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Estimating leaf area index of maize using airborne full-waveform lidar data

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\textbf{ABSTRACT}

The leaf area index (LAI) is a key input parameter in ecosystem models and plays a vital role in gas–vegetation exchange processes. Several studies have recently been conducted to estimate the LAI of low-stature vegetation using airborne discrete-return light detection and ranging (lidar) data. However, few studies have been carried out to estimate the LAI of low-stature vegetation using airborne full-waveform lidar data. The objective of this research is to explore the potential of airborne full-waveform lidar for LAI estimation of maize. First, waveform processing was conducted for better extraction of waveform-derived metrics for LAI estimation. A method of faint returns retrieval was also proposed to obtain ground returns. Second, the LAIs of maize were estimated based on the Beer–Lambert law. Finally, the LAI estimates were validated using field-measured LAIs in Huailai, Hebei Province of China. Results indicated that maize LAI could be successfully retrieved with high accuracy ($R^2 = 0.724$, RMSE = 0.449) using full-waveform lidar data by the method proposed in this study.

\textbf{ARTICLE HISTORY}

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\textbf{1. Introduction}

Leaf area index (LAI) is defined as the total one-sided leaf area per unit ground area (Watson 1947) and is a key biophysical parameter relating to gas–vegetation exchange between vegetation and the atmosphere (Capodici, D’Urso, and Maltese 2013; Zhao and Popescu 2009). It is therefore necessary to accurately estimate vegetation LAI. Traditional methods of determining the LAI, such as direct field measurement, can accurately retrieve vegetation LAI (Riaño et al. 2004). However, it is labour-intensive and time-consuming, making it only practical in small areas.

Remote sensing data, on the other hand, can provide effective solutions to estimate vegetation LAI at regional or global scale (Capodici, D’Urso, and Maltese 2013; Zheng and Moskal 2009). Among the existing remote sensing techniques, light detection and ranging (lidar) is an active remote sensing laser-mapping technology capable of capturing both horizontal and vertical vegetation structure information with high accuracy (Lefsky et al. 2002; Mallet and Bretar 2009). In addition, it can overcome...
the limitation of optical sensors for LAI estimations such as the saturation problems (Armston et al. 2013; Lin and Zhang 2014; Zheng and Moskal 2009). It has therefore been a very useful tool for accurately estimating vegetation LAI. Many studies have demonstrated the capability of airborne discrete lidar data to retrieve forest LAI using the method based on the Beer–Lambert law (Morsdorf et al. 2006; Solberg 2010). However, airborne discrete lidar data cannot accurately estimate vegetation LAI in short, dense vegetation areas because the data do not contain sufficient ground returns due to the poor penetration ability of discrete lidar in high-LAI regions (Cui et al. 2011; Luo et al. 2014, 2015). In recent years, airborne full-waveform lidar, an emerging and rapidly advancing lidar sensor, has provided new opportunities for estimating vegetation parameters. Unlike conventional small-footprint discrete-return lidar data that record only the most significant echoes, this new generation of sensors records the entire backscattered energy, which greatly improves the penetration ability in high-LAI regions (Mallet and Bretar 2009; Pirotti 2011; Wang et al. 2011). Full-waveform lidar sensors can therefore become a more appropriate choice for accurately estimating the LAI of short, dense vegetation.

The objective of this study is to examine the capability of airborne full-waveform lidar data to estimate LAI of maize. To fulfil this goal, three main steps were carried out: (1) processing of the full-waveform lidar data, including a method for retrieving faint ground returns; (2) estimating the LAI of maize using the method based on the Beer–Lambert law; (3) validating the accuracy of LAI estimations by comparing full-waveform lidar-derived LAI with field measurements.

2. Materials
2.1. Study area
The study area is located in Huailai, Hebei Province of China (Figure 1). The terrain in this experiment site is relatively flat, and the average elevation is about 480 m above sea level. The dominant crop in the study area is maize.

