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ARTICLE

Agronomic Application of Genetic Resources

Cotton row spacing and unmanned aerial vehicle sensors

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Abstract

The use of unmanned aerial vehicles (UAVs) to identify the number and area of cotton (*Gossypium hirsutum* L.) bolls in a field plot can serve as an important high-throughput phenotyping strategy for predicting seedcotton yield. The objectives of this study were to determine if the prediction of seedcotton yield using a UAV could be improved in skip-row spacing versus solid-row spacing and if a genotype × row-spacing interaction occurs for important yield and fiber traits. A split-plot design was used with the main plot being row spacing and the sub-plot consisting of five cotton genotypes. Trials were conducted at three locations in 2017 and 2018. Seedcotton yield, lint yield, lint percent, and fiber qualities were measured for all treatments. In 2018, UAVs with red, green, and blue (RGB) cameras were flown across the fields at two locations to estimate open-boll count and boll area at the end of the growing season. In general, lint yield and fiber quality were not affected by genotype × row spacing interactions. Seedcotton yield estimations from UAV-based RGB sensors were improved when cotton was planted on a skip-row spacing versus a solid row configuration. However, several issues beyond the improvement of seedcotton yield predictions with UAVs need to be considered before research programs use skip-row spacing.

1 | INTRODUCTION

Field trials are some of the most resource intensive components of cotton (*Gossypium hirsutum* L.) breeding and other agronomy-related research programs. Recently, technological advances in high-throughput phenotyping technologies have enabled researchers to quickly take measurements of crop field trials with a wide array of sensors (Berni et al., 2009). Recent studies involving cotton and unmanned aerial vehicle (UAV) images demonstrated numerous applications, such as validating cotton germination (Chen et al., 2017; Oh et al., 2020), estimating cotton leaf area index (Tian et al., 2016), monitoring crop water stress (Bian et al., 2019), identifying diseases (Wang et al., 2020; Xavier et al., 2019), and predicting cotton yield in small plots (Ashapure et al., 2020; Jung et al., 2018; Maja et al., 2016).

In the United States, most cotton is grown on conventionally spaced rows that vary between 76 and 102 cm in width. Occasionally, especially in semi-arid regions with limited irrigation capacity, cotton is grown on row patterns in which there are two conventional rows with a skip in-between to optimize marginal soil moisture. Commercially grown cotton in the United States rarely is planted on a continuous ultra-wide row spacing of ≥150 cm, also known as a skip-row spacing. Consequently, there has been little research dedicated to

Abbreviations: GCP, ground control point; RGB, red green blue; UAV, unmanned aerial vehicle; UNR, ultra-narrow row.

questions surrounding skip-row cotton, such as cultivar interactions, crop nutrition, water use efficiency, rate of crop maturity, light interception, and pest control.

Conversely, ultra-narrow row (UNR) spacing of ≤25 cm has been studied extensively over the past 20 yr. Boquet (2005) reported on nitrogen fertilizer requirements of UNR cotton. The rate of crop maturity in UNR cotton was found to be slightly faster in comparison to cotton on conventionally spaced rows (Brodrick et al., 2010; Jost & Cothren, 2001). Molin et al. (2004) determined that weed control was improved when cotton was grown on UNR as opposed to conventional row spacing. Cotton grown on UNR spacing appears to benefit more in terms of boll set and lint yield from mepiquat chloride as a plant growth regulator than cotton on conventional row patterns (Gwathmey & Clement, 2010). Stephenson et al. (2011) found that cotton grown on twin rows of 19- or 38-cm had no difference in lint yield and fiber qualities in comparison to cotton grown on conventionally spaced rows. In addition, a study that compared cotton grown on UNR, twin-row, and conventional row spacing in the Mississippi Delta concluded that fiber from the UNR and twin rows was slightly better than from cotton grown in conventionally spaced rows (Boykin & Reddy, 2010). In another study in the Mississippi Delta addressing UNR cotton and cultivar interactions, it was determined that cultivars usually did not have an interaction with UNR spacing for lint yield and fiber traits as measured with high-volume instrumentation (Nichols et al., 2004); however, the issue of cultivar interactions on skip-row spacing has not been adequately investigated.

