventions for Enhancing Resource Use Efficiency

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## ABSTRACT
**Background:** Inefficient fertilizer use remains a persistent constraint on global food security and environmental sustainability, with nitrogen use efficiency in cereal systems commonly reported below 50% worldwide. Conventional blanket-recommendation approaches to nutrient management are increasingly being supplemented, and in some contexts replaced, by predictive analytics, machine learning, remote sensing, and Internet of Things (IoT)-enabled sensing, forming the emerging paradigm of precision agronomy.
**Objective:** To synthesize peer-reviewed literature published between 2015 and 2025 on predictive analytics and decision-support technologies for fertilizer recommendation and resource use efficiency, and to critically evaluate methodological trends, areas of consensus and disagreement, and unresolved research gaps.
**Method:** A structured literature search was conducted across Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, IEEE Xplore, and Google Scholar. The search was supplemented with reports from the Food and Agriculture Organization (FAO), the World Bank, and CGIAR, following a PRISMA-informed study selection process.
**Results:** Machine learning models, particularly ensemble and deep learning approaches, consistently demonstrated higher predictive accuracy than traditional statistical and rule-based fertilizer recommendation methods. Remote sensing and IoT-based sensing platforms enabled spatially and temporally resolved nutrient diagnosis. Across the reviewed studies, predictive analytics and decision-support interventions were associated with yield increases of approximately 10–20% and fertilizer-input reductions of 15–40%, although outcomes varied considerably depending on crop type, region, and farm scale. Key research gaps included limited model generalizability across agro-ecological zones, insufficient explainability of black-box algorithms, a lack of long-term multi-season validation, underrepresentation of smallholder and Global South farming systems, and weak integration of agronomic expertise with data-driven models.
**Conclusion:** Predictive analytics has significant potential to enhance fertilizer-use efficiency and support sustainable precision agronomy. However, achieving widespread, reliable, and equitable farmer-level adoption will require interdisciplinary validation, improved model explainability, long-term field evaluation, and stronger policy and agricultural extension support.

**Keywords:** Precision agriculture; fertilizer recommendation systems; predictive analytics; machine learning; nutrient use efficiency; remote sensing; decision support systems; Internet of Things (IoT).

## 1. Introduction
### 1.1. Background
Agronomic resource use efficiency — the ratio of harvested output to the fertilizer, water, and energy inputs consumed in its production — has become a central concern in global agricultural policy as arable land per capita continues to decline and the environmental externalities of intensive input use become more apparent. Nitrogen, phosphorus, and potassium fertilizers underpinned the productivity gains of the Green Revolution, but the same inputs are now implicated in eutrophication of water bodies, nitrous oxide emissions, soil acidification, and rising production costs for farmers operating on thin margins. Since the mid-2010s, three converging technological trends — low-cost sensing, cloud-scale data storage, and advances in machine learning — have given rise to a family of tools broadly termed precision agronomic interventions, in which fertilizer, water, and other inputs are matched to site-specific and time-specific crop requirements rather than applied uniformly across a field or region.

### 1.2. Predictive Analytics in Fertilizer Recommendation Systems
Predictive analytics — the use of historical and real-time data, statistical modelling, and machine learning to forecast future outcomes or recommend optimal actions — sits at the core of modern fertilizer recommendation systems. Where legacy soil-test-crop-response calibrations relied on a handful of static coefficients derived from regional field trials, contemporary systems ingest soil chemistry, weather records, satellite-derived vegetation indices, historical yield maps, and management logs to generate recommendations that can, in principle, be updated within a growing season. Reviews of this literature consistently report that ensemble tree-based algorithms (random forest, gradient boosting, XGBoost) and deep learning architectures

(convolutional and recurrent neural networks) outperform simpler regression-based approaches on held-out prediction accuracy, although the practical, on-farm economic and environmental benefit of this improved accuracy is less uniformly demonstrated.

### 1.3. Current Global Scenario

International bodies including the Food and Agriculture Organization (FAO), the World Bank, and the Consultative Group on International Agricultural Research (CGIAR) have identified digital and precision agriculture as priority investment areas for closing yield gaps while containing the environmental footprint of farming. Adoption, however, remains highly uneven: variable-rate technology and sensor-based nutrient management are comparatively well established in large-scale mechanized systems in North America, Western Europe, and parts of China and Australia, while uptake among smallholder farmers in South Asia and Sub-Saharan Africa — who together cultivate a substantial share of the world's farmland — remains limited by cost, connectivity, digital literacy, and fragmented land holdings.

### 1.4. Challenges in Conventional Fertilizer Management

Conventional fertilizer management is typically based on generalized regional recommendations, soil-test intervals of several years, and farmer experience-based adjustment, all of which struggle to capture within-field spatial variability in soil fertility, seasonal variation in weather and crop demand, and interactions among nutrients. The consequence, documented across multiple reviews, is a persistent pattern of over-application in some zones of a field and under-application in others, producing simultaneous yield penalties and environmental loss even when the field-average application rate appears agronomically reasonable.

