SHORT COMMUNICATION

Influence of the scanned side of the row in terrestrial laser sensor applications in vineyards: practical consequences

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Abstract Terrestrial laser scanners (TLS) have been used to estimate leaf area and optimise the site-specific management in vineyards. The tree area index (TAI) is a parameter that can be obtained from TLS measurements and has been highly successful in predicting the leaf area index (LAI) in vineyards using linear regression models. However, there are concerns about the possible variation of the models according to the row side on which the scan is performed. A field trial was performed in a North-South oriented vineyard using a tractor-mounted LiDAR system to determine the influence of this operational factor. Four vineyard blocks were scanned from both sides and then defoliated to obtain the real LAI values for 1-m row length sections. Specifically, LAI values were obtained considering the total canopy width and, after separation of the leaves of the right and left sides, LAI values of half canopy were also calculated. To estimate the LAI from the TAI, dummy-variable regression models were used which showed no differences with respect to the scanned side of the canopy. Two consequences are immediate. First, TLS made it possible the LAI mapping of two different rows by scanning from the alley-way with an appropriate laser scanner.

Secondly, the same model can be used to estimate the LAI of half canopy (right or left) in operations that require going through all inter-rows (e.g., when applying plant protection products in a vineyard to estimate the vegetation exposed to the sprayer).

Keywords LiDAR · Ground-based laser sensor · TAI · LAI · Dummy-variable regression

Introduction

The use of sensors in viticulture is already known and accepted. Among their applications, canopy characterisation has been the focus of much of the research, and the estimation of leaf area or leaf area index (LAI) remains a clear objective of the studies published to date (Jonckheere et al. 2004). The technologies used are also different, with ultrasonic sensors, plant canopy analysers (ceptometers), and radiometric devices widely studied (Goutouly et al. 2006; Johnson and Pierce 2004; Llorens et al. 2011). In the latter case, differences between the use of satellite, airborne, and ground-based sensors have been highlighted. However, all these technologies have some constraints. It is known, for example, that vegetation indices derived from remote sensing typically require a specific calibration according to the different growth stages of the vines (Johnson et al. 2003). The presence of soil and/or weeds between rows also complicates the correct interpretation of reflectance data in the images. Additionally, the cost of the images is not always affordable for small and medium-size winegrowers. Compared to remote sensors, ground-based radiometric sensors have also been referenced by several authors (Drissi et al. 2009; Mazzetto et al. 2010; Stamatiadis et al. 2010). Although their operation avoids the previously mentioned problems, their drawback is probably the difficulty in covering the total height of vine vegetation and, consequently, in obtaining a reliable reflectance measurement of the total canopy volume.

Ultrasonic sensors have also been successfully applied in viticulture. In this case, problems are related to their low vertical sampling resolution, which does not allow a detailed measurement of the canopy unless a sensor array is implemented (Lee and Ehsani 2009). Both radiometric and ultrasonic sensors enable continuous evaluation of the canopy along the row. This feature is currently impossible for ceptometers and similar optical instruments, which also tend to significantly underestimate the LAI (Johnson and Pierce 2004).

In recent years, interest in laser sensors, as well as new applications of light detection and ranging (LiDAR) technologies in agriculture, has greatly increased. Experiments in vineyards have been referenced, among others, by Rosell et al. (2009), López-Lozano et al. (2009), and Llorens et al. (2011). Specifically, given their higher resolution, better adaptation to the crop, and possible on-the-go use, laser scanners have been used to estimate LAI and canopy density. More recently, Arnó et al. (2013) developed an algorithm to calculate the tree area index (TAI) from data supplied by terrestrial laser scanners (TLS). The LAI is then estimated through the TAI using linear regression models.

In relation to this procedure, TLS are used laterally either from the right or from the left of the row, thus there may be some doubts whether the same model can be applied to estimate the LAI from TAI regardless of the scanned side of the canopy. Previous works propose estimating the LAI from LiDAR data using together the scans performed on both sides of the row (Rosell et al. 2009; Sanz et al. 2011). This implies a more complex management of LiDAR data and, in any case, complicates the estimation of the leaf area index on-the-go. Additionally, these systems increase the operation costs. Faced with this approach, Arnó et al. (2013) propose using the LiDAR from one side of the row but without specifying the right or left side. However, the potential influence of the orientation of the rows in the differential growth in both sides of the vines makes it necessary to study whether the scanned side significantly influences the result of the estimation. Moreover, it is not clear whether this approach is also applicable to the estimation of the LAI of only half the row width. This is especially relevant in plant protection product applications in which the sprayer travels along all the alley-ways, as it is necessary to estimate the vegetation exposed to the sprayer. Since dose adjustment to the canopy is crucial to improve the efficiency of applications (Gil et al. 2007; Llorens et al. 2011), LAI estimation for half canopy for two adjacent rows is necessary and makes sense to the use of a single model that only considers this partial vegetation.

