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# TECHNIQUES FOR THE ESTIMATION OF LEAF AREA INDEX USING SPECTRAL DATA

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ABSTRACT

The key to the fixation of carbohydrates and the determination of the net primary productivity for global carbon cycle and crop yield is the green leaf area index (LAI). Its determination, on a global scale, is realistically possible only with satellite spectral data. A number of transformations, such as reflectance ratios and greenness, have been shown to be related to LAI. In general, these transformations are sensitive to soil variability and saturate at moderate LAI. A few of the transformations, such as greenness and perpendicular vegetation index, minimize sensitivity to soil variability but at the expense of sensitivity to LAI. This is because these transformations are from a linear space of reflectance bands, which radiative transport models have shown to be nonlinearly related to LAI. In addition, the relationships between these transformations and LAI were obtained simply by regression techniques and are not transferable from one data set to another. The fundamental problem is to find transformations of spectral data that maximize the sensitivity to LAI and simultaneously minimize the sensitivity to soil variability, cultivars, sun angle, etc., and are predictable from a minimum of input data. It is difficult to define such an "optimum" transformation. Based on radiative transport theory of a homogenous canopy, a new approach to obtain these transformations is suggested. These transformations show low sensitivity to soil variability, and are linearly related to LAI with relationships which are predictable from leaf reflectance, transmittance properties, and canopy reflectance models. These transformations are obtained without any ground knowledge of LAI. Results obtained on winter and spring wheat and corn using only nadir view data are presented.

## I. INTRODUCTION

A renewed interest in the global carbon cycling with particular emphasis on vegetative phytomass has recently emerged. A number of mechanistic models have been proposed in the last decade that attempt to incorporate detailed processes, such as photosynthesis, respiration, and growth and necrosis of plant tissues. The performance of these models is generally less than that of purely empirical models. As pointed out by Warring (1982), this is due to lack of detailed information on the key processes. A large volume of data, points to the fact that the key to the determination of the fixation of carbohydrates and hence to the determination of the net primary productivity is the leaf area index (LAI), defined as the one-sided leaf surface area per unit of ground area. This is the reference base chosen for comparing the site fertility and vigor for forest sites (Grier and Running, 1977) and for crop yield models (Mitchel, 1970). Measurements of leaf area index are very difficult and tedious, particularly for dense and tall canopies (presumably the region of most interest for carbon cycling problems).

The phenomenon of multiple reflections makes it possible to have much higher reflectance from multiple layers of leaves than the single leaf reflectance. The maximum reflectance, in the near-infrared, occurs when the number of leaf layers is about 8 (Gausman, et al., 1976). Hence, the near-infrared reflectance increases monotonically as LAI increases. However, in most typical field situations, LAI is not as high as 8, which makes canopy reflectance sensitive to soil reflectance.

With the availability of multispectral data, there is the possibility of minimizing the soil background effects. A vast array (about 4 dozen) of reflectance combinations has been proposed to accomplish this. Many of these are functionally equivalent (Perry and Lautenschlager, 1984). Blad et al. (1982), among many others, have concluded that Kauth and Thomas (1976) greenness index, the ratio of near-infrared reflectance to red (chlorophyll absorption) reflectance bands, RVI, are "best" suited of these transformations to estimate LAI. The perpendicular vegetation index, PVI, (Richardson and Wiegand, 1977) and the normalized difference, TVI, (Tucker et al., 1979) are functionally equivalent to greenness index and the band ratios.

All of the work to date relating the leaf area index to spectral reflectance has been empirical. Kanemasu et al. (1977) regressed winter wheat leaf area measurements to the RVI. Pollack and Kanemasu (1979) later on used a larger data set and stepwise regression and obtained a completely different set of regression equations. Wiegand et al. (1979) again on winter wheat data showed that greenness and PVI responded to changes in LAI with time for LAI>0.2.

