Modeling Variability and Scale Integration of LAI Measurements

Kris Nackaerts and Pol Coppin

Abstract.—Rapid and reliable estimation of leaf area at various scales is important for research on chance detection of leaf area index (LAI) as an indicator of ecosystem condition. It is of utmost importance to know to what extent boundary and illumination conditions, data aggregation method, and sampling scheme influence the relative accuracy of stand-level LAI measurements. This knowledge should lead to a high repeatability and relative accuracy of the LAI measurements. In this research, LI-COR is recorded with a Licor LAI-2000, one of the more modern and widely used plant canopy analyzer instruments. The impact of external factors (boundary and illumination conditions) is minimized by means of a viewcap. The impact of sampling scheme and data aggregation method on the relative accuracy of the retrieved stand-level LAI value is quantified by means of Monte Carlo simulation.

In studies of the Earth's ecosystems, leaf area index (LAI) plays a prominent role as an indicator of the ecosystem condition at various scales. In the past decades, much attention has been given to the simplification and optimization of biophysical attribute measurement techniques (Goel and Norman 1990). At almost the same time, information content of multispectral satellite imagery has been studied, confirming its usefulness for large-scale quantitative assessment of biophysical attributes such as LAI. Most of these activities concentrate on model development and calibration, defining the relation between field inventory LAI data and remotely sensed vegetation indices (Carlson and Ripley 1997, Price and Bausch 1995).

LAI can be assessed directly by destructive sampling or litter traps. But this type of sampling is time consuming, labor intensive, and not compatible with long-term ecosystem monitoring. Different indirect measurement techniques have been developed and commercialized, speeding up LAI assessment considerably in a non-destructive way. The LI-COR LAI-2000 plant canopy analyzer (PCA) is an example of these techniques and will be used in this study.

However, indirect LAI measurements are liable to different types of errors. Inaccuracies are induced by both external and internal factors. Weather or illumination conditions and boundary effects are external factors, not related to characteristics of the element of interest (forest canopy). Sampling scheme (design and intensity), data aggregation method, and measurement errors caused by imperfections and simplifications of the foliage distribution model, which assumes a random distribution of foliage in the canopy, are considered as internal factors.

Most scientific literature focuses on the calibration of retrieved LAI-values due to a non-random distribution of foliage at different scales. Smolander *et al.* (1994) and Stenberg (1996) discuss the impact of foliage clumping at the shoot level for conifers. The ratio of the mean shoot silhouette area to total needle area has been proposed as the calibration factor for LAI-2000 PCA measured LAI values. The assessment of the mean shoot silhouette area is rather labor intensive and the calibration factor is highly dependent on stand characteristics such as age and species composition. Chen and Cihlar (1995) studied the effect of canopy architecture on optical LAI measurements. A new instrument has been developed to assess the gap-size distribution used to calculate the element-clumping index, which quantifies the effect of non-random spatial distribution of foliage elements. This index is then used as a calibration factor for the LAI value measured with the LAI-2000 PCA. The labor-intensive characteristics and high costs of these methods limit their application.

Up until now, the impact of a data aggregation method and sampling scheme–necessary to relate data of different topological dimensions-on the accuracy of the estimated LAI has not been investigated well. However, data aggregation is an inevitable step in observations where point-level field data are related to area- or pixel-level remotely sensed data. The confidence limits of stand-level LAI values play a prominent role in quantitative change detection, because they define the accuracy of the monotemporal reference data. What is more, no elements outside the area of interest (e.g., forest stand) should be drawn into the measurement of a site-specific LAI value.

Research Assistant and Professor of Spatial Data Sciences, respectively, Laboratory for Forest, Nature and Landscape Research, KULeuven, Vital Decosterstraat 102, 3000 Leuven, Belgium.

This is of utmost importance when the information content of medium resolution imagery is related to biophysical attributes of highly fragmented and/or small-scale natural communities, as is the case in the study area. The impact of the external factors (illumination conditions and boundary effects) is minimized. The impact of a sampling scheme with integrated data aggregation method is quantified. An adequate sampling design and minimal sampling intensity (minimize field labor) is defined based on a selected acceptable relative accuracy with respect to the assessed stand-level LAI.

The present study is part of an ongoing research project on the modeling of LAI as a scale-integrated indicator of vitality and biodiversity in Flemish forest communities. An accurate detection and quantification of change or a high relative accuracy of monotemporal LAI data is therefore of utmost importance.

