Regression-Based Models to Predict Rice Leaf Area Index Using Biennial Fixed Point Continuous Observations of Near Infrared Digital Images

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Abstract: A weatherproof digital imaging system for the near infrared band (NIR, 820–900 nm) was positioned 12 m above a 600-m² rice field. During the 2008 and 2009 paddy rice seasons, the system automatically logged images at 10-min intervals throughout the day. Radiometric corrections for the NIR images utilized a solar irradiance sensor and prior calibrations to calculate daily-averaged reflectance factors (DARF). Prior to heading, empirically derived equations for predicting leaf area index (LAI) using the 2008 DARF values in NIR, the cosines of angles between the view and the planting row directions, and between the view and the meridian directions were verified with the 2009 data set. Transformation of a model variable by arcsine square root function improved the performance of the LAI prediction by reducing the errors and bias at low LAI values. Adding variables to incorporate lateral angular components to the horizontal viewing angular parameters hardly affected the overall performance of the models and did not reduce variation. This was probably because the height and position of the camera system were the same in successive years. In-plot means of two or four predicted values in each plot reduced the root-mean square error 30%. These results indicate that radiometric NIR images derived using a fixed-point observation system can accurately predict LAI and the simple multiple linear regression equations developed for a given year can be used the following year without in-situ recalibration.

Key words: Digital camera, Leaf area index, Near infrared, Reflectance factor, Rice.
might improve measurement accuracy and repeatability. An imaging device such as a digital camera, instead of a non-imaging, unified-field-of-view radiometer, can be used for repeated, instantaneous observations of a fixed field of vision without mechanical movement of the optical sensing unit. The advantage of image sensing then can be combined with reflectance measurement. Shibayama et al. (2009) suggested that measurements of visible and near infrared narrow band reflectance images of crop canopies provided by a weather-proof camera system could be used to collect agronomic data. Although LAI is a major indicator of photosynthetic production, measurements require expensive equipment such as leaf area meters or plant canopy analyzers, and data collection is time-consuming. Shibayama et al. (2011) recorded the near infrared band (NIR, 820–900 nm) digital images of a rice paddy to calculate daily-averaged reflectance factor (DARF) values in target areas and developed a linear regression model for estimating prior-to-heading rice LAI from the DARF values in NIR (DARF-in-NIR). However, the model has not been fully tested and the year-to-year and inter-varietal applicability were not assessed. The objective of the present study was to test and improve the reliability of the model for predicting LAI of paddy rice from a 2-year radiometric and agronomic sample data set.

### Materials and Methods

1. **Instruments**

The specifications of the portable dual-band digital camera (PDC, Kimura OyoKogei Inc., Saitama, Japan) used to make measurements in 2008 and 2009 were described by Shibayama et al. (2009). Two digital camera boards, one for visible red (RED, 630–670 nm) and another for near-infrared (NIR, 820–900 nm) were installed in a waterproof housing. The PDC was mounted on a remotely controlled motorized camera platform that adjusted the view zenith angle of the PDC on top of a 12-m-high pole.

In the present study, the term “reflectance factor” (RF) is used for observed radiometric value instead of “reflectance”. The whole incident and reflected radiant flux (W) values on the target are required from all directions to measure reflectance, whereas RF indicates the intensity of light reflected from the target divided by that reflected from a perfect reflecting diffuser illuminated in the same lighting conditions, view directions and view solid angles (Emori and Yasuda, 1985). The configuration of the PDC results in observations that are closer to the RF measurement than reflectance. The PDC was adjusted for radiometric values prior to field measurements in 2008 and estimated RF values were validated by placing a gray scale board at the center of the PDC sight (Shibayama et al., 2011). The PDC has separate solar irradiance sensors fitted with the same-spec filters used in the cameras; the measured solar irradiance provides a correction for fluctuating illumination to enable calculation of the instantaneous values of each-band RF. The calculations of RF were also evaluated against short-wavelength solar radiation data provided by Weather Data Acquisition System of the National Institute for Agro-Environmental Sciences, Tsukuba, Japan.

