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Assessment of rice leaf growth and nitrogen status by hyperspectral canopy reflectance and partial least square regression

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Abstract

Diagnosis of rice growth and nutrient status is critical for prediction of rice yield and grain quality and prescription of nitrogen topdressing at panicle initiation stage. Two experiments, one in 2000 and one in 2003 were conducted to construct a partial least square model for assessing rice leaf growth and nitrogen status non-destructively at the Experimental Farm (37°16′N, 126°59′E) of Seoul National University, Suwon, Korea. The experiment included two cultivars (Hwasungbyeo and Dasanbyeo) and four levels of nitrogen (N) application in year 2000 and four rice cultivars (Hwasungbyeo, SNU-SG1, Juanbyeo, and Surabyeo) and 10 N treatments in year 2003. Hyperspectral canopy reflectance (300–1100 nm) data recorded at various growth stages before heading were used for partial least square regression (PLS) model to predict four crop variables: leaf area index, leaf dry weight, leaf N concentration, and leaf N density. Three hundred and forty two observations from two experiments were randomly split for model calibration (75%) and validation (25%). Coefficient of determination (R^2), root mean square error in prediction (RMSEP) and relative error of prediction (REP) of model calibration and validation were calculated for the model quality evaluation. The results revealed that PLS model using hyperspectral canopy reflectance data to predict four plant variables produced an acceptable model precision and accuracy. The model R^2 and REP ranged from 0.84 to 0.87 and 10.0 to 23.8% for calibration and 0.79 to 0.84 and 11.1 to 25.6% for validation, respectively. The most important reflectance as judged by factor loading in PLS model for rice leaf characterization was at various bands such as near-infrared (>760 nm) and visible (355, 420, 524–534, 583 and 687 nm) and red edge (707 nm) region.

Keywords: Partial least square; Leaf; Biomass

1. Introduction

Rice yield is closely related to crop growth and nitrogen (N) status before the heading stage (Cui and Lee, 2002; Ntanos and Koutroubas, 2002). Therefore, indicators related to crop growth and N status before heading stage have been frequently employed in various models to predict grain yield and yield components, time and amount of N fertilizer application (Cui and Lee, 2002; Ntanos and Koutroubas, 2002; Casanova et al., 2000) to increase crop yield and N use efficiency, and protect environment. However, measurements of these indicators are laborious and time-consuming processes.

Remote sensing technique has been recognized as a reliable method for the estimation of various variables related to crop physiology and biochemistry (Hinzman et al., 1986; Takebe et al., 1990; McMurtrey et al., 1994; Cassanova et al., 1998; Diker and Bausch, 2003; Hansen and Schjoerring, 2003). Due to its fast, non-destructive and relatively cheap characterization of crop status (Bouman, 1995) and potential of extension to regional level (Ishiguro et al., 1993), remote sensing has attracted a great deal of attention in terms of application for crop monitoring and yield prediction so far (Cassanova et al., 1998).

Hyperspectral remote sensing acquiring images in narrow (<10 nm) and continuous spectral bands provides a continuous spectrum for each pixel, unlike multi-spectral systems that acquire images in a few broad (>50 nm) spectral bands. Therefore, its data is considered more sensitive to specific crop variables (Hansen and Schjoerring, 2003). The common method for acquiring data from multi-spectral or hyperspectral systems is that they were converted and averaged into reflectance of blue, green, red, near-infrared (450–520, 520–600, 630–690, 760–790 nm) wavebands similar to the Landsat Thematic Mapper wavebands (Bausch et al., 1990; Duggin, 1980). The reflectance of the broad wavebands was then used for

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predicting plant parameters such as leaf N concentration, leaf chlorophyll concentration, LAI, grain yield using simple ratio or normalized vegetation index (Hinzman et al., 1986; Diker and Bausch, 2003; Shanahan et al., 2001). However, it is believed that the average spectral reflectance over a broad waveband, in principle, results in critical loss of spectral information available in a specific narrow band (Tilley et al., 2003; Hansen and Schjoerring, 2003; Graeff and Claupein, 2003). Reflectance of a specific wavelength or average reflectance of a narrow waveband selected for a given plant parameter have been reported (Penuelas et al., 1994; Carter, 1994; Tilley et al., 2003; Hansen and Schjoerring, 2003).

