Drone-Based Sensing for Leaf Area Index Estimation of Citrus Canopy

Rahul Raj, Saurabh Suradhaniwar, Rohit Nandan, Adinarayana Jagarlapudi and Jeffrey Walker

Abstract Leaf Area Index (LAI) is an important parameter in the measuring of crop health. Temporal changes in the LAI provide important information about changes in the structure of the canopy and biomass over time. In this study, RGB images of the top of the canopy are collected by using a drone and through image processing; the coverage of green canopy is calculated from the images. Subsequently, by using the gap fraction, the LAI is estimated through the Beer-Lambert law. The data is collected from Warud taluka of Amravati district of Maharashtra, India. The area is severely under biotic and abiotic stresses. A multi-rotor quadcopter, which can carry a camera, is used to fly over the citrus farm on a predefined path. A camera that is mounted on the drone takes RGB images of the top of the canopy at a continuous interval with 70% frontal and 50% side overlap. These images are stitched together and an orthomosaic image layer is formed. Mathematical models are used to find the LAI from the images. Ground truth data is collected by a ceptometer within two hours of the flight of the drone. The two LAI datasets (LAI from the digital image and the LAI values from the LAI meter) are correlated, with R^2 equal to 0.73.

Keywords Leaf area index · Drone-based mapping · Precision agriculture · Citrus · Image processing

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K. Jain et al. (eds.), *Proceedings of UASG 2019*, Lecture Notes in Civil Engineering 51,
https://doi.org/10.1007/978-3-030-37393-1_9

1 Introduction

Good-quality, high-resolution farm data is very useful to biotech companies, government agencies, fertilizer manufacturers and commodity traders. However, due to the limited workforce and costly instruments/sensors, the collection of high spatial and temporal resolution farm data is a challenging and time-consuming process. Leaf area index (LAI) is an important crop physical parameter, which needs to be collected in order to quantify the light-use-efficiency of the vegetation [1]. The LAI is unit-less and is defined as the leaf area of half of the vegetation canopy (one-side of the leaf area) per unit ground surface area [2]. The LAI shows the amount of foliage area per unit ground surface area [3]. The definition holds good for broadleaved trees with flat leaves; however, if foliage elements are wrinkled, bent or not flat then vertical projection may not result in the highest value [4]. The LAI affects CO2 uptake of vegetation by affecting the effective stomatal area. Therefore, measuring temporal/seasonal variations of the LAI is important not only in the quantification of available biomass but also in the enhancing of the understanding of gaseous exchanges between the atmosphere and the canopies, so that crop growth models can be calibrated [5, 6]. The direct method of LAI measurement is a destructive method in which every green leaf of a plant is destructively sampled and one-sided area of each leaf is measured. The cumulative sum of the leaf area is then divided by the total ground area from which the LAI is to be calculated. Non-green leaves are not considered, because they do not contribute to photosynthesis [7]. The LAI values that are obtained using the direct method should be considered as a reference while comparing the LAI values that are obtained from an indirect method. In various researches that have been conducted at different palaces, it has been established that an indirect method instrument such as LAI-2000 or LAI-2200 is strongly correlated with the direct method LAI, with R^2 greater than 0.8 [8, 9].

In this study, instead of a destructive method, the LAI-2200 instrument is used to calculate the LAI. These LAI values are considered as ground truth and are compared with the LAI values that are estimated by using digital images of the top of the canopy, which are taken by a drone-based camera. A citrus farm (mandarin orange) is researched by placing an RGB camera on a quadcopter, which is flown at a height of 25 meters in the afternoon. Subsequently, within two hours, the LAI is collected through Licor's LAI-2200 instrument (ceptometer) from across the farm with high spatial resolution. The drone images are stitched and divided into smaller grids such that it represents the same area that is captured by the ceptometer. Each cropped image is converted to a grayscale image of greenness values, which is followed by the separating of the green and non-green pixels to calculate the gap fraction, by using the histogram method. The modified Beer-Lambert law is used to find the LAI through gap-fraction values. It is found that the LAI that is obtained through two different methods are correlated, with R^2 equaling 0.73. The framework of the study is shown in Fig. 1.

