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Multispectral Remote Sensing for the Estimation of Green Leaf Area Index [and Discussion]

P. J. Curran and M. D. Steven

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Multispectral remote sensing for the estimation of green leaf area index

By P. J. Curran
Department of Geography, University of Sheffield, Western Bank, Sheffield S10 2TN, U.K.

The causal relation between multispectral reflectance and green leaf area index (l.a.i.) has enabled the estimation of green leaf area index by the judicious use of remotely sensed multispectral reflectance measurements.

In this paper three topics are discussed. First, the reflectance properties of a vegetation canopy and the problems of determining the form of the relation between green l.a.i. and red and near-infrared reflectance: these problems include variability in substrate and leaf reflectance and the geometry of the scene and sensor. Second, the methodologies currently employed for estimating green l.a.i.: these methodologies are based on the production of simple, complex or modelled calibration curves. Third, current research at the University of Sheffield: this includes not only studies with multispectral reflectance collected from aircraft-mounted sensors to estimate the green l.a.i. of heathlands and grasslands but also multispectral reflectance collected from satellites to map estimated green l.a.i.

It is concluded that the main applications for this remote-sensing technique are within the fields of agricultural intelligence, agricultural management and ecological research.

1. Introduction

Electromagnetic radiation that is reflected or emitted from the Earth's surface can be recorded by a sensor from the ground, from an aircraft or from a satellite and these data can be used to measure and map the Earth's terrestrial, aquatic and atmospheric environments. Most of the data collected by remote sensors have been used in image form to study the spatial disposition of objects. Today an increase in the spatial and radiometric resolution of remote-sensing instrumentation, coupled with an increasing knowledge of the way in which electromagnetic radiation interacts with our environment, have enabled workers to use remotely sensed data to determine for example the amount of soil moisture in a field or the amount of suspended sediment in estuarine waters. One very promising area of remote estimation is the use of multispectral reflectance (which is defined as the spectral radiance standardized by the spectral irradiance) to estimate green leaf area index or green l.a.i., where green l.a.i. is the area of green leaves per unit area of ground. Accurate and timely information on green l.a.i. has application in agriculture for yield estimation and stress evaluation and in ecology for the study of primary production and environmental change.

This paper will review first the reflectance properties of a vegetation canopy; second, the relation between remotely sensed reflectance and green l.a.i.; third, methodologies for the estimation of green l.a.i. from remotely sensed measurements of multispectral reflectance, and fourth, examples of green l.a.i. estimation drawn from work undertaken at the University of Sheffield.

2. Reflectance properties of a vegetation canopy

Of the solar irradiance impinging upon a vegetation canopy some is reflected, some is transmitted and some is absorbed. The intensity with which radiation is reflected at any particular wavelength is dependent upon both the spectral properties and also the area of the three main remotely sensed components of a vegetation canopy: leaves, substrate and shadow.

(a) *Spectral properties of leaves*

Leaves usually reflect weakly in the blue and red wavelengths owing to absorption by pigments and strongly in the near-infrared wavelengths owing to cellular refraction (figure 1) (Curran 1980*c*; Kondratyev & Fedchenko 1982).

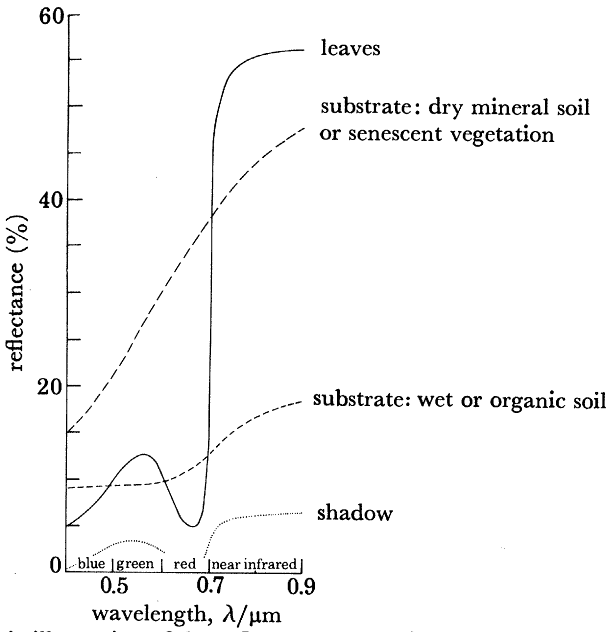

FIGURE 1. A diagrammatic illustration of the reflectance properties of three components of a vegetation canopy, leaves, shadow and either a light-toned mineral substrate or a dark-toned organic substrate.

(b) *Spectral properties of substrate*

The reflectance of vegetation substrates is usually spectrally simple but variable. Three common substrates, senescent vegetation, light-toned mineral soil and dark-toned organic soil, are illustrated in figure 1.

