Extracting Red Edge Position Parameters from Ground- and Space-Based Hyperspectral Data for Estimation of Canopy Leaf Nitrogen Concentration in Rice

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Abstract: To realize non-destructive and real-time monitoring of crop nitrogen status for precision management in rice fertilization, we characterized the reflectance spectra in the red edge area from ground- and space-based data, and quantified the relationships between the red edge position (REP) derived from different algorithms and canopy leaf nitrogen concentrations (LNC) at various nitrogen rates in four seasons in various cultivars of field-grown rice (Oryza sativa L.). The results showed that the spectrum in the red edge area was significantly affected by the nitrogen level and cultivar type, and “three-peak” feature could be observed in the first derivative spectrum in this area. Traditional REP (maximum value of the first derivative spectra in red-edge region) was not sensitive to canopy LNC because of the three-peak property, but the REPs based on inverted Gaussian fitting, linear four-point interpolation, linear extrapolation and adjusted linear extrapolation generated continuous REP values, and could be used for estimating canopy LNC. REP from a three-point Lagrangian interpolation with three first-derivative bands (690 nm, 700 nm and 705 nm) had a good relationship with canopy LNC. Among the six REP approaches, REP based on adjusted linear extrapolation algorithm was found to have the best relations with canopy LNCs in Hyperion image data. Comparison of the different REPs with both ground-based and space-borne hyperspectral data indicated that the adjusted linear extrapolation method (755FD_730 + 675FD_700) / (FD_730 + FD_700) proposed here gave the best prediction of canopy LNC. This simple and reliable REP approach to monitoring canopy LNC in rice requires further verification with other hyperspectral sensors and crop types.

Key words: Adjusted linear extrapolation, Ground-based remote sensing, Leaf N concentration, Red edge position, Rice canopy, Space-borne remote sensing.

Nitrogen (N) is the most important nutrient element affecting growth and yield in agronomic crops. Luxurious N supply is a major cause for farmland pollution, while nitrogen deficiency cannot assure high crop yield and excellent quality. Thus scientific and effective N fertilization has become important agricultural practice in crop production management (Woodard & Bly, 1998). The key step in realization of precision N management is to determine the proper amount of N topdressing based on growth performance and plant N status (Welsh et al., 2003). This would rely on accurate and fast monitoring of crop N status during crop production.

With the rapid development of remote sensing (RS) techniques, non-destructive growth monitoring has been explored for estimation of biophysical, biochemical and physiological parameters such as N, photosynthetic efficiency and capacity (Takebe et al., 1990; Inoue et al., 2008) in crop plants. Many scholars have proved that plant nitrogen levels could be evaluated by reflectance spectra in visible and near infrared regions measured at leaf or canopy scale (Takebe et al., 1990; Blackmer et al., 1996; Xue et al., 2004). The position of the red-edge is defined as the position of the main inflection point of the red-NIR slope (670−780 nm), which is also denoted as the red-edge position (REP) and can be used for studying the chlorophyll or N concentration as a measure of plant growth status (Horler et al., 1983; Bonham-Carter, 1988). Since an increase in chlorophyll concentration results in a shift of REP towards longer wavelengths (Gates et al., 1965), and as compared with vegetation indices, red edge parameters are relatively insensitive to changes of biophysical factors, such as soil cover percentage and optical properties (Horler et al., 1983), REP is usually referred to as a good red-edge parameter for indicating...
chlorophyll concentration and biochemical content (Filella & Peñuelas, 1994; Mutanga & Skidmore, 2007). Both chlorophyll concentration and chlorophyll density in rice, wheat and corn crops have been shown to correlate strongly with derivative spectra and REP at leaf and canopy levels (Wu et al., 2000), while quantitative relationships between classical REP and chlorophyll content have also been evaluated in ten different trees (Collins, 1978).

