Precision Agric (2016) 17:507–530
DOI 10.1007/s11119-016-9433-1

Evaluation of red and red-edge reflectance-based vegetation indices for rice biomass and grain yield prediction models in paddy fields

Yumiko Kanke[1] · Brenda Tubaña[1] · Marilyn Dalen[1] · Dustin Harrell[2]

Published online: 29 January 2016

Abstract Remote sensing-based nitrogen (N) management has been evaluated in many crops. The water background and wide range of varieties in rice (*Oryza sativa*), are unique features that require additional consideration when using sensor technology. The commonly calculated normalized difference vegetation index is of limited use when the crop has reached complete canopy closure. The objective of this research was to evaluate mid-season agronomic parameter and grain yield prediction models along with the effect of water background and of different varieties using a red- and red-edge-based vegetation index. Varieties × N trials were established at the LSU AgCenter Rice Research Station located in Crowley, Louisiana in 2011 and 2012. Canopy spectral reflectance under clear and turbid water, biomass yield, N content, plant coverage, and water depth were collected each week for three consecutive weeks beginning 2 weeks before panicle differentiation. Grain yield was also determined. Water turbidity had an influence on spectral reflectance when canopy coverage was less than 50 %. While water depth influenced red reflectance, this was not carried over when reflectance was transformed to vegetation indices. The red-edge-based vegetation indices, especially those computed by ratio, had stronger relationships with measured agronomic parameters as compared with red-based indices. Furthermore, the effect of variety on the yield prediction model was observed using derivative-based red-edge indices but not with other ratio-based indices. Future researches should

✉ Brenda Tubaña
BTubana@agcenter.lsu.edu

Yumiko Kanke
YKanke@agcenter.lsu.edu

Marilyn Dalen
mdalen1@tigers.lsu.edu

Dustin Harrell
DHarrell@agcenter.lsu.edu

[1] School of Plant, Environmental, and Soil Sciences LSU AgCenter, 104 Sturgis Hall, Baton Rouge, LA 70803, USA

[2] LSU AgCenter H. Rouse Caffey Rice Research Station, 1373 Caffey Road, Rayne, LA 70578, USA

focus on developing a generalized yield prediction model using ratio-based red-edge indices across different varieties to extend its applicability in production fields.

Keywords Remote sensing · Rice · Red-edge · Water background · Nitrogen

Introduction

Water and nitrogen (N) are the most limiting inputs in crop production. Since rice is grown in a flooded environment, N is often considered the most important input that limits grain yield. Currently in the mid-southern United States, N rate recommendations for rice (*Oryza sativa*) are variety dependent and determined from multi-year N response trials across sites, which are further adjusted by soil type, and cultural practice (Harrell et al. 2011; Norman et al. 2000). Generally, two N fertilizer applications are made seasonally in drill-seeded, delayed-flood rice. The first is made just before permanent flood establishment and the second is applied mid-season. Nitrogen fertilizer recommendations made in this manner can potentially over- or under-estimate N rate due to the lack of consideration of spatial and temporal variability. Remote sensing technology has recently been investigated as a tool to predict optimum mid-season N application rates while accounting for both field spatial and temporal variability (Cao et al. 2015; Harrell et al. 2011; Tubaña et al. 2008).

Remote sensing-based N management has been studied in many crops, including corn (*Zea mays*), wheat (*Triticum aestivum*) and cotton (*Gossypium hirsutum*) (Raun et al. 1999; Tubaña et al. 2008). Raun et al. (2005) established an N algorithm for mid-season N requirements based on estimating N uptake and yield potential using a GreenSeeker® hand held sensor (Trimble, CA, USA). This N rate recommendation, derived from spectral indices, has been tested and showed promise in increasing N use efficiency (NUE). A sensing-based N fertilization algorithm reduced the traditional N rate by 33 % while maintaining a similar rice grain yield (Xue and Yang 2008). Dobermann et al. (2002) conducted site-specific N management in 179 fields based on SPAD chlorophyll meter readings. Their approach was to modify N rates depending on the critical value of the SPAD meter at specific growing stages and variety. It resulted in an increase in NUE by 30–40 %. A similar approach was tested by Xue and Yang (2008) using the normalized difference vegetation index (NDVI) from a sufficient-N fertilized reference field and from farmers practice. According to these studies, determining optimum mid-season N rates using remote sensing technology is highly feasible.

Based on Raun et al. in 2005, it is necessary to have an established yield prediction model in order to develop an N algorithm for determination of N rates that will maximize crop yield. Wells et al. (1989) found that biomass production is closely related to rice grain yield. Harrell et al. (2011) demonstrated that the NDVI was related to both above-ground biomass measured early in the season and rice grain yield. They showed that 42 % of the total variability in grain yield can be explained by the NDVI collected at panicle differentiation (PD). Calculated NDVI from second derivative analysis also showed a high potential for predicting rice grain yield (Shibayama and Akiyama 1991). Along with predicting grain yield at mid-season, many researchers have also monitored plant N status using spectral reflectance (Sims and Gamon 2002; Stroppiana et al. 2009; Zhang et al. 2006).

Unlike corn, wheat or other crops, the water background in rice is a unique feature which may require additional consideration when using sensor technology. A water-compared to a soil-background may affect the spectral reflectance and vegetation indices values. Normally, water transmits most of the incident radiation in the visible wavelength, which results in the small reflection of light. In contrast to pure water, water in paddy rice may be turbid due to suspended soil sediments. In addition, when collecting sensor data using a handheld sensor, the degree of turbidity increases due to disturbances created by walking in the paddy field. In turn, the turbidity may alter the absorption and reflection of light. Water absorbs near-infrared (NIR) wavebands; thus, the reflectance in that region decreases as the area of exposed surface water increases in rice fields. There is also a potential interference on spectral reflectance especially with low rice biomass observed during early growth stages. Many studies have been conducted to investigate spectral reflectance on turbid water surfaces mainly to monitor water quality (Abd-Elrahman et al. 2011; Wu et al. 2014; Vincikova et al. 2015). Their results indicated that water surfaces can generate different spectral signatures. For example, a study conducted by Han (1997) showed that a change in the degree of suspended sediment concentration (SSC) altered spectral reflectance between 400 and 900 nm. Based on his research, the strongest correlation between SSC and spectral reflectance was observed at 800–900 nm. Hoshi et al. (1984) showed that an increase in water depth reduced spectral reflectance due to increased radiant absorption in water. The findings of these previous studies warrant further research of a similar scope to explore the possibilities of increasing the accuracy and precision of rice grain yield predictive models established from canopy reflectance. Understanding and addressing the effect of different water backgrounds on spectral reflectance in rice production can improve the use and application of this technology for midseason N applications.

The most commonly used and tested vegetation index, NDVI, which is computed using reflected light at red and NIR bands, is of limited use when biomass and leaf area index (LAI) are high or when the crop has reached complete canopy closure. The sensitivity of the NDVI decreased due to the insusceptible rate of change in the amount of reflected light at the red or NIR bands as plant canopy ground coverage increased (Gitelson et al. 2002). In fact, the use of the current rice yield prediction model using the NDVI in Louisiana is limited when grain yield exceeds 8000 kg ha^{-1} (Harrell et al. 2011). This phenomenon was also detected in a variety of crops, including corn and cotton (Galvão et al. 2005; Jackson and Pinter 1986). To address this problem, many studies evaluated an alternative spectral region called red-edge. Red-edge approximately refers to 680–740 nm in the electromagnetic spectrum and is the wave band between the red and NIR bands. Radiation in the red band is strongly absorbed by chlorophyll pigments whereas radiation from the NIR band is reflected based on leaf structure.

