UNMANNED AERIAL SYSTEM (UAS) PLATFORMS FOR COTTON BREEDING: FINDINGS AND CHALLENGES

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Abstract

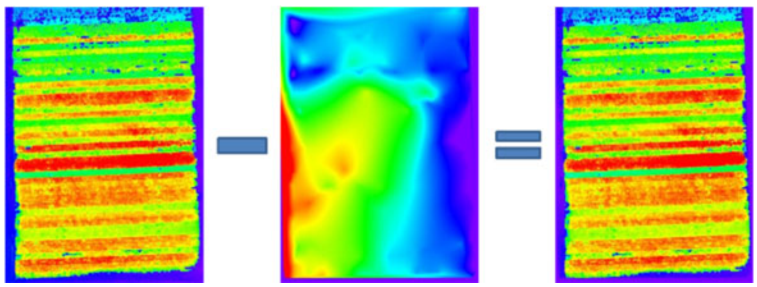
Unmanned Aerial System (UAS) and advanced computational technology are rapidly evolving. The development of methodologies to extract meaningful biological and physiological crop information from UAS imagery presents a unique opportunity for agriculture researchers and plant breeders alike. The possibility to obtain accurate growth, development, health, and productivity estimates for every square meter of a field does not come without its challenges, however. In 2016 researchers from Texas A&M AgriLife Research & Extension and Texas A&M University at Corpus Christi teamed-up with Texas A&M AgriLife cotton breeders to conduct a genotype evaluation trial and further explore the potential of UAS technology for plant breeders. The field trial consisted of 31 genotypes which included 23 breeding lines and 8 cultivars. Plots were 2 rows by 10m in a paired plot design. UAS platforms equipped with natural color (RGB), multispectral, and thermal infrared sensors were flown over the test field once to twice a week during the growing season. From these sensors, parameters such as plant height, growth rate, canopy cover, canopy cover progression, and boll count and size estimates were extracted. The test provided insight into the potential of this technology. The main challenge will be to develop systems and methodologies to deal with the massive amount of data generated.

Introduction

Recent advances in Unmanned Aerial System (UAS) platforms and sensor technology are now making it possible to accurately assess overall crop growth and health status with fine spatial and high temporal resolutions previously unobtainable from traditional remote sensing platforms, at a relatively low cost. In the past, the acquisition of temporal and spatial crop data was performed by destructive, expensive, and labor-intensive hand sampling techniques. Such constraints often lead to under-representative crop information due to limited sampling area and the introduction of possible human errors. When properly equipped with sensors, UAS platforms enable fast and accurate data collection throughout the growing season. Combined with state-of-the-art image processing algorithms, visualization techniques, and geospatial data analysis, UAS offers an innovative opportunity for the development of high-throughput phenotyping and precision agriculture applications. The interaction between genetics (genotype) and environment will greatly affect the phenotype and ultimately, plant productivity. UAS technology allows plant breeders and researchers to characterize crop development and its responses to biotic and abiotic stresses through a combination of several different parameters extracted from UAS imagery. As a result cultivar development can be accelerated, which will ultimately lead to the improvement of U.S. agriculture and food security.

Materials and Methods

Platforms used include DJI Phantom 2 Vision+, DJI Phantom 4, 3DR IRIS+, and 3DR X8+. Natural color RGB (Canon S110, Sony RX1R II), multispectral (Tretracam ADC Snap), and thermal (FLIR VUE Pro and FLIR VUE Pro R) were used to collect crop data. In order to obtain plant height, a pre-planting flight is conducted to obtain the Digital Elevation Model (DEM), which represents the base elevation map of the field. For each flight thereafter a Digital Surface Model (DSM) is captured and represents the crop canopy elevation surface. By subtracting the base field elevation (DEM) from the canopy elevation (DSM) we obtain the crop height model (CHM), or actual plant height values (Fig. 1).



(DSM) (DEM) (CHM)

Figure 1. Digital Surface Model (DSM, ground elevation + crop height) images taken are adjusted by the Digital Elevation Model (DEM, ground elevation), resulting in the Crop Height Model (CHM, crop height estimate).

Crop grids (1m²) are used for high-density crop data. The grid structure also enables detailed analysis such as the ability to remove grids with no plants (i.e. skips) from statistical analysis, and even its surrounding neighbors that may also be affected due to the lack of plant competition (Fig. 2). Plants growing on the edges of the plots are known to grow taller and yield more than the others (Holman and Bednarz, 2001). Grids containing these plants may also be removed from statistical analysis, thus removing the "alley effect". Plot size and intended use of the data will determine number and size of grids. From each individual grid, information such as plant height, growth rate, canopy cover, canopy cover progression rate may be extracted for analysis. These grids function as an in-field "mailbox". After each flight mission images are processed, and data extracted is "deposited" in their respective grids. These data may be used as a stand-alone measurement at any given time during the season, or combined to generate averages on per row or per plot basis.

