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Performance assessment of predictive models for morphological and biomass traits using image-derived canopy parameter at early stage of sunflower

Kwang-O JONG[1,*], Ye-Kwang SIN[1], Yu-Jin JANG[2], and Kum-Sil RI[3]

[1] *Department of Landscape Plant Breeding, Faculty of Life Science, Kim Il Sung University, Pyongyang, Democratic People's Republic of Korea*
[2] *Pyongyang Turf Institute, Landscaping Technology Agency, Pyongyang, Democratic People's Republic of Korea*
[3] *Institute of Industrial Crops, Academy of Agricultural Science (AAS), Pyongyang, Democratic People's Republic of Korea*

*Corresponding author: E-mail: life5@ryongnamsan.edu.kp

Abstract

Image-derived phenotyping at individual plant level can provide more accurate and more comprehensive information than manual measuring for quantitative traits related to canopy growth in field environment. Aims of this study were to: (i) assess smartphone image-derived canopy parameter at early stage of sunflower, and (ii) to evaluate performance of predictive models for morphological and biomass traits related to canopy growth using smartphone image-derived parameter. Original top-view image datasets taken with a smartphone camera were processed, and necessary information was extracted with image analysis software developed using fuzzy *c*-means clustering algorithm. Canopy cover rate per plant (CCR) was not only the relative value but also image-derived phenotyping feature. CCR were significantly and positively correlated ($r \geqq 0.90$; $^{**}P < 0.01$) with plant height, total leaf area per plant, plant dry mass, aboveground plant dry and leaf dry mass, respectively. Ground measured and predicted values from linear regression model for plant height, total leaf area per plant, plant dry mass, aboveground total dry mass, leaf dry mass per plant with CCR showed an accurate prediction with high coefficients of determination (R) of more than 0.8063, respectively. The present study documented the robustness of predictive models using several metrics.

Keywords: biomass, canopy, image-derived phenotyping, leaf, regression linear model.

Introduction

Sunflower (*Helianthus annuus* L.) is one of the world most important annual crops grown for edible vegetable oil and for use as snack throughout the world together with soybeans, peanut and rapeseed due to its high oil content (40 - 52%), no cholesterol and high nonsaturated fatty acids content that ranges between 85 - 91% (Leon et al., 2003).

In addition, sunflower is a temperate zone crop, which can perform well under a variety of climatic and soil conditions and combines high yield with great adaptation capacity (Canavar et al., 2010).

Leaves are the largest proportion of the total canopy surface in most plants (Nakanwagi et al., 2018). Especially, leaf area is a very important component for determining growth rate and yield as it can be captured during different growing periods (Islam et al., 2017). The description of canopy architecture includes the morphological characteristics such as leaf area index (LAI), plant height, leaf inclination angles and leaf area density (Monsi and Saeki, 2005). Estimation of crop canopy growth parameters

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Abbreviations: CCR - canopy cover rate per plant; IA - image analysis; LAI - leaf area index; LSD - least significant difference; MAE - mean absolute error; RMSE - root mean squared error; rRMSE - relative RMSE.
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including leaf cover area, aboveground biomass and canopy height, are essential for site-specific management practice (Ehlert et al., 2010). Measurements of crop growth parameters inculding LAI, canopy cover, and biomass are typically performed only a few times throughout growth period at irregular time intervals (Linker and Ioslovich, 2017).

Visual assessment is a traditional method used to estimate canopy cover in the field environments, but it is limited by the costs, subjectivity and non-reproducibility of the produced estimates (Chianucci et al., 2018). In general, plant phenotypic traits were quantified using invasive, time-consuming, cost-inefficient, labor-intensive, and often destructive manual sampling methods (An et al., 2016). Recently, measurements for leaf growth were performed with the help of digital image-derived methods, which can quantify leaf growth at a high temporal resolution (Friedli and Walter, 2015). Image-derived plant phenotyping is intended to measure complex traits related to growth, development, yield component, grain yield and tolerance to different biotic and abiotic stress with a certain accuracy and precision at different scales of organization (Muraya et al., 2017; Chen et al., 2018; Zheng et al., 2019; Jong et al., 2025). Using digital imaging techniques could enable researchers to measure a variety of phenotypic parameters from the high-resolution images in field crops.

