Predictive Analytics for Optimizing Fertilizer Recommendations: A Systematic Review of Machine Learning, Decision Support Systems, and Sensor-Enabled Nutrient Management

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ABSTRACT
Background: Fertilizing wastefully and indiscriminately is a constant obstacle on the road toward sustainable farming because it creates both nutrient shortages and environmental damage by means of excessive fertilizer applications. There was a steady increase in five years of global mineral fertilizer consumption which went up from 142 million tonnes in 2002 to around 190 million tonnes in 2023, with nitrogen accounting for more than half of all consumption; that's why it became necessary to implement site-specific approaches for managing fertilizers. Analyzing and predicting the future of crops is considered to be an innovative way to achieve a balance between production efficiency and environmental safety with the help of diverse predictive analytics technologies including machine learning (ML), deep learning (DL), IoT, remote sensing, etc.
Objective: This paper is a review of academic literature published in the span of 2015-2025 on applying predictive analytics methods in fertilizers recommendation aiming at recognizing trends in methodologies, assessing model's efficiency and identifying research gaps.
Sources of literature: An organized search was performed using Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, MDPI, IEEE Xplore, as well as Food and Agriculture Organization (FAO) and International Fertilizer Association. Some major studies published before 2015 were also used in this review.
Major findings: 58 full-text studies were eligible and finally 39 studies were considered useful for thematic synthesis. In terms of efficiency of tree-based ensemble algorithms, both random forest and XGBoost, as well as artificial neural network methods achieved more than a 90% accuracy rate for predicting fertilizers based on crops and locations. The use of decision support systems including Nutrient Expert and the Fertilizer Recommendation Support Tool showed positive outcomes for the field level. Moreover, the application of IoT farming helped farmers get better results.
Research: There are many limitations regarding the alleged development of useful insights in relation to predictive analytics. Thus, the weak adaptability of a fixed model to real-time scenarios, low generalizability of results in terms of evidence from different regions of the world, unclear reasoning, absence of data in relation to small-scale farmers along with benchmark datasets for cross-comparisons among studies on the subject limit the research process. At the same time, predictive analytics can be effectively applied as a means for improving fertilizer recommendations and indeed achieving the goals of food security, profitability of agricultural endeavors, and environmental protection, providing that future investigations will focus on the development of models that can generate information that is comprehensible, regionally adjusted, and verified.

Keywords: Predictive analytics; fertilizer recommendation; precision agriculture; machine learning; decision support systems; site-specific nutrient management; sustainable agriculture

1. Introduction
1.1 Background
Essential roles of mineral fertilizers in boosting global cereal production have led to the tripling of the output from the 1950s onwards, and they are vital in the nutritional needs of the world population that will reach approximately 9.7 billion by 2050. All three macronutrients have been applied in agriculture in growing amounts, starting from 142 million tonnes in 2002 and reaching over - 190 million that year, of which nitrogen fertilizers accounted for almost 58% or 208 million tonnes. Crooped land, available nitrogen per hectare, rose from 54 kilograms to 68 sourced to intensification trends between the two reference points, also dependent on region: while Europe states an 8% decrease, Africa marks a 65% growth.
The increase in fertilizer use has not been equally effective in all cases. Past practices have been primarily based on generic guidelines at the national level, based on universal calibrations of soil tests which do not account for the differences in variability of soil productivity, climatic conditions and farming practices within and between the agricultural fields [4].

This has resulted in two diametrically opposed situations: on the one hand, many countries in Sub-Saharan Africa and South Asia suffer from under-fertilization of nutrient-poor smallholder farms, which limits their ability to use their full potential, while on the other hand countries in East Asia, North America and part of Europe over-use artificial fertilizers and the surplus of nutrients is lost to the environment via runoff, leaching and volatilization [5, 6]. In fact, the results of the surveys conducted in South Asian rice farming systems revealed that the bulk of respondents use nitrogen fertilizer excessively; moreover, cost savings in the nitrogen application can be achieved without loss in yields, thanks to more precise application methods [7].

1.2. Importance of the subject and current global scenario

The use of too much nitrogen has been identified as a cause of many environmental issues, such as water and soil pollution, changes in air quality, and biodiversity loss. Fertilizer inefficiency also creates significant financial losses for agricultural producers. This paradox creates pressure for agricultural science and practice to pivot from static, ill-suited to particular circumstances, advice to dynamic flexible site-specific nutrient management (SSNM) based on data.

Predictive analytics refers to the application of statistical and computer methodologies to anticipate effects based on retrospective information as well as available data. Predictive analytics has therefore firmly entered its break-in period. The latest developments in both machine and deep learning, the reduction in costs of soil sensors based on IoT technologies, the increase in capabilities of remote sensing with the use of satellites and UAVs, and the emergence of new generations of systems aimed at supporting decision-making processes, like the QUEFTS model and Nutrient Expert, have formed a basis of the creation of innovation fertilizer recommendations [11-14]. Such initiatives as the Indian Soil Health Card scheme or the US joint initiative Fertilizer Recommendation Support Tool can serve as the representatives of this new wave of the use of the achieve success.

