Hyperspectral Reflectance-Based Estimation of Crop Nitrogen Status in Wheat: A Systematic Review of Methods, Trends, and Research Gaps

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ABSTRACT
Background: Background: Nitrogen (N) is the single most yield-limiting and most frequently mismanaged nutrient in wheat (Triticum aestivum L.) production, and conventional destructive tissue analysis cannot support the timely, spatially explicit fertilization decisions required by modern precision agriculture. Hyperspectral reflectance sensing, which resolves canopy and leaf optical signals across hundreds of narrow contiguous bands spanning the visible, near-infrared, and shortwave-infrared regions, has emerged as a non-destructive alternative capable of capturing subtle biochemical and structural signatures associated with plant N status.
Objective: This review synthesizes peer-reviewed literature published mainly between 2015 and 2026 on hyperspectral reflectance-based estimation of wheat N status, with the aim of critically comparing methodological families, quantifying reported predictive performance, and identifying unresolved research gaps.
Sources of literature: A structured search of Scopus, Web of Science, PubMed, and Google Scholar identified 612 initial records; after de-duplication, title/abstract screening, and full-text assessment following a PRISMA-style workflow, 40 studies met the inclusion criteria for detailed qualitative and comparative synthesis.
Major findings: Four methodological families dominate the literature: empirical vegetation-index regression, chemometric/partial least squares regression (PLSR) full-spectrum models, machine-learning and deep-learning approaches, and physically based or hybrid radiative-transfer models. Red-edge-centred indices and their derivatives consistently show the strongest and most transferable correlations with leaf N concentration (LNC) and leaf N accumulation (LNA), with coefficients of determination typically between 0.60 and 0.90 across independent validation datasets. Machine-learning and deep-learning models frequently outperform classical indices in accuracy but at the cost of transferability and interpretability. Unmanned aerial vehicle (UAV) and airborne platforms have substantially expanded the operational scale of hyperspectral N diagnosis, while spaceborne imaging spectroscopy missions remain in an early operational phase.
Research gaps: Persistent gaps include limited cross-cultivar and cross-site model transferability, confounding of N signals with water stress and disease, inconsistent validation protocols, and a scarcity of studies translating spectral N diagnostics into field-deployable, cost-effective decision support tools.
Conclusion: Hyperspectral reflectance sensing offers a scientifically mature but operationally incomplete pathway toward precision N management in wheat. Future work should prioritize standardized multi-site benchmark datasets, hybrid physical-machine-learning frameworks, and integration with emerging satellite imaging spectroscopy missions to bridge the gap between research prototypes and on-farm application.

Keywords: hyperspectral reflectance; wheat; nitrogen status; vegetation indices; precision agriculture; machine learning; remote sensing; nitrogen nutrition index

1. Introduction
Wheat (Triticum aestivum L.) is cultivated on more than 220 million hectares worldwide and supplies approximately one-fifth of the calories and protein consumed by the global population, making its productivity and grain quality directly relevant to food security [1, 2]. Nitrogen (N) is the macronutrient most strongly associated with wheat yield formation, canopy photosynthetic capacity, and grain protein content, and its management represents both an agronomic opportunity and an environmental liability [1, 3]. Globally, cereal systems consume tens of millions of tonnes of synthetic N fertilizer annually, yet the recovery efficiency of applied N in wheat remains far from complete, with meta-analytical estimates of global N recovery efficiency clustering near 40-50% [3, 4]. The consequence of this inefficiency is twofold: economically avoidable input costs for farmers, and substantial losses of reactive N to waterways and the atmosphere as nitrate leachate and nitrous oxide, a potent greenhouse gas [3-5].
Conventional approaches to diagnosing crop N status, including wet chemical analysis of plant tissue (Kjeldahl or Dumas combustion methods) and visual assessment of canopy greenness, are accurate but destructive, labor-intensive, and poorly suited to the within-season, spatially explicit decision-making that variable-rate fertilization requires [1, 6].

This limitation has motivated three decades of research into optical remote sensing as a non-destructive proxy for plant N status. Multispectral sensors, which sample reflectance in a small number of broad spectral bands, were the first to be operationalized in commercial crop sensors and satellite platforms, but their coarse spectral resolution constrains sensitivity to the subtle absorption features associated with foliar nitrogen, chlorophyll, and protein [6, 7].

