

Review

Remote Sensing and Machine Learning for Monitoring Soil Nitrogen Dynamics and Crop Nitrogen Status in Field Conditions

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Abstract

Efficient nitrogen (N) management is essential for sustaining crop productivity while minimizing environmental impacts associated with nitrogen losses. However, the high spatial and temporal variability of soil nitrogen dynamics and crop nitrogen status makes field-scale monitoring challenging, while conventional soil and plant sampling methods are labor-intensive, destructive, and provide limited spatial coverage. Recent advances in remote sensing technologies and machine learning (ML) offer promising alternatives for high-throughput, non-destructive monitoring of crop nitrogen status and related nitrogen dynamics in agroecosystems. This review synthesizes current progress in the use of proximal and remote sensing platforms, including unmanned aerial vehicles (UAVs), satellites, and ground-based sensors for assessing crop nitrogen status and inferring soil nitrogen availability. We examine spectral, thermal, and structural indicators, together with emerging sensor-fusion and time-series approaches. We also evaluate ML algorithms, including emerging foundation model approaches, for estimating crop nitrogen status and inferring soil nitrogen indicators, highlighting their performance, limitations, and transferability across environments. Particular emphasis is placed on field-scale applications in heterogeneous and water-limited systems, where nitrogen-water interactions critically influence crop responses. Finally, we discuss current challenges, including data scarcity, model generalization, and operational constraints, and outline future directions toward integrated, real-time decision support systems for precision nitrogen management. Overall, this review provides a comprehensive framework for leveraging remote sensing and data-driven approaches to improve nitrogen monitoring and enhance nitrogen use efficiency in diverse cropping systems.



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1. Introduction

Nitrogen (N) is a fundamental nutrient governing plant growth, crop productivity, and global food security. Modern agricultural systems rely heavily on nitrogen fertilization to

achieve high yields; however, nitrogen use efficiency (NUE) remains low in many cropping systems, with estimates suggesting that less than 50% of applied nitrogen is effectively utilized by crops [1,2]. The remaining nitrogen is vulnerable to losses through leaching, volatilization, and denitrification, contributing to environmental challenges such as ground-water contamination, eutrophication, and greenhouse gas emissions [3,4]. These losses are strongly influenced by landscape characteristics, soil properties, hydrological processes, and management practices, highlighting the need for integrated monitoring approaches that account for both nitrogen dynamics and environmental transport processes [5]. Improving nitrogen management is therefore a central objective for sustainable agriculture.

A major constraint to improving NUE lies in the complex and dynamic nature of soil nitrogen processes and plant nitrogen uptake under field conditions. Soil nitrogen exists in multiple forms and undergoes rapid transformations driven by microbial activity, environmental factors, and management practices [6]. At the same time, crop nitrogen status varies spatially and temporally due to heterogeneity in soil properties, water availability, genotype, and agronomic inputs [7]. This variability is particularly pronounced in rainfed and water-limited agroecosystems, where interactions between nitrogen and water availability strongly influence crop growth and yield [8].

Traditional methods for assessing soil nitrogen and crop nitrogen status, such as soil sampling, laboratory analysis, and plant tissue measurements, provide accurate but localized information [9]. However, these approaches are labor-intensive, time-consuming, and destructive, limiting their applicability for large-scale or high-frequency monitoring. Consequently, they are often insufficient for capturing the spatial and temporal variability required for precision nitrogen management [10].

Recent advances in remote sensing technologies provide new opportunities to overcome these limitations. Platforms such as satellites, unmanned aerial vehicles (UAVs), and ground-based sensors enable non-destructive, high-throughput monitoring of crop and soil conditions across multiple spatial and temporal scales [11–13]. Spectral reflectance data, particularly in the visible and near-infrared regions, have been widely used to estimate vegetation properties related to nitrogen status, including chlorophyll content, leaf area index (LAI), and biomass [14,15]. Additionally, hyperspectral and thermal sensors offer enhanced capabilities for detecting subtle variations in plant physiological status associated with nitrogen availability [16]. Beyond crop monitoring, emerging studies have explored the indirect estimation of soil nitrogen dynamics by integrating vegetation signals, soil properties, and environmental variables with remote sensing data [10,17].

Parallel to these developments, machine learning (ML) approaches have gained prominence as powerful tools for modeling complex, nonlinear relationships between remotely sensed data and nitrogen-related variables. Algorithms such as random forests, support vector machines, gradient boosting methods, and deep learning architectures have been successfully applied to predict crop nitrogen content, biomass, and yield [18–20]. More recently, ML techniques have been extended to estimate soil nitrogen indicators, including nitrate concentration and total nitrogen, by integrating multisource datasets [21–23]. The combination of remote sensing and ML enables improved prediction accuracy and scalability, particularly when dealing with large, high-dimensional datasets.

Despite these advances, several challenges remain. Model performance often depends on site-specific conditions, limiting transferability across environments [24–26]. Data availability, quality, and standardization continue to constrain model development, especially in underrepresented regions such as sub-Saharan Africa [27–29]. Further, the integration of remote sensing and ML outputs into actionable decision support systems for nitrogen management is still in its early stages [30].

Although remote sensing and machine learning have each been reviewed extensively in agricultural contexts, existing reviews have generally focused on individual sensing platforms, specific machine learning techniques, or particular crop applications. Fewer reviews have examined how these approaches can be integrated to monitor crop nitrogen status, infer soil nitrogen dynamics, and support field-scale nitrogen management. Current reviews rarely address the emerging transition from traditional ML algorithms toward deep learning and foundation model approaches.

Important gaps remain in synthesizing how nitrogen-water interactions affect remote sensing signals in heterogeneous and water-limited environments, how model transferability limits operational deployment and how emerging deep learning and foundation model approaches may complement traditional ML algorithms.

In addition, data scarcity and limited validation in underrepresented regions, including sub-Saharan Africa, continue to constrain the development of globally applicable precision nitrogen management tools. This review addresses these gaps by providing a multi-scale framework that links soil and crop nitrogen status, evaluates advances in remote sensing and data-driven modeling, and highlights operational constraints affecting deployment across diverse agroecosystems. This review aims to synthesize current knowledge on the use of remote sensing and machine learning for monitoring soil nitrogen dynamics and crop nitrogen status under field conditions. Specifically, we (i) examine the principles and limitations of conventional nitrogen assessment methods; (ii) review advances in remote sensing technologies for detecting nitrogen-related traits in crops and soils; (iii) evaluate machine learning approaches for predicting nitrogen variables; and (iv) discuss opportunities and challenges for integrating these tools into precision nitrogen management frameworks. By providing a comprehensive and critical analysis, this review seeks to support the development of scalable, data-driven strategies to improve nitrogen use efficiency in diverse agroecosystems.

The remainder of the manuscript is organized as follows. Section 2 describes the literature search methodology. Sections 3–7 provide a comprehensive overview of conventional nitrogen assessment methods, recent advances in remote sensing technologies, machine learning approaches, crop-model integration, and key concepts related to nitrogen monitoring and prediction. Section 8 presents representative case studies demonstrating the application of these approaches across diverse crops and production environments. Sections 9 and 10 discuss the major technical, agronomic, and operational challenges, together with emerging opportunities and future research directions for advancing robust, scalable, and data-driven precision nitrogen management. Finally, Section 11 concludes with the key findings and broader implications.

2. Methods

This study was designed as a structured narrative review using a systematic literature search to provide a comprehensive synthesis of remote sensing and machine learning (ML) applications for monitoring soil and crop nitrogen status. A structured literature search was conducted across major electronic databases, including Web of Science, Scopus, and Google Scholar. The search strategy utilized combinations of key terms, such as (“remote sensing” OR “UAV” OR “satellite” OR “proximal sensing”) AND (“machine learning” OR “deep learning” OR “foundation models”) AND (“soil nitrogen” OR “crop nitrogen status” OR “nitrogen use efficiency” OR “nitrate”). The search included peer-reviewed journal articles, review papers, books, chapters, indexed conference proceedings, and selected preprints relevant to rapidly emerging topics such as foundation models, published through May 2026.

Publications were screened using predefined inclusion and exclusion criteria. Studies were included if they focused on remote sensing, machine learning, or AI-based approaches for assessing soil or crop nitrogen status and provided sufficient methodological detail. Duplicate records, studies unrelated to nitrogen monitoring, non-scientific publications, and articles lacking technical relevance were excluded. The remaining studies were screened based on title, abstract, and full-text evaluation, resulting in a final selection of 157 publications for qualitative synthesis. As a structured narrative review, this study provides a qualitative synthesis of the literature rather than a formal systematic review or quantitative meta-analysis; stage-specific numerical exclusion counts were not prospectively recorded. Consequently, the emphasis is on identifying methodological trends, emerging technologies, research gaps, and future directions rather than statistically comparing model performance across studies.

The final set of selected publications ($n = 153$) was reviewed to extract relevant thematic information, including the sensing platforms used (e.g., UAV, satellite, ground-based), spectral indicators evaluated (multispectral vs. hyperspectral data), machine learning algorithms applied, and targeted soil or plant nitrogen metrics (e.g., total nitrogen, nitrate, chlorophyll content, biomass). To ensure a broad perspective, attention was given to the geographical distribution of the studies, model transferability and data scarcity or operational constraints across diverse agroecosystems, including underrepresented regions such as sub-Saharan Africa. The synthesized findings were qualitatively evaluated to identify current research gaps, performance limitations, and future directions for real-time precision nitrogen management.

3. Conventional Methods for Nitrogen Assessment

Before the emergence of remote sensing and machine learning approaches, nitrogen assessment relied primarily on direct measurements of soil and plant samples. These conventional methods remain the reference standard for quantifying nitrogen status and continue to play a critical role in calibration, validation, and fertilizer management studies. The main approaches include soil sampling, laboratory analysis, and plant tissue analysis.

Soil Sampling: Soil sampling remains the foundation of nitrogen assessment and nutrient management in agricultural systems. Soil samples collected from different depths and locations are analyzed to determine nitrate (NO_3^- -N), ammonium (NH_4^+ -N), total nitrogen, and other soil fertility indicators. These measurements provide valuable information for fertilizer recommendations and environmental monitoring; however, the strong spatial and temporal variability of soil nitrogen often requires intensive sampling to obtain representative estimates [31,32].

Laboratory Analysis: Laboratory methods, including Kjeldahl digestion, combustion-based elemental analysis, and colorimetric assays for nitrate or ammonium, provide reference measurements for different soil and plant nitrogen pools. These methods provide accurate and reliable measurements of soil and plant nitrogen status and are routinely used in agronomic research and nutrient management programs [9,33]. Nevertheless, laboratory analyses are often time-consuming, costly, and dependent on specialized equipment and trained personnel.

Plant Tissue Analysis: Plant tissue analysis provides a direct assessment of crop nutritional status by measuring nitrogen concentration in leaves, stems, or whole-plant samples. Indicators such as leaf nitrogen content (LNC) and plant nitrogen concentration (PNC) are commonly used to diagnose nitrogen deficiencies, evaluate fertilizer effectiveness, and establish critical nitrogen thresholds for crop management [34,35]. Because tissue nitrogen reflects actual crop uptake, it is often considered one of the most reliable indicators

of plant nitrogen status. However, interpretation depends on crop species, growth stage, sampled tissues, and the availability of calibrated critical nitrogen thresholds.

Limitations of Conventional Approaches: Despite their accuracy, conventional nitrogen assessment methods provide localized snapshots of soil and crop nitrogen status. Soil and plant tissue analyses are destructive, labor-intensive, and often require substantial time between sampling and obtaining results. Furthermore, measurements are typically collected from a limited number of locations, resulting in low spatial resolution and reduced ability to characterize within-field variability. These constraints make repeated monitoring across large agricultural areas difficult and costly, limiting scalability for precision agriculture applications and motivating the development of remote sensing and machine-learning-based alternatives [10,11].

Figure 1 compares conventional and remote sensing approaches for nitrogen assessment. While soil sampling, laboratory analysis, and plant tissue analysis provide accurate reference measurements, they are often destructive, labor-intensive, and limited in spatial coverage. In contrast, proximal, UAV, and satellite sensing can extend nitrogen monitoring across larger areas and repeated time points, supporting precision nitrogen management when calibrated and validated against field measurements.