(c) *Spectral properties of shadow*

The most common type of shadow in a vegetation canopy results from the transmission of radiation through leaves and its re-radiation from other leaves or substrate. As a result canopy shadow is very dark in visible wavelengths, where most of the visible radiation is absorbed by leaves, and fairly dark in near infrared wavelengths, where little radiation is absorbed by leaves (Colwell 1974).

The relative area of these three spectrally dissimilar canopy components determines the reflectance of the total canopy. The canopy component with most variation in time and space is the area of green leaves and this in turn has most influence on the red and near-infrared reflectance of the vegetation canopy. Workers have therefore sought to use multispectral reflectance, particularly in red and near-infrared wavelengths, as a means of remotely estimating the green l.a.i. of vegetation canopies, especially when the vegetation canopies cover large areas of terrain.

3. The relation between remotely sensed red and near-infrared reflectance and green l.a.i.

Green l.a.i. has a negative relation with red reflectance and a positive relation with near-infrared reflectance, as illustrated in figure 2. To express this increasing difference between red and near-infrared reflectance with increasing green l.a.i., a ratio of red to near infrared reflectance is customarily used (Curran 1980*a*). One of the more popular is the vegetation index, I_v:

$$I_v = (R_{ir} - R_r)/(R_{ir} + R_r), \tag{1}$$

where R_r is red reflectance and R_{ir} is near-infrared reflectance.

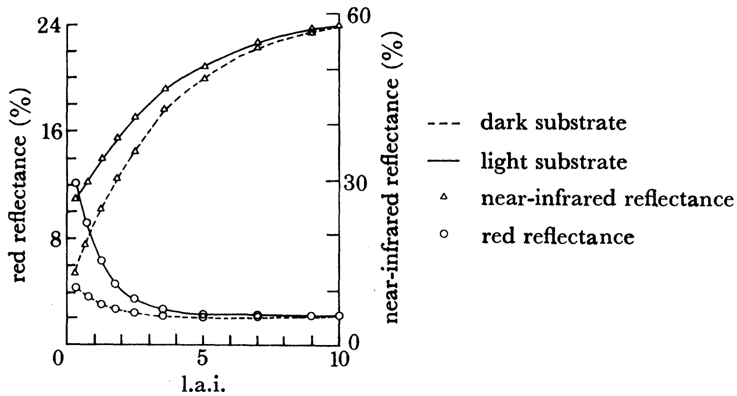

FIGURE 2. The relation between leaf area index (l.a.i.) and red and near-infrared reflectance for a vegetation canopy growing on a light-toned and a dark-toned substrate, derived from modelled data. (Modified from Colwell (1974).)

The form of the relation between the vegetation index and green l.a.i. is generally curvilinear, reaching an asymptote when the substrate is covered by several layers of leaves. The actual form of the relation is dependent upon the species and to a lesser extent the conditions of measurement. For example, in figure 3*a* the asymptote of the graph, and therefore the point at which the vegetation index ceases to be sensitive to changes in l.a.i., never occurs. For canopies in figure 3*b* it occurs at l.a.i.s of around 3 and for canopies in figure 3*c* it occurs at l.a.i.s of over 4. For this reason workers have tended to restrict their attention to cereal canopies with low green l.a.i.s because these canopies are thought to have a near-linear relation between the vegetation index and green l.a.i.

When looking at satellite images of large areas of land it is evident that one of the variations in canopy reflectance is the reflectance of the substrate rather than the leaves. However, it is possible to remove the effect of the substrate from the canopy reflectance by expressing the canopy reflectance relative to the substrate reflectance. This is done by first plotting the substrate line, which is a graph of substrate reflectance in red and near-infrared wavebands (figure 4). This relation is linear because light-toned substrates reflect both red and near-infrared radiation strongly and dark-toned substrates reflect both red and near-infrared radiation weakly (Curran *et al.* 1981).

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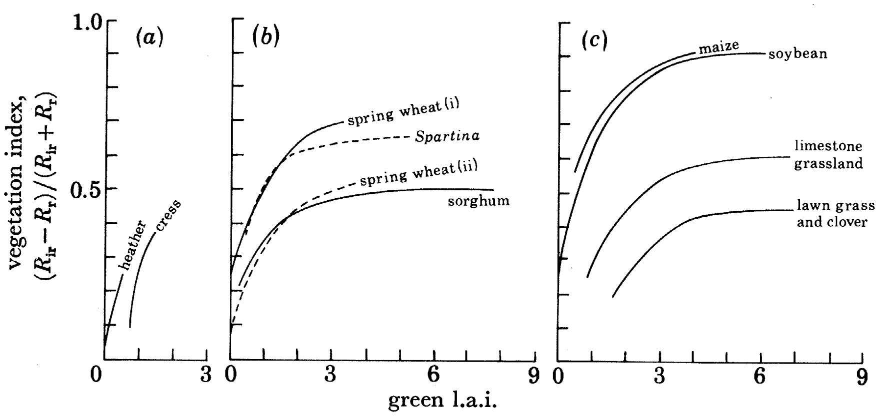

