ESTIMATION OF LAI USING LIDAR REMOTE SENSING IN FOREST

Doo-Ahn Kwak[a], Woo-Kyun Lee[a], Hyun-Kook Cho[b]

[a] Division of Environmental Science and Ecological Engineering, Korea University, Seoul 136-701, South Korea – tulip96@korea.ac.kr
[b] Korean Forest Research Institute, Cheongryangri-Dong, Dongdaemun-Ku, Seoul 136-012, Korea – hcho@foa.go.kr

KEY WORDS: LiDAR, Leaf Area Index (LAI), Point density, Vegetation Index, Photosynthetically Active Radiation

ABSTRACT:

Light Detection and Ranging (LiDAR) has been used to extract surface information as it can acquire highly accurate object shape characteristics using geo-registered 3D-points. Therefore, LiDAR can be used to effectively measure tree parameters in forested areas. In this research, we estimated the LAI (Leaf Area Index) for *Pinus koraiensis*, *Larix leptolepis* and *Quercus* spp. using LiDAR data. For calculating the LAI (Leaf Area Index), the LPI (Laser Penetration Index) and LII (Laser Interception Index) were generated by LiDAR data having High Vegetation Returns (HVR), Medium Vegetation Returns (MVR), Low Vegetation Returns (LVR) and Ground Returns (GR). The LPI was calculated with point density using first returns ($h \geq 1m$) and ground returns ($h < 1m$), and the LII was computed with the ratio of all returns to HVR and MVR. The LAI is calculated through the regression analysis by tree species with the LPI and LII. Afterward, we assessed the accuracy of LiDAR-derived and field-measured LAI with the coefficient of determination and root mean square error. As a result, the slope of *Pinus koraiensis* was the steepest, and the slope of *Quercus* spp. was the gentlest of three tree species. This can be explained by the fact that the amount of transmitted sunlight through the canopy in *Quercus* spp. can be different by seasons. Moreover, in the LAI generated by the LII, the coefficients of determination were estimated higher than those by the LPI. This can be attributed to the fact that the original information of the number of laser points was lost when the point data was transformed to raster data for generating the LPI. And the LII allows normalizing biased local variation of the number of laser points while the raster data has some noise due to unbalanced distribution of laser points.

1. INTRODUCTION

There are several definitions for the LAI in the field according to Jonckheere *et al*. (2004). The LAI can be defined as the total one-side area of leaf tissue per unit ground surface area (Watson, 1947). But this is only used for deciduous forests. Schulze *et al*. (2005) mentioned that the LAI could be determined as the sum of the projected leaf surface per soil area and Myneni *et al*. (1997) defined the LAI as the maximum projected leaf area per unit ground surface area. By these definition, the LAI can derive both the within and the below canopy microclimate, control canopy water interception, radiation extinction, water and carbon gas exchange (Bréda, 2003). Moreover, they provide as the information for biosphere modeling (Bonan, 1993) and fire behavior models (Finney, 1998), since they have information for a number of relevant ecological process (Morsdorf *et al*., 2006). Therefore, the LAI can play a key role of biogeochemical cycles in ecosystem. Various methods for the LAI can be classified into two categories as direct and indirect estimation (Bréda, 2003). The direct methods can be measured as harvesting vegetation but these methods are destructive and exhaustive. Furthermore, such methods are suitable for the vegetation of small structure, not applied to large area or trees (Bréda, 2003). And previous methods have time-consuming and labor-intensive problems when the LAI is measured in the field. On the other hands, indirection methods can be estimated without destructive works and easily with the radiative characteristic of the sunlight, which is dispersed or penetrated around the vegetation area. In such methods, remote sensing techniques using satellite imagery and aerial photograph have applied to deriving this measurement. Such many approaches were based on passive optical sensor system and regression models (Cohen *et al*., 2003) or radiative transfer modeling (Koetz *et al*., 2004). However, a serious problem of remote sensing using passive sensor system is that it can not describe the canopy shape and structure because it doesn't have the elevation information by itself. However, Light Detection and Ranging (LiDAR) with active sensor system, especially, has recently been used to extract surface information, as it can acquire highly accurate object shape characteristics using geo-registered 3D-points (Kwak *et al*., 2006). Therefore, the LiDAR system can measure both vertical and horizontal forest structures in forested areas, such as tree heights, sub-canopy topographies and distributions, with high precision (Holmgren *et al*., 2003). As such characteristic of the LiDAR is used for extracting the forest information, some research derived the LAI and the fCover (fractional cover) (Morsdorf *et al*., 2006) and Riãno *et al.* (2004) obtained the LAI using the gap fraction distribution. Moreover, Lovell *et al*. (2003) used the ground-based laser scanner to model the LAI using canopy profile and Koetz *et al.* (2006) applied the LiDAR waveform model to generating the fCover and the LAI from large footprint LiDAR data. However, it is difficult for the large footprint LiDAR used to extract forest information for small area. The use of the ground based Laser scanner is limited by topography conditions of study area and can estimate only limited small forest area, not broad forest area. Therefore in this research, we verified the usefulness of small footprint LiDAR data for estimating the LAI. Furthermore, we compared the LAI extracted from our study with previous research, which Barilotti *et al*. (2006) analyzed the LAI with the LPI (Laser Penetration Index). Thereby, we examined which method would be suitable for estimating the LAI in the forests of South Korea.

