



# Advances in plant nutrition diagnosis based on remote sensing and computer application

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## Abstract

Hyperspectral remote sensing, visible light remote sensing and canopy color analysis have been widely concerned for rapid diagnosis of crop growth and nutrition. They are expected to develop into potential nondestructive diagnostic techniques for crop nitrogen nutrition in the new era on account of the advantages of stable, rapid, convenient and nondestructive results, together with the good correlation between canopy color parameter NRI and plant nitrogen nutrition index and yield satisfying the demand for nondestructive diagnosis of nitrogen nutrition, and their feasibility to monitor plant growth status and nitrogen nutrition level in real time and quickly. At present, with the rapid development of remote sensing satellite, unmanned aerial vehicles remote sensing and Internet of things, remote sensing will be more and more widely used in plant nutrition diagnosis.

**Keywords** Plant nutrition diagnosis · Hyperspectral · Canopy color · Satellite remote sensing · UAV

## 1 Introduction

Traditional plant nutrition diagnosis and fertilization recommendation are mainly based on field sampling and laboratory chemical analysis. This method needs a lot of manpower, material and financial resources in sample collection, testing and data processing. It is not suitable for popularization and application. A series of changes in leaf color, thickness, moisture content and morphological structure are caused by vegetation deficiency, which results in changes in spectral reflectance characteristics. Therefore, remote sensing based on spectral reflectance features of objects to identify objects has become a possible means for real-time monitoring and rapid diagnosis of plant nutrient status. Thomas et al. [1] studied the spectral characteristics of leaves of seven plants under different nitrogen nutrient levels and found that the reflectance of light wave region was increased in all plants under nitrogen

deficiency; however, the increase in degree of reflectivity was different among different plants. The spectral characteristics of rice leaves under nitrogen deficiency and normal nutrition were significantly different, and chlorophyll was considered as the main internal factor leading to the difference of spectral characteristics [2]. In recent years, with the rapid development of remote sensing satellite, UAV remote sensing and Internet of things, remote sensing has been widely used in plant nutrition diagnosis [3, 4]. Compared with other diagnostic methods, hyperspectral remote sensing, visible light remote sensing and canopy color analysis have the advantages of simplicity, rapidity and nondestructiveness by judging canopy color to understand the nitrogen nutrient status of crops and then carrying out fertilization recommendation or yield prediction. Commonly used remote sensing platforms, such as aircraft, UAVs and artificial satellites, have the advantages of high efficiency, high spatial–temporal resolution and high mobility. In recent years, they have developed rapidly and are widely used in plant nutrition diagnosis [5, 6].

The lack of plant elements causes changes in the color and morphological structure of the leaves of plants, and the nutritional status of plants can be quickly diagnosed by changes in the spectral reflectance of plants. Borhan et al.

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[7] designed a multispectral image system with red, green and blue features and three multispectral bands of 550 nm and 670 nm, and found that the multispectral image features were linearly correlated with the chlorophyll content of potato leaves in greenhouse. The correlation coefficient is 0.95. Oklahoma State University has developed an instrument based on canopy multispectral analysis (GreenSeeker) and established a diagnostic recommendation model for the recommendation of topdressing in wheat and corn. However, visible light remote sensing and multispectral and hyperspectral remote sensing all utilize the absorption, reflection and refraction of light from soil and plant canopy. Soil type, solar incidence angle, atmospheric conditions and other factors will affect the absorption and reflection of light, thus affecting the canopy image and spectral characteristics of plants.

## 2 Research status of plant nutrition diagnosis based on remote sensing and computer

With the gradual application of remote sensing technology in agriculture, many scholars have a better understanding of the change in crop spectral characteristics under water and fertilizer stress. Plant growth and nutrition can be monitored in real time by remote sensing. In recent 10 years, hyperspectral remote sensing technology has promoted the development of quantitative agricultural remote sensing because of its characteristics of high resolution, strong continuity and massive information collection. Hyperspectral remote sensing has shown great potential in quantitative determination of plant nutrition [8]. Many scholars have realized the hyperspectral detection of a large number of physiological and biochemical parameters of crops and vegetation, and proposed several methods for the quantitative inversion and detection of crop parameters based on spectral features [9] and [10, 11]. Leaf nitrogen content (LNC) is the main index to reflect the nitrogen status of plant leaves. Through monitoring of LNC, reasonable fertilization measures can be formulated. Crop parameters such as leaf area index, biomass, chlorophyll content and protein content may vary with nitrogen content [12]. Using remote sensing to estimate N in wheat canopies is effective, and calculation of the canopy chlorophyll content index (CCCI) from canopy spectral reflectance of wheat showed good correlation with N uptake (kg N/ha) [13, 14].

With the development of hyperspectral remote sensing technology, using crop canopy spectral information can better monitor and accurately determine LNC. At present, some scholars have studied the estimation and monitoring model of crop nitrogen concentration using hyperspectral

data [15, 16]. At present, hyperspectral data can be non-imaging or imaging. Non-imaging hyperspectral techniques for obtaining hyperspectral data from surface spectrometers have been developed and widely used in geology, agriculture and other fields [17]. Hyperspectral imaging technology, usually satellite-borne or airborne, has more applications [18–20].

Remote sensing technology based on UAV (UAV) has the advantages of low weight control, ease of use and high resolution, low operation cost and high spatial resolution. It has become a hot spot in the research and application of new remote sensing [21–23]. Liu et al. [24] obtained hyperspectral data and LNC data on the basis of hyperspectral data and corresponding LNC data of winter wheat based on UAV (UAV) and established a quantitative model. The modeling result of BP neural network is better than that of multivariate linear regression. At present, plant nutrition diagnosis based on remote sensing is mostly applied to the diagnosis of a large number of elements nitrogen and phosphorus, among which nitrogen diagnosis is the main one, and the diagnosis of other medium elements is rarely reported.

