Smart Agricultural Technology 12 (2025) 101507

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

UAV hyperspectral remote sensing for crop nitrogen monitoring: progress, challenges, and perspectives

Kang Yu [a,*], Anirudh Belwalkar [a], Wuhua Wang [a], Yuncai Hu [a], Addisu Hunegnaw [b], Abdul Nurunnabi [b], Thorsten Ruf [c], Fei Li [d], Liangliang Jia [e], Lammert Kooistra [f], Yuxin Miao [g], Félicia N. Teferle [b]

[a] Precision Agriculture Lab, Technical University of Munich, Freising 85354, Germany
[b] Department of Engineering, Faculty of Science, Technology and Medicine, University of Luxembourg, L-1359 the Grand Duchy of Luxembourg
[c] Institute for Organic Agriculture and Agroecology Luxembourg a.s.b.l., Medernach L-7664, the Grand Duchy of Luxembourg
[d] College of Resources and Environment, Inner Mongolia Agricultural University, Hohhot 010011, China
[e] Institute of Agricultural Resources and Environment, Hebei Academy of Agriculture and Forestry Sciences, Shijiazhuang 050051, China
[f] Laboratory of Geo-Information Science and Remote Sensing (GRS), Wageningen University & Research, the Netherlands
[g] Precision Agriculture Center, Department of Soil, Water and Climate, University of Minnesota, St. Paul., MN 55108, USA

ARTICLE INFO

Keywords:
Crop nitrogen response
Deep learning
Drone remote sensing
Imaging spectroscopy
Canopy structural variations
Vegetation index
Plant nitrogen absorption features
Vegetation radiation transfer

ABSTRACT

Nitrogen (N) is the most important macro nutrient for crop productivity. However, precise N input balancing productivity and environmental footprint is always challenging due the difficulty of measuring plant N status in a timely manner. Uncrewed aerial vehicles (UAVs) and hyperspectral imaging (HSI) have revolutionized smart vegetation monitoring, offering unprecedented capabilities for mapping plant traits and precision crop nutrient management. This review evaluates recent advancements in crop N monitoring, highlights key challenges in N prediction, and provides recommendations for improving UAV-based HSI to support decision-making and enhance N use efficiency. Our analysis reveals that traditional machine learning (ML) methods have surpassed the vegetation index-based regression methods in N prediction. However, most studies report significant gaps between model training accuracy and validation performance, with independent testing being insufficiently addressed in the literature. Some research highlighted the integration of solar-induced chlorophyll fluorescence (SIF) and plant traits to enhance N prediction by leveraging narrow-band and sub-nanometer resolution hyperspectral imagery. Additionally, we discuss the challenges of disentangling phenological and physiological effects from canopy structural and biochemical properties in hyperspectral analysis. Addressing these confounding factors through advanced modeling techniques like deep neural networks will significantly improve N prediction throughout the growing season. To overcome these challenges, we recommend adopting deep learning and hybrid modeling approaches that combine radiative transfer models, crop simulation models, and advanced machine learning algorithms. Such integrated methods, coupled with transparent data sharing, can enhance plant N prediction accuracy, improve model transferability, and ultimately support precision N management in agriculture.

Introduction

Nitrogen in agriculture

Nitrogen (N) is a double-edged sword in agriculture. Balanced N fertilization is vital to boosting crop yields and feeding the world's population sustainably [125]. However, excessive use of this fertilizer causes significant environmental problems [14]. Agriculture 4.0 not only faces the immense challenge of feeding 10 billion people but also must take action to optimize its benefits and minimize environmental footprints. Growing awareness of the adverse effects of N fertilizers has led to international efforts such as the European Union (EU) Nitrate Directive [27,92] targeting N pollution from agricultural sources. These global initiatives popularized the importance of improving N use efficiency (NUE), reducing N losses, and promoting sustainable agricultural practices. Ecological farming practices incorporating cover crops and

* Corresponding author.
E-mail address: kang.yu@tum.de (K. Yu).

https://doi.org/10.1016/j.atech.2025.101507
Received 10 May 2025; Received in revised form 24 September 2025; Accepted 5 October 2025
Available online 6 October 2025
2772-3755/© 2025 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

legumes can improve soil N availability while maintaining soil structure [2]. Advanced fertilizer manufacturing technologies like slow-release fertilizers or enhanced-efficiency fertilizers can also reduce N losses [83].

Growing concerns over N overuse have spurred the development of precision agriculture and better fertilization application technologies [38], i.e., sensor and global navigation satellite systems (GNSS)-enabled equipment for in-season site-specific fertilizer applications. Precision agriculture applies the '4R' principles [87] to improve nutrient management by using the suitable type of fertilizer for specific crop needs (Right source), applying the appropriate amount of fertilizer (Right rate), timing applications to maximize crop uptake efficiency (Right time), and placing fertilizer where roots can access it while minimizing losses (Right place). By adhering to these 4R guidelines and leveraging advanced technologies, farmers can address nutrient inefficiencies while maintaining sustainable crop production.

Brief history of proximal and remote sensing of crop N status

Precision N management and the 4R principles are highly dependent on proximal and remote sensing of plants and soil, which enables quantitative assessment of spatiotemporal variability in the field. In the 1970s, airborne remote sensing technology was first applied in agriculture, where aerial photography and multispectral imaging were used to detect maize (*Zea mays*) leaf blight disease [68]. As this technology evolved, spectroscopic techniques such as near-infrared (NIR) analysis were introduced for soil measurements and the characterization of chlorophyll content, an indicator closely linked to plant N levels. Based on similar principles, handheld sensors, including chlorophyll meters (e.g., the Soil Plant Analysis Development (SPAD) Konica Minolta handheld devices), further facilitated real-time assessment of leaf N status and became popular tools in crop management [77,81].

Starting from the 1990s, sensors mounted on tractors and other farming equipment began to measure canopy reflectance, chlorophyll fluorescence, and other N-related indicators during field operations [50]. In the late 1990s, with the popularization and application of GNSS and geographic information systems (GIS), remote sensing and spatial data analysis were brought to the forefront of agriculture. By combining proximal and remote sensing with GIS, farmers could implement variable-rate N application strategies to improve NUE [72]. GNSS adoption by farmers has been found to exceed 50 % and 70 % in the US and Australia, respectively [66]. Variable rate technology (VRT) has been primarily adopted for fertilization and is most popular for maize cultivation, with adoption rates estimated at approximately 30–50 % on large farms in the US and Australia [66].

Since the early 2010s, uncrewed aerial vehicles (UAVs) or drones have become one of the most popular camera- and sensor carrying platforms for crop stress detection and N sensing due to their high spatial resolution, operational flexibility, and cost-effectiveness [1,3,122]. Compared with crewed aircraft or satellites, UAVs offer the ability to fly at lower altitudes and customize flight paths, allowing for rapid, on-demand, high spatial resolution data acquisition under variable field conditions [20].

Low-altitude hyperspectral remote sensing of plant N

Low-altitude remote sensing (LARS) refers to the acquisition of data and imagery from sensors mounted on platforms operating at relatively low altitudes above the Earth's surface. These platforms typically include UAVs, crewed aircrafts flying at low altitudes, balloons, kites, and other aerial systems. By bridging the gap between ground-based observations and higher-altitude platforms (e.g., satellites), LARS provides high-resolution spatial and temporal data for a wide range of agricultural and environmental applications.

A variety of sensors can be deployed in LARS. These include basic Red-Green-Blue (RGB) imagers, multispectral imagers, hyperspectral systems in the visible and near-infrared (VNIR) and shortwave infrared (SWIR) wavelengths [45], thermal infrared cameras [121], and Light Detection and Ranging (LiDAR) sensors [42]. In some cases, compact Synthetic Aperture Radar (SAR) may also be used [103], though it is less prevalent than optical and LiDAR sensors.

LARS has emerged as a highly efficient approach for monitoring crop N status, offering precise spatial and temporal insights into crop nutritional conditions. Accurate monitoring of crop N is critical to optimize fertilizer application, reduce environmental impacts, and improve crop productivity [12]. While most LARS studies employ imaging sensors, non-imaging sensors on UAVs have shown promise for crop N prediction. For instance, Jiang et al. [48] successfully employed an active spectrometer with its own light source on a UAV to capture canopy reflectance data, which were effectively correlated with ground-measured N levels using spectral indices and regression models. Although non-imaging sensors can offer benefits such as reduced data complexity and faster processing, their application in nitrogen prediction remains very limited, and their coarse spatial resolution often leads to mixed-pixel effects, making them impractical for precision crop management. Therefore, this review will focus on imaging sensors that use sunlight as the primary illumination source.

Review objectives and literature search strategy

In this review, we aim to assess recent advancements in crop N monitoring by exploring how ground-truthing approaches, spectral features, and modeling approaches may affect N prediction outcomes. In addition, we discuss key challenges in N prediction and offer recommendations for improving UAV-based hyperspectral imaging (HSI) to support decision-making and increase NUE. This review focuses on studies of UAV hyperspectral remote sensing and related modeling technologies for crop N sensing, while also including the studies of other LARS applications such as crewed aircraft in agricultural settings. These technologies facilitate enhanced N mapping and bolster precision agriculture across spatial scales.

Literature search and screening

We searched the Web of Science (WOS) and Scopus to ensure broad coverage of peer-reviewed journals. A set of key terms and phrases was developed based on the review topic. These included terms related to UAV applications, non-imaging sensors (e.g., spectrometers, crop sensors), and crop N prediction. Boolean operators (AND, OR) were used to combine keywords and construct search strings. The search string was: "nitrogen" AND "UAV" OR "drone" AND "hyperspectral" OR "imaging spectroscopy".

The search was limited to articles published in English between 2014 and 2024 to capture recent developments. Studies were included if they reported using imaging sensors mounted on UAVs or aircraft for crop N prediction or related agricultural applications (e.g., grass protein). Articles were excluded if they focused on non-imaging sensors or soil parameter prediction or if they lacked experimental data, e.g., review articles. The WOS identified records and the Scopus records were imported into the reference management software Zotero and merged, then duplicates removed. The final set of articles was critically appraised, and pertinent data were extracted regarding study region, crop type, sampling method and sample size, sensor type, UAV platform, modeling methodology, and model outcomes (training, validation) related to crop N prediction. This information was then qualitatively synthesized to provide a comprehensive overview of the current state of the art in UAV-based hyperspectral approaches for crop nitrogen monitoring. In addition to the query-based database search, the reference lists of the included studies were manually reviewed to retrieve the data and identify additional relevant articles, e.g., some publications based on airborne HSI systems. After screening and excluding irrelevant papers, we retained 105 publications for analysis.

Geographic and crop-specific trends of publications

Fig. 1 displays the global distribution of publication counts by country and, at the centroid of each continent, the leading crop types among the top eight categories for each continent. In Africa, research predominantly focuses on non-crop species (trees), while in Asia, Europe, North America, and Oceania, wheat (*Triticum aestivum*) has been the primary subject of study in recent decade (2014–2024). Overall, as indicated by the large pie charts, Asia and Europe account for most of the studies, highlighting the critical role of precision crop N management and crop-related focus in these two continents.

Wheat, maize, rice (*Oryza sativa*), and potatoes (*Solanum tuberosum*) are the top four crops in the dataset (Fig. 2). Wheat stands out as the most studied crop, with around 30 publications, followed closely by maize (10) and grasses (9). Rice, and orchard trees also show moderate publication counts, while the remaining crops—such as cotton (*Gossypium hirsutum*), barley (*Hordeum vulgare*), soybean (*Glycine* max), and sugar beet (*Beta vulgaris*)—each have fewer than five publications. Oats (*Avena sativa*), rye (*Secale cereale*), and grapevine (*Vitis vinifera*) round out the lower end of the chart, indicating that these crops have received comparatively less attention.

Overall, these findings suggest that while UAV hyperspectral remote sensing has become increasingly popular for high-value grain and forage crops, future research could broaden to incorporate less-studied species, thus further expanding the utility of precision N management across diverse agricultural systems.

Plant N traits and their temporal trends

Leaf-level and plant-level N traits

Leaf N concentration (LNC) in young cereal leaves often tends to be relatively high for the rapidly developing photosynthetic machinery and enzymes needed for growth. During this period, crop roots take up N from the soil, so while individual leaves are rich in N, the overall leaf biomass is still low.

As the canopy expands and leaves mature, the increase in biomass tends to "dilute" the N concentration in each unit of leaf tissue (Fig. 3), even though the total amount of N taken up by the plant continues to rise [5,91]. As most cereal plants approach anthesis (flowering), their demand for N is at its peak, and the rate of nitrogen uptake is at its maximum. However, soon after flowering, the plant shifts its priorities: N stored in the leaves and other vegetative tissues is gradually remobilized and transported to the developing grain. Consequently, LNC drops further as senescence sets in, even though much of the previously accumulated N is being efficiently reallocated to support grain filling.

Plant N concentration (PNC) usually declines as the plant develops (Fig. 3). This gradual reduction represents the dilution effect as the plant biomass increases while the total N content does not keep pace with the growth [52]. Such a trend is commonly observed in cereal crops. Plant N uptake (PNU) measures the total weight per unit of ground area (e.g., ha) and is usually calculated as the product of PNC and the dry weight of above-ground biomass. PNU increases during the vegetative phase, peaks around flowering or anthesis, and then declines gradually or even plateaus during grain filling. For example, it has been demonstrated that in several crops, while N uptake peaks near anthesis, the subsequent decline is generally moderate due to continued N uptake from the soil and internal remobilization [69].

In summary, while the total N uptake is highest during the vegetative-to-reproductive transition, the concentration in individual leaves and the whole plant declines over time because of both biomass expansion and the remobilization process. This asymmetric development trend between N and biomass makes the prediction of N dependent on phenology. It is also important to note that the product of LNU and leaf area index (LAI) is considered as the canopy nitrogen concentration per ground area (CNC, g/m^2) [55]. LAI is the total one-sided leaf area per unit ground area [8]. Multiplying LNU by LAI enables scaling from leaf-level measurements to canopy or field-level nitrogen status, which is essential for linking nitrogen to yield.

