Estimation of Canopy-Average Surface-Specific Leaf Area Using Landsat TM Data

Leo Lymburner, Paul J. Beggs, and Carol R. Jacobson

Abstract
Specific leaf area (SLA) is an important ecological variable because of its links with plant ecophysiology and leaf biochemistry. Variations in SLA are associated with variations in leaf optical properties, and these changes in leaf optical properties have been found to result in changes in canopy reflectance. This paper utilizes these changes to explore the potential of estimating SLA using Landsat TM data.

Fourteen sites with varying vegetation were sampled on the Lambert Peninsula in Ku-ring-gai Chase National Park to the north of Sydney, Australia. A sampling strategy that facilitated the calculation of canopy-average surface SLA (SLA_{G},s) was developed. The relationship between SLA_{G}, reflectance in Landsat TM bands, and a number of vegetation indices, were explored using univariate regression. The observed relationships between SLA_{G} and canopy reflectance are also discussed in terms of trends observed in a pre-existing leaf optical properties dataset (LOPEX 93).

Field data indicate that there is a strong correlation between SLA_{G} and red, near-infrared, and the second mid-infrared bands of Landsat TM data. A strong correlation between SLA_{G} and the following vegetation indices: Soil and Atmosphere Resistant Vegetation Index (SARVI2), Normalized Difference Vegetation Index (NDVI), and Ratio Vegetation Index (RVI), suggests that these vegetation indices could be used to estimate SLA_{G} using Landsat TM data.

Introduction
A number of important biophysical and biochemical parameters for ecosystem modeling, including leaf area index (LAI), specific leaf area (SLA), biomass, fraction of photosynthetically active radiation absorbed (FPAR), and total nitrogen, have been identified in recent years. Specific leaf area, the one-sided area of the leaf divided by the dry weight of the leaf, has been the focus of recent research into plant ecophysiology and leaf biochemistry, and has been found to link plant functional types around the world. Table 1 shows average SLAs associated with major vegetation types. Examples of significant relationships between ecological and biochemical variables and SLA which have been described in recent research are described in Table 2.

Some recently developed ecological and biogeochemical models have included SLA values as aspatial parameters. BIOM3 (Haxeltine and Prentice, 1996) and the Terrestrial Uptake and Release of Carbon model (TURC) (Ruimy et al., 1996) are two examples. There is potential for improving these models by including remotely sensed, rather than aspatial, SLA datasets. A spatial SLA dataset could be incorporated into ecological and biogeochemical models in a similar fashion to a leaf area index (LAI) dataset, potentially allowing the inclusion of parameters such as leaf life span, litterfall rate, leaf carbon to nitrogen ratio, and canopy nitrogen content. The inclusion of SLA and associated parameters into future ecological models would facilitate parameterization of more plant ecophysiological constraints. The incorporation of such parameters into biogeochemical models could assist in the calculation of carbon and nitrogen turnover rates.

SLA and its inverse, leaf mass per unit area (LMA, also known as specific leaf weight, SLW), have also been shown to be important for the remote sensing of canopy biochemical content. Recently, methods of remotely sensing canopy biochemistry have been developed using hyperspectral scanners to measure the specific absorption of individual compounds (Curran et al., 1997; Jacquemoud et al., 1996; Martin and Aber, 1997). However, according to Baret and Fourt (1997), these methods, while successful for their individual sites, do not transfer well to other sites or, in some cases, even to other times of the year for the same site. They found that the only biochemical variables that could be reliably estimated from canopy reflectance were SLW and leaf water content.

Although SLA is an important biophysical variable, few previous studies have examined the possibility of estimating SLA from remotely sensed data. An important study by Pierce et al. (1994) reported relationships between LAI and canopy-average SLA and leaf nitrogen content, and suggested that both SLA and leaf nitrogen could be predicted from remotely sensed LAI values. Other studies include Running et al. (1995) which proposed the calculation of SLA based on leaf life span, calculated from a normalized difference vegetation index (NDVI) time series, and Fourt and Baret (1997) which examined the calculation of canopy SLA using hyperspectral data. The present study aims to more directly examine the effect of SLA on canopy reflectance, and, therefore, the possibility of monitoring SLA using low spectral resolution satellite data.

