

RESEARCH ARTICLE OPEN ACCESS

Mapping *Vitis vinifera* L. Leaf Area Index Using Side-View Imagery Continuously Captured by a Smartphone

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Received: 3 April 2025 | **Revised:** 25 September 2025 | **Accepted:** 18 November 2025

Academic Editor: Stefano Poni

Keywords: canopy size | image analysis | LAI | vineyard

ABSTRACT

Background and Aims: Leaf area index (LAI) is an important parameter to support vineyard management decisions. However, the common indirect methods for LAI measurement using imagery pose significant challenges, including over-estimation, impracticality in block-level LAI mapping, and interaction with non target foliage.

Methods and Results: This study proposes a method to map the LAI based on side-view imagery collected continuously by mounting a smartphone on a farm vehicle. The proposed method first estimated the absolute leaf area (LA) for the trunk-to-trunk area of each vine based on the Beer–Lambert law and then calculated the LAI by dividing this by the ground surface area. The LAI estimation from the side view was evaluated against the LAI from the traditional bottom-up view imagery and the direct destructive LAI measurements. Data were collected at four different dates during the season from a vineyard in Australia. Results showed a near 1-to-1 relationship between the proposed LAI method and the direct LAI measurements with a mean absolute error (MAE) of 0.2, whereas the traditional bottom-up view imagery showed an overestimation error with a MAE of 0.4, suggesting a need to introduce a calibration procedure specific for the vineyard. The R^2 value of the proposed LAI method and LAI from a destructive assessment ranged from 0.75 to 0.94.

Conclusions: The proposed LAI method demonstrates the capability to robustly and continuously map the vine-level LAI for the whole block easily and efficiently.

Significance of the Study: This method offers an easy and inexpensive option for vineyard managers to use maps of LAI to support informed decision making.

1 | Introduction

Knowledge of grapevine canopy size and resulting light interception is a useful parameter to support a range of vineyard management decisions that affect productivity and fruit quality [1–3]. LAI is used in the calculation of the crop coefficient (K_c) as an aid to irrigation scheduling [4, 5] and to relate canopy size to grape and wine style or quality [2, 6]. Canopy size is normally

presented as LAI, the total one-sided leaf area per unit of ground surface area [3]. The direct assessment of a canopy leaf area can be arduous, involving defoliation and manual measurement of leaves using a scanner or similar. Outside of a research, setting this precludes its direct measurement on a large scale, for example, to map leaf area across a vineyard or for regular assessments to support management decisions.

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Environmental variation within the vineyard, especially variation in the soil, its depth, and water holding capacity, impacts on vine growth and canopy development [7]. Maps of canopy size across a vineyard can be used to select sections of the vineyard with specific characteristics; depending on the environment and the timing of the assessment, canopy size can relate to yield and fruit composition [8, 9]. The maps can also be used as a guide to aid manual sampling, for example, to improve the accuracy of yield estimation [10]. Traditionally, maps of canopy size have been collected using remote sensing [11, 12] and have been calculated using reflectance in the visible and near-infrared spectrum to calculate indices such as the normalized difference vegetation index (NDVI) and plant cell density (PCD) [7]. Remote sensing of canopy size offers a cost-effective option for grape growers to collect this information; but generally, this is an extra task that requires specialist permits and equipment for the collection and processing of data [12–14]. For example, in Australia, the use of an unmanned aerial vehicle in a commercial setting requires licensing [15] and specialist software for image processing and analysis. Across an individual site, the NDVI is driven by the canopy size as measured by the planimetric leaf as opposed to the LAI; however, all of these measures are correlated ($R^2 > 0.75$) [16]. Unfortunately, the relationship between spectral indices and LAI is curvilinear which means that for larger canopies (and especially those from sprawling vines), differences in LAI between larger vines may be difficult to distinguish using spectral measures [16].

For row crops such as grapevines, the spectral signature from the interrow space can interfere with the accurate calculation of the spectral index when the data are collected from a nadir view [9]. When the spatial resolution of the sampling is high enough, the pixels that represent the interrow space can be removed from the analysis [17]; however, for lower resolution images such as those provided by satellites, this option is not available. This means that grape growers often need to rely on higher resolution imagery collected from fixed wing planes or unmanned aerial vehicles [7], which also comes at a higher cost.

High- and low-reflectance targets of known spectral characteristics can be used to calibrate spectral indices and allow absolute values to be calculated that are consistent between sampling events (e.g., [16]). This is rarely completed in either a research or commercial context and results in the spectral index acting as a map of the relative variation in canopy size across a management unit as opposed to absolute values [7]. This limits the usefulness of these measurements to the identification of sections of the vineyard with larger and smaller canopies and, as these patterns are temporally stable between seasons [9], a dataset can be used for many years unless management practices are changed. The use of the relative measurement of canopy size means that the absolute range of canopy size (e.g., between the smallest to largest vines in the block) is not known, reducing the ability of the grower to make assured decisions. The relative data are often displayed in percentiles which highlight the relative canopy size, but in some cases, this may exaggerate the variation across the block as the absolute variation in canopy size may not be meaningful in a management context. This means that direct assessments are needed to validate variation across a block. The measurement of absolute canopy size offers the potential to realize additional value from the data; this includes its use as an aid to irrigation scheduling [18, 19] or the benchmarking of

canopy size as a trigger for canopy management practices that aim to optimize fruit quality [20].

Unmanned aerial vehicles have been widely used by researchers to survey vineyards. These systems normally rely on standard (red-green-blue) cameras to collect images at high resolution and generate point clouds which can be used to quantify canopy size and shape and estimate LAI [21, 22]. This approach avoids the interference from plants growing in the inter-row but requires specialist software for data processing and licensing of the UAV operator as described above. In a similar manner, ground-based laser scanning (LiDAR) can measure canopy size and density and estimate LAI [22–24]. These systems generally include a very accurate mapping capability but once again require expensive and sophisticated hardware and software for data collection and processing. Other ground-based platforms are available for the measurement of LAI, but these also rely on specialist equipment such as the LAI-2000 (LI-COR, Lincoln, Nebraska, USA), a ceptometer or a camera with a fisheye lens [25, 26]. None of these systems readily lend themselves to automated mapping without extensive custom modification that is better matched to a research context (e.g., [27]). When ground-based platforms are able to collect location data to complement estimates of LAI, this is often completed with a consumer-grade global navigation satellite system (GNSS) that is limited in accuracy to between 1 and 3 m. This limits application to the development of maps of LAI rather than on an individual row or plant level that is needed for precise management such as repairing a broken irrigation line or remedial treatment of trunk disease.

One of the most accessible indirect methods to estimate LAI is based on the gap-fraction method utilizing digital imagery. Macfarlane et al. [28] measured LAI in eucalypt vegetation using both fisheye and nonfisheye digital photography and demonstrated a strong correlation with direct measurements. Fuentes et al. [29] improved this method by automating LAI image analysis for an Australian eucalyptus woodland and extended this approach by developing a smartphone application VitiCanopy to estimate the LAI using upward-looking (bottom-up) digital images [30, 31]. Results from VitiCanopy on grapevines showed robust correlations with traditional methods including LAI-2000 and direct measurements. Confalonieri et al. [32] have also developed a smartphone application which estimates LAI based on the gap fraction and the projection function via automatic processing of images acquired below the canopy. The performance from the app was evaluated in a scatter-seeded rice field and with results demonstrating correlation with measurements from a LAI-2000 and a ceptometer. Orlando et al. [33] extended the application of this app to vineyards and converted the LAI value from the app to vineyard LAI. The results have been compared with hemispherical photography and direct measurements, which showed good correlation ($R^2 = 0.94$). However, the results showed constant overestimation, which indicated the need of a correction factor specific for vineyards. Most of these camera-based methods rely on imagery from a limited section of the plant to represent the whole plant for the calculation of LAI, thus potentially compromising accuracy. These approaches also require the operator to manually take photos below the canopy and then process them, which is difficult to automate if large areas need to be mapped and may lead to operator error [31]. Pagliai et al. [22] also used a smartphone to collect images from a position perpendicular to the vine row that

were then processed into a point cloud to estimate canopy dimensions and LAI. This system required 150–200 images from each side of the canopy and is unlikely to be suitable for mapping LAI across a vineyard. Vehicle-mounted LiDAR systems have been developed for evaluating tree or vine canopies [35, 36]. However, establishing a reliable relationship between LiDAR-derived leaf volume and LAI remains a challenge, as it requires predefined calibration parameters for each vineyard—parameters that may also vary across different seasons [37].