Canopy reflectance sensors were used to identify biomass and nitrogen status in sugarcane (Amaral et al., 2015). In the previous studies, researchers used the complex and expensive apparatus such as canopy reflectance sensor and hyperspectral imaging line scan sensor equipped with a *Specim V10* spectrometer and a *Basler PiA190032 gm* sensor.

Because of the exorbitant price of instruments and equipment and limitation by the resolution, the time cycle, the geography, and the weather conditions, the existing image-based phenotyping systems are difficult to apply low-costly and simply to elevated plant number and large breeding populations in field environments (Sankaran et al., 2015). Thus, data analytic methods were designed for specific study projects.

Visible light imaging in the image-derived phenotyping is primarily employed to measure aspects of plant architecture including image-based projected leaf area, biomass, growth and development dynamics, seedling vigor, seed and root morphology and yield (Hu et al., 2018; Jong et al., 2021).

Currently, with the tremendous advances in compact wireless technology, smartphones have been attracted significant attention in studies for agricultural traits (Qian et al., 2018; Barman et al., 2020; Tao et al., 2020; Jong et al., 2025). Since the smartphone offers the high-resolution camera, it can be used as a convenient instrument for capturing image from field environments (Hufkens et al., 2019; Mohan and Gupta, 2019; Tan et al., 2021). Moreover, it has some advantages over specialized monitoring systems involving ubiquity, low-cost, and ease of implementing updates (Petrie et al., 2019). To promote application of image-derived field phenotyping for agricultural traits, the inexpensive and efficient data acquisition and processing approaches and more accessible image analysis (IA) infrastructures will need to be developed (Shakoor et al., 2017).

To our knowledge, quantitative methods to monitor canopy and measure their growth in crops are rarely employed in the image-derived phenotyping studies. Since morphological and biomass traits are influenced by the interaction between genes and environmental factors, it is essential to comprehensively and accurately understand and evaluate these phenotypes using image-derived phenotyping technique.

The following hypothesis was tested in this study: the predicted values through the models constructed using image-derived canopy parameter are similar to the ground measured values for the morphological and biomass traits during the early growing period of sunflower. The aims of this study were to: (i) assess smartphone image-derived canopy parameter at early growth stage of sunflower in field envrionment, and (ii) to evaluate performance of predictive models for morphological and biomass traits related to canopy growth using smartphone image-derived parameter.

Materials and methods

Plant material: This study used nine sunflower cultivars (DW167, DW776, EUDALIS, X3939, YZ3638, Bogchareze, Bujulluk, Pung 9, Unsan). Seeds of all the cultivars were provided by the Institute of Industrial Crops, the Academy of Agricultural Science of DPR Korea.

Site description: Field experiment was conducted in the experimental station (latitude 39°01'17"N, longitude 125°44'14"E, altitude 30 m a.s.l.) of the Faculty of Life Science of Kim Il Sung University in 2022.

Experimental design: A randomized complete block design with three replicates was used for laying out the field experiment. Each block was divided into nine plots, to which the cultivars were assigned randomly. The plot dimensions were 6 m in length and 3 m in width. Three seeds were sown manually in holes of 30 cm distance along the ridge in each plot on 2 July 2022, and then thinned to one plant per hole, one week after sowing. Complete fertilizer was applied at 180 kg (N) ha^{-1}, 120 kg (P_2O_5) ha^{-1} and 75 kg (K) ha^{-1}. Pesticides were used to prevent pest damage.

Capturing the top-view canopy images with a smartphone camera: We intended to use top-view images for image-derived phenotyping in the present study, since top-view images are more suitable for investigating canopy growth than side-view images in field environment (Fig. 1). Top-view images for each accession grown for 15 days after sowing were captured using the smartphone camera (*type 2418*, Pyongyang, DPR Korea, 8 Mega Pixels) between 10:00 and 12:30 h on sunny day and under natural light without using external light source.

A *B*

Fig. 1. Canopy architecture in sunflower plant grown in field conditions during 15 days after sowing (online color). *A* - Side-view canopy architecture, *B* - Top-view canopy architecture. The symetrical architecture of sunflower enables easy evalutation of plant traits by image acquisition using smartphone camera (online color).

Fig. 2. Acquiring top-view images in the field environment, the height of the smartphone camera was set at 30 cm using a selfie stick (online color).