Bauer et al. (1979) acquired spectral and agronomic data over Kansas, North Dakota, and South Dakota over a number of years. Linear correlation analysis between LAI and reflectance in Landsat MSS bands and thematic mapper (TM) bands indicated similar response to leaf area index. Kollenkark et al. (1982) found that greenness was strongly related to the leaf area index and showed that it was more strongly related to soil cover. They also showed that greenness reached a maximum, although LAI continued to increase, suggesting that greenness may be "saturating." Daughtry et al. (1983) also showed a similar relationship for their corn data. Hatfield et al. (1984) based on this analysis suggest that greenness and leaf area index may be directly related. Aase and Siddoway (1980) found no significant general relationship between LAI and PVI or TVI and the slope of the linear regression lines depended on the initial seeding rate of their plots. Blad et al. (1983) have suggested shadow effects as a possible cause of this lack of relationship, which effects greenness a lot less than PVI and TVI.

## II. THEORY

This brief overview of the work relating LAI to canopy reflectance is based on empirical regression analysis and is not necessarily transferable from one data set to another. Tucker et al.(1979) earlier have observed that these transformation indices respond asymptotically to LAI and suggested the need to reevaluate the data in terms of an index that responds linearly to LAI. Linear transformations permit one to employ an extensive body of mathematical techniques to develop "best" possible combination of these linear relationships to estimate leaf area index. The Allen and Richardson (1968) canopy reflectance model predicted the general shape of LAI versus canopy reflectance. The relationship in the visible is logarithmic, asymptotically reaching a constant value for LAI>1 and increasingly dominated by soil reflectance for decreasing LAI. In the infrared, the curvilinear relationship is always affected by soil reflectance up to an LAI of about 8.0. In the last decade a number of canopy reflectance models of varying complexity have become available. A review of these models has been reported by Smith (1983).

Three of these models, Suits (1972), SAIL (1981), and CUPID (1979), have been subjected to more rigorous testing and it has been shown that the SAIL model is "best" in performance while requiring the least input information (Badhwar, 1984).

These models, based on sound physical principals of radiative transport theory (Chandarshekar, 1960) provide a quantitative way to develop transformations of reflectance data that are linear in leaf area index and minimally sensitive to soil background effects. This approach is in marked contrast to the regression approach in that the origin of coefficients can be directly traced to leaf component properties and limitation of their validity investigated. It does not require extensive data sets of canopy reflectance and leaf area index (tedious to obtain in best of circumstances). In the next section we briefly review the SAIL model and our approach to obtaining LAI from spectral data.

The basic physical mechanism of the spectral radiance of a canopy is the scattering of the electromagnetic radiation by the canopy elements (leaves, stems, etc.). These elements are characterized by their reflectance, $\rho(\lambda)$, and transmittance, $\tau(\lambda)$, properties, which can be measured in a laboratory setup, and leaf area. Suits (1972) idealized the canopy geometry by replacing each plant component with three orthogonal projections of that component and assigning them the same hemispherical spectral properties as the actual components. This uniform canopy model also assumes that the canopy could be stratified into layers, infinite in horizontal extent, in which plant components are randomly distributed and homogenously mixed. The location of the layers, above the soil background are so chosen as to logically quantize the vertical distribution of the components. This idealization with the additional assumption of azimuthal isotropy, then permits the calculations of five parameters in Duntley's (1942) differential equation, the solution of which then provides the upwelling and downwelling diffuse flux density for sun and observer orientation. Verhoeff and Bunnik (1981) extended this model by removing the constraint that the scattering elements in a given layer had fixed orientation, as is in fact observed in nature. Evaluation of this model, called a SAIL (Scattering by Arbitrarily Inclined Leaves) on corn and soybean crops shows excellent agreement for <u>nadir</u> view observation. In brief, the model gives an <u>implicit</u> relation that for nadir view and Sun zenith angle of $\theta_s$ from nadir, the canopy reflectance, $R^\lambda$, is a function, $F^\lambda$, at observed wavelength, $\lambda$, of the form

$$R^\lambda(\theta_s) = F^\lambda(\mathrm{LAI}, \rho^\lambda, \tau^\lambda, \rho_s^\lambda, f(\theta_L), \eta^\lambda) \qquad (1)$$