## 3 Visible light remote sensing and computer application for plant nutrition diagnosis

Changes in the nutritional status of crops have a direct impact on the canopy color of crops. For example, the color of leaves of nitrogen-deficient plants is lighter and the color of canopy is yellowish green. The nitrogen nutrition status of crops is diagnosed by observing the color change of plant canopy leaves (Fig. 1). Visible light remote sensing is

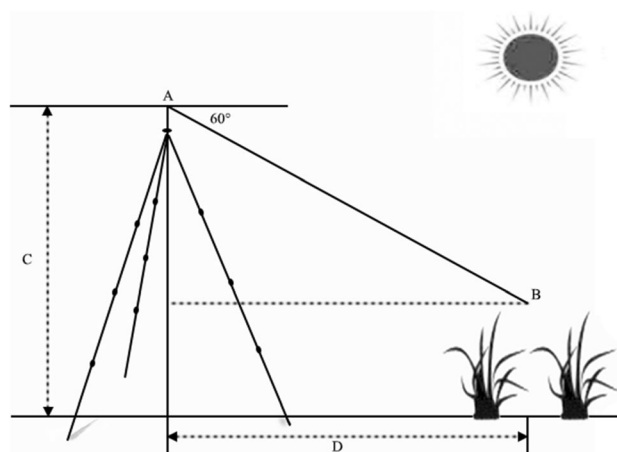


Fig. 1 Color analysis of plant canopy [25]

simple, easy to operate, intuitive and convenient, causing people's attention and a lot of research [25, 26].

The green condition of plant canopy is usually related to the chlorophyll content of leaves, and the chlorophyll content has a significant correlation with the total nitrogen content of plants [27]. The change in chlorophyll content affects the light absorption or reflection of leaf canopy [28]. Because of the effective absorption of chlorophyll to visible light, the light reflection of canopy in visible light band (400–700 nm) increases with the increase in nitrogen deficiency [29]. Zhang et al. [30] found that red and green light reflectance could well predict nitrogen content in *Kandelia candel* plants (Table 1).

The results showed that plants with nitrogen deficiency reflected more light in the whole visible band than those with sufficient nitrogen supply, and the band with the greatest difference in canopy light reflection was usually in the range of 550–600 nm [31]. The band with the largest difference in light reflection of soybean leaves under different chlorine supply levels was at 550 nm [32]. Ling et al. [33] used the “the difference color between the top 3rd leaf and the 4th leaf” to diagnose rice nitrogen nutrition. When the top 4 leaf (SPAD value) = the top 3 leaf, it indicates that nitrogen nutrition is suitable and nitrogen fertilizer is not necessary to be applied; if the top 4 leaf < the top 3 leaf, it indicates that nitrogen is excessive; if the top 4 leaf was higher than the top 3 leaf, it indicates that the nitrogen nutrition of rice is insufficient. Similarly, the “fertilizer window” method is used to recommend crop

nitrogen fertilizer by comparing the color of crop leaves under different nutrient conditions to determine crop nutritional status. The visible green band of crop canopy reflectance may be a diagnostic tool for crop nitrogen status.

Sun et al. [34] analyzed the correlation between the image detection parameters and chlorophyll content in field maize. Flowchart of multispectral image and data processing is shown in Fig. 2. The results showed that the average gray value of R, G and B bands was negatively correlated with the chlorophyll index, and the correlation coefficients were  $-0.73$  and  $-0.71$  and  $-0.71$ , respectively. The average gray value of NIR (near-infrared) band was weakly positively correlated, and the correlation coefficient is 0.23. RVI (vegetation index) was negatively correlated with chlorophyll index, and the correlation of NDVI (normalized difference vegetation index), MSAVI2 (modified secondary soil-adjusted vegetation index), RVI and SAVI (soil-adjusted vegetation index) was better than other vegetation indices, and the absolute value of correlation coefficient was above 0.80. The 6-leaf stage of maize is a suitable period for the application of digital images for nitrogen nutrition diagnosis.  $B/(R + G+B)$  is suitable as a sensitive color parameter for corn nitrogen nutrition diagnosis, when  $B/(R + G+B) < 0.1587$  o'clock, the corn is in a state of severe nitrogen deficiency. When  $B/(R + G+B) > 0.1812$ , the corn is in an excessive nitrogen supply state [35].

**Table 1** Effects of different nitrogen treatments on the index of N nutrient in rice plants and canopy NDVI values, respectively, at different growth stages [25]

Growth stage	Treatment (%)	Leaf N content (%)	Plant total N content (%)	N accumulation (t/hm <sup>2</sup> )	NDVI value
Tillering stage	N0	1.46 Cc	1.05 Cc	1.31 Cc	0.39 Bc
	N75	2.07 Bb	1.57 Bb	2.70 Bb	0.55 Ab
	N150	2.72 Aa	2.07 Aa	4.58 Aa	0.63 Aa
	N225	2.76 Aa	2.17 Aa	4.86 Aa	0.60 Aab
Jointing stage	N0	1.21 Cc	0.90 Cc	2.06 Cc	0.38 Cc
	N75	1.37 Cc	0.93 Cc	3.19 Cc	0.55 Bb
	N150	1.79 Bb	1.26 Bb	6.20 Bb	0.62 ABa
	N225	2.23 Aa	1.64 Aa	8.69 Aa	0.65 Aa
Booting stage	N0	1.06 Cc	0.70 Aa	2.86 Bb	0.33 Ad
	N75	1.27 BCb	0.90 Aab	5.40 ABab	0.45 Bc
	N150	1.44 Bb	0.84 Aab	5.36 ABab	0.54 Ab
	N225	1.82 Aa	1.12 Aa	8.61 Aa	0.60 Aa
Filling stage	N0	1.00 Cc	0.62 Cc	2.59 Bb	0.35 Cd
	N75	1.35 BCb	0.74 BCbc	4.58 ABab	0.47 Bc
	N150	1.58 ABb	0.93 ABb	6.22 ABab	0.56 Ab
	N225	1.90 Aa	1.15 Aa	8.60 Aa	0.60 Aa