Hyperspectral reflectance sensing, by contrast, captures continuous or near-continuous spectral information across hundreds of narrow (typically 1-10 nm) contiguous bands spanning the visible (400-700 nm), near-infrared (700-1300 nm), and shortwave-infrared (1300-2500 nm) regions [7, 8]. This fine spectral resolution enables the isolation of diagnostic absorption features, most notably the red-edge inflection point near 700-750 nm, which shifts and changes shape in response to chlorophyll and N status, as well as protein- and nitrogen-related absorption features in the shortwave-infrared that are inaccessible to conventional multispectral sensors [8, 9]. Since the foundational work relating canopy reflectance to wheat N status using normalized difference indices and partial least squares regression [10], and subsequent controlled multi-season, multi-cultivar experiments establishing quantitative hyperspectral models of leaf N concentration (LNC) and leaf N accumulation (LNA) in wheat [1], an extensive and increasingly sophisticated body of literature has accumulated.

The current global scenario is characterized by a convergence of three trends that make a synthesis of this literature timely. First, the proliferation of low-cost UAV-mounted hyperspectral and multispectral sensors has moved hyperspectral N diagnostics from controlled plot experiments toward field-scale and near-operational deployment [11, 12]. Second, machine-learning and deep-learning algorithms, including random forest, support vector regression, gradient boosting, and convolutional neural networks, have been widely adopted to model the non-linear relationships between spectral data and wheat N status, often outperforming classical vegetation indices in predictive accuracy [2, 13, 14]. Third, a new generation of spaceborne imaging spectroscopy missions, including PRISMA, EnMAP, and NASA's forthcoming Surface Biology and Geology mission, is beginning to make hyperspectral data available at continental scale, raising the prospect of routine, satellite-based crop N monitoring [9, 15].

Despite this rapid growth, no single narrative synthesis has systematically compared the accuracy, transferability, and operational readiness of these methodological families specifically for wheat. Existing reviews tend either to focus narrowly on vegetation indices [2], to address crop N monitoring across multiple species without wheat-specific granularity [9], or to emphasize sensor engineering rather than agronomic decision-relevance. This review addresses that gap.

Objectives of the Review

- To synthesize peer-reviewed literature (2015-2026) on hyperspectral reflectance-based estimation of wheat nitrogen status.
- To critically compare the four dominant methodological families: vegetation-index regression, chemometric/PLSR models, machine-learning/deep-learning models, and radiative-transfer/hybrid physical models.
- To identify areas of convergence and contradiction in reported predictive performance across growth stages, cultivars, and sensing platforms.
- To map unresolved research gaps and emerging technological trends relevant to operational precision nitrogen management.

Scope of the Review

This review is restricted to studies that used hyperspectral (narrow-band, contiguous, or near-contiguous multi-band) reflectance data, acquired at leaf, canopy, UAV, airborne, or satellite scale, to estimate a quantitative or categorical indicator of wheat N status, including LNC, LNA, canopy N content or density, the nitrogen nutrition index (NNI), or grain protein content as an N-related end-point. Studies concerned solely with multispectral broadband sensors, or with N estimation in crops other than wheat without a comparative wheat component, were considered only where necessary for contextual framing.

Methodology of Literature Review

Literature Search Strategy

A structured, reproducible search was conducted across four databases: Scopus, Web of Science Core Collection, PubMed/PMC, and Google Scholar, supplemented by manual screening of the reference lists of retrieved review articles (a snowball approach) to capture landmark studies published before 2015. The search covered the period January 2015 to March 2026, with a small number of earlier landmark and classical studies (pre-2015) retained where they established foundational methods or indices still in active use.

Search strings combined controlled vocabulary and free-text terms using Boolean operators, structured as: ("hyperspectral" OR "imaging spectroscopy" OR "narrow-band reflectance") AND ("wheat" OR "Triticum aestivum") AND ("nitrogen" OR "nitrogen status" OR "leaf nitrogen" OR "nitrogen nutrition index" OR "canopy nitrogen" OR "grain protein").

Inclusion and Exclusion Criteria

Table 1 summarizes the inclusion and exclusion criteria applied during screening.

