ESTIMATION OF LEAF NITROGEN CONCENTRATION IN BARLEY WITH IN SITU HYPERSPECTRAL MEASUREMENTS

Xingang Xu, Jihua Wang, Cunjun Li, Xiaodong Yang, Hao Yang

Beijing Research Center for Information Technology in Agriculture, China

ABSTRACT

Leaf nitrogen concentration (LNC), a good indicator of nitrogen status in crop, is of special significance to diagnose nutrient stress and guide nitrogen fertilization in fields. Due to its non-destructive and quick advantages, hyperspectral remote sensing plays a unique role in detecting LNC in crop. Many studies have reported the successes of monitoring LNC with spectral techniques for main crops such as wheat, maize and soybean, but there are few researches for barley, especially malting barley, a kind of crop very demanding for nitrogen fertilization. In the study, canopy reflectance spectra (between 350 and 1050nm) from 38 typical barley fields were measured as well as the corresponding LNC in Hailar Nongken (farming cultivate), China's Inner Mongolia Autonomous Region in July, 2010. Some existing spectral indices considered to be better candidates for evaluating LNC were tested to estimate LNC in barley. In addition, the optimal combination (OC) method was tried to extract sensitive bands responding to leaf nitrogen in barley, and expected to develop a combination model for improving the precision of LNC estimates. The results showed that a regression relationship of LNC to spectral indices NPCI and PRI could well describe the dynamic changes of LNC in barley with R^2 of 0.67 and 0.65, RMSEs of 0.58 and 0.59, respectively. A combined model of integrating the first-order spectral derivatives of 496,499,689,797, and 882nm based on OC method exhibited the good performance with R^2 of 0.82, RMSE of 0.50 for LNC in barley. The high fitting revealed an excellent agreement with ground-measured truth, and indicated that hyperspectral reflectance and OC method have a good potential for assessing nitrogen concentration in barley leaves.

Keywords: Leaf nitrogen concentration, Barley, Spectral indices, Optimal combination method

INTRODUCTION

Nitrogen (N) is the most demanding nutrient elements for crop development, and plays a profoundly important role in improving crop photosynthesis and promoting productivity (Scheromm et al., 1992; Guo et al., 2005). N fertilizer requirements of crop vary temporally and spatially (Mamo et al., 2003). However, farmers usually fertilize crop with more N supply to ensure higher yield, regardless of N requirements change of crop. So excessive N supply may bring about not only the overgrowth of crop population, but also the environment pollution in the farmlands, and this will greatly influence the sustainable development of farming agriculture. Thus it is still worthy of attention how to make nitrogen fertilization strategies to scientifically fertilize crops at right physiological stage and time with the opportune amount. Leaf nitrogen concentration (LNC), as a good indicator of N status in crop, can be applied to diagnose and evaluate N nutrient status. Therefore, it is very significant to effectively estimate LNC for assessing N nutrient stress, making N supply strategy (Feng et al., 2008)

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) Some existing researches based on the reflectance of dried and ground leaves, had demonstrated that N sensitive absorption wavebands were located in SWIR (shortwave infrared) region, such as at 1510nm, 1940nm, 2060nm, and 2180nm, etc (Curran, 1989; Fourty et al., 1996). Nevertheless, spectral diagnoses of N nutrient status mainly focus on fresh crop plants in fields, but not dry crop. Reflectance spectra of fresh vegetation in SWIR have the two strong water absorption wavebands near 1450nm and 1940nm, which mask the above N absorption bands mentioned (Kokaly and Clark, 1999). Therefore, reflectance spectra data in visible and near-infrared region are often used to assess LNC in crop. The optimal combination (OC) 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, OC are tested to select the N sensitive wavebands to construct the model of estimating LNC in barley.

