Meta-analysis assessing potential of drone remote sensing in estimating plant traits related to nitrogen use efficiency

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Abstract: Unmanned Aerial Systems (UASs) are increasingly vital in precision agriculture, offering detailed, real-time insights into plant health across multiple spectral domains. However, this technology's precision in estimating plant traits associated with Nitrogen Use Efficiency (NUE), and the factors affecting this precision, are not well-documented. This review examines the capabilities of UASs in assessing NUE in crops. Our analysis specifically highlights how different growth stages critically influence NUE and biomass assessments in crops and reveals a significant impact of specific signal processing techniques and sensor types on the accuracy of remote sensing data. Optimized flight parameters and precise sensor calibration are underscored as key for ensuring the reliability and validity of collected data. Additionally, the review delves into how different canopy structures, like planophile and erect leaf orientations, uniquely influence spectral data interpretation. The study also recognizes the untapped potential of image texture features in UAV-based remote sensing for detailed analysis of canopy micro-architecture. Overall, this research not only underscores the transformative impact of UAS technology on agricultural productivity and sustainability but also demonstrates its potential in providing more accurate and comprehensive insights for effective crop health and nutrient management strategies.

Keywords: Nutrient use efficiency; Unmanned aerial vehicle (UAV); Meta-analysis; Growth stage; Vegetation indices; Signal process technique; Sensor type
1. Introduction

Nitrogen plays a crucial role as the primary limiting nutrient for essential processes in plants, including photosynthesis, regulation of phytohormones such as auxins and cytokinins, and proteomics changes throughout their lifecycle [1]. However, the excessive and inefficient use of nitrogen fertilizers not only increases crop production costs but also leads to environmental issues such as soil degradation, water pollution, and biodiversity loss [2]. To address these challenges, it is essential to assess the efficiency of nitrogen utilization in crop production and evaluate its potential environmental impacts. NUE is a measure of how effectively a plant utilizes available nitrogen for growth. A variety of indicators of NUE are widely used for this purpose. NUE is critical in understanding nitrogen cycles and guiding nitrogen management practices. By accurately measuring NUE, we can optimize nitrogen application, minimize wastage and leaching to soil, and improve crop yield without compromising environmental sustainability. To date, several methods have been employed for plant NUE assessment, including the system nitrogen balances methods [3], calculated by comparing the difference between nitrogen inputs and nitrogen outputs [4]; soil-based methods which focus on the rate of soil nitrogen mineralization, nitrification, and denitrification [5]; plant-based methods which involve the nitrogen content collected and analyzed from plant tissues [6]; and isotope-labeled method which could track the fate and movement of nitrogen in the soil-plant system [7]. In addition, with the development of remote sensing technologies, research is increasingly using images taken by satellites and drones to monitor arable crops [8, 9] and estimate NUE over large area cropping systems [10] for a more comprehensive understanding of NUE in a spatially explicit manner.

Drones, distinct from other remote sensing technologies, provide unparalleled flexibility and accessibility. They can transmit data in real-time, allowing for immediate analysis and decision-making [11]. Combining different kinds of sensors with high spatial resolution imagers (i.e., multispectral, hyperspectral, thermal, LiDAR), it can be used for different types of monitoring tasks such as drought stress [12], yield prediction [13], weed detection [14], nitrogen status [15], growth vigor [16]. So far, there have been articles on drone remote sensing-based assessment of NUE. For instance, Yang et al., [17] predicted the NUE variations among the winter wheat genotypes, where it was discovered that drone-carrying multispectral cameras can effectively predict time-series of NUE throughout the growing season. This study has proved valuable in selecting elite genotypes and monitoring crop performance under various nitrogen treatments. Liang et al., [18] used UAV-based multispectral imagery to identify high NUE varieties of rice through the entire growth duration. Their investigation indicated that UASs have immense potential to determine NUE phenotypes.

The findings from these studies highlight the significant capability of drones in NUE assessment. While the progression of UASs enhances the scope and precision of NUE assessments across various crops and agricultural practices, it also presents several challenges. Key among these are the inconsistencies arising from variations in growth stage, signal processing technology, and sensor type [18]. Additionally, it's important to emphasize that different methods of calculating NUE might result in significant variations in NUE values, even when applied within the same experimental field and cropping system [19]. Therefore, it is critical to select and standardize the most appropriate UAV remote sensing metrics for assessing NUE to ensure accuracy and consistency. This review aims i). to examine the moderators which affect remote sensing of crop nitrogen status; ii). to quantify the effects of various influencing moderators on crop NUE; iii). evaluate the potential of UASs for remote assessment of NUE quantitatively; and iv). provide recommendations for optimizing UAS technology for NUE assessment in agricultural practices.

2. Materials and Methods

2.1 Literature Search

Using the PRISMA protocol, we conducted a systematic review and meta-analysis of studies that use UAVs to estimate NUE in agricultural systems. Figure 1 presents a flow diagram of the study selection process. In the identification step, relevant literature was retrieved from Scopus and Web of Science using search terms comprising keywords related to UAVs and nitrogen use efficiency.
(shown in Appendix B). The search was limited to English-language research articles published from January 1995 to February 2023. The studies classified as review papers, book chapters, reports, Ph.D. theses or errata were not considered.

A total of 153 articles were obtained from the Scopus and Web of Sciences searches. To be included in the review, a study was required to fulfill the following three criteria: i). the study uses UAS type; ii). it focuses on vegetation NUE; iii). it uses at least one of the NUE indicators. A total of 35 studies were included in the quantitative analysis, as they met the criteria and provided extractable data for all features. For each article, we extracted metadata, including information related to the characteristics of the location, vegetation, measurement period, sensor type, signal processing technique, vegetation index, R², and NUE indicators manually (Supplementary Materials).

Figure 1. PRISMA flow diagram of the study selection process for the systematic review.

2.2 Data Extraction

Typically, the NUE is gauged in an indirect manner by measuring a suite of N-related crop and soil traits. The plant traits pertinent to the assessment of NUE typically encompass plant nitrogen content and uptake, grain protein content, biomass, and yield. These traits are intrinsically linked to the calculation and assessment of NUE. Plant N-related traits such as nitrogen content, leaf chlorophyll content, and protein content offer an in-depth insight into the plant's nitrogen dynamics. Similarly, attributes like biomass, yield, and plant height, while serving as indicators, also elucidate the associations between plant vitality and its nitrogen consumption. Moreover, the LAI and the Thousand Grain Weight (TGW) reveal the plant's photosynthetic efficiency and grain morphological characteristics, which are both closely influenced by N-related traits and trait interactions [20, 21]. Figure 2 summarizes the plant traits we extracted from the literatures and used in this review for the NUE evaluation included. For a comprehensive and robust meta-analysis, we honed our focus on six core trait categories directly related to NUE: nitrogen content (covering both Plant Nitrogen Content (PNC) and Plant Nitrogen Accumulation (PNA)), biomass, direct NUE measurements, LAI, Plant Height, and...
and Grain Yield. Ensuring the validity of our research, we included only those studies that transparently reported both the coefficient of determination ($R^2$) and the associated sample size for each trait in the quantitative analysis section. Through our analysis, we pinpointed five pivotal variables (i.e., Sensor Types, Signal Processing Techniques, Model Evaluation Procedures, Growth Stages, and Crop Types) that influence the accuracy of plant trait estimation:

![Figure 2. Percentages of the plant traits used in the included publications (PNC: Plant Nitrogen Content, LAI: Leaf Area Index, PH: Plant Height, TGW: Thousand Grain Weight, NG: Number of Grains Per Area, SN: Spike Number, PNA: Plant Nitrogen Accumulation).](image)

- **a. Sensor Types:** We identified four sensor types that could potentially influence the accuracy of trait estimation: RGB, MS, HSI, and a combination of RGB and MS sensors.

