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Evaluation of image acquisition parameters and data extraction methods on plant height estimation with UAS imagery

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Abstract.

Aerial imagery from unmanned aircraft systems (UAS) has been increasingly used for field phenotyping and precision agriculture. Plant height is an important crop growth parameter that can be estimated from 3D point clouds and digital surface models (DSMs) derived from UAS imagery. However, many factors can affect the accuracy of the plant height estimation. This study examined the effects of image overlap, pixel resolution, and data extraction methods on estimation accuracy. An experimental field containing 16 plots with four crops (cotton, corn, grain sorghum and soybean) and four replications was set up for this study. An imaging system consisting of two consumer-grade Nikon D7100 cameras with 6000 x 4000 pixels was mounted on a rotary hexacopter for image acquisition. One camera was used to capture red-green-blue (RGB) color images, while the other was equipped with a 720-nm long-pass filter to obtain near-infrared (NIR) images. Aerial images were captured along seven flight lines from the field at four altitudes (30 m, 60 m, 90 m and 120 m) above ground level three times during a growing season. Plant height was also measured manually from selected sampling points across the 16 plots. The RGB and NIR images taken at the four altitudes with varying overlaps were processed using Pix4Dmapper to create orthomosaics, 3D point clouds, DSMs and digital *terrain models (DTMs). Both DSM-based and point cloud-based methods were used to extract plant height data. The data values falling within a circular area centered at each sampling point across the 16 plots were extracted from both DSMs and point clouds. The 80th to 99th percentiles and the maximum of the extracted height values were calculated. Correlation and regression analyses were performed to determine the relations between ground plant height measurements and estimates derived from the DSMs and the point clouds for the four crops. Preliminary results based on the data from a single date indicate that the point cloud-based method is superior to the DSM-based method and that the 99% and 100% percentiles are good indicators of plant height. Moreover, correlations between measured and estimated plant height data tend to increase as image overlap increases at the same altitude or as flight altitude decreases with the same overlap. The results from this study will be useful for selecting appropriate flight parameters and data extraction methods for accurate plant height estimation using UAS imagery.*

Keywords.
Aerial image, digital surface model, plant height, point cloud, unmanned aircraft system.

Introduction

Remote sensing has been used as an important data acquisition tool for precision agriculture for decades. Based on their height above the earth, remote sensing platforms mainly include satellites, manned aircraft, unmanned aircraft systems (UAS) and ground-based vehicles. In recent years, UAS have become a popular remote sensing platform to fill the gap between manned and ground-based platforms due to their low cost, ease of deployment and low flight height for high resolution imagery. The improved spatial and temporal resolutions of UAS imagery offer new opportunities for plant phenotyping and some precision agriculture applications.

Plant height is an important plant phenotypic attribute that is directly related to crop biomass and yield potential (Bendig et al. 2014; Tilly et al. 2015; Feng et al., 2019). Therefore, measuring plant height during the growing season provides useful crop growth information for precision management and phenotyping. Manual methods and vehicle-mounted ultrasonic sensors have been traditionally used for measuring plant height (Sui and Thomasson 2006; Escola et al. 2011; Bai et al. 2016; Yuan et al. 2018). However, these ground-based methods are costly and time-consuming and may not have continuous sampling for every area of the field. Therefore, non-destructive aerial methods for measuring crop height and other canopy characteristics provide an attractive alternative.

As the ground coverage of low-flying UAS is relatively small, large numbers of overlapping images need to be acquired along multiple flight lines to cover a field. With high resolution overlapping images, it is possible to create high resolution 3D point cloud models. Structure-from-motion (SfM) photogrammetry is an image-based 3D reconstruction method for automatic creation of digital surface models (DSMs) and orthomosaics from overlapping images (Westoby et al. 2012; Li et al. 2016; Shi et al. 2016; Hassan et al. 2019).