Sensors such as nadir and LiDAR mounted on ground vehicles have demonstrated the ability to closely measure cotton plant height (Sun et al., 2017; A. Thompson et al., 2019). The RGB and multi-spectral cameras carried by UAVs can closely estimate cotton plant height, and predicting lint yield has been relatively effective with UAV-based cameras and sensors under particular conditions (Feng et al., 2020; A. Thompson et al., 2019). Maja et al. (2016) reported that prediction accuracy of cotton yield based on RGB images captured by commercial off-the-shelf cameras was as high as $R^2 = .78$, and the accuracy of their yield predictions improved when lint yields were relatively low. In a study conducted on the High Plains of Texas, normalized difference red edge was found to provide the best method of predicting lint yield when images were captured at peak bloom, with r^2 values ranging from .41 to .68 (C. Thompson et al, 2020). In the same region of Texas, Dube et al. (2020) used a ground-based three-dimensional sensor system to map boll distribution and had a yield estimation as high as $r^2 = .87$. All of these studies were conducted on conventionally spaced rows but were in cotton that had growth limited by water availability or used data from multiple UAV flights and/or ground-based sensors to construct predictive algorithms.

Core Ideas

- Evaluation of the accuracy of UAV sensors to predict lint yield validates high-throughput phenotyping technology.
- Our findings demonstrated the improvement of cotton yield predictions with UAV sensors in skip-row patterns.
- The genotype × row spacing interaction was minimal, so UAVs can be used to predict cotton yield.

In many areas of the U.S. Cotton Belt, it is not possible to operate ground vehicles in the field at the end of the season because of the height and lodging of the cotton crop. Therefore, the best alternative to a ground vehicle is the use of UAVs to collect images and other measurements to predict lint yield, plant height, and boll distribution. In Georgia, researchers were able to use three-dimensional high-throughput phenotyping systems to identify boll number and positions (Sun et al., 2020). This group used a ground-based vehicle to examine cotton grown on skip rows. They estimated boll numbers with an accuracy of R^2 of up to .90 in some cases, and lint yield was predicted with as much as $R^2 = .87$ effectiveness. Image-based three-dimensional point cloud systems can provide researchers with powerful insight into lint yield, boll distribution, and plant height (Dube et al., 2020; Sun et al., 2020; A. Thompson et al., 2019); however, in order for these images to be captured with UAV-mounted cameras, cotton needs to be grown on skip-row patterns so that the cameras can capture images from the side of the row and can use bare ground as a reference point. What is not well understood is the value of making plant breeding and other research decisions based on data from these three-dimensional images captured from skip rows. In other words, will data from cotton grown on ultra-wide rows translate to similar results from cotton grown on a solid row spacing?

The objectives of our study were (a) to determine the extent of genotype × row spacing effects upon cotton lint yield, lint percent, and fiber qualities and (b) to compare the accuracy of UAV-mounted RGB cameras in predicting seedcotton yield from cotton grown in conventional solid-row spacing versus skip-row spacing.

2 | MATERIALS AND METHODS

2.1 | Trial designs, genotypes, and production conditions

Field trials were conducted at the Texas A&M AgriLife Research and Extension Centers in Weslaco, Corpus Christi, and College Station, TX, in 2017 and 2018. Trials included the early-maturing cotton cultivar Tamcot 73' (PI 662044) (Smith et al., 2011) and four experimental germplasm lines: an okra-leaf line, 'Tamcot exp. 211'; a mid-maturity line, 'Tamcot exp. 421'; a full-season line with high-quality fiber traits, 'TAM exp. T-08'; and a drought-tolerant, high-quality fiber line, 'TAM exp. X-26-3'. All recommended production practices were followed. In 2017, trials were furrow irrigated at Weslaco and College Station, whereas the trials at Corpus Christi were only rainfed. In 2018, the same trial production systems were used, but an additional rainfed trial was planted at College Station. The irrigated and rainfed trials at College Station were in the same field ~90 m apart. Soil types were a Westwood silt loam, a fine-silty, mixed thermic Fluventic Ustochrept, intergraded with Ships clay, a very fine, mixed, thermic Udic Chromustert at College Station; a Hidalgo sandy clay loam, a fine-loamy, mixed, active, hyperthermic Typic Calciustolls at Weslaco; and a Houston black clay, a fine smectitic, thermic Udic Haplustert at Corpus Christi.