2. **Sample site and agronomic survey**

The experimental paddy field was located on the campus of the National Institute for Agro-Environmental Sciences in Tsukuba, Japan (36°01′27″N 140°06′27″E, 25 m a.s.l.). Table 1 summarizes the cultivation conditions of the test rice plants grown in 2008 and 2009. In 2008, plots of rice (Oryza sativa L. ssp. japonica, cv. ‘Nipponbare’) were established in two adjacent concrete-framed paddy fields of 10 × 50 m filled with Alluvial soil. Seedlings were transplanted on two dates using a ride-on transplanter in approximate northeast-southwest rows with a row width of 30 cm and an inter-hill space of 15 cm. The leaf area index (LAI) was collected periodically from 18 June at 4- or 5-day intervals with a plant canopy analyzer (LAI-2000, LI-COR, Inc., Lincoln, NE, USA). Four below-the-canopy measurements were repeated at three different locations in each plot. One operator mainly used particular equipment during the experiment to avoid seasonal fluctuation. High band-to-band correlation in remotely sensed reflectance values is common in adjacent wavelength-band radiometric variables. However, the present study used RF in a near infrared band captured with the camera, and LAI-2000 value that is derived from transmission of light in the shorter wavelength of the visible range. Hence we supposed that the two variables were independent in principle, and the models describing the relationship between the two variables (LAI-2000 and RF) would be appropriate.

Further details of the 2008 experimental design and agronomic survey were as reported by Shibayama et al. (2011).
In the 2009 cropping season, plots of two rice varieties ('Nipponbare' and 'Koshihikari') were established in the same fields (Table 1). All seedlings were transplanted on a single date. The topdressing fertilization levels, 1 and 3 g N m\(^{-2}\), were lower than in 2008, as variety 'Koshihikari' has relatively poor lodging resistance. The variety 'Nipponbare' is shorter and has more erect leaves than 'Koshihikari'. There were four repetitions of two treatments for each variety and topdressing, providing 16 plots. The experimental design is illustrated in Fig. 1. The LAI and plant height (cm) were measured in each plot from 18 June to 18 September at 7-day intervals. Three measurements of LAI values were taken in each plot and arithmetic means were used for further analysis. The experimental field is facilitated with irrigation system with water valve for each fertilization plot. The plots were separated with plastic corrugated strip-shaped sheet, and flooded irrigation was employed except the midseason drainage. Ten-day-average air temperature (2 m above the ground) in late June 2009 was about 3ºC higher than in 2008 whereas it was 3ºC lower in late July 2009 than in 2008 (Weather Data Acquisition System of National Institute for Agro-Environmental Sciences). The weather condition in both years might affect rice growth; variations in LAI due to the natural and experimental conditions were within the range that can be used for model validation.

Analysis of variance (ANOVA) was completed for all 2009 data (including those plots outside the viewing field of the PDC; see Fig. 1) for the factors “date” (number of levels = 8), “variety” (number of levels = 2) and “fertilization level” (number of levels = 2). A model, hereafter denoted as “model-static” to distinguish this model from radiometric LAI prediction models, estimated LAI using three qualitative variables.

3. Image collection in the 2009 cropping season

The PDC system was set up on 1 June 2009, 4 days after transplantation. Images were recorded at 10-min intervals from 0700 to 1700 JST daily until 9 October at five arbitrary exposure speeds for both bands. The PDC view azimuth direction was from southwest to northeast and the view zenith angle was approximately 56º.

The PDC digital number (DN) ranged between 0 and 255 (8 bits) and the images measured 640 × 480 pixels. Each DN in the image was spatially corrected using equations provided for each band and exposure speed (Shibayama et al., 2009) and then converted to spectral irradiance (μW cm\(^{-2}\) nm\(^{-1}\)). Assuming the targets are uniform diffusers, the spectral irradiance value of the target was divided by the corresponding solar spectral irradiance to derive the RF.

Four target areas in each of the five plots in view (plot IDs [2], [6], [7], [10] and [11], Fig. 2) and two areas each in the two outside plots in partial view (plot IDs [3] and [15]) were selected. The coordinates of the 24 target areas in the images were determined manually using an image taken at harvest, since ripening and just lodging plants made it easy to recognize the boundaries between plots.
Fig. 2. Each target area was 20×20 pixels regardless of the distance between the PDC and the target (Shibayama et al., 2011).

