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## Article

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# Leaf Area Index Estimation from Multi-angle Gap Fractions Using a Tilted Smartphone Camera

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**Abstract:** Leaf area index (LAI) is a key descriptor of canopy structure, widely used as a standard land-surface parameter in Earth observation products and as an essential input to quantitative remote sensing, ecological, and climate models. Fast and accurate in situ LAI measurements are therefore crucial for product validation and model development. This study proposes an LAI retrieval method using a tilted consumer smartphone with a narrow field of view. Multi-angle gap fractions are extracted from a single upward-looking image by partitioning pixels into concentric zenith-angle bins. LAI is then calculated using a discretized form of the Miller integral without prescribing a canopy G-function. Field experiments were conducted across three sites in China, covering seven vegetation types (row crop and natural woody canopies). LAI-2200 measurements were used as reference. Among tested tilt angles (0°, 30°, 45°, and 60°), a 30° tilt provided the best agreement with LAI-2200, with RMSE = 0.65 and  $r = 0.66$  for effective LAI. After correcting for canopy clumping using the finite-length averaging approach, accuracy and stability further improved (RMSE = 0.47,  $r = 0.75$ ) and the regression approached the 1:1 line. Results across vegetation types indicate good general applicability. The improved performance is attributed to the expanded effective zenith-angle coverage achieved by tilting, which better represents hemispherical canopy structure within a narrow-FOV camera. This work extends practical LAI measurement options and suggests that smartphones can provide rapid, low-cost, and robust LAI estimates.

**Keywords:** smartphone; leaf area index; multi-angle gap fraction; Miller integral; clumping index; effective LAI

## 1. Introduction

Vegetation is a fundamental component of the Earth system, and leaves are the primary organs for photosynthesis in most terrestrial plants. Leaf area index (LAI) is commonly defined as the one-sided leaf area per unit ground area (CHEN & BLACK, 1992). LAI is a core parameter characterizing canopy structure. Variations in LAI influence canopy microclimate and biophysical processes (e.g., photosynthesis, respiration, transpiration, and decomposition), which in turn affect plant growth and LAI itself, forming feedbacks that propagate to ecosystem and climate scales (Willems et al., 2012). Because of its central role, LAI is a key input to many quantitative remote sensing, ecological, and climate models (Asner et al., 2003; Gastellu-Etcheberry et al., 2015; Verhoef, 1984). LAI can be obtained by destructive sampling (direct methods) or estimated from radiation transmission and canopy gap fraction (indirect optical methods). Direct methods are accurate but labor-intensive and impractical for large-scale or repeated measurements. Indirect optical methods are therefore widely used in field campaigns.

Direct methods estimate LAI through destructive sampling, in which stems and leaves are harvested and measured to calculate leaf area (Jonckheere et al., 2004), for example using the LI-3000C portable leaf area meter (LI-COR, Lincoln, NE, USA), or the specific leaf area (SLA) approach (Chen et al., 1997a). Although these methods generally provide high accuracy, they require substantial labor and material resources. Therefore, indirect approaches are more commonly adopted in practical field measurements. Indirect methods typically infer LAI from canopy transmittance measured by photosensitive sensors, offering greater operational convenience in field campaigns. Over the past decades, a number of studies have reviewed both direct and indirect approaches (Jonckheere et al., 2004; Weiss et al., 2004; Welles, 1990), and Yan et al. provided a detailed overview of indirect optical methods (Yan et al., 2019). Building on recent research, camera-based optical techniques have become one of the mainstream options for in situ LAI acquisition due to their low cost and high accessibility.

Camera-based optical methods estimate LAI by extracting canopy gap fraction from digital images and then applying the Beer–Lambert law, as expressed in Eq.(1), to compute LAI (Campbell, 1986; Campbell & Norman, 1990; Miller, 1964, 1967; WILSON, 1959; Wilson, 1960, 1963).

$$P_0(\theta) = e^{-\frac{G(\theta)LAI}{\cos \theta}} \quad (1)$$

In Eq.(1),  $\theta$  denotes the camera viewing zenith angle (VZA), i.e., the angle between the normal vector of the camera image plane and the vertical direction.  $P_0(\theta)$  is the gap fraction in the viewing direction at VZA  $\theta$ , which can be obtained by classifying and quantifying canopy elements from digital images.  $G(\theta)$  represents the mean projection of unit leaf area onto a plane perpendicular to the viewing direction  $\theta$ , and it depends on the leaf angle distribution (LAD). Assuming that foliage elements are randomly distributed in space and ignoring the

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clumping index(Chen & Cihlar, 2000), , the estimated LAI is referred to as the effective LAI (LAI<sub>e</sub>). The true LAI (LAI<sub>t</sub>) can be derived by correcting LAI<sub>e</sub> using the clumping index (Ryu et al., 2010). By rearranging Eq.(1), Eq.(2) is obtained.

$$LAI = -\frac{\cos \theta}{G(\theta)} \ln(P_0(\theta)) \quad (2)$$

In Eq.(2), two variables are unknown, namely LAI and  $G(\theta)$ . When LAI is treated as the target variable, determining  $G(\theta)$  requires prior knowledge of the canopy leaf angle distribution (LAD) or the mean tilt angle (MTA). Because direct measurement of leaf angles is complicated, different retrieval approaches adopt different assumptions and computational schemes for MTA and  $G(\theta)$ . Digital hemispherical photography (DHP) provides a field of view of up to 180°, enabling estimation of the gap fraction function over zenith angles from 0° to 90° (Weiss & Baret, 2017). DHP images are commonly processed with the CAN-EYE software, which solves Eq.(2) by searching simulated look-up tables to identify optimal combinations of LAI and MTA. Lang(Lang, 1987) and Gonsamo(Gonsamo et al., 2018b) applied the Miller integral (Miller, 1967) and estimated LAI using linear and robust regression approaches. However, these methods rely on instruments with a wide field of view; when applied to digital images acquired with narrow field-of-view optics such as telephoto lenses or smartphone cameras, they may introduce substantial errors.

Smartphone cameras and eye-equivalent lenses typically have a relatively narrow field of view (FOV). For example, the FOV of a smartphone camera is approximately 70°, whereas that of a 35-mm lens is about 63.4°. Consequently, when the camera is held horizontally (i.e., pointing vertically upward), the accessible viewing zenith angle (VZA) range is limited to roughly 0–35°. Owing to this restricted zenith-angle coverage, Eq.(2) cannot be readily solved using conventional DHP-based approaches. Therefore, prior to LAI estimation, it is usually necessary to assume a leaf angle distribution (LAD) or specify the  $G(\theta)$  function.

LAISmart and PocketLAI are two smartphone-based applications for LAI estimation. LAISmart acquires images with an upward-looking configuration and assumes a spherical LAD; thus, it simplifies Eq. (2) by adopting a constant  $G = 0.5$  to solve for LAI. PocketLAI, in contrast, uses observations at a VZA of 57.5°, at which  $G(\theta)$  is close to 0.5 for a wide range of LADs. Both LAISmart (Qu et al., 2016) and PocketLAI(Confalonieri et al., 2013) reduce the complexity of solving Eq. (2) by introducing simplifying assumptions. However, when the assumed  $G(\theta)$  differs from the true canopy conditions, the resulting LAI estimates may exhibit substantial bias and uncertainty. For instance, the 57.5° approach requires the gap fraction to be computed specifically at VZA = 57.5° (Wilson, 1963), rather than using an image-averaged value. For

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LAISmart, the actual canopy foliage arrangement is often more complex and may deviate from the spherical LAD assumption. Fang et al. compared LAI estimates obtained from several optical instruments (Fang et al., 2018) and reported that, relative to LAI-2200 reference measurements, LAISmart achieved a relative error within 20–30%, whereas PocketLAI exhibited a relative error exceeding 40%.

To mitigate biases induced by mismatches between the assumed  $G(\theta)$  function and the actual canopy structure, Qu et al. proposed a shape-matching algorithm to fit  $G(\theta)$  based on tilted-smartphone measurements (Qu et al., 2021). This method exploits the relationship between gap fraction and zenith angle derived from a large number of digital images, and identifies a  $G(\theta)$  function consistent with the observed canopy by pattern matching, thereby enabling LAI estimation. By tilting the camera, the method expands the effective viewing range, and the use of multiple images allows  $G(\theta)$  to be fitted in a manner more representative of real canopy conditions. As a result, it can provide relatively accurate estimates of LAI and MTA. However, the procedure requires a large number of images, and its applicability may be limited for canopies with pronounced spatial heterogeneity.