Cao et al. (2015) compared the performance of different vegetation indices to predict rice grain yield at different growth stages. Based on their study, at early growth stage (stem elongation), the red-based vegetation indices, such as NDVI or simple ratio (RVI), resulted in better relations with rice grain yield. However, as the plant approaches the maturity stage (booting and heading stage), red-edge-based ratio indices performed better when compared with red-based ratio indices. Similar results were found by Peng and Gitelson (2012) in estimating crop gross primary productivity (GPP) using total canopy chlorophyll content and incoming photosynthetically active radiation. Their study showed that the NDVI had good sensitivity at low to moderate chlorophyll content and GPP, but the sensitivity drastically decreased once the crop stand reached moderate to high density. Furthermore, normalized difference red edge (NDRE) had showed a stronger degree of linear relationship with GPP ($R^2 = 0.87$ and 0.86) than the red-based NDVI ($R^2 = 0.83$ and 0.89) in soybean and corn, respectively.

Within the red-edge band, scientists are also focusing on the red-edge inflection point (REIP), defined as the maximum of the first derivative reflectance between the red and NIR regions. Van der Meer and De Jong (2006) showed that the REIP had a strong correlation with N concentration at dense plant canopy ground coverage. The red-edge inflection point determined by various techniques also had a high correlation coefficient ($r > 0.85$) with leaf N in rye (*Secale cereale*) and corn (Cho and Skidmore 2006). The vegetation index using red-edge band has potential to improve the current yield prediction algorithm.

Varietal differences in yield and physiological N response are important information to refine N rate recommendations. However, many varieties are currently used in the southern United States for large scale production, and N rate recommendations are slightly different depending on variety (Saichuk et al. 2012; Walker and Street 2003). The varietal differences in geometrical canopy structure and foliar chemical compositions give a unique spectral signature. Darvishsefat et al. (2011) showed the differences in spectral signatures among varieties in rice. Jackson and Pinter (1986) obtained 20 % higher reflectance values in wheat with planophile canopies (non-erect) as compared with erectophile canopies (erect). Similar results were also observed in sugarcane (*Saccharum officinarum*) (Galvão et al. 2005). Therefore, it is important to understand the potential impact of using different varieties with different canopy structures on spectral reflectance.

This study was conducted to evaluate the use of red and red-edge spectral reflectance-based indices as predictors of mid-season agronomic parameters (biomass, N uptake and plant coverage) and grain yield of two rice varieties with different canopy structure. Given this objective, the relationship of biomass with spectral reflectance readings under undisturbed and turbid water background and varying water depth was evaluated. In addition, the relationships of red-edge reflectance with mid-season agronomic parameters and yield were also evaluated. Finally, the impact of varietal difference on the grain yield prediction model using red-edge vegetation indices was examined. The findings from this study is vital for refining the rice yield potential predictive model as well as the working algorithm for determination of midseason N rate recommendations in rice.

Materials and methods

Location and experimental design

A study was established at the Louisiana State University AgCenter H. Rouse Caffey Rice Research Station located in Crowley, Louisiana in the U.S.A. (30°14′23″N, 92°20′44″W). Experimental plots were established under conventional tillage on a Crowley silt loam soil (fine, smectic, thermic TypicAlbaqualfs). The experiment consisted of seven preflood N rates (0, 34, 68, 101, 135, 168, and 202 kg ha^{-1}) with four replications arranged in a randomized complete block design. For each replication, one unplanted plot was added as a reference. Two varieties, CL152 (an early-maturing, semidwarf long-grain) and CL261 (an early maturing, short stature medium grain), were tested. CL152 is generally taller than CL261. Rice was drill-seeded on March 16, 2011 and on March 19, 2012 at a depth of 40 mm at a seeding rate of 300 seeds m^{-2} using a small-plot grain drill. Each plot was 1.38 by 4.8 m^2. Once rice seedling reached the 4- to 5-leaf stage, N fertilizer in the form of urea (46 % N) was broadcasted and permanent flood was established 1 day later.

Sampling area and data collection

After rice seedlings reached the 3 leaf-stage, 1 m × 1 m × 0.3 m (l × w × h) galvanized borders were carefully pressed onto the ground around each plot to a depth of 25 mm creating a 1 m^2 sampling area. The borders protected the sampling area from disturbance while taking measurements (reflectance readings, digital picture and depth of water) under a clear, non-turbid water background. Reflectance readings were measured again with a turbid water background. To make the water turbid, water inside the 1 m^2 sampling area was carefully mixed with a meter stick. Whole plant samples were taken for biomass yield and total N determination at each sampling period. Reflectance and biomass measurements were taken each week for three consecutive weeks beginning 2 weeks before PD (about 1500 cumulative growing degree days, GDD). At maturity, whole plots were harvested using a small plot combine to determine grain yield. Detailed field activities are listed in Table 1.

Canopy reflectance measurements were taken using the Ocean Optics Jaz spectrometer (Ocean Optics, Dunedin, FL, USA), which detects continuous wavebands from 300 to 1100 nm with an optical resolution of 1.5 nm. Incident light (down-welling irradiance) and the outgoing light (upwelling) from a 1 m^2 white steel plate coated with barium sulfate was determined and used to correct environmental noise interference before plant canopy measurements were taken. Dark readings were measured by covering the sensor with a cap and fabric material. The distance between the fiber optic sensor and target (white plate or rice canopy) was determined to make sure that the field of view covered a 1 m^2 area (sampling area size). The distance between the rice canopy and fiber optic sensor was calculated based on the len's field of view using trigonometry functions. The cosine corrector and Gershun tube with a 28° field of view was attached to the fiber optic sensor. Since the field of view was 28°, the height required to cover 1 m^2 was computed by multiplying tangent 14° with the length of the adjacent side.

Digital pictures taken from the sampling area were analyzed using Integrated Land and Water Information System (ILWIS) software (The Faculty of Geo-Information Science and Earth Observation of the University of Twente, The Netherlands) to compute the percentage of ground coverage by plant. A digital camera was attached to a hand-held, self-telescopic stand stick with a constant height of 1.5 m to take a top-view shot of the plots.

Table 1 Dates of field activities and corresponding number of days from planting and cumulative growing degree days for the trials established in Crowley, LA in 2011 and 2012

	2011			2012		
	Date	DFP[a]	CGDD[b]	Date	DFP[a]	CGDD[b]
Planting	16-Mar	0	0	19-Mar	0	0
N fertilization	20-Apr	36	385	23-Apr	40	441
Panicle differentiation	23-May	76	927	25-May	64	851
Panicle Differentiation + 1 week	6-Jun	82	1044	30-May	73	936
50 % Heading	13-Jun	89	1169	6-Jun	79	1035
Harvest	5-Aug	143	2166	1-Aug	136	2028

[a] DFP refer to days from planting

[b] CGDD refer to cumulative growing degree days computed as (maximum daily temperature + minimum daily temperature)/2) − 10 °C

Biomass samples (one of 1-month long rows) were cut at the soil level at each sampling date. Biomass samples were then oven-dried at 60 °C for 48 h, weighed, ground, and analyzed for total N analysis using the dry combustion method (Elementar Americans Inc., Mount Laurel, NJ, USA). Grains sub-samples were also processed and analyzed for total N.

