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NOTE

ARTHROPOD MANAGEMENT

Preliminary Approach in Detecting Cotton Fleahopper Induced Damage Via Unmanned Aerial Systems and Normalized Difference Vegetation Indices

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ABSTRACT

The use of unmanned aircraft systems (UAS) delivering imaging technologies in agricultural settings has become more prevalent over the past five years and is growing in pest management programs. Here, spectral data from a three-band consumer-grade camera with a filter to obtain Near Infrared (NIR) data, mounted on a fixed-winged UAS, was used to assess the ability to detect cotton fleahopper, *Pseudatomoscelis seriatus* (Reuter) (Hemiptera: Miridae), injury to immature fruiting bodies on cotton. In a small plot experiment conducted two years and two planting periods each year, cotton fleahopper densities were manipulated with insecticide. Variable populations of cotton fleahopper across the plots were achieved in 2015, ranging between 0 and 3.5 cotton fleahopper-days over a five-week period when squares were forming. Derived from spectral data of multiple UAS flights, unexpected but inconsistent trends (by regression analysis) of increasing Normalized Difference Vegetation Index (NDVI), values with increasing cotton fleahopper days were detected in both plantings and years (five of 12 regressions were significant). Our preliminary data suggest that differences in cotton fleahopper activity on cotton may be reflected in NDVI values using a modified consumer-grade camera in-season. But the interpretation of NDVI may be complicated by the feeding site of cotton fleahopper, leading to unexpected and inconsistent regressions. Exploration of image resolution and bandwidth to define optical sensor needs appears important for cotton fleahopper, given its feeding habitat and injury to cotton. The application of UAS-derived remotely sensed data to detect insect-induced plant stress continues to have merit, but a merging of best suited UAS technology to the needs of detecting insect-induced cotton stress will be a research-intensive endeavor.

One benefit of airborne remote sensing technologies in the agricultural sector is the potential time saved by automating plant stress detection in the field. There are multiple studies investigating the use of handheld spectrometers and ground-based spectral imaging technologies (hyper- and multi-spectral sensors) to detect and quantify arthropod-induced stress in crops (Nansen and Elliott, 2016). Satellites, manned aircraft, and more recently unmanned aircraft systems (UAS) are three platforms allowing researchers to utilize remotely sensed data. Satellite imagery has been used for automated mapping and classification over large geographic areas, such as detection of defoliation caused by bark beetles in forests and drought-related stress (Eklundh et al., 2009). Although satellite imagery can cover large geographic areas, there are practical constraints for pest management such as low temporal resolution, low spatial resolution, susceptibility to cloud cover effects on image quality, and slow data translation into useable products for land managers (Zhang and Kovacs, 2012). Manned aircraft provide higher resolutions than satellite imagery, but image quality is also prone to similar cloud cover effects, and data collection is limited by the availability of pilots, aircraft with proper equipment, and camera operators. Unmanned aircraft systems (UAS) can fly at lower altitudes, providing high-resolution imagery comparable with ground-based sensors. This can offer more flexibility, automation, and efficiency to perform repeat surveys

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at higher frequencies relevant to grower needs for use in precision agriculture. The downside, however, is the geographic area coverage is more appropriate to individual field-scaled applications compared with the other satellite or traditional airborne platforms.

With advances in reducing the size and weight of optical sensors, including the use of commercial-grade (three-band) cameras, and their placement on more accessible UAS platforms, the use of remote sensing in agricultural systems has been on the increase in the past decade. There are multiple studies investigating the effects of fertilization (Muñoz-Huerta et al., 2013), irrigation (Ha et al., 2013), weed detection (Sudbrink et al., 2015; Thorp and Tian, 2004), and yield predictions using wavelengths in the visual spectra from remotely sensed data. Studies using handheld sensors acquiring a wide range of spectral data from insect-stressed plants are plentiful in cropping and forest systems. They support the feasibility of using remotely sensed reflectance data from optical sensors mounted on a UAS for insect-induced stress detection (Nansen et al., 2013). Studies using data from multi-spectral or simpler commercial-grade (modified to acquire near-infrared data) cameras mounted on UAS are rare and provide mixed results in the ability to detect plant stress caused by insects (e.g., Marston et al., 2020; Stanton et al., 2017). Remote sensing technologies delivered on UAS platforms for mixed uses may be particularly valuable in large-scale agricultural systems, such as field crop, forest, and forage systems, where crop monitoring resources are limited.