Main categories of the plant N sample and variable types

N concentrations are measured with different types of samples and equipment across scales. Most studies were based on destructive leaf sampling and laboratory analysis such as Kjeldahl digestion, which accounts for 44.1 % of the publications (Fig. 4). Plant and canopy level

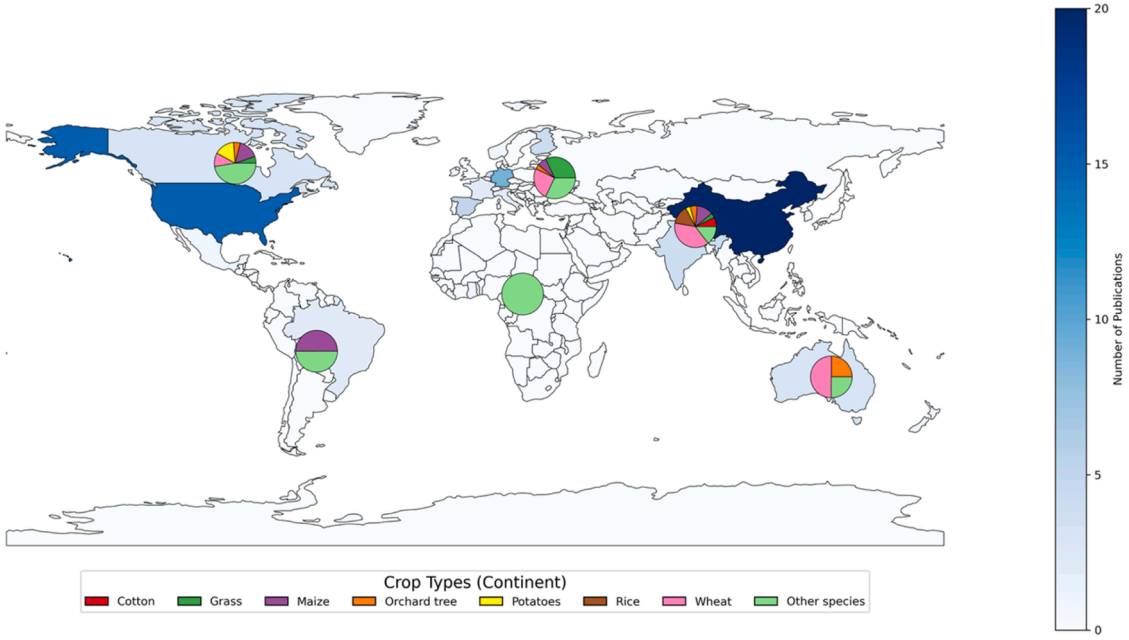


Fig. 1. Global distribution of publications (2014–2024) by country and crop types by continent. The blue color intensity is scaled relative to the total publication count for that country, with darker shades indicating more research activity. The slice sizes within each pie represent the proportion of publications for each crop type in that continent.

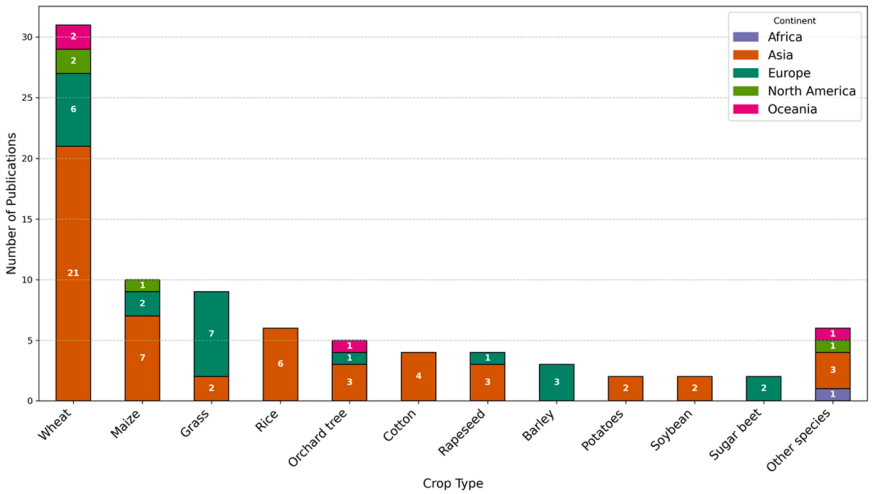


Fig. 2. Number of publications associated with each crop type as recorded in the reviewed literature. Numeric labels with each segment show the number of publications per continent for that crop.

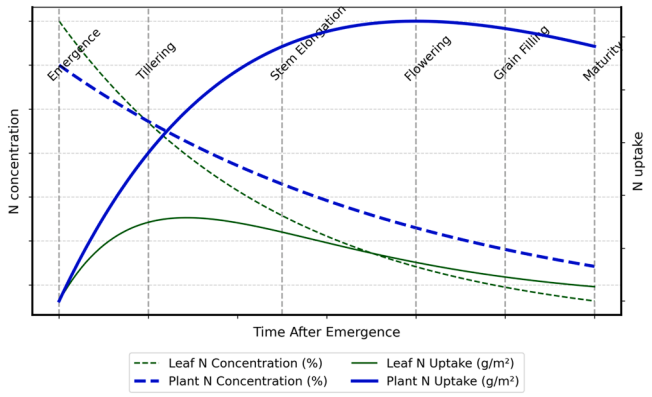


Fig. 3. Schematic of seasonal trends of leaf N concentration (LNC, %), leaf N uptake (LNU, g/m2), plant N concentration(PNC, %), and plant N uptake (PNU, g/m2) in cereal crops.

studies differ mainly in whether sampling the whole plant including stems, accounting for 26.5 % and 25.5 % of the publications, respectively, followed by a minor proportion of stem- and grain-based samples, i.e., 1 % and 2.9 % of the total publications.

Studies based on leaf samples usually have higher training and validation accuracies than studies based on plant samples (Fig. 5a, b). Typically, leaf samples are collected from the upper canopy or flag leaves exclusively, where N concentration is often the highest and most reflective of the current plant's nutritional status. In contrast, plant-level samples generally involve sampling entire plants (including stems, leaves, and sometimes spikes) followed by homogenization of the material prior to N determinations.

Canopy sampling methods fall somewhere between leaf and plant sampling. Canopy sample methods often refer to sampling over different leaf layers and aggregation of leaf samples. Leaves may be gathered from multiple vertical layers of the canopy spanning upper, middle, and sometimes lower leaves and aggregated into a composite sample. Canopy N can be calculated as the product of leaf N concentration per area (also known as the N uptake) and LAI [62]. By incorporating information from multiple vertical canopy strata, canopy sampling can account for differences in N distribution throughout the canopy. N concentration usually decreases from top to bottom of the canopy; the upper leaves are more photosynthetically active and N-rich, while lower leaves often senesce earlier and have lower N [58]. This vertical gradient can bias canopy N composites if not sampled consistently. For instance, lower leaves of the canopy are often more sensitive to N deficiency than are the upper leaves. As a result, N measurements of low leaf layers might not be fully reflected in canopy-level spectral data and thus may show slightly lower prediction accuracies than is the whole-plant sampling method (Fig. 5a). In addition, there are practical challenges due to methodological variation, such as inconsistent definition and sampling of leaf

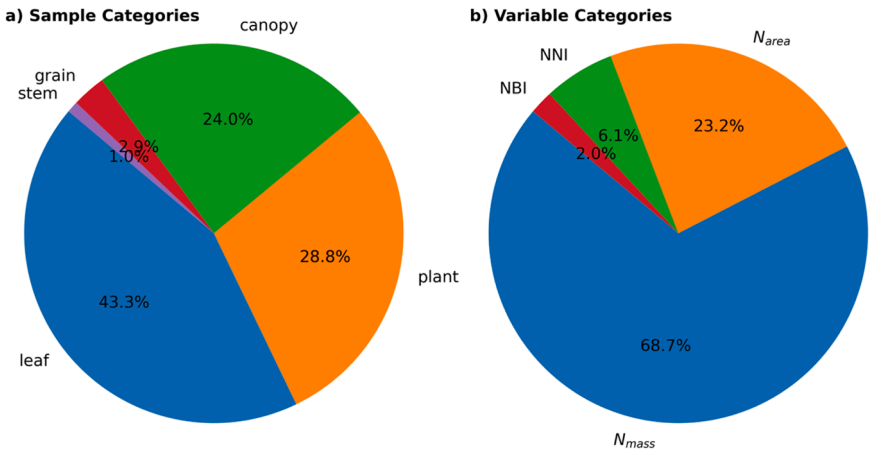


Fig. 4. Pie chart showing the proportion of different sample method categories (a) and the distribution of the four categories of N variables (b).

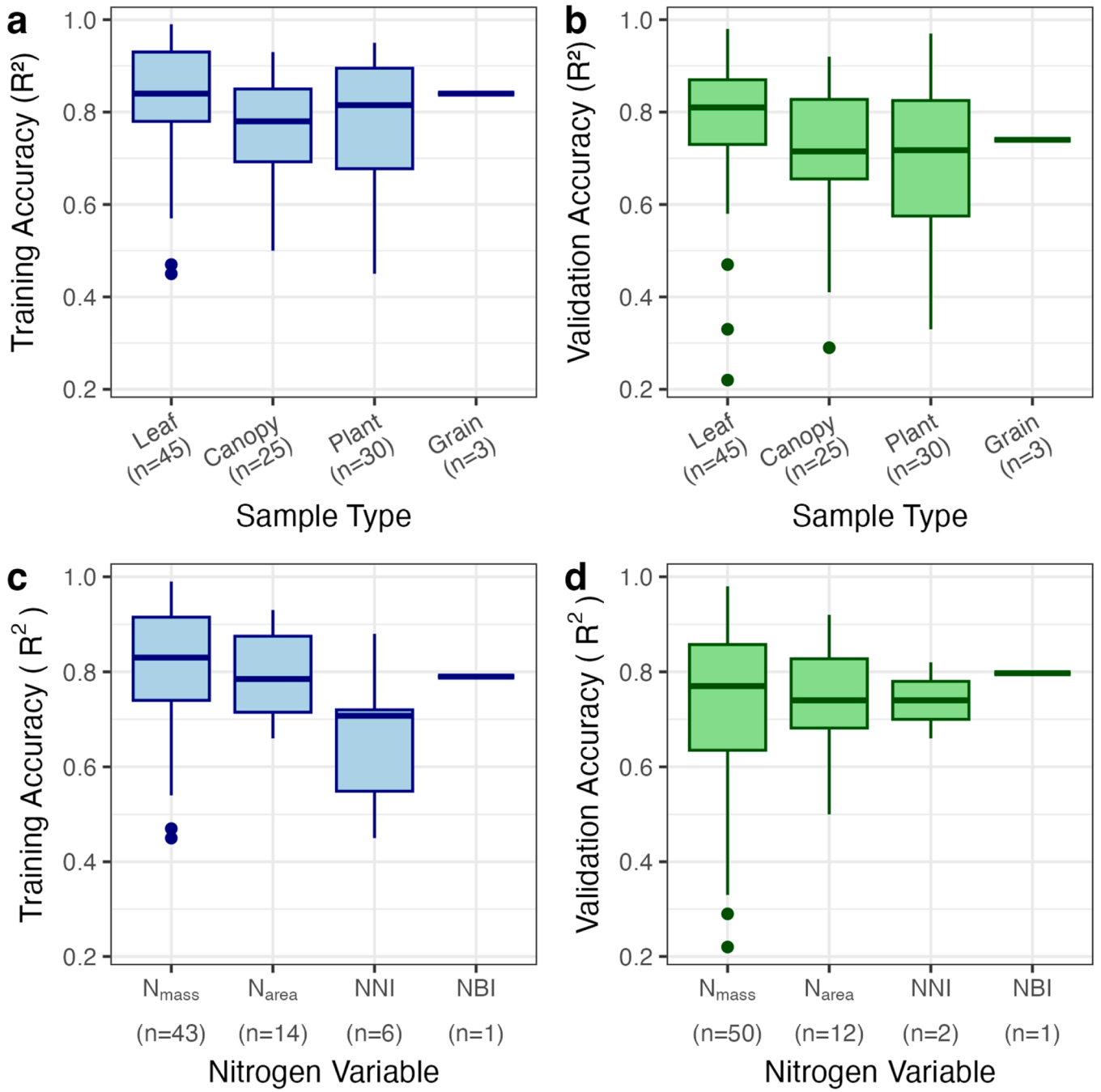


Fig. 5. Boxplots illustrating model training (a, c) and validation (b, d) accuracies (Coefficient of determination, R^2) across different sample types (a, b) and N variable units (c, d). Panels (a) and (b) show model training and validation accuracies, respectively, when comparing sample types. Panels (c) and (d) show model training and validation accuracies, respectively, when comparing different N variables – area-based N concentration (N_{area}) and mass-based N concentration (N_{mass}). The number of publications (n) for each category is indicated on the x-axis.

layers, crop-specific canopy structure, contributing to differences in prediction accuracy across studies.

Overall, these sampling strategies (leaf-, canopy-, and plant-level) vary in systems, cost, complexity, and reliability. Leaf sampling tends to be the most precise for detecting upper canopy N status changes, while canopy and plant-level sampling provides a comprehensive snapshot of plant health condition and often returns a more reliable estimate of N requirement for a given target yield.

Plant N-related secondary traits

We found in our literature review four main categories of plant N indicators, including the mass-based N concentration (Nmass, %), area-based N content ($N_{area,}$ g/m^2), N Nutrition Index (NNI), and N Balance Index (NBI). Mass-based N variables occupy the most significant portion of the publications, about 69 %, while area-based N variables occupy 23 % of the total publications. The NNI and NBI represent 6 % and 2 %, respectively. There is only one study [33] that used the Angular Insensitivity Vegetation Index (AIVI) to predict leaf N concentration (%), which was not indicated here in Fig. 4b

The NNI is calculated as the ratio of the actual N concentration in the plant tissue to the critical N concentration needed for optimal growth [53].

NNI = (Actual N Concentration) / (Critical N Concentration).