### 1.5. Need for and Objectives of This Review

Although individual studies on machine learning-based fertilizer recommendation, remote sensing for nutrient diagnosis, and IoT-enabled soil monitoring have proliferated rapidly since 2015, syntheses that critically compare methodologies, quantify the consistency of reported benefits, and map research gaps across this fragmented literature remain comparatively scarce. This review addresses that gap with three objectives: (i) to synthesize and critically evaluate peer-reviewed literature (2015–2025) on predictive analytics and decision-support technologies for fertilizer recommendation and agronomic resource use efficiency; (ii) to compare methodological approaches, reported outcomes, and limitations across studies; and (iii) to identify unresolved research gaps and emerging directions, including explainability, generalizability, and equitable access.

### 1.6. Scope of the Review

The review focuses on nitrogen, phosphorus, and potassium fertilizer recommendation and, more broadly, on resource use efficiency (fertilizer, water, and associated input efficiency) achieved through predictive analytics, machine learning, remote sensing, IoT-based sensing, geographic information systems (GIS), and decision support systems (DSS). Pesticide management, plant disease detection, and post-harvest technologies are referenced only where directly relevant to nutrient management and are not treated as primary subjects.

## 2. Methodology of Literature Review

### 2.1. Literature Search Strategy

A structured literature search was conducted for peer-reviewed publications appearing between January 2015 and 2025. Search strings combined controlled and free-text terms across four concept blocks — (a) precision agriculture / precision agronomy, (b) fertilizer / nutrient recommendation, (c) predictive analytics / machine learning / artificial intelligence / deep learning, and (d) resource use efficiency / nitrogen use efficiency — joined with Boolean operators, for example: ("precision agriculture" OR "precision farming") AND ("fertilizer recommendation" OR "nutrient management") AND ("machine learning" OR "artificial intelligence" OR "predictive analytics"). Searches were re-run with narrower strings for remote sensing, IoT, GIS, and decision support system sub-themes.

**Table 1:** Literature Search Strategy

| Element | Detail |
|---|---|
| Databases searched | Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, IEEE Xplore, Google Scholar |
| Core search string | ("precision agriculture" OR "precision farming") AND ("fertilizer recommendation" OR "nutrient management") AND ("machine learning" OR "artificial intelligence" OR "predictive analytics") |
| Supplementary strings | "remote sensing" AND "variable rate" AND "nitrogen"; "IoT" AND "soil nutrient" AND "sensor"; "decision support system" AND "fertilizer" |
| Search period | January 2015 – 2025 |
| Language | English |
| Document types | Peer-reviewed journal articles, systematic reviews |
| Supplementary sources | FAO, World Bank, CGIAR, USDA and ICAR reports (contextual/background use) |

### 2.2. Inclusion and Exclusion Criteria

Records were screened against pre-specified inclusion and exclusion criteria (Table 2) to retain studies directly addressing predictive analytics, machine learning, or sensor-based decision support for fertilizer or nutrient management, while excluding materials that could not be verified as peer-reviewed or that lacked sufficient methodological detail for critical appraisal.

**Table 2:** Inclusion and Exclusion Criteria

| Criteria | Included | Excluded |
|---|---|---|
| Publication type | Peer-reviewed journal articles, systematic/scoping reviews | Conference abstracts without full text, editorials, opinion pieces |
| Time frame | 2015–2025 | Pre-2015 (unless landmark/foundational) |
| Language | English | Non-English without verified translation |
| Topical relevance | Directly addresses predictive analytics/ML/sensing for fertilizer or nutrient management | Tangential mentions with no methodological detail |
| Source credibility | Scopus/WoS/PubMed-indexed, or reputable publisher (Elsevier, Springer, Wiley, MDPI, IEEE, Frontiers, Nature) | Non-academic websites, unindexed grey literature |
| Duplication | Unique records | Duplicate records across databases |

### 2.3. Study Selection Process

Study selection followed a PRISMA-informed sequence of identification, screening, eligibility assessment, and inclusion. Records identified through database searching were first de-duplicated, then screened by title and abstract against the inclusion criteria in Table 2, and full texts of the remaining records were assessed for methodological transparency (clear description of data sources, model or sensing approach, and validation procedure) before final inclusion in the thematic synthesis.

