Radiometric Estimation of Canopy Leaf Inclination Angles of Various Crop Species Using Multi-Band Polarization and Reflectance

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The stand geometry of crop canopies usually cannot be detected by conventional remote sensing using spectral reflectance alone. The polarization of light reflected from the canopies has been used to give information about the vegetation canopy, such as the structure of leaf layers (Rondeaux and Herman, 1991) and the emergence of panicles above the canopy (Fitch et al., 1984). Theoretical and practical research has indicated the possibility of using polarization to detect the geometry of vegetation canopies (Egan, 1970; Curran, 1981; Ghosh et al., 1993; Herman and Vanderbilt, 1997; Shibayama, 2003).

A previous study suggested the possibility of detecting differences in the mean leaf inclination angle (MLI) using polarization (Shibayama, 2004). A plant with completely horizontal leaves has an MLI of 0°, and a plant with almost all leaves near vertical has larger MLI values, in extreme cases reaching 90°. MLI is an important parameter for characterizing canopy structure, since it varies greatly between crop species, cultivars, nutrient conditions, and growth stages. However, because the data were obtained at one visible band (660 nm) in that study, the potential of other wavelength bands for surveying canopy geometry is still unknown. It should be noted that there is little variation in polarization between visible wavelength bands because of the spectral homogeneity of the inflection coefficient of the cuticle of the leaf epidermis (Vanderbilt et al., 1985). However, few studies have been performed using polarization in the near- and shortwave infrared wavelength ranges. Hence, this paper sets out to demonstrate the possibility of multi-band polarization measurements for assessing crop canopy geometry. Clarification of the response of polarization of each wavelength band to the leaf orientation for selecting optimal bands, and the building of a practical model are beyond the scope of this short paper, and remain as future projects.

Materials and Methods

1. Experiment 1
(1) Plant materials

The experiments were conducted on the campus of the National Institute for Agro-Environmental Sciences (NIAES), Tsukuba. Wheat (Triticum aestivum L. cv. “Norin-61”) was drilled in early November 2001 in three fields fertilized differently. Soybeans (Glycine max (L.) Merr. cv. "Pickett 71"), sorghum (Sorghum bicolor (L.) Moench cv. “Hit-Sorgo”), sesame (Sesamum indicum L. cv. unknown, but called “Kurogoma,” meaning “black sesame”), and upland rice (Oryza sativa L. cv. “Yumenohatamochi”) were sown in mid-June 2002.

(2) Radiometric observations

The reflectance is the ratio of the intensity of reflected light to the intensity of incident light, and the polarized reflectance is the ratio of the intensity of polarized reflected light to the intensity of incident
light. The degree of polarization is the ratio of the polarized reflectance to the reflectance. A portable spectropolarimeter (Donarec Co. Ltd., Machida, Tokyo) was used to measure the light intensity and the degree of polarization in the wavelength bands centered around 490, 560, 660, 830, 1150, 1250, 1650, and 2200 nm, with a 10° field of view for the optical system. Reflectance and polarization were measured according to Shibayama (2004).

Observations of the wheat canopies were made on six clear-sky days in March, April, and May 2002. The summer crops were observed on nine clear-sky days in the period from June to September 2002. The optical sensing unit of the spectropolarimeter was mounted on a 1.7 m high tripod standing at the north side of the field, and observations were taken twice at each view zenith angle, 0°, 15°, 30°, 45°, 60°, and 75°. The variation in the area of the viewing ellipse of the sensor dependent on the angle was ignored. The azimuth direction of the view was always set towards the sun.

(3) Three-dimensional (3-D) measurements for MLI

Canopy geometry measurements were made using a Polhemus 3Space Isotrak II tracking system (Polhemus Inc., Colchester, VT, USA). The procedures for 3-D measurement and data processing were carried out according to Shibayama (2001). In the case of wheat, to avoid interference from spring breezes, a clump of plants was uprooted from the field, placed in a plastic pot with a diameter of 15 cm, and taken to the laboratory, where the 3-D canopy geometry measurements were made. The 3-D measurements of the summer crops were carried out in the field on single plants on calm days. Virtual leaves were reproduced with computer memory using 3-D coordinates to estimate the MLI of the canopies. The arithmetic mean of the MLI was 59.1°.

(4) Linear regression (LR)

In total, the data (n = 1893) obtained from 5 crops consisted of 27 variables, including the 8-band reflectance, normalized difference vegetation index (NDVI), 8-band degree of polarization and polarized reflectance, solar and view zenith angles (degrees). The data-set was analyzed on a microcomputer to estimate the MLI using a stepwise linear regression procedure provided by JMP, version 4 (SAS Institute Inc., Cary, NC, USA). A widely accepted vegetation index, NDVI, which is the ratio of the difference of the reflectance values to the sum in the visible red (660 nm) and near infrared (830 nm) bands, was also used in addition to the 8 single band reflectance values.