The critical N concentration is typically derived from a dilution curve that describes how the minimum N requirement decreases as plant biomass increases [49]. An NNI value of 1 indicates optimal N nutrition, values below 1 suggest N deficiency, and values above 1 imply luxury consumption. This simple metric allows agronomists to assess crop N status and make informed decisions regarding fertilizer applications [60,61,127]. In a study targeting smallholder farming systems in the North China Plain, Chen et al. [19] used a multispectral camera mounted on a fixed-wing UAV to provide village-scale N status diagnosis through vegetation indices (VIs) and the N Sufficiency Index (NSI). Liu et al. [64] utilized hyperspectral remote sensing data collected from ground-based and UAV platforms to analyze NNI across different growth stages of winter wheat, and they emphasized the identification of sensitive spectral bands (e.g., green, red edge, and NIR) for accurate NNI estimation.

The NBI is a measurement used to assess the N status of plants by comparing leaf chlorophyll content with other pigments (flavonoids or anthocyanins) [13]. For instance, UAV-based hyperspectral imagery was used to analyze the leaf chlorophyll content (LCC), flavonoids (Flav), and hence the NBI across five growth stages of soybean [105]. In practice, canopy sensors or leaf-clip devices measure these pigment levels to generate the NBI, which indicates whether a crop has sufficient N for healthy growth. Monitoring the NBI can detect potential N deficiencies or excesses [24], allowing for more targeted fertilization strategies that optimize yield while curbing excessive N use and its associated environmental impacts. Interestingly, while the model training accuracy differs between the N variable types, model validation accuracy does not show differences (Fig. 5c,d).

Hyperspectral predictors for plant N traits

Vegetation indices (VIs)

UAV-based HSI has enabled the extraction of spatially explicit VIs that are highly effective in predicting crop N status. High-resolution hyperspectral data acquired from drones capture subtle variations in the visible and near-infrared spectra (VNIR, 400–1000 nm) that are closely related to canopy chlorophyll content and, as a proxy of leaf N concentration. For instance, Feng et al. [29] explored UAV-based VNIR hyperspectral imaging to estimate CNC in Chinese hickory (*Carya cathayensis Sarg*) trees across four locations with varying environmental conditions. They improved CNC estimation by optimizing the narrow bands used for Normalized Difference Vegetation Index (NDVI) and integrating these with machine learning algorithms.

Vegetation indices that exploit the red-edge (approximately 680–750 nm) region have proven especially effective in predicting crop N status. Well-known examples include the normalized difference red-edge index (NDRE) [4], the modified simple ratio (mSR705) [90], and the MERIS Terrestrial Chlorophyll Index (MTCI) [23] use reflectance measurements in the red-edge wavelengths where subtle shifts in spectral reflectance correspond closely to variations in canopy chlorophyll and structure associated with variation in N content. In most cases, these red-edge indices have been shown to outperform traditional indices that rely solely on visible or near-infrared bands.

By incorporating red-edge indices into empirical or machine learning (ML) models, researchers can accurately estimate in-season N content at multiple growth stages [104,114], facilitating precision N management and reducing fertilizer waste. Using UAV-based HSI, ML models (e.g., random forest) have proven to be more effective when integrating hyperspectral VIs and color indices for estimating organ-scale N concentration in rice [102]. Similarly, Farella et al. [28] combined multi-source remote sensing data (VIs, color indices, hyperspectral SWIR) to predict foliar N across biomes, achieving higher accuracy than traditional statistical methods. However, a notable limitation of many studies is that they predominantly rely on data from the visible to near-infrared bands (400–1000 nm), with very few investigations integrating information from the shortwave infrared (SWIR) region (1000–2500 nm). Since the SWIR bands offer additional insights into plant water status and biochemical composition, their underutilization may restrict the overall predictive accuracy of N models [30]. This highlights the need for future research to incorporate the entire spectral range (400–2500 nm) to further enhance N estimation in crops [56,124].

Solar-induced chlorophyll fluorescence (SIF)

UAV and airborne HSI have significantly advanced the applications of solar-induced chlorophyll fluorescence (SIF), a signal closely related to photosynthetic efficiency [94]. In recent years, SIF has been increasingly used to predict plant physiology [108]. SIF is retrieved from hyperspectral data using specialized algorithms - such as the Fraunhofer Line Discrimination (FLD) method, its improved version (iFLD), and spectral fitting techniques - which separate the weak fluorescence signal from the reflected radiance [71]. These methods typically exploit subtle absorption features in solar lines to accurately isolate SIF. Since SIF is directly linked to the functioning of the photosystem and, thus, the N-rich chlorophyll molecules, it serves as a promising indicator of crop N traits [11,47]). Compared with red-edge indices, SIF might lead to a robust prediction of species-specific N traits such as NUE [46]. Watt et al. [110] found that SIF and the photochemical reflectance index (PRI) were superior to other hyperspectral indices in predicting N in N- and P-limited Pinus radiata trees.

Recent studies [6,11,85,108] emphasize the integration of SIF extracted from airborne hyperspectral imagery with a radiative transfer model (RTM)-modeled plant traits such as chlorophyll content (Cab) and LAI to improve N assessment in crops and forests. Wang et al. [108] demonstrated that combining SIF with FluSAIL-derived Cab significantly enhanced leaf N predictions in almond orchards ($R^2 = 0.95$), overcoming limitations of traditional spectral indices. Similarly, Raya-Sereno et al. [85] identified SIF and Cab as key predictors for detecting N fertilizer rates and residual effects in wheat, highlighting structural and chlorophyll indices as complementary tools. Belwalkar et al. [6] demonstrated that narrow-band hyperspectral imagery quantified SIF was comparable to those from sub-nanometer hyperspectral imagery in predicting N concentration in rainfed wheat, despite lower spectral resolution. Camino et al. [11] earlier established that incorporating SIF with RTM-modeled leaf chlorophyll and water content into N retrieval models improved accuracy ($R^2 \geq 0.89$) in wheat under Mediterranean conditions, outperforming traditional VIs. Overall, common findings highlight the superiority of SIF over structural traits (e.g., LAI) for N assessment, the synergy between SIF and biochemical traits (e.g., Cab), and the adaptability of hyperspectral methods across crops and forests. However, key limitations involve sensor resolution trade-offs [6], structural complexity in tree crops [108], and the need for multi-year validation [85].

Although hyperspectral narrow-band data bring new opportunities for applying sophisticated algorithms for VI optimization and SIF retrieval in crop monitoring, hyperspectral based studies generally have relatively low model validation accuracy compared to the model training results (Fig. 6). In contrast, multispectral data-based studies showed relatively small drops in validation accuracy.

Full-spectrum modeling approaches

A comparison of the "full-spectrum" approach and the use of specific VIs or SIF indicators reveals a distinct difference in the methodologies employed. The "full-spectrum" approach, encompassing the entirety of available bands and an array of spectral and texture features (TFs) extracted from them, necessitates the implementation of sophisticated modeling methodologies to effectively process high-dimensional full-spectrum data. Textural features are commonly derived from the gray-level co-occurrence matrices (GLCM), such as entropy, contrast,

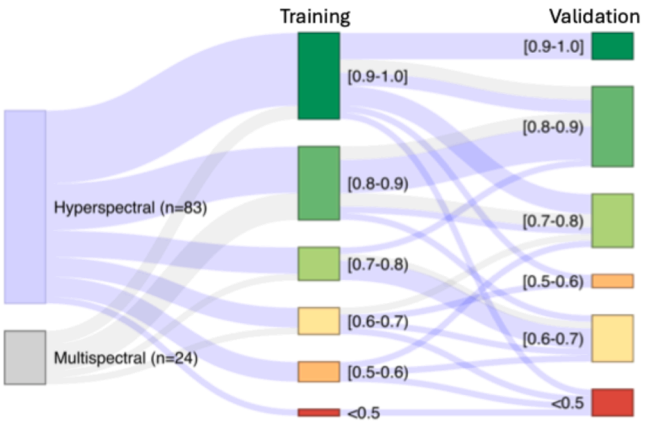


Fig. 6. Sankey diagram illustrating the flow of studies from sensor type to model training and validation R^2 accuracy levels. The left column displays sensor types. The middle and right columns show R^2 accuracy binned into six levels (<0.5, [0.5–0.6), [0.6–0.7), [0.7–0.8), [0.8–0.9), [0.9–1.0]). Flow lines represent the proportion of studies moving through each stage.

homogeneity, and correlation [104]. The textural features are relevant to nitrogen status because canopy N levels influence leaf density, tillering, and canopy structural heterogeneity, which are captured in spatial reflectance patterns [116]. In contrast, the utilization of specific VIs, TFs or SIF indicators typically reduce the dimension to a small number of bands, followed by employing simple regression models or often an ML model. The full-spectrum modeling approaches handling high dimensional spectral data are often considered as non-parametric methods [99].

In the context of plant N prediction, there are several modeling approaches available. Broadly, these can be grouped into four main categories (Fig. 7), including i) Statistical and traditional ML methods, which encompass traditional statistical techniques such as multiple linear regression (MLR), partial least squares (PLS), as well as traditional ML algorithms such as support vector machines (SVM), and random forest (RF). These methods rely on data-driven relationships between inputs and outputs and are often used when ample historical data is available; ii) Physical and Process-Based Models: These models simulate the underlying physical, biological, or chemical processes involved in plant growth and N dynamics. Radiative transfer models (RTMs) and crop growth simulation models (such as APSIM or DSSAT) fall under this category [26,41]. RTMs and crop growth simulation models serve fundamentally different roles. RTMs simulate the interaction of radiation with vegetation canopies based on physical principles, whereas crop growth simulation models represent physiological and ecological processes governing plant development and biomass accumulation under varying environmental and management conditions [16]. They provide mechanistic insights by explicitly modeling processes like light interaction, photosynthesis, and nutrient cycling. iii) Deep learning (DL), which is considered as a more advanced ML method such as convolutional neural networks (CNN) and recurrent neural networks (RNN), are particularly effective at capturing complex, nonlinear relationships compared to traditional ML methods [51], though DL relies on training on large datasets. They are widely used in remote sensing image analysis for classification and automated diagnosis of stresses [88], where patterns may be too intricate for traditional methods; and iv) Hybrid Approaches: Hybrid models combine elements from the above groups. For instance, a hybrid approach might integrate process-based models with either traditional ML or advanced DL models to leverage both the interpretability of physical models and the predictive power of data-driven methods. This hybrid approach can improve robustness and transferability by compensating for the weaknesses of individual approaches.

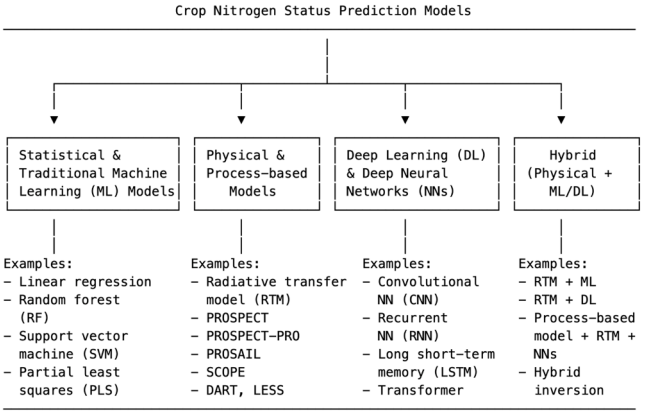


Fig. 7. The identified four modeling approaches for remote sensing of plant N traits.

Statistical and traditional machine learning models for N prediction

Advancements in statistical modeling software and packages, particularly those enabling multivariate statistics (e.g., R, Python packages), have led to significant progress in hyperspectral data analysis for agricultural applications. For instance, the MLR or stepwise MLR can systematically screen or utilize the full range of spectral bands, providing baseline models that capture linear relationships between spectral features and crop N variables, which has been instrumental in this development [96]. However, while useful as benchmarks, the MLR methods are prone to overfitting in high-dimensional hyperspectral datasets, leading to inflated training performance but poor generalization and low validation accuracy. Consequently, their utility in current research and practice lies mainly in providing a reference rather than predictive tools.

On the other hand, multivariate and chemometric models including the partial least squares (PLS) regression (PLSR) have been used to reduce dimensionality of spectral bands [10]. PLS is often regarded as an algorithm of ML given its supervised modeling manner. PLSR have been extensively employed to predict plant traits including N content from hyperspectral data, providing easily interpretable models with low computational complexity [115]. PLSR, in particular, is effective in mitigating multicollinearity issues inherent in hyperspectral datasets by extracting a smaller number of latent variables, thus enhancing predictive performance compared to traditional MLR methods. Collectively, these methods and their variants remain essential tools for establishing benchmark models and for uncovering valuable insights into interpreting the relationships between spectral variables and N variables.

Machine learning has revolutionized crop N status prediction using UAV-acquired hyperspectral data [35,86]. Algorithms such as RF, SVM, and PLS models are now routinely employed to extract key spectral features from high-dimensional datasets and uncover complex, non-linear relationships between canopy reflectance and N content [78, 114]. These methods have been shown to significantly improve prediction accuracy and robustness over traditional linear regression and MLR models, enabling the mapping of N distribution that is crucial for precision N management. For example, Peng et al. [80] demonstrated that RF models could reliably predict leaf N concentration from UAV hyperspectral imagery. Chen et al. [18] explored combining UAV hyperspectral remote sensing with ML methods to estimate winter wheat PNC and they found that SVM and RF outperformed MLR models. Their study highlighted the effectiveness of shallow ML methods, particularly SVM- and RF regressions, in improving estimation accuracy. Nevertheless, shallow ML methods may still face challenges of reduced transferability when extrapolating to new spatial contexts or across seasons.

Physical and process-based models for plant N traits

Recent advances in hyperspectral remote sensing research have increasingly combined radiative transfer models such as variants of the PROSPECT series, with UAV-acquired hyperspectral imagery to quantitatively estimate crop N status [30]. In these approaches, models like PROSPECT-PRO simulate leaf optical properties based on internal biochemical constituents, including leaf chlorophyll and protein. By inverting these models using high-resolution hyperspectral data from UAVs and crewed aircrafts, researchers can retrieve key leaf biochemical parameters that serve as proxies for N content. This physics-based method reduces reliance on empirical correlations and enhances the transferability of N prediction across different crops and field conditions. To date, however, only the PROSPECT-PRO model supports the reflectance-to-nitrogen direct estimation of leaf nitrogen that is parameterized as protein content in the model. All the other models current do not parameterize protein or nitrogen; thus, these models themselves do not support the direct estimation of leaf nitrogen content.