1.3. Need for the review, objectives, and scope

There has been considerable empirical research into predictive analytics of fertilizer recommendations; however, the available literature on this topic is still frugal with respect to cross-diciplinary sharing of information. The research's environment is characterized by a heterogeneous reporting of some elements like model performances, validation processes, or deployment conditions. Only a few literature reviews have managed to summarize findings to yield valuable insights into this area of scientific research. This article is aimed at fulfilling this gap.

The specific objectives of this review are to: (i) synthesize peer-reviewed literature on predictive-analytics approaches to fertilizer recommendation published primarily between 2015 and 2025; (ii) critically compare the methodologies, data sources, and reported performance of machine learning models, sensor-integrated systems, and decision support tools; (iii) identify points of agreement and contradiction across studies; and (iv) map research gaps and emerging trends to inform future research and policy. The scope encompasses machine learning and deep learning algorithms, IoT and remote-sensing-based data acquisition, and computational decision support systems, with attention to both developed- and developing-country contexts. Original experimental data collection, laboratory soil chemistry methods, and fertilizer manufacturing technologies fall outside the scope of this review.

2. Methodology of Literature Review

2.1. Literature search strategy

A structured, though not formally registered, literature search was conducted between 2015 and 2025, with a small number of methodologically foundational studies published before 2015 retained where conceptually indispensable (e.g., the original QUEFTS formulation and early random forest and gradient-boosting methodological papers). Databases searched included Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, MDPI, IEEE Xplore, Google Scholar, and institutional repositories of the FAO and the International Fertilizer Association. Search terms were combined using Boolean operators and included: "fertilizer recommendation" AND "machine learning"; "predictive analytics" AND "nutrient management"; "precision agriculture" AND "fertilizer"; "decision support system" AND "soil fertility"; "IoT" AND "soil nutrient monitoring"; "remote sensing" AND "nitrogen management"; and "site-specific nutrient management". Table 1 summarizes the search strategy.

Table 1: Literature search strategy

Parameter	Details	Examples
Databases searched	Multidisciplinary and subject-specific academic databases	Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, MDPI, IEEE Xplore, Google Scholar, FAO/FAOSTAT reports
Search period	2015–2025, with limited pre-2015 landmark exceptions	QUEFTS (1990); random forest (2001); XGBoost (2016)
Search keywords	Boolean-combined terms targeting fertilizer prediction	"fertilizer recommendation" AND "machine learning"; "predictive analytics" AND "nutrient management"; "IoT" AND "soil nutrient monitoring"; "decision support system" AND "soil fertility"
Language	English-language publications only	—
Document types	Peer-reviewed journal articles, indexed conference papers, international organization reports	Scopus/WoS-indexed journals; FAO statistical briefs

2.2. Inclusion and exclusion criteria

Studies were included if they were peer-reviewed journal articles, conference papers from recognized academic publishers, or reports from international organizations (FAO, CGIAR centers); were published in English; addressed predictive modeling, machine learning, sensor-based monitoring, or decision support systems applied specifically to fertilizer or nutrient-rate recommendation; and were published between 2015 and 2025 (with limited pre-2015 landmark exceptions). Studies were excluded if they were duplicate records across databases, non-peer-reviewed grey literature (blogs, unreviewed preprints without subsequent publication, and commercial white papers), focused exclusively on crop-yield prediction without a fertilizer-recommendation component, or reported only laboratory soil-chemistry methods without a predictive or decision-support element. Table 2 details these criteria.

Table 2: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles and indexed conference papers	Duplicate records across databases
English-language publications	Non-peer-reviewed grey literature (blogs, unreviewed preprints, commercial white papers)
Published 2015–2025 (select pre-2015 landmark studies retained)	Studies published outside the defined period without landmark relevance
Directly addresses fertilizer/nutrient-rate prediction, ML, sensors, or DSS	Focus limited to general crop-yield prediction without a fertilizer component
Reports methodology, data source, and outcome/performance metrics	Laboratory soil-chemistry studies without predictive or decision-support element

2.3. Study selection process

The selection process followed a PRISMA-style approach. An initial search yielded 612 records. After removal of 125 duplicate records, 487 unique records were screened by title and abstract, of which 291 were excluded as irrelevant or non-academic. The remaining 196 full-text articles were assessed for eligibility, and 138 were excluded for insufficient focus on fertilizer-specific prediction (as opposed to general crop-yield modeling) or inadequate methodological detail. Fifty-eight studies met the full inclusion criteria, of which thirty-nine were retained for detailed thematic synthesis after a final relevance and quality check; the remaining nineteen were used as supporting or contextual references. Figure 1 presents the PRISMA-style flow diagram, and Figure 2 illustrates the distribution of the retained studies by publication year, which shows a marked increase in research output from 2021 onward, coinciding with the wider availability of low-cost IoT sensing hardware and accessible machine learning frameworks.