(5) Artificial neural network (ANN)

The architecture of the ANN is shown in Fig. 1. First, a principal component analysis (PCA) was applied to the original data-set consisting of the 8-band reflectance, degrees of polarization, solar and view zenith angles, to reduce the number of independent variables from 18 to 7. The seven variables were entered into a hidden layer consisting of 14 neurons, which were log-sigmoid transfer functions, and output layers for estimating the MLI. The Levenberg-Marquardt algorithm, a back propagation method, was used to train the network (Demuth and Beale, 2001). To avoid overfitting, the entire data-set was randomly divided into three subsets; 50% of the data was used for training, 25% for evaluation, and 25% for testing. The Neural Network Toolbox from MATLAB (The MathWorks, Inc., Natick, MA, USA, version 4) was used to perform the calculations on a microcomputer.

2. Experiment 2

(1) Plant materials

The cultivars of soybeans and sorghum used in
Experiment 1 were sown in the same field in late June and early July 2004. Rice plants (Oryza sativa, L., cv: "Koshihikari") were also transplanted into two 25 m × 10 m paddy fields on the NIAES campus, one field in mid-May 2004 and the other at the end of May 2004. Glutinous rice (Oryza sativa, L., cv: "Mochiminori") was planted in another 50 m × 10 m paddy field in late April 2004. Wheat and sesame were not used in this verification test. Instead of wheat, paddy rice was the major subject in Experiment 2. Both wheat and rice have sward leaves and rather similar leaf orientation geometry.

(2) Radiometric observations

The soybean canopies were measured on 9 days with a clear-sky in the period from early August to late October 2004. Because sorghum plants require a shorter growth period before maturing, the sorghum plot sown early was measured only on the first four days, and the sorghum plot sown late was measured on the first six of the nine measurement days. The paddy rice plots were measured on 11 fair days in the period from mid-June to early September 2004. The radiometric observation method was the same as described in Experiment 1 (2), except that the view zenith angle of 0° was not used. Measurements were repeated three times at each view zenith angle.

(3) Measurements of canopy geometry and verification of the models

A plant canopy analyzer (LAI-2000, Li-Cor Inc., Lincoln, NE, USA) was used in the field to estimate the LAI and mean tip angle (MTA) of the canopy stands (Welles and Norman, 1991). The definitions of MTA and MLI are equivalent. Therefore, instead of labor-intensive 3-D MLI measurements using the digitizer, MTA was used for the verification for the models. The MLI and the MTA had a high correlation (r > 0.99, n = 4) in the wheat canopy at around the booting stage, although they did not show a perfect one-to-one match (Shibayama and Watanabe, submitted). The radiometric observation data were substituted into the models built in Experiment 1 for verifying their abilities to estimate MLI, and this was compared with the MTA from the LAI-2000.

Results and Discussion

1. MLI predictions with LR

The results of regression analyses to estimate the MLI for the Experiment 1 data-set are summarized in Table 1. In the LR model (1) that has the view and solar zenith angles, polarized reflectance in the 660 nm band and NDVI accounted for 40% of the variation. The variables were selected arbitrarily according to the previous study (Shibayama, 2004).

| Model | Independent variables | Statistics of model (n = 1893) | Verification (n = 42) |
|-------|-----------------------|--------------------------------|----------------------|
| LR (1) | Q660*, NDVI*, Zv*, Zs* | F-variable 326.1* RMSE 6.4* R² 0.41 | RMSE 3.2* R² 0.46 |
| LR (2) | Q660*, NDVI*, Zs*, Zs*, 4 dummy variables for differentiating crop species* | 2862.9* F-variable 2.3* RMSE 0.92 | R² 0.83 |
| LR (3) | R490*, R560*, R660, R830*, R1150*, R1250*, NDVI*, P490*, P660, P830*, P1150*, P2200*, Q490, Q560, Q830*, Q1150*, Q1650*, Q2200*, Zv*, Zs | 202.8* F-variable 4.7* RMSE 0.68 | R² 0.51 |
| ANN | R490, R560, R660, R830, R1150, R1250, R1650, R2200, P490, P560, P660, P830, P1150, P1250, P1650, P2200, Zv, Zs | – F-variable 3.2* RMSE 0.81 | R² 0.76 |

*: The independent variables in the models LR (1) and LR (2) were chosen manually. Those in the model LR (3) were selected from all variables by the stepwise regression procedure.