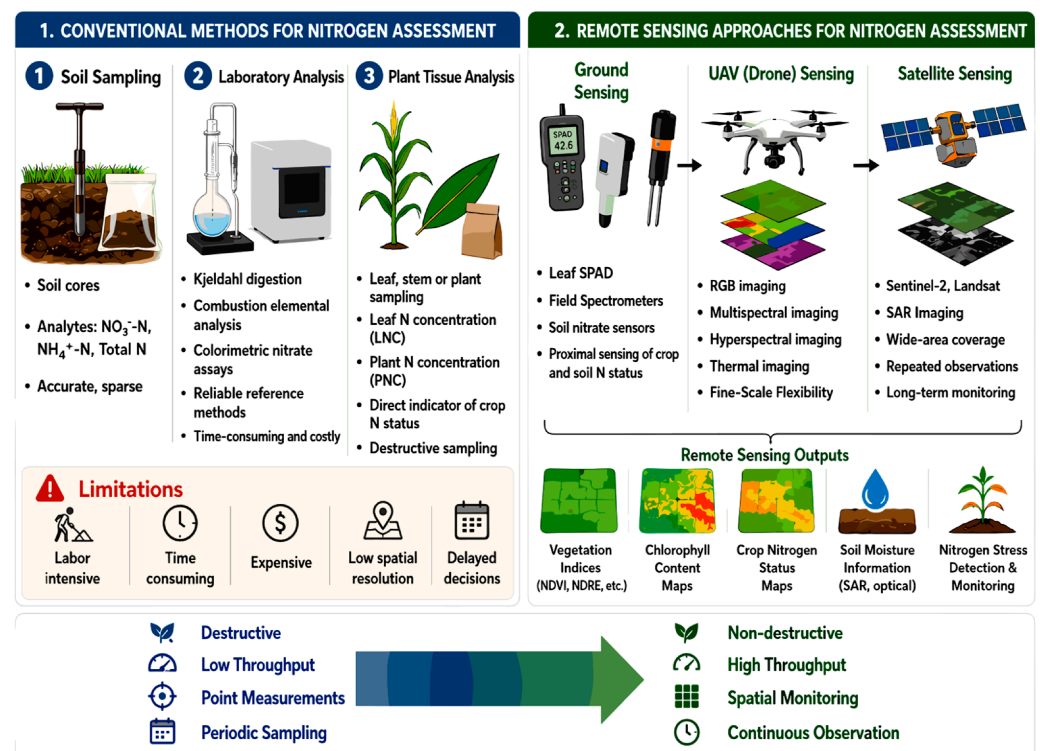


Figure 1. Conceptual overview of conventional methods and multi-scale remote sensing approaches for agricultural nitrogen assessment. Top: Conventional workflow including soil auger sampling, laboratory analysis equipment, and plant tissue collection. Middle: Remote sensing platforms spanning proximal ground instruments (e.g., SPAD meter, active optical leaf sensor, and soil probe), UAV / drone, SAR (synthetic aperture radar) imaging, and satellite observation. Bottom: Comparison of outputs and limitations between conventional and remote sensing methods. (Note: NO_3^- -N = nitrate-nitrogen; NH_4^+ -N = ammonium-nitrogen).

Despite their limitations in labor, cost, and scalability, conventional soil and plant analyses remain the reference standard for nitrogen assessment. These measurements are indispensable for calibrating and validating remote sensing observations, developing robust machine learning models, and evaluating crop-model predictions. Consequently, advances in remote sensing and AI should be viewed as complementary technologies that enhance,

rather than replace, conventional field and laboratory measurements. Building upon this foundation, the following section reviews recent advances in remote sensing technologies that enable high-throughput, non-destructive monitoring of crop nitrogen status while continuing to rely on conventional measurements for calibration and validation.

4. Recent Advances in UAV-Based Phenotyping for Nitrogen Monitoring

Unmanned aerial vehicles (UAVs) have become an important platform for crop nitrogen (N) phenotyping because they help bridge the scale gap between destructive ground sampling and coarser satellite observations [36,37]. By flying relatively close to the crop canopy, commonly at altitudes of approximately 20–120 m, UAVs can acquire high-resolution imagery at field, plot, or sub-plot scales. Their flexible deployment also allows image acquisition at key crop growth stages and can partially mitigate limitations imposed by satellite revisit intervals or cloud-contaminated imagery [38]. These properties make UAVs useful for capturing within-field spatial heterogeneity in crop N status, especially in heterogeneous and water-limited agroecosystems. A recent review of UAV-based hyperspectral N monitoring reported that published studies are concentrated mainly in crops such as wheat, maize, rice, and potato, with stronger representation in Europe and Asia and comparatively fewer studies from Africa and Latin America [36]. The following subsections summarize the main UAV sensor modalities used for N phenotyping, the vegetation indices derived from them, and current developments in sensor fusion.

4.1. Sensors

RGB: RGB cameras are widely used on UAV platforms for crop N monitoring because they are relatively low-cost, easy to operate, and capable of producing high-resolution imagery [39]. RGB imagery can provide several types of features for N estimation, including visible-band vegetation indices (VIs) such as ExG, GLI, VARI, and NGRDI; color-based features from different color spaces such as HSV or $L^*a^*b^*$; and canopy traits such as canopy cover, plant height estimated from UAV image reconstruction, and image texture features [39,40]. In winter wheat, combining RGB vegetation indices, canopy color features, and texture information improved N estimation and produced results comparable to multispectral approaches when modeled with Gaussian process regression [39]. In rice, an RGB-based study found that models performed best at the leaf scale, while canopy- and plot-scale predictions were less accurate but still useful. At the canopy scale, separating rice plants from the soil background improved model performance. The plot-scale results also suggested that UAV flight altitude did not strongly affect accuracy within the tested range, although canopy- and plot-level models were more sensitive to environmental differences than leaf-level models [40].

The main limitation of RGB sensors is their restricted spectral resolution. With only three broad visible bands, RGB imagery cannot capture red-edge and near-infrared (NIR) regions, which are often informative for chlorophyll- and N-related responses [36,41]. RGB-based estimates are also sensitive to illumination conditions, shadows, solar angle, canopy structure, and soil background, which can complicate comparisons across flights. However, in resource-limited settings, the simplicity and affordability of RGB phenotyping can be an advantage. For example, UAV-derived RGB/green-based vegetation information has been used to assess maize vigor and yield in complex smallholder farming systems in sub-Saharan Africa, suggesting that low-cost UAV imaging can provide an entry point for precision crop monitoring where multispectral or hyperspectral systems are less accessible [42].

Multispectral: Multispectral cameras typically capture 4–10 discrete bands across the visible, red-edge, and NIR regions and are widely used for UAV-based N phenotyping [41,43]. Red-edge bands, usually around 710–740 nm, are useful for N monitoring

because they respond strongly to changes in chlorophyll content, which is closely related to leaf N status. Compared with NDVI, red-edge indices often remain more sensitive when crop canopies become dense later in the season [43,44].

Multispectral data can provide practical N-monitoring performance at lower cost and lower processing complexity than hyperspectral data. A recent winter wheat study compared UAV hyperspectral data with simulated multispectral data from DJI P4M, PlanetScope, and Sentinel-2 for estimating plant nitrogen concentration. Although hyperspectral data generally produced slightly higher accuracy, optimized multispectral indices from PlanetScope- and Sentinel-2-like bands achieved comparable performance when combined with machine learning models such as random forest and support vector regression. These findings indicate that optimized multispectral data can approach hyperspectral performance for crop N monitoring when appropriate feature-selection strategies and ML models are used. However, practical transfer remains constrained by cross-scale differences between UAV hyperspectral imagery and operational multispectral or satellite observations, including spatial-resolution mismatch, atmospheric effects, sensor viewing geometry, temporal revisit intervals, and greater heterogeneity under real field conditions [38].

Hyperspectral: UAV-mounted hyperspectral sensors acquire hundreds of narrow, contiguous bands across the visible, near-infrared, and short-wave infrared regions, allowing researchers to extract detailed spectral features related to chlorophyll content, canopy biochemical properties, and plant physiological responses associated with N status [36,45–47]. However, these signals can be influenced by crop growth stage, canopy structure, water status, illumination conditions, and sensor calibration. Therefore, hyperspectral-based N estimation usually requires careful preprocessing, feature selection, and validation against field-measured N data.

Because hyperspectral imagery produces high-dimensional data with many correlated bands, effective N estimation often depends on feature selection, dimensionality reduction, and appropriate modeling strategies. For example, one UAV hyperspectral study used vegetation-index selection with random forest regression and support vector regression to estimate maize LNC and LNA [48]. For more complex field conditions where N and water stress occur together, a multimodal approach combining UAV hyperspectral, RGB, and thermal imagery improved stress classification compared with hyperspectral-derived trait maps alone [49].

Overall, hyperspectral imagery has strong potential for fine-scale crop N estimation because it captures detailed spectral variation that may be missed by broader multispectral bands. However, its practical advantage depends on data quality, calibration, feature-selection strategy, model robustness, and validation across independent field conditions. The high dimensionality of hyperspectral data can also increase the risk of overfitting when ground-truth N measurements are limited. Therefore, hyperspectral sensing should be viewed as a powerful but data- and processing-intensive approach rather than an automatically superior solution for every N-monitoring application.

Thermal: Thermal infrared (TIR) sensors measure canopy radiometric temperature, which is closely linked to transpiration, stomatal conductance, and crop water status. Therefore, TIR imagery is more directly related to water stress than to N status. However, it can still support N monitoring when combined with spectral imagery because water stress and N deficiency often produce overlapping effects on canopy vigor, biomass, and reflectance. UAV-based thermal studies commonly use canopy temperature or the Crop Water Stress Index (CWSI) to assess crop water status, but reliable use of TIR data requires careful radiometric calibration, accurate canopy-soil separation, and appropriate flight timing because canopy temperature is affected by environmental conditions such as time of day, humidity, wind, and irrigation status [50–52]. In winter wheat, optimized extraction of

canopy temperature improved CWSI-based diagnosis of water stress compared with using raw or less refined thermal information [52]. Recent work on sesame further showed that combining UAV hyperspectral, RGB, and thermal imagery improved the classification of combined N and water treatments compared with hyperspectral-derived trait maps alone, highlighting the value of multimodal sensing for separating interacting stress signals [49].

Sensor fusion: No single UAV sensor fully captures the different components of crop N status. Spectral sensors provide information related to canopy reflectance, chlorophyll, and biochemical status; thermal sensors capture canopy temperature and plant water status; and LiDAR or SfM-derived 3-D data provide structural information such as canopy height, density, and biomass. Because crop N responses are often linked with both canopy biochemistry and canopy structure, combining multiple sensing modalities can improve the characterization of N-related traits. In maize, UAV-based fusion of hyperspectral, thermal, and LiDAR data within a multi-task deep learning framework has been used to predict multiple phenotypic traits, including grain N content, total plant N content, biomass, and yield [53]. In sugarcane, multispectral imagery and UAV LiDAR were used to predict fine-scale biomass and leaf N content; however, combining multispectral and LiDAR predictors did not significantly outperform the best single-sensor models for biomass prediction [54]. Similarly, integration of UAV multispectral data with proximal hyperspectral sensing has been explored for maize canopy nitrogen estimation [55]. These findings suggest that the value of sensor fusion depends on the crop, target trait, growth stage, sensor combination, model design, and the quality of spatial and temporal alignment among datasets.

Recent developments in UAV sensing have expanded beyond conventional RGB and multispectral imaging to include lightweight snapshot multispectral sensors, compact hyperspectral cameras, multimodal systems integrating thermal and spectral information, and UAV-mounted LiDAR platforms. These advances have improved the ability to characterize crop nitrogen status, canopy structure, and field variability at increasingly finer spatial and temporal scales. Figure 2 summarizes the major UAV sensor modalities used for crop nitrogen monitoring and highlights their complementary roles in precision nitrogen management.

Representative commercial sensors are shown for educational and illustrative purposes only. Inclusion does not constitute endorsement, recommendation, or commercial affiliation. Equivalent sensors from other manufacturers may provide similar capabilities.

4.2. Vegetation Indices for Nitrogen

Vegetation indices remain among the most widely used and interpretable features for linking canopy reflectance with crop N status. In most UAV-based studies, these indices are used as indirect N proxies because they capture changes in chlorophyll content, canopy greenness, biomass, and crop vigor rather than N itself. This relationship is biologically meaningful because leaf pigments strongly influence visible reflectance, while canopy structure and leaf area strongly affect near-infrared reflectance [44,56]. Therefore, vegetation indices that combine visible, red-edge, and near-infrared bands can provide useful information about crop N status, although their performance depends on crop species, growth stage, canopy density, soil background, and environmental stress conditions.

The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used indices for assessing crop vigor and nutrient-related stress. It is useful during early growth stages when canopy cover is still developing, but its sensitivity can decrease once the canopy becomes dense because red and near-infrared reflectance may begin to saturate. For this reason, red-edge-based indices are often preferred for N monitoring in dense canopies. Indices such as the Normalized Difference Red Edge (NDRE), red-edge chlorophyll indices, and the Canopy Chlorophyll Content Index (CCCI) use red-edge

information that is closely related to chlorophyll variation and can remain more sensitive than broadband NDVI under some crop conditions [44,56]. In menthol mint, for example, NDRE showed the strongest relationship with foliar N concentration among the tested vegetation indices, followed by red-edge NDVI and simple ratio indices [57]. Similarly, CCCI has been reported as a useful index for assessing crop N status because it combines information related to canopy cover and chlorophyll-sensitive red-edge reflectance [58].

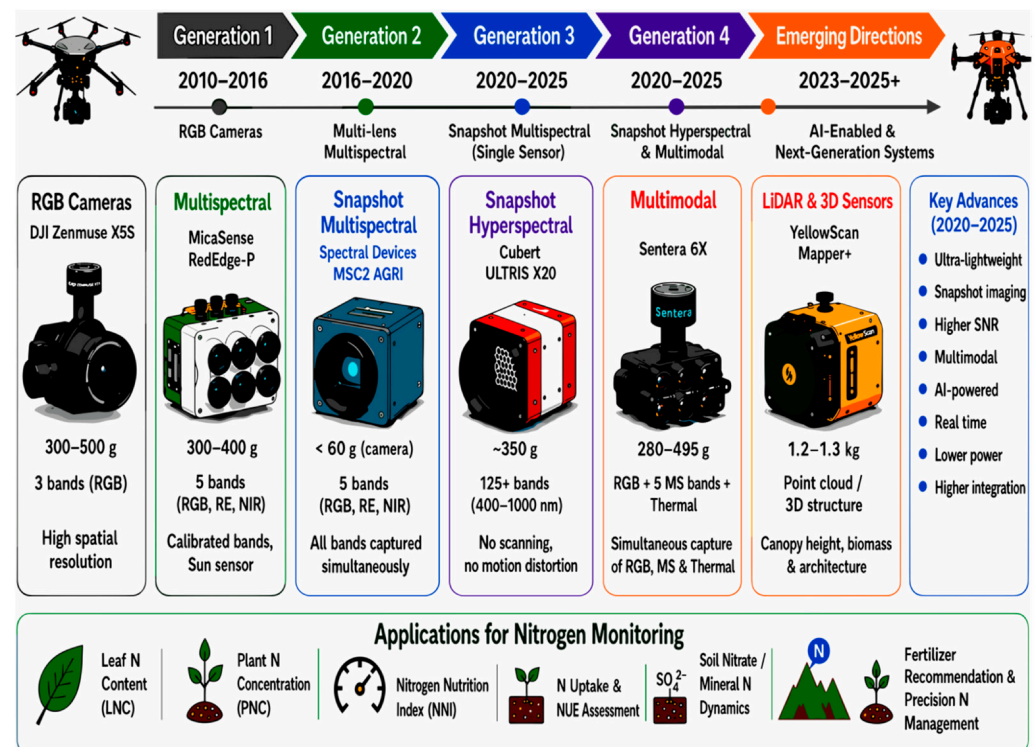


Figure 2. Technological evolution of UAV sensors for nitrogen monitoring, including multispectral, hyperspectral, multimodal, and LiDAR-based systems. *Note: Specifications are indicative and may vary by model and configuration. Sources: Manufacturer datasheets and recent product announcements (2020–2025).*

Pigment-sensitive and stress-related indices such as PRI, NPCI, and SIPI can also provide complementary information, particularly when N stress interacts with changes in pigment composition or photosynthetic activity. However, these indices are usually more useful as additional features within multivariate or machine learning models than as standalone N indicators. This is because individual indices capture only part of the crop response and may be affected by other stresses such as drought, disease, or differences in canopy architecture.