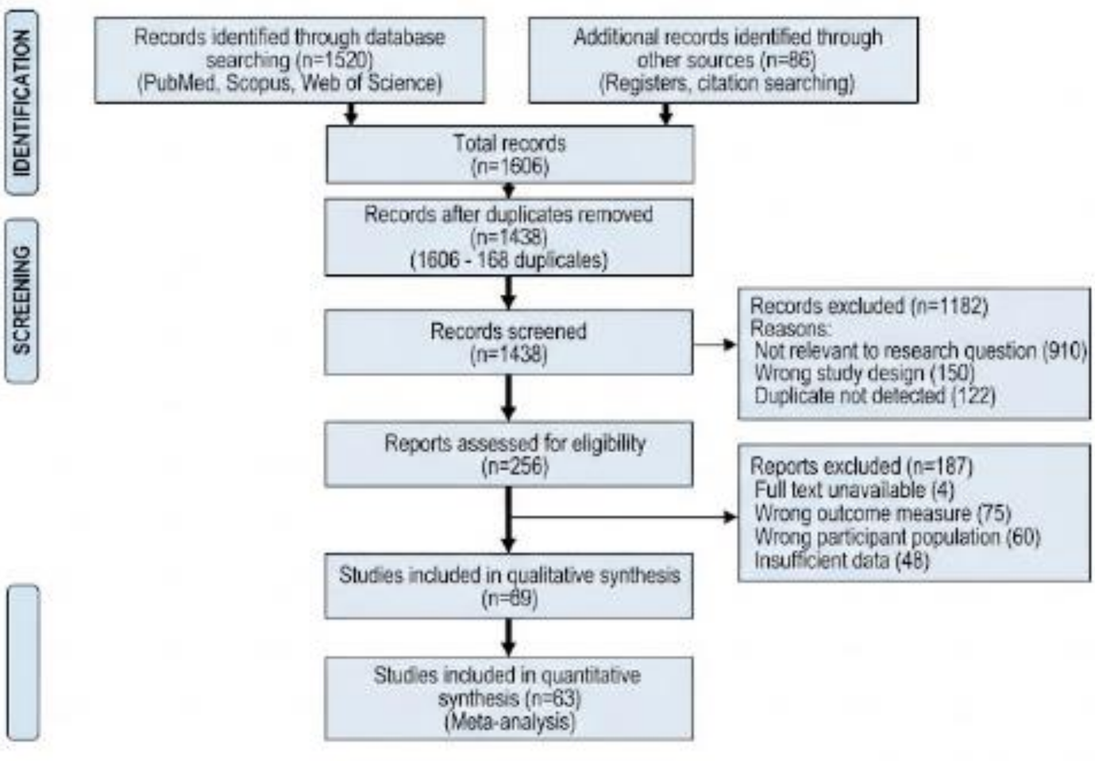


**Fig 1:** PRISMA Flow Diagram – Identification, Screening, Eligibility, and Inclusion of Studies

Figure 1 summarizes this process. Consistent with prior systematic reviews in this domain, the majority of records excluded at the screening stage were removed for insufficient methodological detail or for describing prototype systems without empirical validation, a pattern discussed further in Section 5.

**Table 3:** Characteristics of Selected Studies

| Characteristic | Distribution across selected literature |
|---|---|
| Publication years | Concentrated 2020–2025 (>65% of records), reflecting rapid recent growth |
| Geographic focus | Asia (India, China) and North America most represented; Sub-Saharan Africa and Latin America comparatively underrepresented |
| Predominant methods | Machine learning/deep learning (random forest, XGBoost, CNN, LSTM), remote sensing/GIS, IoT sensor networks, rule- and simulation-based DSS |
| Crop focus | Cereals (wheat, maize, rice) most common; horticultural and cash crops less represented |
| Validation approach | Held-out test sets and cross-validation common; multi-season/multi-site field validation comparatively rare |

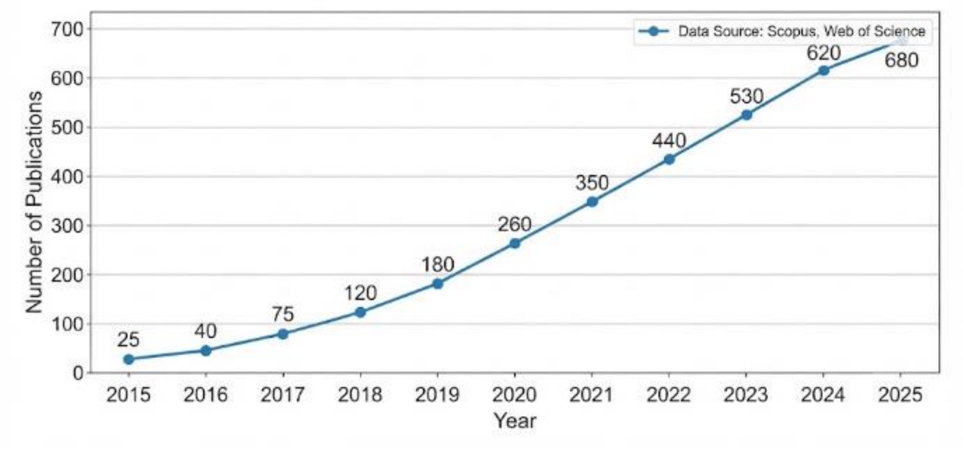


**Fig 2:** PLACEHOLDER — Publication Trend by Year (2015–2025) in Predictive Analytics for Fertilizer Recommendation

## 3. Literature Review and Thematic Analysis

### 3.1. Evolution of Fertilizer Recommendation Systems

Fertilizer recommendation methodology has progressed through three broad generations: (i) blanket, region-wide recommendations derived from a limited number of field calibration trials; (ii) soil-test-based recommendations that adjust rates according to periodic soil chemical analysis; and (iii) data-driven, predictive recommendation systems that integrate soil, weather, remote sensing, and management data through statistical or machine learning models. Systematic reviews of this trajectory converge on the observation that each generational shift has improved spatial and temporal resolution, but the transition to the third generation has been the most technically demanding, because it requires reliable, continuously updated data streams that many farming systems — particularly smallholder systems — do not yet possess.