The trial design at all locations and years was a split-plot design. Row spacing was the main treatment, and genotype was the subtreatment. Main plots were replicated four times in each trial. The subtreatments, which were genotypes, were randomized within each of the main plots. Each solid-row plot had two planted rows, and each skip-row plot had one row planted. The row spacing at Corpus Christi was 96 and 192 cm for solid-row patterns and skip-row patterns, respectively. The row spacing at Weslaco and College Station was 102 and 206 cm for solid-row patterns and skip-row patterns, respectively.

From each solid-row and skip-row pattern plot, a 30-boll sample from one row was hand harvested to estimate lint percent and fiber quality. Samples were weighed and then ginned on a 10-saw laboratory gin without a cleaner for lint percent calculation. A 50-g lint sample from each plot was sent to Texas Tech University's Fiber and Biopolymer Research Institute at Lubbock, TX, for high-volume instrumentation analysis. One row from each solid-row pattern plot was harvested with a mechanical cotton picker harvester, and seed cotton was weighed to estimate lint yield (kg ha^{-1}) using the formula: seed cotton yield (kg ha^{-1}) × lint percent. The same process was repeated for skip-row pattern plots.

Unmanned aerial vehicle flights and manual boll counting were only performed in 2018. All open bolls from the entire row that was later mechanically harvested were manually counted prior to harvest at College Station and Corpus Christi in 2018. At the time of the manual counts, plants were almost completely defoliated, and all harvestable bolls were open. At College Station, the manual counting of bolls and the UAV flight occurred on 27 Sept. 2018 in both the irrigated and rainfed trials, but they were not harvested until 17 Nov. 2018. The delay in harvest was due to frequent rainfall, which began shortly after the bolls were counted and the UAV flown. The precipitation prohibited the cotton from drying and the mechanical plot picker harvester from entering the field. At Corpus Christi, the manual boll counts and UAV flight occurred on 31 July 2018 with the mechanical harvesting on 2 Aug. 2018. There was no rainfall in between those dates at Corpus Christi.

2.2 | UAV sensor data collection and processing

Unmanned aerial vehicle platforms equipped with sensors were used to collect data over the test field with a similar protocol at Corpus Christi and College Station in 2018 to investigate the efficacy of UAV images to predict cotton lint yield from field-based small-plot trials. To collect red-green-blue (RGB) data, a DJI Phantom 4 Pro (SZ DJI Technology Co.) was equipped with an RGB camera, the standard 20MP gimbal-stabilized DJI sensor.

Autonomous flight missions were performed based on the following conditions at College Station for RGB and multispectral sensor, respectively. The UAV with RGB sensors was programmed to capture images at a 30-m altitude with 80–90% forward overlap and side overlap, resulting in about 550 raw images over the study area. The UAV with multispectral sensor was programmed to fly at an altitude of 50 m with 60–70% forward overlap and side overlap, resulting in about 4,000 raw images over the study area. The same flight configurations were conducted at Corpus Christi, but, due to different field sizes, the collected raw images numbered about 350 and 700 for RGB and multispectral sensor, respectively.

Wooden panels were constructed with a cross pattern to use as ground control points (GCPs). The center of nine GCPs was measured by Post Processed Kinematic global positioning system (model 20 Hz V-Map Air, Micro Aerial Project L.L.C.), which can provide a subcentimeter location accuracy. Orthomosaic images and digital elevation models with precise goereferencing where generated in PhotoScan software from coordinates of the GCPs. Raw images were processed using Agisoft Photoscan Professional version 1.2 (Agisoft LLC, 11 Degtyarniy per.). Structure from Motion was used to generate geospatial data products (Turner et al., 2012). In Structure from Motion processing, key points from a series of overlapping images are identified by using scale invariant feature transform. Interior and exterior orientation parameters are computed from those key points identified before by using block bundle adjustment. Deploying densification, a dense point cloud can be constructed to build a digital surface model. Finally, the digital surface model is used to project every image pixel to generate an orthomosaic.