Many studies have evaluated SfM methods to estimate crop height from UAS images over the growing season (Bendig et al. 2014; Holman et al. 2016; Madec et al. 2017; Varela et al. 2017; Malambo et al. 2018; Xie et al. 2021). Results from these studies have shown significant correlations between UAS-based estimates and ground or Lidar data. Despite the encouraging results, estimation accuracy varies with camera types, image resolution, flight parameters, and other imaging and crop growing conditions. Therefore, the objectives of this study were to evaluate the effects of image overlap, pixel resolution, and data extraction methods on plant height estimation accuracy with UAS imagery.

Materials and methods

Study site

This study was conducted over a 1-ha area (30°31'19.2"N, 96°24'0.7"W) at the Texas A&M University AgriLife Research Farm near College Station, Texas. Four crops, including cotton, corn, grain sorghum and soybeans, were planted to the area in 16 plots with four replications (Fig. 1). Each plot contained eight rows with a length of 15 m and a row spacing of 1.016 m.

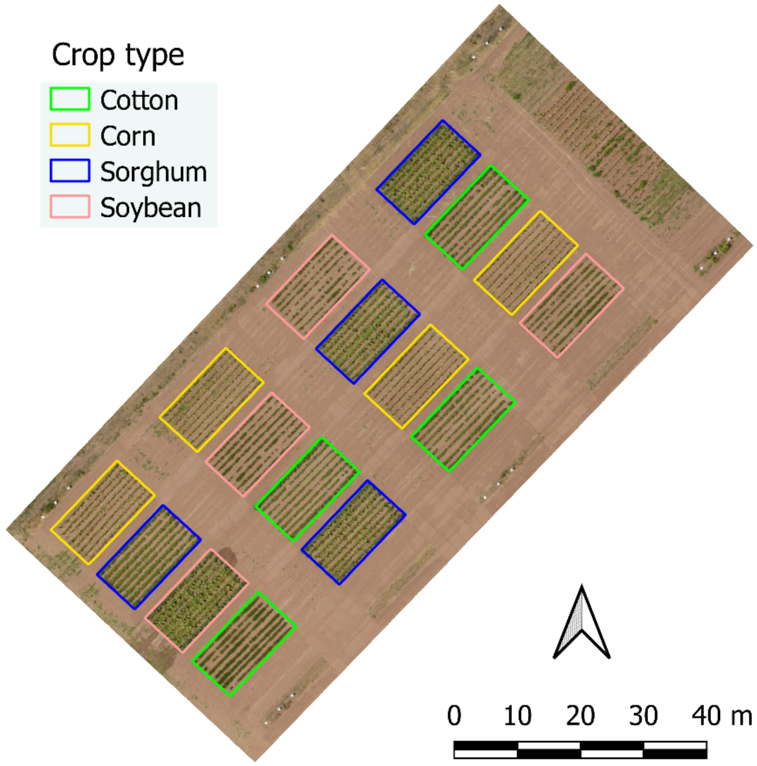

Fig. 1. Test plot layout for four crops near College Station, Texas. Each plot measured approximately 8 m by 15 m.

UAS image acquisition

A two-camera imaging system mounted on a rotary AG-V6A hexacopter (Homeland Surveillance & Electronics, LLC, Casselberry, FL) was used for image acquisition. The imaging system consisted of two consumer-grade Nikon D7100 cameras with a pixel array of 6000 x 4000 (Nikon Inc., Melville, NY). One camera was used to capture red-green-blue (RGB) color images, while the other was modified with a 720-nm long-pass filter to collect near-infrared (NIR) images. Image acquisition was conducted along seven flight lines at altitudes of 30 m, 60 m, 90 m and 120 m above ground level on 28 June, 16 July, and 8 August 2019. For this paper, only the 8 August images were used. Images captured at any given altitude had approximately the same side and forward overlap. The side/forward overlaps at the four altitudes from 30 m to 120 m were 67%, 83%, 89%, and 92%, respectively. Pixel sizes ranged from approximately 0.5 cm at 30 m to 2.0 cm at 120 m.