Coupling PROSPECT-PRO with canopy radiative transfer models (e.g., SAIL) has further improved the estimation of canopy N by accounting for both leaf-level and canopy-level structural effects [100]. For instance, Li et al. [63] constructed multiple lookup tables (Multi-LUTs) based on the N-PROSAIL radiative transfer model for different growth stages, allowing for estimating canopy N density (CND) in winter wheat from UAV-based hyperspectral imagery. Such integrative techniques enable spatially explicit mapping of crop N status, highlighting the potential of combining UAV hyperspectral imagery with radiative transfer models for precision N management. Based on airborne hyperspectral imagery, Wang et al. [109] demonstrated a coupled RTM-inversion approach by integrating the PROSPECT-5 leaf model [31] that incorporates leaf protein and cellulose and lignin effects, with the INFORM canopy reflectance model. This inversion method successfully estimated N content at both the leaf and canopy levels in a forest setting. However, further testing is required in crops. Collectively, these studies demonstrate that multi-scale radiative transfer modelling, when combined with hyperspectral data, can provide mechanistic insights into plant N status by linking reflectance signals to processes such as nitrogen-induced changes in leaf pigment concentration and canopy architecture.

Different from the commonly used one-dimensional (1D) models that are based on the assumption of horizontally homogeneous canopy, 3D RTMs can capture 3D heterogeneity such as in urban surface, vegetation canopy, and topography [84]. Particularly, the RAMI (Radiation Model Intercomparison) initiative [111] and the active development of true 3D RTMs have greatly improved the capacity for accurate plant trait prediction, though application in predicting plant N is still underrepresented. Modern 3D RTMs, often benchmarked and validated via the RAMI platform, allow for detailed simulations of heterogeneous crop canopies and complex structural effects [89], better capturing the influence of N distribution at both leaf and canopy levels. A recent study applied the 3D RTM model LESS [84] in combination with PROSAIL to predict chlorophyll, which was then linked to measured N concentrations [76], though it was not a direct estimation of N concentration. This study also found that machine learning models outperformed both the 1D and 3D RTMs in predicting the almond canopy N concentration [76], suggesting potential knowledge gaps in developing and applying 3D RTMs to arable crops that are strcuturally less hetrogeneous than forest landscapes.

Deep learning for plant N prediction

Deep neural networks are commonly referred to as DL models which have emerged as powerful tools for analyzing imagery and other formats of sensing data (e.g., LiDAR) in various applications including stress detection [97], mapping crop types [36], yield [95], plant- and soil properties [25,78,120], and objects surface classification [75]. Despite these various applications, only a few studies have so far applied deep learning to estimate canopy nitrogen status. For instance, a recent study demonstrated that 1D (one-dimensional) CNN outperformed PLS regression for retrieving canopy nitrogen concentration (CNN) and aboveground biomass using VNIR hyperspectral reflectance data, with a total sample size of 450 for training, validation and testing [78]. Peng et al. [82] successfully utilized deep neural networks to estimate canopy N status across different growth stages in rice. This integration of CNN with UAV hyperspectral sensing holds great promise for optimizing fertilizer applications and enhancing NUE in modern cropping systems.

Despite the promising performance demonstrated by DL models, traditional ML models have often been found to yield the best model training accuracies (Fig. 8). It is worth mentioning that the sample size of studies based on DL models in this review is too small. Therefore, more investigations are needed to understand whether DL models have better transferability than the traditional ML models or not and what is the minimum sample size needed. Nguyen et al. [74] demonstrated that employing CNN and fusing hyperspectral, LiDAR, and thermal UAV data exceeded traditional ML (e.g., SVM, RF) in predicting traits like grain N content. However, small sample sizes and data distribution imbalances were persistent challenges, partially mitigated by data augmentation. Moving forward, further research is needed to assess the generalizability of DL models for plant N prediction, especially under varying environmental and management conditions. Rigorous multi-site trials, larger labeled datasets, and standardized evaluation metrics will be essential to confirm whether these newer algorithms can consistently outperform well-established ML techniques.

Integrating machine learning and physical models

The fundamental distinction between RTMs and statistical ML methods lies in their contrasting approaches to modeling and interpreting canopy trait-reflectance relationships (Table 1). RTMs simulate photon transport through vegetation canopy using leaf optical properties (e.g., chlorophyll absorption coefficients), structural parameters (e.g., LAI, leaf angle distribution), and radiative transfer equations, with explicit assumptions about canopy architecture [43]. For instance, 1D models such as PROSAIL assume horizontal homogeneity, whereas 3D models such as DART represent discrete canopy elements including plant row arrangement, tree crowns and shadows [37]. In contrast, ML approaches infer empirical mappings from spectral reflectance to target variables or plant traits without modeling underlying physical processes, presuming that the training data represent the statistical distribution of application scenarios, i.e., testing data [59]. However, this assumption may not hold across diverse environments, resulting in limited model transferability.

Hybrid approaches strategically bridge the data-driven advances of ML and mechnistic insights of physical modeling by using synthetic datasets generated from RTMs to train ML or DL algorithms (for example, training a GPR model with PROSAIL simulations) [39], or by incorporating physical constraints directly within neural networks [93].

Hybrid approaches combining RTMs and ML have achieved accurate estimation of plant N and other traits. Li et al. [63] optimized LUT-based RTM inversion for canopy N density (CND) in winter wheat using UAV hyperspectral data, achieving $R^2 = 0.83$. Their study highlights the robustness of RTM-LUT methods while acknowledging computational challenges. Berger et al. [7] coupled PROSAIL-PRO with Gaussian Process regression (GPR) to estimate aboveground N content, emphasizing the value of heteroscedastic GPR for uncertainty quantification. Li et al. [59] integrated in-situ UAV data with PROSPECT-PRO simulations, achieving a 10 % relative RMSE for leaf N content (LNC) and demonstrating superior robustness compared to purely data-driven methods. Wang et al. [107] further advanced hybrid methods with process-guided ML (PGML), combining synthetic RTM data and field measurements to predict cover crop N content ($R^2 = 0.69$), outperforming traditional RTM inversions. Despite the promising results achieved with the hybrid

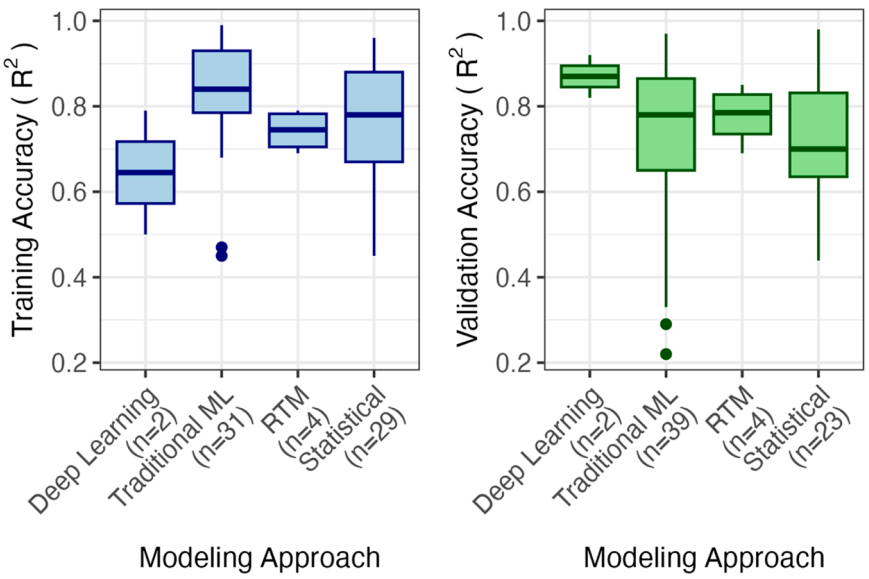


Fig. 8. Comparison of model training and validation accuracies between modeling approaches, including deep learning, traditional machine learning (ML) methods, radiative transfer models (RTMs), and statistical models.

Table 1
FundamNental differences between the machine learning (ML), radiative transfer models (RTMs), and hybrid approaches in terms of methodology, assumptions and interpretability.

Aspect	Machine Learning (ML)	Radiative Transfer Models (RTMs)	Hybrid Approaches
Methodology	• Data-driven empirical /statistical pattern • Learn mappings from input-output data through optimization algorithms	• Physical laws of electromagnetic radiation and light interactions • Model photon transport, scattering, absoprtion with radiative transfer equation	• Combination of physical principles with data-driven optimization • Use RTM as forward model structure or constrain ML with physical knowledge
Assumption	• Training and application domains are similar • Past patterns may predict future behavior • Non-linear mappings may be learned by deep learning (DL)	• Homogeneous leaf optical properties • assume 1D or 3D canopy structure • Valid scattering coefficients • Assumes turbid medium or discrete element representation	• Physical model structure is correct • Physical constraints enhance generalization • Allow ML to capture variance not explained by RTM • Trade-off between accuracy and interpretability is acceptable
Interpretability	• Low • Black-box predictions • No physical meaning of learned weights • Difficult to understand decision process	• High • Model parameters have clear physical meaning • Direct relationship to plant properties • Transparent cause-effect relationships	• Moderate • RTM component provides physical interpretation • ML captures complex interactions • Balance between transparency and flexibility

approach, limitations persist, such as canopy structural complexity (e.g., spikes), which may reduce the accuracy of canopy-level N estimation.

Each of these modeling groups offers distinct strengths and is often chosen based on factors like data availability, desired interpretability, and the complexity of the modeled processes [89,99]. Empirical models and traditional ML methods are often easier to implement when large, high-quality datasets are available [114]. Combining ML and RTM is not only useful for generating artificial training data but also for predicting multiple traits related to N deficiency, allowing for optimizing trait-specific models [106,113]. Still, they can be limited by their applicability outside the data ranges used to train them. In contrast, physical and process-based models can be more flexible in testing specific hypotheses and exploring the "what-if" scenarios (e.g., changing canopy structure, weather or soil conditions) [17,26,41]. However, they require more detailed input data and a thorough understanding of the underlying morphophysiological processes that are related to N variations. Hybridizing these frameworks is expected to leverage mechanistic insights while retaining the predictive power and scalability of data-driven methods for improved prediction of plant N traits.

Although these modeling approaches, a critical limitation of UAV-based studies is their focus on the visible–near-infrared (VNIR) range (400–1000 nm). While this range captures chlorophyll-related features and canopy structure effects, it does not encompass the key nitrogen- and protein-related absorption features that are primarily located in the shortwave infrared (SWIR) region between 1000 and 2400 nm (Fig. 9). Specifically, N–H stretching and combination bands occur around 1020, 1510, 1730, 1980, 2060, 2130, 2180, 2240, and 2300 nm, reflecting direct biochemical absorption linked to proteins and nitrogen compounds [7,21,32]. The absence of these SWIR bands in most UAV platforms suggests that many current studies rely on indirect proxies of nitrogen status, rather than targeting the biochemical absorption features themselves. Future UAV sensor development and research efforts should therefore prioritize extending spectral coverage into the SWIR region, which would enable more direct and physiologically meaningful detection of crop nitrogen status.

Challenges and future directions

Area-based vs. mass-based N parameters

Predicting N content remains challenging, particularly when distinguishing between area-based and mass-based N traits [56]. Area-based estimates, which represent the total nitrogen (N) per unit leaf or canopy area and are closely tied to photosynthetic capacity, are highly sensitive to variations in leaf morphology and canopy structure.

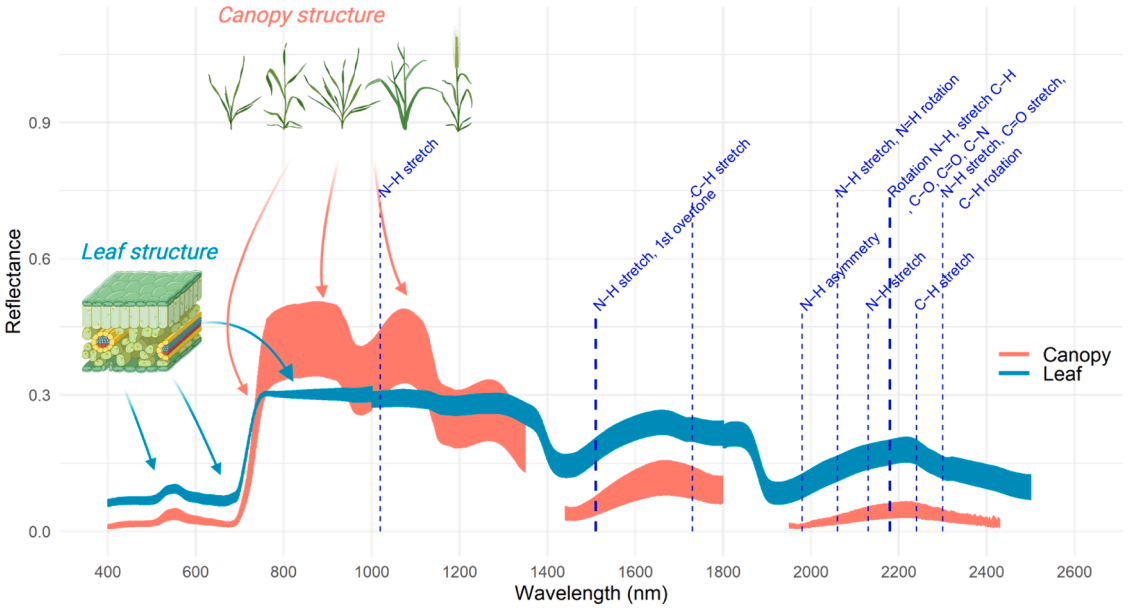


Fig. 9. Comparison of leaf- and canopy-level reflectance measured on the same day across 18 wheat varieties. Blue vertical lines mark nine nitrogen (protein) absorption features (1020, 1510, 1730, 1980, 2060, 2130, 2180, 2240, and 2300 nm) as summarized in Berger et al. [7].