Building on the studies reviewed above, this paper proposes a tilted-smartphone-camera approach to estimate LAI from multi-angle gap fractions derived from a single image. The primary objective is to enable LAI retrieval using narrow field-of-view cameras, while the secondary objectives are to improve the accuracy and efficiency of LAI estimation, broaden the applicability of smartphone-based LAI measurements, and reduce the workload associated with data acquisition and computation. To this end, we analyze a set of digital images acquired with a smartphone camera at different tilt angles and develop an algorithm that meets these goals.

## 2. Methods

### 2.1. Smartphone field-of-view model and pixel-wise VZA

The proposed algorithm operates on digital images acquired by a smartphone camera. Because LAI is derived from multi-angle gap fractions, it is necessary to determine the viewing zenith angle (VZA) corresponding to each pixel in the image. To this end, we developed a smartphone field-of-view (FOV) model that explicitly accounts for multi-angle observations during data acquisition. As illustrated in Fig. 1, the effective FOV of a smartphone camera varies with the observation configuration. When the smartphone camera is positioned on a horizontal plane (Fig. 1a), i.e., in an upward-looking mode with the primary optical axis (POA) aligned with the vertical direction, the maximum VZA of image pixels equals half of the full FOV. For a camera with a  $70^\circ$  FOV—

a common specification for most consumer-grade smartphones—the VZA is therefore constrained to approximately  $0^{\circ}$ – $35^{\circ}$ , consistent with the range reported by Qu et al. Under this configuration, pixels are arranged symmetrically around the POA in the azimuthal plane. Such symmetry around the POA restricts the effective VZA coverage of the captured image, resulting in a relatively narrow angular sampling range.

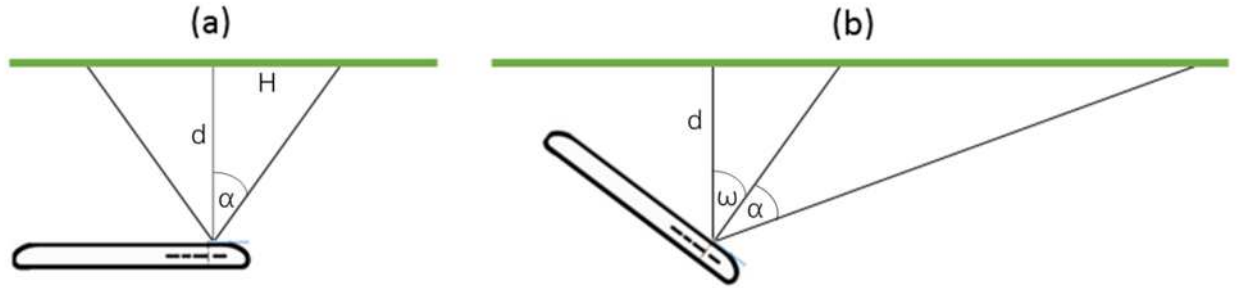


Fig.1 Relationship between the camera field of view ( $\text{FOV} = 2\alpha$ ) and the viewing zenith angle (VZA) of pixels in the captured image: (a) camera in the horizontal (upward-looking) configuration; (b) camera tilted by an angle  $\omega$ .

However, when the smartphone camera is tilted by an angle  $\omega$  relative to the vertical axis, the symmetry of pixels around the primary optical axis changes accordingly (Fig. 1b). If the camera is tilted by half of its FOV, the minimum VZA remains zero, whereas the maximum VZA reaches the upper bound of the FOV. This indicates that a simple tilt of the smartphone camera can effectively alleviate the limitation of the narrow VZA range.

For a smartphone camera with a field-of-view half-angle  $\alpha$ , the viewing zenith angle (VZA) corresponding to each pixel can be computed from the camera tilt angle  $\omega$  during image acquisition and the image resolution. We describe the relative geometry between the smartphone camera and the image using a two-dimensional coordinate system. Point  $O$  denotes the camera center and  $O'$  denotes the image center;  $f$  is the distance from the camera center to the image plane center, and  $H$  is half of the image diagonal length. The vector  $\overrightarrow{OZ}$  represents the direction of the camera optical axis (Fig. 2).

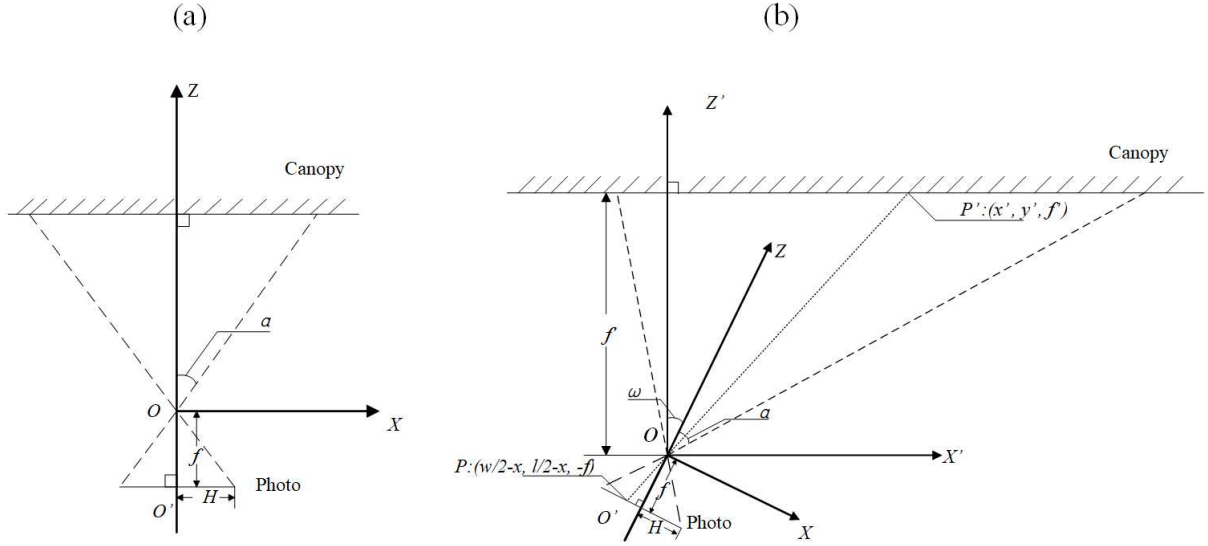


**Fig. 2.** Camera coordinate system for image geometry: (a) camera in the horizontal (upward-looking) configuration; (b) camera tilted by an angle  $\omega$ .

Let the digital image have a width of  $w$  pixels and a length of  $l$  pixels. In the proposed camera FOV model, the image center corresponds to the pixel at row  $w/2$  and column  $l/2$ , which is projected onto the origin  $O(0,0)$  on the  $X$ -axis. Accordingly, the pixel located at row  $x$  and column  $y$  has coordinates  $P(\frac{w}{2} - x, \frac{l}{2} - y)$  in the defined coordinate system.

Therefore, the image diagonal length can be computed from its pixel width and height.

$$2H = \sqrt{w^2 + l^2} \quad (3)$$

Given that the camera field of view is  $2\alpha$ , the camera-to-image distance (effective focal length in the model) can be derived using trigonometric relationships.

$$f = \frac{H}{\tan \alpha} \quad (4)$$

The viewing zenith angle corresponding to the pixel at row  $x$  and column  $y$  can be calculated using Eq. (5).

$$\tan \theta = \frac{\sqrt{(x-w)^2 + (y-l)^2}}{f} \quad (5)$$

In Eq. (5),  $\theta$  denotes the viewing zenith angle corresponding to the pixel.

When the camera is rotated by an angle  $\omega$  about the origin during image acquisition, a tilted-imaging model is established as illustrated in Fig. 2b.

The  $XOZ$  coordinate system denotes the camera FOV coordinate system shown in Fig. 2b, whereas  $X'OZ'$  denotes the scene coordinate system. The vector  $\overrightarrow{OZ'}$  is aligned with the zenith (vertical) direction and

$\overrightarrow{OX'}$  represents the horizontal direction. Here,  $\omega$  is the camera tilt angle, and the shaded plane indicates the vegetation canopy. Let  $P(\frac{w}{2} - x, \frac{l}{2} - y, -f)$  be the coordinates of the pixel at row  $x$  and column  $y$  in the camera FOV coordinate system; the corresponding point in the scene coordinate system is  $P'$  with coordinates  $P'(x', y', f')$ . Notably, the  $X'OZ'$  coordinate system can be obtained by rotating the  $XOZ$  coordinate system counterclockwise about the origin by  $\omega$ , and the corresponding rotation matrix is given in Eq. (6). In particular, when  $\omega = 0$ , the camera is oriented vertically upward.