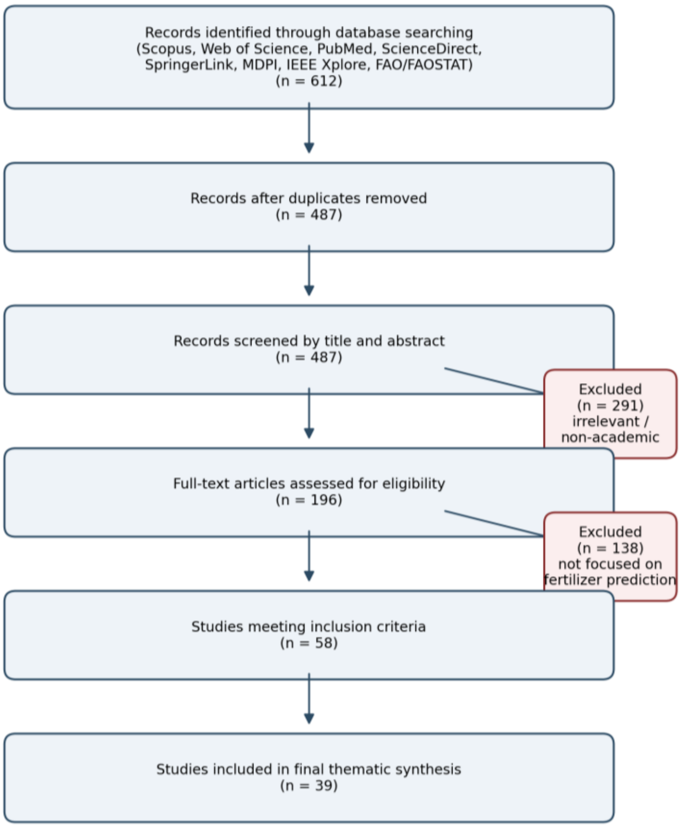

Fig 1: PRISMA-style flow diagram of the literature selection process

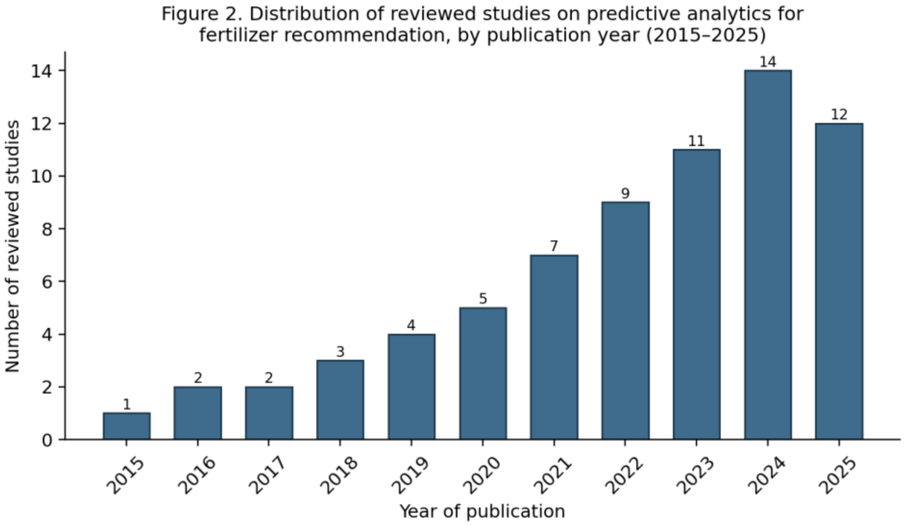

Fig 2: Distribution of reviewed studies by publication year (2015–2025)

3. Literature Review and Thematic Analysis

Figure 3 presents a conceptual framework synthesizing how the reviewed literature connects data sources, predictive modeling approaches, and field-level outcomes; Figure 4 summarizes the proportional thematic composition of the reviewed corpus. The synthesis below is organized into five major themes.

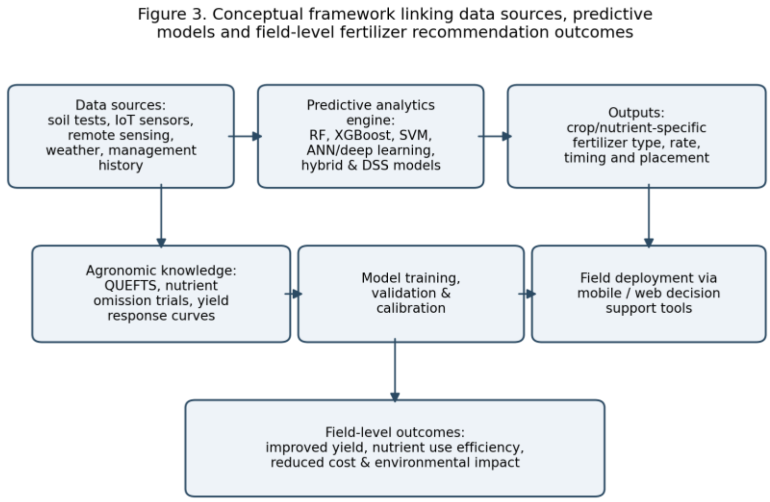

Fig 3: Conceptual framework linking data sources, predictive models, and field-level fertilizer-recommendation outcomes