Plant height measurements

Plant height was manually measured at three selected plant canopies in each of the 16 plots on each imaging date. The geographic coordinates (X, Y, Z) for the 48 sampling locations were measured with a centimeter-grade Trimble R2 GPS receiver with the virtual reference station (VRS) real-time kinematic (RTK) corrections (Trimble Inc., Sunnyvale, CA). The GPS data were converted to the Universal Transverse Mercator (UTM), World Geodetic System 1984 (WGS-84), Zone 14, coordinate system.

Creation of point clouds, orthomosaics and DSM from images

The RGB and NIR images with different combinations of altitudes and overlaps were processed to create point clouds, orthomosaics, DSMs and digital terrain models (DTMs) using Pix4DMapper Pro (Pix4D S.A., Prilly, Switzerland). The default settings in all processing steps were used for identifying keypoints, densifying point clouds, and generating orthomosaics, DSMs and DTMs. To simulate smaller overlaps, subsets of the images were selected for processing. For example, if the images captured at 120 m were selected from every other flight line and from every other image, the number of images was reduced by a factor of ¼ and the overlap was reduced from 92% to 83%. To ensure the positional accuracy, 18 white panels were placed around the field during image acquisition. The center coordinates of the panels were measured with the R2 GPS receiver and then used as the ground control points (GCPs) during image processing. The root mean square error was less than 0.015 m in both horizontal and vertical directions.

Extraction of plant height from DSMs and point clouds

A polygon shapefile consisting of circles with a diameter of 30 cm centered at the 48 sampling points was created. The circles were overlaid on the DSMs and point clouds to extract all the points falling within the circles. The extracted points were then sorted by elevation (Z values) in ascending order. To convert the extracted points from DSMs and point clouds from above the sea level to above ground level, the digital terrain models (DTMs) could be subtracted from extracted points. In this study, the ground elevation values measured by the GPS at the sampling sites were used as the ground reference and then subtracted from the extracted elevation points as estimated plant height. The 80th, 85th, 90th, 95th, and 99th percentiles and the maximum (100% percentile) of the estimated plant height data were calculated for the 48 samples.

Correlation and regression ananlyses

Correlation analysis was performed to determine the correlations between measured plant height and the percentiles derived from the DSMs and the point clouds for different combinations of flight altitudes and overlaps. To examine the effects of image overlap, pixel resolution and data extract methods, results from the four flight altitudes with different overlaps were compared for both DSM-based and point cloud-based data extraction methods. Linear regression was also performed between measured plant height and the best percentiles among the four crops for plant height estimation.

Results and discussion

Point clouds and DSMs and ground plant height

Fig. 2 shows the point cloud and DSM for the 8 August 2019 images at the 60 m flight altitude. All four crops were in their late growth stages for the season, and corn was senescing and losing its chlorophyll. Table 1 presents the simple statistics of plant height for the four crops on the imaging date.

