벼 수잉기 군락반사스펙트럼의 미분분석을 이용한 수량 및 수량구성요소 예측

훙 구엔[1], 탄 구엔[2], 이변우[1]
[1]서울대학교 식물생산과학부, [2]베트남 타이구엔대학교 농학부

Predicting rice yield and yield components using hyperspectral canopy reflectance at booting and first derivative analysis

Hung T. Nguyen[1], Thanh D. Nguyen[b], and Byun-Woo Lee[1*]
[1]*Department of Plant Science, College of Agriculture and Life Science, Seoul National University,*
[2]*Faculty of Agronomy, Thai Nguyen University, Vietnam*
(Correspondence: leebw@snu.ac.kr)

1. Introduction

Crop growth and nitrogen (N) status at booting stage (BS) of cereal crops are of critical importance for prescription of late N fertilizer topdressing and prediction of grain yield and quality. Therefore, a fast, non-destructive and in-situ method for their measurement using remote sensing technique should be developed. It is believed that broad waveband reflectance, in principle, results in critical loss of spectral information available in a specific narrow band (Hansen and Schjoerring, 2003). Therefore, hyperspectral remote sensing, a technology using very high spectral resolution (1-10 nm), has been increasingly used in hand-held spectroradiometer, airborne hyperspectral sensors and satellite hyperspectral sensors. However, hyperspectral remote sensing results in larger data volume and therefore, more time and effort for data analysis. Among several proposed methods for hyperspectral data analysis including stepwise multiple linear regression (Grossman et al., 1996), selection of sensitive narrow waveband reflectance for a given crop parameter to calculate normalized difference vegetation index (Hansen & Schjoerring, 2003; Nguyen & Lee, 2004), and partial least square regression (Hansen and Schjoerring, 2003), derivative spectra analysis was recognized as one of the most reliable methods (Imanishi et al., 2004). Therefore, the objectives of our study were: (i) to select the maximum slopes of reflectance spectra from 400-1050 nm and (ii) to predict yield and yield components by reflectance and first derivative at the selected maximum slope positions.

2. Methods

Data used in this study were collected from two split-split-plot design experiments, one in year 2003 and one in year 2004 with three replications at the Experimental Farm of Seoul National University, Suwon, Korea (37°16' N, 126°59' E). Experiment included three factors: 10 N rates at tillering and PIS (panicle initiation stage) and four rice varieties (Hwasungbyeo, SNU-SG1, Surabyeo and Juanbyeo) in year 2003 and 16 N rates and two rice varieties (Hwasungbyeo and Daeanbyeo) in year 2004. Canopy reflectance of rice crop was measured using GER 1500 (GER Inc. USA) equipped with fiber optic probe of FOV 20°. The sensor was fixed on a frame of 2.0 m high so that the view zenith angle of sensor is kept at 23°. The spectral range was from 300 to 1100 nm with spectral resolution of about 1.55 nm. The measurement was conducted under clear and cloudless sky between 11:00 to 13:00 local time (GMT + 9) on 31 July, 2003 and July 29, 2004. After canopy reflectance measurement, plant was sampled to measure shoot dry weight (SDW, g m^{-2}) and shoot N concentration

(SN, mg g^{-1}) at booting and yield (g m^{-2}), number of filled spikelet (FPSK, 1000 m^{-2}), and 1000-grain weight (P1000, g) at harvest.

Canopy reflectance which was smoothed by method as proposed by Tsai and Philpot (1998) and agronomic data were averaged over replicates to reduce noises and then randomly separated into calibration set (data from year 2003 and a part of year 2004) and validation set (a part of data from 2004). The canopy reflectance data of calibration set were used for first derivative analysis to select the waveband region of maximum slope of reflectance from 400-1050 nm. The first derivatives of the canopy reflectance in region of 400-1050 nm were calculated by finite difference approximation method (Zhao et al., 2005). The canopy reflectance data or first derivative at the selected maximum slope positions in combination with crop data from the calibration set were used to calibrate models for predicting SDW and SN at booting and yield and yield components at harvest using Stepwise multiple linear regression (SMLR). The calibrated models were then validated by data of the validation set. The performance of the models were measured by coefficient of determination of the models (R^2) and the root mean square error in prediction (RMSEP) and relative error of prediction (REP, %) (Kvalheim 1987).