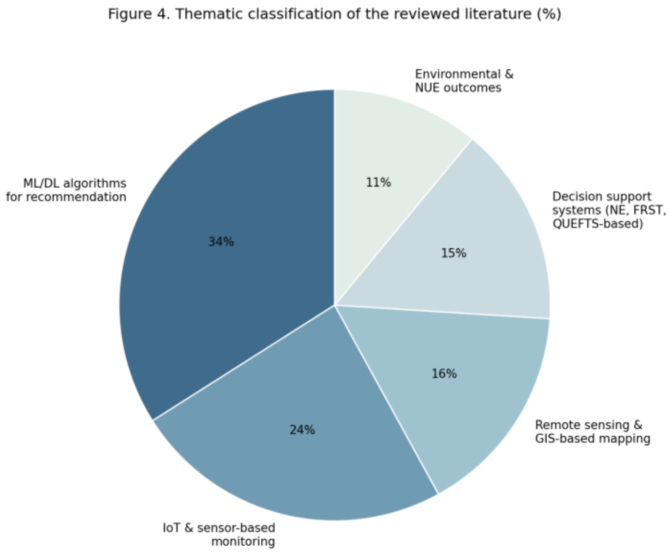

Fig 4: Thematic classification of the reviewed literature

3.1. From blanket recommendations to site-specific nutrient management

The methodological lineage of predictive fertilizer recommendation begins with agronomic decision-support frameworks predating contemporary machine learning. The QUEFTS model, which estimates balanced nutrient requirements for a target yield from indigenous soil nutrient supply, established a generic, transferable structure that could be calibrated across diverse soils and climates with comparatively limited input data [11, 17]. Building on this foundation, Nutrient Expert was developed as a simple computer- or mobile-based decision support tool that translates on-farm nutrient omission trial data, local yield potential, and farmer objectives into field-specific nitrogen, phosphorus, and potassium recommendations [12, 13]. Large-scale evaluation across more than 1,590 side-by-side comparison trials in the Indo-Gangetic Plains of India found that Nutrient Expert-based recommendations reduced nitrogen input by 15–35%, increased grain yield by 4–8%, and lowered global warming potential by 2–20% relative to farmers' conventional fertilization practices, with more than 80% of participating farmers reporting increased yield and income [13]. Calibration of Nutrient Expert for maize across Nigeria, Ethiopia, and Tanzania using 735 on-farm nutrient omission trials similarly demonstrated the transferability of the underlying QUEFTS-based logic to sub-Saharan African agroecologies, provided sufficient local trial data are available for calibration [12].

These decision-support tools illustrate an important point of agreement across the literature: mechanistic or semi-mechanistic agronomic models retain value as an interpretable backbone even as purely data-driven methods have proliferated, and several of the highest-performing recent systems are hybrids that embed machine learning within, rather than as a replacement for, agronomic response-curve logic [14, 18]. In the United States, the collaborative Fertilizer Recommendation Support Tool exemplifies a parallel, database-driven approach: rather than a single predictive algorithm, it aggregates decades of multi-state soil-test correlation and calibration data into a relational database with a web-based interface, providing science-based phosphorus and potassium recommendations while explicitly avoiding recommendations where no yield response is expected [19, 20]. This design choice — explicitly modeling the probability of a null response — addresses a recurring criticism of blanket recommendations, namely their tendency to recommend fertilizer even where soils are already sufficient.

3.2. Machine learning and deep learning algorithms for fertilizer prediction

A substantial share of the recent literature applies supervised machine learning directly to fertilizer type and dosage prediction, typically framing the task as either a classification problem (recommending a fertilizer category) or a regression problem (recommending an application rate). Ensemble tree-based methods — particularly random forest and extreme gradient boosting (XGBoost) — recur as strong performers. One study using a publicly available soil-and-crop fertilizer dataset reported that an XGBoost model achieved 93.4% accuracy, an F1-score of 0.92, and an area under the curve of 0.96 in predicting optimal fertilizer type and dosage, with field-level simulation suggesting a 17% yield increase and a 23% reduction in fertilizer usage relative to conventional application [21]. A separate comparative ensemble study evaluating multiple algorithms for nutrient-requirement prediction across crops found that a LightGBM-based model offered the strongest performance for capturing rainfall-sensitive nutrient requirements, delivered through a farmer-facing web interface [14]. Similarly, an integrated system combining a neural network-based crop recommendation module with a rule-based fertilizer module, developed for smallholder conditions in Rwanda, reported prediction accuracy near 97% for crop recommendation, underscoring the popularity of neural architectures in this domain even though rule-based logic was retained for the fertilizer-dosage component itself, reflecting persistent caution about applying purely learned models to prescriptive nutrient decisions [18, 22].