2. MATERIALS AND METHODS

2.1 Study area

The study area was located in Mt. Yumyeong (the upper left 127°28′45.76074″E, 37°35′59.75109″N and lower right 127°30′6.98627″E, 37°35′6.27425″N), central South Korea . Situated from 321m to 573m above sea level, the study area was dominated by steep hills, with the main tree species being *Pinus koraiensis* (Korean Pine), *Larix leptolepis* (Japanese Larch) and *Quercus* spp. (Oaks). Approximately 312ha were selected for this study and the 30 plots (10 plots by tree species) of the study area were investigated for measuring the LAI. These plots were selected in such a way that the composition of tree species was homogeneous.

2.2 LiDAR data

In this study, Optech ALTM 3070 (a small footprint LiDAR system) was used for acquisition of the LiDAR data, with the flight performed on 28th April 2004. The study area was measured from an altitude of 1,500m, with a sampling density of 1.8 points per square meter, and the radiometric resolution, scan frequency and scan width were 12bits, 70Hz and ±25°, respectively. Field data were obtained on 28~30th April 2007, although the LiDAR data were acquired on 28th April 2004. However, the difference in the tree height growth relevant to the period between the acquisition of the ground data and LiDAR-derived values was not considered, as an increase in the quantity of needle leave (*Pinus koraiensis* and *Larix leptolepis*) during 3 years is relatively small and broad leave were come out little. In order to calculate the LAI from the LiDAR data, pre-classified points were used with the TerraScan software (Terrasolid Corporation); therefore, raw LiDAR points were classified into one of 4 groups; Ground Return (GR), Low Vegetation Return (LVR), Medium Vegetation Return (MVR) and High Vegetation Return (HVR) (Lim *et al.*, 2001). The HVR and GR were used to estimate the LPI, and the LII was calculated from the GR and all point data.

2.3 Field data

The number of sample plots was 10 sites by tree species. Each plot was composed of 20m x 20m (400m^2) size and the LAI of plots was measured using the AccuPAR-80 Linear PAR/LAI Ceptometer of Decagon Devices, INC. The LAI was calculated automatically, as shown equation 1 in the device (Decagon INC, 2001).

$$LAI = \frac{\left[\left((1-\frac{1}{2K})f_b - 1\right)\right]\ln\tau}{A(1-0.47f_b)} \quad (1)$$

where f_b is the fraction of incident PAR (Photosynthetically Active Radiation) which is beam, K is the extinction coefficient for the canopy, and τ is scattered and transmitted PAR. A is defined as below equation 2 and the a of equation 2 is the leaf absorptivity in the PAR band.

The f_b was estimated at 0.85 in the barely field before beginning the measurement of the LAI below the canopy and used the same value for all tree species. The a was determined as 0.9 which was assumed by AccuPAR in LAI sampling routines. K could be calculated with zenith angle (37°) of the sun in the study area (Equation 3) (Campbell, 1986). And τ could be computed as the ratio of PAR measured below the canopy to PAR above the canopy (Equation 4).

