Plant height and biomass estimations on wheat using high-resolution aerial imagery in an experimental field in Sonora, Mexico

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Abstract

At present, there are already many global efforts to improve food security, including those that seek to increase crop productivity of small farmers through providing better crop varieties. Wheat is an important source of food intake for many communities, especially in developing countries. Thus, the work of physiological improvement of wheat crop can contribute to accelerate genetic gains using new technologies. This study contributes to explore high throughput phenotyping methodologies, with estimations of plant height and biomass above ground in wheat were obtained using high resolution aerial images from unmanned aerial vehicles in an experimental field in Sonora, Mexico. Two different image resolutions (0.5 cm and two cm), and two different methods of georeferencing the digital three-dimensional model were evaluated (using ground control points and geotagging of images during image-acquisition with differential correction on the UAV navigation system).
The study confirms promising results in the estimation of plant height (correlations between 0.52 to 0.87) and above-ground biomass (correlations from -0.01 in booting to 0.40 in anthesis stage). The direct georeferencing method using the differential correction has been identified to be the better option, especially, because it is saving time and costs in the data collection process, while providing enough accuracy. The overall image resolution was two cm, but not with great and consistent differences.

Keywords: Plant height, biomass, wheat, photogrammetry, UAV

1. Introduction

There are many global efforts aligned to the United Nations' second goal of the sustainable development goals for 2030: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture" (UN, 2015, p. 15). Wheat (Triticum spp) is the cereal with major consumption worldwide (FAO, 2018), an important source of food for humanity. However, its production faces environmental and social challenges that mostly affects small-scale farmers, e.g. unfavorable weather conditions that threaten to lower yield (FAO, 2018). To support small-scale farmers' productivity, international crop improvement centers are developing improved varieties, i.e. high-yielding in unfavorable conditions.
Physiological wheat breeding characterizes the genetic resources available to make crosses based on known desirable characteristics to pass them to the next generations. Breeding cycles are accelerated through pre-selection of varieties with desirable traits based on "genomic selection" models involving genotyping and phenotyping. With sufficient information, lines don't need to be evaluated in the field before being selected as parents for the next cycle (Heffner, Sorrells, & Jannink, 2009). Extensive in-field measurements in experimental plots are required, associated to high costs in manual labor and time.
Two traits of interest are plant height (PH) and dry above ground biomass (AGB) in wheat. PH is useful for assessing susceptibility of lodging (Berry, Sterling, Baker, Spink, & Sparkes, 2003), to evaluate varieties under water stress and can be a proxy measure for flowering (Madec et al., 2017). PH is also correlated with yield and the plant carbohydrate storage capacity (Pask et al., 2012). Biomass is an

indicator of crop growth, radiation use efficiency and nutrients and metabolite analysis. Better adapted genotypes are able to maintain biomass production during stress conditions (Pask et al., 2012).
Technology now allows efficient data capture: PH and AGB of wheat and other crops have been estimated with true color imagery (Walter, Edward, McDonald, & Kuchel, 2018; Bendig, Bolten & Bareth, 2013) and combinations of sensors (Geipel, Link, & Claupein, 2014). Unmanned aerial vehicles (UAV) platforms are widely used for crop monitoring because of low cost, high versatility and advances in sensors (Bendig et al., 2013).
Photogrammetry is a technique that allows to reconstruct 3D scenes from 2D images by stereoscopy. After the digital surface model (DSM) is created, the original pictures are projected and merged in it to produce an image free of distortions with uniform scale called orthomosaic. A digital terrain model (DTM) represents the bare soil of an area (Geipel et al., 2014). A crop surface model (CSM) represents the height of the objects above ground (Bendig et al., 2014). The DSM minus the DTM results in the CSM. The level of detail in the input imagery influences what scale of a phenomena can be seen (Madec et al., 2017). This is related to the altitude and resolution of the camera. Cases of low correlations to ground truth measurements have been attributed to coarse resolution issues, however, very high resolution imagery is easier influenced by wind introducing noise to the model, especially when fewer images are available (Madec et al., 2017; Walter et al., 2018). A model quality increases when more photos are used (Walter et al., 2018), however, collecting more photographs also increases collection time, and consequently costs (Bendig et al., 2013).
Additionally, accurate geolocation is needed to give the model its true location on earth. One classic technique to do it is by using ground control points (GCPs) in the field with known accurate location (Marshall et al., 2012). Alternatively, the model can be georeferenced directly during the photogrammetric process if the imagery is geotagged based on the UAV navigation system (Geipel et al., 2014), with several meters of accuracy (De Souza et al., 2017). Precision enhancements of the mobile receiver in the UAV can be implemented using a base receiver on a known position (Madec et al., 2017) with the technique called Real Time Kinematic (RTK). If direct georeferencing is used time and costs are saved during data capture and processing (Madec et al., 2017).
The research questions in the study are (1) What is the correlation between manually measured PH compared to estimations obtained from a photogrammetric 3D model-reconstruction of wheat breeding experimental plots at key stages of the crop development? (2) What is the correlation between AGB compared to estimations of volume obtained from a photogrammetric 3D model-reconstruction of wheat breeding experimental plots at key stages of the crop development? (3) What is the optimal image resolution for the 3D model reconstruction of wheat breeding experimental plots for PH and volume estimations at key stages of the crop development? (4) What is the difference in spatial accuracy of RTK correction on the UAV location compared to the use of GCPs in the field to georeference the imagery products?

