Extracting Leaf Area Index Using Viewing Geometry Effects—A New Perspective on High-Resolution Unmanned Aerial System Photography

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Abstract

Extraction of leaf area index (LAI) is an important prerequisite in numerous studies related to plant ecology, physiology and breeding. LAI is indicative for the performance of a plant canopy and of its potential for growth and yield. In this study, a novel method to estimate LAI based on RGB images taken by an unmanned aerial system (UAS) is introduced. Soybean was taken as the model crop of investigation. The method integrates viewing geometry information in an approach related to gap fraction theory. A 3-D simulation of virtual canopies helped developing and verifying the underlying model. In addition, the method includes techniques to extract plot based data from individual oblique images using image projection, as well as image segmentation applying an active learning approach. Data from a soybean field experiment were used to validate the method. The thereby measured LAI prediction accuracy was comparable with the one of a gap fraction-based handheld device (R^2 of 0.92, RMSE of $0.42 \text{ m}^2\text{m}^{-2}$) and correlated well with destructive LAI measurements (R^2 of 0.89, RMSE of $0.41 \text{ m}^2\text{m}^{-2}$). These results indicate that, if respecting the range ($\text{LAI} \leq 3$) the method was tested for, extracting LAI from UAS derived RGB images using viewing geometry information represents a valid alternative to destructive and optical handheld device LAI measurements in soybean. Thereby, we open the door for automated, high-throughput assessment of LAI in plant and crop science.

Keywords: LAI, gap fraction, high-throughput phenotyping, soybean, active learning, segmentation

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Highlights

- Novel, robust self-calibrating leaf area index estimation based on RGB photography
- Combining viewing geometry effects with gap fraction theory
- Oblique image based data extraction, avoiding orthorectification and orthomosaic blending
- Image segmentation enhanced by an active learning component

1. Introduction

Unmanned aerial systems (UASs) are increasingly used for high resolution monitoring purposes (Colomina and Molina, 2014). Particularly in agriculture, it is assumed that large collections of data with high spatial and temporal resolution will facilitate basic research, but also industry-related tasks such as innovative breeding, crop protection, or fertilizer monitoring programs (Walter et al., 2017). Moreover, high-throughput, automated phenotyping approaches for traits such as leaf area index (LAI), canopy cover (CC) or plant height are urgently needed to facilitate the assessment of large breeding populations or precision agriculture approaches (Fiorani and Schurr, 2013; Walter et al., 2015).

Especially plant growth is a trait of enduring interest—the ability to grow is a central driver of yield in crops (White et al., 2016) and an important parameter in assessments in plant ecology (Asner et al., 2003; Moser et al., 2007; Clark et al., 2008). For soybean, growth of canopies is an essential part of the vegetative stage which directly affects yield: Board and Harville (1992) and Malone et al. (2002) could show that higher yield is related to a larger LAI in later growth stages. In addition, Shibles and Weber (1965) showed that larger LAI caused a higher light interception and hence a higher photosynthetic rate. LAI and canopy structure, both essential elements of growth, depend on environment and management practice, but also on genotype (Board and Harville 1992). It is therefore reasonable to assume that breeding for optimized LAI and canopy structure has the potential to increase and stabilize yield. In plant breeding, it is widespread practice to do visual vigor ratings in early growth stages, which supports this hypothesis. Nevertheless, quantitative methods to monitor canopies and measure their growth are to our knowledge rarely used in phenotyping, even though some of the underlying theory was developed decades ago, for example by Monsi and Saeki (1953).

The description of canopy structure includes characteristics such as LAI, plant height, leaf inclination angles and leaf area density (Monsi and Saeki, 1953, 2005; Anderson, 1966; Nilson, 1971; Campbell

and Norman, 1990). Direct methods to extract LAI are based on the technique of harvesting and measuring the leaf area or leaf dry biomass (Bréda, 2003). In remote sensing, techniques to extract canopy structure information are mainly related to optical reflectance and transmission measurements. Calibrated passive transmission measurements combined with gap fraction theory allow to estimate LAI (Monsi and Saeki 1953, 2005), and are implemented in commercially available products, for example the LAI-2200 from LI-COR Biosciences (Welles and Norman, 1991) or the DEMON instrument from CSIRO (Bréda, 2003), while Campos-Taberner et al. (2016) used affordable smartphone hardware to achieve the same goal. Segmentation approaches aim to classify calibrated or uncalibrated reflectance images in plant and soil, hence gaining a CC value related to LAI (e.g. Guo et al. 2013). Another approach to estimate LAI is based on passive multispectral reflectance measurements, processed with band arithmetic calculations and regression models (e.g. Brown et al. 2000; Colombo et al. 2003; Haboudane et al. 2004; Hunt et al. 2010; Gonsamo and Pellikka 2012; Reichenau et al. 2016) or inverted radiative transfer models (e.g. Ross 1981; Myneni et al. 2002; Schlerf and Atzberger 2006). Hybrid methods combine regression and radiative transfer models (Verrelst et al., 2015). Thermal sensing (Neinavaz et al., 2016) and radar (Jin et al., 2017) represent additional sources for LAI estimations. Nevertheless, while band arithmetic approaches based on all these sources have a restricted power due to the required empirical calibration, radiative transfer models are not widely in use either, most probably due to their complexity and computation power requirements (Jacquemoud et al., 2000; Verrelst et al., 2015). Promising new approaches adapt machine learning techniques to overcome these restrictions (Yuan et al., 2017), and allow to combine different sensing sources like spectral sensing and radar (Jin et al., 2017) or RGB photography, spectral sensing and thermal sensing (Maimaitijiang et al., 2017; Houborg and McCabe, 2018). The vast amount of spectral and other data may even call for dimensionality reduction techniques to estimate biophysical variables (Rivera-Caicedo et al., 2017). Finally, gap fraction theory is also applicable to active reflectance measurements, for example made with an air-borne laser-scanning system (Morsdorf et al., 2006).

To our knowledge, applying gap fraction theory to visual images is yet uncommon: Classification techniques segmenting reflectance measurements in plants and soil are mainly applied to nadir images, with some rare, but promising exceptions (e.g. Liu et al. 2013). In remote sensing, much effort has been put into algorithms compensating for distorted images by ortho-rectification (Luan et al., 2008). Nevertheless, while providing more abundant information for geospatial analyses, the process of ortho-

rectification presumably reduces information content for canopy structure analysis, as recently shown by Duan et al. (2017) and Roosjen et al. (2018).

As a consequence, this study focuses on enhancing measurements with viewing geometry information by combining uncalibrated reflectance measurements (by the use of RGB photography), a segmentation approach, and gap fraction theory. The assumption is that including viewing geometry effects (off-nadir views) in RGB photography allows to link canopy structure and remotely sensed visible plant area.

Using the described techniques, the following hypotheses are tested in this study: (1) The projected visible plant area on an RGB image is related to plant traits such as LAI and canopy structure, but also related to other viewing geometry effects such as row interference and leaf overlap. (2) If correcting for the two effects—row interference and leaf overlap—remaining viewing geometry effects are sufficiently related to canopy structure to allow a reliable LAI estimation.