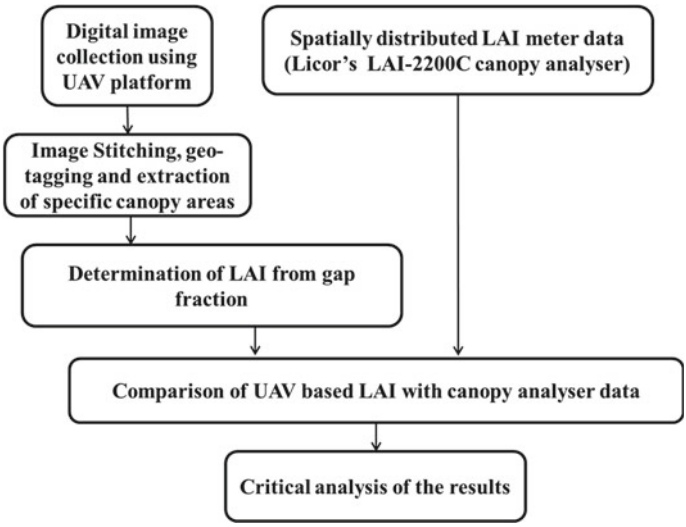

Fig. 1 The framework of the study

2 Materials and Methods

The overall approach of this proposed method in order to estimate the LAI from RGB images of the top of the canopy consists of five key steps:

(1) Acquisition of high spatial resolution RGB images of the top of the canopy of the citrus-farm by using a low-altitude quadcopter-camera system; (2) collection of in situ LAI values by using the ceptometer; (3) post-processing of Drone-based images to create an orthomosaic, to geo-reference and to extract the area of interest from the orthomosaic; (4) application of image processing techniques on images of the area of interest to quantify the gap fraction and to find the LAI; and (5) comparison and analysis of the extracted LAI by using drone images along with the LAI that is collected by using the ceptometer.

2.1 Site Description, Ground Truth LAI, and Acquisition of Images from UAV

The experiment was carried out on a 15-year-old citrus crop farmland that is located in Nagziri village of Warud taluka of Amravati district in Maharashtra, India. Amravati is in the north-east area of Maharashtra. Geographically, the study area lies approximately between 21026′54.4″ N - 21026′59.1″ N and 78009′13.1″ E - 78009′10.2″ E, as shown in Fig. 2a [10]. The drone-based RGB images of the top of the canopy were collected in the JPEG format on 24 Feb 2016 between 11:00 a.m. and 01:00

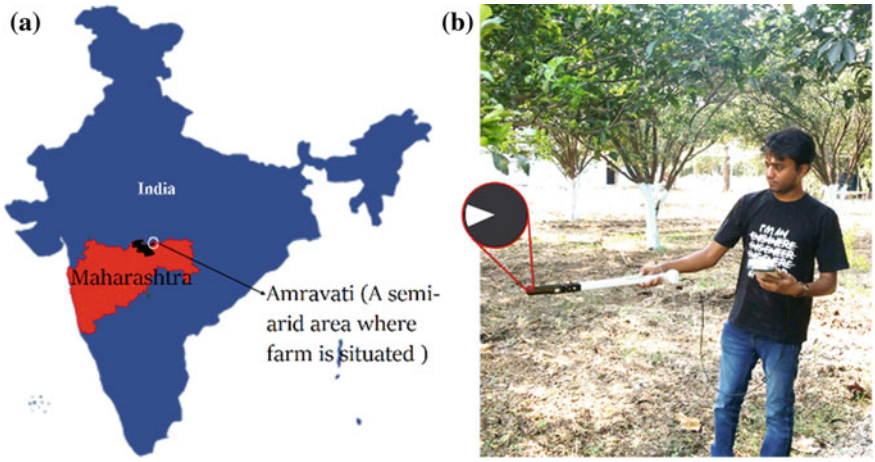

Fig. 2 **a** Geographical location of the farm that lies in the central part of India and falls under a semi-arid zone. **b** The orientation of 45° view angle cap of the ceptometer while collecting the LAI data

