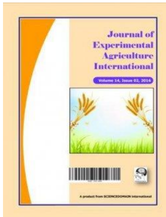

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Monitoring of Wheat and Rice Nitrogen Status by Remote Sensing

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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ABSTRACT

Crop growth and production are dependent on the amount of total nitrogen (N) absorbed by plants, but as well as also on the N distribution within plant canopies. Nitrogen (N) is the major agricultural input in all over the world and applying the optimum amount of N at the right time, place and at the critical physiological stage is a major challenge for wheat and rice growers. Assessment of canopy nitrogen content (CNC) at the right timing in crops is important for growth diagnosis and precision management of crops to gain maximum yield and better quality while also reducing adverse environmental impacts. Hence, to minimize the losses of nitrogen fertilizer, environmental pollution from cropping activities, a reliable, real time and non -destructive techniques of remote sensing are needed to monitor crop N status and site-specific N management in agricultural fields. Remote sensing has been widely used for determination of crop N status. In this review paper the results of previous studies that investigated the monitoring of crop nitrogen content (CNC) and the remote sensing methods that have been proposed to monitor this phenomenon for wheat and rice crops has been discussed. When a complete understanding of monitoring of N status in the crop is achieved, researchers will be able to improve related quantitative modeling. Regarding monitoring of

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crop nitrogen content (CNC) by using remote sensing, the few existing methods can be mentioned according to the hyper spectral data used. This paper has reviewed the results of different technological methods of remote sensing to monitor the nitrogen content of wheat and rice. All these methods and techniques for the monitoring of (CNC) are presented here and it is hoped that this work can provide helpful information for future work.

Keywords: Nitrogen; remote sensing; vegetation indices; green scanning laser; wheat and rice; remote sensing techniques.

1. INTRODUCTION

Nitrogen (N) is needed in largest amount for plant growth, and significantly effects on photosynthesis and yield in agronomic crops, thus N fertilization has become one of main yield-enhancing technique in modern agriculture [1-3]. N accumulation and N concentration in plant tissues are major indicators to characterize the N status in crop plants. Plant nitrogen accumulation, as a product of plant mass and plant nitrogen content, strongly affects yield and quality in crop product [4,5]. In a field management, nitrogen fertilization strategy is a major consideration to ensure N supply at the right time and appropriate amount, it is necessary to evaluate tissue N status and recommend an N dressing plan from indicative nitrogen accumulation and nitrogen content in crop plants. Dynamic regulation of the plant N status and effective diagnosis must be based on real-time monitoring of growth parameters and nitrogen levels in crop plants. Until now, the traditional method of measuring the crop N status has depended on plant sampling of the field and chemical assay in the laboratory [6]. Now a day, several new methods have been proposed for estimation of plant N status, such as using chlorophyll meters, leaf color charts, chlorophyll fluorescence or leaf positional differences [7-9]. Since, these methods only focus on individual leaves, and thus have difficulty in reflecting the population status of crop plants in practical application. In contrast, remote sensing has the capability to sample a plant population or community rather than individual plants and to assess the spatial variability of a crop rapidly. In several studies, spectral determinations have provided quick, automatic, and non-destructive method of assessing the nutrient level and physiological parameters in crop plants [10,11]. Thus, the technique of remote sensing can potentially assist in monitoring of growth parameters, tissue N status and recommending fertilization strategy, which leads to reducing the environmental risks of high N rates and increasing the N use efficiency in crop production [12].Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and thus in contrast to on site observations. In modern usage, the term generally refers to the use of aerial sensor technologies to detect and classify objects on Earth (both on the surface, and in the atmosphere and oceans) by means of propagating signals (e.g. Electromagnetic radiation). It may be split into active remote sensing (when a signal is first emitted from aircraft or satellites) [13,15] or passive (e.g. sunlight) when information is merely recorded [16].

Previous studies showed that monitoring of N status in crop plants by remote sensing techniques can be a reliable method. However, the spectral parameters may be crop specific, and the regression equations may not extrapolate to other years and sites as they are affected by viewing and canopy morphology, radiation geometries, and soil background besides treatment conditions. Hence, development of general and accurate models to predict and monitor N status in crop plants from reflectance data is still an on-going task [17,18].