Partial least square (PLS) can easily treat data matrices in which each object is described by several hundreds of variables (Galadi and Kowalski, 1986; Haaland and Thomas, 1988) like hyperspectral reflectance data. This technique can extract the relevant part of the information for the very large data matrices and produce the most reliable models compared to other calibration method (Thomas and Haaland, 1990). PLS regression has been successfully applied to NIR spectral data for predicting soil nitrate ($R^2 = 0.94$–0.95) (Ehsani et al., 1999), sodium chloride content of commercial king and hot smoked salmon ($R^2 = 0.82$–0.82) (Lin et al., 2003), and several chemical components of sunflower seeds ($R^2 = 0.90$–0.96) (Fassio and Cozzolino, 2003). Recently, PLS also has been employed for predicting plant biomass, LAI, nitrogen and chlorophyll concentration and density of wheat using reflectance measurement of wheat canopy (Hansen and Schjoerring, 2003). In general, studies reported so far have confirmed that PLS appeared as one of the most efficient method in extracting and creating reliable models in wide range of fields.

The objective of this study was to evaluate the ability of partial least square regression using hyperspectral canopy reflectance to predict rice crop leaf area index (LAI, $m^2\,m^{-2}$), leaf dry weight (LDW, $g\,m^{-2}$), leaf nitrogen concentration (LN, $mg\,g^{-1}$), and leaf nitrogen density (LND, g N in leaf m^{-2}).

2. Materials and method

2.1. Field experiment design and management

Two experiments were conducted in 2000 and 2003 at the Experimental Farm (37°16′N, 126°59′E) of Seoul National University, Suwon, Korea. The soil was clay loam with pH: 5.4; CEC: 11.9 $cmol^+\,kg^{-1}$; O.M: 14.4 $mg\,g^{-1}$; total N: 0.75 $mg\,g^{-1}$. Rice cropping season started from mid of May (transplanting) and ended on October (harvesting).

The experiments were laid out according to split plot design with three replicates and two factors: N level (main plot factor) and cultivars (subplot factor). The N rates and rice cultivars were randomly assigned into main plot and subplot, respectively. The subplot size was 21.6 m^2. In year 2000, the experiment included two cultivars (Hwasungbyeo and Dasanbyeo) four levels of N (range of 120, 240, 360, 480 kg N ha^{-1}). Nitrogen was split for six applications at 0, 23, 39, 44, 49, and 55 days after transplanting (DAT). In year 2003, There were 10 N treatments: 3 N rates applied at 13 DAT (0, 36, 72 kg ha^{-1}) × 3 N rate applied at 55 DAT (0, 36, 72 kg ha^{-1}) in combination with basal N of 48 kg ha^{-1} and no N treatment. Four rice cultivars (Hwasungbyeo, SNU-SG1, Juanbyeo, and Surabyeo) were used. Rice was transplanted with spacing of 30 cm × 15 cm. Five rice cultivars selected for the experiments based on mainly two criteria: (a) quite similar growth and development time to ensure that some of their critical growth stages like panicle initiation, booting and heading stages coincide and (b) difference in leaf color to test the capacity of using canopy reflectance to predict plant biomass and nitrogen concentration. Leaf color of Dasanbyeo, Hwasungbyeo, SNU-SG1, Surabyeo, and Juianbyeo are green, green, dark green, pale green, and medium dark green, respectively. Throughout cropping season, algaecide and herbicide have been applied twice to minimize the effect of algae and weed on radiation absorption and reflectance.

2.2. Spectral measurement

Canopy reflectance of rice crop was recorded using a GER 1500 spectroradiometer (GER 1500; GER Inc. USA Corporation) with field of view (FOV) of 3° in year 2000 and 15° in year 2003. The reason for changing FOV from 3° to 15° was due to the fact that FOV of 15° was potentially better but not available in year 2000. The measurement range was from 300 to 1100 nm with spectral resolution of 1.55 nm. For each measurement eight scans performed and the spectral data was averaged over the scans. The sensor was held approximately over 2.0-m above the ground by hand at nadir position. The spatial coverages on the ground were about 86 cm^2 for sensor with FOV of 3° (in year 2000) and 2174 cm^2 for sensor with FOV of 15° (in year 2003). Due to lower spatial coverage of GER 1500 with FOV of 3° in year 2000, the spectral measurement was repeated three times per plot at location where plant was sampled to reduce error from spectral measurement. The measurements were conducted under clear and cloudless sky between 11:00 and 13:00 local time (GMT + 9) on 11 June, 27 June, 2 July, 7 July, 14 July of the experiment year 2000 and on 14 July and 31 July of the experiment year 2003. Prior to each plant reflectance measurement, reflectance of a white standard panel coated with $BaSO_4$ was taken. The spectroradiometer automatically calculated percent plant reflectance by dividing plant sample reflectance by reflectance of the white standard panel.