2. Area of study

This study was carried out in the Yaqui Valley, Sonora, Mexico, at the CENEB experimental station from the International Maize and Wheat Improvement Center (CIMMYT). The trial is located at 27.3955 N, 109.9283 W. The Yaqui Valley is characterized by intensive irrigated agriculture. It shares its agroclimate with 40 percent of the land where wheat is grown in the developing countries. It has a semiarid climate with an annual average rainfall rate of 317 mm.

3. Methodology

3.1 DATA USED FOR THE STUDY

The data corresponds to a wheat yield trial with 150 genotypes with 2 replicates for 2016-2017 winter cycle. The stages monitored were beginning of booting stage, seven days after anthesis and maturity. Plot size was four meters long by 2 beds of 0.8 m. The PH was measured with a ruler vertically from the ground to the top of the spike in four plants per plot in 49 genotypes. AGB was cut from an area of 50 cm by two beds, dried and weighted from 149 genotypes. The UAV data was captured the same day or two days after or before field measurements. Unfortunately, the data for the PH at booting and several field plot measurements were unavailable. An extra measurement of PH was done on the eighth of March. Pearson's correlation was used to assess the relationship between the remote and proximal data as done by Chapman et al. (2014). RMSE was used as an accuracy measure as done by Harwin & Lucieer (2012). Figure 1 shows a diagram of the steps followed in the study.

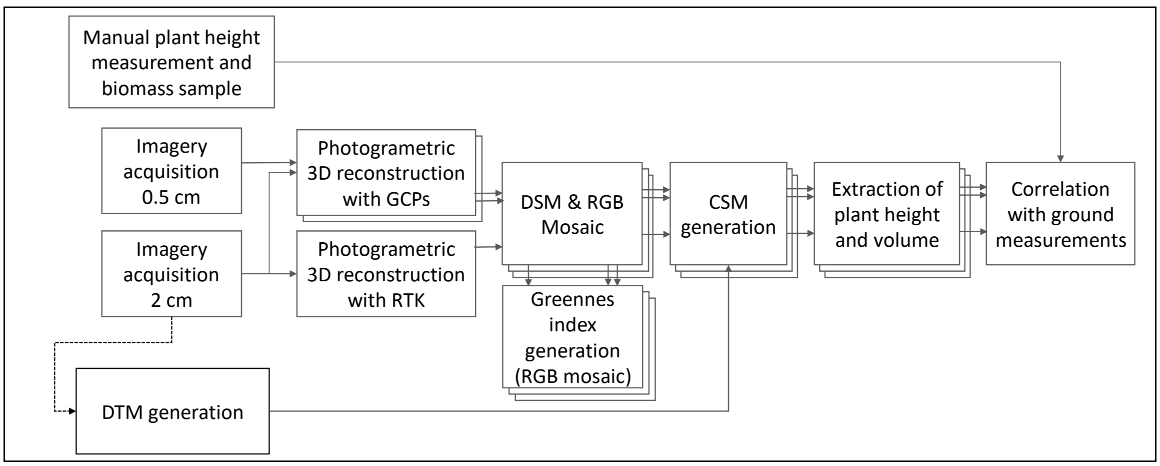

Figure 1. Methodology workflow

3.2 IMAGERY ACQUISITION

Two cm and 0.5 cm/pixel imagery were acquired in 13 flights trying to match the PH and AGB samplings. A fixed-wing UAV, eBee RTK by Sensefly, was used to acquire imagery of two cm/pixel with an RGB Canon PowerShot 110 camera with a perpendicular flightplan as De Souza et al. (2017). The lateral overlap was 80% and the longitudinal was 50%. A multirotor platform, Matrice 100 by DJI, was used to acquire imagery of 0.5 cm/pixel using the camera SONY NEX 5.