where $f(\theta_L)$ is the leaf inclination distribution [and can be described by a Beta distribution, the mean angle, $\bar{\theta}_L$, and skewness, $\varepsilon_L$, of the distribution (Horie and Udagawa, 1971)] and $\eta^\lambda$ is the ratio of the diffuse-to-direct solar flux. Test indicates that for clear observing conditions, $R^\lambda(\theta_s)$ is very weakly dependent on $\eta^\lambda$. Thus, for a given LAI, the canopy reflectance depends on <u>laboratory</u> measured $\rho^\lambda$, $\tau^\lambda$, $\rho_s^\lambda$, and $f(\theta_L)$. One thus needs five independent measurements to estimate the leaf area index. Because of the high degree of correlation between individual band reflectances (Kauth and Thomas, 1976), there are no more than three independent reflectance bands in TM data. Thus, the model is not invertable, even in principle, without additional ancillary data. However, the canopy component reflectance and transmittance a few days after emergence and before senescence sets in, for a given species is relatively constant. A number of techniques exist to map species. With this reasonable assumption, one needs only three independent measurements of $R^\lambda$. The function $F^\lambda$ is different for different wavelength bands as has already been noted. The problem of the estimation of LAI from reflectance can thus be stated as:

find linear or nonlinear combinations of $R^\lambda$ (acquired at a given Sun zenith angle) that (1) give maximum sensitivity to changes in LAI and simultaneously, (2) are minimally sensitive to changing background reflectance $\rho_s^\lambda$, and (3) leaf inclination angle distribution $f(\theta_L)$, that changes among cultivars and changing planting configurations.

In this preliminary investigation, we have concentrated on linear transformation of LAI. As will be seen, with the current precision (>±20%) in ground measurements of LAI, this is sufficient. This task will be facilitated if an analytic representation of $F^\lambda$ in equation (1) can be obtained.

Figure 1 is the plot of the model calculated (nadir view) corn canopy reflectance in MSS bands. The input to the model were the laboratory measured $(\rho^\lambda)$, $(\tau^\lambda)$, $(\eta^\lambda)$, and measured leaf inclination angle distribution. Points were generated at four different sun angles and one soil type. The calculated reflectance at various wavelengths was integrated over the Landsat MSS bands. Plot (1a) is in the chlorophyll band and plot (1b) is in the infrared. As expected the form of these curves appears to be logarithmic. The solid lines are fits to the model generated data by equations of the form:

$$
\begin{aligned}
R_1 &= R_1^s + (\rho_1 - R_1^s)e^{-C_1 \mathrm{LAI}} \\
R_2 &= R_2^s + (\rho_2 - R_2^s)e^{-C_2 \mathrm{LAI}} \\
R_3 &= \rho_3 + (R_3^s - \rho_3)(1-e^{-C_3 \mathrm{LAI}}) \\
R_4 &= \rho_4 + (R_4^s - \rho_4)(1-e^{-C_4 \mathrm{LAI}})
\end{aligned}
\qquad (2)
$$

where, $\rho$'s are the soil reflectances and $R^s$ are the asymptotic (LAI→∞) canopy reflectance. $R^s$ do not depend on $\rho$'s.

The $R^2$-square of these fits exceeds 0.95. Data on canopy reflectance and LAI taken by Bauer et al. (1982) confirms that the model calculated values of the coefficients in equation (2) in these bands are, within errors, the same as calculated by fitting real data on LAI and corn canopy reflectance The coefficients $C_i$ contain in them information about the leaf inclination angle. Wiegand et al. (1979) have noted that they will change by small amounts among cultivars and planting configuration.