Mobile phones have recently been released with dual frequency GNSS receivers (band L5 in addition to L1) with the expectation that this will improve the accuracy of the GNSS [38]. This provides the opportunity to use a mobile phone as the survey instrument as it can both survey canopy using the onboard camera and relatively accurately map the sample locations.

Given the potential benefits of the measurement of the absolute leaf area as opposed to relative spectral indices, we aimed to develop a system that would allow a smartphone camera mounted on a vineyard vehicle to continuously capture side-view images with relatively high locational accuracy. The first contribution of this paper is the development of this system with a focus on automated vine-level sensing across an entire vineyard block. This was supported by an evaluation of the ability of the smartphone to provide vine-level positioning accuracy. The second contribution is a method for converting side-view vine imagery to leaf area to form the basis for the system. Evaluation was completed by comparing the image-based method and quantitative data from destructive sampling. Finally, a qualitative evaluation of the leaf area at four stages of canopy development within a season was undertaken to demonstrate the practical application of the system. The expected outcome is that this system will provide an inexpensive option for grape growers to assess spatial variation in canopy growth and development with standalone commercially available smartphones.

2 | Materials and Methods

2.1 | Data Collection

All data were acquired from a vineyard located in Nuriootpa, in the Barossa Valley of Australia (34°28'34.7"S 139°00'44.2"E) (Figure 1(a)). The vineyard is spur pruned where grapevines retain a pair of permanent bilateral cordons trained along a single wire and the canopy was allowed to sprawl during the growing season (Figure 1(b)). In total, the vineyard consists of 49 east-west orientated rows and each row normally consists of 82 vines, with row spacing of approximately 3 m and vine spacing of 2.25 m. Note that the shorter rows on the southern side of the vineyard were not included in the full block data.

The proposed imaging system consists of two Samsung S21+ phones (Samsung Electronics Co. Ltd., Maetan-dong, Suwon, South Korea), which were horizontally mounted on a trailer linked to a farm vehicle. Although four cameras were seen in the figure to evaluate different viewing angles, only the two horizontally mounted cameras were ultimately used for data collection, as they provided sufficient coverage for the intended application. The vehicle travelled forward at approximately 8 km/h with the mobile phones facing left and right (Figure 2). Mounting the phones on the trailer allowed them to be located close to the ground to minimise interference in the image of vines from the neighbouring row (Figure 3); the trailer also minimized changes in the phone's orientation due to bumps or undulations in the vineyard surface. The data collection was completed through a custom app [39] that captures approximately five images per second with a resolution of 1280 × 720 ($W \times H$) (Table 1). The images were manually transferred to an offline computer for processing; the app could be further developed to allow real-time estimation and mapping of vineyard of LAI in a similar manner to Tang et al. [39].

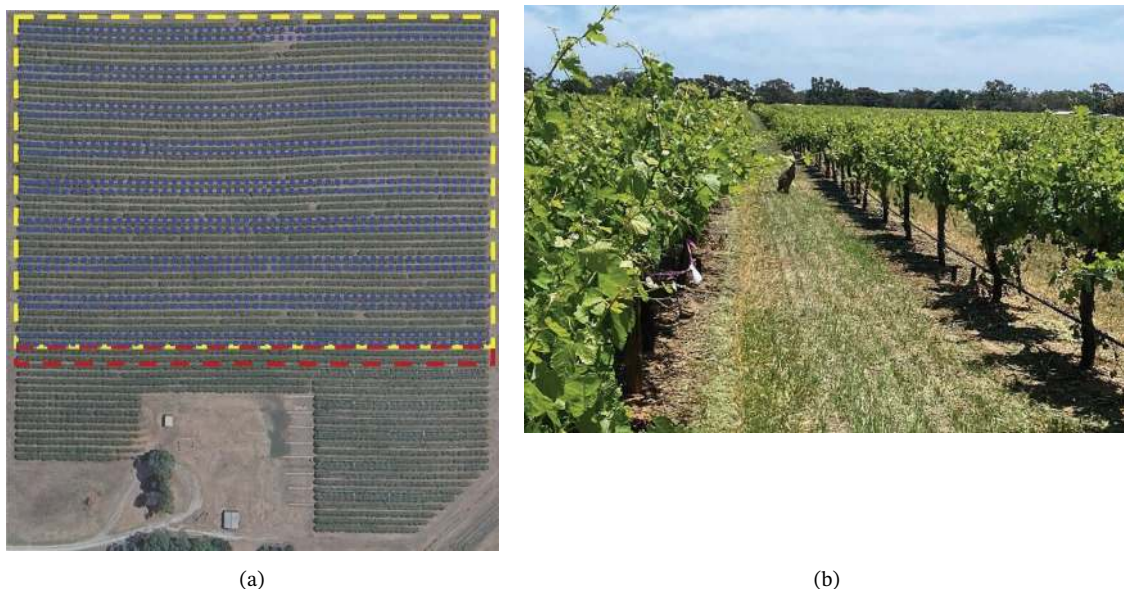


FIGURE 1 | The study vineyard. (a) Aerial view with the yellow dashed rectangular box, full block data collection area; red dashed rectangular box, validation data collection area; and blue dot lines, iPhone full block data collection rows and GNSS positioning survey rows. (b) Example of the surveyed vines.



(a)



(b)

FIGURE 2 | The imaging system. (a) Trailer carrying the array of imaging sensors; note that this manuscript focuses only on the horizontally mounted mobile phones. (b) Two mobile phones mounted. Two phones were used as part of method development, but only one phone would be required for surveying.

The data collection was conducted between 5th November 2021 (2021-11-05) and 25th February 2022 (2022-02-25) which covered vines from EL-12 stage to EL-37 stage (Table 2, Figure 3). Data

were captured for the whole block within 2–3 days of the nominated sample date. The number of images from each date collected by both cameras was around 70,000 images, which can



(a)



(b)



(c)



(d)

FIGURE 3 | Example images on each data collection date (different vines shown). (a) 2021-11-05. (b) 2021-11-25. (c) 2021-12-17. (d) 2022-02-25.

TABLE 1 | Description of the imaging system.

Data collection system	
Timing	Day
Type	RGB
Camera	Samsung S21+
Field of view	120° (12 MP ultra-wide camera)
Resolution	1280 × 720 pixels ($W \times H$)
Speed	8 km/h
Frequency	~5 images per second
Images per vine	6.3

cover a vineyard block with approximately 4000 vines and a corresponding total file size of around 64 GB.

2.2 | Method Validation: Direct LAI Measurement

The direct measurement of leaf area was based on the correlation between leaf area (as measured using a scanner) and dry weight [30, 40]. Leaves were removed from 27 vines across a range of dates (Table 3) from the rows indicated in red dashed lines in Figure 1. Immediately prior to this destructive sampling, images were collected of both sides of the vines (for the proposed method) and from the bottom-up view (for the traditional method) (Figure 4). In this study, “south” means a camera facing south and “north” means a camera facing north, as the study block is located in the southern hemisphere with images facing north will be facing towards the equator.

2.3 | Traditional Method: Bottom-Up View LAI Data Capture

A popular indirect method to estimate grapevine LAI is to use bottom-up view imagery [29, 30]. To compare the proposed method with the traditional method, the front facing camera of an iPhone was used to capture bottom-up view images on the same dates (Table 3, Figure 4) for both the validation data collection rows and the iPhone full block data collection rows (Figure 1(a)). The iPhone was placed below the cordon and orientated so that the cordon was central to the image. Due to the field of view, bottom-up view imagery only covering part of the vine (compared to the whole trunk-to-trunk region for the side-view imagery, see below); this portion of the vine was used to calculate LAI to represent the whole vine.