p.m. Immediately after the collection of data from the drone, Licor's LAI-2200C plant canopy analyzer was used to acquire ground truth LAI data from the farm. A view angle of 45° (315° masking) was used for the ceptometer. The masking cap of the ceptometer's lens was oriented in such a way that the view angle remained the farthest from the person who collected the data (Fig. 2b). For this study, the plot is virtually marked into 23 rows (R_0–R_{22}) (Fig. 3), and from those rows, ground truth LAI values are obtained using the ceptometer. In each row, certain LAI points were collected; however, rows 6, 15 and 22 were not considered, because it was subsequently found that the data from these rows were not acquired properly. Total 60 useful data points are collected from ceptometer by moving the ceptometer in a serpentine motion under the citrus canopy farms. After approx. every five metres of the walk under the canopy, ceptometer-based geotagged LAI data is collected.

Fig. 3 Rows of the farm for LAI data collection

The FOV of the fisheye lens of ceptometer was 136°, and it was manually operated approximately at a height of 1 m from the ground. The estimated area from where the light was supposed to be captured by the fisheye lens of ceptometer was around 25 square metres at 2.5 metres from the ground, which is assumed to be the average height of the canopy when measured from the ground.

A digital camera (Canon IXUS 160 20MP) that was mounted on a multirotor UAV (Fig. 4) was programmed to capture images continuously at three-second intervals while the UAV flew along a predefined path over the citrus growing area. The camera had FoV of 55° × 50°. The sky was clear, and the day was sunny. The drone that was used in the experiment was a quadcopter with GPS, IMU and a DJI controller on it. The quadcopter had the ability to fly on autopilot along a predefined path that was defined by using open-source software, 'Mission planner'. The drone was flown at a height of 25 meters. In two consecutive images that were taken by the drone-mounted camera, 70% frontal and 50% side overlap of ground-pixels was maintained (Fig. 5). It is very important to maintain sufficient overlapping between consecutive and side images because otherwise an orthomosaic cannot be formed [11]. To maintain this minimum frontal and side overlap, the speed of the drone was maintained at 2.6 m/s. With these restrictions, the image capturing speed of the camera is fixed to one image per three seconds. The drone was flown in a serpentine motion, as shown in Fig. 5.

These images are stitched together by the PiX4D software and geotagged by the QGIS open-source software. The geotagged layer has a spatial resolution of around 3 cm ∗ 3 cm. From the ortho-mosaic image, those areas that are supposed to be seen through the ceptometer lens are manually cropped with the help of the geotagged LAI map and stored separately as a JPEG file. Sixty sub-images are cropped from the orthomosaic map. These cropped images are further processed and LAI values are calculated and correlated with Licor's LAI instrument data.