2.3. Plant sampling and measurement

Immediately after canopy reflectance measurement, five hills at the location for canopy reflectance measurement were sampled in the same day of canopy reflectance measurement. The plant samples were weighed for total fresh weight and then a sub sample of 15 tillers (ca. 20% of total sample) consisting of three tillers selected randomly from each hill was taken. The subsamples were weighed for fresh weight and separated into leaf and stem. The leaf was used for area determination by Laser Area Meter (CID Inc.). After that it was dried at 70 °C to constant weight. The dry samples were weighed, ground, and analyzed for total N by Kejeltec Auto 1035 System. The records measured from the subsamples were then used for calculating LAI ($m^2\,m^{-2}$), LDW ($g\,m^{-2}$), LN ($mg\,g^{-1}$) and LND ($g\,m^{-2}$) with the known ratio of sample fresh weight to subsample fresh weight and sampling area (5 hills × 0.15 m × 0.30 m).

2.4. Data pretreatment

A database including all of the observations from two experiments was constructed. To avoid the number of variables greater than number of observations, we reduced the number of spectral reflectance data by averaging three consecutive data. To detect observations as outlier, studentized residuals were calculated for each observation from stepwise regression model to predict crop variables using 170 averaging reflectance variables. Eleven observations with studentized residuals higher than 3 or less than −3 were removed. After outliers and missing values were removed and transformed into log form, the database included 342 observations and each was described by four dependent plant variables (LAI, LDW, LN, and LND) and 170 independent spectral reflectance variables (log transformed). The database was randomly separated into two subdatabases for PLS model calibration (calibration set: 75% of observations) and PLS model validation (validation set: 25% of observation).

2.5. Partial least square regression analysis

The two sub datasets were used in model calibration and validation. PLS regression procedure of SAS 8.1 version (SAS Institute Inc., 1999–2000) was used to evaluate capacity of PLS regression to predict several plant variables using canopy spectral data. Brief description of option selection for the PLS regression procedure was as follows:

- Proc PLS: request for PLS regression procedure.
- Method = PLS: partial least square is requested for factor extraction.
- CV = ONE: requests one-at-a-time cross validation. Using this option, SAS will use all observations but one for calibrated model which then was used to predict the left-out observation. This process was repeated for every observation.
- CVTEST: specifies that randomization-based model comparison test be performed to test models with different numbers of extracted factors against the model that minimizes the predicted residual sum of squares (PRESS).

3. Results

3.1. Summary statistics of crop variables

The wide range in crop variables (Table 1) resulted from a wide variation in nitrogen rates (0–480 kg ha^{-1}), N application time (three to six times), experimental years (2 years) and rice cultivars (five cultivars). The maximum values of LAI (13.53 $m^2\,m^{-2}$) and LN (56.39 mg g^{-1}) were abnormal in rice cultivation, however, this was designed in order to make relationship between crop growth and N status and canopy reflectance as realistic and universal as possible. Three crop variables: LAI, LDW and LND showed very high correlation with each other regardless of N rates, cultivars and years of the experiments. The correlation coefficients of LN with LAI, LDW, and LND were 0.45, 0.39 and 0.67, respectively. The lower correlation between LN with the other variables potentially resulted from the dilution effect as discussed by Cui et al. (2002).

3.2. Effect of N rates and rice cultivars on canopy reflectance

Application of N rates of 36 and 72 kg ha^{-1} at tillering stage (13 DAT) increased reflectance at near-infrared waveband (>760 nm) but reduced reflectance at red waveband (630–690 nm) bands (Fig. 1). The increases of reflectance at near-infrared band were related to increases of crop biomass, LAI and canopy water content (Thenkabail et al., 2000) while the reduction in reflectance at red waveband potentially resulted from the increase of leaf chlorophyll and N concentration (Hansen and Schjoerring, 2003). The differences among canopy reflectance spectrums of different cultivars were also high at near-infrared band but small at visible band. The larger differences in reflectance at near-infrared and smaller at visible wavebands were in agreement with the larger coefficients of variation among rice cultivar in leaf weight and LAI (6.6 and 8.6% for leaf weight and LAI, respectively) and the smaller coefficient of variation among rice cultivars in leaf N concentration (3.5%).