Not all evidence points unambiguously toward high real-world accuracy, however. A rigorously designed on-farm precision experimentation study using 255 covariate combinations derived from eight soil properties, applied to winter wheat basal and top-dressed nitrogen–phosphorus–potassium fertilization, found that economically optimal input rate (EOIR) predictions and associated profit estimates were highly sensitive to the choice of machine learning algorithm and covariate selection, with coefficients of variation in derived EOIRs ranging from roughly 13% to 32% depending on model and covariate choice [23]. This finding is significant because it directly contradicts an implicit assumption in much of the classification-oriented literature — that a model demonstrating high predictive accuracy for yield or fertilizer category necessarily yields an accurate and stable economic recommendation. The authors of that study explicitly caution that accurate yield-prediction models can still generate highly inaccurate input-rate recommendations, a distinction that is frequently elided in studies reporting only classification accuracy metrics [23].

A further point of methodological divergence concerns model interpretability. Several recent studies have begun to prioritize interpretable or explainable deep learning architectures for fertilizer and crop recommendation, motivated by the recognition that opaque "black-box" predictions are poorly suited to advisory contexts where extension officers and farmers must trust and act on a recommendation [24]. Support vector machines, logistic regression, k-nearest neighbor, and Gaussian naive Bayes classifiers have also been benchmarked against ensemble and neural methods in IoT-integrated systems, with Gaussian naive Bayes reported in one study to outperform alternatives for real-time nutrient application decisions, illustrating that no single algorithm dominates uniformly across data contexts and problem framings [24].

3.3. IoT and sensor-enabled real-time soil monitoring

The integration of low-cost soil sensors with wireless connectivity has extended predictive fertilizer models from static, pre-season recommendations toward continuous, real-time nutrient monitoring. Multi-parameter soil probes capable of simultaneously measuring moisture, temperature, electrical conductivity, pH, and nitrogen–phosphorus–potassium levels have been coupled with cloud-based analytics platforms to provide near-real-time fertilizer and crop recommendations [25, 26]. A systematic review of 93 studies on soil nutrient monitoring technologies categorized approaches into five groups — traditional laboratory methods, remote sensing, IoT applications, smart sensor systems, and artificial intelligence approaches — and found a clear and accelerating trend toward combining IoT data acquisition with machine learning and deep learning analytics for real-time, data-driven precision agriculture [27]. A comparative review of ML-IoT crop and fertilizer recommendation systems similarly documented accuracy levels frequently exceeding 97–99% for crop recommendation tasks using multilayer perceptron, random forest, and support vector machine classifiers, though the same review noted that many of these high-accuracy studies relied on limited or non-representative datasets (for example, datasets restricted to only two soil types), raising concerns about external validity [25].

A further comprehensive review of sensor technologies for soil health monitoring highlighted those dielectric-based moisture sensors (time-domain and frequency-domain reflectometry) and remote sensing have proven effective for irrigation management, while ion-sensitive field-effect transistors and optical sensing systems have improved realtime nutrient and pH profiling, with IoT-enabled sensor networks increasingly supporting predictive analytics and data-driven decision-making at field scale [28]. Nonetheless, this same body of work consistently flags soil-specific calibration requirements, sensor cost, and limited rural connectivity as persistent barriers to widespread adoption, particularly in smallholder-dominated agricultural systems of South Asia and sub-Saharan Africa [27, 28].

3.4. Remote sensing and GIS-based spatial fertilizer prescription

Beyond point-based soil sensing, remote sensing and geographic information system (GIS) techniques have been used to generate spatially explicit, variable-rate fertilizer prescription maps. Geographic object-based image analysis applied to satellite or UAV imagery has supported the creation of variable-rate nitrogen prescription maps in perennial cropping systems such as olive orchards, enabling differentiated fertilization within a single field according to vegetation vigor and canopy characteristics [29]. Deep reinforcement learning-based crop classification systems have also been explored to support broader agricultural decision-making pipelines, although these approaches remain constrained by the computational demands of achieving simultaneously high accuracy, processing speed, and operational consistency in field deployment [29]. Remote sensing's principal advantage — extensive spatial coverage without the logistical burden of dense point sampling — is tempered in smallholder and fragmented-field contexts by atmospheric interference, mixed-pixel effects, and a shortage of local ground-truth data for calibration, a limitation noted consistently across the reviewed sensor-technology literature [27–29].

3.5. Environmental and economic outcomes of predictive nutrient management

A recurring and largely convergent finding across the reviewed literature is that predictive, site-specific nutrient management delivers simultaneous gains in productivity, farmer income, and environmental performance relative to conventional blanket fertilization. Beyond the Nutrient Expert evaluations discussed above, a large-scale analysis of more than 31,000 farmer fields across Nepal, Bangladesh, and India found that 55% of surveyed rice farmers over-applied nitrogen fertilizer, with an estimated potential saving of 18 kg of nitrogen per hectare achievable without compromising yield, primarily by disincentivizing excess application and improving complementary management practices such as transplanting timing [7]. At the global policy level, FAO analysis emphasizes that while nitrogen fertilizer use has been central to twentieth-century gains in food security, improving nitrogen use efficiency is now essential to limit associated harms to human health and environmental quality, including elevated respiratory and cardiovascular disease risk linked to nitrogen pollution [8]. Meta-analytic evidence from China further documents that long-term, excessive nitrogen fertilizer application drives soil acidification and disrupts soil microbial community structure and enzymatic activity, with consequences for long-term soil fertility that static, single-season recommendation models do not capture [9]. Collectively, this body of evidence indicates that the environmental and agronomic case for predictive, data-driven fertilizer recommendation is stronger and more consistent than the case for any single algorithmic approach, an important distinction for practitioners evaluating competing technological claims.