SLA has been shown to be genetically encoded (Mooney et al., 1978), though variations do occur in plants of single species. Preliminary fieldwork in a study area with a wide variety of water and nutrient availability, and therefore diverse vegetation, indicated spatial relationships between reflectance data and plant species. Areas of high reflectance at near-infrared (NIR) wavelengths were associated with forest eucalypts, for example, Angophora floribunda, while low reflectances were associated with open heath species, for example, Banksia ericifolia. The wide range of leaf structures, and data from Summerhayes (1996), indicated a wide range of SLA values would be obtained in the field.

Photogrammetric Engineering & Remote Sensing
0099-1112/00/6602–183$3.00/0
© 2000 American Society for Photogrammetry and Remote Sensing
The rationale for examining the use of low spectral resolution data to estimate SLA is based on research examining the use of vegetation indices to estimate LAI, both in the field (for example, Coops et al., 1997; Gong et al., 1995; Spanner et al., 1990) and using models to simulate reflectance spectra (for example, Gobron et al., 1997; Myneni et al., 1997). The estimation of LAI from a vegetation index is based on the effect that the optical depth (number of leaves) of the canopy will have on that vegetation index (Gobron et al., 1997; Myneni et al., 1997), i.e., a high number of leaves will imply a large optical depth, which will result in a high vegetation index. A number of authors have recently suggested that the optical properties of the elements (leaves) that make up the canopy may also affect canopy reflectance and the response of vegetation indices (Asner et al., 1998; Huemmrich and Goward, 1997; Huete et al., 1997; van Leeuwen and Huete, 1996). Therefore, the expected relationship between SLA and the optical properties of the leaves, and the accumulative effect on canopy reflectance, imply that it may be possible to estimate SLA using low spectral resolution satellite data.

**SLA and Leaf Optical Properties**

The expected influence of SLA on leaf optical properties in the wavelengths associated with Landsat TM bands are shown in Table 3. The source and rationale for these relationships is outlined briefly below.

**SLA and reflectance in the green band:**

- Leaf surface modifications associated with low SLA, i.e., trichomes, waxes, and salt bladders, increase the amount of reflectance in the green band (Sinclair and Thomas, 1970; Thomas and Barber, 1974).
- Low chlorophyll a concentrations, associated with low SLA, increase green reflectance by decreasing absorption at these wavelengths (Gitelson et al., 1996; Yoder and Waring, 1994).

**SLA and reflectance in the red band:**

- Leaf surface modifications associated with low SLA, also increase the amount of reflectance in the red band (Sinclair and Thomas, 1970; Thomas and Barber, 1974).
- Low chlorophyll a, chlorophyll b, and xanthophyll concentrations, associated with low SLA, result in an increase in red reflectance (Curran et al., 1997; Fourny et al., 1996; Govaerts et al., 1996; Jacquemoud et al., 1996; Martin and Aber, 1997; Vogelmann, 1994; Wooley, 1971).

**SLA and reflectance in the near-infrared (NIR) band:**

- The presence of non-vascular sclerenchyma and rhexoids, that reduce SLA, also reduce the amount of NIR reflectance (Gausman, 1974; Vogelmann, 1996).
- The presence of non-metabolic carbon compounds such as cellulose, hemicellulose, and lignin in cell walls, that reduce SLA, also act to decrease the amount of NIR reflectance (Fourny et al., 1996; Govaerts et al., 1996; Jacquemoud et al., 1996).
- It should be noted, however, that refraction at air-water interfaces at cell walls is the dominant influence on NIR reflectance.

**SLA and reflectance in the mid-infrared bands, MIR1 and MIR2:**

- Leaf water content varies in a pattern similar to SLA, i.e., high SLA is associated with high leaf water content (Reich et al., 1997), and increases in leaf water content decrease reflectance in the MIR1 and MIR2 bands (Fourny and Baret, 1997).
- Although the presence of non-metabolic carbon compounds, that reduce SLA also act to decrease the amount of MIR1 and MIR2 reflectance (Fourny et al., 1996; Govaerts et al., 1996), in these bands the effect of leaf water content on canopy reflectance can override the effect of non-metabolic carbon content (Jacquemoud et al., 1996).