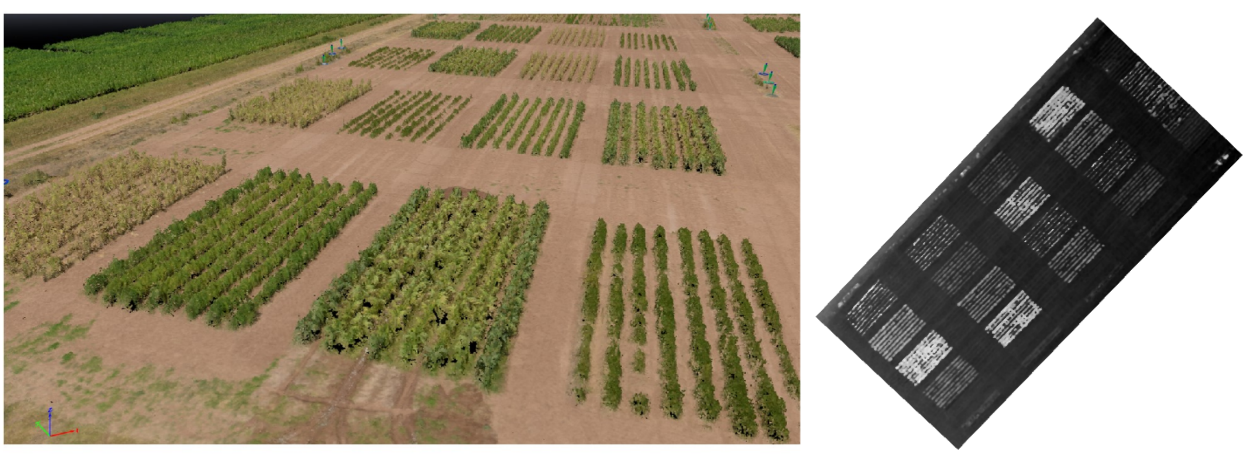

Fig. 2. Point cloud (left) and digital surface model (right) for 16 test plots based on images taken at 60 m on 8 August 2019. On the right map, light gray color represents high elevation, whereas dark gray color depicts low elevation.

Table 1. Descriptive statistics of plant height for four crops.

Statistic	Cotton	Corn	Sorghum	Soybean

Minimum (m)	0.56	1.03	0.76	0.34
Maximum (m)	0.72	1.36	1.13	0.62
Mean (m)	0.64	1.18	1.04	0.45
Standard deviation (m)	0.05	0.09	0.11	0.08

Correlations of measured plant height with estimated height at different aititudes with different overlaps

Table 2 summarizes the correlation coefficients between ground-measured plant height and estimated height based on the DSMs and point clouds at the four flight altitudes with the four overlaps. As the images for all four altitudes were captured along the same flight lines at the same framing rate, the numbers of images among the four altitudes were about the same. Correlation coefficients for DSM-based plant height estimates had highest values at the maximum or 100% percentile, while those for the point cloud-based estimates had highest values at the 100% percentile for 30 m and 99% for the other three altitudes. These results indicate that the 99% and 100% percentiles could be used as indicators of plant height. The best coefficients decreased from 0.927 at 30 m to 0.582 at 120 m for the DSM-based method, whereas the best r values were very similar (0.947-0.968) among the four altitudes for the point-cloud-based method. Moreover, the best r values from the point clouds were higher than those from the DSMs, indicating that the point cloud-based method was more accurate and consistent than the DSM-based method for plant height extraction.

Table 2. Correlation coefficients between measured plant height and estimated plant height from DSMs and point clouds at four flight altitudes with four different overlaps.

Extraction method	DSM-based				Point cloud-based			
Flight altitude	30 m	60 m	90 m	120 m	30 m	60 m	90 m	120 m
Number of images	858	856	816	876	858	856	816	876
Overlap*	67%	83%	89%	92%	67%	83%	89%	92%
80th percentile	0.780	0.857	0.547	0.525	0.884	0.850	0.873	0.851
85th percentile	0.784	0.865	0.576	0.560	0.906	0.889	0.920	0.886
90th percentile	0.788	0.879	0.585	0.568	0.917	0.927	0.953	0.928
95th percentile	0.793	0.897	0.597	0.573	0.929	0.947	0.967	0.954
99th percentile	0.925	0.901	0.637	0.580	0.943	**0.968**	**0.968**	**0.962**
Maximum	**0.927**	**0.904**	**0.644**	**0.582**	**0.947**	0.958	0.967	0.961

* Side overlap was approximately the same as forward overlap. Bold r values indicate maximum values for the given altitude.

Fig. 3 shows the scatterplots and regression lines between ground measured plant height and estimates based on the DSMs and point clouds at 30 m and 90 m for the four crops. At 30 m, both methods provided strong linear relations between measured and estimated plant height. At 90 m, estimates based on the point cloud had a very strong linear relation for all the crops. However, the DSM-based method underestimated the height of some corn canopies at this altitude, even though it appeared to be accurate for the other three crops. The underestimates were probably due to the smoothing effect in the DSMs. The smoothing may have not greatly affected the other three corps as they had relatively uniform and closed canopies compared with the sparse and open canopy in the senescing corn.