FIGURE 3. The relation between the vegetation index and leaf area index for different vegetation canopies: (*a*) asymptote not reached; (*b*) asymptote reached at low l.a.i.; (*c*) asymptote reached at high l.a.i. Modified from the following sources: for heather, Curran (1981 *b*); for cress, Curran & Milton (1983); for spring wheat (i), Daughtry *et al.* (1980); for spring wheat (ii), Ahlrichs *et al.* (1979); for *Spartina*, Bartlett & Klemas (1980); for sorghum, Brakke *et al.* (1981); for soybean, Holben *et al.* (1980); for maize, Kimes *et al.* (1981); and for limestone grassland and lawn grass and clover, N. W. Wardley (unpublished).

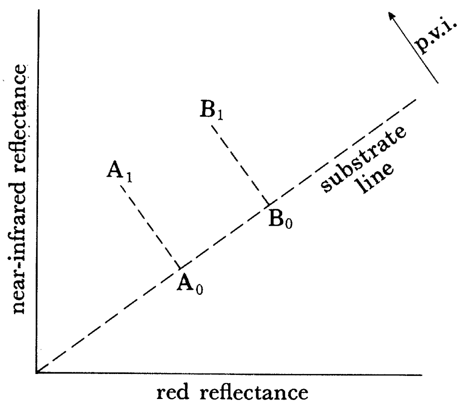

FIGURE 4. The coordinates in a red–near-infrared plot for sites A and B, where A_0 and B_0 are bare substrate and A_1 and B_1 are vegetation-covered. The index that can be used to record the spectral change from A_0 to A_1 and B_0 to B_1 is the perpendicular vegetation index (p.v.i.) (see text for discussion).

If vegetation were to grow on two sites on this substrate line, for example at sites A_0 and B_0, then as green leaf area increases the red reflectance will probably decrease and the near-infrared reflectance will probably increase. This will result in the movement of the reflectance coordinates for sites A_0 and B_0 away from the substrate line to coordinates A_1 and B_1 (figure 4). The coordinate distance between A_0 to A_1 and B_0 to B_1 is directly correlated to the green l.a.i. of the canopy at sites A and B respectively, and can be calculated from remotely sensed reflectance data by using the perpendicular vegetation index (p.v.i) of Richardson & Wiegand (1977):

$$\text{p.v.i.} = \sqrt{\{(R_{s,r}-R_{v,r})^2+(R_{s,ir}-R_{v,ir})^2\}}, \tag{2}$$

where R_s is substrate reflectance and R_v is vegetation reflectance.

These relations between a reflectance ratio and green l.a.i. and between a reflectance transform and green l.a.i. are not entirely dependent upon the area of green leaves but vary with other characteristics of the environment. Some of these characteristics are rarely of great importance (e.g. topography or microclimate), some are predictable and therefore correctable (e.g. phenology and atmospheric effects) (Curran 1982*b*; Slater & Jackson 1982), and some are difficult to predict (e.g. reflectance of the substrate, presence of senescent vegetation and geometry of the scene and sensor). These will be discussed below.

(*a*) *Reflectance of the substrate*

The possibility of detecting a change in green l.a.i. by a change in reflectance is dependent upon the reflectance contrast between green leaves and substrate. This is illustrated in figure 2, where it can be seen that (i) reflectance in near-infrared wavelengths is more sensitive to changes in the l.a.i. of vegetation on dark-toned substrates than on light-toned substrates, and (ii) reflectance in red wavelengths is more sensitive to changes in the l.a.i. of vegetation on light-toned substrates than on dark-toned substrates. In some environments the substrate can be so dark as to make red wavelengths insensitve to changing l.a.i., for example on the organic soils of the Somerset levels (Curran 1983) or so light as to make near-infrared wavelengths insensitive to changing l.a.i., for example in arid environments (Curran 1981*b*).

(*b*) *The presence of senescent vegetation*

As vegetation senesces, the near-infrared leaf reflectance does not significantly decrease. However, the breakdown of plant pigments causes a rise in red reflectance. Therefore if the amount of senescent vegetation in a canopy increases, the positive relation between near-infrared reflectance and green l.a.i. will probably remain unchanged whereas the relation between red reflectance and green l.a.i. will weaken and probably disappear (Curran 1980*c*). This is a problem in semi-natural vegetation, particularly grasslands, where there is some senescent vegetation in the canopy throughout the year.

