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FROM SPECTRAL SIGNATURES TO AGRONOMIC DECISIONS: SUSTAINABLE NUTRIENT MANAGEMENT IN FIELD CROPS

Barenya Gogoi^{1*}, Kalyan Pathak¹, Bipul Deka¹, Jonali Goswami², Madhumita Barooah¹, Nandini Das¹, Rahul Gogoi¹, Shabir Bhat³, Boishali Dutta¹, Prakshiya Boruah¹, Rosy Chamuah¹ and Debjani Dutta¹.

¹Assam Agricultural University, Jorhat, Assam, India

²North Eastern Space Applications Center, Umiam, Meghalaya, India

³Sher-e-Kashmir University of Agricultural Sciences and Technology, Shalimar, J&K, India

*Corresponding author e-mail: barenya.gogoi@gmail.com

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ABSTRACT

Nitrogen (N) management is one of those persistent challenges in field crop production owing to its dynamic interactions among crop demand, soil nutrient supply and environmental conditions. Sensor-based technologies have emerged as promising tools for enabling site-specific, in-season N management by integrating crop spectral information with fertilizer decision algorithms. This review synthesizes the underlying principles and practical applicability of active optical sensors, hyperspectral remote sensing and spectral reflectance for precision N management. It examines widely used N recommendation approaches, including the Nitrogen Fertilization Optimization Algorithm (NFOA) and INSEY-based models, highlighting their operational frameworks, strengths, and limitations. The review further discusses vegetation spectral properties, hyperspectral data analysis and commonly used vegetation indices for crop assessment. Finally, the agronomic, economic and environmental performance of sensor-based N management is evaluated in terms of N input, grain yield and nitrogen use efficiency (NUE). On the whole, sensor-guided fertilization offers significant potential to improve nitrogen management, although its effectiveness depends on robust calibration, field variability and integration with complementary decision-support tools. Given the increasing demand for sustainable intensification of agriculture, this review consolidates current knowledge on sensor-based nitrogen management and offers a scientific foundation for improving fertilizer recommendations, nitrogen use efficiency and environmental sustainability.

Key words: Sensor-based nitrogen management, hyperspectral remote sensing, agronomy, vegetation indices, NDVI, NFOA, nitrogen-use efficiency.

Introduction

Optimal nitrogen (N) fertilizer use should be based on an understanding of the nutrient demand and supply balance. Although it might sound simple, this is a complex task as both sides of the equation are hard to predict. From a biological perspective, the optimum N rate depends on many variables such as the expected quantity and quality of the final product, the N supply from other sources besides fertilizer and N losses to the environment. Pragmatically, economics are also fundamental to identification of optimal rates. Crop response curves to applied N empirically derived from N rate experiments

are alternatives to determine the optimum rate without the necessity of predicting all the variables affecting the crop soil N system. Yet, due to their simplicity, recommendations derived from these cannot be confidently generalized to conditions beyond those of the experiment (Bramley *et al.*, 2013; Singh *et al.*, 2021). Alternatively, simulation models predicting crop, soil and climate variables have been developed in many parts of the world to support more robust recommendations (Pampolino *et al.*, 2012; Sela *et al.*, 2016; Setiyono *et al.*, 2011). An added complexity in recommending N fertilizer rates is the fact that all parameters affecting

nutrient dynamics in the cropping system can vary both spatially (between fields and within a single field) and temporally (between cropping seasons and/or during one season). The capacity to account for the variability of both crop N demand and soil supply is the key aspect distinguishing Precision Agriculture (PA) strategies from traditional methods of N management in which uniform application is assumed to be the optimal strategy. In the context of PA, the use of electronic sensors is common for providing site-specific diagnostics of various soil and crop parameters (Heege, 2013). During the past two decades, non-destructive proximal canopy reflectance sensors have been identified as potentially valuable tools for site-specific N management (Ali *et al.*, 2017; Mulla, 2013). These have been developed to assess plant nutritional status and guide variable rate N application for different grain crops (Cao *et al.*, 2016; Raun *et al.*, 2002; Shanahan *et al.*, 2008), cotton (e.g. Oliveira *et al.*, 2013; Vories *et al.*, 2014) and sugarcane (e.g. Amaral *et al.*, 2015a,b; Portz *et al.*, 2012), and have been one of the most heavily investigated topics in PA. Typically, proximal canopy sensors make measurements of reflected light at selected wavelengths in the electromagnetic spectrum and convert these to vegetation indexes (such as NDVI “normalized difference vegetation index”) representing the amount of photo synthetically active biomass (Heege *et al.*, 2008). Based on calibration against crop biomass, N nutritional status or yield potential, these sensors are typically used to provide insight into the ‘demand’ side of the equation and, assuming other factors are non-limiting, in-season N prescriptions can be generated and applied site-specifically. After decades of development, several commercial sensors are available as well as different methods to transform their readings into N rates. Recent nation-wide surveys in Australia, Brazil and USA indicate that the adoption of variable rate fertilizer application (VRA) is around 15 - 25% of grain growers (Llewellyn and Ouzman, 2014; Molin, 2017; Schimmelpennig and Ebel, 2016). However, the adoption of sensor-based technology to support VRA (not specified in these studies) can be expected to be much lower (R Bramley, CSIRO - unpublished data, 2017; Franzen *et al.*, 2016; Lowenberg-Deboer, 2013; Scharf *et al.*, 2011). Such low adoption indicates that more development is needed and/or that research has failed to demonstrate the usefulness of the technology to farmers; perceived usefulness is pointed as one of the main drivers for the adoption of PA technologies (Pierpaoli *et al.*, 2013; Aubert *et al.*, 2012; Robertson *et al.*, 2012; Gogoi *et al.*, 2025). Thus, in order to fully explore the factors driving adoption, some important questions should be asked: has current

sensor-based N application been able to increase profit and improve environmental protection? Is there enough evidence to support its potential and if not, what can be learned from two decades of development? Several studies have compared sensor-based N approaches against other methods of N recommendation. However, evaluating studies individually does not help answer the key questions. Current reviews are based on summaries of different sensors and methods available and not on the outcome from their use (Ali *et al.*, 2017; Franzen *et al.*, 2016; Muñoz-Huerta *et al.*, 2013; Mulla, 2013). Our objective was to review the outcomes from the use of crop sensors for site-specific N management, focusing on studies that have tested whether the technology can improve yield, N use efficiency (NUE), profitability and environmental protection. We also sought to identify the main limitations of the current technology and the experimental methods used in developing and evaluating it, thereby providing a framework for future investigations and technology enhancement.