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \omega & -\sin \omega \\ 0 & \sin \omega & \cos \omega \end{pmatrix} \quad (6)$$

The coordinates of  $P'$  in the  $X'OZ'$  system can be obtained by applying a rotation transformation to point  $P$  expressed in the  $XOZ$  coordinate system.

$$(x', y', f') = \left( \frac{w}{2} - x, \frac{l}{2} - y, -f \right) \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \omega & -\sin \omega \\ 0 & \sin \omega & \cos \omega \end{pmatrix} \quad (7)$$

The viewing zenith angle  $\theta$  associated with  $P'$  can be computed as the angle between  $\overrightarrow{OZ'}$  and  $\overrightarrow{OP'}$ .

$$\cos \theta = \frac{|f'|}{\sqrt{(x')^2 + (y')^2 + (f')^2}} \quad (8)$$

Using Eqs. (5) and (8), the viewing zenith angle of each pixel can be determined for both the vertically upward and the tilted imaging configurations.

## 2.2. Multi-angle gap fraction extraction

### 2.2.1. Image segmentation and classification

The above workflow uses the smartphone FOV model to derive the viewing zenith angle (VZA) for each pixel in the digital image. The angular information is obtained by partitioning the original image into multiple regions; within each segmented region, the gap fraction corresponding to the VZA and the contact number  $C$  are calculated. Because reliable estimation of gap fraction and the contact number requires a sufficient number of pixels, the VZA range is discretized into bins using a predefined angular interval.

For a smartphone camera with a  $70^\circ$  field of view, when the device is oriented vertically upward to observe the canopy, the corresponding viewing zenith angles (VZAs) range from  $0^\circ$  to  $35^\circ$ . To obtain multi-angle gap fractions, we partition the image into seven concentric annular regions using  $5^\circ$  angular bins, yielding seven VZA classes, as shown in Fig. 3.

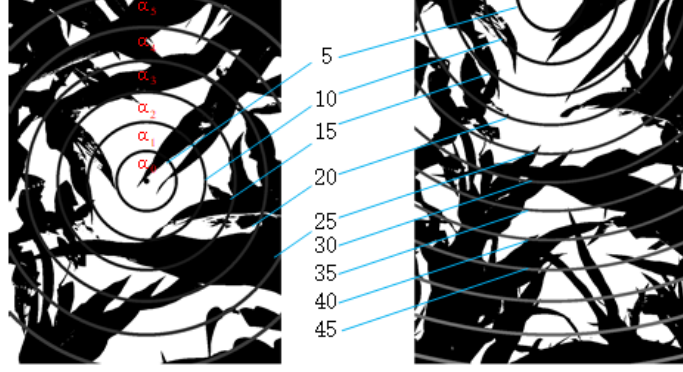


Fig. 3. Digital image after multi-angle partitioning for both the vertically upward and tilted observation configurations.

Figure 3 illustrates the multi-angle partitioning of images acquired under different shooting configurations. The left panel shows an image captured in the vertically upward mode; due to azimuthal symmetry, the effective viewing zenith angle (VZA) range is limited to  $35^\circ$ . In contrast, the right panel corresponds to the tilted configuration, which provides a wider range of viewing angles. For any annular region  $\alpha_i$ , the associated VZA is denoted as  $\theta_i$ . Let  $N_{\text{total}}(\theta_i)$  be the total number of pixels within the region and  $N_{\text{sky}}(\theta_i)$  be the number of sky pixels. The gap fraction  $P(\theta_i)$  within the region is then calculated using Eq. (9).

$$P(\theta_i) = \frac{N(\theta_i)_{\text{sky}}}{N(\theta_i)_{\text{Total}}} \quad (9)$$

Image binarization was performed using Otsu's method, which determines the optimal threshold by maximizing the between-class variance (Otsu, 1979).

### 2.2.2. LAI estimation from multi-angle gap fractions

The above procedure yields the VZA associated with each pixel in the digital image, thereby enabling the relationship between gap fraction and VZA to be established. According to the Miller integral, LAI is related to gap fraction as follows. (Miller, 1964)

$$\text{LAI} = 2 \int_0^{\frac{\pi}{2}} -\ln P_0(\theta) \cos \theta \sin \theta d\theta \quad (10)$$

Equation (10) is discretized, and Eq. (11) is used as a numerical approximation.

$$\begin{aligned} \text{LAI} &= 2 \sum_{i=1}^n \int_{\theta_{i-1}}^{\theta_i} -\ln P_0(\theta_i) \cos \theta_i \sin \theta d\theta \\ &= 2 \sum_{i=1}^n -\ln P_0(\theta_i) \cos \theta_i \times \cos \theta \Big|_{\theta=\theta_{i-1}}^{\theta=\theta_i} \end{aligned} \quad (11)$$

For smartphone images acquired at different tilt angles, different ranges of the  $P_0$ -VZA relationship can be

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obtained. Using Eq. (11), the LAI corresponding to each digital image can then be estimated.

### 2.2.3. Clumping index correction

In canopies where foliage elements are not randomly distributed, the clumping effect causes the effective LAI to underestimate the true LAI. The clumping index is a parameter that characterizes the degree of canopy aggregation and is commonly used to convert effective LAI to true LAI. Black et al. used  $\Omega$  to denote the clumping index. (Black et al., 1991)

$$\Omega = \frac{LAI_{eff}}{LAI_{tru}} \quad (12)$$

Here,  $LAI_{eff}$  denotes the effective leaf area index, which is the product of the clumping index and the true leaf area index.

A variety of methods have been proposed to estimate the clumping index, such as the finite-length averaging method (Chen et al. 1997; Lang and Xiang 1986) and the gap-size distribution method (Macfarlane et al. 2007). Among them, the finite-length method requires gap-fraction measurements at multiple points (or viewing angles) but does not require the explicit linear distance between sampling points. Because gap fractions at multiple viewing zenith angles have already been obtained in this study, we adopt the finite-length averaging method to estimate the clumping index  $\Omega$ , i.e., as given in Eq. (13).

$$\Omega = \frac{\ln(mean(P(\theta)))}{mean(\ln P(\theta))} \quad (13)$$

Therefore, the true LAI corresponding to a given digital image can be obtained using Eq. (14), by correcting the effective LAI with the clumping index.

$$LAI_{tru} = \frac{LAI_{eff}}{\Omega} \quad (14)$$

## 3. Experimental data

### 3.1. Study area description

Data used in this study were collected from three study sites: the Daman site in Zhangye City, Gansu Province; the Ejina Banner site in Inner Mongolia; and the Beibei site in Chongqing Municipality.

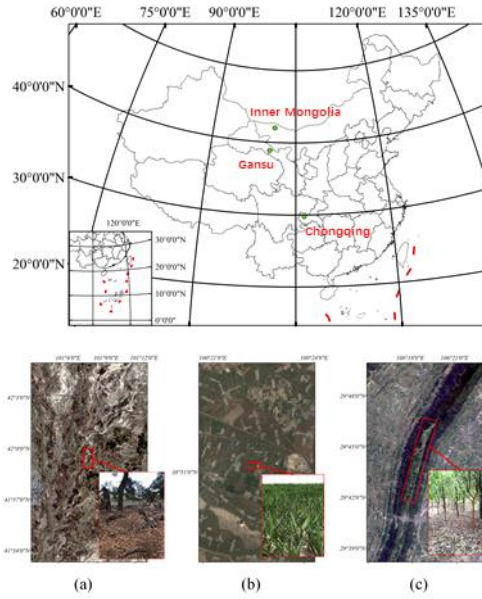


**Fig. 4.** Location map of the study sites: (a) Ejina Banner, Inner Mongolia; (b) Zhangye (Daman site), Gansu; (c) Beibei, Chongqing.

The geographic locations of the three study sites are shown in Fig. 4. The Ejina Banner site is located in Ejina Banner, Inner Mongolia (42°0'N, 101°8'E), as shown in Fig. 4(a), and lies in the lower reaches of the Heihe River Basin. The area is characterized by complex landforms, including desert, Gobi, sand dunes, lakes, and oases. The climatic conditions are harsh, belonging to an extremely arid temperate desert zone with relatively low biodiversity. Vegetation is dominated by xerophytic and hyper-xerophytic species, with *Tamarix* spp. and *Populus euphratica* as the principal vegetation types. The vegetation shown in Fig. 4(a) is *Populus euphratica*.

The Zhangye (Daman) site in Gansu Province is shown in Fig. 4(b). It is located in Daman Town, Zhangye City (38°51'N, 100°22'E), in the middle reaches of the Heihe River Basin. The site is situated on a piedmont plain with an average elevation of approximately 1550 m. The region is arid with low precipitation, uneven rainfall distribution, and large diurnal temperature variations. However, due to the presence of numerous rivers, an annual runoff of  $2.66 \times 10^9 \text{ m}^3$ , abundant groundwater resources, and long sunshine duration ( $\sim 3000 \text{ h yr}^{-1}$ ), land cover in this area is primarily grassland and cropland. The vegetation shown in Fig. 4(b) is maize (*Zea mays*), the dominant crop in the region.