Spectral reflectance and indices

Normalized and simple ratio

Ratio-based vegetation indices using visible and NIR are the most widely used due to their feasibility in practical field conditions. The normalized form of the vegetation index is generally the ratio of difference and the sum of red and NIR reflectance. Vegetation indices, which showed strong relations with yields based on literature reviews, were computed using the following formulae:

Red simple ratio vegetation index, RVI (Tubaña et al. 2011)

$$\mathrm{RVI} = \rho_{780}/\rho_{670} \tag{1}$$

Normalized difference vegetation index, NDVI (Harrell et al. 2011)

$$\mathrm{NDVI} = \frac{\rho_{780} - \rho_{670}}{\rho_{780} + \rho_{670}} \tag{2}$$

Red-edge simple ratio vegetation index, RERVI (Cao et al. 2015)

$$\mathrm{RERVI} = \rho_{780}/\rho_{730} \tag{3}$$

Normalized difference red-edge, NDRE (Peng and Gitelson 2012)

$$\mathrm{NDRE} = \frac{\rho_{780} - \rho_{730}}{\rho_{780} + \rho_{730}} \tag{4}$$

Red-edge re-normalized difference vegetation index, RERDVI (Cao et al. 2015)

$$\mathrm{RERDVI} = (\rho_{780} - \rho_{730})/\sqrt{(\rho_{780} + \rho_{730})} \tag{5}$$

Red-edge difference vegetation index, REDVI (Cao et al. 2015)

$$\mathrm{REDVI} = \rho_{780} - \rho_{730} \tag{6}$$

Red-edge soil adjusted vegetation index, RESAVI (Huete 1988)

$$\mathrm{RESAVI} = 1.5 * [(\rho_{780} - \rho_{730})/(\rho_{780} + \rho_{730} + 0.5)] \tag{7}$$

Red-edge optimal soil adjusted vegetation index, REOSAVI (Cao et al. 2013)

$$\mathrm{REOSAVI} = (1 + 0.16)(\rho_{780} - \rho_{730})/(\rho_{780} + \rho_{730} + 0.16) \tag{8}$$

Red-edge wide dynamic range vegetation index, REWDRVI (Gitelson 2004)

$$\mathrm{REWDRVI} = (0.15 * \rho_{780} - \rho_{730})/(0.15 * \rho_{780} + \rho_{730}) \tag{9}$$

Red-edge chlorophyll index, $\mathrm{CI_{RE}}$ (Gitelson et al. 2005)

$$\mathrm{CI_{RE}} = \rho_{780}/\rho_{730} - 1 \tag{10}$$

In this study, the REIP was determined by using: maximum first derivative analysis by polynomial fitting technique ($REIP_{DF}$), linear interpolation technique ($REIP_{LI}$), linear extrapolation technique ($REIP_{LE}$), and the Lagrangian technique.

Fifth order polynomial fitting technique

A polynomial function was fitted to the spectral reflectance between red and NIR (670–780 nm) using TableCurve 2D v5.01 software (Systat Software Inc, San Jose, CA, USA). The maximum first derivative reflectance was computed as $REIP_{DF}$ (Cho and Skidmore 2006).

$$\rho(\lambda) = a_0 + \sum_{i=1}^{5} a_i \lambda^i \tag{11}$$

where λ (wavelength) is from 670 to 780 nm.

Linear interpolation technique

The linear interpolation method was used to estimate the REIP by employing reflectance at four different wavebands (Cho and Skidmore 2006; Guyot and Baret 1988). The benefit of this method is that it does not require continuous wavebands for derivative analysis. The reflectance between red and NIR is assumed to be simple straight line (Van der Meer and De Jong 2006).

$$REP_{LI} = 700 + 40 * \frac{(\rho_{REP} - \rho_{700})}{(\rho_{740} - \rho_{700})} \tag{12}$$

where

$$\rho_{REP} = \frac{\rho_{670} + \rho_{780}}{2} \tag{12a}$$

Linear extrapolation technique

The linear extrapolation technique was developed by Cho and Skidmore (2006). This method eliminates the problem from the double-peak which can be observed in high N treated plant or when the chlorophyll concentration is high using the first derivative analysis. The two straight lines, one from NIR and the other from red points, were computed based on the first derivative reflectance and the intersection of those straight lines was considered as the REIP.

$$REP_{LE} = \frac{-(b_1 - b_2)}{(a_1 - a_2)} \tag{13}$$

where NIR line: 1st derivative reflectance $(\lambda) = a_1\lambda + b_1$; red line: 1st derivative reflectance $(\lambda) = a_2\lambda + b_2$

In rice, two major peaks around 700 nm and between 720 and 730 nm (depending on plant health conditions, such as high N or low N) have been reported in the first derivative reflectance (Evri et al. 2008; Tian et al. 2011). In this study, similar characteristics were observed; a sharp drop of the first derivative reflectance around 760 nm (Tian et al. 2011).

Therefore, to determine the NIR lines, 725- and 750-nm bands were selected while 680- and 700-nm bands were selected for the red line.

The Lagrangian technique

This technique was tested by Dawson and Curran (1998) using a three-point Lagrangian interpolation, and the REIP computed in this method showed positive correlation with leaf chlorophyll content. Dawson and Curran (1998) stated that this method was suitable for discontinuous spectra, since it only requires the three derivative bands which do not have to be equally spaced, but the later study conducted by Pu et al. (2003) concluded that it was not suitable because it requires first derivative reflectance.

$$\mathrm{REP_{LAG}} = \frac{\mathrm{A}(\lambda_i + \lambda_{i+1}) + \mathrm{B}(\lambda_{i-1} + \lambda_{i+1}) + \mathrm{C}(\lambda_{i-1} + \lambda_i)}{2(\mathrm{A} + \mathrm{B} + \mathrm{C})} \tag{14}$$

where

$$\mathrm{A} = \frac{\text{Derivative reflectance}_{(i-1)}}{(\rho_{i-1} - \rho_i)(\rho_{i-1} - \rho_{i+1})} \tag{14a}$$

$$\mathrm{B} = \frac{\text{Derivative reflectance}_{(i)}}{(\rho_i - \rho_{i-1})(\rho_i - \rho_{i+1})} \tag{14b}$$

$$\mathrm{C} = \frac{\text{Derivative reflectance}_{(i+1)}}{(\rho_{i+1} - \rho_{i-1})(\rho_{i+1} - \rho_{i1})} \tag{14c}$$

In this method, central band (λ_i) should be close to the maximum first derivative reflectance. In rice, double peaks have been reported (Cho and Skidmore 2006; Tian et al. 2011) in the first derivative reflectance. The wavebands should be adjusted depending on plant conditions which would be problematic when this technology is brought into practical field use. In this study, plants which received general pre-plant application in producer's field showed that the maximum first derivative reflectance was around 730 nm. Therefore, $\rho_{i-1} = 710$ nm, $\rho_i = 730$ nm and $\rho_{i+1} = 750$ nm were selected to extract the REIP using the Lagrangian technique for this study.

Statistical analysis

Statistical analysis was performed using SAS 9.2. (SAS Institute 2009) and R (Comprehensive R Archive Network). The regression analysis model was built to identify the impact of water turbidity and depth on the reflectance using R at each wavelength with the following equations. For water turbidity, samples were categorized by plant coverage (25–50, 50–75, and 75–100 %) and statistical analyses were performed.

$$Y_i = b_0 + b_1X_1 + b_2X_2 \tag{15}$$

where b_1 = coefficient of water background; b_2 = coefficient of plant biomass; $X_1 = 0$ if water is clear, = 1 if water is turbid; X_2 = dry plant biomass kg ha^{-1}; Y_i = spectral reflectance at each wavelength

$$Y_i = b_0 + d_1W_1 + d_2W_2 \tag{16}$$

where d_1 = coefficient of water depth; d_2 = coefficient of plant biomass; W_1 = depth of water; W_2 = dry plant biomass kg ha^{-1}; Y_i = spectral reflectance at each wavelength

The analysis of variance (ANOVA) and analysis of covariance (ANCOVA) were performed with PROC MIXED procedure using SAS. Categorical variables, such as the effect of N rate and variety, are easily analyzed using ANOVA while regression analysis is applied when variables are quantitative or continuous. Since both analyses were performed under the concept of a least squares technique, it is valid to put both analyses into a single analysis, which is called ANCOVA. The ANCOVA can evaluate the effect of categorical variables on a linear relationship of quantitative variables. First, the effect of variety on the yield, biomass and plant coverage was determined using ANOVA. The effects of variety on the relationship between spectral indices and agronomic parameters at different growth stage were also investigated by ANCOVA with the following equation:

$$Y_i = b_0 + b_1 I + b_2 V + b_3 I^* V \tag{17}$$

where b_1 = coefficient of vegetation indices based on red-edge reflectance; b_2 = coefficient of variety; b_3 = coefficient of variety*vegetation indices; I = vegetation indices based on red-edge reflectance; $V = 0$ if variety is CL261, $V = 1$ if variety is CL152 Y_i = grain yield kg ha^{-1}

If Y-intercepts (b_2) are significantly different from zero, this indicates grain yield of variety CL152 is significantly different from CL261. If slopes (b_3) of the regression lines are significantly different, this indicates that the increase of yield per unit increase of vegetation is different between CL152 and CL261.

