Coniferous Forest Leaf Area Index Estimation along the Oregon Transect Using Compact Airborne Spectrographic Imager Data

Peng Gong, Ruiqiang Pu, and John R. Miller

Abstract
Leaf area index (LAI) is an important structural variable for quantitative analysis of the energy and mass exchange characteristics of a terrestrial ecosystem. Previous research on estimating forest LAI by remote sensing is limited to the use of conventional multispectral data. Methods used for LAI estimation involved primarily simple statistical relationships between LAI and vegetation indices (VI) derived from remote sensing data.

In this paper, the potentials of an imaging spectrometer, the Compact Airborne Spectrographic Imager (CASI), have been studied for coniferous forest LAI estimation using three types of modeling techniques: univariate regression, multiple regression, and vegetation-index (VI) based LAI estimation. Four study sites have been selected along a forest transect in Oregon. LAI measurements were collected from these study sites. CASI data of two imaging modes — spatial and spectral — had been calibrated and corrected. The relationships between the LAI measurements and the corrected CASI data were then explored.

Results indicate that the CASI data acquired with the two imaging modes have similar accuracies for LAI prediction. All three LAI estimation methods resulted in LAI with reasonably low root-mean-squared errors (RMSEs). The use of the normalized difference vegetation index (NDVI) produced more accurate LAI estimates than did the use of channel ratio for the univariate regression and the VI-based LAI prediction methods. For the univariate regression, a non-linear hyperbola relationship between the LAI and the NDVI was the most appropriate for LAI estimation. In this study, the VI-based LAI estimation method has proven to be simple to use and effective.

Introduction
Leaf area index (LAI), the projected leaf surface area per unit ground area, is an important structural variable for quantifying the energy and mass exchange characteristics of a terrestrial ecosystem (Lathrop and Pierce, 1991; Herwitz et al., 1990; Spanner et al., 1990a; Nemani and Running, 1989; Running et al., 1989; Curran and Williamson, 1987; Asrar et al., 1988). It is probably the most useful parameter to be extracted from remote sensing data for crop yield prediction and crop stress assessment in agricultural studies, and for estimation of forest canopy characteristics and determination of forest exchange rates of carbon dioxide, water, and oxygen. For instance, the relationships between LAI and vegetation indices derived from various kinds of remote sensing data were studied in order to estimate a number of agro-ecological variables (Curran, 1983; Asrar et al., 1984; Baret et al., 1990; Batista and Rudorff, 1990; Clevens, 1991). That a strong correlation between LAI and vegetation indices exists was reported in those studies. Running et al. (1989) used forest LAI as an important variable in a forest biogeochemical (FOREST-BGC) model to map regional forest evapotranspiration and photosynthesis by coupling satellite sensor data with ecosystem simulation. Based on an assumption that an equilibrium exists between climate, soil water-holding capacity, and maximum leaf area in water-limited coniferous forest ecosystems, Nemani and Running (1989) developed a quantitative relationship among the three factors. This relationship allows the prediction of either equilibrium LAI or soil water-holding capacity if the other is known. In addition, the determination of LAI by remote sensing would also allow calculation of canopy photosynthesis and evapotranspiration over a global scale at a relevant time interval (Gutman, 1991; Spanner et al., 1990a).

Running et al. (1986) attempted to estimate the LAI of coniferous forests using an airborne Thematic Mapper Simulator (TMCS) data by establishing a relationship between the forest LAI and the ratio of a near infrared (NIR) band to a red (R) band. The LAI of temperate coniferous forests across a regional gradient was found to be related to the ratio of NIR to R TMS spectral bands (Peterson et al., 1987). Using multitemporal Advanced Very High Resolution Radiometer (AVHRR) data, Spanner et al. (1990a) derived the normalized differ-

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ence vegetation index (NDVI) for large area LAI studies. They found that there was an asymptotic relationship between maximum July AVIRIS NDVI data and the seasonal LAI maximum of coniferous forests of the western United States while the winter minimum NDVI values could not be explained entirely by phenological reduction of LAI probably due to some abiotic factors. After examining the relationships between LAI of temperate coniferous forests and Landsat Thematic Mapper (TM) spectral bands, ratios, and transforms, Spanner et al. (1990b) found that LAI estimation was affected by canopy closure, understory vegetation, and background reflectance. LAI changes of closed-canopy pine plantations in central Massachusetts were evaluated using Landsat TM data (Herwitz et al., 1990) and it was concluded that the TM data might provide a more reliable guide to changes in the LAI of closed canopy plantations at local scales than field measurements based on allometric equations. Seasonal LAI in slash pine was estimated based on the NDVI derived from Landsat TM data of three different seasons for the study of forest seasonal dynamics (Curran et al., 1992). A discrepancy between LAI values derived from ground-based canopy transmittance and those from Landsat TM NIR/R ratios has been noted in LaBarge and Pierce (1991). The differences are especially evident at low overstory LAI levels where differential background reflectance becomes important. A spectral derivative method was used to suppress the effects of background soil on tree spectra leading to improved correlation between LAI values measured from a low canopy closure ponderosa pine stand and data from the Compact Airborne Spectrographic Imager (CASI) (Gong et al., 1992).