The main objective of this communication was to study the influence of the scanned side of the canopy on the effectiveness of TLS to estimate LAI in vineyards. This work is focused on the estimation of the LAI in *Vitis vinifera* L. *cv*. Merlot and complements the results obtained by Arnó et al. (2013). As the scanned side was the factor under analysis, dummy-variable regression was used to compare and evaluate the regression models and their structural stability. This regression analysis procedure is explained in more detail in the following paragraphs.

Materials and methods

Terrestrial laser scanner (TLS)

The TLS (or LiDAR sensor) used in this study was the LMS-200 model (SICK AG, Waldkirch, Germany). More detailed information can be found in Arnó et al. (2013). As a basic feature, the sensor operation is based on the time-of-flight (TOF) principle to estimate the distance to the canopy. A two-dimensional fan-shaped scan is obtained because the beam is pulsed with an angular resolution of 1º in the vertical cross-sectional plane. Thus, by scanning the vines from one side of the row, the sensor provides the polar coordinates of each interception point, i.e., the radial distance and the angle of the laser beam. When the laser sensor is mounted on a moving tractor, multiple vertical scans along the row can be obtained. Table 1 lists the configuration and operation settings used in the field test. Data transfer from the sensor to a laptop was done via the RS-232 protocol using a MATLAB-based program for sensor control and data acquisition. This same software was used to process the information and obtain the tree area index (TAI) parameter.

Table 1 SICK LMS-200 configuration and operation settings

Maximum measurement distance (m)	8
Accuracy (mm)	±15
Angular resolution (º)	1
Scanning angular range (º)	180
Scanning sampling frequency (scans s^{-1})	12
Horizontal scanning resolution or distance between scans (cm)	2.3
Travel speed (km h^{-1})	1

Tree area index measurement

The process for obtaining the TAI is explained in detail in Walklate et al. (2002), and was later adapted for use in a vineyard by Arnó et al. (2013) as shown in Figure 1. The tractor-mounted LiDAR sensor was moving in the direction of the *Oz* axis (not shown) parallel to the ground. Several scans were obtained along the row in different vertical planes parallel to plane *Oxy*. Finally, all interception points within the canopy were projected relative to the *Oz* axis onto a two-dimensional grid of polar cells in the *Oxy* plane (Fig. 1). In particular, the overall projected cross-section of the canopy volume was divided into cells with equal angular increments of $\Delta\theta$ = 3º and equal radial increments of Δr = 100 mm. For each (*k*-th, *j*-th) cell, it was possible to calculate the number of laser beams reaching the input side of the polar cell, $n_{k,j}$, and the number of interceptions, $\Delta n_{k,j}$, within the cell. The TAI was finally calculated using equation [1]

$$TAI = -\frac{\Delta\theta}{W}\sum_{k=1}^{K}\sum_{j=1}^{J_K} r_j\,\delta_{k,j}\,\ln\left(1-\frac{\Delta n_{k,j}}{n_{k,j}}\right) \tag{1}$$

where, apart from the abovementioned $\Delta\theta$, $\Delta n_{k,j}$, and $n_{k,j}$, W (m) is the distance between vine rows, r_j (m) is the radial distance between the polar cell and the sensor position, and $\delta_{k,j}$ is a function that detects the presence or absence of foliage in each cell ($\delta_{k,j}$ =1 when the coefficient $\Delta n_{k,j} / n_{k,j}$ is greater or equal to 0.01, and $\delta_{k,j}$ =0 when the coefficient is less than 0.01). In practical terms, the TAI obtained from equation [1] is formulated as the ratio between the crop area detected by the TLS and the ground area. In the calculation of the TAI, it is also assumed that the probability of the laser beam transmission within vines can be approximated by the Poisson probability model when sufficiently small distances (Δr) and random spatial distribution of the leaves are considered.