Hyperspectral imaging or hyper spectral remote sensing, like other spectral imaging, collects and processes information from across the electromagnetic spectrum. The goal of hyperspectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes [19,20].

Spectral Reflectance**,** the reflectance characteristics of earth surface features may be quantified by measuring the portion of incident energy that is reflected. This is measured as a function of wavelength *(l)* and is called spectral reflectance, *rl.*

$$rl = ER(l)/EI(l)$$

Where *ER* is reflected energy and *EI* is incident energy.

A graph of the spectral reflectance of an object as a function of wavelength is termed as a spectral reflectance curve.

In the previous studies multi-spectral sensors and systems have been normally used to assess plant N status, but their estimation accuracy of crop nitrogen status relatively low, because multi-spectral systems acquire several broad (>50 NM) spectral bands, which results in loss of spectral information that is available in a specific narrow band [21,11,22]. However, the newly emerged hyper spectral remote sensing consists of getting images in many continuous spectral (continuous spectrum for each pixel) and (<10 NM) narrow bands which are sensitive to crop specific variables and weak differences in plant parameters could be detected [23]. By converting spectrum parameters and extracting sensitive bands to reduce background effect can help to improve quality and level of capturing crop growth information, so hyper spectral remote sensing technology can better technique to predict various growth variables related to crop biochemistry and physiology [11]. However, different forms of vegetation indices, such as *NDVI*, can track deviations of various plant growth parameters from normal conditions. The reflectance in the red- edge (far red) wavelengths has been used for detecting N (chlorophyll) content [24]. Found that ratios between near-infrared (755–900 and 1000 NM) and red-edge (700 or 716 mm) provided the best correlation of N concentrations in the leaves of cotton.

Many reports have indicated that the 550–710 NMregions is preferred for maize [25], While 530–560, 630–660 and 760–900 NM are the spectral regions most suited for estimating N levels in rice [26,27]. Suggested the best predictor for N concentration of maple leaves that is a first-different transformation of log(*1/R*) and it is derived from shortwave infrared bands. Similar investigations were made with short wave infrared ratio indices vs. leaf N concentration and REP in cotton [28], and a normalized index composed of 447 and 692 nm [11] vs. leaves Nitrogen concentration in wheat. Wheat is a major food crop in the world, hence among the agricultural crops it is a large consumer of nitrogen fertilizer. The current nitrogen use efficiency in wheat production is only about 35% in China that are much lower than in developed countries [29,30]. Thus, it is an urgent need of time to develop an effective method for non-destructive monitoring of N status in wheat and other crops based on hyper spectral remote sensing, which would help to improve nitrogen management and enhance food productivity. The objective of this paper is to review the results of previous studies on the crop related to the nitrogen content and remote sensing techniques which were used previously and to address the suitable techniques to access the crop nitrogen content effectively. This work also discussed possible remote sensing methods for estimating N content of the crop, using hyper-spectral imaging or by coupling canopy N content models with remotely sensed data.

1.1 Monitoring Leaf Nitrogen Accumulation in Wheat and Rice with Hyper-Spectral Remote Sensing

Weak differences in plant parameters could be detected by hyper-spectral remote sensing makes possible acquiring images in many spectral bands, which are sensitive to specific crop variables [31]. To improve the quality and level of capturing crop growth information, hyper-spectral remote sensing technology can be used to better estimate different growth variables by extracting sensitive bands and converting spectral parameters to reduce background effects. The canopy spectra obtained via remote sensing show complicated information of vegetation, including spikes, stems, leaves, soils and other backgrounds. Compared with multi-spectral indices the hyper-spectral indices can improve accuracy of estimation of many vegetable parameters [32] but sometimes show instability among sites and season [33]. As a product of leaf nitrogen content and leaf mass, leaf nitrogen accumulation (*LNA*) includes not only canopy coverage properties, but also nitrogen content information. By increasing of N fertilizer leaf N content and canopy coverage increase, which promotes early increment of leaf N accumulation. The differences in cultural management practices and levels of soil fertility in the fields often result in apparent various growths among individual plants which severely affect yield and quality formation in crop production [34]. Therefore, to predict crop yield and production capability and quality monitoring, *LNA* and dynamic changes is useful. The determining quantitative relationship of *LNA* with canopy spectra should help to support real time, non-destructive monitoring and diagnosis of N status in wheat production.