Different lowercase letters or uppercase letters within the same column indicate significant difference at the 5% and 1% probability

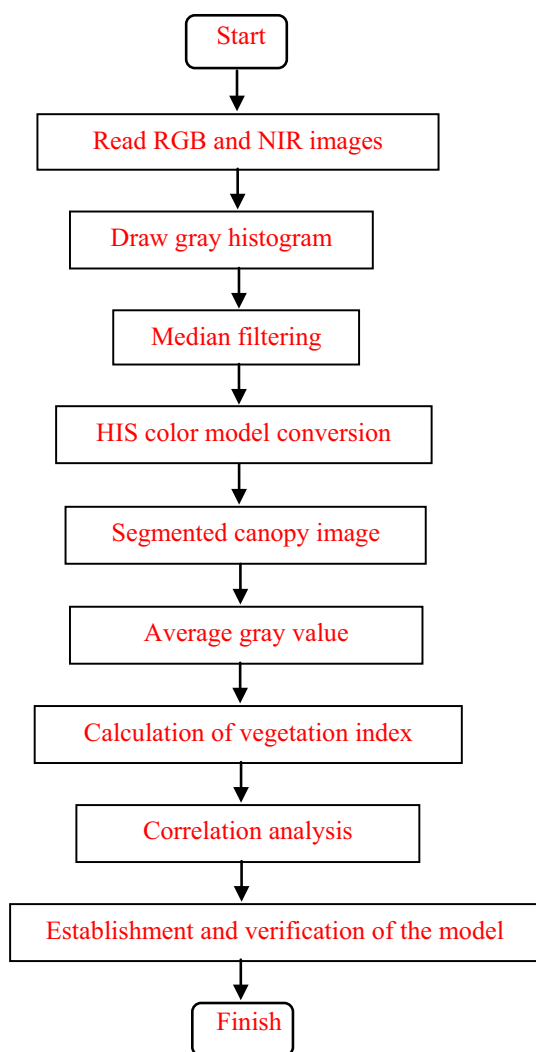


Fig. 2 Flowchart of multispectral image and data processing [34]

The rapid and accurate diagnosis of crops using a digital camera requires effective segmentation of the canopy and non-canopy parts of the crop. Tao et al. [36] took the maize canopy image vertically and segmented the image. It was found that the extracted coverage had a good correlation with canopy characteristics such as LAI (leaf area index), plant nitrogen content and aboveground biomass. Wang et al. [37] obtained the canopy image of rice using a digital camera and segmented the image according to the threshold of the digital image green channel and the red channel difference. There was a good correlation between the characteristic parameters extracted from the segmented image and SPAD value, leaf nitrogen content and other indicators, and the correlation coefficient between the normalized value of red light NRJ and the two was 0.87 and 0.65. These studies show that the visible light remote sensing based on digital camera image acquisition and digital image analysis has a good prospect in crop nitrogen

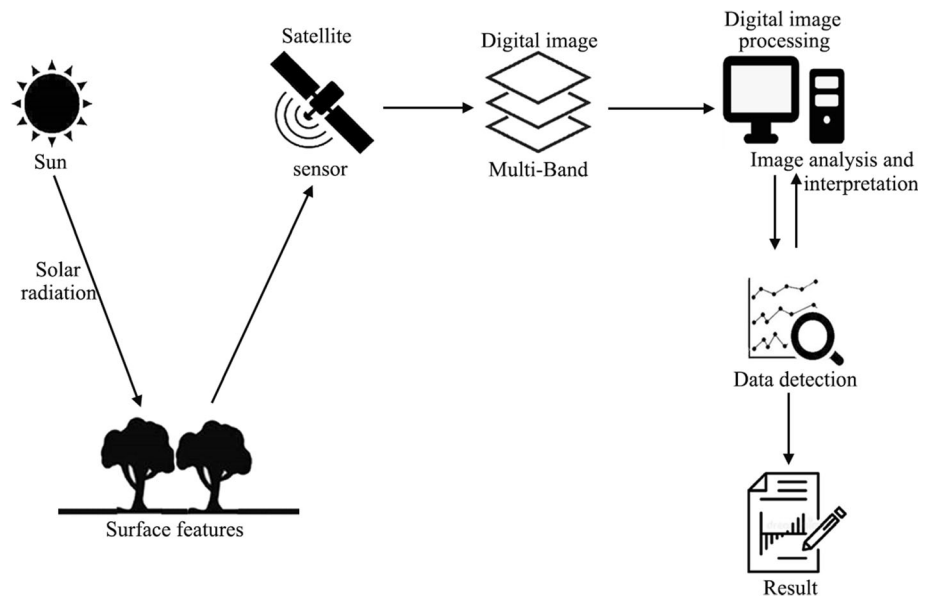
nutrition diagnosis and nitrogen fertilizer recommendation. Based on the measured data of ground spectrometer, the chemical components of leaves were detected by remote sensing with imaging spectrum. It was found that at 99% confidence level, a good regression equation for phosphorus and potassium content was obtained [38]. This greatly increases the possibility of monitoring crop fertility by remote sensing with imaging spectrum.

