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

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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_{CS}) was developed. The relationship between SLA_{CS}, reflectance in Landsat TM bands, and a number of vegetation indices, were explored using univariate regression. The observed relationships between SLA_{CS} 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_{CS} and red, near-infrared, and the second mid-infrared bands of Landsat TM data. A strong correlation between SLA_{CS} 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_{CS} 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. BIOME3 (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 Fourty (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 Fourty and Baret (1997) which examined the calculation of canopy SLW 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 health 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.

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TABLE 1. MAJOR VEGETATION TYPES AND THEIR AVERAGE SLA (FROM TABLE 1 IN SCHULZE *ET AL.* (1994))

Major vegetation type	Average SLA (m^2/kg)	Standard error
Evergreen conifers	4.1	0.4
Monsoonal forest	4.3	0.6
Temperate evergreen broadleaf	5.7	0.8
Sclerophyllous shrubland	6.9	0.7
Tropical rainforest	9.9	1.4
Deciduous conifers	11.3	1.4
Temperate deciduous trees	11.5	2.4
Tropical deciduous forest	14.1	2.3
Temperate grassland	16.9	1.3
Broadleaved crops	23.6	1.7
Cereals	25.3	1.9

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; Fourty *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-veinal sclerenchyma and sclereids, that reduce SLA, also reduce the amount of NIR reflectance (Gausman, 1974; Vogelmann, 1994).
- 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 (Fourty *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 (Fourty 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 (Fourty *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).
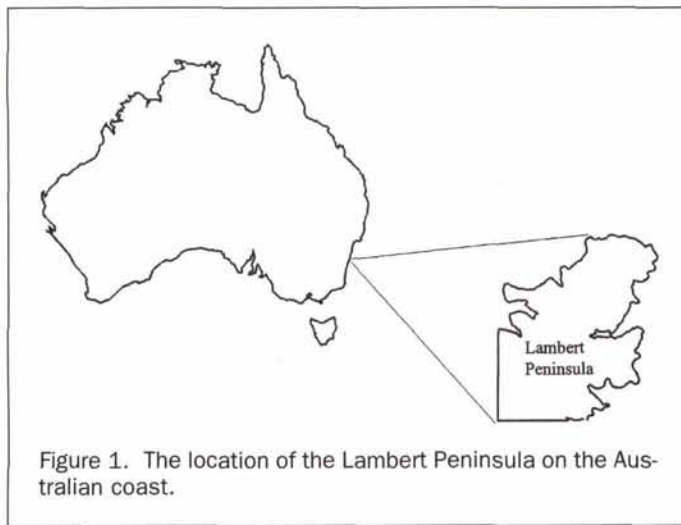
Based on these reported relationships, it may be possible to remotely sense SLA using low spectral resolution satellite data, facilitating the estimation of canopy biochemistry over a range of vegetation types, and providing improved parameters for inclusion into ecological and biogeochemical models.

TABLE 2. THE RELATIONSHIP BETWEEN SLA AND ECOLOGICAL AND BIOCHEMICAL VARIABLES

Ecological variable	Relationship with SLA	Authors
Net photosynthesis	Direct	Reich *et al.*, 1998; Reich *et al.*, 1997; Schulze *et al.*, 1994
Leaf area index	Direct	Fassnacht and Gower, 1997; Jose and Gillespie, 1997; Schulze *et al.*, 1994
Ecosystem production efficiency	Direct	Reich *et al.*, 1997; Jose and Gillespie, 1997
Above-ground net primary productivity	Direct	Fassnacht and Gower, 1997
Leaf life span	Inverse	Reich *et al.*, 1998; Reich *et al.*, 1997; Atkin *et al.*, 1996; Ryser, 1996
Biochemical variable		
Leaf nitrogen content	Direct	Baret and Fourty, 1997; Schulze *et al.*, 1994
Leaf cellulose and lignin content	Inverse	Baret and Fourty, 1997; Fourty and Baret, 1997; Jacquemoud *et al.*, 1996
Leaf water content	Direct	Shipley, 1995

TABLE 3. THE EXPECTED INFLUENCE OF SLA ON CANOPY REFLECTANCE

Landsat TM band	Green	Red	Near-infrared	Mid-infrared 1	Mid-infrared 2
Wavelength (nm)	520–600	630–690	760–900	1550–1750	2080–2350
Expected relationship with SLA	Inverse	Inverse	Direct	Inverse	Inverse

Figure 1. The location of the Lambert Peninsula on the Australian coast.