1.2 Monitoring Leaf Nitrogen Status with Hyper-Spectral Reflectance in Wheat

In the previous studies on plant N monitoring, multi-spectral system and sensors have been normally used to assess plant N status, but with low estimation accuracy, because multi spectral systems get several broad (>50 NM) spectral bands, which results in loss of spectral data that is available in a specific narrow band [21,11,22]. However, the newly emerged hyper-spectral remote sensing consists of acquiring images in many continuous spectral bands (continuous spectrum for each pixel) and (<10 NM) narrow bands, which are sensitive to crop specific variables and differences in plant parameters could be detected [23]. The major food crop in the world is wheat, and among the agricultural crops it is a large consumer of nitrogen fertilizers. In china, the current nitrogen use efficiency in the production of wheat is only about 35%, lower than in developed countries [29,30]. Thus, it is a need of time to develop an effective method for non-destructive monitoring of N status in wheat based on hyper-spectral remote sensing, which would help to enhance food productivity and improve nitrogen management.

1.3 Measuring Leaf Nitrogen Concentration in Winter Wheat Using Double-Peak Spectral Reflection Remote Sensing Data

The potential of hyper-spectral remote sensing for assessment of plant N content have demonstrated by previous studies [35,36], but their robustness and accuracy may be inadequate to guide N application during critical growth stages at both regional and individual field levels. Leaf N concentration (*LNC*) is sensitive to amount of N fertilizer present and soil fertility, and correlation coefficients of leaf N absorption and remobilization within the grain yield are higher than for the shoot and stem [37,38]. Reported more grain N concentration associated with uptake and *LNC*, and at different growth stages leaf N was used to predict grain protein content for different genotypes. The determination coefficient (R2) for the relationship between the spectral indices and shoot N concentration (0.6) was lesser than the *LNC* (0.8) [39,40]. Therefore, it is important for crop N management to improve remote sensing capabilities for the measurement of *the LNC*. The ratio spectral index (*RSI*) proved superior to other methods for the diagnostic mapping of canopy N content using the first derivative gave values of 740 nm and 522 nm [41]. For predicting cotton *LNC* the combination of red-edge wavelengths with very near infrared wavelengths provided good accuracy and precision [28]. The modified simple ratio (mSR705) and modified normalized difference (mND705), which were developed by combining R445 to the existing two-band vegetation indicesSR705 and ND705, effectively overcome the impact of differences in leaf surface reflectance and improve the N content estimation and sensitivity of pigment [42,35]. The optimum three-band vegetation index of $(R\ 924 - R\ 703 + 2^*\ R\ 423) / (R924 + R\ 703 - 2^*\ R\ 423)$ was constructed to effectively monitor plant N status in both rice and wheat [40].

1.4 LiDAR Based Biomass and Crop Nitrogen Estimates of Wheat Nitrogen Status

For calculating the critical crop N concentration *(%Nc)* which is defined as (the minimum *% Nc* that allows maximum growth), crop biomass information is necessary, With increasing crop biomass, *%Nc* decreases along a mathematical trajectory described by the critical N dilution curve [43].