The LAI estimation for the vine using bottom-up view imagery is based on the canopy gap fraction method following the Beer–Lambert law and assuming that the foliage is randomly distributed

in space [28–30]. In detail, the bottom-up view images were first converted to binary images by autothresholding the blue channel in RGB [29] with black pixels as foliage and white pixels as sky (Figure 5(b)). Following the method in [29], each binary image was then divided into 8 by 8 tiles to calculate the effective LAI as follows:

$$f_f = 1 - \frac{t_g}{t_p}, \quad (1)$$

$$f_c = 1 - \frac{l_g}{t_p}, \quad (2)$$

$$\Phi = 1 - \frac{f_f}{f_c}, \quad (3)$$

$$\text{LAI}_M = -f_c \frac{\ln \Phi}{k}, \quad (4)$$

$$\Omega(0) = \frac{(1 - \Phi) \ln(1 - f_f)}{\ln \Phi \times f_f}, \quad (5)$$

$$\text{LAI}_e = \text{LAI}_M \times \Omega(0), \quad (6)$$

where f_f is the foliage projective cover, t_g is the total gap (sky) pixels in all tiles which is the sum of all white pixels in all tiles, t_p is the total pixels of the image which is the sum of total pixels among all tiles, f_c is the crown cover, l_g is the large gap pixels where the gap (sky) pixels are considered as large gap when the ratio between the sky pixels and the foliage pixels is larger than a threshold value, Φ is the crown porosity, LAI_M is the measured LAI, k is the light extinction coefficient ($0 < k < 1$), Ω is the clumping index at the zenith angle 0, and LAI_e is the effective LAI.

The large gap threshold in this study was set as 0.75 in line with the value in other literature [29, 30]. The light extinction coefficient (k) is set as 0.7, since this value has been described to be the most accurate for grapevine canopies [41]. De Bei et al. [30] also statistically tested five different methods to obtain the k value for grapevines and the results have indicated a common $k = 0.7$ rendered very good results.

2.4 | Proposed Method: Side-View Trunk-to-Trunk LAI Measurement

A novel approach was used for LAI measurement based on side-view imagery. It is difficult to distinguish the boundary between vines along and between vineyard rows and, to overcome this, the LAI measurement used the canopy between two adjacent vine trunks and the cordon as the measurement unit. This was

TABLE 2 | Summary of the side-view image dataset collected using the Samsung S21+ and include the date of capture, the timing of capture, and the phenological stage when images were collected and number of images.

Date (Y-M-D)	Timing (ACDT)	Stage of development	No. of rows	No. of images ¹
2021-11-05	14:46 to 16:47	6 leaves separated (EL-13)	43	36,289 (left ²) + 36,431 (right ²)
2021-11-25	11:29 to 13:15	80% cap fall (EL-25)	43	31,568 (left) + 31,667 (right)
2021-12-17	11:00 to 12:35	Beginning of bunch closure (EL-32)	43	28,561 (left) + 30,764 (right)
2022-02-25	10:07 to 12:09	Berries not quite ripe (EL-37)	43	36,560 (left) + 34,144 (right)

¹Image numbers per day vary with vehicle operation (exact speed and turning time); and per side depending on camera operation and running time.

²Cameras are designated left and right as their orientation changes depending on the direction of travel.

TABLE 3 | Summary of ground-truthing vines from rows indicated with red dashed lines in Figure 1.

Date (Y-M-D)	Timing	Number of vines	Direction of camera
2021-11-05	15:27	9	North and south
2021-11-25	13:41	6	North and south
2021-12-17	12:43	6	North and south
2022-02-25	12:42	6	North and south

effective as the planting distance between trunks along a row is consistent, but it meant that the cordons (representing half a vine) at each end of the rows were excluded from the results.

2.5 | Image Preprocessing Pipeline

The image preprocessing pipeline is shown in Figure 6, with the first step being data collection at 5 FPS. The second step was to identify images where the section between adjacent trunks was centred in the image. Trunk detection was applied to all images using a YOLOv5s [39, 42] model and, for the images that contained two trunks, a local minimum algorithm was used to identify images where the pair of vine trunks was located in the centre. The trunk detection object detection model was specifically trained not to detect the trunks in the next rows. The pipeline was designed to identify images only containing both trunks centrally located within the frame; therefore, images captured outside of the vine rows will be excluded and do not affect the performance.

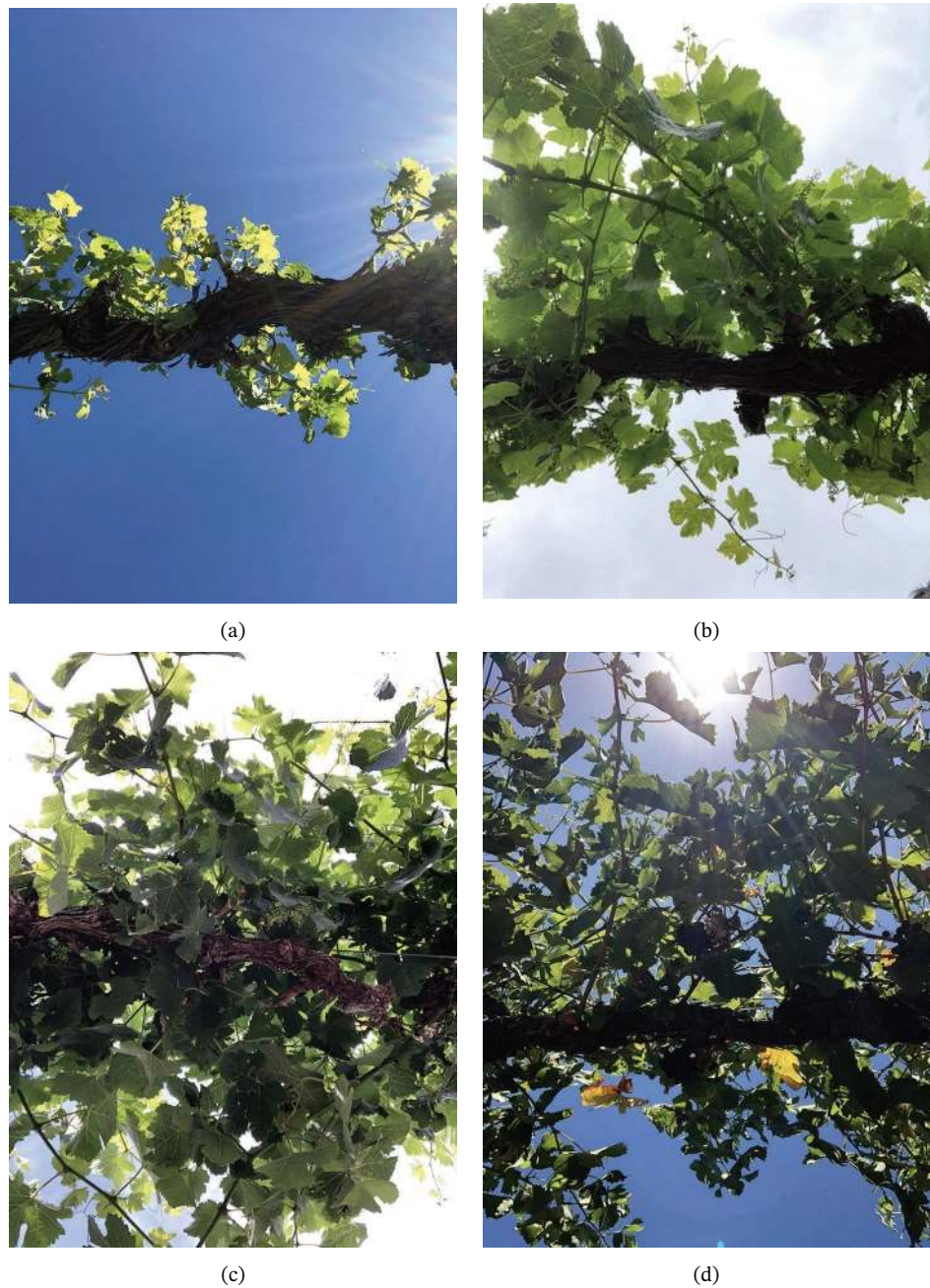


FIGURE 4 | Example iPhone images on each data collection date (different vines shown). (a) 2021-11-05. (b) 2021-11-25. (c) 2021-12-17. (d) 2022-02-25.