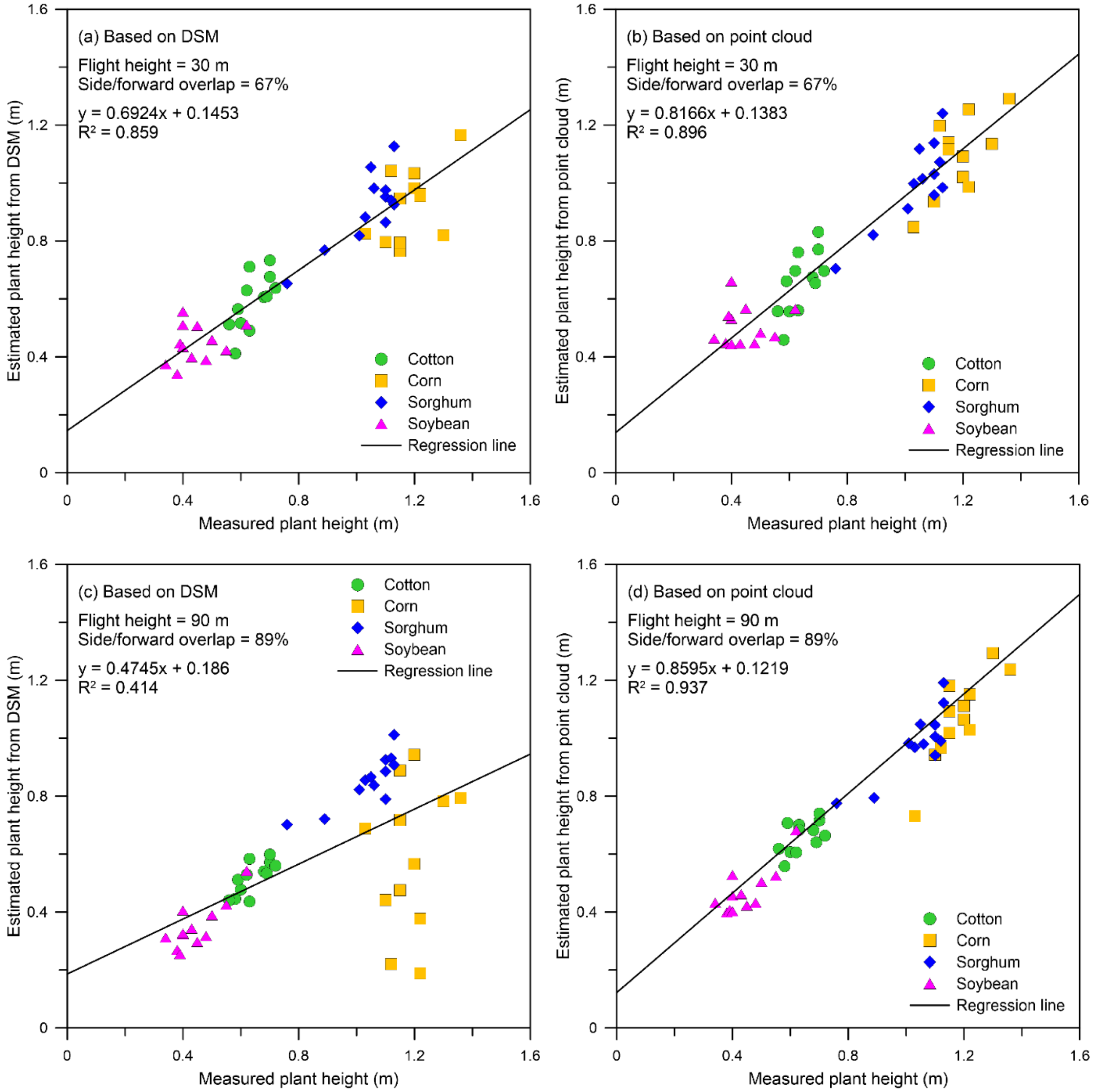

Fig. 3. Scatterplots and regression lines between measured plant height and estimates based on digital surface models and point clouds at 30 m and 90 m for four crops.