In contrast, mass-based N estimates, which represent the N concentration within the tissue, are affected by biochemical variability and confounding factors such as water content and non-protein N compounds. Recent studies have begun to address these challenges. For example, Li et al. [54] demonstrated that continuous wavelet analysis applied to water-removed hyperspectral data can robustly retrieve both area- and mass-based N contents in wheat and rice crops, mitigating calibration issues due to spectral variability. In contrast, Peanusaha et al. [79] found that calibrating N based on leaf dry mass (N_{mass}) outperforms calibration based on leaf area (N_{area}) due to the age-dependent variation of chlorophyll and that a hybrid model combining physical-based modeling and ML can alleviate the impact of leaf age on prediction accuracy while reducing spectral dimensionality. Nonetheless, the accuracy differences highly depend on the dataset, for instance in an environmental setting where leaf-level biochemical variation is dominant (i.e., biomass varies less) compared to leaf dry matter variation, N_{mass} is predicted often with a relatively high accuracy, or vice versa.

In many field crop applications, area-based N (e.g., kg/ha) often shows stronger predictive relationships because it ties directly to total canopy biomass and N content—both of which influence reflectance [57,63,80]. In contrast, in settings where leaf-level biochemical variation is large, N_{mass} based N concentration (% N) can also be successfully predicted. For instance, in a recent study in cover crops where N uptake did not differ significantly between treatments but different species varied the N concentration significantly by altering biomass [22], N_{mass} was predicted with a much higher accuracy ($R^2 = 0.80$) than was the N_{area} ($R^2 = 0.56$) when using UAV-based RGB and multispectral images. Looking ahead, integrating advanced spectral analysis, multi-sensor data fusion, and standardized calibration strategies tailored to specific species and growth stages appears to be a promising pathway for optimizing N prediction and management in precision agriculture. Deep learning approaches such as the self-supervised spectral–spatial attention-based transformer network proposed by Zhang et al. [126] have shown capability in capturing complex spatial and spectral patterns from UAV-based RGB imagery, further enhancing prediction performance. To fully leverage the potential of DL architectures, assembling a huge, diverse training dataset that encompasses a wide range of environmental conditions, phenological stages, and varietal differences is essential, which remains a significant challenge in agriculture crops.

Disentangling the effects of phenological and physiological changes

Disentangling the effects of phenological and physiological changes using canopy hyperspectral sensing to predict N and chlorophyll status remains challenging because both factors co-vary and jointly influence canopy reflectance. Phenological changes—such as variations in canopy structure, leaf age, and growth stage—can modify the spectral signal independent of the underlying biochemical properties [118], whereas physiological variations (e.g., changes in chlorophyll concentration or N content) are often superimposed on these structural shifts. However, research indicates that it is possible to partially disentangle these effects. For instance, Merlier et al. [70] found that the photochemical reflectance index (PRI) can be used at the canopy scale to differentiate the influences of phenological development from physiological performance, thereby enhancing the interpretation of N and chlorophyll signals in complex canopies.

Integrating multiple spectral indices, advanced radiative transfer modeling, and ML approaches has enabled researchers to progressively decouple physiological signals—such as N and chlorophyll content—from the confounding influences of phenological changes. For example, studies have shown that by combining spectral indices with physically based models like PROSPECT and employing robust regressions, it is possible to mitigate the effects of canopy structural variability across varieties and species on the retrieved biochemical properties [114,118]. Verrelst et al. [99] presented a hybrid inversion approach that synergistically leverages physics-based and data-driven models to improve the retrieval of vegetation biochemistry from hyperspectral data. Likewise, Peanusaha et al. [79] demonstrated that a hybrid approach could retrieve N in grapevine leaves with reduced spectral dimensionality while maintaining acceptable accuracy. This highlights that such integrative methods help isolate the physiological changes independent of phenology. These findings, together with work by Merlier et al. [70] who disentangled the effects of phenology from physiological processes using the PRI, support the view that advanced feature selection and integrative modeling is key to overcoming the challenges inherent in canopy hyperspectral sensing for N- and chlorophyll predictions. Nonetheless, achieving a complete decoupling requires extensive, well-calibrated datasets that include auxiliary information about canopy structure – an ongoing challenge in diverse agricultural contexts.

Disentangling the effects of structure and biochemical changes

Disentangling the effects of leaf or canopy structure from biochemical changes in hyperspectral data is challenging because both structural attributes—such as leaf internal structure and surface, leaf thickness, LAI, leaf angle distribution—and biochemical properties like chlorophyll, N, and water content jointly influence the observed reflectance [90]. Nonetheless, several studies suggest that integrative approaches can partially separate these effects. For instance, Verrelst et al. (2019) demonstrated that a hybrid inversion approach combining physically based radiative transfer models with ML techniques could isolate biochemical signals from confounding structural influences, thereby improving N and chlorophyll retrieval accuracy [99]. Similarly, Li et al. [62] showed that continuous wavelet analysis applied to water-removed spectra minimized the impact of leaf structure when estimating both area- and mass-based N content [54]. Merlier et al. [70] further illustrated that spectral indices like the PRI could help disentangle phenological influences from physiological changes [70]. Complementing these findings, Yu et al. [119] revealed that variations in foliar optical traits due to sealed planting conditions in urban trees are strongly linked to leaf structural changes, underscoring the need to decouple structure from biochemical signals [119]. Moreover, Sims and Gamon [90] developed spectral indices for predicting leaf pigment content that are robust across a wide range of species and structural differences—demonstrating that the first derivative of reflectance in the red-edge region can be insensitive to leaf structure and reliably indicate chlorophyll content [90]. Although complete decoupling remains complex due to the intertwined nature of structure and biochemistry, these integrative approaches provide promising pathways to reduce the confounding effects of leaf and canopy structure when predicting N and chlorophyll from hyperspectral sensing.

Accounting for the directional effects of sun illumination and viewing angles is another strategy for decoupling canopy structures from biochemical signals [9]. Recent studies indicate that incorporating multi-angular UAV imaging can help correct structural heterogeneity and shadowing effects. Jafarbiglu and Pourreza [44] found that sun–-view geometry significantly influences canopy spectral reflectance variability, suggesting that multi-angular observations may help isolate true biochemical variations by minimizing the impact of viewing and illumination differences. In a complementary study, He et al. [40] demonstrated that remote sensing of leaf N concentration in winter wheat is notably improved when using multi-angular hyperspectral data, as this approach better captures the directional effects of canopy structure and reduces the confounding effects of shadows and anisotropic reflectance. Yu et al. [117] proposed a conceptual index assuming that every measured canopy reflectance is a linear function of the biochemical responding reflectance [117]. This index used the ratio of reflectance difference to eliminate the multiplicative and additive effects of canopy structure on canopy reflectance, especially in NIR and red-edge bands. This concept coincides with the concept of MTCI, explaining the consistently good performance of the red-edge band index MTCI in predicting chlorophyll in various studies. Liu et al. [65] utilized the near-infrared reflectance of vegetation (NIRv) to mitigate the effects of canopy structure on the bidirectional reflectance factor (BRF), thereby reducing the influence of canopy structural changes on the remote estimation of LNC in winter oilseed rape across various growth stages and seasons. Together, these findings reinforce that integrating multi-angular imaging into hyperspectral sensing frameworks offers an effective pathway to further decouple structural influences from the biochemical signals of N and chlorophyll. Nevertheless, the operational adoption of multi-angular or advanced structural corrections may require additional sensor capabilities, computational resources, and standardized calibration practices. These factors merit further study in large-scale precision agriculture settings.

Explainable AI and deep learning

Recent advances in deep learning, natural language processing, and computer vision have revolutionized many fields. Yet, their application in UAV hyperspectral remote sensing for predicting leaf and plant traits remains relatively underexplored. Pioneering studies using Explainable AI (XAI) techniques, such as the self-supervised spectral-spatial attention-based transformer [126] and the CNN-transformer networks [34] have demonstrated the potential of using XAI and deep neural networks to automatically extract and interpret complex spectral–spatial-temporal features and transfer the learning features. However, such approaches remain rarely applied in operational plant trait prediction or validated across environments [112]. Ma et al. [67] proposed a hybrid approach combining deep multitask learning with the N-based PROSAIL mechanistic model to predict wheat leaf N content (LNC). Their method outperformed spectral indices, PLSR, and ANN. Peng et al. [82] enhanced rice LNC estimation by integrating hybrid feature selection (XGBoost and Pearson correlation) with deep neural networks (DNN). Their combined PCC-XGBoost feature selection improved inversion accuracy, and the DL model achieved superior performance in mapping spatial LNC distribution. These results underscore how DL can address certain limitations of purely empirical methods

The adoption of these state-of-the-art methods in hyperspectral remote sensing is hampered by challenges such as the scarcity of large, well-labeled training datasets and the inherent complexity of integrating high-dimensional spectral data with multi-modal data, and physical canopy models. Consequently, although early outcomes have been encouraging, more research is required to fully exploit the power of explainable, robust, and generalizable AI solutions for plant trait prediction in real-world agricultural contexts. Efforts such as expanded data-sharing platforms and multi-institutional collaborations may help build the large, diverse datasets necessary to drive further breakthroughs.

Data fusion and model integration for N mapping

Recent advances in multi-model data fusion and model integration are opening up exciting opportunities for improving the prediction of plant traits using remote sensing data and multi-source data considering weather data, soil landscape data and management information [17,26,101]. Texture features (TFs) and multi-source data fusion also can enhance model accuracy. For instance, Wang et al. [102] combined VIs, TFs, and hyperspectral parameters (HPs) with ML to estimate rice N content, outperforming traditional methods. Zhang et al. [126] integrated spectral and texture features and employed the variance inflation factor (VIF) for feature optimization, achieving improved prediction accuracy for winter wheat LNC [123]. In contrast, combing 3D photogrammetric features does not always improve N estimation compared to using hyperspectral data alone [73]. This finding suggests that the observed challenges may be due to factors such as limited sample size or environmental noise, and not solely due to technical limitations. Nonetheless, most of the existing studies are restricted to specific growth stages, indicating a need for cross-environment validations to fully evaluate the transferability.

Integrative modeling approaches that combine spectral indices, physically based radiative transfer models, crop growth models, and advanced ML techniques have the potential to overcome inherent challenges associated with canopy structure and environmental variability. For instance, Dong et al. [26] illustrated that coupling proximal sensing with crop growth modeling enables dynamic in-season diagnosis of N status in maize. Complementing these efforts, Hu et al. [41] integrated a crop growth model (APSIM-Wheat) with a radiative transfer model (PROSAIL) to estimate aboveground biomass dynamics at small spatial scales by assimilating trial-level Sentinel-2 NDVI data. Their APSIM-PROSAIL framework not only reproduced the NDVI dynamics

across a variety of trials with a relative RMSE of 18.2 % but also enabled the inverse estimation of key variables such as initial soil water and N content, thus highlighting the potential of combining mechanistic crop models with satellite remote sensing data to better capture genotype–environment–management interactions [41]. Based on a meta-analysis, Zhang et al. [124] emphasized that integrating various fusion approaches, including data-, feature-, and raw-level fusion, can significantly enhance the estimation of plant traits from drone imagery. In addition, Castilho et al. [15] highlighted the importance of assembling a global drone-based N traits dataset to serve as a standardized benchmark across diverse cropping systems. It is encouraging to note that there has been an increasing trend of publishing UAV remote sensing datasets on public data repositories such as Zenodo in recent publications [98,104]. While these integrative approaches offer the potential for more robust and transferable models, they also present challenges, including managing the big data, the need for sophisticated data structures and indexing systems based on open-access data repositories, and the development of user-friendly software tools for practical applications.

Conclusions

This review systematically examined over 100 publications from the past decade (2014–2024) on UAV and airborne remote sensing for crop N monitoring. Our analysis highlights several key factors influencing model accuracy, including plant sampling methods and the selection of N variables at the leaf, canopy, or plant level. These choices significantly impact the prediction performance of the N predictive models. Differences in prediction accuracy between area-based and mass-based N concentrations depend on the species and ecosystem (e.g., annual vs. perennial systems) in which UAV hyperspectral imaging is applied. Traditional ML models have become increasingly popular for N prediction, yet they often exhibit a drop in validation accuracy compared to training accuracy. In contrast, physical models, while not achieving the same level of accuracy as machine learning approaches, demonstrate better generalizability across different crop species.

Bridging the scale from leaf-level to whole-plant N measurements is essential for improving N management and NUE in real-world agricultural applications. In many arable farming systems, remote predictions of area-based plant nitrogen status (uptake) can be particularly practical. Although DL has shown promise in N prediction, its accuracy has not yet surpassed that of traditional ML methods primarily due to limitations in the availability of training data. To advance crop N monitoring, future research should focus on incorporating phenology-driven N dynamics, correcting for canopy structural and illumination geometry effects, and integrating multi-source data with DL and hybrid modeling approaches. Such efforts, coupled with standardized data formats and collaborative data-sharing initiatives, will be vital to ensure robust, scalable and transferable UAV-based N mapping in modern precision agriculture.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

CRediT authorship contribution statement

Kang Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anirudh Belwalkar:** Writing – review & editing. **Wuhua Wang:** Writing – review & editing, Data curation. **Yuncai Hu:** Writing – review & editing. **Addisu Hunegnaw:** Writing – review & editing. **Abdul Nurunnabi:** Writing – review & editing. **Thorsten Ruf:** Writing – review & editing. **Fei Li:** Writing – review & editing. **Liangliang Jia:** Writing – review & editing. **Lammert Kooistra:** Writing – review & editing. **Yuxin Miao:** Writing – review & editing. **Félicia N. Teferle:** Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was supported by the AgroMissionHub funded AmAIzed (2013619) project and the Luxembourg National Research Fund (FNR) and the Luxembourg Ministry of Agriculture, Viticulture and Rural Development (MAVDR) funded PRECISION project (17949865).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2025.101507.