Results and discussions

The effect of water turbidity and depth on spectral reflectance

During the sampling period [PD, 1 week after PD (PD + 1 week), and 50 % heading (50 % HD)], canopy coverage from planted plots ranged from 35 to 100 % (Fig. 1). Majority of plots reached more than 50 % of plant coverage at PD (Table 2). Since supply-unfertilized plot had at least 25 % plant coverage at PD, the statistical analysis was performed for 25–50, 50–75 and 75–100 %. There was significant effect of water turbidity on the visible spectral reflectance, at plant coverage between 25 and 50 % (Fig. 2). Hoshi et al. (1984) also represented the different levels of spectral reflectance depending on water background (color), and it was evident at 600–750 nm. The effect of water turbidity can be an issue. However, from a practical point of view, most fields are treated with pre plant N. Therefore, there would be more than 50 % of the plant coverage during the sensing period. Once the plant covered 50 % of the area, the effect of water turbidity was not observed on the spectral reflectance. The graph in Fig. 3 shows the coefficient of water turbidity on the linear regression. Since the upper and lower 95 % confidence interval of the coefficient includes zero across all wavelengths, it can be concluded that water turbidity had no measurable effect on spectral reflectance measured from 400 to 900 nm. The study conducted by Vaesen et al. (2000) showed a similar result. Their study examined the effect of water turbidity only on vegetation indices, not on each wavelength; the relationship between the LAI and NDVI or RVI was not influenced by water turbidity. For the current study, the impact of water turbidity on spectral reflectance can only be substantial when canopy coverage is low and then becomes negligible when crop canopy goes beyond 50 %

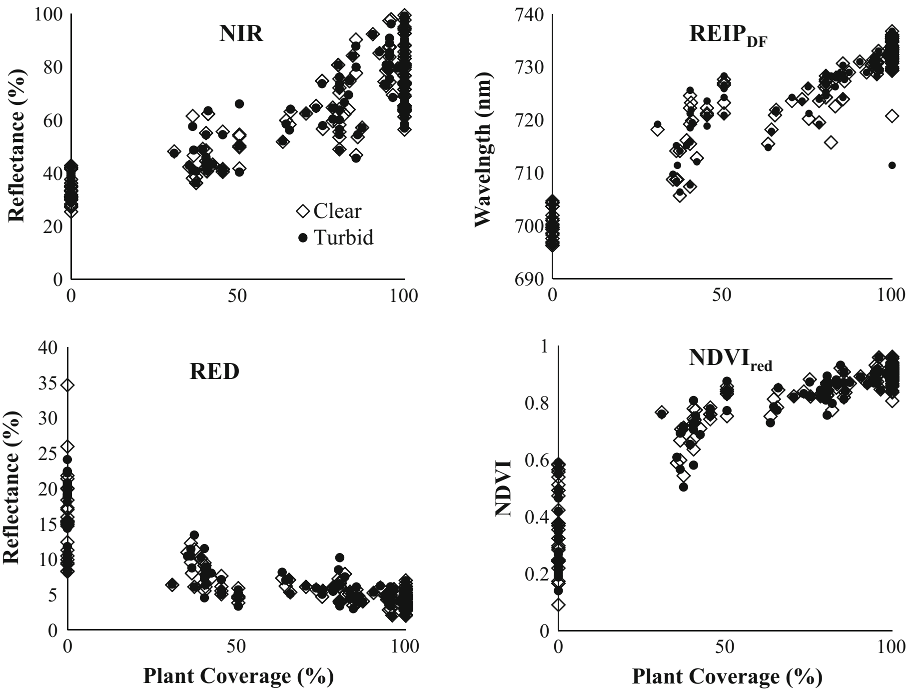

Fig. 1 Evaluation of near-infrared (NIR = ρ_{780}), red (RED = ρ_{670}) spectral reflectance, normalized difference vegetation index (NDVI), and red-edge position (REIP$_{DF}$) with increasing plant coverage based on polynomial technique under clear and turbid water background

coverage. No significant effect of water depth on the spectral reflectance was observed except at red wavelength (Fig. 4). Theoretically, an increase in water depth should decrease reflectance due to the increased radiant absorption in the water (Hoshi et al. 1984). However, the results from this study show otherwise. One of the potential reasons relies on the relationship between water depth and growth of algae and weeds. For both cropping years, growth of ducksalad (*Heteranthera limosa*) on the surface of water was evident at the research sites. According to Sen et al. (2002), water depth can affect the population or growth of certain weed species; an increase in water depth reduced weed growth. This further implies an increase in red reflectance since weed or algae interference increases absorbance of red light. Thus, even with the coefficients of NIR and green regions being not significant, this assumption can explain the slight negative coefficient values obtained from the linear regression. Since the population of algae or weeds was not determined, further research is required to understand this behavior of red reflectance associated with water depth. With this observation, regression between vegetation indices derived from the red reflectance and measured plant variables was performed for each sampling time using a statistical regression model with the following equation;

$$Y_i = b_0 + d_{11} W_1 + d_{22} W_2 \tag{18}$$

where d_{11} = coefficient of water depth; d_{22} = coefficient of plant biomass; W_1 = depth of water; W_2 = dry plant biomass kg ha^{-1}; Y_i = NDVI or RVI

According to the model, water depth had no significant effect on the NDVI ($p = 0.11$, 0.97 and 0.09 at PD, PD + 1 week and 50 % HD, respectively) and RVI ($p = 0.73$, 0.33

Table 2 Analysis of variance for the effect of variety and N rate on plant coverage (%) at panicle differentiation (PD), panicle differentiation + 1 week (PD + 1 week), and 50 % heading (50 % HD) in rice in Crowley, LA in 2011 and 2012

Treatment	2011				2012		
	Plant coverage (%)						
	PD		PD + 1 week	50 % HD	PD	PD + 1 week	50 % HD
Variety							
CL152	ξ†		81b	85a	83a	84a	86a
CL261	ξ		84a	83a	81a	82a	85a
Nitrogen rate kg ha^{-1}	CL261	CL152					
0	39d	39c	41c	44c	29c	32d	42
44	67c	76b	78b	78b	88b	76c	87b
88	84b	96a	95a	100a	93ab	95b	99a
132	93a	97a	100a	100a	99a	100a	100a
176	99a	100a	100a	100a	100a	100a	100a
Variety × N level	*		NS	NS	NS	NS	NS

NS no significant at $\alpha = 0.05$ level

* Significant at $\alpha = 0.05$ level

† Same letter within column indicate no significant differences between the treatment means based on the Tukey's post hoc analysis

ξ Significant at variety × N level; therefore means are listed by variety at each N rate