Most previous studies on forest LAI estimation using remote sensing methods are primarily limited to the use of conventional multispectral data with a selected number of relatively broad spectral bands. Most of these studies have focused on finding a linear or non-linear relationship between LAI and various vegetation indices (VI) derived from remote sensing data. In a recent study, multitemporal remotely sensed data collected on three different airborne platforms over a transect of coniferous forest stands in Oregon were analyzed with respect to seasonal LAI (Spanner et al., 1994). Four different sensors were used including the broad spectral-band TMS and three narrow spectral-band high spectral resolution sensors: the CASI, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), and a Spectron SE590 spectroradiometer. Strong logarithmic relationships were observed between seasonal maximum and minimum LAI and the NIR/R for all these sensors ($R^2 = 0.82$ to 0.97). The correlation was examined at the forest stand level for all six study sites selected in the Oregon Transect Ecosystem Research (OTTER) project (Peterson and Waring, 1994).

In this study, efforts were focused on estimating LAI at a level of spatial scale smaller than that in Spanner et al. (1994), using data collected from a CASI instrument over four of the six OTTER coniferous forest sites. CASI acquires images in two modes, spatial and spectral, with very high spectral resolution (Anger et al., 1990). The objectives of this paper are

- to determine what technique is more appropriate for coniferous LAI estimation using CASI data, and
- to compare the effectiveness of the spatial and spectral imaging modes of CASI for LAI estimation.

### The Study Sites

The six OTTER study sites are located along a temperature-moisture gradient across west-central Oregon, called the Oregon transect. They are Cascade Head (Site 1), Waring's Woods (Site 2), Scio (Site 3), Santiam Pass (Site 4), Metolius River (Site 5), and Juniper (Site 6) (Peterson and Waring, 1994). The transect cuts across seven vegetation zones from the western coast to the eastern high desert of Oregon. The distributions of various zones and locations of study sites as well as coniferous species composition of each zone were described in detail in Gholz (1982). The LAI variation (from > 10 to < 1) across this transect is controlled by both temperature and moisture (Runyan et al., 1994). Canopy closure is greater than 90 percent for some of the western stands, and is less than 50 percent for some of the eastern stands. The understory vegetation along the transect consists of highly varying proportions of ferns, shrubs, and various grasses, with little exposed rock or soil along the first four study sites. Sites 5 and 6 have about 10 to 30 percent of soil exposure. In this study, only four sites — Sites 1, 2, 3, and 5 — were used. Major tree species for the four study sites are listed in Table 1.

### Data Collection and Preprocessing

#### Field LAI Measurements

An LAI-2000 Plant Canopy Analyzer (PCA) was used in the field to measure forest LAI. The operation instructions for the LAI instrument were followed carefully to make sure that the measured LAI values were within 10 percent of the mean values with a 0.95 confidence level (LI-COR Inc., 1990). From 15 May to 22 May, 1991, a total of 58 LAI measurements were taken by the authors at the six study sites. Out of these, 52 LAI measurements were collected under coniferous forest stands. The time involved in taking one LAI measurement ranged from a few minutes to half an hour depending on the accessibility of the site and the weather condition. The numbers of LAI measurements for four of these study sites are

<table>
<thead>
<tr>
<th>Tree Species</th>
<th>No. of LAI</th>
<th>Dates and Resolution (m) of CASI Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red Alder, Western Hemlock, Sitka</td>
<td>13</td>
<td>16 May (1.12×2.46)</td>
</tr>
<tr>
<td>Spruce (Site 1)</td>
<td>11</td>
<td>16 May (2.23×2.46)</td>
</tr>
<tr>
<td>Douglas Fir (Site 2)</td>
<td>11</td>
<td>15 May (2.23×2.46)</td>
</tr>
<tr>
<td>Western Hemlock, Douglas Fir</td>
<td>20 May (1.71×2.5)</td>
<td></td>
</tr>
<tr>
<td>Red Alder (Site 3)</td>
<td>8</td>
<td>20 May (1.71×2.5)</td>
</tr>
<tr>
<td>Ponderosa Pine (Site 5)</td>
<td></td>
<td>20 May (1.71×2.5)</td>
</tr>
</tbody>
</table>