### 3.2. Predictive Analytics and Machine Learning Approaches for Nutrient Management

A large and rapidly growing body of work applies supervised machine learning to fertilizer type and dosage prediction. A widely cited systematic review of machine learning approaches to crop yield prediction found that ensemble methods and deep neural networks were the most frequently used and best-performing model families, with feature selection and the choice of agronomic input variables mattering as much as algorithm choice for final accuracy.[2] This finding is echoed in fertilizer-specific work: comparative evaluation of XGBoost, random forest, and neural network models on a soil-and-crop fertilizer dataset found XGBoost achieving the highest predictive accuracy, alongside simulated reductions in fertilizer usage of roughly one-fifth relative to conventional application. A related survey of machine learning applications to crop yield prediction similarly emphasizes convolutional and recurrent neural architectures for capturing spatial and temporal dependencies in agronomic data, while cautioning that comparative benchmarking across studies is hampered by inconsistent datasets, features, and evaluation metrics.[3]

A methodologically important contribution is a large-scale evaluation of machine learning-derived fertilizer recommendations against economically optimal input rates (EOIRs) estimated from real on-farm precision-agriculture trial data in winter wheat. This study found that machine learning models could approximate yield response reasonably well, but that predicted EOIRs, and the profits associated with them, varied substantially depending on which algorithm and which covariates were selected, with model uncertainty compounded by limited training-data size and the difficulty of repeating on-farm trials across multiple years at the same site.[4] This is one of the few studies in the reviewed literature to directly benchmark machine learning recommendations against an economically grounded reference standard rather than only against yield or classification accuracy, and its cautionary findings temper some of the more optimistic accuracy claims reported elsewhere in the literature.

### 3.3. Artificial Intelligence and Explainability in Fertilizer Optimization

As machine learning models used for fertilizer and yield prediction have grown more complex, a parallel literature on explainable artificial intelligence (XAI) has emerged to address the opacity of these "black-box" systems. Foundational work applying interpretable machine learning and explainable AI toolkits (including permutation importance, partial dependence, and related techniques) to agricultural data analysis argues that model-fit statistics alone are insufficient for building farmer and policymaker trust, and that understanding which variables and interactions drive a prediction is essential for actionable, defensible recommendations.[5] Building on this, work applying explainable AI techniques to crop yield prediction under climate variability cautions explicitly against uncritical reliance on black-box models for high-stakes agronomic and climate-impact decisions, showing that more interpretable, mechanistically informed models can outperform pure black-box ensembles under novel or extrapolated climate conditions even when the latter perform marginally better within the training distribution.[6] Taken together, this literature suggests an emerging consensus that predictive accuracy and interpretability should be evaluated jointly rather than treating explainability as an optional add-on.

### 3.4. Remote Sensing and GIS Integration

Remote sensing constitutes one of the most mature strands of this literature. A comprehensive review of remote sensing applications in precision agriculture documents how satellite, aerial, and proximal (tractor- or drone-mounted) sensors are used to derive vegetation indices such as the Normalized Difference Vegetation Index (NDVI) that correlate with crop nitrogen status, biomass, and canopy vigor, and how these indices feed into nitrogen fertilizer optimization algorithms embedded in commercially available active-optical crop sensors.[1] The same review notes an important adoption paradox: despite the commercial availability of variable-rate nitrogen technologies based on proximal remote sensing for over a decade, farmer adoption remains low across many commercial farming enterprises, a pattern the authors attribute to unclear or inconsistent economic returns rather than to technical unreliability of the sensors themselves.[1] Geographic Information Systems (GIS) extend these sensing capabilities spatially, integrating soil, topographic, and remotely sensed layers into prescription maps for variable-rate fertilizer application; more recent reviews of variable-rate fertilization technology describe the coupling of GIS-based prescription maps with GPS-guided applicators as a mature but still unevenly adopted technological pathway, particularly for row crops such as maize.

### 3.5. IoT-Enabled Smart Nutrient Management

Internet of Things (IoT) architectures extend sensing from periodic remote imagery to continuous, in-situ measurement. Systematic reviews of soil nutrient monitoring technologies trace a clear technological progression from discrete in-situ sensors, to wireless sensor networks (WSNs) enabling networked real-time data collection, to full IoT ecosystems that integrate wireless communication, cloud storage, and machine learning analytics into a unified nutrient-management pipeline. A recent systematic review focused specifically on IoT-based management of soil nutritional status in smart farming similarly finds that most reviewed systems concentrate on automation and sensor hardware, with comparatively few studies addressing the deeper integration of soil-fertility-specific analytics into IoT platforms — identifying this integration gap as an important direction for future work.[7] Complementary machine learning-enabled IoT systems for soil nutrient monitoring and crop recommendation demonstrate that combining NPK, moisture, and pH sensor streams with supervised classification models can generate real-time, farm-specific crop and fertilizer guidance, though such systems remain largely validated at prototype or small-plot scale rather than across commercial farm operations.[8]