Nitrogen is one of the most important components of chlorophyll, and there are close relationships between nitrogen and chlorophyll (Yoder and Pettigrew-Crosby, 1995; Cho and Skidmore, 2006; Botha et al., 2006), so chlorophyll can be used as an indicator of N status. Many spectral features of chlorophyll in visible are designed as N indicators of crop such as wheat, rice, corn and cotton (Blackmer et al., 1996; Feng et al., 2008; Takebe et al., 1990; Tarpley et al., 2000). However, there are few reports on spectral estimation of LNC in barley. Barley, especially malting barley, is an important source material for beer production. And the key indicator of malting barley quality is the grain protein content that must be kept within a reasonable range. Thus for barley beer production, it is an urgent need to quickly evaluate N status in barley fields to enhance N fertilizer management and adjust grain quality. So it is very important to develop an effective method of rapidly and non-destructively assessing LNC in barley based on hyperspectral measurement.

The objectives of this study are to (1) to evaluate the analysis capability of some typical spectral indices for LNC estimates in barley; (2) to assess the performance of OC method how to select the sensitive wavebands to establishing the combination models to effectively estimate LNC.

DATA AND METHODs

Study area and data acquisition

The study area is situated in Hailar Nongken (farming cultivate), China's Inner Mongolia Autonomous Region, where barley is mainly used for beer production as malting barley and the large planting areas account for about one-third of total areas of malting barley in China. In this study, thirty-eight barley fields with each the unanimous field management in Hailar Nongken were selected to collect the experimental data.

Data acquisition included canopy spectral reflectance measurements in fields and the determination of LNC indoors. An ASD spectrometer (FieldSpec Pro VNIR, Anaytical Spectral Devices, Inc., USA) that operates in a spectral range from 350nm to 1050nm was utilized to measure canopy spectral reflectance in the 38 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 barley 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). Data collection was conducted between 8th and 10th July, 2010.

Methods

preprocessing of hyperspectral data

The following preprocessing of hyperspectral data was done by using the methods of Pu (2009). First, the spectral curves were truncated below 400nm due to extreme noise out of the range. Next, the raw spectral band width was interpolated to 1nm. So, about 650 bands remain. And then, these spectral curves were smoothed by a simple average over blocks of five neighbouring bands. Finally, the normalization of the spectral curves for constant area was conducted by dividing the mean reflectance for that curve, as the following equation (1). All of the following analyses in the paper used the normalized spectral data.

$$R_i = \rho_i / \left(\frac{1}{k} \sum_{i=1}^{k} \rho_i \right) \qquad (1)$$

Where R_i is the normalized reflectance, ρ_i is the smoothed reflectance before normalized, and *k* represents the total bands of the spectral reflectance.

spectral indices

In this study, some existing spectral indices considered to be good candidates for evaluating N status were selected to test their capabilities of estimating LNC in barley (Table 1). Among these indices, ones aiming at N estimation such as *MCARI/MTVI2, REP-le, DCNI*, and RI_{ldB}, are tested, and the other as the better indicators of assessing pigments, especially chlorophyll, such as *PRI*, *SDr/SDb*, *TCARI/OSAVI*, *mND705*, *MCARI*, and *NPCI* are also utilized to evaluate N status in barley.

Table 1. Spectral indices used in this study

Spectral indices	Formulas	References
MCARI/MTVI2	*MCARI*:$[(R_{700}-R_{670})-0.2(R_{700}-R_{550})](R_{700}/R_{670})$ *MTVI2*:$1.5[1.2(R_{800}-R_{550})-2.5(R_{670}-R_{550})]/\mathrm{sqrt}[(2R_{800}+1)^2-(6R_{800}-5\mathrm{sqrt}(R_{670}))-0.5]$	Eitel et al., 2007
REP-le	Red edge position based on linear extrapolation method	Cho et al., 2006
DCNI	$(R_{720}-R_{700})/(R_{700}-R_{670})/(R_{720}-R_{670}+0.03)$	Chen et al., 2010
PRI	$(R_{570}-R_{531})/(R_{570}-R_{531})$	Gamon et al., 1992
RI_{ldB}	R_{735}/R_{720}	Gupta et al., 2003
SDr/SDb	Sum of 1st derivative within the red edge(680~780 nm) divided by sum of 1st derivative within the blue edge(490~530 nm))	Gong et al., 2002; Wang et al., 2003
TCARI/OSAVI	*TCARI*: $3[(R_{700}-R_{670})-0.2(R_{700}-R_{550})(R_{700}/R_{670})]$ *OSAVI:* $1.16(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)$	Haboudane et al., 2002
mND705	$(R_{750}-R_{705})/(R_{750}+R_{705}-2R_{445})$	Sims & Gamon, 2002
MCARI	$[(R_{700}-R_{670})-0.2(R_{700}-R_{550})](R_{700}/R_{670})$	Daughtry et al., 2000
NPCI	$(R_{680}-R_{430})/(R_{680}+R_{430})$	Peñuelas et al., 1994