Fig. 1 Two-dimensional grid of polar cells to calculate the TAI (Arnó et al. 2013). Each polar cell is defined by two coordinates (r_j, θ_k). The first one, r_j, is the distance from the reference origin (LiDAR sensor), and the second one, θ_k, is the angle between the *Oy* axis and the radial direction (clockwise). H_g is the height of the LiDAR sensor measured from the ground (approximately constant, 1.60 m), and d_t is the distance used to exclude intercepted points at ground and trunk levels

<u>Field trial</u>

A field test was conducted on an experimental vineyard located in Raimat (Lleida, Spain). Specifically, the vineyard chosen had a surface area of 16.92 ha and was planted in 1998 with *Vitis vinifera* L. *cv*. Merlot using a pattern of 3 × 2 m. Vertical shoot position (VSP) was used as a training system. The cordon height was 1.10 m, two parallel wires were placed at 1.40 m, and a third wire was placed at 1.80 m. During the measurements, the height of vines reached about 2.10 m at the stage of higher vegetative growth. The vineyard was drip irrigated, and rows were oriented north-south (N–S).

Four vineyard blocks at different locations within the study vineyard were selected because field measurements were conducted at four different developmental stages of the vines. According to BBCH-scale (Meier 2001), tests were performed respectively in crop stages 17 (leaf development), 65 (flowering), 77 (development of fruits) and 83 (ripening of berries). The used methodology was simple and can be consulted in Arnó et al. 2013. Vineyard blocks were 4-m-long row sections corresponding to the distance between three consecutive vine trunks. Once delimited, four measurements were performed with the TLS (two from the left side and two from the right side of the row) by moving the laser sensor along the row at a rate of about 1 km h^{-1}. Blocks were then manually completely defoliated by sections (vertical stripes) of 1 m in length, differentiating the right side and the left side of the vine row using the line of trunks as a reference. The objective was to obtain, for each block, the left LAI and right LAI for the four 1-m sections. Subsequently, values of total LAI over the entire row width for each 1-m long section were also obtained. Therefore, 12 LAI measurements were performed for each block. A planimeter (Delta-T Devices Ltd., Cambridge, UK) was used to measure the surface area of a sample of leaves taken from each of the defoliated blocks. The total leaf area was obtained by the gravimetric method. In short, a sample of *n* leaves was taken from each of the blocks tested. The leaf surface of this sample was measured, and the total surface area of each strip (right or left side of 1 m in length) was finally obtained from the surface area-weight ratio of the sample and the weight of all the leaves of the strip. In each case, the sample size *n* was previously established using the expression [2]

$$n = \frac{z_{\alpha/2}^2 \cdot CV^2}{E_R^2} \tag{2}$$

where E_R was the relative error assumed (10%), $z_{\alpha/2}$ the value of the standard normal variate (SNV), and *CV*, the resulting value of leaf area variability (Coefficient of Variation) of a pilot sample of 30 leaves.

The LiDAR sensor was always used before defoliating the vines. Therefore, TAI values were obtained with the vineyard vegetation occupying the entire width of the canopy. Then, an appropriate statistical analysis made it possible to assess the suitability of a single model to estimate the LAI for the whole canopy and a different model to estimate the LAI for only half of the canopy.

Statistical analysis

A linear regression analysis was performed to assess the suitability of the TAI parameter for estimating LAI. However, models for estimating the LAI could differ, depending on the scanning side used (i.e. scanning from the left side or from the right side of the row). To determine this, the patterns obtained for both sides were compared using dummy-variable regression. This statistical procedure allowed proposing the following dummy-regression model with interactions,

$$Y_i = \alpha + \beta X_i + \gamma D_i + \delta(X_i D_i) + \varepsilon_i \quad (3)$$

where Y_i is the LAI, X_i is the quantitative regressor for the TAI, D_i is the dummy regressor for the '*scanning row side*', coded '0' for the right side and '1' for the left side, and X_iD_i is the interaction regressor between both the '*TAI*' and the dichotomous explanatory variable '*scanning row side*'. The omitted category (right side) serves as a baseline against which the other category (left side) is compared. Therefore, the regression models used were in the following form,

Right side of the row (D_i = 0): $Y_i = \alpha + \beta X_i + \varepsilon_i$ (4)