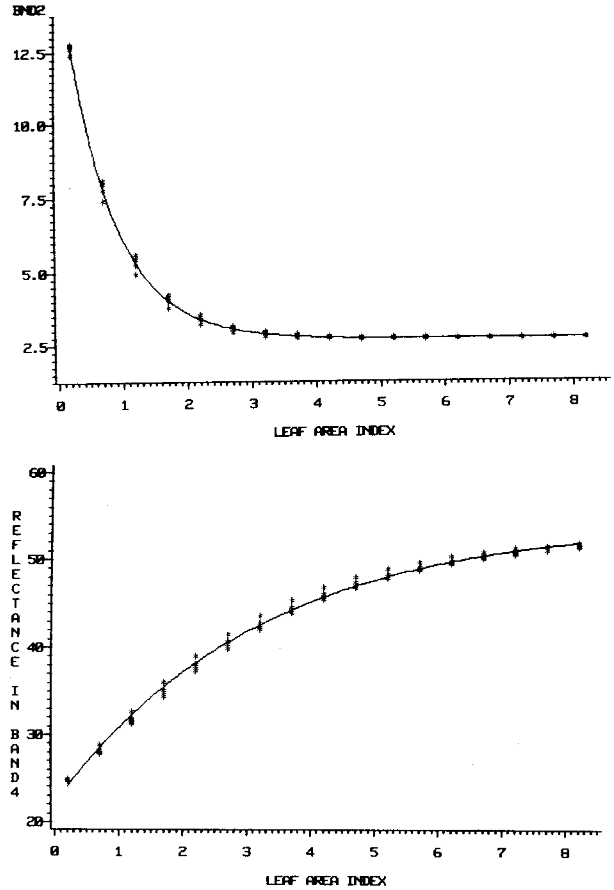


Figure 1. A plot of the SAIL model calculated reflectance in MSS bands 2 and 4 as a function of LAI for a nadir viewed corn canopy. The solid curves are the fits to the data (stars) by equations of the form (2). The input parameters are given in Equation (1).

Equation (2) makes it explicit that the relation R4/R2 with LAI is nonlinear and depends explicitly on the soil type. Even though the relative relationship between $\rho_4$ and $\rho_2$ is fairly stable for a large number of soil types (and varying soil moisture), the soil term does not cancel out. Clearly, R4/R2 transformation does not minimize soil background effects. Greenness increases as the crop develops from its initial value on the plane of soils to a maximum that, for a given crop type, is the same regardless of the soil type. Figure 2 shows the same data as in Figure 1, but generated for 12 different soil types at a given sun zenith angle—each curve representing a different soil type. The greenness direction by definition is perpendicular to the soil direction. This figure demonstrates that while greenness minimizes the effect of soil variability, it does so at the expense of sensitivity to LAI.

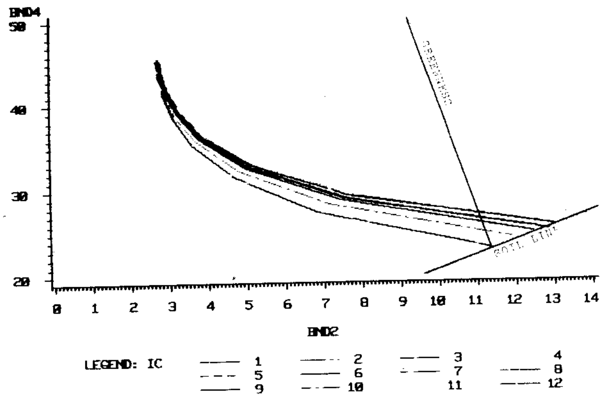


Figure 2(a). A cross plot of the data in Figure 1, but calculated for 12 different soil types (IC). The soil and greenness directions are marked. Note direction of maximum LAI sensitivity is not along greenness direction.

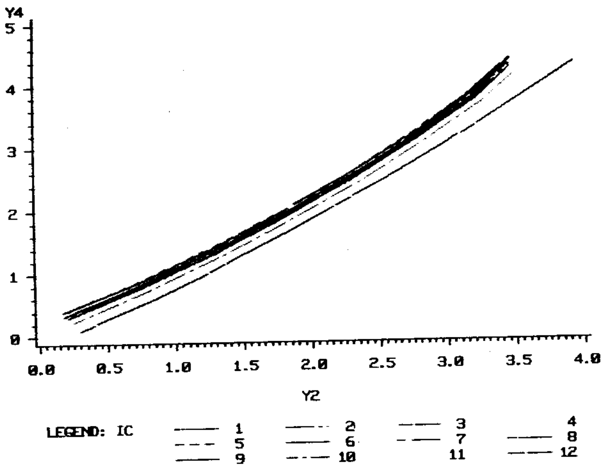


Figure 2(b). The same plot as Figure 2(a) but in the transformed variable of equation (3). Note the direction of LAI sensitivity is almost linear and nearly orthogonal to the soil direction.

