Using Canopy Hyperspectral Measurements To Evaluate Nitrogen Status In Different Leaf Layers Of Winter Wheat

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Abstract

Nitrogen (N) is one of the most important nutrient matters for crop growth and has the marked influence on the ultimate formation of yield and quality in crop production. As the most mobile nutrient constituent, N always transfers from the bottom to top leaves under N stress condition. Vertical gradient changes of leaf N concentration are a general feature in canopies of crops. Hence, it is significant to effectively acquire vertical N information for optimizing N fertilization managements. Especially, if crop growth status in the middle and bottom leaf layers can be detected early, optimal N utilization might come true. So, it is critical to obtain N vertical information especially in lower leaf layers for accurate evaluation of N nutrient status in winter wheat and timely N recommendation. The rapid detection of vertical N information is difficult by conventional ways. Spectral detecting, especially hyperspectral remote sensing with hundreds of very narrow spectral bands plays a unique role in determining crop biochemical parameters including N status thanks to the notable characteristics of non-destruction and quickness. This technique contributes to the development of fertilizer recommendations and is likely to avoid both the environmental pollution of excessive N fertilization and the effects of N-deficiency in crops. The paper aimed at the relationships between canopy hyperspectral reflectance and N estimation at the different layers of winter wheat canopy and developed a method to estimate N status in different leaf layers of winter wheat canopies. This study used the field data from anthesis of winter wheat in 2016 and coupled a mathematical algorithm, OWC (optimal weight combination) with hyperspectral reflectance to estimate N concentration in different leaf layers of winter wheat. The results showed that OWC yielded R^2 *values of 0.45, 0.59, 0.25, 0.43 for the first, second, third and fourth leaf from top to bottom in wheat canopies, respectively. So, it is feasible to use canopy hyperspectral information to evaluate the vertical N status in winter wheat canopies, which is promising for optimizing N use by detecting N status in lower leaf layers of crop canopies.*

Keywords: *Winter wheat, Vertical distribution, leaf Nitrogen concentration, Canopy hyperspectral data, Optimal weight combination method.*

Introduction

Nitrogen (N) is the most demanding nutrient elements for crops and strongly related to crop yield and quality, and also plays an important role in improving photosynthesis and promoting productivity (Scheromm et al., 1992; Guo et al., 2005). Leaf nitrogen concentration (LNC) as a good indicator of N status in crop can be used to assess N nutrient status. Therefore, it is very significant to effectively estimate LNC for assessing N nutrient stress and making N supply strategy (Feng et al., 2008). Many existing studies had proved the non-uniformity of vertical leaf N distribution of crop canopy, i.e. the upper leaves generally have a higher LNC than that of the lower leaves (Archontoulis et al., 2011; Bertheloot et al., 2008; Milroy et al., 2001). Especially, when crops start to suffer from N stress, N will transfer from bottom to top leaves and the bottom leaves begin to become senescence, then the middle leaves, and at last the top leaves. So, if N status of the middle or bottom leaves can be monitored timely and effectively, early N stress will be able to be diagnosed, and it is significant for N fertilizer decision.

Hyperspectral remote sensing technology with using a large number of narrow wavebands has been proved to be a powerful means for in-situ measurements of many crop biochemical constituents such as pigments content, leaf water content and LNC (Cho and Skidmore, 2006; Houborg et al., 2009; Moran et al., 1994). In this study, hyperspectral data were tested to evaluate LNC in different leaf layer of winter wheat canopies. In addition, the optimal weight combination (OWC) principle is a method how to determine the weight of each individual model participating in the combination (Bates and Granger, 1969; Wallis, 2011), and widely applied in economic forecasting field, but there are few reports in the application of N spectral detection. In this study, OWC are tested to select the N sensitive wavebands to construct the model of estimating LNC of different leaf layers in winter wheat.

The objectives of this study are to (1) to assess the feasibility of hyperspectral measurement for estimating LNC of different leaf layer in winter wheat canopies; (2) to assess the performance of OWC method how to select the sensitive wavebands to form the combination models to effectively estimate LNC.

Data and Methods

Data acquisition

The experimental data for winter wheat derived from National Experiment Station for Precision Agriculture (40˚10.6′N, 116˚26.3′E) in the northeast of Beijing in China, which has been used for precision agriculture research since 2001. In this study, the data were collected from 24 fields during anthesis growth stages of winter wheat, and the collection date was on May 11th, 2016. Data acquisition included canopy spectral reflectance measurements in fields and the determination of LNC indoors. An ASD spectrometer (Anaytical Spectral Devices, Inc., USA) that operates in a spectral range from 350 to 2500 nm was utilized to measure canopy spectral reflectance in the 24 fields. Spectral measurement with ASD in each field was done by averaging 20 times to get reliable mean estimates for reflectance. When measuring canopy spectral reflectance, twenty representative wheat plants from the same field were collected for determination of LNC. All green leaves as separated from the plants indoors were de-enzymed at 105℃, then oven-dried at 80℃ to constant weight for chemical analysis. LNC (g 100 g-1, %) measurements from the dried leaf samples were performed by using an elemental analyzer (vario MACRO cube, Elementar Analysensysteme GmbH, Germany).

