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Selection of the Most Sensitive Waveband Reflectance for Normalized Difference Vegetation Index Calculation to Predict Rice Crop Growth and Grain Yield

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ABSTRACT: A split-plot designed experiment including four rice varieties and 10 nitrogen levels was conducted in 2003 at the Experimental Farm of Seoul National University, Suwon, Korea. Before heading, hyperspectral canopy reflectance (300-1100 nm with 1.55 nm step) and nine crop variables such as shoot fresh weight (SFW), leaf area index, leaf dry weight, shoot dry weight, leaf N concentration, shoot N concentration, leaf N density, shoot N density and N nutrition index were measured at 54 and 72 days after transplanting. Grain yield, total number of spikelets, number of filled spikelets and 1000-grain weight were measured at harvest. 14,635 narrow-band NDVIs as combinations of reflectances at wavelength λ1 and λ2 were correlated to the nine crop variables. One NDVI with the highest correlation coefficient with a given crop variable was selected as the NDVI of the best fit for this crop variable. As expected, models to predict crop variables before heading using the NDVI of the best fit had higher r^2 (>10%) than those using common broad- band NDVI red or NDVI green. The models with the narrow-band NDVI of the best fit overcame broad- band NDVI saturation at high LAI values as frequently reported. Models using NDVIs of the best fit at booting showed higher predictive capacity for yield and yield component than models using crop variables.

Keywords: *Remote sensing, Hyperspectral reflectance, canopy, nitrogen, rice, NDVI, narrow band.*

Rice yield is closely related to crop growth and nitrogen status before the heading stage (Cui & Lee, 2002; Ntanos & Koutroubas, 2002). Leaf area index (LAI), biomass and plant nitrogen (N) concentration and content have been employed in various models to optimize time and amount of N fertilizer application (Cui & Lee, 2002; Ntanos & Koutroubas, 2002; Casanova *et al.*, 2000). However, LAI, biomass and plant N concentration measurements are very laborious and time-consuming processes.

So far various variables related to crop physiology and biochemistry such as LAI, plant N concentration, N uptake and chlorophyll content have been reliably predicted by remote sensing techniques (Hinzman *et al.*, 1986; Takebe *et al.*, 1990; McMurtrey *et al.*, 1994; Casanova *et al.*, 1998; Diker & Bausch, 2003; Hansen & Schjoerring, 2003). These techniques have provided a fast, non-destructive and relatively inexpensive characterization of crop status and have had a high benefit when applied at regional levels. Therefore, over the past several decades, remote sensing techniques have been used increasingly for crop monitoring and yield prediction (Casanova *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 single crop variables (Hansen & 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 calculating a normalized difference vegetation index (NDVI) or ratio vegetation index (RVI) to predict plant parameters such as leaf N concentration, leaf chlorophyll concentration, LAI and grain yield (Hinzman *et al.*, 1986; Diker & 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 & Schjoerring, 2003; Graeff & Claupein, 2003).

Reusch (2003) suggested that the ratio of reflectance at 830 nm to reflectance at 730 nm was superior to standard NDVI and IR/R or IR/G ratios to predict winter wheat N uptake. The NDVI calculated from reflectance of a single waveband or average reflectance of a narrow waveband to predict green biomass, LAI, N and chlorophyll concentration and density of winter wheat have been reported by Hansen & Schjoerring (2003). Ratios that combined a red-edge measure (700-716 nm) with a waveband of high reflectance in the very near infrared region (755-920 and 1000 nm) have been reported to provide good precision and accu-

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racy for cotton leaf N prediction (Tilley *et al.*, 2003).

The objectives of this study were (i) to determine the specific waveband reflectance sensitive to each of nine rice crop growth and nitrogen indicators of rice, (ii) to compare the predictive power of regression models to predict the crop variables before heading and at harvest using NDVIs calculated by the selected waveband reflectance in comparison to the standard NDVI green and NDVI red. Nine crop variables before heading included shoot fresh biomass (SFW, g m^{-2}), leaf area index (LAI), leaf dry weight (LDW, g m^{-2}), shoot dry weight (SDW, g m^{-2}), leaf nitrogen concentration (LN, mg g^{-1}), shoot nitrogen concentration (SN, mg g^{-1}), leaf nitrogen density (LND, g m^{-2} ground), shoot nitrogen density (SND, g m^{-2} ground) and nitrogen nutrition index (NNI). Grain yield (Yield, g m^{-2}), total number of spikelet (TSPK, no. m^{-2}), filled spikelet (FSPK, no. m^{-2}) and 1000-grain weight (P1000, g) were crop variables measured at harvest.

MATERIALS AND METHODS

Field experimental design and management

An experiment was conducted in 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} and total N 0.75 mg g^{-1}. Rice cropping season started in mid- May (transplanting) and ended in October (harvesting).

The experiment was subjected to split plot design with three replicates and two factors: ten N levels ranging from 0 to 292 kg N ha^{-1} as a main plot factor and four varieties including Hwasungbyeo, SNU-SG1, Juanbyeo and Surabyeo as a subplot factor (Table 1). The experiments were well managed so as to be free of water and disease stress, and other nutrient deficiencies. Throughout the cropping season, algaecide and herbicide have been applied twice to minimize the effect of algal and weeds on radiation absorption and reflectance.

Spectral measurement

Canopy reflectance of the rice crop was recorded using a GER 1500 spectrophotometer (GER 1500; GER Inc. USA) with field of view (FOV) of 15°. The measurement range was set from 300 to 1100 nm with spectral resolution of 1.55 nm. For each measurement 8 scans were performed and the spectral data represented averages of these scans.

The sensor was held by hand approximately 2.0-m above the ground with zenith angle of about 25°. Measurements were taken between 11 : 00 to 13 : 00 local time (GMT + 9) on 14 July and 31 July (Table 1). Prior to each plant reflectance measurement, reflectance ($BaSO_4$) of a white standard was taken. The spectrophotometer automatically calculated the percent plant reflectance by dividing plant sample reflectance by reflectance of the white standard panel.

Plant sampling and measurement

Immediately after canopy reflectance measurements, five hills at the location for canopy reflectance measurement were sampled for agronomic measurements. The plant samples were weighed for total fresh weight and then a sub sample was taken. The sub samples were separated into leaf and stem. The leaf was used for LAI determination using Laser Area Meter (CID Inc.). After that leaves and stems were dried at 70°C to constant weight, the dry samples were weighed, ground and analyzed for total N by Kejeltec Auto 1035 System. The values obtained were then used for calculating shoot fresh weight (g m^{-2}), LAI (m^2 m^{-2}), leaf and shoot (leaf + stem) weight (g m^{-2}), leaf and shoot N concentration (mg g^{-1}) and leaf and shoot N density (g m^{-2} ground).