However, the maximum first derivatives of continuous spectra occur within two principal spectral regions, around 700 nm with low chlorophyll concentration and 725 nm with high chlorophyll concentration, causing a bimodal distribution of REP data around 700 and 725 nm and a discontinuity in the REP/chlorophyll relationship (Horler et al., 1983; Boochs et al., 1990; Cho & Skidmore, 2006). Several other studies have revealed the existence of this double-peak feature in the first derivative of continuous spectra with different plants. Boochs et al. (1990) found the peak at 703 and 735 nm; Smith et al. (2004) identified two peaks in canopy spectra of grass near 702 and 725 nm; Clevers et al. (2004) observed two peaks near 700 and 720 nm; Zarco-Tejada et al. (2003) characterized the double-peak feature at 690 and 750 nm in Acer negundo ssp. Californium canopies. In order to mitigate the discontinuity in REP data caused by the double-peak feature, some model-fitting techniques were developed to generate continuous REP from the reflectance spectrum data. For instance, REP could be extracted from the inverted Gaussian (IG) function (Bonham-Carter, 1988), with a good relationship with the plant chlorophyll status (Miller et al., 1990). Guyot et al. (1992) defined a simple linear four-point interpolation method. Dawson and Curran (1998) proposed a three-point Lagrangian interpolation approach. Moreover, Cho and Skidmore (2006) defined the linear extrapolation method for extracting the REP from the first derivative spectrum of four coordinate wavebands, for instance, two bands near 680 and 700 nm and two bands near 725 and 760 nm. These techniques have been proved to perform well in monitoring nitrogen, pigment and leaf area indices of several plant types (Cho & Skidmore, 2006; Nguyen & Lee, 2006; Darvishzadeh et al., 2008). However, the four-point approach is a practical and suitable method for extracting REP from spectra data because only four bands and a simple interpolation computation are needed; the Lagrangian and IG approach method is applicable only if the first derivative spectra are available (Pu et al., 2003); REP extracted by the linear extrapolation method has higher correlation with leaf chlorophyll content with minimal effects of canopy biophysical confounders such as leaf area index (LAI) compared to traditional techniques, and a good applicability to various crops, since it does not need to arbitrarily fix the wavelength values for the calculation of REP, except the drawback that it uses spectral values of four first derivative wavebands, which is complicately identified (Cho et al., 2008). Whether these approaches can be applied to quantitative estimation of canopy leaf nitrogen concentration in rice crop remains to be further elucidated, although Evi et al. (2008) extracted REPs by the inverted Gaussian and linear extrapolation methods for prediction of LNC and plant chlorophyll index in rice.

The recent availability of the data from Airborne Imaging Spectrometer (AIS), Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), Hyperion and so on, has facilitated the identification of some biophysical features such as crop nitrogen status using red edge parameters from the large space scales. Some scholars reported obvious correlations between biochemical compositions including N and chlorophyll concentrations in the forest canopy and first-difference-at sensor radiance measured by the AIS (Sripada et al., 2005). AVIRIS spectra have been used to estimate N concentrations in mixed-species forest canopies (Johnson et al., 1994; Martin & Aber, 1997) and single-species canopies (Curran et al., 1997) with first difference reflectance data and regression techniques. Airborne multispectral data acquired by the Compact Airborne Spectral Imager (CASI) were also successfully applied to evaluating the potential and efficiency of forest canopy N concentration with spectral derivative technique (Pu and Gong, 1997). Boegh et al. (2002) also reported that REPs on the basis of CASI had significant linear correlations with plant nitrogen concentrations in eight different crops including winter wheat, winter barley and so on. Other investigators reported that Eucalypt leaf N concentration (Coops et al., 2003) and forest canopy N concentration in temperate zone (Smith et al., 2003) could be estimated by Hyperion data. Yet information is limited for estimating the biochemical composition in field crops using space-borne hyperspectral data.

In the present paper, we (1) extracted the REP parameters of rice canopy from ground- and space-based hyperspectral data; (2) quantified the relationships between REPs and canopy LNC at different N levels; and (3) tested the performance of different REP algorithms using ground-based and space-borne hyperspectral data in rice. The results will be useful in establishing the optimal REP fitting technique for LNC monitoring in rice crop both on the ground and in space.

### Materials and Methods

#### 1. Experiment design

The data used in the present study were obtained from five field experiments involving different rice (*Oryza sativa* L.) cultivars, N rates, sites and years, as summarized in Table 1. A detailed description of the experiment design is provided as follows.

Experiment 1 was conducted at the experiment station of Jiangsu Academy of Agricultural Science (118°52′ E,
transplanted on 19 June with a density of 512.8×10^3 plants ha⁻¹. The experiment was a complete block design with three replications and 18 m² area for each plot. For all treatments, monocalcium phosphate (Ca(H₂PO₄)₂) and 190 kg ha⁻¹ K₂O (as KCl) were applied prior to transplanting. The fertilizer. For all treatments, 135 kg ha⁻¹ P₂O₅ (as monocalcium phosphate [Ca(H₂PO₄)₂]) and 190 kg ha⁻¹ K₂O (as KCl) were applied prior to transplanting. The experiment was a randomized complete block design with three replications. Other management procedures were according to the local standard practices for rice production. The data from experiment 2 were used for model calibration.

Experiment 3 was conducted in 2006 with the same cultivars and location as in experiment 2. Two cultivars were planted on 18 May and transplanted on 18 June with the row and plant spacing of 25 cm × 15 cm, and the plot size was 25 m² areas with 5 m long and 5 m wide. N was applied at 0, 90, 240 and 360 kg N ha⁻¹ as urea, and N dressing ratio and combined application of phosphate and potassium fertilizers were the same as in experiment 2. The experiment was a randomized complete block design with three replicates. The data from experiment 3 was used for model validation.