Based on these reported relationships, it may be possible to remotely sense SLA using low spectral resolution satellite data, facilitating the estimation of canopy biochemistry over a range of vegetation types, and providing improved parameters for inclusion into ecological and biogeochemical models.

### Table 1. Major Vegetation Types and Their Average SLA (from Table 1 in Schulze et al., 1994)

<table>
<thead>
<tr>
<th>Major vegetation type</th>
<th>Average SLA (m²/kg)</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen conifers</td>
<td>4.1</td>
<td>0.4</td>
</tr>
<tr>
<td>Monsoon forest</td>
<td>4.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Temperate evergreen broadleaf</td>
<td>5.7</td>
<td>0.8</td>
</tr>
<tr>
<td>Sclerophyllous shrubland</td>
<td>6.9</td>
<td>0.7</td>
</tr>
<tr>
<td>Tropical rainforest</td>
<td>9.9</td>
<td>1.4</td>
</tr>
<tr>
<td>Deciduous conifers</td>
<td>11.3</td>
<td>1.4</td>
</tr>
<tr>
<td>Temperate deciduous trees</td>
<td>11.5</td>
<td>2.4</td>
</tr>
<tr>
<td>Tropical deciduous forest</td>
<td>14.1</td>
<td>2.3</td>
</tr>
<tr>
<td>Temperate grassland</td>
<td>16.9</td>
<td>1.3</td>
</tr>
<tr>
<td>Broadleaved crops</td>
<td>23.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Cereals</td>
<td>25.3</td>
<td>1.9</td>
</tr>
</tbody>
</table>

### Table 2. The Relationship Between SLA and Ecological and Biochemical Variables

<table>
<thead>
<tr>
<th>Ecological variable</th>
<th>Relationship with SLA</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net photosynthesis</td>
<td>Direct</td>
<td>Reich et al., 1998; Reich et al., 1997; Schulze et al., 1994</td>
</tr>
<tr>
<td>Leaf area index</td>
<td>Direct</td>
<td>Fassnacht and Gower, 1997; Jose and Gillespie, 1997; Schulze et al., 1994</td>
</tr>
<tr>
<td>Ecosystem production efficiency</td>
<td>Direct</td>
<td>Reich et al., 1997; Jose and Gillespie, 1997</td>
</tr>
<tr>
<td>Above-ground net primary productivity</td>
<td>Direct</td>
<td>Fassnacht and Gower, 1997</td>
</tr>
<tr>
<td>Leaf life span</td>
<td>Inverse</td>
<td>Reich et al., 1998; Reich et al., 1997; Atkin et al., 1997; Ryser, 1996</td>
</tr>
<tr>
<td>Biochemical variable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leaf nitrogen content</td>
<td>Direct</td>
<td>Baret and Fourny, 1997; Schulze et al., 1994</td>
</tr>
<tr>
<td>Leaf cellulose and lignin content</td>
<td>Inverse</td>
<td>Baret and Fourny, 1997; Fourny and Baret, 1997; Jacquemoud et al., 1996</td>
</tr>
<tr>
<td>Leaf water content</td>
<td>Direct</td>
<td>Shipley, 1985</td>
</tr>
</tbody>
</table>

### Table 3. The Expected Influence of SLA on Canopy Reflectance

<table>
<thead>
<tr>
<th>Landsat TM band</th>
<th>Green (nm)</th>
<th>Red (nm)</th>
<th>Near-infrared (nm)</th>
<th>Mid-infrared Band 1 (nm)</th>
<th>Mid-infrared Band 2 (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelength</td>
<td>520–600</td>
<td>630–690</td>
<td>760–900</td>
<td>1550–1750</td>
<td>2080–2350</td>
</tr>
<tr>
<td>Expected relationship</td>
<td>Inverse</td>
<td>Inverse</td>
<td>Direct</td>
<td>Inverse</td>
<td>Inverse</td>
</tr>
</tbody>
</table>

**February 2000**

PHOTOMGRAMMETRIC ENGINEERING & REMOTE SENSING
Study Area
Fourteen sample sites were located in the Ku-ring-gai Chase National Park on Lambert Peninsula which is located in coastal New South Wales, Australia (Figure 1). The study area has an elevation ranging from sea level to 227 meters. The climate of the Sydney region surrounding the Lambert Peninsula is temperate, with warm to hot summers and cool to cold winters and mainly reliable rainfall year round (Australian Bureau of Meteorology, 1991).