$$A = 0.283 + 0.785a - 0.159a^2 \quad (2)$$

$$K = \frac{(x^2 + \tan^2\theta)^{\frac{1}{2}}}{x + 1.744(x + 1.182)^{-0.733}} \quad (3)$$

$$\tau = \frac{PAR_{\min}}{PAR_{\max}} \quad (4)$$

where θ is the zenith angle of the sun and x is a leaf angle distribution parameter. When the LAI was estimated in the study area, x was determined as 1 which means that the angle distribution was spherical. Therefore K can be simplified to equation 5.

$$K = \frac{1}{2\cos\theta} \quad (5)$$

Through this process of the AccuPAR, we acquired the average LAI as estimating 9 positions for avoiding the LAI value fluctuating by changing the value according to the directions. The LAI estimation was begun at the centers of the plots and determined at 8 positions with 8 directions as we moved with 45° from the north and 10m distant from the center. The LAI value per 1 position was also estimated 4 times with 4 directions, where were East, West, South and North. Therefore we could obtain the one average LAI per a plot and compare field-derived LAI with LiDAR-derived LPI and LII through 30 LAI values totally. The measurement was carried out from 11 A.M to 14 P.M. since the solar altitude was the highest during a day. The positions of the plots were acquired at the breast height of the center of each plot, using GPS Pathfinder Pro XR® manufactured by Trimble™.

2.4 Estimation of LAI

2.4.1 Potential of LiDAR for estimating LAI

It is possible to apply various remote sensing techniques for estimating the LAI. However, the LiDAR has the potential for obtaining geo-registered 3D-points whereas satellite imagery and aerial photograph are difficult to extract the 3 dimensional information of forested area. Moreover, the laser is similar to the sunlight at the aspect based on reflectance or transmission through the canopy; therefore, we could estimate the LAI as acquiring the 3D points reflected on the canopy and the ground in forested area. On the other hands, instead of the radiation reach from the sun to the ground and vegetation, with the number of ground returns and vegetation returns (including HVR, MVR and LVR) reach from an aircraft, we could analyze the LAI. Monsi and Saeki (1953) estimated the LAI as measuring both incident (I_0) and below-canopy radiation (I)

like equation 6 .

$$LAI = -1/k \ln(I/I_0) \tag{6}$$

where I_0 is the incident radiation, I is the radiation transmitted below-canopy, k is the extinction coefficient. In above equation, I/I_0 describes the ratio of sunlight interception. With such aspect of interception or penetration, we could estimate the LAI when using total amount of laser point emitted from an aircraft and reflected from the canopy although physical and chemical characteristics of laser and sunlight were different each other. In other words, the total emitted laser point from an aircraft could be considered as the total amount of sunlight, and the total intercepted or penetrated laser point through the canopy could be regarded as the total amount of blocked or incident sunlight. Therefore, for estimating the LAI, we applied the LPI and LII which could be generated using the density and number of laser point penetrated and intercepted through the canopy. However, we didn't apply the equation 6 directly because that equation was applied to only natural radiation. Thereby, in our study, new regression functions were used instead of equation 6 after regression analysis was performed with field-derived LAI and LiDAR-derive LPI and LII. Furthermore, we didn't consider the extinction coefficient as k of equation 6 because we conducted this study with only the number of laser point, not laser intensity value.

2.4.2 Laser Penetration Index (LPI)

For estimating the LAI, Barilotti *et al*. (2006) suggested the LPI using point density of ground returns and vegetation returns in the sample plots. The classification of LiDAR points into ground returns and vegetation returns was conducted by Terracan™ software. Afterward, vegetation returns were divided into two classes; one was first returns (height ≥ 1m), the other was ground returns (height < 1m). For generating the LPI, the ground and high vegetation returns were used only.

$$LPI = \frac{D_{gnd}}{D_{gnd} + D_{high}} \tag{7}$$

where D_{gnd} is the density of ground returns and D_{high} is the density of first returns. The LPI was calculated with raster data by a neighbor statistical analysis using a radius of 5m because of the heterogeneous distribution of LiDAR points. If the LPI value is close to 0, it means the vegetation is dense, however, if the value is close to 1, it describes the vegetation is sparse. We generated the LPI using the same methods and then compared the accuracy with the result of the LII as conducting the regression analysis with the LPI value and the field-derived LAI.