#### 4 Hyperspectral remote sensing and computer application in plant nutrition diagnosis

Hyperspectral technology refers to the quantitative acquisition of biochemical properties and structural characteristics of ground objects by means of electromagnetic wave information reflected by ground objects and chemometrics [39]. Hyperspectral remote sensing technology is characterized by high spectral resolution, up to 3 nm, and strong band continuity (there are hundreds of bands in the range of 350–2500 nm). Hyperspectral data can reveal the characteristics of objects in a narrower spectral range, so as to provide more sufficient information for the study of objects. High-resolution remote sensing data can provide information about plant structure and chemical composition [40]. Remote sensing monitoring of large amounts of elements in some plants, especially high levels of nitrogen and phosphorus, is becoming more and more common [41]. With the increase in hyperspectral remote sensing data acquisition means and development of data processing technology, hyperspectral remote sensing data are more and more widely used in various fields (Fig. 3).

All objects in nature have different spectral characteristics of reflection due to their different composition and attribute structure. Among them, the spectral reflection characteristics of plant leaves are determined by their chemical and morphological characteristics, which are closely related to the development, health and growth conditions of vegetation [42]. When plants are deficient in nutrients, a series of changes in leaf color, thickness and morphological structure will occur, which will lead to changes in spectral absorption, reflection and transmission characteristics [43]. It is possible to monitor and rapidly diagnose the nutrient status of plants through changes in spectral reflectance characteristics [44]. Since the 1970s, scientists at home and abroad have conducted a lot of research on the diagnostics of plant nitrogen spectroscopy, firstly looking for the performance of nitrogen sensitive bands and their reflectivity under different nitrogen levels. The results show that many plants have increased visible light reflectance in both leaf and plant canopy levels during nitrogen deficiency [45, 46], and the most sensitive band

**Fig. 3** Schematic diagram of hyperspectral remote sensing in plant nutrition diagnosis



for changes in nitrogen content of rice is in the 400–1350-nm region [47]. Rice nitrogen deficiency can cause changes in leaf color and morphology, and thus can be inverted by spectral information between 450 and 950 nm [48]. The leaf and canopy spectra of rape plant had different reflectance characteristics at different nitrogen levels, and the difference is most obvious in visible and near-infrared bands, showing different reflectance peaks (550 nm) and absorption valleys (1000 nm) [49]. The spectral reflectance estimation model of nitrogen content in rape was:  $N = 3633.62 \times R'_{401} - 6695.31 \times R'_{451} + 2050.48 \times R'_{549} + 0.15 \times R'_{1321} - 223.37 \times R'_{2245} + 1.41$  (Table 2). The fitting results passed a very significant test. The model can be used to estimate the nitrogen content and nitrogen nutrition of rape [49]. Li et al. [46] studied the canopy spectral changes of rice under different nitrogen and phosphorus levels. The spectral reflectance increased with the increase in nitrogen supply in near-infrared region, but decreased with the increase in nitrogen supply in visible region. Liu et al. [50] studied the response characteristics of canopy reflectance spectra to different nitrogen application levels. It was concluded that the reflectance increased in visible light region with the increase in nitrogen application level, but showed the opposite trend in near-infrared region. Different nitrogen nutrition levels can be distinguished by spectral analysis and operation analysis of variables.

After identifying the sensitive bands of nitrogen in plants, many researchers have established models for estimating nitrogen content of crops through spectral reflectance or its derivatives. The results of Bao et al. [51] showed that the linear combination of D 736, R 900 and R 720 had a good regression relationship with leaf nitrogen content per unit land area of wheat. Lee et al. [52] believed that the feasibility of a simple spectral index (SI) using the

first derivative of canopy reflectance spectrum at 735 nm ( $dR/d\lambda|_{735}$ ) to assess  $N$  concentration of rice (*Oryza sativa* L.) plants. Fernandez et al. [53] also reported that the linear combination of red (660 nm) and green (545 nm) bands could be used to predict the nitrogen content of wheat, which was not affected by nitrogen fertilizer treatment. Tarpley et al. [54] analyzed the relationship between nitrogen content in cotton leaves and 190 spectral ratio indices, and carried out clustering analysis according to the prediction precision and accuracy. The results showed that the prediction precision of the ratio of red edge position to short-wave near-infrared band was higher.

With the rapid development of remote sensing, hyperspectral remote sensing can detect the fine spectral information of vegetation (especially the absorption spectrum information of various biochemical components of vegetation), retrieve the content of each component and monitor the vegetation growth status with its characteristics of ultra-multi-band (dozens, hundreds) and high spectral resolution (3–20 nm). Glenn et al. [55] used spectral diagnosis to predict wheat nitrogen levels. The relative coefficient of wheat nitrogen model prediction reached 0.97, and the mean square error was 0.65. The results of Niu et al. [38] also showed that the linear regression equation of the first derivative of reflectivity at 2120 nm and 1120 nm could predict the nitrogen content of fresh leaves, and the correlation between measured and predicted values was above 80%.