Whole fields from the orthomosaic images were clipped together. Grids were placed over the images to differentiate between plot rows, which were further divided into columns, with each column representing a single field plot. Each

TABLE 1 Analysis of variance components for the main effects and interactions of cotton lint yield, lint percent, and fiber qualities from field trials at Weslaco, Corpus Christi, and College Station, TX, in 2017 and 2018

Source	df	Mean squares				
		Lint	Lint percent	Fiber micronaire	Fiber UHML	Fiber strength
		kg ha^{-1}	%		Mm	kNm kg^{-1}
Year	1	13,458,508***	161.7***	0.034	2.725**	692.8**
Location	2	13,904,890**	138.0	5.254	1.999	22.4
Year × location	2	461,743***	38.6**	5.435***	3.127***	261.4
Rep (year × location)	18	33,635	5.7	0.091	0.191***	72.0***
Row	1	12,110,872	24.7	0.203	0.338	96.4
Year × row	1	3,586,086***	19.1*	0.205	0.191*	7.9
Location × row	2	1,607,140	29.8	0.014	0.033	0.8
Year × location × row	2	53,281	7.3	0.263*	0.030	53.3
Rep × row (year × location)	18	17,919	2.8	0.063	0.038	17.8
Genotype	4	794,579*	74.4*	6.241***	7.038***	2356.9**
Year × genotype	4	94,055	7.4	0.103	0.058	38.8
Location × genotype	8	195,655	6.5	0.096	0.036	30.1
Year × location × genotype	8	160,393	5.4	0.209***	0.086*	10.4
Row × genotype	4	83,406	4.3	0.102*	0.079*	5.5
Year × row × genotype	4	107,930	6.7	0.012	0.008	15.8
Location × row × genotype	8	78,632	2.6	0.050	0.010	18.1
Year × location × row × genotype	8	77,025	2.5	0.100	0.015	18.0
Residual	144	38,706	3.8	0.053	0.030	17.2

Note. UHML, upper-half mean length.
*Significant at the .05 probability level. **Significant at the .01 probability level. ***Significant at the .001 probability level.

column was divided into 11 grids (0.9 × 1.0 m). Because of the low-altitude flight pathway and high-resolution images captured by sensors, it is possible to delineate cotton bolls from background images within the orthomosaic image. The proposed methodology of Yeom et al. (2018) was used in this project. The first step was to select a cotton boll candidate from the background. Random seed points were extracted, and a region growing algorithm was used on each subset image. Based on collective spectral information of cotton boll candidates, the Otsu method (Otsu, 1979), which is used to automatically perform clustering-based image thresholding, was applied to determine the brightness threshold in order to differentiate cotton bolls from background. Finally, a binary classification was displayed by applying the derived threshold value to the orthomosaic image. The patch size analysis was used to calculate the total number of open bolls and boll area (m^2) in each grid. These estimates of bolls and boll area were pooled together for each row to generate a total for each row within the plot.

2.3 | Data analysis

Unmanned aerial vehicle–derived data from 2018 trials in College Station and Corpus Christi were processed using the procedure described in the previous section in 2018 at College Station and Corpus Christi. Regression analysis using SAS v.9.4 (SAS Institute Inc.) and JMP Version 13 Pro (SAS Institute Inc.) was performed to compare the ability of manually counted bolls, UAV-derived boll counts, and UAV-derived boll area to predict seedcotton yield (kg). The accuracy of RGB sensors mounted on a UAV from different row patterns was compared using the same method.

Variances were analyzed to characterize genotype × row pattern interactions and how location and year affected those interactions using fiber traits and yield data in 2017 and 2018 at Weslaco, College Station, and Corpus Christi.

3 | RESULTS AND DISCUSSION

3.1 | Solid rows vs. skip rows

Years and locations each had significant effects upon lint yield, lint percent, fiber length, and fiber strength (Table 1). Genotypes also were different for all measured traits. Except for fiber micronaire, there were no interactions involving genotypes that were significant in the pooled data set.