Figure 2. Site locations and numbers shown on a Landsat TM image of NDVI values.

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 (Djikstra, 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
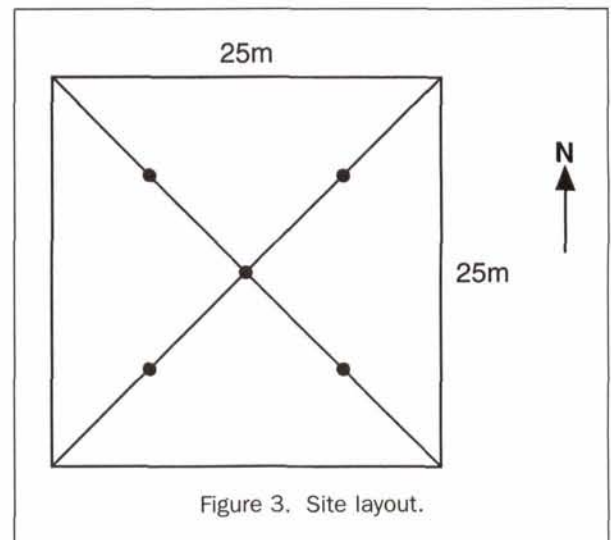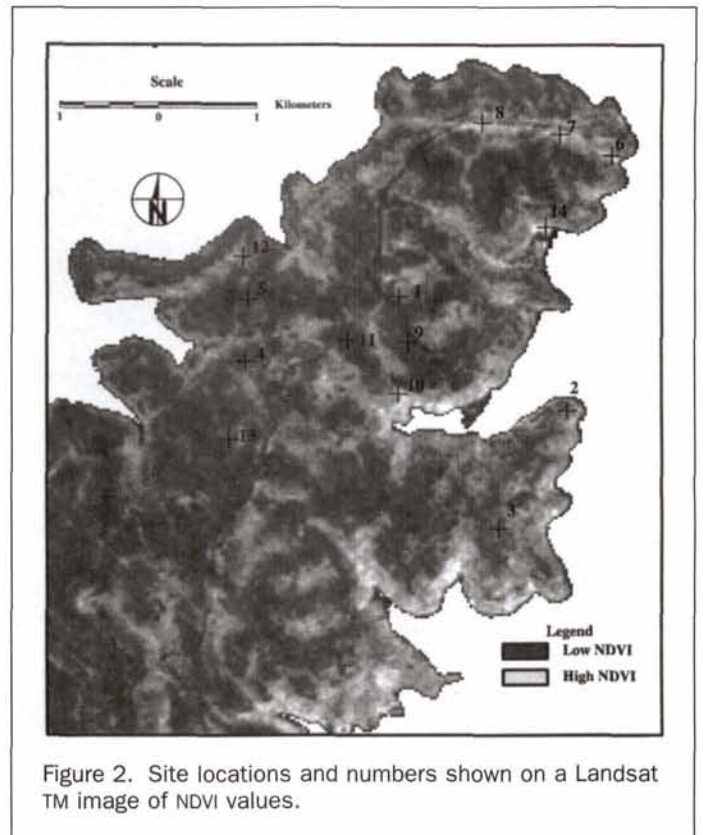

Figure 3. Site layout.

TABLE 4. VEGETATION TYPES FOUND ON THE LAMBERT PENINSULA

Vegetation type†	Foliage cover of the tallest stratum	Growth form and height of tallest stratum	No. of sample sites
Closed forest	>70%	Trees 10–30 meters	1
Low closed forest with emergent trees	>70%	Trees < 10 meters	1
Open forest	30–70%	Trees 10–30 meters	5
Low woodland/low open woodland	0–30%	Trees < 10 meters	2
Closed scrub/scrub-heath	30–70%	Shrubs > 2 meters	4
Pockets of heath on rocky outcrops	10–30%	Shrubs < 2 meters	1

†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 (SLA$_{CS}$). 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. SLA$_{CS}$ was calculated as follows:

$$SLA_{CS} = \sum_i \frac{A_i}{W_i} \times \frac{D_i}{D_t} \qquad (1)$$

where *i* 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 distance along the transect for each species, and D_t is the sum of all D_i. (D_t 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, SLA$_{CS}$ was calculated for each story.