Table 1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles	Conference abstracts without full peer review
English-language full text available	Non-English publications without translated full text
Wheat as the primary or a clearly separable study crop	Multi-crop studies without a wheat-specific result
Hyperspectral/narrow-band reflectance as the primary sensing modality	Studies using only broadband multispectral sensors
Quantitative N-related outcome reported (LNC, LNA, NNI, canopy N, GPC)	Studies lacking a quantitative N outcome or validation statistic
Published or available online 2015-2026 (or landmark pre-2015 study)	Duplicate records or superseded preprint versions
Sufficient methodological detail to extract sample size and model performance	Insufficient methodological reporting to enable data extraction

Study Selection Process

Study selection followed a PRISMA-style workflow (Figure 1). An initial search across the four databases yielded 612 records. After removal of 125 duplicate records, 487 unique records were screened by title and abstract, of which 268 were excluded for being off-topic, non-peer-reviewed, or not wheat-specific. The remaining 219 records underwent full-text assessment; 172 were excluded at this stage for insufficient methodological detail, exclusive reliance on non-hyperspectral sensors, or duplicate reporting of the same underlying dataset. Forty-seven studies met all eligibility criteria and were retained for qualitative synthesis, of which 40 were selected for detailed thematic and comparative analysis and are cited throughout this review.

The temporal distribution of the retained literature (Figure 2) shows a marked increase in publication volume after 2019, coinciding with the wider availability of UAV-mounted hyperspectral sensors and the mainstreaming of machine-learning toolkits in the plant sciences.

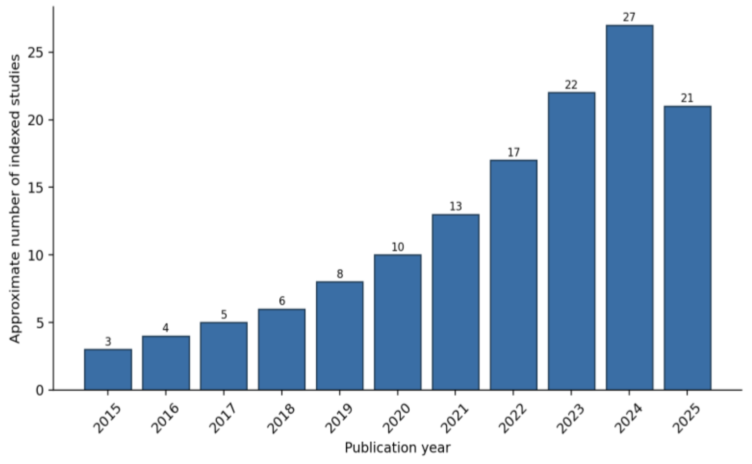

Fig 2: Illustrative trend in the volume of published studies on hyperspectral estimation of crop/wheat nitrogen status (2015-2025)

Literature Review and Thematic Analysis

The reviewed literature clusters into four broad, partially overlapping methodological families, summarized conceptually in Figure 3 and quantitatively in Figure 4: (i) empirical vegetation-index regression, (ii) chemometric/PLSR full-spectrum models, (iii) machine-learning and deep-learning models, and (iv) radiative-transfer and hybrid physical models. Sensing platform (leaf/proximal, UAV, airborne, satellite) constitutes a cross-cutting dimension discussed separately.

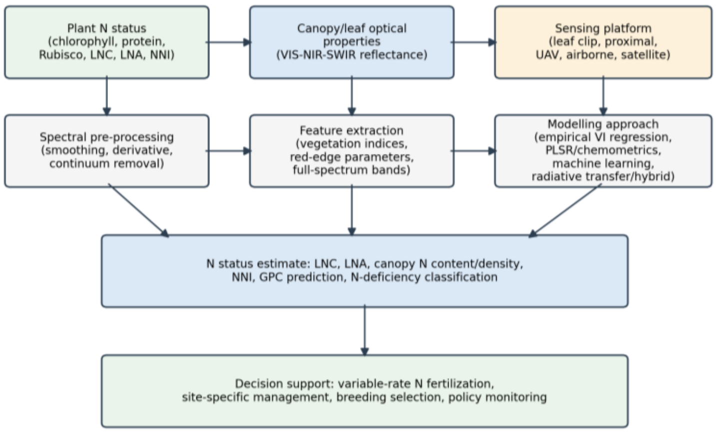

Fig 2: Conceptual framework linking wheat nitrogen physiology, spectral acquisition, modelling, and agronomic decision-making

