HIGH THROUGHPUT PHENOTYPING OF PHYSIOLOGICAL GROWTH DYNAMICS FROM UAS-BASED 3D MODELING IN SOYBEAN

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ABSTRACT:

Nowadays, an essential tool to improve the efficiency of crop genetics is automated, precise and cost-effective phenotyping of the plants. The aim of this study is to generate a methodology for high throughput phenotyping the physiological growth dynamics of soybeans by UAS-based 3D modelling. During the 2018 growing season, a soybean experiment was performed at the Agronomy Center for Research and Education (ACRE) in West-Lafayette (Indiana, USA). Periodic images were acquired by G9X Canon compact digital camera on board senseFly eBee. The study area is reconstructed in 3D by Image-based modelling. Algorithms and techniques were combined to analyse growth dynamics of the crop via height variations and to quantify biomass. Results provide practical information for the selection of phenotypes for breeding.

1. INTRODUCTION

Estimating biophysical plant variables and non-destructive characterization of quantitative traits with high accuracy and cost-effectiveness is imperative for high-throughput phenotyping in precision agriculture (Furbank and Tester, 2011). Recent advances in sensor technology open great opportunities to UAS (Unnamed Aerial Systems) as a low-cost platform to derive high throughput and precise quantitative phenotyping datasets (Araus et al., 2018). In this context, due to the increasing use of UAS (Haghighattalab et al., 2016), the development of software tools and methodologies to automatically phenotype crops is urgently required. Regarding photogrammetric sensors on board UAS, the application of digital image analysis to cover plant height estimation (Malambo et al., 2018), yield estimation (Roth and Streit, 2018), early emergence, senescence rate (Hassan et al., 2018), disease detection (Whalley and Shanmuganathan, 2013) and quality evaluation (Herrero-Huerta et al., 2019). Using active optical sensors, Light Detection and Ranging (LiDAR) is capable of providing 3D data including height and vegetation density areas on canopy structure (Herrero-Huerta et al., 2016). It has been used to derive canopy height, fractional cover and above ground biomass (Wallace et al., 2012).
Plant height is a crucial variable connected to stability, yield potential and lodging resistance. This variable has been assessed by UAS as a Structure from Motion (SfM), obtaining high correlations with ground reference measurements for barley (Bendig et al., 2014), wheat (Khan et al.,2018), poppy (Iqbal et al., 2017) and sorghum (Hu et al., 2018).
In this research, senseFly eBee was chosen as a UAS, providing great flexibility and speed to accomplish mapping at high spatial and temporal resolution using an onboard Canon G9X compact digital camera, working in the visible spectrum (Red-Green-Blue).The images are processed through a fully automatic photogrammetric pipeline by the computation of the view of each image and, subsequently, the generation of a dense and scaled 3D model of the crop. Once temporal point clouds are generated, algorithms were employed to analyse the growth dynamics of the crop via height variations. In addition, mesh calculations were applied to quantify biomass with a high level of resolution. The main output of this workflow will allow the selection of phenotypes for practical breeding.
The paper is organized as follow: after this brief introduction, the materials and methods are explained. Consequently, the experimental results reached are discussed. To end with, the conclusions and further studies are summarized.

2. MATERIALS AND METHODS

2.1 Materials

The materials used for the data acquisition are described below:

- A GNSS device from TopCon to georeference the Ground Control Points (GCP).
- Canon PowerShot G9 X Digital Camera as a passive sensor for image acquisition, with the following technical specifications:

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Canon G9 X	
Optical Sensor Type	BSI-CMOS
Optical Sensor Size	16 mm
Image Size	5742*3648 pixels
Optical Sensor Resolution	20.2 MPixels

Table 1. Technical specifications of the photographic sensor

- The senseFly eBee, designed as a fixed wing UAV for application in precision agriculture with incorporated GPS, IMU and magnetometer. It has a weight of 700 g and a payload of 150 g. The digital camera is controlled by the senseFly eBee autopilot during the flight.