The SLA$_{CS}$ for each story was weighted using a sky view factor (SVF) to calculate SLA$_{CS}$ 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 SLA$_{CS}$ was then calculated according to the following equation:

$$SLA_{CS} = OS\_SLA_{CS} \times (1 - \Psi) + US\_SLA_{CS} \times \Psi \qquad (2)$$

where Ψ is the sky view factor, OS_SLA$_{CS}$ is the overstory SLA$_{CS}$ and US_SLA$_{CS}$ is the understory SLA$_{CS}$. SLA$_{CS}$ was calculated as the average of the two transect SLA$_{CS}$ 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 subpixel 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:

- SLA$_{CS}$ and individual band reflectances,
- SLA$_{CS}$ 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: $Y = ae^{bX}$
- a natural logarithm equation: $Y = a + b*\ln X$

where Y is SLA or SLA$_{CS}$, a and b are regression coefficients, and X is the independent variable.

Results and Discussion
The SLA$_{CS}$ value for each site is presented in Table 6. SLA$_{CS}$ ranged from 3.92 to 17.15 m²/kg, with low SLA$_{CS}$ values associated with heath and low woodland, and high SLA$_{CS}$ values associated with open forest and closed forest.

The high SLA$_{CS}$ 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 SLA$_{CS}$ 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 SLA$_{CS}$ (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

TABLE 5. VEGETATION INDICES USED IN THIS STUDY

Vegetation index (acronym)	Formula	Author
Ratio Vegetation Index (RVI)	NIR/Red	Jordan (1969)
Normalized Difference Vegetation Index (NDVI)	(NIR − Red)/(NIR + Red)	Rouse *et al.* (1973)
Green Normalized Difference Vegetation Index (GNDVI)	(NIR − Green)/(NIR + Green)	Gitelson *et al.* (1996)
Soil Adjusted Vegetation Index (SAVI)	((NIR − Red)/(NIR + Red + L)) × (1 + L)†	Huete (1988)
Perpendicular Vegetation Index (PVI)	sin(a)NIR − cos(a)Red††	Richardson and Wiegand (1977)
Soil and Atmosphere Resistant Vegetation Index (SARVI2)	(25 × (NIR − Red))/ [1 + NIR + (6 × Red) − (7.5 × Blue)]	Huete *et al.* (1997)
Specific Leaf Area Vegetation Index (SLAVI)	NIR/(Red + MIR2)	Present Study

†L is the fractional vegetation cover.
††a is the angle between the soil line and the axis on which NIR is plotted.

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, SLA_{CS} 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 SLA_{CS} (from an average 5.00 m²/kg in heathland areas, to 7.45 m²/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 SLA_{CS} (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 SLA_{CS} values and low reflectances: open forest had higher SLA_{CS} 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 SLA_{CS} measured directly for both overstory and understory species in the field, has shown a high correlation between SLA_{CS} 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 SLA_{CS} (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.

TABLE 6. THE SLA_{CS} OF THE VEGETATION TYPES ON THE LAMBERT PENINSULA

SLA_{CS} (m²/kg)	Vegetation type†	Nutrient availability††	Water availability††	Site no.
3.92	Heath	*	**	11
4.27	Low woodland	*	**	1
5.13	Low woodland	*	**	3
5.16	Scrub-heath	*	**	9
5.19	Scrub-heath	*	**	13
5.29	Scrub-heath	*	**	5
5.53	Closed scrub	*	**	4
6.56	Open forest	*	**	2
6.64	Open forest	*	**	12
6.81	Low closed forest	**	***	6
7.00	Open forest	**	***	10
7.39	Open forest	**	***	7
10.32	Open forest	***	***	8
17.15	Closed forest	****	****	14

†See Table 4.
††The nutrient and water availability values are based on the values described in Chapman and Murphy (1989), *i.e.*, extremely low = * and high = ****. These values are provided as a guide only.