2. Materials and Methods

First (Part I), a model was developed describing viewing geometry effects on segmented images using canopy cover (CC) and lateral cover (LC) values, the “CC/LC viewing geometry model” (Section 2.1). This model was then enriched with gap fraction theory, resulting in a combined model performing LAI estimation based on viewing geometry effects, the “gap fraction viewing geometry model” (Section 2.2). In Part II, 3-D simulations were used to verify the models (Section 2.4f.), while in Part III, field experiment data were collected and used to validate them (Section 2.6ff.).

Part I: Canopy Structure Estimation Based on Viewing Geometry Effects

To precisely describe viewing geometry effects on visible plant area, one has to define a suitable coordinate system. The viewpoint of an observer in relation to the observed object can be defined in an celestial coordinate system, the horizon system (Encyclopaedia Britannica, 2017). In this celestial system, the position of an object is specified by the zenith angle θ (the diverging angle to a zenith position) and an azimuth angle δ (the angle clockwise around the horizon from a pre-defined direction) (Figure 1).

2.1. The CC/LC Viewing Geometry Model

As a simplification, one may assume a single plant leaf to be perfectly planar, to have a certain inclination angle θ_L , to have no preferred azimuth orientation, and a leaf area L (defined as the one-

Figure 1: Viewing geometry parameters in the horizon coordinate system: The zenith angle θ and the azimuth angle δ

109 sided leaf area). The leaf area L can then be expressed as leaf area projected to a horizontal plane h ,
 110 $L_{proj \rightarrow h}$, and as leaf area projected to a vertical plane v , $L_{proj \rightarrow v}$. The relation between L , $L_{proj \rightarrow h}$, $L_{proj \rightarrow v}$
 111 and θ_L is Euclidean geometry:

$$L = \sqrt{L_{proj \rightarrow h}^2 + L_{proj \rightarrow v}^2},$$

$$\tan(\theta_L) = \frac{L_{proj \rightarrow v}}{L_{proj \rightarrow h}}. \quad (1)$$

112 If estimating LAI (defined as the proportion of one-sided leaf area per ground surface area, Watson
 113 1947), one is interested in the leaf area of a whole canopy rather than the leaf area of a single leaf. For
 114 soybean, leaf inclination angles are known to change significantly in time, but to be synchronized in
 115 space (e.g. Oosterhuis et al. 1985; Rosa et al. 1991; Friedli et al. 2016). If assuming all leaves to have
 116 the same inclination angle θ_L at any point in time, the canopy leaf area can be expressed as the sum of
 117 single leaf areas,

$$C = \sum_i L_i = \sum_i \sqrt{L_{i,proj \rightarrow h}^2 + L_{i,proj \rightarrow v}^2}, \quad (2)$$

118 where C denotes the canopy leaf area and L_i the leaf area of the i -th leaf. One can approximate Equation
 119 2 by replacing the sum of projected leaf areas of single leaves $L_{i,proj \rightarrow h}$ and $L_{i,proj \rightarrow v}$ by the canopy leaf
 120 area projected to a horizontal plane $C_{proj \rightarrow h}$, and by the canopy leaf area projected to a vertical plane
 121 $C_{proj \rightarrow v}$, respectively. Nevertheless, this approximation will lead to an underestimation of the canopy
 122 leaf area C due to overlapping effects in the horizontal and vertical plane and is therefore consequently
 123 called apparent canopy leaf area C_{app} ,

$$C \geq C_{app} = \sqrt{C_{proj \rightarrow h}^2 + C_{proj \rightarrow v}^2}. \quad (3)$$

Images show a canopy from a specific viewpoint and are therefore related to a certain viewing geometry, determined by a certain zenith and azimuth angle. The probability of a ray with a given zenith angle θ entering the canopy while encountering zero intersection with leaves is commonly called the gap fraction $P_0(\theta)$ (Nilson, 1971; Campbell and Norman, 1990). In segmented images which differentiate between plants and soil, $P_0(\theta)$ relates to the fraction of pixels classified as soil. The fraction of pixels classified as plants $P_p(\theta)$ complements $P_0(\theta)$ to one. $P_p(\theta)$ may be expressed as the ratio between projected canopy leaf area as function of the zenith angle, $C_{proj \rightarrow h}(\theta)$, and total projection area $A_h(\theta)$,

$$P_p(\theta) = 1 - P_0(\theta) = \frac{C_{proj \rightarrow h}(\theta)}{A_h(\theta)}. \quad (4)$$

A special case of $P_p(\theta)$ is if all pixel are recorded in nadir view: If the zenith angle is zero, P_p corresponds to the canopy leaf area projected to a horizontal plane in nadir view, divided by the total area of this horizontal plane. This ratio corresponds to the definition of CC (e.g. Duan et al. 2017),

$$P_p(\theta) = \text{CC} \quad | \quad \text{if } \theta = 0^\circ. \quad (5)$$

If the zenith angle increases now from zero towards 90° , P_p follows with $2/\pi \tan(\theta)$ of the vertically projected leaf area, $C_{proj \rightarrow v}$, divided by the total area of the horizontal plane, A_h . In the following, this ratio is called lateral cover (LC),

$$\text{LC} = \frac{C_{proj \rightarrow v}}{A_h}. \quad (6)$$

$P_p(\theta)$ can now be expressed as

$$P_p(\theta) = \text{CC} + \frac{2}{\pi} \tan \theta \text{ LC}. \quad (7)$$

Field crops are usually sown in rows. Therefore, it is reasonable to expect a row effect with increasing LC due to increasing overlap of single plants. This effect may be modeled in form of an interference pattern depending on the viewing geometry azimuth angle δ and the row azimuth angle δ_r . One form of interference pattern are overlapping sinus or co-sinus waves with varying frequencies and amplitudes (Figure 2). Using two co-sinus waveforms with frequency 2π and 4π , Equation 7 can be extended by row effects,

$$P_p(\theta, \delta) = \text{CC} + \frac{2}{\pi} \tan \theta \left(\text{LC} + \sum_{i=1}^2 c_i \cos(2i(\delta - \delta_r)) \right), \quad (8)$$

Figure 2: Interference pattern (solid line) consisting of two overlapping co-sinus waveforms with frequency 2π (dashed line) and 4π (dotted line)

where c_1 and c_2 are parameters related to the intensity of the row interference effect.

Fitting this final CC/LC viewing geometry model (Equation 8) to experimental $P_p(\theta, \delta)$ data will yield estimations for CC and LC, assuming planar leaves with uniform inclination angles and random azimuth orientation.

Nevertheless, overlapping effects will restrict the ranges of CC and LC: While CC values range between zero and one, LC values will depend on CC values following

$$CC + LC \leq 1, \quad (9)$$

as $P_p(\theta, \delta)$ can not exceed one. As a consequence, the viewing geometry independent apparent leaf area fraction ($P_{p,app}$) calculated from LC and CC values according to Equation 3 will range between zero and one:

$$P_{p,app} = \sqrt{CC^2 + LC^2} \leq 1. \quad (10)$$

Estimations based on CC and LC values therefore need further processing to include underestimation effects (Section 2.2). Even though, if empirical LAI values for a sub sample are available, a first LAI estimation based on CC values is possible: one can then perform a regression in the form

$$LAI_{CC} = CC \times a, \quad (11)$$

where a represents the slope parameter and LAI_{CC} the LAI estimation based on CC.