The Lambert Peninsula includes a wide range of soil types that vary in nutrient and water availability from extremely deficient to high (Chapman and Murphy, 1989). Nutrient and water availability have an influence on SLA (Dijkstra, 1990; Summerhayes, 1996), for example, high SLA is associated with areas of high water and nutrient availability. A wide range of vegetation types is found in the area. Small areas of marginal rainforest are found in some deep gullies, while open forest is found on south facing slopes which are cooler and more moist than north facing slopes, in gullies, and in areas with fertile soils. Ridgetops and headlands have shallow soils which generally lack nutrients; the vegetation in these areas is variable, but is usually described as heath (Benson and Howell, 1994). Intermediate vegetation includes open forest which grades into woodland and low woodland. Open forest and woodland communities are heterogeneous, with different degrees of canopy closure, and a variety of understory species (see Table 4).

Data Collection and Processing
Field SLA Measurements
Field data were collected between 01 November 1997 and 31 January 1998. The location of the sample sites is shown in Figure 2. Each site was north oriented, and 25 meters by 25 meters in size as seen in Figure 3. The size and orientation of the sites

<table>
<thead>
<tr>
<th>Vegetation type</th>
<th>Foliage cover of tallest stratum</th>
<th>Growth form and height of tallest stratum</th>
<th>No. of sample sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closed forest</td>
<td>&gt;70%</td>
<td>Trees 10-30 meters</td>
<td>1</td>
</tr>
<tr>
<td>Low closed forest with emergent trees</td>
<td>&gt;70%</td>
<td>Trees &lt; 10 meters</td>
<td>1</td>
</tr>
<tr>
<td>Open forest</td>
<td>30-70%</td>
<td>Trees 10-30 meters</td>
<td>5</td>
</tr>
<tr>
<td>Low woodland/low open woodland</td>
<td>0-30%</td>
<td>Trees &lt; 10 meters</td>
<td>2</td>
</tr>
<tr>
<td>Closed scrub/scrub-heath</td>
<td>30-70%</td>
<td>Shrubs &gt; 2 meters</td>
<td>4</td>
</tr>
<tr>
<td>Pockets of heath on rocky outcrops</td>
<td>10-30%</td>
<td>Shrubs &lt; 2 meters</td>
<td>1</td>
</tr>
</tbody>
</table>

*Classification based on Specht (1970).*
was chosen to correspond with the pixel size and orientation of the satellite data. The vegetation at each site was sampled along two diagonal transects.

Remotely sensed reflectances are affected predominantly by the upper portions of the canopy (Goward et al., 1994). Therefore, procedures were developed to measure canopy-average surface SLA (SLACs). All leaves used to estimate species SLA were sun leaves chosen from the top part of the canopy. This is of particular importance with SLA which has been shown to vary with depth in the canopy (Ellsworth and Reich, 1993), though this effect is less important in open canopies (Bartelink, 1997). Because the vegetation was heterogeneous in terms of species composition, it was necessary to develop a process in which the SLAs of individual species within the canopy could be averaged. Further, in the open canopies it was necessary to incorporate SLA from the understory vegetation because this vegetation will affect remotely sensed data (Spanner et al., 1990).

At each site one (small) branch which contained sun leaves was chosen at random for each species. Leaves were removed from the branch, catalogued, and, to ensure they remained flat, transported to the laboratory in a plant press. Species were collected sequentially along each transect for all species with more than approximately 1 percent cover on that transect. The percentage cover of each species was estimated using its cumulative length along the transect. Once all the species in the overstory had been collected, the process was repeated for the understory species (where such existed). Leaf area was determined by scanning five fresh leaves for each species using a Delta T™ scanner (Delta T Devices, Cambridge, UK). The leaves were then oven dried at 80°C for 48 hours and weighed. SLACs was calculated as follows:

\[
SLACs = \sum \frac{A_i}{W_i} \times \frac{D_i}{D_j}
\]