Because we detected significant interactions between years and among locations for lint yield, lint percent, fiber

TABLE 2 Analysis of variance components for the main effects and row spacing interactions for cotton lint yield, lint percent, and fiber qualities from field trials by location and year

			Mean squares						
Trait	Source	df	College Station, 2017	Corpus Christi, 2017	Weslaco, 2017	College Station (irrigated), 2018	College Station (rain-fed),2018	Corpus Christi, 2018	Weslaco, 2018
Lint, kg ha^{-1}	Rep	3	5,217	2,117	26,500	36,595	37,865	10,455	19,436
	Row	1	2,662,044***	2,250,554***	7,732,564***	196,792	60,924	28,008	765,589*
	Rep × row	3	2,397	2,841	6,392	24,080	13,584	4,565	29,719
	Genotype	4	478,976***	35,529*	213,032	25,034	203,375***	41,462**	428,160**
	Genotype × row	4	195,680***	11,349	21,421	35,033	15,829	3,978	91,632
	Residual	24	16,862	12,676	27,085	20,633	9,828	7,408	67,182
Lint percent, %	Rep	3	0.35	0.51	0.76	28.34	28.39	4.17	0.41
	Row	1	3.14	7.94	4.32**	83.22*	81.29*	0.11	6.98*
	Rep × row	3	0.81	0.51	0.00	773	7.78	7.50	0.52
	Genotype	4	15.08**	3.00	3.08**	28.85	28.89	22.93**	26.63**
	Genotype × row	4	0.77	0.50	0.27	14.80	10.08	1.60	2.45
	Residual	24	0.84	0.87	0.23	13.60	14.19	3.44	4.08
Fiber micronaire, units	Rep	3	0.115	0.221	0.013	0.030	0.027	0.021	0.179
	Row	1	0.016	0.013	0.545	0.108*	0.100*	0.001	0.123
	Rep × row	3	0.147	0.025	0.113	0.006	0.007	0.070*	0.021
	Genotype	4	1.646***	0.554**	0.481*	1.475***	1.368***	1.426***	2.742***
	Genotype × row	4	0.104	0.073	0.045	0.076*	0.077*	0.031	0.125
	Residual	24	0.070	0.073	0.108	0.068	0.026	0.024	0.068
Fiber UHML, mm	Rep	3	0.505	0.472	0.003	0.013	0.020	0.147	0.071
	Row	1	0.015	0.015	0.013	0.236*	0.107	0.480*	0.058
	Rep × row	3	0.081	0.046	0.018	0.048	0.010	0.003	0.020
	Genotype	4	1.054***	1.107**	0.638*	1.717***	1.768	1.278***	2.192***
	Genotype × row	4	0.020	0.020	0.028	0.013*	0.023	0.048*	0.008
	Residual	24	0.056	0.028	0.056	0.015	0.015	0.028	0.015
Fiber strength, kNm kg^{-1}	Rep	3	279.36***	98.30*	5.97	6.85	4.18	5.02	10.15
	Row	1	0.70	52.73	0.59	131.20	110.95	0.16	42.47
	Rep × row	3	19.96	77.40*	4.68	20.40	22.94	9.18	6.36
	Genotype	4	496.22***	449.34***	250.55***	326.49***	361.62***	589.37***	494.97***
	Genotype × row	4	5.46	19.37	19.21	13.36	8.31	16.40	15.07
	Residual	24	25.89	12.81	11.51	13.00	9.20	16.94	16.41

Note. UHML, upper-half mean length.

*Significant at the .05 probability level. **Significant at the .01 probability level. ***Significant at the .001 probability level.

micronaire, and fiber strength, data were analyzed by year and location (Table 2). Based on the second set of analyses, we determined that genotype × row spacing interactions for lint yield were significant only in College Station in 2017. The genotype × row spacing interaction for lint percent, which is an important yield component, was not significant in any of the seven tests. There were a few instances in which the row spacing affected fiber micronaire and length of the genotypes, but, in general, fiber quality was not affected by row spacing. Our findings are similar to those of previous studies that reported that the interaction of row width and genotype had little effect on fiber quality (Fowler & Ray, 1977; Hawkins & Peacock, 1971).

3.2 | Yield prediction with a UAV

From among the three methods used to predict seedcotton yield at College Station and Corpus Christi in 2018, the UAV-derived boll counting method was the most consistent, with

