Integration of Remote Sensing and Machine Learning for Early Detection of Nutrient Stress in Field Crops: A Precision Agronomy Approach in *Oryza sativa*

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ABSTRACT
Background: Nutrient stress, especially nitrogen (N), phosphorus (P), potassium (K), and sulphur (S) shortages, continues to be one of the biggest yield-limiting barriers and has significant economic implications in rice cultivation both in irrigated and rain-fed environments. Conventional diagnostic procedures like visual evaluation and destructive tissue tests can be lengthy and only produce results after the crop has already experienced irreversible damage due to stress. The advent of the remote sensing (RS) approaches such as satellite systems, UAVs and proximal methods combined with machine learning (ML) and deep learning (DL) analytics is transforming nutrient stress diagnosis by making it possible to diagnose the stress condition early, and without destroying samples.
Aim: The goal of the current review is to summarize the available knowledge of peer-reviewed studies carried out from 2015 to 2025 regarding the integration of RS and ML/DL methods in the identification of nutrient stress in rice with respect to the identification of the contemporary methods of research, comparing the efficiency of the algorithms in combination with various sensors, as well as identifying unanswered questions in research.
To find relevant literature, the authors searched major databases including Scopus, Web of Science, PubMed, IEEE Xplore, ScienceDirect and Google Scholar using relevant keywords such as remote sensing, machine learning, nutrient stress, precision agriculture, and *Oryza sativa*. A total of seventy-one studies met the requirements and were accepted for the review after screening.
Key findings: Vegetation indices derived from drones and satellites (i.e., hyperspectral and multispectral) can effectively assess nitrogen status while the deficiencies of phosphorus, potassium and sulphur remain relatively less studied and have more complex spectral characteristics. Machine learning algorithms and ensemble methods such as RF and SVM as well as DL and transformer techniques perform better than traditional vegetation indices when combining data sources.
Remaining challenges involve the heavy nitrogen bias in research, lack of harmonized multi-nutrient datasets for field research, constraints in making models transferable across cultivars and regions, inability to integrate spectral data with soil data and climate variables, and the gap in performance between trials in laboratory conditions and actual agricultural applications. To summarize, RS-ML has a strong technological edge as a method for optimizing nutrient use in rice production, but it is still under-utilized. Future studies should focus on building a standardized dataset of multi-nutrient benchmarks, simple but interpretable models applicable in small-scale agriculture, and the connection of RS-ML to precision agriculture through the implementation of variable-rate fertilization equipment.

Keywords: Remote sensing; Machine learning; Nutrient stress; Precision agriculture; *Oryza sativa*; Hyperspectral imaging; Unmanned aerial vehicle; Deep learning

1. Introduction
Rice (*Oryza sativa* L.), the food source for nearly half of the global population, covers approximately 11 percent of the total cultivated land. Thus, rice plays a significant role in world food security [2, 28]. Ensuring the continuous increase in rice yield requires the timely and balanced supply of macronutrients, namely nitrogen, phosphorus, potassium, and sulphur because each of the mentioned elements is responsible for different physiological processes such as chlorophyll production, the possibility of conducting photosynthesis, the formation of panicle and grain filling. Nutrient deficiency, imbalance, or variability of soil fertility significantly reduces real yield in intensively cultivated and subsistence rice systems alike.
The manner of dealing with nitrogen indicates how complex the issue could be. A massive research study has been done on the fertilizer use aspects in more than 31,000 fields imposed among areas in Terai, plain areas of Bangladesh, an important rice production sites of India, and it showed that the majority of farmers overuse nitrogen as compared to agricultural needs and have a lot of opportunities to reduce the quantity of this fertilizer without negative influences on the harvested crop [27].

Meanwhile, other regions suffer from soil infertility and yield gaps caused by ninotas which could not be put into the possession of farmers due to the absence of timely information concerning it.