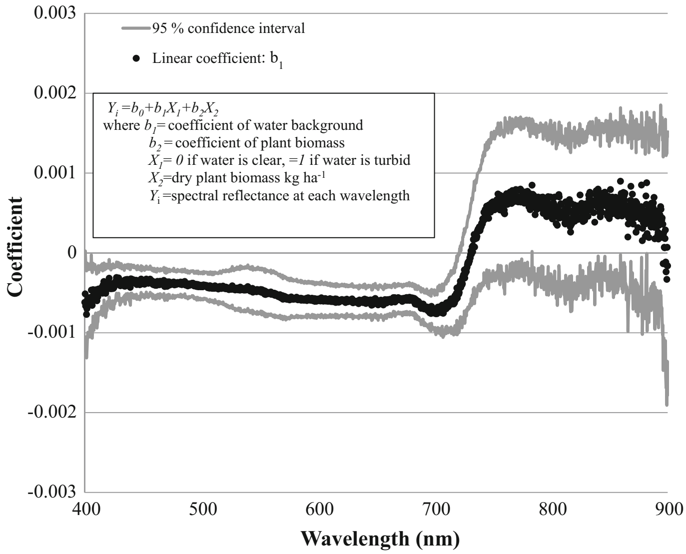

Fig. 2 Effect of water turbidity on the spectral reflectance from 400 to 900 nm at plant coverage between 25 and 50 %

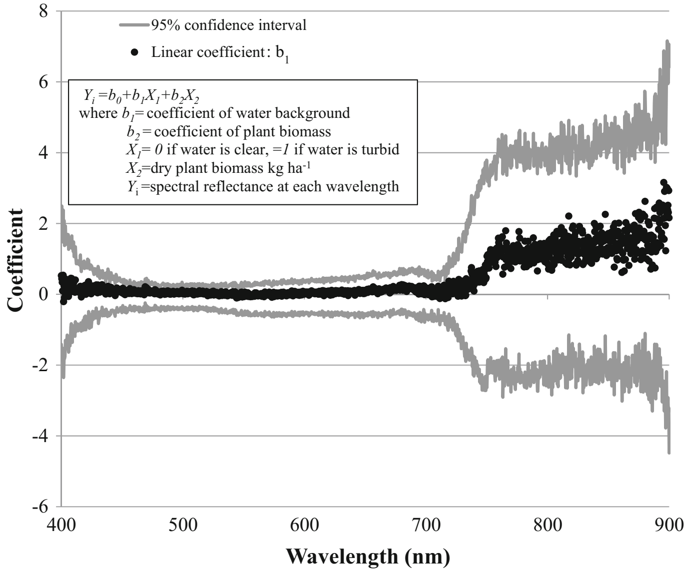

Fig. 3 Effect of water turbidity on the spectral reflectance from 400 to 900 nm at plant coverage between 50 and 75 %

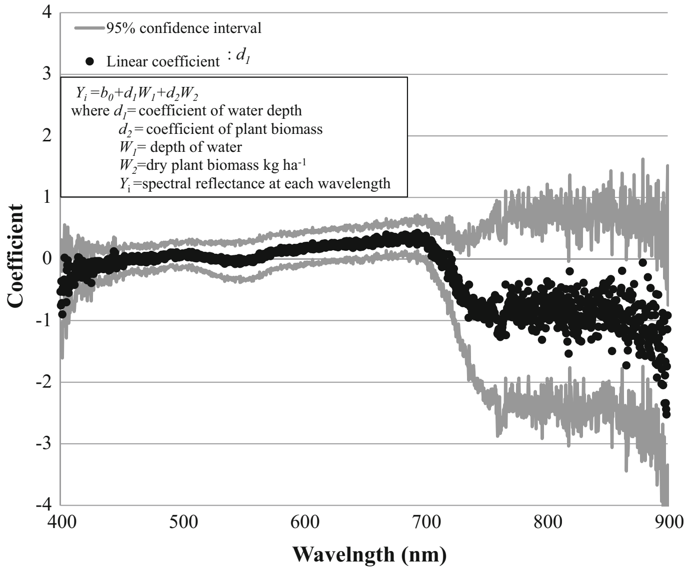

Fig. 4 Effect of water depth on the spectral reflectance from 400 to 900 nm

and 0.06 at PD, PD + 1 week and 50 % HD, respectively). This may have resulted from the relative small shifts of red reflectance as the plant biomass or coverage increased. As shown in Fig. 1, the change of red reflectance associated with plant coverage which ranged from 35 to 100 % was extremely small compared with NIR reflectance. This behavior of red reflectance is related to its saturation point at relatively low chlorophyll contents (Sims and Gamon 2002). Therefore, if the red band is used as a single red wavelength, the effect of water depth on the spectral reflectance would be significant. However, when expressed as a vegetation index in combination with other bands, the effect of water on the spectral reflectance can be negligible, especially at mature plant growth stages. Substantial plant coverage is achieved at PD, the growth stage where N fertilization is commonly done in the mid-southern United States rice production systems and the optimal time for sensing to estimate in-season yield and N response index according to Harrell et al. (2011) and Tubaña et al. (2011), respectively. From a practical stand point, the problem associated with water depth in rice at this growth stage is expected to be minimal.

The relationship between vegetation indices and agronomic parameters

There were significant differences on dry biomass, N uptake, plant coverage, and grain yield between the two varieties in 2011 but not in 2012 (Tables 2, 3, 4, and 5). The variety CL261 had higher biomass, N uptake and plant coverage at PD in 2011. The varietal differences on biomass as well as percent of plant coverage were significant at PD and PD + 1 week (Tables 2, 4). In terms of N uptake, the significant difference was only observed at PD (Table 5). The varietal effect on these agronomic parameters was more evident until PD + 50 % but not at 50 % HD. In 2012, blast disease caused by a fungal pathogen (*Pyricularia oryzae*) substantially decreased plant vigor which ultimately reduced biomass production and N uptake. This was especially true for CL261 which is classified as very susceptible to blast (Tables 4, 5). This reduction in mid-season biomass production potentially affected the grain yield resulting in a significant variety × N rate interaction effect on grain yield in 2012. Grain yields were decreased by about

Table 3 Analysis of variance for the effect of variety and N rate on rice grain yield in Crowley, LA in 2011 and 2012

Treatment	2011	2012	
	Grain yield kg ha^{-1}		
Variety			
CL152	8911b†	ξ	
CL261	9373a	ξ	
Nitrogen rate kg ha^{-1}		CL152	CL261
0	6404d	3611d	3851e
44	8111c	5832c	5114d
88	9747b	7354b	6727c
132	10380ab	8454a	7383b
176	11067a	8794a	8002a
Variety × N level	NS	**	

NS no significant at $\alpha = 0.05$ level

** Significant at $\alpha = 0.01$ level

† Same letter within column indicate no significant differences between the treatment means based on the Tukey's post hoc analysis

$^{\xi}$ Significant at Variety × N level; therefore means are listed by variety at each N rate

Table 4 Analysis of variance for the effect of variety and N rate on biomass at panicle differentiation (PD), panicle differentiation + 1 week (PD + 1 week), and 50 % heading (50 % HD) in rice in Crowley, LA in 2011 and 2012

Treatment	2011			2012		
	Biomass kg ha^{-1}					
	PD	PD + 1 week	50 % HD	PD	PD + 1 week	50 % HD
Variety						
CL152	3743b	5024b	10837a	3181a	3565a	3284a
CL261	4913a	6574a	12090a	3350a	3671a	3181a
Nitrogen rate kg ha^{-1}						
0	2345c	3233b	6605c	1315d	1727c	1312d
44	3850b	4892b	10486bc	2445c	3335b	2445c
88	4853ab	7137a	12863ab	3453b	4000ab	3453bc
132	5007a	6813a	12886ab	4148ab	4421a	4148ab
176	5586a	6921a	14476a	4968a	4609a	4804a
Variety × N level	NS	NS	NS	NS	NS	NS