Experiment 4 was conducted on the Fangqiang Farm in Dafeng City (120°28' E, 33°31' N) of Jiangsu Province during the 2006 rice season. The primary soil type was salinized fluvo-aquic soil which contains 16.4 g kg⁻¹ organic matter, 1.70 g kg⁻¹ total N, 14.03 mg kg⁻¹ available phosphate, 118.78 mg g kg⁻¹ available potassium (0–25 cm soil depth). Three japonica rice cultivars Wuxiangjing 9, Nipponbare and Huajing 2 were planted on 16 May, and transplanted on 19 June with a density of 512.8×10^3 plants ha⁻¹. N fertilizer was applied at 0, 90, 210, and 315 kg N ha⁻¹, with three splits (60% at pre-planting, 20% at elongation, and 20% at booting). The experiment was a two-way factorial arrangement of treatments within the randomized complete block design with three replications and 18 m² area for each plot. For all treatments, monocalcium phosphate and potassium chloride were applied at basal dose of 135 kg P₂O₅ ha⁻¹ and 210 kg K₂O ha⁻¹, respectively. We followed the local standard practice of chemical control for management of diseases, pests and weeds. The data from experiment 1 were used for model validation.

Experiment 2 was conducted at the experiment station of Nanjing Agricultural Bureau in 2005 (118°59' E, 31°56' N). Two japonica rice cultivars, Wuxiangjing 14 and 27123, were planted on 18 May and transplanted on 18 June with the row and plant spacing of 25 cm × 15 cm, and the plot size was 31.5 m² area with 9 m long and 3.5 m wide. N was applied at 0, 90, 270 and 405 kg N ha⁻¹ as urea, N fertilizer was applied at pre-planting, 15% as tillering fertilizer, 25% as spikelet-promoting fertilizer, and 25% as spikelet-ensuring fertilizer. For all treatments, 135 kg ha⁻¹ P₂O₅, 190 kg ha⁻¹ K₂O (as monocalcium phosphate [Ca(H₂PO₄)₂]) and 190 kg ha⁻¹ K₂O (as KCl) were applied prior to transplanting. The experiment was a randomized complete block design with three replications. Other management procedures were according to the local standard practices for rice production. The data from experiment 2 were used for model calibration.

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Experiment 4 was conducted on the Fangqiang Farm in Dafeng City (120°28' E, 33°31' N) of Jiangsu Province during the 2006 rice season. The primary soil type was salinized fluvo-aquic soil which contains 16.4 g kg⁻¹ organic matter, 1.10 g kg⁻¹ total N, 9.05 mg kg⁻¹ available phosphate, 90.78 mg g kg⁻¹ available potassium (0–20 cm soil depth). The japonica rice cultivar Yanjing 9967 was planted on 12 May, and transplanted on 16 June at a density of 512.8×10^3 plants ha⁻¹. N was applied at 0, 90, 240 and 360 kg N ha⁻¹ as urea, and N dressing ratio and combined application of phosphate and potassium fertilizers were the same as in experiment 2. The experiment was a randomized complete block design with 4 replications and plot size of 90×90 m². P and K were applied at a basal dose of 150 kg P₂O₅ ha⁻¹ and 200 kg K₂O ha⁻¹, respectively. Other field management practices followed local rice production practices. The data from experiment 4 were used for model validation.

Experiment 5 was also conducted on the Fangqiang Farm, but the fields were different from those in experiment 4, during the 2007 rice season. The soil properties and plot size were the same as in experiment 4. The japonica rice cultivar Yangfujing 8 was planted on 11 May, and transplanted on 15 June at a density of 518×10^3 plants ha⁻¹. N was applied at a rate of 0, 90, 210, 315 kg N ha⁻¹ as urea, and N dressing ratio and combined application of phosphate and potassium fertilizers were the same as in experiment 4. The experiment was arranged in a randomized complete block design with 4 replications. Fertilization with P and K and other field management practices were the same as in experiment 4. The data from experiment 5 was used for model validation.

| Experiment | Year | Variety | Nitrogen rate (kg N·ha⁻¹) | Plot area | Sampling time (month/day) | Number of Sampling |
|------------|------|---------|--------------------------|-----------|--------------------------|-------------------|
| Exp. 1     | 2004 | Wuxiangjing 9 | 0, 105, 210, 315 | 18 m² (4×4.5 m) | 9/2, 9/12, 9/23, 9/30, 10/12 | 111 |
|            |      | Huajing 2   |                          |           | 8/27, 9/2, 9/11, 9/23, 9/30 |                  |
|            |      | Nipponbare |                          |           | 8/27, 9/2, 9/11, 9/23 |                  |
| Exp. 2     | 2005 | Wuxiangjing 14 | 0, 90, 270, 429 | 31.5 m² (3.5×9 m) | 7/5, 7/15, 8/9, 8/16, 9/5, 9/13, 9/29, 10/10, 10/25 | 143 |
|            |      | 27123      |                          |           | 9/25, 10/5 |                  |
| Exp. 3     | 2006 | Yanjing 9967 | 0, 90, 270, 405 | 25 m² (5×5 m) | 7/28, 8/9, 8/18, 9/7, 9/17, 9/25, 10/5 | 148 |
| Exp. 4     | 2006 | 0, 105, 210, 315, 420 | 8100 m² (90×90 m) | 7/29, 9/10 | 946 |
| Exp. 5     | 2007 | Yangfujing 8 | 0, 210, 420 | 8100 m² (90×90 m) | 9/8, 10/9 | 44 |
were used for model validation.