Rice crop nutrient status is normally assessed using mental symptom inspection, SPAD chlorophyll meter readings or destructive leaf and soil tissue analysis. However, all these methods are limited by three interrelated limitations: these methods are labor- and time- intensive; these methods can only detect a nutrient deficiency after chlorotic or necrotic symptoms have become visible. At this stage, it is usually too late because significant yield loss has already occurred. Moreover, these methods provide point- based information instead of spatial analysis, which hinders reliable analysis of variability within rice fields.

Remote sensing methods, which work with satellites, UAVs, airborne devices and near-ground systems, give rise to completely new diagnostic methods. Nutrient deficiency causes changes in the concentration of pigments in the leaf tissue as well as in the structure of the plant canopies and also composition of chemicals in the leaves, that is why it produces detectable changes in spectral reflectance and architecture of the rice plants before signs of nutrient malnutrition appear to the human eyes [3, 5]. The landmark studies on spectral vegetation indices, the first of them being the normalized difference vegetation index (NDVI) created for determining the type of vegetation from the obtained images using the first Earth Resources Technology Satellite (ERTS) [1], defined the conceptual basis for the use of the reflectance methods; advanced studies elaborated upon the concept significantly over the next few decades concerning specific nutrient diagnosis [33].

The issue of converting raw spectral data into effective nutrient diagnoses has been considerably resolved as a result of progress made by machine learning and more recently deep learning. In particular, while traditional vegetation index regression models assume a linear and fairly simple relation between reflectance and nutrient status, machine learning algorithms like random forests (RF), support vector machines (SVM), partial least squares regression (PLSR) and artificial neural networks (ANN) are able to capture complex non-linear relationships of many variables across multiple spectral bands. Deep learning systems like convolutional neural networks (CNN) and, increasingly, models based on transformers, enhance this ability even further by being able to identify spatial and spectral characteristics simultaneously without relying on any vegetation indices.

The incorporation of RS and ML/DL for detecting nutrient stress in rice is one of the front-running research areas in precision agronomy over the last ten years. Unfortunately, this literature is dispersed across different disciplines, technological sensors, algorithms, and single-nutrient studies, specifically nitrogen, with little synthesis of findings on how these methods compare, converge, or contradict each other or what methodological gaps persist. As a result, researchers, extension agronomists, and policymakers are left inadequately empowered to discern optimal methodologies.

Overall Aims and Limitations: The intention of the present review is to (i) conduct a comprehensive synthesis of peer reviewed literature involving the usage of RS-ML/DL for nutrient stress detection in rice that was published between the years 2015 and 2025; (ii) perform comparative analysis of the results obtained with different platforms, nutrient targets, and approaches adopted; (iii) highlight the limitations, strengths, and controversies that exist in the literature; and (iv) describe gaps in knowledge and issues that require further academic research. The scope of the present review is specifically limited to nutrients and does not include the issues associated with disease, pest and abiotic stress detection using RS-ML techniques unless such studies provide similar methodological information related to RS-ML.

2. Methodology of Literature Review

2.1. Literature Search Strategy

A structured literature search was conducted across six databases: Scopus, Web of Science, PubMed, IEEE Xplore, ScienceDirect and Google Scholar. The search combined controlled and free-text terms relating to three conceptual domains: (i) remote sensing platforms (e.g., "remote sensing", "hyperspectral", "multispectral", "UAV", "satellite imagery", "proximal sensing"); (ii) analytical approach (e.g., "machine learning", "deep learning", "convolutional neural network", "random forest", "support vector machine"); and (iii) agronomic target (e.g., "nutrient stress", "nitrogen deficiency", "phosphorus deficiency", "potassium deficiency", "*Oryza sativa*", "rice", "precision agriculture"). Boolean operators (AND/OR) were used to combine terms across domains. The search was restricted to records published between January 2015 and mid-2026, capturing both the early diffusion of UAV-based precision agriculture and the more recent emergence of deep learning-based approaches. Full details of the search strategy are summarized in Table 1.