- **b. Signal Processing Techniques:** To estimate vegetation characteristics, we employed a range of signal processing techniques as outlined by [22]. These include Multivariate Linear Methods (e.g., Partial Least Squares Regression, Stepwise Multiple Linear Regression, and Multiple Linear Regression), Multivariate Non-Linear Methods (e.g., Random Forest and Support Vector Machine), Physically Based Approaches (utilizing specific formulas), and Univariate Methods (involving Vegetation Indices and either Linear or Non-Linear Regressions).

- **c. Model Evaluation Procedures:** In the existing literature, two predominant strategies for model evaluation are calibration and validation. Calibration $R^2$ serves as a measure of the model’s accuracy when derived from a training data set. In contrast, validation $R^2$ gauges the model’s capacity for estimating trait values in an independent test data set, thereby providing insights into the model’s generalizability and stability.

- **d. Growth Stages:** To standardize the data monitoring period across all studies, we converted the reported growth stages to the BBCH scale, a globally recognized scale for phenological staging in plants. We categorized the growth stages as follows: early stage (BBCH 0-30), mid-stage (BBCH 31-60), and late stage (BBCH 61-90). Additionally, we considered the entire growth period (BBCH 0-90) as a separate category. These categorizations were employed to assess the impact of different growth stages on the accuracy of plant trait prediction.

- **e. Crop Types:** The articles analyzed for prediction accuracy primarily focused on the following crops: winter wheat, maize, barley, winter oilseed, and rice. These crops were individually categorized to evaluate the differential impact of crop type on the accuracy of plant trait estimation.

### 2.3 Data Analysis

Electronic copy available at: https://ssrn.com/abstract=4666863
In this meta-analytic review, we employ plant traits estimation accuracy as the designated effect size metric, typically quantified using the $R^2$. It is acknowledged that variances in reported accuracies exist both between and within individual studies. Between-study discrepancies often arise from contextual differences such as geographical location and types of drones used in data collection. Additionally, within the same study, variations in traits estimation accuracy can also be observed, attributable to the application of diverse signal processing techniques [22]. To quantitatively estimate these two sources of variance and identify the moderating variables that could influence the prediction accuracy, we utilize a three-level meta-analytic model, in line with established methodologies. This approach allows for a nuanced understanding of the factors contributing to accuracy disparities both within and across studies [23].

2.3.1 Data Transformation and Standardization

Plant traits estimation accuracy was typically expressed in terms of the $R^2$. Initially, the data set is imported from a CSV file (Appendix A) and cleaned to ensure robustness in the subsequent steps. This involves eliminating entries with missing $R^2$ values. Because meta-analytical three-level models assume normally distributed data to enable a standardized comparison of accuracy across various studies, we transform the $R^2$ into Fisher’s $Z$ values. This transformation is performed using the Eq. 1:

$$Z = \frac{r}{2} \ln \left(\frac{1+r}{1-r}\right)$$

where $r$ represents the correlation coefficient, derived from the square root of the $R^2$. 

2.3.2 Model Formulation: Three-Level Random Effects Model

Upon standardizing the data, the first step in our modeling exercise involves establishing a baseline model, commonly referred to as the “null” model. This foundational model captures the overall effect size and provides initial estimates of between- and within-study variances. Mathematically, the null model is formulated as:

$$Z_{ijk} = \gamma_{00} + \nu_{0k} + \mu_{jk} + e_{ijk}$$

here, $Z_{ijk}$ represents the observed Fisher’s $Z$ value for the $i^{th}$ samples in the $j^{th}$ study from the $k^{th}$ data set. $\gamma_{00}$ represents the overall mean effect size across all samples, studies, and data sets. $\nu_{0k}$ represents the random effect due to the $k^{th}$ data set, accounting for variability between data sets. $\mu_{jk}$ represents the random effect due to the $j^{th}$ study within the $k^{th}$ data set, capturing the within-data set between-study variability. $e_{ijk}$ (Level 1) represents the random effect due to the $i^{th}$ sample within the $j^{th}$ study and $k^{th}$ data set, representing the residual error.

2.3.3 Incorporating Moderator Variables (Fixed Effect)

To delve deeper into the nuances of traits estimation accuracy, we expand this null model by incorporating moderating variables such as Sensor Type, Crop Type, Model Evaluation Procedures, Signal Processing Technique, and Growth Stage. These variables are introduced with the presumption that they systematically influence the traits estimation accuracy, thereby allowing us to explore the intricacies of the data more comprehensively.

2.3.4 Assessing Variability and Intra-Class Correlation

Following the introduction of moderators, we quantify the dispersion of effect sizes using the Intra-class Correlation Coefficient (ICC). The ICC is calculated using the Eq. 3:

$$ICC = \frac{\sigma_{\mu}^2}{\sigma_{\mu}^2 + \sigma_{\nu}^2}$$

where $\sigma_{\mu}^2$ represents the estimated variance at the study level (Level 2). $\sigma_{\nu}^2$ represents the estimated variance at the data set level (Level 3). This metric elucidates the proportion of total variance between studies that’s due to variations within individual studies.
It not only ensures that our statistical inferences are accurate but also aids in interpreting results. When a significant chunk of variance stems from within studies, it suggests that individual conditions or measurements within those studies greatly influence the observed discrepancies.

2.3.5 Evaluating the Explained Variance

Finally, we assess the performance of the model by calculating the amount of variance explained by the moderating variables at both the study (Level 2) and data set (Level 3) levels. These are our overall levels in this analysis, and they help provide a comprehensive understanding of the data’s structure. This is performed using the following equations:

\[ R^2_2 = 1 - \frac{\sigma^2_{\mu(1)}}{\sigma^2_{\mu(0)}} \]  
\[ R^2_3 = 1 - \frac{\sigma^2_{\nu(1)}}{\sigma^2_{\nu(0)}} \]

where \( R^2_2 \) and \( R^2_3 \) represent the proportion of the variance at the study level (Level 2) and data set level (Level 3), respectively. These metrics serve as robust indicators of the model’s explanatory power, providing valuable insights into the influence of moderating variables on traits estimation accuracy. \( \sigma^2_{\mu(1)} \) and \( \sigma^2_{\nu(1)} \) represent the estimated variances at Levels 2 and 3, respectively, with moderator variables included. \( \sigma^2_{\mu(0)} \) and \( \sigma^2_{\nu(0)} \) represent the estimated variances at Levels 2 and 3, respectively, in the null model, without moderator variables.