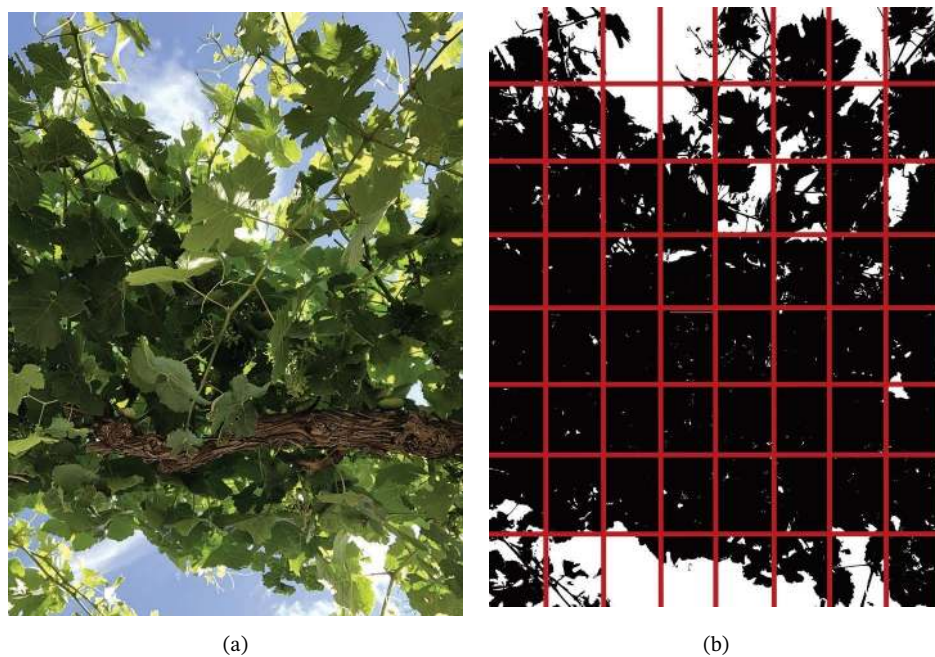


FIGURE 5 | LAI measurement for iPhone imagery, traditional bottom-up method. (a) Original iPhone image; (b) 8 by 8 tiles superimposed on the binary thresholded image.

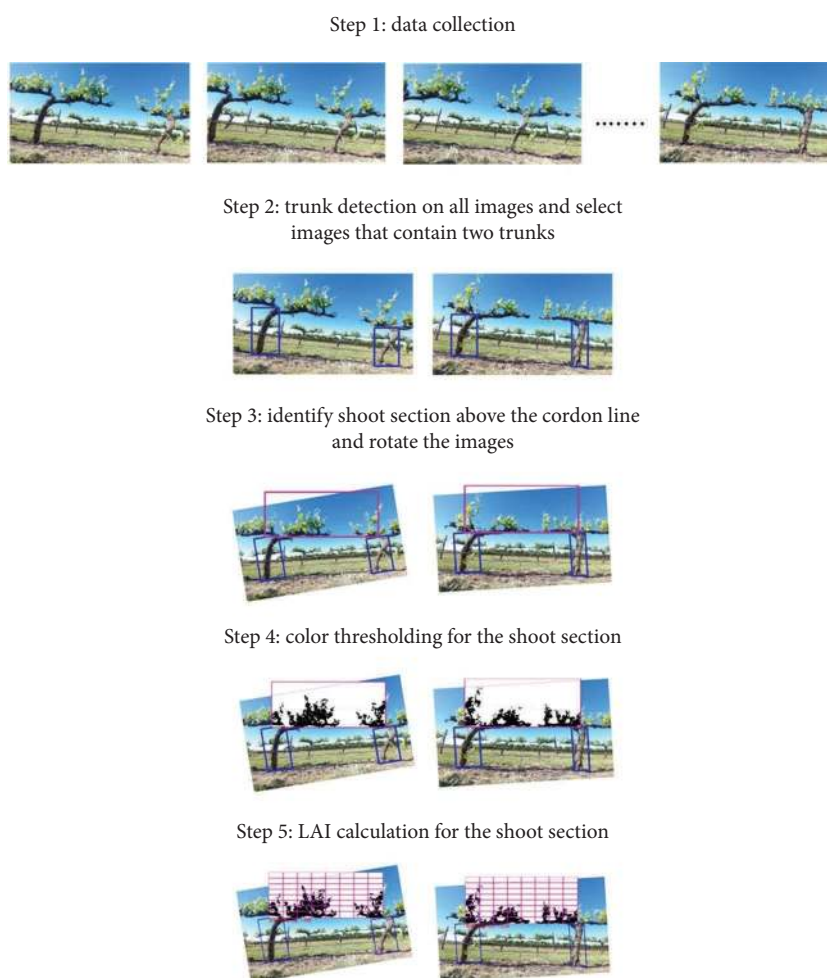


FIGURE 6 | The processing pipeline of side-view LAI calculation.

Once the trunks were identified, their locations were used to demarcate to the box that encompassed the section of canopy to be analysed (Figure 7). The middle of the top border of the left trunk box to the middle of the top border of the right trunk box denoted the lower and left and right boundaries of the analysis box.

In Step 3, the height of the canopy box was set at a fixed value; the key point was to ensure that it contained the full canopy and was consistent across all images. For this camera, image and vine configuration a height of 350 pixels was determined by observation and used consistently at all growth stages. Inclusion of additional noncanopy area well beyond the top of the canopy does not affect the calculation so the canopy box height may be set conservatively. The canopy box may even extend virtually beyond the image boundaries if the cordon is in the upper part of the image, or the camera is tilted as shown in Figure 7. As the camera may be tilted due to uneven ground or inaccurate mounting, as shown in Step 3 of Figure 6, using the top of each of the detected trunk boxes, the image was rotated about the centre of the image plane to ensure the cordon appeared horizontal. The rotation process was applied to selected images containing two trunks, with a computation time of less than one second per image.

In Step 4, the images were binarized using a threshold in the blue channel of the RGB images to distinguish between leaf and nonleaf elements [29]. Finally, the canopy box was subdivided into 8 by 8 tiles and in each the leaf area was estimated using the method below. Increasing the number of tiles in the canopy box beyond this did not significantly impact the results and mirrored the number of tiles used in the LAI calculation for the bottom-up view imagery [28].

2.6 | Leaf Area Estimation

The analysis of LAI from images is based on the Beer–Lambert law (using a turbid medium analogy) and its underlying assumption that the leaves are randomly distributed. Most foliage elements exhibit nonrandom distribution in space [43] and, in vineyards, the leaves are “clumped” along the cordon. By

dividing the sample area (canopy box) into small tiles, we increase the likelihood that leaf distribution is consistent within each tile and can sustain this assumption better than applying it across the entire sample area. Thus, the clumping index was not explicitly considered during the analysis, i.e., ($\Omega(0) = 1$) [44].

Hence, the full area of the canopy box (Area) is divided into N small tiled areas, each of Area_i ($i = 1 \sim N$), where the foliage is assumed to be randomly distributed in each tile.

In each tiled area, the canopy gap fraction $P_i(\theta)$ is calculated simply from the number of leaf pixels.

$$P_i(\theta) = 1 - \frac{\text{number of leaf pixels in Area}_i}{\text{number of pixels in Area}_i} \quad (7)$$

In prior work, θ denotes the zenith angle and is grounded in the assumption that a measurement of LAI is made with reference to the ground plane; historically, measurements have been taken using a sensor facing vertically upward to measure incident light as it would be shadow lit to the ground.

Then, taking the Beer–Lambert law, the LAI is calculated for each tile as

$$\text{LAI}_i = -\frac{1}{G(\theta)} \ln P_i(\theta) \cdot \cos(\theta), \quad (8)$$

where $G(\theta)$ is the leaf projection function which corresponds to the fraction of unit foliage area projected in the direction θ . The direction θ corresponds to the ray traced by centre point of each tile towards the canopy. For each tile, it is assumed that the measurement of LAI is being made normal to the direction θ (thus $\cos(\theta)$ is 1) and variation in θ within each tile is small. We make the simplifying assumption that leaf angles are spherically distributed, therefore $G(\theta)$ is a constant 0.5 in all tiles [32, 44]. This LAI_i then represents the LAI of the canopy observed within each tile.

We then use knowledge of the structure of the vines and camera intrinsic parameters to estimate the leaf area for each tile (LA_i). We can calculate the corresponding width covered by each tile at the depth of the cordon based on interpolation from the width of the canopy box and knowledge of the grapevine spacing, the



FIGURE 7 | Trunk-to-trunk canopy measurement (2021-11-05 example).

latter being 2.25 m in our test vineyard. Making the assumption the camera pixels are square (or otherwise correcting based on camera intrinsic parameters) allows calculation of the height of each tile in pixels and thus the height of the tile when projected from the camera onto a parallel plane which intersects the cordon, as shown in Figure 8.

Then, the area of the tile observed on this parallel plane, A_i , is multiplied by the LAI of the tile (LAI_i) so as to determine the leaf area (LA_i) measured from the vine observed within that tile.