2.4.3 Laser Intercept Index (LII)

The LII can be generated from the number of ground and low vegetation returns and all returns including HVR, MVR, LVR and GR. Practically, however, the LII can be described as shown equation 8 because the LII means the ratio of laser points intercepted by the canopy.

$$LII = \frac{N_{(high+mid)}}{N_{all}} = 1 - \frac{N_{gnd} + N_{low}}{N_{all}} \tag{8}$$

where $N_{(high+mid)}$ is the sum of high and medium vegetation returns, N_{gnd} and N_{low} are the number of ground and low vegetation returns respectively and N_{all} is the sum of all returns in a plot. With above equation 6, we could predict that the LII is proportioned to the LAI since the LAI increases when the ratio of points intercepted by the canopy increase. We generated the LII by three tree species with the number of laser points, and then created the relationship function as comparing with field-derived LAI values.

3. RESULTS AND DISCUSSION

For the accuracy analysis of estimated regression function with field-derived LAI and LiDAR-derived LPI and LII, the coefficient of the determination (R^2) and root mean square error (RMSE) were calculated. As a result, on the whole tree species, coefficients of the determination of the LII were higher than those of the LPI. The coefficients of determination for the LPI were 0.81, 0.73 and 0.81 respectively for *Pinus koraiensis*,

Species	Statistics	LPI	LII
Pinus koraiensis	Function	$LAI = -54.561 \cdot LPI + 7.3411$	$LAI = 50.184 \cdot LII - 42.573$
	Range	0.04~0.07	0.92~0.96
	R^2	0.81	0.88
	RMSE	0.31	0.24
Larix leptolepis	Function	$LAI = -8.3405 \cdot LPI + 3.5776$	$LAI = 8.2604 \cdot LII - 4.6359$
	Range	0.07~0.19	0.78~0.91
	R^2	0.73	0.85
	RMSE	0.25	0.18
Quercus spp.	Function	$LAI = -1.7093 \cdot LPI + 1.2168$	$LAI = 1.8422 \cdot LII - 0.6043$
	Range	0.02~0.34	0.66~0.98
	R^2	0.81	0.86
	RMSE	0.09	0.08

Table 1. Accuracies of the LAI estimations with LPI and LII

Larix leptolepis and *Quercus* spp. (Table 1). The LII were estimated at 0.88, 0.85 and 0.86 respectively. Likewise with the result of the coefficient of determination, RMSEs of the LII were evaluated higher than those of the LPI. RMSEs of the LPI were determined as 0.31, 0.25 and 0.09 by three tree species, and LIIs were estimated at 0.24, 0.18 and 0.08 respectively.

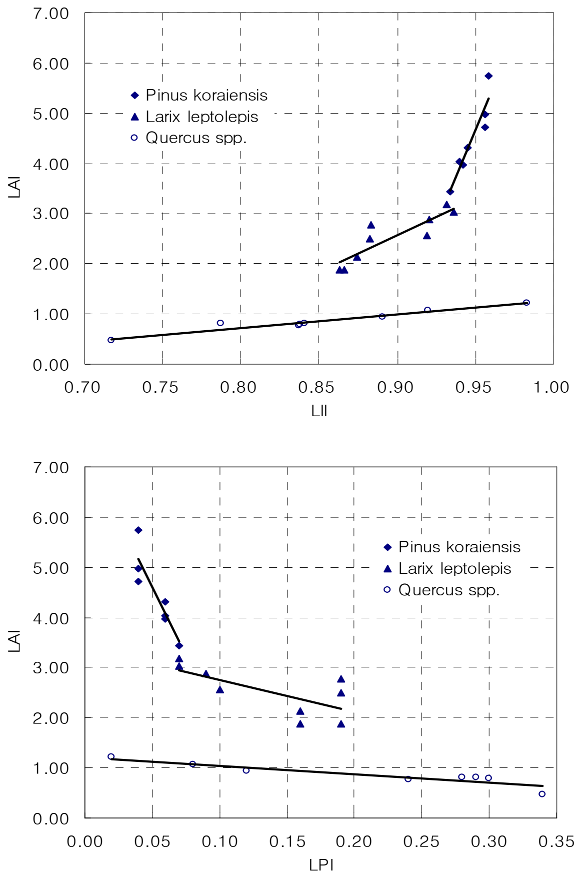

Figure 1. Distribution of LAI according to LPI and LII, and comparison of slope by tree species

When seeing the results, we could find out the accuracy of regression function was rarely different. However, the coefficient of determination for the LPI was totally lower than those of the LII. The reason for the difference could be judged as the original information of laser point was lost when the point data was transformed to raster data for generating the LPI. On the other hands, because the LII maintains the properties of laser points without losing peculiar individual value of laser points according to being changed into raster data, it can represent the LAI close to the sunlight through the canopy. Furthermore, the LII allows normalizing biased local variation of laser points since it uses only the number of laser points in a plot, whereas raster data has some noise which is caused by unbalanced distribution of laser points due to different distance of across track and along track (Kwak *et al.*, 2007).