Assuming a fixed crop cultivar, Equation (2) can be inverted.

$$
\begin{aligned}
y_1 &= -(1/C_1)[\ln(R_1-R_1^s) - \ln(\rho_1-R_1^s)] \\
y_2 &= -(1/C_2)[\ln(R_2-R_2^s) - \ln(\rho_2-R_2^s)] \\
y_3 &= -(1/C_3)[\ln(R_3^s-R_3) - \ln(R_3^s-\rho_3)] \qquad \text{(3A)} \\
y_4 &= -(1/C_4)[\ln(R_2^s-R_4) - \ln(R_4^s-\rho_4)]
\end{aligned}
$$

These variables, by definition, are linear in leaf area index. Figure 2, in transformed space of $y_2$ and $y_4$, shows that the variability in the soil direction is nearly orthogonal to the changing leaf area index.

If we now take linear combination of y's, they are linearly proportional to leaf area index. The soil variability is in additive terms. A possible way of finding the "best" linear combination of y's would be the principal component analysis. Such an analysis offers the advantage that it does not depend on the additive term. In this paper, it is the principal component analysis in y's which was used. Note, by this choice, the line of soil in reflectance space will be a line in transformed space.

The principal component analysis will provide us with a linear combination of y's that is maximally sensitive to the changes in LAI. However, the effect of the changing background reflectance is not considered in this analysis. An alternative solution to finding the "best" linear combination of y's would be to find $T(y)=\sum t_i y_i$ such that corr (T(y), LAI), the correlation between T(y) and LAI, is high and corr (T(y), Soil) is low. Or more specifically, we want to find $T(y) = \sum t_i y_i$ such that corr (T(y), LAI) is maximized subject to $|\text{corr}\ (T(y),\ \text{Soil})|<\varepsilon$ for some small $\varepsilon>0$ and $\sum t_i^2=1$.

This alternative technique will perhaps give us a linear combination of the y's that is highly correlated to LAI and simultaneously insensitive to the soil background effect.

## III. DATA SETS USED

Three extensive sets of Exotech 100-A reflectance and leaf area index values acquired over experimental plots of wheat in Arizona (1978-80, Jackson et al.), wheat in South Dakota (Best, 1982), and corn at LARS-Purdue University (1979-80, Bauer et al.) were used in this study. These data sets contain leaf area index values ranging from 0 to 7. It was found that some measurement errors exist in the leaf area index value. The errors were smaller for low leaf area index values and larger for high leaf area index values (C.V. ≈ 20%). The corresponding MMR reflectance data are available for analysis as well.

## IV. DATA ANALYSIS AND RESULTS

Using the SAIL model, the corn canopy reflectance values were generated for four different sun angles and one soil type. The coefficients in the nonlinear transformations (3) were first obtained by fitting equation (2) to the model generated data points. Since the LARS data set contains both the reflectance and leaf area index values for corn, the fitting was done to the real data as well. The coefficients obtained from the model-based data were found to be essentially the same as those obtained using real data. This indicates that we can use the model to estimate the coefficients in equation (3) which are linear in LAI.

The first principal component of y's is the linear combination of y's which corresponds to the direction of maximum variance in the sample scatter configuration. The changes in y's are, by definition, linearly related to the changes in leaf area index. Therefore, the first principal component should demonstrate the "best" linear relationship with leaf area index. Using each of the three data sets, the first principal component was found and plotted against leaf area index as shown in Figure 3. The straight lines in the plots are the regression lines obtained by regressing leaf area index on the first principal component. Table 1 shows the percentage of variance explained by the first principal component and the $R^2$ between leaf area index and the first principal component for each of the three data sets.

Multiple regressions of leaf area index on the y's and on the raw channel values R's and simple regressions on RVI and greenness were also performed for these three data sets. The purpose of these regression analyses is to compare the performance of their first principal components. The $R^2$ values are presented in Table 1.