Left side of the row (D_i = 1): $Y_i = (\alpha + \gamma) + (\beta + \delta) X_i + \varepsilon_i$ (5)

The proposed model is relevant because the dummy regressor (D_i) allows the incorporation of a new explanatory variable when there is reason to believe that the model coefficients are different between subsamples 'right' and 'left'. Any structural change in the regression model was detected by the *t*-statistic, which was used individually to test the dummy and the interaction regressor coefficients. In our case [3], the contrasts were $H_0 : \delta = 0, \quad H_a : \delta \neq 0$, for a difference in slope between 'right side' and 'left side', and $H_0 : \gamma = 0, \quad H_a : \gamma \neq 0$, for a difference in the intercept. Statistical analysis was performed using JMP® 10.0.0 (SAS Institute Inc.).

Results

The first analysis addressed the influence of the scanned side of the row on the estimation of the LAI for the entire canopy width ('full LAI') from the LiDAR. Two simple linear regression models were built from field data. The models were fitted to a basic structural expression in the form $\mathrm{LAI}_i = \beta_0 + \beta_1 \cdot \mathrm{TAI}_i + \varepsilon_i$, showing the linear relationship between the LAI (dependent variable) and the TAI (explanatory variable) for left and right scanned row sides. Figure 2 shows the two models obtained. In both cases (scanning from the right side or from the left side), the TAI was able to explain a high percentage (~92%) of the variation in the leaf surface. This value can be considered satisfactory given the particular working difficulties in field conditions. As to the question whether the two models are significantly different, the statistical analysis (Table 2) confirmed that a single model can be used in both cases. In fact, Figure 2 clearly shows that both regression lines are practically coincident. On the other hand, the regression coefficient of about 1.3 (disregarding the intercept) also confirms that TAI usually underestimates LAI because of the clumping effect normally observed in a vineyard.

Table 2 Statistical analysis of dummy-regression models for LAI estimation in Merlot depending on the LiDAR scanning row side (left or right)

Model	Term	Estimate	Standard error	*t* ratio	p > *t*
Estimation of LAI of the total row width (1-m-long sections)					
LAI-right (baseline)	Intercept (α)	-0.2615	0.0827	-3.16	0.0025*
LAI-right (baseline)	X_i (β)	1.3275	0.0720	18.43	<0.0001*
LAI-left	D_i (γ)	0.0549	0.1148	0.48	0.6342
LAI-left	X_iD_i (δ)	-0.0500	0.0998	-0.50	0.6179
Estimation of LAI for only half the row width (right or left sides, 1-m-long sections)					
LAI-right (baseline)	Intercept (α)	-0.3460	0.1199	-2.89	0.0054*
LAI-right (baseline)	X_i (β)	1.4540	0.1043	13.94	<0.0001*
LAI-left	D_i (γ)	0.1906	0.1664	1.15	0.2564
LAI-left	X_iD_i (δ)	-0.2729	0.1446	-1.89	0.0639

The second analysis evaluated the LAI estimation by the TLS corresponding to half canopy width (‘partial LAI’), i.e., the possibility of estimating the amount of vegetation between the trunk line and the outer surface of the foliage in which the laser sensor is projected. Regarding the differences between models (Fig. 2), there is a certain similarity of the lines, but the similarities are somewhat smaller than for the models for the ‘full LAI’, given the higher slope obtained when scanning the row from the right side. However, statistical analysis (Table 2) again confirmed that the two models were not significantly different.

Fig. 2 Linear regression models of leaf area index (LAI) in a vineyard (*cv*. Merlot) depending on the scanned side (left or right). The first column shows the models for the 'full LAI' (32 points, 8 per block/vine growth stage), and the second column shows the models for the 'partial LAI' (32 points, 8 per block/vine growth stage)

The interpretation of these results is interesting for two reasons. First, all regression models must be formulated with a negative intercept. This is an expected result because when the sensor is used in leafless vines (for example, in winter), LiDAR readings also provide TAI values as the laser beam is intercepted by the wooden structure of vines. Secondly, and more importantly, vines may be scanned easily and efficiently by TLS either from the right or from the left side of the row to estimate the full or partial LAI by applying the appropriate model in each case. Table 3 lists the resulting regression analysis models.