where \( r \) represents the individual species, \( A_i \) is the five-leaf area (mm²), \( W_i \) is the five-leaf dry weight (mg), \( D_i \) is the cumulative length along the transect for each species, and \( D_j \) is the sum of all \( D_i \). (\( D_i \) could be greater than the transect length due to overlapping canopies, or less than the transect length where understory and overstory existed.) Where an understory and overstory existed, SLACs was calculated for each story. SLACs for each story was weighted using a sky view factor (SVF) to calculate SLACs for that transect. SVF was recorded at five points within each site (Figure 3). Photographs, looking up at the sky zenith point, taken at a height of 2 meters, were used to quantify the degree of canopy closure (the inverse of SVF) in the overstory. SVF was determined by using the image processing software Erdas Imagine 8.2® (Erdas Inc., Atlanta, Georgia) to perform a supervised classification of the photos taken of the canopy. Each photograph was classified into two classes: canopy or sky. From the classified image, the SVF was calculated as the number of "sky" pixels divided by the total number of pixels. The transect SLACs was then calculated according to the following equation:

\[
SLACs = OS_{SLAC} \times (1 - \Psi) + US_{SLAC} \times \Psi
\]

where \( \Psi \) is the sky view factor, \( OS_{SLAC} \) is the overstory SLACs and \( US_{SLAC} \) is the understory SLACs. SLACs was calculated as the average of the two transect SLACs values.

Landsat TM Image Data

Landsat TM data, re-sampled to 25 meters resolution, was acquired for 25 November 1997 to correspond with the field sample dates. All image processing was done using Erdas Imagine 8.2®. The Landsat TM scene was georeferenced to a sub-pixel root-mean-square error using eight ground control points.

Sample sites were located on the ground using a 1:25,000-scale map, because the GPS data proved inaccurate when measured beneath some canopies. To reduce the effects of canopy heterogeneity, a nine-pixel mean was calculated for each site (Wessman et al., 1988). This process also takes account of the small residual uncertainty in registration between satellite data and ground area.

LOPEX Data

Data from the Leaf Optical Properties Experiment (LOPEX 93) (Hosgood et al., 1995) dataset was used to examine the impact of SLA on leaf optical properties in a laboratory environment. The LOPEX 93 dataset was created using Northern Hemisphere woody and herbaceous species to examine the impact of leaf biochemistry on leaf optical properties: the measurements of leaf area and leaf dry weight which are needed to calculate SLA were also made. Species were selected from the LOPEX 93 dataset which had SLAs between 1.0 and 20.0 m²/kg, which is the same range as those found in the field study. The narrow band reflectances from a stack of ten leaves for each species were averaged across the wavelengths associated with the bands of Landsat TM data. This is similar to the process described in Asner et al. (1998) which convolves individual leaf reflectance and transmittance spectra to the bands of AVHRR and MODIS data, to examine the impact of leaf optical properties on satellite-based reflectance data.

Data Analysis Techniques

Univariate Regression

Univariate regression was used to examine the relationship between the following variables:

- \( SLACs \) and individual band reflectances,
- \( SLACs \) and the vegetation indices listed in Table 5, and
- \( SLA \) and the reflectance from a stack of ten leaves in the LOPEX 93 dataset,

using the following four equations:

- a linear equation: \( Y = a + bX \)
- a power equation: \( Y = aX^b \)
- an exponential equation: \( Y = abX \)
- a natural logarithm equation: \( Y = a + b \ln X \)

where \( Y \) is SLA or SLACs, \( a \) and \( b \) are regression coefficients, and \( X \) is the independent variable.

Results and Discussion

The SLACs value for each site is presented in Table 6. SLACs ranged from 3.92 to 17.15 m²/kg, with low SLACs values associated with heath and low woodland, and high SLACs values associated with open forest and closed forest.

The high SLACs value recorded for the closed forest site (site 14) results from the presence of exotic species with high SLA values. These exotic species were only present in a very small section of the study area, which limited the number of possible sample sites that could be located in that vegetation type. The pattern of SLACs distribution is consistent with the pattern of interspecific SLA distribution described in Summerhayes (1996), i.e., high SLA occurs in areas with high water and nutrient availability, and low SLA occurs in areas with low water and nutrient availability. The range is also consistent with the average SLA values reported by Schulze et al. (1994), and falls within the lower part of the range for broadleaved evergreens reported by Reich et al. (1997).