$$\%N\,c = a_{\,c} * W^{-b}$$

Where ac (in kg N ha −1) is a crop species specific constant representing the *% Nc* for one metric ton of crop dry mass per hectare (W in t ha −1) and the dimensionless exponent b describes the decline of *%Nc* with increasing W. Nitrogen nutrition index *(NNI)* can be calculated as *%Nc* and the actual crop N concentration *(%Na)* [43]:

$$NNI = \%Na / \%Nc$$

NNI values > 1 indicate excess N and *NNI* values < 1 indicate crop growth is limited by N. For improving N management decisions the *NNI* could be a valuable measure, its operational use has been restricted due to the lack of good methods that allow simultaneous measurement of both W and *%Na* [44,45]. Traditionally, for determining *%Na* and W destructive sampling methods have been used. However, these destructive sampling methods aretime-consuming and laborious and, limiting operational use for measuring *NNI*. Non-destructive alternatives for deriving *%Na* and W include chlorophyll meters and line quantum sensors, respectively [46-48]. Although these methods are comparably less expensive and faster, they are point- based and limited to fully capturing the variability of crop N status within a field. Time-of-flight terrestrial LiDAR (light detection and ranging) scanning (TLS) is a remote sensing technology that may reduce these challenges because it can measure physical, easy to interpret crop biomass proxies such as crop height and volume. TLS is able to survey the x,y, and height (z) location of object surfaces at a rate of tens of thousands of survey points per second. To determine the relative x,y, z location, the TLS measures the horizontal (azimuth) and vertical (zenith) angles between itself and each given survey point as well as inclined distance. Distance measurements are obtained by measuring the time of flight (t) of a laser pulse incident on a survey point to the sensor (distance= *(ct)/2*, where and t is round-trip elapsed time of light propagation) and c is the speed of light. Based on the distance and two electronically measured angles (azimuth and zenith), the x, y, and z location can be calculated for each point using trigonometric principles.

1.5 Predicting Plant Nitrogen Uptake in Winter Wheat

Previous studies were mainly focused on content estimation or on N concentration to evaluate the plant N status, but research on the relationship between plant N uptake and canopy reflectance was insufficient. Sembiring et al. [49] reported a high correlation between the normalized difference vegetation index (*NDVI* (671, 780) and early-season (Feekes 4-8) plant N uptake. Further, plant N uptake needs to be calibrated by specific stages while using *NDVI* as a predictor for early season, since at the different stages linear regression equations differed significantly. Stone et al. [50] observed that the plant N spectral index *(PNSI)* was correlated with winter wheat forage N uptake at all stages of growth and locations. *NDVI* was a better predictor of early-season (Feekes 4-8) plant N uptake under different varieties, years and sowing dates [51-53,36]. Used the canopy chlorophyll content index *(CCCI)* combined with the canopy N index *(CNI)* to predict canopy N (g m-2) from Zadoks 14-37 with an R2of 0.97 and RMSE of 0.65 g Nm-2. However, those researchers just used specific red band((671±6) NM) combined with broadband *NDVI* or *NIR*((780±6) NM) to monitor plant N uptake. No result of using hyper-spectral data to construct narrow band indices for early-season (Feekes 4-8) plant N uptake prediction has been published, to our knowledge.

1.6 Remote Estimation of Crop Nitrogen Content by Using Red- Edge Bands in Sentinel -2 and -3

Currently a multitude of satellite data has been available already, and this availability will increase enormously in the near future. Five new programs called Sentinels specifically for the operational needs of the “Global Monitoring for Environment and Security” (GMES) program developed by The European Space Agency (ESA) [54].