Table 1. Summary of experiment design and sampling time.

N level (g m^{-2})	Rice variety (leaf color)	Note
(0 0 0)$^{\$}$	Hwasungbyeo (green)	- Plant sampling and canopy reflectance measurement at: 54 and 72 DAT
(4.8 0 0)	SNU-SG1 (dark green)	
(4.8 0 3.6)	Juanbyeo (pale green)	
4 8 0 7.2)	Surabyeo (medium dark green)	
(4.8 3.6 0)		
(4.8 3 6 3.6)		- N was applied at 0, 13 and 55 DAT
(4.8 3.6 7.2)		
(4.8 7.2 0)		
(4 8 7 2 3.6)		
(4 8 7 2 7.2)		

$^{\$}$N applied at 0, 13 and 55 days after transplanting (DAT), respectively.

Nitrogen nutrition index (NNI) was calculated using the equation reported by Cui *et al.* (2002).

$$\mathrm{NNI} = \frac{\mathrm{Na}}{\mathrm{Nc}} \qquad \text{(Eq. 1)}$$

Where Na is rice shoot N concentration (%) and Nc was calculated by:

Nc = 4.08 when shoot dry weight (W) < 1.73 t ha^{-1}.

Nc = $5.197W^{-0.4253}$ when 1.73 t ha^{-1} <W < 12.00 t ha^{-1}.

Data pretreatment

A database was constructed and examined for outliers. To minimize dangers that the number of variables was greater than number of observations, the number of spectral reflectance data was reduced by averaging reflectance from every three consecutive wavebands. The final database included 239 observations described by nine dependent plant variables before heading, four plant variables at harvest and 170 independent spectral reflectance variables.

Broad-band NDVI calculation

One hundred and seventy discrete 4.65-nm-narrow waveband reflectance measurements were averaged over spectral wavebands of 760 to 900 nm (Rnir), 630-690 nm (Rred) and 520-600 nm (Rgreen). Then NDVI red and NDVI green were calculated as (Rnir-Rred)/(Rnir+Rred) and (Rnir-Rgreen)/(Rnir+Rgreen), respectively.

Narrow-band NDVI calculation

Narrow-band NDVI was calculated as:

$$\mathrm{NDVI} = \frac{R_{\lambda 2} - R_{\lambda 1}}{R_{\lambda 2} + R_{\lambda 1}} \qquad \text{(Eq. 2)}$$

where $R_{\lambda 2}$ and $R_{\lambda 1}$ were reflectances at waveband $\lambda 2$ and $\lambda 1$ ($\lambda 2 > \lambda 1$), respectively.

All possible waveband reflectance combinations from 300 nm to 1100 nm in 4.65 nm steps (14,365 combinations) were correlated with each of nine crop variables. The resulting coefficient of correlation (r) was sorted to select two combinations of *single wavebands* with the highest positive r (S1) and the highest negative one (S2). It is noted that the term single waveband means waveband with 4.65 nm step due to averaging three consecutive bands in data pretreatment section. Then r values were used to create two-dimensional maps to show pattern of r values. The NDVI with a range of $\lambda 1$ and $\lambda 2$ was determined by hot spots with 5% topmost of r (C1) and the hot spots with the 5% highest negative r value (C2), similarly. This process was repeated for each of nine crop variables. After that the NDVI value that had the highest r derived from correlation between S1, S2, C1, C2 with each crop variable was selected as the NDVI of the best fit for this crop variable. The NDVIs of the best fit were further examined by correlation and regression with four selected crop variables at harvest such as grain yield (g m^{-2}), number of filled spikelets (No. m^{-2}), number of total spikelets (No. m^{-2}) and 1000-grain weight.

RESULTS

Plant growth and nitrogen variables

Table 2 shows that the variation in crop variables was high before heading. With the exception of leaf and shoot N con-

Table 2. Summary statistics of crop variables.

Crop variables	Unit	Mean	S.D $	Min	Max	Range
Shoot fresh weight	g m^{-2}	1481	660	256	3495	3239
LAI	m^2 m^{-2}	3.05	1 14	0.53	6.47	5.94
Leaf Dry weight	g m^{-2}	135	50	29	290	261
Shoot dry weight	g m^{-2}	313	127	60	663	603
Leaf N conc.	mg g^{-1}	24.2	3.6	17 6	35 1	17.5
Shoot N conc.	mg g^{-1}	16.0	2 9	10.5	25.9	15.4
Leaf N density	g m^{-2}	3.35	1 58	0 71	8.36	7.65
Shoot N density	g m^{-2}	5 07	2.49	1 05	12 93	11.88
N nutrition index		0.492	0.140	0 268	0 939	0 671
Grain yield	g m^{-2}	600	112	297	852	555
Filled Spikelet	No m^{-2}	22957	3747	11547	29969	18422
Total Spikelet	No. m^{-2}	26680	5660	13533	41903	28370
1000-grain weight	g	26.4	1.1	24 0	28.6	4 6

$Standard deviation†

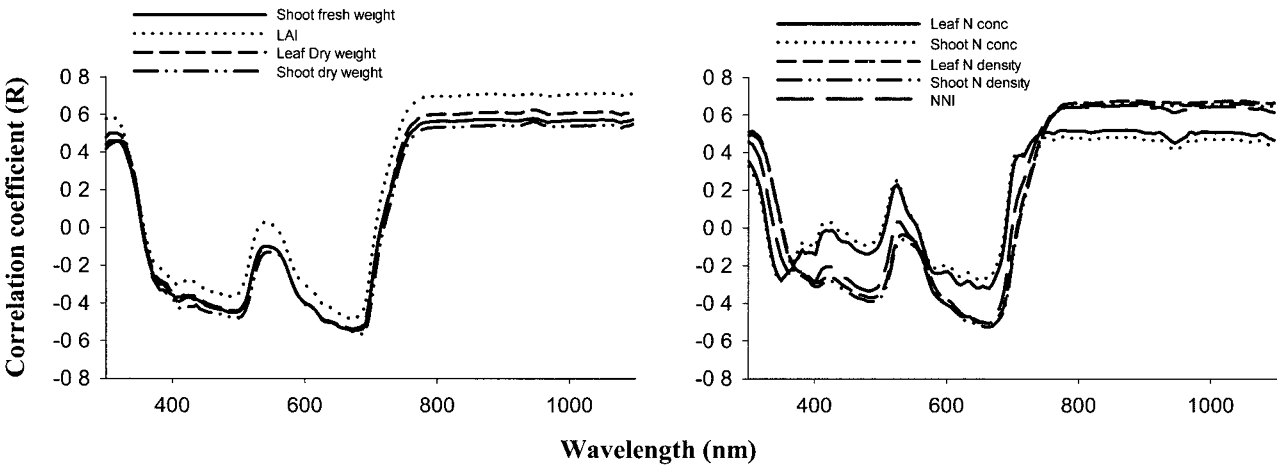

Fig. 1. Wavelength dependence of coefficient of correlation (r) between canopy reflectance and each of selected crop variables measured before heading stage of rice