Reflectance in the Visible Bands

The green and red bands of the Landsat TM data showed strong correlation with SLACs (Figures 4a and 4b and Table 7). The negative nature of the relationship is consistent with the associations described in the Introduction, implying that leaf surface...
modifications and low chlorophyll a concentrations associated with low SLA are detectable at canopy level. In general, as the vegetation type changed from heath on low nutrient soils, to forests in areas with the highest water and nutrient availability, SLACS increased. This gradient was associated with a decrease in reflectance values. However, changes in the amount of vegetation cover can also have an impact on reflectances at visible wavelengths (Huete, 1988; Gitelson et al., 1996). Therefore, the correlation between the range of SLACS (from an average 5.00 m\(^2/\)kg in heathland areas, to 7.45 m\(^2/\)kg in forest areas) and reflectance data may have been strengthened by the high reflectivity of soil at these wavelengths.

With the LOPEX dataset, at wavelengths equivalent to both the green and red bands, there was no significant correlation between SLA and reflectance (Table 8). This may be because leaf surface characteristics of the sclerophyll vegetation in this study have a larger effect on reflectance than do those of the species used in the LOPEX dataset. This is consistent with the findings of Thomas and Barber (1974) who reported that leaf surface characteristics of Eucalyptus species can have a large impact on reflectance in the visible part of the spectrum.

**Reflectance in the NIR Band**

The NIR band showed a positive correlation with SLACS (Figure 4c and Table 7). This is in accordance with the predicted trends, that SLA would be reduced by the presence of non-metabolic carbon compounds. A similar trend from heath vegetation to open forest, noted for visible wavelengths, was apparent in the NIR data. Data for heathland vegetation had low SLACS values and low reflectances; open forest had higher SLACS and reflectances.

It is possible that changes in LAI that are dependent on vegetation type and, therefore, related to changes in SLA, may contribute to changes in the reflectance values that were found. The relationship between LAI and reflectance has been the subject of numerous studies using field measurements and remotely sensed data, simulation studies to model reflectance values, and laboratory measurement of leaf reflectance. In laboratory studies, Yoder and Waring (1994) found that the dominant change in reflectance spectra from canopies of different LAIs was an increase in NIR reflectance for their high LAI canopy. Using field measurements and remotely sensed data, Spanner et al. (1990) reported a strong correlation between LAI and reflectance in the NIR region, for stands of high (89 percent) canopy closure. Deviations from the relationship occurred in stands with less complete canopy closure. The present study, using SLACS measured directly for both overstory and understory species in the field, has shown a high correlation between SLACS and NIR across a variety of different canopy closures.

With the LOPEX dataset, at wavelengths equivalent to the NIR band, there was a weak positive correlation with SLA (Table 8). This is likely to be due to interdependencies between SLA and LAI in the field, which have been lost when a stack of ten leaves have been used for laboratory measurements.

**Reflectance in the MIR2 Band**

A strong negative correlation was found between MIR2 and SLACS (Figure 4d and Table 7). This is contrary to the trend that would be expected if leaf modifications associated with SLA were the only contributing factors but, because leaf water content affects reflectance at this wavelength, it was expected.
High water availability is associated with higher SLA, but an increase in leaf water content will decrease reflectance.

Finally, with the LOPEX dataset, a weak positive correlation was observed between reflectance at wavelengths equivalent to MIR2 (compared to the strong negative correlation in the field data) (Table 8). The positive correlation is predicted from the leaf characteristics. The effect of leaf water content, important in the field, would be less important in laboratory measurements.

### Relationships between SLA and Vegetation Indices

The relationships between red, NIR, and MIR2 reflectance and SLA were prompted the calculation of a new vegetation ratio, called in this study, specific leaf area vegetation index (SLAVI), with the equation

$$\text{SLAVI} = \frac{\text{NIR} + \text{MIR2}}{\text{Red}}.$$  \hspace{1cm} (3)

The MIR2 band was included to supplement the relationship between red and NIR that forms the underlying principle of most vegetation indices. NIR reflectance forms the numerator because, when NIR reflectance is low (associated with low SLA), low values of SLAVI will be obtained, and, similarly, red and MIR2 reflectances are included in the denominator because high reflectance values at these wavelengths are associated with low SLA values.

All of the vegetation indices examined were strongly positively correlated with SLA (Table 9). Figures 5a to 5d show the correlations between RVI, SARVI2, SLAVI, and NDVI and SLA. The other vegetation indices listed in Table 9 provided no meaningful improvements on these.