Two important considerations should guide the use of vegetation indices for N monitoring. First, the most informative index can vary across growth stages. NDVI and soil-adjusted indices may be more useful when the canopy is sparse, whereas red-edge indices often become more informative once the canopy is well developed and chlorophyll-related variation becomes more important. Second, soil background can strongly influence reflectance under sparse canopy conditions. This makes soil-adjusted indices such as SAVI, MSAVI2, and OSAVI, as well as canopy segmentation before index calculation, useful for reducing non-vegetation effects [40,41].

For physiology-based N diagnosis, the Nitrogen Nutrition Index (NNI) provides a more direct agronomic measure of crop N status because it relates actual plant N concentration to the critical N concentration required for optimal growth. However, NNI cannot be retrieved from a single reflectance measurement alone because it depends on both plant

N concentration and biomass. Therefore, UAV-derived vegetation indices, hyperspectral bands, and structural traits are increasingly used as input variables in machine learning models to estimate or map NNI across fields [59,60]. More broadly, recent studies are moving away from relying on a single vegetation index and instead combine multiple indices, texture features, structural traits, and spectral variables within ML pipelines. Such approaches allow feature-selection or learning algorithms to identify combinations of variables that better capture crop N variability than any single index alone [55,61].

While sensing technologies provide the observational foundation for nitrogen monitoring, transforming these data into accurate estimates of soil and crop nitrogen requires advanced machine learning and artificial intelligence approaches, which are discussed in the following section.

5. Machine Learning for Nitrogen Estimation

The transition from index-based regression to machine learning (ML) has been a major methodological shift in UAV- and satellite-based N monitoring over the past decade [36,61]. ML models can handle high-dimensional, nonlinear, and correlated inputs from multi-sensor or multi-temporal datasets, and they can also incorporate soil, weather, terrain, and management covariates that are difficult to include in simple empirical index-based models [62,63]. This section reviews the main model families used for N estimation, from classical ML and deep learning to emerging foundation-model and decision-support AI approaches, and then summarizes their applications to two representative prediction targets: leaf N content as a canopy trait and soil nitrate or soil N as soil-related properties.

5.1. Models

Classical machine learning: Random Forest (RF), Support Vector Machine/Regression (SVM/SVR), Partial Least Squares Regression (PLSR), Gradient Boosting Machines (GBM), and boosted variants such as XGBoost, LightGBM, and CatBoost are commonly used for N prediction from remote sensing [36,61]. These methods are useful because they can handle correlated spectral inputs, provide some level of feature importance or interpretability, and often perform well with the modest training sample sizes typical of field trials [61,64]. RF in particular is widely used as a baseline model. In maize, an RF model trained on UAV VIs and Landsat-8 imagery achieved $R^2 = 0.64$ and $RMSE = 0.58$ for leaf N content, outperforming SVM, LSTM, XGBoost, and linear regression in 10-fold cross-validation [65]. In a winter wheat study conducted across the 2023 and 2024 growing seasons, UAV multispectral vegetation indices and hyperspectral reflectance bands were used for cross-year prediction of the Nitrogen Nutrition Index. The study compared MLR, RF, XGBoost, KNN, and the Extra Tree models and found that using the top 10 multispectral vegetation indices generally improved prediction accuracy. Among the tested models in this study, ExtraTree achieved the best performance, with $R^2 = 0.60$, $RMSE = 0.14$, and $MAE = 0.12$, and its spatial prediction maps captured within-field variability in winter wheat N status [60].

PLSR remains widely used for hyperspectral data because it can handle multicollinearity among adjacent spectral bands, while SVR is often applied to small-sample and high-dimensional datasets. For high-dimensional spectral datasets, recent studies increasingly use hybrid pipelines that combine feature selection with machine learning or deep learning models. In rice canopy, LNC estimation, a combined PCC-XGBoost feature-selection strategy improved nitrogen inversion from UAV hyperspectral imagery, with the DNN model showing the strongest performance among the evaluated models for field-scale LNC mapping [66].

These studies suggest that selecting informative spectral, texture, and index-based features before model training can improve nitrogen estimation while also making model interpretation more practical. However, for precision N management, accurate prediction alone may not be sufficient. Prediction models do not necessarily estimate the causal effect of additional nitrogen fertilizer on yield. When models are trained using observational farm data, fertilizer rates are often not randomly assigned; instead, farmers may apply more or less N based on prior knowledge of soil fertility, yield potential, or field history. This can create confounding, meaning that conventional predictive ML models may identify correlations without accurately estimating how crops would respond to additional N. To address this limitation, recent work has explored causal machine learning approaches such as Double Machine Learning, doubly robust learners, and causal forests. These methods aim to estimate heterogeneous N treatment effects by integrating remote sensing, soil, climatic, and management data, allowing decision-support systems to identify field zones where additional N is likely to increase yield while avoiding overfertilization in non-responsive areas [62].

Deep learning and convolutional neural networks: Deep learning extends traditional ML by learning hierarchical features from raw imagery, spectral vectors, or full spectral cubes, reducing reliance on manually designed vegetation indices and hand-crafted features [67]. One-dimensional CNNs are particularly useful for hyperspectral data because they can model patterns across spectral bands. In wheat, a recent study integrated a spatial attention mechanism into a 1D-CNN to emphasize spectral features more strongly associated with leaf nitrogen concentration, and this model outperformed PLSR, SVR, baseline 1D-CNN, and 1D-ResNet approaches [67]. Two- and three-dimensional CNNs can further incorporate spatial or spatio-spectral information, allowing models to capture canopy texture, row structure, and spatial heterogeneity in addition to spectral variation. These features may be useful when soil background, canopy architecture, or genotype-specific growth patterns affect the spectral signal [61,64].

When multi-date UAV or satellite imagery is available, temporal models such as LSTM, GRU, or Transformer-based architectures can be used to capture crop development across phenological stages. Instead of relying on a single image date, these models can learn patterns in canopy change over time, which may be useful for monitoring dynamic traits such as crop growth, stress development, and N status. However, deep learning models often require larger labeled datasets than classical ML methods and can be sensitive to domain shifts across sites, seasons, sensors, and crop varieties. These limitations motivate the use of transfer learning, data augmentation, self-supervised learning, and foundation-model approaches, which are discussed in the next section.

Foundation models: Foundation models are large neural networks that are pre-trained on broad datasets and then adapted to specific downstream tasks. In remote sensing, recent models such as Prithvi and other geospatial foundation models have shown the potential of self-supervised or weakly supervised pre-training for learning general representations from satellite imagery [68,69]. These approaches are attractive for agricultural applications because many crop-monitoring tasks, including N estimation, are constrained by limited labeled field data. However, direct applications of foundation models to UAV-scale nitrogen estimation remain limited. Most current geospatial foundation models are trained primarily on satellite imagery, whereas UAV-based nitrogen monitoring often relies on very high-resolution RGB, multispectral, hyperspectral, or thermal data with different spatial resolutions, viewing geometries, and spectral band configurations. For N monitoring, the main value of foundation models lies in their potential to improve transferability and reduce dependence on large labeled datasets. Remote sensing foundation models can learn spatial, spectral, and temporal patterns from large image archives, while agriculture-

specific models such as AgriFM indicate a growing shift toward domain-adapted models for crop mapping and agricultural monitoring [70]. Emerging multimodal foundation models further extend this capability by integrating heterogeneous data sources, including optical imagery, SAR, LiDAR, temporal observations, and ancillary environmental information, to learn richer representations for Earth observation and agricultural applications [70]. Although these architectures have demonstrated considerable potential for multi-source remote sensing tasks, their application to UAV-based crop nitrogen estimation remains limited. Future research should prioritize the development of UAV-specific multimodal pre-training datasets, cross-platform transfer learning strategies, standardized benchmark datasets, and field-scale validation across diverse crops and environmental conditions.

Fine-tuning frameworks such as FARM further suggest that geospatial foundation models can be adapted to agricultural tasks using limited labeled data [71]. However, direct applications of foundation models to UAV-scale N estimation are still limited. Because these pre-trained weights are inherited from satellite platforms, adapting them to UAV-based N monitoring requires overcoming significant differences in spatial resolution, viewing geometry, and spectral band configurations. Therefore, future work is needed to develop band-adaptation strategies, UAV-specific pre-training datasets, and robust fine-tuning protocols before foundation models can be reliably used for operational crop N estimation.

Large language models and agentic AI: Large language models and agentic AI are not nitrogen-estimation models in the same sense as RF, SVR, CNNs, or geospatial foundation models, but they may support the broader nitrogen-monitoring workflow. Rather than directly estimating N status from imagery, LLMs excel at integrating heterogeneous information, including remote sensing outputs, weather data, soil information, crop-management records, and agronomic literature [72,73]. In this role, LLMs may be useful for summarizing model outputs, generating management reports, explaining uncertainty, and assisting researchers or agronomists in interpreting complex multi-source datasets.

Agentic AI extends this idea by allowing an AI system to coordinate multiple tools or models toward a management objective. In precision agriculture, an agentic system could potentially connect UAV image-processing pipelines, N prediction models, crop-growth models, soil databases, weather forecasts, and fertilizer recommendation rules [72,74]. For N management, this is important because the decision is not only whether the crop appears N deficient, but also whether additional fertilizer is likely to improve yield under current soil, water, economic, and environmental conditions. However, these systems remain at an early stage. Major challenges include hallucination risk, lack of field validation, limited integration with calibrated quantitative models, uncertainty communication, and the need for agronomic safeguards before any automated recommendation is used in practice [73–75]. Therefore, LLMs and agentic AI should currently be viewed as promising decision-support interfaces and workflow coordinators rather than standalone tools for crop N estimation.

The progression from empirical regression models to classical machine learning, deep learning, foundation models, and emerging agentic AI reflects a broader shift toward increasingly data-driven and autonomous nitrogen monitoring systems. Figure 3 provides an overview of this evolution and illustrates how multi-source data are transformed into nitrogen predictions and management recommendations. Although LLMs and agentic AI offer promising capabilities for coordinating workflows and supporting agronomic decision-making, their deployment in precision nitrogen management requires careful oversight. Practical concerns include data privacy, liability associated with automated recommendations, limited field validation, and the risk of generating agronomically incorrect or insufficient site-specific recommendations (“hallucinations”). Consequently, these systems should be regarded as decision-support tools that complement, rather than replace, validated crop models, field measurements, and expert agronomic judgment.

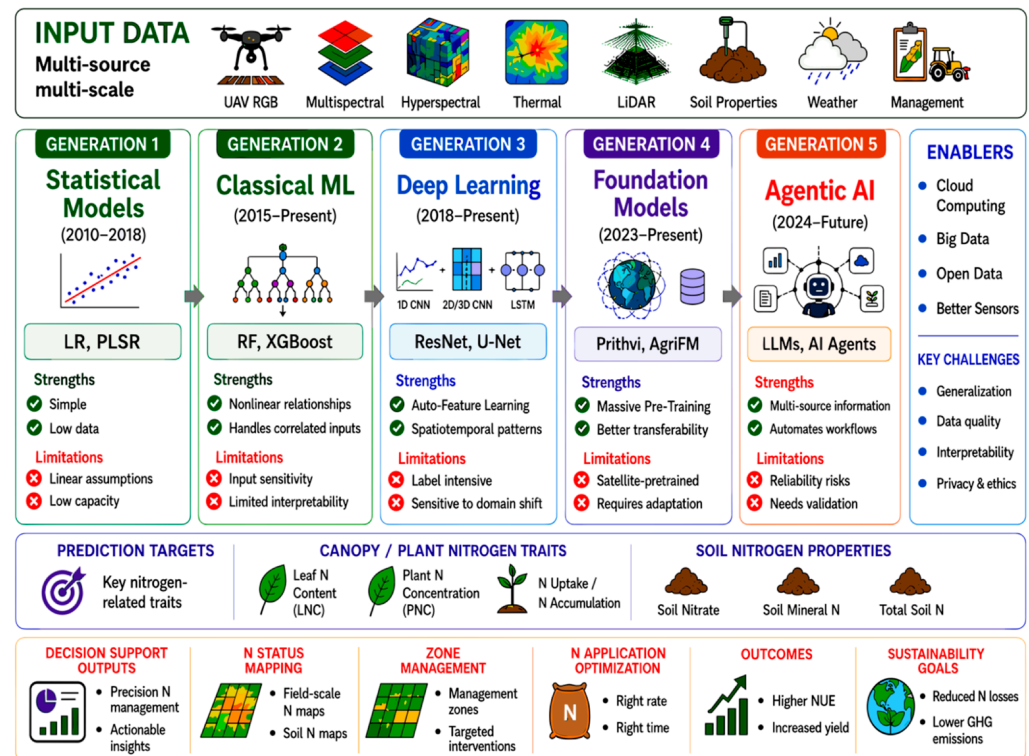


Figure 3. Evolution of machine learning approaches for crop and soil nitrogen estimation: from empirical models to foundation models and agentic AI.

