High-throughput measurement of peanut canopy height using digital surface models

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Abstract
Peanut (Arachis hypogaea L.) is an important food and oilseed crop in the United States and worldwide with high net returns. However, input costs are high (US$1,970–$2,220 ha$^{-1}$), and yield in excess of 4,500 kg ha$^{-1}$ is needed to offset the costs. Since yield is limited by biotic and abiotic stresses, newer cultivars with tolerance to these stresses are needed to optimize yield. Plant height and canopy architecture may affect crop water use and plant disease resistance. However, measuring canopy height is a time-consuming process. Surface elevation models from red–green–blue (RGB) aerial images have been successfully developed to estimate genetic differences of plant height for tall crops like corn (Zea mays L.) and sorghum [Sorghum bicolor (L) Moench]; but they have not been tested for short crops like peanut with a runner growth habit and much smaller height differences among genotypes. The objective of this study was to derive canopy height of peanut from digital surface models (DSM). Images were aerially taken using a digital camera mounted on an unmanned aerial vehicle (UAV). Images were orthomosaiced to create the DSM and the digital terrain model (DTM) of the plot. Canopy height was derived by subtracting the DTM from the DSM in ArcGIS software. Results showed that the RGB derived canopy height was highly correlated to the manually measured height ($R^2 = .953$). We propose the methods used here as fast and relatively easy selection tools for breeders and crop growth evaluators of peanut plant height.

1 | INFORMATION

Peanut (Arachis hypogaea L.) is an important oil and food crop, grown on 17 million ha worldwide. In the United States, peanut is a high net return crop grown annually on approximately 580,000 ha in 11 states and with an average production of 4,483 kg ha$^{-1}$. Input costs are also high. For example, the North Carolina State University 2019 Peanut Production Information (https://content.ces.ncsu.edu/peanut-information) recorded variable and fixed production costs of $1,970–$2,220 ha$^{-1}$, which may suggest that yields in excess of 4,500 kg ha$^{-1}$ are required for economically feasible cultivation.

Abiotic and biotic stresses represent major constraints to peanut production by limiting peanut yield. For example, leaf

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water status had affected peanut growth and yield (Kramer, 1969). Though water deficit had minimal effects on the vegetative growth and flower production, it produced significant decrease in peg development and subsequent pod formation (Pahalwan & Tripathi, 1984; Prasad, Craufurd, & Summerfield, 1999; Smartt, 1994; Stansell et al., 1976). Water deficit had been directly related to reduction in N fixation (Devries, Bennett, Albrecht, & Boote, 1989; Venkateswarlu, Maheswari, & Saharan, 1989) and aflatoxin contamination of peanut (Williams et al., 2004; Arunyanark et al., 2009). Along with water deficit, fungal diseases such as early leaf spot (caused by Cercospora arachidicola Horp), late leaf spot (caused by Cercosporidium personatum (Berk and Curt) Deighton), southern stem rot (caused by Sclerotium rolfsii Sacc.), and Sclerotinia blight (caused by Sclerotinia minor Jagger) can cause severe reduction in peanut yield. It has been estimated that without fungicides the southeast Virginia and the Carolinas, and the southwest peanut growing regions could experience 78, 72, and 59% yield losses, respectively (Bridges, Kvien, Hook, & Stark Jr, 1994). Therefore, deployment of new cultivars with tolerance and resistance to abiotic or biotic stressors is a sustainable approach for increasing peanut crop production.