A model based on the relationship between plant nitrogen content and spectral reflectance or its derivative index can be used to estimate crop nitrogen content, guide crop fertilization management and improve nitrogen use efficiency. A lot of research has been done in this area, and some of the results have been successfully applied to production. In the 1990s, a ground-based active remote

**Table 2** Results of stepwise regressions modeling nitrogen concentration in canopy scale for rape ( $n = 200$ ) [49]

Spectral form	Stepwise regressions modeling	$R^2$	F value
$R$	$N = 18.65 \times R_{538} - 26.40 \times R_{700} + 10.21 \times R_{1663} - 0.07 \times R_{2373} + 0.23 \times R_{2390} + 1.47$	0.58	37.15
$R'$	$N = 3633.62 \times R'_{401} - 6695.31 \times R'_{451} + 2050.48 \times R'_{549} + 0.15 \times R'_{1321} - 223.37 \times R'_{2245} + 1.41$	0.66	53.18
$\text{Log } 1/R$	$N = 695.76 \times (\text{Log } 1/R)_{1305} - 695.73 \times (\text{Log } 1/R)_{1306} + 5.42 \times (\text{Log } 1/R)_{2083} - 4.97 \times (\text{Log } 1/R)_{2201} - 0.10 \times (\text{Log } 1/R)_{2390} + 1.73$	0.67	55.57
$(\log 1/R)'$	$N = 195.92 \times (\text{Log } 1/R_{401})' + 433.10 \times (\text{Log } 1/R_{455})' - 639.44 \times (\text{Log } 1/R_{674})' + 372.83 \times (\text{Log } 1/R_{1107})' + 0.15 \times (\text{Log } 1/R_{2391})' + 1.40$	0.73	73.00

sensing hyperspectral instrument, GreenSeeker Spectrometer, was developed by the University of Oklahoma in the USA. It can analyze crop growth by observing NDVI data, diagnose nitrogen in real time and provide the best fertilization scheme. The instrument has been successfully applied to study nitrogen utilization and precision agriculture, and has achieved good results. Chen et al. [56] estimated plant nitrogen accumulation by using DVI index at jointing stage of rice and constructed a model of nitrogen topdressing regulation, which made a more accurate estimation of the application rate of panicle fertilizer. Compared with the traditional methods of experiential nitrogen fertilizer application, the reflectance spectroscopy-based nitrogen fertilizer topdressing technology could be used to recommend the amount of nitrogen fertilizer topdressing by predicting plant nitrogen accumulation and soil nitrogen supply.

Nitrogen and potassium deficiency in olive trees can be distinguished by using 26 specific wavelengths plus several vegetation indices [57]. Osborne et al. [58] confirmed in corn that the increase in the number of cells per unit of leaf area in phosphorus-stressed plants was translated into a significant spectral response in the NIR part of the spectrum. Phosphorus stress was related to the increase in anthocyanin content, which resulted in purple discoloration of leaf edge, which was consistent with the observed increase in wavelength reflectivity. Although it has been reported that the use of spectral remote sensing to predict phosphorus and potassium nutrition in plants, more specific indices or algorithms are needed for predicting the nutrient condition of potassium and phosphorus.

### 5 UAV remote sensing and computer application in plant nutrition diagnosis

Nowadays, all countries in the world attach great importance to the development of remote sensing satellites and UAV (Fig. 4), and continue to expand the relevant



**Fig. 4** Application of UAV remote sensing in plant nutrition diagnosis

**Table 3** Results of representative band modeling [24]

The growth period and the corresponding typical bands (nm) of winter wheat	Modeling results				Verification results			
	Multiple linear regression		BP neural network		Multiple linear regression		BP neural network	
	$R^2$	RMSE (N%)	$R^2$	RMSE (N%)	$R^2$	RMSE (N%)	$R^2$	RMSE (N%)
Jointing stage (466, 690, 710, 718, 918)	0.658	0.312	0.829	0.248	0.878	0.279	0.968	0.152
Flag leaf stage (462, 698, 722, 754)	0.863	0.179	0.948	0.127	0.898	0.219	0.969	0.133
Flowering stage (474, 710, 730, 738, 746)	0.861	0.161	0.948	0.117	0.872	0.214	0.948	0.155
Flowering stage (458, 570, 722, 734, 758)	0.661	0.393	0.844	0.281	0.567	0.198	0.850	0.139

application fields. Satellite remote sensing is coming to a new stage of development. At present, the main foreign resource satellites are Landsat, SPOT, IKONOS, Quick Bird, Geoeye and so on. Quick Bird is the only commercial satellite in the world that can provide sub-meter-level services, whose single-view image is 2–10 times higher than other commercial high-resolution satellites. There are Beijing-1, China–Brazil Earth Resources Satellite (CBERS, also known as Resource One), China Resources Satellite (ZY-2, ZY-3), Gaofen (GF-1, GF-2), Formosat-2 and other resources satellites in China. Compared with the near-surface and low-altitude remote sensing, the application of satellite remote sensing has the advantages of wide coverage, no site constraints and all-weather observation. In addition, the resolution of sensors carried by satellites is getting higher and higher. High-precision satellite remote sensing is more and more widely used in plant nutrition diagnosis.

Zhang et al. [59] captured maize canopy images with a digital camera equipped with an UAV. Combined with the analysis of variation coefficient of color parameters, it was found that the normalized value of green light [ $G/(R + G + B)$ ] and the ratio of green light to brightness ( $G/L$ ) were significantly correlated with the routine nitrogen nutrition diagnostic indexes of summer maize at different growth stages ( $P < 0.01$ ), and the coefficient of variation was small and stable. Wright et al. [60] applied Quick Bird satellite images to the management of wheat grain protein content. It was found that the vegetation index GNDVI extracted from Quick Bird satellite images and the reflectance NIR in near-infrared band had a good correlation with the total nitrogen content of plants. Knyazikhin et al. [61] studied the correlation between the near-infrared directional reflectance function and nitrogen accumulation in plant leaves in depth, providing a simple and effective method for monitoring nitrogen content in plant leaves by remote sensing satellite. Liu et al. [24] established a quantitative model for simulating the growth stages of typical LNC combinations of winter wheat by means of multiple linear regression and BP neural network. At the

same time, the results of the model are compared and analyzed using the hyperspectral data measured on the ground (Table 3). Through the analysis of the modeling results, it can be seen that both the modeling and verification results of the two different modeling methods are ideal, and the modeling results of BP neural network are generally superior to the results of multiple linear regression modeling. The response of the hyperspectral data based on UAV to the typical bands of winter wheat LNC is relatively accurate, and the established model is reliable and effective.