Various Sensor-Based Nitrogen Recommendations

The methods used to determine in-season nitrogen (N) fertilizer requirements with crop sensors vary considerably. They range from simple rate redistribution functions to advanced calibrated algorithms based on agronomic principles. The simplest approach involves redistributing a pre-defined average N application rate. These functions are commonly provided by sensor manufacturers. Prior to sensor-based field assessment, users define the average, minimum and maximum limits of N application rates in different parts of the field. Based on the sensor readings, the system adjusts the N application rate according to the selected redistribution function. In a simple linear redistribution model, the user can select either a negative or a positive slope. A positive slope increases N application in areas with greater crop biomass. This approach assumes that these areas have higher yield potential, often because of better water availability, and therefore require more N to achieve their full productivity. In contrast, a negative slope reduces N application in areas with higher biomass while increasing it in areas with lower biomass. This strategy assumes that well-performing crop areas already have sufficient N, whereas weaker areas may benefit from additional fertilizer. Negative slope algorithms are the most commonly used approach in commercial systems. The Yara N-Sensor™ is one such commercial sensor. It integrates basic rate redistribution approaches with proprietary algorithms for nitrogen management decisions. More sophisticated approaches use agronomic models to estimate crop N requirements. One widely

adopted method is based on the mass balance concept. In this approach, the fertilizer requirement is calculated by estimating the total N needed to achieve a target grain yield and a desired protein concentration (Meisinger *et al.*, 2008). Additional N supplied from sources other than fertilizer may also be credited. The model can further account for expected N losses, which are generally assumed to range from 35% to 75% (Meisinger *et al.*, 2008). Expected crop yield is estimated from sensor measurements using previously developed calibration models. In some models, sensor data are also used to estimate the amount of N already taken up by the crop. This value is then subtracted from the total crop N requirement to determine the remaining fertilizer need (Lukina *et al.*, 2001). A major limitation of these demand-based approaches is that they primarily focus on crop N demand while giving limited attention to soil N supply. However, accurately estimating the amount of N supplied by the soil is difficult because it depends on several environmental factors. Soil organic matter, microbial activity, temperature, and soil moisture all influence the rate of N mineralization. Consequently, soil N supply varies substantially across locations and growing seasons. Although total crop N demand can often be estimated with reasonable accuracy, the amount of N supplied by the soil ultimately determines the crop response to fertilizer application (Kindred *et al.*, 2015; Meisinger *et al.*, 2008). Therefore, neglecting soil N supply can reduce the accuracy of fertilizer recommendations. Crop response to applied N also changes over time and across different parts of a field. These variations result from differences in soil properties, weather conditions, and plant water stress. As a result, the economically optimum N rate may vary both spatially and temporally (Johnson and Raun, 2003; Kablan *et al.*, 2017). Moreover, optimum N rates are often poorly related to the expected crop yield (Doerge, 2005; Scharf *et al.*, 2006).

To address these challenges, many sensor-based systems use in-season, site-specific reference areas to estimate crop responsiveness to additional N. Instead of directly measuring soil N supply, these reference areas provide an indirect assessment of the supply side of the N balance. The most common approach is the establishment of an N-rich strip. This strip receives a non-limiting amount of N fertilizer and serves as a reference for comparison with the rest of the field. If crop growth at a particular location is poorer than that in the N-rich strip, the crop is assumed to be N deficient and likely to respond positively to additional fertilizer. Several alternative reference methods have also been developed. These include calibration stamps (Raun *et al.*,

2005b), ramped calibration strips (Roberts *et al.*, 2011b) and the virtual reference concept (Holland and Schepers, 2013). Despite differences in implementation, all these methods rely on the assumption that the reference area accurately represents the surrounding field or management zone (Lawes and Bramley, 2012). Ensuring that the reference area is truly representative is often the greatest limitation of these approaches. Spatial variability within both the field and the reference strip can make it difficult to determine which vegetation index (VI) value should be used as the reference. Similarly, there is ongoing debate regarding the appropriate number and placement of reference strips required to adequately represent field variability. The N-rich strip concept has been widely used since the early development of handheld chlorophyll meters (Schepers *et al.*, 1992; Blackmer and Schepers, 1994, 1995; Varvel *et al.*, 1997). It continues to be an important component of many sensor-based N management systems.

Algorithm Frameworks for Nitrogen Recommendation

The Nitrogen Fertilization Optimization Algorithm (NFOA) developed by Raun *et al.*, (2002) and later refined by Raun *et al.* (2005a) is based on the N-rich strip concept. Although the algorithm has been modified in different studies, its fundamental principle remains the same. It estimates the optimum N application rate using a mass balance approach. The recommended fertilizer rate represents the additional N required to increase the expected yield at a given location to the yield potential estimated from the N-rich strip, or to a specified proportion of that potential. The expected yield without additional N is estimated from crop sensor measurements. This is achieved using calibration equations that relate the In-Season Estimate of Yield (INSEY) to grain yield. INSEY is calculated by dividing the Normalized Difference Vegetation Index (NDVI) by the accumulated growing degree days at the time of sensing. The potential yield after N application is then estimated by multiplying the predicted yield at a specific location by the Response Index (RI). The RI is calculated as the ratio of NDVI measured in the N-rich strip to the NDVI measured in the corresponding field area (Raun *et al.*, 2002; Raun *et al.*, 2005a). The NFOA became one of the most influential approaches for sensor-based N management in cereal crops. It served as the basis for numerous studies conducted by research groups worldwide. The algorithm was successfully adapted and evaluated in Mexico (Ortiz Monasterio and Raun, 2007), China (Li *et al.*, 2009), India (Bijay-Singh *et al.*, 2012), and Brazil (Povh *et al.*, 2008; Povh and Anjos, 2014). It also became commercially available as one of the fertilizer recommendation options

for users of the GreenSeeker sensor. The GreenSeeker sensor measures canopy reflectance at 656 and 774 nm to calculate NDVI. Around the same period, Holland and Schepers (2010) proposed another sensor-based N recommendation approach. This method later became one of the recommended algorithms for the Crop Circle sensor. The earlier Crop Circle ACS-210 model operated using wavelengths of 590 and 880 nm. A later version, the ACS-430, incorporated three wavelengths (670, 730, and 780 nm), allowing calculation of the Normalized Difference Red Edge (NDRE) index. Compared with NDVI, NDRE is less affected by saturation at advanced crop growth stages, where NDVI often fails to respond to further increases in biomass (Sharma *et al.*, 2015).