Two systems are relevant to land applications using the solar reflective domain. Sentinel-2 (equipped with the Multi Spectral Instrument, MSI), will provide images with high temporal, spectral and spatial resolution, aims at ensuring continuity of SPOT (Système Pour l’Observation de la Terre) and Land-sat observations. It covers the near-infrared (VNIR) and visible and the shortwave- infrared (SWIR) spectral region in 13 bands, incorporating two new spectral bands in the so-called red-edge region, which are very important for the retrieval of chlorophyll content [55-57]. It will carry3 bands at 60 m and 4 bands at 10 m (cf. SPOT), 6 bands at 20 m and spatial resolution. The latter is dedicated to cloud screening and atmospheric corrections [58]. Sentinel-3 is an ocean mission and a medium resolution land, to be seen as a continuation of the Envisat mission. The ocean and land color instrument (OLCI) has similar specifications as the Medium Resolution Imaging Spectrometer (MERIS) on Envisat [59], thus it will provide data continuity of MERIS [60]. Red-edge bands can be used for the retrieval of chlorophyll content, all beitona different scaleas Sentinel-2 [61,55]. Both Sentinel-3 and Sentinel-2 missions are based on a constellation of two satellites each in order to fulfill coverage and revisit requirements, providing accurate datasets for GMES services. Since this first publication, the red-edge position (REP) has often been used as an estimate for chlorophyll content. With the limited number of red-edge bands of MERIS and the proposed Sentinel-3 and Sentinel-2 bands, the REP can be derived by applying a simple linear model to the red-infrared slope [62]. MERIS terrestrial chlorophyll index is another type of index based on the MERIS red-edge bands MTCI [55]. This index has been applied successfully for many applications. MTCI is the Heritage of MERIS basis for the Level 2Bmain terrestrial products of Sentinel-3, called the OLCI Terrestrial Chlorophyll Index (OTCI) [63].

1.7 Remote Estimation of Wheat Nitrogen Status Using a Green Scanning Laser

Traditionally handheld chlorophyll meter measurements have been used to monitor the crop N status [64], but at the scale of entire farm fields they are impractical for characterizing the spatial variability in plant N status. The use of laser scanners to determine the reflective properties and location of objects provides a promising avenue for implementation in precision agriculture. In addition to the timing and quantity of laser pulse returns [65,66], the signal strength of a backscattered laser pulse (i.e., laser return intensity) can be used to infer chemical and physical properties of natural surfaces [67,68]. Because of the small ground instantaneous field of view GIFOV (<4 mm diameter) and fast sampling rate (25–50 kHz routinely possible), lasers could be used to separate leaf tissue from soil, resolve small targets and other background features [69]. Suggested that canopy returns could be separated from soil returns using a simple threshold of the normalized difference vegetation index *(NDVI);* [70] calculated from the return intensity of near-infrared (780 NM) and reflected red (670 NM) laser signals.

Eitel et al. [67] found a strong relationship (r2= 0.77) between leaf chlorophyll content of two tree species (Acer saccharum and Quercus macrocarpa) and the intensity of reflected green (532 NM) laser light, suggesting that green laser return intensity may be useful for sensing the crop N status. To improve the relationship between chlorophyll content and green laser return intensity [67]. Used a simple threshold value to filter out green laser return intensity values that were negatively affected by the edge-strike-effect or foliar edge effect. Though green laser measurements provide information about the crop N status during early crop growth stages, this concept has not yet been tested in either greenhouse-or field-based settings.

1.8 Remote Estimation of Canopy Nitrogen Content in Rice

Rice (*Oryza sativa* L.) is an important crop of the world, and the assessment of canopy nitrogen content (CNC) in rice is important for growth diagnosis and management to achieve higher yield and better grain quality while also minimizing adverse environmental impacts. Agricultural applications are more demanding in terms of timeliness, accuracy, spatial resolution, and practicability when compared to other remote sensing applications [71-75].

In rice diagnostic information for nitrogen management has to be obtained critical just before the panicle formation stage. To ensure efficient harvesting strategy predictive information on ricegrain quality must be obtained during the middle maturity stage [76]. Many remote sensing approaches have been suggested for the assessment of *CNC* [77-79], but their robustness accuracy and may be insufficient for practical use at regional scales. Previous spectral indices may not be optimized using the merits of continuity of hyper spectra and data richness [80]. Moreover, commonmetric approaches such as a partial least-squares regression (PLSR; e.g. [78] may not always be useful, as suggested by [76].