Correlations of measured plant height with estimated height at different aititudes with the same overlap

Table 3 shows the r values between measured plant height and estimated plant height from the DSMs and point clouds at the four flight altitudes with the same 67% overlap. The r values at 30 m are the same as those in Table 2. The r values for the other three altitudes were based on the subset images derived from the respective original datasets at each altitude. Clearly, the r values decreased with the increase of flight altitude for both methods, though the point cloud-based method had higher r values at each altitude for all the percentiles than the DSM-based method. Similarly, the 99% and 100% percentiles had the highest r values for all the altitudes except that the 95% percentile had the highest r value at 120 m for the point cloud.

Table 3. Correlation coefficients between measured plant height and estimated plant height from DSMs and point clouds at four flight altitudes with the same overlap.

Extraction method	DSM-based				Point cloud-based			
Flight altitude	30 m	60 m	90 m	120 m	30 m	60 m	90 m	120 m
Number of Images	858	237	114	69	858	237	114	69
Overlap*	67%				67%			
80th percentile	0.780	0.428	0.337	0.272	0.884	0.736	0.554	0.524
85th percentile	0.784	0.560	0.382	0.276	0.906	0.773	0.639	0.535
90th percentile	0.788	0.595	0.392	0.283	0.917	0.797	0.787	0.536
95th percentile	0.793	0.604	0.398	0.289	0.929	0.828	0.814	**0.630**
99th percentile	0.925	**0.634**	0.434	**0.302**	0.943	0.854	**0.876**	0.612
Maximum	**0.927**	**0.634**	**0.439**	**0.302**	**0.947**	**0.857**	**0.876**	0.612

* Side overlap was approximately the same as forward overlap. Bold r values indicate maximum values for the given altitude.

Correlations of measured plant height with estimated height at the same altitude with different overlaps

Table 4 presents the correlation coefficients between measured plant height and estimated plant height from the DSMs and point clouds at 120 m with four different overlaps. For the DSM-based data extraction, the r values were generally very low, even though they tended to increase with the increase of overlap. However, the highest correlation occurred at the 75% overlap. From the scatterplots between measured and estimated plant height (not shown), it was obvious that the DSMs with all four overlaps underestimated the plant height for corn. On the other hand, the r values based on the point clouds had a clear increasing trend with the increase of overlap, and the best r values ranged from 0.630 at the 67% overlap to 0.962 at 92%. Although three of the four best r values from the point clouds occurred at the 95% percentile, the 99% and 100% percentiles provided very similar r values.

Table 4. Correlation coefficients between measured plant height and estimated plant height from DSMs and point clouds at the same flight height with four different overlaps.

Extraction method	DSM-based				Point cloud-based			
Flight altitude	120 m				120 m			
Number of Images	69	118	236	876	69	118	236	876
Overlap*	67%	75%	83%	92%	67%	75%	83%	92%
80th percentile	0.272	0.612	0.471	0.525	0.524	0.803	0.879	0.851
85th percentile	0.276	0.616	0.475	0.560	0.535	0.836	0.906	0.886
90th percentile	0.283	0.620	0.488	0.568	0.536	0.854	0.915	0.928
95th percentile	0.289	0.626	0.508	0.573	**0.630**	**0.907**	**0.930**	0.954
99th percentile	**0.302**	0.634	0.530	0.580	0.612	0.893	0.902	**0.962**
Maximum	**0.302**	**0.638**	**0.541**	**0.582**	0.612	0.893	0.902	0.961

* Side overlap was approximately the same as forward overlap. Bold r values indicate maximum values for the given altitude.

Summary

Preliminary results based on the data from a single date indicate that DSMs and point clouds derived from UAS images have the potential for estimating plant height of multiple crops. It appears that the point cloud-based method is superior to the DSM-based method. The 95%, 99% and 100% percentiles of the DSMs or point clouds are good indicators of plant height. Moreover, correlations between measured and estimated plant height data tend to increase with the increase of image overlap at the same altitude or with the decrease of flight altitude at the same overlap. Image data from other dates in this study and more data from additional years need to be analyzed to further validate these observations. More research is also needed to evaluate how image processing parameters and other environmental factors affect plant height estimation.