4. Comparative Analysis of Previous Studies

Table 3 summarizes key characteristics of representative studies reviewed, and Table 4 extends this comparison across methodological approach and reported limitations, to support the critical synthesis presented in Section 3.

Table 3: Summary of selected studies

Author(s)	Year	Location/context	Methodology	Sample/dataset	Major findings
Sapkota *et al.* [13]	2021	Indo-Gangetic Plains, India	Field comparison trials, Nutrient Expert DSS	1,594 side-by-side rice/wheat trials	N input reduced 15–35%; yield increased 4–8%; GWP reduced 2–20%
Kihara *et al.* [12]	2020	Nigeria, Ethiopia, Tanzania	QUEFTS-based DSS calibration	735 on-farm nutrient omission trials	Nutrient Expert successfully calibrated across maize agroecologies
Malik [21]	2025	Not region-specific (public dataset)	XGBoost, neural network classification	Public soil-and-crop fertilizer dataset	93.4% accuracy; 17% yield gain; 23% fertilizer reduction (simulated)
Tanaka *et al.* [23]	2024	On-farm, winter wheat	RF, XGBoost, SVR, ANN on-farm precision experimentation	255 covariate combinations, 8 soil properties	EOIR estimates highly sensitive to algorithm/covariate choice (CV 13–32%)
Nkurunziza *et al.* [18]	2023	Rwanda	Neural network (crop) + rule-based (fertilizer)	Field data, major Rwandan crops	~97% crop recommendation accuracy; hybrid ML/rule-based fertilizer module
Systematic review [27]	2025	Global (93 studies)	Systematic review of sensor technologies	93 reviewed studies	Growing integration of IoT + AI for real-time soil nutrient monitoring

Table 4: Comparative analysis of previous research: methodological approach and limitations

Study	Methodological approach	Reported limitations
Sapkota *et al*. [13]	Multi-season, multi-site independent field validation	Requires access to extensive on-farm trial infrastructure; limited to rice–wheat systems
Kihara *et al*. [12]	Region-specific calibration of a generic agronomic model	Cross-region transfer requires substantial local trial data; not a pure ML approach
Malik [21]	Ensemble machine learning classification	Performance derived from public dataset; limited independent field validation
Tanaka *et al*. [23]	Multi-algorithm on-farm precision experimentation	High sensitivity of recommendations to algorithm and covariate choice reduces reliability
Nkurunziza *et al*. [18]	Hybrid neural network and rule-based system	Fertilizer component remains rule-based rather than fully data-driven
Systematic review [27]	Narrative/systematic synthesis of sensor literature	Many underlying studies rely on small or non-representative datasets

5. Research Gaps and Emerging Trends

Despite methodological diversity and generally favorable reported outcomes, the reviewed literature exhibits several recurring and unresolved limitations, summarized in Table 5 and visually mapped in Figure 5.

Table 5: Research gaps identified in the reviewed literature

Gap	Description	Representative sources
Real-time adaptability	Static models trained on historical data perform poorly under changing field conditions within a season	[30]
Cross-regional generalizability	Models require substantial recalibration when transferred across soils, climates, or cropping systems	[12,27,28]
Model interpretability	Black-box outputs limit trust and adoption among extension advisers and farmers	[18,24]
Smallholder data scarcity	Limited, non-representative, or simulated datasets constrain training and external validity	[25]
Longitudinal field validation	Most ML studies report cross-validated accuracy rather than multi-season independent field outcomes	[13,21,23]
Standardized benchmark datasets	Absence of shared, public fertilizer-recommendation datasets impedes cross-study comparison	[19,20]