#### Spectral-mode

<table>
<thead>
<tr>
<th>Tree Species</th>
<th>No. of LAI</th>
<th>Dates and Resolution (m) of CASI Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red Alder, Western Hemlock, Sitka</td>
<td>13</td>
<td>16 May (2.23×2.46)</td>
</tr>
<tr>
<td>Spruce (Site 1)</td>
<td>11</td>
<td>16 May (2.23×2.46)</td>
</tr>
<tr>
<td>Douglas Fir (Site 2)</td>
<td>11</td>
<td>15 May (2.23×1.7)</td>
</tr>
<tr>
<td>Western Hemlock, Douglas Fir</td>
<td>20 May (1.71×2.5)</td>
<td></td>
</tr>
<tr>
<td>Red Alder (Site 3)</td>
<td>8</td>
<td>20 May (1.71×2.5)</td>
</tr>
<tr>
<td>Ponderosa Pine (Site 5)</td>
<td></td>
<td>20 May (1.71×2.5)</td>
</tr>
</tbody>
</table>

#### Spatial-mode
listed in Table 1. Each LAI measurement represents an average of five to ten point PCA readings which were taken in an area between 40 and 100 m². The locations of LAI measurements in each study site were selected based on the canopy closure, age of stands, and nutrient level so as to make them representative of the variability in the site. Separated at least 10 m away from each other, the LAI measurements were considered as independent samples. The exact locations from which the LAI measurements were taken were marked on color infrared aerial photographs. These have been used as references for spectral data extraction from CASI images. A conversion factor has been used for each forest species to transform readings from an LAI-2000 PCA to LAI values (LI-COR Inc., 1990).

CASI Data Acquisition and Calibration

CASI is a relatively portable imaging spectrometer developed for use on board small aircraft or in laboratories. Due to the limitation of data recording rate, CASI is operated in two modes, a spatial mode and a spectral mode. In the spatial mode, the CASI acquires spatial images with each line having the full spectral resolution (512 pixels) and with up to 16 spectral channels. In addition, the spectral band widths, number, and ground cell resolutions are programmable in the spatial mode. In the spectral mode, the CASI generates images in which each pixel has a complete spectrum from approximately 417 nm to 927 nm in 266 bands, with an average spectral bandwidth of 1.76 nm and a spectral resolution of the spectral mode of CASI is approximately 3.5 nm. In this case, each image line has only 39 pixels, resulting in an image covering only stripes of areas along an aircraft flight track. The viewing direction along the swath can be selected interactively by the operator.

CASI data were acquired during the period of 16 to 21 May 1991 as part of the OTTER multiparameter airborne remote sensing campaign. Due to poor weather conditions or pilot misjudgement, LAI measurement locations from only four of the six OTTER study sites can be clearly identified from the data acquired (Table 1). The flight heights for these CASI data range from 900 m to 1800 m. Eight spectral channels were selected for the spatial mode according to the characteristics of a general vegetation spectral reflectance curve. These spectral channels are located at spectral regions including the blue, the inflection point of the blue-green slope, the green peak, the red well, the inflection point of the red edge, the red-edge shoulder, and two near-infrared bands (Table 2). Although the CASI spectral-mode data were calibrated using the CASI manufacturer’s parameters, the resultant radiance values for each image pixel are noisy. The noise came from two major sources: the specific atmospheric absorption features and the system errors. The first noise source has been suppressed using a radiance-to-reflectance conversion procedure described later. The second noise source has strong effects on the radiance values collected at wavelengths longer than 800 nm. Thus, radiance values at spectral bands whose wavelengths are longer than 800 nm have not been used in this study. The lack of spectral bands with wavelengths ranging from 800 nm to 1100 nm was not a problem in this study because there were enough spectral bands covering the shoulder of a true spectral curve in both the spectral- and spatial-mode CASI imagery.

All the spatial-mode and spectral-mode CASI images have been checked to identify LAI measurement locations by referring to the marked aerial color-infrared photographs. As a result, 30 LAI measurement locations have been identified from the four study sites for the spatial-mode images, while 28 LAI measurement sites have been located on the spectral-mode CASI images. Spectral data were then extracted from both the spatial-mode and the spectral-mode CASI images. Because of different sky conditions among different study sites, it is impossible to use radiance data directly from CASI images for LAI estimation. For this reason, the CASI data were converted from radiance to reflectance using simple linear relationships between reflectance measured from pseudo-invariant targets for each scene and the corresponding radiance from the CASI images. Ground reflectance measurements were taken using a SPECTRON SE-590 radiometer during the same field study period. The pseudo-invariant targets include roads, gravel pits, roof tops, and parking lots (Freemantle et al., 1992).