In recent years, the application of satellite remote sensing spectral information in canopy nutrition diagnosis of field crops has developed rapidly, which has greatly improved the efficiency of nutrition diagnosis, but it also has its shortcomings: Satellite remote sensing information is susceptible to weather and long access period [62], and satellites equipped with SAR can reduce the impact of adverse factors such as the weather. Synthetic aperture radar (SAR) has the following advantages as compared with traditional optical remote sensors [63]: (1) all-weather, all-time working ability; (2) strong penetration; (3) large area and low cost of one-time imaging by side view; (4) SAR texture features to obtain faults that are difficult to see in other remote sensing systems, which is conducive to the study of surface structure and prediction of new sources; and (5) high resolution and not affected by platform height or distance.

## 6 Conclusions

Both light remote sensing and multispectral remote sensing make use of the absorption, reflection and refraction of light by soil and plant canopy. However, the factors affecting light absorption and reflection will affect crop canopy image information and spectral characteristics, such as field weed states, diseases, pests and water stress, soil types, atmospheric conditions and solar incidence angle. Therefore, it is not accurate to rely solely on plant

canopy image information and spectral features obtained from remote sensing technology for plant nutrition diagnosis and fertilization recommendation, which must be combined with traditional soil and plant testing. At present, there are still many problems in the application of remote sensing and hyperspectral technology in plant nutrition diagnosis and recommended fertilization. The application of multispectral remote sensing technology in agriculture is still in the research stage, and its extensive application is still some time away, mainly because of its high equipment price and complex technology, and the rapid standardization. The establishment of simple spectral analysis method and monitoring index also needs further study.

With the increasing maturity of technologies such as thermal infrared imaging and airborne multi-polarized synthetic aperture radar, the spectral domain will continue to expand; with the application of new sensors with high spatial resolution, the spatial resolution of remote sensing images will continue to increase; large, medium and small satellites cooperate with each other, combining high, medium and low orbits; and their time resolution varies from a few hours to 18 days, forming a series of complementary time resolution. Technological advances such as digital image processing, geographic information systems (GIS) and global positioning systems (GPS) have jointly promoted the development of remote sensing. It is foreseeable that the links between different disciplines will become more closely in the future, and more fields of science and technology will be applied to remote sensing for plant nutrition diagnosis.

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## References

1. Thomas JR, Gausman HW (1977) Leaf reflectance vs. leaf chlorophyll and carotenoid concentration for eight crops. *Agron J* 69:799
2. Jiao Q, Zhang B, Liu J, Liu L (2014) A novel two-step method for winter wheat-leaf chlorophyll content estimation using a hyperspectral vegetation index. *Int J Remote Sens* 35(21):7363–7375
3. Shibayama M, Akiyama T (1986) A spectroradiometer for field use IV. Radiometric estimation for chlorophyll index of rice canopy. *Jpn J Crop Sci* 55(4):433
4. Liu H, Zhu H, Wang P (2017) Quantitative modelling for leaf nitrogen content of winter wheat using UAV-based hyperspectral data. *Int J Remote Sens* 38(8–10):2117–2134
5. Li JW, Zhang F, Qian XY, Zhu YH, Shen GX (2015) Quantification of rice canopy nitrogen balance index with digital imagery from unmanned aerial vehicle. *Remote Sens Lett* 6(3):183–189
6. Gabriel JL, Zarco-Tejada PJ, López-Herrer PJ, Pérez-Martín E, Alonso-Ayuso M, Quemada M (2017) Airborne and ground level sensors for monitoring nitrogen status in a maize crop. *Biosys Eng* 160:124–133
7. Borhan MS, Panigrahi S, Lorenzen JH, Gu H (2004) Multispectral and color imaging techniques for nitrate and chlorophyll determination of potato leaves in a controlled environment. *Trans ASAE* 47(2):599–608
8. Daniel AS, Gamon JA (2002) Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote Sens Environ* 81(2–3):337–354
9. He J, Liu B, Li J (2014) Monitoring model of leaf area index of winter wheat based on hyperspectral reflectance at different growth stages. *Trans Chin Soc Agric Eng* 30(24):141–150
10. Li F, Mistele B, Hu Y, Chen X, Schmidhalter U (2014) Reflectance estimation of canopy nitrogen content in winter wheat using optimised hyperspectral spectral indices and partial least squares regression. *Eur J Agron* 52(1):198–209
11. Li F, Mistele B, Hu Y, Chen X, Schmidhalter U (2014) Optimising three-band spectral indices to assess aerial N concentration, N uptake and aboveground biomass of winter wheat remotely in China and Germany. *ISPRS J Photogramm Remote Sens* 92(2):112–123
12. Curran PJ, Dungan JL, Peterson DL (2001) Estimating the foliar biochemical concentration of leaves with reflectance spectrometry: testing the Kokaly and Clark methodologies. *Remote Sens Environ* 76:349–359
13. Fitzgerald G, Rodriguez D, Garry O (2010) Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index—the canopy chlorophyll content index (CCCI). *Field Crops Res* 116:318–324
14. Perry EM, Fitzgerald GJ, Nuttall JG, O’leary GJ, Schulthess U, Whitlock A (2012) Rapid estimation of canopy nitrogen of cereal crops at paddock scale using a canopy chlorophyll content index. *Field Crops Res* 134:158–164
15. Chen P, Haboudane D, Tremblay N, Wang J, Vigneault P, Li B (2010) New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat. *Remote Sens Environ* 114(9):1987–1997
16. Wang L, Wei Y (2013) Progress in inversion of vegetation nitrogen concentration by hyperspectral remote sensing. *Spectrosc Spectr Anal* 33(10):2823–2827
17. Schlerf M, Atzberger C (2006) Inversion of a forest reflectance model to estimate structural canopy variables from hyperspectral remote sensing data. *Remote Sens Environ* 100:281–294. <https://doi.org/10.1016/j.rse.2005.10.006>
18. Tan HZ, Li SK, Wang KR, Xie RZ, Gao SJ, Ming B, Yu Q, Lai JC, Liu GQ, Tang QX (2008) Monitoring canopy chlorophyll density in seedlings of winter wheat using imaging spectrometer. *ACTA Agron* 34(10):1812–1817
19. Wang W, Peng Y, Ma W, Huang H, Wang X (2010) Prediction of chlorophyll content of winter wheat using leaf-level hyperspectral data. *Trans Chin Soc Agric Mach* 41(5):172–177
20. Zhang DY, Huang WJ, Wang JH, Yang GJ, Zhu DZ, Liu RY, Ma ZH (2010) In-situ crop hyperspectral acquiring and spectral features analysis based on push broom imaging spectrometer. *Trans CSAE* 26(12):188–192
21. Saari H, Pellikka I, Mäkinen J, Kai O (2011) Unmanned aerial vehicle (UAV) operated spectral camera system for forest and agriculture applications. *Proceedings of SPIE*. *Int Soc Opt Eng* 8174(1):466–471
22. Hruska R, Mitchell J, Anderson M, Glenn NF (2012) Radiometric and geometric analysis of hyperspectral imagery acquired from an unmanned aerial vehicle. *Remote Sens* 4(12):2736–2752
23. Lucieer A, Malenovsky Z, Veness T, Wallace L (2014) Hyperspectral-imaging spectroscopy from a multirotor unmanned aircraft system. *J Field Robot* 31(4):571–590