Optimal combination principle and algorithm

Optimal combination (OC) 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:

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

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:

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

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).

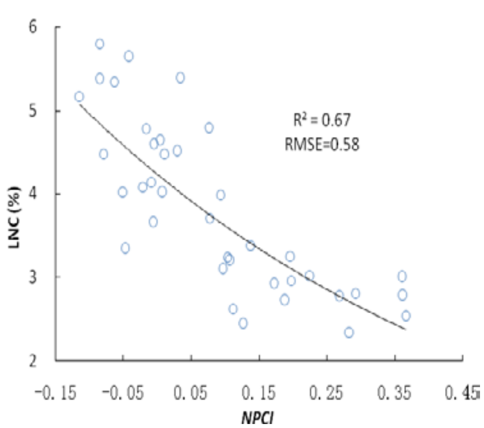
RESULT AND ANALYSIS

Relationship of LNC to spectral indices

After extracted from spectral reflectance measured from 38 barley fields, the ten spectral indices in Table 1 were related with LNC to find the sensitive indices for LNC in barley. Linear, logarithm, and exponential model were used to make fit, and the best fitting with highest R^2 and lowest RMSE were expressed, Table 2 showed the results of regression analysis between spectral indices and LNC in barley. It could be seen that the two indices, *PRI* and *NPCI*, had the better performance of estimating LNC in barley, with R^2 of 0.65 and 0.67, RMSE of 0.59 and 0.58. Fig. 1 exhibited the plotted relationships of LNC to the two spectral indices

Table 2. Results of regression analysis between spectral indices and LNC in barley (n=38).

Spectral indices	R^2	RMSE	Spectral indices	R^2	RMSE
MCARI/MTVI2	0.02	0.98	*SDr/SDb*	0.56	0.66
REP-le[#]	0.62	0.62	*TCARI/OSAVI*	0.50	0.70
DCNI	0.57	0.65	*mND705*	0.62	0.62
PRI	**0.65**	**0.59**	*MCARI*	0.10	0.94
RI_{ldB}	0.58	0.64	*NPCI*	**0.67**	**0.58**



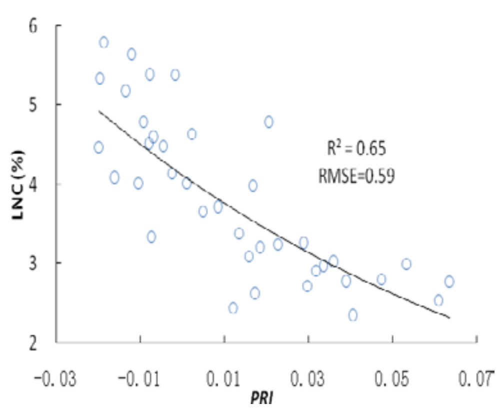


Fig. 1. Regression relationships of LNC to the two spectral indices *NPCI* and *PRI* (n=38).

LNC estimates based on optimal combination algorithm

Considering that spectral derivative has the advantages of weakening soil noise and highlighting the inflexion points on a spectral curve, the first order derivatives of spectrum were used to assess LNC in barley. At the same time, the OC method based on linear programming algorithm was tried for estimating LNC. The processing steps of adopting OC were as the following: (1) calculated 1st spectral derivatives; (2) made linear fit between spectral derivatives from each wavelength and LNC in barley; (3) took every linear fit of all wavelength as individual models; (4) use OC to calculate the optimal weights to form the combination model for estimating LNC.