centration, maximum values of the variables were more than ten times higher than minimum values At harvest, grain yield had the highest variation (max/min ~ 3) and 1000-grain weight had the least variation (max/min ~ 1.2). The high variation in crop variables before heading and at harvest was expected due to the wide range of N application levels (0 - 292 kg ha^{-1}), N application time (0 - 3 times) and rice varieties (four varieties). Four rice varieties were selected for the experiment based on (i) quite similar growth and development time to ensure that panicle initiation, booting, heading and harvest stages coincide, and (ii) difference in leaf color to challenge canopy reflectance to predict crop characteristics. Leaf colors of Hwasungbyeo, SNU-SG1, Juanbyeo and Surabyeo are green, dark green, pale green and medium dark green, respectively.

Correlation between crop variables and hyperspectral single band reflectance

Fig. 1 presents the correlation between canopy reflectance at various wavebands ranging from 300 nm to 1100 nm with crop variables measured when canopy reflectance was taken. It can be seen from Fig. 1 that for most of the crop variables, high positive or negative correlation coefficients were obtained at about ranges of 300 - 310 nm, 490 - 500 nm, 670 - 680 nm and higher than 770 nm. However, it also indicates that no single waveband reflectance would be successfully used to predict the crop variables because the highest r values were lower than 0.8.

Selection of the most sensitive wavebands

For each crop variable, single wavebands for two NDVI

Table 3. The selected single waveband for NDVI based on the maximum and positive (S1) and maximun and negative (S2) coefficient of correlation (r) and the selected waveband range for NDVI from black spot (C1) and white spot (C2) of 2-dimemtion maps in Fig 2

Crop variables		Sensitive wavebands	
		λ1	λ2
Shoot fresh weight	C1	743 - 753	768 - 882
	C2	341 - 351	541 - 617
	S1	758	804
	S2	334	721
LAI	C1	743 - 753	841 - 965
	C2	355 - 364	646 - 666
	S1	744	954
	S2	355	707
Leaf and shoot dry weight	C1	745 - 753	786 - 923
	C2	315 - 351	713 - 725
	S1	749	836
	S2	355	707
Leaf and shoot N concentration	C1	754 - 767	791 - 850
	C2	446 - 457	466 - 475
	S1	763	786
	S2	451	466
Leaf and shoot N density	C1	743 - 753	795 - 850
	C2	311 - 345	720 - 726
	S1	763	791
	S2	334	726
Nitrogen nutrition index	C1	755 - 765	768 - 805
	C2	312 - 328	725 - 730
	S1	763	791
	S2	323	730

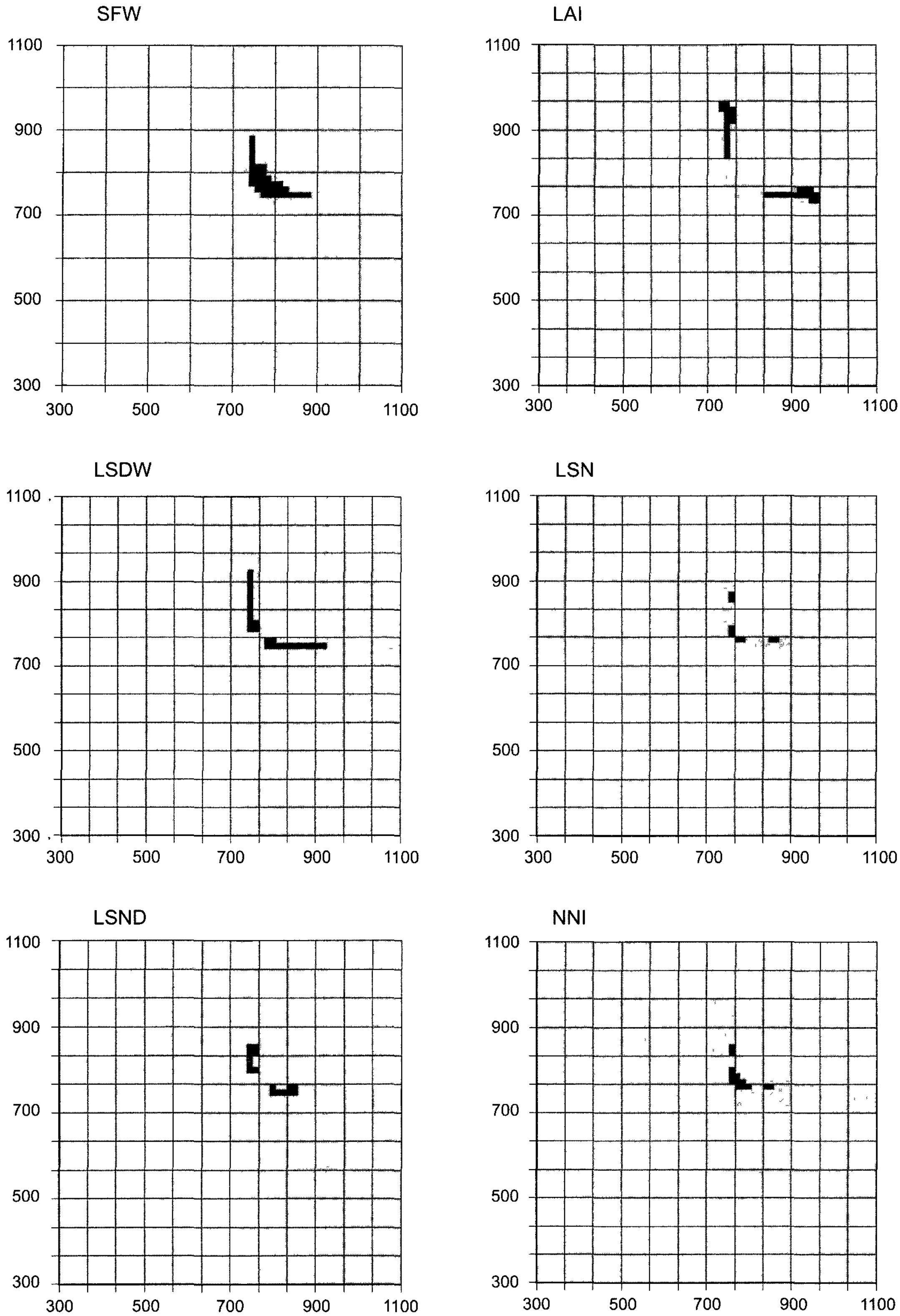

Fig. 2. Wavelength dependence of coefficient of correlation (r) between NDVI calculated from all of possible combinations and the crop variables. Black and white spots are top of 5% of r for positive and negative correlation, respectively. SFW, LAI, LDW, LSN, LSND, NNI are shoot fresh weight, leaf and shoot dry weight, leaf and shoot N concentration, leaf and shoot N density and N nutrition index, respectively.