Prior to sampling values from the target areas, daily-averaged reflectance factor (DARF) values were calculated from RF images taken at 10-min intervals from 0900 to 1500 JST each day. The advantage of using DARF instead of instantaneous RF values was discussed in Shibayama et al. (2011). We selected NIR images taken at three exposure speeds, 10, 20 and 30 (dimensionless), and at corresponding minimum threshold solar spectral irradiance levels, 30, 25 and 20 μW cm⁻² nm⁻¹, selected according to Shibayama et al. (2011). Images taken at < 20 μW cm⁻² nm⁻¹ were omitted from daily averages. DARF images were obtained by averaging pixel-by-pixel for the whole images taken on each day fulfilling the above-mentioned conditions.

DARF-in-NIR values from 20×20 pixel target areas and LAI measured in seven plots on eight occasions (18 and 25 June; 1, 8, 16, 24, 30 July; and 6 August) provided 56 data sets for analysis. Two or four radiometric measurements were made in each plot (Fig. 2) and LAI values were assigned to values in corresponding plots, thus providing 192 matched DARF-in-NIR and LAI values.

4. Viewing geometry and equations of linear regression models

The 2009 data set comprised DARF-in-NIR values, view direction angles A and B for the 24 target areas and LAI values for seven plots (Fig. 2). View angles (degrees) were: angle A between a line from the PDC to the center of the target area and the planting-row running through the target area; and angle B between a line from the PDC to the target area and the meridian (Fig. 3).

In model-0 (Shibayama et al., 2011) both angles were derived from horizontally projected geometry excluding vertical angular configuration (angle C in Fig. 3). Model-0 was derived from four central target areas out of 10 target areas in total scattered in the viewing field. The model-0 equation is:

\[
\text{Model-0: } \text{LAI} = -5.349 + 11.686 \text{DARF-in-NIR} + 5.223 \cos A - 2.285 \cos B. \quad (1)
\]

In the present study, three new models were constructed, in which the entire data set from 2008 (130 observations from the 10 target areas) was used to predict 2009 LAI. Model-1 was identical to model-0 but the regression coefficients were newly estimated from the entire 2008 dataset of 130 observations for the 10 target areas.

\[
\text{Model-1: } \text{LAI} = b_0 + b_1 \text{DARF-in-NIR} + b_2 \cos A + b_3 \cos B. \quad (2)
\]

Two variable transformations, natural logarithm (Wonnacott and Wonnacott, 1981) and arcsine square root (Osborne, 2002) were tested:

\[
\text{Model-2: } \ln(\text{LAI}) = b_0 + b_1 \ln(\text{DARF-in-NIR}) + b_2 \ln(\cos A) + b_3 \ln(\cos B), \quad (3)
\]

where, \(\ln(x)\) indicates natural logarithm of \(x\) and

\[
\text{Model-3: } \sin^{-1}\sqrt{\frac{\text{LAI}/10}{10}} = b_0 + b_1 \text{DARF-in-NIR} + b_2 \cos A + b_3 \cos B. \quad (4)
\]

where \(\sin^{-1}\sqrt{x}\) denotes arcsine square root transformation.

In Eq. (4), the LAI was arbitrarily divided by 10 to restrict the value in the function of arcsine to one or less on the assumption that paddy rice LAI does not exceed 10. These transformations effectively describe phenomena where the magnitude of data fluctuation varies with the increase of explanatory variable (Kawabata, 1982). We assume that radiometric data fluctuation increases with increased LAI as increases in the number and size of stems and leaves increases plant canopy complexity (Muñoz et al., 2010).

Effective and thorough validation might be possible by case resampling, where the combined 2-year data are separated at random into one dataset for building models and a second for validation. The present study was designed to demonstrate verification in a realistic situation; a model built in one year could be applied the next year, rather than to provide the best tuned model. The performance of each model, derived from the 2008 dataset and applied to the 2009 dataset, was evaluated using coefficient of determination (\(R^2\)), root-mean-square error (RMSE) and the slope and intercept of the regression equation between the measured and predicted LAI values. Software JMP 7 (SAS Institute Inc., Cary, NC, USA) was used for the statistical analyses.
Shibayama et al. — Rice LAI Prediction with Near Infrared Digital Images

369

variety × topdressing) was 0.3 to 5.0, standard deviation (SD) 0.01 to 1.0, depending on growth stage, variety and fertilization levels (Fig. 5). The coefficient of variation (CV) was 20% or more of the mean LAI values in early vegetative growth and maturing stages; the minimum CV was 2% and the average CV was 10%. This variation is not excessive but indicates uneven plant growth in the experimental fields.