Methods

Optimal weight combination algorithm

Optimal weight combination is one method that computationally gives optimal weights of different individual models settling the same problem to form one combination model with the least errors (Tang, 1991; Wallis, 2011), and its principle is as the following.

Given that different N models computing the same object based on n samples are viewed as individual models, the combination model integrating N models can be formulated as the following:

$$M = \sum_{i=1}^{N} k_i m_i \quad (i = 1, 2, 3, \cdots, N) \tag{2}$$

where, M is the combination model, m_i the individual models, and k_i are weights of N individual models and meet the constraint conditions that each k must be positive and their sum be equal to 1.

If set e_{ij} as the error for *j* sample with *i* individual model, so the error E_j of combination model for *j* sample can be expressed by the following:

$$E_j = O_j - M_j = \sum_{i=1}^{N} e_{ij} k_i \quad (j = 1, 2, 3, \cdots, n) \tag{3}$$

Here, O_j is the observed value, M_j estimated value of combination model for *j* sample.

In order to get k_i, OC usually takes E_j on as independent variable of the cost function to construct the mathematic expression as $E = minE(k_1, k_2, \ldots, k_i)$, and here *minE* as cost function may be MAES (minimum absolute error sum), or MESS (minimum error square sum), or the other objective function. Considering the computational convenience, MAES is selected as the cost function of OC, and the linear programming algorithm is utilized to calculate the optimal weights of the combination model in this study, the detailed algorithm can see Yang et al. (1998).

Result and Analysis

Changes of LNC from different leaf layers of winter wheat

It can be seen from Figure 1 that LNC decreases for the same N fertilizer treatment as leaf position moves down from top to bottom, on the contrary LNC increases basically for the same leaf layer as N fertilizer amount rises in fields. In addition, it is also shown that for the third and fourth leaf layer the changes of LNC are more drastic due to more N stress. So, it is significant if N information from the middle and low layers of crop canopies can be detected effectively for diagnosing N nutrient status, especially early N stress.

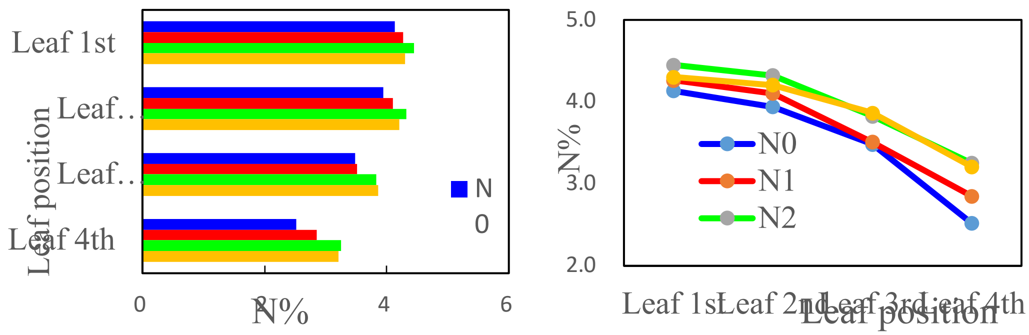

Fig. 1. Comparison of LNC from different leaf layers from top to bottom in winter wheat canopies. N0 means no N fertilizer, N1 half of normal N fertilizer, N2 normal fertilizer, and N3 one and a half times of normal N.

Relationship of LNC from different leaf layers to hyperspectral reflectance

Figure 2 shows the results that LNC from four different leaf layers of winter wheat correlated with hyperspectral reflectance. It indicates from Figure 2 that LNC from different leaf layers has better correlation with reflectance the visible and near infrared areas, especially the green, red-edge range and 760-1300nm wavebands. What's more, LNC from the second leaf has the most significant correlation with reflectance from the visible and near infrared regions, it is probably because the second leaf has the higher light interception and is the leading function leaf for photosynthesis in crop canopy.

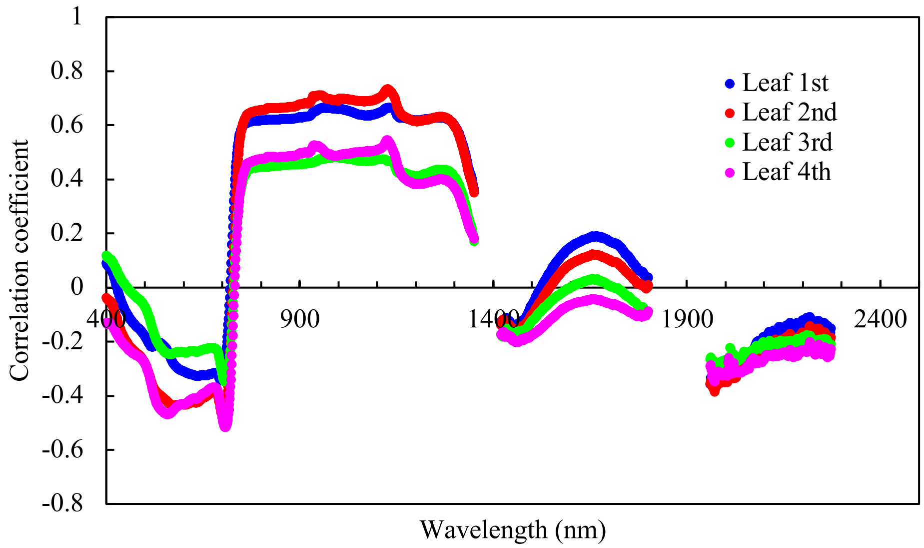

Fig. 2. Correlation of LNC from different leaf layers of winter wheat with hyperspectral reflectance.