The current breeding approach has been successful in developing high-yielding and stress-resistant cultivars, but traditional methods of manually selecting lines for trait of interest are slow and uneconomical for large breeding populations when compared with the current remote sensing tools (Branch, Brenneman, & Hookstra, 2014; Jones and Vaughan, 2010; Tester & Langridge, 2010). Nigam et al. (2005) showed that several morphological and physiological traits were associated with peanut tolerance to water deficit stress and breeding for these traits was superior to breeding for yield alone. According to Kiniry, Simpson, Schubert, and Reed (2005), Nigam and Aruna, (2007), and Arunyanark et al. (2008) the physiological traits that breeders can measure to select peanut genotypes with tolerance to water deficit stress include early biomass accumulation and leaf area index (LAI). In their studies, water deficit stress reduced biomass and LAI more for drought-sensitive than for drought-tolerant cultivars. Shortening of the main axis and cotyledonary branches of peanut under soil moisture stress has been reported by Chung, Vercelotti, and Sanders (1997) and thoroughly discussed by Reddy, Reddy, & Anbumozhi (2003). Reduction in plant height under soil water deficit was attributed to reduction of internodal length, and it was suggested to change dry matter partitioning, plant density, spatial arrangements of the plants, and light interception under drought (Bell, Wright, & Harch, 1993; Collino, Dardanelli, Sereno, & Racca, 2001; Pandey, Herrera, Villegas, & Pendleton, 1984). In other crops, such as corn (Zea mays L.), plant height was directly related with yield and proposed as a selection tool for this crop (Freeman et al., 2007; Yin, McClure, Jaja, Tyler, & Hayes, 2011).

Peanut canopy architecture can affect crop water use and disease resistance. Upright and less dense canopies contributed to plant resistance to soil-borne diseases by creating microclimates with reduced opportunities for plant contact with infested soil (Chappell, Shew, Ferguson, & Beute, 1995; Hollowell, Isleib, Tallury, Copeland, & Shew, 2008). For example, upright canopies of the Spanish-market type peanut cultivars were more resistant than runner and Virginia market types to Sclerotinia blight (Chappell et al., 1995; Coffelt & Porter, 1982; Goldman, Smith, Simpson, & Melouk, 1995). Studies by Blad, Steadman, and Weiss (1978) compared soybean cultivars with different canopy architectures. These authors found that dense and shorter canopies had the coolest, wettest microclimate and increased severity of white mold (caused by Sclerotinia sclerotiorum (Lib.) de Bary) than the cultivars with open canopies and upright growth habit, which were warmer, drier, and with low incidence of white mold. Similarly, treatments supporting or maintaining dense foliar canopies such as higher irrigation in peanut resulted in the highest incidences of stem rot (caused by Sclerotium rolfsii Sacc.; Shew & Beute, 1984). Therefore, canopy height is an important characteristic. However, measurements of canopy height over large breeding populations or land area is difficult and impractical because a large number of data points are needed to generate representative height information. Therefore, measuring plant height remotely could be a good option (Tattaris, Reynolds, & Chapman, 2016).

Unmanned aerial vehicles (UAV) photogrammetry was successfully used to determine plant height in sorghum [Sorghum bicolor (L) Moench], wheat (Triticum aestivum L.), barley (Hordeum vulgare L), and corn (Bendig, Bolten, & Bareth, 2013; Freeman et al., 2007; Holman et al., 2016; Watanabe et al., 2017; Demir, Sönmez, Akar, & Ünal, 2018; Han et al., 2018; Wang, Singh, Marla, Morris, & Poland, 2018; Yuan et al., 2018). In these studies, the authors compared manually measured plant height with height derived

Core Ideas
- Peanut height can be successfully estimated from RGB images aerially collected at 20 m above the canopy.
- Both methods described here, ground point (GP) and digital terrain method (DTM), were time efficient and accurate for peanut height phenotyping.
- The GP method was proposed for height estimation in small plots, such as breeding plots.
- The DTM was better suited for agronomic applications using large plots and multiple times of data collection.
TABLE 1 Weekly dates for unmanned aerial vehicle (UAV) flight with red–green–blue (RGB) camera and manual height measurement of peanut plots for the mini-core study, 2017 along with weeks after planting (WAP) and growth stage

| UAV flights with RGB camera          | Manual height measurement          |
|-------------------------------------|------------------------------------|
| Date                  | Image no. | Cloud condition | Date | WAP | Growth stage | Used for   |
| 19 June 2017          | 330       | 40%             | 19 June 2017 | 4 WAP | R1, beginning bloom | Regression |
| 22 June 2017          | 330       | 0%              | 23 June 2017 | 5 WAP | R1, beginning bloom | Validation |
| 27 June 2017          | 330       | 10%             | 27 June 2017 | 6 WAP | R2, beginning peg | Regression |
| 19 July 2017          | 330       | 20%             | 18 July 2017 | 9 WAP | R4, beginning pod | |