TABLE 7. THE RELATIONSHIP BETWEEN SLA_{CS} AND INDIVIDUAL BAND REFLECTANCE

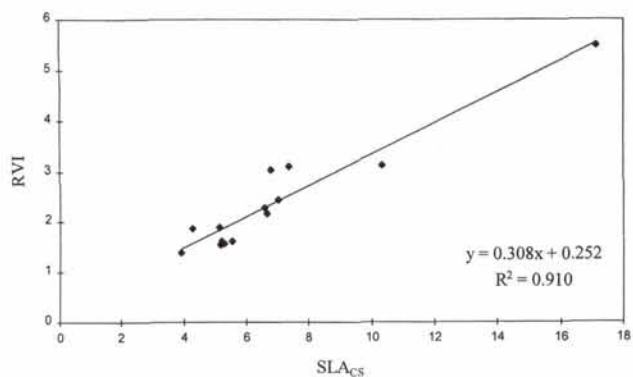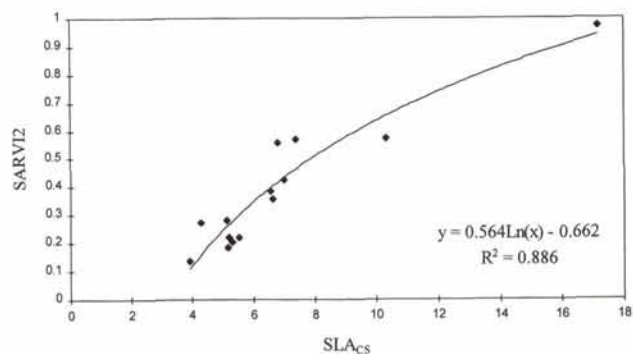| Band	Regression equation	Correlation coefficient (R^2)
Green	$Y = 0.243X^{-0.198}$	0.64
Red	$Y = 0.248e^{-0.066}$	0.87
NIR	$Y = 0.128Ln(X) + 0.116$	0.58
MIR1	$Y = 0.566X^{-0.274}$	0.26
MIR2	$Y = 0.741X^{-0.792}$	0.63

Figure 4. The relationship between SLA_{CS} and (a) green, (b) red, (c) NIR, and (d) MIR2 reflectance.

TABLE 8. COMPARISON OF THE RELATIONSHIP BETWEEN SLA AND REFLECTANCE FOR THE FIELD AND LOPEX DATA

Band	Field Data	LOPEX Data
Green	$R^2 = 0.64$	$R^2 = 0.08$
	Negative correlation	No correlation
Red	$R^2 = 0.87$	$R^2 = 0.03$
	Negative correlation	No correlation
NIR	$R^2 = 0.58$	$R^2 = 0.15$
	Positive correlation	Weak positive correlation
MIR2	$R^2 = 0.63$	$R^2 = 0.24$
	Negative correlation	Weak positive correlation

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_{CS} and Vegetation Indices

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

$$SLAVI = \frac{NIR}{Red + MIR2}. \qquad (3)$$

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_{CS} (Table 9). Figures 5a to 5d show the correlations between RVI, SARVI2, SLAVI, and NDVI and SLA_{CS}. 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 biophysical and biochemical 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 9. THE RELATIONSHIP BETWEEN SLA_{CS} AND THE VEGETATION INDICES IN THIS STUDY