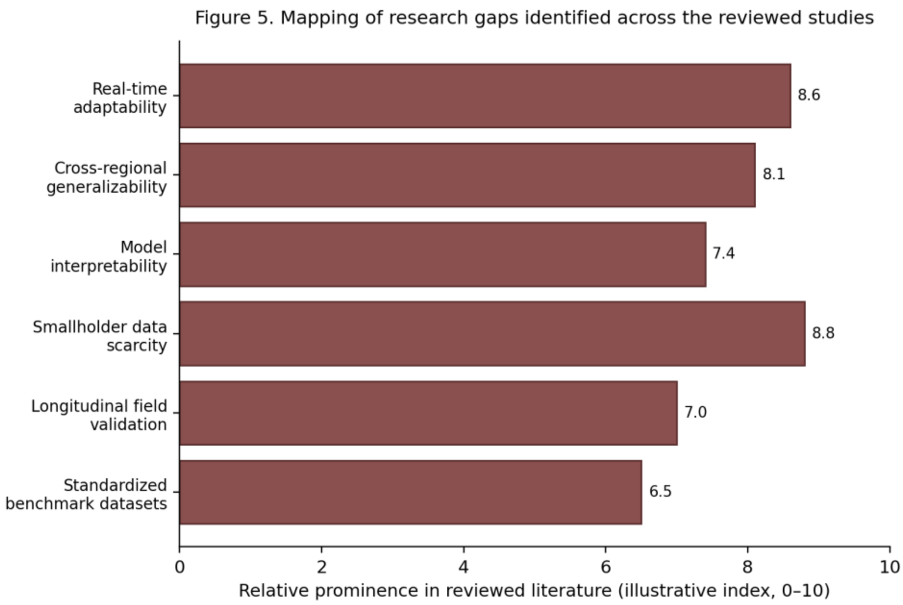

Fig 5: Mapping of research gaps identified across the reviewed studies

First, real-time adaptability remains limited: many machines learning models, including widely used convolutional neural network, XGBoost, and random forest implementations, are trained on static historical datasets and consequently perform poorly when environmental conditions shift within a growing season, a limitation explicitly identified in recent precision-agriculture optimization research [30]. Second, cross-regional generalizability is weak; models calibrated on data from one agroecological zone, soil type, or cropping system frequently cannot be transferred without substantial recalibration to other regions, a constraint evident in the region-specific calibration requirements documented for Nutrient Expert across African agroecologies [12] and in the soil-specific calibration needs noted for IoT sensor systems [27, 28]. Third, model interpretability remains a barrier to field adoption; the persistence of rule-based fertilizer logic alongside machine-learned crop-recommendation modules in several deployed systems reflects an implicit acknowledgment that black-box dosage recommendations are not yet trusted for direct agronomic prescription [18, 24]. Fourth, data scarcity in smallholder systems constrains model training and validation, since many high-accuracy studies rely on limited, non-representative, or purely simulated datasets rather than extensive, geographically diverse ground-truth data [25]. Fifth, longitudinal field validation is uncommon; the substantial majority of machine learning studies reviewed report only cross-validated performance on held-out historical data rather than multi-season, independently verified field trial outcomes of the type conducted for Nutrient Expert in the Indo-Gangetic Plains [13]. Sixth, the absence of standardized, publicly available benchmark datasets for fertilizer (as distinct from crop-yield) prediction impedes direct comparison of reported model performance across studies, a methodological gap that mirrors challenge long recognized in other applied machine learning domains.

5.1. Emerging trends

Several emerging trends, summarized in Table 6 and Figure 6, indicate plausible pathways to address these gaps. Hybrid approaches that embed machine learning within mechanistic agronomic structures such as QUEFTS are gaining traction, seeking to combine the transferability and interpretability of process-based models with the pattern-recognition capacity of data-driven methods [11, 14]. Explainable artificial intelligence (XAI) techniques are increasingly being incorporated into fertilizer and crop recommendation systems to render model reasoning transparent to extension advisers and farmers [24]. Edge computing and lightweight on-device deep learning architectures, including vision-transformer-based models optimized for low-resolution inputs, are being explored to reduce dependence on continuous cloud connectivity in rural, connectivity-limited settings [26]. Reinforcement learning is being investigated for adaptive, within-season nutrient dosing that responds dynamically to changing soil and weather conditions, addressing the real-time adaptability gap directly [30]. Finally, multi-institution data-sharing collaborations such as the Fertilizer Recommendation Support Tool point toward a broader movement toward standardized, pooled datasets and shared validation frameworks, which could substantially improve cross-study comparability going forward [19, 20].

Table 6: Emerging trends in predictive fertilizer-recommendation analytics

Trend	Description	Representative sources
Hybrid physics-informed/ML models	Embedding ML within agronomic response-curve structures such as QUEFTS	[11,14]
Explainable AI (XAI)	Techniques to render model reasoning transparent for advisory use	[24]
Edge AI and on-device inference	Lightweight architectures reducing dependence on continuous cloud connectivity	[26]
Reinforcement learning	Adaptive, within-season nutrient dosing responsive to real-time conditions	[30]
Multi-omics/soil microbiome integration	Incorporating biological soil health indicators into predictive frameworks	[9]
Standardized open datasets	Multi-institution data pooling and shared validation frameworks	[19,20]

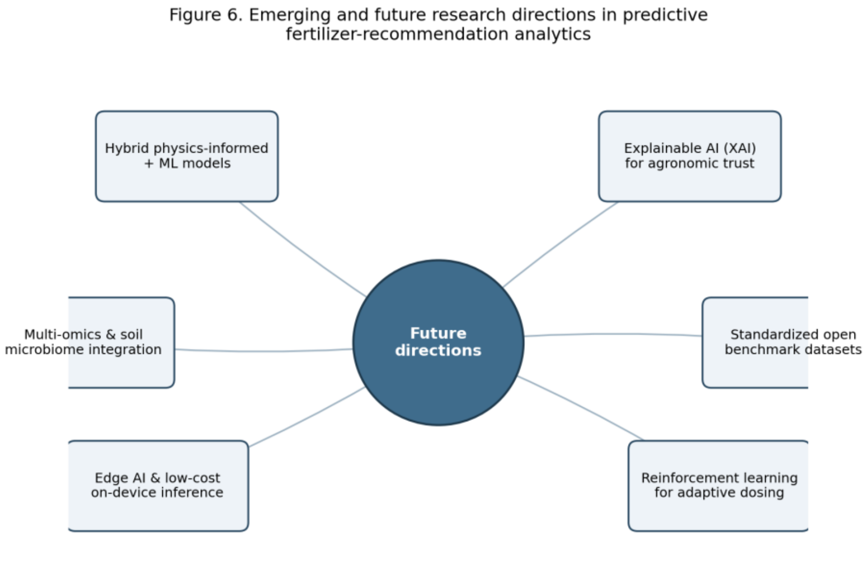

Fig 6: Emerging and future research directions in predictive fertilizer-recommendation analytics