The height of smartphone camera was set at 30 cm using a selfie stick (Fig. 2). Images were saved in JPEG format (joint photographic experts group). Altogether, there were 10 images for each plant.

Plant measurements: After capturing the top-view canopy images for each accessions (except the border plant at plots), plant height, width, and length of emerged leaves in plant were hand-held measured, respectively. Every leaf area was calculated as 0.65 [width (cm) × length (cm)], according to Dosio et al. (2003) and then the total leaf area per plant (cm^2) was estimated as the sum of every leaf area. Plant dry mass was weighed after 48 h drying of samples in an oven at 70°C, till a constant mass was achieved, and after cutting roots from plant dried in the oven, aboveground total dry mass was determined. In addition, after cutting leaves from plant dried in the oven, leaf dry mass was also determined.

Image processing with IA software: In the present study, to improve quality of IA on sunflower, we newly developed and used IA software (*Golden Field 3.0*) using fuzzy *c*-means (FCM) clustering algorithm (Gong et al., 2013). In general, R (red), G (green), and B (blue) image in IA has been widely used in machine vision applications due to low cost, high information volume, and simplicity of access (Singh et al., 2016). After RGB values of each pixel were obtained from the corresponding top view images, these values were transformed into HSV color system to obtain the average H (hue), S (saturation), and V (value, also known as brightness) values. H, S, V values were obtained from the RGB values, respectively (Vesali et al., 2015).

FCM algorithm using the color feature indices above was used to distinguish the green pixels from HSV components. Pixel gross of canopy cover was obtained from the HSB data. CCR was estimated from the top-view digital image of individual plant and calculated as the rate of pixel gross of canopy cover and pixel gross of input image using IA software according to the following equation (Eq. 1).

$$\text{CCR (\%)} = (\text{Canopy cover pixel gross/Input image pixel gross}) \times 100 \quad (1)$$

Statistical analysis: Statistical analyses were performed using the *IBM® SPSS® Statistics version 21*. Means were compared based on the *Fisher*'s least significant difference (LSD) test at the 0.05 level. Correlation analysis with two-tailed test was used to determine whether a significant relationship between CCR and ground measured morphological and biomass traits existed at the $^*P < 0.05$ or $^{**}P < 0.01$ probability levels. Linear regression models were used to quantify the relationship between ground measured morphological and biomass traits with CCR. These were constructed using the *SPSS 21.0* (*SPSS Inc.*, Chicago, IL, USA).

Performance evaluation of the predictive models: To evaluate the performance of the predictive models, linear regression models were tested by comparing predicted outcomes with the ground measurements. The goodness of fit in linear regression model was expressed as the coefficient of determination (R^2) (Eq. 2), which can be interpreted as an explained variation. The predicted outcomes were estimated from linear regression models with the high R^2, respectively. Finally, the predicted outcomes were compared with the ground measurements. The predictions for the morphological and biomass traits were quantified using several metrics according to Madec et al. (2019). Root mean squared error (RMSE) (Eq. 3), relative RMSE (rRMSE) (Eq. 4), Bias (BIAS) (Eq. 5), and mean absolute error (MAE) (Eq. 6) were calculated for assessing the robustness of the predictive models. In addition, accuracy of models with respect to the benchmark of the ability of prediction was also evaluated by percent bias (PBias) (Eq. 7) according to Mohan and Gupta (2019):

$$R^2 = 1 - \frac{\sum_{k=1}^{n} (t_k - c_k)^2}{\sum_{k=1}^{n} (t_k - \bar{t}_k)^2} \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{n} (t_k - c_k)^2} \quad (3)$$

$$\text{rRMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{n} \left(\frac{t_k - c_k}{t_k} \right)^2} \quad (4)$$

$$\mathrm{BIAS} = \frac{1}{N}\sum_{k=1}^{n}(t_k - c_k) \quad (5)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{n}\left|t_k - c_k\right| \quad (6)$$

$$\mathrm{PBias} = \frac{\sum_{k=1}^{n}(t_k - c_k)}{\sum_{k=1}^{n}(c_k)} \times 100 \quad (7)$$

where n denotes the number of test images, t_k and c_k are the ground measured and estimated values for image k, respectively and $\bar{t}_k$ is the mean ground measurements.

rRMSE provide a good indication of level of error of a prediction and it is more meaningful than RMSE (Wallach et al., 2013). If R^2 value is higher and the rRMSE value, BIAS value and MAE value lower, the predictive model constructed from image-derived canopy parameter performs well.