By adopting this thorough methodological approach, we aim to offer a nuanced, robust, and comprehensive analysis, enhancing our understanding of traits estimation accuracy across a diverse array of conditions and studies.

The ‘lme4’ package (1.1.34), ‘nlme’ package (3.1.162), and ‘dplyr’ package (1.1.34) were used for data analysis, ‘ggplot2’ package (3.4.3) was used for data visualization in R (version 4.3.0).

3. Results

3.1. Geographical Distribution and Research Trends

Figure 3. Locations of the study sites included in the meta-analytical data sets.

Figure 3 depicts the geographical spread of the 35 studies encompassed in this review, spanning 12 different countries. In Asia, China emerges as a leading research hub with 17 studies, while in North America, the USA accounts for 5 studies. European research contributions were diverse. Germany, Denmark, and Switzerland presented 2 studies each, whereas Spain, France, Czechia, and Belgium had one study apiece. South America and Africa were represented by Brazil and Morocco, respectively, each contributing one study. From a climatic perspective, most studies focused on temperate regions, especially in Europe and the USA. However,
the Brazilian study offered insights into tropical conditions, and arid perspectives were gleaned from studies in regions like Mexico and Morocco.

Climatic variations distinctly affect nitrogen absorption, transformation, and leaching [24]. For instance, rainwater can dissolve nitrogen in the soil and move it to deeper soil layers or into rivers, lakes, and groundwater. This leaching results in a significant loss of available nitrogen from the topsoil, affecting plant growth [25]. In arid regions, drought conditions might lead to nitrogen accumulation as they can inhibit plant growth, thus reducing nitrogen uptake [26]. It is evident that diverse climatic conditions necessitate distinct management strategies and technological applications.

3.2. Comparing Indicators for Assessing NUE

![Figure 4. Number of publications per indicator over time.](https://ssrn.com/abstract=4666863)

Figure 4 presents the trend in the annual number of articles from 1995 to 2022, showcasing the various indicators used for assessing NUE. One of the first articles, published in 2015 reported the use of the nitrogen balance index (NBI) to precisely assess the nitrogen concentrations of paddy rice at a canopy level [27]. Subsequently, there has been a marked upswing in publications centered around utility of UAV remote sensing for NUE, which indicated the growing importance of assessing NUE for sustainable agriculture. After rigorous screening, seven different indicators were extracted from the 35 references cited in this article. The Nitrogen Nutrition Index (NNI) was prominently featured [28], being referenced 20 times, showcasing a steady uptrend over time. Followed by the Partial Factor Productivity (PFP), which was mentioned in 7 publications [29]. The agronomic Nitrogen Use Efficiency (aNUE) [30] and Nitrogen Utilization Efficiency (NutE) [18] were equally represented, each being mentioned in 5 studies. Among the indicators, the Nitrogen uptake Efficiency (NUpE) [31] was the least cited, appearing in 2 publications.

While NNI does not directly measure NUE, it assesses the nitrogen status in plants, providing insights into their nitrogen dynamics. NNI is calculated as the ratio of the actual N concentration to the critical N concentration, that is, the nitrogen concentration required for plants to achieve maximum growth rate (Eq.6). While it provides insights into crop nitrogen dynamics, it differs from traditional metrics directly quantifying NUE [32]. Similarly, the chlorophyll-to-polyphenol ratio, known as the NBI (Eq.7) [27], does not directly appraise NUE. Essentially, NBI, as measured by the Dualex, taps into the fluorescence properties of chlorophyll and polyphenols in plant leaves to infer the physiological nitrogen response [33]. It could be a useful tool to infer aspects of
nitrogen management, but it does not directly evaluate NUE. However, in a broad understanding of nitrogen dynamics in plants, both NNI and NBI can be perceived as pivotal indicators related to nitrogen management [34].

\[
NNI = \frac{\text{Actual concentration}}{\text{Maximum growth rate}}
\]

\[\text{Eq.6}\]

\[
NBI = \frac{\text{Fluorescence, chlorophyll}}{\text{Fluorescence, polyphenol}}
\]

\[\text{Eq.7}\]

On the other hand, aNUE (Eq.8) specifically quantifies the increase in yield directly attributed to the applied nitrogen, effectively distinguishing between the contribution of soil nitrogen and the impact of nitrogen fertilizer in enhancing crop yields [17]. Conversely, PFP (Eq.9) assesses the total productivity of the farming system in relation to its nitrogen inputs without distinguishing the base yield at zero nitrogen inputs [30, 35].

\[
aNUE = \frac{\text{Yield}_{\text{with } N \text{ fertilizer}} - \text{Yield}_{\text{without } N \text{ fertilizer}}}{N_{\text{total applied}}}
\]

\[\text{Eq.8}\]

\[
PFP = \frac{\text{Yield}}{N_{\text{total applied}}}
\]

\[\text{Eq.9}\]

NutE (Eq.10) quantifies the efficiency with which a plant converts absorbed nitrogen into yield, serving as a direct indicator of yield-related nitrogen use. On the other hand, NIE (Eq.11) and NCE (Eq.12), as defined by Olson et al., [36] are specific types of NutE. NCE assesses how effectively a plant converts absorbed nitrogen into above-ground biomass, while NIE focuses on the conversion efficiency of absorbed nitrogen into grain yield. Although both NCE and NIE fall under the broader category of NutE, they examine different aspects of nitrogen use: NCE considers the total biomass produced, making it relevant for both grain and biomass crop systems, whereas NIE is more specific to grain yield, thus being particularly pertinent to grain-oriented agriculture.

\[
\text{NutE} = \frac{\text{Yield}}{N_{\text{total uptake}}}
\]

\[\text{Eq.10}\]

\[
\text{NIE} = \frac{\text{Yield}}{N_{\text{total uptake}}}
\]

\[\text{Eq.11}\]

\[
\text{NCE} = \frac{\text{Above ground biomass}}{N_{\text{total uptake}}}
\]

\[\text{Eq.12}\]

While NIE is important in yield-oriented cropping systems, NCE encompassing the entire above-ground biomass is of great interest in biomass product-oriented cropping systems.