Fig. 4 Quadcopter used in the study

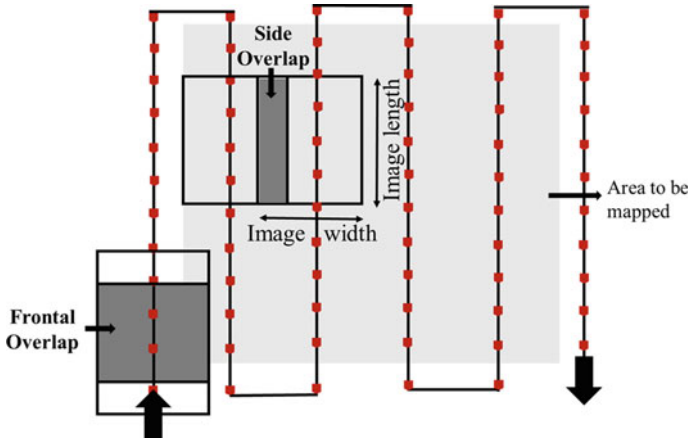

Fig. 5 Frontal and side overlap of images taken by the drone-mounted camera

2.2 Green Canopy Cover and LAI Estimation from Drone-Based Images

Various empirical methods can be employed to estimate the LAI from satellite images. In these techniques, ground measurements of the LAI are correlated with indices such as Normalized Difference Vegetation Index (NDVI), which are obtained from satellite images. However, it is seen that as the LAI increases above 3, NDVI values start to saturate; the NDVI values also do not show much sensitivity to canopies that have an LAI that is greater than 3 [12]. The technique used in this study does not use the NDVI index method to calculate the LAI. Here, the concept of light absorption by the canopy is used. If the density of the canopy in an image is likened to the concentration of solvent in a solution, then the light that is absorbed by the canopy can be likened to the light that is absorbed by the solution. Similarly, as a higher concentration of solvent leads to higher absorption of light, a higher density of leaves or a lower number of background pixels in an image can be likened to a higher LAI based on the Beer-Lambert–Bouguer law. In order to use this law to estimate the LAI, it is very important to quantify green canopy cover or gap fraction in an image. Green canopy cover is the representation of the density of the canopy over a ground area that is captured in that image. Gap fraction simply means the ratio of the total number of non-green pixels to the total number of pixels in the image. This gives us a quantification of the extent of the sparseness of the canopy. The process of estimating the LAI from the gap fraction can be linked to the 'Beer-Lambert–Bouguer' law [13, 14]. Sixty data points are used to compare the drone-based image results with ground truth values. To estimate the green canopy cover from a digital RGB image, it is recommended that the image be converted to the grayscale format by using a combination of red, green and blue bands [15]. For vegetation images, to retain the greenness of the image, Eq. (1) is the best combination, in which R, G and B are

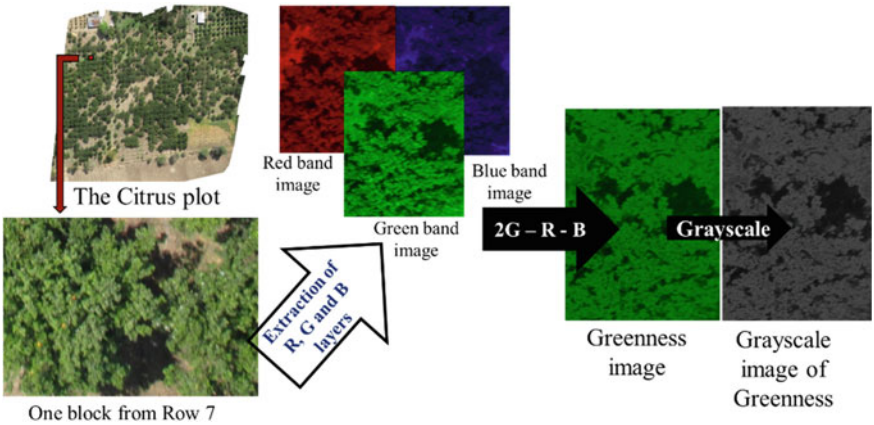

Fig. 6 From the orthomosaic layer, an area of interest is cropped out. Red, Green and Blue layers are separated, and the greenness layer is formed by using the formula, 2G-R-B. This greenness image is converted to grayscale to plot the histogram

digital numbers of the pixel [16].