Standard errors calculated from three repeated LAI measurements for each plot (SEL) were 0.02 to 0.3. The ratio of SEL to LAI varied from 1% to 20%; variations were larger early in the growing season and most were 5% or less.

5. Attempts to improve performance of LAI predictions

In a previous study, we found no evident effect of view zenith angle on DARF values (Shibayama et al., 2011). Hence, the view direction angles A and B have been simply defined in two-dimensional plane (Fig. 3). However, those angles in three-dimensional space could be defined anew using the view zenith angle between the target and camera. It is feasible to check the performance of newly defined view angles for verifying impact of view zenith angle again.

In addition to angles A and B, two sets of angular parameters were introduced: \( A', B', A'' \) and \( B'' \) (all in degrees) to indicate the angles in three-dimensional space between the view and planting-row vectors and the view and the meridian vectors (Fig. 4). Angles \( A' \) and \( B' \) were calculated neglecting the height of targets and assumed no plant elongated for the whole growing period. Angles \( A'' \) and \( B'' \) were obtained using measured plant height, at each survey, as one component. Unlike angles A and B, which are measured from a two-dimensional diagram (Fig. 3), \( A', B', A'' \) and \( B'' \) accounted for the zenith angle \( C' \) in Fig. 4.

We also tested 3-day averages of DARF values collected on, before and after LAI measurement days, as the radiometric variable in the models. Furthermore, means of predicted LAI in each plot (in-plot mean value), where two or four sampling areas were used to evaluate in-plot averaging.

Results

1. Measured LAI in 2009 experimental plots

Average LAI of four repetitions for each treatment (variety × topdressing) was 0.3 to 5.0, standard deviation (SD) 0.01 to 1.0, depending on growth stage, variety and fertilization levels (Fig. 5). The coefficient of variation (CV) was 20% or more of the mean LAI values in early vegetative growth and maturing stages; the minimum CV was 2% and the average CV was 10%. This variation is not excessive but indicates uneven plant growth in the experimental fields. Standard errors calculated from three repeated LAI measurements for each plot (SEL) were 0.02 to 0.3. The ratio of SEL to LAI varied from 1% to 20%; variations were larger early in the growing season and most were 5% or less.
LAI values observed on 13 August (DOY 225) were abruptly higher than the values taken 7 days earlier (Fig. 5); LAI data taken on and after 13 August were omitted from subsequent analysis even though the heading of ‘Nipponbare’ plants was observed on 18 August (Table 1). We have not yet found a cause of the rapid increase in LAI in mid-August.

ANOVA for prior-to-heading LAI was significantly influenced by fertilizer (topdressing) level and observed date (the probabilities less or equal 0.0001) (Table 2). An underlying assumption of ANOVA is that the observations are independent. However, repeated observations were taken from the same experimental plots in the analyses.

### Table 2. Analysis of variance (ANOVA) summary for the leaf area index (LAI) measured using a plant canopy analyzer (LAI-2000) at 16 experimental plots on eight dates in 2009. ANOVA of average of three observations for each plot.

| Factor               | Degree of freedom | Sum of square | F-value | Probability |
|----------------------|-------------------|---------------|---------|-------------|
| Variety              | 1                 | 0.39          | 6.44    | 0.013       |
| Fertilizer           | 1                 | 0.97          | 16.17   | 0.0001      |
| Date                 | 7                 | 266.11        | 630.54  | <0.0001     |
| Date × Variety       | 7                 | 0.98          | 2.32    | 0.031       |
| Date × Fertilizer    | 7                 | 0.41          | 0.97    | 0.456       |
| Variety × Fertilizer | 1                 | 0.01          | 0.13    | 0.717       |
| Date × Variety × Fertilizer | 7 | 0.16 | 0.38 | 0.914 |
| Error                | 96                | 5.79          |         |             |

- R²: 0.98
- RMSE: 0.25
- F-value: 143.94 <0.0001

![Graph](image1)

**Fig. 6.** Residuals (difference between the measured and estimated paddy rice LAI values) versus LAI estimated by model-static using the observed date, variety and topdressing level as the explanatory variables (Table 2). The LAI values were measured using a plant canopy analyzer (LAI-2000). The open triangle indicated by the arrow was omitted and replaced with a model-estimated value for the further analyses (see text).