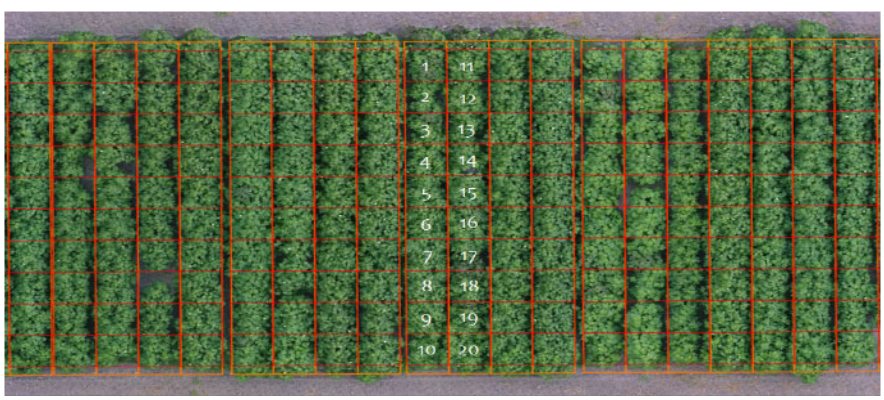


Figure 2. Example of plot boundary (orange) and grid (red) over a 2-row cotton plot. The number and size of grids per plot is determined by rows/plot, plot length, or intended use of the data.

Canopy cover (or ground cover) is estimated by performing a binary classification of the images acquired. Three parameters within the visible color range (red, green, and blue) are used to discriminate canopy versus non-canopy pixels (Patrignani and Ochsner, 2015). Once the image classification is performed, the ratio between canopy and background is calculated to obtain an estimate of canopy cover, which may be presented as a color-coded map (Fig. 3).

(a.) (b.) (c.)

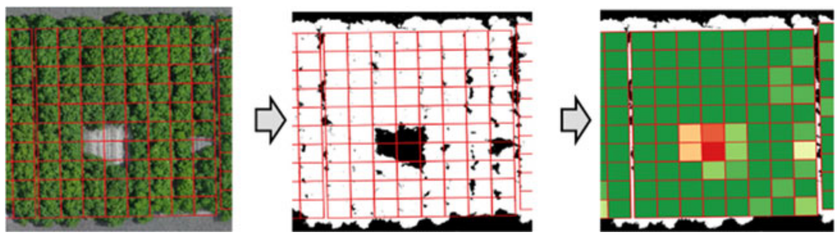


Figure 3. Images show binary image classification workflow. (a.) raw color image; (b.) classified image; (c.) color-coded canopy cover map.

To analyze time-series data, crop height measurements within each grid are extracted from the CHM time series and measurements fitted to a non-linear sigmoidal model to create a crop growth curve (Fig. 4, top). The first derivative of the growth curve is calculated as a growth rate curve (Fig. 4, bottom). The growth rate curve is used to obtain crop growth characteristics including maximum growth rate, date of maximum growth rate, and its duration (Fig. 4). The same models may be fitted to canopy cover time-series data to obtain information on crop canopy cover expansion rates and respective duration. When combined with other UAS-derived parameters (e.g. canopy temperature and vegetation indices) these features can be used not only to characterize growth patterns of individual genotypes and their response to the environment, but also to estimate plant performance (yield) for genotype selection (i.e. breeding).

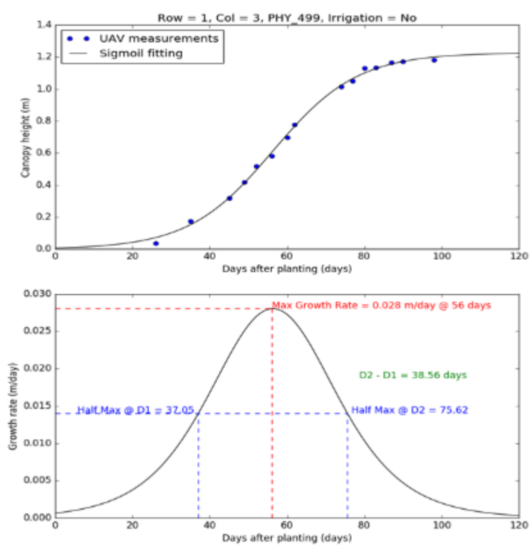


Figure 4. UAS-derived crop growth (top) and growth rate curves (bottom) for cotton. Texas A&M AgriLife Research and Extension Center, Corpus Christi, TX (2016).

The ability to determine crop earliness and maturity may be facilitated by bloom counts. Automated computer programs have been developed to analyze and classify UAS-derived images for bloom counts (Fig. 5). Likewise, open boll counts and boll size estimates are of interest at the end of the season. As shown on Fig. 6, computer algorithms are able to analyze sections of an image (sub images) and automatically determine a suitable brightness threshold value to classify white pixels (i.e. open cotton bolls). Areas that do not meet certain size and brightness criteria are filtered out of the classification workflow in order to improve computation efficiency. At the end of the process, boll counts and size estimates can be obtained from classified UAS imagery (Fig. 7).