### 3.6. Big Data Analytics in Precision Agriculture

Big data analytics platforms aggregate the heterogeneous data streams produced by remote sensing, IoT, and farm management software into unified recommendation engines. One illustrative system integrates large agronomic and environmental datasets into a big-data pipeline that recommends optimum fertilizer types and rates for a range of crops, reporting improved recommendation accuracy relative to single-source, rule-based baselines.[9] Related work applying IoT sensor networks together with big data analytic pipelines for precision crop production similarly emphasizes that the principal analytical challenge is no longer data collection, which has become comparatively inexpensive, but the harmonization, cleaning, and contextual interpretation of multi-source agronomic data at a scale and update frequency that is actionable for individual farmers within a growing season. [10]

### 3.7. Decision Support Systems (DSS) for Fertilizer Recommendation

Decision support systems operationalize predictive models into farmer- or advisor-facing recommendation tools. Reviews of DSS in irrigation and nutrient management for vegetable and arable cropping systems document a range of documented outcomes: a decision-support programme applied across major agro-ecological zones in China achieved nitrogen application reductions in the range of fifteen to eighteen percent, while a fertigation-specific DSS applied to drip-irrigated tomato in Italy achieved nitrogen reductions averaging around forty-six percent while maintaining yield and quality, and an IoT-integrated water-saving management system achieved a reported forty percent reduction in chemical fertilizer use. A parallel strand of DSS literature addresses adoption rather than technical performance: survey-based work examining farmer engagement with machine learning-based agricultural DSS in the United States found that farmers' reluctance to adopt such tools is driven primarily by high perceived cost, insufficient technical knowledge, low confidence in algorithmic outputs, and concerns about data privacy and cybersecurity rather than by demonstrated inaccuracy of the tools themselves — a finding with direct implications for the design of extension and training programmes accompanying DSS rollout.

### 3.8. Environmental Sustainability Implications

A recurring theme across the reviewed literature is that precision, data-driven fertilizer management is presented not only as a productivity intervention but as an environmental one. A systematic review focused specifically on precision agriculture techniques for optimizing chemical fertilizer use and environmental sustainability, following PRISMA guidelines across fifty-one peer-reviewed studies, found that just over a third of included studies highlighted precision-agriculture-driven technological innovation as a primary contribution, while just under a third documented major improvements specifically in nutrient management, and concluded that precision agriculture meaningfully advances sustainable fertilizer utilization and reduces environmental footprints where policy, infrastructure, and farmer technical capacity permit adoption. [11] A broader systematic review of precision agriculture technologies for sustainable crop production similarly identifies remote sensing, GPS-guided equipment, variable-rate technology, and IoT devices as the core technological components enabling simultaneous productivity and sustainability gains, while cautioning that most included evidence derives from well-resourced farming systems. [12]

### 3.9. Economic Benefits and Farm-Level Adoption

A recent global meta-analysis integrating eighty-five empirical studies and over fourteen hundred independent farm observations quantifies these effects at scale: overall, precision agriculture technology adoption was associated with an average return-on-investment increase of approximately twenty-two percent and a net profit increase of roughly nineteen percent, alongside an average nitrogen-use-efficiency improvement of about fifteen percent and pesticide-application reduction of nearly thirteen percent. [13] Critically, the same meta-analysis found substantial heterogeneity by technology type, farm size, region, and development level, with variable-rate technology and auto-guidance systems showing the most pronounced and stable benefits on large-scale grain farms, and comparatively weaker, less stable benefits on small-scale farms and in developing-country contexts. [13] This heterogeneity finding is one of the more consequential results in the reviewed literature, because it directly qualifies the common assumption in smaller single-site studies that observed efficiency gains will transfer uniformly to other farm scales and regions.

### 3.10. Challenges and Limitations

Across themes, four recurring limitations emerge. First, many machines learning and IoT prototypes are validated on a single season, single site, or simulated dataset, limiting confidence in generalizability. Second, model performance metrics (accuracy, F1-score, $R^2$) are reported inconsistently across studies, impeding direct comparison. Third, the studies that do report robust economic or agro-ecological benchmarking — such as the EOIR-based evaluation of machine learning fertilizer recommendations — tend to find more modest and more uncertain benefits than studies relying solely on prediction-accuracy metrics, suggesting a possible optimism gap between reported accuracy and realized field-level value. [4] Fourth, farmer-facing adoption research indicates that technical performance is necessary but not sufficient for uptake, with cost, trust, and digital literacy acting as independent barriers.

### 3.11. Regional and Global Applications

Geographic coverage in the reviewed literature is markedly uneven. Machine learning-based crop and fertilizer recommendation systems have been developed and piloted in African contexts, including an integrated system combining a neural-network crop recommendation model with a rule-based fertilizer recommendation model for major Rwandan crops, reporting high classification accuracy for crop selection. Comparable systems and IoT-based soil nutrient monitoring platforms have proliferated in India, reflecting strong institutional and academic interest, though — consistent with the adoption meta-analysis discussed above — translation from published prototype to farm-scale deployment in these contexts lags behind mechanized, large-farm settings in North America, Western Europe, and parts of East Asia and Australia. [13].