Spectral characteristics of plants such as reflectance and absorption by leaves can provide an understanding of physiological responses to growth conditions and stressors in the environment (Carter and Knapp, 2010), including those caused by insects (Carroll et al., 2008). The potential of remote sensing to assess crop health, biomass and yield with the use of vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), has been well noted in the literature. Applied to stress detection, these indices can estimate the amount of photosynthetic radiation absorbed by plants as chlorophyll concentration change brought on by metabolic disturbances caused by stresses. Stressors include nutrient deficiencies, water stress, and pest-induced stress in plants (Knipling, 1970). Normalized Difference Vegetation Index is a ratio expressed as the difference between Near Infrared and Red bands normalized by their sum, with a resulting scale of -1 to 1. It was initially developed to differentiate green vegetation from a non-vegetative background with higher values indicative of greener (healthier) vegetation (Silleos et al., 2006). Specific to cotton, remotely sensed spectral data has been successful in detecting aphid and spider mite infestations by using spectral changes in the leaves (Reisig and Godfrey, 2007). This study found that wavelengths in the Near Infrared (NIR) region acquired by a portable spectrometer were moderately accurate predictors of aphid and mite infestations and were able to detect infestations above economic thresholds. Further, they found that these changes were linked to other plant stressors such as nitrogen or water deficiency, making it challenging to distinguish nitrogen and insect-induced stress. Reay-Jones et al. (2016) reported variation of within-field spatial data for stink bug, cotton boll injury, and NDVI measurement using tractor-mounted and handheld sensors.

The agricultural region of South Texas is a large-scale growing system consisting mainly of cotton, sorghum, and corn. The system may benefit from the automation of crop monitoring via UAS to supplement or serve as a substitute for direct observations by crop consultants serving this large-scale system. In this region, UAS has been used to measure plant height and quantify lodging in maize with comparable accuracy to ground human sampling (Chu et al., 2017). Unmanned aircraft systems have also been used in sorghum, where the use of vegetation indices detected the effects of aphid stress on yield, although with considerable variability (Stanton et al., 2017). There have been few studies to our knowledge relating UAS-derived data to insect-induced injury to reproductive structures of cotton. Reisig and Godfrey (2007) focused on aphids and spider mites causing stress symptoms on leaves, while Reay-Jones et al. (2016) reported mixed capabilities to relate NDVI within-field data to stink bug activity and cotton boll injury.

In South Texas, the main cotton insect pests are a complex of plant bugs with the predominant species being the cotton fleahopper, *Pseudatomoscelis seriatus* (Reuter) (Hemiptera: Miridae). Cotton fleahopper in high numbers can cause square abscission reducing boll set and results in a significant reduction of yield (Ring et al., 1993). They have piercing-sucking mouthparts similar to aphids, but they primarily injure immature fruiting buds (squares) and not leaves nor fertilized bolls, providing an opportunity to investigate whether remotely sensed reflectance data using a consumer-grade/low-fidelity camera sensor is useful to detect stress derived from injury to rapidly growing reproductive tissue. Using these data, we discussed constraints and future research needed to adapt the current use of imaging drones in large-scale agricultural systems for mixed applications, including monitoring and assessing insect-induced plant stress.

MATERIALS AND METHODS

Experimental Design. In 2015 and 2016, a replicated field experiment was conducted at Corpus Christi, TX, to investigate the effect of different spray regimens on cotton fleahopper populations and cotton yield. We acquired data from optical sensors mounted on a UAS to investigate the use of remotely sensed imagery and vegetation indices to detect cotton fleahopper-induced stress caused by their feeding on immature fruiting buds. All plantings were Phytogen PHY-333-WRF varieties (Dow Agrosciences, Indianapolis, IN). Crop management followed normal agronomic procedures for the region (Morgan, 2018). In South Texas, growers use a threshold between 0.1 and 0.25 cotton fleahoppers per plant to time an insecticide application (Vyavhare et al., 2018), which was exceeded in the field experiments on multiple occasions.