*: Significant at 0.1% level.
n: Number of observation.
RMSE: Root mean square error.
Rxxx: Reflectance at the xxx nm band.
Pxxx: Degree of polarization at the xxx nm band.
Qxxx: Polarized reflectance at the xxx nm band (= Rxxx × Pxxx).
Zv: View zenith angle (°). Zs: Solar zenith angle (°).
Since the MLI of each crop species was distributed in a specific range, dummy variables for identifying crops were introduced into the LR model (2). The performance was drastically improved and accounted for 92% of the variation. Without the dummies, even the stepwise regression analyses using up to 20 independent variables in an LR model (3) resulted in an $R^2$ value of 68%. In addition to the large number of variables selected in the LR model (3), the variables came from the entire wavelength range, and reflectance and polarization measuring modes were also used. This may indicate that polarization at near- and shortwave infrared bands can provide some information on the MLI of crop canopies, or at least help cancel out the difference in the crop species. However, the coefficients of determination of the LR model (3) never achieved the 92% that was easily achieved in the LR model (2) by the introduction of dummy variables. This means that a specific LR model must be prepared for each crop species. The use of variables from neighboring wavelength bands, such as in the LR model (3), may cause unstable performance in predictions due to multi-collinearity problems (Wonnacott and Wonnacott, 1981).

2. Verifications tests for the LR models

In the interannual verification of the LR models using the dataset obtained in Experiment 2, the data measured before the leaves completely covered the soil surface were excluded ($n = 42$). The dummy variable in the LR model (2) estimated for the upland rice in Experiment 1 was used for the verification calculations for the paddy rice. The MLI values predicted by the LR model in the 5 view angles were averaged in advance and correlated with the measured MTA. The LR models (1), (2) and (3) showed the correlations ($r^2$) of 0.46, 0.83, and 0.51, respectively (Table 1). The verification result of the LR model (1) showed a non-linear relationship between the predicted and measured values. The relatively large value of the root mean square error (RMSE) 3.8° in the LR model (2) might be due to the separately clustered distributions of the data obtained for the three crop species. A rather large variation (RMSE = 3.9°) was observed in the verification result for the LR model (3).

3. MLI predictions with an ANN and a verification test

The ANN accounted for 81% of the variation in the MLI of the entire dataset of Experiment 1 in the training phase (Table 1). Estimated MLIs in the lower angle range (MLI < 40°) were overestimated, suggesting that the nonlinear characteristics in the relationship have not been modeled completely (Fig. 2). The performance was intermediate between the LR model (2) with dummy variables and the LR model (3) without dummies. Although the ANN has not yet been finely tuned, it gave a better estimate of MLI than the LR model (3) without information about the targeted crop species. As dummy variables were not required in the ANN, some sort of compensation for the difference in crop species may be possible with radiometric inputs if the model was well established.

In the interannual verification of the ANN using
the data-set obtained in Experiment 2, just as in the verifications for the LR models, the MLI values predicted by the ANN in the 5 view angles were averaged in advance and correlated with the measured MTA (Fig. 3). The predicted MLI showed a correlation with the measured MTA of $r^2 = 0.76$, excluding the data measured before the leaves completely covered the soil surface ($n = 42$). The MLI and the MTA had a high correlation but did not match one to one, so the observed MTA and predicted MLI values were not on the 1:1 line. The ANN gave the RMSE 2.5°, that was the best score among the RMSE values shown in the verified 4 models (Table 1).

The ANN performed well for crop canopies with a high MLI (>50°), but it made slight underestimates for canopies with lower MLIs where the leaves tended to be relatively close to the horizontal (<50°). The ANN has not yet been finely tuned to fit various crop species, especially for planophyll canopies. To build a more reliable ANN, we may need to collect data for training the ANN by date for each crop species instead of being selected randomly. The method should be thoroughly verified with an inconsistent canopy variable (MLI or MTA). Further work is also required for the selection of wavelength bands for estimating geometrical parameters using polarization for crop growth diagnosis or management. This will be dealt with in a future study in the current project.

**Summary and Conclusions**

The reflectance and degrees of polarization of several crop canopies were measured using a portable spectropolarimeter. The leaf inclination angles (MLI and MTA) of the observed crop canopies were probed using a 3-D digitizer and a plant canopy analyzer (LAI-2000), respectively. The multi-band and multi-view angle polarization and reflectance acquired at visible, near-, and shortwave infrared wavelength bands were used to train an artificial neural network (ANN) to predict the MLI of several crop species. In the next cropping season, the ANN was verified as being promising for differentiating the MTA of different crop species. This preliminary result has implications for obtaining structural information remotely about canopies using polarization data acquired in wide spectral ranges.

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