![Graph](image2)

**Fig. 7.** Daily-averaged reflectance factor (DARF) values June to October 2009 and the corresponding daily-accumulated solar radiation for 0900-1500 JST.

![Graph](image3)

**Fig. 8.** LAI of two varieties of rice during the 2009 prior-to-heading period predicted by model-0 (Eq. (1) in text) against measured LAI.
Hence, the $R^2$ and $F$-values might be overrated, and the probability-level for statistical significance should be 0.01 or 0.005 instead of 0.05. In that case, no interaction terms were significant. A scatter diagram of residuals (measured–estimated LAI values) against the estimated LAI values derived from the model-static found one outlier (indicated by the arrow in Fig. 6) in observed LAI data. The cause of the outlier was unexplained and a correction derived from the model-static was used for subsequent regression analyses.

2. **Seasonal DARF-in-NIR observed for the 2009 paddy rice**

PDC images were collected every day for 131 days between 1 June and 9 October except for 3 days beginning 7 August, when electric power failed after a lightning strike in a nearby area.

The seasonal pattern of DARF-in-NIR was a smooth curve (Fig. 7) despite fluctuating short-wavelength solar radiation, indicating an accurate calibration system. On 5 dark days, there was insufficient solar irradiance to acquire DARF-in-NIR images. Four of these days were in the late ripening period and only one image DARF-in-NIR (2 July) was missed in the prior-to-heading period.

The DARF-in-NIR values (0.2 to 0.6) were similar to previous results (Shibayama et al., 2011). The DARF-in-NIR values were low immediately after transplantation in the rooting period, increased steeply during the tillering and reached an asymptotic plateau during late panicle development.

There was no obvious difference between plots in seasonal DARF-in-NIR patterns throughout the cropping season.

| Model 1: $\text{LAI} = b_0 + b_1 \text{DARF-in-NIR} + b_2 \cos A + b_3 \cos B$ |
|---------------------------------|-----------------|-----------------|--------------|-----------------|
| $R^2$                           | 0.88            | $F$-value       | 516.76       | $<0.0001$       |
| Sample size                     | 130             |                 |              |                 |

| Model 2: $\text{Ln} (\text{LAI}) = b_0 + b_1 \text{Ln}(\text{DARF-in-NIR}) + b_2 \text{Ln}(\cos A) + b_3 \text{Ln}(\cos B)$ |
|---------------------------------|-----------------|-----------------|--------------|-----------------|
| $R^2$                           | 0.92            | $F$-value       | 491.40       | $<0.0001$       |
| Sample size                     | 130             |                 |              |                 |

| Model 3: $\text{Sin}^{-1} \text{LAI}/10 = b_0 + b_1 \text{DARF-in-NIR} + b_2 \cos A + b_3 \cos B$ |
|---------------------------------|-----------------|-----------------|--------------|-----------------|
| $R^2$                           | 0.89            | $F$-value       | 323.55       | $<0.0001$       |
| Sample size                     | 130             |                 |              |                 |

DARF-in-NIR: Daily-averaged reflectance factor in the NIR (820–900 nm) band.

$\text{Ln}(x)$: Natural logarithm of $x$.

A: Angle (degrees) between a line from the camera to the center of the target area and the planting-row running through that target.

B: Angle (degrees) between a line from the camera to the target area and the meridian.
3. Performance of model-0 for predicting 2009 paddy rice LAI

The values of DARF-in-NIR and the cosines of A and B obtained in 2009 were substituted into Eq. (1) of model-0 and predicted LAI values plotted against the measured LAI (Fig. 8). The $R^2$ value between the measured and predicted LAI within the range 0.0 to 4.5 was 0.90, the slope 1.05 and the intercept was 0.006. The slope was significantly larger than 1.0 ($P < 0.05$) and the null-hypothesis intercept = 0 was not rejected. Although the regression was linear, a slope $>1.0$ indicates a discrepancy between model-0 prediction and measured data from 2009. There were no significant differences arising from variety and topdressing treatments (Fig. 8). However, at low values of LAI (less than 0.5), model-0 predicted unrealistic negative LAI. This may arise from the slightly non-linear relationship of the measured and predicted LAI values.