2.2. The Gap Fraction Viewing Geometry Model

A common way to account for LAI underestimation effects in canopies is the use of the gap fraction theory. Gap fraction theory was developed based on measurements of radiation transmission through

161 a canopy. Monsi and Saeki (1953) suggested that the relative light intensity in a canopy decreases
 162 exponentially with increasing LAI,

$$I = I_0 \exp(-K \text{ LAI}), \quad (12)$$

163 where I is the light intensity at the bottom of the canopy, I_0 is the light intensity above the canopy, and
 164 K is the extinction coefficient, defined as the average projected area of canopy elements if projected to
 165 a horizontal plane (Campbell and Norman, 1990). If using fraction values, I may be replaced with the
 166 gap fraction P_0 and I_0 with one.

167 As Anderson (1966) mentioned, K is rarely a constant factor, but rather dependent on the dis-
 168 tribution of leaf inclination angles (θ_L) and leaf azimuth angles (δ_L), and on the viewing geometry
 169 (θ, δ). Assuming plants have a vertical symmetry axis, the leaf azimuth angle distribution becomes
 170 uniform and δ_L can therefore be neglected, likewise the azimuth angle δ . Subsequently, following Nil-
 171 son (1971) and Campbell and Norman (1990), the gap fraction can be defined in dependence to the
 172 viewing geometry zenith angle θ as

$$P_0(\theta) = \exp(-K(\theta) \text{ LAI}_\theta), \quad (13)$$

173 where LAI_θ is the LAI estimation based on viewing geometry zenith angle effects, presuming a canopy
 174 consisting of a very large number of statistically independent horizontal layers (Nilson, 1971). For a
 175 constant leaf inclination, Campbell and Norman (1990) proposed $K(\theta)$ to be only dependent on the
 176 leaf inclination angle θ_L ,

$$K = \cos \theta_L. \quad (14)$$

177 θ_L may be approximated with CC and LC values,

$$K \approx \cos \left(\left| \tan^{-1} \frac{\text{LC}}{\text{CC}} \right| \right). \quad (15)$$

178 As a consequence, P_0 is not dependent on the viewing geometry zenith angle anymore:

$$P_0 \approx \exp \left(-\cos \left(\left| \tan^{-1} \frac{\text{LC}}{\text{CC}} \right| \right) \text{ LAI}_\theta \right). \quad (16)$$

179 This viewing geometry independent gap fraction P_0 will complement $P_{p,\text{app}}$ (Equation 10) to one,

$$P_0 \approx 1 - P_{p,\text{app}} = 1 - \sqrt{\text{CC}^2 + \text{LC}^2}. \quad (17)$$

Equation 16 and 17 form a simple system of linear equations which can be solved to yield LAI_θ estimations,

$$LAI_\theta \approx \ln \left(\frac{\sqrt{LC^2 CC^{-2} + 1}}{1 - \sqrt{CC^2 + LC^2}} \right). \quad (18)$$

One may thereby conclude that if CC and LC values for a canopy are known, the gap fraction viewing geometry model (Equation 18) will yield LAI estimations, provided that the assumption of planar leaves with uniform inclination angles is reasonable.

2.3. Model Fitting and Validation

Fitting of the CC/LC viewing geometry model to both simulation and field data was done using the statistical programming language R (R Core Team, 2017) and the package nls2 for non-linear regressions (Grothendieck, 2013). The algorithm was set to Gauss-Newton, starting values for CC and LC were 0.5, for c_1 0.1 and for c_2 0.05.

To validate the CC/LC viewing geometry model and assess its prediction error, a cross-validation was performed using the leave-one-out technique (Hastie et al., 2009). For each set of plot-based data, one validation run was done, leading to 72 independent cross-validation runs per campaign. A mean root mean square error (RMSE) of prediction based on cross validation (RMSECV) was subsequently calculated per campaign,

$$RMSECV = \sqrt{\frac{\sum_{i=1}^k \frac{\sum_{j=1}^n (y_{ij} - \hat{y}_{ij})^2}{n}}{k}}, \quad (19)$$

where k is the number of plot based data sets, i one specific plot based data set, n the number of observations in a data set, j a specific observation, y_{ij} the observed value in this observation, and $\hat{y}_{ij}$ the predicted value.

Part II: Simulation of Virtual Canopies

2.4. 3-D Simulation Construction and Image Rendering

To simulate viewing geometry effects, images of virtual canopies were produced using the open-source 3-D computer graphics software Blender (Blender Online Community, 2017). A virtual camera was positioned 30 m above a group of simulated plants, for its part placed on a plane simulating the soil. Plant placeholders were grouped in rows with 0.125 m row spacing. Spacing between plants was

set to a random value between 0 and 0.15 m. The final plot size of this virtual canopy was 1 x 6 m and correspond to the plot size used in the field experiment.

Camera parameters in Blender were imitating the camera used for the field experiment, a Sony DX100 II (focal length 10.4 mm, vertical sensor size 13.2 mm, vertical resolution 5472 pixel, ratio 4:3). Sunlight was simulated using a "sun light source" with default orientation settings (X: 37.3°, Y: 3.2°, Z: 107.0°, Euler rotation) and a ray shadow configuration with default settings (samples: 15, soft size: 15). The camera was sequentially moved to 81 predefined positions (Figure 3a) using a custom-written Python 3.5 script (Python Software Foundation, <https://www.python.org/>). At each position, the scene was rendered and the resulting image saved in a dedicated TIFF file (Figure 3b-f).

Two different simulation objects were used as plant placeholder: A simple cylinder (Figure 3f), and a soybean plant growth simulation developed by the group of crop science, ETH Zürich (personal communication with A. Walter and H. Dietz, ETH Zürich. Software licensed under Creative Commons Attribution-Noncommercial-Sharealike 3.0 Unported License) (Figure 3g). The simple cylinder had a constant diameter of 0.1 m and varying heights of 0.0 to 0.3 m in steps of 0.05 m. The soybean plant growth simulation was based on climate chamber data with fixed light intensity and allowed to vary days after sowing (DAS) from 24 to 40.

2.5. Extraction of Projected Visible Plant Area Using an Arithmetic Index

Rendered images were segmented into plant and soil based on chromatic coordinates,

$$r = R/(R+G+B), \quad g = G/(R+G+B), \quad b = B/(R+G+B), \quad (20)$$

were R , G and B are pixel values of the RGB color space and r , g and b corresponding chromatic coordinates (Woebbecke et al., 1995). A preliminary calculation of Excess Green (ExG) and Excess Red (ExR) index was followed by subtracting the former from the later, finally gathering the ExG-ExR index (Meyer and Neto, 2008),

$$\begin{aligned} \text{ExG} &= 2g - r - b, \\ \text{ExR} &= 1.4r - b, \\ \text{ExG-ExR} &= \text{ExG} - \text{ExR}. \end{aligned} \quad (21)$$

Pixels with ExG-ExR values greater than zero were assumed to be plant related parts, pixels with values equal or lower than zero were assumed to show soil. For each image, pixels corresponding to a plot

area of 0.8 x 1.6 m were extracted, and the fraction of plant pixels (P_p) calculated as the ratio between pixels classified as plants and the total number of pixels.