(*c*) *The geometry of the scene and sensor*

The elevation and azimuth of the Sun and the sensor have a considerable effect on the reflectance of a vegetation canopy.

(i) *Solar elevation*

Two interrelated factors contribute to the effect of solar elevation on the reflectance of a vegetation canopy. The first is the degree to which solar radiation can penetrate the canopy, and this is negatively related to solar elevation. The second is the amount of canopy shadow and this is positively related to solar elevation. As a result, most canopies have a negative relation between near-infrared reflectance and solar elevation and a poor relation or none between visible reflectance and solar elevation. This is illustrated for a sedge canopy in figure 5 and is discussed in Curran (1983) and Kondratyev & Fedchenko (1982).

(ii) *Sensor elevation*

The elevation of the sensor determines the amount of substrate and shadow seen, for as the elevation moves from the vertical, the area of soil and shadow seen by the sensor decreases, and the area of vegetation seen increases. To move the sensor from the vertical will therefore increase near-infrared and decrease red reflectance, as illustrated in figure 5. The implications of this effect on multispectral reflectance measured at the edge of a Landsat satellite multispectral scanner image or from an oblique SPOT satellite high-resolution visible image are discussed in Curran (1983).

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(iii) *Relative solar and sensor azimuth*

The reflectance of a canopy is usually higher if the sensor is looking onto as opposed to away from the Sun, and away from the Sun as opposed to at right angles to the Sun (Kondratyev & Fedchenko 1982) (figure 5).

For most remote sensing applications where the sensor look-angle is nearly vertical, the effect of the solar azimuth on reflectance increases with a decrease in solar angle and an increase in vegetation canopy roughness, as discussed in Curran (1983).

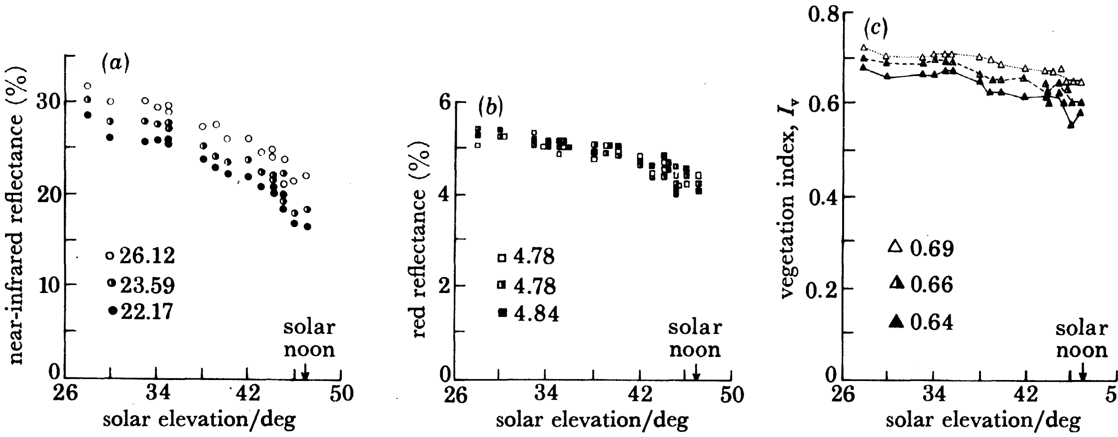

FIGURE 5. The effect of solar and sensor elevation and azimuth on the reflectance properties of a sedge canopy. These data were collected by using a ground radiometer in August 1982 at the Lakkasuo peatland complex near Hyytiälä in Southern Finland (61° 47′ 33″ N, 24° 18′ 40″ E). The vegetation, which has a green l.a.i. of 1.8, is dominated by *Carex lasiocarpa*, *Sphagnum papillosum* and *Sphagnum fallax*, and overlies wet sedge peat. Open symbols, 20° upsun; half filled symbols, 20° downsun; filled symbols, vertical. The numbers in each portion of the figure are mean reflectance values for each of the data sets.

4. Methodologies for the estimation of green l.a.i. by using multispectral reflectance

Two stages are involved in the estimation of green l.a.i. from remotely sensed multispectral reflectance: first, the determination of a calibration curve for the relation between multispectral reflectance and green l.a.i.; and second, the use of multispectral reflectance data collected from aircraft or spacecraft as input to this calibration curve. Ultimately the applicability and accuracy of green l.a.i. estimates are dependent upon the quality of either simple, complex or modelled calibration curves (Wiegand *et al.* 1979).

(*a*) *Simple calibration curves*

In this method the multispectral reflectance data used for the construction of the calibration curve are collected at the same place and time as the multispectral reflectance used for the prediction of green l.a.i. This can either be a subset of the remotely sensed multispectral reflectance data or can be ground-based measurements of multispectral reflectance. The advantage of the method is that it gives a very high accuracy of green l.a.i. prediction. The disadvantage is that the calibration curve is specific to site and time.