The Holland and Schepers approach evolved from long-term research on chlorophyll meters initiated during the early 1990s. Unlike the NFOA, it does not rely on the mass balance concept or on calibration equations relating vegetation indices to grain yield. Instead, the optimum N requirement is determined empirically under field conditions. According to the authors, this provides a more robust and science-based method for estimating crop N requirements than mass balance-based recommendations (Holland and Schepers, 2010). The foundation of this method is a generalized quadratic-plateau N response curve developed from traditional N fertilizer experiments. In these experiments, relative grain yield is expressed as the ratio of yield obtained at a given N rate to the yield achieved under a non-limiting N treatment. Because grain yield is unknown during the growing season, the approach replaces relative yield with the Sufficiency Index (SI). The SI is calculated as the ratio of the vegetation index measured at a specific field location to the vegetation index measured in the non-limiting N reference strip. Thus, the SI represents the inverse of the Response Index proposed by Raun *et al.*, (2002, 2005a). This method assumes that normalized vegetation index values are directly related to crop growth and relative grain yield. However, this assumption may not always hold true because it ignores potential variation in harvest index (Raun *et al.*, 2005a). Nevertheless, when both a zero-N check strip and a non-limiting N strip are included in the field, the model can be calibrated to estimate the required N application rate. The recommendation is generated using the local SI together with previously established optimum regional N rates. The objective is to apply sufficient fertilizer to increase the crop from its current SI to the SI corresponding to the optimum N rate. Consequently, the method focuses on redistributing fertilizer according to the crop response curve rather than directly estimating total N demand. A comparable strategy emphasizing

economic return rather than biological optimization was later described by Adamchuk (2013).

An important characteristic of both the NFOA and the Holland and Schepers approaches is that neither explicitly incorporates important environmental covariates, such as soil water availability or soil moisture status, into the N recommendation process. Although algorithm development and sensor calibration continue to evolve (Barker and Sawyer, 2010, 2013; Solie *et al.*, 2012; Tagarakis and Ketterings, 2017; Wang *et al.*, 2017), these two approaches and their variations have remained the most widely evaluated methods in validation studies. These approaches have established the foundation for sensor-based, in-season nitrogen management. Building on these developments, recent research has increasingly explored hyperspectral remote sensing to further enhance crop nitrogen assessment and fertilizer management.

Hyperspectral Remote Sensing

Hyperspectral remote sensing, can be referred to as both imaging and non-imaging spectroscopy, has seen significant advancement due to recent progress in remote sensing technologies as well as geographic information systems (GIS). These developments have led to the evolution of hyperspectral sensors, a relatively modern innovation increasingly employed by researchers and scientists for identifying and analysing materials, crop types, soil properties, vegetation, and artificial surfaces. While spectral analysis has been in use for over a century to study the chemical and biological composition of various substances, hyperspectral sensors now provide a non-invasive alternative for examining the physical and chemical characteristics of materials. Spectroscopy enables the detection of specific absorption features linked to molecular bonds in solids, liquids, or gases. With continual technological improvements, imaging spectroscopy has expanded its focus to a wide array of Earth-based applications. Originating in the mid-1980s, the concept of hyperspectral remote sensing has been especially valuable for mineral mapping by geologists.

Hyperspectral sensors generally record light within the spectral range of approximately 350 to 2500 nanometres, encompassing the visible, near-infrared (NIR) and shortwave infrared (SWIR) regions. Unlike multispectral sensors that record information in a limited set of broad spectral bands, hyperspectral sensors measure reflectance across numerous narrow and contiguous spectral bands, offering substantially enhanced spectral detail.

Spectral Reflectance

Remote sensing relies on the principle of detecting

energy that is either reflected or emitted by various surfaces. Different materials interact with sunlight uniquely, some absorb more, while others reflect more based on their surface characteristics. The reflectance behaviour of a material is influenced by its specific composition, its biophysical and biochemical conditions, surface roughness and geometric factors such as the angle at which sunlight strikes the surface. Key surface features like colour, texture and structure play a crucial role in this interaction.

These variations in reflectance allow for the identification of different surface materials by analysing their unique spectral reflectance patterns, also known as spectral signatures. These signatures are typically represented using spectral reflectance curves, which show how reflectance varies across different wavelengths. The following figure illustrates the spectral signatures for soil, water and vegetation (Saho *et al.*, 2015).

Hyperspectral Remote Sensing for Agriculture

Spectral Properties of Vegetation

In addition to their vital role in photosynthesis, leaves also help shield plants from environmental stress. Within plant tissues, three main types of pigments are typically present:

- Chlorophyll
- Anthocyanin
- Carotenoid

Chlorophyll-a and chlorophyll-b are essential pigments that help convert light energy into chemical energy, which plants utilize for growth and metabolism.

Carotenoids, which absorb strongly in the blue region of the light spectrum, are unevenly distributed within the photosystem (Janse *et al.*, 2016). Variations in leaf carotenoid content and its ratio to chlorophyll are widely used indicators to assess a plant's physiological condition,

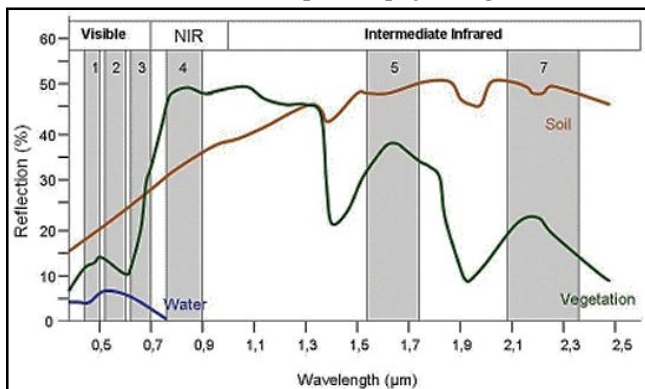


Fig. 1: Spectral signature of soil, vegetation and water, and spectral bands of LANDSAT-7.

particularly in relation to growth, environmental adaptation, and stress responses.