Part III: Field Experiment

2.6. Experimental Design

The field experiment was located at the ETH plant research station Eschikon-Lindau, Switzerland (47.449°N, 8.682°E, 520 m.a.s.l.). Soil type was a skeleton rich Cambisol with 21 % clay, 21 % silt and 3.5 % organic matter and a pH of 6.7. Twenty-one Soybean cultivars (*Glycine max* (L.) MERR.) were grown in field plots of 1 x 6 m in a randomized block design with three replications (Figure 4a). One part of each plot was used for destructive harvesting methods (1 x 3 m), the other part remained untouched for repeated remote sensing. The cultivar selection included 18 releases from Agroscope / Delley Samen und Pflanzen AG, Switzerland (Amarok, Aveline, Bagera, Coraline, Falbala, Galice, Gallec, Idefix, Obélix, Opaline, Paradis, Protéix, Pollux, Protibus, Tequila, Tiguan, Tourmaline, and Toutatis), two releases from Saatbau Linz, Austria (Lissabon and Merlin) and one release from Agriculture Canada, Central Experimental Farm (CEF), Canada (Maple Arrow). The selected genotypes depict mostly indeterminate but also semi-determinate and intermediate growth habits. All cultivars were repeated at least three times. As spatial check, the cultivar Gallec was repeated nine times, and the cultivar Opaline six times, which led to a total of 72 plots.

The preceding crop was winter wheat followed by a cover crop mixture (50 % *Trifolium alexandrinum* L. (Egyptian clover), 30 % *Trifolium resupinatum* L. (Persian clover), 20 % *Phacelia tanacetifolia* BENTH.). For P and K fertilization, 45 kg ha⁻¹ triple superphosphate (46 % P₂O₅) and 60 kg ha⁻¹ Patentkali (60 % K₂O) were applied four days prior to plowing.

Table 1: Flight campaign dates, corresponding days after sowing (DAS), and accompanying ground validation leaf area index (LAI) measurements. Ground validation measurements consisted of LAI measured with a LI-COR 2200 device (LAI_{LI-COR}), planimetric LAI (LAI_{true}) and gravimetric LAI (LAI_{grav})

Date	DAS	Flight	LAI _{LI-COR}	LAI _{true}	LAI _{grav}
2017/06/16	65	x (one day earlier)	x	x (72 plots)	x
2017/06/19	68	x	x		
2017/06/21	70	x	x		
2017/06/23	72	x	x		
2017/06/26	75	x	x	x (28 plots)	x

Figure 3: Virtual canopy simulation overview. 3-D viewport of the Blender software showing the camera locations (black pyramids) and plants (green cylinders) and soil (orange plane) placeholders (a), plant placeholders rendered from four different viewing angles (b-e, left) and corresponding segmented and masked images (b-e, right), plant placeholders with varying cylinder heights (f) and the soybean plant growth simulation in a 3-D view (g, left) and in a horizontal (g, middle) and vertical (g, right) projection

Figure 4: Experimental design (a) with plots (white boxes) and ground control points (crosses). Ground control point measurements with differential positions system equipment (b)

Sowing took place on April 12, 2017, one and a half month after plowing and two days after soil bed preparation with a rotary harrow. Soybeans were sown using a row seeding machine with 0.125 m spacing between rows. Seeds were inoculated shortly before sowing using HISTICK Soy (BASF, Ludwigshafen am Rhein, Germany) with an approximate concentration of 8 g kg⁻¹. Actual germination rates in plots varied between 22 and 53 plants m⁻² while the target sowing density was 40 plants m⁻².

For weed control, one pre-emergence treatment containing Dual Gold (active ingredient (a.i.) S-Metolachlor, Syngenta, Basel, Switzerland) and Molipan Pro (a.i. Linuron, Syngenta, Basel, Switzerland) was applied on April 13 and one top dressing of Bolero LG (a.i. Imazamox, BASF, Ludwigshafen am Rhein, Germany) and Fusilade Max (a.i. Fluazifop-P-butyl, Syngenta, Basel, Switzerland) was applied on June 1. Snail and slug pellets were spread on April 18 and May 19. No other plant protection measures were needed. BBCH growth stages (Meier, 2001) were between BBCH 10 (leaf development) and 22 (formation of side shoots) during measurements.

2.7. Ground Validation Measurements

LAI was determined using three techniques: (1) Non-destructive measurements with a LI-COR LAI-2200 Plant Canopy Analyzer (LI-COR Biosciences, Lincoln, U.S.A.), (2) destructive sampling followed by a planimetric approach, and (3) destructive sampling followed by a gravimetric approach. Measurement dates were synchronized with the five flight campaign dates (Table 1).

LAI-2200 device measurements were performed using the 270° view cap to block the operator from the view, and placing the sensor at nine different positions in between plant rows. Above-canopy reference measurements were made for each plot shortly before and after the measurements below canopy. Measurements were done between 2 and 4 p.m. (local time, GMT+2). Whenever possible, measurements were taken under overcast sky. Nevertheless, this was not always possible: On 2017-06-19 and 2017-06-23, the sky was completely cloudless, while on 2017-06-21, the first 40 measurements were made under sunshine, while the rest was taken under cloudy conditions. If measurements had to be made under sunny conditions, care was taken that the sensor was not exposed to direct sunlight (LI-COR, 2012). Measurements were processed in the software FV2200 v.2.1.1 provided by LI-COR using the standard LAI-2000 model and all five ring measurements.

For destructive sampling methods, five plants per plot were cut, fully unfolded leaves were removed, and photographed on a blue screen background. Images of leaves were then segmented using a custom written MatLab script (The Mathworks, Natick, U.S.A.) based on differences in the blue and red band.

Subsequently, LAI_{true} was calculated by multiplying the average leaf area per plant with the manually determined germination rate per square meter (Jonckheere et al., 2004).

In addition, sampled leaves were dried in an oven at 60 °C for 48 hours and then weighted. By calculating a linear regression between leaf weight and LAI_{true} , the LAI based on gravimetric measurements (LAI_{grav}) was calculated (Daughtry, 1990; Liebisch et al., 2015). LAI_{grav} measurements were performed at two points in time for all plots. In contrast, LAI_{true} measurements for the first campaign included all plots (72), but only one repetition out of three plus four spatial checks (28 plots) for the last campaign (Table 1). Error estimations for the planimetric LAI measurements and the gravimetric LAI measurements were made based on literature and own preliminary studies.

2.8. Flight Campaigns

In total, five flight campaigns were performed (Table 1), all of them between 1 and 3 p.m. (local time, GMT+2). A GreenCopter Imager-Quadro DualCam (RUCON Engineering, Großschwabhausen, Germany) based on a Mikrokopter setup (HiSystems GmbH, Moormerland, Germany) served as UAS. The UAS was operated in autonomous flight mode using the software Mikrokopter tool 2.14e (HiSystems GmbH, Moormerland, Germany). Flight height was 30 m over ground, and horizontal speed 3 m s⁻¹. The camera trigger sequence and flight lane spacing were chosen to result in an image overlap of >95 % for both sensor axis.