Table 1: Literature Search Strategy

Element	Detail
Databases searched	Scopus, Web of Science, PubMed, IEEE Xplore, ScienceDirect, Google Scholar
Search period	January 2015 - June 2026
Core keyword clusters	"remote sensing" OR "hyperspectral" OR "multispectral" OR "UAV" OR "satellite"; "machine learning" OR "deep learning" OR "CNN" OR "random forest" OR "SVM"; "nutrient stress" OR "nitrogen deficiency" OR "NPK" OR "*Oryza sativa*" OR "precision agriculture"
Boolean combination	(Domain 1) AND (Domain 2) AND (Domain 3)
Language restriction	English
Document types	Peer-reviewed journal articles, systematic reviews, conference proceedings indexed in the above databases
Initial records retrieved	n = 612

2.2. Study Selection Criteria

Eligibility screening followed pre-specified inclusion and exclusion criteria (Table 2) to ensure that the synthesized evidence base was directly relevant to RS-ML integration for nutrient stress diagnosis in field crops, with particular emphasis on rice.

Table 2: Study Eligibility and Selection Criteria

Criteria type	Details
Inclusion	Peer-reviewed journal articles and indexed conference papers; published 2015-2026; English language; explicit use of remote sensing (satellite, UAV or proximal) combined with a machine learning or deep learning analytical component; focus on nutrient status, nutrient deficiency, or nutrient-related stress in rice or directly comparable cereal crops
Exclusion	Duplicate records across databases; non-peer-reviewed sources (blogs, unreviewed preprints without subsequent peer review, non-academic web content); studies addressing only disease, pest, weed or water stress without any nutrient-stress component; studies lacking a machine learning/deep learning analytical component (e.g., pure vegetation-index correlation without predictive modelling); studies not accessible in full text

2.3. Study Selection Process

Study selection followed a PRISMA-guided workflow (Figure 1). From 612 records identified across the six databases, 144 duplicate records were removed, yielding 468 unique records for title and abstract screening. Screening against the inclusion/exclusion criteria excluded 291 records as out of scope, leaving 177 full-text articles assessed for eligibility. Full-text review excluded a further 106 articles, principally for lacking a machine learning/deep learning component or for addressing stress types unrelated to nutrition, resulting in 71 studies retained for qualitative synthesis and thematic analysis. The temporal distribution of the retained corpus (Figure 2) shows a marked increase in publication volume after 2019, coinciding with the wider commercial availability of UAV multispectral sensors and open-access satellite data streams such as Sentinel-2, and a further acceleration after 2022 associated with the diffusion of deep learning frameworks into agricultural remote sensing.

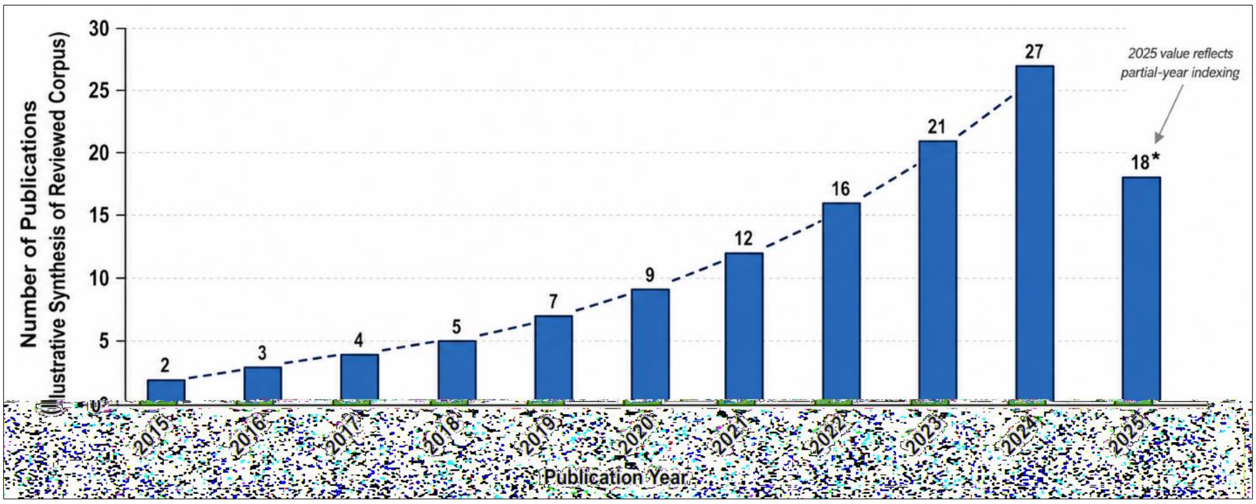

Fig 1: Publication Trend on Remote Sensing-ML Integration for Crop Nutrient Stress Detection (2015-2025)