2.2. Airborne lidar data
Small footprint full-waveform airborne lidar data were acquired in July 2014 using a Leica ALS70-HA system (Leica Geosystems Ltd., Aarau, Switzerland), with a pulse rate of 50 KHz and a scanning angle of ±12° from nadir. The system was operated at 1600 m above ground level, with the beam divergence fixed with 0.22 mrad, leading to a footprint diameter of approximately 0.35 m. The average pulse density was approximately 8 return echoes /m².

To generate a digital terrain model (DTM) from lidar data for better calculating waveform metrics, the discrete point clouds data were extracted from full-waveform signals using a waveform decomposition approach in this study. This approach is based on fitting sums of Gaussian functions to the lidar waveform data (Wagner et al. 2006). After retrieving the point clouds, the processing of point clouds was also conducted to obtain the accurate DTM. The frequency histogram method was first carried out to remove outliers. Then lidar point clouds were classified as canopy and ground returns using the TerraScan software (TerraSolid Ltd., Helsinki, Finland; Axelsson 2000), and a
DTM was finally created using the ground returns within each grid cell of 0.5 m × 0.5 m. In addition, the height accuracy of DTM was assessed using GPS points as being 0.05 ± 0.12 m. Using this DTM, we calculated the relative height of full-waveform lidar data above ground to eliminate the effect of ground.

2.3. Field measurement

Forty samples of maize were collected from 7 to 12 July 2014 in test site. The size of each plot is 6.0 m × 6.0 m. The geographic coordinates of each plot were determined using a real-time kinematic GPS (RTK GPS). In addition, the field LAIs were measured using a Plant Canopy Analyser (LAI-2200, Li-COR, Inc., Lincoln, NE, USA) based on gap fraction measurements. Effective LAI values were calculated using the vendor-provided FV-2000 software (LI-COR 2010).

3. Methods

3.1. Waveform processing

In this study, waveform processing was performed to accurately retrieve waveform parameters for effectively estimating LAI of maize. The procedure was performed in three stages: waveform preprocessing, waveform normalization, and waveform stacking.

Figure 1. The location of field samples shown on the airborne lidar-derived DTM.
3.1.1. Waveform preprocessing
To ensure the reliability of the retrieved waveform parameters, airborne full-waveform data must be first preprocessed. Waveform preprocessing mainly involves the retrieval of real waveform signal and waveform smoothing. The full-waveform lidar system continuously records the entire backscattered energy. The raw waveform contains useless signal not including any information of the Earth’s surface. A step was therefore necessary to extract the actual waveform signal from the raw waveform. To retrieve the actual waveform signal, the mean and standard deviation of background noise were first estimated from the raw waveform based on the frequency histogram (Sun et al. 2008), and the mean background noise was subtracted from the raw waveform to remove the background noise (Duong et al. 2008). Then the waveform start and waveform end were identified according to the threshold, which was set as three times standard deviation of background noise, and the real signal waveform was finally extracted as the part of waveform between waveform start and waveform end (Pirotti et al. 2014). In addition, the actual waveform signal contains noise due to the limitations of sensor capacity and interactions between the emitted pulses with the Earth’s surface. To reduce the noise and obtain the smoothed waveform, waveform smoothing was also performed using a Gaussian filter in this study (Mallet and Bretar 2009).

3.1.2. Waveform normalization
The preprocessed waveform was normalized to enable a comparison or accumulation of waveforms captured within the same plot. Due to different emitted pulses and different atmospheric conditions, the returned waveforms may be different, even if the Earth’s surface is homogeneous, and the preprocessed waveform must therefore be normalized to remove those effects (Duong et al. 2008). The normalization is a procedure in which the received energy at moment \( i, V_i \), was divided by the total energy \( V_T \), as shown in Equation (1):

\[
V_N(i) = \frac{V_i}{V_T} \quad \text{with} \quad V_T = \sum_{i=1}^{N} V_i
\]

where \( N \) is the number of waveform bins. In this research, \( N \) equals 128.