3.3. Correlation between crop variable and canopy reflectance over waveband

The coefficients of correlation (r) between each crop variable and reflectance changed dramatically over wavebands. In general, crop variables showed positive correlation with

Table 1
Summary statistics and correlation among crop variables

Crop variables	Summary statistics				Correlation among variables			
	Mean	S.D.	Min.	Max.	LAI	LDW	LN	LND
LAI ($m^2\,m^{-2}$)	4.04	2.46	0.27	13.53	1			
LDW ($g\,m^{-2}$)	159.9	76.0	29.3	429.3	0.95***	1		
LN ($mg\,g^{-1}$)	27.84	7.7	18.14	56.39	0.45***	0.39***	1	
LND ($g\,m^{-2}$)	4.68	3.08	0.71	12.28	0.94***	0.93***	0.67***	1

SD, standard deviation; LAI, leaf area index; LDW, leaf dry weight; LN, leaf N concentration; LND, leaf N density.
*** Significant at the probability level of 0.1%.

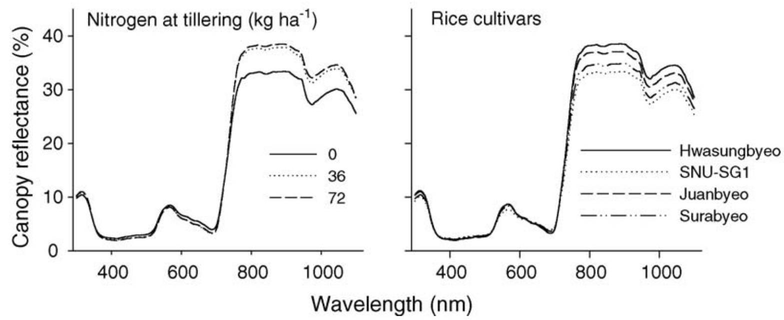

Fig. 1. Average reflectance spectrum on July 14, 2003 (54 DAT) of the different experimental treatments: N rates applied at 13 DAT ($n = 30$) and four cultivars ($n = 30$).

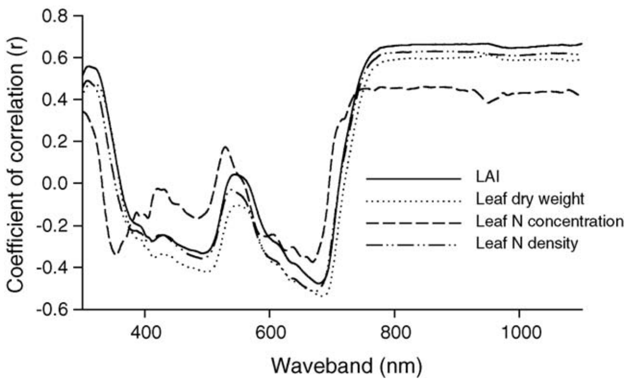

Fig. 2. Wavelength dependence of coefficient of correlation (r) between canopy reflectance and each of crop variables measured before heading stage of rice in calibration set ($n = 256$).

reflectance at near-infrared bands and negative at visible wavelength range (Fig. 2). Three variables: LAI, LDW and LND showed very similar patterns potentially due to high correlation among three crop variables (Table 1). The high correlation coefficient between reflectance at waveband 760–1100 nm (near-infrared) and 670–690 nm (red) with all crop variables indicated that reflectance at these wavebands might be important for crop variable prediction.

3.4. PLS model quality

The performance of the model is measured by coefficient of determination of the model (R^2) and the root mean square error in prediction (RMSEP) that is an indicator of the average error in the analysis expressed in original measurement unit (Kvalheim, 1987). RMSEP was calculated by Eq. (1):

$$\mathrm{RMSEP} = \left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right]^{0.5} \quad (1)$$

where y_i and $\hat{y}_i$ were observed and predicted values of crop variables, respectively, and n was number of sample in dataset ($n = 256$ for calibration set and 86 for validation set). Another useful parameter is the relative error of prediction (REP) that shows the predictive ability of the model and calculated from Eq. (2):

$$\mathrm{REP}(\%) = \frac{100}{\bar{y}}\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right]^{0.5} \quad (2)$$

Similar to Eq. (1) y_i and $\hat{y}_i$ were observed and predicted values of crop variables, respectively, and n was number of sample in datasets ($n = 256$ for calibration set and 86 for validation set) and $\bar{y}$ was mean of the observed values of crop variables.