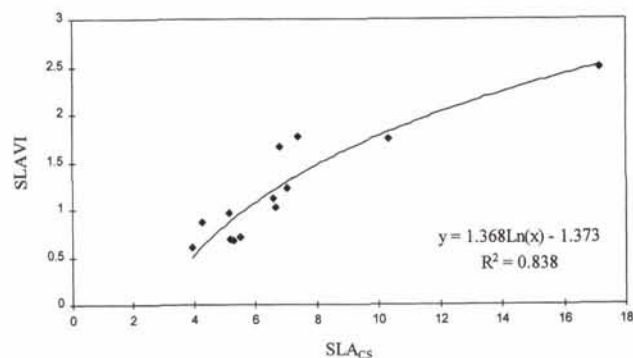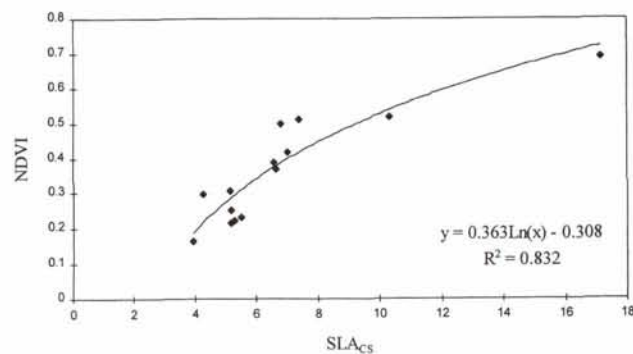| Vegetation index	Regression equation	Correlation coefficient (R^2)
RVI	$Y = 0.308X + 0.252$	0.91
SARVI2	$Y = 0.564Ln(X) - 0.662$	0.89
SLAVI	$Y = 1.368Ln(X) - 1.373$	0.84
NDVI	$Y = 0.363Ln(X) - 0.308$	0.83
SAVI	$Y = 0.524Ln(X) - 0.430$	0.82
PVI	$Y = 36.962Ln(X) - 35.535$	0.76
GNDVI	$Y = 0.233Ln(X) - 0.088$	0.74
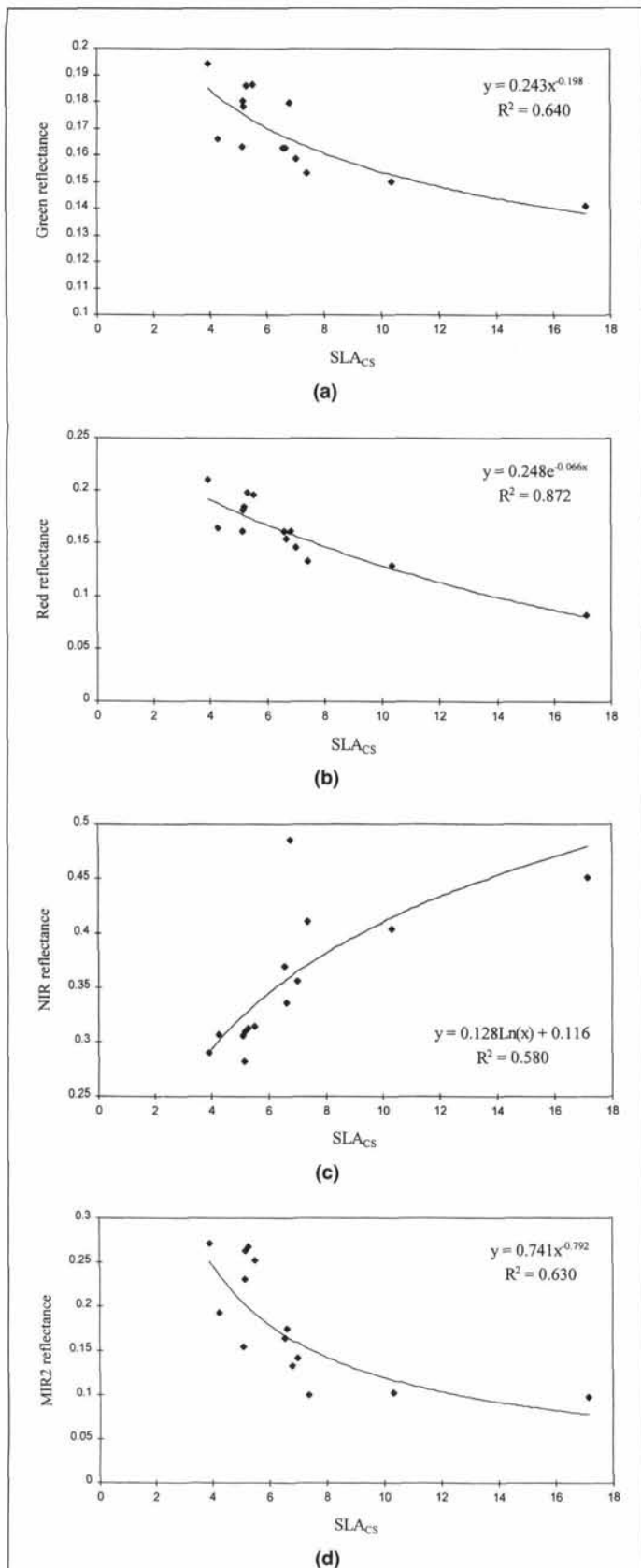
Figure 5. The relationship between SLA$_{CS}$ and (a) RVI, (b) SARVI2, (c) SLAVI, and (d) NDVI.