which had the highest positive r (S1) and the lowest negative r (S2) were selected (namely NDVI of the best fit and the most sensitive wavebands for selected NDVI and waveband, respectively). Fig. 2 shows dependence of r values between NDVI and crop variables on reflectance of $\lambda1$ and $\lambda2$ used for calculating NDVI. The NDVI of the best fit with a range of $\lambda1$ and $\lambda2$ was determined by hot spots with 5% topmost of r (C1) and the hot spots with the 5% of the topmost negative r values (C2). This process was repeated for each of nine crop variables.

The selected single wavelengths and the selected narrow waveband for NDVI of the best fit are shown in Table 3. It is noted that LDW and SDW had the same S1, S2, C1 and C2 and so were LN and SN, and LND and SND. Table 4 presents r values derived from correlation between NDVI calculated from S1, S2, C1, C2 with crop variables. It can be seen that in comparison within one crop variable, correlation between the crop variable and NDVIs from the single wavelength reflectance (S1 and S2) had higher r than that with narrow waveband reflectance (C1 and C2). Similarly, r between the crop variables with NDVI calculated from reflectance of near-infrared red wavebands and red waveband (S1, C1) were higher than those with NDVI calculated from reflectance of red and ultraviolet wavebands except for leaf and shoot N concentration. The correlation between a crop variable and NDVIs calculated from single or narrow waveband reflectance values was definitely higher than the correlation between the crop variable and NDVI calculated from broad waveband reflectance (NDVI green and NDVI red). The NDVIs with the highest r for SFW, LAI, LSDW,

Table 4. Coefficient of correlation (r) between the selected NDVIs and nine crop variables before heading stage

NDVI		Crop variables								
		FW	LAI	LDW	SDW	LN	SN	LND	SND	NNI
NDVI#$_{SFW}$	C1	0.818$	0.750	0.810	0.782	0.695	0.574	0.884	0.897	0.895
	C2	-0.776	-0.695	-0.766	-0.745	-0.665	-0.549	-0.838	-0.852	-0.845
	S1	0.820	0.725	0.796	0.775	0.721	0.601	0.886	0.905	0.901
	S2	-0.786	-0.716	-0.780	-0.751	-0.689	-0.578	-0.859	-0.870	-0.870
NDVI$_{LAI}$	C1	0.808	0.763	0.809	0.777	0.671	0.552	0.875	0.884	0.880
	C2	-0.756	-0.720	-0.766	-0.737	-0.597	-0.487	-0.816	-0.821	-0.807
	S1	0.781	0.762	0.790	0.759	0.593	0.473	0.831	0.837	0.824
	S2	-0.772	-0.723	-0.775	-0.751	-0.602	-0.490	-0.825	-0.834	-0.818
NDVI$_{DW}$	C1	0.816	0.753	0.810	0.781	0.694	0.574	0.884	0.896	0.894
	C2	-0.782	-0.709	-0.774	-0.744	-0.702	-0.590	-0.859	-0.871	-0.874
	S1	0.820	0.746	0.810	***0.784***	0.709	0.587	0.890	0.904	0.902
	S2	-0.772	-0.723	-0.775	-0.751	-0.602	-0.490	-0.825	-0.834	-0.818
NDVI$_{N}$	C1	0.814	0.720	0.789	0.767	0.726	0.608	0.882	0.901	0.897
	C2	-0.626	-0.585	-0.636	-0.581	-0.757	-0.669	-0.776	-0.777	-0.829
	S1	0.814	0.729	0.797	0.770	0.734	0.616	0.890	0.906	0.908
	S2	-0.571	-0.539	-0.586	-0.526	-0.766	-0.688	-0.739	-0.739	-0.806
NDVI$_{ND}$	C1	0.820	0.746	0.810	0.781	0.700	0.578	0.886	0.908	0.907
	C2	-0.777	-0.703	-0.768	-0.736	-0.716	-0.606	-0.860	-0.871	-0.878
	S1	0.820	0.728	0.798	0.774	0.731	0.611	0.891	0.909	0.908
	S2	-0.772	-0.687	-0.756	-0.728	-0.724	-0.616	-0.855	-0.869	-0.876
NDVI$_{NNI}$	C1	0.820	0.736	0.803	0.779	0.721	0.601	0.892	0.909	0.907
	C2	-0.754	-0.678	-0.743	-0.707	-0.746	-0.642	-0.852	-0.863	-0.880
	S1	0.820	0.728	0.798	0.774	0.731	0.611	0.891	0.909	0.908
	S2	-0.737	-0.654	-0.720	-0.686	-0.761	-0.660	-0.840	-0.853	-0.875
NDVI red		0.604	0.614	0.630	0.610	0.332	0.234	0.605	0.604	0.580
NDVI green		0.684	0.671	0.703	0.680	0.451	0.341	0.704	0.706	0.689

$Italics are the highest r within single, narrow or broad waveband, bold and italics indicate the highest r among single, narrow and broad wavebands (NDVIs of the best fit for each crop variables, respectively).

#NDVI$_{SFW}$, NDVI$_{LAI}$, NDVI$_{DW}$, NDVI$_{N}$, NDVI$_{ND}$, and NDVI$_{NNI}$ are NDVI of the best fit for shoot fresh weight, LAI, leaf and shoot dry weight, leaf and shoot N concentration, leaf and shoot N density, and N nutrition index respectively NDVI$_{ND}$ and NDVI$_{NNI}$ are similar and named NDVI$_{ND\ and\ NNI}$

LSN, LSND and NNI were reselected as NDVIs of the best fit for each crop variable and stood for $NDVI_{SFW}$, $NDVI_{LAI}$, $NDVI_{DW}$, $NDVI_{N}$ and $NDVI_{ND\ and\ NNI}$, respectively (Table 4).