1.9 Analysis of Nitrogen Content of Rice at the Heading Stage by Using air Borne Hyper Spectral Remote Sensing

Nitrogen fertilizer and climatic conditions such as the intensity and duration of sunshine, air and water temperature, and the available water supply are extremely sensitive to the growth of rice plants, and the quantity and quality of rice grains [81]. At the heading stage the amount of nitrogen content is mainly affected by the amount of nitrogen fertilizer at topdressing, which is calculated based on the uptake of nitrogen from the soil and the amount of nitrogen content at the panicle initiation stage [82]. However, the quantity and quality of rice grains are closely related to the growth and nitrogen content status at the heading stage [83]. To identify the nitrogen content status and growth of rice plants at the heading stage is very important. It has also been confirmed that a variable rate fertilizer application is adaptable for controlling the nitrogen content status and growth of rice plants uniformly. Remote sensing has great potential for identifying the growth and nitrogen status of rice plants, because it enables wide-area, real-time and non-destructive acquisition of information on Eco physiological plant conditions [73,84]. Research on hyper-spectral remote sensing for rice plants has been separated into two groups: (1) multivariate analysis and (2) narrow-band vegetation indices [85].

1.10 Midseason Nitrogen Fertilization Rate Decision Tool for Rice Using Remote Sensing Technology

More time and research has been devoted to understanding N than any other nutrient. It is the most limiting nutrient in non-legume cropping systems and the least predictable. Mismanagement of N fertilizer can impact both economic and environmental aspects of crop production. Available soil N and yield level are the determinants of a crop's N requirement and are essential parameters to quantify optimal N application rates. Making precise N prescriptions are difficult because tremendous variability exists for available soil N and yield across time and space. Several destructive and non-destructive methods have been tested and established to assist in making midseason N fertilization rate decisions for rice. The chlorophyll meter and leaf color chart are among the tools that were developed to monitor rice N status [86,87]. Nitrogen use efficiency was increased when in-season, sensor-based estimates of yield potential and crop responsiveness to N fertilization were used to determine the midseason N rate for corn and wheat [88,89].

1.11 Biophysical Basis of Agricultural Remote Sensing

Modern applications of remote sensing for agriculture have their foundation in pioneering work by ARS scientists William Allen, Harold Gausman, and Joseph Woolley, who provided the basic theory relating physical characteristics of crop plants to their optical properties [90-92]. These scientists and their teams also published many high resolution spectral signatures for cultivated and natural spaces, identifying spectral characters associated with normal plant growth conditions and those caused by pests, nutrient deficiency and a biotic stresses [93].

Scientists with the Agricultural Research Service (ARS) and various government agencies and private institutions have provided a great deal of fundamental information relating spectral reflectance and thermal emittance properties of soils and crops to their agronomic and biophysical characteristics. This knowledge has facilitated the development and use of various remote sensing methods for non-destructive monitoring of plant growth and development and for the detection of many environmental stresses which limit plant productivity. Coupled with rapid advances in computing and position locating technologies, remote sensing from ground, air and space-based platforms is now capable of providing detailed spatial and temporal information on plant response to their local environment that is needed for site specific agricultural management approaches.

1.12 Spectral Reflectance Properties of Leaves

Green leaves typically show very low transmittance and reflectance in visible regions of the spectrum (i.e., 400 to 700 nm) due to strong absorption 0f photosynthetic and accessory plant pigments [94]. Transmittance and reflectance are both usually high in the near-infrared regions (NIR, 700 to 1300 nm) because there is very little absorption by sub cellular particles because there is considerable scattering as mesophyll cell wall interfaces [92]. This sharp dissimilarity in reflectance properties between *NIR* and visible wavelengths underpins a majority of remote approaches to managing and monitoring natural vegetation and crop communities [95,96]. In a third region of the solar spectrum Optical properties of leaves, the middle- or shortwave-infrared (SWIR, 1300 to2500 nm), are strongly mediated by water in tissues. Reflectance in this region decreases as tissues dehydrate but relatively high in vigorously growing vegetation. However, the research proposed such drought-induced decreases in SWIR reflectance are not sufficiently large over biologically significant changes in plant water content for the practical use of this wavelength interval in the diagnosis of water stress in the field [97,98].

1.13 Crop Canopies and Vegetation Indices

The spectral signatures of crop canopies in the field are more complex and often quite dissimilar from those of single green leaves measured under carefully controlled conditions. Even when leaf spectral properties remain relatively constant throughout the season, canopy spectra change dynamically as the proportions of vegetation and soil and change and the architectural arrangement of plant components vary. From complex canopy spectra Vegetation indices (VIs) provide a very simple yet elegant method for extracting the green plant quantity signal.