Data availability

data in supplements

References

[1] H. Aasen, E. Honkavaara, A. Lucieer, P. Zarco-Tejada, Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: a review of sensor technology, measurement procedures, and data correction workflows, Remote Sens. 10 (2018) 1091, https://doi.org/10.3390/rs10071091.

[2] M. Abdalla, A. Hastings, K. Cheng, Q. Yue, D. Chadwick, M. Espenberg, J. Truu, R.M. Rees, P. Smith, A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity, Glob. Change Biol. 25 (2019) 2530–2543, https://doi.org/10.1111/gcb.14644.

[3] G. Bareth, H. Aasen, J. Bendig, M.L. Gnyp, A. Bolten, A. Jung, R. Michels, J. Soukkamäki, Low-weight and UAV-based hyperspectral full-frame cameras for monitoring crops: spectral comparison with portable spectroradiometer measurements, Photogramm. - Fernerkund. - Geoinformation (2015) 69–79, https://doi.org/10.1127/pfg/2015/0256, 2015.

[4] E.M. Barnes, T.R. Clarke, S.E. Richards, P.D. Colaizzi, J. Haberland, M. Kostrzewski, P. Waller, C. Choi, E. Riley, T. Thompson, R.J. Lascano, H. Li, M. S. Moran, Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data, in: Proceedings of the Fifth International Conference on Precision Agriculture. Presented at the International Conference on Precision Agriculture, Bloomington, MN, USA, 2000.

[5] P.B. Barraclough, R. Lopez-Bellido, M.J. Hawkesford, Genotypic variation in the uptake, partitioning and remobilisation of nitrogen during grain-filling in wheat, Field Crops Res 156 (2014) 242–248, https://doi.org/10.1016/j.fcr.2013.10.004.

[6] A. Belwalkar, T. Poblete, A. Longmire, A. Hornero, R. Hernandez-Clemente, P. J. Zarco-Tejada, Evaluation of SIF retrievals from narrow-band and sub-nanometer airborne hyperspectral imagers flown in tandem: modelling and validation in the context of plant phenotyping, Remote Sens. Environ. 273 (2022) 112986, https://doi.org/10.1016/j.rse.2022.112986.

[7] K. Berger, J. Verrelst, J.-B. Féret, T. Hank, M. Wocher, W. Mauser, G. Camps-Valls, Retrieval of aboveground crop nitrogen content with a hybrid machine learning method, Int. J. Appl. Earth Obs. Geoinformation 92 (2020) 102174, https://doi.org/10.1016/j.jag.2020.102174.

[8] N.J.J. Bréda, Ground-based measurements of leaf area index: a review of methods, instruments and current controversies, J. Exp. Bot. 54 (2003) 2403–2417, https://doi.org/10.1093/jxb/erg263.

[9] N.H. Broge, E. Leblanc, Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density, Remote Sens. Environ. 76 (2001) 156–172, https://doi.org/10.1016/S0034-4257(00)00197-8.

[10] A.C. Burnett, J. Anderson, K.J. Davidson, K.S. Ely, J. Lamour, Q. Li, B. D. Morrison, D. Yang, A. Rogers, S.P. Serbin, A best-practice guide to predicting plant traits from leaf-level hyperspectral data using partial least squares regression, J. Exp. Bot. 72 (2021) 6175–6189, https://doi.org/10.1093/jxb/erab295.

[11] C. Camino, V. González-Dugo, P. Hernández, J.C. Sillero, P.J. Zarco-Tejada, Improved nitrogen retrievals with airborne-derived fluorescence and plant traits quantified from VNIR-SWIR hyperspectral imagery in the context of precision agriculture, Int. J. Appl. Earth Obs. Geoinformation 70 (2018) 105–117, https://doi.org/10.1016/j.jag.2018.04.013.

[12] Q. Cao, Y. Miao, F. Li, X. Gao, B. Liu, D. Lu, X. Chen, Developing a new Crop Circle active canopy sensor-based precision nitrogen management strategy for

winter wheat in North China Plain, Precis. Agric. 18 (2017) 2–18, https://doi.org/10.1007/s11119-016-9456-7.
[13] A. Cartelat, Z.G. Cerovic, Y. Goulas, S. Meyer, C. Lelarge, J.-L. Prioul, A. Barbottin, M.-H. Jeuffroy, P. Gate, G. Agati, I. Moya, Optically assessed contents of leaf polyphenolics and chlorophyll as indicators of nitrogen deficiency in wheat (*Triticum aestivum* L.), Field Crops Res 91 (2005) 35–49, https://doi.org/10.1016/j.fcr.2004.05.002.
[14] K.G. Cassman, A. Dobermann, D.T. Walters, Agroecosystems, nitrogen-use efficiency, and nitrogen management, Ambio 31 (2002) 132–140.
[15] D. Castilho, D. Tedesco, C. Hernandez, B.E. Madari, I. Ciampitti, A global dataset for assessing nitrogen-related plant traits using drone imagery in major field crop species, Sci. Data 11 (2024) 585, https://doi.org/10.1038/s41597-024-03357-2.
[16] Q. Chen, B. Zheng, T. Chen, S.C. Chapman, Integrating a crop growth model and radiative transfer model to improve estimation of crop traits based on deep learning, J. Exp. Bot. 73 (2022) 6558–6574, https://doi.org/10.1093/jxb/erac291.
[17] X. Chen, F. Li, Q. Chang, Y. Miao, K. Yu, Improving winter wheat plant nitrogen concentration prediction by combining proximal hyperspectral sensing and weather information with machine learning, Comput. Electron. Agric. 232 (2025) 110072, https://doi.org/10.1016/j.compag.2025.110072.
[18] X. Chen, F. Li, B. Shi, Q. Chang, Estimation of winter wheat plant nitrogen concentration from UAV hyperspectral remote sensing combined with machine learning methods, Remote Sens. 15 (2023) 2831, https://doi.org/10.3390/rs15112831.
[19] Chen, Z., Miao, Y., Lu, J., Zhou, L., Li, Y., Zhang, H., Lou, W., Zhang, Z., Kusnierek, K., Liu, C., 2019. In-season diagnosis of winter wheat nitrogen status in smallholder farmer fields across a village using unmanned aerial vehicle-based remote sensing. Agron.-BASEL 9. https://doi.org/10.3390/agronomy9100619.
[20] I. Colomina, P. Molina, Unmanned aerial systems for photogrammetry and remote sensing: a review, ISPRS J. Photogramm. Remote Sens. 92 (2014) 79–97, https://doi.org/10.1016/j.isprsjprs.2014.02.013.
[21] P.J. Curran, Remote sensing of foliar chemistry, Remote Sens. Environ. 30 (1989) 271–278, https://doi.org/10.1016/0034-4257(89)90069-2.
[22] P. Dal Lago, N. Vavlas, L. Kooistra, G.B. De Deyn, Estimation of nitrogen uptake, biomass, and nitrogen concentration, in cover crop monocultures and mixtures from optical UAV images, Smart Agric. Technol. 9 (2024) 100608, https://doi.org/10.1016/j.atech.2024.100608.
[23] J. Dash, P.J. Curran, The MERIS terrestrial chlorophyll index, Int. J. Remote Sens. 25 (2004) 5403–5413, https://doi.org/10.1080/01431160420002740 15.
[24] R. de Souza, M.T. Peña-Fleitas, R.B. Thompson, M. Gallardo, R. Grasso, F. M. Padilla, Use of fluorescence indices as predictors of crop N status and yield for greenhouse sweet pepper crops, Precis. Agric. 23 (2022) 278–299, https://doi.org/10.1007/s11119-021-09837-4.
[25] X. Deng, Z. Zhang, X. Hu, J. Li, S. Li, C. Su, S. Du, L. Shi, Estimation of photosynthetic parameters from hyperspectral images using optimal deep learning architecture, Comput. Electron. Agric. 216 (2024) 108540, https://doi.org/10.1016/j.compag.2023.108540.
[26] L. Dong, Y. Miao, X. Wang, K. Kusnierek, H. Zha, M. Pan, W.D. Batchelor, In-season dynamic diagnosis of maize nitrogen status across the growing season by integrating proximal sensing and crop growth modeling, Comput. Electron. Agric. 224 (2024) 109240, https://doi.org/10.1016/j.compag.2024.109240.
[27] European Council, Council Directive 91/676/EEC concerning the protection of waters against pollution caused by nitrates from agricultural sources, Off. J. Eur. Communities. (1991).
[28] M.M. Farella, M.L. Barnes, D.D. Breshears, J. Mitchell, W.J.D. van Leeuwen, R. E. Gallery, Evaluation of vegetation indices and imaging spectroscopy to estimate foliar nitrogen across disparate biomes, Ecosphere 13 (2022) e3992, https://doi.org/10.1002/ecs2.3992.
[29] H. Feng, T. Zhou, K. Wang, J. Huang, H. Liang, C. Lu, Y. Ruan, L. Xu, From spectral characteristics to index bands: utilizing UAV hyperspectral index optimization on algorithms for estimating canopy nitrogen concentration in Carya Cathayensis Sarg, Remote Sens. 16 (2024), https://doi.org/10.3390/rs16203780.
[30] J.-B. Féret, K. Berger, F. de Boissieu, Z. Malenovský, PROSPECT-PRO for estimating content of nitrogen-containing leaf proteins and other carbon-based constituents, Remote Sens. Environ. 252 (2021) 112173, https://doi.org/10.1016/j.rse.2020.112173.
[31] J.-B. Feret, C. François, G.P. Asner, A.A. Gitelson, R.E. Martin, L.P.R. Bidel, S. L. Ustin, G. le Maire, S. Jacquemoud, PROSPECT-4 and 5: advances in the leaf optical properties model separating photosynthetic pigments, Remote Sens. Environ. 112 (2008) 3030–3043, https://doi.org/10.1016/j.rse.2008.02.012.
[32] Th. Fourty, F. Baret, S. Jacquemoud, G. Schmuck, J. Verdebout, Leaf optical properties with explicit description of its biochemical composition: direct and inverse problems, Remote Sens. Environ. 56 (1996) 104–117, https://doi.org/10.1016/0034-4257(95)00234-0.
[33] B. Fu, L. Deng, W. Sun, H. He, H. Li, Y. Wang, Y. Wang, Quantifying vegetation species functional traits along hydrologic gradients in karst wetland based on 3D mapping with UAV hyperspectral point cloud, Remote Sens. Environ. 307 (2024), https://doi.org/10.1016/j.rse.2024.114160.
[34] C. Fu, T. Zhou, T. Guo, Q. Zhu, F. Luo, B. Du, CNN-Transformer and Channel-Spatial Attention based network for hyperspectral image classification with few samples, Neural Netw. 186 (2025) 107283, https://doi.org/10.1016/j.neunet.2025.107283.
[35] Y. Fu, G. Yang, R. Pu, Z. Li, H. Li, X. Xu, X. Song, X. Yang, C. Zhao, An overview of crop nitrogen status assessment using hyperspectral remote sensing: current status and perspectives, Eur. J. Agron. 124 (2021) 126241, https://doi.org/10.1016/j.eja.2021.126241.
[36] D. Gackstetter, M. Körner, K. Yu, Approaching holistic crop type mapping in Europe through winter vegetation classification and the Hierarchical Crop and Agriculture Taxonomy, Int. J. Appl. Earth Obs. Geoinformation 134 (2024) 104159, https://doi.org/10.1016/j.jag.2024.104159.
[37] J.P. Gastellu-Etchegorry, E. Martin, F. Gascon, DART: a 3D model for simulating satellite images and studying surface radiation budget, Int. J. Remote Sens. 25 (2004) 73–96, https://doi.org/10.1080/0143116031000115166.
[38] R. Gebbers, V.I. Adamchuk, Precision agriculture and food security, Science 327 (2010) 828–831, https://doi.org/10.1126/science.1183899.
[39] A. Guo, W. Huang, B. Qian, H. Ye, Q. Jiao, X. Cheng, C. Ruan, A hybrid model coupling PROSAIL and continuous wavelet transform based on multi-angle hyperspectral data improves maize chlorophyll retrieval, Int. J. Appl. Earth Obs. Geoinformation 132 (2024) 104076, https://doi.org/10.1016/j.jag.2024.104076.
[40] L. He, X. Song, W. Feng, B.-B. Guo, Y.-S. Zhang, Y.-H. Wang, C.-Y. Wang, T.-C. Guo, Improved remote sensing of leaf nitrogen concentration in winter wheat using multi-angular hyperspectral data, Remote Sens. Environ. 174 (2016) 122–133, https://doi.org/10.1016/j.rse.2015.12.007.
[41] P. Hu, B. Zheng, Q. Chen, S. Grunefeld, M.R. Choudhury, J. Fernandez, A. Potgieter, S.C. Chapman, Estimating aboveground biomass dynamics of wheat at small spatial scale by integrating crop growth and radiative transfer models with satellite remote sensing data, Remote Sens. Environ. 311 (2024) 114277, https://doi.org/10.1016/j.rse.2024.114277.
[42] C. Hütt, A. Bolten, H. Hüging, G. Bareth, UAV LiDAR metrics for monitoring crop height, biomass and nitrogen uptake: a case study on a winter wheat field trial, PFG – J. Photogramm. Remote Sens. Geoinformation Sci. (2022), https://doi.org/10.1007/s41064-022-00228-6.
[43] S. Jacquemoud, W. Verhoef, F. Baret, C. Bacour, P.J. Zarco-Tejada, G.P. Asner, C. François, S.L. Ustin, PROSPECT+SAIL models: a review of use for vegetation characterization, Remote Sens. Environ., Imaging Spectroscopy Special Issue 113 (2009) S56–S66, https://doi.org/10.1016/j.rse.2008.01.026.
[44] H. Jafarbiglu, A. Pourreza, Impact of sun-view geometry on canopy spectral reflectance variability, ISPRS J. Photogramm. Remote Sens. 196 (2023) 270–286, https://doi.org/10.1016/j.isprsjprs.2022.12.002.
[45] A. Jenal, H. Hüging, H.E. Ahrends, A. Bolten, J. Bongartz, G. Bareth, Investigating the potential of a newly developed UAV-mounted VNIR/SWIR imaging system for monitoring crop traits—A case study for winter wheat, Remote Sens. 13 (2021) 1697, https://doi.org/10.3390/rs13091697.
[46] M. Jia, R. Colombo, M. Rossini, M. Celesti, J. Zhu, S. Cogliati, T. Cheng, Y. Tian, Y. Zhu, W. Cao, X. Yao, Estimation of leaf nitrogen content and photosynthetic nitrogen use efficiency in wheat using sun-induced chlorophyll fluorescence at the leaf and canopy scales, Eur. J. Agron. 122 (2021), https://doi.org/10.1016/j.eja.2020.126192.
[47] M. Jia, J. Zhu, C. Ma, L. Alonso, D. Li, T. Cheng, Y. Tian, Y. Zhu, X. Yao, W. Cao, Difference and potential of the upward and downward sun-induced chlorophyll fluorescence on detecting leaf nitrogen concentration in wheat, Remote Sens. 10 (2018) 1315, https://doi.org/10.3390/rs10081315.
[48] J. Jiang, Z. Zhang, Q. Cao, Y. Liang, B. Krienke, Y. Tian, Y. Zhu, W. Cao, X. Liu, Use of an active canopy sensor mounted on an unmanned aerial vehicle to monitor the growth and nitrogen status of winter wheat, Remote Sens. 12 (2020), https://doi.org/10.3390/rs12223684.
[49] E. Justes, B. Mary, J.-M. Meynard, J.-M. Machet, L. Thelier-Huche, Determination of a critical nitrogen dilution curve for winter wheat crops, Ann. Bot. 74 (1994) 397–407, https://doi.org/10.1006/anbo.1994.1133.
[50] J. Lammel, J. Wollring, S. Reusch, Tractor based remote sensing for variable nitrogen fertilizer application, in: W.J. Horst, M.K. Schenk, A. Bürkert, N. Claassen, H. Flessa, W.B. Frommer, H. Goldbach, H.-W. Olfs, V. Römheld, B. Sattelmacher, U. Schmidhalter, S.v. Schubert, N. Wirén, L. Wittenmayer (Eds.), Plant Nutrition: Food Security and Sustainability of Agro-Ecosystems through Basic and Applied Research, Springer Netherlands, Dordrecht, 2001, pp. 694–695, https://doi.org/10.1007/0-306-47624-X_336.
[51] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444, https://doi.org/10.1038/nature14539.
[52] Lemaire, G., 1997. Diagnosis of the nitrogen status in crops.
[53] G. Lemaire, M.-H. Jeuffroy, F. Gastal, Diagnosis tool for plant and crop N status in vegetative stage: theory and practices for crop N management, Eur. J. Agron. 28 (2008) 614–624, https://doi.org/10.1016/j.eja.2008.01.005.
[54] D. Li, X. Wang, H. Zheng, K. Zhou, X. Yao, Y. Tian, Y. Zhu, W. Cao, T. Cheng, Estimation of area- and mass-based leaf nitrogen contents of wheat and rice crops from water-removed spectra using continuous wavelet analysis, Plant Methods 14 (2018) 76, https://doi.org/10.1186/s13007-018-0344-1.
[55] D. Li, Y. Wu, K. Berger, Q. Kuang, W. Feng, J.M. Chen, W. Wang, H. Zheng, X. Yao, Y. Zhu, W. Cao, T. Cheng, Estimating canopy nitrogen content by coupling PROSAIL-PRO with a nitrogen allocation model, Int. J. Appl. Earth Obs. Geoinformation 135 (2024), https://doi.org/10.1016/j.jag.2024.104280.
[56] D. Li, S. Yang, Z. Du, X. Xu, P. Zhang, K. Yu, J. Zhang, M. Shu, Application of unmanned aerial vehicle optical remote sensing in crop nitrogen diagnosis: a systematic literature review, Comput. Electron. Agric. 227 (2024) 109565, https://doi.org/10.1016/j.compag.2024.109565.
[57] F. Li, M.L. Gnyp, L. Jia, Y. Miao, Z. Yu, W. Koppe, G. Bareth, X. Chen, F. Zhang, Estimating N status of winter wheat using a handheld spectrometer in the North China Plain, Field Crops Res 106 (2008) 77–85, https://doi.org/10.1016/j.fcr.2007.11.001.

