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Review Article
Detecting and Monitoring Plant Nutrient Stress Using Remote Sensing Approaches: A Review

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Abstract
Determination of plant stress factors is often challenging as it can be a compound result of water deficit, nutrient deficiency and disease infection. Symptoms arising from these stress factors may also be similar. Hence, visual observation alone could result in flawed diagnosis which would eventually disrupt remedial action for the affected plant/crop. Spectral reflectance measurements can help identify and select wavelengths sensitive to different types plant stress. Previous studies have found that plant stress will change spectral reflectance pattern in the visible range (380-720 nm or F380-F720) and the infrared range (720-1500 nm or F720-F1500). Typically, the magnitude of change will vary at different wavelengths. Such information facilitates early detection of plant stress, particularly nutrient deficiency. This approach can potentially lower operating cost in fertilization and minimize acute loss of productivity. This review examines a range of spectral techniques that deploy remote sensing for detecting plant nutrient stress and monitoring plant nutritional status.

Key words: Remote sensing, spectral properties, plant stress, nutrient deficiency

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INTRODUCTION

In addition to water and sunlight availability, plants require adequate nutrients for proper growth and vitality. Basically, macronutrients are acquired in greater amount as compared to micronutrients as they are part of the fundamental substances in plant cell and tissue development. A shortage of any mineral nutrients, particularly nitrogen, potassium and phosphorus can result in different stress-induced responses such as restricted shoots and roots growth, early defoliation of older leaves and decreased biomass yield as described in many studies[1,2]. Nevertheless, nutrient surplus typically that of nitrogen as a result of over application of fertilizer may lead to losses via leaching which ultimately pollutes the environment. Therefore, understanding plant nutrient requirement is important to ensure its availability in the surrounding environment, which is characteristically achieved through sufficient fertilization for rapid and continuous uptake by plants. Precise estimation of plant nutrient needs based on leaf optical properties such as fluorescence, reflectance and transmittance is also gaining wide attention in agriculture. This has been facilitated by development of various sensing techniques. Among all nutrients, nitrogen is used more often as a reference element in many studies focusing on nutrient uptake pattern and dynamics because of its importance as a key protein component in chlorophyll molecules and enzymes, which are crucial for photosynthetic processes[3,4].

Generally nutrient uptake by roots is governed by a range of factors that limit the nutrient concentration available to plant as all nutrients, except nitrogen are found in soils. These soil related factors including temperature, pH, moisture and organic materials greatly influence nutrient concentration at the root surface[5]. For instance, low temperature and moisture tend to reduce nutrient content in soil due to decreased root activity and slow mobilization and dispersion of nutrient. While low soil moisture may cause colloidal particles to become impeded as a result of micronutrient absorption on surfaces of soil particles. The relationship associated with each of these factors is complicated, even though the interaction between them is explainable. Cooke and Gething[6] suggested that interaction between two or more nutrients may be positive (synergistic), negative (antagonistic) or even absent. This interaction seemingly occurs only when the supply and distribution of one nutrient is affected by another nutrient. For instance, lower level of a particular nutrient in the soil may interfere and alter uptake mechanism to allow the plant to acquire more of that nutrient. This eventually causes other nutrients to be absorbed less readily and this accentuates the fact that plant capability to take up other non-limiting nutrient decreases with one or more scarce nutrients acting as a limiting factor[7]. In this review, we examine a range of remote sensing approaches as a means to detect plant nutrient stress and to monitor plant nutritional status.

APPROACH

Spectral reflectance data is inversely related to leaf chlorophyll level and relies on the interaction that occurs when light penetrates plant tissue, where it will be absorbed, reflected from the surface or transmitted through the leaf[8]. These optical spectra are dependent on the leaf pigment content of different absorption wavelengths as suggested by Zwiggelaar[9] based on a compilation of existing studies reported in the literature (Table 1).