Vegetation indices have served as the basis for many applications of remote sensing to crop management because they are well correlated with leaf area index and green biomass of crop canopies. Of particular interest from energy balance, crop management and modeling perspectives, VIs have also been shown to provide accurate estimates of the fractional amount of net radiation going into soil [99,100], as well as the fraction of absorbed photo synthetically active radiation (FAPAR) captured by the canopy for potential use in photosynthesis.

1.14 Exogenous Factors Affecting Remote Observations

It is important to recognize that remote assessment of plant response and crop growth in an environmental stress is by no means as straightforward or simple as identifying chemicals in vitro via their spectral absorption features. Thermal and optical properties of plant canopies change with the stage of growth due to and architectural arrangement of organs and age of individual tissues [101]. They are also strongly affected by viewing angles, topography, row orientation, meteorological phenomena, and other factors not directly related to biophysical or agronomic plant properties [102,103]. A significant challenge for agricultural remote sensing applications is to be able to separate spectral signals originating with a plant response to a specific stress from signals associated with background “noise” or normal plant biomass that is introduced by exogenous non-plant factors. Results from multiple crops across a number of different locations indicate that general relationships between plant response and spectral properties are achievable [104].

1.15 Nutrient Management

The main challenge facing by agricultural production is the efficient management of nutrients. However, remote sensing is provided field-scale diagnostic methods that will enable detection of nutrient deficiencies early enough to avoid quality or yield losses. When interfaced with variable rate sprayer equipment, real-time canopy sensors could supply site specific application requirements that the requirement of nitrogen and ultimately improve the overall nutrient use efficiency [105].

1.16 Nitrogen

Optimum supplies of nitrogen (N) are essential for modern crop production. However, N is often over applied without regard to crop requirements or potential environmental risk. A case in point involves corn grown in the upper Midwestern United States where synchronizing N applications to coincide with maximum crop uptake is desirable, but tissue testing of leaves is not widely employed for determining crop needs and thus fields are often over fertilized. Relative techniques were developed for using a color photograph, SPAD chlorophyll meter, or canopy reflectance factors to assess spatial variation in N concentrations [106,107]. Because these techniques were based on comparisons with readings obtained from an adequately fertilized strip in the same field, they obviated strict requirements for beforehand knowledge of the relationship between crop reflectance and nutrient concentration, precise sensor calibration, the need to convert data to surface reflectance factors. Because this index was based on the plant canopy as opposed to the individual leaf measurements obtained with SPAD readings, it has potential for larger scale applications and direct input into variable rate fertilizer application technology.

2. CONCLUSIONS

In crops timely assessment of crop nitrogen content *(CNC)* is necessary for growth diagnosis and precision management to achieve higher yield and better quality while also minimizing adverse environmental impacts. Hence, it is convenient to predict the nitrogen status through the integration of remote sensing technology and an agronomical model. However, use of remote sensing data to predict quality indices such as nitrogen status of crops can be feasible and realized. As remote sensing technology can provide crop nitrogen content *(CNC)* information with big-scale coverage, it is important for us to pay more attention towards the monitoring of crop nitrogen status, as well as the methods and mechanism to forecast crop nitrogen content using remote sensing data. The paper showed that chlorophyll and nitrogen content in wheat and rice can be estimated by the same remote sensing techniques and suggesting that absorption by Chl, provides the necessary link between remote sensing observations and canopy-state variables that are used as indicators of N status. Remote sensing of crop N status is important to assessment of high-efficiency, high-yield and environment friendly modern agriculture. Therefore, it is of high scientific value to explore remote sensing approaches or techniques for the estimation of crop nitrogen content. The few existing studies that have concentrated on this issue have made important progress, but also have some key limitations. In spite of these limitations, it is hoped that this paper can provide useful information for researchers working in related fields, and also promote studies of the physiological mechanisms of N status within the crop canopy, as well as its remote estimation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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