2.7 | LAI Calculation

The leaf area was then summed over all the tiles so as to estimate the leaf area for the entire trunk-to-trunk section of the canopy. Finally, to give a consistent measure with the validation data, the estimated leaf area was divided by the effective ground area of each trunk-to-trunk section giving the LAI for the corresponding section of the vine.

$$LAI = \frac{\sum LA_i}{\text{rowspacing [m]} \times \text{trunk to trunk length [m]}} \quad (9)$$

2.8 | Evaluation of GNSS Accuracy From the Proposed System Based on Geolocated Posts

To investigate the accuracy of the side-view images, 486 posts across 18 rows of the vineyard block were tagged with red or yellow tape (Figure 9). All tagged posts were surveyed using real-time kinematic -global navigation satellite system (RTK-GNSS) to an accuracy of 0.015 m (Reach RS2, Emlid, Budapest, Hungary). To evaluate the GNSS accuracy of the proposed system, images that contained a coloured post located close to the centre of the frame were extracted across all the full-block datasets. Coordinates for each image were extracted from the file metadata and the post location was projected horizontally using half the row width and assuming the camera was perpendicular to the row. For each of the 486 posts, the x-y error was calculated by comparing the projected post location from the images with the surveyed post location.

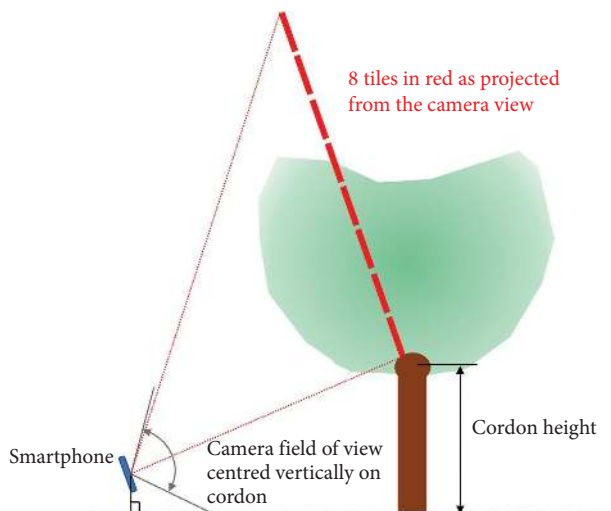


FIGURE 8 | Cross-section of camera and vine configuration.

3 | Results

3.1 | Evaluation of Side-View LAI Measurement With Direct Measurement and Traditional Bottom-Up View LAI Measurement

The LAI calculated from the side-view images (independently imaged from both sides of the vines) and the bottom-up view images (one image per vine) were compared to the LAI calculated from the destructive sampling (Figure 10). As described below, some datasets from 2021-12-17 appeared to contain outliers due to significant overexposure and these points are shown as unfilled shapes.

Side-view LAI showed a strong 1-to-1 relationship with the direct LAI measurements (very close to the blue dash-dotted 1:1 line) for images from both sides of the vine ($a = 1.00$ for south, $a = 1.07$ for north), whereas the bottom-up view method consistently overestimated LAI ($a = 0.68$). There was no significant difference between side-view LAI for south and north. The R^2 obtained for both sides was more than 0.75 with a slope of 1.00, an MAE of 0.20, and a RMSE of 0.31 at $p < 0.00001$. In contrast, bottom-up view LAI measurement has a higher R^2 of 0.89 but a slope of 0.68 (further away from 1-to-1 line), a MAE of 0.41, and a RMSE of 0.53 at $p < 0.00001$ (Table 4).

The relationship between side-view LAI and direct LAI was significantly affected by some data collected on 2021-12-17 (Figure 10). Most images collected on this date had severe overexposure which resulted in an underestimation of the LAI due to the inaccurate colour thresholding of leaf pixels as shown in Figure 11. If the significantly overexposed images collected on 2021-12-17 are excluded from the relationship between indirect measurement and direct measurement, the coherence between side-view LAI and direct LAI measurement is markedly improved (Figure 10). The new R^2 values obtained have increased from 0.75 to 0.94 for south and from 0.77 to 0.93 for north. Meanwhile, both MAE and RMSE have approximately reduced by 50% (Table 4). The slope for south has slightly reduced to 0.90, whereas the slope for side B remains at 1.00. Note that no imagery was removed for bottom-up view analysis.

The evolution of the canopy was described by the LAI measurements throughout the season, spanning from the beginning of November to the end of February (Figure 12). The LAI values derived from direct measurements of individual vines in the study ranged from 0.175 to 2.17. These observations align consistently with other literature [30, 33, 45]. The full-block data further confirmed the consistent overestimation by the bottom-up view LAI, particularly for denser canopy observed from 2021-12-17. In contrast, the side-view LAI remained consistently closer to direct measurements across all dates. The slight underestimation for side-view LAI full block data on 2021-12-17 was attributed to the overexposure of some of the images. The consistency between the full-block and ground-truthing side-view LAI data further validates the robustness of the proposed method, in contrast to the significant discrepancies observed between the bottom-up LAI estimates for both the full block and the validation surveys.

3.2 | Large-Scale Comparison Between Side-View LAI Measurement and Bottom-Up View LAI Measurement

The manual collection of LAI through destructive sampling is onerous so an additional six full rows of side-view vine images were



FIGURE 9 | Example images of posts. (a) Example post with yellow tape. (b) Example post with red tape.

extracted and matched with the corresponding bottom-up view imagery for the same vines to conduct further comparison on a large scale (Figure 13, Table 5). For the vineyard-scale dataset, the slope between side-view LAI and bottom-up view LAI was similar to the slope between the direct LAI and bottom-up view LAI (as previously seen in Table 4). Assuming that the bottom-up LAI to direct LAI relationship remains consistent (as observed in Figure 10), the side-view LAI method is able to perform well on vineyard scale datasets, where direct measurement is infeasible.

3.3 | Full Block Comparison Between Side-View LAI and Bottom-Up View LAI

The full block results of side-view LAI measurements from images taken between 2021-11-05 and 2022-02-25 from the south-facing orientation were mapped (Figure 14). The results of bottom-up view LAI measurements using images collected with an iPhone on the same dates as the side-view imagery were also

plotted (Figure 15). Due to the manual data collection required for bottom-up view images, the number of rows collected for this dataset has been reduced to 18 to represent the whole block. Maps are provided to show the development of LAI over time and to identify the scale of the sampling undertaken. Given the method specifically identifies individual trunk-to-trunk sections rather than extrapolating from a subsection of the vine to the whole vine or interpolating from one vine to adjacent vines, these maps are presented in point form rather than continuous surfaces.

To quantitatively assess the efficiency of each method, it took approximately 1.8 h to collect the bottom-up view images for 18 rows by a human operator, whereas it only took around 18 min to gather data from the same 18 rows by the proposed system (using the cameras towed at 8 km/h). The bottom-up view imagery was only collected for every third vine, whereas side-view LAI collects every vine within the row. In summary, side-

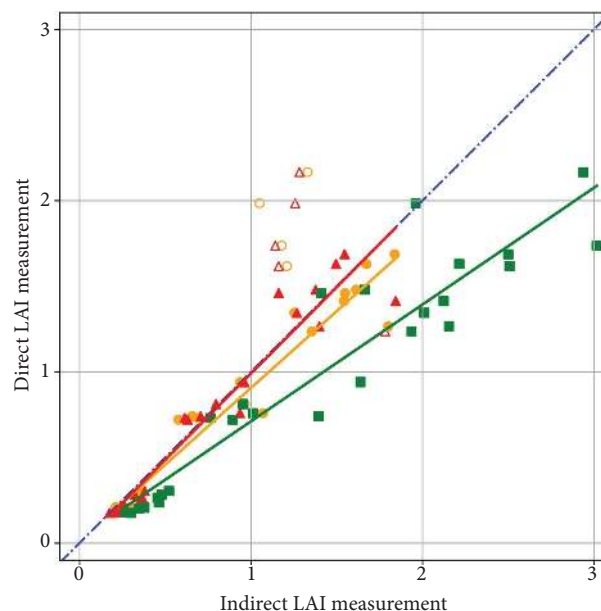


FIGURE 10 | Relationship between direct LAI measurements and indirect measurements calculated from the side-view and bottom-up-view images. The trend lines had the outliers from the 2021-12-17 data excluded (outliers). There were two side-view images (from the north and south) and one bottom-view image collected from each vine. The continuous line represents the regression between direct measurement and indirect measurement and the dash-dotted line represents the 1:1 relationship. Legend explanation: — 1:1 line; — fitted line, bottom-up view LAI; — fitted line, north side-view LAI (outliers excluded); — fitted line, south side-view LAI (outliers excluded); ■ bottom-up view LAI; ▲ proposed side-view LAI, north; ● proposed side-view LAI, south; ▲ proposed side-view LAI, north (outliers); ○ proposed side-view LAI, south (outliers).