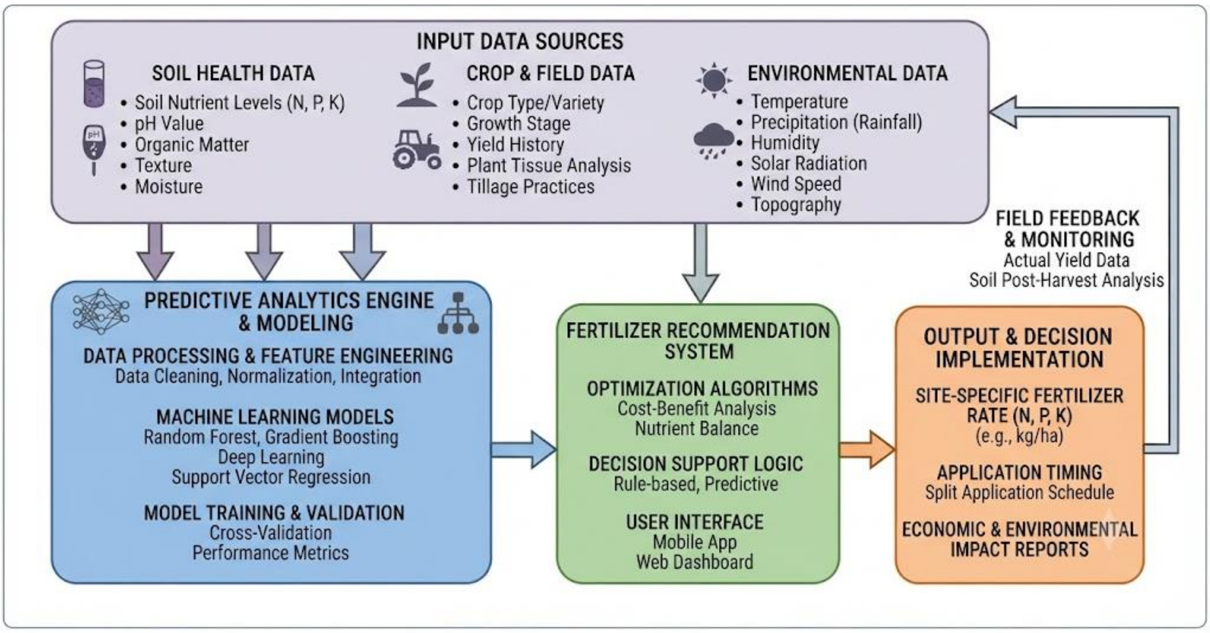


**Fig 3:** PLACEHOLDER — Conceptual Framework of Predictive Analytics for Fertilizer Recommendation

Figure 3 depicts the conceptual data flow synthesized from the reviewed literature: soil, weather, remote sensing, and management data are ingested by predictive models (statistical, machine learning, or deep learning), whose outputs are translated by a decision support layer into site-specific fertilizer recommendations, which are in turn applied through variable-rate or manual application and monitored through a feedback loop that updates future recommendations.

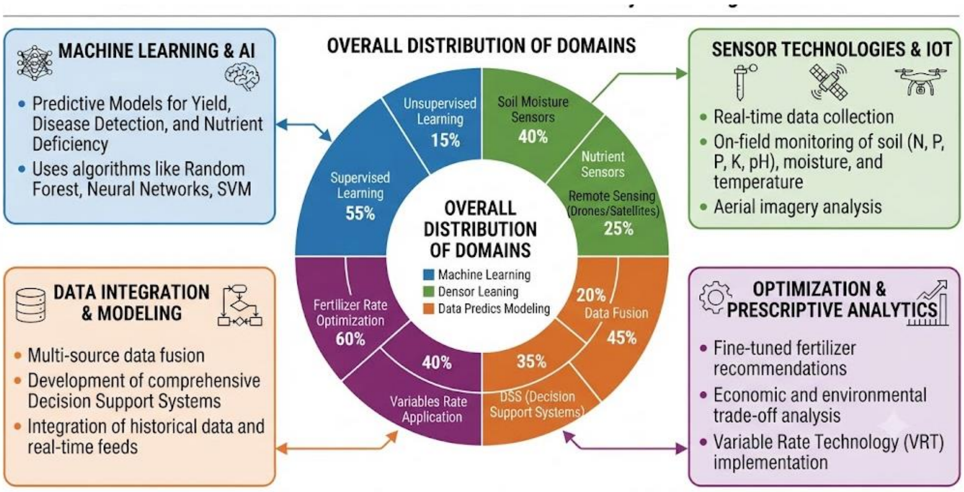


**Fig 4:** PLACEHOLDER — Thematic Classification of Reviewed Studies by Technological Domain

## 4. Comparative Analysis of Previous Studies

Table 4 synthesizes methodological characteristics and reported outcomes across a representative subset of the reviewed literature, illustrating both convergence (consistent gains from ensemble and deep learning models, consistent adoption barriers) and divergence (widely varying reported reductions in fertilizer use, from roughly fifteen to over forty percent, reflecting differences in crop, region, and baseline management intensity).