*Boote, 1982.
https://weatherspark.com/.

using 3D surface models created using structure from motion (SfM) photogrammetry (Bendig et al., 2013; Holman et al., 2016; Demir et al., 2018). For example, in sorghum and corn, Watanabe et al. (2017), Han et al. (2018), and Wang et al. (2018) successfully estimated plant height using SfM photogrammetry and digital surface model (DSM) models. In contrast, Wang et al. (2018) and Yuan et al. (2018) used LiDAR mounted on an UAV for height estimation in sorghum and corn, and suggested that LiDAR is a reliable method for height estimation.

However, sorghum, wheat, barley, and corn have less lateral branching than peanut and the ground was visible for ground point addition and digital elevation model (DEM) creation. At the same time, the height difference of the genotypes is easier to capture for plants with vertical growth habit, making remotely estimations of plant height easier for tall than for small plants. Consequently, the use of remote sensing technologies to estimate plant height on short and ground covering crops with lateral growth habit has not been explored yet. The objective of this study was to derive peanut canopy height maps using DSM and digital terrain model (DTM) from red–green–blue (RGB) aerial images taken using a UAV, compare these to manual measurements, and determine if the digital models can be used to remotely estimate peanut plant height.

2 | MATERIALS AND METHODS

2.1 | Study plots

The experiment was performed at the Virginia Tech Tidewater Agricultural Research and Extension Center (TAREC), Suffolk, VA (36.66 N, 76.73 W). One hundred four peanut genotypes were tested in 2017 from the U.S. mini-core collection (Holbrook, Anderson, & Pittman, 1993). Genotypes were planted in two-row plots of 3.05 m long × 0.9 m wide, using a randomized complete block design (RCBD) and three replications. Seeding rate was 13 seeds m⁻² with a 2.13-m alley between each block. The size of each block was 37.3 m long × 13.7 m wide. There were a total of 1248 individual rows for direct measurements for remote estimation of the canopy height. Peanut was planted on 15 May in 2017 on uniformly raised beds 30 cm in height and with one seed planted every 7 cm in the center of the bed.

2.2 | Ground measurements of height

Canopy height was measured starting at 4 wk after planting. Two plants were randomly selected within each row and height of each plant was determined by measuring the length of the main stem from the base of the stem to the newest leaf. The height of two plants were averaged to get the manually measured height of each row. Manual measurements were taken regularly until physiological maturity (Table 1).

2.3 | Aerial measurements of height

For derivation of plant height, UAV flights on 19, 22, and 27 June 2017 were used. The flights of 19 and 27 June were used for correlation and regression analysis and the flight on 22 June was used for validation of the derived regression equation (Table 1). The flight of 19 July was not used because the peanuts vines were fully mature and completely covering the ground. This made it difficult to measure the bare ground elevation required for aerial height measurements of plants in later steps.