TABLE 4 | Statistics of the correlation among the side-view LAI, bottom-up view LAI, and the direct measurement for all data and the data excluding the data collected on 2021-12-17.

	Side-view LAI (south) versus direct measurement	Side-view LAI (north) versus direct measurement	Bottom-up view LAI versus direct measurement	Side-view LAI (south) versus direct measurement (outliers excluded)	Side-view LAI (north) versus direct measurement (outliers excluded)
Slope	1.00	1.07	0.68	0.90	1.01
Intercept	0.03	0.01	0.03	0.01	−0.02
R^2	0.75	0.77	0.89	0.94	0.93
MAE	0.20	0.20	0.41	0.11	0.10
RMSE	0.31	0.31	0.53	0.16	0.14
p	4.58×10^{-9}	1.97×10^{-9}	1.45×10^{-13}	1.43×10^{-13}	2.89×10^{-12}

Note: R^2 = coefficient of determination.

Abbreviations: MAE = mean absolute error, RMSE = root mean squared error.

view LAI is six times faster than bottom-up view LAI and also collects three times more data.

The temporal trend of the average LAI for the full block data including both side-view LAI results and bottom-up view LAI results was similar to the trend for the directly measured LAI values and corresponding image analysis (Figure 12). There was no significant difference between images collected from south and north for side-view LAI. The full block bottom-up view LAI has larger differences for the images captured on 2021-12-17 and 2022-02-25 compared to other dates, which indicates that the bottom-up view imagery did not represent the whole block very well or the number of directly measured ground-truth vines was too small to provide a sufficiently representative sample. Across all four dates' data, the bottom-up view LAI for full block still constantly overestimated the LAI measurements, in a similar manner to the bottom-up view LAI measurements as part of the validation process. The side-view imagery provides similar trend and values to the direct measurements except the data on 2021-12-17, which has been defined as an outlier discussed in previous sections.

3.4 | Results of GNSS Accuracy Based on Geolocated Posts

When the locations of the surveyed posts and the corresponding images were compared, most differences are less than 2.25 m (Figure 16, Table 6). The average error and the median error for

all data were 1.97 and 1.56 m, respectively (Table 6). The data on 2022-02-25 showed the smallest difference and indicate that 90% of the data fell below the length of the vines (2.25 m). The rest of the data showed similar accuracy except 2021-11-05.

4 | Discussion

In general, the LAI values using side-view images and those measured from destructive methods were consistent and a linear relationship has been observed in the proposed system, with a coefficient of determination ranging from 0.75 to 0.94, depending on the inclusion of the data from 2021-12-17. In the same region, the maximum canopy density for Shiraz typically occurs from the end of November to the beginning of December [46]; after this period, the vines start to defoliate due to water stress. This suggests that the LAI values obtained on 2021-12-17 were expected to be the peak compared to other observation dates. The significant underestimation of the LAI values of 2021-12-17 may have been due to image overexposure (Figure 11). The overexposure adversely impacted the accuracy of colour thresholding, resulting in a reduction in the number of identified leaf pixels. Hence, the side-view imagery collected on 2021-12-17 has been flagged as an outlier.

As the proposed system provides mapping for individual trunk-to-trunk sections, the precision of the geolocation of the proposed imagery system plays a key role in identifying the individual vine



FIGURE 11 | An example of side-view imagery collected on 2021-12-17 showing a portion of leaves overexposed and hence calculated as sky pixels. (a) Original image. (b) Thresholded image.

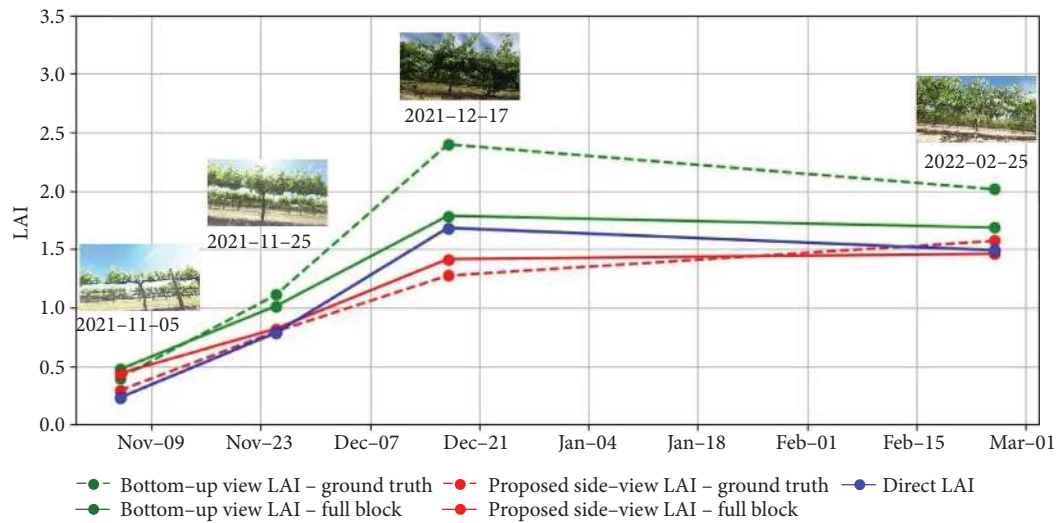


FIGURE 12 | Average trend of direct LAI measurement and indirect LAI measurement observed across all dates during the season from the beginning of November to the end of February. Both validation data from vines that were destructively measured and data from the survey of the full block are shown in the figure. Images from the north and south sides of the vines are averaged.

and the row. Precise GNSS data are essential, particularly when growers find specific issues with certain vines, such as unexpected instances of low canopy density. In these scenarios, growers can rely on the location provided by the smartphone to pinpoint the problematic vine and take corrective actions [47]. The smartphone model used in this work was specifically chosen due to its inclusion of a dual-frequency (L1 and L5) receiver while being a commercial off the shelf device at the time of data capture. In most of the cases, the average difference between the GNSS location obtained from images and the surveyed GNSS location falls below the length of the vines (i.e., 2.25 m). The

proposed system uses only a single smartphone to achieve a vine-level accuracy most of the time without the need for external correction data, which makes it capable of implementing a plant identification and tracking system [48]. For this vineyard, this level of precision is sufficient for both identifying the individual vines and accurately determining their corresponding rows based on GNSS coordinates from the proposed system. In higher density planting systems, the accuracy of the GNSS may not be sufficient for vine/row identification.

Compared to other commercial LAI measurement tools such as the LAI-2000, side-view LAI can operate over a wider range of conditions. The proposed side-view LAI system exhibits greater resilience to variable light due to cloud cover, which is not easily tolerated with the LAI-2000 which is often used under diffuse radiation (dawn or dusk or uniform high cloud). The LAI measured using the bottom-up imaging underestimated canopy size relative to the LAI estimated from the side-view imaging (Figure 10). We observed that the canopy extended beyond the field of view of the camera used for the bottom-up measurements, and it is likely that this led to a “saturation” of the LAI measurements for the large canopies, where the portion of the shoots that extended beyond the field of view was not captured as part of the LAI estimate. While the smartphone model was chosen for its dual-frequency GPS receiver, the high quality of the

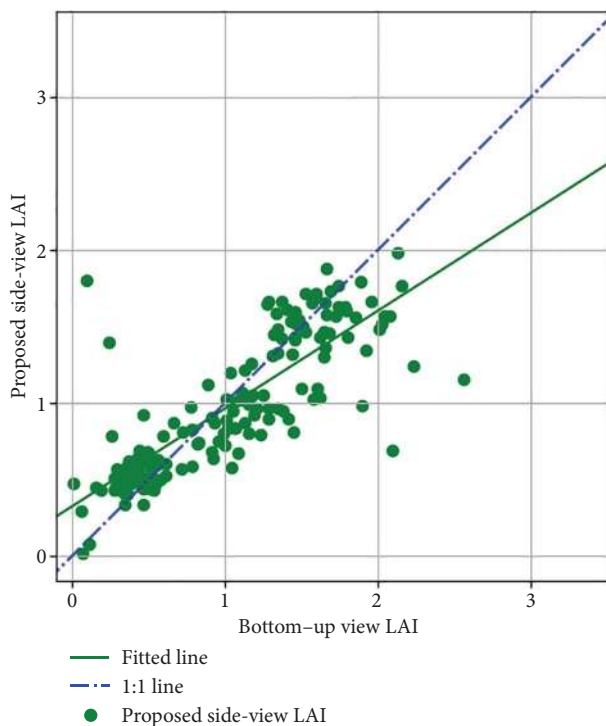


FIGURE 13 | Relationship between side-view LAI and bottom-up view LAI for 6 full rows.