The Chongqing site is shown in Fig. 4(c) and is located on Jinyun Mountain in Beibei District, Chongqing. Jinyun Mountain is a national nature reserve in China with a forest cover of 96.6%. The reserve hosts diverse vegetation types, including extensive evergreen broadleaf forests and multiple representative ecosystems. The vegetation shown in Fig. 4(c) is osmanthus (*Osmanthus fragrans*).

Overall, the vegetation across the study sites can be grouped into two categories: (i) agricultural crops and (ii) naturally grown forests. Crops are typically planted in rows and thus exhibit relatively uniform spatial distributions with a single dominant species within each plot. To evaluate the performance and robustness of the proposed algorithm under natural conditions, we complemented the relatively homogeneous cropland data with forest data. In naturally grown forests, species composition is more complex and the spatial distribution is more heterogeneous and stochastic, which provides a rigorous test of the algorithm’s applicability.

### 3.2. Data acquisition and classification

The experimental dataset comprises seven vegetation types across the three study sites, including maize, *Populus euphratica*, *Tamarix* spp., osmanthus, bamboo, pomelo, and shrubs. LAI measurements were obtained using two approaches: the LAI-2200 plant canopy analyzer and a smartphone-based imaging method.

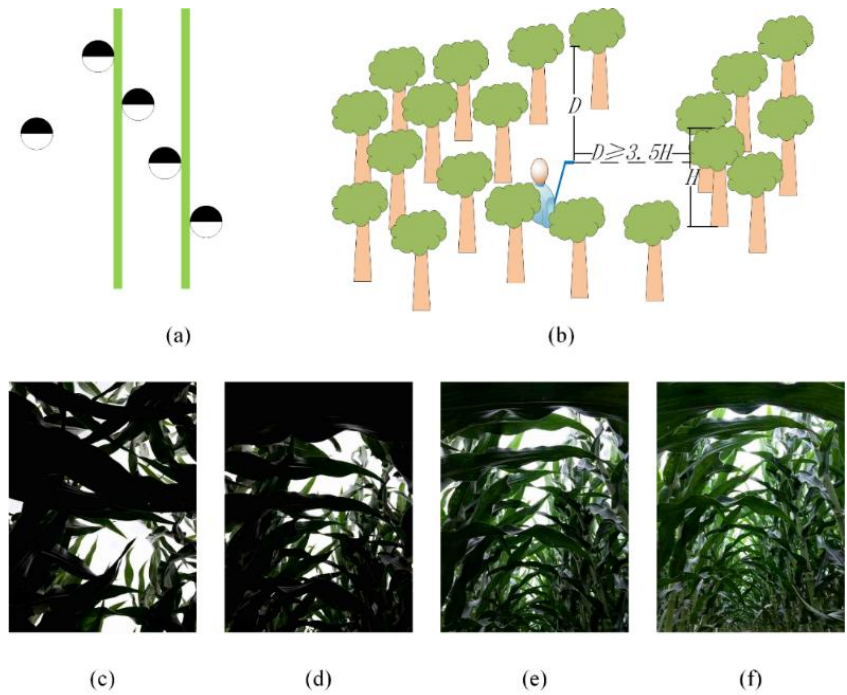


**Fig. 5.** Schematic of the measurement configurations: (a) LAI-2200 measurements for row crops; (b) LAI-2200 measurements for forest plots; (c–f) smartphone image acquisition at tilt angles of 0°, 30°, 45°, and 60°, respectively.

Vegetation types differed among the study sites, as summarized in Table 1.

**Table 1.** Vegetation types at the study sites

| Vegetation group | Species         | Study site(s)            |
|------------------|-----------------|--------------------------|
| Crop             | <i>Zea mays</i> | Zhangye (Gansu Province, |

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|                     |                                                                                    |                                                                    |
|---------------------|------------------------------------------------------------------------------------|--------------------------------------------------------------------|
|                     |                                                                                    | China)                                                             |
| Tall (>10 m)        | <i>Populus euphratica</i> ; <i>Garcinia mangostana</i>                             | Ejina Banner (Inner Mongolia, China) and Beibei (Chongqing, China) |
| Low (<3 m)          | <i>Tamarix chinensis</i> ; <i>Camellia petelotii</i> ; <i>Alsophila metteniana</i> | Ejina Banner (Inner Mongolia, China) and Beibei (Chongqing, China) |
| Medium (3 m - 10 m) | <i>Osmanthus fragrans</i> ; <i>Citrus maxima</i> ; <i>Citrus reticulata</i>        | Beibei (Chongqing, China)                                          |

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Because vegetation types differed among the study sites, the LAI-2200 measurements were conducted using two protocols based on vegetation category. Vegetation at the Ejina Banner (Inner Mongolia) and Zhangye (Gansu) sites was relatively homogeneous within each plot. For maize and low-stature shrubs, measurements were collected following the configuration shown in Fig. 5(a). A “one above–four below” sampling scheme was used, and a 180° view cap was mounted to minimize operator interference. For below-canopy readings of diffuse radiation, the optical sensor was held level at approximately 5 cm above the ground.

The Beibei site in Chongqing exhibited more complex vegetation and dense forest stands, where different species occurred in mixed communities. Therefore, the measurement protocol shown in Fig. 5(b) was adopted. A “one above–four below” sampling scheme was used. To avoid canopy obstruction during above-canopy reference measurements of diffuse skylight, reference readings were collected in nearby open areas within the forest. A 270° view cap was used, and the distance  $D$  between the sensor’s viewing window and the nearest tree was maintained at more than 3.5 times the tree height  $H$ .

Smartphone canopy images were acquired using the front-facing camera of a Honor 7 smartphone. Data were collected with the LAISmart application at a height of approximately 5 cm above the ground, while the device tilt angle was recorded simultaneously. For each plot, 12 sampling positions were randomly selected. At each position, four images were acquired at tilt angles of 0°, 30°, 45°, and 60°. All images had a resolution of 720 × 960 pixels. For image segmentation, sky and vegetation were separated using the intensity of the blue channel. Examples of canopy images acquired at different viewing configurations are shown in Fig. 5(c–f). (Qu et al., 2016)

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## 4. Results and analysis

### 4.1. Viewing zenith angle coverage under different smartphone tilt angles

Compared with conventional LAI instruments, smartphone cameras have a narrower field of view; therefore, tilting the smartphone changes the resulting viewing zenith angle (VZA) range captured in the image. Taking a smartphone with a 70° FOV as an example, when the tilt angle is smaller than half of the FOV, the lower bound of the VZA remains at 0°, indicating that canopy information near the zenith (0°) is still observable under these configurations. Once the tilt angle exceeds half of the FOV, the 0° zenith direction is no longer included in the image. When the tilt angle reaches 60°, the upper bound of VZA increases to approximately 80°. The dynamic range of VZA as a function of smartphone tilt angle is summarized in Table 2.

Table 2. Relationship between viewing zenith angle (VZA) range and camera tilt angle.

| Tilt angle (°) | Lower bound (°) | Upper bound (°) | Range (°) |
|----------------|-----------------|-----------------|-----------|
| 0              | 0               | 35              | 35        |
| 30             | 4               | 60              | 56        |
| 45             | 20              | 73              | 53        |
| 60             | 34              | 80              | 46        |

Using the ellipsoidal leaf angle distribution (LAD) function proposed by Campbell (Campbell, 1986), By combining the VZA ranges associated with different smartphone tilt angles, the corresponding range of the observed  $G(\theta)$  function for each tilt configuration can be obtained.