An AscTec Falcon 8 octocopter UAV platform (Ascending Technologies) was used to acquire aerial images of peanut plots. Images were collected using a Sony α6000 digital camera around the same dates as ground measurements (Table 1). The images were collected in 24.3-megapixel-format (6000 × 4000) JPEG images in true color bands (RGB) with 24-bit radiometric resolution using shutter priority mode for shutter speed and auto mode for aperture and ISO. The camera lens used was the Sony 20 mm f/2.8. The camera setting for image compression was “fine” with a 10:1 compression ratio. Images were collected by waypoint navigation at a height of 20 m with 90% overlap between images for forward direction and 75% overlap for side directions. The ground sampling distance of the images was 3.92 mm. The flight was auto piloted.
FIGURE 1 The steps in Pix4D for creation of digital surface model. (a) Major steps of the algorithm for image processing by Pix4D, (b) point cloud created in the first step, and (c) 3D mesh created in the second step after a flight plan was created in AscTec Navigator 3.4.5 software (Ascending Technologies). The built-in global positioning system (GPS) of the UAV was used for flight navigation, nadir image acquisition, and recording coordinates of individual images. The collected images were then orthomosaiced in Pix4Dmapper Version 4.2.26 software (Prilly) to create an RGB field map, the DSM, and the DTM. The software created the DSM by interpolation of 3D point clouds in three steps (Figure 1a, b, and c).

1. Processing and computing of initial key points. Images were matched and calibrated for overlaps and keypoint generation. The calibration parameter was set to “standard” and the internal and external parameter optimization was set to “All.”

2. Using point cloud to create 3D mesh. Point clouds were generated to create 3D mesh using the calibrated images from the first step. For point cloud densification the default settings were used (image scale at “half” and point density at “optimal”). The 3D mesh generation was set at medium.

3. Creating the DSM, orthomosaic, and index. Three-dimensional models were created using the point clouds and 3D mesh from the second step using SfM method. The resolution for DSM and orthomosaic was set at original ground sample distance (GSD) (0.49 cm).

Next, a DTM was created automatically using Pix4D by smoothing non-terrain point clouds representing elevated ground features such as vegetation, raised beds, vehicles, and weather stations from the DSM. The terrain point clouds included bare ground and road surface, which were only included in creation of the DTM. For better smoothing of non-terrain points, the default resolution of DTM was five times the default GSD of the DSM (2.43 cm).

2.4 | Generation of height maps

Height measurements were calculated by subtracting the DTM from the DSM in the ArcMap (version 10.6) tool of the ArcGIS (ESRI). Two separate methods were followed to generate the DTM, such as the ground point (GP) and automatic DTM methods.

2.5 | The ground point method

The first step in the process was loading and aligning the DSM and orthomosaic image created in Pix4D to ArcMap (Figure 2a). Although only DSM orthomosaic was needed for height measurement, the RGB orthomosaic was useful in determining the actual bare ground for placement of the GPs. Next, a shapefile was created, and GPs were manually added on bare ground to serve as zero height. Because peanut was planted on raised beds, GPs were placed on the alleys between plots where there were no plants but continuous raised beds (Figure 2b). Eight GPs were added on the RGB raster to each of the 22 alleys making a total of 176 GPs. This was done to reduce variation within plant height measurements. A shapefile raster layer was further created with all GPs (Figure 2b). Height values were extracted from each GP of the shapefile raster layer using the DSM raster and interpolated to create a spline raster layer (Figure 2c). The spline interpolation method used was regularized, which incorporated the first, second, and third derivative into its curvature minimization calculation. The weight used on third derivative was 0.1 to get an optimal smoothness on the output surface. Twelve points were used to calculate each interpolated cell. The spatial resolution of the spline layer was 1.28 x 1.28 cm. This spline layer served as the zero-plant height or the DTM to be subtracted from the DSM for estimation of the canopy height. After the
spline layer was subtracted from the DSM, a height map was obtained with heights being represented by different colors (Figure 2e). The height map had a spatial resolution of $1.28 \times 1.28$ cm.

2.6 | The digital terrain model method

The first step in the process was loading the DSM and DTM raster created in Pix4D to ArcMap (Figure 2a, d). The DTM generated at the end of SFM processing was then subtracted from the DSM to get a height map with heights being represented by different colors. The height map had a spatial resolution of $3.56 \times 3.56$ cm.