This result was expected because numerous studies have linked vegetation indices to a number of different plant physiochemical parameters. For example, in an early study, Peterson et al. (1987) reported statistically significant relationships between LAI and the ratio NIR/red, for 18 coniferous stands. More recently, Yoder and Waring (1994), using "miniature" canopies, reported correlations between canopy reflectance properties using NDVI and both LAI and fPAR ($R^2 = 0.36$ and $R^2 = 0.60$, respectively). Using the SAIL (scattering

### Table 8. Comparison of the Relationship between SLA and Reflectance for the Field and LOPEX Data

<table>
<thead>
<tr>
<th>Band</th>
<th>Field Data</th>
<th>LOPEX Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>$R^2 = 0.64$</td>
<td>$R^2 = 0.68$</td>
</tr>
<tr>
<td></td>
<td>Negative correlation</td>
<td>No correlation</td>
</tr>
<tr>
<td>Red</td>
<td>$R^2 = 0.87$</td>
<td>$R^2 = 0.03$</td>
</tr>
<tr>
<td></td>
<td>Negative correlation</td>
<td>No correlation</td>
</tr>
<tr>
<td>NIR</td>
<td>$R^2 = 0.58$</td>
<td>$R^2 = 0.15$</td>
</tr>
<tr>
<td></td>
<td>Positive correlation</td>
<td>Weak positive correlation</td>
</tr>
<tr>
<td>MIR2</td>
<td>$R^2 = 0.63$</td>
<td>$R^2 = 0.24$</td>
</tr>
<tr>
<td></td>
<td>Negative correlation</td>
<td>Weak positive correlation</td>
</tr>
</tbody>
</table>

### Table 9. The Relationship between SLA and the Vegetation Indices in this Study

<table>
<thead>
<tr>
<th>Vegetation index</th>
<th>Regression equation</th>
<th>Correlation coefficient ($R^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVI</td>
<td>$Y = 0.308x + 0.252$</td>
<td>0.91</td>
</tr>
<tr>
<td>SARVI2</td>
<td>$Y = 0.506Ln(x) - 0.662$</td>
<td>0.89</td>
</tr>
<tr>
<td>SLAVI</td>
<td>$Y = 1.366Ln(x) - 1.373$</td>
<td>0.84</td>
</tr>
<tr>
<td>NDVI</td>
<td>$Y = 0.363Ln(x) - 0.308$</td>
<td>0.83</td>
</tr>
<tr>
<td>SAVI</td>
<td>$Y = 0.524Ln(x) - 0.430$</td>
<td>0.82</td>
</tr>
<tr>
<td>PVI</td>
<td>$Y = 0.292Ln(x) - 35.535$</td>
<td>0.76</td>
</tr>
<tr>
<td>GNDVI</td>
<td>$Y = 0.234Ln(x) - 0.098$</td>
<td>0.74</td>
</tr>
</tbody>
</table>
from arbitrarily inclined leaves) model, van Leeuwen and Huete (1996) examined relationships between LAI and SAVI, and using the same model, Huemmrich and Goward (1997) modeled relationships between fPAR and NDVI.

Vegetation properties frequently covary in natural vegetation, so a vegetation index that correlates well with one property would be expected to correlate with others. In particular, Pierce et al. (1994) report relationships between LAI and both canopy-average SLA and canopy-average leaf nitrogen, and Reich et al. (1997) found relationships between SLA and net photosynthesis and leaf nitrogen concentration.

The vegetation index with the highest correlation coefficient was the ratio vegetation index (RVI) which had a linear relationship with SLAcs. While this relationship should prove useful in predicting SLA on the same satellite scene, the simple ratio nature of the RVI does not transfer well to satellite scenes for different areas, or different times (Lawrence and Ripple, 1998). For a more widely applicable vegetation index, it is necessary to look at indices such as the normalized difference vegetation index (NDVI) or the soil and atmosphere resistant vegetation index (SARVI2). Based on the vegetation index reviews of Lyon et al. (1998), NDVI is the most versatile and robust of the vegetation indices. However, Huete et al. (1997) suggest that SARVI2 may be preferable because it is more sensitive to changes in NIR than NDVI, and it reduces the effects of soil background and atmospheric path radiance. SARVI2 showed a higher correlation with SLAcs than did NDVI, but there was little difference between the two. Unfortunately, these two vegetation indices, but not RVI, saturate at high SLA values, which will reduce their usefulness for estimating canopy SLA.