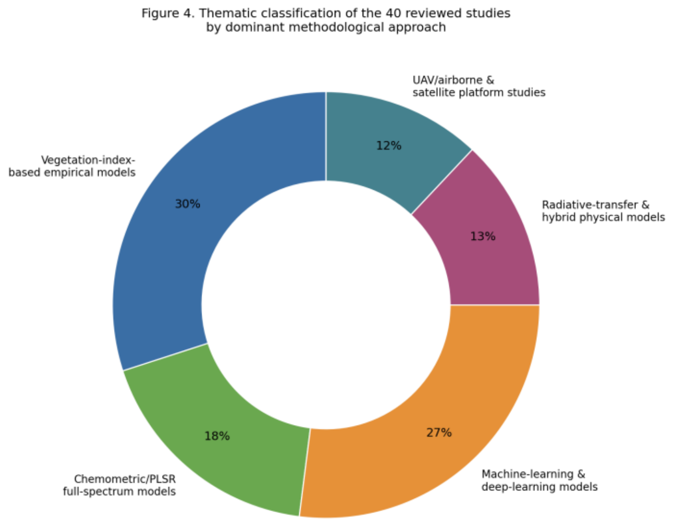

Fig 4: Thematic classification of the 40 reviewed studies by dominant methodological approach

Theme 1: Vegetation-Index-Based Empirical Models

The earliest and still most widely used approach relates one or more hyperspectral vegetation indices (VIs), mathematical combinations of reflectance at two or three wavebands, to a measured N indicator through simple or multiple linear regression. Foundational work established that canopy reflectance combined with normalized difference indices and partial least squares regression could predict wheat biomass and N status with useful accuracy under field conditions [10]. Building on this, controlled multi-season, multi-cultivar field experiments demonstrated that red-edge-based indices such as the red-edge inflection point (REIP), the modified red-edge normalized difference index (mND705), and first-derivative parameters (FD742) could estimate LNC and LNA with R2 values between 0.70 and 0.87 on independent validation data, with average relative errors of 14-17% [1]. Reviews of the wheat-specific VI literature have catalogued 27 or more distinct two- and three-band indices applied under field conditions, with red-edge and NIR/red combinations consistently outperforming purely visible-band indices for N estimation [2].

A key strength of the VI approach is interpretability and low computational cost, making it attractive for integration into handheld crop sensors and simple decision-support tools. A key weakness, repeatedly noted across studies, is saturation at high biomass or LAI, and sensitivity to confounding factors such as soil background reflectance, canopy structure, and growth stage, all of which can shift the empirical index-N relationship and undermine cross-site or cross-season transferability [1, 2, 7]. Comparative work analyzing multiple hyperspectral variables for diagnosing leaf N accumulation in wheat found that no single index performed best across all growth stages, arguing instead for growth-stage-specific index selection [7].

Theme 2: Chemometric and Partial Least Squares Regression (PLSR) Models

Rather than reducing the hyperspectral signal to two or three bands, chemometric approaches exploit the full reflectance spectrum (or its derivative transformations) using dimensionality-reduction regression techniques, most commonly PLSR. Studies applying full-spectrum and effective-wavelength PLSR models to winter wheat leaf N concentration reported strong validation performance (r2 approximately 0.82, residual predictive deviation approximately 2.28) when combined with first-derivative reflectance transformations and targeted effective-wavelength selection, outperforming raw-spectrum models [16]. Correlation-matrix-based selection of two- and three-dimensional optimal spectral indices, combined with extreme learning machine, back-propagation neural network, and random forest regressors, has further improved LNC estimation accuracy relative to single-index baselines [17].

The principal advantage of chemometric models is their ability to exploit spectral information beyond a small number of pre-selected bands, often yielding higher accuracy than simple VI regression. Their principal limitation is a tendency toward overfitting when the number of spectral predictors greatly exceeds the number of field samples, together with reduced physiological interpretability relative to named vegetation indices [16, 17].