The GCP or RTK correction were used to georeference. For the eBee, RTK correction was used. The RTK base equipment was a Trimble R4 GPS receiver (Trimble, Sunnyvale, CA, USA) fixed in a known location. Seven GCPs were placed in the field, distributed in the corners and randomly inside the trial. The GCPs were measured previously with the same equipment used for the RTK correction. To compare the methods, locations of the center of the GCPs marks in each image were compared to the original measured coordinates of the GCP, and residuals were used to calculate the RMSE (Harwin & Lucieer, 2012).

3.4 ESTIMATIONS OF PLANT HEIGHT AND VOLUME

Photogrammetry software Pix4Dmapper (Version 4.4.4) was used to generate the DSM and the orthomosaic, then the CSM was calculated. The PH data per plot was extracted from the CSM as the 99.5% percentile (Madec et al., 2017) inside an area where no AGB cut was done, avoiding 15 cm of border. To compute plot volume, each CSM pixel was multiplied by the pixel area, considering only the ones corresponding to “vegetation pixels” in the orthomosaic filtered with the adapted greenness index filter (Wenzhu et al., 2015).

4. Results

Table 1 shows all the results from all the stages: R, RMSE, and number of ground vs estimate data pairs.

Table 1. Results for all the methods comparison.

Imagery	Trait	Stage	R	RMSE	n
0.5-cm GCP	AGB	Booting	-0.01	0.512	222
two-cm GCP	AGB	Booting	0.07	0.168	85
two-cm RTK	AGB	Booting	0.04	0.143	85
0.5-cm GCP	AGB	Anthesis	0.4	0.408	82
two-cm GCP	AGB	Anthesis	0.29	0.488	80
two-cm RTK	AGB	Anthesis	0.32	0.529	80
0.5-cm GCP	AGB	Maturity	0.22	0.797	77
two-cm GCP	AGB	Maturity	0.3	0.415	296
two-cm RTK	AGB	Maturity	0.29	0.78	296
0.5-cm GCP	PH	Anthesis	0.61	0.407	16
two-cm GCP	PH	Anthesis	0.55	0.441	30
two-cm RTK	PH	Anthesis	0.52	0.385	30
0.5-cm GCP	PH	March 8	0.57	0.171	93
two-cm GCP	PH	March 8	0.87	0.197	93
two-cm RTK	PH	March 8	0.85	0.118	93
0.5-cm GCP	PH	Maturity	-0.25	0.148	19
two-cm GCP	PH	Maturity	0.6	0.311	93
two-cm RTK	PH	Maturity	0.68	0.177	93

4.1 ESTIMATION OF PLANT HEIGHT

From the two-cm GCP imagery, the highest correlation is 0.87 for March eight. Anthesis stage showed an R = 0.55 and RMSE almost double than March eight. The best correlation for RTK imagery was in March eight (R = 0.85). The 0.5-cm imagery data for March eight showed the R = 0.57, R = 0.61 for anthesis but R = -0.25 for maturity, but in that stage very few samples were used.

4.2 ESTIMATION OF BIOMASS

In the anthesis stage, an R between 0.29 and 0.4 was found across all methods; for maturity, R was in between 0.22 and 0.3. No correlation between the estimated volume and the AGB was found at booting for any resolution or georeferencing methods. For the two-cm GCP imagery, anthesis and maturity stage show a correlation of 0.29 and 0.3, respectively; they have a RMSE close to 0.4. The RTK imagery showed an R of 0.32 and 0.29 in the same stages. The 0.5-cm GCP imagery showed for anthesis an R = 0.4 and R = 0.22 for maturity.

4.3 RESOLUTION AND GEOREFERENCING

Comparing two-cm GCP versus two-cm RTK: accuracy in X was four times better with the GCP method, but for the Y component the difference was only 0.006. In anthesis and March eight, the GCP method showed a better correlation than the RTK (0.02 vs 0.03), but a higher RMSE (0.056 vs 0.079). Comparing two-cm GCP method and 0.5-cm GCP: RMSE in X was better for the 0.5-cm by 0.009, but worse in the Y component by 0.007. The 0.5-cm had a lower correlation and the RMSE was in the same range as the two-cm imagery. For PH, the results in the 3 methods follows the same trend for the stages, except for maturity for the 0.5-cm GCP. Figure 2 shows a profile comparing a sample of PH of the different methods, showing correspondence of trends between them. To the left, an issue in the 0.5 cm mosaic can be perceived as an unusual offset.