The flowchart diagram for predicting morphological and biomass traits using CCR during early growing period of sunflower is detailed in Fig. 3.

Results

Assessment of smartphone image-derived canopy parameter: Canopy architecture in sunflower plants grown in field environment for 15 days after sowing was symmetrical as a consequence of the size, shape, angle and

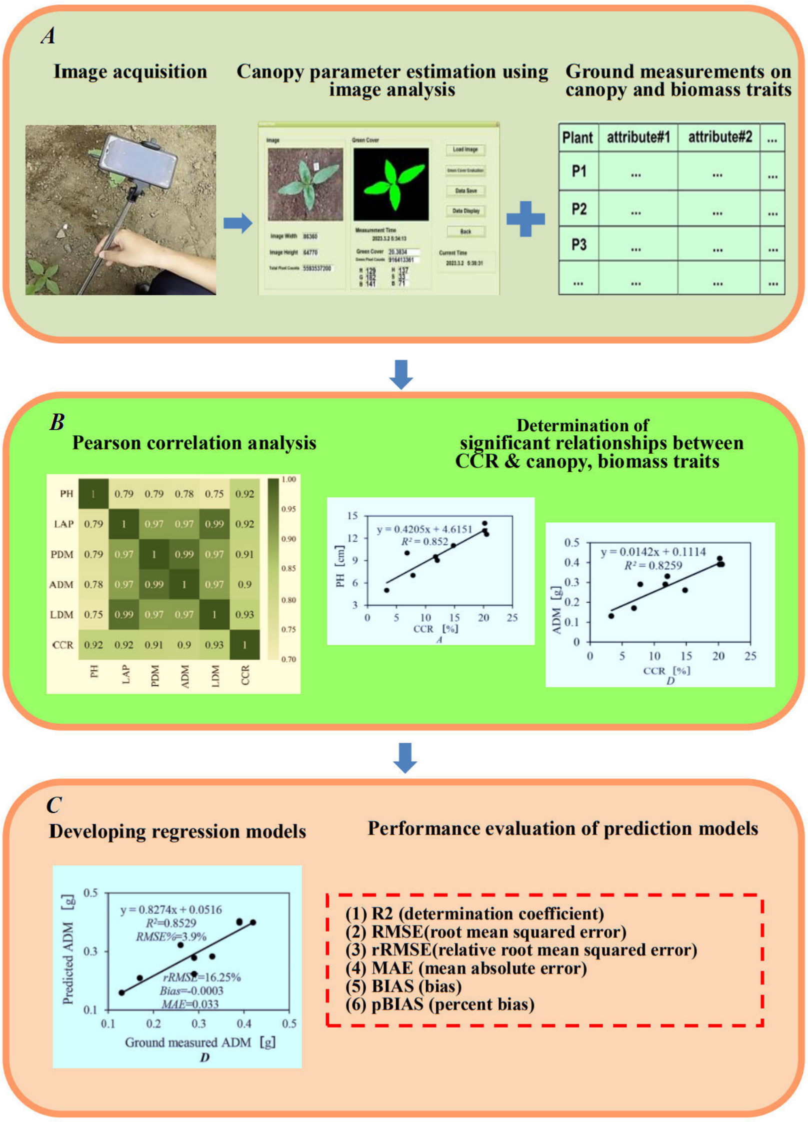

Fig. 3. Flowchart diagram of smartphone image-derived phenotyping. *A* - Image acquisition using smartphone camera in field environment, canopy parameter estimation using image analysis and the ground measurements, *B* - *Pearson* correlation analysis and predicting morphological and biomass traits, determination of siginificant relationships between CCR and morphological and biomass taits, *C* - Developing regression models and predicting morphological and biomass traits, performance evaluation of the models. To evaluate the performance of the predictive models, regression models were tested by comparing predicted values with the ground measurements using several metrics (online color).

distribution of leaves arranged on different layers (Fig. 1). Therefore, the symmetrical architecture of sunflower enables easy evaluation of plant traits by image acquisition using smartphone camera (Fig. 2).

When the original canopy image was processed with IA software, the green area of canopy cover was changed to the corresponding RGB image (Fig. 4). RGB image of canopy cover was the projection of canopy cover to two-dimensional plane. CCR was estimated from RGB image of the top-view canopy image using IA software, and is not only an image-derived phenotyping feature but also a canopy parameter (Fig. 4).