Figure 5. Automated bloom count example. Raw image (left), processed (center), and mapped by grid (right).

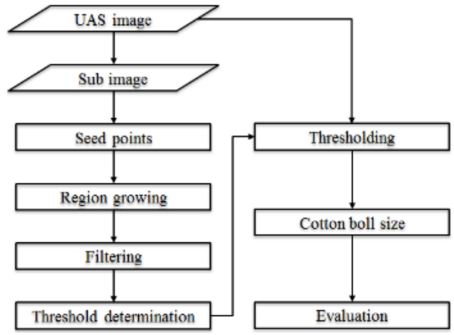


Figure 6. Open cotton boll count and size estimation workflow. Automatic computer algorithm analyze sub image to determine a suitable brightness threshold. Thresholding is performed to obtain boll count and size estimates from UAS image.

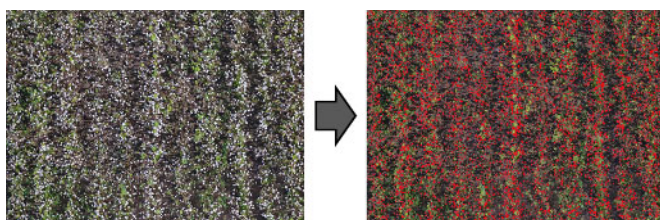


Figure 7. Example of raw (left) and classified (right) images for open boll count and size estimates.

Results and Discussion

Plant height estimates extracted from UAS imagery are very well correlated with ground measurements (Fig. 8). Despite normal plant variability found within a field/plot and limitations of sampling procedures; with rotorcraft platforms flying at low altitude we usually find $r^2 > 0.85$. The ability to track seasonal changes in plant growth, canopy efficiency, and development should help agricultural researchers and plant breeders in the characterization of genotypes' growth patterns and their response to biotic and abiotic stresses. For instance, the same genotype/variety growing in distinct dryland and irrigated conditions will likely show differences in maximum plant height, growth rate, canopy temperature, and earliness, which will ultimately impact final productivity. In such contrasting environments a single parameter (e.g. boll count) may be enough to differentiate high and low yield. However, the biggest challenge is to separate hundreds of similarly-performing breeding lines within a given environment. To be able to achieve such capability, a large combination of parameters is needed. From germination to initial growth, to canopy health and development, to yield components, these parameters combined should "tell a complete story" about the plant's environment, biotic and abiotic stress, as well as its response to these conditions.

By stepwise regression analysis six variables were identified as having a tight correlation with yield, including growth, canopy efficiency, and yield parameters. The potential to estimate plant productivity (yield) is demonstrated on Fig. 9. In all, we have identified a list of approximately sixty parameters that can be extracted from UAS imagery for plant phenotyping and breeding purposes. The possibility to expand this list by using data transformation and interactions creates yet another challenge. The volume of data generated using this technology can rapidly become overwhelming. To address this fundamental issue, computerized expert systems need to be developed. These systems should categorize genotypes by common features (e.g. short, tall, etc.) based on input data from UAS platforms. Predictive

models can also be integrated into expert systems to predict yields based on certain pre-specified parameters, determined by the breeding program goals. The pre-specified parameters (or requirements) can “guide” the expert system in ranking genotypes for specific environments (e.g. dry or wet).
In conclusion, UAS technology presents a unique opportunity for research, plant breeding, and crop precision management applications.

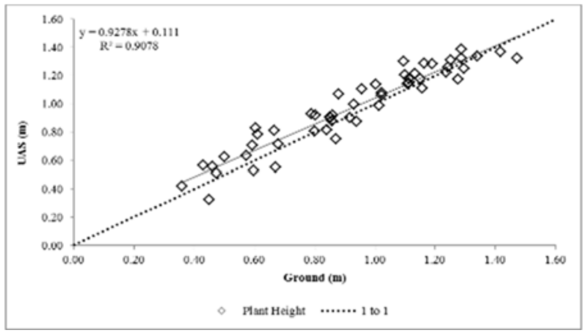


Figure 8. Plant height correlation between UAS estimates and ground measurements for cotton. Texas A&M AgriLife Research and Extension Center, Corpus Christi, TX (2016).

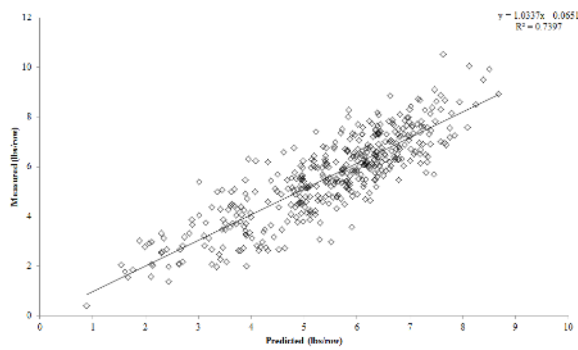


Figure 9. Measured and estimated seedcotton yield per row. Six UAS-derived parameters including growth, canopy efficiency, and boll count & size were used.

Acknowledgements

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