2.7 | Supervised height classification

The canopy heights of all individual plots in the height maps derived from the GP and DTM method were classified by color coding. Each height interval was represented by a color and each height interval was set as 1 cm. White color was assigned to all heights below 0 and above 50 cm so that only the heights of peanut rows were present on the map. Since the height map was in the form of a raster layer, each pixel represented the height of the spatial area represented by the pixel. The color-coded classified height map gave an overview of the height variation of the whole plot.

2.8 | Calibration of height map

The height map raster was checked for false elevations. False elevations were non-zero bare ground heights on the height map unrelated to peanut canopy. This can happen due to irregularities in the field from tillage operations. Peanut was planted on raised beds so that bed height could have been added to the canopy height raster. False heights were identified by sorting the color change in the height map to either soil or plant. Three color class intervals above 0 corresponded to bare ground for the height maps derived using the GP method, and 10 for the DTM method. Since each color class represented 1 cm of elevation and bed heights were uniform, the false elevation was set to 3 cm for GP method and 10 cm for DTM method.

2.9 | Derivation of canopy height

Since main stem was used for manual height measurement, raster information of the centermost region of each row was used to estimate height. A polygon covering the length of the plot and about 10 cm wide was drawn on the center of
each row (Figure 2b). All polygons were placed into one shapefile and every polygon was named by the plot number creating a fishnet. The plant height from the ground to the newest leaf of the main stem was estimated by extracting the raster information from every polygon of the created fishnet (Figure 2b). The height extraction from the polygons was done using zonal statistics option of ArcMap. The height values of all pixels contained in the raster information within each polygon was averaged by zonal statistics to derive the average canopy height of individual rows. Height of all 1,248 rows was derived by this method. The identified false elevations were subtracted from average height of each row to derive the actual canopy height.

2.10 | Statistical analysis

The DSM derived height and manually measured height on 19 and 27 June were subjected to the two-tailed $t$-test to test the null hypothesis that the difference between measured and derived height was zero. Two tailed $t$-test was used because the UAV derived height could have been either greater or smaller than the manually measured height and hence the difference in height could have been either positive or negative. The $t$-test was performed in JMP Pro 14.2.0 (SAS Institute). The UAV derived heights and manually measured heights were also used for correlation and linear regression analysis in JMP Pro 14.2.0 (SAS Institute) to determine the relationship of derived height ($y$) with measured height ($x$). The UAV derived height values from the 22 June flight were used for validation of the methods.

3 | RESULTS

3.1 | Height measurement and estimation

Directly measured plant height ranged from 2.5 to 20.0 cm, whereas the estimated heights using the GP method from 2.3 to 19.9 cm and estimated heights using DTM method from 2.0 to 21.1 cm (Supplemental Table S1). The difference could be explained by the color class selection, which was set so that each color represented 1 cm range of height (Figure 3). The two-tailed $t$-test showed that the heights estimated from the DSM were similar to the manually measured plant heights ($N = 1,248, p = .707; N = 1,248, p = .550$) (Figure 4a and c). The mean difference between estimated and measured height was 0.67 cm for the GP method and 0.95 cm for the DTM method. The estimated heights were significantly correlated to the manually measured heights, but only 85% of the height variation was captured with the GP method ($R^2 = .85; p < .0001$) and only 78% with the DTM ($R^2 = .78; p < .0001$) when all data points were used (Figure 5, 1a and 2a).

Twenty-two plots from the 1,248 total were identified with just a few plants in each row and discontinued cover, which could have been due to poor germination or insufficient seed for planting (Figure 6). These plots were the furthest points from the regression lines in Figure 5, 1a and 2a. After removing these plots from the analysis, the remaining 1,226 plots with complete canopy cover showed an improved relationship between image-estimated and measured plant height. The two-tailed $t$-test showed improved similarities between measured and estimated plant heights ($N = 1,226, p = .956; N = 1,223, p = .428$) (Figure 4b and d). In this way, the GP model explained 95% of the plant height variation ($R^2 = .956; p < .0001$) and DTM explained 86% of the variation ($R^2 = .86; p < .0001$) (Figure 5, 1b and 2b).