2. Measurement of canopy hyperspectra

Ground-based hyperspectral reflectance in rice canopy was measured on each sampling date using a Field Spec Pro FR spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA). Reflectance between 350 and 1000 nm was recorded at a sampling interval of 1.4 nm and a resolution of 3 nm resolution, and reflectance between 1000 and 2500 nm at a sampling interval of 2 nm and a resolution of 10 nm resolution. The instrument has a 25° field of view, attached to a rod, and was placed at nadir 2.25 m above the rice canopy in order to result in a view area of approximately 1 m diameter. All spectral measurements were made during a cloud-free period between 10 a.m. and 14 p.m. A white Spectralon reference panel (Labsphere, North Sutton, NH) was used under the same illumination conditions to convert the spectral radiance measurements to reflectance. In experiments 1, 2 and 3, each plot was scanned 10 times and averaged to produce final canopy spectra. In experiments 4 and 5, there were 5 spectra sampling points in each plot distributed in a line with a distance of 15 m, and observation of single point was used for ground-based analysis, while the average of 3 points produced final data of the plot for satellite-based hyperspectral Hyperion image analysis.

3. Image acquisition and processing

Hyperspectral images from the Hyperion sensor were acquired on 29 July 2006. Hyperion is a hyperspectral instrument on the Earth-Observing 1 (EO-1) spacecraft, which provides a total of 220 channels covering the visible and near-infrared portions of solar spectrum from 350 to 2600 nm in 10 nm increments. Either bandwidth or band interval is nearly 10 nm with spatial resolution of 30 m. The hyperion image was processed with the RS image processing software ENVI 4.3 (2006). The bands that were not instrument-corrected but significantly affected by water vapor were firstly removed, and then geometric precision correction was carried with 30 GPS positioned points. The digital number (DN) values were first converted to radiance values as the top-of-atmosphere (TOA), and then the field reflectance spectra of different treatment plots in the study area were obtained through atmospheric correction with the FLAASH, which is an atmospheric correction model embedded in ENVI software. Finally, paddy rice spectra information was extracted for further analysis from the hyperion image by a simple model of decision tree (Zhen et al., 2008).

4. Determination of agronomic parameters

The canopy leaf N concentration (LNC) was measured at the corresponding spectral sampling points and sampling time as detailed in Table 1. After each measurement of

| REP technique | Algorithm | Reference |
|---------------|-----------|-----------|
| Inverted Gaussian | \( R(\lambda) = \frac{R(\lambda + \delta) - (R(\lambda + \delta) - R(\lambda))}{2\delta} \) | Miller et al., 1990 |
| Linear four-point extrapolation | \( REP = \frac{R_{\lambda_{red\_edge}} - R_{\lambda_{red\_shoulder}}}{R_{\lambda_{red\_edge}} - R_{\lambda_{green}}} \) | Guyot et al., 1992 |
| Lagrangian | \( A = \frac{D_{\lambda_{red\_edge}}}{(\lambda_{red\_edge} - \lambda_{red\_shoulder}) (\lambda_{red\_shoulder} - \lambda_{green})} \) \( B = \frac{D_{\lambda_{green}}}{(\lambda_{red\_shoulder} - \lambda_{green}) (\lambda_{red\_edge} - \lambda_{green})} \) | Dawson and Curran, 1998 |
| Linear extrapolation | Far-red line : \( FDR = m_1 \lambda + c_1 \) | Cho and Skidmore, 2006 |
| | NIR line : \( FDR = m_2 \lambda + c_2 \) | |
| | \( REP = \frac{(755FDR_{\lambda_{green}} + 675FDR_{\lambda_{red\_shoulder}})}{(FD_{\lambda_{red\_edge}} + FD_{\lambda_{green}})} \) | Thi paper |

Note: \( \lambda, \delta, REP, R, D, O, S, \delta, \lambda_{red\_edge}, \lambda_{red\_shoulder} \) are wavelength, number of wavelength, red edge position, reflectance, the first derivative reflectance, wavelength with the minimum reflectance in red edge area, wavelength of red shoulder and inverted Gaussian model half width, respectively. A, B and C are intermediate variables.

Table 2. Algorithms and references of different spectral indices.
canopy spectral reflectance, 6 plants from each plot in experiments 1−3 and 40 plants from each plot in experiments 4−5 were randomly selected, and harvested for determination of leaf weight and LNC. For each sample, all green leaves were separated from the stems, and oven-dried at 105°C for half an hour, and then at 80°C to constant weight before weighing. The dried leaf samples were ground to pass through a 1-mm screen, and then stored in plastic bags prior to chemical analysis. Total N concentration in leaf tissues was determined by the micro-Kjeldahl method and LNC (% or g N g\(^{-1}\) DW) was expressed on the basis of unit leaf dry weight. The leaf area index (LAI) in experiments 2−3 was measured with a Leaf Area Meter (LAI-2000) at the sampling time as shown in Table 1.