The maximum absorption spectrum is generally found in the blue spectral region (400-500 nm or F400-F500) and the red spectral region of chlorophyll band (660-680 nm or F660-F680). This is why healthy plant tends to absorb more blue and red light while reflecting most of green and infrared light, making it appear green to human eyes[10]. Likewise, the yellow-green color of chlorosis is often characterized with greater violet light absorbed while the greater green light absorbance in phosphorus deficiency results in purple coloring of leaf margins and stems[11]. Nutrient deficiency especially that of nitrogen reduces leaf chlorophyll concentration leading to lower light absorption and higher reflectance in the visible or infrared range as tested on different crops including barley, wheat and lettuce[12,13]. This is consistent with most findings that have proven the sensitivity of chlorophyll to physiological stress and the effectiveness of measured reflected spectra in identifying nutrient stress in plants.

However, spectral features are useful in detecting plant stress only if one single factor is involved. This approach may be challenging when discriminating different stress factors

Table 1: Absorption wavelengths of selected leaf pigments

Pigment/molecule	Absorption wavelengths (nm)
Chlorophyll a	435, 670-680, 740
Chlorophyll b	480, 650
α-carotenoid	420, 440, 470
β-carotenoid	425, 450, 480
Anthocyanin	400-550
Lutein	425, 445, 475
Violaxanthin	425, 450, 475
Water (molecule)	970, 1450, 1944

affecting a plant at the same time, which is more likely to happen in reality. This is due to the fact that some stressors may affect plant physiology in a similar manner, as in the case of nutrient deficiency and disease and changes in pigment content, moisture and canopy architecture. As a result, similar spectral responses may be recorded, thus making differentiation of crop disease and nutrient stress very challenging[14].

DISCUSSION

Nutrient deficiency detection using non-imaging and imaging chlorophyll fluorescence: Chlorophyll fluorescence is able to generate quick and precise information regarding most plant stresses based on the fluorescence emission pattern of leaves, tissues and even the whole of plants[15]. The fluorescence emission is captured when parts of light energy absorbed by plant chlorophyll for photosynthesis is re-emitted when excited with UV-A near 340-360 nm or blue-green light[16]. The latter provides detailed information with its ability to reach deeper layers of tissue rather than UV light which is usually intercepted at the epidermal surface. This is due to the fact that very little UV-radiation is able to pass through the green mesophyll cells which contain chlorophyll pigments that absorb rapidly of blue and red photons[17]. The resulting fluorescence ratios are the simultaneous changes between four wavelengths, i.e., blue (F440), green (F520) and red (F690, F740) or more commonly termed as the blue-green and red spectra, where each of their characteristics are described in Table 2.

Excitation with solar-induced light usually emits blue and green fluorescence near the 440 and 550 nm spectral regions whereas blue-green light excitation gives fluorescence from the red region of 650-800 nm. The ratio most frequently used as chlorophyll content indicator is the F690-F735 (blue-red) while early detection of plant stress and nutrient availability relies on F440-F690 (blue-red) and F440-F740 (blue-red)[18,19].

While most research work on non-imaging chlorophyll fluorescence delivered very encouraging results, it can only provide point data measurement with limited information on a small leaf portion sensed instead of the whole leaf or canopy area, where the more advanced chlorophyll imaging aims to overcome. Additional fluorescence signatures presented by the multi-pixel feature of the larger-scale fluorescence sensing with imaging permits thorough screening of all point of leaf. This advantage oversees the slight changes in pattern of fluorescence emission due to a range of plant internal factors which may not be observed with non-imaging techniques and thus reduces measurement errors[18].

The fluorescence emission specific to different level of plant stress was successfully detected and imaged on different crops including deficiency of nitrogen and zinc on maize (*Zea mays*), as well as heat and water stress on zalea

Table 2: Characteristics of blue-green and red fluorescence emitted by plants[18]