$$Greenness = 2G - R - B \tag{1}$$

The greenness image has only one layer, and it can be converted to a grayscale image (Fig. 6). This grayscale image should contain two classes, that is, canopy pixel (brighter colour representing green) and background pixel (darker colour representing non-green). To classify the two classes, different supervised and unsupervised techniques can be used. Here, Otsu's method, which is an unsupervised technique, is implemented on the image. Otsu's method of image classification performs better if the image has two classes [17]. After applying Otsu's method on an image, a histogram that contains two binomial distributions is plotted, as shown in Fig. 7. Since the two distributions usually overlap slightly, the threshold that separates the two classes needs to be found. The point, T_o, in Fig. 7 is the threshold point. All pixel values to the left of T_o represent the background, while all pixel values to the right of T_o represent the green canopy. The two peaks represent two classes, and the threshold point, T_0, separates the two classes. The generated histogram contains high-frequency noise, as shown in Fig. 7. This high-frequency noise should be smoothed with a low-pass filter in order to make the detection of T_o automatic. Once T_o is determined, the green canopy cover can be estimated by dividing the cumulative sum of pixels that are to the right of T_o by the total number of pixels in the histogram. Conversely, the gap fraction of the image can be estimated by calculating the ratio that is obtained after dividing the cumulative sum of pixels that are to the left of T_o by the total number of pixels in the histogram. By considering the random spatial distribution of the leaves, the gap fraction is related to the LAI of the area by a Poisson distribution [13], where the LAI is related to the gap fraction by a formula

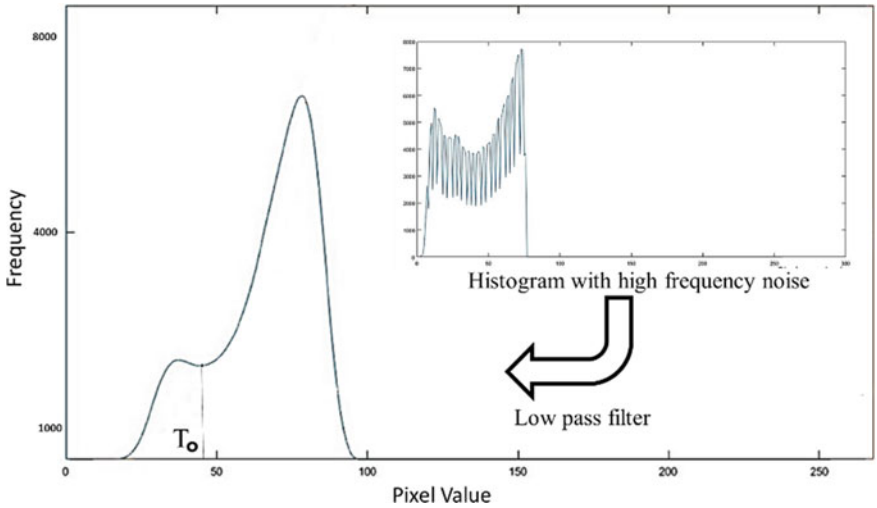

Fig. 7 A smooth histogram is obtained by applying a low-pass filter to the original histogram

that is given in Eq. (2).

$$LAI = -ln(Gapfraction)/k, \tag{2}$$

In Eq. (2), k is termed the canopy extinction coefficient, and its value is estimated at 0.5 [18]. Here, it should be noted that the gap fraction is calculated for images that were taken at a vertically downward angle when the solar zenith angle was also near zero. If solar zenith angle or camera view angle changes, the effect of these changes can be observed in the gap-fraction values, and formula x will need modifications to enable the incorporation of the changes [19]. The gap fraction and the LAI are calculated for all the 60 sub-images that are extracted from the orthomosaic layer.

3 Results and Discussion

3.1 Comparison of Estimated LAI with Its Ground Truth

LAI values that are estimated from drone images and those that are obtained from the ceptometer are compared by applying linear regression to obtain the coefficient of determination (R^2). Python open-source software is used to process the data. By implementing linear regression on all 60 data points, it is found that R^2 between Licor's LAI values and drone-based LAI values is 0.73 (Fig. 8a). The optimised value of canopy extinction coefficient shown in Eq. (2) is also calculated by checking the model accuracy by changing the value of 'k' in the range of 0.3–0.7. It is found