2.2 Methods

2.2.1 Flight planning

Proper flight planning is crucial to guarantee the imagery acquisition reaches the theoretical parameters, produces high quality images, achieves optimization of existing resources as well as minimizes the capture time.
Once the study area is defined, Sensefly software determines the flight strips, the camera orientation and the image acquisition regarding the restricted forward and side overlap and guaranteeing the scale by the required GSD (Ground Sample Distance). The flight planning is illustrated in Figure 1, where the green line is the UAS trajectory, the red points are the image acquisition shots and the red rectangle is the study area. The parameters that define image capture are determined during flight execution depending on the light conditions and the wind and flight speed.

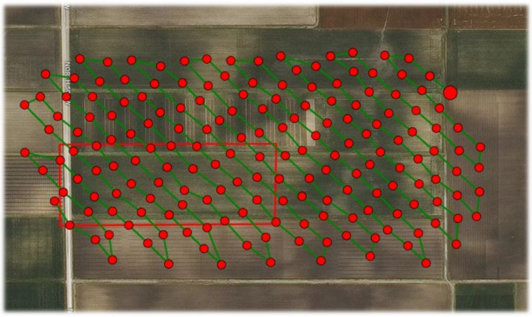

Figure 1: Flight planning

2.2.2 Photogrammetric pipeline

Firstly, a topographic survey is performed that will allow absolute georeferencing and scale the model. For this purpose, accuracy targets were placed along the study area, staying detectable in the acquired images. Once the aerial imagery had been captured, a standard photogrammetric pipeline is performed by image based modelling techniques. Each dataset is handled by a framework based on camera calibration (Remondino and Fraser, 2006), image orientation and dense point cloud extraction (Herrero-Huerta et al., 2015). The Pix4Dmapper software package (Pix4D SA, Lausanne, Switzerland) is employed for image processing. In addition, the GCPs' (Ground Control Points) measurements are employed in retrieving the camera interior parameters and correcting for any systematic error or block deformation.
The generated point cloud of each date allows plant height estimations (Malambo et al., 2018), characterizing crop geometry with a high detail and accuracy.

2.2.3 Point Cloud processing

Generated point clouds are used to extract the soybean height, critical for biomass and yield estimation (Tilly et al., 2015). These point clouds possibly enclose outliers owing to the massive and automated nature of the photogrammetric processing. To filter isolated clusters, a statistical analysis on each point's neighbourhood is performed by assuming a Gaussian distribution of neighbours' distances (Herrero-Huerta et al., 2018). Afterward, to guarantee fully registered point clouds, the Iterative Closest Point algorithm (Besl and Mckay, 1992) is used, getting a negligible mean absolute error among ground points from multi-temporal datasets. Afterwards, point clouds are filtered by a common bounding box. With the aim to derive physiological crop dynamics, deviation point clouds of height variations between multi-temporal datasets are computed. Consequently, an accurate cloud-to-cloud distance is derived giving a local approximation model to the reference cloud by a quadric surface. Outcome deviation point clouds precisely establish the physiological growth dynamics. The next step is the triangulation of the point cloud. The meshing algorithm chosen is 3D Delaunay triangulation (Golias and Dutton, 1997). These meshes have to be refined to remove the errors generated during the automated process, through the approximation of Attene (2010). Finally, subtractions from meshes are applied to quantify volume increments per plot associated to biomass production.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The soybean experiment was performed at the Agronomy Center for Research and Education (ACRE) during the 2018 growing season in West-Lafayette (Indiana, USA). The study area has an extension of 252.4*109.5 m^2, consisting of 20 plots in vertical and 48 plots in horizontal, with different sizes depending of the number of horizontal rows with the same genotype (4, 8 and 6 rows), as Figure 2 shows. The camera configuration was with along-and across-track overlap of ca. 75%, adequate to Pix4D software processing. A flight altitude over the ground of 79 m is obtained by Sensefly software, given the camera focal lengh (10 mm) and the required Ground Sample Distance (GSD). The exposure time was fixed to 1/2000 sec and the ISO was 125. 8 GCPs were placed on the ground for scaling, georeferencing and analysis purposes and measured with GNSS, using RTKNAVI software (Takasu 2009). A total of 66 images (in average) were used for the photogrammetric processing.