MATERIALS AND METHODS

Instrument Description

The LAI-2000 PCA consists of five sensors, each measuring light intensities ((< 490 nm) over five concentric FOV's centered on 7, 23, 38, 53, and 68 degrees zenith, referred to as sensor 1, 2, 3, 4, and 5, respectively. Simultaneously acquired above- and below-canopy readings are combined to calculate overall LAI using the equation (LI-COR 1992)

$$LAI = -2\int_0^{\pi/2} \ln(T(\theta))\cos\theta\,\sin\theta d\theta \qquad [1]$$

where

$T(\theta)$ = canopy gap fraction
θ = zenith angle

This formula can be converted to

$$LAI = 2\sum_{i=1}^{5} K_i W_i \qquad [2]$$

where

$$K_i = -\frac{\ln(T(\theta_i))}{S(\theta_i)} \qquad [3]$$

$$S_i = 1/\cos\theta_i \qquad [4]$$

$$W_i = \sin\theta_i d\theta_i \qquad [5]$$

K_i or contact frequency combines the more measurable terms ($T(\theta_i)$ is computed out of the LAI-2000 PCA readings) and is equivalent to the average number of contacts per unit length of travel that a probe would make passing through the canopy at zenith angle θ_i. A random distribution of foliage in the canopy is assumed. Because the light intensity below a forest canopy is influenced not only by foliage but also by all structural elements of a canopy, the Vegetation Area Index (or VAI) better describes the measured attribute.

Experimental Design

A reference data set was constructed for the study area (Pijnven) located near Hechtel (Belgium). The test site can be described as a uniform, even-aged Corsican pine (*Pinus nigra var. Corsicana*) stand, measuring 150 by 150 m. The average canopy height is 20 m. The reference sampling scheme is based on the relation between the FOV of the sensors (without viewcap) and the canopy height. To minimize data redundancy, overlapping FOV's are avoided. The minimum spacing between sampling points is determined by equation [1] for sensor 1, corresponding to the smallest FOV and equals approximately 10 m. A regular grid design oriented according to the geometry of the test site results in concatenating FOV's covering the whole stand. Contact frequencies are assessed with the LAI-2000 PCA in all sampling points. Data acquired outside the internal area (see below) for a given sensor are influenced by elements beyond the area of interest and will not be retained for further analysis.

Theoretical Background

Illumination Conditions

As mentioned in literature (Welles 1990), direct sunlight is an important cause of variability in VAI measurements with the LI-COR LAI-2000. To increase the number of measurement days, the impact of direct sunlight is minimized. The use of a viewcap of at least 180° (oriented to north) prevents direct sunlight from the FOV. To quantify the impact of direct sunlight on the measured contact frequencies for different zenith angles, a random uniform black and white pattern printed on a transparency was used to simulate a forest canopy. Contact frequencies were measured below the simulated canopy on a clear day. This was repeated 20 times for random canopy orientations. The relative accuracy, defined as:

$$1.96 \times StDev / Mean \qquad [6]$$

was calculated for all sensors covered with different viewcaps (no viewcap, 180° FOV, 90° FOV; FOV oriented to north).

Boundary Effects

It is evident no elements outside the area of interest should be drawn into the measurement of a site-specific VAI value. The influence of elements outside the area of interest is minimized by the use of a 270° viewcap resulting in an effective FOV of 90° combined with an adequate sampling design. Taking the geometric properties of the FOV of each sensor of the PCA into account, the internal area not influenced by external elements can easily be defined for each sensor given the canopy height and site orientation. The maximal radius of the FOV at the canopy top can be calculated for each sensor

$$R = H \times \tan(\alpha) \quad [7]$$

with

H: mean canopy height

α: maximal zenith angle of the FOV of the sensor

For a square test site with a western deviation from north of β ($\beta \leq 45°$), the minimal orthogonal distance to the site boundaries can be calculated as (fig. 1):

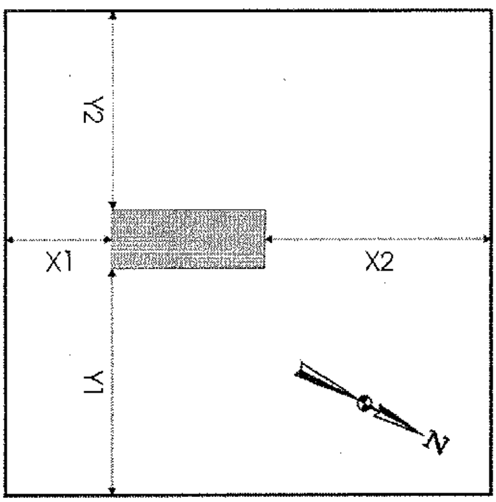

Figure 1.—*Geometric properties of the sensor-specific internal area of a square test site.*

$$Y_1 = R \times \sin(45° + \beta) \quad [8]$$

$$Y_2 = R \times \sin(45° - \beta) \quad [9]$$

$$X_1 = 0 \quad [10]$$

$$X_2 = R \quad [11]$$

The same equations can be used for a square test site with an eastern deviation from north of β' ($\beta' \leq 45°$) with

$$\beta = -\beta' \quad [12]$$

This ensures no elements outside the test site are taken into account when measuring site specific LAI's.