Original top-view image dataset and the corresponding top-view RGB image dataset processed with IA software are shown in Fig. 5. CCRs significantly varied among different accessions investigated (Table 1). Specially, CCR of Bujulluk was the largest (20.6%), while of DW776 was the lowest (3.3%).

Correlation between ground measured morphological and biomass traits with CCR: Positive correlations among CCR and ground measured morphological and biomass traits were established with a high level of significance (Fig. 6). In detail, CCR were significantly and positively

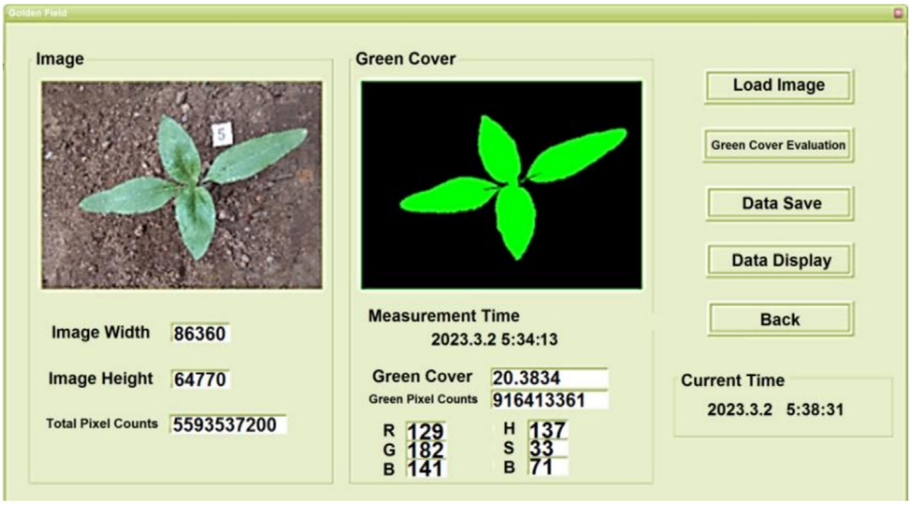

Fig. 4. IA software processing of canopy original images (online color).