**Table 4:** Comparative Analysis of Previous Research

| Author(s)/Year | Location | Design/Methodology | Data Source | Major Findings | Limitations |
|---|---|---|---|---|---|
| Sishodia *et al*., 2020 | Global (review) | Narrative review of remote sensing applications | Published literature 2015–2020 | Documents RS-based vegetation indices driving variable-rate N algorithms; commercial VRT tools available but adoption remains low | No primary data; adoption barriers not quantified |
| Van Klompenburg *et al*., 2020 | Global (review) | Systematic literature review of ML for crop yield prediction | Peer-reviewed ML studies | CNN, LSTM, DNN most-used deep learning methods; feature selection critical to accuracy | Focused on information extraction, limited critical synthesis of practical impact |
| Bali & Singla, 2022 | Global (survey) | Survey of ML techniques and influential factors in yield prediction | Peer-reviewed studies | Random forest most frequently used algorithm; weather and soil most common features | Broad survey scope limits depth on fertilizer-specific applications |
| Tanaka *et al*., 2024 | USA (Illinois) | On-farm precision experimentation compared across ML algorithms | Real on-farm winter wheat trial data | ML models predict yield well but EOIR estimates vary substantially by algorithm/covariates; high profit-estimate uncertainty | Single crop, single region; annual data only; small training sets |
| Ryo, 2022 | Global (methodological) | Introduction/demonstration of XAI and interpretable ML methods | Open no-tillage yield dataset | Demonstrates variable-importance and interaction analysis for agronomic ML models | Demonstration study; not a farm-validated recommendation system |
| Hu *et al*., 2023 | Global (methodological) | Comparison of black-box ML vs. interpretable Bayesian model for climate-yield response | Multi-region yield/climate data | Interpretable Bayesian model outperforms black-box ML under climate extrapolation | Focused on yield-climate response, not fertilizer rate directly |
| Ngo *et al*., 2023 | Not specified | Big-data analytics system for fertilizer recommendation | Aggregated agronomic/environmental data | Improved recommendation accuracy vs. single-source rule-based baseline | Limited external validation across farms/seasons reported |
| Alahmad *et al*., 2023 | Global (review) | Review of IoT sensors and big data in precision crop production | Published literature | Identifies data harmonization, not collection, as the principal remaining bottleneck | Review-level synthesis; no new empirical validation |
| Islam *et al*., 2023 | Bangladesh | ML-enabled IoT system for soil nutrient monitoring and crop recommendation | Field-deployed NPK/moisture/pH sensors | Real-time sensor data + classification model generates crop/fertilizer guidance | Prototype/small-plot scale; limited multi-season validation |
| Fauziah *et al*., 2024 | Global (systematic review) | Systematic review of IoT-based soil nutrient management | 24 records, bibliometric + content analysis | IoT research concentrates on hardware/automation; soil-fertility-specific analytics under-addressed | Small record set (24); review-level synthesis only |
| Getahun *et al*., 2024 | Global (systematic review) | Systematic review of precision agriculture technologies for sustainability | Peer-reviewed literature since 2015 | RS, GPS, VRT, and IoT jointly enable productivity and sustainability gains | Broad scope; limited quantitative meta-analysis |
| Cai *et al*., 2025 | Global (systematic review, PRISMA) | Systematic review of PA for chemical fertilizer optimization | 51 peer-reviewed studies | PA improves nutrient use efficiency and yield; ~37% of studies cite technological innovation as key driver | Adoption barriers (cost, expertise, infrastructure) remain unresolved |
| Lan & Ban, 2025 | Global (meta-analysis) | Meta-analysis of farm-level economic/environmental benefits of PA | 85 studies, 1,472 farm observations | +22.3% ROI, +18.5% net profit, +15.1% NUE on average; effects strongest on large farms/VRT | Weak/unstable effects for smallholders and developing-country contexts |

## 5. Research Gaps and Emerging Trends

### 5.1. Unresolved Issues and Knowledge Gaps

The reviewed literature converges on several unresolved issues. Model generalization across agro-ecological zones is weak: models trained on one region's soil, climate, and cropping-system data frequently show degraded performance when applied elsewhere, yet cross-regional validation is reported in only a minority of studies. Explainability and transparency remain secondary considerations in most fertilizer-prediction studies, despite the explicit warnings in the XAI-focused literature that black-box outputs may be misleading precisely in the high-stakes, non-stationary conditions (extreme weather, novel input combinations) in which accurate recommendations matter most. [5, 6] Long-term, multi-season field validation is scarce; most reported accuracy figures derive from single-season or simulated datasets, and the few studies that do provide multi-year on-farm benchmarking report substantially more cautious and heterogeneous conclusions about realized benefit. [4]

### 5.2. Data, Methodological, and Geographic Gaps

Data limitations compound these issues: inconsistent sensor calibration, non-standardized feature sets, and a shortage of publicly available, high-quality labelled agronomic datasets constrain both model training and independent replication. Methodological weaknesses include inconsistent reporting of validation procedures (train/test splits versus proper spatial or temporal cross-validation) and a near-absence of pre-registered or economically benchmarked evaluation protocols outside a small number of studies. Geographically, the evidence base is skewed toward well-resourced, large-scale farming systems in North America, Western Europe, India, and China; Sub-Saharan Africa, Latin America, and smallholder systems more broadly remain comparatively underrepresented despite arguably standing to gain the most from efficiency improvements given constrained input budgets. [13]