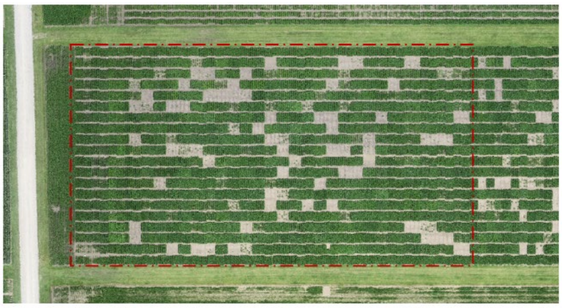

Figure 2: Study area

Periodic flights were done during 2018 growing season in the following dates: June 14th (DAP 14), June 27th (DAP 27), July 14th (DAP 44), July 26th (DAP 56) and August 18th (DAP 79), being the planting date May 31st (DAP 0). Figure 3 illustrates the deviation point clouds using the one from June 14th (DAP 14) as a reference. In addition, Table 2 collects the reached statistical parameters.

Figure 4 analyses one particular plot to quantify the biomass from DAP 44 to DAP 56. The point cloud is converted into a mesh by applying a 3D Delaunay triangulation. Finally, subtractions from these meshes gives us the volume increment of **0.178 m^3** for this specific plot, related to biomass production. Table 3 summarizes the volume increments of this plot at different dates, using DAP 14 as reference.

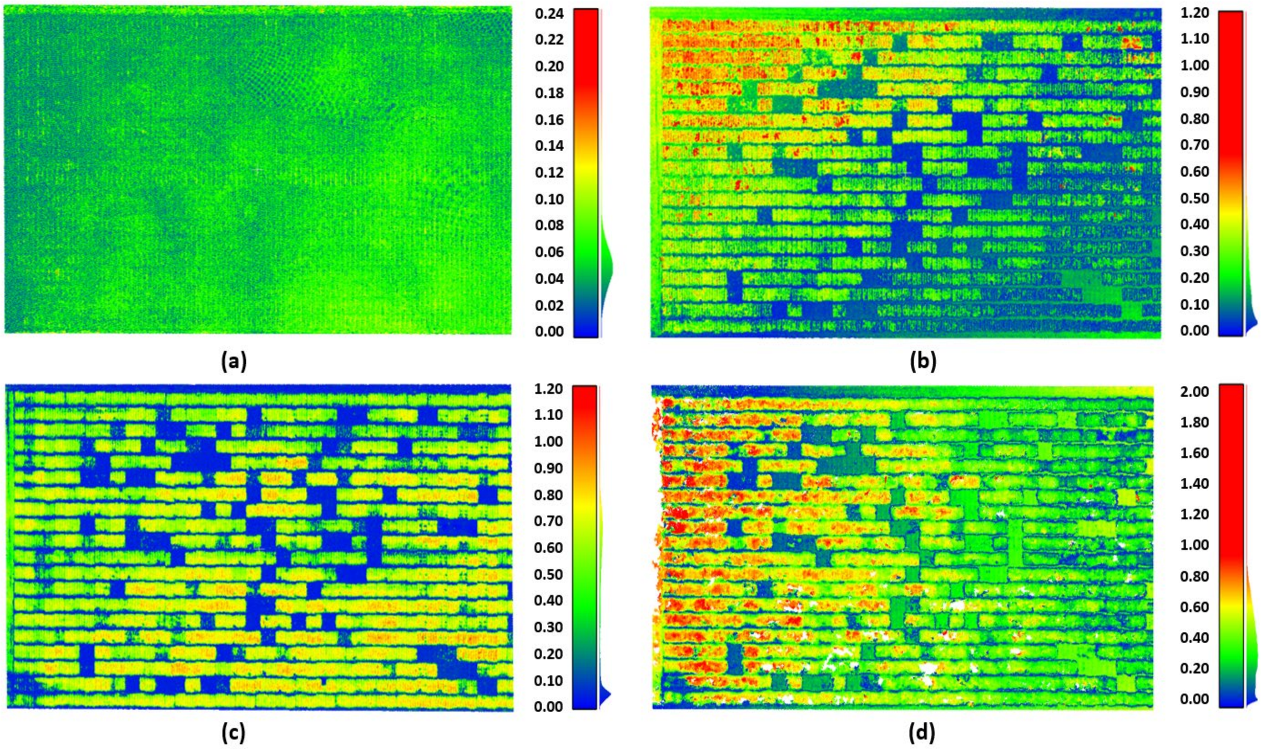

Figure 3: Deviation point clouds over Soybean using DAP 14 as reference at: (a) DAP 27, (b) DAP 44, (c) DAP 56 and (d) DAP 79, in *meters*.