Blue-green fluorescence	
Fluorescing pigments	Mainly ferulic acid covalently bound to cell walls, modulation by cinnamic acids and flavonoids in vacuoles
Extraction	• Cell wall bound ferulic acid, after alkaline hydrolysis • Soluble cinnamic acids and flavonoids with aqueous methanol
Location and origin	• Cell walls (signal coming mainly from leaf epidermis) • Vacuoles (interaction with soluble phenols)
Excitation	UV radiation (N_2 laser at 337 nm, tripled frequency Nd: YAG laser at 355 nm), pulsed flash lamp (with filters)
Fluorescence characteristics	
Emission range	400-570 nm
Maxima	Near 440-450 nm and a shoulder/maximum near 520-530 nm
Stress indication	• Increase or decrease in the ratio of blue fluorescence to red chlorophyll fluorescence: 440-690 nm and 440-740 nm • Increase of green fluorescence in some plants
Chlorophyll fluorescence	
Fluorescing pigment	Chlorophyll a
Extraction	With organic solvents
Location and origin	Leaf mesophyll cells (i.e., chloroplasts)
Excitation by	Red, green, blue light or UV-A radiation, red laser (He/Ne at 632.8 nm), blue laser (dye laser), UV-laser (e.g., Nd: YAG laser at 355 nm), green laser (e.g., doubled frequency Nd: YAG laser at 532.5 nm, pulsed flash lamp (with appropriate filers)
Fluorescence characteristics	
Emission range	650-800 nm
Maxima	Near 690 nm and near 730-740 nm
Short-term stress	Changes in fluorescence induction kinetics at inhibition of photosynthesis, increase of the ratio 690-740 by 30%
Long-term stress	Decline of chlorophyll content, large increase of the ratio 690-740 is an inverse indicator of *in situ* leaf chlorophyll content

(*Rhododendron* sp.)[20]. Cadet and Samson[21] used fluorescence ratios to discriminate scarcity of nitrogen, potassium and phosphorus in sunflower (*Helianthus annuus*). Similarly, these fluorescence ratios were also used in differentiating between nitrogen deficiency and disease infection in winter wheat (*Triticum aestivum*)[22]. Husna *et al*.[23] used fluorescence sensing to as a means to estimate palm oil yield and quality from oil palm (*Elaies guineensis* Jacq.). Use of fluorescence imaging has been extended to irrigation management, fertilization and disease control due to its potential in sensing plant stress induced by water deficit, nutrient deficiency and disease infection.

However, fluorescence imaging have some limitations during field measurement due to the fluctuations in light intensity coupled with varying site conditions which tend to produce results that are different from laboratory trials. In addition, experiments with chlorophyll imaging may run into risk of producing incomparable and even contradictory results unless there is a synchronization of measuring protocols and parameters used[24]. It is also noted that measuring distance can exert a significant effect on the reflected light as compared among several fluorescence sensors[25].

Nutrient deficiency detection using thermography: In contrary to fluorescence imaging, thermography can visualize stomatal movement without the presence of an illumination source[26]. The thermal signal being studied is change of temperature captured in the form of radiation reflected or emitted from the plant being scanned. Thermal intensity is determined by the surrounding temperature, where the intensity of infrared radiation increases with the temperature[26]. The change in leaf temperature generally involves the opening and closure of stomata for gas exchange or cooling. Cooling process through transpiration induces stomatal opening and results in a lower temperature with heat loss to atmosphere. However, transpiration and ultimately stomatal regulation are determined by nutrient availability in soil and water flow within the plant. Water or nutrient scarcity usually disrupts transport of dissolved nutrient and water from soil to root and ultimately to the whole plant where nutrient uptake is limited by higher nutrient concentration in soil[27].

As a result, the stomata closes to prevent further moisture loss and the leaf surface temperature increases. This explains why some studies conclude that nutrient deficiency affects stomatal regulation and can lead to increased temperature within the plant. Chaerle *et al*.[28] found that magnesium starved bean plant under controlled condition showed higher leaf temperature on thermal imaging. Tilling *et al*.[29] reported higher temperature for under fertilized barley (*Hordeum vulgare* L.) as compared to well fertilized barley with nitrogen as the reference nutrient.