The extracted spectral-mode CASI data have been further processed using a band-merging method. Every five successive spectral bands have been merged to form a new channel. This resulted in 43 merged channels with their centers ranging from 421.2 nm to 794.4 nm and each of which has a band width of approximately 8.8 nm (Table 2). There are two reasons for spectral band merging for the spectral mode CASI data. First, band merging grouped originally narrow bands to suppress the noise noted above. Second, the number of channels has to be reduced in order to make better use of a multiple regression algorithm for LAI estimation. As explained later, the piece-wise multiple regression method would produce inflated LAI estimation results if the number of channels to be used as independent variables is much greater than the number of LAI measurements.

Model Developments

In order to estimate LAI from CASI data, the exact forms of LAI as a function of CASI data have to be established. Three types of models have been used in this study. In each model, the LAI of coniferous forests was defined as the dependent variable while spectral reflectance of each channel, its transforms such as its logarithmic transform, and two types of vegetation indices (e.g., $NDVI = (NIR - R)/(NIR + R)$ and $RVI = (NIR - R)/(NIR + R)$) were defined as independent variable(s). On the image each LAI location corresponds to approximately 10 to 20 pixels. The average spectral reflectances for each LAI location were taken from the images. The three types of models are described below.

Univariate Linear and Nonlinear Prediction Models

A total of seven univariate LAI prediction models were used. They include:

- a simple linear function, $Y = a + bX$;
- a power function, $Y = aX^b$;
- an exponential function, $Y = a\exp(bX)$;
- another exponential function, $Y = a\exp(cX)$;
- a logarithmic function, $Y = a + b\log(X)$;
- a hyperbola function, $Y = 1/(a + bX)$; and
- an $S$-model curve, $Y = Y'/(a + b\exp(-X))$;

where $Y$ represents the LAI to be predicted, $a$ and $b$ are regression coefficients, and $X$ denotes the independent variable. Candidates for $X$ included the eight bands in the spatial-mode and the 43 merged channels in the spectral-mode and many ratios and NDVIS. The purpose was to select an optimal model that produced the best goodness of fit (GOF) for LAI estimation using CASI data (Xu, 1988). Those ra-
Table 2. Channel and Merged-Channel Wavelengths (nm) of the CASI Images Used in This Study

<table>
<thead>
<tr>
<th>Spatial-Mode</th>
<th>Spectral-Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH#</td>
<td>λ</td>
</tr>
<tr>
<td>1</td>
<td>440.3</td>
</tr>
<tr>
<td>2</td>
<td>497</td>
</tr>
<tr>
<td>3</td>
<td>551.4</td>
</tr>
<tr>
<td>4</td>
<td>679.2</td>
</tr>
<tr>
<td>5</td>
<td>711.3</td>
</tr>
<tr>
<td>6</td>
<td>738.1</td>
</tr>
<tr>
<td>7</td>
<td>747.9</td>
</tr>
<tr>
<td>8</td>
<td>787.3</td>
</tr>
</tbody>
</table>

Note: CH# = channel number of the spatial-mode CASI data  
MCH# = merged-channel number of the spectral-mode CASI data  
λ = central wavelength (nm).

VI-Based LAI Estimation

After examining the potentials and limits of vegetation indices for LAI and APAR (absorbed photosynthetic active radiation) estimation, Baret and Guyot (1991) published a model in which the variation of VI as a function of LAI, can be expressed by a modified Boer’s law: i.e.,

\[ VI = VI_L + (VI_L - VI) \cdot \exp (-K_V \cdot \text{LAI}) \]  

(1)

where \( VI_L \) is the vegetation index corresponding to that of the bare soil, \( VI \) is the asymptotic value of VI infinity (practically, this limit can always be reached when LAI is greater than 8.0), and \( K_V \) is an attenuation coefficient. For the purpose of this study, Equation 1 has been rearranged in order to estimate LAI: i.e.,

\[ \text{LAI} = -\ln \left( \frac{VI}{VI_L} - \frac{VI_L}{VI} \right) \cdot K_V \]  

(2)

In this approach, \( VI \) was specified with the maximum value appearing in this study, while \( VI_L \) was obtained by averaging vegetation indices on the bare soil from the four study sites.