Because the aim of this method is to obtain a very accurate prediction from a specific data set, workers have tended to use any waveband ratio or transform that will give the necessary results;

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for example, a study in North Dakota obtained a correlation of 0.93 (significant at the 1% level) between the observed and predicted l.a.i. of spring wheat (figure 6*a*). Three wavelengths that had the highest correlation with l.a.i. were selected and applied in a three-variable multiple regression to ground-based radiometric data (Ahlrichs *et al.* 1979). Later studies successfully employed a similar technique with data obtained from the Landsat multispectral scanner (Heilman *et al.* 1977; Pollock & Kanemasu 1979) (figure 6*b*).

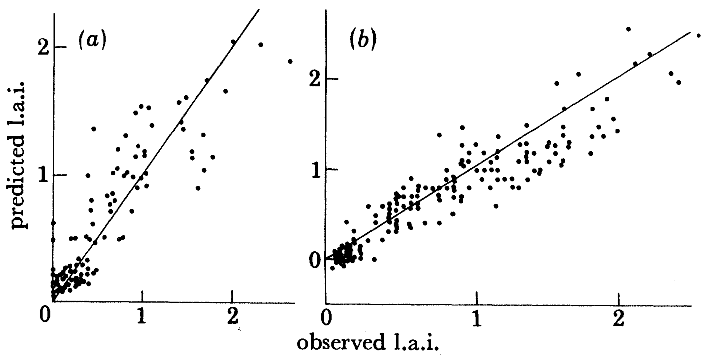

FIGURE 6. A comparison between the observed l.a.i. and the l.a.i. predicted from a simple calibration curve (*a*) Winter wheat (modified from Pollock & Kanemasu (1979)); (*b*) spring wheat (modified from Ahlrichs *et al.* (1979)).

Such approaches are most successful when applied to large data sets for simple crops. When working with small data sets and complex crops, workers have found even the simple calibration curve method unsuitable; for example, Chance (1981) used a transform of near-infrared radiance recorded by the Landsat multispectral scanner to predict the l.a.i. of seven sorghum fields in Texas and obtained a non-significant correlation of 0.38 between observed and predicted l.a.i. For grassland canopies in which l.a.i. is linearly related to biomass (Curran 1981 *b*) it has proved possible to use a simple calibration curve for the estimation of biomass, as has been illustrated by the work of Colwell (1974), Maxwell (1976), Pearson *et al.* (1976), Curran (1980 *b*) and Hielkema (1980).

(*b*) *Complex calibration curves*

In this method the reflectance characteristics of a species or species association are measured over space and time to provide calibration curves for the relations between multispectral reflectance, green l.a.i. and other environmental effects. These calibration curves enable multispectral reflectance to be corrected for the environmental effects considered by the operator to be important, before their use in the prediction of green l.a.i. Early work in this field was undertaken in the estimation of grassland biomass where biomass and l.a.i. were linearly related (Deering *et al.* 1975; Deering & Hass 1980; Bartlett & Klemas 1980). A more recent example of green l.a.i. estimation with this method is presented in §5 of this paper.

(*c*) *Modelled calibration curves*

The complex calibration curve method, while producing satisfactory results, is very time-consuming because it has to be repeated for each species and species association. To overcome this problem it is possible to model the reflectance properties of different physiological types of vegetation canopy by using a canopy model, which can be deterministic, stochastic or empirical.

(i) *Deterministic models*

These describe radiation passing through canopies in terms of diffuse flows scattered and attenuated by absorption. These theories are rather abstract and it was the Suits model (Suits 1972) that brought the deterministic model closer to reality. In this model Suits considers a canopy to be composed of mixed components of horizontal and vertical leaves, flowers and stalks, all with their own reflectance properties (Slater 1980). Data from this model, an example of which is reproduced in figure 2, have now been verified with many simple one-species canopies (Colwell 1974; Chance & LeMaster 1977).

(ii) *Stochastic model*

All of the inputs in this model are based on probability distributions because the processes involved are considered random. The first model of this type, developed by Smith & Oliver (1972), assumes that a vegetation canopy is composed of non-homogeneous layers of material with known optical properties, geometry and statistical composition and which interact with the incoming radiation according to known probabilities.

Both the deterministic and stochastic canopy models require detailed specification of the canopy characteristics. Therefore for semi-natural or forest vegetation the deterministic or stochastic canopy models are unlikely to be a practical option for the construction of calibration curves. However, for agricultural crops where canopy characteristics possess a degree of spatial uniformity it may well be possible to produce calibration curves from canopy models.