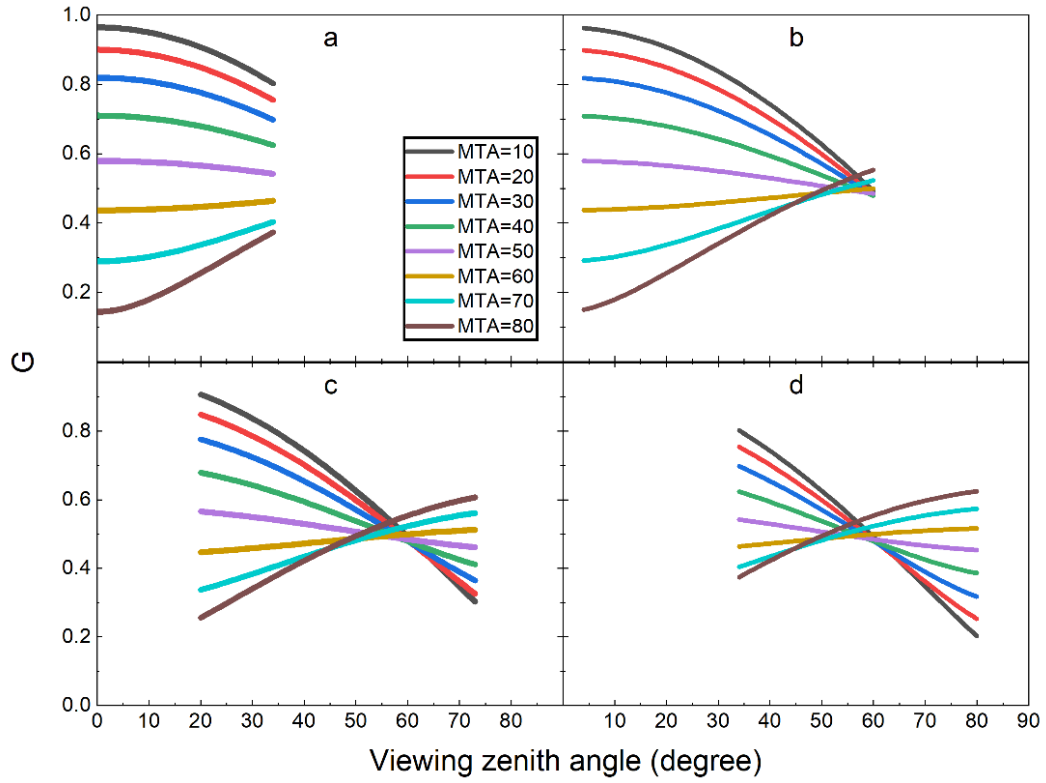


Fig. 6. Simulated  $G(\theta)$  ranges observed by a tilted smartphone: (a)  $0^\circ$  tilt; (b)  $30^\circ$  tilt; (c)  $45^\circ$  tilt; (d)  $60^\circ$  tilt.

Figure 6 provides an intuitive illustration of the  $G(\theta)$  ranges observable under different smartphone tilt configurations. Compared with hemispherical photographs with a  $180^\circ$  field of view, smartphone cameras can sample only a limited portion of the zenith-angle domain. This restricted angular coverage explains the inherent limitations of simplified smartphone applications such as LAISmart and PocketLAI, and it is also a key reason why conventional DHP-based methods cannot be directly applied to narrow-field-of-view cameras (e.g., smartphones).

#### 4.2. LAI estimation results for the simulated dataset

The proposed approach estimates LAI from multi-angle gap fractions extracted from images acquired with a tilted smartphone. We first evaluated the algorithm using a simulated dataset. In the simulated canopy scenes, LAI was set to 1, and leaf inclination followed the ellipsoidal leaf angle distribution (LAD) proposed by Campbell. The mean tilt angle (MTA) was prescribed as  $20^\circ$ ,  $30^\circ$ ,  $40^\circ$ ,  $50^\circ$ ,  $60^\circ$ ,  $70^\circ$ , and  $80^\circ$ . A simulated camera with a  $35^\circ$  field-of-view half-angle was used to observe the canopy from different viewing zenith angles. The simulated images were then processed using the proposed algorithm, and the results are shown in Fig. 7.

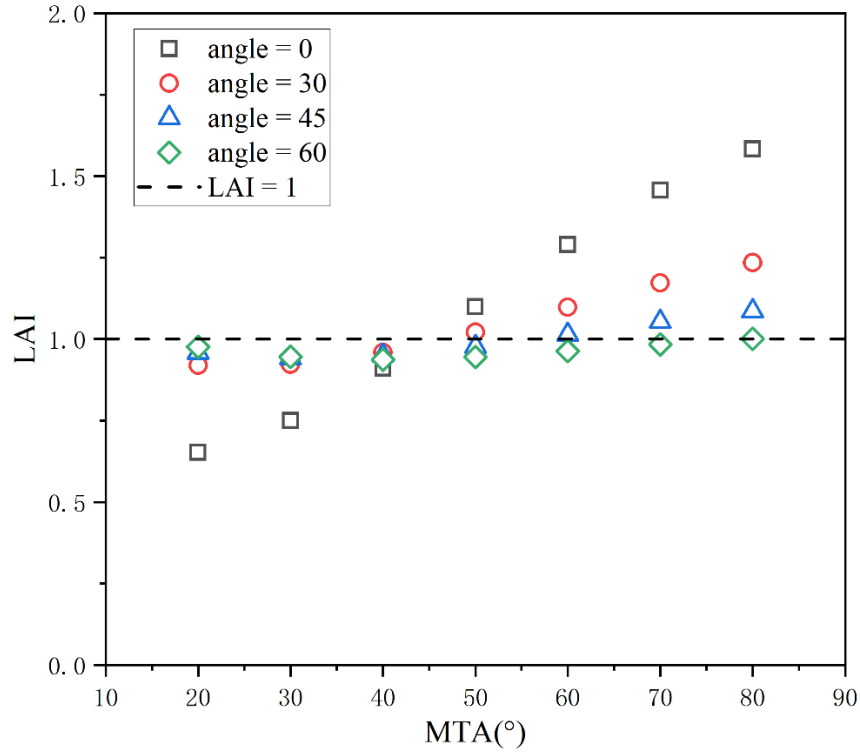


Fig. 7. Results of the proposed algorithm applied to the simulated dataset under different smartphone tilt angles.

Figure 7 shows the LAI estimates produced by the proposed algorithm under different tilt configurations; the dashed line indicates the reference value ( $LAI = 1$ ). As can be seen, the vertically upward configuration yields the least stable estimates across different MTAs and is more sensitive to canopy structure. When  $MTA = 20^\circ$ , the algorithm markedly underestimates LAI, producing a value of only 0.6. As MTA increases, the estimated LAI gradually increases, reaching approximately 0.7 at  $MTA = 80^\circ$ . This indicates a clear dependence of the estimated LAI on MTA under the upward-looking configuration.

With increasing tilt angle, the dependence of estimated LAI on MTA becomes progressively weaker. In particular, at a tilt angle of  $60^\circ$ , the algorithm shows good robustness across all tested MTAs, with LAI estimates clustering around the true value ( $LAI = 1$ ). In addition, when MTA falls within the range of  $40^\circ$  to  $<60^\circ$ , the LAI estimates obtained under different tilt angles are close to the reference value. This pattern also supports the rationale of the LAISmart assumption: when the canopy approximates a spherical LAD, or equivalently when MTA is around  $50^\circ \pm 10^\circ$ , the observation angle has a relatively minor impact on LAI estimation.

However, considering the full MTA range and the  $G(\theta)$  sampling shown in Fig. 6, the limited angular coverage in the vertically upward configuration leads to a small effective zenith-angle domain. When Eq. (13) is used as an approximation, the multi-angle gap fractions available within  $0\text{--}35^\circ$  are insufficient; using them to

approximate the 0–90° domain introduces substantial errors. By contrast, tilting expands the effective angular sampling range (Fig. 7), thereby reducing the influence of canopy structural variability on LAI retrieval. Overall, tilted observations can improve LAI estimation accuracy and enhance the general applicability of the method across different canopy structures.

### 4.3. Comparison of LAI estimates under different smartphone tilt angles

During smartphone-based observations, the FOV simulations indicate that tilting the device can provide a wider effective viewing domain. Therefore, we applied the proposed algorithm to images acquired at multiple tilt angles and compared the resulting LAI estimates with LAI-2200 measurements.

#### 4.3.1. Results for effective LAI (LAI<sub>e</sub>)

The proposed algorithm was used to derive the effective LAI (LAI<sub>e</sub>) from images acquired at four tilt angles, and the resulting estimates were compared with LAI-2200 measurements. The results are shown in Fig. 8.