And in the estimated regression functions, the slopes by functions show large difference by tree species (Table 1 and Figure 1). We can guess that the tendency of slope (the absolute value of slope) in estimated regression functions keeps up with the ratio of the amount of intercepted sunlight. In the equation 1, the LAI is affected by only τ value because the other variables are fixed as constant number in the study area. The τ is defined as the ratio of PAR measured below the canopy to PAR above the canopy. Therefore, the τ has a nearly 1 value due to little difference between minimum and maximum PAR in the case with little leave as *Quercus* spp. in the spring. It means, when the τ is close to 1, $\ln\tau$ is close to 0. Thus, the absolute value of the slope in regression function for *Quercus* spp. is smaller than those of the others because the τ of *Quercus* spp. is close to 1 due to little difference between maximum and minimum PAR. However, τs of *Pinus koraiensis* and *Larix leptolepis* are very small due to large difference between minimum and maximum PAR. Thereby, the absolute values of slopes in *Pinus koraiensis* and *Larix leptolepis* are relatively higher than those of *Quercus* spp. because the increment of the LAI per unit of the LPI or LII is large. By the way, in coniferous trees, the slope of *Pinus koraiensis* is higher than that of *Larix leptolepis*. The reason for the difference is that the leaf density of *Larix leptolepis* is low since leaves of *Larix leptolepis* were rarely come out in April. We can expect that the slope of *Larix leptolepis* will become similar with *Pinus koraiensis* in summer season.

In this study, we used the LiDAR data which had 3 years gap with field measurement. However, we didn't consider the difference of leaves increment according to tree growth for 3 years because we tried to examine the tendency and relationship between field-derived LAI and LiDAR-derived information such as the LPI and LII. For the quantitative analysis of the LAI with the LPI and LII, the growth gap by the lapse of time must be considered. And based on above mentioned objective, we just examined the tendency and relationship of the LAI by LPI and LII without comparison with new sample area (test area). For proving the accuracy of our study, however, we have to estimate the LAI and compare the result with filed-derived LAI with new sample area not included in our training area.

4. CONCLUSION

In this study, we estimated the LAI using LiDAR data classified into 4 type points such as HVR, MVR, LVR and GR. For calculating the LAI, firstly the LPI and LII were generated. The LPI was created with first returns ($h \geq 1$m) and ground returns ($h < 1$m), and the LII was prepared with ground returns, low vegetation returns and all returns. As the result, the accuracy of the LPI was evaluated rather lower than the LII for *Pinus koraiensis*, *Larix leptolepis* and *Quercus* spp.. This is can be attributed to the fact that the characteristic of point data was removed when the LPI was calculated because the LPI was generated using a density map of raster data type which was assigned to point density of plot. Another reason was that the LII allows normalizing biased local variation of the number of laser points while the raster data has some noise due to unbalanced distribution of laser points. The slopes of estimated regression functions were also appeared differently each other. The slope of *Pinus koraiensis* was the steepest and that of *Quercus* spp. was the gentlest of three species. The reason was that the difference between minimum and maximum PAR is large in *Pinus koraiensis* because the sunlight and the LiDAR points were much intercepted above canopy by dense leave density of *Pinus koraiensis*. However, in the case of *Quercus* spp., the difference of minimum and maximum PAR was small because of sparse leave density. Therefore we can expect the increase of the slope of *Quercus* spp. from summer because leave density is gradually higher and higher. In the case of Larix leptolepis, the absolute value of slope was between *Pinus koraiensis* and *Quercus* spp. because leaves of *Larix leptolepis* were rarely come out in April.

5. ACKNOWLEDGMENT

We would like to thank Kang-Won Lee, Managing Director of Hanjin Information System & Telecommunication Corporation, South Korea, for offering the LiDAR data.