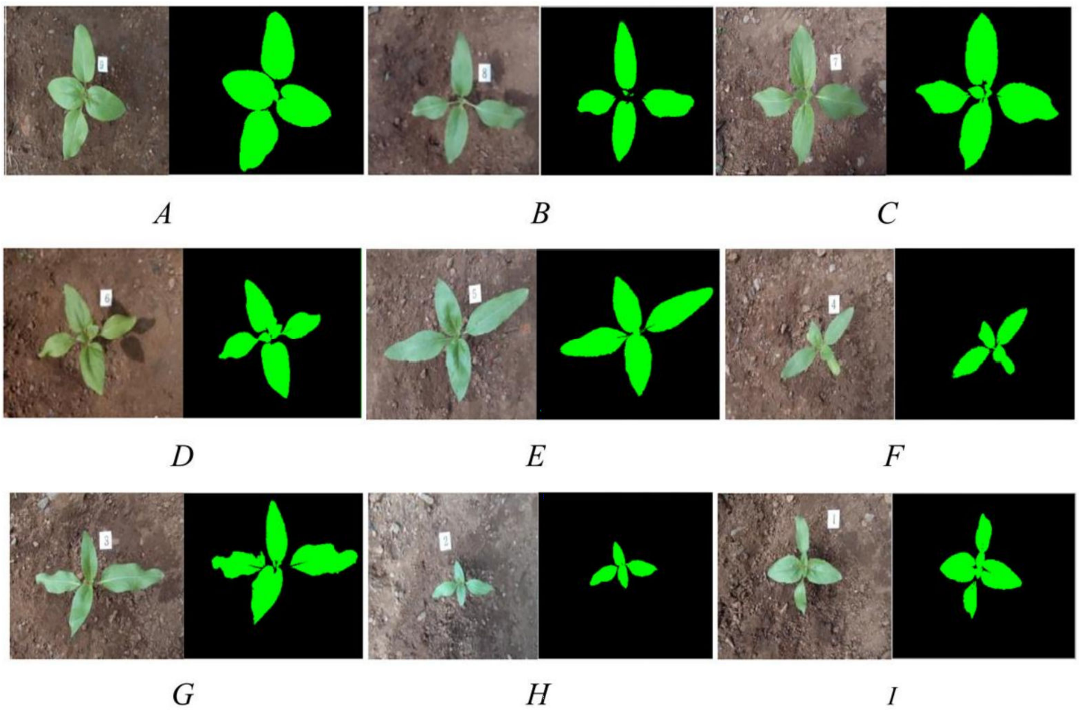

Fig. 5. Original top-view image dataset of plants grown during 15 days after sowing in different accessions (*left*) and corresponding top-view RGB image dataset processed with IA software (*right*) (online color). *A* - DW167, *B* - DW776, *C* - EUDALIS, *D* - X3939, *E* - YZ3638, *F* - Bogchareze, *G* - Bujulluk, *H* - Pung 9, *I* - Unsan.

Table 1. Image-derived canopy parameter, CCR, among different accessions. Values are means ± standard errors ($n = 10$). *Different letters* indicate significant differences between accessions ($P < 0.05$, *Fisher*'s LSD test), CCR - canopy cover rate per plant.

Accessions	CCR (%)
DW167	7.9 ± 0.3^{a}
DW776	3.3 ± 0.4^{b}
EUDALIS	14.8 ± 0.3^{c}
X3939	6.9 ± 0.3^{d}
YZ3638	20.2 ± 0.6^{e}
Bogchareze	11.7 ± 0.3^{f}
Bujulluk	20.6 ± 0.5^{g}
Pung 9	12.1 ± 0.4^{h}
Unsan	20.2 ± 0.5^{e}

correlated ($r \geqq 0.90$; $^{**}P < 0.01$) with plant height, total leaf area per plant, plant dry mass, aboveground plant dry and leaf dry mass, respectively. Additionally, total leaf area per plant also were significantly and positively correlated with plant height ($r = 0.79$; $^{*}P < 0.05$), plant dry mass ($r = 0.97$; $^{**}P < 0.01$), aboveground plant dry ($r = 0.97$; $^{**}P < 0.01$), and leaf dry mass ($r = 0.99$; $^{**}P < 0.01$), respectively.

Linear regression models between morphological and biomass traits with CCR: Linear regression models between morphological and biomass traits with CCR were as follows: $y_1 = 0.4205x + 4.6151$ for plant height, where y denotes plant height (cm), and x stands for CCR (%) in all the linear regression models; $y = 2.574x + 20.07$ for total leaf area per plant, where y indicates total leaf area per plant (cm^2); $y = 0.0147x + 0.1363$ for plant dry mass, where y is plant dry mass (g); $y = 0.014x + 0.114$ for aboveground plant dry mass, where y denotes aboveground plant dry mass (g); $y = 0.009x + 0.0837$ for leaf dry mass, where y indicates leaf dry mass (g). These models showed the close relationships between CCR and plant height, total leaf area per plant, plant dry mass, aboveground plant dry mass, and leaf dry mass with high R^2 of 0.852, 0.8526, 0.8424, 0.8259, 0.8063, respectively (Fig. 1 Suppl.).

Validation of predicted outcomes from linear regression models: Based on models constructed using CCR, we evaluated the performance of the predictive models using several metrics such as R^2, RMSE, rRMSE, BIAS, MAE, and BPias (Fig. 2 Suppl.). All the models exhibited the significant correlations between the ground measured and predicted values with R^2 values of more than 0.8063 for the target traits, and with very small BIAS, respectively. In detail, the measured and predicted values from linear regression models for plant height, total leaf area per plant, plant dry mass, aboveground plant dry mass and leaf dry mass showed the accurate prediction with high R^2 of 0.852, 0.8526, 0.8424, 0.8529, 0.8063, and with low RMSE, rRMSE, MAE, and very small BIAS of 0.0004, 0.0007, 0.0004, 0.0003, 0.0002, respectively. Furthermore, very low BIAS values indicated that the predicted values from the linear regression models were within the acceptable limit.