24. Liu HY, Zhu HC, Wang P (2017) Quantitative modelling for leaf nitrogen content of winter wheat using UAV-based hyperspectral data. *Int J Remote Sens* 38(8–10):2117–2134
25. Li LT, Zhang M, Ren T, Li XK, Cong RH, Wu LS, Lu JW (2015) Diagnosis of nutrition of rice using digital image processing technique. *Plant Nutr Fertil Sci* 21(1):259–268
26. Li J, Zhang F, Qian X, Zhu Y, Shen G (2015) Quantification of rice canopy nitrogen balance index with digital imagery from unmanned aerial vehicle. *Remote Sens Lett* 6(3):183–189
27. Dunn BL, Singh H, Goad C (2018) Relationship between chlorophyll meter readings and nitrogen in poinsettia leaves. *J Plant Nutr* 41(12):1–10
28. Jay S, Maupas F, Bendoula R, Gorretta N (2017) Retrieving LAI, chlorophyll and nitrogen contents in sugar beet crops from multi-angular optical remote sensing: comparison of vegetation indices and PROSAIL inversion for field phenotyping. *Field Crops Res* 210:33–46
29. Hunt ER Jr, Doraiswamy PC, McMurtrey JE, DaughtryT CST, Perry EM, Akhmedov B (2013) A visible band index for remote sensing leaf chlorophyll content at the canopy scale. *Int J Appl Earth Obs Geoinf* 21(1):103–112
30. Zhang WL, Zeng CS, Gao DZ, Hu WF, Chen XY, Lin W (2014) Estimating the chlorophyll content of *Kandelia candel* based on hyper-spectral remote sensing in the Min River Estuarine wetland. *Acta Ecol Sin* 34(21):6190–6197
31. Li JX, Yang LP, Bai YL, Wang L (2015) The correlation of total nitrogen content with leaf spectral reflectance and SPAD values in different maize varieties. *Soils Fertil Sci China* 3:34–39
32. Chappelle EW, Kim MS, Iii MM (1992) Ratio analysis of reflectance spectra (RARS): an algorithm for the remote estimation of the concentrations of chlorophyll A, chlorophyll B, and carotenoids in soybean leaves. *Remote Sens Environ* 39(3):239–247
33. Ling QH, Wang SH, Ding YF, Li GH (2017) Re-evaluation of using the color difference between the top 3rd leaf and the 4th leaf as a unified indicator for high-yielding. *Rice Sci Agric Sin* 50(24):4705–4713
34. Sun H, Zhao Y, Zhang M, Wen Y, Li MZ, Yang W, Qin Z (2015) Multi-spectral image detection for maize canopy's chlorophyll content in jointing stage. *Trans Chin Soc Agric Eng* 31:186–192
35. Xia SS, Zhang C, Li JZ, Li HJ, Zhang YM, Hu CS (2018) Diagnosis of nitrogen nutrient and recommended fertilization in summer corn using leaf digital images of cellphone camera. *Chin J Eco-Agric* 26(5):703–709
36. Tao ZQ, Bagum SA, Ma W, ZhouY BY, Fu JD, Cui RX, Sun XF, Zhao M (2016) Establishment of the crop growth and nitrogen nutrition state model using spectral parameters canopy cover. *Spectrosc Spectr Anal* 36(1):231–236
37. Wang Y, Wang DJ, Zhang G, Wang C (2012) Digital camera-based image segmentation of rice canopy and diagnosis of nitrogen nutrition. *Trans Chin Soc Agric Eng* 28(17):131–136
38. Niu Z, Chen YH, Sui HZ, Zhang QY, Zhao CJ (2000) Mechanism analysis of leaf biochemical concentration by high spectral remote sensing. *J Remote Sens* 4(2):125–130
39. Jiang QH, Tong F, Yu MZ, Zhang Y, Liao C, Liu F (2015) Hyperspectral technique: an opportunity in ecology. *Plant Sci J* 33(5):633–640
40. Ecartnot M, Compan F, Roumet P (2013) Assessing leaf nitrogen content and leaf mass per unit area of wheat in the field throughout plant cycle with a portable spectrometer. *Field Crops Res* 140(140):44–50
41. Homolová L, Malenovský Z, Clevers JGPW, García-Santos G, Schaepman ME (2013) Review of optical-based remote sensing for plant trait mapping. *Ecol Complex* 15(5):1–16
42. Li H, Zhao C, Huang W, Yang G (2013) Non-uniform vertical nitrogen distribution within plant canopy and its estimation by remote sensing: a review. *Field Crops Res* 142(3):75–84
43. Hatfield JL, Gitelson AA, Schepers JS, Walthall CL (2015) Application of spectral remote sensing for agronomic decisions. *Agron J* 100(3):117–131