Aggregation Method

A stand-specific contact frequency is estimated for each sensor individually, assumed to be representative for the whole stand. For this, data are assessed only from within the internal area of a given sensor. This means that when a sampling point is located near the border of a stand, only data from the inner sensors will be used. For sampling points near the center of the stand, data from the outer sensors will also be included. The average of the retrieved contact frequencies for a given sensor is used as a stand-specific estimation of the contact frequency of the respective sensor. The stand-level VAI value is calculated out of the acquired contact frequencies for the five sensors by equation [2].

Quantification of the Impact of the Sampling Scheme

The quantification of the impact of sampling scheme and data aggregation method on the relative accuracy of the estimated VAI value is modeled by a Monte Carlo simulation of point-level contact frequencies for each sensor individually. This requires detailed information on the local and spatial variability of the contact frequencies for all sensors. The local variability of the contact frequency readings is modeled using basic statistical tools. Correlation between contact frequency data of adjacent sensors is expected due to a vertical overlap of the FOV's of both sensors and explored with standard regression techniques. Spatial auto-correlation is assumed to be negligible at the scale of the test site (relevant for most forest stands in Belgium) when the extent of the field of view of the sensor is taken into account.

A Monte Carlo simulation of point-level sensor-specific contact frequencies is applied to generate independent data sets with the same statistical characteristics as the reference data set. This can be interpreted as a simulation of different forest stands with the same LAI.

Due to the assumed absence of spatial auto-correlation, the sampling design only determines sampling intensities for each sensor. Different realistic sampling schemes with intensities ranging from 131 (maximum internal area points for sensor 1) to 1, are applied on point-level sensor-specific simulated contact frequencies. Point-level sensor-specific contact frequency data are simulated by means of a self-written program (the original or executable code can be obtained from the corresponding author). This point-level information is aggregated so that each simulation results in one stand-level VAI value, which can then be considered as an independent sample of the population describing the "real" stand-level VAI value. A population is simulated for each design. The relative accuracy (corresponding to the confidence interval at a significance level of 5 percent) is cross-referenced against the number of sampling points, and a function is graphically fitted to this relationship. The minimum number of simulations is defined by a pre-determined acceptable R^2 for the fitted regression function. An R^2 of 90 percent is considered acceptable.

RESULTS AND DISCUSSION

Illumination Conditions

In figure 2, the relative accuracy of the measured contact frequencies is plotted for the five different sensors of the PCA for three different viewcaps. The relative accuracy is comparable for most sensors for different viewcaps. Only for sensor 3, a large significant difference (at a 0.05 significance level) exists between the accuracy of contact frequencies measured with and without a viewcap. This high variability causes a decrease in relative accuracy of the calculated LAI from approximately 5 percent when a viewcap (180° or 270° viewcap) is used to little more than 20 percent when no viewcap is applied.

The high variability of the sensor 3 readings can be explained by the effect of direct sunlight. At the moment of data acquisition, the sun was located at an average elevation angle of 50°, falling only in the FOV of sensor 3 (ranging from 47° to 58°-zenith angle) when no viewcap is applied. The sun is thus continuous in the FOV of sensor 3 on the instrument acquiring above-canopy readings. High fluctuations in measured light intensities caused by not blocked, or partly or completely blocked direct sunlight in sensor 3 are responsible for the high variability in the calculated contact frequencies for this sensor. When the sun is not blocked or partly blocked, the canopy in the FOV is partly overexposed, resulting in an underestimation of LAI values. This is illustrated by figure 3. A 180° or 270° viewcap is required to minimize the impact of direct sunlight on assessed VAI values as demonstrated.

Boundary Effects

Given an average height of 20 m and a western deviation from north of 28° for the test site, the internal area is defined by equations [8], [9], [10], [11]. Calculated values for the 270° viewcap are shown in table 1.