LNC estimates for different leaf layers based on OWC

Table 1 shows the results that using OWC estimates LNC of different leaf layer with hyperspectral data from winter wheat field during the anthesis. It can be seen that the models of estimating LNC based on OWC have the R^2 values of 0.45, 0.59, 0.25 and 0.43 for the four leaf layers of winter wheat, respectively. Comparatively, there is the best accuracy of evaluating LNC for the second leaf, next for the first leaf, then the bottom (the fourth leaf), and the worst for the third leaf. Generally, the top leaves in crop canopies have the more light interception and should be closely related with canopy reflectance. In this study, LNC of the bottom leaf has better estimation than that of the third leaf, it is possible that the reflection from soil has some influence on the bottom leaf. So, it is necessary to conduct the further research.

Table 1. Estimation of LNC from different leaf layer of winter wheat based on hyperspectral data and OWC

Leaf position	Wavelength(nm)	Models	R^2	RMSE
Leaf 1st	352,777,933,1001	y=8.33x1+1.05x2+1.41x3+4.1x4+2.04	0.45	0.24
Leaf 2nd	713,1145	y=-12.37x1+8.71x2+2.72	0.59	0.27
Leaf 3rd	358,717,1144	y=2.01x1-4.79x2+8.27x3+1.79	0.25	0.37
Lead 4th	715,1127,1147	y=-18.59x1+4.78x2+0.56x3+2.71	0.43	0.36

*x mean the reflectance of the corresponding wavelength in wavelength column

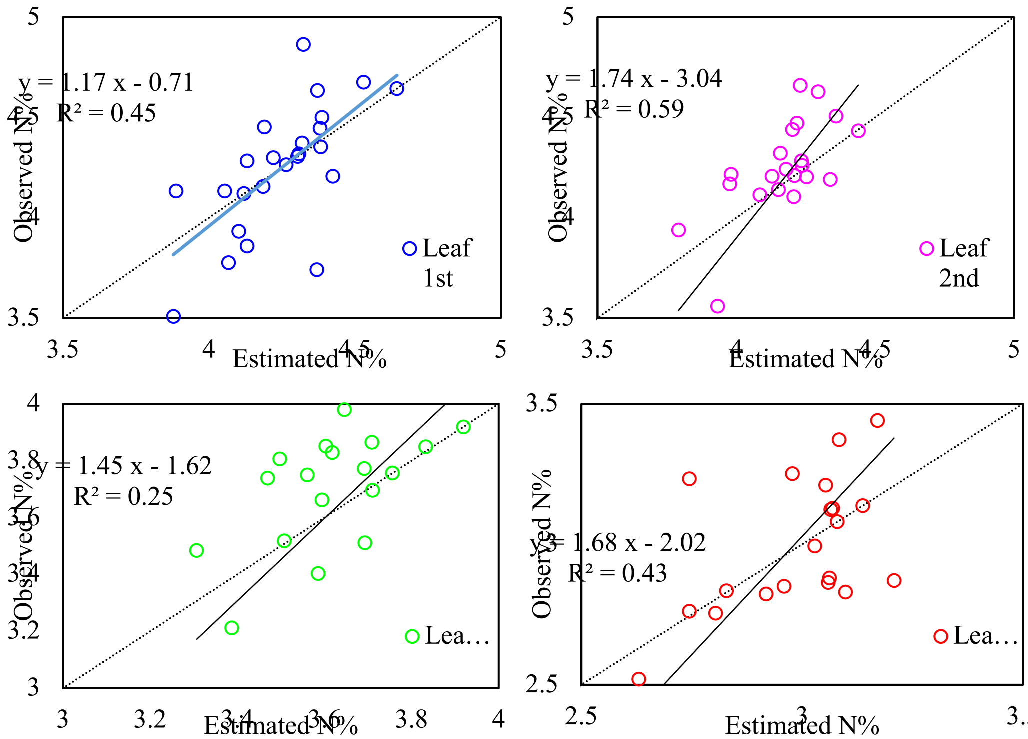

Fig. 3. Correlation between observed and estimated LNC from different leaf layers of winter wheat based on hyperspectral data and OWC.

Conclusion

It is significant to effectively assess N status from different leaf layers for early N stress detection and optimal fertilization management. In this study, hyperspectral measurements were tested to evaluate vertical N status from different leaf layers with OWC algorithm. It is indicated that hyperspectral reflectance and the OWC method have a good potential for assessing nitrogen status from different leaf layers for winter wheat, which is promising for optimizing N use by detecting N status in middle or lower leaf layers of crop canopies.

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