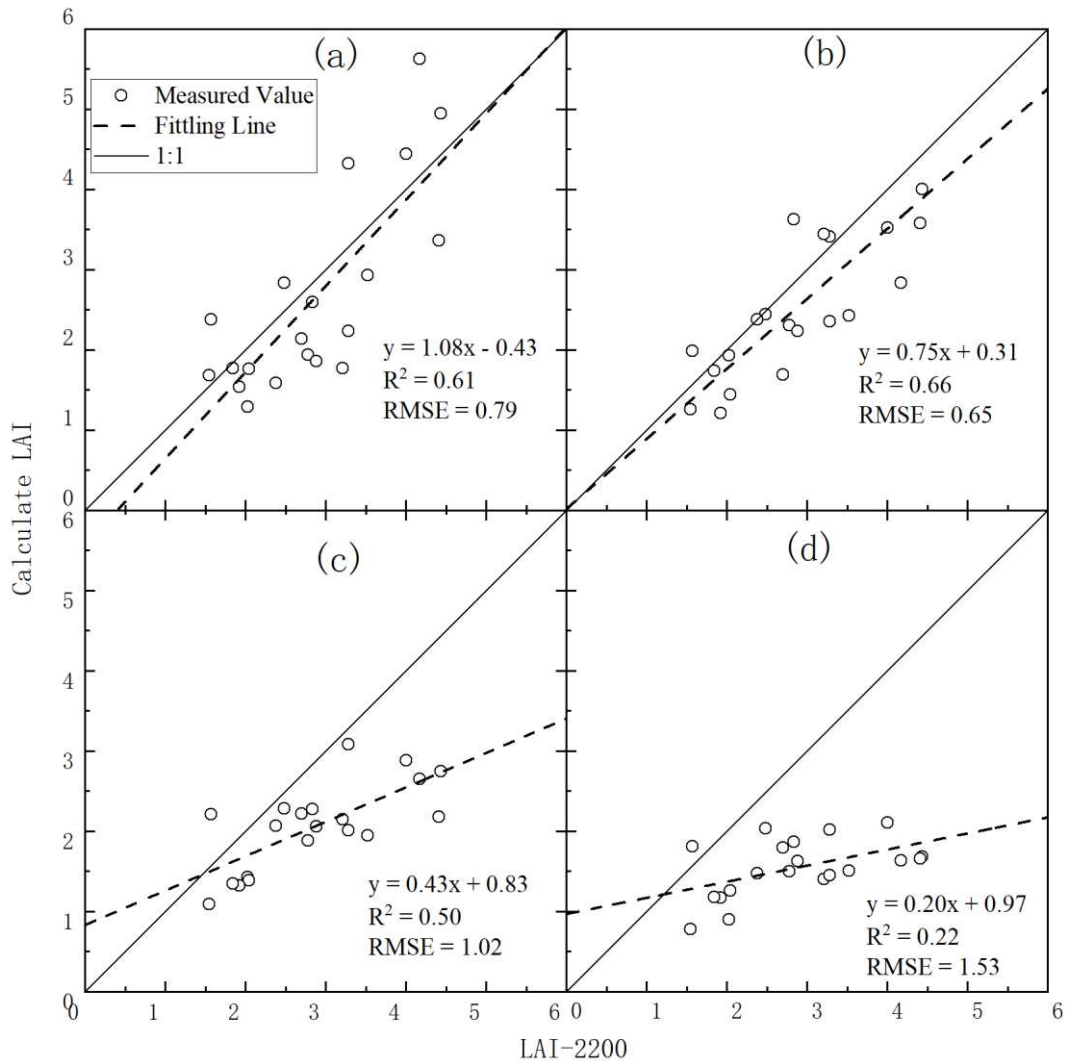


Fig. 8. Comparison between effective LAI (LAI<sub>e</sub>) estimated from smartphone images and LAI measured

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with LAI-2200: (a–d) correspond to smartphone tilt angles of 0°, 30°, 45°, and 60°, respectively.

Figure 8 presents the performance of the proposed algorithm for canopy observations acquired at different tilt angles. Comparing Fig. 8(a–d) shows that the algorithm provides relatively accurate LAI estimates when the tilt angle is 0° or 30°. In particular, the 30° configuration yields the smallest discrepancy among the four angles, with an RMSE of 0.65. Its coefficient of determination ( $R^2 = 0.66$ ) is comparable to that obtained in the vertically upward configuration ( $R^2 = 0.61$ ). Under the vertically upward configuration, the estimated LAIe agrees reasonably well with LAI-2200, and the fitted slope is the closest to 1; however, compared with the 30° tilt, the LAIe estimates are more dispersed. The regression line further highlights the superior performance at 30°: the slope (0.75) is closer to 1 and the intercept (0.31) is closest to 0 among all configurations. Consequently, the regression line in Fig. 8(b) lies close to the 1:1 line, indicating a smaller difference between the 30° tilt estimates and the LAI-2200 reference.

By contrast, the other three tilt angles (0°, 45°, and 60°) produce markedly different LAIe results. For example, RMSE increases from 0.79 in Fig. 8(a) to 1.53 in Fig. 8(d), while  $R^2$  decreases from 0.61 in Fig. 8(a) to 0.22 in Fig. 8(d), corresponding to a 93% increase in RMSE and a 64% decrease in  $R^2$ .

Overall, both the vertically upward and 30° tilt configurations achieve relatively good accuracy in estimating LAIe. However, considering the stability of the estimates, the 30° tilt provides results that are closest to the LAI-2200 reference and are more robust to canopy structural variability. To further evaluate the algorithm's performance across vegetation types, the above results were grouped according to Table 1, and mean values were calculated for each vegetation category, as shown in Fig. 9.

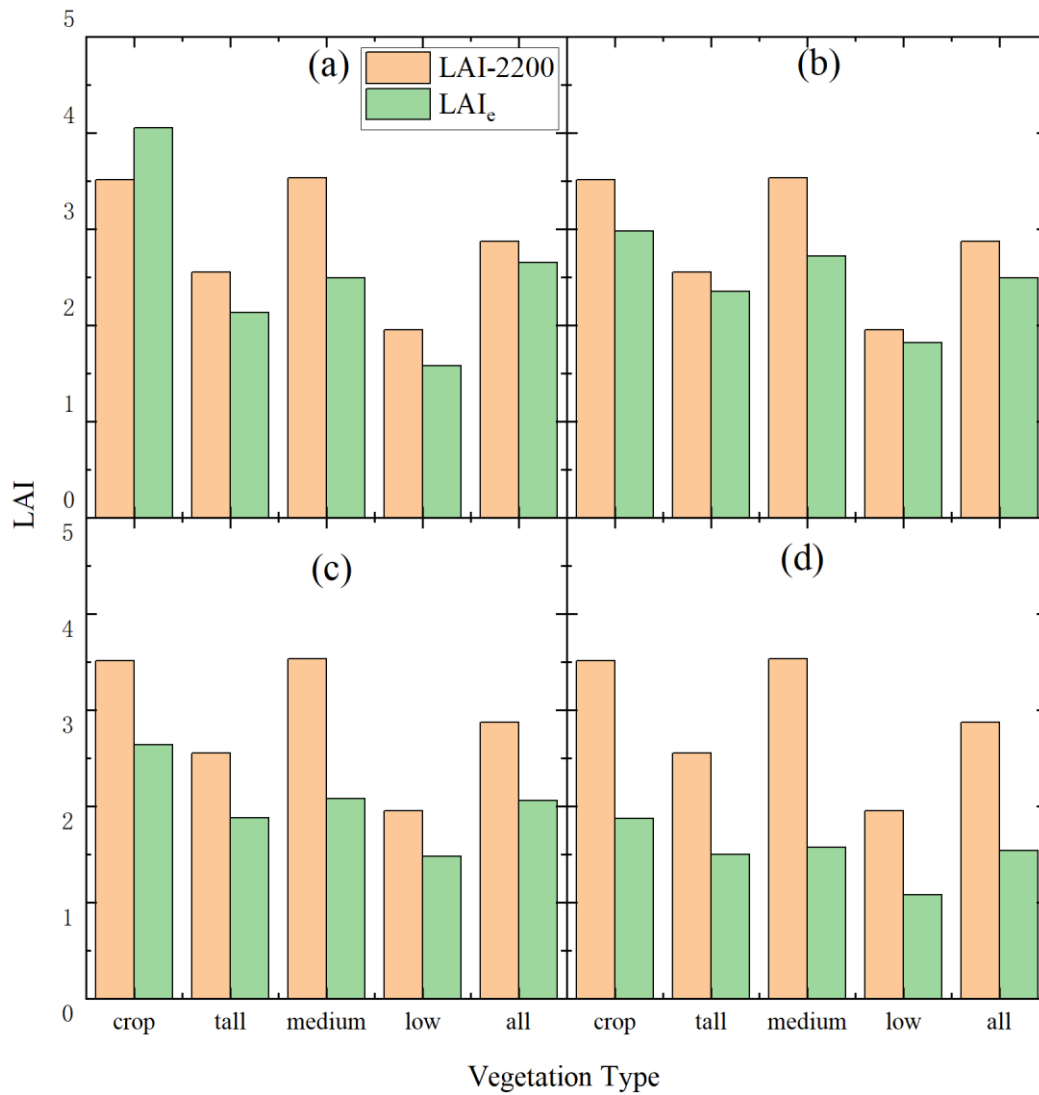


Fig. 9. Comparison of LAI<sub>e</sub> estimated by the proposed method and LAI measured by LAI-2200 across different vegetation types: (a–d) correspond to smartphone tilt angles of 0°, 30°, 45°, and 60°, respectively.