5. Calculation of red-edge position

Table 2 shows six different algorithms for the red edge position. An adjusted linear extrapolation technique was proposed in the present paper to yield a simplified and applicable REP method. The obvious characteristics of the first derivative spectra in rice canopies were two main peaks at about 700 and 730 nm and red vale at about 675 nm. Red vale around 675 nm in first derivative spectra value was about 0, and the \(D_{700}\) displayed a sharp valley in the present spectral data. Therefore, four end points required for the linear extrapolation algorithm (Cho & Skedmore, 2006) were adjusted to 675 and 755 nm X-axis, and the first derivatives at 700 nm (\(D_{700}\)) and 730 nm (\(D_{730}\)). This protocol constructed the farred line with \(D_{700}\) and 675 nm X-axis, and the NIR line with \(D_{730}\) and 755 nm X-axis, and then generated the wavelength value at the intersection of the two lines as the simulated REP. Fig. 1 shows a schematic representation of this adjusted linear extrapolation method, from which the following equation was derived: \(REP = \left( \frac{755D_{700} + 675D_{755}}{FD_{700} + FD_{755}} \right)\), which simplified the linear extrapolation algorithm and was tested with rice crop in the present study.

In addition, Dawson and Curran (1998) presented a technique based upon a three-point Lagrangian interpolation method for locating the REP in spectra. A problem with this method arises when the reflectance spectrum exhibits more than one maximum in its first derivative, that is, REP jumps from one band to another adjacent band (Horler et al., 1983; Clevers et al., 2002). The three-peak feature located at about 700, 720 and 730 nm as two major bimodal peaks of REP data and 720 nm as a minor peak. With higher LNCs, REP shifted toward longer wavelengths. In addition, a slight reflectance spectra vale and a discontinuity of the first derivative spectra with a negative value at about 775 nm band were distinctly observed in the present study.

2. Effects of genotypes on reflectance spectra and first derivative spectra in red edge region

Canopy spectral characteristics with different rice cultivars but similar LNC and growth stage are shown in Fig. 2B as an example. The data samples with LNC of about 2.32 g N g\(^{-1}\) DW for different cultivars at the booting stage were selected for analysis. The cultivar Nipponbare had a significantly higher spectral reflectance and red-edge derivative extreme value than other rice cultivars used in the study. Moreover the change patterns of reflectance spectra and the first derivative spectra of other four rice cultivars followed the order of LAI values in different cultivars. Red-edge derivative extreme values of Wuxiangjing 9, Huajing 2, Wuxiangjing 14 and 27123 increased sequentially, with the LAI values of 7.5, 6.9, 3.2 and 2.2, respectively. Nipponbare was an exception, with a LAI value of 4.2, had the maximum of derivative extreme value in all of the five rice cultivars. This result could contribute to lower plant height, smaller leaf angle and larger leaf N accumulation in Nipponbare as compared with other cultivars. The leaf N accumulation values, LNC x LAI, for Nipponbare, Wuxiangjing 9, Huajing 2, Wuxiangjing 14 and 27123 were 6.12, 6.25, 5.19, 4.95 and
Fig. 1. Schematic representation of the adjusted linear extrapolation technique for extracting the red edge position (REP)—wavelength of the meeting point between two straight lines extrapolated on the far-red and NIR flanks of the first derivative spectra.

Fig. 2. Characteristics of spectral reflectance and its first-derivative spectra in red edge area at different nitrogen levels in Wuxiangjing 9 (A), and in different rice cultivars at about 2.92% N (B) at heading stage from datasets of experiment 1 and experiments 1, 2 and 3, respectively.

Fig. 3. Relationships between LNC of rice and REPs extracted by adjusted linear extrapolation and linear extrapolation methods (A), and linear interpolation, inverted-Gaussian and Lagrangian techniques (B) using the datasets from experiments 2 and 3 (n=291).
3.11 g N m⁻², respectively, whereas the leaf inclination angle sequence was 27123 > Wuxiangjing 14 > Wuxiangjing 9 > Huajing 2 > Nipponbare. Plant type and N status of different rice cultivars may have a combined impact on the reflectance spectra and first derivative spectra in the red edge region.