Prediction of the crop growth variables using the NDVIs of the best fit

The selected NDVIs of the best fit were used for linear and non-linear regression to predict nine crop variables: SFW, LDW, SDW, LN, SN, LND, SND and NNI measured at the same time of canopy reflectance taken. Table 5 indicates that for all crop variables, model r^2 derived from regression between crop variables and NDVIs of the best fit were sufficiently higher than those derived from the crop variables and NDVI green (the NDVI of the best fit of broad-band NDVIs). For most crop variables except LAI, the linear equation (Y= aX + b) was the best model to predict crop variables using NDVI of the best fit. However, the exponential equation ($Y=ae^{bx}$) rather than linear model was the best model to predict the crop variables using NDVI green (Table 5 and Fig. 3).

Prediction of yield and yield components using crop variables and NDVI of the best fit measured before heading

An observed variable receives more attention if it is more

Table 5. Summary of the models derived from regression between the NDVIs of the best fit (X) with each of nine rice crop variables (Y).

Crop variables	NDVI green		NDVI of the best fit		
	Equations	r^2	Equation	r^2 Value	r^2 Difference to NDVI green (%)
Shoot fresh weight	$Y = 150.49e^{3\ 1X}$	0.57	Y = 18810X 14.3	0 67	18
LAI	$Y = 0.463e^{2\ 57X}$	0.54	$Y = 1\ 82e^{4\ 76X}$	0.63	17
Leaf Dry weight	$Y = 20.14e^{2\ 6X}$	0.59	Y = 745.4X + 18.7	0.66	12
Shoot dry weight	$Y = 39.61e^{2\ 8X}$	0.55	Y = 1823 0X + 28.2	0.61	11
Leaf N conc	$Y = 16.43e^{0\ 536X}$	0 19	Y = -274.44X + 30 19	0.59	211
Shoot N conc	$Y = 11.29e^{0\ 474X}$	0 10	Y = -198 14X + 20.32	0.47	370
Leaf N density	$Y = 0.331e^{3\ 14X}$	0 62	Y = 74.4X 0.33	0.79	27
Shoot N density	$Y = 0\ 447e^{3\ 29X}$	0 62	Y = 119.8X 0 85	0.83	34
N nutrition index	$Y = 0\ 1465e^{1\ 670X}$	0.53	Y = 6 745X + 0 159	0.83	57

Table 6. Correlation coefficient (r) derived from crop variables, NDVIs of the best fit at panicle initiation (54 DAT) and booting stages (72 DAT) with crop variables at harvest

Crop variables	Crop variables at PI stages				Crop variables at booting			
	Y ($g\ m^{-2}$)$	FSPK	TSPK	P_{1000} (g)	Y ($g\ m^{-2}$)	FSPK	TSPK	P_{1000} (g)
Shoot fresh weight	0.49	0 43	0.38	-0.06	0.59	0.55	0 51	-0 02
LAI	0.39	0 37	0.27	0.00	0.55	0.51	0 43	0 08
Leaf Dry weight	0.46	0 38	0 32	0.01	0.61	0 55	0 47	0.11
Shoot dry weight	0.48	0.41	0 33	0.05	0.52	0 47	0 38	0.11
Leaf N conc	-0.03	0 02	0.10	-0.45	0.70	0.68	0.70	-0 28
Shoot N conc	-0.18	-0 13	-0 05	-0.38	0.67	0.64	0.67	-0.27
Leaf N density	0 41	0.35	0 31	-0 10	0.73	0 67	0 63	-0 05
Shoot N density	0 42	0.36	0 31	-0 09	0.73	0 67	0 64	-0 08
N nutrition index	0.34	0.31	0 29	-0.21	0.77	0 72	0 72	-0.18
$NDVI^{\#}_{SFW}$	0 26	0.28	0 35	-0 36	0.85	0 81	0 82	-0 25
$NDVI_{LAI}$	0 22	0.23	0 22	-0 14	0.81	0.76	0 74	-0 13
$NDVI_{DW}$	0 27	0.27	0 32	-0 26	0.85	0.81	0 82	-0 22
$NDVI_{N}$	-0 15	-0.21	-0.29	0.42	-0.72	-0.65	-0.66	0 17
$NDVI_{ND\ and\ NNI}$	0 26	0.27	0.34	-0 33	0.85	0 81	0 82	-0 25
$NDVI_{green}$	0 21	0.15	0.15	0.01	0.80	0.73	0 69	-0.01

$Y, FSPK, TSPK and P_{1000} are grain yield, number of filled spikelet, number of total spikelet and 1000-grain weight, respectively
#$NDVI_{SFW}$, $NDVI_{LAI}$, $NDVI_{DW}$, $NDVI_{N}$, $NDVI_{ND\ and\ NNI}$ are NDVIs of the best fit for Shoot fresh weight, LAI, leaf and shoot dry weight, leaf and shoot N concentration, and leaf and shoot N density and nitrogen nutrition index, respectively.