TABLE 5 | Statistics of the correlation between the proposed side-view LAI and the bottom-up view LAI.

Side-view LAI versus bottom-up view LAI	
Slope	0.64
Intercept	0.33
R^2	0.66
MAE	0.19
RMSE	0.26
p	6.41×10^{-40}

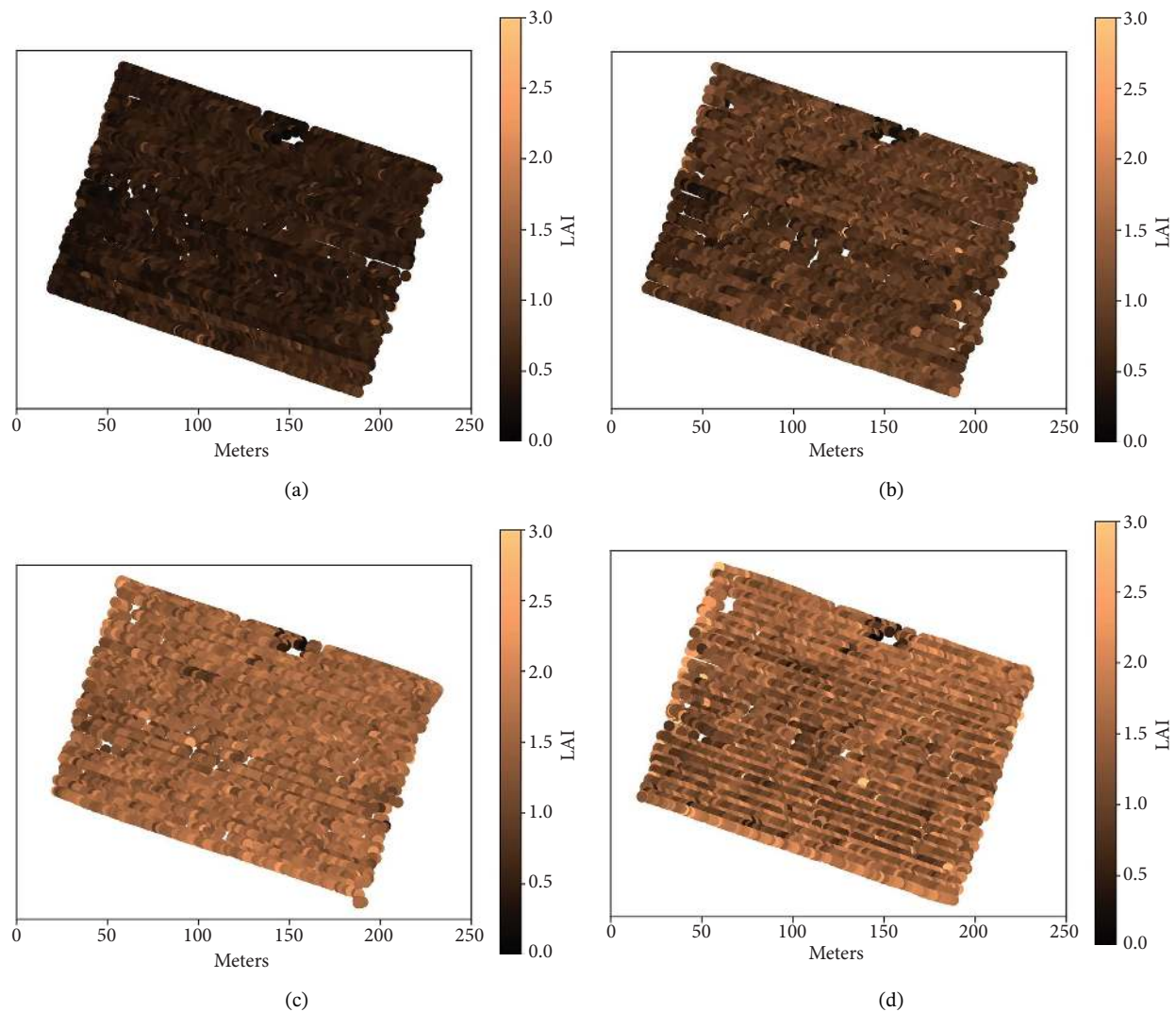


FIGURE 14 | Heatmap of side-view LAI measurement using south full block data from 2021-11-05 to 2022-02-25. (a) 2021-11-05. (b) 2021-11-25. (c) 2021-12-17. (d) 2022-02-25.

inbuilt imaging system meant that images could be captured with minimal blur even in uneven terrain and the ability to adapt to variable lighting conditions. As discussed above, the key drawback observed was due to overexposure in some data, which could have been better controlled by setting limits on camera parameters and selecting the right timing of capturing data. Compared to other indirect methods in the literature, since side-view LAI calculates the actual leaf area first and utilizes knowledge of the vine spacing in the LAI calculation, this makes the comparison meaningful across multiple years within the same vineyard. Moreover, the only input variable is the vine spacing, allowing simple application to other vineyards of single cordon spur pruned vines. Pagliai et al. [22] benchmarked four methods to assess canopy volume, including bottom-up imaging (that we also evaluated), 3D point clouds based on images

captured from the ground using a handheld smartphone, an UAV, and laser scanning (LiDAR) using a vehicle-mounted platform. They found correlations between the assessment methods, especially for canopy volume and LAI measured using bottom-up imaging. While all the techniques were effective, the handheld smartphone was laborious, requiring 150–200 images for each side of every vine assessed.

Future work may concentrate on two primary areas, firstly, mitigating limitations due to poor colour thresholding due to factors such as overexposure. Advanced segmentation techniques, such as deep learning-based semantic segmentation, could be applied. These methods leverage convolutional neural networks (CNNs) to automatically classify and segment objects in images, offering a more robust and accurate solution for