44. Zhao K, Valle D, Popescu S, Zhang X, Mallick B (2013) Hyperspectral remote sensing of plant biochemistry using bayesian model averaging with variable and band selection. *Remote Sens Environ* 132(10):102–119
45. Yue YB, Nie KY, Li RJ, Li LJ, Sun CQ, Peng ZL, Zhao ZY (2014) Correlation of total nitrogen content in overground part of pepper at different nitrogen application level with canopy spectral reflectance. *Guizhou Agric Sci* 11:244–247
46. Li Y, Xue LH, Ma ZH, Pan FY, Yang LZ (2015) Research on sensitive spectrum of rice canopy for nitrogen under nitrogen and phosphorus interaction. *Soils* 47(1):33–41
47. Shao H, Shi QH, Guo X, Zhao XM (2015) Diagnosis of nitrogen nutrition of late rice based on canopy hyper-spectrum in hilly areas of jiangxi province. *Acta Agric Univ Jiangxiensis (Nat Sci Edn)* 6:975–981
48. Qin ZF, Chang QR, Xie BN, Shen J (2016) Rice leaf nitrogen content estimation based on hyperspectral imagery of UAV in Yellow River diversion irrigation district. *Trans Chin Soc Agric Eng* 32(23):77–85
49. Wang Y, Huang JF, Wang FM, Liu ZY (2008) Predicting nitrogen concentrations from hyperspectral reflectance at leaf and canopy for rape. *Spectrosc Spectr Anal* 28(2):273–277
50. Li Y, Xue LH, Ma ZH, Pan FY, Yang LZ (2015) Research on sensitive spectrum of rice canopy for nitrogen under nitrogen and phosphorus interaction. *Soils* 47(1):33–41
51. Bao Y, Xu K, Min J, Xu J (2013) Estimating wheat shoot nitrogen content at vegetative stage from in situ hyperspectral measurements. *Crop Sci* 53(5):2063–2071
52. Lee YJ, Yang CM, Chang KW, Shen Y (2014) A simple spectral index using reflectance of 735 nm to assess nitrogen status of rice canopy. *Agron J* 100(1):205–212
53. Fernandez S, Vidal D, Simon E (1994) Radiometric characteristics of *Triticum aestivum* cv, Astral under water and nitrogen stress. *Int J Remote Sens* 15(9):1867–1884
54. Tarpley L, Reddy KR, Sassenrathcole GF (2000) Reflectance indices with precision and accuracy in predicting cotton leaf nitrogen concentration. *Crop Sci* 40(6):1814–1819
55. Glenn F, Daniel R, Garry O (2010) Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index—the canopy chlorophyll content index (CCCI). *Field Crops Res* 116(3):318–324
56. Chen QC, Tian YC, Yao X, Zhu Y, CAO WX (2010) Effects of nitrogen fertilizer top-dressing based on canopy reflectance spectra in rice. *Sci Agric Sin* 43(20):149–157
57. Gomez-Casero MT, Lopez-Granados F, Pena-Barragan JM, Jurado-Exposito M, Garcia-Torres L, Fernandez-Escobar R (2007) Assessing nitrogen and potassium deficiencies in olive orchards through discriminant analysis of hyperspectral data. *J Am Soc Hortic Sci* 132(5):611–618
58. Osborne S, Schepers J, Francis D, Schlemmer M (2002) Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. *Agron J* 94:1215–1221
59. Zhang L, Cheng XP, Jia LL (2018) Parameter research of using UAV-based visible spectral analysis technology in dynamical diagnosis of nitrogen status of summer maize. *Plant Nutr Fertil Sci* 24(1):261–269
60. Wright D, Philipprasmussen V, Douglasramsey R, Douglasramsey R, Baker D, Ellsworth J (2004) Canopy reflectance estimation of wheat nitrogen content for grain protein management. *Mapp Sci Remote Sens* 41(4):287–300

61. Knyazikhin Y, Schull MA, Stenberg P, Möttus M, Rautiainen M, Yang Y, Marshak A, Carmona PL, Kaufmann RK, Lewis P, Disney MI, Vanderbilt V, Davis AB, Baret F, Jacquemoud S, Lyapustin A, Myneni RB (2013) Hyperspectral remote sensing of foliar nitrogen content. *PNAS* 110(3):E185–E192
62. Li J, Zhang F, Qian X, Zhu YH, Shen GX (2015) Quantification of rice canopy nitrogen balance index with digital imagery from unmanned aerial vehicle. *Remote Sens Lett* 6(3):183–189
63. Mao Y, Jiang QG, Li YH, Xiao CC, Fu CL (2016) Quantitative analysis and evaluation of domestic and overseas commercial RS satellites. *Remote Sens Land Resour* 28(1):1–6

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