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 SLA$_{CS}$. 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 SLA$_{CS}$ 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 SLA$_{CS}$ for other areas of the same satellite scene according to the equations in Table 10. These equations are derived by plotting SLA$_{CS}$ 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 SLA$_{CS}$ 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 SLA$_{CS}$. A strong correlation was also found to exist between SLA$_{CS}$ and the vegetation indices used in this study. This enabled the construction of invertible empirical models that would facilitate estimation of SLA$_{CS}$ 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 SLA$_{CS}$ FROM VEGETATION INDICES

Vegetation index	Predictive equation
RVI	SLA$_{CS}$ = 2.954 (RVI) − 0.125
SARVI2	SLA$_{CS}$ = 3.439$e^{1.571(SARVI2)}$
SLAVI	SLA$_{CS}$ = 1.066$e^{1.268(SLAVI)}$
NDVI	SLA$_{CS}$ = 2.766$e^{2.293(NDVI)}$

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 are 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.

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References

Asner, G.P., C.A. Wessman, D.S. Schimel, and S. Archer, 1998. Variability in leaf and litter optical properties: Implications for BRDF model inversions using AVHRR, MODIS, and MISR, *Remote Sensing of Environment*, 63(3):243–257.

Atkin, O.K., B. Botman, and H. Lambers, 1996. The causes of inherently slow growth in alpine plants: An analysis based on the underlying carbon economies of alpine and lowland *Poa* species, *Functional Ecology*, 10(6):698–707.

Australian Bureau of Meteorology, 1991. *Climatic Survey, Sydney, New South Wales, December 1991*, Australian Government Publishing Service, Canberra, 105 p.

Baret, F., and T. Fourty, 1997. Estimation of leaf water content and specific leaf weight from reflectance and transmittance measurements, *Agronomie*, 17(9–10):455–464.

Bartelink, H.H., 1997. Allometric relationships for biomass and leaf area of Beech (*Fagus sylvatica* L.), *Annales des Sciences Forestieres (Paris)*, 54(1):39–50.

Benson, D., and J. Howell, 1994. The natural vegetation of the Sydney 1:100 000 map sheet, *Cunninghamia*, 3(4):676–719.

Chapman, G.A., and C.C. Murphy, 1989. *Soil Landscapes of the Sydney 1:100 000 Map Sheet*, Soil Conservation Service of NSW, Sydney.

Coops, N., A. Delahaye, and E. Pook, 1997. Estimation of Eucalypt forest leaf area index on the South Coast of New South Wales using Landsat MSS data, *Australian Journal of Botany*, 45(5):757–769.

Curran, P.J., J.A. Kupiec, and G.M. Smith, 1997. Remote sensing of the biochemical composition of a Slash Pine canopy, *IEEE Transactions on Geoscience and Remote Sensing*, 35(2):415–420.

Dijkstra, P., 1990. Cause and effect of differences in specific leaf area, *Causes and Consequences of Variation in Growth Rate and Productivity of Higher Plants*, (H. Lambers, M.L. Cambridge, H. Konings, and T.L. Pons, editors) SPB Academic Publishing bv, the Hague, pp. 125–140.

Ellsworth, D.S., and P.B. Reich, 1993. Canopy structure and vertical patterns of photosynthesis and related leaf traits in a deciduous forest, *Oecologia*, 96(2):169–178.

Fassnacht, K.S., and S.T. Gower, 1997. Interrelationships between the edaphic and stand characteristics, leaf area index and above-ground net primary productivity of upland forest ecosystems in north central Wisconsin, *Canadian Journal of Forestry*, 27(7):1058–1067.

Fourty, T., and F. Baret, 1997. Vegetation water and dry matter contents estimated from top-of-the-atmosphere reflectance data: A simulation study, *Remote Sensing of Environment*, 61(1):34–45.