Finally, NUpE (Eq.13) evaluates a plant’s proficiency in absorbing available nitrogen from its environment, irrespective of the nitrogen source. Conversely, Apparent Recovery Fraction (ARF) quantifies the proportion of applied nitrogen that a crop assimilates[37]. Although both indices center on nitrogen uptake, their application in nitrogen management studies have subtle differences. NUpE measures a plant’s overall efficiency in absorbing available nitrogen, encompassing both soil-derived and other environmental sources. This includes nitrogen from fertilizers, biological fixation, and atmospheric deposition, while ARF calculates the NUE by measuring the proportion of nitrogen from fertilizers that is assimilated by the crop, compared to the total nitrogen applied. Accurately distinguishing between NUpE and ARF is crucial in UAV-based NUE assessments to effectively evaluate and optimize nitrogen fertilization strategies [38].

\[
\text{NUpE} = \frac{N_{\text{total uptake}}}{N_{\text{total applied}}}
\]

\[\text{Eq.13}\]

\[
\text{ARF} = \frac{N_{\text{fertilizer plants}} - N_{\text{non-fertilizer plants}}}{N_{\text{total applied}}}
\]

\[\text{Eq.14}\]

3.3. Specifications and Ground Sampling Distance (GSD)

The utility and effectiveness of UASs in the assessment of NUE related traits are largely dependent upon the type of sensor deployed. Our comprehensive analysis of 35 pertinent research studies reveals the trends and specificities of sensor types, their
frequency of usage, and corresponding GSD. Here, we outlined the landscape of sensor selection by examining their functional attributes and correlating them with GSD values to discuss their suitability for various scenarios.

Figure 5. (a) Distribution of GSD of different sensors; (b) Percentages of the sensors used in the included publications.

Multispectral Imagers (MSI) dominate the field, accounting for 66% of total sensor deployments, making them the predominant choice for NUE studies [39]. Multispectral sensors typically capture light across a few visible and near infrared spectral bands at discrete wavelengths [40], and to a lesser extent use the mid-infrared (MIR) or thermal infrared (TIR) bands [41]. The versatility of multispectral sensors extends their utility across a broad array of traits that indirectly relate to NUE. For example, they have been used for evaluating biomass [42], PNC [43], yield [29], and Plant Nitrogen Uptake (PNU) [44]. Additionally, these sensors are instrumental in measuring key NUE indicators such as the NNI [45], the Nitrogen Partial Factor Productivity (NPFP) [39], and the Nitrogen Utilization Efficiency (NUtE) [10]. Therefore, multispectral sensors offer a comprehensive toolkit for assessing a wide range of variables that contribute to a more holistic understanding of NUE traits. Meanwhile, GSD of MS balances between image detail and spectral resolution, making them versatile for characterizing N related traits.

Accounting for 23.4% of sensor usage in the reviewed studies, RGB (Red, Green, Blue) sensors are typically employed for applications requiring high spatial resolution. RGB sensors have shown effectiveness in predicting NNI [28], PNC, PNU [33], and measuring plant height [35], which is linked to N uptake and NUE. However, their limited spectral bands makes them best suited for studies that emphasize spatial detail (e.g., ground cover) rather than for in-depth research requiring extensive spectral data [27].

Hyperspectral imagers (HSI), which make up just 10.6% of all sensors employed, exhibit unparalleled spectral capabilities. However, their use has been notably limited to three studies: one focusing on quantitative analysis of NNI [46] and two others addressing NutE [10, 36]. Although hyperspectral sensors offer unparalleled spectral detail, their limited adoption in NUE studies might stem from their high price and complex data processing requirements [47]. The large volume and high dimensionality of the data captured by hyperspectral sensors necessitate sophisticated data analysis techniques, often involving machine learning algorithms and specialized software [48].

In conclusion, the choice of sensor for assessing NUE is far from a universal solution. MSI emerge as the most versatile option, with their balanced capabilities positioning them as a frontrunner for diverse NUE-related studies. However, as research evolves, the integration of advanced algorithms and improved sensor technology could reshape this landscape. RGB sensors excel where high spatial resolution is a priority and when color data can offer adequate analytical depth. HSI, although less frequently employed, are indispensable for specialized research that demands detailed spectral information, despite the associated challenges of higher GSD and complex data processing.

3.4. Flight Parameters and Spectral Characteristics
In the realm of UAV-based remote sensing for NUE assessment, flight height significantly impacts data acquisition and interpretation. Within the scope of this review, the minimum flight height was recorded at 1.5 meters above the canopy [49], aimed at optimizing UAV-based data collection for winter wheat growth and nitrogen indicators. The median flight height across reviewed studies approximated 60 meters, optimally balancing spatial resolution and area coverage. This median elevation, in synergy with sensor-specific GSD, governs the spatial resolution essential for capturing plant traits variations.

For heights below 100 meters, high-resolution imagery is emphasized, making it ideal for studies focused on individual plants or small agricultural plots. This range is predominantly the operational domain for RGB sensors, which excel in capturing high-resolution color data. Conversely, moderate heights between 100 and 300 meters offer a balanced GSD conducive for multispectral sensors, thereby extending their applicability to diverse agricultural predictions. Hyperspectral sensors are generally deployed at elevations exceeding 300 meters to capture a comprehensive spectral range according to the studies included in this review [36]. Although higher heights minimize data variance due to short-term atmospheric changes, such as cloud cover, they often compromise spatial resolution, signified by elevated GSD values.

Spectral band selection plays a critical role in NUE evaluation. Prominent bands include Red (620-750 nm), Green (495-570 nm), Near-Infrared (NIR) (780-1000 nm), and Red-Edge (RE) (680-730 nm). The Red and NIR bands are integral to indices like the Normalized Difference Vegetation Index (NDVI) [30, 42], correlating strongly with variables such as leaf nitrogen content [42], biomass [50], and Leaf Area Index (LAI) [51]. The Green band is frequently utilized in combination with Red and NIR bands for assessing early plant vigor [52], providing valuable information related to greenness and chlorophyll [18]. The RE band is sensitive to chlorophyll concentration [53]. In this band, the absorption of light by chlorophyll drops sharply, while the scattering of light by the plant's cellular structure increases. This abrupt transition makes the RE band highly sensitive to variations in chlorophyll concentration [53]. The Blue band is comparatively underutilized owing to its limited canopy penetration and lower reflectance values, making it less suitable for distinguishing plant nitrogen status [54].

In summary, flight height and spectral band selection are not uniform considerations but are influenced by many factors such as research objectives and computational capacities. A harmonized approach to these variables ensures the efficacy of UAV-based remote sensing in NUE assessment. Multispectral sensors, with their balanced GSD and spectral capabilities, emerge as the most pragmatic choice due to their versatility in capturing a range of spectral information while maintaining a reasonable spatial resolution. The MSI bands present a spectrum of opportunities for formulating relevant vegetation indices strongly correlated with NUE. Thus, an intricate understanding of these inter-related parameters is pivotal for researchers in tailoring UAV-based remote sensing experiments for robust NUE evaluation.