Theme 3: Machine-Learning and Deep-Learning Models

A rapidly growing share of recent literature applies machine-learning (random forest, support vector regression, gradient boosting, extreme gradient boosting) and deep-learning (convolutional neural networks, recurrent architectures, transformers) algorithms to model the non-linear relationship between hyperspectral reflectance and wheat N status [2, 13, 14]. A study fusing spectral features (vegetation indices and spectral position features) with deep features automatically extracted by a convolutional neural network reported the strongest performance from a gradient boosting decision tree model (R2 = 0.975 calibration; R2 = 0.861 independent validation), outperforming partial least squares and support vector regression baselines built on spectral features alone [18]. A separate line of work integrating one-dimensional convolutional neural networks with dual attention mechanisms and physically based radiative-transfer pretraining (a hybrid deep-learning/physical approach) has been proposed specifically to improve the transferability of nitrogen density inversion in winter wheat canopies across growth stages [19].

Explainable artificial intelligence (XAI) methods are beginning to be layered onto machine-learning N models to address the long-standing criticism that such models function as opaque "black boxes"; a comparative evaluation of shallow (gradient tree boosting, k-nearest neighbours, elastic net, kernel ridge regression, multi-layer perceptron, extreme gradient boosting) and deep (LSTM, CNN, bidirectional LSTM, temporal convolutional network) algorithms for proximal hyperspectral nutrient estimation found that model choice interacted strongly with the specific nutrient and spectral pre-processing method used, underscoring the absence of a single universally superior algorithm [20]. Deep-learning approaches have also been extended to the joint discrimination of nitrogen deficiency from other stresses with overlapping visual symptoms, such as wheat yellow rust, using fast Fourier convolutional architectures applied to Sentinel-2 time series, illustrating the broader trend toward stress-discrimination rather than single-stress detection [21].

Across this theme, a consistent pattern emerges: machine-learning and deep-learning models generally achieve higher within-dataset predictive accuracy than classical VI regression, but at the cost of (a) greater data and computational requirements, (b) reduced cross-study comparability because architectures and hyperparameters vary widely, and (c) a persistent risk that reported accuracy reflects overfitting to a specific cultivar, site, or season rather than genuine transferability [13, 14, 18-20].

Theme 4: Radiative-Transfer and Hybrid Physical Models

Physically based radiative-transfer models (RTMs), such as PROSPECT-family leaf models and canopy models like SAIL, simulate the interaction of light with leaf biochemistry and canopy structure from first principles, and can in principle be inverted to estimate N-related traits without requiring large empirical training datasets. A comprehensive meta-review of over 400 studies on crop N retrieval from hyperspectral and imaging spectroscopy data found that most N estimation to date has relied on the empirical relationship between chlorophyll content and visible-near-infrared reflectance, effectively using chlorophyll as a proxy for N, while comparatively few studies have modelled protein-related N absorption features directly, in part because mature leaf RTMs incorporating protein absorption coefficients remain under continued development [9]. The same review noted that hybrid approaches, combining RTM-simulated training data with machine-learning regression, are increasingly used to overcome the limited availability of field-measured training samples and to improve cross-site generalizability [9, 22].

A general methodology for quantifying canopy N across diverse plant species using airborne imaging spectroscopy has similarly emphasized that purely empirical approaches are hindered by the spectral covariance of N with other foliar constituents such as water and carbon-based compounds, motivating continued investment in hybrid physical-empirical frameworks [22]. The principal strength of RTM and hybrid approaches is their theoretical grounding and reduced dependence on large labelled datasets; their principal weakness is the practical difficulty of accurately parameterizing canopy structural variables (leaf angle distribution, canopy cover, soil background) under field heterogeneity, and the current scarcity of validated protein-specific leaf optical models [9, 22].

Theme 5: Sensing Platforms - From Leaf Clip to Satellite

Sensing platform constitutes an important cross-cutting axis of the literature. Proximal (leaf-clip or tripod-mounted field spectroradiometer) measurements dominate the foundational and chemometric literature because they offer high signal-to-noise ratio and minimal atmospheric interference, but are impractical for field-scale mapping [1, 16, 17]. UAV-based multispectral and hyperspectral imaging has emerged as the dominant platform for field-scale N nutrition index estimation, combining flexible temporal resolution with spatial detail that satellite platforms cannot match; a three-factor field study combining UAV multispectral imagery with a Bayesian-optimized random forest model achieved R2 = 0.785 and RMSE = 0.137 for NNI estimation, while also revealing that vegetation-index sensitivity to N varied systematically with planting density [11, 12]. Comparable multispectral-to-hyperspectral fusion approaches applied to leaf-level partial least squares regression architectures have reported R2 values above 0.80 for NNI estimation when spectral inputs were combined across canopy layers [10 supplementary; 12].