Conceptual overview illustrating the progression of machine learning methodologies for crop and soil nitrogen estimation, from empirical statistical models to classical machine learning, deep learning, foundation models, and emerging agentic AI systems. The framework summarizes representative input data sources, model categories, key strengths and limitations, prediction targets, enabling technologies, current challenges, and their integration into precision nitrogen management decision support.

5.2. Prediction Targets

5.2.1. Crop Nitrogen Status Targets

Leaf Nitrogen Content (LNC): LNC is one of the most widely used indicators of crop nitrogen status because it is strongly associated with chlorophyll concentration and photosynthetic activity. UAV multispectral and hyperspectral sensors are commonly used to estimate LNC using red-edge and chlorophyll-sensitive features. Random Forest (RF), Support Vector Regression (SVR), ensemble learning, and deep learning approaches are frequently reported, with generally high prediction accuracies across major crops [36,61].

Plant Nitrogen Concentration (PNC): PNC provides a whole-plant assessment of nitrogen status and is commonly used in precision nutrient management. Similar to LNC, PNC is typically estimated using multispectral or hyperspectral imagery combined with vegetation indices and canopy structural traits. RF, XGBoost, and SVR are among the most frequently used algorithms for PNC prediction [76].

Nitrogen Nutrition Index (NNI): NNI is an important diagnostic indicator that evaluates whether crops are deficient, sufficient, or excessive in nitrogen relative to their growth stage. Because NNI integrates biomass and nitrogen concentration, its estimation often requires combining spectral, structural, and environmental variables. Machine learning models such as RF, artificial neural networks, and ensemble methods have shown promising performance for NNI prediction.

Aboveground Nitrogen Accumulation: Aboveground nitrogen accumulation reflects the total nitrogen stored in crop biomass and is useful for evaluating nitrogen-use efficiency and crop productivity. Estimation typically combines spectral information with biomass-related variables such as canopy cover, plant height, or leaf area index. Multi-source data fusion and ensemble-learning approaches generally improve predictive performance [48].

Nitrogen Uptake: Nitrogen uptake is a key indicator for fertilizer management because it represents the amount of nitrogen absorbed by the crop. Accurate estimation often requires integration of canopy spectral information with structural and environmental variables. RF, gradient boosting methods, and deep learning models are increasingly used to quantify nitrogen uptake across different cropping systems.

5.2.2. Soil Nitrogen Targets

Soil Nitrate: Soil Nitrate is one of the most important forms of plant-available nitrogen but is difficult to monitor directly because it is highly dynamic and mobile within the soil profile. Its spatial and temporal distribution is strongly affected by rainfall, irrigation, soil texture, drainage, and landscape position, which influence nitrate transport and leaching risk [5]. Remote sensing is therefore often combined with weather, management, and soil information to estimate nitrate dynamics. Hybrid machine-learning and crop-model approaches are increasingly being explored [77,78].

Soil Mineral Nitrogen: Soil Mineral Nitrogen includes nitrate and ammonium pools that are directly available for crop uptake. Because these pools vary rapidly with environmental conditions and management practices, temporal prediction approaches are often required. Process-based crop models coupled with machine learning methods have shown promise for monitoring mineral nitrogen dynamics [77].

Soil Total Nitrogen (STN): STN is the most commonly mapped soil nitrogen variable because it is relatively stable spatially and exhibits stronger relationships with soil spectral properties. Satellite, UAV, and hyperspectral datasets have been successfully combined with RF, XGBoost, CatBoost, and other tree-based algorithms for digital soil nitrogen mapping [79,80].

Available Nitrogen: Available Nitrogen represents the fraction of soil nitrogen accessible to crops during the growing season and is particularly relevant for fertilizer recommendations. Estimation often requires integrating remote sensing observations with soil measurements, environmental variables, and crop growth information. Consequently, hybrid modelling approaches are becoming increasingly important for operational decision support [77].

The different soil nitrogen pools vary considerably in their environmental dynamics, detectability, and management relevance. Soil nitrate is highly mobile and responds rapidly to rainfall, irrigation, fertilizer application, and crop uptake, making it difficult to estimate directly from remote sensing alone. Soil mineral nitrogen exhibits similar temporal variability because it includes both nitrate and ammonium pools that fluctuate with biological and environmental processes. In contrast, total soil nitrogen is relatively stable over time and more closely associated with soil properties that influence spectral responses, making it more suitable for digital soil mapping. Consequently, remote sensing generally provides indirect information on soil nitrogen availability and achieves the greatest accuracy when integrated with soil, weather, hydrological, and crop growth data.

The appropriate ML approach depends strongly on the nitrogen variable being predicted. Crop nitrogen targets, such as LNC, PNC, NNI, and nitrogen uptake are often linked to canopy reflectance, chlorophyll content, biomass and structural traits. In contrast, soil nitrogen targets, such as nitrate, mineral nitrogen and total nitrogen, are more difficult

to estimate directly from remote sensing and typically require integration with soil, weather, management, and crop-model information (Table 1).

Table 1. Common crop and soil nitrogen prediction targets used in remote sensing and machine learning studies, including their applications, sensors, and modelling approaches.

Target	Purpose	Common Sensors/Data Sources	Common Models
LNC	Early N diagnosis	UAV multispectral, hyperspectral	RF, SVR, DNN
PNC	Whole-plant N status	Multispectral, hyperspectral	RF, XGBoost
NNI	N sufficiency diagnosis	Multispectral + structural traits	RF, ANN, Ensemble
N Uptake	NUE assessment	Multi-source fusion	RF, XGBoost, DNN
Soil Nitrate	Fertilizer timing	Remote Sensing + soil + weather data	Hybrid ML, LSTM
Soil Mineral N	Dynamic N availability	Crop models + Remote Sensing data	DSSAT, LSTM
Soil Total N	Soil fertility mapping	Sentinel, Landsat, hyperspectral	RF, XGBoost, CatBoost
Plant Available N	Nutrient recommendations	Multi-source integration	Hybrid ML + crop models

Note: LNC, leaf nitrogen content; PNC, plant nitrogen concentration; NNI, nitrogen nutrition index; NUE, nitrogen use efficiency; N, nitrogen; UAV, unmanned aerial vehicle; RF, random forest; SVR, support vector regression; DNN, deep neural network; XGBoost, extreme gradient boosting; ANN, artificial neural network; ML, machine learning; LSTM, long short-term memory; DSSAT, Decision Support System for Agrotechnology Transfer.

Although machine learning substantially improves nitrogen estimation, integrating data-driven models with process-based crop models offers additional opportunities to enhance prediction robustness and biological interpretability, as discussed in the next section.

6. Integration with Crop Models and Decision Support

Remote sensing and machine learning approaches provide spatially distributed, in-season estimates of crop nitrogen status. However, these approaches are primarily observational because they characterize the current state of the crop without explicitly representing the underlying biogeochemical processes. Process-based crop models address this limitation by simulating key nitrogen dynamics, including mineralization, nitrification, leaching, and root nitrogen uptake, as functions of soil properties, climatic conditions, and management practices over well-defined temporal scales [81,82]. Integrating remotely sensed biophysical variables such as leaf area index, canopy reflectance, and soil moisture into crop models through data assimilation provides a methodological bridge that combines the spatial coverage of Earth observation with the predictive capability of biophysical simulation [83]. This synergy underpins a new generation of decision support systems capable of delivering spatially explicit and agronomically informed nitrogen management recommendations.

6.1. Integration with APSIM, DSSAT, and STICS

APSIM, DSSAT, and STICS are among the most widely used modeling tools for simulating nitrogen dynamics in agroecosystems. Each approach is based on a distinct design philosophy that determines its suitability for integration into decision-support systems coupled with remote sensing and machine learning approaches (Table 2). The APSIM (Agricultural Production Systems sIMulator) model adopts a modular hub-and-spoke architecture in which a central engine coordinates interchangeable biophysical modules [81]. The SoilN module simulates organic carbon and nitrogen transformations through microbial decomposition of fresh organic matter, humus mineralization, nitrification of NH_4^+ to NO_3^- , and denitrification as functions of soil temperature, moisture, pH, and C:N ratio. A multi-point simulation framework introduced in APSIM [81] enables spatially

distributed nitrogen balance calculations across heterogeneous fields, a key prerequisite for assimilating remote sensing data at the field scale. Furthermore, the open-source APSIM Next Generation platform facilitates coupling with external radiative transfer models and machine learning algorithms. The Decision Support System for Agrotechnology Transfer (DSSAT) employs a Crop System Model (CSM) architecture composed of hierarchically nested modules representing weather, management, soil processes, soil–plant–atmosphere interactions, and crop-specific templates [82]. The CERES-N submodel simulates mineralization through a two-pool humus decomposition approach, nitrification and denitrification through soil moisture and temperature response functions, and root nitrogen uptake as the minimum between nitrogen supply (mass flow and diffusion) and crop growth demand. The explicit linkage between crop parameters and nitrogen response within the CROPGRO templates makes DSSAT a benchmark model for genotype $\times$ environment $\times$ management (G $\times$ E $\times$ M) analyses. Thorp et al. (2012) [84] demonstrated that coupling DSSAT-CSM with the PROSAIL model through parameter inversion reduced the relative root mean square error (RRMSE) of leaf area index (LAI) estimation from 40.7% using PROSAIL alone to 24.1%, highlighting the value of DSSAT as an ecophysiological modeling framework integrated with remote sensing. The Simulateur multIdisciplinaire pour les Cultures Standard (STICS) model [85] is distinguished by its explicit representation of three organic matter pools, namely fresh organic matter, microbial biomass, and stable humus, as well as ammonia (NH₃) volatilization and microbial immobilization during residue decomposition. STICS simulates the effects of nitrogen stress on phenological development, biomass partitioning, and grain protein concentration at a daily time step. Sow et al. (2024) [86] successfully calibrated STICS for pearl millet grown in Faidherbia albida agroforestry parklands of the Senegalese Groundnut Basin, demonstrating its versatility under semi-arid conditions characterized by severe nitrogen limitation in a context directly relevant to nitrogen management in sub-Saharan Africa. Required input variables include climate data, initial soil organic nitrogen content, which is a key driver of mineralization, and the amounts and application dates of both organic and mineral fertilizers.

Table 2. Comparative features of APSIM, DSSAT, and STICS for soil nitrogen simulation and remote sensing integration. RS = remote sensing; EnKF = Ensemble Kalman Filter; DA = data assimilation.

Feature	APSIM	DSSAT	STICS
Key reference	Keating et al. 2003 [81]	Jones et al. 2003 [82]	Brisson et al. 2003 [85]; Sow et al. 2024 [86]
Architecture	Modular hub-and-spoke; pluggable modules	Hierarchical CSM; single soil model	Modular; crop- and soil-specific options
N sub-model	SoilN (organic C–N cycling, nitrification, denitrification)	CERES-N/CROPGRO-N (dual-pool decomposition)	3-pool OM (FOM, microbial biomass, humus) + NH ₃ volatilization
N processes simulated	Mineralization, nitrification, denitrification, leaching, immobilization	Mineralization, nitrification, denitrification, leaching, root uptake	Mineralization, nitrification, denitrification, volatilization, immobilization, leaching
Spatial scale	Paddock to regional (multi-point since v2)	Field to regional (GIS/spatial modes)	Plot → regional (spatialization via RS)
RS/DA integration	Parameter estimation, state forcing, APSIM Next Gen API	Model inversion (PROSAIL), EnKF, parameter re-estimation (Thorp et al., 2012 [84]; Ines et al., 2013) [87]	Re-parameterization via RS (Launay & Guerif, 2005) [88]; radiative transfer coupling
Strengths for N	Long-term soil N dynamics, C–N coupling, agroforestry	Robust cultivar $\times$ N coupling, Model inversion/calibration, genotype parameterization	Strong organic N dynamics, residues, agroforestry parklands, tropical/semi-arid contexts
Limitations	Calibration-intensive; limited built-in RS coupling	Spatial scalability; cultivar parameter availability	Less developed RS interface; primarily temperate/French context

6.2. Data Assimilation

Data assimilation integrates Earth observation data into crop models by correcting state variables or re-estimating model parameters based on discrepancies between simulated and observed values [83]. Four canonical paradigms have been applied in this context. First, direct forcing replaces a simulated state variable with its remotely sensed counterpart, such as MODIS-derived leaf area index (LAI), at each time step. Second, re-parameterization iteratively optimizes model parameters to minimize discrepancies between simulated and observed LAI over the entire growing season [88]. Third, sequential ensemble methods, most notably the Ensemble Kalman Filter (EnKF), propagate state uncertainty through an ensemble of Monte Carlo simulations and update model states probabilistically whenever new satellite observations become available [87,89]. Fourth, coupled model inversion combines a radiative transfer model, such as PROSAIL, with a crop model and inverts the coupled system against spatial observations to simultaneously estimate canopy biophysical properties and nitrogen status [84]. Among these approaches, the EnKF is one of the most widely used and methodologically rigorous frameworks. It explicitly propagates model structural uncertainty, accommodates nonlinear state dynamics, and provides posterior probability distributions for both state variables and nitrogen-related parameters. Ines et al. (2013) [87] demonstrated that the joint assimilation of AMSR-E soil moisture and MODIS-derived LAI into the DSSAT-CSM maize model using the EnKF improved yield prediction accuracy, increasing the correlation coefficient from $R = 0.47$ to $R = 0.65$ while reducing prediction bias by 2.5 to 3.3 Mg ha⁻¹ relative to simulations without data assimilation. The improved performance from simultaneous assimilation likely reflects the strong coupling between soil moisture and nitrogen dynamics. Soil water content directly regulates mineralization, nitrification, and leaching rates in all three crop models (Table 2). At the regional scale, de Wit and van Diepen (2007) [89] showed that assimilating METOP-derived soil moisture observations into the WOFOST model using the EnKF improved the correlation between simulated yields and official agricultural statistics in 66% of European regions. For STICS, re-parameterization using SPOT and airborne imagery reduced yield prediction RMSE from approximately 20% to 10% across 50 sugar beet fields in northern France [88], highlighting the critical importance of image acquisition timing aligned with periods of maximum crop nitrogen uptake (Table 3).