4. Performance of models-1, -2 and -3

All three models estimated the LAI in 2008 with $R^2$ values 0.88 or more, and all the partial regression coefficients were statistically significant ($P \leq 0.024$) (Table 3). Scatter diagrams of predicted and measured LAI values for 2009 are presented in Fig. 9. All three models produced linear estimates for LAI. Model-1 provided the most accurate prediction of LAI ($R^2 = 0.899$), although the model was unrealistic at lower LAI where the model predicted negative values at LAI $\leq 0.5$. In models-2 and -3, transformation of the variables reduced variation at low LAI and eliminated negative LAI values. The slope of model-3 (1.000) and the minimum RMSE value (0.493) indicate that this model provides more accurate prediction than models-1 and -2. However, the difference in performance from models-2 and -3 was small; instead, $R^2$ values for the regressions in 2008 were larger in model-2 than model-3 (Table 3). Overall, model-3 produces the...
most accurate predictions for the 2009 dataset.

For model-3, the residual errors (measured LAI – predicted LAI) were not influenced by zenith angle (C, º), measurement date or experimental plot (Fig. 10). This indicates the view angular corrections employed were successful and a slight non-linear component in the relationship between DARF-in-NIR and LAI observed in models-0 and -1 was eliminated by the variable transformation in model-3.

On close examination of Fig. 10, there were more over-estimates for the variety ‘Nipponbare’ with low topdressing (solid circles) and more underestimates for ‘Koshihikari’ with high topdressing (open triangles). However, ANOVA tests for residual errors applied separately to each-date-subset of data revealed that differences in residuals observed for the two varieties and topdressing levels were not significant (P>0.05), except for the 25 June data, in which the mean residual for the LAI of variety ‘Nipponbare’ was significantly less than that of ‘Koshihikari’.

5. The performance of three-dimensional angular parameters (A’, B’, A” and B’’), 3-day averaged DARF and in-plot means of predicted LAI

Model-3’ (includes terms for A’ and B’, which neglected the plant height (Table 4). However, the terms A’, B’ and/or A” and B” did not improve the prediction performance as much as expected. Instead, models where angles A and B were defined on a two-dimensional plane performed well in terms of R², RMSE values, slopes and intercepts of linear regressions between the predicted and measured LAI. Models-3, 3’ and 3” (incorporating 3-day average DARF-in-NIR) did not improve overall performance. However, incorporation of in-plot means improved the R² values and RMSEs for all three models (Table 4).

In summary, in-plot means (in model-3) was the only modification that improved predictive accuracy for LAI. The RMSE value of 0.356 for model-3 with in-plot means was comparable in magnitude to the RMSE of 0.25 derived by the qualitative-variable model of LAI (model-static, Table 2). The predicted LAI values obtained using model-3 with in-plot means and single-day DARF were plotted...
against measured LAI in Fig. 11. The SDs of in-plot mean LAI values predicted with model-3 varied from 0.001 to 1.0; the CV varied from 1% to 22% and averaged 9.2%. Those CV values were about two times CVs derived from plant canopy analyzer measurements (see Section 1 in Results).

ANOVA tests for residuals applied separately to each-date-subset of data revealed that differences in residuals observed for the two varieties were not statistically significant. Topdressing levels were statistically significant in the data subsets taken on 24 and 30 July, in which the mean residual of lower topdressing plots was significantly less than that of higher topdressing ones; that is, LAI in higher topdressing plots were more likely to be underestimated.