TABLE 1.

| | Wheat (Arizona) | Wheat (South Dakota) | Corn (Indiana) |
|---|---|---|---|
| Number of Data Points | 61 | 54 | 46 |
| % Variance explained (PC1) | 76.82 | 86.66 | 70.25 |
| $R^2$-Regression (on PC1) | 0.818 | 0.836 | 0.740 |
| $R^2$-Regression $(y_1,..,y_4)$ | 0.873 | 0.845 | 0.826 |
| $R^2$-Regression (R1,..,R4) | 0.858 | 0.797 | 0.784 |
| $R^2$-Regression (on Greenness) | 0.818 | 0.732 | 0.770 |
| $R^2$-Regression (on R4/R2) | 0.723 | 0.824 | 0.790 |

It is necessary to point out that the principal component of y's, which is linearly related to leaf area index, can be obtained without the knowledge of leaf area index and, hence, served as a predictor for leaf area index. Whereas, multiple regressions, though showed slightly better $R^2$ values, do require the knowledge of leaf area index and are not transferable from one data set to another. They are, besides other difficulties mentioned earlier, therefore less desirable.

The principal component analysis technique gives us a nonlinear combination of the R's that is maximally sensitive to the changes in LAI. However, at present, we have not checked to see if this direction is minimally sensitive to the background reflectance. Figure 2, however, shows that this may, in fact, be so. Further research in finding the direction that will achieve both simultaneously is needed.

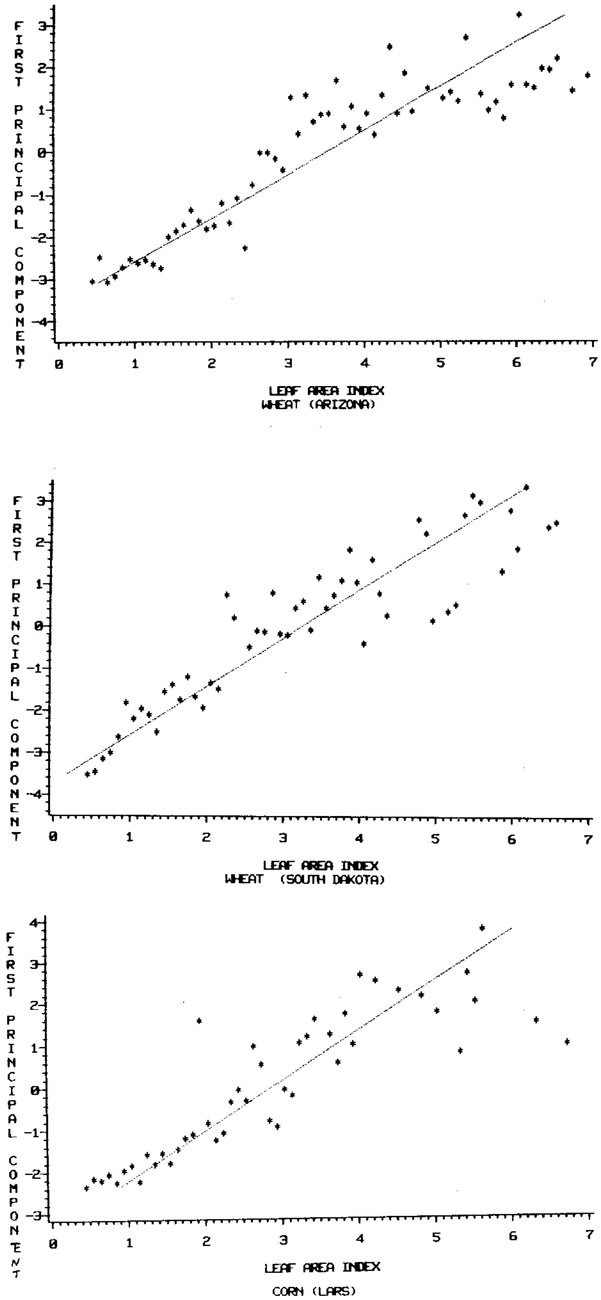


Figure 3. A plot of the first principal component of y's against the observed LAI for three crop types.

## V. ACKNOWLEDGEMENT

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