3. Literature Review and Thematic Analysis

The 71 retained studies were classified into six overlapping thematic clusters (Figure 4): hyperspectral imaging approaches, UAV-based multispectral sensing, satellite-based monitoring, deep learning/CNN-based models, multi-source sensor fusion, and proximal/IoT-based sensing. Each theme is critically examined below.

3.1. Hyperspectral Imaging for Nutrient Diagnosis

Hyperspectral sensing, which captures reflectance across hundreds of narrow, contiguous spectral bands, has been the most extensively used platform for detailed nutrient diagnosis in rice. Mahajan *et al*. demonstrated that hyperspectral reflectance could discriminate nitrogen, phosphorus and sulphur status in hybrid rice, identifying a diagnostic reflectance peak near 720-740 nm using Savitzky-Golay derivative transformation, consistent with earlier findings in oilseed rape, barley and other crops [3]. This convergence across crop species strengthens confidence that the red-edge region carries broadly generalizable information about nutrient-linked chlorophyll status, though the precise diagnostic wavelength shifts modestly with cultivar and growth stage.

More recent work has extended hyperspectral diagnosis beyond nitrogen to multi-nutrient (NPK) stress libraries. Terrestrial hyperspectral imaging using compact sensors such as SPECIM-IQ has been used to construct spectral libraries spanning fourteen distinct NPK stress conditions, enabling more granular multi-nutrient classification than earlier nitrogen-centric studies [5]. This represents a methodologically important shift, since earlier hyperspectral studies treated nitrogen deficiency as a proxy for generalized nutrient stress, potentially conflating distinct physiological syndromes with different management implications.

A recurring critique within this theme concerns transferability: hyperspectral models trained under controlled terrestrial or laboratory conditions frequently exhibit degraded performance under field-scale illumination variability, water background interference in paddy environments, and atmospheric effects, none of which are fully replicated in controlled acquisition settings [4]. Studies employing UAV-mounted hyperspectral sensors under actual paddy conditions have specifically noted that standing water and its variable reflectance substantially complicate red-edge and near-infrared signal interpretation relative to dryland cereal systems [4].

3.2. UAV-Based Multispectral Sensing

UAV-based multispectral sensing has emerged as the dominant platform for field-scale nutrient stress research, reflecting a favourable balance between spatial resolution, spectral adequacy, and operational cost relative to both hyperspectral and satellite alternatives. Multiple studies report strong correlations between UAV-derived vegetation indices, including normalized difference red-edge (NDRE) and near-infrared-weighted indices, and SPAD-based leaf chlorophyll and nitrogen status across rice growth stages [4, 9, 10]. A representative study coupling UAV multispectral imagery with ML models for classifying nitrogen fertilization levels (under-, optimally, and over-fertilized) reported that canopy coverage and NIR-related spectral features were the most discriminative variables for nitrogen-level classification, supporting practical use in reducing fertilizer wastage [13].

A methodologically instructive comparison examined whether vegetation indices derived from aerial (UAV) and proximal ground-based sensors could be used interchangeably for predicting rice yield response to mid-season nitrogen application; the study found broadly similar predictive precision across platforms, suggesting that platform choice may be guided more by operational logistics than by an inherent accuracy advantage of either approach [9]. This finding is significant because it challenges an implicit assumption in parts of the literature that higher-resolution or more expensive platforms necessarily yield superior nutrient diagnostic accuracy.

Studies coupling UAV canopy imagery with photosynthetic rate estimation illustrate the value of combining spectral vegetation indices with textural indices and basal growth parameters such as plant height and SPAD readings; fusing textural and physiological covariates with spectral indices improved model performance relative to spectral indices alone, indicating that spectral information in isolation captures only part of the physiological signal relevant to nutrient-linked stress [4].