6. Discussion

Synthesizing across the themes above, the reviewed literature reveals a clear historical trajectory from generalized, rule-based fertilizer recommendation toward increasingly data-intensive, computationally sophisticated, and in principle more precise systems. This trajectory is broadly consistent with the wider precision-agriculture literature, in which the diffusion of low-cost sensing and cloud computing has progressively lowered the barriers to site-specific management [10, 26]. The convergence of evidence around measurable gains in yield, input-use efficiency, and reduced environmental burden from decision-support tools such as Nutrient Expert, evaluated across thousands of independent field trials, lends this trajectory a degree of empirical credibility that is less consistently available for purely machine learning-based fertilizer classifiers, whose performance claims are frequently derived from held-out partitions of a single dataset rather than independent field validation [13, 21, 25].

At the same time, the literature contains a genuine and underexplored tension between reported classification or regression accuracy and demonstrated economic or agronomic reliability. The on-farm precision experimentation evidence showing that economically optimal input rate estimates vary by up to roughly 30% depending on algorithm and covariate choice represents a direct empirical challenge to the narrower framing, common in computer-science-oriented publications, that a high accuracy or F1-score score is sufficient evidence of practical utility [23]. This divergence likely reflects differing disciplinary standards of evidence: agronomic and precision-agriculture journals tend to emphasize field-validated economic outcomes, whereas computational and informatics-oriented outlets more often emphasize algorithmic benchmarking on fixed datasets. Reconciling these standards, for instance by requiring field-validated economic sensitivity analysis alongside standard machine learning performance metrics, would strengthen the evidentiary basis of future studies.

The theoretical implication of this synthesis is that fertilizer recommendation is not merely a prediction problem but a decision problem embedded within agronomic, economic, and infrastructural constraints; this explains the persistent role of hybrid and rule-based components even within nominally "AI-driven" systems and cautions against treating raw predictive accuracy as a sufficient proxy for recommendation quality. Practically, the evidence suggests that the most field-ready and scalable systems to date are those that combine transferable agronomic logic (as in QUEFTS-derived tools) with selectively applied machine learning for specific sub-tasks such as sensor-data interpretation or rainfall-sensitive nutrient timing, rather than end-to-end black-box models applied without agronomic constraint [11, 14, 18]. For policymakers, the consistent finding that predictive, site-specific nutrient management can simultaneously raise farmer income and lower greenhouse gas emissions provides a strong rationale for continued public investment in decision-support infrastructure, extension-service digitalization, and open agricultural data initiatives, particularly in regions such as sub-Saharan Africa where both nutrient deficiency and data infrastructure gaps remain most acute [7, 12, 13].

7. Conclusion

This review has synthesized literature on predictive analytics for optimizing fertilizer recommendations, spanning machine learning and deep learning algorithms, IoT- and remote sensing-enabled monitoring, and computational decision support systems. The evidence indicates that predictive, site-specific approaches consistently outperform blanket, generalized fertilizer recommendations across yield, input-use efficiency, farmer income, and environmental outcome dimensions, with the strongest and most field-validated gains documented for hybrid decision support tools that combine agronomic response models with data-driven components. Purely algorithmic, classification-oriented studies report high accuracy metrics but less consistently demonstrate field-validated economic reliability, and the literature as a whole remains constrained by weak real-time adaptability, limited cross-regional transferability, opaque model reasoning, smallholder data scarcity, and the absence of standardized benchmark datasets.

For researchers, this review recommends prioritizing multi-season, independently validated field trials over single-dataset cross-validation, adopting explainable modeling approaches suited to advisory contexts, and contributing toward open, standardized fertilizer-recommendation benchmark datasets that would allow meaningful cross-study comparison. For practitioners and policymakers, the findings support continued investment in hybrid decision support platforms, expansion of digital extension infrastructure particularly in smallholder-dominated regions, and cautious, staged validation of machine learning-based tools before large-scale deployment, given the demonstrated sensitivity of economic recommendations to model and covariate choice. Future research would benefit from closer integration of reinforcement learning for adaptive within-season dosing, edge computing for low-connectivity deployment, and multi-omics soil data to capture biological dimensions of nutrient cycling that current models largely omit. Achieving these advances will require sustained interdisciplinary collaboration among agronomists, data scientists, and extension practitioners to ensure that predictive analytics translates into genuinely optimized, trustworthy, and equitable fertilizer recommendations at scale.

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