Anthocyanins are another class of pigments responsible for the red coloration observed in many higher plants. Traditionally, pigment analysis in plants relied on wet chemistry techniques. However, hyperspectral remote sensing has recently emerged as a valuable alternative for studying the biological and biochemical characteristics of plants. A common method employed by researchers involves analyzing changes in reflectance patterns (Berger *et al.*, 2020). As shown in Fig. 2, within the 400–700 nm wavelength range, absorption by leaf pigments is the dominant process, typically resulting in low levels of both reflectance and transmittance.

This is because of:

- Chlorophyll a and chlorophyll b
- Carotenoids
- Xanthophyll
- Polyphenols

All plant pigments exhibit overlapping spectral absorption characteristics. Approximately 65% of the total pigment content in plants comprises chlorophyll a (Chl a) and chlorophyll b (Chl b), with Chl a being the primary pigment found in mature plant species. Chl a absorbs light most effectively in the 410–430 nm and 600–690 nm wavelengths, while Chl b has peak absorption near 470 nm. These absorption patterns lead to a notable reflectance peak around 550 nm in the green spectrum. Carotenoids predominantly absorb light in the 440–480 nm range, while polyphenols exhibit gradually decreasing absorption from the blue toward the red spectrum, becoming prominent particularly in senescing or dead leaves (Feret *et al.*, 2021). In vegetation canopies, Chl b plays a role in absorption at both shorter and longer wavelengths within the visible spectrum. Between 700 and 1300 nm, both pigments and cellulose become highly

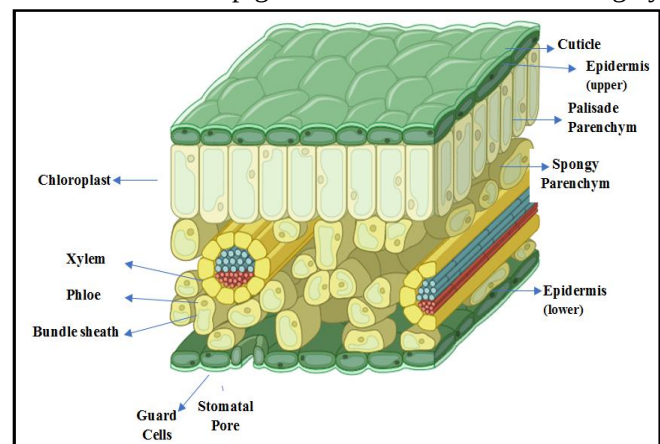


Fig. 2: Anatomy of leaf.

reflective, causing reflectance and transmittance to peak due to minimal absorption. This is largely attributed to internal scattering at the interfaces between air, cells, and water (Hunt *et al.*, 1989). Reflectance in the near-infrared region is influenced by leaf structure, greater intercellular space, thicker cell layers, and larger cells contribute to higher reflectance. This scattering arises from repeated refraction and reflection among hydrated cell walls and air spaces.

In the shortwave infrared (SWIR) spectrum, leaf reflectance is largely determined by water content and other foliar elements. Key water absorption bands are observed at 1450, 1940, and 2700 nm, with additional absorption features at 960, 1120, 1540, 1670, and 2200 nm (Jafarbiglu *et al.*, 2022).

Optimal hyperspectral bands for agricultural studies are identified through thorough literature analysis by:

- (a) Eliminating overlapping spectral bands,
- (b) Correlating spectral data with crop traits and indices and
- (c) Identifying spectral regions that effectively discriminate between crop types and genotypes.

Hyperspectral Remote Sensing Applications for Vegetation

Crop discrimination and Spectral Characterization

Hyperspectral data is highly effective for distinguishing subtle spectral variations among different crop types due to its high spectral resolution. However, one of its main limitations is the presence of redundant spectral information, which can complicate data processing and analysis. To address this issue, feature selection methods combined with discriminant statistical techniques such as Principal Component Analysis (PCA) and Stepwise Discriminant Analysis (SDA) are commonly employed to reduce dimensionality and identify the most informative spectral bands. Numerous studies (Thenkabail *et al.*, 2004; Vaiphasa *et al.*, 2005; Wan *et al.*, 2022) have successfully utilized these approaches to select relevant wavebands and differentiate between vegetation types and plant species.

For instance, Manjunath *et al.*, (2011) applied hyperspectral analysis to classify ornamental plants, pulses, and Cole crops. Using SDA, they identified optimal bands for classification. Their findings indicated that the near-infrared (NIR) and early mid-infrared (MIR) regions, specifically the bands at 750, 800, 940, and 960 nm were most effective for distinguishing pulse crops. In contrast, the discrimination of Cole crops was primarily associated with green, red, and NIR spectral bands, notably at 550,

690, 740, 770, and 980 nm. For flower classification, the study highlighted key bands at 420, 470, 480, 570, 730, 740, 940, 950, 970, and 1030 nm. Similarly, Sahoo *et al.* (2013) employed the SDA technique for band selection and used the Jeffries-Matusita (JM) distance as a separability index to successfully differentiate 70 wheat genotypes using proximal hyperspectral reflectance data. In another study, Kumar *et al.*, (2013) conducted field-based hyperspectral analysis to assess the spectral behavior of tea plants in relation to various factors, including plant type, plantation age, growth stages, pruning status, light availability, and the presence of disease. Processes like Stepwise Discriminant Analysis (SDA) and Principal Component Analysis (PCA) were employed to identify the most relevant spectral bands for extracting the aforementioned crop-related information from hyperspectral datasets. In a related study, Miglani *et al.*, (2008) utilized satellite-based Hyperion imagery to classify various winter crops, including mustard, sorghum, wheat, sugarcane, and potato. For the purpose of feature selection, they applied both band-to-band correlation analysis and PCA to reduce data dimensionality and enhance classification accuracy.

Effect of sensor-based N application on N input, grain yield and NUE

Grain yield, nitrogen (N) input, and N performance are important indicators for assessing the effectiveness of different N management strategies. Several indices have been developed to evaluate nutrient performance (IPNI, 2014). This review focuses on two widely used indicators: partial factor productivity (PFP = grain yield/applied N), which measures crop productivity relative to fertilizer input and nitrogen use efficiency, which represents the proportion of applied fertilizer N recovered in the harvested grain (Raun and Johnson, 1999). Research on the GreenSeeker sensor began in the mid-1990s. Most early studies were conducted in the United States using the Nitrogen Fertilization Optimization Algorithm (NFOA) developed by Raun *et al.*, (2002) and later refined by Raun *et al.*, (2005a). Subsequently, the NFOA was adapted for corn (Ma *et al.*, 2014; Tubaña *et al.*, 2008b), wheat-growing regions outside the United States (Colaço *et al.*, 2012; Sapkota *et al.*, 2014) and rice production systems in China (Yao *et al.*, 2012). Studies involving the Crop Circle sensor emerged later and generally followed the application strategy proposed by Holland and Schepers (2010) or modified algorithms developed in subsequent research (Scharf *et al.*, 2011). Most studies reported that sensor-based N management reduced fertilizer application without significantly affecting grain yield, thereby improving N use efficiency. However,

Table 1: Various vegetation indices commonly used by researchers.