Table 3 Regression models to estimate the leaf area index (LAI) in a vineyard (*cv*. Merlot) for 1-m row lengths

Type of LAI	Regression model
Entire row width ('full LAI')	$\mathrm{LAI} = -0.26 + 1.33 \times \mathrm{TAI}$
Half the row width ('partial LAI')	$\mathrm{LAI} = -0.35 + 1.45 \times \mathrm{TAI}$

TAI: Tree Area Index

Considering 'full LAI', the sensor can be used in an on-the-go manner for mapping the LAI in vineyards with high spatial variability, and subsequently to define zones of differential management. Using new commercially available LiDAR sensors with detection angles of 270° (Fig. 3), the trajectory within the field is simplified, and both data acquisition and post-processing are greatly improved by reducing the scanning time and the amount of recorded data (LAI can be estimated reading only one side of the row and the tractor scanning every other row). Another possibility is the use of LiDAR sensors in combination with agricultural machinery, for example, when applying plant protection products using variable-rate sprayers where continuous monitoring of the LAI of each side of the row (or 'partial LAI') is needed. In this case (Fig. 3), the system operation is again simplified because the same LAI estimation model for both sides of the row can be adopted.

Finally, there is a factor linked to the parcel that may have some importance. In our study, rows were oriented N–S. The question is whether the row orientation may influence the use of TLS in vineyard and, in this regard, further investigations are warranted. It is likely that in E-W oriented rows, there may be differences in the exposure to sunlight experienced by the different sides of the row. In this case, it is not clear that the same model could be applied to both sides, and additional data are needed to corroborate or refute this hypothesis. For now, and for the analysed case, the models (right side/left side) are consistent, which is an advantage for users, requiring less computing resources in both acquisition and post-processing. Other non-operating factors (such as grapevine cultivar and training system) should also be evaluated in future research on the use of TLS in viticulture.

Fig. 3 Trajectory described by a laser sensor to map the LAI (left), and operation of the same sensor in combination with a sprayer for a variable rate application of plant protection products (right). In the first case, the 'full LAI' estimation model could be applied and, in the second, the 'partial LAI' model can be used

Conclusions

LAI can be estimated in vineyards with TLS using the TAI in appropriate linear regression models. In rows oriented N–S, TLS can be applied for either side of the row, and LAI estimation models only differ according to the main use of the sensor. Specifically, mapping the ‘full LAI’ requires using a separate regression model to estimate the leaf surface for the entire row width, making it possible to simplify the scanner trajectory within the field. The model changes when estimating the 'partial LAI’, although it is equally applicable to both scanning sides. The advantages of both applications lie in simplifying field use and reducing data acquisition and processing time.