Statistical parameters for calibration model (Table 2) were calculated by leave-one-out-cross-validation to evaluate the quality of calibration model (Martens and Naes, 1989). In the technique, all but one sample was used to create a calibration model that was used for predicting the left-out sample. The procedure was repeated for each sample in calibration set. Optimum number of latent variables ranges from 10 (for leaf N density) to 13 (for LAI). The selected optimum number of latent variables based on the minimum predicted residual sum of square (PRESS) to avoid over fitting of the model (Fassio and Cozzolino, 2003). Table 2 indicates that PLS regression

Table 2
Statistical parameters of the PLS model calibration and validation by calibration and validation dataset

Crop variables	NLV	PRESS	Calibration ($n = 256$)			Validation ($n = 86$)		
			R^2	RMSEP	REP	R^2	RMSEP	REP
Leaf area index ($m^2\,m^{-2}$)	13	0.430	0.86	0.93	23.3	0.82	1.02	24.6
Leaf dry weight ($g\,m^{-2}$)	12	0.442	0.84	30.5	19.3	0.79	34.4	20.9
Leaf N concentration ($mg\,g^{-1}$)	11	0.369	0.87	2.79	10.0	0.84	3.08	11.1
Leaf N density ($g\,m^{-2}$)	10	0.388	0.87	1.10	23.8	0.84	1.23	25.6

NLV, number of latent variables; PRESS, predicted residual sum of squares; R^2, coefficient of determination; RMSEP, root mean square error in prediction; REP, relative error of prediction (%).

using canopy reflectance data to predict for plant variables has good precision (R^2 ranges from 0.84 to 0.87) and accuracy (REP ranges from 10.0 to 23.8%). Prediction of LN for rice has higher precision and accuracy ($R^2 = 0.87$ and REP = 10.0%).

To confirm the quality of the model, besides the internal validation, we used the model calibrated by calibration set to predict crop variables in another independent validation set. Compared to the statistical parameters of the calibration, R^2 in cross validation is somewhat lower than R^2 in calibration and RMSE is a little bit higher (Table 2).

3.5. Factor loadings of PLS models

All of the techniques implemented in the PLS procedure work by extracting successive linear combinations of the predictors, called latent variables or factors. In order to choose the optimal number of PLS factors, you can explore how well the models based on the training data with different numbers of factors fit the test data. In this study, we used options cv = one cvtest for PLS procedure for optimizing number of latent variables. Although the optimum number of latent variables ranged from 10 to 13 for PLS models to predict LAI, LDW, LN and LND, usually almost all of the variation was accounted for even with some latent variables. The three first latent variables explained 54.2, 56.7, 61.8, and 59.6% variation in LAI, LDW, LN, and LND, respectively.

The factor loadings show how the PLS latent variables were constructed from the centered and scaled predictors that are reflectance at various wavebands in our study. The loading values over the wavebands were presented in Fig. 3. Plots showed at which wavebands reflectance was most critical for each latent variable. Those predictors with small loading value were less important than those with large loadings (Galadi and Kowalski, 1986; Haaland and Thomas, 1988).

The high loading values were at waveband >760 nm and at 687 nm in the first latent variable of all four PLS models to predict LAI, LDW, LN and LND (Fig. 3). The second loadings of the PLS models was highest at 534 nm for LAI and LDW, at 583 nm for LND and at 355 and 583 nm for LN. The loadings for the third latent variable of PLS models were largest at wavebands of 355, 355 and 420 nm (ultraviolet and blue bands) for LAI, LDW and LND, respectively, while at 524 nm (green band) and 707 nm (red edge band) for LN.