REFERENCES

Barilotti, A., Turco, S., and Alberti, G., 2006. LAI determination in forestry ecosystem by lidar data analysis, Proceedings of Workshop on 3D Remote Sensing in Forestry, Vienna, Austria, February, 14~15, 2006., pp.248~252

Bonan, G. B., 1993. Importance of leaf area index and forest type when estimating photosynthesis in boreal forsts. Remote Sensing of Environment, 43(3), pp.303~314

Bréda, N. J. J., 2003. Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. Journal of Experimental Botany, 54(392), pp.2403~2417

Campbell, G. S., 1986. Extinction coefficients for radiation in plant canopies calculated using an ellipsoidal inclination angle distribution. Agricultural and Forest Meteorology, 36, pp.317~321

Cohen, W. B., Maiersperger, T. K., Gower, S. T., and Turner, D. P., 2003. An improved strategy for regression of biophysical variables and landsat etm+ data. Remote Sensing of Environment, 84(4), pp.561~571

Decagon devices, INC., 2001. Operator's manualof AccuPAR, U.S.A,

Finney, M., 1998. Farsite: Fire area simulator-model. Development and evaluation. Research Paper RMRS-RP-4, USDA Forest Service

Holmgren, J., Nilsson, M., Olsson, H., 2003. Estimation of tree height and stem volume on plots using airborne laser scanning, Forest Science, 49(3), pp.419~428.

Jonckheere, I., Fleck, S., Nackaerts, K., Muys, B., Coppin, P., Weiss, M. and Baret, F., 2004. Review of methods for in situ leaf area index determination: Part i. theories, sensors and hemispherical photography. Agricultural and Forest Meteorology, 121(1~2), pp.19~35.

Koetz, B., Morsdorf, F., Sun, G., Ranson, K. J., Itten, K., and Allgöwer, B., 2006. Inversion of a lidar waveform model for forest biophysical parameter estimation. IEEE Geoscience and Remote Sensing Letters,3, pp.49~53

Koetz, B., Schaepman, M., Morsdorf, F., Itten, K., and Allgöwer, B., 2004. Radiative transfer modeling within a heterogeneous canopy for estimation of forest fire fuel properties. Remote Sensing of Environment, 92(3), pp.332~344

Kwak, D. A., Lee, W. K., Lee, J. H., 2006. Predicting Forest Stand Characteristics with Detection of Individual Tree, Proceedings of the MAPPS/ASPRS 2006 Fall Conference, San Antonio, Texas, U.S.A., November 6~10, 2006.

Kwak, D. A., Lee, W. K., Lee, J. H., Biging, G. S., Gong. P., 2007. Detection of individual trees and estimation of tree height using LiDAR data, Journal of Forest Research, Revised submission

Lim, K., Treitz, P., Groot, A., St-Onge, B., 2001. Estimation of individual tree heights using LIDAR remote sensing, Proceedings of the Twenty-Third Annual Canadian Symposium on Remote Sensing, Quebec, QC, August 20~24, 2001.

Lovell, J., Jupp, D., Culvenor, D., and Coops, N., 2003. Using airborne and ground-based ranging lidar to measure canopy structure in Australian forests. Canadian Journal of Remote Sensing. 29(5), pp.607~622

Monsi, M. and Saeki, T., 1953. Über den Lichtfaktor in den Pflanzengesellschaften und seine Bedeutung für die Stoffproduktion. Japanese Journal of Botany 14, pp.22~52

Morsdorf, F., Kötz, B., Meier, E., Itten, K. I. and Allgöwer, B., 2006. Estimation LAI and fractional cover from small footprint airborne laser scanning data based on gap fraction. 104(1), pp.50~61

Myneni, R., Nemani, R., and Running, S., 1997. Estimation of global leaf area index and absorbed par using radiative transfer models. IEEE Transactions on Geoscience and Remote Sensing 35, pp.1380~1393

Riaño, D., Valladares, F., Condés, S., Chuvieco, E., 2004, Estimation of leaf area index and covered ground from airborne laser scanner (Lidar) in two contrasting forests. Agricultural and Forest Meteorology, 124, pp.269~257

Schulze, E. D., Beck, E., Müller-Hohenstein, K., Lawlor, D., 2005. Plant ecology, Springer eds., Berlin

Watson, D. J., 1947. Comparative physiological studies in the growth of field crops. I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. Annals of botany 11, pp.41~76