**Discussion**

The current study is based on the assumption that estimated LAI with the plant canopy analyzer (LAI-2000) is reliable and stable. Direct measurement for the area of representative leaf samples to retrieve the actual LAI, and to correct for stem and dead tissues was not performed prior to using the LAI-2000 values. In fact, the indirect methods do not measure leaf area index, as all canopy elements intercepting radiation are included (Bréda, 2003). However, the discrepancy might be basically small in the prior-to-heading period plants because there is no non-green branch or panicle. Dead plant tissue is also minimal relative to the total biomass. Yamamoto et al. (1995) reported that this machine detected japonica type paddy rice LAI of 5 or less during the vegetative growth period. Stroppiana et al. (2006) showed that LAI-2000 estimates and destructive LAI values of indica type rice were well correlated ($R^2$ > 0.8, not statistically different from the 1:1 line) whereas the correlation decreased when LAI values were lower than one. Accepting some uncertainty and errors in obtained LAI-2000 values, at this stage of the study, we used them as the reference to develop and evaluate the technique with the PDC. It is legitimate to be concerned about the potential discrepancy between LAI-2000 and actual LAI values, especially in the higher LAI range where LAI-2000 values are less sensitive as all light becomes extinguished approaching complete canopy

| Model identifier | Treatment for in-plot mean LAI values | Sample size | $R^2$ | RMSE | Intercept | Slope | 95% confidence interval of slope |
|------------------|--------------------------------------|-------------|------|------|-----------|-------|---------------------------------|
| Model-3 (A, B)   | Single day each area separately       | 192         | 0.898| 0.495| 0.0074**  | 1.000 | ± 0.0084                       |
|                  | 3-day moving average each area separately | 192       | 0.900| 0.505| 0.0092**  | 1.053 | ± 0.0496                       |
|                  | Single day In-plot means              | 56          | 0.944| 0.556| 0.0878**  | 0.993 | ± 0.0648                       |
|                  | 3-day moving average In-plot means    | 56          | 0.945| 0.564| 0.0967**  | 1.027 | ± 0.0664                       |
| Model-3’ (A’, B’) | Single day each area separately       | 192         | 0.876| 0.502| 0.1556**  | 1.004 | ± 0.0041                       |
|                  | 3-day moving average each area separately | 192       | 0.881| 0.505| 0.1633*   | 1.036 | ± 0.0044                       |
|                  | Single day In-plot means              | 56          | 0.931| 0.404| 0.1697**  | 1.002 | ± 0.0735                       |
|                  | 3-day moving average In-plot means    | 56          | 0.935| 0.403| 0.1892**  | 1.035 | ± 0.0735                       |
| Model-3’’ (A’, B’) | Single day each area separately       | 192         | 0.878| 0.546| 0.147**   | 1.030 | ± 0.0356                       |
|                  | 3-day moving average each area separately | 192       | 0.883| 0.549| 0.154**   | 1.035 | ± 0.0359                       |
|                  | Single day In-plot means              | 56          | 0.933| 0.395| 0.162**   | 1.001 | ± 0.0729                       |
|                  | 3-day moving average In-plot means    | 56          | 0.937| 0.396| 0.172**   | 1.034 | ± 0.0729                       |

Models -3, -3’ and -3’’: See Table 3 and the text. A’, B’, A’’ and B’’: See Fig. 4 and the text.

*: The null-hypothesis: slope = 0 was rejected at the significance level of 0.05.

ns: The null-hypothesis: slope = 0 was not rejected at the significance level of 0.05.
cover. Additional retrieval or calibration using direct samples is needed to obtain actual LAI instead of LAI-2000 values.

In the present study, the measured prior-to-heading LAI values (0.3–4.5) are reasonable for the rice varieties grown at the test site location and fertilization rate (Fig. 5). Although model-static (Table 2) estimated LAI with qualitative variables (date, variety and fertilization level), it is not feasible to predict LAI of other new rice paddies from these variables. However, the R² value of 0.98 and an RMSE of 0.25 in LAI represent the best-case goal of LAI prediction technology, achievable using available LAI data.

Martin and Heilman (1986) developed rice LAI prediction equations using two-band reflectance indices. Some of these were derived from normalized difference (difference in reflectance values for 760–900 nm and 630–690 nm divided by the sum of both) transformed with exponential function. For two consecutive years, reported R² values were 0.77 and 0.89 and the SDs from regression were 1.05 and 0.61, respectively, for combined six rice varieties in different morphological plant types. The LAI range reported in that study was about 0.0 to 5.5, larger than that in the present study and observations were completed with spectroradiometer instead of digital camera. However, Martin and Heilman (1986) were not able to demonstrate year-to-year applicability of the models. Without validation, the accuracy of predictions produced by a model developed for one year/location for other years/locations is unknown (Shibayama and Akiyama, 1991; Wiegand et al., 1992). As a first step, it may be feasible to validate models applied for other years in the same location where dates of trial almost overlap. The planting row direction and observation geometry were identical except an additional variety was added and in the second year, rice was planted on one date.