Though thermography is generally passive in nature, it can be active with the introduction of a stimulus such as incident light to induce change in temperature of a targeted subject[28]. Active thermography allows monitoring of leaf internal heterogeneity in relation to disease-induced change or growth, whereas passive thermography assesses change of similar capacity through water evaporation estimation[19]. Thermography may be capable of detecting plant stress, but it does not have the ability to differentiate among the stressors. As such, it should be used in combination with other sensing techniques, such as chlorophyll imaging, in order to monitor and distinguish different stresses simultaneously[28]. This explains that leaf and canopy temperature alone is not a reliable parameter in assessing plant stress and the data obtained is error-prone and subject to uncertainty given the influence of changing environmental condition including light intensity, ambient temperature and humidity, as well as canopy structure in height and density[30,31]. The accuracy in measurement can be affected under different conditions. Source of errors could be the possibility of plant thermal energy and radiance being captured wrongly, the generation of inaccurate image or the disturbance of random noise from different source in thermal data analysis. As an improvement to the data and image qualities, errors could be removed using three step-wise methods, i.e., noise signal transformation, principal component analysis and inter-band relation analysis[32].

Nutrient deficiency detection using multispectral and hyperspectral imaging: Multispectral systems measure reflectance in broad bands of 40 nm in the red, green, blue and near-infrared regions and can be extended to a maximum of ten wavelengths[31,33]. This appears to be the biggest discrimination between hyperspectral and multispectral techniques. The hyperspectral technique utilizes additional spectral bands and brings about higher spectral resolution, or narrower bandwidth of about 10 nm or less in the visible and near infrared band range, providing much complex details covering the broader aspect of vegetation functional and structural properties[34,35]. Similar to thermography, hyperspectral technique can be used together with chlorophyll fluorescence to monitor and differentiate the different plant internal responses to stress based on changes in photosynthetic efficiency and spectral properties[36]. Plant stress of different levels across multiple crops have been shown to be effectively sensed using hyperspectral discrimination such as water content, disease condition and crop nutrient status[14,32,37].

Due to wider wavelengths available in hyperspectal imaging, it is important to filter the unnecessary bands and focus on the distinct ones which have the highest optical sensitivity to a particular plant stress to avoid redundancy in the data and images generated[14,34,38]. The filtering procedure is able to remove noise from the surrounding environment so as to produce spectral data of greater accuracy[31]. For instance, Zhang *et al.*[39] reported that spectral reflectance at certain wavelengths is more effective at characterizing the distribution of nitrogen, phosphorus and potassium in rapeseed (*Brassica napus*) leaves.

However, the performance of the selected waveband selection depends on several factors including number of samples over a location and type of spectral data used which determine the success or failure of the method[32], as shown in the hyperspectral evaluation study by Pacumbaba Jr. and Beyl[13] on detecting nutrient stress in lettuce (*Lactuca sativa*) leaves. Although, changes of reflectance due to nutrient stress were successfully detected using the hyperspectral method, their study suggested that further data processing be made to resolve the confusion that arose from overlapping spectral bandwidths.

Development of vegetative indices based on multispectral wavelengths: Vegetation Indices (VIs) were developed based on several selected bands within the visible (blue, green and red bands) and near-infrared spectral regions in multispectral imagery. These bands are within the spectral regions that are most responsive to chlorophyll pigments where plant reflectance are found to be the strongest[34]. However, the intensity of reflectance light in plant is not dependent on chlorophyll concentration alone but can extend to several other aspects such as leaf shape and geometry, external features such as canopy area which may alter the depth of light absorption and reflectance[34]. The Normalized Difference Vegetative Index (NDVI) has remained the most commonly used index in multispectral application as compared to all other VIs due to its practicality and utility in detecting plant physiological variability[40,41]. In general, visible green range is more useful in detecting plant infection at the early stage while reflectance in the near-infrared is more useful with increasing severity. Zhang *et al.*[42] reported that final stage infection in tomato displayed 10% of reflectance difference in near-infrared against healthy plant while visible range only recorded about 1.2% difference. Depending on the different spectral region used in comparison, the indices developed can be green NDVI (green and NIR), red NDVI (red and NIR) or red and green vegetation indices[3,43]. The red band in the index corresponds more readily to chlorophyll pigment where radiation absorption is the highest whereas green band deals with pigment region other than chlorophyll[33].