3.1.3. Waveform stacking
In previous studies, each small-footprint waveform was usually decomposed into several points using a custom Gaussian decomposition method (Wagner et al. 2006). However, this method has a limitation that it cannot detect the faint returns which are the result of reduced waveform due to obscurant scattering, attenuation, and absorption. The faint returns are the ground returns in an area of short, dense vegetation, which is important for estimating LAI of vegetation using the method based on the Beer–Lambert law. In order to obtain the faint ground returns, waveform stacking was conducted in this research. The lidar waveform stacking is an effective technique for faint ground return detection and enhancement, which has been demonstrated by the previous studies (Allouis et al. 2013; Magruder, Neuenschwander, and Marmillion 2010). The waveform stacking was performed in there stages in this paper. First, since LAS
Specification Version 1.3 (LAS 1.3) data records the elevation of the beginning of each waveform and the vertical height value of each waveform bin, the relative elevation of each waveform bin was therefore calculated using DTM. In addition, the vertical height value of each waveform bin is different for different waveforms, and a new waveform was then generated from each normalized waveform with 15 cm vertical height for each waveform bin. Finally, all those new waveforms located within the same plot were directly summed up to obtain a cumulative waveform. By this way, the random noise can be reduced and the faint returns enhanced. The ground returns can be therefore easily obtained from the cumulative waveform through setting the optical height threshold.

3.2. LAI estimation

The previous studies demonstrated that LAI can be deduced by the Beer–Lambert law. By the transformation equation of the Beer–Lambert law, LAI can be calculated based on the gap fraction \( I/I_0 \) once \( k \) is known, as shown in Equation (2) (Li et al. 2015; Solberg 2010):

\[
\text{LAI} = -\frac{1}{k} \ln \left( \frac{I}{I_0} \right) \tag{2}
\]

where \( I \) is the below canopy light intensity, \( I_0 \) is the above canopy light intensity, and \( k \) is the extinction coefficient (Richardson, Monika Moskal, and Kim 2009).

Following Luo et al. (2013), the gap fraction could be replaced by the ratio \( E_r \) of ground return energy to total return energy of a lidar waveform. But due to the reflectance difference between the canopy and the ground, the gap fraction cannot be replaced by \( E_r \) directly. To reduce the effect of this reflectance difference, we corrected \( E_r \) from the cumulative waveform for better estimating LAI of maize according to Equation (3):

\[
E_r = \frac{R_g / \rho_g}{R_c / \rho_c + R_g / \rho_g} = \frac{nR_g}{R_c + nR_g} \tag{3}
\]

where \( \rho_g \) the average ground reflectance, \( \rho_c \) the vegetation reflectance, \( R_g \) is the ground return energy of the cumulative waveform, \( R_c \) is the canopy return energy of the cumulative waveform, and \( n \) is the adjusting factor of reflectance.

According to Luo et al. (2014), the adjusting factor of reflectance was set to 4 for our study site. Following Zhao and Popescu (2009), we examined a sequence of height thresholds from 0.05 to 0.4 m incremented by 0.05 m. We found that 0.1 m is the optimal height threshold to separate ground and canopy in our study. After obtaining the optimal height threshold, the ground return energy \( R_g \) and the canopy return energy \( R_c \) can be calculated by summing up the energy of the ground returns and the canopy returns, respectively. Once \( R_c, R_g, \rho_c, \) and \( \rho_g \) are known, \( E_r \) can be calculated according to Equation (3), LAI can be therefore estimated using Equation (4) once \( k \) is known:

\[
\text{LAI} = -\frac{1}{k} \ln E_r \tag{4}
\]
To obtain an optimal LAI estimation model, the linear regression analysis of the logarithm of \( E_r \) against the field-measured LAI was carried out. In addition, some field-measured LAIs, not used in building the LAI estimation model, were left for the model validation. In our study, both the coefficient of determination \( (R^2) \) and the root mean square error (RMSE) were calculated for the assessment of LAI estimation accuracy.