4. Discussion

4.1. Important waveband reflectance for crop variable prediction

A wide difference in reflectance at near-infrared waveband was found between N treatments at tillering (0 kg N ha^{-1} versus 36 kg N ha^{-1} and 72 kg N ha^{-1}) and among four rice cultivars (Fig. 1). The near-infrared waveband reflectance and absorption was related with sunflower leaf water and nutrient status (Penuelas et al., 1994), leaf area index and biomass (Thenkabail et al., 2000). The differences in reflectance at visible waveband among N treatments at tillering resulted from more light absorption at blue (450–520 nm) and red (630–690 nm) but more light reflectance at green (520–600 nm) bands as leaf N and chlorophyll concentration and content increased by N application. However, only high linear correlation between leaf characteristics and reflectance at red (670–690 nm) and near-infrared (760–1100) wavebands was found (Fig. 2). The same result was obtained by Hansen and Schjoerring (2003) for wheat crops in Denmark. Therefore, reflectance at red and near-infrared bands was expected to be useful variables for rice leaf variable prediction and discrimination of nitrogen and cultivar effect on variation in crop variables.

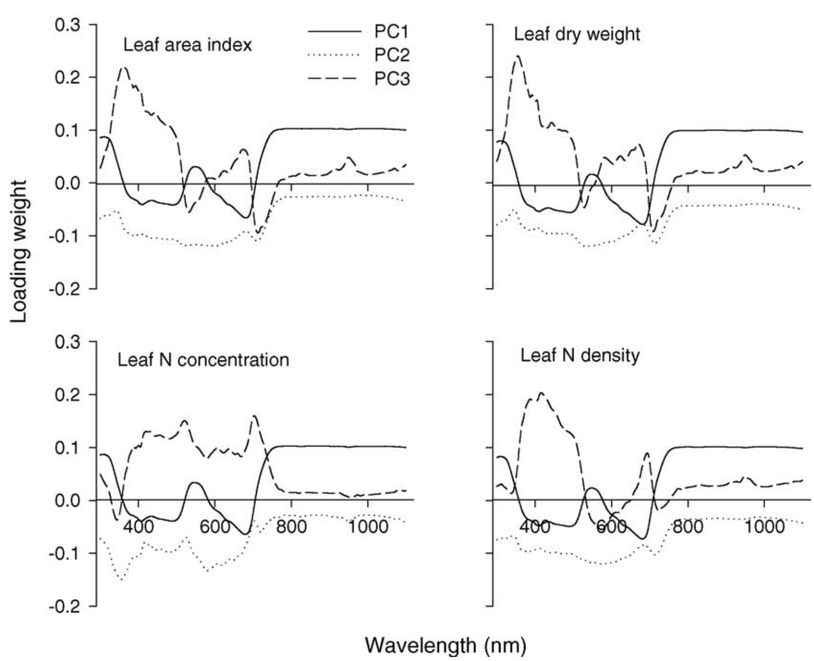

Fig. 3. Loading weights over wavebands for first, second and third latent variables (PC1, PC2 and PC3, respectively) of the PLS models.

The important role of predictor with high loadings in PLS model was discussed by Galadi and Kowalski (1986), Haaland and Thomas (1988) and Martens and Naes (1989). Because wavebands of 355, 420, 524–534, 583, 687, 707, and 760–1100 nm had high loadings in the three first latent variables, their reflectance was expected to provide the most critical information for explaining variation in dependent variables (crop parameters). In addition, PLS regression extracting information from the reflectance only at the above selected wavebands (82 wavebands) explained 80, 80, 85, 84% variation in LAI, LDW, LN, and LND of calibration dataset, respectively, in comparison to 86, 84, 87, 87% of PLS model using reflectance at all 170 wavebands (Table 2). Therefore, we suggested that reflectance at 335, 420, 524–534, 583, 687, 707, and 760–1100 nm was critical for PLS models to predict four agronomic crop variables.

4.2. Potential time series autocorrelation

The wide range of crop variable values due to combination of observations measured at different growth stages like data used in our PLS model could cause serious time series autocorrelation problem in any prediction model (Lattin et al., 2003). Lattin et al. (2003) indicated that the unobserved and immeasurable factors that influence the dependent variable at one point in time might tend to persist to some extent from one period to the next. Due to time series data autocorrelation, we might overstate the precision of our estimates and might in fact conclude that certain model parameters were significant when they were not. To compare the observed and predicted values by PLS model using observations from a single growth stage would precisely measure the model quality without time series autocorrelation problem. In general, pooled model had higher R^2 and lower REP compared to the model created by observations from PIS stage (Table 3) but no considerable difference from the model created by observations from booting stage. The lower precision and accuracy of model at PIS could result from soil background effect or from error in spectral measurement due to low LAI. To clarify error sources causing low precision and accuracy of the model at PIS, we plot LAI versus normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI) and modified soil-adjusted vegetation index (MSAVI) (Fig. 4).