NS no significant at α = 0.05 level

† Same letter within column indicate no significant differences between the treatment means based on the Tukey's post hoc analysis

Table 5 Analysis of variance for the effect of variety and N rate on N uptake (kg ha^{-1}) at panicle differentiation (PD), panicle differentiation + 1 week (PD + 1 week), and 50 % heading (50 % HD) in rice in Crowley, LA in 2011 and 2012

Treatment	2011				2012		
	N uptake kg ha^{-1}						
	PD		PD + 1 week	50 % HD	PD	PD + 1 week	50 %HD
Variety							
CL152	ξ†		91a	176a	76a	72a	53a
CL261	ξ		107a	189a	79a	73a	54a
Nitrogen rate kg ha^{-1}	CL261	CL152					
0	29c	33c	40b	78c	18d	22c	13d
44	50c	63bc	65b	138bc	43 cd	50bc	29d
88	92b	87b	116a	191ab	74bc	80ab	52c
132	96ab	132a	126a	238a	117ab	94a	73b
176	118a	160a	148a	269a	135a	116a	100a
Variety × N level	*		NS	NS	NS	NS	NS

NS No significant at α = 0.05 level

* Significant at α = 0.05 level

† Same letter within column indicate no significant differences between the treatment means based on the Tukey's post hoc analysis

ξ Significant at variety × N level; therefore means are listed by variety at each N rate

Table 6 The coefficient of correlation (r) between vegetation indices and each agronomic variable at panicle differentiation (PD), panicle differentiation +1 week (PD + 1 week), and 50 % heading (50 % HD)

Vegetation index	PD	PD + 1 week	50 % HD	PD	PD + 1 week	50 % HD
	Biomass			N uptake		
RVI	0.72	0.77	0.66	0.56	0.76	0.75
NDVI	0.79	0.76	0.61	0.67	0.75	0.64
RERVI	0.84	0.83	0.70	0.83	0.84	0.75
NDRE	0.84	0.79	0.64	0.83	0.84	0.73
RERDVI	0.85	0.82	0.52	0.80	0.84	0.65
REDVI	0.84	0.85	0.53	0.74	0.82	0.66
RESAVI	0.81	0.69	0.59	0.83	0.81	0.63
REOSAVI	0.76	0.76	0.57	0.68	0.75	0.57
REWDRVI	0.81	0.69	0.59	0.83	0.82	0.63
CI_{RE}	0.81	0.69	0.59	0.83	0.82	0.63
$REIP_{DF}$	0.75	0.69	0.57	0.78	0.76	0.62
$REIP_{LI}$	0.81	0.69	0.61	0.85	0.82	0.72
$REIP_{LAG}$	0.44	0.29	0.39	0.45	0.32	0.41
$REIP_{LE}$	0.75	0.76	0.58	0.75	0.84	0.62
	Plant coverage			Yield		
RVI	0.48	0.67	0.65	0.72	0.83	0.83
NDVI	0.76	0.87	0.81	0.82	0.86	0.84
RERVI	0.77	0.84	0.76	0.82	0.85	0.89
NDRE	0.83	0.88	0.78	0.85	0.88	0.90
RERDVI	0.71	0.80	0.82	0.88	0.86	0.81
REDVI	0.64	0.73	0.81	0.89	0.87	0.81
RESAVI	0.77	0.84	0.81	0.78	0.76	0.81
REOSAVI	0.72	0.88	0.92	0.85	0.84	0.79
REWDRVI	0.76	0.83	0.79	0.78	0.75	0.80
CI_{RE}	0.75	0.82	0.79	0.78	0.75	0.80
$REIP_{DF}$	0.91	0.94	0.81	0.71	0.81	0.85
$REIP_{LI}$	0.82	0.86	0.74	0.78	0.78	0.84
$REIP_{LAG}$	0.55	0.46	0.63	0.43	0.38	0.62
$REIP_{LE}$	0.78	0.92	0.73	0.72	0.88	0.85

3000 kg ha^{-1} for each N rate in 2012 (Table 3). A high yield level associated with high biomass at mid-season supports the sensing-based concept of estimating above ground biomass at mid-season to predict yield. However, in addition to this fact, Harrell et al. (2011) discussed the implementation of additional elements in predicting yield since biomass is not the only parameter which always carried over at harvest and influenced production level of grain yield. For example, they mentioned the risk of decrease in yield due to lodging and disease infection with increasing biomass production.

The red-edge-based vegetation indices had a stronger degree of linear relationship with biomass, N uptake, and grain yield compared with red-based indices (Table 6; Fig. 5). At PD, the *r* values of the linear relationships of biomass was 0.72 and 0.79 for the RVI and NDVI while it improved to 0.84 and 0.84 using the RERVI and NDRE, respectively. Along

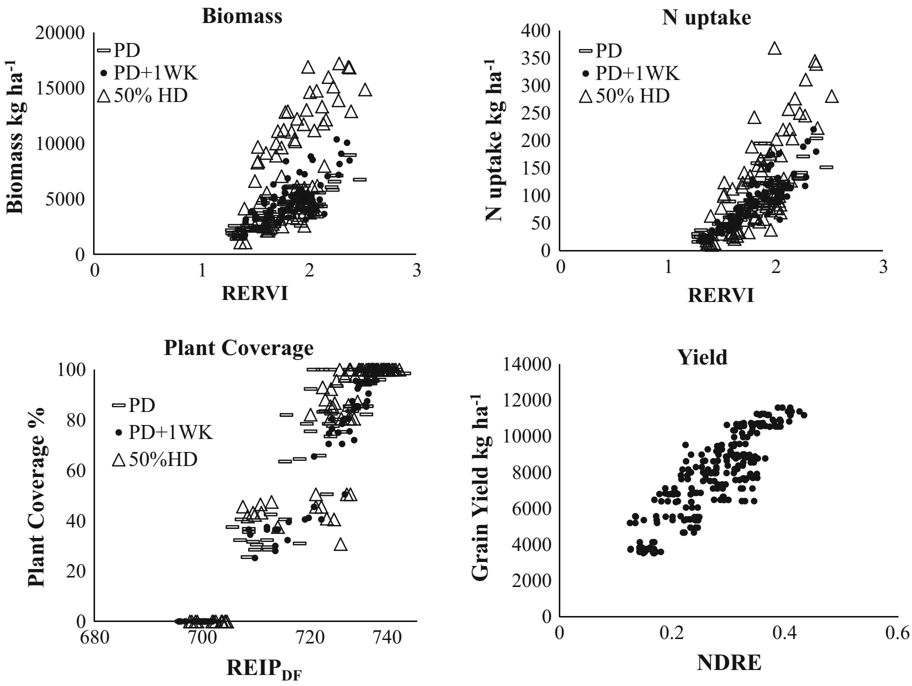

Fig. 5 Relationship between agronomic parameters and red-edge-based vegetation indices

with these two vegetation indices, the REDVI also yielded constant high *r* values across the sampling period. With regards to biomass, the degree of improvement using red-edge-based indices declined as the rice grew. The improvement of linear relationship with N uptake or grain yield using red-edge-based indices was more evident. Across sampling periods, about 50 % of total variability in N uptake was explained by red-based vegetation indices such as the NDVI and RVI while red-edge-based vegetation indices explained about 69 % of total variability in N uptake (Table 6). Similar results were observed between vegetation indices and grain yield. Red-based spectral indices can explain 49–72 % of total variability in grain yield while the range improved from 64 to 81 % using red-edge-based vegetation indices. The relationships between the RERVI and measured parameters (biomass, N uptake and grain yield) resulted in the most frequent number of high *r* values across sampling periods.