The linear regression analysis of UAV estimated plant height vs. manually measured plant height showed the following relationships:

\[
y_1_{\text{ground}} = 0.397 + 0.958 \times x_1_{\text{uav}} \quad \text{for the GP method} \quad (1)
\]

\[
y_2_{\text{ground}} = 0.949 + 0.899 \times x_2_{\text{uav}} \quad \text{for the DTM method} \quad (2)
\]
FIGURE 4  Distribution of derived and measured height difference of peanut plots (in meters) of (a) all data points ($N = 1,248$), and (b) data points after removing outliers ($N = 1,226$) for the ground point (GP) method; and of (c) all data points ($N = 1,248$), and (d) data points after removing outliers ($N = 1,223$) for the digital terrain model (DTM) method. The data points were the differences of the red–green–blue (RGB) derived height and manually measured height in centimeters. To obtain the distribution curves, measured height was subtracted from the derived height and a two-tailed $t$-test was run on the height differences. The red line shows the mean difference.

FIGURE 5  Relationship between manually measured peanut canopy heights and red–green–blue (RGB) derived canopy height of (1a) all data points ($N = 1,248$) and (1b) data points after removing outliers ($N = 1,226$) for height derived by the ground point (GP) method; and (2a) all data points ($N = 1,248$) and (2b) data points after removing outliers ($N = 1,223$) for height derived by the digital terrain model (DTM) method. The data points represent actual height of peanut canopy in centimeters. The relationship was derived by simple linear regression with measured height on the $x$ axis and derived height on the $y$ axis.

where, $x_{1\_uav}$ is the DSM estimated plant height using GP method, $x_{2\_uav}$ is the DSM estimated plant height using DTM method, $y_{1\_ground}$ and $y_{2\_ground}$ are the plant heights taken manually on the ground.

3.2 Validation

For validation, the directly measured and flight data on 22 and 23 June were used (Table 1). Validation used linear regression, with the $y$ axis being the manually measured heights and the $x$ axis the UAV-derived height from Equation 1 for the GP method and Equation 2 for the DTM method. The plant heights of plots with non-continuous canopy were not used in the back calculations. Validation results showed that the GP method had 90.5% correlation ($R^2 = .905; p < .0001$) and the DTM method had 77.9% correlation ($R^2 = .779; p < .0001$) among UAV estimated height and manual heights derived using Equations 1 and 2 (Figure 7a and b).
Results from this study demonstrated that digital surface models from RGB images taken with UAVs can be used to estimate peanut canopy height with an acceptable degree of accuracy ($R^2 = .85-.95$; Figure 5). Similar results were found for wheat, where reported $R^2$ was .91 (Yuan et al., 2018). Our results also indicated that the GP method was slightly better than the DTM method (Figure 5). This could be because the DTM generation is semiautomatic in Pix4D and it failed to represent sharp changes in the terrain (Pix4D support, personal communication, 2017). However, the DTM method was considerably less time consuming than the GP method, which seemed to produce higher-resolution maps (3.56 cm GSD in DTM method, 1.28 cm GSD in GP method). Finally, both methods estimated sufficiently well the height of a short crop with a ground cover growth habit like peanut. Also, derivation of canopy height using UAV took one person 18 min (8 min for flight and 10 min for processing) for a 0.5-ha field compared with 3 h needed by two persons to measure the height manually. Therefore, use of UAVs could be a milestone in reducing time for data collection (Watanabe et al., 2017). For example, our study required 2 h for fishnet development, 30 min for field campaign preparation, and 20 min for height extraction; generation of point clouds and orthomosaic were automated during the night. Even though the cost of hardware (drone, computer, RTK-GPS, etc.) and software (Pix4D, ArcGIS, etc.) appears expensive (around $22,000), this is a one-time cost. In addition, the same equipment can be used for other applications such as extraction of vegetation indices from visible and near infrared reflectance, and canopy temperature from infra-red reflectance. On the other hand, manual data collection is expensive. For example, in breeding programs over 2,000 breeding lines are yearly handled at multiple locations. To manually collect plant height at all locations and for all lines, several weeks over the growing season are necessary. Assuming 4 wk with 40 h wk$^{-1}$, 320 total hours, may be required for collection of plant height by two individuals, one to measure and one to write. The minimum wage at Virginia Tech is $10.25 per hour. This is a minimum cost of $3,280 per season for just collection of plant height information.