The results indicated that model-0 provided reasonable estimations when 0.5 ≤ LAI ≤ 4.5, but modification may improve performance, especially when LAI ≤ 0.5. Transformations of variables by logarithmic and arcsine square root functions corrected the measured- and predicted-LAI relationship in the prior-to-heading period and resulted in a reasonable residual distribution pattern (Fig. 9). The present study achieved 0.94 in R² value and 0.36 in RMSE in a year-to-year application of a regression model for predicting LAI (model-3 with in-plot means, Table 4), though the tested duration is restricted to the prior-to-heading period and only two varieties were grown. Stroppiana et al. (2006) showed that LAI-2000 tends to overestimate when LAI less than one and increasingly underestimate as LAI increases above 1.0. This may have potential to influence the relationship between the linear model predictions and corresponding LAI-2000 values although this is not directly approved with the present data set. Although further theoretical and experimental tests are required to identify the most appropriate equation, model-3 is an improvement over the original model-0. Hence, the initial biennial trial demonstrated the potential LAI estimation based on digital imaging. The method does produce consistent measurements between years and arising from the stability of camera sensitivity and calibration system employed.

In the present study, the equation included two horizontal view-related angles, A and B, but excluded the view zenith angle C to simplify the 2908 model. The hypothesis that angular effects arising from the bird’s eye view observation might influence measurements of reflected light from different target areas was also tested (Kimes, 1983). The results showed variation in this angular range had little influence on model accuracy as the prediction residuals of model-3 showed no distinctive trend or pattern with the view zenith angle (C) (Fig. 10).

The introduction of new angles A’, B’, and A’’ and B’’ to define the measurement in three-dimensional space did not improve prediction accuracy as much as expected. One possible reason is that the identical observation geometrical conditions (camera height and angular view) between years may diminish variation arising from three-dimensional angles. Under the given fixed observation geometry, the assumption that daily-averaging calculation reduces the view zenith angular effects on NIR RF was justified. At the moment, we have no explanation for this phenomenon and further tests and model development for different angular parameters are necessary to draw firm conclusions.

The 3-day means of DARF-in-NIR did not improve model performance by much; as weather conditions were favorable on the selected dates, calculated DARF values over the 3 days were stable and there was no further need to correct measured data by moving average. A moving-average technique may be useful for LAI predictions under variable weather conditions.

In-plot averaging reduced RMSE; that is, the variation of predicted LAI. The arithmetic mean of LAI measured with the plant canopy analyzer was summed in each plot. Therefore, the exact LAI value at each 20 × 20 pixels target area was unknown. The first part of the analyses was completed on the assumption that the LAI in each plot was uniform. Strictly, this assumption is impractical. Therefore, in-plot averaging should improve prediction RMSEs. The present study specifically showed that the use of in-plot means reduced RMSE by 30% (Table 4). A previous study (Shibayama et al., 2011) showed that time-dependent variation in DARF-in-NIR observed in a fixed target area was so small that the stability of the PDC system has less effect than in-plot averaging.

ANOVA of prediction residuals showed that the two rice varieties did not affect LAI prediction. The difference in the morphological characteristics between two varieties
may have little influence on the radiometric prediction (Martin and Heilman, 1986). Although topdressing at the panicle initiation stage influenced subsequent LAI prediction, the mode of influence is unknown. The model may require modifications to be applied for other crops that substantially differ in morphology and/or spatial arrangement with row-planting paddy rice.

Conclusions

We developed regression-based models to predict LAI of rice during vegetative growth using remotely obtained image data. Model parameters were daily-averaged reflectance factors in the near infrared band (DARF-in-NIR; obtained with a low cost digital camera and solar sensor), view azimuth, planting row and the meridian directions. Transformation of model variables improved the prediction accuracy.

A biennial trial of the regression model tested prediction accuracy over two growing seasons and model predications were similar to measurements taken by plant canopy analyzer.

In principle, automatic data collection and LAI models fixed at the beginning of the trial will reduce plant disturbance, increase accuracy of data collection and reduce experimental field survey costs.

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