3. Quantitative relationships between canopy LNCs and different REPs

The relationships between canopy LNCs and REPs extracted from six different fitting techniques were further quantified with the data from varied N rates and cultivars. The results showed that traditional REP determined by the maximum value of the first derivative spectra in red-edge region jumped at several different adjacent wavebands, and thus was discontinuous with the changes of canopy LNCs. This was caused by a three-peak pattern around 700, 720 and 730 nm, and made it difficult to estimate LNC with this technique (Fig. 2). In contrast, REPs calculated with other five methods had continuous and positive relationships with LNCs over the whole growth periods (Fig. 3A and 3B). Canopy LNC moved gently and proportionally with REPs derived from linear interpolation method, inverted Gaussian and Lagrangian methods, while drastically and proportionally with REPs extracted from linear interpolation extrapolation and adjusted linear extrapolation methods, which produced a larger range of REP values than the former three techniques. In addition, the linear interpolation method yielded bigger REP values than inverted Gaussian and Lagrangian techniques in a whole (Fig. 3B).

The results also revealed that the REPs from adjusted linear extrapolation produced the similar relations with canopy LNCs as the linear extrapolation and linear interpolation methods, slightly better than the inverted Gaussian and Lagrangian methods in rice (Fig. 3A and 3B). Overall, REPs of different techniques presented excellent linear relations to LNCs between 1.5 and 4 g N g⁻¹. The prediction errors for canopy LNC were the lowest with the linear regression model based on REP derived by adjusted linear extrapolation method, but the highest with traditional REP, though there were no significant differences among the other REP techniques. Table 3 details the regression models for estimating LNCs of rice based on different REP techniques based on a calibration dataset from Exps. 2 and 3.

4. Validation of REP models for LNC monitoring

In order to evaluate whether the above regression models in Table 3 were reliable and applicable for LNC estimation in rice, the independent data sets from experiments 1, 4 and 5 were used to test the performance of these models, as shown in Table 4. The validation results showed that linear regression models had larger RMSE but...
smaller RE values and performed better than curvilinear regression models with different REP methods. Taking RMSE and $R^2$ as the main evaluation indices, the LNC model based on the adjusted linear extrapolation method performed the best with the lowest RMSE value and the highest $R^2$ values, followed by the Lagrangian and linear extrapolation techniques, although the prediction results of models based on the 5 REP techniques did not exhibit significant differences, which indicated that the simplified and adjusted linear extrapolation method could bring similar or better fitting model parameters than other methods based on ground hyperspectra in rice crop.

5. Influence of LAI on REPs extracted by various methods

LAI is one of the major determinants of canopy reflectance spectra and changed with growth stages over the whole growth period in rice, so the effect of LAI on REPs derived from various methods were further inspected. Two different logarithm relationships between LAI and REP were observed under different growth stages and plotted in Figure 4A (the adjusted linear extrapolation approach as example). Before the heading stage, REP shifted dramatically toward longer wave bands until the value of LAI was 3, and then the saturation feature was observed when the value of LAI increased from 3 to 6. After heading stage, REP shifted slightly toward the short wave bands with decreased LAI (Fig. 4A). This implies that LAI may have different effects on REP depending on the growth and senescence stages of rice. Analysis of the influence of LAI and its interaction with LNC on the REPs derived from various algorithms showed that both LAI and interaction between LNC and LAI produced high impacts on REP regardless of growth stages, which was most

| REP technique                | Model type | Fitting model | $R^2$ | Standard error |
|------------------------------|------------|---------------|-------|----------------|
| $\lambda_{\text{max}}(D_{\lambda})$ in 670–780 nm range | Linear     | $y=0.0455x-30.589$ | 0.64  | 0.45           |
| Linear four-point interpolation | Linear     | $y=0.1147x-80.581$ | 0.79  | 0.34           |
| Inverted Gaussian            | Linear     | $y=0.1098x-75.588$ | 0.78  | 0.35           |
| Lagrangian (690, 700, 705)   | Linear     | $y=0.175x-120.9$ | 0.78  | 0.35           |
| Linear extrapolation         | Linear     | $y=0.067x-41.522$ | 0.80  | 0.34           |
| Adjusted linear extrapolation | Linear     | $y=0.063x-43.9$  | 0.79  | 0.33           |

| REP technique                | Model type | $R^2$ | RMSE (root mean squared error, %) | RE (relative error, %) |
|------------------------------|------------|-------|----------------------------------|------------------------|
| Linear four-point interpolation | Linear     | 0.72  | 10.53                           | 4                      |
| Inverted Gaussian            | Linear     | 0.71  | 10.76                           | 5                      |
| Lagrangian                   | Linear     | 0.71  | 10.36                           | 4                      |
| Linear extrapolation         | Linear     | 0.71  | 10.51                           | 4                      |
| Adjusted linear extrapolation | Linear     | 0.73  | 10.16                           | 4                      |

Table 3. Relationships between canopy leaf nitrogen concentrations (LNC) and normalized red edge positions (REPs) based on different approaches in rice with the calibration datasets from experiments 2 and 3 ($n=291$).

Table 4. Validation results of canopy LNC monitoring models in rice based on different red edge algorithms with the validation datasets from experiments 1, 4 and 5 ($n=251$).

significant when the dataset was classified into two sub-datasets (before and after heading stage) (Table 5). This might contribute to the close relationships between LAI and LNC before and after heading (Fig. 4B). REPs derived by Lagrangian and Inverted-Gaussian techniques are the least and the most sensitive to LAI, respectively, compared with the various alternatives, respectively.