Index	Equation	Full Form	Reference
EVI	$2.5 * (R_{NIR} - R_{red}) / (R_{NIR} + 6R_{red} - 7.5R_{blue} + 1)$	Enhanced Vegetation Index	Huete <i>et al.</i> , 1997
Green NDVI	$(R_{NIR} - R_{green}) / (R_{NIR} + R_{green})$	Green Normalized Difference Vegetation Index	Rouse <i>et al.</i> , 1973
NDVI	$(R_{NIR} - R_{red}) / (R_{NIR} + R_{red})$	Normalized Difference Vegetation Index	Rouse <i>et al.</i> , 1973
SR	R_{NIR} / R_{red}	Simple Ratio	Jorden <i>et al.</i> , 1969
NDWI	$(R_{857} - R_{1241}) / (R_{857} + R_{1241})$	Normalized Difference Water Index	Gao <i>et al.</i> , 1996
WBI	R_{900} / R_{970}	Water Band Index	Penuelas <i>et al.</i> , 1997
SAVI	$[(R_{NIR} - R_{red}) / (R_{NIR} + R_{red} + L)] * (1 + L)$	Soil-Adjusted Vegetation Index	Huete <i>et al.</i> , 2000
VARI	$(R_{green} - R_{red}) / (R_{green} + R_{red} - R_{blue})$	Visible Atmospherically Resistant Index	Gitelson <i>et al.</i> , 2002

the results should be interpreted cautiously because experimental designs and treatment comparisons varied among studies. Improvements in NUE or PFP usually resulted from multiple interacting factors, making it difficult to isolate the contribution of individual management practices.

One important factor is fertilizer application timing. Sensor-guided N is generally applied as an in-season top-dress, which better synchronizes N availability with crop demand. Consequently, split N applications are expected to improve fertilizer efficiency compared with a single pre-plant application, regardless of whether the mid-season application is sensor-guided. Some studies compared split and pre-plant applications separately to distinguish the effect of application timing. For example, Thomason *et al.*, (2002) reported average NUE values of 24.5% for a single pre-plant application and 44.5% for a fixed three-way split application. When the sensor was used to determine the second of the three applications, NUE increased further to 48.1%. Similarly, Tubaña *et al.*, (2008a) observed a 7% increase in wheat yield and a 15% increase in N uptake when a fixed rate of 90 kg N ha⁻¹ was applied during mid-season rather than before planting. The sensor-based treatment improved NUE by approximately 16% compared with the fixed pre-plant application and by about 8% compared with the fixed mid-season application.

In corn, Tubaña *et al.*, (2008b) reported a 5.9% yield increase with sensor-based N management. However, 3.6% of this improvement resulted simply from splitting the conventional N rate into pre-plant and mid-season applications. Similar observations were reported by Boyer *et al.*, (2012) and Ma *et al.*, (2014). Therefore, evaluating the effectiveness of sensor-based N management requires careful consideration of the conventional practice used for comparison. The apparent benefit of sensor technology largely depends on the quality of the existing N management strategy. In many cases, improvements may arise more from better fertilizer recommendations than from crop sensing or variable-rate application itself. Several studies compared sensor-based

recommendations with farmer practices that involved excessive N application. For instance, Li *et al.*, (2009) reported farmer-applied rates exceeding 400 kg N ha⁻¹ in winter wheat in North China, while Cao *et al.*, (2017) documented application rates of approximately 300 kg N ha⁻¹. Excessive N fertilization is widespread in intensive farming systems in China (Miao *et al.*, 2011). This is largely attributed to low fertilizer prices, inefficient application timing, and limited access to agronomic advisory services among smallholder farmers. Similarly, Sapkota *et al.*, (2014) evaluated the GreenSeeker sensor in wheat under Indian conditions, where the conventional farmer practice excluded potassium fertilization. In contrast, the sensor-based treatment received balanced fertilization, including potassium. Consequently, the reported 17% yield advantage may not be attributable solely to sensor-guided N management. Such comparisons can therefore overestimate the benefits of sensor-based approaches and should be interpreted with caution. In contrast, when sensor-based strategies were evaluated against other information-driven N management methods, their advantages were generally small or absent. Phillips *et al.*, (2004) compared the GreenSeeker sensor with a conventional approach based on wheat tiller counts and plant tissue N analysis in Virginia, USA. Both treatments used the same N recommendation procedure, with the sensor estimating tiller density through calibrated NDVI measurements. Sensor-guided management produced no yield advantage and reduced N application by only 11 kg ha⁻¹ (approximately 7%) at two of the six experimental sites. Likewise, Thomason *et al.*, (2011) compared the Virginia Wheat Algorithm, which follows principles similar to the NFOA, with the conventional tiller density and tissue testing method. Across 15 experiments, the sensor-based approach reduced N application by only about 3% while maintaining comparable grain yields. Comparable findings have been reported when sensor-based recommendations were evaluated against soil-based diagnostic methods or crop simulation models. In the North China Plain, GreenSeeker and Crop Circle sensors performed slightly

worse than in-season soil N testing for fertilizer recommendations (Cao *et al.*, 2017). Similarly, Sapkota *et al.*, (2014) evaluated an adapted NFOA across 15 on-farm wheat trials in northwest India. When integrated with the pre-plant decision support tool *Nutrient Expert* (Pampolino *et al.*, 2012), the sensor-based approach increased yield by only 1.7% compared with the decision tool alone, although it achieved an 8.7% increase relative to the regional fertilizer recommendation. Thompson *et al.*, (2015) compared the RapidScan™ sensor, which estimates NDRE similarly to the Crop Circle sensor, with the Maize-N decision model (Setiyono *et al.*, 2011). Although the sensor recommended nearly 40% lower N rates and improved partial factor productivity, yield reductions were frequently observed, and profitability did not improve consistently.