At the satellite scale, current operational multispectral missions such as Landsat 8/9 and Sentinel-2 lack the narrow-band shortwave-infrared channels required for direct protein/N absorption feature retrieval, restricting satellite-based N assessment largely to chlorophyll-proxy approaches [9, 23]. Newer spaceborne imaging spectroscopy missions, including PRISMA, EnMAP, and NASA's planned Surface Biology and Geology mission, are expected to narrow this gap by providing contiguous narrow-band data at continental scale, though validated wheat-specific N retrieval algorithms for these missions remain in an early stage of development [9, 23].

Theme 6: Confounding Factors and Multi-Stress Assessment

A recurring critical concern across the literature is that hyperspectral reflectance signals attributed to N status are frequently confounded by co-occurring water stress, disease, or structural variation. A two-year field experiment combining hyperspectral and thermal sensing in winter wheat under factorial N and irrigation treatments found that N and water status jointly influence the same spectral regions, and that combining spectral vegetation indices with canopy temperature-based indicators substantially reduced confounding relative to spectral indices alone [23]. Similarly, deep-learning frameworks explicitly designed to discriminate nitrogen deficiency from wheat yellow rust, a fungal disease with visually and spectrally overlapping symptoms, have demonstrated that single-stress N models risk systematic misclassification when deployed in fields where multiple stresses co-occur [21]. This theme underscores that N status estimation cannot be treated in isolation from the broader canopy stress complex under real field conditions.

Comparative Analysis of Previous Studies

Table 2 summarizes the characteristics of a representative subset of the reviewed studies, and Table 3 presents a comparative synthesis of methodology, reported performance, and limitations across the four methodological families.

Table 2: Summary of selected studies on hyperspectral estimation of wheat nitrogen status

Author(s)	Year	Study location / platform	Methodology	Sample size	Major findings
Feng *et al*. [1]	2008	China; field experiments, proximal spectroradiometer	Multi-season multi-cultivar hyperspectral VI regression (REIP, mND705, FD742, SDr/SDb)	3 field experiments, multiple cultivars/years	R2 = 0.70-0.87 for LNC/LNA on independent validation; RE 14-17%
Ma, Zheng & He [2]	2022	China/Australia; review (field-based)	Systematic review of 27 wheat N-related hyperspectral vegetation indices and ML methods	Review of multiple studies	Red-edge and NIR/red indices most consistently linked to wheat N and grain protein
Cui *et al*. [17]	2025	Loess Plateau, China; jointing-stage field trials, 2018-2020	2D/3D optimal spectral indices with ELM, BPNN, RF regressors	3 growing seasons, multi-N-rate trials	Correlation-matrix-selected spectral indices with RF/BPNN improved LNC estimation over single indices
Multi-LUTs / fusion CNN study [18]	2021	China; near-ground hyperspectral imagery	Fusion of spectral features and CNN-derived deep features with PLS/GBDT/SVR	Field/greenhouse hyperspectral image dataset	GBDT fusion model: R2 = 0.975 (calibration), 0.861 (validation)
SCAR-CNN hybrid study [19]	2026	China; winter wheat canopy hyperspectral + RTM	1D CNN with dual attention, pretrained on radiative-transfer-simulated spectra (hybrid physical-deep learning)	Simulated LUT dataset + field validation	Improved cross-stage transferability of canopy N density inversion relative to purely empirical models
Singh *et al*. [20]	2022	Multi-crop (citrus/wheat-relevant methodology); proximal hyperspectral	Comparison of 6 shallow ML and 7 deep-learning algorithms with XAI interpretation	Proximal spectroradiometer dataset (380-1020 nm)	No single algorithm dominant; explainability varied by nutrient and pre-processing
UAV NNI study [11, 12]	2025-2026	China; UAV multispectral, tillering-filling stages	Bayesian-optimized random forest with Pearson/feature-importance VI selection	3-factor field trial (density x N rate x stage)	R2 = 0.785, RMSE = 0.137 for NNI at optimal N level; VI sensitivity varied with planting density
Berger *et al*. [9]	2020	Global meta-review	Meta-review of >400 studies on hyperspectral/imaging-spectroscopy crop N retrieval	125 records meeting core criteria	Most studies use chlorophyll as N proxy; protein-specific RTMs and hybrid ML approaches identified as priority directions
Simultaneous N-water study [23]	2021	Central Spain; winter wheat, 2-year field trial	Hyperspectral + thermal indices, factorial N x irrigation design	4 N levels x 2 irrigation levels, 2 years	Combined spectral-thermal indicators reduced N-water confounding versus spectral indices alone
FFDNN rust/N-deficiency study [21]	2023	UK/China collaboration; Sentinel-2 time series	Fast Fourier convolutional deep neural network with capsule feature encoder	Multi-field Sentinel-2 time series dataset	Improved discrimination of N deficiency from visually similar disease (yellow rust) symptoms