The red-edge position reflectance readings ($REIP_{DF}$, $REIP_{LI}$, $REIP_{LAG}$ and $REIP_{LE}$) computed from derivative analysis were also closely related to those agronomic parameters. The advantage of red-edge reflectance has been reported in many studies (Cho et al. 2008; Curran et al. 1990; Mutanga and Skidmore 2004). One of its advantages over red-based indices, such as the NDVI, is an increased sensitivity in detecting plant physiological status at high plant biomass or coverage. This is due to its position being between the bands where strong absorption of light by plant pigments and high leaf reflection occur. The poor estimation using the NDVI is associated with the absorption of red light approaching saturation at full plant canopy coverage (Sims and Gamon 2002; Thenkabail et al. 2000). As shown in Fig. 6, the NDVI reached plateau at lower biomass level (4142 kg ha^{-1}) when compared with the REIP (6057 kg ha^{-1}) based on nonlinear regression analysis. This

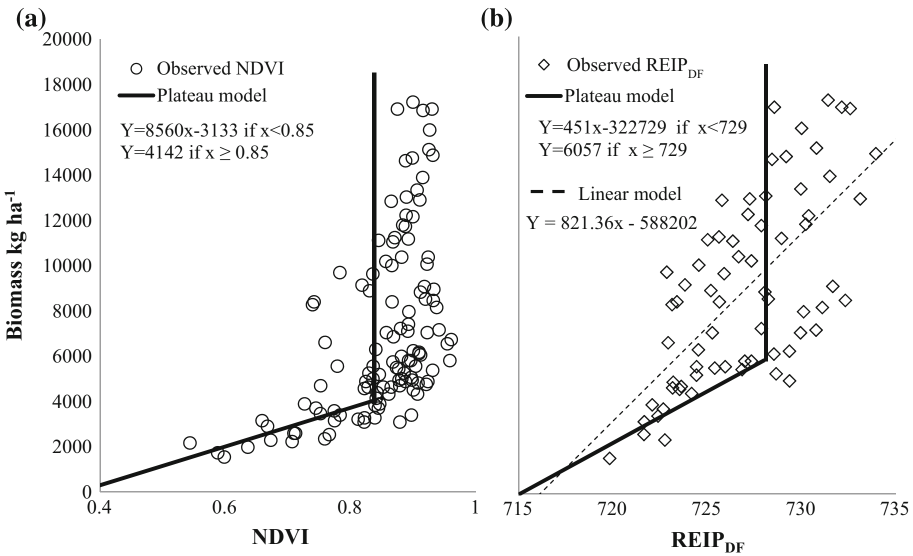

Fig. 6 Comparison of the relationship of biomass with (**a**) normalized difference vegetation index (NDVI) and (**b**) red-edge position ($REIP_{DF}$) using polynomial fitting technique

indicates that the amount of biomass beyond 4142 kg ha^{-1} is not a function of the NDVI. On the other hand, red-edge-based indices remained a function (quadratic) of biomass even when biomass weighed more than 6000 kg ha^{-1} and fitted in a linear regression model. This result demonstrated the improvement in estimating plant physiological conditions using red-edge position waveband at mid-season in rice.

Based on previous studies (Pu et al. 2003; Cho et al. 2008), derivative-based red-edge indices were reported to be more sensitive to changes on both leaf chlorophyll content and the LAI at dense plant canopy or biomass. This higher sensitivity can be attributed to derivative analysis which can magnify signal properties at an absorption region and also changes of scattering properties at longer wavelengths (Boochs et al. 1990). In the present study, the degree of REIPs reflectance relationships with biomass varied across sampling times. For example, the low r values in the $REIP_{LAG}$ at PD show several outliers which are potentially associated with the complex computation of the REIP with the use of multiple wavebands. Several studies also noted the relatively higher complexity of computing the $REIP_{LAG}$ compared with the $REIP_{DF}$, $REIP_{LI}$ or $REIP_{LEP}$ (Cho and Skidmore 2006; Shafri et al. 2006). One of the reasons for the difficult computation of the $REIP_{LAG}$ is that this technique is not suitable if the spectral band used is not continuous. In addition, formulation and computation is relatively complicated compared with other techniques. Shafri et al. (2006) mentioned that the REIP based on the Lagrangian technique had a weaker relationship with the LAI which agreed with the results of this study i.e. it had the lowest r values with agronomic parameters. Curran et al. (1990) summarized the importance of holding right assumptions, such as illumination levels should be independent from REIP and most of measured radiation by the sensor should be reflected from plant leaf, when REIPs were measured. Under dynamic environmental systems, those assumptions might be violated and eventually affect the readings at the REIPs. Overall, the first derivative-based REIP had potential to estimate agronomic parameters in rice but in terms of practical application in the field, such as requiring continuous wavebands, further investigation is required to establish the feasibility of this technique in large production fields.

The red-edge vegetation indices expressed in normalized and ratio forms such as RERVI and NDRE, had no derivative analysis involved, and yielded constant r values across sampling periods (Table 6). In addition to reducing background variation, the feasibility in data comparison due to the standardization is the advantage in using the normalized or ratio-based vegetation indices (Daughtry et al. 2000; Malingreau 1989). Unlike the REIP computation which involves continuous or multiple wavebands, the RERVI and NDRE simply require only two wavebands. With respect to the fact that applying remote sensing technology in nutrient management is still considered cost-inhibitive, the use of fewer bands would facilitate in developing affordable remote sensing systems for crop production.

The effect of rice variety on the relationship between yield and red-edge reflectance

The coefficient table for linear regression to determine the effect of variety on the relationship between red-edge-based spectral indices and grain yields are summarized in Table 7. Differences in variety were more evident when grain yield was related to red-edge normalized or ratio-based vegetation indices. For example, the suggested linear models for yield using the RERVI at PD were

$$Predicted\ grain\ yield = -5712 + 8055^{*}SR_{red-edge} \quad \text{for variety CL152} \tag{19}$$

$$Predicted\ grain\ yield = -3092 + 6005^{*}SR_{red-edge} \quad \text{for variety CL261} \tag{20}$$

This formula indicates that the 0.1 unit increase of the RERVI corresponds to a grain yield increase of 806 kg ha^{-1} in variety CL152 but 600 kg ha^{-1} in variety CL261. Also, when the RERVI is assumed to be one, the base line of grain yield is 2324 kg ha^{-1} for variety CL152 and 2913 kg ha^{-1} for variety CL261. It implies that the corresponding increase in grain yield by one unit increase in the RERVI would be different depending on variety. This interpretation can apply not only at PD but across sampling periods when a linear model of grain yield is established using the RERVI. This result then raised a question on what spectral resolution should be used in predicting grain yield. When the detection limit of the RERVI is assumed to be 0.1 then the minimum unit that the RERVI can differentiate grain yield is 806 kg ha^{-1} for CL152 and 600 kg ha^{-1} for CL261. One unit increase of the RERVI corresponds to a large range of yield increase in variety CL152; therefore, the higher resolution of spectral reflectance would be required compared with variety CL261 in terms of estimating certain unit increase in grain yield. For example, to detect a 1000 kg ha^{-1} difference in grain yield, the RERVI needs to show at least 0.1 differences for variety CL152 but 0.2 for variety CL261. This difference in the resolution of spectral reflectance is small but addressing this difference between varieties by having separate models would pose complexities when remote sensing technology is carried over to practical application. Accounting for the varietal effect when establishing the linear grain yield model using the RERVI improved the R^2 value from 0.67 to 0.73, 0.72 to 0.74, and 0.79 to 0.83 compared with the simple regression model at PD, PD + 1 week, and 50 % HD, respectively. This result showed that the effect of variety on the relationship between the RERVI and grain yield changed with plant growth. The addition of individual variety parameters, such as biomass, height and plant coverage as a predictive parameter improved the model so that 5 % more in total variation in grain yield was explained.