Fourty, Th., F. Baret, S. Jacquemoud, G. Schmuck, and J. Verdebout, 1996. Leaf optical properties with explicit description of its biochemical composition: Direct and inverse problems, *Remote Sensing of Environment*, 56(12):104–117.

Gausman, H.W., 1974. Leaf reflectance of near-infrared, *Photogrammetric Engineering*, 40(2):183–191.

Gitelson, A.A., Y.J. Kaufman, and M.N. Merzlyak, 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS, *Remote Sensing of Environment*, 58(3):289–298.

Gobron, N., B. Pinty, and M.M. Verstraete, 1997. Theoretical limits to the estimation of the leaf area index on the basis of visible and near-infrared remote sensing data, *IEEE Transactions on Geoscience and Remote Sensing*, 35(6):1438–1445.

Gong, P., R. Pu, and J.R. Miller, 1995. Coniferous forest leaf area index estimation along the Oregon transect using Compact Airborne Spectrographic Imager data, *Photogrammetric Engineering & Remote Sensing*, 61(9):1107–1117.

Govaerts, Y.M., S. Jacquemoud, M.M. Verstraete, and S.L. Ustin, 1996. Three-dimensional radiation transfer modeling in a dicotyledon leaf, *Applied Optics*, 35(33):6585–6598.

Goward, S.N., K.F. Huemmrich, and R.H. Waring, 1994. Visible-near infrared spectral reflectance of landscape components in western Oregon, *Remote Sensing of Environment*, 47(2):190–203.

Haxeltine, A., and I.C. Prentice, 1996. BIOME3: An equilibrium terrestrial biosphere model based on ecophysiological constraints, resource availability, and competition among plant functional types, *Global Biogeochemical Cycles*, 10(4):693–709.

Hosgood, B., S. Jacquemoud, G. Andreoli, J. Verdebout, J. Pedrini, and G. Schmuck, 1995. *Leaf Optical Properties Experiment 93 (LOPEX 93)*, Report EUR-16095-EN, European Commission, Joint Research Center, Institute for Remote Sensing Applications, Ispra, Italy.

Huemmrich, K.F., and S.N. Goward, 1997. Vegetation canopy PAR absorptance and NDVI: An assessment for ten tree species with the SAIL model, *Remote Sensing of Environment*, 61(2):254–269.

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI), *Remote Sensing of Environment*, 25(3):295–309.

Huete, A.R., H.Q. Liu, K. Batchily, and W. van Leeuwen, 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS, *Remote Sensing of Environment*, 59(3):440–451.

Jacquemoud, S., S.L. Ustin, J. Verdebout, G. Schmuck, G. Andreoli, and B. Hosgood, 1996. Estimating leaf biochemistry using the PROSPECT leaf optical properties model, *Remote Sensing of Environment*, 56(3):194–202.

Jordan, C.F., 1969. Derivation of leaf-area index from quality of light on the forest floor, *Ecology*, 50(4):663–666.

Jose, S., and A.R. Gillespie, 1997. Leaf area-productivity relationships among mixed-species hardwood forest communities of the central hardwood region, *Forest Science*, 43(1):56–64.

Lawrence, R.L., and W.J. Ripple, 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington, *Remote Sensing of Environment*, 64(1):91–102.

Lyon, J.G., D. Yuan, R.S. Lunetta, and C.D. Elvidge, 1998. A change detection experiment using vegetation indices, *Photogrammetric Engineering & Remote Sensing*, 64(2):143–150.

Martin, M.E., and J.D. Aber, 1997. High spectral resolution remote sensing of forest canopy lignin, nitrogen, and ecosystem processes, *Ecological Applications*, 7(2):431–443.

Mooney, H.A., P.J. Ferrar, and R.O. Slatyer, 1978. Photosynthetic capacity and carbon allocation patterns in diverse growth forms of *Eucalyptus*, *Oecologia*, 36:103–111.

Myneni, R.B., R.R. Nemani, and S.W. Running, 1997. Estimation of global leaf area index and absorbed PAR using radiative transfer models, *IEEE Transactions on Geoscience and Remote Sensing*, 35(6):1380–1393.