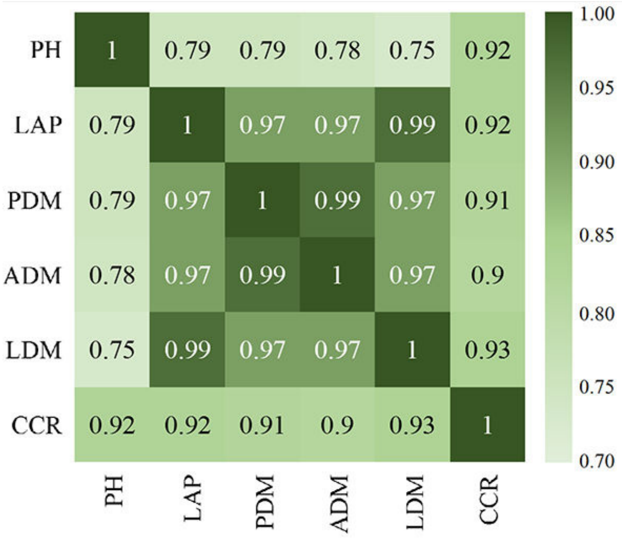

Fig. 6. Heatmap dataset of correlation coefficients among CCR and the ground measured morphological and biomass traits. PH - plant height, LAP - leaf area per plant, PDM - plant dry mass, ADM - aboveground plant dry mass, LDM - leaf dry mass per plant, CCR - canopy cover rate per plant.

Discussion

In the present study, we evaluated the performance of predictive models for morphological and biomass traits using smartphone image-derived CCR at early growth stage of sunflower. CCR estimated from the top-view canopy image of an individual plant was not only a canopy parameter but also an image-derived phenotyping feature. Results showed that CCR depended on accession in an identical growth conditions.

There are different methods of determining the leaf area (Padrón et al., 2016; dos Santos et al., 2016; Nakanwagi et al., 2018) and biomass (Wen et al., 2017), these can either be destructive or nondestructive.

In the present study, CCR related to leaf area and biomass can be easily estimated from the top-view canopy image of an individual plant using IA software. It had the significant and positive correlations with not only total leaf area per plant related to leaf area development but also biomass traits (Fig. 6).

Because total leaf area per plant in sunflower was estimated as the sum of every leaf area [0.65 (width × length)] according to Dosio et al. (2003), it is time-consuming and labor-intensive. However, estimation of CCR using IA software from smartphone images could be proposed as one of the low-cost and simple, repeatable assessment methods. These results that CCR was closely related to both leaf area development and biomass increase during early growing period supported that the rate of canopy coverage over the ground has a strong correlation with LAI (Banerjee et al., 2018).

CCR can be estimated by the non-destructive and non-invasive method using IA software without any significant alteration of plant morphology. Significant levels for linear regression models between the morphological and biomass traits with CCR were shown with high R^2, respectively (Fig. 1 Suppl.). Furthermore, linear regression models constructed using CCR produced the accurate prediction for the morphological and biomass traits (Fig. 2 Suppl.). Especially, the predicted values from models showed the accurate prediction with high R^2 of more than 0.8529. The predicted values were in relatively good agreement with the ground measured ones for morphological and biomass traits, respectively. In other words, the prediction performance of all the models was relatively high.

The predicted results from top-view images at early growth stage of sunflower supported the ones that constructed the predictive models to examine the quantitative relationship between the side-view image-based features and plant biomass accumulation in barley (Chen et al., 2018) and the models between the side-view image-derived parameter and quantitative traits related to plant architecture and biomass in rice (Jong et al., 2021; 2025). These findings suggested that using top-view image-derived field phenotyping can estimate the morphological and biomass traits exactly and simply during early growing period of plant, and reduce the field workload largely and increase also the work efficiency clearly.

The overall results from this study showed that CCR extracted from the top-view images can be used as the indirect and comprehensive descriptor for predicting morphological and biomass traits during early growing period in sunflower. In addition, our results provided the support for the hypothesis that the predicted values from the models constructed using image-derived canopy parameter are similar to the ground measured values for the morphological and biomass traits during early growing period of sunflower.

Its application would be beneficial in the process of optimizing crop management, comparing the performance of different cultivars, and detecting potential adaptation to biotic or abiotic stress (disease, insects, drought, and salinity) in field environments. This methodology using smartphone camera is adequate to the early growing period of short and high crops, but it is inadequate to the maturing period of high crops such as maize, sugarcane and sorghum, because capturing the top-view canopy image for high plants is difficult with smartphone camera. In the future study, we intend to evaluate yield components from CCR in accessions or lines with high-yielding potential in crops.

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