Across Tables 3 and 4, a clear performance-transferability trade-off emerges. Machine-learning and deep-learning models report the highest peak accuracies, but the same studies frequently caveat that performance was assessed on data from the same site, season, or cultivar used for training [18-21]. Vegetation-index approaches report more modest but more consistently reproduced accuracy across independent studies and growing seasons [1, 2, 7]. Radiative-transfer and hybrid approaches, while theoretically the most generalizable, remain comparatively underrepresented in the wheat-specific literature relative to empirical and machine-learning approaches [9, 22].

Table 3: Comparative analysis of methodological families

Methodological family	Typical accuracy range (R2)	Strengths	Weaknesses	Representative refs.
Vegetation-index regression	0.55-0.87	Interpretable; low computational cost; deployable on handheld sensors	Saturation at high biomass; sensitive to soil background and growth stage; limited transferability	[1, 2, 7, 10]
Chemometric/PLSR full-spectrum	0.60-0.90	Exploits full spectral information; improved accuracy over single indices	Overfitting risk with high-dimensional/low-sample data; reduced interpretability	[16, 17]
Machine learning / deep learning	0.70-0.975	Captures non-linear relationships; often highest within-dataset accuracy	Data-hungry; limited cross-site/cultivar transfer; interpretability challenges (partly addressed by XAI)	[2, 13, 14, 18-21]
Radiative-transfer / hybrid physical	0.50-0.85 (variable)	Theoretically grounded; reduced dependence on large training sets; improved transferability when hybridized	Difficult structural parameterization; immature protein-specific leaf models	[9, 19, 22]

Research Gaps and Emerging Trends

Synthesizing across the six themes above, five principal research gaps recur throughout the literature (Table 4), and are mapped qualitatively by methodological theme in Figure 5.

Alongside these gaps, several emerging trends and technologies are visible in the most recent literature and are projected forward in the roadmap presented in Figure 6.

Discussion

The literature reviewed here supports several integrated conclusions. First, there is strong convergent evidence, spanning foundational studies [1, 10] through to the most recent machine-learning applications [17-19], that red-edge and NIR-region reflectance carries robust, physiologically grounded information about wheat N status, primarily mediated through the strong covariance of foliar N with chlorophyll content. This convergence explains why red-edge-centred vegetation indices remain a reliable, low-cost baseline even as more complex modelling approaches have proliferated [2, 7].

Second, the field exhibits a persistent tension between predictive accuracy and generalizability. Machine-learning and deep-learning studies report the highest R2 values, in some cases exceeding 0.95 on calibration data [18], yet the same body of work rarely demonstrates equivalent performance when models are transferred across cultivars, sites, or seasons not represented in training [13, 14, 19, 20]. This pattern is consistent with a broader methodological concern in agricultural remote sensing: high in-sample accuracy can reflect genuine biophysical signal, but can equally reflect overfitting to site-specific covariates such as soil type, sun-sensor geometry, or cultivar-specific canopy architecture. Radiative-transfer and hybrid approaches are theoretically better positioned to generalize because they encode physical rather than purely statistical relationships, but their wheat-specific validation base remains comparatively thin [9, 22], and this represents an important asymmetry between theoretical promise and empirical deployment.