[58] H. Li, C. Zhao, W. Huang, G. Yang, Non-uniform vertical nitrogen distribution within plant canopy and its estimation by remote sensing: a review, Field Crops Res 142 (2013) 75–84, https://doi.org/10.1016/j.fcr.2012.11.017.

[59] J. Li, Y. Ge, L.A. Puntel, D.M. Heeren, G. Bai, G.R. Balboa, J.A. Gamon, T. J. Arkebauer, Y. Shi, Integrating UAV hyperspectral data and radiative transfer model simulation to quantitatively estimate maize leaf and canopy nitrogen content, Int. J. Appl. Earth Obs. Geoinformation 129 (2024), https://doi.org/10.1016/j.jag.2024.103817.

[60] X. Li, S.T. Ata-UI-Karim, Y. Li, F. Yuan, Y. Miao, K. Yoichiro, T. Cheng, L. Tang, X. Tian, X. Liu, Y. Tian, Y. Zhu, W. Cao, Q. Cao, Advances in the estimations and applications of critical nitrogen dilution curve and nitrogen nutrition index of major cereal crops. A review, Comput. Electron. Agric. 197 (2022) 106998, https://doi.org/10.1016/j.compag.2022.106998.

[61] Y. Li, Y. Miao, S.T. Ata-UI-Karim, X. Liu, Y. Tian, Y. Zhu, W. Cao, Q. Cao, Sustainability assessment of nitrogen nutrition index based topdressing nitrogen application, Field Crops Res 307 (2024) 109260, https://doi.org/10.1016/j.fcr.2024.109260.

[62] Z. Li, X. Jin, G. Yang, J. Drummond, H. Yang, B. Clark, Z. Li, C. Zhao, Remote sensing of leaf and canopy nitrogen status in winter wheat (Triticum aestivum L.) based on N-PROSAIL model, Remote Sens 10 (2018) 1463, https://doi.org/10.3390/rs10091463.

[63] Z. Li, Z. Li, D. Fairbairn, N. Li, B. Xu, H. Feng, G. Yang, Multi-LUTs method for canopy nitrogen density estimation in winter wheat by field and UAV hyperspectral, Comput. Electron. Agric. 162 (2019) 174–182, https://doi.org/10.1016/j.compag.2019.04.005.

[64] H. Liu, H. Zhu, Z. Li, G. Yang, Quantitative analysis and hyperspectral remote sensing of the nitrogen nutrition index in winter wheat, Int. J. Remote Sens. 41 (2020) 858–881, https://doi.org/10.1080/01431161.2019.1650984.

[65] S. Liu, X. Bai, G. Zhu, Y. Zhang, L. Li, T. Ren, J. Lu, Remote estimation of leaf nitrogen concentration in winter oilseed rape across growth stages and seasons by correcting for the canopy structural effect, Remote Sens. Environ. 284 (2023) 113348, https://doi.org/10.1016/j.rse.2022.113348.

[66] J. Lowenberg-DeBoer, B. Erickson, Setting the record straight on precision agriculture adoption, Agron. J. 111 (2019) 1552–1569, https://doi.org/10.2134/agronj2018.12.0779.

[67] Ma, X., Chen, P., Jin, X., 2022. Predicting wheat leaf nitrogen content by combining deep multitask learning and a mechanistic model using UAV hyperspectral images. Remote Sens. 14. https://doi.org/10.3390/rs14246334.

[68] R.B. MacDonald, M.E. Bauer, R.D. Allen, J.W. Clifton, J.D. Erickson, D. A. Landgrebe, Results of the 1971 Corn Blight Watch Experiment (LARS Technical Reports No. Paper 107), 1972.

[69] S.S. Malhi, A.M. Johnston, J.J. Schoenau, Z.L. Wang, C.L. Vera, Seasonal biomass accumulation and nutrient uptake of wheat, barley and oat on a black Chernozem Soil in Saskatchewan, Can. J. Plant Sci. 86 (2006) 1005–1014, https://doi.org/10.4141/P05-116.

[70] E. Merlier, G. Hmimina, E. Dufrêne, K. Soudani, Explaining the variability of the photochemical reflectance index (PRI) at the canopy-scale: disentangling the effects of phenological and physiological changes, J. Photochem. Photobiol. B 151 (2015) 161–171, https://doi.org/10.1016/j.jphotobiol.2015.08.006.

[71] G.H. Mohammed, R. Colombo, E.M. Middleton, U. Rascher, C. van der Tol, L. Nedbal, Y. Goulas, O. Pérez-Priego, A. Damm, M. Meroni, J. Joiner, S. Cogliati, W. Verhoef, Z. Malenovský, J.-P. Gastellu-Etchegorry, J.R. Miller, L. Guanter, J. Moreno, I. Moya, J.A. Berry, C. Frankenberg, P.J. Zarco-Tejada, Remote sensing of solar-induced chlorophyll fluorescence (SIF) in vegetation: 50 years of progress, Remote Sens. Environ. 231 (2019) 111177, https://doi.org/10.1016/j.rse.2019.04.030.

[72] D.J. Mulla, Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps, Biosyst. Eng., Special Issue 114 (2013) 358–371, https://doi.org/10.1016/j.biosystemseng.2012.08.009.

[73] R. Näsi, N. Viljanen, J. Kaivosoja, K. Alhonoja, T. Hakala, L. Markelin, E. Honkavaara, Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features, Remote Sens. 10 (2018), https://doi.org/10.3390/rs10071082.

[74] C. Nguyen, V. Sagan, S. Bhadra, S. Moose, UAV multisensory Data fusion and Multi-task deep learning for high-throughput maize phenotyping, Sensors 23 (2023), https://doi.org/10.3390/s23041827.

[75] A. Nurunnabi, F.N. Teferle, J. Li, R.C. Lindenbergh, A. Hunegnaw, An efficient deep learning approach for ground point filtering in aerial laser scanning point clouds, in: Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLIII-B1-2021, 2021, pp. 31–38, https://doi.org/10.5194/isprs-archives-XLIII-B1-2021-31-2021.

[76] D. Oswald, A. Pourreza, M. Chakraborty, S.D.S. Khalsa, P.H. Brown, 3D radiative transfer modeling of almond canopy for nitrogen estimation by hyperspectral imaging, Precis. Agric. 26 (2024) 12, https://doi.org/10.1007/s11119-024-10207-z.

[77] F.M. Padilla, M. Gallardo, M.T. Peña-Fleitas, R. de Souza, R.B. Thompson, Proximal optical sensors for nitrogen management of vegetable crops: a review, Sensors 18 (2018) 2083, https://doi.org/10.3390/s18072083.

[78] M.K. Patel, J. Padarian, A.W. Western, G.J. Fitzgerald, A.B. McBratney, E. M. Perry, H. Suter, D. Ryu, Retrieving canopy nitrogen concentration and aboveground biomass with deep learning for ryegrass and barley: comparing models and determining waveband contribution, Field Crops Res. 294 (2023) 108859, https://doi.org/10.1016/j.fcr.2023.108859.

[79] S. Peanusaha, A. Pourreza, Y. Kamiya, M.W. Fidelibus, M. Chakraborty, Nitrogen retrieval in grapevine (*Vitis vinifera* L.) leaves by hyperspectral sensing, Remote Sens. Environ. 302 (2024) 113966, https://doi.org/10.1016/j.rse.2023.113966.

[80] J. Peng, K. Manevski, K. Korup, R. Larsen, M. Andersen, Random forest regression results in accurate assessment of potato nitrogen status based on multispectral data from different platforms and the critical concentration approach, Field Crops Res. 268 (2021), https://doi.org/10.1016/j.fcr.2021.108158.

[81] S. Peng, F.V. García, R.C. Laza, K.G. Cassman, Adjustment for specific leaf weight improves Chlorophyll Meter's estimate of rice leaf nitrogen concentration, Agron. J. 85 (1993) 987–990, https://doi.org/10.2134/agronj1993.00021962008500050005x.

[82] Y. Peng, W. Zhong, Z. Peng, Y. Tu, Y. Xu, Z. Li, J. Liang, J. Huang, X. Liu, Y. Fu, Enhanced estimation of rice leaf nitrogen content via the integration of hybrid preferred features and deep learning methodologies, Agronomy 14 (2024), https://doi.org/10.3390/agronomy14061248.

[83] E. Priya, S. Sarkar, P.K. Maji, A review on slow-release fertilizer: nutrient release mechanism and agricultural sustainability, J. Environ. Chem. Eng. 12 (2024) 113211, https://doi.org/10.1016/j.jece.2024.113211.

[84] J. Qi, D. Xie, T. Yin, G. Yan, J.-P. Gastellu-Etchegorry, L. Li, W. Zhang, X. Mu, L. K. Norford, LESS: largE-scale remote sensing data and image simulation framework over heterogeneous 3D scenes, Remote Sens. Environ. 221 (2019) 695–706, https://doi.org/10.1016/j.rse.2018.11.036.

[85] M.D. Raya-Sereno, M. Alonso-Ayuso, J.L. Pancorbo, J.L. Gabriel, C. Camino, P. J. Zarco-Tejada, M. Quemada, Residual effect and N fertilizer rate detection by high-resolution VNIR-SWIR hyperspectral imagery and solar-induced chlorophyll fluorescence in wheat, IEEE Trans. Geosci. Remote Sens. 60 (2022), https://doi.org/10.1109/TGRS.2021.3099624.

[86] R.N. Sahoo, R.G. Rejith, S. Gakhar, R. Ranjan, M.C. Meena, A. Dey, J. Mukherjee, R. Dhakar, A. Meena, A. Daas, S. Babu, P.K. Upadhyay, K. Sekhawat, S. Kumar, M. Kumar, V. Chinnusamy, M. Khanna, Drone remote sensing of wheat N using hyperspectral sensor and machine learning, Precis. Agric. 25 (2024) 704–728, https://doi.org/10.1007/s11119-023-10089-7.

[87] D. Shanmugavel, I. Rusyn, O. Solorza-Feria, S.-K. Kamaraj, Sustainable SMART fertilizers in agriculture systems: a review on fundamentals to in-field applications, Sci. Total Environ. 904 (2023) 166729, https://doi.org/10.1016/j.scitotenv.2023.166729.