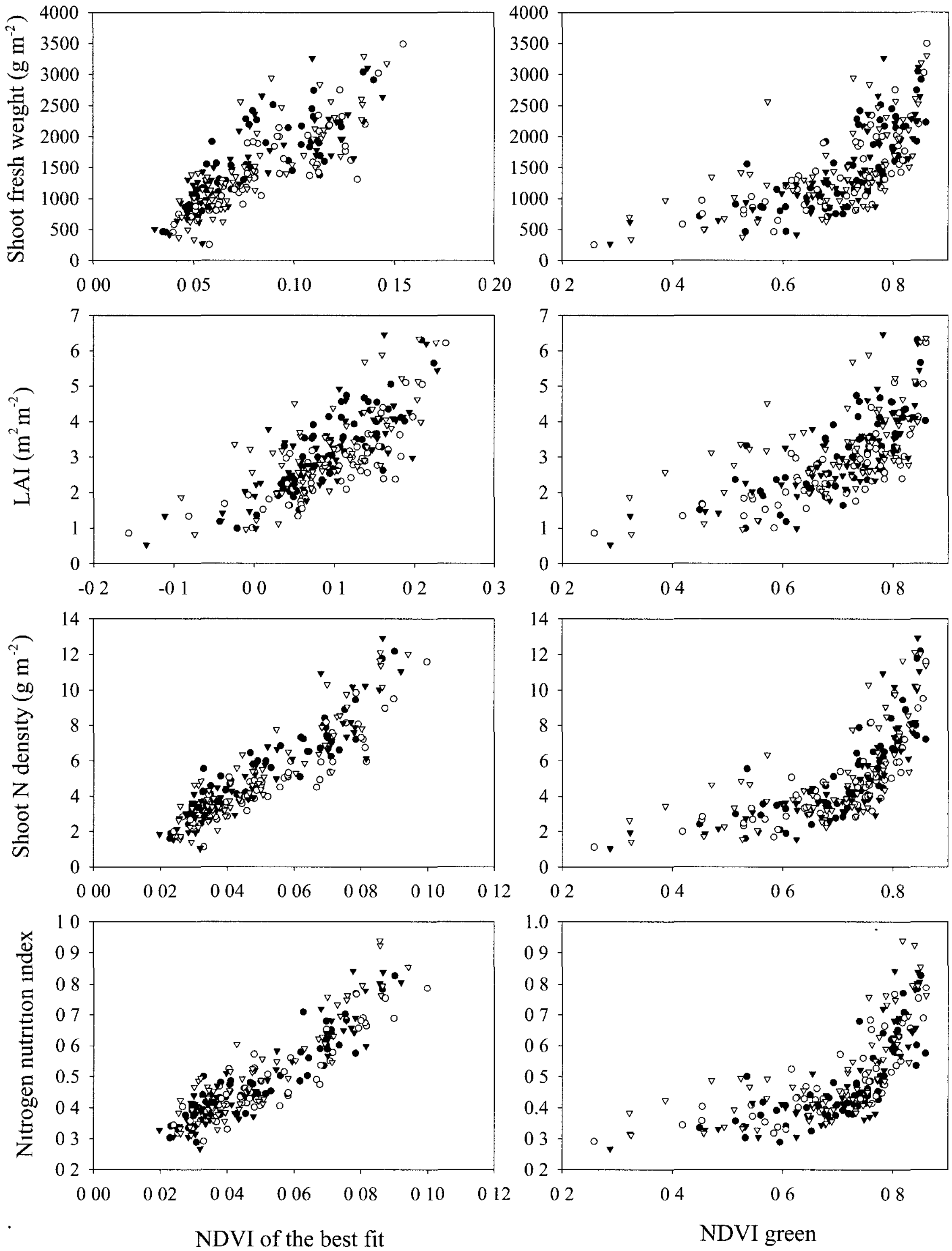

Fig. 3. The regression between NDVI of the best fit and NDVI green with some selected crop variables. Filled circles, open circles, filled triangles, and open triangles present for Hwasungbyeo, SNU-SG1, Juanbyeo, and Surabyeo, respectively

closely related to yield All crop variables and NDVIs of the best fit were correlated to crop variables measured at harvest (grain yield, filled and total number of spikelets, 1000-grain weight) (Table 6). In general, crop variables and NDVIs of the best fit measured at panicle initiation stage (PI) or booting stage had higher correlation with grain yield than the other yield components. At booting, NDVIs of the best fit had higher correlation with yield and yield components than crop variables had, and should be used to predict grain yield at harvest or as estimators for N application at booting or heading. However, at PI, crop variables showed higher correlation with yield and yield components than that their NDVIs of the best fit did.

To address the question as to why both crop variables and NDVI of the best fit had been loosely correlated with grain yield, we analyzed correlation between the crop variables

Table 7. Dependence of correlation between crop variables, NDVI measured at PI and yield on varieties and amount of N applied at PI.

Crop variables	Hwasungbyeo			SNU-SG1			Juanbyeo			Surabyeo		
	0[$]	36	72	0	36	72	0	36	72	0	36	72
Shoot fresh weight	0.75	0.48	0.49	0.74	0.77	-0.45	0.67	0.49	-0.55	0.85	0.68	0.42
LAI	0.72	0.23	0.21	0.61	0.65	-0.50	0.68	0.64	-0.69	0.85	0.48	0.58
Leaf Dry weight	0.74	0.35	0.53	0.68	0.82	-0.38	0.74	0.39	-0.43	0.81	0.66	0.55
Shoot dry weight	0.75	0.54	0.59	0.74	0.80	-0.43	0.60	0.32	-0.32	0.86	0.76	0.45
Leaf N conc	0.29	0.31	0.10	0.13	0.67	-0.40	-0.27	0.67	-0.55	-0.04	0.40	0.37
Shoot N conc.	-0.03	0.22	0.06	-0.24	0.52	-0.32	-0.31	0.60	-0.65	-0.37	-0.01	0.38
Leaf N density	0.76	0.49	0.38	0.67	0.84	-0.42	0.69	0.56	-0.46	0.73	0.67	0.59
Shoot N density	0.78	0.67	0.38	0.70	0.83	-0.45	0.60	0.57	-0.45	0.76	0.70	0.58
N nutrition index	0.81	0.72	0.26	0.62	0.79	-0.45	0.62	0.64	-0.56	0.64	0.59	0.57
$NDVI^{\#}_{SFW}$	0.65	0.75	0.14	0.41	0.27	-0.20	0.37	0.82	-0.66	0.71	0.16	-0.05
$NDVI_{LAI}$	0.71	0.49	-0.04	0.75	-0.35	-0.38	0.80	0.12	-0.67	0.79	-0.13	-0.46
$NDVI_{DW}$	0.65	0.62	0.04	0.59	0.05	-0.34	0.59	0.65	-0.68	0.76	0.33	-0.10
$NDVI_{N}$	-0.42	0.17	-0.19	-0.59	-0.38	0.35	-0.40	0.01	0.57	-0.40	0.61	0.10
$NDVI_{ND\ and\ NNI}$	0.62	0.63	0.07	0.46	0.27	-0.27	0.40	0.83	-0.67	0.73	0.39	0.02
$NDVI_{Green}$	0.51	0.42	-0.08	0.57	-0.25	-0.46	0.63	0.27	-0.75	0.65	0.37	-0.18

[&]0, 36 and 72 are N amount applied at 55 DAT

[#]$NDVI_{SFW}$, $NDVI_{LAI}$, $NDVI_{DW}$, $NDVI_{N}$, $NDVI_{ND\ and\ NNI}$ are NDVI of the best fit for Shoot fresh weight, leaf area index , leaf and shoot dry weight, leaf and shoot N concentration, and leaf and shoot N density and nitrogen nutrition index, respectively

Table 8. Coefficient of determination (r^2) derived from regression to predict grain yield (Yield), number of filled spikelets (FSPK) and total number of spikelets (TSPK) using crop variables and N rates applied at PI or only crop variables measured at booting