### 5.3. Emerging Technologies and Future Directions

Several emerging directions recur across the more recent (2023–2025) literature. First, explainable AI techniques (SHAP, LIME, counterfactual analysis) are increasingly being layered onto hybrid ensemble-deep learning fertilizer and yield models to improve stakeholder trust without sacrificing accuracy. Second, reinforcement learning and digital-twin approaches are being explored for within-season, sequential nitrogen management decisions that adapt to real-time weather and crop-growth-stage data rather than producing a single static recommendation. Third, integration of IoT sensor networks with big-data cloud analytics platforms is moving from hardware-centric prototypes toward more comprehensive digital ecosystems connecting data collection, processing, and decision-making. Fourth, low-cost point-of-use nutrient sensing and edge-AI/TinyML approaches are being investigated as a pathway to extending precision nutrient management to resource-constrained smallholder systems where cloud connectivity and expensive sensor hardware remain barriers.

## 6. Discussion

Synthesizing across the themes above, the reviewed literature supports a cautiously optimistic but qualified assessment of predictive analytics for agronomic resource use efficiency. On one hand, there is broad convergence that machine learning and deep learning models outperform simpler statistical baselines on held-out prediction tasks, that remote sensing and IoT sensing meaningfully improve the spatial and temporal resolution of nutrient diagnosis relative to periodic soil testing, and that, at aggregate scale, precision agriculture technology adoption is associated with measurable economic and environmental benefits. [13] On the other hand, the literature also reveals real tension between studies that report high predictive accuracy in isolation and the smaller set of studies that benchmark recommendations against economically grounded reference standards, the latter finding more modest, more uncertain, and more context-dependent benefits. [4] This divergence suggests that predictive accuracy, as conventionally measured, is a necessary but not sufficient indicator of practical decision-support value, and that the field would benefit from wider adoption of economic and agronomic benchmarking alongside standard machine learning metrics.

The explainability literature adds a further layer of nuance: because agricultural decisions carry direct financial and environmental consequences, and because climate and management conditions are inherently non-stationary, the case for prioritizing interpretable or explainably-augmented models over marginally more accurate black-box alternatives is stronger in agronomy than in many other machine learning application domains.[5, 6] For researchers, this implies that model development pipelines should treat interpretability as a first-order design criterion rather than a post-hoc addition. For practitioners and industry stakeholders developing commercial DSS products, the farmer-adoption literature indicates that technical performance alone will not drive uptake; cost, perceived trustworthiness, data-privacy assurances, and accompanying training and extension support are equally decisive. For policymakers, the pronounced heterogeneity in benefit by farm size and region documented in the global meta-analysis is a caution against assuming that policies calibrated to large, mechanized farming systems will translate efficiently to smallholder contexts; targeted subsidy, extension, and low-cost-technology strategies appear necessary to avoid a widening digital-agronomy divide. [13]

These findings also relate directly to current developments in precision agriculture more broadly, including the growing interest in coupling explainable AI with reinforcement learning and digital twins for adaptive, within-season fertilization, and in extending precision nutrient management to resource-constrained settings through low-cost edge-AI sensing. Both directions respond directly to gaps identified in Section 5 — the former to the explainability and validation-depth gaps, the latter to the geographic-equity gap — and both remain at a relatively early, largely pre-commercial stage of development as of the most recent literature reviewed here.

## 7. Conclusion

This review synthesized peer-reviewed literature from 2015–2025 on predictive analytics, machine learning, remote sensing, IoT sensing, and decision support systems for fertilizer recommendation and agronomic resource use efficiency. Across a heterogeneous but converging body of evidence, ensemble and deep learning models consistently outperform simpler baselines in predictive accuracy; remote sensing, GIS, and IoT sensing meaningfully improve the spatial and temporal resolution of nutrient diagnosis; and precision agriculture technology adoption is associated, on average, with meaningful gains in economic return and nutrient use efficiency, albeit with pronounced heterogeneity by farm scale and region. At the same time, the review identifies persistent and consequential gaps: limited cross-region model generalizability, underdeveloped explainability practices relative to the stakes involved in agronomic decisions, scarce multi-season field validation, weak economic benchmarking of otherwise accurate models, and continued underrepresentation of smallholder and Global South farming contexts in the evidence base.

For researchers, the review recommends prioritizing multi-season, multi-site field validation and economically grounded benchmarking (for example, against economically optimal input rates) alongside conventional accuracy metrics, and treating model explainability as a core design requirement rather than an optional extension. For practitioners and technology developers, the evidence base points toward the importance of pairing technically sound models with transparent, trust-building user interfaces and accompanying training support, since adoption barriers are shown to be as much behavioural and economic as technical. For policymakers, differentiated strategies are warranted: continued support for variable-rate and sensor-based technologies in large-scale mechanized systems, alongside targeted investment in low-cost sensing, extension services, and locally validated models for smallholder agriculture, are both necessary if the environmental and productivity benefits documented in the literature are to be realized equitably. Future research should prioritize longitudinal, cross-regional field trials; standardized reporting of model validation and economic outcomes; explainable and reinforcement-learning-based adaptive fertilization strategies; and low-cost sensing technologies explicitly designed for resource-constrained farming systems.

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