3.5. Commonly Used Vegetation Indices in NUE Assessment
In summary, flight height and spectral band selection are not uniform considerations but are influenced by many factors such as research objectives and computational capacities. A harmonized approach to these variables ensures the efficacy of UAV-based remote sensing in NUE assessment. Multispectral sensors, with their balanced GSD and spectral capabilities, emerge as the most pragmatic choice due to their versatility in capturing a range of spectral information while maintaining a reasonable spatial resolution. The MSI bands present a spectrum of opportunities for formulating relevant vegetation indices strongly correlated with NUE. Thus, an intricate understanding of these inter-related parameters is pivotal for researchers in tailoring UAV-based remote sensing experiments for robust NUE evaluation.

Vegetation indices provide a simplified yet precise method for evaluating essential agronomic parameters by reducing complex spectral data to easily interpretable metrics [55]. Evaluating vegetation indices necessitates careful consideration of factors such as saturation thresholds, sensitivity to plant attributes, growth stage-specific applicability, canopy architecture, and environmental influences [56]. In this review, the NDVI and the Normalized Difference Red Edge (NDRE) were identified as the two most frequently used vegetation indices (Figure 7). NDVI, which uses the Red and NIR bands, is a versatile, general-purpose index sensitive to various plant attributes. However, in high biomass conditions, NDVI tends to saturate. This happens because chlorophyll almost completely absorbs the red light, while the leaf cell structure primarily scatters the NIR light [57]. NDVI saturation can limit its effectiveness in dense vegetation, as the index may not reflect additional biomass or nitrogen content beyond a certain leaf area density. Beyond a certain threshold of leaf area or canopy cover [51], NDVI becomes less sensitive to subtle variations of the canopy. In contrast, NDRE uses the Red-Edge and NIR bands and is particularly sensitive to variations associated with plant N trait [58, 59]. Additionally, Green Normalized Difference Vegetation Index (GNDVI) incorporates the green band along with the NIR band and is commonly used for early plant vigor assessment [60]. It is less prone to saturation compared to NDVI and usually has strong relation with dry matter [58], NNI [42], and aNUE [17].

The Chlorophyll Index (CI) is commonly calculated using various spectral bands, specifically the Red Edge and Green bands. These variations give rise to different forms of the index, namely the Chlorophyll Index in the Red Edge (CI-rededge) and the Chlorophyll Index with Green (CI-green). CI-rededge has been found had a higher estimation accuracy for NNI [40] and nitrogen content than CI-green [58]. For example, CI-rededge is generally more sensitive to changes in chlorophyll concentration [61], making it suitable for assessing N deficiency-associated chlorophyll change.

**Figure 7.** Frequency distribution of vegetation index (Frequency > 2).

Similarly, the Green Ratio Vegetation Index (GRVI) is tailored to chlorophyll concentration and serves as a dependable index for evaluating both plant health and nitrogen status. It has a good performance when estimate AGB, NNI, and PNU [62].
In addition to the aforementioned VIs, indices such as SAVI, OSAVI, TCARI, VARI, and EVI also provide specialized advantages in UAV-based remote sensing for NUE assessment. For instance, the Soil-Adjusted Vegetation Index (SAVI) and the Optimized Soil-Adjusted Vegetation Index (OSAVI) minimize soil background influences[63], making them ideal for regions with sparse vegetation. Even when the vegetation is not dense, SAVIs provide more accurate estimates of vegetation attributes like biomass [64] and LAI [65]. The Transformed Chlorophyll Absorption in Reflectance Index (TCARI) is often used in combination with OSAVI to form the TCARI/OSAVI ratio, which further enhances its ability to estimate N related traits [66]. Additionally, the Visible Atmospherically Resistant Index (VARI) was designed to work with standard RGB imagery, eliminating the need for near-infrared (NIR) or red-edge bands [67]. While this makes the index accessible and easy to implement, it does come with limitations in its ability to detect subtle variations in plant health or nutrient status. This is because VARI does not incorporate NIR or red-edge bands, which are typically sensitive to these plant/canopy structural attributes. Therefore, the index is most suitable for broader assessments focusing on overall vegetation cover rather than detailed evaluations of physiological traits [68]. Lastly, the Enhanced Vegetation Index (EVI) developed for satellite remote sensing has been also employed for UAV-based nitrogen use efficiency assessments [30] and gained significant attention recently [69, 70]. Because it incorporates the blue band to correct for atmospheric influences and includes a soil adjustment factor to account for the effects of the ground surface beneath the vegetation, it is less sensitive to atmospheric conditions and background soil variations compared to NDVI[71].

In the context of UAV-based NUE assessment, MTVI2, SR, EXG, MSAVI, and MGRVI are used less frequently when compared to other VIs in UAV-based remote sensing for NUE assessment. Several factors contribute to their less frequent usage. For example, the Modified Triangular Vegetation Index 2 (MTVI2) is specifically engineered for extracting the LAI [72] unless it is combined with MCARI to form the MCARI/MTVI2 ratio [31]. The Simple Ratio (SR) index has variations such as Simple Ratio-Red Edge (SR-RE) and Simple Ratio-Near Infrared (SR-NIR), which focus on the red-edge and near-infrared bands, respectively. Notably, SR-RE has been shown to have a stronger correlation with dry matter compared to SR-NIR [73]. However, the use of only two spectral bands in the SR index limits its capacity to capture the complexity and diversity of vegetation physiology and lacks the soil adjustment features like SAVI or OSAVI [74]. Excess Green Index (ExG), which is commonly applied in RGB is designed to maximize the response to green vegetation but may not be as sensitive to other plant attributes such as NNI [33, 75]. Modified Soil-Adjusted Vegetation Index (MSAVI) and Modified Green Ratio Vegetation Index (MGRVI) are variations of existing indices and might be overshadowed by their more established counterparts [50]. In summary, while these indices have their own specialized advantages, their adoption for NUE assessment remain limited and are not commensurate with that of widely recognized indices like NDVI and NDRE.

3.6. UAV-Based Trait Estimation for NUE Analysis
Using mixed-effects models, we discerned that the positive aggregate effect sizes for these traits ranged between 1.06 and 1.51, a trend distinctly illustrated in Figure 8. Intriguingly, certain traits, namely Plant Height, LAI, and Grain Yield, despite their biological relevance, found limited representation in extant literature. This limited number of studies for these traits has led to broader confidence intervals, suggesting caution when interpreting these results due to potential sample bias. Consequently, in our analytical approach, we adopted a conservative stance, eschewing exhaustive performance analysis for these traits, details of which are elaborated in Tables S1-S3 and Figure S1-S3 (Supplementary Materials).

Traits that have been extensively studied, such as NUE and biomass, exhibited robust predictive performances with effect sizes of 1.21 and 1.2, respectively. In contrast, the nitrogen content, despite its fundamental biological relevance, displayed a slightly conservative model effect size, pegged at 1.06.

**Figure 8.** Overall mean effect size and 95% confidence interval of each trait (n: Number of observations, Studies: Number of unique studies for each trait).