The impact of the 270° viewcap on the extent of the internal area relative to other viewcaps is visualized for sensor 5 in figure 4. Sensor-5 measurements inside the specified area are not influenced by elements outside the test site. With no viewcap, this area is more than 40 times smaller than when the 270° viewcap is used.

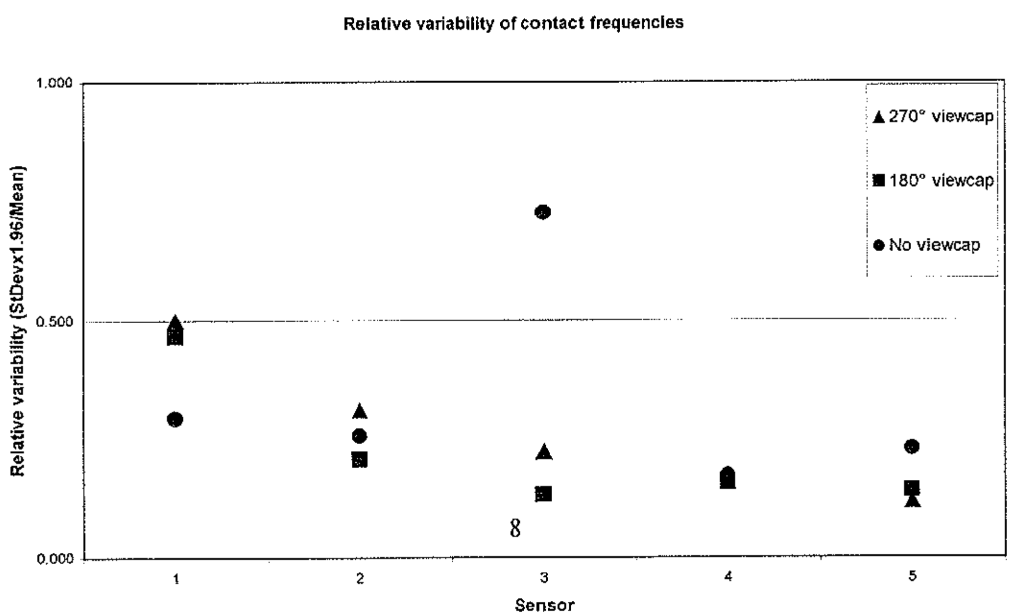

Figure 2.—*Relative variability of contact frequencies for different viewcaps under clear sky conditions.*

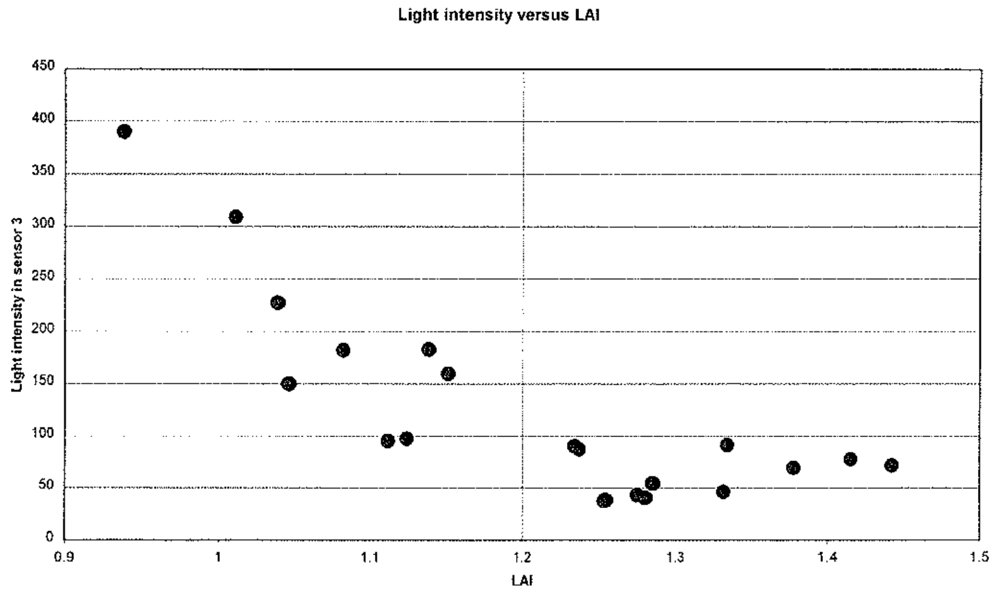

Figure 3.—*Impact of direct sunlight on LAI measurements.*

Table 1.—*Geometry of the internal area for the 270° viewcap with an eastern declination of 28°*