Overall, these findings suggest that the additional benefits of sensor-based N management are limited when reliable in-season decision-support tools or diagnostic methods are already integrated into fertilizer management. Under such conditions, crop sensors are less likely to substantially improve mid-season N recommendations. A major advantage of sensor-based nitrogen (N) management over conventional approaches is its ability to apply fertilizer at variable rates according to the spatial variability of crop growth. Under commercial farming conditions, however, crop variability occurs across both small and large spatial scales, ranging from a few metres to several tens of metres within a field. Therefore, if sensor-based variable-rate application (VRA) is not evaluated under realistic field conditions, its potential advantages over other information-based N management strategies may be underestimated. Although small plot experiments are often considered inadequate for evaluating site-specific management practices, they have occasionally demonstrated the benefits of variable-rate N application. For example, Raun *et al.*, (2002) reported positive results in winter wheat using 24 m² plots in Oklahoma, USA. The strong response was likely due to substantial short-distance variability within the plots. Their strategy targeted spring applications during the tillering stage, when uneven crop establishment caused by limited stored soil moisture and winter injury often creates patchy crop stands. Compared with a uniform mid-season N application at a similar fertilizer rate, the sensor-guided treatment increased grain yield by 273 kg ha⁻¹ (17%) and improved NUE to 40%, approximately 15% higher than the uniform treatment. Achieving the same yield with uniform application required nearly twice the N rate, resulting in the lowest NUE (17%). These findings indicate that the improvement largely resulted from

varying N application at a very fine spatial resolution (approximately 1 m²), a level of precision that is generally not achievable with commercial VRA equipment.

Other studies have reported little or no advantage of variable-rate application in conventional plot experiments. Tubaña *et al.*, (2008a) observed similar NUE whether sensor-based recommendations were applied uniformly or site-specifically within 26.8 m² plots. Likewise, Ma *et al.*, (2014), using large plots (>2,000 m²), found no significant advantage of variable-rate over uniform sensor-based N application. They concluded that improvements in grain yield and partial factor productivity (PFP) resulted primarily from delaying N application until side-dressing rather than from spatially varying fertilizer rates, as both uniform and variable side-dress treatments produced similar outcomes. Traditional randomized complete block designs are generally unsuitable for evaluating variable-rate technologies because they assume that spatial variability is eliminated through randomization or incorporated into experimental error. Consequently, these experiments often overlook the effects of field-scale variability that variable-rate management is intended to address. Even when variability exists within experimental plots, treatment responses are typically assessed using average plot yield, which masks localized crop responses to variable-rate fertilization. Strip-trial designs, combined with variable-rate applicators and yield monitors, provide a more appropriate framework for evaluating site-specific management, although within-strip variability must also be considered (Bramley *et al.*, 2013). Scharf *et al.*, (2011) used this approach to evaluate GreenSeeker and Crop Circle sensors through 55 on-farm strip trials across the corn-growing regions of Missouri, USA. The experimental treatments were simple and directly comparable, although the average strip length of approximately 450 m limited the evaluation scale. Nitrogen recommendations were generated using a calibrated linear relationship between vegetation index (VI) values, normalized with a high-N reference strip, and fertilizer requirement. Compared with farmers' conventional practice using the same application timing, the sensor-based approach reduced N application by 16 kg ha⁻¹ (7.7%) while increasing grain yield by about 1%, resulting in a 9.5% improvement in PFP. Although these results demonstrate modest benefits, the recommendation algorithm relied on a generalized regional calibration despite using local reference strips. This limits its ability to fully exploit site-specific variability. Bullock *et al.*, (2002) argued that reliance on generalized regional equations may explain the limited success of some variable-rate technologies. In contrast, Cook and Bramley (2000) suggested that regional calibration, when combined

with local sensor measurements, can enhance the effectiveness of precision agriculture practices.

Conclusion

Nitrogen management remains one of the most challenging components of crop production because of the pronounced spatial and temporal variability in crop nitrogen demand and soil nitrogen supply. Sensor-based approaches have emerged as an effective alternative to conventional blanket fertilizer recommendations by enabling in-season assessment of crop nitrogen status and site-specific fertilizer application. This review demonstrates that active optical sensors, hyperspectral remote sensing, and spectral reflectance-based vegetation indices have substantially advanced nitrogen management by providing rapid, non-destructive, and spatially explicit information on crop physiological condition. Algorithms such as the Nitrogen Fertilization Optimization Algorithm (NFOA) and INSEY-based models have shown considerable potential for translating canopy spectral responses into operational nitrogen recommendations, resulting in improved nitrogen use efficiency (NUE) while maintaining or increasing grain yield under diverse production environments. However, the agronomic benefits of sensor-based nitrogen management are not universal. The accuracy of spectral diagnostics is influenced by crop genotype, growth stage, canopy architecture, soil background, atmospheric conditions, water availability, and sensor calibration, leading to variability in recommendation performance across environments. Furthermore, most existing recommendation algorithms rely primarily on crop spectral information and often fail to explicitly incorporate dynamic environmental variables such as soil moisture, weather fluctuations, and soil nitrogen mineralization, which limits their robustness under heterogeneous field conditions. The high dimensionality of hyperspectral datasets, computational complexity, and the need for region-specific calibration also remain significant barriers to large-scale adoption. Future advances should focus on integrating hyperspectral sensing with machine learning, crop growth models, proximal and satellite observations, and environmental covariates to develop adaptive, transferable and data-driven nitrogen recommendation frameworks. Standardization of calibration protocols, extensive multi-location validation and assessment of long-term agronomic, economic and environmental outcomes are essential for improving the reliability and scalability of these technologies.