**Figure 9.** Observed Fisher’s $Z$ effect sizes with their 95% confidence interval for Nitrogen.
A recurring observation from our analysis was the significant role of data processing methods in influencing the accuracy of trait predictions across all examined traits (Tables 1-3 and Figures 9-11). In a comparative analysis of Fisher’s $Z$ effect sizes for Nitrogen, NUE, and Biomass, several patterns emerge (Figures 9-11). Multivariate non-linear signal processing techniques have marked influence on Nitrogen and NUE assessments, whereas univariate techniques have pronounced effect on biomass. In all three metrics, the Sensor type consistently displays the highest effect size, underscoring its pivotal role in these agricultural studies. Conversely, crop type appears to have minimal significance. Interestingly, growth stages, demonstrate varied influences: while the Early stage and Late stage show a negative impact on Nitrogen (Figure 9), they are positive for NUE (Figure 11). This finding further confirms that drone remote sensing enables the accurate forecasting of NUE during the early stages of vegetation development. The impact of Signal Processing Technique was especially pronounced in predicting Nitrogen ($ICC = 0.337$) and NUE ($ICC = 0.337$).
= 0.563), both with significant results (p < 0.001) as shown in Table 1 and Table 2, where it significantly modulated both intra-study and inter-study prediction accuracies. To further compare Signal Processing Techniques, we assessed the average R² values for each trait, specifically noting the performance of different methods. Figure 12 highlighted that the Multivariate Non-linear approach yielded the highest R² values across biomass, LAI, N, NUE, and Plant Height. In contrast, the Univariate technique demonstrated the lowest R² in these assessments. Interestingly, the Physically based method showcased notable accuracy in estimating NUE, although its confidence intervals suggest that the findings should be interpreted cautiously, given the limited sample size [42].

The choice of sensor type, especially its spectral resolution and range, emerged as another significant determinant, notably in biomass (p = 0.003) and nitrogen (p = 0.001) estimations. The sensor type's spectral resolution and range are critical as they directly determine the level of detail and the range of wavelengths that can be captured, affecting the precision of biomass and nitrogen estimations. Here, it showed considerable influence, indicating the variability observed in the biomass data within each individual study (R² = 0.632). This finding reinforces the long-held assertion in remote sensing literature about the criticality of judicious sensor selection to ensure optimal predictions. In contrast, factors such as crop types and growth stages, while relevant, exhibited a more nuanced influence, often overshadowed by the more pronounced effects of signal processing technique and sensor type.

Furthermore, for both NUE and biomass, the distinction between Calibration R² and Validation R² metrics has a significant influence. While the variances between Calibration and Validation R² were relatively small in our data set, such variations often indicate a risk of overfitting. Overfitting, is a challenge in statistical modeling that occurs when a model is too specifically tailored to the training data, which can make it less accurate or reliable when applied to new, different data sets [76]. While these models might perform well on training data, their accuracy can decrease when used to predict outcomes in situations they haven't encountered before. In our analysis, the growth stage was crucial for nitrogen content estimation, as plants uptake nitrogen differently at various stages, leading to distinct spectral signatures that can be captured in remote sensing data. The growth stage is a key variable in remote sensing, as it affects the plant's spectral signature and, consequently, the precision of trait estimation using UAV-based data. While our study may not have highlighted its influence on every trait, the growth stage's significance is well-recognized in the remote sensing community [77].

In summarizing our findings, it's evident that both signal processing techniques and sensor selection profoundly influence the accuracy of trait predictions. The relationship between these factors, intertwined with plant traits and their spectral reactions, necessitates comprehensive consideration. Factors like growth stage, crop type, and environmental conditions further exemplify the complexity of UAV-based plant trait predictions.

**Figure 12.** Mean estimation accuracy and 95% confidence interval of the Signal Processing Techniques for each trait.
Table 1. Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R² Type, respectively) for Nitrogen.

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Regression model statistics</th>
<th>Anova Test</th>
<th>Variance of effect</th>
<th>Heterogeneity measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed effects</td>
<td>F</td>
<td>df</td>
<td>p</td>
</tr>
<tr>
<td>Null</td>
<td>Esti. 1.065, SE 0.066, t 16.010</td>
<td>16.591</td>
<td>4; 7.155</td>
<td>0.001</td>
</tr>
<tr>
<td>Sensor Type</td>
<td>HSI 1.176, SE 0.240, t 4.911</td>
<td>0.067</td>
<td>2; 2.813</td>
<td>0.936</td>
</tr>
<tr>
<td></td>
<td>MS 1.073, SE 0.102, t 10.504</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RGB 0.922, SE 0.162, t 5.711</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>RGB, MS 1.137, SE 0.163, t 6.982</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop</td>
<td>Barley 0.959, SE 0.287, t 3.338</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Maize 1.176, SE 0.209, t 5.632</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rice 1.329, SE 0.161, t 8.233</td>
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<td></td>
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<tr>
<td></td>
<td>Winter Wheat 0.999, SE 0.076, t 13.194</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Signal Processing Technique</td>
<td>Multivariate Linear 1.277, SE 0.071, t 17.960</td>
<td>37.878</td>
<td>2; 275.779</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Multivariate Non-linear 1.413, SE 0.076, t 18.700</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Univariate 0.891, SE 0.064, t 13.980</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Growth Stage</td>
<td>All 1.170, SE 0.076, t 15.442</td>
<td>6.614</td>
<td>3; 275.029</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Early 0.808, SE 0.132, t 6.143</td>
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</tr>
<tr>
<td></td>
<td>Late 1.028, SE 0.082, t 12.487</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Medium 1.032, SE 0.071, t 14.447</td>
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<tr>
<td>R² Type</td>
<td>Calibration 0.947, SE 0.067, t 14.090</td>
<td>0.148</td>
<td>1; 275.808</td>
<td>0.701</td>
</tr>
<tr>
<td></td>
<td>Validation 1.138, SE 0.065, t 17.560</td>
<td></td>
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</tbody>
</table>

Number of obs: 290  Groups: Study 12

Table 2. Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R² Type, respectively) for NUE.

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Regression model statistics</th>
<th>Anova Test</th>
<th>Variance of effect</th>
<th>Heterogeneity measures</th>
</tr>
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<td>Fixed effects</td>
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<td>df</td>
<td>p</td>
</tr>
<tr>
<td>Null</td>
<td>Esti. 1.207, SE 0.079, t 15.250</td>
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</tr>
<tr>
<td>Sensor Type</td>
<td>2.346</td>
<td>4; 11.72</td>
<td>0.115</td>
<td>0.121</td>
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### Table 3. Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R^2 Type, respectively) for Biomass.