Table 3
Model precision and accuracy for single crop growth stage in year 2003

Crop variables	PIS (54 DAT)		Booting (72 DAT)		Pooled	
	R^2	REP	R^2	REP	R^2	REP
Leaf area index ($m^2\ m^{-2}$)	0.62	19.9	0.76	15.7	0.78	17.5
Leaf dry weight ($g\ m^{-2}$)	0.59	18.6	0.71	15.0	0.80	16.7
Leaf N concentration ($mg\ g^{-1}$)	0.45	5.8	0.85	7.0	0.79	6.7
Leaf N density ($g\ m^{-2}$)	0.70	17.8	0.85	14.7	0.88	16.2

PIS, panicle initiation stage; DAT, days after transplanting; R^2, coefficient of determination; REP, relative error of prediction (%).

Three vegetation indices, using narrow bands as discussed by Haboudane et al. (2004) were calculated by Eqs. ((3)–(5)) as

$$\mathrm{NDVI} = \frac{(R_{800} - R_{670})}{(R_{800} + R_{670})} \tag{3}$$

$$\mathrm{SAVI} = \frac{(1 + L)(R_{800} - R_{670})}{(R_{800} + R_{670} + L)} \tag{4}$$

$$\mathrm{MSAVI} = \frac{1}{2}\left[2R_{800} + 1 - \sqrt{(2R_{800} + 1)^2 - 8(R_{800} - R_{670})}\right] \tag{5}$$

where R was reflectance at the subscripted waveband (nm). $L = 0.5$ as optimum value to account for first order soil background variation (Huete, 1988).

NDVI has been found to be high correlation with leaf area index in many studies (Curran et al., 1992). However, this index was sensitive to optical properties of soil background (Baret and Guyot, 1991). When the soil background effect was considerable, SAVI which minimized spectral variation due to background soil type could be a good alternative (Huete, 1988). In SAVI, soil adjustment factor L was used to account for soil background variations. The L factor of 0.5 was found to reduce soil effect for vegetation with intermediate density. For more variable vegetation cover density, Qi et al. (1994) modified SAVI (MSAVI) by replacing the constant L with a self-adjustment factor that does not appear in the formulation of MSAVI. We found from Fig. 4 that relationships between two soil-adjusted

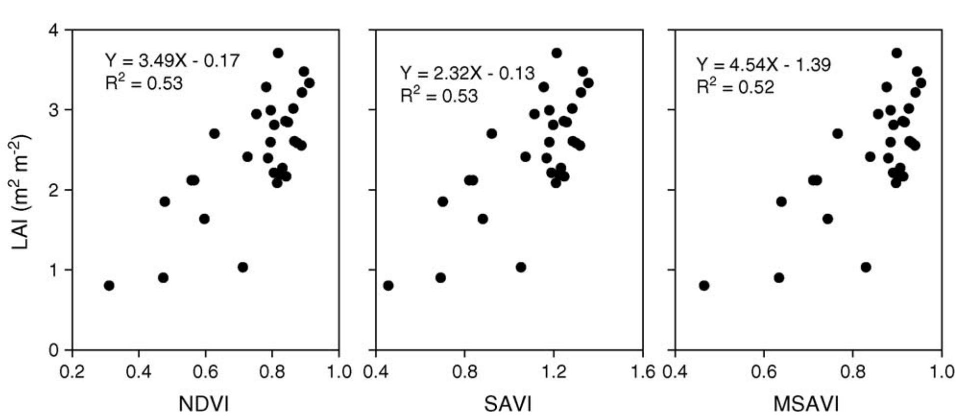

Fig. 4. Relationship between vegetation indices and LAI at panicle initiation stage in year 2003 (data were averaged over three replications).