For the AGB comparison, at booting, the higher correlation was 0.065 at the two-cm GCP, but the two-cm RTK imagery presented the lower RMSE (0.143), while the 0.5-cm GCP presented the higher RMSE (0.512). For anthesis, the 0.5-cm GCP imagery showed the highest R (0.40) and the two-cm GCP for maturity (0.30). The RTK method and the 0.5-cm GCP presented more frequently higher RMSE than the two-cm GCP.

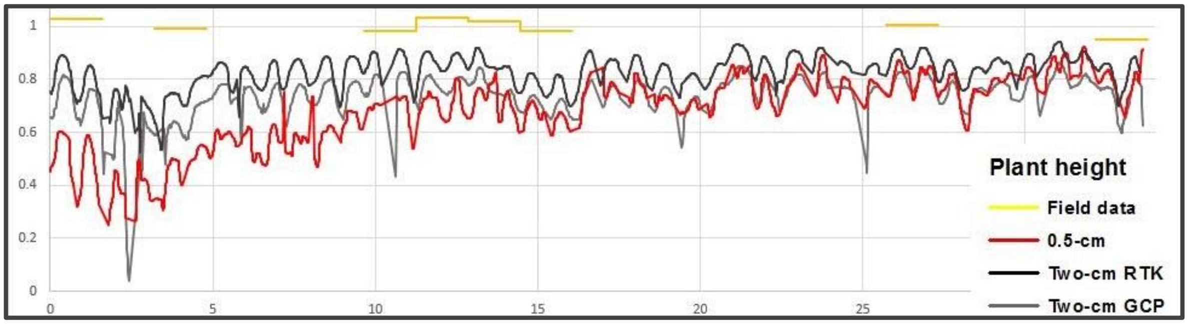

Figure 2. Plant height profile comparison

5. Discussion and conclusion

This work focused in the estimation of PH and AGB in wheat experimental plots using photogrammetry based on aerial imagery acquired with UAV. The focus was in the comparison of two different spatial resolutions for the imagery, *i.e.* two and 0.5 centimeters, and two georeferencing methods, *i.e.* using GCP and direct georeferencing based on the geotagging of the imagery with RTK correction on the UAV.

The highest correlations for PH were on March eight, when measurements where made all in the same day for all the sampling plots, giving a R from 0.57 to 0.85 for the different methods. Next remarkable stage was maturity (R = 0.6 and 0.68). The PH obtained from the CSM is underestimated compared to the manual measurements (De Souza et al., 2017), possibly related to limitations in photogrammetry to reconstruct the spikes in detail at the used image resolution (Madec et al., 2017). Comparing the indirectly estimated height (from UAV) to a directly measured one (with ruler) that can have low representativity of the crop (Bendig et al., 2014), due to very few samples taken, the method has great opportunities for improvement. An alternative to validate height estimated from UAV 3D models could be LIDAR terrestrial scanning.

Correlation of AGB with volume are moderately low in all the datasets for maturity and anthesis (R between 0.29 and 0.40), but absent in booting. Previous studies showed lower correlations for individual stages compared to the use of all the growing cycle data (Madec et al., 2017). The method for calculating the volume can improve, which may lead to a better estimation of AGB. In Walter et al. (2018), higher correlations were found between estimated volume and AGB. A main issue may be that they used higher spatial resolution and more images per plot.

Constrains in data quality and availability included measurements in windy conditions, low image overlap, uncertainty of the true fixed location of GCPs during the cycle, possible field measurement human errors in PH and AGB and missing ground truth data for some dates.

Regarding the identification of the most suitable resolution and georeferencing method for the imagery to estimate PH and AGB, the two-cm GCP dataset presented in general the higher correlations and lower RMSE. All models had enough accuracy to match them to the true plot location (RMSE <0.086 m). The GCP method gave slightly better results than the RTK, but it requires more field work and user intervention in the processing. Regarding the best location accuracy by resolution in general, better estimations of PH were observed for the two-cm GCP model compared to the 0.5-cm GCP, but a definitive conclusion could not be drawn because the X and Y components of the RMSE results supported different methods. For AGB, moderately low correlations were observed for both resolutions with an R < 0.4. The minor differences between methods made it difficult to select an obvious best choice and further research with different resolutions is suggested to clarify the differences. PH estimations on wheat using high-resolution aerial imagery in an experimental field is possible and as well as AGB from anthesis onwards.

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