6. Application of REP techniques to Hyperion hyperspectral image

To assess whether the REPs extracted from Hyperion hyperspectral image could be used for estimating canopy LNCs in rice, we calculated the REP values in different plots in experiment 4 using different methods from acquired Hyperion images and correlated with the average canopy LNCs of individual plots. The results showed that REP extracted by adjusted linear extrapolation generated the best and significant linear relations with LNCs, followed by linear extrapolation, inverted Gaussian, linear interpolation method and Lagrangian techniques in this order, which was consistent with ground-based datasets except Lagrangian technique (Fig. 5). The minor different result between ground-based and space-borne sensors is likely because the band sampling interval (about 10 nm) and three central bands (691.37, 701.55 and 711.72 nm) of Hyperion image are somewhat different from those of Field Spec Pro FR spectroradiometer. This implies that the adjusted linear extrapolation algorithm is a good REP technique for estimating canopy LNC in rice using both ground-based and space-based (Hyperion) hyperspectral data.

Discussion

REP has been widely used for monitoring plant chlorophyll concentration (Filella & Penuelas, 1994; Wu et al., 2000), due to its feature of red-shifting with increased chlorophyll concentration (Gates et al., 1965; Collins, 1978; Curran et al., 1990). Since plant chlorophyll concentration is highly correlated with nitrogen status (Hansen & Schjoerring, 2003; Haboudane et al., 2004), REP has also been used for evaluating plant nitrogen status (Lamb et al., 2002; Jongseapa & Booji, 2004). However, as most often encountered, REP is not adequate to track the variations in chlorophyll concentration due to its double-peak feature (Clevers et al., 2004; Cho and Skidmore, 2006). Various techniques of analysis such as four-point interpolation (Linear), Gaussian, Lagrangian, linear extrapolation have been developed to minimize errors in determining the REP and mitigate the discontinuity in REP data (Cho and Skidmore, 2006; Shafri et al., 2006.). In the present study, we systematically tested and compared these REP techniques using the hyperspectral data and canopy LNC from multiple experiments with rice crop. The results revealed the existence of three-peak feature in the first derivative of continuous spectra and a discontinuity in the REP/N relationship in rice. By inverted Gaussian and Lagrangian with three first-derivative bands (690, 700 and 705 nm), linear and linear extrapolation methods (Bonham-Carter, 1988; Miller et al., 1990; Dawson & Curran, 1998; Cho and Skidmore, 2006) mitigated the discontinuity in REP data caused by the three-peak feature, and thus provided good regressive relations with canopy LNC of rice in the present study. Although green LAI is one of the major determinants of

| Table 5. Main and interaction effects (quantified by the coefficient of determination, $R^2$) between leaf nitrogen concentration and leaf area index on the red-edge position extracted by different methods in rice. |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| $\lambda_{\text{max}}(\lambda_{\text{D}})$ in 670–780 nm range | Linear four-point interpolation | Inverted-Gaussian | Lagrangian | Linear extrapolation | Adjusted linear extrapolation |
| Before heading | LNC | 0.39 | 0.62 | 0.59 | 0.60 | 0.57 | 0.61 |
| | LAI | 0.65 | 0.79 | 0.81 | 0.54 | 0.78 | 0.79 |
| | LNC×LAI | 0.59 | 0.85 | 0.85 | 0.60 | 0.82 | 0.82 |
| After heading | LNC | 0.71 | 0.82 | 0.83 | 0.75 | 0.83 | 0.84 |
| | LAI | 0.51 | 0.63 | 0.64 | 0.47 | 0.51 | 0.56 |
| | LNC×LAI | 0.70 | 0.83 | 0.85 | 0.69 | 0.75 | 0.79 |
| Before and after heading | LNC | 0.64 | 0.79 | 0.78 | 0.78 | 0.80 | 0.79 |
| | LAI | 0.36 | 0.40 | 0.41 | 0.21 | 0.40 | 0.40 |
| | LNC×LAI | 0.64 | 0.77 | 0.78 | 0.56 | 0.71 | 0.72 |
| LAI, leaf area index; LNC, leaf nitrogen concentration.
canopy reflectance spectra, its relationships with REPs before and after heading stages were not quite consistent, as compared with canopy LNC. This is because canopy LNC values decrease while LAI may stay relative stable around heading stage (Fig. 4, 5). However, REPs extracted by 6 different techniques in this study are sensitive to LAI in rice, especially before heading stage, which is similar to the results of Pu et al. (2005) and different from Cho et al. (2008), who concluded that the REPs extracted by the various methods are in general less sensitive to LAI compared with leaf chlorophyll content based on modeled spectra.