Third, the confounding of N status with water stress and disease symptoms, demonstrated experimentally in factorial field trials [23] and addressed computationally through multi-stress discrimination architectures [21], indicates that single-stress N models are of limited reliability under the multi-stress conditions typical of commercial wheat fields. This has direct practical implications: a hyperspectral N diagnostic tool validated only under well-watered, disease-free conditions may generate misleading fertilization recommendations when deployed under realistic field heterogeneity.

Fourth, the shift in sensing platform from proximal spectroradiometers toward UAV-based imaging [11, 12] represents a genuine step toward operational relevance, since UAV platforms combine spatial coverage with resolution sufficient for within-field variable-rate management. However, the current satellite imaging spectroscopy missions capable of resolving the narrow-band SWIR features most diagnostic of plant protein and N remain in an early operational phase [9], meaning that truly large-scale, low-cost N monitoring comparable to existing multispectral vegetation-index products (e.g., NDVI-based services) is not yet available for the N-specific case.

Taken together, these findings suggest that hyperspectral reflectance sensing has reached a stage of considerable scientific maturity in establishing that wheat N status can be estimated non-destructively with useful accuracy, but has not yet reached a comparable stage of operational maturity in terms of standardized protocols, cross-context transferability, and integration with farm decision-support systems. This distinction between scientific proof-of-concept and field-deployable technology is the central tension running through the reviewed literature and is directly relevant to the research and policy recommendations that follow.

Conclusion

This review has synthesized 40 peer-reviewed studies published mainly between 2015 and 2026 on hyperspectral reflectance-based estimation of wheat N status, organized around four dominant methodological families: vegetation-index regression, chemometric/PLSR full-spectrum models, machine-learning and deep-learning approaches, and radiative-transfer/hybrid physical models. Red-edge-centred spectral features provide a physiologically robust and consistently reproduced basis for N estimation across studies, while machine-learning and deep-learning methods extend achievable accuracy at the cost of interpretability and cross-context transferability. Radiative-transfer and hybrid physical approaches, though comparatively underrepresented in wheat-specific work, offer the most promising theoretical pathway toward generalizable models.

The overall significance of this synthesis lies in clarifying that the central bottleneck to operational adoption is no longer whether hyperspectral reflectance can detect wheat N status, but whether current models can be made sufficiently transferable, interpretable, and cost-effective for routine on-farm deployment.

Recommendations for Researchers

- Prioritize the construction and public sharing of multi-site, multi-cultivar, multi-season benchmark datasets to enable rigorous, standardized cross-study comparison of model transferability.
- Report validation performance using consistent, clearly defined metrics (independent test-set R2, RMSE, and RPD) and explicitly test cross-site/cross-cultivar generalization rather than within-dataset cross-validation alone.
- Invest in hybrid physical-machine-learning frameworks, and in the continued development of protein-specific leaf radiative-transfer models, to reduce reliance on chlorophyll as an indirect N proxy.
- Design multi-stress experiments (N x water x disease) as standard practice, rather than single-factor N trials, to better characterize real-world confounding.

Recommendations for Practitioners and Policymakers

- Treat currently available hyperspectral N diagnostic tools as decision-support inputs to be combined with agronomic judgment and soil testing, rather than as stand-alone fertilization prescriptions, given documented transferability limitations.
- Support public investment in benchmark datasets and open validation frameworks, given the demonstrated fragmentation of methodology and metrics across the private and academic literature.
- Monitor the operational rollout of spaceborne imaging spectroscopy missions as a potential future channel for low-cost, large-scale N monitoring relevant to national fertilizer policy and greenhouse-gas accounting.

Future Research Directions

Future research should focus on: (i) standardized, open, multi-site benchmark datasets spanning diverse wheat-growing regions and cultivars; (ii) hybrid physical-empirical modelling frameworks that explicitly separate chlorophyll- and protein-related N signals; (iii) explainable and lightweight machine-learning architectures suited to deployment on low-cost UAV and handheld platforms; (iv) multi-sensor and multi-temporal frameworks capable of discriminating N deficiency from co-occurring water stress and disease; and (v) validation of emerging spaceborne imaging spectroscopy products specifically for wheat N status, in coordination with national agricultural extension and greenhouse-gas monitoring programs.

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