Although, studies generally show the usefulness of NDVI in detecting plant stress, it comes with limitations in terms of sensitivity to higher chlorophyll content. Hence, indices with narrower bands have been developed, particularly targeted near 550 and 700 nm, which is the range most sensitive to pigment change. As the name suggests, Narrow Band Vegetative Indices (NBVI) focuses on band range between R700-R750 and R550-R750[44]. This is especially effective for nitrogen status assessment as shown by Zhao *et al.*[45] on sorghum (*Sorghum bicolor*), where reflectance signal specific to nitrogen scarcity was found to be near the 555 and 715 nm wavelengths.

Real time monitoring of crop nutritional status and yield prediction using satellite and airborne platforms: On-going monitoring of crop condition is important to track crop growth and development dynamics over time. This practice provides timely information that can help identify problem areas affected by various vegetative factors including water status, nutrient distribution and potential disease and weed encroachment which may manifest only in longer periods of time. In doing so field operations such as fertilizer application and pesticide recommendation can be adjusted in terms of timing and application rate to accommodate the different growth requirement of crops at distinct points of time throughout the growing period for enhanced agricultural productivity and food supply[46,47]. Crop nutrient demand is typically dynamic across different growth stages. Wang *et al.*[47] clearly showed that crop nitrogen status changed constantly over the entire growing period and fertilization strategies should respond to these changes. Crop dependence on nitrogen supply in natural soil is unrealistic as its availability is subjected to soil type, previous crop management and the climate at that particular time[48]. In addition, long-term monitoring records are needed for farmers to observe crop yield pattern and evaluate its sustainability against changing climatic condition, which alters the rainfall distribution and temperature variation from time to time[46].

Remote monitoring of crop condition and yield prediction can be achieved using satellite and aircraft platforms by combining their multiple image data with suitable process-based simulation models[49-52]. Data derived from Moderate Resolution Imaging Spectroradiometer (MODIS) has been used for crop yield forecasts on selected crops including barley, rapeseed, field peas (*Pisum sativum*) and spring wheat (*Triticum aestivum* L.)[53] while Herrmann *et al.*[54] assessed vegetation changes of wheat (*Triticum* spp.) and potato (*Solanum tuberosum*) through Leaf Area Index (LAI) estimation with vegetation and environmental new micro spacecraft (VENμS) and sentinel-2. Although some of these examples show that satellite sensors are useful in most crop condition assessments, they have limited utilization in precision agriculture management due to their lower spatial and spectral resolutions and longer revisit time[55]. Landsat for instance is not a good choice for monitoring due to its 16 day revisit period and SPOT about 2-6 days of repeat cycle[56] as compared to the maximum time span of 1 day. This will delay the data acquisition process which is critical to address any crop disturbance before it becomes worse and affects crop quality.

Technology advances in recent years brought about airborne sensors with higher spatial and spectral resolutions as well as shorter revisit time, but some problems remain unsolved such as considerable data processing time and higher acquisition cost making them less operationally and economically efficient at a large scale[57]. For the low-cost alternatives, Berni *et al.*[55] suggested the use of unmanned aerial vehicles mounted with cheaper thermal and multispectral sensors. Meanwhile, Goel *et al.*[58] used Compact Airborne Spectrographic Imager (CASI) to monitor weed infestation on corn. However, Pimstein *et al.*[59] cautioned that the types of sensor and information generated will determine the accuracy of the results in monitoring crop nutritional status, as shown for wheat with regard to potassium and phosphorus contents.

CONCLUSION

The study reviewed and discussed the different remote sensing techniques applied to solve agricultural problems specifically related to nutrient stress that could have been influenced by other stressors including pest infestation, disease infection and water deficit. These techniques detect and interpret shapes and patterns of remotely-sensed imagery based on their respective spectral signatures to quantify and visualize the morphological and physiological changes in plant in response to various stresses. Generally, remote sensing tools assessed in this study proved to be effective and efficient in detecting and monitoring plant nutrient stress but each of them has advantages and disadvantages which makes them unreliable when used solely. However, the possibility of using them in combination with other geospatial tools is expected to overcome the constraints and enhance their capabilities to obtain more reliable outcomes.

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