Figure 9 compares LAI<sub>e</sub> estimates from the proposed method with LAI-2200 measurements across different vegetation types. When images were acquired at a 0° tilt, the overall difference between the proposed method and LAI-2200 was relatively small; however, LAI tended to be overestimated for maize, while underestimation was observed for the other vegetation types (Fig. 9a). At a 30° tilt, the discrepancy relative to LAI-2200 was slightly larger than that at 0°, yet the results were the most stable across vegetation types, showing the smallest sensitivity to vegetation type (Fig. 9b). In contrast, measurements acquired at 45° and 60° exhibited pronounced underestimation (Fig. 9c–d).

These results indicate that a 30° tilt yields accurate and stable LAI<sub>e</sub> estimates, which deviates to some extent from the simulation-based findings. As shown in Fig. 5(c–f), when canopy images are captured at different tilt angles, automatic exposure leads to varying exposure levels among images, which makes it more difficult to

distinguish the sky background from the canopy during post-processing. This issue is particularly evident in Fig. 5f: at a 60° tilt, the mean brightness within the camera FOV is the highest, increasing the likelihood of misclassification and consequently biasing gap-fraction estimates. At a 30° tilt, the smartphone camera not only achieves a wider effective VZA range but also preserves sufficient separability between canopy and sky. Together, these findings suggest that a 30° tilt is an optimal configuration for accurate LAI estimation using narrow-field-of-view smartphone cameras.

#### 4.3.2. Results for true LAI (LAI<sub>t</sub>)

During smartphone-based canopy observations, mutual occlusion among foliage elements can cause the estimated LAI<sub>e</sub> to be biased low. Therefore, LAI<sub>e</sub> was corrected using a clumping index to obtain the true LAI (LAI<sub>t</sub>). In this study, the clumping index  $\Omega$  was calculated using the finite-length averaging method (Eqs. 14–16), and LAI<sub>e</sub> was corrected accordingly to derive LAI<sub>t</sub>. The results are shown in Fig. 10.

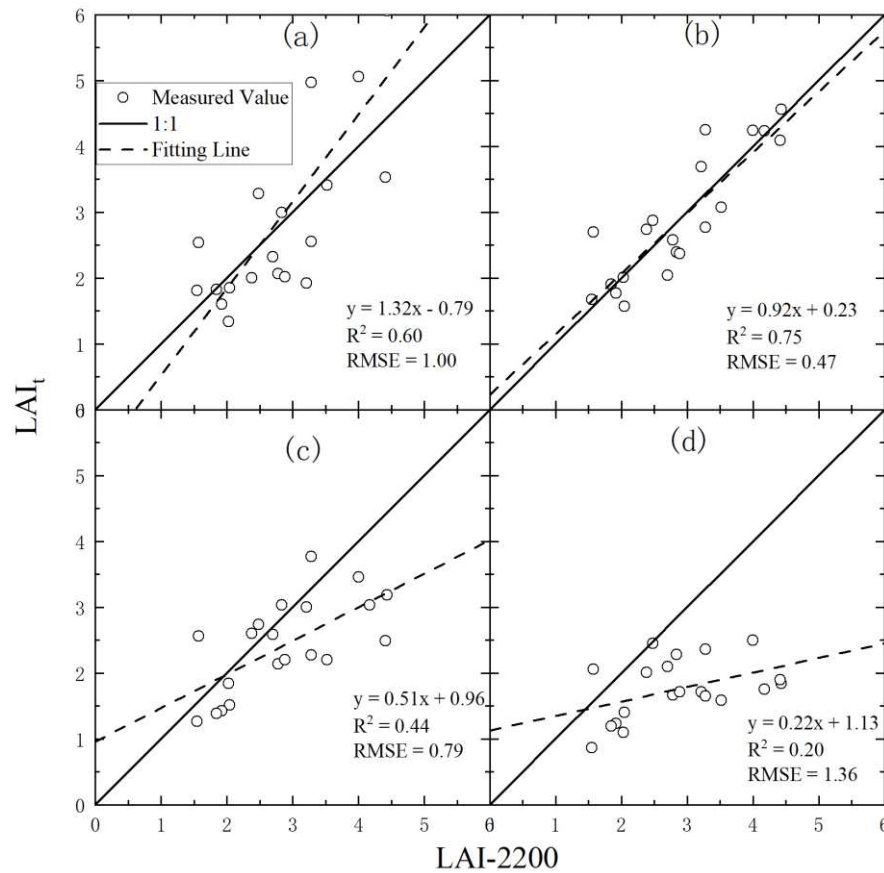


Fig. 10. Comparison between true LAI (LAI<sub>t</sub>) estimated from smartphone images and LAI measured with LAI-2200: (a–d) correspond to smartphone tilt angles of 0°, 30°, 45°, and 60°, respectively.

Figure 10 compares the LAI<sub>t</sub> estimates after clumping-index correction with LAI-2200 measurements. After

accounting for canopy clumping, the 30° tilt configuration yields LAIt values that are closest to the LAI-2200 reference. Relative to LAI-2200, this configuration achieves the smallest error after correction (RMSE = 0.47), and the coefficient of determination increases from 0.66 to 0.75. The regression results further indicate that the 30° tilt provides the best agreement: the fitted slope (0.92) is closest to 1 and the intercept (0.23) is close to 0, such that the fitted line nearly overlaps with the 1:1 line in Fig. 10(b). This suggests that, after clumping correction, LAI estimates obtained at a 30° tilt show no notable difference from the LAI-2200 measurements.

In contrast, substantial changes are observed for the other three tilt angles (0°, 45°, and 60°). For the vertically upward configuration, clumping correction increases the dispersion of LAIt estimates and leads to pronounced overestimation when  $\text{LAI} \geq 2.5$ . Although the 30° tilt produces LAIt values closer to the 1:1 line than LAIe, the 45° and 60° configurations still underestimate canopy LAI. To further examine performance across vegetation types, we grouped the results by vegetation class and summarized LAIt estimates for each tilt angle, as shown in Fig. 11.

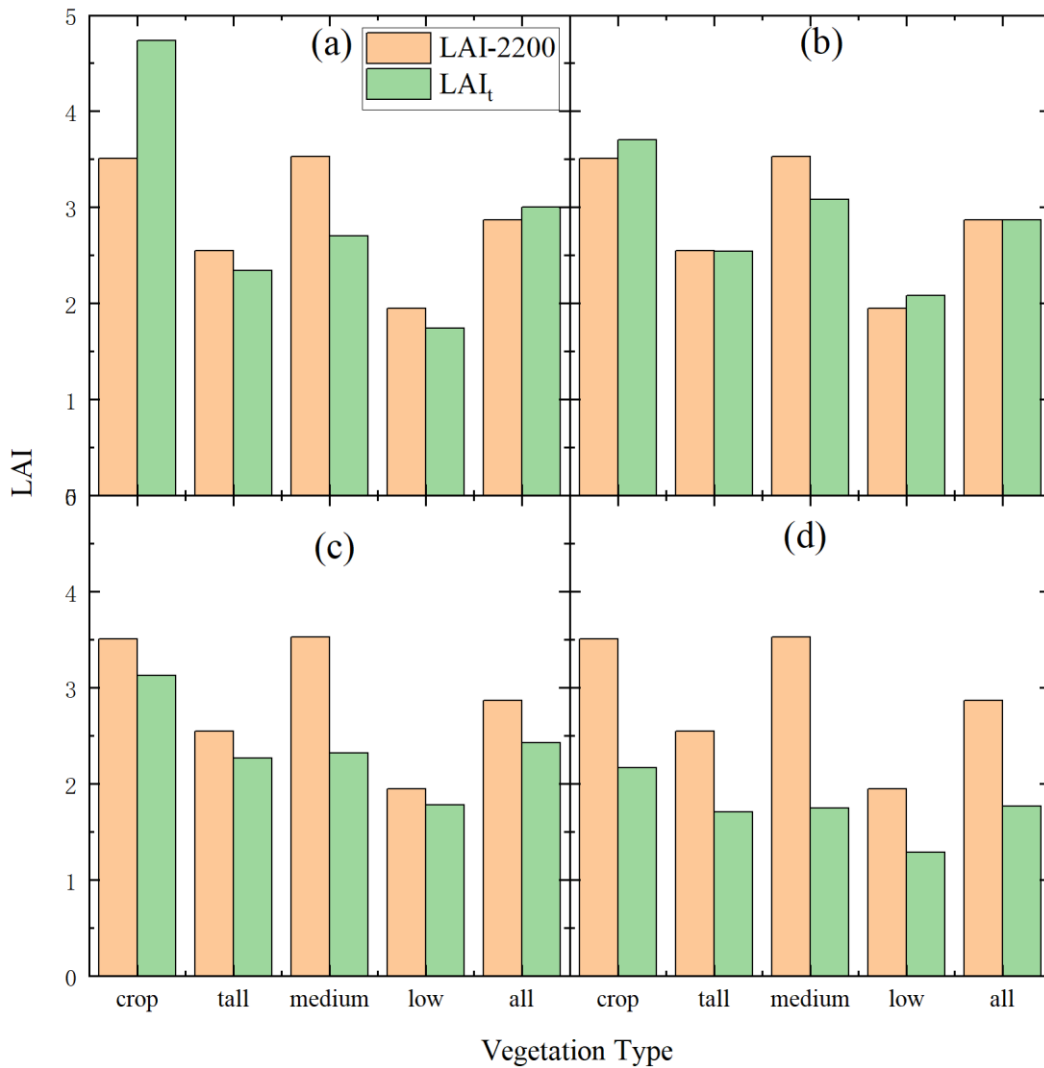


Fig. 11. Comparison of LAIt estimated by the proposed method and LAI measured by LAI-2200 across