(iii) *Empirical model*

The empirical model is much more useful for the production of calibration curves because it is based on the creation of relatively simple data banks of green l.a.i. and multispectral reflectance data collected for different canopy types under a range of conditions. Such a model is under construction at the University of Sheffield for testing during 1983.

5. Estimating green l.a.i. from multispectral radiance: examples from the University of Sheffield

At the University of Sheffield work is currently in progress on a three-phase experiment designed to estimate green l.a.i. remotely. Phase one is a pilot study to determine a methodology for estimating green l.a.i. of a study site by using reflectance measured at aircraft altitudes. Phase two is designed to determine the feasibility of estimating the green l.a.i. of a larger area of terrain by using reflectance also measured at aircraft altitudes. Phase three is the estimation of green l.a.i. of large areas by using radiance measured at satellite altitudes.

Phase one will be discussed in detail and phase two and three will be outlined.

(*a*) *Phase one: pilot study to determine a methodology for estimating the green l.a.i. of a limited area by using reflectance measurements from aircraft altitudes*

(i) *Study area*

The pilot study was undertaken on Snelsmore Common, a heathland in Berkshire. Four vegetation types were chosen for study: young and mature *Calluna* (heather), *Pteridium* (bracken) and *Pteridium–Calluna* (bracken–heather association). Further details of these are to be found in Curran (1981*c*, 1982*a*).

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(ii) *The collection of ground data for the construction of complex calibration curves*

Snelsmore Common was visited on 12 occasions over a period of 14 months. At each random point, radiometric red and near-infrared reflectance measurements or photographic red and near-infrared reflectance measurements, or both, were taken and on the vegetated areas vegetation samples were collected. These data were expressed as one mean red reflectance value, one mean near-infrared reflectance value and one mean green l.a.i. value per random sample point (Curran 1982*a*).

(iii) *Ground data manipulation and the construction of the complex calibration curves*

The diurnal relation between reflectance and solar elevation was determined for each vegetation association and for bare ground. For all of the sites there was no significant deviation in red reflectance from the mean red reflectance (Curran 1982*a*). However, because the near-infrared reflectance did decrease markedly with solar elevation the reflectance data were corrected to a constant solar elevation.

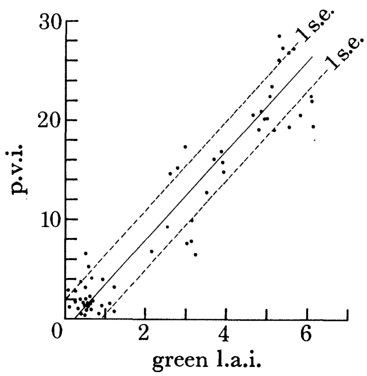

FIGURE 7. The linear relation between the perpendicular vegetation index (p.v.i.) and the green leaf area index (green l.a.i.) for a *Pteridium–Calluna* association. The solid line is described by the equation $x = 0.24+0.22\,y$. The s.e. of the estimate is 0.66 and of the forecasts is 0.73 ($y = 20$), 0.72 ($y = 10$) and 0.72 ($y = 2$); $n = 60$; $r = 0.83$; significance level, 1%.

These corrected data were then used to calculate the p.v.i. (equation (2)), which was regressed against the green l.a.i. of the four vegetation associations. In each case p.v.i. was positively related to green l.a.i. over the green l.a.i. range of 0–0.5 for young and mature *Calluna* and over the green l.a.i. range of 0–8 for the *Pteridium* and the *Pteridium–Calluna* (figure 7).

(iv) *The collection of multispectral aerial photography and observed green l.a.i.*

Near-vertical 35 mm format aerial photography was taken at around 11h00 local time, on 20 dates, from June 1980 to August 1981, from a light aircraft with a camera with the same film–filter combination used for ground multispectral photography (Curran 1981*a*). The reflectance of the vegetation or soil or both was calculated by using the method proposed by Lillesand & Kiefer (1979). At each random sample point the vegetation was harvested and the green l.a.i. determined by using the methods discussed in Curran (1982*a*). The results were presented as the mean green l.a.i. within the sample area.

(v) *Estimating green l.a.i.*

For each flight the aerial photographic red and near-infrared reflectance data were transformed to p.v.i. values. The p.v.i. values were then used to estimate the l.a.i. of each of these areas via the complex calibration curves. The mean of the estimated green l.a.i. range was plotted against the observed green l.a.i. for each site. One of these graphs, that for the *Pteridium–Calluna* association, is reproduced in figure 8. In all cases this expected l.a.i. was linearly related to, and slightly overestimated, the observed l.a.i.