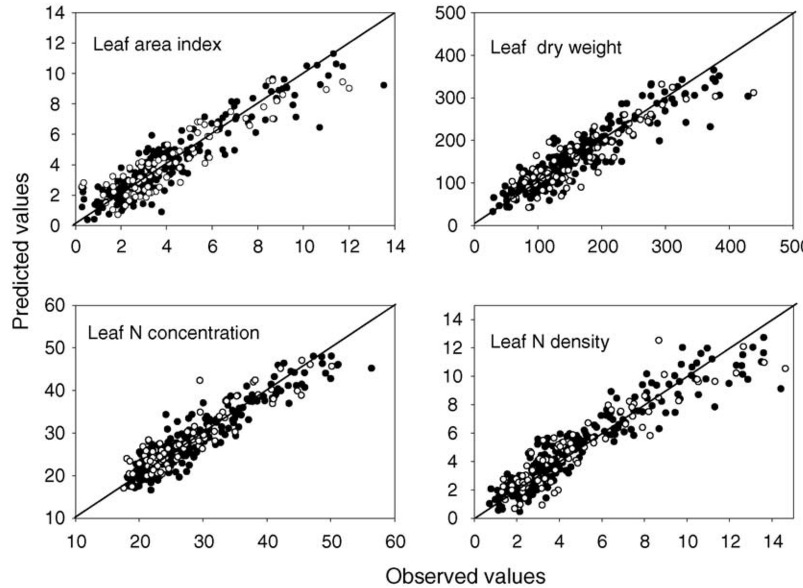

Fig. 5. Correlation between observed and predicted values by PLS. Filled and open circles are observations used for calibration ($n = 256$) and validation ($n = 86$), respectively. Solid line is 1:1 line.

vegetation indices and LAI were very similar to that between NDVI and LAI. No improvement in LAI prediction was obtained when SAVI and MSAVI were used instead of NDVI. Therefore, we suggested that soil background effect might have not been a problem in our models to predict crop variables at PIS. The minor error from soil background effect in our study might result from the high and homogenous absorption of the water layer on the surface of rice field. Also from Fig. 4 we found that at LAI values around 1.0 $m^2\ m^{-2}$ vegetation indices (NDVI, SAVI, and MSAVI) were much more disperse than those at higher LAI values. This might have been caused by error from spectral measurement at low LAI because spectral measurement by GER 1500 optics with low spatial coverage might be less representative for the rice canopy at low rice cover. Therefore, we may conclude that the lower precision and accuracy of models for crop variable prediction at PIS might have been caused by error from spectral measurement at the treatment of low LAI and no considerable time series autocorrelation may be existed in the PLS model.

4.3. Applicability of PLS model

Because the PLS model to predict LAI, LDW, LN and LND achieved quite good precision (R^2 ranged from 0.79 to 0.84 for validation) and accuracy (REP ranged from 11.1 to 25.6% for validation), it promised well as an applicable in situ non-destructive method for rice leaf characterization. However, its application for controlling within-field spatial variation in crop growth would be practical if REP (relative error in prediction) was significantly smaller than within-field coefficient of variation value for the same crop variables. For the successful application of the PLS model, the error in prediction should be reduced as much as possible. Outlier and noise was the most significant sources of error (Fig. 5) that might have been caused by unexpected variation in radiation during the canopy reflectance measurement. The error due to variation in radiation would be unavoidable except that canopy reflectance should be measured under clear and cloudless sky days between 11:00 and 13:00 local time. Extremely deviated observations would be excluded by correlating predicted values from the repeated measurements and then averaging among the repeated values would critically reduce errors from outliers and noise. Unfortunately, an increase of number of repeated measurements lengthens the measuring duration and results in potentially larger variation in solar radiation. Therefore, repeated measurement times and number of samples should be compromised to keep measuring duration not longer than 2 h between 11:00 and 13:00 local time. Error would also result from non-linear relationship between predicted and observed values at very high value of almost all variables (Fig. 5). The phenomena of canopy reflectance saturation at high LAI values as discussed by Huete (1988) was also occurred in our experiment. Fortunately, the observations with the very high LAI values (>9 $m^2\ m^{-2}$) which resulted from extraordinarily high N application rate of above 360 kg N ha^{-1} in the year 2000 experiment would not be encountered in ordinary rice cultivation situation.

5. Conclusion

PLS regression model using hyperspectral canopy reflectance produced acceptable precision and accuracy in characterizing rice leaf characteristics. The most important reflectance for rice leaf characterization was at various bands such as near-infrared (>760 nm) and visible (355, 420, 524–534, 583 and 687 nm) and red edge (707 nm) region. Although model was constructed by data collected from different years, measuring times, N status and rice cultivars with hundreds variables, no time series autocorrelation or collinearity among independent variables was evident. However, more effort should be paid to improve model precision and accuracy before its application for controlling spatial variation in crop growth and N status.

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