The experiments were laid out in a split-plot design. Individual split-plot sizes were four rows by 12m with four replications in 2015 and six in 2016. In 2015, the main plot factor was planting date with two levels, early (May 1, 2015) and late (May 13, 2015) planted plots. In 2016, the planting dates were March 30 (early) and April 20 (late). For both years, an insecticide regime of four levels was the split factor, in which insecticide treatment was applied when weekly monitoring indicated populations exceeding 0.15, 0.30, and 0.45 cotton fleahoppers per plant along with an unsprayed control. For both years, the insecticide used was thiamethoxam (Centric, Syngenta Crop Protection, Greensboro, NC) and applied label rates via tractor-mounted spray boom as experimental thresholds were reached until the second week of bloom. All cotton fleahopper per plant threshold treatments triggered only one insecticide application, but timing differed across the three treatments. In 2015, the 0.15 cotton fleahopper per plant threshold was exceeded on June 10, and insecticide was applied the same day. The 0.3 and 0.45 cotton fleahopper per plant thresholds were exceeded on June 17 and insecticide was applied the same day. In 2016, the cotton fleahopper per plant threshold of 0.15 was exceeded on May 27 and treated the same day. The 0.3 and 0.45 cotton fleahopper per plant thresholds were exceeded on June 8, triggering same-day insecticide application. Functionally, the 0.3 and 0.45 treatments were the same but were kept in analyses to keep the design (number of replications and physical layout) in balance across treatments.

For both years, insect counts were taken weekly over a five-week period (2015: June 10 to July 24, 2016: May 27 to July 14) beginning at the first week of occurrence of fruiting buds (first detection of pinhead-sized squares) which are most susceptible to cotton fleahopper feeding (Ring et al., 1993). To estimate cotton fleahopper density, 20 plants in the middle two rows of each four-row plot (to avoid disturbances from plot to plot) were sampled using the beat bucket method (Brewer et al., 2012). Briefly, a five-gallon bucket was used to beat foliage of plants in groups of two or three for a total of 20 plants. Dislodged nymphs and adults were counted in the bucket and recorded. After defoliation at the end of the season, the middle two rows were harvested using a two-row John Deere picker (Moline, IL, USA). A hand-grabbed sample selected from the weighed seed cotton of each plot was ginned using a ten-saw Eagle Continental gin (Birmingham, AL, USA) to determine percent lint turnout. The weight of the seed cotton per plot and percent lint turnout was used to calculate lint weight per plot.

UAS Data Collection. For both years, the imagery was acquired from a fixed-wing eBee UAS (senseFly, Cheseaux-Sur-Lausanne, Switzerland) containing a 12-megapixel (4048x4048) Powershot S110 (Canon USA, Melville, NY) consumer-grade sensor with a sensor size of 7.44 by 5.58 mm. This UAS has a fully autonomous flight that can be programmed to capture imagery at the user-defined flying height, percent image endlap, and percent image sidelap. The eBee can fly a maximum time of about 50 minutes on a fully charged battery, dependent on weather conditions and sensor weight. The camera stored images in RAW and JPEG format and was modified with a filter to capture imagery in three bands of the electromagnetic spectrum: green (500-575 nm), red (575-650 nm), and near-infrared (800-900 nm). The camera was programmed to auto-capture imagery triggered by the onboard navigation and processor control system of the UAS platform.

All flights were conducted with at least 60% endlap and 70% sidelap to ensure sufficient image overlap for photogrammetric processing. The flight and flight plan was conducted under the supervision of a certified pilot who adhered to FAA regulations concerning drone use for research purposes. The facility (Texas A&M AgriLife Research and Extension Center) where the experiment was conducted had necessary permits for drone use.