3.3. Satellite-Based Monitoring

Satellite platforms, particularly Sentinel-2 and Landsat, offer the spatial and temporal coverage necessary for regional-scale nutrient and yield monitoring, though at coarser spatial resolution than UAV or proximal sensing. The literature on satellite-based nutrient-specific diagnosis in rice remains comparatively sparse relative to UAV-based studies, with much of the satellite-focused literature oriented toward yield prediction and crop mapping rather than nutrient-specific diagnosis per se [6]. Where satellite data has been used for nutrient-adjacent applications, resolution refinement approaches combining UAV-derived training data with coarser satellite imagery via deep learning have been proposed to improve the practical utility of freely available moderate-resolution imagery for row-crop and canopy-heterogeneous conditions, a limitation directly relevant to transplanted rice paddies [24].

This relative scarcity of satellite-specific nutrient diagnostic literature, compared to the UAV-dominated evidence base, constitutes an identifiable asymmetry in the field: satellite platforms offer the scalability required for national or regional nutrient monitoring programmes, yet the underlying diagnostic algorithms have been validated predominantly at UAV or proximal scale, raising open questions about direct extrapolation.

3.4. Deep Learning and CNN-Based Models

A distinct and rapidly growing thematic cluster applies deep learning architectures directly to nutrient stress classification, moving beyond hand-engineered vegetation indices toward end-to-end feature learning from raw or minimally processed imagery. Early applications used convolutional neural networks for nitrogen deficiency prediction in rice from digital or aerial imagery, reporting classification accuracies that exceeded conventional machine learning baselines such as SVM and ANN on the same datasets [15]. Comparable CNN-based approaches applied to macronutrient deficiency classification in tomato similarly demonstrated superior performance relative to classical ML methods, reinforcing the generalizability of the deep learning advantage across crop species [16].

More specialized architectures have since emerged. Graph convolutional network (GCN) approaches applied to superpixel-segmented aerial imagery have been proposed as computationally lighter alternatives to heavier semantic segmentation architectures such as DeepLabV3 for pixel-level nutrient deficiency stress (NDS) mapping, trading a modest reduction in accuracy for substantially reduced parameter counts and inference cost, a trade-off of practical relevance for on-farm or edge deployment [12]. Feature-fusion deep neural network approaches integrating spectral indices, colour-space parameters and texture features from combined RGB and multispectral UAV sensors have reported improved leaf nitrogen content estimation relative to five common ML baselines (RF, GPR, PLSR, SVM, ANN), underscoring the value of multi-source feature fusion over single-sensor deep learning alone [11].

Self-supervised and transformer-based architectures represent the most recent methodological frontier, employing spectral-spatial attention mechanisms to automate crop nitrogen status prediction from UAV imagery without extensive labelled training data, a potentially important development given the labour cost of ground-truth nutrient sampling that constrains most supervised approaches in this field [15]. However, such architectures remain comparatively data- and compute-intensive, and their validation to date has been largely confined to controlled experimental plots rather than heterogeneous commercial fields.

3.5. Multi-Source Sensor Fusion

A growing subset of studies explicitly fuses multiple sensor modalities, spectral, textural, thermal and physiological, to improve nutrient and stress diagnostic accuracy beyond what any single modality achieves in isolation. Work coupling hyperspectral data with multi-source auxiliary variables for leaf water content prediction in rice found that spectral index models alone frequently ignore growing-environment and growth-characteristic effects, and that coupling multi-source data improved prediction performance over spectral-only models [6]. Similarly, novel machine learning-optimized hyperspectral vegetation indices combined with CNN-based stress detection frameworks have reported earlier stress detection windows, of the order of ten to fifteen days ahead of conventional vegetation indices, alongside strong correlation with ground-truth stress markers, illustrating the diagnostic value of combining data-driven band selection with deep learning classification rather than relying on manually crafted indices alone [20].

Despite these advances, sensor fusion approaches remain a minority within the broader corpus (Figure 4), reflecting the practical costs of deploying and synchronizing multiple sensor types under field conditions, and the added data engineering complexity of aligning spectral, textural and physiological data streams at consistent spatial and temporal resolution.