Table 7 The coefficient table for linear regression to determine the effect of variety on the relationship between red-edge-based spectral indices and grain yields at panicle differentiation (PD), panicle differentiation +1 week (PD + 1 week), and 50 % heading (50 % HD) in Crowley LA, in 2011 and 2012

Indices	Growth stage	R2	Coefficients			
			B0	B1	B2	B3
RERVI	PD	0.73	−3092	6005	−2620	2050
	PD + 1 week	0.74	−5310	608	7154	–
	50 % HD	0.83	−4238	6432	−3058	1999
NDRE	PD	0.73	596	25,639	890	–
	PD + 1 week	0.76	−117	27,617	573	–
	50 % HD	0.82	−648	28,587	508	–
RERDVI	PD	0.83	2362	3207	−432	839
	PD + 1 week	0.77	2621	2898	−894	863
	50 % HD	0.66	1996	3417	–	–
REDVI	PD	0.84	3698	229	−428	76
	PD + 1 week	0.79	3876	195	−842	73
	50 % HD	0.65	3025	276	–	–
RESAVI	PD	0.66	231	30,904	924	–
	PD + 1 week	0.59	922	28,310	589	–
	50 % HD	0.67	−37	30,015	621	–
REOSAVI	PD	0.74	−242,182	218,025	597	–
	PD + 1 week	0.71	−317,387	283,356	–	–
	50 % HD	0.63	−345,374	307,816	–	–
REWDRVI	PD	0.65	73,450	92,101	942	–
	PD + 1 week	0.56	66,707	82,148	–	–
	50 % HD	0.66	69,882	87,786	641	–
CIRE	PD	0.66	2166	14,120	−1095	5606
	PD + 1 week	0.58	1915	14,895	612	–
	50 % HD	0.66	1178	15,366	647	–
$REIP_{DF}$	PD	0.45	−124,104	182	–	–
	PD + 1 week	0.64	−175,646	252	–	–
	50 % HD	0.72	−185,746	266	–	–
$REIP_{LI}$	PD	0.63	−401,254	798	563	–
	PD + 1 week	0.6	−394,877	544	–	–
	50 % HD	0.71	−371,885	522	–	–
$REIP_{LG}$	PD	0.18	−54,026	84.9	–	–
	PD + 1 week	0.15	−23,469	43	–	–
	50 % HD	0.38	−83,653	125	–	–

Table 7 continued

Indices	Growth stage	R2	Coefficients			
			B0	B1	B2	B3
$REIP_{LE}$	PD	0.52	−100,169	149	–	–
	PD + 1 week	0.78	−149,918	216	–	–
	50 % HD	0.72	−137,077	199	–	–

* $Yi = b0 + b1I + b2\ V + b3\ I*V$

where b1 = coefficient of vegetation indices based on red-edge reflectance

b2 = coefficient of variety

b3 = coefficient of variety*vegetation indices

I = vegetation indices based on red-edge reflectance

V = 0 if variety is CL261, =1 if variety is CL152

Yi = grain yield kg ha^{-1}

− effect (I, V or I*V) is not significant at $\alpha = 0.05$ level

Although there was a significant effect of variety on the linear grain yield model using the RERVI, the improvement in the relationship with yield was not evident. Therefore, one simple model can be sufficient to relate yield based on the RERVI.

When the NDRE, RESAVI, REOSAVI and REWDRVI were used, there were no effects of I*V indicating that there were no corresponding different relationships with grain yield per unit increase of those indices between varieties (Table 7). However, there were still notable effects of variety on the model by having different intercept values. As shown in Table 7, when grain yield was regressed by the REIPs coefficients, b_2 and b_3, were not significant. This indicates that there was no effect of variety or interaction of variety and vegetation index on the yield regression model. Red-edge position has been reported to be less sensitive to the changes of canopy structure, plant coverage, and leaf properties (Guyot et al. 1992; Curran et al. 1995; Pu et al. 2003) which more likely result from different varieties or species. Therefore, contrary to normalized or ratio-based indices, all REIP indices which were defined as the point of red-edge waveband, did not require the separation of the regressed model for two rice varieties. More complex computation is required for the REIP indices. However, this result that varietal influence is minimized in the grain prediction model may be after all advantageous since the prediction model does not require calibration across varieties. This will be an important key to adopting technology when many varieties exist in production fields.

The influence of variety on the relationship between grain yield and spectral reflectance readings and their vegetation indices can be explained by the inherent differences in physical and physiological attributes among varieties. Generally, reflectance at the NIR band is associated with the plant geometrical structures as well as internal biophysical structure rather than pigment composition, while reflectance within the visible wavelength, especially red and blue, is highly related to absorption of two major pigments, chlorophyll *a* and *b*. Reflectance at the REIP was reported to be a good indicator of biomass, N content, and chlorophyll content (Cho et al. 2008; Elvidge and Chen 1995; Van der Meer and De Jong 2006). Jackson and Pinter (1986) observed differences between planophile (non-erect) and erectrophile (erect) canopies in wheat and Galvão (2005) also reported the varietal effect on infrared spectral reflectance in sugarcane. Based on their study, distinct differences were observed in the green (550 nm) and NIR (800 nm$\sim$) bands. Therefore, in this study, the distinct differences of biomass accumulation in varieties affected the reflectance reading in the NIR region and then carried-over to vegetation indices computation using simple or normalized ratio; this was not the case for the REIP. It is important to note as well that the regression lines describing the relationship of the RERVI, RERDVI, and REDVI with grain yield for each variety had different slopes but not when NDRE, RESAVI, REOSAVI, and REWDRVI were used as predictors. This difference can be explained by analyzing the mathematical expression of these two forms of vegetation indices. The weighted impact of NIR and red-edge reflectance readings is eliminated when expressed in normalized form (as in the NDVI). This explains why the distribution of the NDVI readings was narrow even if there was a wider range in reflectance readings for NIR than for the REIP. Unlike the NDVI, RERVI is simply a ratio which utilized reflectance readings within the NIR and red-edge position without normalizing the values. This tends to bring wide distribution of RERVI values. Even though RERDVI is not an RERVI form, the square root properties of the denominator may enhance the difference of NIR and red bands on the numerator and minimize the effect of normalization. The distinct behavior of these two vegetation indices has been reported in several studies (Chang et al. 2005; Tubaña et al. 2011).

Conclusions

Water background (turbid or clear) did not significantly alter spectral reflectance at PD, PD + 1 week, and 50 % HD once plant coverage exceeded 50 %. Water depth slightly influenced the behavior of red reflectance but this effect was not carried over when vegetation indices, RVI or NDVI were computed. The red-edge-based vegetation indices had a stronger degree of linear relationship with measured agronomic parameters as compared with red-based indices. Vegetation indices expressed in normalized or ratio forms computed from derivative spectral analysis ($REIP_{DF}$, $REIP_{LI}$, $REIP_{LAG}$ and $REIP_{LE}$), resulted in consistent r values across sampling periods. The effect of variety on the accuracy of the yield prediction model varied depending on the transformation of reflectance within the red-edge and NIR bands i.e., into normalized (NDVI) and ratio forms of vegetation indices. This result was associated with the behavior of NIR wavebands on the geometrical structure of the plant canopy. There were no significant effects of variety on grain yield regression models using derivative-based red-edge indices. The findings from this study showed that rice grain yield may be more accurately predicted using red-edge-based normalized and ratio indices than red-based normalized and ratio indices. Further studies should focus on developing a generalized model using these vegetation indices across different varieties.

Acknowledgments This study was supported in part by the Louisiana Rice Research Board.

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