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References

Bai, G., Ge, Y., Hussain, W., Baenziger, P. S., & Graef, G. (2016). A multi-sensor system for high throughput field phenotyping in soybean and wheat breeding. *Computers and Electronics in Agriculture*, 128, 181–192.

Bendig, J., Bolten, A., Bennertz, S., Broscheit, J., Eichfuss, S., & Bareth, G. (2014). Estimating biomass of barley using Crop Surface Models (CSMs) derived from UAV-based RGB imaging. *Remote Sensing*, 6, 10395–10412.

Escolà, A., Planas, S., Rosell, J. R., Pomar, J., Camp, F., Solanelles, F., et al. (2011). Performance of an ultrasonic ranging sensor in apple tree canopies. *Sensors*, 11, 2459–2477.

Feng, A., Zhang, M., Sudduth, K. A., Vories, E. D., & Zhou, J. (2019). Cotton yield estimation from UAV-based plant height. *Transactions of the ASABE*, 62, 393–403. https://doi.org/10.13031/trans.13067

Hassan, M. A., Yang, M., Fu, L., Rasheed, A., Zheng, B., Xia, X., et al. (2019). Accuracy assessment of plant height using an unmanned aerial vehicle for quantitative genomic analysis in bread wheat. *Plant Methods* 15, 37. https://doi.org/10.1186/s13007-019-0419-7

Holman, F. H., Riche, A. B., Michalski, A., Castle, M., Wooster, M. J., & Hawkesford, M. J. (2016). High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV based remote sensing. *Remote Sensing*, 8, 1031.

Li, W., Niu, Z., Chen, H., Li, D., Wu, M., & Zhao, W. (2016). Remote estimation of canopy height and aboveground biomass of maize using high-resolution stereo images from a low-cost unmanned aerial vehicle system. *Ecological Indicators* 67, 637–648. https://doi.org/10.1016/j.ecolind.2016.03.036

Madec, S., Baret, F., de Solan, B., Thomas, S., Dutartre, D., Jezequel, S., et al. (2017). High-throughput phenotyping of plant height: Comparing unmanned aerial vehicles and ground LiDAR estimates. *Frontiers in Plant Science*, 8, 2002. doi:10.3389/fpls.2017.02002

Malambo, L., Popescu, S. C., Murray, S. C., Putman, E., Pugh, N. A., Horne, D. W., et al. (2018). Multitemporal field-based plant height estimation using 3D point clouds generated from small unmanned aerial systems high-resolution imagery. *International Journal of Applied Earth Observation and Geoinformation*, 64, 31–42.

Shi, Y., Thomasson, J. A., Murray, S. C., Pugh, N. A., Rooney, W. L., Shafian, S., et al. (2016). Unmanned aerial vehicles for high-throughput phenotyping and agronomic research. PLoS ONE 11(7): e0159781. doi:10.1371/journal.pone.0159781

Sui, R., & Thomasson, J. A. (2006). Ground-based sensing system for cotton nitrogen status determination. *Transactions of the ASABE*, 49, 1983–1991.

Tilly, N., Aasen, H., & Bareth, G. (2015). Fusion of plant height and vegetation indices for the estimation of barley biomass. *Remote Sensing*, 7, 11449–11480.

Varela, S., Assefa, Y., Prasad, P. V. V., Peralta, N. R., Griffin, T. W., Sharda, A., et al. (2017). Spatio-temporal evaluation of plant height in corn via unmanned aerial systems. *Journal of Applied Remote Sensing*, 11(3), 036013.

Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). “Structure-from-Motion” photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology*, 179, 300–314.

Xie, T., Li, J., Yang, C., Jiang, Z., Chen, Y., Guo, L., et al. (2021). Crop height estimation based on UAV images: methods, errors, and strategies. *Computers and Electronics in Agriculture*, 185, 106155.

Yuan, W., Li, J., Bhatta, M., Shi, Y., Baenziger, P. S., & Ge, Y. (2018). Wheat height estimation using LiDAR in comparison to ultrasonic sensor and UAS. *Sensors* 18, 3731. https://doi.org/10.3390/s18113731