A Sony RX100 II (DSC-RX100M2, Sony Corporation, Tokio, Japan) was used as RGB sensor. The RX100 II was operated at full resolution of 5472 x 3648 pixel, while focal length was set to 10.4 mm. These settings in combination with the flight height resulted in a theoretical instantaneous field of view of 0.007 m. Fixing the shutter speed to 1/1000 s ensured that the camera movement in relation to the ground was less than 0.003 m during integration. Focus was set to infinity, and ISO to 125. The aperture was manually adjusted before each flight to either f/4.0 or f/4.5, depending on lighting conditions. All flights were performed under nearly-clear to clear sky conditions.

Four ground control points (GCPs) were defined at the corner of the experimental design (20 x 36 m, Figure 4a). The longer sides of the design were further divided in three equal parts using four additional GCPs. This resulted in a spacing of 12 x 20 m between GCPs. The position of GCPs was measured using differential global position system equipment (Trimble TSC3 Controller & Trimble R7 GNSS, Trimble Ltd., Sunnyvale, U.S.A., Figure 4b). Position measurements could all be performed with a root mean square error lower than 0.019 m (horizontally and vertically). Frequent mowing or clipping

of the vegetation in the surrounding area ensured that GCPs were always visible for image acquisition in the investigated range of growth stages.

2.9. Indirect Camera Position and Orientation Estimation

To apply the viewing geometry models described in this paper, the sensor orientation and position needs to be known. Therefore, images from flight campaigns were processed using the Structure-from-Motion-based (SfM) software Agisoft PhotoScan Professional 1.3.2 (Agisoft LLC, St. Petersburg, Russia). The coordinate reference system was set to EPSG:2056 (CH1903+ LV95). Workflow steps and parameter settings were identical to the one used in Roth and Streit (2018). In brief, images were imported, GCPs manually marked on each image, and all images aligned. For the first campaign, the workflow was continued to yield a digital elevation model (DEM). This DEM was then exported as triangle mesh in STL format. For all other campaigns, the process was stopped after image alignment. Aligning images in Agisoft PhotoScan using only GCPs as reference yielded the camera position and orientation for each image in an indirect sensor orientation approach (Benassi et al., 2017). For further processing, this location and orientation information was exported to a text file.

2.10. Georeferencing Using Image Projection

In addition to sensor orientation and position information, georeferenced images represent another prerequisite for the method proposed in this paper. Therefore, images were projected to a DEM using ray tracing (Figure 5), scripted in a custom developed Python 3.4 program (available upon request). In ray tracing, every pixel of an image is represented as a vector l connecting the pixel location on the sensor plane and the focal point f . To calculate these vectors, a 2-D matrix was initialized where each

Figure 5: Data extraction approach including the process of estimating camera position and orientation and digital elevation model through Structure-from-Motion algorithm (SfM), image projection with ray tracing, and the extraction of visible leaf area values using plot masks and segmentation.

element correspond to a pixel of an image. This pixel matrix was then scaled to the dimension of the sensor and enhanced by the focal length as third dimension, representing now a 3-D position vector for each image pixel. This position vector matrix was then placed in the reference coordinate system and rotated according to the camera position and orientation information provided by the SfM software, x , y , z , κ , ϕ and ω , using a 3-D rotation matrix.

Hereafter, georeferencing of pixels was done performing a line-plane intersection, where lines were represented by preliminary calculated rays, and the plane by the DEM triangle mesh in STL file format:

$$G = \frac{(p_0 - f) \cdot n}{l \cdot n} \cdot l + f, \quad (22)$$

where f is the focal point, l the vector of the ray, n a normal vector to a plane representing the ground, p_0 a point on this plane, and G the point of intersection on the ground (Hughes, 2014).

G point coordinates were calculated for 50 x 50 equally distributed pixels on the sensor plane, while intermediate coordinates were linearly interpolated. Resulting coordinates for each pixel were round to 3 digits precision and saved as 32-bit float TIFF. Viewing geometry information were then calculated pixel-wise using trigonometric relations between the focal point of the camera f and the intersection point G ,

$$\theta = \frac{\pi}{2} - \tan^{-1} \left(\frac{f_z - G_z}{A} \right) \text{ where} \quad (23)$$

$$A = \sqrt{(f_x - G_x)^2 + (f_y - G_y)^2},$$

$$\delta = \tan^{-1} \left(\frac{f_y - G_y}{f_x - G_x} \right), \quad (24)$$

where θ is the zenith angle and δ the azimuth angle, and the subscripts x , y and z denote the corresponding directions in the coordinate space. Viewing geometry information were round to 5 digits precision and saved as 32-bit float TIFF.

2.11. Georeferencing Accuracy

The accuracy of georeferencing was evaluated by comparing image coordinates of GCP positions in individual images—a by-product of the manual GCP placement in the Agisoft PhotoScan process—and the corresponding image coordinates of GCP world coordinates as calculated in the georeferencing process. A preliminary run of this validation showed that border pixels are frequently prone to inaccurate georeferencing (Figure A1). Correction was not possible, as the cause was clearly not a lens distortion problem, but rather an effect varying from image to image. Excluding a strip of 300 pixels at borders

increased accuracy by up to 50 %. In addition, all images having image coordinate deviations larger than 30 pixel were entirely excluded from subsequent steps.

2.12. Extraction of Viewing Geometry Specific Plot Image

After applying the validation filter, image specific plot masks were generated. To exclude mixed pixels at borders between plots, initial plot masks were reduced using a 0.25 m buffer. Reduced plot masks were then used to clip plot areas and save image parts to separate TIFF files for further processing. At same time, plot-based viewing geometry information were saved in a separate metadata file.

2.13. Segmentation of Images Using Machine Learning

Extraction of projected visible plant area was done using the decision tree based segmentation model proposed by Guo et al. (2013, 2017). Briefly, this model transforms training data in three color spaces (RGB, HSV, and CIELab) and builds a decision tree based on the CART algorithm (Breiman et al., 1984). This decision tree can then be applied to unclassified images.

Training data were generated separately for each flight campaign, but ultimately combined for a final segmentation run of all campaigns to make results comparable. To improve the accuracy and speed of training, a custom written user interface was developed in R using Shiny (R Core Team, 2017). This user interface randomly chooses plot images and allows the user to classify selected pixels on this image. After classifying a few pixels, the user could decide to continue to classify other images, or start an intermediate segmentation run to gather first results. These results were then interactively analyzed by calculating a linear regression between fraction of pixels classified as plants and zenith angles of same plots. If implying an auto-correlation between close-by zenith angle measurements for the same plot, the goodness of fit of this regression can be seen as a measurement of the quality of segmentation. Data points with large residuals indicate samples where the segmentation performed sub-optimal.

As a consequence, the next image presented to the user was randomly selected from a subset of 100 images with largest residuals. This optimized selection allowed to maximize information gain per newly classified plot image, an approach called active learning (MacKay, 1992).