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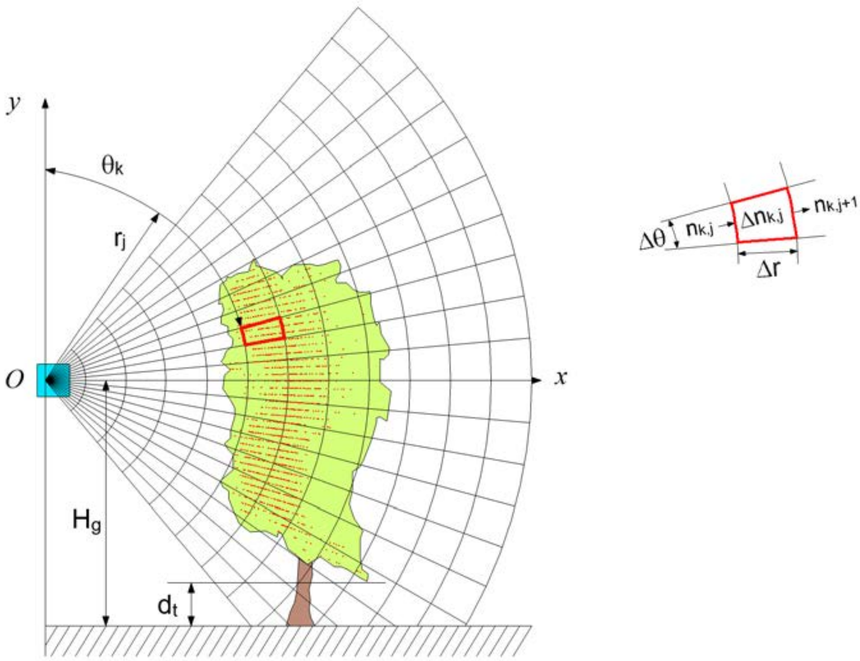
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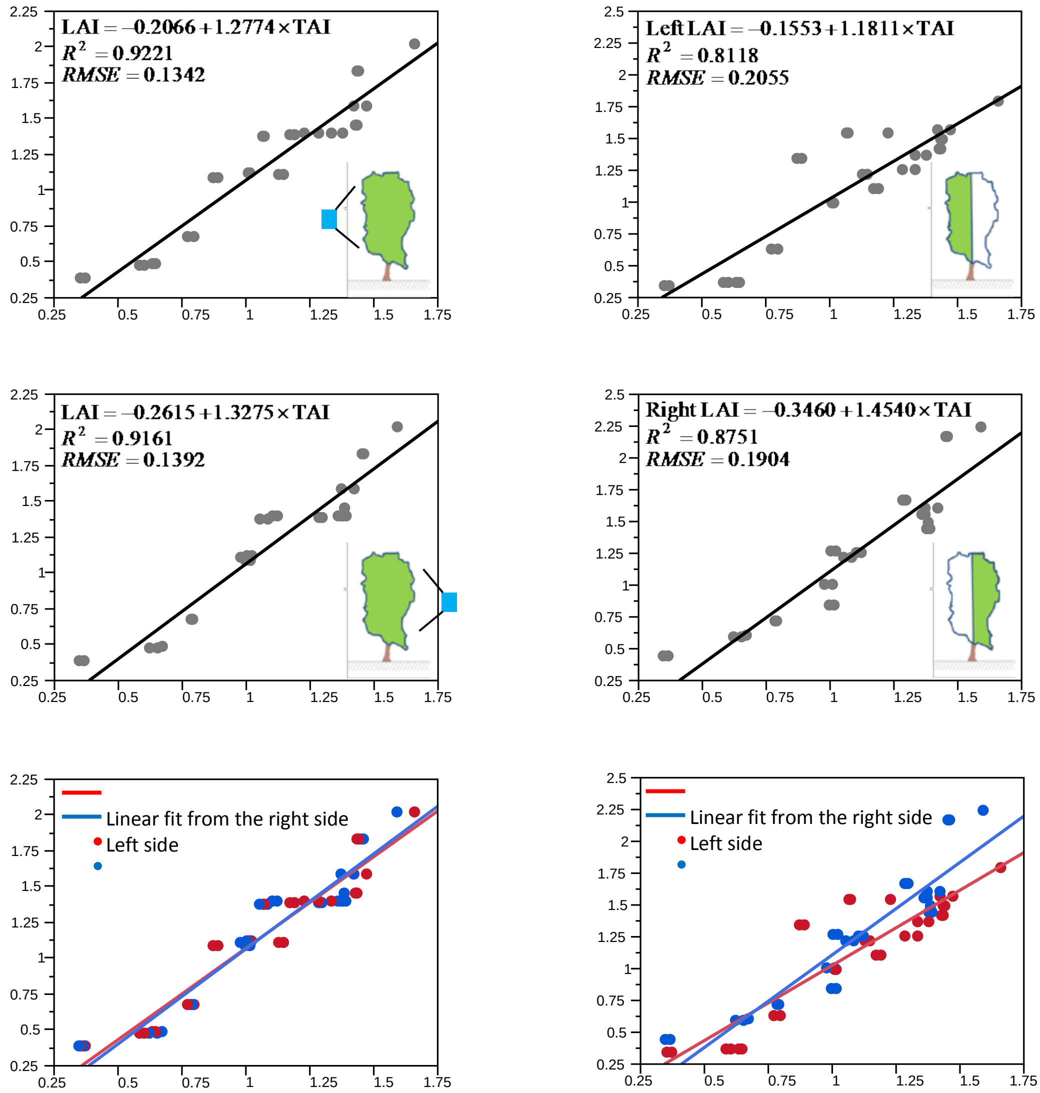

LAI = −0.2066 + 1.2774 × TAI
R² = 0.9221
RMSE = 0.1342
Left LAI = −0.1553 + 1.1811 × TAI
R² = 0.8118
RMSE = 0.2055
LAI = −0.2615 + 1.3275 × TAI
R² = 0.9161
RMSE = 0.1392
Right LAI = −0.3460 + 1.4540 × TAI
R² = 0.8751
RMSE = 0.1904
Linear fit from the right side
Left side
Linear fit from the right side
Left side