Table 3. Selected remote sensing data assimilation studies with process-based crop models for nitrogen and yield estimation. EnKF = Ensemble Kalman Filter; RRMSE = relative root mean square error; RMSE = root mean square error; LAI = leaf area index.

Study	Crop Model	Data	Method	Target Variable	Key Outcome
Ines et al. (2013) [87]	DSSAT-CSM-Maize	AMSR-E soil moisture; MODIS-LAI	EnKF (ensemble Sqrt filter)	Maize yield; soil moisture; LAI	Yield R: 0.47 to 0.65; RMSE: 2.5 Mg ha ⁻¹ (joint assimilation)
Thorp et al. (2012) [84]	DSSAT-CSM + PROSAIL	GER 1500 hyperspectral reflectance	Model inversion (PEST algorithm)	LAI; canopy weight; plant N; yield	LAI RRMSE: 40.7% (PROSAIL); 24.1% (CSM-PROSAIL)
Launay & Guerif (2005) [88]	SUCROS/STICS	SPOT + aerial (4 to 6 images per season)	Re-parameterization (optimization)	Sugar beet yield; LAI	Yield RMSE: 20–10% across 50 fields
de Wit & van Diepen (2007) [89]	WOFOST (CGMS framework)	METOP satellite soil moisture	EnKF (ensemble approach)	Winter wheat & maize yield (regional)	Yield-statistics correlation improved: 66% of EU regions
Dorigo et al. (2007) [83] [Review]	Multiple SVAT models	VNIR-SWIR optical RS (400 to 2500 nm)	Forcing, updating, variational, parallel proc.	LAI, fAPAR, canopy Chl, soil moisture	Comprehensive review of methods and limitations

6.3. Digital Twins for Nitrogen Management

The concept of a digital twin, defined as a dynamic virtual representation of a physical system that leverages real-world data, simulation, and machine learning to support understanding, learning, and reasoning [90], provides an integrative framework for operationalizing the remote sensing-crop model coupling described above. Applied to field-scale nitrogen management, a digital twin could assimilate satellite-, UAV-, or sensor-derived estimates of canopy development, soil moisture, and meteorological conditions into a calibrated crop model such as APSIM, DSSAT, or STICS. This process would enable repeated updating of crop nitrogen status and support prediction of nitrogen deficiencies, fertilizer timing, and potential crop responses under different management scenarios [91]. Verdouw et al. (2021) [91] formalized six typological categories of agricultural digital twins, ranging from conceptual or imaginary twins to shadow twins synchronized in real time, and proposed a reference architecture encompassing device, connectivity, service, and application layers. Within this framework, site-specific management of within-field zones has emerged as one of the most impactful use cases for arable cropping systems. In their review of 28 agricultural digital twin applications, Pylaniadis et al. (2021) [90] observed that most implementations remain at the prototype stage, with the computational cost associated with running ensembles of crop model simulations in real time representing the principal bottleneck to large-scale deployment.

7. Nitrogen Use Efficiency (NUE) Optimization

Nitrogen use efficiency (NUE) in global cereal production has often been estimated at approximately 33%, indicating that a large fraction of applied nitrogen is not recovered in harvested grain and may be vulnerable to environmental losses through leaching, denitrification, volatilization, and surface runoff [92]. Good and Beatty (2011) [93] estimated that the economic value of unused fertilizer nitrogen exceeded US\$15.9 billion annually in 1999, with associated environmental externalities including N₂O emissions, nitrate contamination of groundwater resources, and eutrophication of coastal ecosystems. Three complementary metrics of nitrogen use efficiency, namely agronomic efficiency, recovery efficiency, and partial factor productivity, provide a multidimensional framework for evaluating fertilizer performance. Remote sensing and machine learning contribute to NUE optimization by delivering spatially explicit, in-season estimates of crop nitrogen status, thereby enabling targeted, demand-driven nitrogen management interventions that better match fertilizer applications to crop requirements.

7.1. Variable Rate Fertilization

Variable-rate fertilization applies spatially differentiated nitrogen rates in response to within-field variability in crop nitrogen demand, crop nitrogen status or soil nitrogen supply capacity. The pioneering study by Raun et al. (2002) [92] demonstrated that nitrogen use efficiency (NUE) in winter wheat could be improved by more than 15% when mid-season nitrogen application rates were determined at a spatial resolution of 1 m² using in-season yield estimates and a Nitrogen Fertilization Optimization Algorithm (NFOA). The NFOA integrates NDVI-derived crop nitrogen status, cultivar-specific yield potential (YP₀), and a response index (RI = NDVI_{non-limiting}/NDVI_{farmer practice}) to calculate mid-season nitrogen requirements for each 1 m² management unit, thereby translating spectral reflectance measurements into site-specific fertilizer recommendations. Solari et al. (2008) [94] extended this framework to the assessment of maize nitrogen status using active optical sensors, comparing passive NDVI₅₉₀ measurements with the chlorophyll index CI₅₉₀ (active sensor; NIR/Green − 1) acquired using the Crop Circle ACS-210 sensor. Unlike passive sensing systems, active sensors generate their own modulated illumination

and are therefore independent of ambient light conditions and solar angle effects that often affect satellite-based observations. CI_{590} values collected during vegetative growth stages explained 85% of the variability in maize grain yield ($r^2 = 0.85$), compared with only 55% for $NDVI_{590}$ over the same period. This enhanced sensitivity is particularly important in dense canopies where NDVI becomes saturated at leaf area index (LAI) values exceeding approximately 2. The integration of proximal active sensing technologies with satellite multispectral imagery, particularly Sentinel-2 red-edge bands, within a unified prediction framework enables the scaling of nitrogen recommendations from 1 m² management units to landscape-scale nitrogen assessments. Such integration can support spatially continuous and agronomically informed nitrogen management strategies [92,94].

7.2. Precision Agriculture

Precision agriculture encompasses technologies that collect, process, and analyze spatial and temporal data to support targeted agronomic interventions [95]. Despite the widespread perception that adoption has been slow, Lowenberg-DeBoer and Erickson (2019) [95] demonstrated that GNSS-based guidance systems have been adopted in mechanized agriculture at rates comparable to those of other major agricultural innovations. Variable-rate technology (VRT), the precision agriculture tool most directly relevant to nitrogen use efficiency (NUE), has been adopted on approximately 20% of large-scale farms in developed regions. For smallholder farmers in developing countries, the primary barriers to adoption remain the economic threshold associated with farm mechanization, limited digital infrastructure, and the lack of decision-support systems calibrated to local soil and climatic conditions. For nitrogen management, next-generation precision agriculture architectures integrate satellite and unmanned aerial vehicle (UAV) remote sensing, proximal active sensors, soil electrical conductivity maps, historical yield data, and weather forecasts within cloud-based decision platforms that generate spatially distributed fertilizer prescriptions updated at each satellite overpass. Machine learning and deep learning algorithms, particularly ensemble methods such as gradient boosting and random forests, as well as convolutional neural networks trained on multi- and hyperspectral time-series data, have often improved nitrogen status estimation compared with single-model approaches [83,95].

However, translating improved prediction accuracy into reliable nitrogen recommendations requires calibration against field measurements, uncertainty estimation, and consideration of economic, environmental, and management constraints. Furthermore, coupling data-driven nitrogen status estimates with calibrated crop-model digital twins can help fertilizer recommendations account for temporal variation in nitrogen mineralization, leaching and crop demand between remote sensing observations. For NUE optimization, the value of precision agriculture lies not only in detecting spatial variability, but also in converting that variability into calibrated and economically feasible nitrogen decisions. Because nitrogen recommendations directly influence economic returns and environmental outcomes, uncertainty associated with remote sensing observations, machine learning predictions, and crop-model simulations should be explicitly quantified and communicated to end users. Confidence estimates or probabilistic prediction intervals can help distinguish between high-confidence fertilizer recommendations and situations requiring additional field sampling or expert agronomic assessment, thereby reducing the risk of over- or under-application of nitrogen.

7.3. Genotype $\times$ Environment $\times$ Management ($G \times E \times M$)

The efficiency with which a crop genotype converts applied nitrogen into grain yield is not an intrinsic and fixed property of the crop, but rather an emergent outcome of genotype $\times$ environment $\times$ management ($G \times E \times M$) interactions. A genotype exhibiting

high nitrogen use efficiency (NUE) in an organic matter-rich soil under temperate conditions may perform poorly under the combined effects of water stress and sandy soils that characterize many smallholder farming systems in sub-Saharan Africa. Understanding these interactions is essential for designing fertilizer management strategies that remain productive across the target population of environments addressed by breeding programs and agricultural advisory systems. Cooper et al. (2016) [96] pioneered the integration of crop growth models with whole-genome prediction through the Crop Growth Model–Whole Genome Prediction (CGM-WGP) framework. In this approach, physiologically meaningful traits simulated by APSIM, including biomass accumulation, leaf area index (LAI) dynamics, water use, and nitrogen use, are incorporated as interpretable intermediate phenotypes within a Bayesian genomic prediction model. Applied to a multi-environment maize trial under drought conditions, the CGM-WGP framework achieved positive predictive accuracy for hybrid grain yield by capturing genetic variation through five component traits associated with plant responses to water and nitrogen availability. Van Eeuwijk et al. (2019) [97] extended this paradigm through genotype-to-phenotype (G2P) models that integrate dense molecular marker profiles and high-throughput phenotyping data, including remotely sensed canopy traits such as NDVI time series, canopy temperature derived from thermal imagery, and Sentinel-2 red-edge chlorophyll indices, within multi-trait and multi-environment statistical frameworks. Temporal canopy dynamics, which can be directly observed through Earth observation data, have been shown to constitute informative intermediate variables that help decompose the $G \times E \times M$ variance affecting NUE by providing genotype-specific trajectories of nitrogen uptake at satellite observation scales. Within this integrated framework, remote sensing serves a dual role as both an operational platform for monitoring crop nitrogen status and a high-throughput phenotyping tool for breeding programs targeting improved nitrogen use efficiency across diverse agroecological environments.

The integration of sensing technologies and predictive models has enabled numerous practical applications across diverse cropping systems, which are reviewed in the following section.

8. Case Studies and Lessons Learned

8.1. Applications in Smallholder and Data-Scarce Regions

Remote sensing and machine learning (ML) approaches have emerged as powerful alternatives for rapid, non-destructive, and high-throughput monitoring of soil and crop nitrogen status under field conditions [38,98]. Optical and multisource remote sensing approaches are widely used to infer spatial patterns in soil nitrogen, particularly soil total nitrogen, because soil spectral reflectance is influenced by soil organic matter, moisture, mineral composition, surface condition, and vegetation cover. Multispectral satellite platforms such as Landsat, Sentinel-2, and WorldView-2 have been extensively used to estimate total soil nitrogen (STN) from vegetation indices (VIs), spectral reflectance bands, and environmental covariates. For instance, Xu et al. (2018) [99] investigated the effects of spatial resolution on the prediction of STN in smallholder farming systems in South India using Landsat 8, RapidEye, and WorldView-2 imagery combined with regression kriging. Soil prediction models with different spatial resolutions showed similar spatial patterns of STN. Their results showed that very high-resolution imagery improved soil N prediction, although finer spatial resolution data inputs did not always translate into higher prediction accuracy. The red-edge, near-infrared, coastal, and yellow bands from WorldView-2 showed relatively strong correlations with STN, demonstrating the importance of spectral sensitivity in digital soil mapping.

Similarly, Mashaba-Munghemezulu et al. (2021) [100] evaluated the use of Sentinel-2 imagery and ML regression models and environmental variables for mapping soil N content in smallholder maize farms in South Africa. The study compared random forest (RF), gradient boosting (GB), and extreme gradient boosting (XGBoost) algorithms and found that RF achieved the highest prediction performance ($R^2 = 0.90$). Sentinel-2 red and red-edge bands were identified as the most important predictors, outperforming environmental variables and soil indices. The authors concluded that Sentinel-2 imagery provides an effective framework for generating high-resolution soil N maps to support soil fertility management and food security interventions in resource-limited farming systems. Zhou et al. (2019) [101] explored the potential of multi-temporal Sentinel-1 SAR data for mapping STN in the Heihe River Basin of China using boosted regression trees (BRTs), RF, and support vector machines (SVMs). The addition of multi-temporal Sentinel-1A data significantly improved prediction accuracy using the BRT method compared with optical-only models, reducing RMSE and MAE by more than 17%. Remote sensing variables contributed more than 50% of the explanatory power in the RF and BRT models, confirming the strong capability of SAR-based features to characterize STN variability.