Sensor	Max zenith angle of FOV	R	X1	X2	Y1	Y2
	Degree	- - -	- - -	m	- - -	- - -
1	13	5	0	5	4	1
2	28	11	0	11	10	3
3	43	19	0	19	18	5
4	58	32	0	32	31	9
5	74	70	0	70	67	20

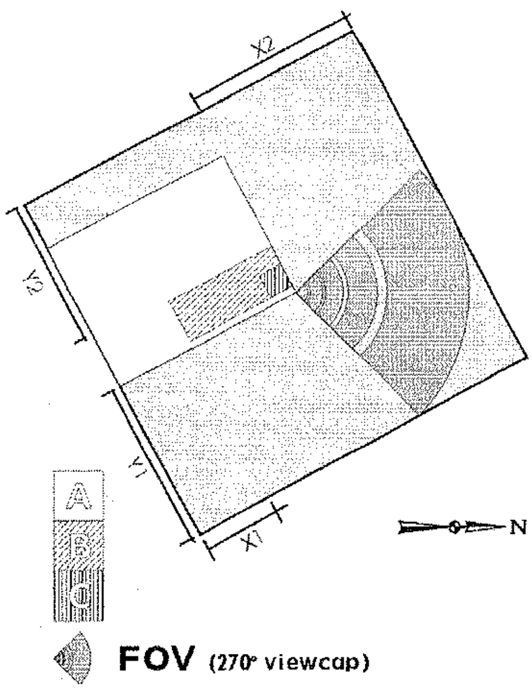

Figure 4.—*Internal area for different viewcaps with respect to sensor 5. Viewcaps: A: 270°; B: 180°; C: none*

Quantification of the Sampling Scheme and Integrated Aggregation Method

Modeling of Contact Frequency

Contact frequencies were sampled on a regular grid (10-m spacing) covering the whole test site (150 by 150 m). Taking the internal area of each sensor into account, 132, 110, 110, 81, and 24 samples for sensor 1, 2, 3, 4, and 5, respectively, were retained. A weak but significant correlation was found between contact frequencies of adjacent sensors with an average R^2 of 20 percent and normally distributed residuals. Due to the low exploratory characteristics of the assessed correlations, the distribution of the contact frequencies was also analyzed without taking the correlations into account. Contact frequencies are normally distributed for each sensor and can thus be described by the mean and standard deviation (see table 2).

Table 2.—*Parameters describing the distribution of contact frequencies for each sensor*

Sensor	Mean	Standard deviation
1	0.94	0.48
2	0.85	0.24
3	0.89	0.15
4	0.87	0.08
5	0.78	0.05

Simulation of Contact Frequency

Contact frequencies were simulated based upon the retrieved statistical information of the reference data set. Taking the correlation of contact frequencies between adjacent sensors into account did not result in significantly different simulated VAI values with respect to values simulated without this characteristic, as could be expected due to the low explanatory characteristics of the correlation as mentioned before. For this reason, contact frequencies were assumed not correlated in further analysis.

The confidence limit of the simulated VAI values is plotted for different sampling schemes against the sampling intensity. A power function was fitted through these data with Microsoft Excel and R^2 was calculated. This was repeated for different numbers of simulations. The lower the number of simulations, the higher the variability of the calculated confidence limit and the lower the R^2 of the fitted regression function as illustrated in table 3.

Table 3.—*R^2 of the fitted regression function describing the relation between sampling intensity and relative accuracy of estimated VAI*

Number of simulations	R^2
5	0.60
10	0.72
20	0.89
50	0.93
100	0.91
500	0.97

Based on the retrieved information, it was decided to use 50 simulations. Figure 5 illustrates the impact of sampling intensity on the accuracy of the retrieved VAI values.

Because no spatial autocorrelation is modeled, the sampling design influences only the number of internal area sampling points for each sensor. Different sampling schemes with the same sampling intensity having different orientations may thus result in a different relative accuracy of the retrieved VAI values, as can be seen in figure 5 (e.g., sampling intensity of 36). This relatively small difference is caused by the different orientation of the designs, resulting in differences in the number of internal area points with respect to each sensor individually. For example, two regular-grid sampling schemes were applied with an intensity of 36 sampling points. Due to their different orientation, 36, 30, 30, 25, and 6 internal area sampling points were retained for sensor 1, 2, 3, 4, and 5, respectively, for one design, and only 36, 25, 25, 20, and 6 internal area sampling points were retained for sensor 1, 2, 3, 4, and 5, respectively, for the other.