Crop variables	At PI			At Booting		
	Yield	FSPK	TSPK	Yield	FSPK	TSPK
Shoot fresh weight	0.65	0.53	0.53	0.34	0.29	0.25
LAI	0.62	0.52	0.51	0.29	0.25	0.18
Leaf Dry weight	0.63	0.53	0.51	0.37	0.29	0.21
Shoot dry weight	0.65	0.53	0.52	0.27	0.21	0.14
Leaf N conc.	0.55	0.47	0.51	0.49	0.45	0.49
Shoot N conc	0.56	0.47	0.50	0.44	0.41	0.45
Leaf N density	0.62	0.51	0.52	0.53	0.44	0.39
Shoot N density	0.62	0.51	0.52	0.53	0.45	0.41
N nutrition index	0.60	0.50	0.52	0.59	0.52	0.51
$NDVI^{\$}_{SFW}$	0.57	0.49	0.54	0.72	0.65	0.67
$NDVI_{LAI}$	0.58	0.49	0.52	0.66	0.58	0.55
$NDVI_{DW}$	0.58	0.49	0.54	0.72	0.65	0.66
$NDVI_{N}$	0.56	0.48	0.53	0.51	0.42	0.43
$NDVI_{ND\ and\ NNI}$	0.57	0.49	0.54	0.72	0.64	0.67
$NDVI_{Green}$	0.57	0.48	0.50	0.64	0.52	0.47

[$]$NDVI_{SFW}$, $NDVI_{LAI}$, $NDVI_{DW}$, $NDVI_{N}$, $NDVI_{ND\ and\ NNI}$ are NDVIs of the best fit for Shoot fresh weight, LAI, leaf and shoot dry weight, leaf and shoot N concentration, and leaf and shoot N density and nitrogen nutrition index, respectively.

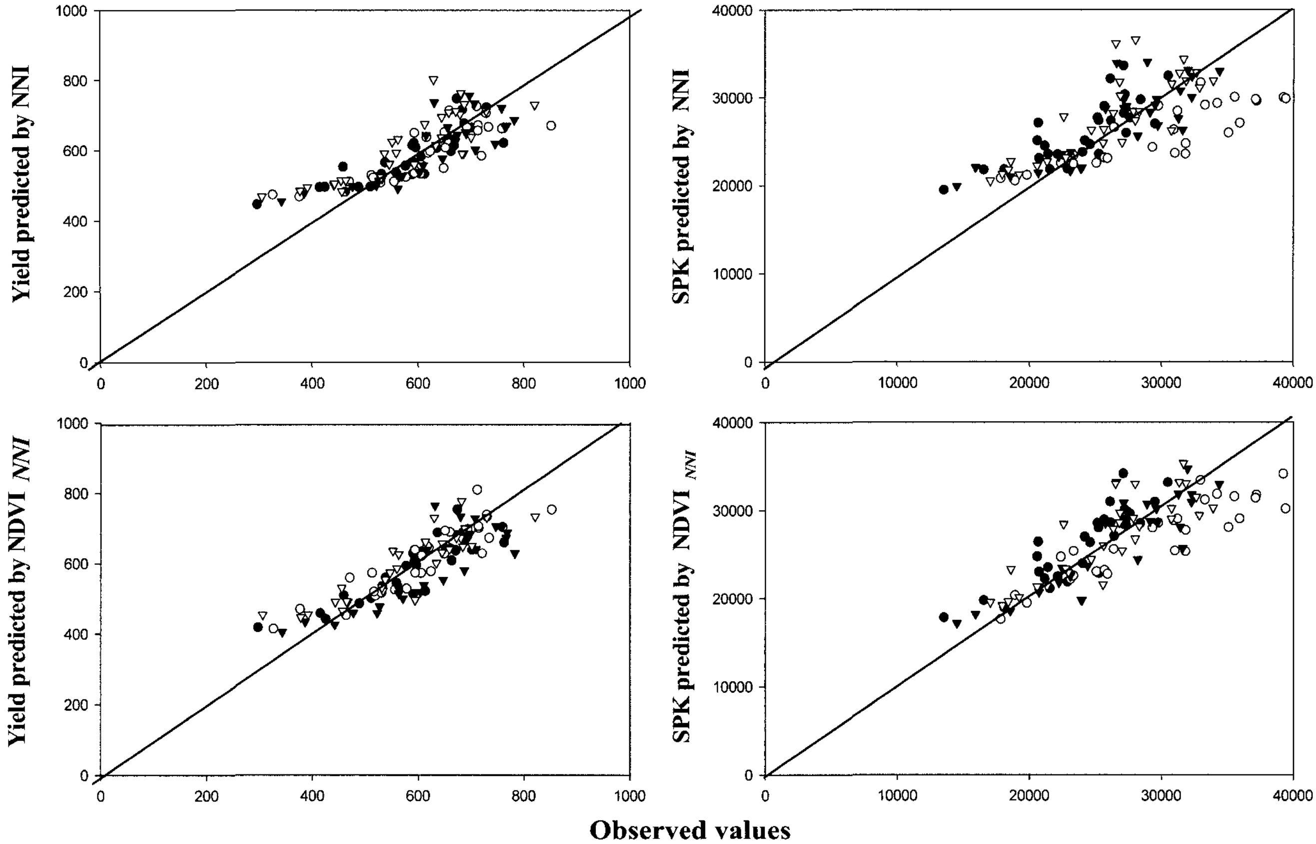

Fig. 4. Regression between grain yield, total number of spikelets observed (X) and predicted by NNI and $NDVI_{NNI}$ of the best fit measured at booting stage (Y). Filled circles, open circles, filled triangles, and open triangles present for Hwasungbyeo, SNU-SG1, Juanbyeo, and Surabyeo, respectively Solid line is 1:1 line.

and NDVIs of the best fit measured at PI with grain yield of each variety at a certain level of N applied at PI (Table 7). For most varieties the correlation was higher where there was no N applied at PI treatments compared to 36 or 72 kg ha^{-1} treatments. The low correlation between crop variables and NDVI of the best fit measured at PI with grain yield resulted from the different responses to N application (especially at 72 kg N ha^{-1}) among all four varieties and a large effect of N application at PI on grain yield.

Further multiple regression analysis to predict grain yield, number of filled spikelets and total number of spikelets (Table 8) revealed that regression models to predict grain yield and yield components using one crop variable and N application at PI explained more variation in grain yield and yield components at harvest than the models using one crop variable alone measured at booting. In contrast, regression models to predict grain yield and yield components using one NDVI of the best fit and N application at PI explained less variation in grain yield and yield components at harvest than the models using one NDVI of the best fit alone measured at booting.