Piece-Wise Multiple Regression

A forward piece-wise regression procedure (Tang, 1984) was employed to determine channel combinations that were most strongly associated with the LAI. The input to the piece-wise regression procedure is the LAI values measured in the field and spectral reflectances at each channel. The output is a series of multivariate linear equations which are different from each other by the number of spectral channels involved, and the goodness of fit (R2) and the standard deviation associated with each equation. In this method, the regression equation is developed by successive insertion of a predictor variable (e.g., a spectral channel) into the equation based on the ranking of the partial correlations of all variables that are not selected with the dependent variable (LAI). The final regression equation, after running the piece-wise program, can be expressed in the following form:

\[ Y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k \]  

(3)

where \( X_i \) represents the ith predictor (independent) variable, usually channel reflectance or channel logarithmic reflectance. \( Y \) denotes the predicted LAI, and \( b_i \) is the ith regression coefficient (\( b_0 \) is a constant) having the “best” GOF. The accuracy of LAI estimation by the univariate and multiple regression models was evaluated using the root-mean-squared error (RMSE).

Results and Discussion

Correlating LAIs with Spatial-Mode CASI Data

Univariate Correlations between the LAIs and the Spatial-Mode CASI Data

As mentioned above, spectral data corresponding to 30 LAI measurements were extracted from the spatial-mode CASI data for the four sites. The distributions of the 30 LAI measurements locations are ten for site 1, six for site 2, six for site 3, and eight for site 5. The highest GOFs were obtained from those derivative data consisting of channel ratios and NDVIS calculated from a combination of the NIR channels and the red channel. The linear and highest non-linear GOFs for the eight single channels and the six sets of derivative data with the highest GOFs are listed in Table 3. It is interesting to note that the highest non-linear GOFs were all obtained using the hyperbola model. The 5-model curve fitting consistently resulted in the second best GOFs, while the two models based on power functions produced the third best GOFs. From a

<table>
<thead>
<tr>
<th>Code</th>
<th>Channel Types</th>
<th>Linear Fitting (R²)</th>
<th>Nonlinear Fitting (R²)</th>
<th>Hyperbola Model</th>
<th>Nonlinear Fitting (R²)</th>
<th>Exponential Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ch 1 (440.3 nm)</td>
<td>0.25</td>
<td>0.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>ch 2 (497.0 nm)</td>
<td>0.36</td>
<td>0.58</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>ch 3 (551.4 nm)</td>
<td>0.11</td>
<td>0.21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>ch 4 (679.2 nm)</td>
<td>0.46</td>
<td>0.72</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>5</td>
<td>ch 5 (711.3 nm)</td>
<td>0.01</td>
<td>0.06</td>
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<td></td>
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</tr>
<tr>
<td>6</td>
<td>ch 6 (738.1 nm)</td>
<td>0.36</td>
<td>0.39</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>ch 7 (747.9 nm)</td>
<td>0.42</td>
<td>0.46</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>ch 8 (787.3 nm)</td>
<td>0.49</td>
<td>0.55</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>(ch7−ch4)/(ch7+ch4)</td>
<td>0.65</td>
<td>0.86</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>(ch8−ch4)/(ch8+ch4)*</td>
<td>0.65</td>
<td>0.87</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>(ch8−ch4)/(ch8+ch4)</td>
<td>0.65</td>
<td>0.87</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>ch5/ch4</td>
<td>0.70</td>
<td>0.87</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>ch7/ch4</td>
<td>0.71</td>
<td>0.87</td>
<td>0.80</td>
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<tr>
<td>14</td>
<td>ch6/ch4</td>
<td>0.72</td>
<td>0.88</td>
<td>0.80</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>the highest among codes 9, 10, 11</td>
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<td></td>
<td></td>
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</tbody>
</table>

*the highest among codes 9, 10, 11.
TABLE 4. Root-Mean-Square Errors (RMSE), Goodness of Fit, and Mean Attenuation Coefficients (K) Obtained from Different Analysis Methods with the Spatial-Mode CASI Data

<table>
<thead>
<tr>
<th>Independent Variables in Equations</th>
<th>RMSE</th>
<th>R²</th>
<th>K/Sk*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piece-wise Regression Analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOG(ch1),LOG(ch2),LOG(ch3),LOG(ch6)</td>
<td>0.982</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>LOG(ch1),LOG(ch3),LOG(ch6)</td>
<td>0.836</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>LOG(ch6),LOG(ch8)</td>
<td>0.873</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>Univariate Regression</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ch6/ch4</td>
<td>1.697</td>
<td>0.88</td>
<td></td>
</tr>
<tr>
<td>ch7/ch4</td>
<td>1.729</td>
<td>0.87</td>
<td></td>
</tr>
<tr>
<td>ch9/ch4</td>
<td>1.727</td>
<td>0.87</td>
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</tr>
<tr>
<td>(ch8-ch4)/(ch8+ch4)</td>
<td>1.117</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td>(ch7-ch4)/(ch7+ch4)</td>
<td>1.110</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td>(ch6-ch4)/(ch6+ch4)</td>
<td>1.117</td>
<td>0.85</td>
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</tr>
<tr>
<td>VI-based LAI Estimation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(ch8-ch4)/(ch8+ch4)</td>
<td>1.172</td>
<td>0.42</td>
<td>0.119</td>
</tr>
<tr>
<td>(ch7-ch4)/(ch7+ch4)</td>
<td>1.206</td>
<td>0.37</td>
<td>0.110</td>
</tr>
<tr>
<td>(ch6-ch4)/(ch6+ch4)</td>
<td>1.227</td>
<td>0.36</td>
<td>0.109</td>
</tr>
</tbody>
</table>

*: K/Sk=mean attenuation coefficient/standard deviation of K; †: significant at p=0.01.