DAP	**No. of Points**	**Statistics**			
		Min	***Max***	***Mean***	***Sigma***
14 (ref.)	1613588	-	-	-	-
27	1580992	0	0.241	0.021	0.158
44	1711892	0	0.780	0.448	0.592
56	1713237	0	1.299	0.578	0.614
79	1421094	0	1.254	0.544	0.611

Table 2. Statistical parameters of the deviation point clouds in *m* using DAP 14 as reference.

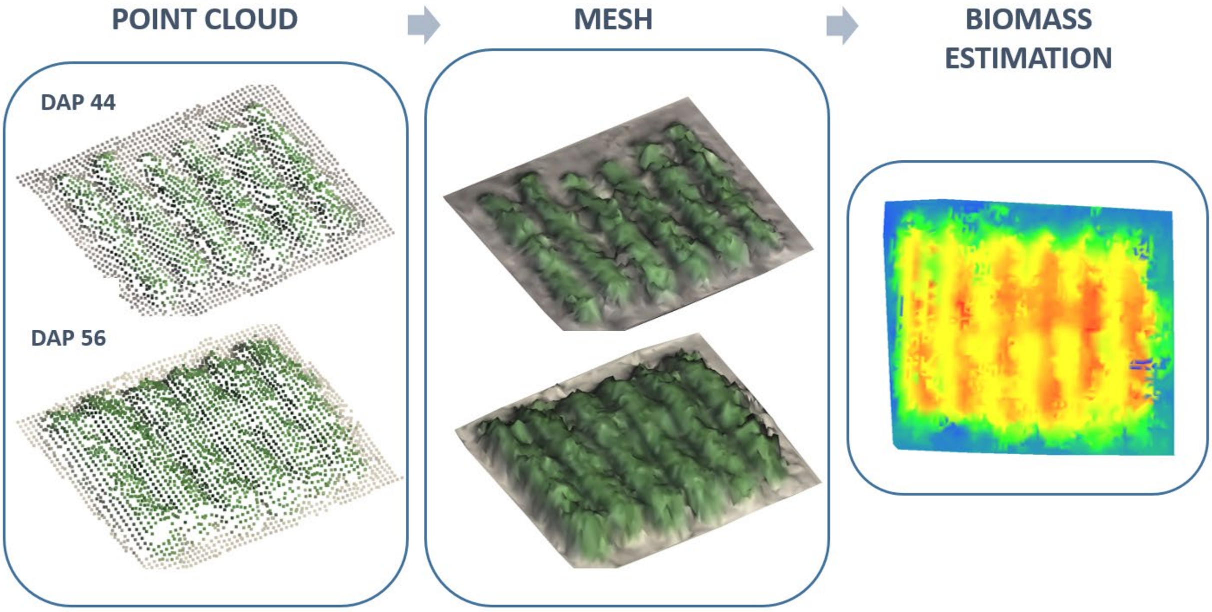

Figure 4: Biomass estimations from plots between DAP 44 and DAP 56.

DAP	Volume increment (m^3)
27	0.108
44	0.291
56	0.469
79	0.601

Table 3. Increment volume (m^3) at different dates, using DAP 14 as reference, linked to biomass production.

4. CONCLUSIONS

This study is evidence of the great potential of UAS to generate 3D models for soybean phenotyping as a rapid, accurate and cost-effective tool. Specifically, this study evaluates the power of high spatial and temporal resolution RGB data to soybean phenotyping selection. Additionally, this workflow can be successfully used for other HTPPs and crops planted in breeding nurseries. Even so, more comprehensive studies are necessary, including studies on different crop species. Furthermore, the UAS approach for precision farming is in constant evolution and represents an extremely dynamic sector. In this context, this research is our contribution as a methodology for soybean high throughput phenotyping from UAS-based image modelling.

The proposed framework demonstrates that it is highly feasible to provide relatively accurate physiological growth dynamic and biomass estimations of soybean, providing valuable insight for high spatial and temporal resolution in agriculture, genetic inference and phenotyping selection (Sankaran et al., 2015).

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