DISCUSSION

Sensitivity of hyperspectral waveband reflectance to crop variables

From the variation of r, derived from correlation between each of nine crop variables with each reflectance of 170 wavebands, it is shown in Fig. 1 that most crop variables have the highest negative correlation with reflectance occurred at a waveband centered around 670-680 nm. Thenkabail *et al.* (2000) and Hansen & Schjoerring (2003) reported the same results when they correlated single band reflectance with crop variables of cotton, potato, soybean, corn and winter wheat. The negative correlation between reflectance and crop variable may result from high chlorophyll absorption at this waveband. The sharp change from maximum negative to maximum positive correlation from approximately 670 nm to 780 nm reflected the high reduction in light absorption of green vegetation with increasing wavelength. Increasing wavelength after 780 nm did not significantly change the correlations except the slight change in

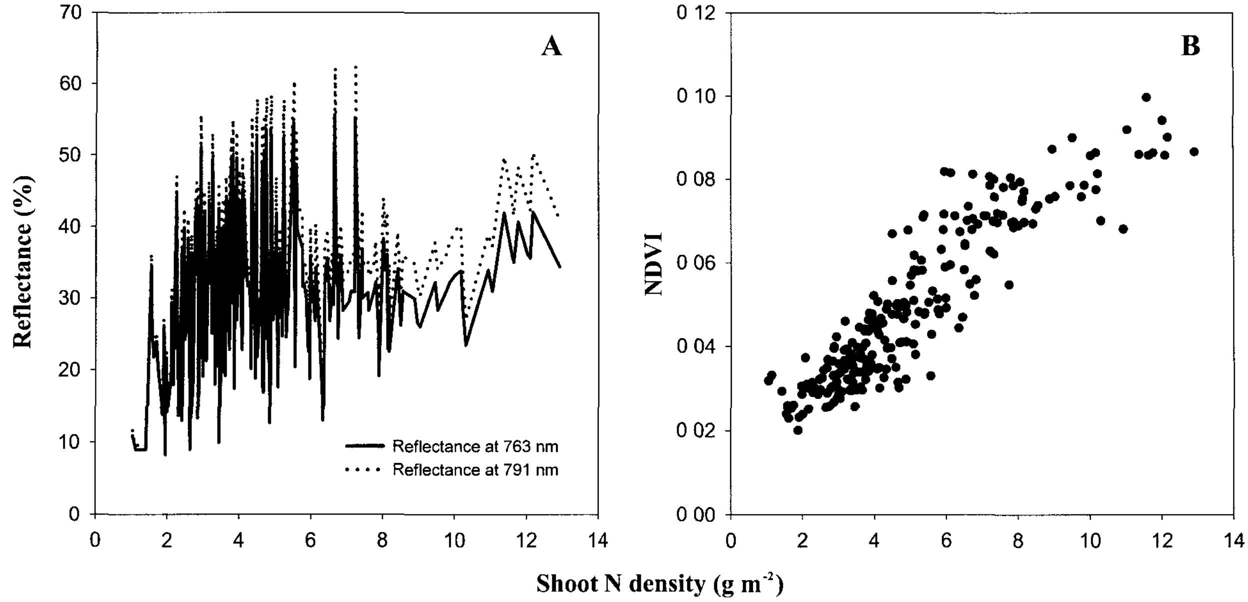

Fig. 5. Correlation between shoot N density with reflectance at λ1=763 and λ2=791 (A) and NDVI calculated from reflectance of the two bands (B).

the correlations at wavelength of approximately 950 nm. This may be related to high light absorption of water. Leaf N concentration and SN showed the same correlation pattern as the other crop variables but a lower correlation coefficient. Similarly, changing from high positive to high negative correlation between the crop variables and reflectance with increasing wavelength from approximately 300 nm to 500 nm indicates that green vegetation increased light absorption over these wavelengths. The highest Pearson correlation of 0.714, derived from correlation between LAI and reflectance of $\lambda = 1047$ nm, suggests that no single wavelength reflectance may successfully explain variation in crop variables.

The low correlation between the crop variables with hyperspectral single band reflectance may result from several types of errors that occurred in reflectance measurement. One of the possible errors that caused reflectance error with a band was the variation of sensor position relative to targets due to hand held operation. The variation of sensor position relative to targets resulted in quite severe changes in absolute reflectance values with a band. However, if comparison of band- to band reflectance values were used, the errors could be ignored (Fig. 5).

Relationship between NDVI and crop growth variables measured at the same time of reflectance measurement

The r derived from correlation between NDVIs and crop variables ranged from high to low in order of single-band NDVI, narrow-band NDVI and broad- band NDVI. This suggests that reflectance was very sensitive to crop variables at a given waveband and any aggregation of reflectance over waveband, even narrow band, resulted in a lower correlation between the variables (Table 4). A frequent use of reflectance at wavebands ranging from 740 to 790 nm as the most sensitive waveband reflectance for NDVI calculation indicates that the chlorophyll red-edge (710 - 780 nm) portion of the spectrum region (Thenkabail *et al.*, 2000) had a critical impact on reflectance at the region. An important role of reflectance at wavelength ranging from 710 - 780 nm on predicting crop growth and nitrogen variables has been widely reported (Hansen & Schjoerring, 2003; Thenkabail, 2000; Yoder & Crosby, 1995; Elvidge & Chen, 1995). The best fit linear regression ($Y = aX + b$) to predict the crop variables using the narrow-band NDVI of the best fit in comparison to the best fit non-linear regression ($Y=ae^{bx}$) using NDVI green (Table 5, Fig. 3) reveals that narrow-band NDVIs of the best fit overcame NDVI saturation at high LAI values as reported by Huete (1988) and Haboudane *et al.* (2004)

Relationship between NDVI and crop growth variables before heading and yield and yield components

It is unclear why crop variables at PI stage were more sensitive to yield and yield components than NDVIs of the best fit when NDVIs of the best fit were more sensitive than crop variables at booting stage. We hypothesize that NDVIs of the best fit selected for one variable not only contain information related to this crop variable but also other unclarified information related to crop health at the time of reflectance measurement. As a result, NDVIs of the best fit may be were easily changed with the change of crop health if any large influence on crop growth occurred such as N application at PI in this study. Therefore, NDVIs of the best fit at booting stage without the large influence of N application at PI showed more sensitivity to yield and yield component than NDVIs of the best fit measured at PI. Moreover, predictive capacity (R^2) of regression models using NDVI of the best fit and N amount applied at PI were higher than that of the model using crop variables and N amount applied at PI to predict total number of spikelets. We may suggest that NDVIs of the best fit is better crop health indicator at PI than crop variables because total number of spikelets which were determined mainly by crop growth status before PI and N application at PI (Cui & Lee, 2002).

CONCLUSION

As expected, models to predict crop variables before heading using the NDVI of the best fit had higher r^2 (>10%) than those using common broad- band NDVI red or NDVI green. The models with the narrow-band NDVI of the best fit overcame broad- band NDVI saturation at high LAI values as frequently reported. The NDVI of the best fit selected for a given crop variable reflected crop health status better than the crop variable. NDVI calculated from hyperspectral single band reflectance showed higher correlation with corresponding crop variable than any NDVI calculated using reflectance aggregated over narrow or broad bands.

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