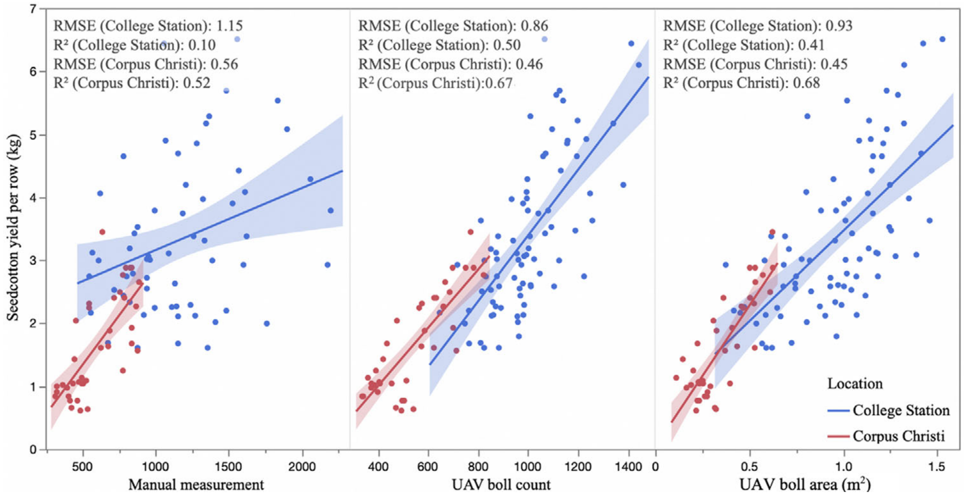

FIGURE 1 Relationships between unmanned aerial vehicle (UAV)-derived and manually acquired data from cotton field plots at College Station and Corpus Christi, TX, in 2018

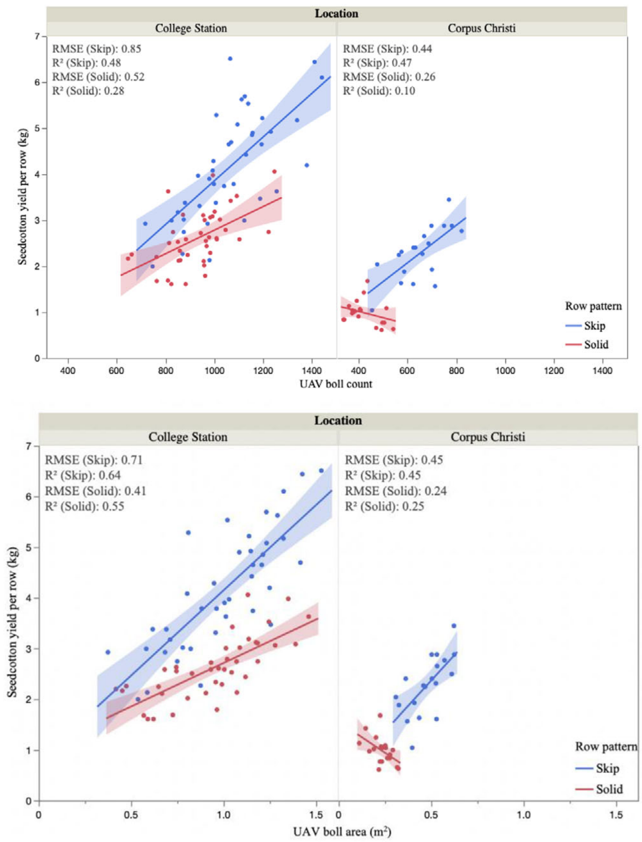

FIGURE 2 Relationship between unmanned aerial vehicle (UAV)-derived boll counts and boll areas in skip-row and solid-row planting configurations from cotton field plots at College Station and Corpus Christi, TX, in 2018

r^2 values of .50 at College Station and .67 at Corpus Christi (Figure 1). The UAV-derived boll area estimate resulted in r^2 values of .68 at Corpus Christi but only .41 at College Station. The method of manually counting bolls was less effective than either of the UAV methods at predicting seedcotton yield. The processing technology for UAV-based open boll counts can identify open cotton bolls visible in the orthomosaic images but often cannot count open bolls hidden within the canopies of the plant. Additionally, some cotton boll candidates were wrongly classified because the cotton spectral signature did not have adequate contrast with the background because of shadows, branches, and leaves. Another potential classification error is the bare soil, which may be identified as cotton bolls because of the similar spectral signature with open cotton bolls. These factors may result in poor relationships between UAV-based open boll count data and manual measurements.