References

- Adamchuk, V.I. (2013). Theoretical basis for sensor-based in-season nitrogen management. *Precision agriculture*, **13**, 403-410. Wageningen Academic.
- Ali, M.M., Al-Ani A., Eamus D. and Tan D.K. (2017). Leaf nitrogen determination using non-destructive techniques—A review. *Journal of Plant Nutrition*, **40**(7), 928-953.
- Amaral, L.R., Molin J.P. and Schepers J.S. (2015). Algorithm for Variable Rate Nitrogen Application in Sugarcane Based on Active Crop Canopy Sensor. *Agronomy Journal*, **107**(4), 1513-1523.
- Aubert, B.A., Schroeder A. and Grimaudo J. (2012). IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. *Decision support systems*, **54**(1), 510-520.
- Barker, D.W. and Sawyer J.E. (2010). Using active canopy sensors to quantify corn nitrogen stress and nitrogen application rate. *Agronomy Journal*, **102**(3), 964-971.
- Barker, D.W. and Sawyer J.E. (2013). Factors affecting active canopy sensor performance and reflectance measurements. *Agronomy Journal*, **105**(4), 1079-1086.
- Berger, K., Verrelst J., Féret J.B., Hank T., Wocher M., Mauser W. and Camps-Valls G. (2020). Retrieval of aboveground crop nitrogen content with a hybrid machine learning method. *International Journal of Applied Earth Observation and Geoinformation*, **92**, 102174.
- Bijay-Singh, Varinderpal-Singh, Yadvinder-Singh, Kumar A., Jagmohan-Singh, Vashistha M., Thind H.S. and Gupta R. K. (2012). Fixed-time adjustable dose site-specific fertilizer nitrogen management in transplanted irrigated rice (*Oryza sativa* L.) in South Asia. *Field Crops Research*, **126**, 63-69.
- Blackmer, T.M. and Schepers J.S. (1995). Use of a chlorophyll meter to monitor nitrogen status and schedule fertigation for corn. *Journal of production agriculture*, **8**(1), 56-60.
- Blackmer, T.M., Schepers J.S. and Varvel G.E. (1994). Light reflectance compared with other nitrogen stress measurements in corn leaves. *Agronomy Journal*, **86**(6), 934-938.
- Cao, Q., Miao Y., Shen J., Yu W., Yuan F., Cheng S. and Liu F. (2016). Improving in-season estimation of rice yield potential and responsiveness to topdressing nitrogen application with Crop Circle active crop canopy sensor. *Precision agriculture*, **17**(2), 136-154.
- Colaço, A.F. and José Paulo Molin (2017). Variable rate fertilization in citrus: A long term study. *Precision Agriculture*, **18**(2), 169-191.
- Doerge, T.A. (2005). Nitrogen Measurement for Variable Rate N Management in Maize. *Communications in soil science and plant analysis*, **36**(1-3), 23-32.
- Féret, J.B., Berger K., De Boissieu F. and Malenovsky Z. (2021). PROSPECT-PRO for estimating content of nitrogen-containing leaf proteins and other carbon-based constituents. *Remote Sensing of Environment*, **252**, 112173.
- Franzen, D., Kitchen N., Holland K., Schepers J. and Raun W.

- (2016). Algorithms for in season nutrient management in cereals. *Agronomy Journal*, **108**(5), 1775-1781.
- Gogoi, B. and Pathak K. (2025). Precision agriculture: Leveraging technology for sustainable crop production. *Modern Approaches in General Agriculture and Allied Sciences*, **16**, 219-230.
- Heege, H.J. (2013). Site-specific fertilizing. *Precision in crop farming: Site specific concepts and sensing methods: Applications and results*, 193-271.
- Heege, H.J., Reusch S. and Thiessen E. (2008). Prospects and results for optical systems for site-specific on-the-go control of nitrogen-top-dressing in Germany. *Precision Agriculture*, **9**(3), 115-131.
- Holland, K.H. and Schepers J.S. (2010). Derivation of a variable rate nitrogen application model for in season fertilization of corn. *Agronomy journal*, **102**(5), 1415-1424.
- Holland, K.H. and Schepers J.S. (2013). Use of a virtual-reference concept to interpret active crop canopy sensor data. *Precision agriculture*, **14**(1), 71-85.
- Hunt, E.R. and Rock B.N. (1989). Detection of changes in leaf water content using near- and middle-infrared reflectances. *Remote Sensing of Environment*, **30**(1), 43-54.
- Jafarbiglu, H. and Pourreza A. (2023). Impact of sun-view geometry on canopy spectral reflectance variability. *ISPRS Journal of Photogrammetry and Remote Sensing*, **196**, 270-286.
- Jansen, V.S., Kolden C.A., Taylor R.V. and Newingham B.A. (2016). Quantifying livestock effects on bunchgrass vegetation with Landsat ETM+ data across a single growing season. *International Journal of Remote Sensing*, **37**(1), 150-175.
- Johnson, G.V. and Raun W.R. (2003). Nitrogen response index as a guide to fertilizer management. *Journal of plant Nutrition*, **26**(2), 249-262.
- Kablan, L.A., Chabot V., Mailloux A., Bouchard M.È., Fontaine D. and Bruulsema T. (2017). Variability in corn yield response to nitrogen fertilizer in eastern Canada. *Agronomy Journal*, **109**(5), 2231-2242.
- Keating, B.A., Carberry P.S., Hammer G.L., Probert M.E., Robertson M.J., Holzworth D. and Smith C.J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European journal of agronomy*, **18**(3-4), 267-288.
- Kersebaum, K.C. (2007). Modelling nitrogen dynamics in soil-crop systems with HERMES. *Nutrient Cycling in Agroecosystems*, **77**(1), 39-52.
- Kindred, D.R., Milne A.E., Webster R., Marchant B.P. and Sylvester-Bradley R. (2015). Exploring the spatial variation in the fertilizer-nitrogen requirement of wheat within fields. *The Journal of Agricultural Science*, **153**(1), 25-41.
- Kumar, A., Manjunath K.R., Bala R., Sud R.K., Singh R.D. and Panigrahy S. (2013). Field hyperspectral data analysis for discriminating spectral behavior of tea plantations under various management practices. *International Journal of Applied Earth Observation and Geoinformation*, **23**, 352-359.
- Lawes, R.A. and Bramley R.G.V. (2012). A simple method for the analysis of on farm strip trials. *Agronomy journal*, **104**(2), 371-377.
- Li, X., Shi Q. and Guo J. (2009). The response of the NDVI to climate variability in northwest arid area of China from 1981-2001. *Journal of Arid Land Resources and Environment*, **23**(10), 12-16.
- Llewellyn, R. and Ouzman J. (2014). Adoption of precision agriculture-related practices: status, opportunities and the role of farm advisers. *Canberra, Australia: CSIRO*.
- Lukina, E.V., Freeman K.W., Wynn K.J., Thomason W.E., Mullen R.W., Stone M.L., Solie J.B., Klatt A.R., Johnson G.V., Elliott R.L. and Raun W.R. (2001). Nitrogen fertilization optimization algorithm based on in-season estimates of yield and plant nitrogen uptake. *Journal of plant nutrition*, **24**(6), 885-898.
- Manjunath, K.R., Ray S.S. and Panigrahy S. (2011). Discrimination of spectrally-close crops using ground-based hyperspectral data. *Journal of the Indian Society of Remote Sensing*, **39**(4), 599-602.
- Meisinger, J.J., Schepers J.S. and Raun W.R. (2008). Crop nitrogen requirement and fertilization. *Nitrogen in agricultural systems*, **49**, 563-612.
- Miglani, A., Ray S.S., Pandey R. and Parihar J.S. (2008). Evaluation of EO-1 Hyperion data for agricultural applications. *Journal of the Indian Society of Remote Sensing*, **36**(3), 255-266.
- Mulla, D.J. (2013). Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems engineering*, **114**(4), 358-371.
- Ortiz-Monasterio, J.I. and Raun W. (2007). Reduced nitrogen and improved farm income for irrigated spring wheat in the Yaqui Valley, Mexico, using sensor-based nitrogen management. *Journal of agricultural science-Cambridge*, **145**(3), 215.
- Pierpaoli, E., Carli G., Pignatti E. and Canavari M. (2013). Drivers of precision agriculture technologies adoption: a literature review. *Procedia Technology*, **8**, 61-69.
- Portz, G., Molin J.P. and Jasper J. (2012). Active crop sensor to detect variability of nitrogen supply and biomass on sugarcane fields. *Precision Agriculture*, **13**(1), 33-44.
- Povh, F.P. and dos Anjos W.D.P.G. (2014). Optical sensors applied in agricultural crops. In *Optical sensors-New developments and practical applications*. IntechOpen.
- Povh, F.P., Molin J.P., Gimenez L.M., Pauletti V., Molin R. and Salvi J.V. (2008). Comportamento do NDVI obtido por sensor ótico ativo em cereais. *Pesquisa Agropecuária Brasileira*, **43**(8), 1075-1083.
- Raper, T.B., Varco, J.J. and Hubbard K.J. (2013). Canopy-based normalized difference vegetation index sensors for monitoring cotton nitrogen status. *Agronomy Journal*,