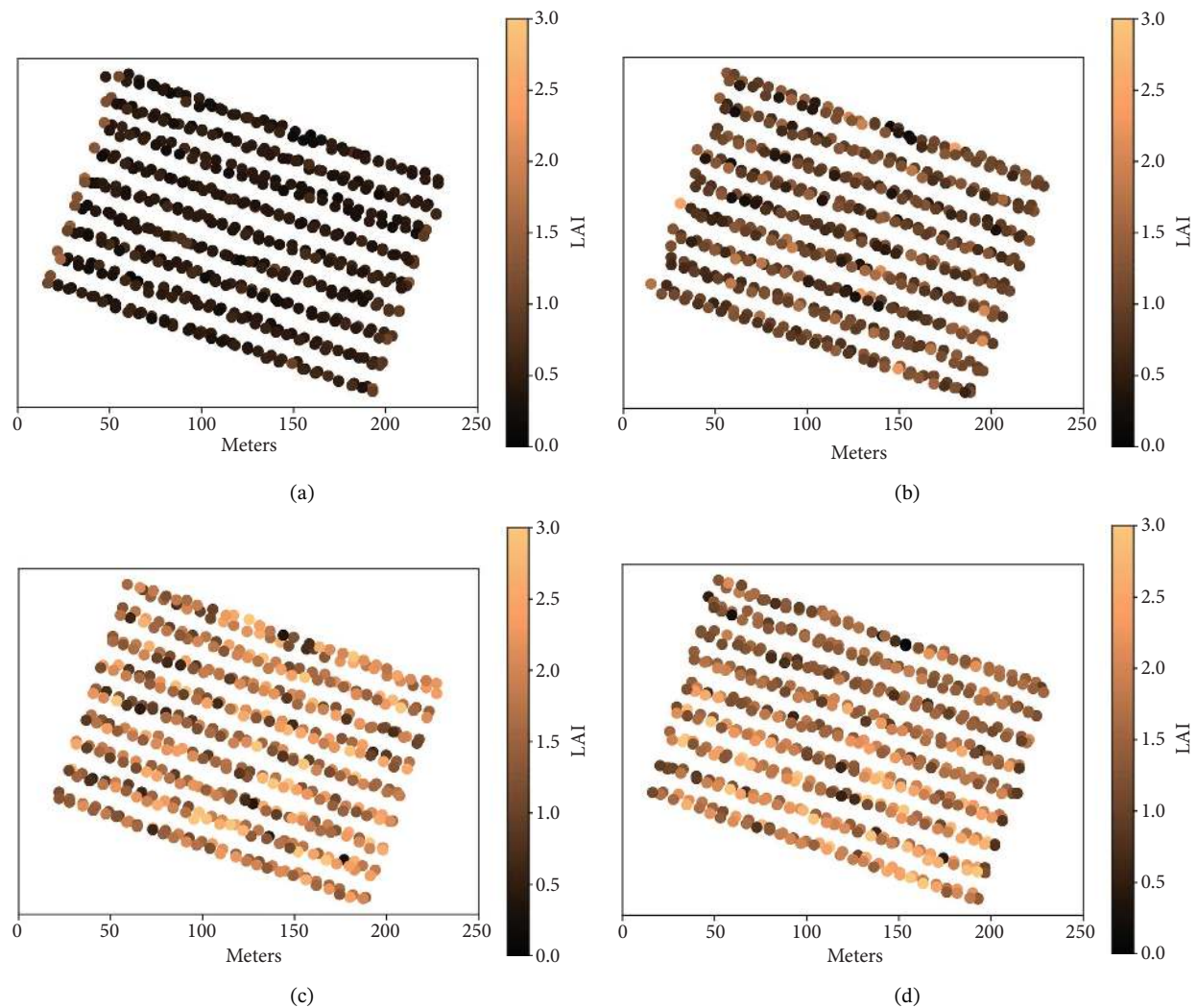


FIGURE 15 | Heatmap of bottom-up view LAI measurement using iPhone full block data from 2021-11-05 to 2022-02-25. (a) 2021-11-05. (b) 2021-11-25. (c) 2022-12-17. (d) 2022-02-05.

complex and challenging environments. Deep learning models can learn more complex patterns and features, making them capable of distinguishing between leaves and objects with similar colours. This may improve the delineation between the canopy and the sky, thus improving the accuracy of LAI estimation. Secondly, research may explore the adaptability and efficacy of

the proposed side-view LAI in vineyards employing different trellis styles and different terrains (e.g., slopes) and ground cover or even in other crops. Further training of the YOLOv5s model may be needed so that the lower cordon on vines trained to multiple cordons can be identified. The process has been validated for sprawling vineyards, however vineyards with shoot

TABLE 6 | Average difference between the GNSS location obtained from images and the surveyed GNSS location.

Date	Average error (m)	Median error (m)	Percentage of data less than half the length of the vine ¹ (%)	Percentage of data less than the length of the vine ¹ (%)
2021-11-05	2.77	2.91	12	32
2021-11-25	1.72	1.25	40	78
2021-12-17	1.92	1.73	28	66
2022-02-25	1.45	1.12	50	90

¹Half of the distance between two vines was used as the benchmark as accuracy better than this would allow individual vines to be located.

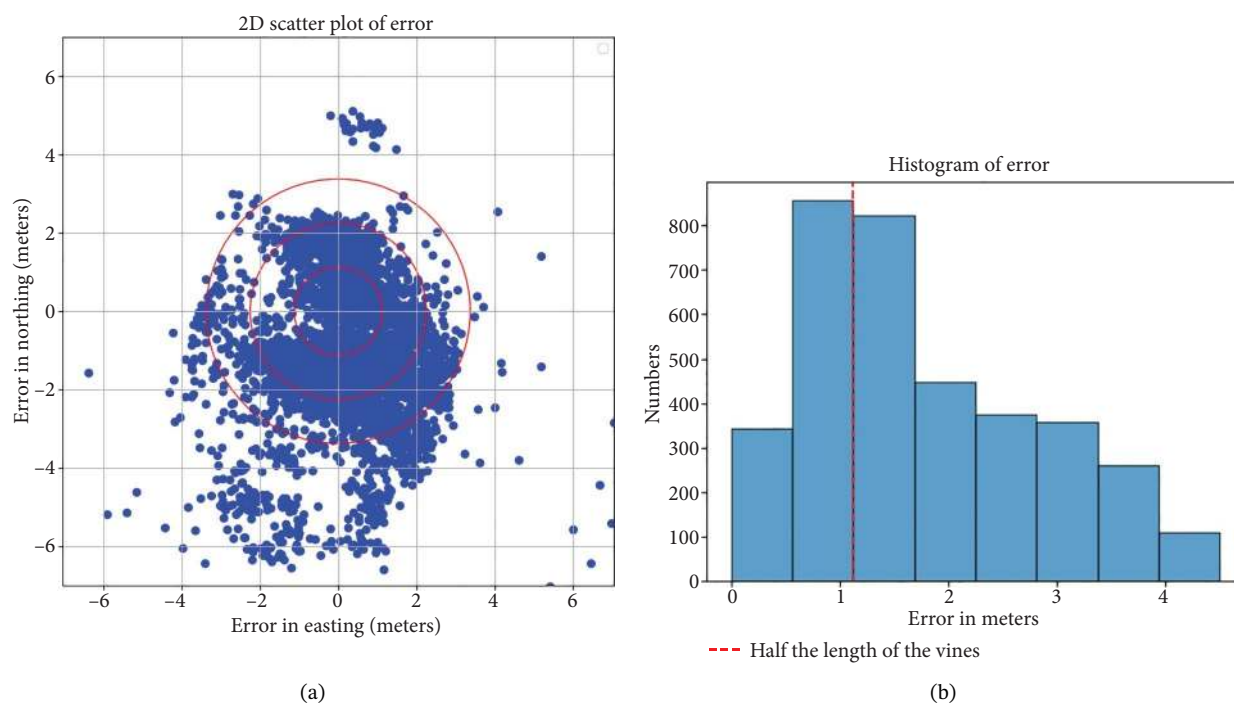


FIGURE 16 | The 2D scatter plot of error (a) and the histogram of error (b) between the GNSS coordinates from the system and the actual GNSS coordinates aggregated across all of the sample dates. The radii of three red circles in (a) were 1.125, 2.25, and 3.375 m, respectively (2.25 m is the vine spacing). The red dashed vertical line in (b) was 1.125 m which is half the length of the vines. See Figure S1 for scatter plots and Figure S2 for histograms of each date presented separately.

positioning represent a different canopy structure and may require further refinement.

5 | Conclusions

This work has proposed an automatic and indirect system of estimating the LAI for individual trunk-to-trunk segments in a vineyard, by collecting images from the side of the canopy using only a smartphone-based camera system. Through the comprehensive evaluation for a vineyard over the multiple dates, results have shown a near 1-to-1 relationship between the proposed side-view LAI values and the direct LAI measurements. The GNSS receiver in the proposed system achieves a vine-level accuracy most of the time using only a smartphone without an external correction device. The results demonstrated its reliability and accuracy, compared to the traditional indirect method, bottom-up view imagery. The output from the proposed method does not require any correction factors for the studied vineyard with the spur pruned trellis style and can be potentially applied to the vineyard management system directly, whereas the LAI values generated by the bottom-up view imagery were consistently overestimated, thus requiring calibration. The proposed method showed some uncertainty for the overexposed imagery due to the simple colour thresholding currently used. However, this can be significantly improved if more advanced techniques were applied. The proposed method indicated high possibilities for commercialization as it is an operationally friendly and easy platform.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

No direct funding was received for this manuscript, but we appreciate the support of the South Australian Research and Development Institute and the University of New South Wales to complete this work.

Acknowledgments

We would like to acknowledge the support of Hiranya Jayakody, early versions of the app for data collection; Cameron Stewart, updated version of the app for data collection; Finn Russell, further app updates and support; Kangying Lin, app ideation; and Roger Maywald, management of the vineyard and access to the vehicle for image collection.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting Information 1. 2D scatter plots of error for individual datasets. Figure S1: The 2D scatter plot of error between the GNSS coordinates from the system and the actual GNSS coordinates for individual datasets. The radii of three red circles were 1.125, 2.25 and 3.375 m, respectively (2.25 is vine spacing in metres). (a) 2021-11-05. (b) 2021-11-25. (c) 2021-12-17. (d) 2022-02-25.

Supporting Information 2. Histograms for individual datasets. Figure S2: The histogram of the distance between the GNSS coordinates from the system and the actual GNSS coordinates for individual datasets. The red dashed vertical line in (b) was 1.125 m which is half the vine spacing. (a) 2021-11-05. (b) 2021-11-25. (c) 2021-12-17. (d) 2022-02-25.

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