<table>
<thead>
<tr>
<th>Moderator</th>
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<th>Anova Test</th>
<th>Variance of effect</th>
<th>Heterogeneity measures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Null</strong></td>
<td>Fixed effects</td>
<td>F</td>
<td>df</td>
<td>p</td>
</tr>
<tr>
<td></td>
<td>Esti.</td>
<td>SE</td>
<td>t</td>
<td>(num; den)</td>
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<tr>
<td></td>
<td>1.201</td>
<td>0.097</td>
<td>12.440</td>
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<tr>
<td><strong>Sensor Type</strong></td>
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<td>MS</td>
<td>1.142</td>
<td>0.071</td>
<td>15.980</td>
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<td>RGB</td>
<td>1.928</td>
<td>0.184</td>
<td>10.490</td>
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<td>RGB, MS</td>
<td>1.107</td>
<td>0.086</td>
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<tr>
<td><strong>Crop</strong></td>
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</tr>
<tr>
<td>Barley</td>
<td>0.666</td>
<td>0.442</td>
<td>1.507</td>
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<tr>
<td>Rice</td>
<td>1.252</td>
<td>0.212</td>
<td>5.909</td>
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<tr>
<td>Winter Wheat</td>
<td>Wheat</td>
<td>1.225</td>
<td>5.214</td>
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### Signal Processing Technique

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<th>$p$</th>
<th>$t$</th>
<th>$p$</th>
<th>$F$</th>
<th>$p$</th>
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</thead>
<tbody>
<tr>
<td>Multivariate Linear</td>
<td>1.531</td>
<td>2; 86.003</td>
<td>0.000</td>
<td>0.144</td>
<td>0.079</td>
<td>0.645</td>
<td>0.154</td>
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<tr>
<td>Multivariate Non-linear</td>
<td>1.622</td>
<td>11.494</td>
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<tr>
<td>Univariate</td>
<td>1.010</td>
<td>7.585</td>
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</table>

### Growth Stage

<table>
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<th>$F$</th>
<th>$p$</th>
</tr>
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<tbody>
<tr>
<td>All</td>
<td>1.277</td>
<td>11.460</td>
<td></td>
</tr>
<tr>
<td>Late</td>
<td>1.232</td>
<td>10.350</td>
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</tr>
<tr>
<td>Medium</td>
<td>1.158</td>
<td>11.080</td>
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</table>

<table>
<thead>
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<th>Type</th>
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<th>$F$</th>
<th>$p$</th>
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</thead>
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<tr>
<td>Calibration</td>
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</tr>
<tr>
<td>Validation</td>
<td>1.242</td>
<td>13.080</td>
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</tr>
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</table>

Number of obs: 202  
Groups: Study 9

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### 4. Critical Factors for UAV remote sensing in NUE

#### 4.1. Growth Stage

Growth stage determine traits and trait development. Typically, plant growth can be separated into two cardinal phases: the vegetative and the reproductive stages. During the vegetative phase, plants are in a growth spurt, making it the peak time for NUE, as cited by [38]. For example, during the vegetative stage, NUE is maximized as plants actively synthesize proteins, while during the reproductive stage, NUE may decline as energy is diverted to seed production[78]. In this stage, plants are building more cells [79], involved in the production of chlorophyll for photosynthesis [80], creating genetic materials like DNA and RNA [81], root expansion [82], and maximizing sunlight absorption. All these activities require nitrogen, a vital component for proteins and other essential molecules. So, it's during this phase that plants are most efficient in using available nitrogen to support their rapid growth.

As a result, when considering the growth stages, the vegetative stage is particularly revealing. In this stage, plants are in their most dynamic phase of growth, heightened chlorophyll content in plants results in reduced red reflectance in the visible spectrum. This spectral behavior is compounded by the plant's increasing LAI and its dynamic canopy structure [83]. This period not only showcases the plant's growth vigor [84], but also its heightened nitrogen demand, making it a fertile ground for UASs to extract insights about growth rates [85], canopy density [86], and nutrient utilization [87]. Transitioning from the vegetative phase, the reproductive stage presents a distinct set of opportunities. As plants transfer to the reproductive stage, their physiological and spectroscopic profiles undergo notable shifts. As the chlorophyll content recedes, there's an increased reflectance in the visible spectrum. Concurrently, the canopy undergoes subtle transformations, marked by the emergence of flowers, fruits, and seeds [77]. Growth vigor might decelerate, but the canopy's complexity augments [88]. For instance, nitrogen may migrate from the aging leaves to the nascent reproductive structures [38]. This migration results in a subtle decrease in the foliar nitrogen content, impacting the overall canopy spectral patterns.

#### 4.2. Canopy structures

Based on current literature, winter wheat stands out as the predominant crop subjected to extensive assessment [89]. The intricacies of wheat canopy structure, influenced by both genetic predispositions and environmental interactions, have consequential effects on the plant's physiological processes [90], subsequently influencing growth, yield, and overall vitality [91]. The structural characteristics of the canopy, such as leaf density and orientation, directly influence the absorption and reflection of light across different spectral bands, thereby affecting the spectral signatures captured by UAV-based sensors[92]. Notably, the canopy structure

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significantly modulates the spectral signatures detectable through UAV remote sensing, making it critical to consider canopy structural variations when gleaning insights on NUE of plant health [93, 94].

Wheat canopies can be classified into four main structures based on the orientation and disposition of their leaves, including horizontally spreading type, erect type, semi-erect type, and mixed type [95]. The horizontally spreading type is characterized by leaves that predominantly lie flat, parallel, or nearly so to the ground. Such type of canopy maximizes light interception when sunlight is abundant throughout the day [96]. Spectrally, this orientation yields consistent readings, though areas interposed between leaves might exhibit shadow effects, potentially attenuating reflectance [97].

Conversely, the Erect Type presents leaves that are oriented almost perpendicularly, facilitating sunlight to permeate deeper layers, a trait that is beneficial for promoting photosynthesis, especially in densely cultivated terrains [98]. This varied leaf orientation introduces a degree of spectral variability due to complex interactions between light and the canopy. With sunlight striking leaves at different angles, this orientation enhances multiple scattering, characterized by photons undergoing several interactions with the canopy before they are reflected. This directional reflectance means that the captured spectral signatures can change based on the time of day or the position of the sensor, leading to potential inconsistencies in the data [99]. To address these challenges and ensure accurate analyses, advanced preprocessing methods become essential. One such method involves integrating bidirectional reflectance distribution function (BRDF) corrections, which normalize the spectral data to a standard set of conditions, effectively removing variability introduced by differing measurement angles [100].

The Semi-erect Type, situated between the other canopy orientations, represents an intermediate type of leaf angle distributions. Its distinct canopy structure, neither fully flat nor completely upright. The canopy's mixed orientations can lead to varied spectral responses and create nuances, which introduces unique challenges in image preprocessing due to the interplay of light conditions and spatial heterogeneity within the canopy [101]. In contrast, the mixed type is characterized by a more diverse blend of leaf orientations. This multifaceted structure further intensifies the complexity, as the canopy encompasses a spectrum of light interactions, ranging from deep penetrations to significant shadowing effects [102].

In summary, the structural diversity of wheat canopies, ranging from flat, horizontally spreading leaves to erect ones and intermediate structures, plays a pivotal role in determining their spectral signatures as captured by UAV imagers. This demands a variety of image processing techniques, ranging from conventional methods to sophisticated preprocessing algorithms, each tailored to suit the specific characteristics of the canopy under observation. As UAV-based remote sensing continues to gain traction in agronomic research, understanding these canopy structural effects remain critical for accurate and consistent UAS data interpretation.