Hyperspectral sensing offers substantial advantages for soil N estimation due to its narrow spectral bands and its ability to detect subtle absorption features associated with N compounds and soil organic matter. Compared with multispectral sensors, hyperspectral imagery provides much greater spectral detail, enabling improved identification of N-sensitive wavelengths. Misbah et al. (2024) [102] investigated the use of PRISMA hyperspectral imagery combined with ensemble ML approaches for estimating STN in semi-arid agricultural fields in Morocco. Their ensemble framework integrated partial least squares regression (PLSR), support vector regression (SVR), and Gaussian process regression (GPR) to identify N-sensitive spectral bands in the visible near-infrared (VNIR) and shortwave infrared (SWIR) regions. The study identified strong N-sensitive absorption regions within 900–1300 nm and 1900–2200 nm wavelengths. While individual models achieved moderate prediction performance, the ensemble approach substantially improved estimation accuracy ($R^2 = 0.84$; RMSE = 0.08 g kg^{-1}). These results demonstrate the capability of hyperspectral imagery and ensemble learning to enhance soil N estimation while facilitating the development of N-specific remote sensing tools for precision agriculture.

Large-scale remote sensing and machine learning approaches are also beginning to address the severe soil information gap across sub-Saharan Africa. Hengl et al. (2017) [103] developed one of the first continental-scale soil nutrient mapping frameworks for sub-Saharan Africa using approximately 59,000 soil observations integrated with extensive remote sensing, landform, and environmental covariates. Using ensemble machine learning approaches combining Random Forest and Gradient Boosting algorithms, the study generated 250 m resolution maps of total nitrogen and other key soil nutrients across the region. Model validation showed moderate to high predictive performance for most soil properties, demonstrating the potential of satellite-derived environmental data and machine learning to support nutrient management and agricultural decision-making in data-scarce regions.

Although remote sensing and ML applications for nitrogen monitoring have demonstrated promising results in smallholder and data-scarce farming systems, their adoption and validation remain limited across much of sub-Saharan Africa. Expanding research efforts in these regions is essential to improve model transferability, address local agronomic and environmental conditions, and support sustainable nitrogen management. Furthermore, despite our comprehensive literature search, some relevant studies may not have been captured due to publication accessibility, language barriers, or limited indexing of regional journals. Greater dissemination and visibility of research from underrepresented regions will be critical for developing globally applicable nitrogen-monitoring frameworks.

8.2. Crop Nitrogen Monitoring Across Diverse Cropping Systems

Several studies have demonstrated the applicability of remote sensing and machine learning approaches for monitoring crop nitrogen status across a wide range of cropping systems [104–106]. These studies collectively show that spectral, structural, and textural information derived from UAV platforms can provide reliable indicators of crop nitrogen status, although the most effective predictors often vary among crop species and management conditions. For instance, Ballester et al. (2017) [104] evaluated the use of UAV multispectral imagery to assess in-season cotton N status and lint yield prediction under varying fertilizer treatments. Their results showed that the normalized difference red edge (NDRE) and simplified canopy chlorophyll content index (SCCCI) were highly effective for distinguishing N treatments and predicting plant N concentration and uptake. Statistically significant relationships between SCCCI, NDRE, and lint yield were detected as early as 83 days after sowing, demonstrating the value of UAV imaging for early-season N management in cotton systems. Similarly, Li et al. (2018) [105] investigated the use of UAV-derived spectral and morphological traits for estimating sorghum biomass, chlorophyll, and N content under N stress treatments. The study integrated canopy cover, plant height, and VIs derived from RGB and multispectral imagery. Strong exponential relationships were observed between UAV-derived traits and biomass (r up to 0.88), while VIs showed moderate relationships with leaf N concentration and chlorophyll content. Their findings suggested that integrating structural and spectral information improves N estimation accuracy.

In winter wheat, Han et al. (2025) [106] applied UAV multispectral imagery combined with ensemble learning approaches to estimate leaf N content (LNC). The study evaluated SVR, RF, Ridge Regression, K-Nearest Neighbors (K-NN), and ensemble learning methods. Results showed that the Voting-based ensemble learning model outperformed individual algorithms, highlighting the advantage of combining multiple learners for N prediction in wheat. Moghimi et al. (2020) [107] used aerial multispectral imagery and several ML classifiers for grapevine leaf N estimation. SVM achieved the highest classification performance, while XGBoost provided the best regression accuracy for N concentration estimation. Likewise, Li et al. (2023) [108] fused spectral and textural features extracted from UAV RGB and multispectral sensors to estimate total N content in winter wheat using Gaussian Process Regression (GPR), Random Forest Regression (RFR), Ridge Regression, and Elastic Net Regression. Ensemble learning achieved the highest prediction accuracy ($R^2 = 0.726$), demonstrating that texture features significantly enhance N estimation beyond spectral information alone.

8.3. Toward Operational Nitrogen Monitoring Systems

While many studies have demonstrated the feasibility of nitrogen estimation under experimental conditions, recent research increasingly focuses on developing operational monitoring systems capable of supporting large-scale and repeated nitrogen management decisions [109–111]. These approaches combine advanced machine learning, multi-source data fusion, and scalable satellite or UAV platforms to improve robustness, transferability, and practical deployment. For instance, Hammouch et al. (2024) [109] evaluated hybrid-AI and ensemble modeling approaches using UAV RGB imagery for sorghum N estimation. Their framework integrated deep learning, hybrid AI, and model-ensembling strategies to improve N prediction performance. The study demonstrated that even low-cost RGB imagery can provide valuable N information when combined with advanced AI architectures, thereby reducing the dependence on expensive hyperspectral systems. Zhou et al. (2026) [110] further developed an AI-driven framework for assessing N concentration, N uptake, N nutrition index (NNI), and dry matter in barley using UAV multispectral imagery. The study applied RF and Keras-based feedforward neural networks (KFNN), alongside

feature optimization through non-dominated sorting genetic algorithms (NSGA). KFNN consistently outperformed RF for complex N-related traits, while NSGA-based feature optimization improved model stability and predictive performance. These findings emphasize the growing importance of deep learning and optimization algorithms in precision N management.

A key component of operational nitrogen monitoring is the use of satellite imagery, which enables repeated observations across large spatial extents at relatively low cost. Platforms such as Sentinel-2, PlanetScope, and Landsat have become increasingly important because of their high revisit frequency, broad coverage, and free or relatively low-cost accessibility. In sugarcane systems, Soltanikazemi et al. (2022) [111] used Sentinel-2 spectral bands and VIs to estimate leaf N concentration through RF and SVR models. The global environmental monitoring index (GEMI), chlorophyll index green (C_{green}), and Sentinel-2 red-edge position index (S2REP) emerged as the most important predictors. RF slightly outperformed SVR, demonstrating the effectiveness of Sentinel-2 red-edge bands for crop N estimation. Pan et al. (2025) [112] integrated high-resolution PlanetScope imagery and environmental data with RF, SVM, and Artificial Neural Network models to predict winter wheat NNI. RF achieved the highest prediction accuracy (77.08%), while the inclusion of weather variables improved performance across all algorithms. The study further demonstrated that the crop growth stage strongly influenced model performance, with the elongation stage providing the most reliable NNI estimation.

Beyond multispectral satellite systems, hyperspectral sensing offers additional opportunities for operational monitoring where higher spectral sensitivity is required, particularly for detecting subtle biochemical changes associated with nitrogen status [66,67]. For instance, Peng et al. (2024) [66] combined UAV hyperspectral imagery with deep neural networks and hybrid feature selection methods, including XGBoost and Pearson correlation analysis, for rice leaf nitrogen estimation. Their results demonstrated that combining preferred spectral features with deep learning significantly enhanced nitrogen prediction accuracy and enabled detailed field-scale mapping of rice N variability.

A major trend toward operational deployment is the integration of multiple data streams within a single prediction framework. Combining spectral, structural, soil, topographic, and environmental variables provides a more comprehensive representation of crop physiological status and field heterogeneity, often improving model transferability across locations and seasons. For example, Yu et al. (2021) [113] compared UAV and PlanetScope satellite imagery for estimating canopy N weight in wheat using RF and SVR models. Their results demonstrated that the satellite-based RF model achieved excellent performance ($R^2 = 0.92$), outperforming UAV-based models. Integrating leaf area index (LAI), plant height, soil moisture, and vegetation indices significantly improved N prediction accuracy. The study highlighted the potential of combining satellite imagery with environmental data for operational N management. Morales-Ona et al. (2025) [114] integrated UAV imagery, satellite data, soil properties, and topographic metrics to assess early-season corn N uptake. Plant height and canopy cover fraction emerged as the strongest predictors of N uptake, while the addition of soil and topographic variables provided only limited improvement. Simple linear regression models performed comparably to more complex ML algorithms, suggesting that simpler approaches may sometimes provide sufficient operational performance.

Operational nitrogen management requires not only crop nitrogen assessment but also characterization of soil nitrogen availability. Consequently, recent studies have expanded beyond crop-focused monitoring to incorporate UAV-based soil nitrogen mapping using multispectral, hyperspectral, and spectroscopic approaches. For example, Hossen et al. (2021) [115] developed an AI-driven UAV multispectral sensing framework for es-

timating STN in agricultural fields. Their study integrated UAV multispectral imagery, laser-induced breakdown spectroscopy (LIBS), and ML models. The framework incorporated multispectral reflectance, VIs, temperature, and relative humidity variables into the prediction models. LIBS analysis provided rapid chemical characterization of soil N content and served as ground-truth calibration data for ML training. The integration of UAV imagery, spectroscopy, and AI enabled near real-time N assessment and demonstrated the potential for precision fertilization planning.

Luo et al. (2026) [116] investigated the potential of UAV-based hyperspectral sensing combined with ML for estimating STN in plateau agricultural regions. Several feature selection techniques were evaluated alongside ML models. The results demonstrated that integrating variable importance in projection (VIP) feature selection with PCA dimensionality reduction and support vector regression with radial basis function kernel (SVR-RBF) provided the highest prediction accuracy for STN, achieving a test R^2 of 0.77 and RMSE of 0.45 g kg^{-1} . The generated spatial maps successfully captured field-scale variability in soil N distribution, revealing substantial heterogeneity across agricultural fields.

The ultimate goal of operational nitrogen monitoring is to integrate crop, soil, and management information into decision-support systems capable of guiding fertilizer recommendations. Studies increasingly combine soil and plant observations to improve nitrogen balance assessment, nutrient-use efficiency, and environmental sustainability. For instance, Mittermayer et al. (2021) [117] investigated site-specific N balances using georeferenced soil and plant properties derived from satellite imagery, tractor-mounted sensors, and combine harvester data. Their study indicated substantial within-field variability in N surplus, ranging from -76.4 to 91.3 kg ha^{-1} . Soil organic carbon showed strong relationships with total N content and N uptake, while nitrate concentrations strongly correlated with calculated N surplus. The findings highlight the importance of integrating spatial soil variability, crop uptake information, and sensor-based technologies for precise N management and mitigation of nitrate losses.

8.4. Nitrogen Monitoring Under Water-Limited Conditions

Several studies have demonstrated that water availability strongly influences spectral responses associated with nitrogen status, making it important to evaluate nitrogen and water stress jointly [118–125]. For example, Becker et al. (2020) [118] investigated whether UAV multispectral imagery could differentiate water stress from N deficiency in maize. Their combined index successfully identified stress treatments under controlled conditions, although model transferability remained limited under broader field scenarios. Similarly, Mwinuka et al. (2022) [122] investigated the application of UAV-based multispectral VIs for assessing the interactive effects of water and N in irrigated African eggplant under tropical sub-humid conditions. GNDVI consistently performed best for differentiating N treatments across irrigation regimes during vegetative and full vegetative stages. NDVI and OSAVI also showed sensitivity to nitrogen variation, although their discriminatory power varied across irrigation treatments. Ihuoma and Madramootoo (2020) [119] evaluated narrow-band hyperspectral reflectance indices for detecting combined water and N stress in field-grown tomatoes. The results showed that the Normalized Photochemical Reflectance Index centered at 550 nm (PRI550), normalized PRI (PRI_{norm}), and Water Index (WI) were the most sensitive indices for distinguishing crop water stress. The PRI_{norm} emerged as the most sensitive indicator for the combined effect of water and N stress. At the same time, Renormalized Difference Vegetation Index (RDVI), PRI_{norm}, and Transformed Chlorophyll Absorption in Reflectance Index (TCARI) strongly correlated with N stress indicators.

Wen et al. (2026) [18] proposed a canopy-stratified and multi-source remote sensing framework for diagnosing maize N status under varying water and N regimes. By inte-

grating VIs, texture features, and ML algorithms, the framework significantly improved NNI estimation. The study also demonstrated that upper and middle canopy leaves best represented overall plant N status, highlighting the importance of canopy stratification in N diagnosis. Ding et al. (2022) [126] demonstrated that integrating multispectral, RGB, and thermal infrared imagery improved N prediction accuracy in winter wheat compared with single-source approaches. Likewise, Li et al. (2025) [39] combined RGB, multispectral, and hyperspectral UAV datasets with transfer learning strategies and Gaussian Process Regression for winter wheat plant N prediction across different regions. The integration of multiple sensors and transfer learning substantially improved model transferability and robustness under varying environmental conditions. Wang et al. (2025) [63] further demonstrated the value of integrating crop growth modeling, remote sensing, weather data fusion, and ML for precision N management in maize. Their integrated strategy improved N recommendation accuracy while reducing fertilizer application rates and increasing N use efficiency compared with conventional management practices.