LAI Estimation with Spatial-Mode CASI Data

LAI of coniferous forests were predicted using three techniques: univariate regression, piece-wise multivariate regression, and the VI-based estimation. For each prediction technique, the 30 samples were divided into two groups: predicting and testing. The predicting group consisted of 20 samples while the remaining ten were used as test samples. The predicting group was used in coefficient estimation to establish the LAI prediction equations, while the test group was used to calculate the root-mean-square errors (RMSEs). The division of predicting sample and test sample was made randomly so as to have the test sample as representative to the total sample as possible. The variable types used in LAI predicting equations, accuracies of the predictions measured by RMSEs, and GOFs (R²) are listed in Table 4. While the RMSEs were obtained from test samples, the GOFs were calculated from the predicting samples at the same time as the predicting equations were derived.

It can be seen from Table 4 that the only comparable measure for all the three types of LAI estimation techniques is the RMSE. The lowest estimation errors have been achieved with the use of piece-wise regression. After comparing the effectiveness of multiple regression using different types of variables (e.g., original reflectance, transforms, etc.), it was found that the logarithmic value of channel reflectance had the best relationship to LAIs. Therefore, in the multiple regression analysis, each of spectral reflectance was transformed into its logarithmic counterpart. For the univariate regression case, even though some of the channel ratios had high GOFs in relation to LAIs, they produced greater RMSEs as compared to NDVI (Table 4). The univariate regression

TABLE 5. Root-Mean-Square Errors (RMSE), Goodness of Fit, and Mean Attenuation Coefficients (K) Obtained from Different Analysis Methods with Spectral Mode

<table>
<thead>
<tr>
<th>Independent Variables in Equations</th>
<th>RMSE</th>
<th>R²</th>
<th>K/Sk*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piece-wise Regression Analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOG(mch2),LOG(mch3),LOG(mch14),LOG(mch34)</td>
<td>1.405</td>
<td>0.89</td>
<td></td>
</tr>
<tr>
<td>LOG(mch3),LOG(mch14),LOG(mch34)</td>
<td>1.052</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>LOG(mch3),LOG(mch14)</td>
<td>1.042</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>Univariate Regression</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(mch40-mch22)/(mch40+mch22)</td>
<td>0.764</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>(mch40-mch25)/(mch40+mch25)</td>
<td>0.848</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>(mch43-mch29)/(mch43+mch29)</td>
<td>1.151</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>VI-based LAI Estimation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(mch40-mch22)/(mch40+mch22)</td>
<td>1.079</td>
<td>0.29</td>
<td>0.060</td>
</tr>
<tr>
<td>(mch40-mch25)/(mch40+mch25)</td>
<td>1.033</td>
<td>0.32</td>
<td>0.068</td>
</tr>
<tr>
<td>(mch43-mch29)/(mch43+mch29)</td>
<td>1.218</td>
<td>0.43</td>
<td>0.130</td>
</tr>
</tbody>
</table>

*: K/Sk=mean attenuation coefficient/standard deviation of K; †: significant at p=0.01.
method based on NDVI has produced slightly smaller errors than the VI-based LAI estimation.

For the VI-based LAI estimation method, the mean attenuation coefficient ($K$) was calculated directly from Equation 2. This was done by first calculating each $K$, using the corresponding LAI and VI, and then the $K$ were averaged to form the $K$ to be used in the LAI prediction. $S_k$ is the standard deviation of $K$. The GOFs obtained using the multiple regression method are significant at the 0.99 probability level. Among the results obtained from each of the three techniques, all the errors are relatively small when compared to the magnitude of the LAIs.

The field measured LAI values have been compared with those predicted ones for the multiple regression, univariate regression, and the VI-based model, respectively (Figures 2, 3, and 4). It is evident when compared with Figure 2 that data points in Figures 3 and 4 tend to have a larger scattering pattern, indicating a poorer agreement between the predicted and measured LAIs. It is interesting to note that in every figure a larger discrepancy between the predicted LAIs and the LAI measurements can be observed as the LAI value exceeds approximately 6.0. From a computational point of view, the VI-based LAI estimation is the simplest. On the other hand, the multiple regression algorithm is more flexible. It does not require channels to be in the red and NIR spectral regions.