4.3. Texture features (TFs)

Recent literature highlights a noticeable gap in research delving into the utilization of TFs for image analysis, especially concerning the extraction of NUE related traits. TFs complement spectral data by providing additional context that helps differentiate between crops with similar spectral signatures but different structural characteristics [103]. They have been recognized as an instrumental tool in characterizing wheat canopy structures using UAV-based remote sensing [104]. These features offer a granular view of the spatial organization and interplay of pixels, revealing intricate details of the canopy's micro-architecture that might be overlooked when exclusively depending on spectral data [105].

Unlike traditional methods, which primarily rely on average reflectance values or a straightforward correlation between spectral data and traits [18, 39], integrating spectral and texture data can provide a more holistic view of plant health and NUE [106], as texture features can reveal spatial patterns not discernible through spectral analysis alone. TFs delve deeper into the unique characteristics of image spatial patterns of the canopy. Their strength lies in discerning the differences in canopy spatial patterns such as leaf overlap, orientation, and density, providing invaluable insights into the spatial characteristics of the canopy [107].

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The unique strength of texture analysis thus allows for evaluating the canopy's spatial heterogeneity. For instance, erect leaf structures exhibit distinct texture patterns due to increased light penetration, contrasting with horizontally oriented leaves that are susceptible to shadow-induced spectral variations [93]. This intricate detailing, when harmonized with spectral data, amplifies classification precision, facilitating the distinction between canopies that are spectrally analogous yet structurally divergent.

As mentioned before, complex canopy structures, notably the mixed type, pose considerable challenges in remote sensing data analysis. The inherent variability of these canopies, marked by their diverse leaf orientations, often confounds the interpretation of traditional spectral analyses. Such structures, characterized by interlaced, overlapped, or diversely angled leaves, in combination with soil background and plant biochemical properties, interact with the light and finally produce the canopy reflectance captured by UAV-borne imagers. These multifaceted interactions can result in spectral readings that appear inconsistent or ambiguous when examined solely through broad spectral indices [98].

Given the complexity of analyzing intricate canopy structures, the role of TFs is vital. Various image analysis methods enable detailed examination of texture patterns and attributes. Typic texture patterns identifying basic patterns such as stripes or spots [108]. Local Binary Patterns (LBP) is an example TF attribute method, which emphasizes the local texture information, comparing the intensity of the central pixel against its neighbors [109]. Most commonly used method is the Gray Level Co-occurrence Matrix (GLCM), which encapsulates the co-occurrence frequency of gray levels, allowing the derivation of various texture metrics. The Gray Level Difference Method and Gray Level Histograms offer insights into differences in gray levels between pixels and the frequency of gray levels within the image, respectively [109]. There are some advanced mathematic transformation techniques, including the Fourier and Wavelet Transforms that convert image from its spatial domain to frequency domain, enabling nuanced texture attribute extraction, while other image analysis filters (e.g., Gabor Filters for extracting orientations) focus on capture texture attributes of specific frequency content in an image in specific directions [110].

In essence, the current research landscape in UAV-based remote sensing reveals a gap in the comprehensive exploration of TFs, especially in assessing NUE related traits. TFs, going beyond the scope of traditional spectral data, may help capture nuanced spatial differences and dynamics between crop canopies; thus, opening up new opportunities for plant phenotyping. This capability becomes particularly crucial when analyzing complex canopy structures like the mixed type, which exhibit diverse leaf orientations and intricate light interactions. Techniques like GLCM, Gray Level Difference, and LBP are pivotal in this domain. They not only provide a richer understanding of the canopy's spatial configurations but also enhance the accuracy of classification, especially when distinguishing between spectrally similar but structurally different canopies.

5. Conclusions

UASs have significantly impacted the landscape of modern agriculture, serving as crucial instruments in offering granular insights into plant health, growth, and NUE. This review sheds light on the factors influencing UAV assessments. These range from plant attributes, such as growth stages and canopy structures, to technical aspects like sensor calibrations and flight parameters.

The incorporation of TFs in data analysis represents a pivotal advancement, enabling more detailed and accurate canopy assessments. These features provide a detailed view of the plant canopy's micro-architecture. They enhance the information gained from spectral data and offer a more accurate interpretation, particularly in cases where traditional spectral indices are not sufficient. Furthermore, in an era where agriculture faces challenges like sustainability, changing climate patterns, dwindling resources, and the ever-growing demand for increased productivity, the role of UASs becomes indispensable. Their ability to provide timely high-resolution data is invaluable, but the real potential lies in integrating UAV-derived insights with data from other sensing platforms and scales. Such multi-modal integrations can potentially offer a comprehensive, multi-scale view of agricultural landscapes, thereby enabling more informed decisions and effective interventions.

Electronic copy available at: https://ssrn.com/abstract=4666863
In the future, as the nexus between technology and agriculture deepens, UAVs, fortified by advanced analytical methodologies and artificial intelligence (AI), are poised to be at the forefront of precision farming. These technologies, when applied judiciously and integrated seamlessly with other data sources, hold the promise of transforming current agricultural practices to more productive and resource-efficient ones.

Supplementary Materials: The following supporting information can be downloaded at: https://doi.org/10.5281/zenodo.10396362, Figure S1: Observed Fisher's $Z$ effect sizes with their 95% confidence interval for Grain Yield; Figure S2: Observed Fisher's $Z$ effect sizes with their 95% confidence interval for Leaf Area Index; Figure S3: Observed Fisher's $Z$ effect sizes with their 95% confidence interval for Plant Height; Table S1: Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R$^2$ Type, respectively) for Plant Height; Table S2: Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R$^2$ Type, respectively) for Grain Yield; Table S3: Regression models without moderator (Null) and with one moderator (Sensor Type, Crop, Signal Processing Technique, Growth Stage, R$^2$ Type, respectively) for Leaf Area Index.

Author Contributions: Conceptualization, Jingcheng Zhang and Kang Yu; methodology, Jingcheng Zhang; software, Jingcheng Zhang; validation, Jingcheng Zhang and Kang Yu; formal analysis, Jingcheng Zhang; investigation, Jingcheng Zhang; resources, Jingcheng Zhang; data curation, Jingcheng Zhang; writing—original draft preparation, Jingcheng Zhang; writing—review and editing, Yuncai Hu, Fei Li, Kadeghe Fue, and Kang Yu; visualization, Jingcheng Zhang; supervision, Yuncai Hu, Fei Li, and Kang Yu; All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The data set included in this review can be downloaded at: https://doi.org/10.5281/zenodo.10396362

Appendix B

Appendix B can be downloaded at: https://doi.org/10.5281/zenodo.10396362
References


Electronic copy available at: https://ssrn.com/abstract=4666863