### 4. Results and discussion

To estimate the vegetation LAI, the extinction coefficient \( k \) must be first obtained according to the Beer–Lambert law. In this study, a simple linear regression between field-measured LAI and the logarithm of \( E_r \) was conducted to obtain the best extinction coefficient \( k \). Among all the 40 field-measured LAIs, 25 samples were used for the linear regression analysis, while the other 15 samples were used for model validation. The regression model between the full-waveform lidar-derived variable and the field-measured LAI was shown in Equation (5). The scatter plot of the field-measured LAI versus \(-\ln E_r\) and the corresponding regression line were illustrated in Figure 2.

\[
y = 0.740x + 0.597
\]

where \( y \) is LAI and \( x \) is \(-\ln E_r\).

The linear regression result showed a strong relationship between the field-measured LAI and \(-\ln E_r\) \((R^2 = 0.734, \text{RMSE} = 0.439)\).

To assess the reliability of the model, the accuracy of the LAIs predicted using the full-waveform lidar was evaluated using the other 15 field-measured LAIs. Figure 3 is a scatter plot of the full-waveform lidar-predicted LAI against the field-measured LAI. The results in Figure 3 indicated that the accuracy of the full waveform lidar-predicted LAI is high \((R^2 = 0.724, \text{RMSE} = 0.449)\).
Many previous studies have demonstrated that airborne discrete lidar data cannot accurately estimate the LAI of short, dense vegetation because discrete lidar does not yield sufficient ground returns due to its poor penetration ability in high-LAI regions (Luo et al. 2015; Richardson, Monika Moskal, and Kim 2009). However, the results in this study indicated that the LAI of short, dense vegetation can be estimated based on the Beer–Lambert law using airborne full-waveform lidar data. A possible explanation is that the full-waveform lidar system records the entire backscattered energy, which greatly improved the penetration ability in high-LAI regions (Richardson, Monika Moskal, and Kim 2009). In addition, a method of faint returns retrieval was also proposed to better obtain ground returns in this study, which also greatly contributed to the LAI estimation of vegetation. In addition, unlike the previous studies, this paper utilized the lidar intensity instead of lidar counts to estimate the LAI of maize, which was also helpful for the improvement of LAI estimation accuracy, as demonstrated by Luo et al. (2014).

Since the scanning angles in this area were less than 12°, the influence of scanning angles on lidar intensity was not taken into account in this study. Future studies should evaluate the influence of scanning angles on lidar intensity values. In addition, this paper only conducted the LAI estimation of maize using airborne full-waveform lidar data, and the ability of airborne full-waveform lidar data has not yet demonstrated for other low-height vegetation types with different canopy structure. Moreover, the method of faint returns retrieval proposed in this paper may not be suitable for all vegetation types. Therefore, future studies should be carried out to explore the potential of full-waveform lidar data for estimating parameters of other short vegetation types, and further studies on faint returns retrieval for low-height vegetation are also needed.
5. Conclusions

In this study, a method for retrieving the LAI of short, dense vegetation using airborne full-waveform lidar data was proposed and applied to the LAI estimation of maize. To estimate LAI of maize, three steps were performed. First, the processing of point clouds and waveform were conducted to generate DTM and accurately retrieve waveform parameters, respectively. In addition, a method of faint returns retrieval was also proposed to obtain ground returns. Second, the LAIs of maize were estimated using the method based on the Beer–Lambert law. Finally, the LAI estimations were validated by field-measured LAs. Results showed that the LAI of maize was successfully estimated using airborne full-waveform data with an RMSE of 0.449.

This research can be useful for improving LAI estimation accuracy of short vegetation. Further study is needed to develop the method of ground return retrieval, which is very critical for the LAI estimation of short vegetation. In addition, to better estimate the LAI of short vegetation, future studies should also place an emphasis on intensity correction algorithms to decrease the influence of scanning angles on lidar intensity.

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