105(5), 1345–1354.

- Raun, W.R., Solie J.B., Johnson G.V., Stone M.L., Mullen R.W., Freeman K.W. and Lukina E.V. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agronomy journal*, **94(4)**, 815-820.
- Raun, W.R., Solie J.B., Stone M.L., Martin K.L., Freeman K.W., Mullen R.W. and Johnson G.V. (2005). Optical sensor based algorithm for crop nitrogen fertilization. *Communications in soil science and plant analysis*, **36(19-20)**, 2759-2781.
- Raun, W. R., Solie J.B., Taylor R.K., Arnall D.B., Mack C.J. and Edmonds D.E. (2008). Ramp calibration strip technology for determining midseason nitrogen rates in corn and wheat. *Agronomy Journal*, **100(4)**, 1088-1093.
- Roberts, D.C., Brorsen B.W., Solie J.B. and Raun W.R. (2011). The effect of parameter uncertainty on whole-field nitrogen recommendations from nitrogen-rich strips and ramped strips in winter wheat. *Agricultural Systems*, **104(4)**, 307-314.
- Robertson, M.J., Llewellyn R.S., Mandel R., Lawes R., Bramley R.G.V., Swift L. and O'callaghan C. (2012). Adoption of variable rate fertiliser application in the Australian grains industry: status, issues and prospects. *Precision agriculture*, **13(2)**, 181-199.
- Sahoo, R.N., Biswas A., Singh G.P., Singh R., Gupta V.K., Krishna G. and Pargal S. (2013). Discrimination of wheat genotypes through remote sensing. Annual Report of Agricultural Physics, Indian Agricultural Research Institute, New Delhi, 70.
- Sahoo, R.N., Ray S.S. and Manjunath K.R. (2015). Hyperspectral remote sensing of agriculture. *Current science*, 848-859.
- Scharf, P.C., Brouder S.M. and Hoeft R.G. (2006). Chlorophyll meter readings can predict nitrogen need and yield response of corn in the north central USA. *Agronomy Journal*, **98(3)**, 655-665.
- Schepers, J.S., Francis D.D., Vigil M. and Below F.E. (1992). Comparison of corn leaf nitrogen concentration and chlorophyll meter readings. *Communications in soil science and plant analysis*, **23(17-20)**, 2173-2187.
- Sela, S., van Es H.M., Moebius Clune B.N., Marjerison R., Melkonian J., Moebius Clune D. and Gomes S. (2016). Adapt N outperforms grower selected nitrogen rates in northeast and midwestern United States strip trials. *Agronomy Journal*, **108(4)**, 1726-1734.
- Shanahan, J.F., Kitchen N.R., Raun W.R. and Schepers J.S. (2008). Responsive in-season nitrogen management for cereals. *Computers and electronics in agriculture*, **61(1)**, 51-62.
- Sharma, L.K., Bu H., Denton A. and Franzen D.W. (2015). Active-optical sensors using red NDVI compared to red edge NDVI for prediction of corn grain yield in North Dakota, USA. *Sensors*, **15(11)**, 27832-27853.
- Singh, B. and Craswell E. (2021). Fertilizers and nitrate pollution of surface and ground water: an increasingly pervasive global problem. *SN Applied Sciences*, **3(4)**, Article 518.
- Solie, J.B., Monroe A.D., Raun W.R. and Stone M.L. (2012). Generalized algorithm for variable rate nitrogen application in cereal grains. *Agronomy Journal*, **104(2)**, 378-387.
- Tagarakis, A.C. and Ketterings Q.M. (2017). In season estimation of corn yield potential using proximal sensing. *Agronomy Journal*, **109(4)**, 1323-1330.
- Thenkabail, P.S., Enclona E.A., Ashton M.S. and Van Der Meer B. (2004). Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. *Remote sensing of environment*, **91(3-4)**, 354-376.
- Vaiphasa, C., Ongsomwang S., Vaiphasa T. and Skidmore A. K. (2005). Tropical mangrove species discrimination using hyperspectral data: A laboratory study. *Estuarine, Coastal and Shelf Science*, **65(1-2)**, 371-379.
- Varvel, G.E., Schepers J.S. and Francis D.D. (1997). Ability for in season correction of nitrogen deficiency in corn using chlorophyll meters. *Soil Science Society of America Journal*, **61(4)**, 1233-1239.
- Wan, L., Zhou W., He Y., Wanger T.C. and Cen H. (2022). Combining transfer learning and hyperspectral reflectance analysis to assess leaf nitrogen concentration across different plant species datasets. *Remote Sensing of Environment*, **269**, Article 112797.