The relationships shown in Figures 5a to 5d could be used to predict SLAcs for other areas of the same satellite scene according to the equations in Table 10. These equations are derived by plotting SLAcs as the dependent variable against the relevant vegetation index and using the regression equation to form a predictive equation. For a meaningful comparison of these vegetation indices, it would be necessary to test predictive equations based on each index on a different scene, or different vegetation types.

Concluding Remarks
SLA is an important plant attribute. There would be much to be gained through the remote estimation of SLA, and the underlying plant characteristics which lead to variations in SLA would indicate that remote estimation is feasible. The field-based results of this study indicate that it is possible to estimate SLAcs over a range of vegetation types using low spectral resolution Landsat TM data. A strong correlation was found between reflectance in the green, red, NIR, and MIR2 bands and SLAcs. A strong correlation was also found to exist between SLAcs and the vegetation indices used in this study. This enabled the construction of invertible empirical models that would facilitate estimation of SLAcs from low spectral resolution Landsat TM data.

The cause of lack of correlation between SLA and laboratory measurements of reflectance in the LOPEX dataset remains unclear. The construction of a leaf optical properties dataset for sclerophyllous vegetation of the type used in this study may provide further clarification of these results.

Table 10. Equations for Predicting SLAcs from Vegetation Indices

<table>
<thead>
<tr>
<th>Vegetation index</th>
<th>Predictive equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVI</td>
<td>SLAcs = 2.954 (RVI) - 0.125</td>
</tr>
<tr>
<td>SARVI2</td>
<td>SLAcs = 3.439e^0.574(SARVI2)</td>
</tr>
<tr>
<td>SLAI</td>
<td>SLAcs = 1.066e^0.280(SLAI)</td>
</tr>
<tr>
<td>NDVI</td>
<td>SLAcs = 2.766e^0.298(NDVI)</td>
</tr>
</tbody>
</table>
It is probable that environmental factors have enhanced the correlations found in this study. Obvious relationships include:

- soil conditions, which influence both plant species composition (and, therefore, SLA) and reflectivity at visible wavelengths;
- water availability, which influences both plant species composition (and, therefore, SLA) and reflectivity at mid-infrared wavelengths; and
- the interrelationship between canopy properties such as LAI, fPAR, leaf nitrogen, and SLA, which influence reflectivity at near-infrared wavelengths.

However, the vegetation characteristics resulting from these environmental factors cannot be divorced from each other in the natural vegetation that ecological models seek to simulate. The role of LAI in these results is uncertain, although the strength of the correlations (being greater than is typically found for LAI alone) suggests that a relationship between SLA and reflectance does exist in its own right. Future remote sensing studies focusing on either SLA or LAI must endeavor to account for both SLA and LAI.

Further work on heterogeneous stands is required. Such stands not only contain multiple species, and therefore a range of SLAs, but also often of a complex structure, for example, with the presence of both an overstory and an understory. This study is one of few that have examined the potential of estimating SLA using remotely sensed data. Given the importance of this parameter in ecological and biogeochemical models, and as a plant attribute in its own right, further such studies are needed which will supplement these results.

Acknowledgments

The authors are grateful to their colleagues, Malcolm Reed and Amanda Bollard, who assisted with the field data collection. Thanks also go to the New South Wales National Parks and Wildlife Service for approving access to the study area. The authors also wish to thank Mark Westoby and Carlos Fonseca in the School of Biological Sciences, Macquarie University, who assisted with the field work design and equipment. Our colleagues in the School of Earth Sciences, Macquarie University, have also provided valuable feedback and support.

References


Summerhayes, B., 1996. Structural Changes in Leaf Anatomy as a Cause of Specific Leaf Area (SLA) in Species Found in Two Environmental Gradients, Nutrients and Rainfall, Using Phylogenetically Independent Contrasts, unpublished honours thesis, School of Biological Sciences, Macquarie University, Sydney, Australia.


(Received 29 July 1998; revised and accepted 16 March 1999)