3. Results

3.1. Verification of the CC/LC Viewing Geometry Model with Simulation Data

The cylinder simulation data supported well the assumptions of the CC/LC viewing geometry model—for varying cylinder heights, the zenith angle effect increased with increasing cylinder height (Figure

6a). Looking in more detail at the data for a cylinder height of 0.3 m, the CC/LC viewing geometry model mapped well not only increasing zenith angle effects, but also azimuth angles effects (Figure 6b-c).

For the soybean growth simulation based data, the zenith angle effect was ambiguous for early DAS growth stages and showed an asymmetric pattern (Figure 6d). However, for later growth stages, the zenith angle effect became more pronounced, and the CC prediction was precise for CC values up to $0.50 \text{ m}^2\text{m}^{-2}$ (Figure 7a). For larger values, the CC/LC viewing geometry model showed a trend to underestimate CC. In contrast, LC predictions were inaccurate for values lower than $0.05 \text{ m}^2\text{m}^{-2}$, but more precise for higher values (Figure 7b). In accordance to gap fraction theory (Section 2.2, Equation 12), the predicted leaf area based on CC and LC values showed a saturation function to the true LAI (Figure 7c).

3.2. Georeferencing Accuracy

The execution of the five flight campaigns was successful, but due to limited storage writing speed of the camera, the number of images captured per campaign was not constant, but varied between 227 and 307 images. Nevertheless, the distribution of viewing geometry angles per campaign remained nearly constant (Figure 8). For close-zero zenith and azimuth angles, measurement point density approached zero, indicating that close-nadir views happened rarely in the chosen flight setup.

Georeferencing of the five flight campaigns resulted in referencing errors in the range of 0.1 to 0.2 m (Table 2). The exclusion of border pixels and filtering of inaccurately referenced images led to an improved mean accuracy error of less than 0.09 m (Table 2 and Figure A1), but also reduced the

Table 2: Flight campaigns with number of images per campaign (#) and resulting georeferencing precision in pixel and meter. Given are mean values and standard deviations (sd). The filtered images section included only images with a georeferencing accuracy < 30 pixel for non-border pixels

Date	Total images			Filtered		
	#	Precision (mean and sd)		#	Precision (mean and sd)	
		Pixel	m		Pixel	m
2017/06/15	247	14.8 (12.5)	0.132 (0.111)	191	9.1 (6.3)	0.081 (0.057)
2017/06/19	235	10.7 (8.6)	0.091 (0.074)	213	8.5 (5.4)	0.073 (0.048)
2017/06/21	227	16 (14.6)	0.201 (1.701)	168	9.5 (6.7)	0.081 (0.057)
2017/06/23	307	14 (11.8)	0.123 (0.104)	261	10.1 (6.2)	0.087 (0.056)
2017/06/26	299	12.9 (10.5)	0.108 (0.090)	259	9.2 (5.9)	0.076 (0.051)

Figure 6: Cylinder simulation for various cylinder heights h with dependency of fraction of pixel classified as plants (P_p) on the zenith angle θ (the solid line denotes the fitted CC/LC viewing geometry model and the dashed line the canopy cover) (a). Cylinder simulation with dependency of P_p on both zenith angle θ and azimuth angle δ for a specific cylinder height of 0.3 m (the dashed line denotes the canopy cover) (b), and the corresponding CC/LC viewing geometry model with the relative contributions ΔP_p of the zenith angle θ and the azimuth angle δ to P_p (c). Plant growth simulation with dependency of fraction of pixel classified as plants (P_p) on the zenith angle θ for selected days-after-sowing (DAS) stages (the solid line denotes the fitted CC/LC viewing geometry model) (d)

Figure 7: Prediction performance of the CC/LC viewing geometry model for soybean growth simulation data for canopy cover (CC, **a**), lateral cover (LC, **b**) and apparent plant area fraction ($P_{p,app}$) versus leaf area index (LAI) (**c**). Black lines show an implied 1:1 relationship (**a** and **b**) respectively a negative exponential relationship (**c**)

Figure 8: Distribution of viewing geometry angles per plot (zenith and azimuth) for the five flight campaigns

Figure 9: Selection of four randomly chosen plot samples, showing the dependency of fraction of pixel classified as plants (P_p) on zenith angle θ and azimuth angle δ

number of suitable images by up to 26 %. As a result, each plot appeared on average in 45 images per campaign, with a standard deviation of 10 images.

3.3. Image Segmentation Accuracy

Based on visual checks of miss-classified pixels, the active learning process showed suitable segmentation results after five to six reclassification-runs (see for example Figure A2). The final training set consisted of 461 samples for soil and 268 samples for plants. Based on a manual check on hundred randomly selected plot images per campaign, no images had to be excluded. We therefore assumed a valid segmentation for the remaining images. The interactive approach with graphical representation of intermediate segmentation results facilitated the training process for the user, and it was possible to process the five campaigns successfully within less than 6 hours.

3.4. Validation of the CC/LC Viewing Geometry Model with Field Data

Georeferencing and segmenting field data yielded projected visible plant area along the azimuth and zenith angle (Figure 9). The derived fraction of pixels classified as plants showed a clear dependency on viewing geometry parameters. Zenith angle effects were comparable with the one observed on simulated data (Figure 6a and d). Azimuth angle effects in the field data were less pronounced than in the simulation data. In addition, the depression in fraction of pixels classified as plants in the simulation data at 0° and 90° azimuth (Figure 6b) indicated an interference pattern with at least three overlaying waveforms with increasing frequencies, while the field data indicated no more than two overlaying waveforms (Figure 9). This observation led to the decision to define the model with only two interference waveforms (Figure 6c and Equation 8). Hereby, we assume that other effects in the field like for example inhomogeneous seed emergence suppress the effect of interference waveforms with higher frequencies.

Fitting the non-linear CC/LC viewing geometry model to field data yielded CC, LC, and row interference effects (c_1 and c_2) values for all plot-based data. Cross-validation runs resulted in RMSECV of 0.0272, 0.0288, 0.0390, 0.0307 and 0.0384 $P_p(\theta, \delta)$ for the first, second, third, fourth and fifth campaign respectively, indicating a high predictive capacity. However, the significance of fit for variables varied among plots and campaigns (Figure 10). For all campaigns and all plots, CC values were highly significant. For later campaigns, up to 95 % of all plots showed significant or highly significant LC values, while for the first campaign, significance of LC values remained low at a total of 60 % significant values. The significance of row interference effects varied from campaign to campaign and for c_1 and

c_2 values: While for c_2 values, any of the campaigns had high significant counts, for the first, third and fourth campaign, a few c_1 values were highly significant.

3.5. Validation of the Gap Fraction Viewing Geometry Model with Field Data

LAI values measured by the LI-COR device ranged between LAI 0.25 and LAI 3.72 with a mean of 1.70 and a standard deviation of 0.63. Planimetric LAI measurements resulted in LAIs between 0.25 and 3.05 with a mean of 1.07 and a standard deviation of 0.69. Correlating dry weight with LAI_{true} yielded a robust linear regression with an R^2 of 0.985 and an RMSE of $0.165 \text{ m}^2 \text{ m}^{-2}$. Nevertheless, due to soil residues in the samples, two plot measurements had to be removed. This correction resulted in gravimetric LAI between 0.31 and 3.53 with a mean of 1.45 and a standard deviation of 0.81.