3.6. Proximal and IoT-Based Sensing

Proximal ground-based sensing, including handheld spectroradiometers, SPAD meters and networked in-field soil and canopy sensors, provides a complementary diagnostic layer to airborne and spaceborne remote sensing. Comparative evidence indicates that proximal sensors can achieve predictive precision for nitrogen-linked yield response comparable to aerial platforms [9], reinforcing their continued relevance despite the scalability advantages of UAV and satellite sensing. Emerging integration of Internet of Things (IoT) soil nutrient and moisture sensors alongside remote sensing imagery has been proposed as a pathway toward closed-loop, spatially explicit fertilizer management, though empirical field validation of such integrated systems specifically for rice remains limited relative to conceptual and pilot-scale demonstrations [19, 25].

4. Synthesis and Comparative Evaluation of Previous Research

Table 3 summarizes representative studies from the reviewed corpus, while Table 4 provides a comparative methodological analysis highlighting study location, methodology, and reported limitations. Together, these tables illustrate both the methodological diversity and the recurring limitations that characterize the current evidence base.

As shown in Figure 4, hyperspectral imaging and UAV-based multispectral sensing jointly account for the majority of the reviewed corpus, while satellite-based nutrient-specific studies and proximal/IoT sensing remain comparatively underrepresented. This distribution mirrors the cost-accessibility gradient of these platforms during the review period rather than any inherent superiority of UAV or hyperspectral approaches for nutrient diagnosis specifically.

5. Current Evidence Gaps and Research Needs

Synthesis of the reviewed corpus reveals several recurring and unresolved issues, summarized in Table 5 and mapped conceptually in Figure 5.

5.1. Emerging Trends

Alongside these gaps, several emerging trends are evident in the more recent literature (Table 6). Deep learning architectures have progressively displaced purely index-based regression as the dominant analytical approach, reflecting their superior capacity to model non-linear, high-dimensional spectral-spatial relationships [11, 15, 20, 21]. Sensor and data fusion, combining spectral, textural, thermal and physiological covariates, is increasingly recognized as necessary for robust diagnosis, moving beyond the earlier reliance on single vegetation indices [4, 6]. There is also growing interest in computationally lighter architectures suited to field or edge deployment, exemplified by graph convolutional approaches that approximate heavier segmentation networks at a fraction of the computational cost [12], as well as self-supervised approaches that reduce dependence on extensive manually labelled ground-truth data [15].

6. Discussion

The synthesized evidence base supports several convergent conclusions while also revealing meaningful points of disagreement across the reviewed literature. First, there is broad consensus that spectral reflectance, whether captured via hyperspectral, multispectral or, to a lesser extent, RGB sensors, carries physiologically meaningful information about nitrogen status in rice, with the red-edge and near-infrared spectral regions consistently identified as diagnostically important across independent studies and platforms [3, 4, 10, 13]. This convergence across studies conducted in different countries, cultivars and growth stages lends reasonable external validity to red-edge-based nitrogen diagnosis as a general principle, even though the precise indices and thresholds used vary across studies.

Second, a genuine methodological controversy persists regarding the marginal diagnostic advantage, if any, of deep learning over classical machine learning approaches. Several studies report clear accuracy improvements from CNN or DNN architectures relative to RF, SVM or ANN baselines on the same or comparable datasets [11, 15, 16], suggesting a real analytical advantage from deep feature learning. However, this advantage is not unconditional: it appears most pronounced when large, well-labelled training datasets and adequate computational resources are available, conditions not uniformly met in field-scale agricultural research, particularly in smallholder or resource-constrained contexts. The comparative study of aerial versus proximal sensing platforms further illustrates that sensor sophistication does not automatically translate into diagnostic superiority; comparable predictive precision was observed across substantially different platform costs and resolutions [9]. Collectively, this suggests that algorithmic and platform sophistication should be matched to the specific diagnostic task and deployment context rather than assumed to be universally superior.