Four wavelength positions of the first derivative spectra \((\overline{FD}_{675}, \overline{FD}_{700}, \overline{FD}_{725}, \text{ and } \overline{FD}_{755})\) are required for the linear extrapolation method (Cho and Skidmore, 2006), so REP extraction based on this model is relatively complicated. Here, we proposed an adjusted linear extrapolation technique to yield a simplified and applicable REP method based on the characteristics of the first derivative spectra in rice canopy. Two main peaks of the three-peak feature were located around 700 and 730 nm, respectively, and red vale with first derivative spectra value of about 0 around 675 nm. Moreover the \(\overline{FD}_{755}\) displays a sharp peak or valley owing to the strong absorption by oxygen in the spectral measurements (Clevers et al., 2002; Guanter et al., 2006), which was also obvious with the present spectral data. Therefore, four end points of the linear extrapolation method were adjusted to 675 and 755 nm X-axis, and the first derivative of reflectance at 700 nm \((\overline{FD}_{700})\) and 730 nm \((\overline{FD}_{730})\). The far-red line was constructed with \(\overline{FD}_{730}\) and 675 nm X-axis, the NIR line with \(\overline{FD}_{700}\) and 755 nm X-axis, which generated the wavelength value at the intersection of the two lines as the simulated REP. This lead to the following REP equation by the adjusted linear extrapolation technique: \(\text{REP} = \frac{755 FD_{730} + 675 FD_{700}}{FD_{700} + FD_{730}}\). Apparently, the adjusted linear extrapolation technique requires two less wavelength positions than linear extrapolation method, and also performed better than LE and other REP techniques in this study. This suggests that the present adjusted linear extrapolation can be a more suitable REP technique for estimating canopy LNC in rice crop.

An obvious problem in the Lagrangian technique arises when the reflectance spectrum exhibits more than one maximum in its first derivative; that is, REP jumps from one band to another (Horler et al., 1983; Clevers et al., 2002). In the first derivative spectra of rice canopy in the present study, the three-peak feature around 700, 720 and 730 nm and a discontinuity in the Lagrangian-based REP were observed distinctly. The Lagrangian technique uses wavebands with no equal-space requirement, and minimizes interpolation errors and soil background effects, so it is a simpler curve fitting technique for deriving REP (Shafri et al., 2006). The performance of Lagrangian algorithm was validated with rice spectra obtained in this study. In addition, based on a priori knowledge of the rice canopy spectrum, multi-variant REP values using the Lagrangian technique were systematically calculated to obtain the continuous REP values. By using three wavebands centered around 700, 720 and 730 nm, another two adjacent bands were determined by setting 5 nm or 10 nm equal or unequal space around the center band. As a result, the REP by Lagrangian algorithm calculated with \(\overline{FD}_{730}, \overline{FD}_{700}\) and \(\overline{FD}_{675}\) had the best correlation with canopy LNC in rice. This implies that three bands required by Lagrangian might be determined around the first main peak of 700 nm from the three-peak feature. Whether this formulation works in other crop types remains to be tested.

Performance of REPs extracted by different techniques from Hyperion hyperspectral image was also evaluated in the present study. Among the six REP approaches, REP with adjusted linear extrapolation performed the best, followed by linear extrapolation, inverted Gaussian, linear interpolation method and Lagrangian techniques in this order, the results were consistent with ground-based datasets except Lagrangian technique. This may be due to the differences in the band sampling interval of central bands between Hyperion and the Field Spec Pro FR spectroradiometer. It could also be caused by a less desirable band setting of the Hyperion sensor for the Lagrangian model. The four-point interpolation approach produced an attractive result, just the same as reported for forest LAI estimation (Pu et al., 2003). Since the adjusted linear extrapolation technique performed well in both ground-based and satellite-based hyperspectral data and required relatively less hand information, the REP technique should have practical values for estimating canopy LNC in rice by using hyperspectral data with appropriate band setting compared with the linear extrapolation method which also had good performance in this study. The REP techniques and derived LNC monitoring models proposed here require further verification with other hyperspectral sensors and crop types.

Conclusions

Spectrum in red edge area was significantly affected by N levels and rice cultivars, and “three-peak” feature was observed in the first derivative spectrum at about 700 nm, 720 nm and 730 nm. Traditional REP was not sensitive to canopy LNC due to the three-peak feature, but REPs extracted by the newly developed adjusted linear extrapolation method, linear extrapolation method, inverted Gaussian fitting technique and linear four-point interpolation technique, all generated continuous REP data, and could be used for estimating canopy LNC in rice. REP from a three-point Lagrangian interpolation with three first-derivative bands (690 nm, 700 nm and 705 nm)
also had a good relationship with canopy LNC. Among the six REP approaches, the adjusted linear extrapolation method gave the best prediction of canopy LNC in rice based on Hyperion hyperspectral image. Comparison of different REP techniques revealed that the adjusted linear extrapolation method with a simplified algorithm \( (755FD_{730} + 675FD_{700})/ (FD_{730} + FD_{700}) \) had the best prediction performance for canopy LNC in rice with ground-based hyperspectral data and satellite-based hyperspectral image.

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