Error estimations for the planimetric and gravimetric LAI methods need to consider at least three categories of errors: Errors due to non-planar and not fully unfolded leaves, segmentation errors, and up-scaling errors. Soybean foliage tends to be thin and flat, and preliminary analysis has shown that the area of unfolded leaves in the examined growth stages is negligible in comparison to the total leaf area of a plant (smallest measured single leaf area: 280 mm^2 , mean measured total leaf area: 0.092 m^2 for the first campaign, 0.273 m^2 for the second campaign, proportion of smallest measured leaf area on total leaf area: 0.3 % and <0.01 %, respectively). Therefore, errors due to non-planar and unfolded leaves were assumed to be insignificant in comparison to segmentation and up-scaling errors. According to literature, errors in the segmentation process may be as high as 5 % for digital cameras, but drop below 1.2 % if correcting for distortion, as was done in this study (Easlon and Bloom, 2014). The up-scaling error was minimized by individually determining the plant density per plot and keeping the sample size greater than $1/10$ of the maximum plant density value. Therefore, the resulting total error for LAI_{true} values is estimated to be in the order of 10 %. For LAI_{grav} values, the estimation error may be slightly higher due to errors caused by the drying and weighing process.

Predictions of LAI based on either the CC value from the CC/LC viewing geometry model, the LAI from the gap fraction viewing geometry model, or the LAI from the LI-COR device resulted in good correlations with ground validation measurements (Figure 11a-f and Table 3). An effect of genotype or growth habit on LAI estimation was not visible. The performance of the LI-COR device and the LAI estimation based on the CC/LC and gap fraction viewing geometry model were comparable (Figure 12) with an RMSE of $0.32 \text{ m}^2 \text{ m}^{-2}$ for LAI_{CC} and $0.42 \text{ m}^2 \text{ m}^{-2}$ for LAI_{θ} . While the LI-COR device showed a trend to overestimate the LAI, the gap fraction viewing geometry model did not (Figure 11b, c, e, f).

Figure 10: Goodness of fit of the CC/LC viewing geometry model. The total number of plots per campaign was 72, given are aggregated numbers of plots by significance group

Table 3: Linear regression parameters for the three different leaf area index (LAI) estimation methods (canopy cover (CC) derived from the CC/LC viewing geometry model, leaf area index derived from gap fraction viewing geometry model (LAI_{θ}) and leaf area index measured with the LI-COR device (LAI_{LI-COR})) versus two ground validation measurements (LAI based on gravimetric measurements (LAI_{grav}) and LAI based on true surface measurements (LAI_{true})). R^2 is the coefficient of determination, RMSE is the root mean square error in m^2m^{-2} , slope the slope of the linear regression, the intercept was forced to 0, n is the number of samples.

Estimation method	LAI_{grav}				LAI_{true}			
	R^2	RMSE	Slope	n	R^2	RMSE	Slope	n
Canopy cover (CC)	0.93	0.44	2.90	142	0.95	0.29	2.66	100
LAI_{θ}	0.89	0.56	1.05	142	0.89	0.41	0.96	100
LAI_{LI-COR}	0.91	0.49	0.87	142	0.91	0.38	0.80	100

Figure 11: Scatter plot and regression of leaf area index (LAI) estimation methods (canopy cover (CC, a and d) derived from the CC/LC viewing geometry model, leaf area index derived from the gap fraction viewing geometry model (LAI_θ , b and e) and leaf area index measured with the LI-COR device ($\text{LAI}_{\text{LI-COR}}$, c and f) versus two ground validation measurements (LAI based on gravimetric measurements (LAI_{grav}) and LAI based on true surface measurements (LAI_{true})). Solid black lines represent the regression line, dashed lines the 1:1 line

Figure 12: Scatter plot of leaf area index (LAI) estimations based on CC values from the CC/LC viewing geometry model (LAI_{CC}) and the LAI values from the gap fraction viewing geometry model (LAI_θ) versus LI-COR LAI measurements ($\text{LAI}_{\text{LI-COR}}$). Solid black lines represent the regression line, dashed lines the 1:1 line

4. Discussion and Conclusion

4.1. Georeferencing Individual Images

Georeferencing in this study yielded referencing errors of up to 0.09 m with standard deviations of up to 0.06 m. To extract information of plots of 1 x 3 m, this accuracy is appropriate. Nevertheless, for smaller plot sizes like for example one-row plots used in early breeding stages, this precision may be not suitable.

Only few studies were published which georeferenced individual images taken by UASs using projection techniques: Turner et al. (2014) and Carbonneau and Dietrich (2017) used on-board differential GPS and an inertial navigation system to direct georeference images and found an average error of 0.11 m with a standard deviation of 0.02 m at a flying height of 40 m and an average error of 0.06 m at a flying height of 60 m, respectively. These results are within the same range as the precision found in this study. Benassi et al. (2017) also used direct georeferencing techniques, but found smaller average errors of 0.014 m in x direction and 0.003 m in y direction of the sensor at a flight height of 80 m. Nevertheless, all mentioned authors agree that the use of GCPs usually leads to much higher accuracy. Reasons for larger errors in direct georeferencing are extensively elaborated in the paper of Carbonneau and Dietrich (2017), and include lens distortion effects, but also errors in the SfM process caused by inaccurate camera position and orientation measurements. Taking into account that this study worked with camera position and orientation information gathered from a SfM process, it is justified to assume that similar reasons caused measured errors. Therefore, eliminating the SfM step by using a differential GPS device and inertial navigation system mounted to the UAS would most probably further improve the accuracy of the methods described, beside reducing effort for GCP measurements. In addition, skipping the SfM process would overcome two big limitations of UAS based remote sensing in agriculture: Large image overlaps and clearly distinguished features would not be needed anymore to successfully process image series. Non-existing distinguished features caused by rapidly changing perspectives are clearly a problem if dealing with close-ranged images of crops, especially if working with low-resolution cameras, for example thermal or multispectral snapshot cameras. Direct georeferencing individual images would allow to process such images independent of their suitability as input for SfM processes.

4.2. *Segmenting Plants and Soil*

Segmentation of RGB images into plant and soil pixels yielded reasonable results, but was a tricky task. The performance of machine learning based segmentation algorithm is strongly affected by the quality of training samples (Guo et al., 2013). Whereas ultra-high ground resolutions confront users with the problem of high intra-class variation and therefore call for methods able to deal with nonlinear responses (Tuia et al., 2011), a lower ground resolution of 5 to 10 mm as used in this study may avoid large intra-class variations, but promotes more class-ambiguous pixels. In addition, the class-ambiguity may change during image acquisition, influenced by lighting conditions, wind speed and direction, viewing geometry, and other factors. These changes can result in a large discrepancy between training data and test data. In the remote sensing community, the shift between a trained algorithm and new, unseen data is known as covariate shift (Quiñonero-Candela et al., 2009) and was faced by applying active learning techniques which interactively requested the user to classify new "critical" regions with low probabilities of correct classification (e.g. Tuia et al. 2011). Multiple viewing geometry-dependent data of the same ground truth in combination with a CC/LC viewing geometry model offer a suitable opportunity to implement such active learning approaches and therefore improve segmentation results, as shown by this study.