**Correlating LAIs with Spectral-Mode CASI Data**

**Univariate Correlation Analysis between LAIs and Merged Channels**

GOFs obtained from both the linear correlation and the best non-linear correlation have been plotted versus the central wavelengths of the merged channels (Figure 5). Most of the visible channels have resulted in surprisingly high GOFs.
while the NIR channels have led to very low GOFs. A number of factors might have contributed to low GOFs among the NIR channels. First, the spectral-mode data had relatively large pixel sizes and only covered a portion of the study area in a systematic manner. These made it difficult to precisely locate the LAI measurement sites. In other words, location mismatching between ground and the spectral-mode CASI images could introduce errors. While little variation may occur in the visible bands because of the low spectral reflectances of tree stands, in the near infrared bands the sensor may be very sensitive to the large pixel-averaging effects and possible misplacement of LAI sites. Second, sensor calibration errors may also contribute to the low GOFs in the NIR bands. Such errors are related to (1) the relatively poor internal data calibration in the NIR bands, (2) the inconsistency of the narrow band wavelengths between the CASI and the Spectron Engineering 590 field spectroradiometer used to collect spectra for pseudo-invariant targets, and (3) the temporal differences caused different weather conditions during the period of CASI and the field spectroradiometer data acquisition across the four study sites.

LAI Estimation Using Spectral-Mode CASI Data

Similar to the LAI prediction analysis with the spatial-mode CASI data, the three LAI estimation techniques were also applied to the spectral-mode CASI data. The most accurate prediction results in terms of the lowest RMSEs have been listed in Table 5. A total of only 19 LAI measurement locations have been found from the spectral-mode images. Again, 20 samples were divided into the predicting group while the remaining eight were used as test sample. "Mch" was used to represent merged channels. Similar to the use of the spatial-mode CASI data, the logarithm of original channel reflectance had a greater power of LAI prediction than the original reflectance and various channel combinations for the multiple regression case.

Different from the spatial-mode’s case, however, the NIR channels of the spectral-mode CASI data made little contribu-

Figure 3. Measured LAI S compared with predicted LAI S using the univariate regression with spatial-mode CASI data. Predicted LAI S were obtained from both the 20 predicting samples used for setting up the predicting equation and the ten test samples. (a) Predicted with NDVI between NIR CH8 and R CH4; (b) predicted with NDVI between NIR CH7 and R CH4; and (c) predicted with NDVI between NIR CH6 and R CH4. Channel wavelengths can be found in Table 2.

Figure 4. Measured LAI S compared with predicted LAI S using the vi-based LAI estimation method with CASI spatial data. Predicted LAI S were calculated by using both the 20 predicting samples used to derive the average attenuation coefficient (K) and the ten test samples. (a) Predicted with NDVI between NIR CH8 and R CH4; (b) predicted with NDVI between NIR CH7 and R CH4; and (c) predicted with NDVI between NIR CH6 and R CH4. Channel wavelengths can be found in Table 2.
tion to LAI prediction with multiple regression possibly due to the reasons mentioned in the previous section (Table 3). For the univariate regression analysis and the Vi-based LAI estimation methods, NDVI has shown better performance than have other variables such as channel ratios and individual merged channels. In combination with what has been found from the use of spatial-mode CASI data, NDVI as a measure of LAI seems to be more robust than channel ratios. The NDVI is less sensitive to variations in location, viewing angle, and lighting conditions when compared with the NIR channels because the NIR channels acquired from different sites and at different times of the day produced very low GOFS.

The RMSEs for the piece-wise regression method are the highest among the three methods (Table 5). By comparing the RMSEs obtained from the univariate regression and Vi-based LAI estimation methods, we see that the univariate method has lower RMSEs than does the Vi-based method. When comparing GOFS derived from the piece-wise method with univariate regression, the GOFS of the latter are considerably higher than those of the former. The predicted LAs and the measured LAs are compared for each of the three methods (Figures 6, 7, and 8). Again, better agreements can be found when LAI values are less than 6.0. This is consistent with what Figures 2, 3, and 4 show.

A Comparison of the Two CASI Imaging Modes for LAI Estimation

The results obtained by correlating each individual channel (or merged channel) with measured LAs show that in the visible region the spectral-mode CASI data have a considerably stronger correlation with LAs than the spatial-mode CASI data. For instance, for the spectral-mode CASI data, the GOFS obtained using the merged channel 30 (676 nm) of the spectral-mode data are 0.65 and 0.86 using a linear and a non-linear hyperbola model, respectively (see Figure 5). On the other hand, the highest linear and non-linear GOFS for the spatial-mode data obtained from the use of channel 4 (679 nm) are 0.46 and 0.72, respectively. At the NIR region, however, the GOFS obtained with the spectral-mode data are much lower than those obtained with the spatial-mode data.