Based on a pre-defined acceptable relative accuracy of 10 percent and the variability caused by the design, it was decided to use 16 sampling points to estimate stand-level VAI. Due to ergonomic considerations, a regular grid design was selected.

ACKNOWLEDGMENTS

We thank the following two reviewers for their constructive comments: Marvin Bauer, Professor of Remote Sensing, Department of Natural Resources, University of Minnesota, St. Paul, MN, USA, and Bart Muys, Assistant Professor of Forestry, Department of Land Management, Catholic University of Leuven, Leuven, Belgium.

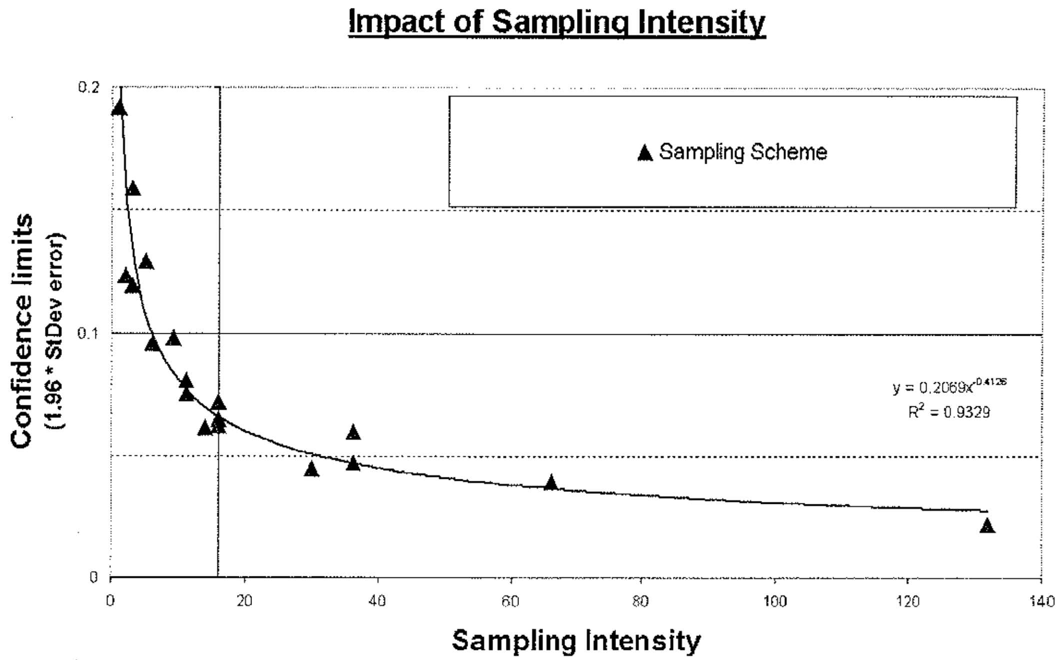

Figure 5.—*Impact of sampling intensity on the relative accuracy of retrieved VAI.*

LITERATURE CITED

Carlson, T.N.; Ripley, D.A. 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of the Environment. 62: 241-252.

Chen, J.M.; Cihlar, J. 1995. Quantifying the effect of canopy architecture on optical measurements of leaf area index using two gap size analysis methods. IEEE Transactions on Geoscience and Remote Sensing. 33 (3): 777-787.

Goel, N.S.; Norman, J.M. 1990. Instrumentation for studying vegetation canopies for remote sensing in optical and thermal infrared regions. In: Remote Sensing Reviews. 5(1). Reading, UK: Hardwood Academic Publishers. 360 p.

LI-COR. 1992. LAI-2000 plant canopy analyzer: instruction manual. Lincoln, NE: LI-COR, Inc.

Price, J.C.; Bausch, W.C. 1995. Leaf area index estimation from visible and near-infrared reflectance data. Remote Sensing of the Environment. 52: 55-65.

Smolander, H.; Stenberg, P.; Linder, S. 1994. Dependence of light interception efficiency of Scots pine shoots on structural parameters. Tree Physiology. 14: 971-980.

Stenberg, P. 1996. Correcting LAI-2000 estimates for the clumping of needles in shoots of conifers. Agricultural and Forest Meteorology. 79 (1-2): 1-8.

Welles, J. 1990. Some indirect methods of estimating canopy structure. In: Norman, J.; Geol, N., eds. Instrumentation for studying vegetation canopies for remote sensing in optical and thermal infrared regions (Hardwood, London,): 31-43.