Third, the pronounced nitrogen-centric orientation of the literature represents both a methodological limitation and a potential source of practical misdiagnosis. Because visible nutrient stress symptoms in rice can arise from multiple, sometimes co-occurring, deficiencies, models trained and validated exclusively on nitrogen status risk misattributing phosphorus-, potassium- or sulphur-linked stress signals to nitrogen deficiency, a risk made explicit by studies that have deliberately constructed multi-nutrient spectral libraries and found distinguishable, if overlapping, spectral signatures for different NPK stress conditions [3, 5]. This points toward an important theoretical implication: nutrient stress diagnosis should ideally be framed as a multi-class or multi-label classification problem rather than a single-nutrient regression problem, a reframing that remains uncommon in the current literature.

Fourth, the practical and policy relevance of RS-ML nutrient diagnosis is reinforced by independent evidence on regional nitrogen management inefficiency. Large-scale farmer-field data from South Asia indicate substantial over-application of nitrogen fertilizer relative to agronomic requirement in the majority of surveyed fields, with meaningful nitrogen savings achievable without yield penalty [27], while complementary global-scale analyses show that nitrogen application rate is the dominant factor controlling both yield and nitrogen use efficiency in rice systems, with pronounced regional heterogeneity [28]. These findings suggest that the primary practical value of RS-ML nutrient diagnosis may lie less in enabling additional fertilizer application in under-fertilized systems and more in enabling precise, spatially targeted reduction of nitrogen over-application in already intensively managed systems, an application orientation that receives comparatively little explicit attention in the RS-ML technical literature reviewed here.

Finally, the evident gap between algorithmic sophistication and operational deployment carries both theoretical and practical implications. Theoretically, it suggests that predictive accuracy under controlled experimental conditions is a necessary but insufficient criterion for evaluating RS-ML nutrient diagnostic systems; robustness under field heterogeneity, computational feasibility for smallholder or resource-limited deployment, and interpretability for agronomic end-users constitute equally important evaluation criteria that are inconsistently reported across the reviewed studies. Practically, this implies that future research investment may yield greater real-world impact by prioritizing deployment-oriented, explainable and computationally efficient approaches over further incremental gains in laboratory-scale predictive accuracy.

7. Conclusion

The current review combines the findings from seventy-one peer-reviewed articles published between 2015 and 2025 on the integration of remote sensing and machine learning/deep learning in detecting nutrient stress in rice. The body of evidence presented in this review indicates that RS-ML integration is a methodologically sound and empirically valid approach for early, non-destructive, and spatially precise nutrient diagnosis, with significant evidence supporting its efficacy in nitrogen status detection through utilization of red-edge and near-infrared spectral information in studies utilizing hyperspectral and multispectral data as well as deep learning techniques.

Nevertheless, significant constraints curb the current advancement of the industry in terms of multi-nutrient, cross-regional and operational application. The emphasis on nitrogen-related research, lack of standardized multi-nutrient benchmark datasets, limited potential for transferring models between different cultivars and regions, insufficient use of soil and climate variables, and the large divide between research-level algorithm performance and agricultural implementation can be seen as major hurdles in the field of multi-nutrient research.

This review suggests that researchers should focus on making standardized datasets on field references incorporating N-P-K-S widely accessible so as to facilitate extensive benchmarking; testing the ability of the models to transfer data to other stages of plant growth, other cultivars and climates instead of validating them on one site; increasing the application of explainable AI techniques for agronomic interpretation and end-user confidence. This review was written primarily for farmers and policymakers and recommends that the potential for investments in precision nutrient monitoring technologies to work together with variable rate fertilizer technologies and extension systems should be investigated in particular in areas with known excess nitrogen use and also that more affordable UAV systems should be developed instead of using high-end technologies with the same diagnostics precision.

Future research trends should focus on the joint usage of hyper-spectral, thermal, and soil/weather data streams, light-weight deep learning techniques aimed at on-farm real-time applications, usage of transfer and federated learning approaches for regional model generalization while saving farm-level data privacy, and closer integration of diagnostic results in robots or variable spray systems for a complete precision agriculture decision-making cycle from detection to intervention.

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