At College Station, the discrepancies between manual boll counts and to a lesser extent the UAV-based boll area estimates and seedcotton yield were likely a result of the weathering that caused many bolls to hard-lock, which makes much of that cotton unharvestable with a mechanical picker (Raper et al., 2013), or the locks became loosely attached and strung out of the boll, which would have caused an overestimation of seedcotton yield based on boll area. Due to the orthographic view used in the orthomosaic images, cotton bolls on the upper canopy and lower canopy may look like they are connected in the orthomosaic images, and consequently the algorithm may count them as one boll. Just as adverse weathering upon a cotton field trial can introduce experimental error into yield estimates based on mechanical harvesting, adverse weathering can complicate seedcotton yield predications with UAVs.

When comparing the seedcotton yield prediction methods in skip-row spacing and solid-row spacing, neither the UAV boll count nor the UAV boll area methods were particularly effective, with r^2 values ranging from −.25 to .64 (Figure 2).

Nevertheless, seedcotton yield from plants grown with skip-row spacing was consistently predicted at a closer value than from plants grown with solid-row spacing. The skip-row spacing correlations with seedcotton yield ranged from .45 to .64. The UAV-derived estimates based on boll counts and boll area were particularly difficult in the solid-row spacing treatments at Corpus Christi. This could be the result of bolls in the lower portion of the canopy that contributed a large portion to final seedcotton yield being undercounted while bolls at the top of the canopy and easily counted were relatively small and contributed less to seedcotton yield. Boll size and subsequent contribution to yield can fluctuate depending upon growing conditions during the boll maturation period and sympodial position (Jenkins et al., 1990).

4 | CONCLUSIONS

Results from our study suggest that predicting seedcotton yield with RGB sensors mounted on UAVs is more effective when cotton is grown on ultra-wide or skip-row spacing as opposed to conventional solid-row spacing. Boll counts and boll area can be more accurately estimated by the UAVs when plants are less crowded by an adjacent row of cotton. Meanwhile, other researchers are using ultra-wide rows to map boll distribution and estimate maturity habits, so understanding the potential for genotype × row spacing interaction is critical. In our trials, row spacing appeared to have a limited interaction with cotton genotypes for lint yield, lint percent, and fiber traits. This is important because cotton researchers could use UAVs to predict seedcotton yield on skip-row spacing without having to manually harvest test plots with some level of confidence that the results are transferable to solid-row spacing production systems.

In most cotton breeding programs, hundreds and sometimes thousands of early-generation lines are grown in nonreplicated progeny rows. If UAV-derived seedcotton yield estimates could be made even with a moderate level of reliability, it would allow breeders to discard many lines with low yield potential prior to harvest. Such a strategy would present a substantial savings of resources for the breeding program. In another scenario, if an impending adverse weather event such as a tropical storm or hurricane is likely to take place at a testing location, UAVs could be quickly deployed to estimate seedcotton yield before storm damage occurs. Such an approach would allow researchers to claim at least some amount of insight about yield potential for the various experimental treatments.

There is still much to be learn about managing experimental cotton plots in an ultra-wide or skip-row spacing configuration. Weed control is likely to be more problematic with skip rows than in solid rows, but individual plants in a skip-row spacing should be more water-use efficient. Lodging and harvesting difficulties will probably more prevalent with the wide spacing, so more plant growth regulators may need to be used or less nitrogen fertilizer applied. Lint and seed yield on a per hectare basis, in all likelihood, will be greater with solid-row spacing than with skip-row spacing. However, seed multiplication will likely be higher with skip-row spacing than with solid-row spacing. Finally, land use would almost double for the same field trials when using skip-row spacing as opposed to solid-row configuration. Each research program needs to consider all of these potential costs and benefits when considering skip-row spacing for research plots.

AUTHOR CONTRIBUTIONS

Wenzhou Wu: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Validation; Visualization; Writing-original draft; Writing-review & editing. Steve Scott Hague: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Writing-review & editing. Jinha Jung: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing-review & editing. Murilo Maeda: Formal analysis; Methodology; Writing-review & editing. Anjin Chang: Conceptualization; Data curation; Formal analysis; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing-review & editing. Akash Ashapure: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Supervision; Validation; Visualization; Writing-review & editing. Andrea Maeda: Conceptualization; Investigation; Methodology; Resources; Validation; Visualization; Writing-review & editing. Don Jones: Funding acquisition; Writing-review & editing. Alex Thomasson: Methodology; Supervision. Juan Landivar: Conceptualization; Supervision.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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