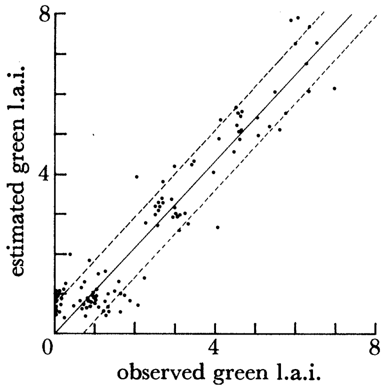

FIGURE 8. A comparison between the observed green l.a.i. and the predicted green l.a.i. for a *Pteridium–Calluna* association. The solid line is described by the equation $y = 1.07x$. The s.e. of the estimate is 0.64; $n = 100$; $r = 0.91$; significance level, 1%.

(vi) *Discussion*

The accuracy of the estimated green l.a.i. is dependent upon the acceptable error of the estimate, the type of vegetation and the season. If only very low errors are acceptable for each estimate, then accuracies are near to 0%. If very high errors are acceptable for each estimate, then accuracies are near to 100%. Between these two extremes the actual error will be directly related to the initial standard error of the forecast and the accuracy with which the observed l.a.i. can be measured. For example, if the green l.a.i. was observed without error on the *Pteridium–Calluna* site, the accuracy with which this green l.a.i. could have been estimated would have been 68% at an error of 0.72 green l.a.i., as this is the standard error of the forecast given on figure 7.

In practice a user will wish to estimate a wide range of l.a.i. values at a predetermined range of acceptable error. The relation between error range and accuracy is therefore illustrated by means of three possible error ranges, which are comparable between the four vegetation associations (see table 1).

(1) Low error of estimate: this was chosen to represent one eighth of the total green l.a.i. range for each vegetation association and is ± 0.05 green l.a.i. for the young and mature *Calluna* and ± 0.5 green l.a.i. for the *Pteridium* and *Pteridium–Calluna*. (2) Medium error of estimate: this was chosen to represent one quarter of the total green l.a.i. range for each vegetation association and is ± 0.1 green l.a.i. for the young and mature *Calluna* and ± 1.0 green l.a.i. for the *Pteridium* and *Pteridium–Calluna*. (3) High error of estimate: this was chosen to represent one half of the total green l.a.i. range for each vegetation association and is ± 0.2 green l.a.i. for the young and mature *Calluna* and ± 2.0 green l.a.i. for the *Pteridium* and *Pteridium–Calluna*.

An estimate of green l.a.i. can be made with a low error of the estimate to an overall accuracy of 42 %; at a medium error of the estimate the overall accuracy increases to 74% and at a high error of the estimate the overall accuracy increases to 98 % (see table 1).

Table 1. The relation between the error of a green l.a.i. estimate and the accuracy of that estimate

(For example the green l.a.i. of *Pteridium* can be estimated with an error of ± 1.0, 73 times out of every 100.)

vegetation association	error of green l.a.i. estimate	accuracy (%) of green l.a.i. estimate at given error level
young *Calluna*	± 0.05 (low)	34
	± 0.1 (medium)	62
	± 0.2 (high)	92
mature *Calluna*	± 0.05 (low)	41
	± 0.1 (medium)	73
	± 0.2 (high)	100
Pteridium	± 0.5 (low)	39
	± 1.0 (medium)	73
	± 2.0 (high)	100
Pteridium–Calluna	± 0.5 (low)	53
	± 1.0 (medium)	89
	± 2.0 (high)	98

The accuracy of estimation varied with season. The accuracy of the green l.a.i. estimate was highest in the winter and spring, from December to early May, when it is an average of 84%. In the summer and autumn, from late May to November, the accuracy of the green l.a.i. estimate dropped to an average of 52%. The two reasons for this seasonal variation are first the flowering of *Calluna*, which obscures green leaves, and second seasonal canopy changes resulting from the growth and senescence of *Pteridium*

(vii) *Conclusions*

(1) Multispectral aerial photography used in conjunction with complex calibration curves was successfully employed in the estimation of green l.a.i. for four different vegetation canopies.

(2) At an error of estimate of ± 0.1 green l.a.i. for the young and mature *Calluna* and ± 1.0 green l.a.i. for *Pteridium* and *Pteridium–Calluna*, green l.a.i. could be estimated with an overall accuracy of 74 %. At higher levels of error the overall accuracy increases.

(3) At times of canopy stability in the winter and early spring and at an error of estimate of ± 0.1 green l.a.i. for the young and mature *Calluna* and ± 1.0 green l.a.i. for the *Pteridium* and *Pteridium–Calluna* the overall accuracy increased to 84 %.