Although DSM and other methods (e.g., LiDAR, proximal imagery) have been previously used to measure plant and canopy heights, they were used for crops like sorghum, wheat, and corn with vertical growth habit (Han et al., 2018; Madec et al., 2017; Watanabe et al., 2017; Wang et al., 2018; Yuan et al., 2018).
Vertical growth habit of these crops is an advantage in placing the GPs. No lateral branching also means that plant height is uniform throughout the canopy cover, unlike peanut, whose canopy height is maximum in the center and tapers down toward the edge of the plot. Peanut genotypes of all botanical types have relatively short canopies (e.g., in the range of 50 cm) but, depending on the environmental conditions, could be no taller than 30 cm at full maturity, with lateral branching and ground cover growth. For these crops, estimating plant height from digital surface models has not been addressed until this work.

Peanut breeders can use these models to extract canopy height of the breeding lines accurately and in a timely manner. Chappell et al. (1995) concluded that growth habit and resistance to Sclerotinia blight might contribute to actual field resistance for peanuts; therefore, selection for open and upright canopy should be preferred for genotype selection. For the breeding programs, plots need to have continuous plants in the row without gaps. Our data showed that discontinued rows could lead to incorrect estimations of plant height. This problem with discontinuous rows agrees with findings by Wang et al. (2018) in sorghum. Planting peanut on raised beds also caused height estimation issues. Height maps had false elevations, which over-estimated the plant heights by 3 cm with the GP method and 7 cm with the DTM method. Calibration of the false elevation increased the time cost of height extraction. In our study, measurements were performed at early growth stages when bare soil was available for GP determination. Later in the season, plants could cover the soil entirely. To avoid false elevations due to raised beds and ground coverage by plant foliage, in future work, we propose creating a raster layer of bare ground before plant emergence to be used later with the DSM method. Generating DTM from bare ground before seedling emergence has been successfully used for wheat height estimation (Holman et al., 2016; Yuan et al., 2018). In summary, this work provides a suitable method for peanut height estimation to be used in peanut breeding programs. Growers also can use the methods proposed here to identify field areas with poor crop growth and make corrections by applying variable rates of nutrients and pesticides.

5 | CONCLUSION

In conclusion, this study showed that remote height measurement of shorter crops with ground cover growth habit is possible. The correlation between actual height and height derived from UAVs was very strong (85–90%). The methods proposed here could help breeders by reducing the time and labor for collection of phenotypic data. The methods could also be helpful for growers adopting precision agriculture tools for sustainable crop production. Comparing both methods (GP and DTM) for time and accuracy, the GP method is a better option for small plots, like those used in breeding programs, with minimal differences in plant height among the lines. The DTM method, instead, seems better suited for agronomic applications where big plots and multiple times of data collection are the priority.

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AUTHOR CONTRIBUTIONS

M. B. wrote the grant proposal and helped with selecting the peanut genotypes to be used. J. O. prepared the flight plan and flew the UAV for aerial images. J. O. and A. B. C. helped developing protocols and routines for image processing and analysis. The hypothesis and objective development were mainly accomplished by S. S. with advices and comments from M. B., D. M., L. A., and W. T. S. S. wrote the manuscript and M. B. made significant revisions to it.

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CONFLICT OF INTEREST

The authors hereby declare that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers’ bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge, or beliefs) in the subject matter or materials discussed in this manuscript.

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Additional supporting information may be found online in the Supporting Information section at the end of the article.

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