Table 3 showed the optimal weights of all individual LNC models with 1st spectral derivatives from different wavelengths based on OC, it could be found that within the range from 400nm to 1050nm, the only five wavelength, namely, 496nm, 499nm, 689nm, 797nm and 882nm, were given weights while all of the other zero weights, which indicated that except for the five wavelengths, all models of the other wavelengths with the 1st spectral derivatives provided the redundant or repetitive information on N status in barley.

Table 3. Optimal weights of all individual LNC models with 1st spectral derivatives from different wavelengths based on OC.

Models with 1st spectral derivatives from different wavelengths	Weights	R^2	RMSE
496nm	0.139	0.64	0.60
499nm	0.140	0.61	0.62
689nm	0.113	0.60	0.63
797nm	0.289	0.52	0.69
882nm	0.319	0.59	0.64
All of the other wavebands	0	--	--
Combination model	--	0.82	0.50

From Table 3, the combination model had the highest R^2 of 0.82, and the lowest REMS of 0.50 by comparison with those five nonzero-weight individual models, and could be expressed as the equation (4). Fig. 2 showed the comparison between observed and estimated LNC with the combination model that integrated the individual fitting models using 1st spectral derivatives from 496nm, 499nm, 689nm, 797nm, and 882nm, respectively

$$\begin{aligned} LNC(\%) &= 0.139 * M_1(fd_{496}) + 0.14 * M_2(fd_{499}) + 0.113 * M_3(fd_{689}) \\ &+ 0.289 * M_4(fd_{797}) + 0.319 * M_5(fd_{882}) \end{aligned} \quad (4)$$

where M_1, M_2,……, and M_5 were denoted as the five models of the above nonzero-weight wavelengths, respectively (see Table 3), *fd* was the 1st spectral derivative of the corresponding wavelength.

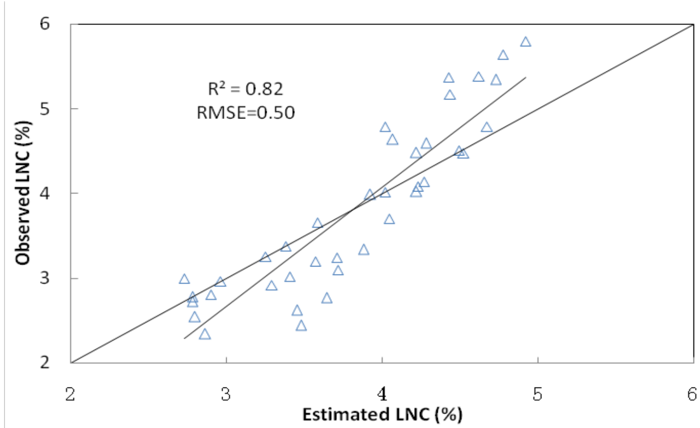


Fig. 2. Comparison between observed and estimated LNC with the combination model that integrates the individual fitting models using 1st spectral derivatives from 496nm, 499nm, 689nm, 797nm, and 882nm, respectively.

CONCLUSION

Barley, especially malting barley, requires the demanding nitrogen (N) fertilization management. As a good indicator of N status, LNC can be used to well monitor N nutrient in crop, so it is very significant to effectively estimate LNC for N fertilizer strategies in barley fields. This study analyzed the capabilities of the ten spectral indices considered to be good candidates of evaluating N status, and assess the performance of OC for estimating LNC in barley. The analysis shows that the two spectral indices, *NPCI* and *PRI*, can well describe the change of LNC in barley, and the OC method can markedly improve the precision of LNC estimates in barley. It is indicated that hyperspectral reflectance and the OC method have a good potential for assessing nitrogen concentration in barley leaves.

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