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different vegetation types: (a–d) correspond to smartphone tilt angles of 0°, 30°, 45°, and 60°, respectively

Figure 11 compares LAIt estimates from the proposed method with LAI-2200 measurements across vegetation types. The 30° tilt configuration achieves the highest overall accuracy and shows the closest agreement with the LAI-2200 reference. Under this configuration, LAI is slightly overestimated for maize and low-stature vegetation, measurements for tall vegetation are relatively accurate, and LAI is underestimated for medium-height vegetation (Fig. 11b). In the vertically upward configuration, LAI is overestimated for maize, whereas underestimation is observed for the other vegetation types (Fig. 11a). In contrast, images acquired at tilt angles of 45° and 60° lead to severe underestimation (Fig. 11c–d). Overall, these results demonstrate that the proposed algorithm provides both stable and accurate LAIt estimates at a 30° tilt, achieving reliable performance across different canopy types.

## 5. Discussion

This study proposes a rapid, accurate, and robust LAI measurement approach based on narrow-field-of-view smartphone imagery. By discretizing the Miller integral and expanding the effective angular sampling through camera tilting, the method provides a practical option for extending smartphone applications in scientific research, such as in situ acquisition of land-surface parameters for quantitative remote sensing.

The results indicate that a 30° tilt yields the best performance. Under this configuration, LAI estimated using the discretized Miller integral, followed by clumping-index correction, produces accurate LAIt estimates. Without accounting for clumping, the proposed method achieves an RMSE of 0.65 and a correlation coefficient of 0.66 relative to LAI-2200 measurements, demonstrating that the algorithm can provide reliable LAI estimates. After applying clumping correction, the influence of canopy aggregation is substantially reduced, improving the RMSE to 0.47 and the correlation coefficient to 0.75, with the regression line approaching the 1:1 line.

### 5.1. Effects of camera parameters on the proposed algorithm

The proposed method relies on smartphone imagery to estimate canopy LAI; therefore, results may vary across smartphone models. Such variability mainly arises from differences in camera hardware and acquisition settings

First, cameras generally exhibit similar radiometric resolution in the visible spectrum. During canopy imaging, camera-intrinsic sampling and quantization may cause slight variations in the recorded grayscale values.

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However, because vegetation and sky typically show a strong contrast in the blue channel, differences attributable to radiometric resolution are unlikely to substantially affect the binary classification of canopy versus sky.

A second factor is lens distortion, which can alter the distribution of viewing zenith angles (VZAs) across the image. Due to manufacturing and assembly tolerances, real camera optics deviate from the ideal pinhole model, leading to nonlinear optical distortions between the actual image formation and the ideal projection. In general, distortion increases toward the edge of the field of view, potentially introducing larger VZA errors in peripheral image regions. (Faig, 1975; Lucchese, 2005). In the current implementation, lens distortion was not explicitly corrected. Instead, the spatial geometry was solved using an ideal pinhole projection model. Consequently, partitioning the image into VZA bins directly from the raw digital image may deviate from the true angular distribution and introduce errors. A potential improvement is to perform nonlinear lens-distortion correction (camera calibration) prior to VZA partitioning, so that the segmented VZA intervals better match the actual viewing geometry.

When acquiring canopy images, Beckschäfer et al. reported that using automatic exposure can lead to an overestimation of canopy gap fraction. (Beckschäfer et al., 2013), Some studies have also suggested that the optimal exposure settings vary with the size and number of canopy gaps. In our dataset, tilted acquisitions with automatic exposure often resulted in overexposure (Macfarlane et al., 2014). Therefore, when capturing canopy images with a smartphone, setting the exposure compensation to one stop lower (i.e.,  $-1$  EV) is recommended, as it can improve the separability between canopy and sky and thus enhance segmentation performance in subsequent processing.

## **5.2. Potential and limitations of the proposed method**

Smartphone-based approaches for measuring canopy structural parameters are conceptually similar to those using conventional digital cameras. Previous studies have demonstrated that both downward-looking (Baret et al., 2010; Liu & Pattey, 2010) and upward-looking (Fuentes et al., 2008; Ryu et al., 2012) configurations can be used to estimate LAI. The downward-looking mode is typically suited to row crops, whereas the upward-looking mode has broader applicability, ranging from crops to tall trees. The method proposed here follows an upward-looking configuration but introduces a controlled tilt relative to the zenith. Given the advantages of smartphones—such as convenient integration of multiple sensors (e.g., GPS, gyroscope, and ambient light sensors), portability (light weight and small size), and on-device computational capability—this smartphone-based solution is potentially more attractive than approaches relying on conventional digital cameras.

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The proposed method estimates canopy LAI by using multi-angle gap fractions within the camera's effective field of view as a surrogate for the gap-fraction distribution over the hemispherical domain. Although LAI retrieval has become a popular topic in smartphone-based measurements of vegetation structure, (Aquino et al., 2015; Bauer et al., 2016; Confalonieri et al., 2013; de Bei et al., 2016; Fuentes et al., 2008; Qu et al., 2017), However, unlike conventional approaches such as LAISmart and PocketLAI, which simplify the problem by assuming  $G = 0.5$ , or the shape-matching  $G(\theta)$  fitting method proposed by Qu et al., the proposed algorithm does not explicitly assume or estimate the  $G(\theta)$  function. Consequently, our method cannot retrieve the mean tilt angle (MTA) of the canopy.

### 5.3. Application potential of multi-angle digital imagery

In this study, canopy observations were acquired using a smartphone at multiple tilt angles. However, during data processing, the proposed workflow only applied Otsu thresholding for image binarization, without further exploiting the richer information contained in the images. As shown in Fig. 5(c–f), tilting the smartphone changes exposure conditions, and the increased brightness of vegetation pixels can complicate canopy–sky classification. Nevertheless, tilted images undeniably contain more detailed canopy information. Conventional processing pipelines typically use canopy images only for binary classification, which inevitably discards structural cues embedded in the original imagery. Therefore, an alternative strategy is to acquire multiple images of the same canopy from different viewing angles and reconstruct canopy three-dimensional structure using structure-from-motion (SfM) techniques.

SfM estimates 3D structure from a set of overlapping 2D images that capture parallax and viewpoint changes. By detecting and matching feature points across images, SfM can recover camera intrinsic and extrinsic parameters and subsequently reconstruct a 3D point cloud via photogrammetric triangulation. This approach can generate a textured 3D representation of the canopy, providing realistic surface information from the images. Based on such 3D canopy reconstructions, structural parameters such as LAI and MTA can potentially be derived. Therefore, SfM-based processing of multi-angle smartphone imagery offers promising potential for canopy structural measurement.

## 6. Conclusions

To address the limitation of the narrow field of view (FOV) of smartphone cameras, this study proposes an LAI measurement method that increases the effective angular sampling by tilting the smartphone. In the proposed

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workflow, multi-angle gap fractions are extracted from tilted images and LAI is estimated using a discretized Miller integral. The results demonstrate that smartphone-based measurements can provide accurate and stable estimates of canopy LAI, and that tilting the device can effectively improve LAI retrieval accuracy.

After accounting for canopy clumping, the proposed method performs best at a tilt angle of 30°, where the regression against the LAI-2200 reference approaches the 1:1 line. The performance improvement is mainly attributed to the expanded effective FOV provided by tilting and to the fact that, at a 30° tilt, the sampled multi-angle gap fractions better represent hemispherical canopy structural information, enabling more accurate LAI estimation. Nevertheless, the method remains sensitive to external illumination conditions and camera exposure settings. To further enhance robustness, future work will explicitly consider these factors. In addition, the current workflow does not fully exploit the detailed structural information contained in multi-angle imagery; future studies will investigate how to leverage such information to broaden the applicability of the method and improve performance across a wider range of canopy conditions.

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## 8. Data availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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