4.3. *Leaf Area Index Estimations*

The simulation of virtual canopies was a useful tool to develop and validate the CC/LC and gap fraction viewing geometry model—predicted row interference pattern and zenith angle effects were distinct and corresponded to observed effects in field data. Hence, both the CC/LC and the gap fraction viewing geometry model were considered as valid base for a LAI prediction.

The performance of the CC from the CC/LC viewing geometry model as LAI indicator was comparable to the one of the LI-COR device. This good performance corresponds to results of Liu et al. (2013): For soybean, they found coefficients of determinations of 0.94 for linear regressions between ground validation and nadir view based LAI estimations. However, the distribution of zenith angles indicates that close-nadir views are almost never present in flight campaigns (Figure 8). Nevertheless, since the proposed CC/LC viewing geometry method approximates the CC based on viewing geometry effects, it overcomes this issue. At the same time, the relation between CC and LAI is not intrinsic since a ground validation reference is needed to establish valid estimations. Hence, parameters for CC as LAI indicator may vary among crops—or even genotypes of the same crop—, thereby reducing the universality of the

method.

Extending the pure CC/LC viewing geometry model to a viewing geometry model using gap fraction theory overcomes the need for further calibration. Compared to the CC regression method developed specific for this soybean data set, the performance of the more general gap fraction viewing geometry model was slightly lower. Nevertheless, considering the advantage of self-calibration, this constraint is acceptable.

The precision of the method presented in this study was examined using planimetric and gravimetric LAI measurements. The error estimations for these two validation methods indicated a total error in the order of 10 %. This error corresponds well to the measured RMSE for the LAI_{CC} and LAI_{θ} methods, but would also restrict the reliability of these results if being systematic rather than random. On the other hand, the considerably high estimation error for the two destructive sampling methods does underline the need for a robust non-destructive LAI estimation method, such as the one presented in this study.

LAI can also be derived from spectral data at different scales: Proximal spectral sensing methods yield good results (Nguy-Robertson et al., 2012), but are as work intensive as handheld LAI meter measurements. In contrast, for remote sensing methods, gap fraction methods yield better results in comparison with spectral remote sensing from satellites (e.g. Colombo et al. 2003). In addition, while satellites are able to cover large areas, they still have limited flexibility and might miss critical phases in crop development, for example due to cloud cover. Although progress has been made in spectral remote sensing from UAS (Aasen et al., 2015; Yuan et al., 2017), gap fraction theory with uncalibrated RGB images has its clear advantages considering that spectral cameras are more expensive and calibration is challenging (Bareth et al., 2015).

Despite the work intensity of handheld LAI meter measurements, the results for the LI-COR LAI-2200 also stressed some restrictions of the specific device: The LAI-2200 showed a trend to overestimate the true LAI (Figure 11c and f). This result is not in accordance with Welles and Norman (1991), who reported LAI underestimations of about 15% for soybean, measured with a comparable LI-COR LAI-2000 device. In contrast, Jovanovic and Annandale (1998) found an LAI overestimation for soybean when comparing LAI-2200 measurements and destructive sampling. Their regression results are comparable to those measured in this study. Here, the LI-COR device tends to clump measurements of the same campaign (Figure 11c and f), while the CC/LC and gap fraction viewing geometry model based estimations did not show such tendency (Figure 11a, b, d, e). One may therefore conclude that it is

reasonable to consider the LI-COR measurements as valid ground validation reference, although with a systematic overestimation error and a tendency to clump data on measurement date.

4.4. Limitations

Some limitations of the method proposed have to be pointed out: As the plant growth simulation used in this study was restricted regarding coverage of later growth stages, an extrapolation of these results to larger LAIs should be avoided. It might be reasonable to assume that with advancing plant development and thus advancing canopy closure the influence of azimuth angle effects will decrease. The field experiment data support this hypothesis—interference effects showed some significance for campaign 3 and 4, but not for other campaigns (Figure 10). Similar restrictions may apply to zenith angle effects: As the canopy starts to close in later growth stages of plants, the zenith angle effect may flat out and reach a slope of zero for closed canopies. Although several canopies reached a coverage of nearly 100 % for the last campaign, the goodness of fit of the CC/LC viewing geometry model did not decrease (Figure 10), indicating that the data was still within the limits of the method.

Successful segmentation of images in plants and soil represents another crucial prerequisite of the LAI estimation method presented in this paper. Complex canopies in combination with shadow cast may complicate segmentation, or even prevent reasonable segmentation. In addition, leaf chlorosis, senescence and diseases as well as varying soil conditions and weed occurrence may affect the quality of segmentation. Hence, the structure and state of investigated canopies and soils needs to be known and considered depending on application.

Saturation effects represent another common limitation in optical sensing. Particularly for LAI estimation, most studies report pronounced saturation at later growth stages (e.g. Thenkabail et al. 2000). The gap fraction theory applied in this study is per definition based on visible gaps of a canopy. Consequently, the foreseeable disappearance of gaps after canopy closure will bring the presented method to the limit. Nevertheless, the LAI range of 0 to 3 in this study represents a crucial phase of crop growth, in which plants have to establish in the field, and the method represents therefore a valid alternative to manual early vigor ratings. A validation of the method for LAI ranges closer to the saturation limit may, if successful, loosen this limitation and hopefully empower the method for other applications like for example yield estimations.

Finally, the assumption of constant leaf inclination angles may not be applicable in all situations. Nevertheless, a non-constant inclination would cause non-linear extinction coefficients (Norman and

Welles, 1983) and as a consequence reduce the significance of the fitted CC/LC viewing geometry model parameters. Such an effect was not observed. It seems therefore justified to neglect inclination angle effects in soybean and assume constant inclination, at least for viewing geometries with zenith angles in a range of 0 to 30°.

5. Conclusions and Outlook

This study shows that viewing geometry LAI estimation based on uncalibrated RGB images represents a valid replacement for ground validation measurements in soybean. Processing original oblique images avoids the need for ortho-rectification and orthomosaic blending and therefore allows to process complex scenes such as agriculture fields. The higher robustness of image projection as data extraction pipeline in contrast to Structure-from-Motion techniques thereby enables high throughput LAI estimation urgently needed in plant phenotyping.

Valuable contributions in further studies may include the validation of the presented method regarding broader LAI ranges, but also testing the method for other crops and under different environments. Increasing availability of functional-structural plant models (Vos et al., 2010) and 3-D radiative transfer models (e.g. DART, CESBIO 2017) may provide the underlying tools to facilitate such research.

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Conflicts of interest

None

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Figure A1: Georeferencing precision on a spatial scale for two selected campaigns (2017-06-15 and 2017-06-26) before and after filtering border pixels. Circles indicate the true position of a reference point, lines the recovery accuracy of this position after georeferencing

Figure A2: Original and segmented images for one specific plot and three different zenith angles (θ)