Peterson, D.L., M.A. Spanner, S.W. Running, and K.B. Teuber, 1987. Relationship of Thematic Mapper Simulator data to leaf area index of temperate coniferous forests, *Remote Sensing of Environment*, 22(3):323–341.

Pierce, L.L., S.W. Running, and J. Walker, 1994. Regional-scale relationships of leaf area index to specific leaf area and leaf nitrogen content, *Ecological Applications*, 4(2):313–321.

Reich, P.B., M.B. Walters, D.S. Ellsworth, J.M. Vose, J.C. Volin, C. Gresham, and W.D. Bowman, 1988. Relationships of leaf dark respiration to leaf nitrogen, specific leaf area and leaf life-span: A test across biomes and functional groups, *Oecologia*, 114(4):471–482.

Reich, P.B., M.B. Walters, and D.S. Ellsworth, 1997. From tropics to tundra: Global convergence in plant functioning, *Proceedings of the National Academy of Sciences USA*, 94(25):13730–13734.

Richardson, A.J., and C.L. Wiegand, 1977. Distinguishing vegetation from soil background information, *Photogrammetric Engineering & Remote Sensing*, 43(12):1541–1552.

Rouse, J.W., R.H. Haas, J.A. Schell, and D.W. Deering, 1973. Monitoring vegetation systems in the Great Plains with ERTS, *Proceedings of the Third ERTS Symposium*, NASA SP-351, 1:309–317.

Ruimy, A., G. Dedieu, and B. Saugier, 1996. TURC: A diagnostic model of continental gross primary productivity and net primary productivity, *Global Biogeochemical Cycles*, 10(2):269–285.

Running, S.W., T.R. Loveland, L.L. Pierce, R.R. Nemani, and E.R. Hunt, Jr., 1995. A remote sensing based vegetation classification logic for global land cover analysis, *Remote Sensing of Environment*, 51(1):39–48.

Ryser, P., 1996. The importance of tissue density for growth and life span of leaves and roots: A comparison of five ecologically contrasting grasses, *Functional Ecology*, 10(6): 717–723.

Schulze, E.-D., F.M. Kelliher, C. Körner, J. Lloyd, and R. Leuning, 1994. Relationships among maximum stomatal conductance, ecosystem surface conductance, carbon assimilation rate, and plant nitrogen nutrition: A global ecology scaling exercise, *Annual Review of Ecology and Systematics*, 25:629–660.

Shipley, B., 1995. Structured interspecific determinants of specific leaf area in 34 species of herbaceous angiosperms, *Functional Ecology*, 9(2):312–319.

Sinclair, R., and D.A. Thomas, 1970. Optical properties of leaves of some species in arid south Australia, *Australian Journal of Botany*, 18(3):261–273.

Spanner, M.A., L.L. Pierce, D.L. Peterson, and S.W. Running, 1990. Remote sensing of temperate coniferous forest leaf area index. The influence of canopy closure, understory vegetation and background reflectance, *International Journal of Remote Sensing*, 11(1):95–111.

Specht, R.L., 1970. Vegetation, *The Australian Environment, Fourth Edition* (G.W. Leeper, editor), CSIRO in association with Melbourne University Press, Melbourne, pp. 44–67.

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.

Thomas, D.A., and H.N. Barber, 1974. Studies on leaf characteristics of a cline of *Eucalyptus urnigera* from Mount Wellington, Tasmania. II Reflection, transmission and absorption of radiation, *Australian Journal of Botany*, 22:701–707.

van Leeuwen, W.J.D., and A.R. Huete, 1996. Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices, *Remote Sensing of Environment*, 55(2):123–138.

Vogelmann, T.C., 1993. Plant tissue optics, *Annual Review of Plant Physiology and Plant Molecular Biology*, 44:231–251.

Wessman, C.A., J.D. Aber, D.L. Peterson, and J.M. Melillo, 1988. Remote sensing of canopy chemistry and nitrogen cycling in temperate forest ecosystems, *Nature*, 335:154–156.

Woolley, J.T., 1971. Reflectance and transmittance of light by leaves, *Plant Physiology*, 47(5):656–662.

Yoder, B.J., and R.H. Waring, 1994. The normalized difference vegetation index of small Douglas-Fir canopies with varying chlorophyll concentrations, *Remote Sensing of Environment*, 49(1):81–91.