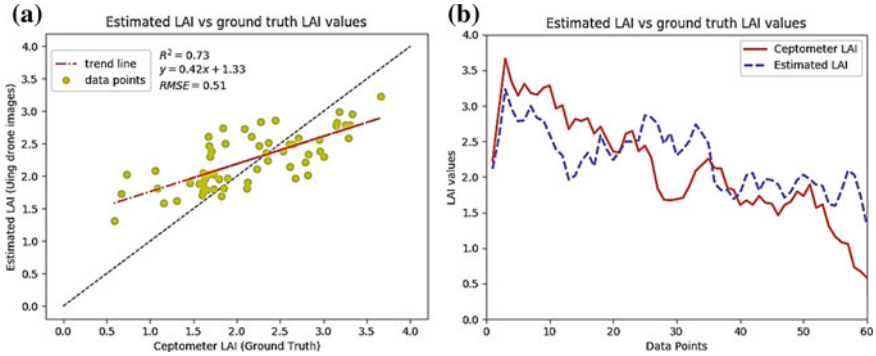

Fig. 8 **a** The scatter plot of LAI data obtained from ceptometer and estimated using drone images. The R^2 found is 0.73. **b** The visual trend analysis plot of LAI data obtained from ceptometer and estimated using drone images

that at k = 0.5 the two different platforms LAI values are best correlated i.e. $R^2 = 0.73$. The estimated root mean square error (RMSE) is 0.51. It is observed that the LAI of those images that have a lower canopy density (higher gap fraction) is slightly overestimated, while the LAI of those areas that have a denser canopy (lower gap fraction) is slightly underestimated when compared to the LAI values of the ceptometer. The underestimation or overestimation is because the ceptometer has fisheye lens; therefore, the effect of the lights that emanate from its sides affects it more along with the scattered light from those areas that are not in the view angle of the lens. However, in the case of drone images, the only deciding factor of the LAI is the gap fraction that is seen from the top of the canopy images; the areas that are outside that particular image do not affect the LAI values at all. In Fig. 8b, a comparison between the ground truth LAI and the estimated LAI can be observed. It can also be observed that when the ground truth LAI is greater than 3, the estimated LAI is underestimated, but the increase/decrease change trend remains the same (Fig. 8b). When the ground truth LAI is less than 1.5, that is, the canopy is open, the estimated LAI is overestimated, and even the increase/decrease change trend is not maintained. However, overall, both methods seem to yield well-correlated LAI values.

3.2 Critical Analysis of the Limiting Factors of LAI Estimation

The difference in LAI values between the same data points are also contributed to by the fact that the area of the cropped image (cropped from orthomosaic layer) will always be different from the area that is seen by the fisheye lens of the ceptometer;

this is because the ceptometer view area is in the shape of a triangle, while the cropped images are approximated to a rectangular shape.

The classification of the canopy and the non-canopy pixels are not infallible because any background pixel that is not a part of the canopy but green in color (for example, weed, green plastic and such others) can be classified as a green canopy pixel and will contribute to error. Otsu's method, which is used for the classification, works well when the image has two classes with sufficient areas of visibility of both the classes in the image. If the canopy is extremely dense or highly open, its histogram will contain only one peak, and the identification of the classification threshold point, T_0, will be impossible. In such cases, LAI cannot be quantified by using this technique. It is also difficult to fly the drone at a constant height with a constant speed and angle (due to changing wind conditions), which, sometimes, blurs the image pixels. To reduce this blur, the drone should fly at a low wind condition, and different flight paths and directions should be used while collecting the images from multiple flights.

Acknowledgements The authors would like to acknowledge Ms Mrunalini R. Badnakhe for her help in acquiring the necessary permissions to fly the drone. The help of Drona Aviation Company has also been critical in the collection of drone images.

Conflicts of Interest The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; and in the decision to publish the results.

Funding This research was funded by Information Technology Research Academy (ITRA), division of Department of Electronics and Information Technology (DeitY), Ministry of Communications and Information Technology (MCIT), Government of India.

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