[88] Y. Shi, B. Fu, N. Wang, Y. Cheng, J. Fang, X. Liu, G. Zhang, Spectral-spatial attention rotation-invariant classification network for airborne hyperspectral images, Drones 7 (2023) 240, https://doi.org/10.3390/drones7040240.

[89] B.S. Sibiya, J. Odindi, O. Mutanga, M.A. Cho, C. Masemola, The utility of radiative transfer models (RTM) on remotely sensed data in retrieving biophysical and biochemical properties of terrestrial biomes: a systematic review, Adv. Space Res. 75 (2025) 7424–7444, https://doi.org/10.1016/j.asr.2025.02.052.

[90] D.A. Sims, J.A. Gamon, Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages, Remote Sens. Environ. 81 (2002) 337–354, https://doi.org/10.1016/S0034-4257(02)00010-X.

[91] G.A. Slafer, F.H. Andrade, Physiological attributes related to the generation of grain yield in bread wheat cultivars released at different eras, Field Crops Res. 31 (1993) 351–367, https://doi.org/10.1016/0378-4290(93)90073-V.

[92] H. Středová, P. Fukalová, F. Chuchma, J. Haberle, T. Středa, Nitrates directive restriction: to change or not to change in terms of climate change, that is the question, Sci. Total Environ. 917 (2024) 170381, https://doi.org/10.1016/j.scitotenv.2024.170381.

[93] P. Sun, P.M. van Bodegom, J. Timmermans, S. Liu, J. Wu, M.D. Visser, Hybrid modelling of leaf traits: integrating neural networks with radiative transfer theory, Remote Sens. Environ. 329 (2025) 114958, https://doi.org/10.1016/j.rse.2025.114958.

[94] Y. Sun, J. Wen, L. Gu, J. Joiner, C.Y. Chang, C. van der Tol, A. Porcar-Castell, T. Magney, L. Wang, L. Hu, U. Rascher, P. Zarco-Tejada, C.B. Barrett, J. Lai, J. Han, Z. Luo, From remotely-sensed solar-induced chlorophyll fluorescence to ecosystem structure, function, and service: part II—Harnessing data, Glob. Change Biol. 29 (2023) 2893–2925, https://doi.org/10.1111/gcb.16646.

[95] R. Tanabe, T. Matsui, T.S.T. Tanaka, Winter wheat yield prediction using convolutional neural networks and UAV-based multispectral imagery, Field Crops Res 291 (2023) 108786, https://doi.org/10.1016/j.fcr.2022.108786.

[96] P.S. Thenkabail, R.B. Smith, E. De Pauw, Hyperspectral vegetation indices and their relationships with agricultural crop characteristics, Remote Sens. Environ. 71 (2000) 158–182, https://doi.org/10.1016/S0034-4257(99)00067-X.

[97] A. Upadhyay, N.S. Chandel, K.P. Singh, S.K. Chakraborty, B.M. Nandede, M. Kumar, A. Subeesh, K. Upendar, A. Salem, A. Elbeltagi, Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture, Artif. Intell. Rev. 58 (2025) 92, https://doi.org/10.1007/s10462-024-11100-x.

[98] Vavlas, N.-C., Seubring, T., Elhakeem, A., Kooistra, L., De Deyn, G., 2024. Remote sensing of cover crop legacies on main crop N-uptake dynamics (Dataset). https://doi.org/10.5281/zenodo.14711032.

[99] J. Verrelst, Z. Malenovský, C. Van der Tol, G. Camps-Valls, J.-P. Gastellu-Etchegorry, P. Lewis, P. North, J. Moreno, Quantifying vegetation biophysical variables from imaging spectroscopy data: a review on retrieval methods, Surv. Geophys. (2018), https://doi.org/10.1007/s10712-018-9478-y.

[100] J. Verrelst, J.P. Rivera-Caicedo, P. Reyes-Muñoz, M. Morata, E. Amin, G. Tagliabue, C. Panigada, T. Hank, K. Berger, Mapping landscape canopy nitrogen content from space using PRISMA data, ISPRS J. Photogramm. Remote Sens. 178 (2021) 382–395, https://doi.org/10.1016/j.isprsjprs.2021.06.017.

[101] S. Wakahara, Y. Miao, M. McNearney, C.J. Rosen, Non-destructive potato petiole nitrate-nitrogen prediction using chlorophyll meter and multi-source data fusion with machine learning, Eur. J. Agron. 164 (2025) 127483, https://doi.org/10.1016/j.eja.2024.127483.

[102] D. Wang, R. Li, T. Liu, S. Liu, C. Sun, W. Guo, Combining vegetation, color, and texture indices with hyperspectral parameters using machine-learning methods to estimate nitrogen concentration in rice stems and leaves, Field Crops Res. 304 (2023), https://doi.org/10.1016/j.fcr.2023.109175.
[103] D. Wang, M. Zhao, Z. Li, X. Wu, N. Li, D. Li, S. Xu, X. Liu, Classification of maize lodging types using UAV-SAR remote sensing data and machine learning methods, Comput. Electron. Agric. 227 (2024) 109637, https://doi.org/10.1016/j.compag.2024.109637.
[104] F. Wang, J. Zhang, W. Li, Y. Liu, W. Qin, L. Ma, Y. Zhang, Z. Sun, Z. Wang, F. Li, K. Yu, Characterization of N variations in different organs of winter wheat and mapping NUE using low altitude UAV-based remote sensing, Precis. Agric. 26 (2025) 40, https://doi.org/10.1007/s11119-025-10234-4.
[105] L. Wang, R. Gao, C. Li, J. Wang, Y. Liu, J. Hu, B. Li, H. Qiao, H. Feng, J. Yue, Mapping soybean maturity and biochemical traits using UAV-based hyperspectral images, Remote Sens. 15 (2023), https://doi.org/10.3390/rs15194807.
[106] S. Wang, K. Guan, Z. Wang, E.A. Ainsworth, T. Zheng, P.A. Townsend, N. Liu, E. Nafziger, M.D. Masters, K. Li, G. Wu, C. Jiang, Airborne hyperspectral imaging of nitrogen deficiency on crop traits and yield of maize by machine learning and radiative transfer modeling, Int. J. Appl. Earth Obs. Geoinformation 105 (2021) 102617, https://doi.org/10.1016/j.jag.2021.102617.
[107] S. Wang, K. Guan, C. Zhang, C. Jiang, Q. Zhou, K. Li, Z. Qin, E.A. Ainsworth, J. He, J. Wu, D. Schaefer, L.E. Gentry, A.J. Margenot, L. Herzberger, Airborne hyperspectral imaging of cover crops through radiative transfer process-guided machine learning, Remote Sens. Environ. 285 (2023), https://doi.org/10.1016/j.rse.2022.113386.
[108] Y. Wang, L. Suarez, T. Poblete, V. Gonzalez-Dugo, D. Ryu, P.J. Zarco-Tejada, Evaluating the role of solar-induced fluorescence (SIF) and plant physiological traits for leaf nitrogen assessment in almond using airborne hyperspectral imagery, Remote Sens. Environ. 279 (2022) 113141, https://doi.org/10.1016/j.rse.2022.113141.
[109] Z. Wang, A.K. Skidmore, R. Darvishzadeh, T. Wang, Mapping forest canopy nitrogen content by inversion of coupled leaf-canopy radiative transfer models from airborne hyperspectral imagery, Agric. For. Meteorol. 253–254 (2018) 247–260, https://doi.org/10.1016/j.agrformet.2018.02.010.
[110] M.S. Watt, H. Buddenbaum, E.M.C. Leonardo, H.J.C. Estarija, H.E. Bown, M. Gomez-Gallego, R. Hartley, P. Massam, L. Wright, P.J. Zarco-Tejada, Using hyperspectral plant traits linked to photosynthetic efficiency to assess N and P partition, ISPRS J. Photogramm. Remote Sens. 169 (2020) 406–420, https://doi.org/10.1016/j.isprsjprs.2020.09.006.
[111] J.-L. Widlowski, C. Mio, M. Disney, J. Adams, I. Andredakis, C. Atzberger, J. Brennan, L. Busetto, M. Chelle, G. Ceccherini, R. Colombo, J.-F. Côté, A. Eenmäe, R. Essery, J.-P. Gastellu-Etchegorry, N. Gobron, E. Grau, V. Haverd, L. Homolová, H. Huang, L. Hunt, H. Kobayashi, B. Koetz, A. Kuusk, J. Kuusk, M. Lang, P.E. Lewis, J.L. Lovell, Z. Malenovský, M. Meroni, F. Morsdorf, M. Mõttus, W. Ni-Meister, B. Pinty, M. Rautiainen, M. Schlerf, B. Somers, J. Stuckens, M.M. Verstraete, W. Yang, F. Zhao, T. Zenone, The fourth phase of the radiative transfer model intercomparison (RAMI) exercise: actual canopy scenarios and conformity testing, Remote Sens. Environ. 169 (2015) 418–437, https://doi.org/10.1016/j.rse.2015.08.016.
[112] Q. Xiao, W. Tang, C. Zhang, L. Zhou, L. Feng, J. Shen, T. Yan, P. Gao, Y. He, N. Wu, Spectral preprocessing combined with deep transfer learning to evaluate chlorophyll content in cotton leaves, Plant Phenomics (2022) 9813841, https://doi.org/10.34133/2022/9813841, 2022.
[113] H. Yang, Y. Hu, H. Yin, Q. Jin, F. Li, K. Yu, Improving potato leaf chlorophyll content prediction using a machine learning model with a hybrid dataset, Int. J. Remote Sens. (2025) 1–25, https://doi.org/10.1080/01431161.2025.2465916.
[114] H. Yang, H. Yin, F. Li, Y. Hu, K. Yu, Machine learning models fed with optimized spectral indices to advance crop nitrogen monitoring, Field Crops Res 293 (2023) 108844, https://doi.org/10.1016/j.fcr.2023.108844.
[115] C.R. Yendrek, T. Tomaz, C.M. Montes, Y. Cao, A.M. Morse, P.J. Brown, L. M. McIntyre, A.D.B. Leakey, E.A. Ainsworth, High-throughput phenotyping of Maize leaf physiological and biochemical traits using hyperspectral reflectance, Plant Physiol 173 (2017) 614–626, https://doi.org/10.1104/pp.16.01447.
[116] H. Yin, H. Yang, Y. Hu, F. Li, K. Yu, Identifying optimized spectral and spatial features of UAV-based RGB and multispectral images to improve potato nitrogen content estimation, Smart Agric. Technol. 12 (2025) 101255, https://doi.org/10.1016/j.atech.2025.101255.
[117] K. Yu, M.L. Gnyp, L. Gao, Y. Miao, X. Chen, G. Bareth, Estimate leaf chlorophyll of rice using reflectance indices and partial least squares, Photogramm. - Fernerkund. - Geoinformation (2015) 45–54, https://doi.org/10.1127/pfg/2015/0253, 2015.
[118] K. Yu, V. Lenz-Wiedemann, X. Chen, G. Bareth, Estimating leaf chlorophyll of barley at different growth stages using spectral indices to reduce soil background and canopy structure effects, ISPRS J. Photogramm. Remote Sens. 97 (2014) 58–77, https://doi.org/10.1016/j.isprsjprs.2014.08.005.
[119] K. Yu, M. Van Geel, T. Ceulemans, W. Geerts, M.M. Ramos, N. Sousa, P.M. L. Castro, P. Kastendeuch, G. Najjar, T. Ameglio, J. Ngao, M. Saudreau, O. Honnay, B. Somers, Foliar optical traits indicate that sealed planting conditions negatively affect urban tree health, Ecol. Indic. 95 (2018) 895–906, https://doi.org/10.1016/j.ecolind.2018.08.047.
[120] J. Yue, H. Yang, H. Feng, S. Han, C. Zhou, Y. Fu, W. Guo, X. Ma, H. Qiao, G. Yang, Hyperspectral-to-image transform and CNN transfer learning enhancing soybean LCC estimation, Comput. Electron. Agric. 211 (2023), https://doi.org/10.1016/j.compag.2023.108011.
[121] P.J. Zarco-Tejada, V. González-Dugo, J.A.J. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, Remote Sens. Environ., Remote Sens. Urban Environ. 117 (2012) 322–337, https://doi.org/10.1016/j.rse.2011.10.007.
[122] C. Zhang, J.M. Kovacs, The application of small unmanned aerial systems for precision agriculture: a review, Precis. Agric. 13 (2012) 693–712, https://doi.org/10.1007/s11119-012-9274-5.
[123] J. Zhang, T. Cheng, L. Shi, W. Wang, Z. Niu, W. Guo, X. Ma, Combining spectral and texture features of UAV hyperspectral images for leaf nitrogen content monitoring in winter wheat, Int. J. Remote Sens. 43 (2022) 2335–2356, https://doi.org/10.1080/01431161.2021.2019847.
[124] J. Zhang, Y. Hu, F. Li, K.G. Fue, K. Yu, Meta-analysis assessing potential of drone remote sensing in estimating plant traits related to nitrogen use efficiency, Remote Sens. 16 (2024) 838, https://doi.org/10.3390/rs16050838.
[125] X. Zhang, E.A. Davidson, D.L. Mauzerall, T.D. Searchinger, P. Dumas, Y. Shen, Managing nitrogen for sustainable development, Nature 528 (2015) 51–59, https://doi.org/10.1038/nature15743.
[126] Zhang, X., Han, L., Sobeih, T., Lappin, L., Lee, M., Howard, A., Kisdi, A., 2022b The self-supervised spectral-spatial attention-based transformer network for automated, accurate prediction of crop nitrogen status from UAV imagery. https://doi.org/10.48550/arXiv.2111.06839.
[127] Y. Zhao, J. Wang, L. Chen, Y. Fu, H. Zhu, H. Feng, X. Xu, Z. Li, An entirely new approach based on remote sensing data to calculate the nitrogen nutrition index of winter wheat, J. Integr. Agric. 20 (2021) 2535–2551, https://doi.org/10.1016/S2095-3119(20)63379-2.