Studies in sweet maize by Colovic et al. (2022) [121] further demonstrated that hyperspectral indices such as the modified normalized difference vegetation index (mNDVI) and the ratio of the water band index to the normalized difference vegetation index (WBI/NDVI) showed the strongest capability to differentiate irrigation $\times$ N interactions, with their discriminatory performance being most pronounced under low N conditions. In addition, red-edge-based vegetation indices showed greater sensitivity to variations in N status than structural and water band indices. Rice systems have also shown strong irrigation-N interactions. Carracelas et al. (2024) [124] assessed drone-based VIs for monitoring rice N uptake under continuous flooding and alternate wetting and drying (AWD) irrigation systems. SCCCI consistently provided the strongest relationships with nitrogen uptake under both irrigation regimes, although standing water conditions significantly affected spectral responses. Altogether, these studies highlight the application of remote sensing and ML for monitoring soil and crop N status.

Across crops and environments, water availability consistently modifies spectral signals associated with nitrogen status. Red-edge vegetation indices remain useful for detecting nitrogen variability, but their predictive power can decline when water stress, canopy temperature, or reduced biomass confound chlorophyll-related signals. Integrating thermal imagery, hyperspectral sensing, and multi-source ML approaches improves the ability to separate nitrogen and drought effects, highlighting the need for coupled water–nitrogen monitoring frameworks in rainfed and water-limited systems.

Table 4 presents a summary of case studies for crop N monitoring using remote sensing and ML applications.

Table 4. Summary of representative case studies using remote sensing and machine learning (ML) for crop nitrogen (N) monitoring, including crop type, sensing platform, ML algorithm, performance metrics, validation strategies, and key findings. WUE = water use efficiency; NR = not reported; CV = cross-validation.

Crop	Main Stress	Technology	Performance & Validation	Key Findings	References
Cotton	N deficiency	UAV multispectral imagery (NDRE, SCCCI, NDVI)	NDRE, $R^2 \approx 0.84$ SCCCI, $R^2 \approx 0.80$ NR	NDRE and SCCCI effectively tracked temporal variability in plant N uptake and N concentration.	[104]
Grapevine	N variability	UAV multispectral imagery + SVM, RF, XGBoost, DNN	$R^2 = 0.56$ and RMSE = 0.23% Cross-Validation	SVM achieved the highest classification accuracy for grapevine N status, while XGBoost provided the best regression performance for N concentration estimation.	[107]

Table 4. Cont.

Crop	Main Stress	Technology	Performance & Validation	Key Findings	References
Sorghum	N stress	UAV RGB and multispectral imagery + morphological traits	$r = 0.52$ for leaf nitrogen Cross-Validation	UAV-derived plant height, canopy cover, and VIs showed strong relationships with biomass and moderate correlations with N and chlorophyll content. Integrating structural and spectral traits improved N estimation.	[105]
Wheat	N management	UAV and PlanetScope imagery + RF and SVR	R^2 of 0.80 and RMSE of 2.62 g/m ² Train/Test Split	Satellite-based RF models outperformed UAV-based models for canopy N weight estimation. Integrating LAI, plant height, soil moisture, and topographic variables enhanced prediction accuracy.	[113]
Winter wheat	N nutrition imbalance	Proximal fluorescence sensors + multi-source data fusion + ML	PNC: $R^2 = 0.75$, RRMSE = 28.71% NNI: $R^2 = 0.60$, RRMSE = 24.62% Cross-Validation	Integrating meteorological data, soil fertility, and cultivation practices improved N nutrition diagnosis across growth stages. Multi-source fusion enhanced robustness and universality of N diagnosis models.	[127]
Corn	N deficiency	UAV multispectral imagery + RF, SVR, linear regression	$R^2 = 0.85$ and RMSE = 4.52 g/m ² Train/Test Split	Random Forest produced the highest accuracy for canopy N weight prediction. UAV imagery successfully mapped within-field spatial variability in crop N.	[128]
Sugarcane	N deficiency	Sentinel-2 multispectral imagery + RF and SVR	RF; $R^2 = 0.59$, RMSE = 0.08% SVR; $R^2 = 0.58$, RMSE = 0.09% Spatial CV	Sentinel-2 red-edge bands and vegetation indices effectively estimated sugarcane leaf N concentration. Random Forest slightly outperformed SVR.	[111]
Winter Wheat	N deficiency	UAV RGB and multispectral imagery + ensemble learning	$R^2 = 0.72$, RMSE = 3.203 mg·g ⁻¹ , MSE = 10.25 mg·g ⁻¹ Train/Test Split	Fusion of spectral and texture features significantly improved total N content prediction. Ensemble learning produced the highest estimation accuracy.	[108]
Rice	N deficiency	UAV hyperspectral imagery + XGBoost + Deep Neural Networks (DNN)	XGBoost; $R^2 > 0.8$ DNN; $R^2 = 0.89$ and RMSE = 0.17% for LNC; Cross-Validation	Hybrid feature selection combined with deep learning significantly improved rice leaf N content estimation and enabled accurate spatial mapping of N variability at field scale.	[66]
Maize	N deficiency	UAV hyperspectral imagery + spectral decomposition + ML	$R^2 = 0.68$; Train/Test split	Spectral decomposition reduced interference from canopy structure (AGB and LAI), improving estimation accuracy of leaf N concentration and density.	[129]
Tomato	Combined water and N stress	Hyperspectral reflectance indices (PRI, RDVI, TCARI, WI)	$R^2 = 0.66$ for the relationship between water and nitrogen stress indicators; NR	PRInorm was the most sensitive indicator for combined water and N stress detection. RDVI and TCARI were strongly correlated with N stress indicators.	[119]
Sweet maize	Combined water and N stress	Hyperspectral VIs	22–26% increase in yield & WUE under high N, limited under water stress; NR	Hyperspectral indices effectively distinguished between irrigation and N interactions.	[121]
Maize	N and water stress interaction	UAV multispectral imagery + VIs	NDRE, $R^2 \approx 0.63$; Spatial Validation	Combined spectral indices successfully differentiated N and water stress under controlled conditions, though transferability across sites remained limited.	[118]

Table 4. *Cont.*

Crop	Main Stress	Technology	Performance & Validation	Key Findings	References
Rice	N uptake under different irrigation systems	Drone-based multispectral VIs	SCCCI, $R^2 = 0.78$, up to 0.84; NR	SCCCI showed the strongest relationship with N uptake under continuous flooding and alternate wetting and drying irrigation systems.	[124]
African eggplant	Combined water and N stress	UAV multispectral imagery + VIs	$R^2 \approx 0.46$ – 0.53 and VIs accounted for 50% of the variance; NR	GNDVI effectively differentiated N treatments, while TDVI best distinguished canopy water stress. Combined use of GNDVI, NDVI, and OSAVI improved detection of water–N interactions.	[122]

Overall, the reviewed studies demonstrate that sensor performance depends on the monitoring objective, crop type, and spatial and temporal scale of application. While UAV-based multispectral and hyperspectral sensors generally provide the highest accuracy for estimating crop nitrogen traits such as leaf nitrogen content and the nitrogen nutrition index, soil nitrogen variables (e.g., nitrate and total nitrogen) are rarely observed directly and are typically inferred by integrating remote sensing with soil properties, weather data, and process-based crop models. Furthermore, robust validation across multiple crops, seasons, and environments remains essential to improve model transferability and operational deployment.

9. Challenges and Limitations

9.1. Sensor Limitations

Although proximal and remote sensing technologies have greatly improved nitrogen monitoring and management, several sensor-related limitations still exist. A fundamental limitation of optical sensors is that they do not directly measure nitrogen in chemically meaningful forms. Instead, they infer crop nitrogen status indirectly from canopy reflectance, chlorophyll content, vegetation indices, biomass, or leaf area index, all of which can also be influenced by other biotic and abiotic factors [130]. Consequently, spectral signatures associated with nitrogen deficiency can overlap with responses to drought, pest damage, disease, salinity, or soil compaction, making stress attribution difficult under field conditions.

RGB sensors, although inexpensive and widely accessible, often lack the spectral details necessary to detect subtle variations in crop nitrogen status, particularly during early deficiency stages [40]. Multispectral sensors improve upon this by incorporating narrower bands aligned with chlorophyll absorption and canopy reflectance features [40,49]. However, multispectral indices like NDVI are prone to saturation under dense canopy conditions, where reflectance values plateau and lose sensitivity to further changes in nitrogen status [131]. Beyond saturation, the red-edge signal tracks chlorophyll concentration, which correlates with foliar nitrogen only when nitrogen is the dominant limiting factor [132]. In degraded soils and rainfed systems where water, phosphorus, sulfur, or micronutrient deficiencies frequently co-occur, the relationship between red-edge reflectance and foliar nitrogen weakens, reducing the reliability of spectral nitrogen estimates [132]. Furthermore, hyperspectral sensors capture nitrogen-specific absorption features near 1510 nm and 2060 nm with greater biochemical specificity, but these wavelengths are sensitive to canopy water content and structural variation [130,133]. Additionally, atmospheric water vapor strongly absorbs radiation at these wavelengths, making accurate airborne measurements difficult without proper atmospheric correction. Thermal sensors, increasingly used to estimate crop nitrogen demand through canopy temperature, cannot easily dis-

tinguish between stomatal responses caused by nitrogen deficiency and those caused by water stress, a particularly important limitation in dryland systems where both stresses commonly occur together [49].

Even when advanced multispectral and hyperspectral sensors are used, measurement quality depends heavily on environmental and operational factors. UAV-based imaging is susceptible to variable illumination, wind speed, cloud cover, shadow interference, inconsistent image overlap between flight lines, radiometric drift between missions, and radiometric calibration issues [130]. These factors can introduce systematic errors that propagate through downstream indices, latent features, and model predictions. Collectively, all these limitations underscore that sensor outputs, regardless of platform or spectral range, must be carefully calibrated, validated, and interpreted within their agronomic and environmental context before they can be translated into reliable nitrogen recommendations.

9.2. ML Generalization Issues

Machine learning methods have improved nitrogen estimation by capturing nonlinear relationships between spectral features, crop traits, soil properties, and environmental variables [134,135]. Models such as random forests, support vector machines, gradient boosting algorithms, and convolutional neural networks (CNNs) have demonstrated strong predictive performance across numerous experimental studies. However, model generalization remains one of the major barriers to operational use of ML-driven nitrogen estimation systems [136].

In the context of agricultural sensing, generalization refers to the ability of a model trained under a specific set of environmental, management, and crop conditions to maintain predictive accuracy when applied to new and unseen conditions. A generalized model should perform reliably across locations, years, genotypes, soil types, climatic conditions, growth stages, and sensing platforms without requiring extensive retraining or recalibration. Many current ML models are trained and tested within a single crop, site, season, sensor type, or management system. Under these conditions, high prediction accuracy may be reported [136], but the same model may perform poorly when applied to different cultivars, soil types, climates, growth stages, or imaging platforms [137].

This limitation can arise from overfitting to local experimental conditions and from validation strategies that do not fully represent real-world scenarios [138]. Overfitting is particularly problematic in hyperspectral applications where the number of predictor variables can greatly exceed the number of observations [138]. Under these conditions, models may achieve high accuracy during internal validation but perform poorly when evaluated on independent datasets [139]. Furthermore, random data splitting strategies may place similar plots, dates, or environments in both training and testing datasets, leading to overly optimistic estimates of model performance [140].

For nitrogen monitoring systems to become more reliable, models should be evaluated using independent datasets across multiple seasons, locations, crops, sensors, and nitrogen treatments [141]. Emerging approaches like transfer learning, domain adaptation, mechanistic or process-based machine learning, and hybrid approaches that combine crop models with remote sensing may help improve model robustness and interpretability under heterogeneous field conditions (genotype $\times$ environment $\times$ management interaction) [134].

Future studies should also adopt more rigorous validation strategies to better reflect real-world deployment. Evaluating models across independent site-year datasets, leave-one-site-out or leave-one-year-out approaches provides a more realistic assessment of model generalization than random cross-validation within a single field or season, which may overestimate performance due to spatial or temporal autocorrelation and data leakage. In addition, sensor transfer, calibration drift, domain adaptation, and uncertainty

quantification should be explicitly considered to improve the robustness and reliability of operational nitrogen monitoring systems.

9.3. Data Scarcity

The development of robust machine learning models for nitrogen estimation is fundamentally dependent on the availability of high-quality, representative, and well-annotated datasets. However, data scarcity remains a major limitation in both crop nitrogen monitoring and soil nitrogen prediction [20,142]. Compared with other computer vision domains where large, labeled datasets are readily available, agricultural sensing studies often rely on relatively small and fragmented datasets collected under narrow environmental conditions [61]. This limitation restricts model robustness, reduces transferability across production systems, and increases the likelihood of overfitting.

One of the primary challenges is the ground-truth problem, particularly the difficulty of measuring nitrogen at the appropriate spatial and temporal scale [143]. Conventional ground-truth measurements require labor-intensive field sampling and laboratory analysis, such as Kjeldahl digestion or combustion-based methods [143]. These procedures are destructive, costly, and time-consuming, yet they generate small datasets compared to UAVs. This mismatch between dense remote sensing data and sparse ground-truth measurements can affect model performance by introducing scale mismatch, sampling bias, and uncertainty.

Data scarcity is particularly problematic for deep learning applications because neural network frameworks require large volumes of labeled training data to achieve stable and generalized performance [20,137]. In nitrogen monitoring, however, available datasets are often limited in size. Nitrogen response varies with crop species, cultivar, soil texture, irrigation regime, climate, fertilizer type, and growth stage [143]. If these sources of variability are not adequately represented, ML models may not capture the full range of field conditions.