By comparing the RMSEs in Table 4 with those in Table 5, the LAI prediction accuracies are better with the spatial-mode data than those with the spectral-mode data for the multiple regression method. On the other hand, most of the prediction accuracies obtained from using the spectral-mode data are higher than those obtained from using the spatial-mode data for the univariate regression and the Vi-based LAI estimation method.

The same trend holds when the practical effectiveness of the three LAI estimation methods were further validated. LAI prediction equations were used to estimate the LAs of coniferous forests in a broader spatial scale for three selected study sites (Sites 2, 3, and 5) using the available CASI images. An average radiance value was extracted from every spectral channel for each study site. These radiances were then converted to spectral reflectances. Having been converted to logarithmic values or transformed into NDVs, they were used as inputs to the LAI prediction equations. Table 6 summarizes the LAI estimation results as compared to ground-based LAI estimates for each selected study site (ground-based LAs were provided by R. Waring). A relative error, defined as the ratio of the standard deviation (between the remote sensing estimates and ground-based estimates) and the average.

Figure 5. Goodness of fit obtained from linear and nonlinear regressions between LAI and merged channels.

Figure 6. Measured LAs compared with predicted LAs using the piece-wise regression with CASI spectral data. Predicted LAs were obtained from both the 20 predicting samples used for setting up the predicting equation and the eight test samples. (a) Predicted with four channels corresponding to 429.9 nm, 438.5 nm, 534.7 nm, and 712.1 nm, respectively; (b) predicted with three channels corresponding to 438.5 nm, 534.7 nm, and 712.1 nm, respectively; and (c) predicted with two channels corresponding to 438.5 nm and 534.7 nm, respectively.
ground-based estimates, was calculated for each method (Table 6). The relative errors range from 11 percent to 17 percent. In this comparison, results from the VI-based LAI estimation method have shown the best agreement with the ground-based LAI estimates, while the multiple regression and univariate regression ranked the second and the third, respectively. The spectral-mode CASI data have resulted in slightly better LAI estimates than have the spatial-mode data. The LAI values in Table 6 were estimated using the following equations:

For the spatial mode,

Model I: \( \text{LAI} = 4.620 + 4.334 \cdot \text{Log}(MCH2) - 4.909 \cdot \text{Log}(MCH1) - 1.570 \cdot \text{Log}(MCH14) + 1.655 \cdot \text{Log}(MCH34) \),

Model II: \( \text{LAI} = 1/(1 - 0.7970 + 1.0824/(\text{NDVI} + 0.3924)) \), and

Model III: \( \text{LAI} = - \ln \left( \frac{\text{NDVI} - 0.85}{0.03616 - 0.85} \right) / 0.3187 \)

where \( \text{NDVI} = (MCH40 - MCH25)/(MCH40 + MCH25) \).

Conclusions

One of the objectives of this study was to evaluate three methods — piece-wise multiple regression, univariate regression, and the vegetation-index-based method — for LAI estimation using two different modes of CASI data: the spatial and spectral modes. The piece-wise multiple regression method resulted in lower RMSE prediction errors as com-
Table 6. Cross Validation of Predicted LAI Using Three Techniques: Piece-wise (I), Univariate Regression (II), and VI-based LAI Estimation (III) with CASI Data*

<table>
<thead>
<tr>
<th>Study Area</th>
<th>G.B.LAI</th>
<th>Spatial-mode</th>
<th>Spectral-mode</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>site 2</td>
<td>6.33</td>
<td>6.42</td>
<td>6.24</td>
</tr>
<tr>
<td>site 3C</td>
<td>7.23</td>
<td>8.77</td>
<td>5.62</td>
</tr>
<tr>
<td>site 3F</td>
<td>8.46</td>
<td>9.03</td>
<td>9.14</td>
</tr>
<tr>
<td>site 5C</td>
<td>0.8</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>site 5F</td>
<td>1.8</td>
<td>1.18</td>
<td>1.20</td>
</tr>
<tr>
<td>Average relative error</td>
<td>0.16</td>
<td>0.17</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Note: "G.B.LAI" = ground-based LAI measurement; "C-control study area; F-fertilized study area; and IF-intensive fertilized study area. *These ground-based LAI measurements were provided by Richard Waring. They were collected from the study site level which is completely different from the other LAI measurements used in the rest of this study.

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References


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