3. Results

3.1. *Selection of wavelength with the maximum slope of reflectance spectra*

The maximum slope position (peak or trough) of reflectance spectra in this study was defined as a wavelength at which reflectance increase (the positive first derivative value) or decrease (the negative first derivative value) per a unit of wavelength was maximum. Based on the definition, the maximum slopes of reflectance were selected at 540, 585, 624 and 673 nm in the visible waveband and 726, 750, and 778 nm in the red edge region and 957 nm in near infrared region (Fig. 1a). Among the selected wavebands, the maximum slopes of reflectance at 585, 624, 673, and 957 nm were negative, reflecting the maximum decrease in reflectance per a unit wavelength at these positions. At the maximum slope position, standard deviation of first derivative values also were maximum compared to adjacent wavebands (Fig. 1b).

3.2. *Prediction of yield and yield components by reflectance or first derivative at the maximum slope positions.*

The stepwise multiple linear regression equations for predicting yield and yield components were as follows:

Model using canopy reflectance at the maximum slope positions:

$$\text{Yield} = 927.7 - 104CR_{624} \quad (1a)$$

$$\text{FSPK} = 28.4 + 10.4CR_{624} - 5.4CR_{726} + 1.2CR_{750} - 8.2CR_{673} \quad (1b)$$

$$\text{P1000} = 22.5 + 0.17CR_{750} \quad (1c)$$

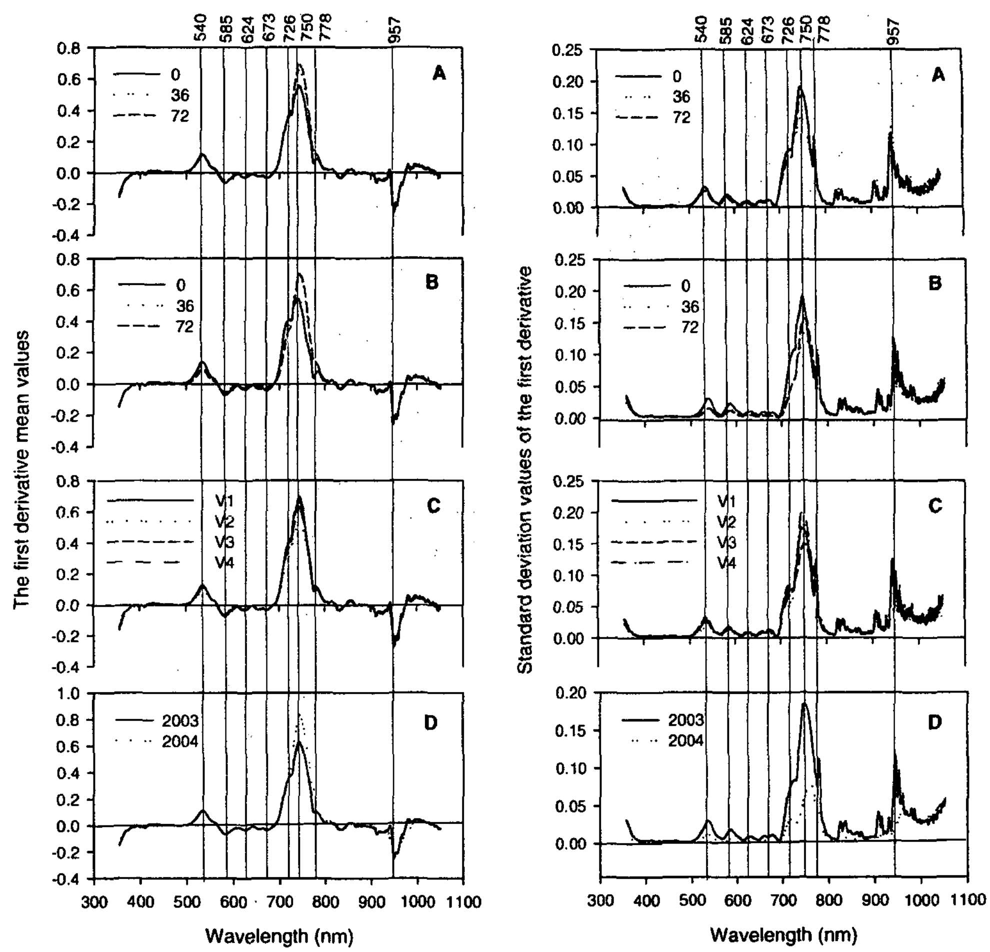

Fig. 1a

Fig. 1b

Fig. 1a-b. The first derivative mean and standard deviation values of mean, respectively, over wavebands of reflectance pooled by tillering (A) and PIS (B) N rates, rice varieties (C) (from data in year 2003) and year of experiments (D). Numbers on the top of the graph are spectral values (nm) for the maximum slopes of reflectance determined by the first derivative analysis.

Models using first derivative values at the maximum slope positions:

$$\text{Yield} = 619.4 + 5252FD_{673} + 253FD_{750} \quad (2a)$$

$$\text{FSPK} = 26.77 - 322FD_{673} + 128FD_{750} - 506FD_{540} - 428FD_{585} \quad (2b)$$

$$\text{P1000} = 22.5 + 10.5FD_{726} \quad (2c)$$