(*b*) *Phase two: an experiment to determine the feasibility of estimating the green l.a.i. of a large area by using measurements of multispectral radiance from aircraft altitudes*

During 1981 and 1982 the seasonal change in multispectral reflectance and green l.a.i. were recorded and complex calibration curves constructed for Lathkill Dale, a limestone grassland in Derbyshire. As part of the Natural Environment Research Council's remote-sensing programme MSS-82, multispectral radiance data were collected by a multispectral scanner mounted on an aircraft at the same time that green l.a.i. was measured on the ground. This work took place in

September 1982 over an area 8 square miles (2072 ha) in extent centred on Lathkill Dale. Preliminary analysis of these data indicates that accuracies of green l.a.i. prediction may well be superior to those obtained during the pilot study.

(c) *Phase three: the estimation of green l.a.i. of large areas by using measurements of multispectral radiance from satellite altitude*

During early work at the University of Sheffield, the multispectral radiance data collected by the Landsat multispectral scanner were used to generate simple calibration curves with green l.a.i. The green l.a.i. was then mapped to give estimates of ground cover and green biomass. Initially this work was undertaken for hill and upland areas in the U.K., for example the North York Moors and Peak District (Hastings 1982). More recently this approach has been used abroad and has included monitoring the area of date palm cultivation in Saudi Arabia (Curran & Adawi 1983).

Future work will concentrate on the use of p.v.i. and modelled calibration curves to produce maps of the green l.a.i. of grasslands from satellite measurements of multispectral radiance. The accuracy goal of such maps will be 80 % with an error of ± 1 l.a.i.

The problem that besets this work is the relatively low spatial and radiometric resolution of the multispectral reflectance data collected by the civilian satellites to which we have access (Lillesand & Kiefer 1979). This situation will be improved in 1984 when multispectral reflectance data collected by the Thematic Mapper sensor on the satellite Landsat-4 and the High-Resolution Visible sensor on the satellite SPOT are available.

6. Comment

Remote estimation of the green l.a.i. of vegetation canopies has been made possible by an increased understanding of how radiation interacts with a vegetation canopy, coupled with improved techniques for measuring that radiation. Today, rapid improvements in the method of green l.a.i. estimation by remote sensing have lead to accuracies that, on a field by field or association by association basis, are acceptable for application in studies where it is difficult or impossible to obtain green l.a.i. measurements by any other method, as would be true of some of the examples discussed in this paper. For this reason the three largest areas of application have been and are likely to continue to be in agricultural intelligence, agricultural management and ecological research. Agricultural intelligence, for the monitoring of your own or a foreign nation's cereal yield, as the U.S.A. monitors their own and the U.S.S.R.'s; agricultural management, for the location of stressed crops in times of drought, or in areas of known disease and ecological research, as an input to primary production studies or as a means of inferring environmental conditions.

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Discussion

M. D. Steven (*University of Nottingham School of Agriculture, Sutton Bonington, U.K.*). The interaction of light with a crop canopy depends both on leaf area and leaf angle. Relations established between spectral reflectance and leaf area index are species-specific, depending on the leaf angle distribution, and although this may be no great problem in the study of monocultures as in most agricultural crops, it will cause considerable difficulties in the interpretation of reflectance data over mixed canopies or natural vegetation. It may be more appropriate to measure vegetation by an index such as fractional cover that combines both leaf area and angle distributions in an appropriate way.

P. J. Curran. There are several species-specific factors that determine the form of the relation between green l.a.i. and the spectral reflectance of a particular species. These factors include the many facets of a plant's chemistry and physiology: for example, stem pigmentation, senescent rates, plant height, leaf thickness and as Dr Steven correctly points out, leaf angle. For the estimation of green l.a.i. there is no need to measure all of these species-specific factors if the spatial sampling used in the determination of green l.a.i. is adequate. The measurements of green l.a.i. must represent the species diversity within the area of canopy that is sensed by the instantaneous field of view (i.f.o.v.) of the sensor. Although this means that one must collect more ground data in complex semi-natural sites, this is not a 'considerable difficulty': it is the cornerstone of spatial sampling. For example, during the Natural Environment Research Council's multispectral scanner flights (reported in my paper), it was found that a canopy sample of 0.25 % of the i.f.o.v. area was adequate to express the green l.a.i. of a homogeneous agricultural pasture. By contrast, a canopy sample of over 2 % of the i.f.o.v. area was required to express the green l.a.i. of some of the heterogeneous semi-natural grasslands.

The use of fractional cover does not dispense with the need for a spatial sampling framework that is linked to canopy diversity. In laboratory studies I have found that fractional cover, when used in conjunction with green l.a.i., can provide a very useful indication of short-term changes in leaf angle, for example during times of drought. However, as a general index of vegetation amount, fractional cover is a most inappropriate measure on all but the sparsest canopies. This is because once the ground is covered by vegetation the index of fractional cover, unlike green l.a.i., is insensitive to further changes in vegetation amount. This is a serious limitation of this index as owing to the near infrared translucence of leaves these further changes in vegetation amount can be sensed remotely, as is reported in my paper.

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