Another challenge is the lack of standardized public datasets for crop nitrogen monitoring, unlike fields such as medical imaging or autonomous driving. Differences in sampling protocols, nitrogen units, sensor specifications, preprocessing methods, and validation metrics make it difficult to compare studies or reuse models. Future research should prioritize large-scale collaborative efforts to develop larger open datasets, harmonized protocols, standardized metadata, and shared benchmark frameworks.

9.4. Cost and Scalability

Despite rapid technological advances in UAV sensing and machine learning, cost and scalability remain major limitations for their adoption in nitrogen monitoring technologies [137]. Although many experimental studies demonstrate promising prediction accuracy under controlled research conditions, translating these technologies into scalable, economically viable tools for routine farm management remains challenging.

UAV platforms can provide high spatial resolution and flexible image acquisition, but their use requires trained operators, flight planning, batteries, sensors, calibration panels, software licensing, and data-processing capacity [137]. Battery endurance can be limiting for large fields, especially when UAVs carry heavier multispectral or hyperspectral payloads [144]. Sensors like hyperspectral cameras are particularly expensive and generate large data volumes that require advanced computing resources [145]. Also, data processing is another limitation as it requires high computational infrastructure and technical expertise for radiometric correction, orthomosaic generation, feature extraction, and model deployment [137]. These requirements may limit adoption by small and medium-sized farms.

Scalability challenges also arise from the mismatch between research-scale and real-world agricultural scale. Many UAV-based nitrogen monitoring studies are conducted on relatively small experimental plots under controlled conditions, whereas commercial agricultural systems often involve substantially larger and more heterogeneous production environments [30].

Addressing these challenges will require more streamlined and lower-cost UAV workflows, improved automation for image processing and model deployment, and the development of alternative low-cost, scalable, and operationally efficient sensing systems tailored to diverse agricultural contexts. These solutions will be especially important for small and medium-sized farms and for smallholder systems where equipment cost, technical expertise, and digital infrastructure remain major barriers to adoption.

10. Future Perspectives

Despite substantial advances in remote sensing and increasing use of machine learning for nitrogen monitoring, several challenges continue to limit their implementation under diverse agricultural conditions. Future progress will likely depend on the development of integrated monitoring frameworks that combine multiscale sensing (satellite and UAV), artificial intelligence, crop modeling, and real-time decision support systems. At the same time, future research should also emphasize affordable and scalable deployment strategies for smallholder farming systems alongside the development of more advanced high-investment technologies for large-scale commercial agriculture. An overview of the proposed framework for integrated nitrogen monitoring and decision support is presented in Figure 4.

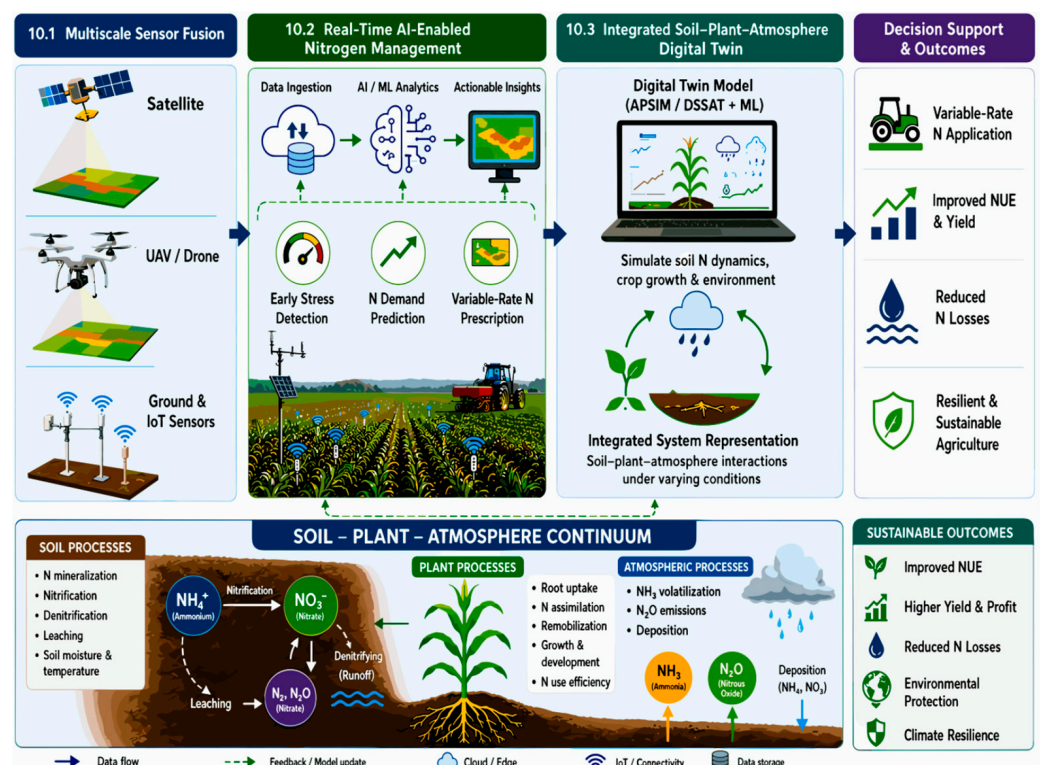


Figure 4. Conceptual framework linking soil nitrogen pools, plant nitrogen uptake, canopy spectral responses, multiscale sensor observations (satellite, UAV, and ground sensors), machine learning, crop-model assimilation, and AI-enabled decision support for precision nitrogen management. The framework illustrates how nitrogen and water dynamics are translated through remote sensing observations into predictive models and ultimately into site-specific management recommendations.

10.1. Multiscale Sensor Fusion (Satellite + UAV)

No single sensing platform can simultaneously satisfy the spatial resolution, coverage, temporal frequency, and cost requirements needed for operational nitrogen monitoring across heterogeneous agricultural systems. Future nitrogen monitoring frameworks will therefore likely function as hierarchical sensing networks in which satellites, UAVs, and proximal sensors operate in complementary roles according to their comparative advantages. Rather than relying exclusively on a single sensing platform, future approaches should emphasize multiscale data fusion to improve robustness, scalability, and temporal continuity.

The integration of satellite and UAV observations represents one of the most promising pathways for scalable nitrogen monitoring. Satellites provide wide-area coverage, repeated observations, and long-term temporal records, while UAVs provide very high spatial resolution and flexible image acquisition during critical crop growth stages. Combining these platforms can help overcome the limitations of each individual system. UAV imagery may be used to calibrate or downscale satellite products, whereas satellite observations can provide continuous temporal coverage between UAV flights. Although UAV platforms remain highly effective for research trials and high-resolution phenotyping, their operational cost and technical requirements may limit large-scale deployment (discussed in Section 9.4). While current satellite spatial resolution may remain insufficient for small-plot breeding trials, these datasets are increasingly accessible through freely available platforms like Sentinel-2 and Landsat-8 [146,147] and can provide valuable information for larger experimental fields and commercial production systems.

Future sensor fusion frameworks may also incorporate synthetic aperture radar (SAR) [30,148,149], Internet of Things (IoT) networks, and in situ sensing systems. Unlike optical sensors, SAR operates independently of cloud cover and solar illumination, making it particularly valuable in humid tropical and monsoon-influenced environments where optical imagery is frequently unavailable during periods of rapid crop growth and peak nitrogen demand. In addition, SAR-derived soil moisture information may improve nitrogen–water interaction modeling and strengthen predictive nitrogen frameworks [150]. Integration of all these sensing streams with edge computing and real-time analytics may ultimately support operational nitrogen monitoring systems capable of delivering scalable, reliable, and field-ready agronomic decision support.

10.2. Real-Time Nitrogen Monitoring with Sensing and AI

Future nitrogen management will likely shift from reactive assessment toward predictive and decision-oriented frameworks. Conventional approaches often rely on periodic measurements and delayed responses to emerging nutrient deficiencies, whereas AI-enabled systems can integrate continuous sensing, predictive analytics, and real-time decision support to facilitate earlier stress detection and more timely fertilizer interventions [92,141].

Artificial intelligence can play a central role in integrating heterogeneous agricultural datasets, including UAV imagery, satellite observations, soil measurements, weather data, and crop management records [30,61]. Rather than solely estimating nitrogen status like spatial maps, future AI-driven systems should be able to provide recommendations such as variable-rate fertilizer prescriptions, nitrogen deficiency detection, and strategies for improving nitrogen use efficiency. Machine learning approaches may also help address several limitations associated with current sensing systems through improved calibration, automated annotation, noise reduction, and stress classification.

The long-term vision for precision nitrogen management involves closed-loop decision systems in which sensing, prediction, and fertilizer application are connected through calibrated decision rules. Edge computing and Internet of Things (IoT) sensor networks

may support rapid field-level data processing without relying entirely on cloud-based infrastructure, particularly for time-sensitive management operations such as in-season nitrogen topdressing. However, future systems must also incorporate uncertainty estimation, continuous model updating, and biologically meaningful agronomic interpretation to ensure reliable and practical decision support under field conditions.

10.3. Towards Integrated Soil–Plant–Atmosphere Digital Twins

Future nitrogen monitoring systems must move beyond canopy reflectance alone and toward integrated representations of the soil–plant–atmosphere continuum that governs nitrogen availability and crop response under field conditions. Nitrogen dynamics are regulated by various complex interactions among soil nitrate (highly mobile) and ammonium pools, soil moisture, temperature, mineralization, volatilization, plant uptake, canopy development, and weather variability. Consequently, future monitoring frameworks should integrate remote sensing observations with soil measurements, crop models, environmental data, and management information to enable more mechanistic and predictive nutrient management.

Future progress will likely depend on integrating real-time sensing data with process-based crop models such as APSIM and DSSAT, as discussed in Section 6. These models explicitly represent nitrogen mineralization, nitrification, soil water dynamics, and plant uptake under varying environmental conditions. Hybrid frameworks that combine process-based crop simulation models with nonlinear statistical and machine learning approaches are especially promising because they can link data-driven prediction with agronomic and biological mechanisms [84,87]. Such systems could forecast nitrogen demand ahead of critical management decision windows using weather forecasts, crop developmental trajectories, and soil nitrogen status. Yang et al. 2026 [151] recently developed a physiology-informed framework for rice nitrogen status estimation that outperformed conventional machine learning approaches, suggesting the potential benefits of integrating mechanistic crop knowledge with data-driven modeling for nitrogen monitoring and prediction.

In the longer term, these integrations can support the development of agricultural digital twins [152] capable of representing nitrogen availability, transport, uptake and loss across soil, plant, and atmospheric compartments. Such digital twin frameworks may ultimately enable predictive nitrogen management under climate variability by continuously updating system states using real-time sensing, crop growth simulations, and environmental forecasts.

10.4. Low-Cost and Accessible Nitrogen Monitoring Systems

For nitrogen monitoring technologies to achieve broad agricultural impact, they must become accessible not only to large commercial operations but also to smallholder farming systems. Future progress will therefore depend on the development of low-cost, scalable, and operationally simple sensing platforms that can function across diverse production environments. This may occur through either reductions in the cost of existing technologies, such as UAV-based sensing systems, or through the development of alternative low-cost monitoring platforms.

The long-term outlook remains encouraging as sensing technologies continue to decline in cost while computational accessibility improves. As seen with other agricultural technologies such as genotyping, continued advances in sensor manufacturing, cloud computing, and AI infrastructure may improve the affordability of precision nitrogen monitoring technologies over time. As hardware becomes cheaper and machine learning workflows become more automated, technologies that are currently restricted to research programs may become increasingly practical for broader agricultural deployment.

Another important direction involves the development of lower-cost monitoring platforms such as smartphone-assisted crop diagnostics, portable chlorophyll meters, open-source soil nitrate sensors, and satellite-based advisory systems. These technologies should emphasize ease of use, low maintenance requirements, and compatibility with existing farm management practices. Emerging biosensor-based approaches may also provide promising alternatives for low-cost nitrogen monitoring. In one recent study, tomato plants were engineered to exhibit color changes under nitrogen-deficient conditions [153], demonstrating the potential of biosensor plants as an experimental route toward field-level nitrogen diagnostics. Such approaches, particularly when integrated with IoT networks and simplified decision-support systems, may offer cost-effective alternatives for continuous nitrogen stress monitoring without requiring heavier capital investment.

11. Conclusions

Nitrogen is a major nutrient-limiting crop productivity, making accurate and timely assessment essential for improving nitrogen use efficiency and sustainable fertilizer management. Recent advances in UAV, satellite, and proximal sensing technologies, combined with machine learning and artificial intelligence, have improved the ability to estimate crop nitrogen status and infer soil nitrogen indicators at multiple spatial and temporal scales. The integration of remote sensing with crop models, digital twins, and genotype $\times$ environment $\times$ management ($G \times E \times M$) frameworks further provides a pathway toward more biologically informed and operational nitrogen management. Classical machine learning methods remain widely used due to their robustness and interpretability, while deep learning and foundation-model approaches are expanding opportunities for multi-source data integration, representation learning, and improved transferability. In parallel, emerging LLM-based and agentic AI systems may help translate nitrogen predictions, crop-model outputs, weather information, and management records into more interpretable and actionable decision-support workflows.

Despite these advances, several challenges remain, including model generalization across crops, environments, sensors, and growing seasons, as well as the limited availability of large, standardized datasets. Future research should prioritize multimodal data fusion, stronger calibration and validation against field measurements, foundation-model adaptation for agricultural sensing, causal machine learning for nitrogen recommendation, deeper integration of digital twins and process-based crop models, and incorporation of $G \times E \times M$ interactions into AI-enabled decision-support systems. Together, these developments can help move nitrogen monitoring from status assessment toward actionable, site-specific management that supports both productivity and environmental sustainability.

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