where CR and FD stand for canopy reflectance (%) and first derivative values and numbers following CR and FD were waveband centers of CR and FD. It can be seen from Eq.1-2 that CR624 or FD673 (red waveband) were the most importance and then the red-edge region (CR and FD at 726 and 750 nm). The close relationship between red and red edge reflectance and first derivative has been discussed by (Imanishi et al., 2004; Thenkabail et al, 2000). Although the quality parameters of models to predict yield and yield components using Eq.1-2 were quite similar, the higher R^2 but lower RMSEP and REP for Eq. 1 (using reflectance) than Eq.2 (using first derivative values) were obtained in validation set.

Table 1. Quality parameters of multiple stepwise regression model to predict yield and yield components by selected waveband canopy reflectance or its first derivative at booting stage of rice

Predicted crop variables	Using reflectance (Eq.1a-c)			Using derivative (Eq.2a-c)		
	R^{2a}	RMSE	REP	R^2	RMSE	REP
	Calibration set (n=70)					
Grain yield (g m^{-2})	0.76	48.5	7.6	0.77	47.2	7.4
Filled spikelet (1000. m^{-2})	0.81	1.61	6.8	0.79	1.69	7.1
1000-grain weight (g)	0.25	0.97	2.6	0.25	0.97	3.6
	Validation set (n=18)					
Grain yield (g m^{-2})	0.67	69.3	9.6	0.57	67.0	9.3
Filled spikelet (1000. m^{-2})	0.74	2.35	8.9	0.74	2.20	8.3
1000-grain weight (g)	0.16^{NS}	-	-	0.06^{NS}	-	-

[a]R^2, RMSE, and REP were coefficient of determination, root mean square of error in prediction and relative error in prediction, respectively.

References

Hansen, P. M., & Schjoerring, J. K. 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote Sensing of Environment, 86*, 542-553.

Imanishi, J., Sugimoto, K., & Morimoto, Y. 2004. Detecting drought stress status and LAI of two *Quercus* species canopies using derivative spectra. *Computers and Electronic in Agriculture, 43*, 109-129.

Kvalheim, O.M. 1987. Latent- structure decompositions (projections) of multivariate data. *Chemometrics and Intelligent Laboratory System, 2*, 283-290.

Nguyen, H. T., & Lee, B. W. 2004. Selection of the most sensitive waveband reflectance for normalized difference vegetation index calculation to predict rice crop growth and grain yield. *Korean Journal of Crop Science, 49*, 394-406.

Thenkabail, P. S., Smith, R. B., & Pauw, E. D. 2000. Hyperspectral vegetation indices and their relationship with agricultural crop characteristics. *Remote Sensing of Environment, 71*, 158-182.

Tsai F. and Philpot W. 1998. Derivative analysis of hyperspectral data. *Remote Sensing of Environment*, 66, 41-51.