Images from three UAS flights were considered for use in 2015: June 10, June 23, and July 29. All three flights were used for analysis, but we note that the flight of June 23 most closely coincided with early bloom when squares were plentiful and the experimental cotton fleahopper per plant thresholds had been exceeded. Cotton fleahoppers were counted within three days of each flight. Flights were flown with the Cannon PowerShot S110 (R-G-NIR) commercial-grade camera with a filter to obtain NIR data at altitudes between 90m and 100m above ground level resulting in an average ground sample distance of 2.9cm. In 2016, images from three flying dates (June 23, July 15, and July 21) were considered. Flight specifications and parameters were the same as in 2015.

Image Processing and Indices Derivation and Analysis. Over 250 raw images were captured during each UAS flight that covered approximately 38 hectares, which included the experimental plots. These images were downloaded and transferred to portable hard drives for post-processing. The software Pix4Dmapper Pro (Pix4D SA, 1015 Lausanne, Switzerland) was used to process the imagery using structure from motion (SfM) photogrammetry. SfM is different from traditional photogrammetry in that it does not need the use of precisely calibrated metric cameras to extract three-dimensional information from a scene. Instead, it uses a highly redundant and iterative bundle adjustment by automatically extracting and corresponding thousands of features from multiple overlapping images to simultaneously solve for camera internal and external parameters (position and orientation) and reconstruct the 3-D scene (Westoby et al., 2012). Outputs from SfM photogrammetric processing included a densified 3-D point cloud, a digital surface model (DSM), and three-band orthomosaic imagery. During data processing, ground control points (GCPs) were used for improving the absolute georeferencing of the created data products. The ground control points consisted of aerial control targets placed around the perimeter of the field whose coordinates were precisely surveyed using s Real-time kinematic (RTK) GPS instrument. Georeferencing was accurate within 1.0 to 5.0 cm horizontally and vertically. Full details of the RTK-enabled UAS platform and SfM process are available (Chu et al., 2017; Stanton et al., 2017).

We computed the band ratio index Normalized Difference Vegetation Index (NDVI) of all three flights for each year by using two bands (R and NIR) of the three-band (R-G-NIR) orthomosaic image from the flights. This image was imported into a geographic information system (GIS) program, ArcMap (ESRI, Redlands, CA). Using a raster calculator function, NDVI maps were created for each flying date using the common band ratio: NDVI = (NIR – Red) / (NIR + Red). The experimental plots were georeferenced as a vector using the orthomosaiced images for each year. The two middle rows of each subplot were further delineated as individual polygons in the GIS to extract NDVI values corresponding with pest data collection. Polygons had identical sizes (8m x 0.8m) for both years and were individually placed at the best positions aligning with the cotton rows. The polygons mainly contained vegetation pixels due to good canopy coverage. Therefore no filtering for low soil reflectance values was done prior to NDVI calculations as done when considering stress on young plants with low ground coverage (Stanton et al., 2017). Zonal statistics were computed for each plot to include the range, mean, standard deviation, minimum, and maximum NDVI values in the area within the data row polygons.

Analysis of variance (ANOVA) following the experimental design was used to compare the response variables across the cotton fleahopper per plant thresholds of 0.15, 0.25, and 0.45 cotton fleahoppers per plant (and unsprayed control) for the early and late plantings. Since cotton fleahopper per plant thresholds received only one insecticide application at varying dates, cotton fleahopper density was converted into cumulative cotton fleahopper days for analysis. Using the averages of cotton fleahoppers per 20 plants per plot on a given sampling day, cumulative cotton fleahopper days was calculated using the formula $\sum[(x_i + x_{i-1})/2] \times (t_i - t_{i-1})$, where $(x_i + x_{i-1})/2$ is the cotton fleahopper density x between two consecutive sampling dates sampling periods i, and $(t_i - t_{i-1})$ is the number of days t between sampling dates (Gordy et al., 2019; Kieckhefer et al., 1995). To initiate the cumulative cotton fleahopper days, a start sampling date one week before the first detection was selected, with monitoring results set to 0 cotton fleahoppers per plant for sampling date t_0. The response variables for each plot were cumulative cotton fleahopper days, average NDVI values extracted from data row polygons, and estimated lint weight at the plot level. If a significant effect of cotton fleahopper per plant threshold on a response variable was found, a means separation test using Tukey's HSD ($\alpha = 0.05$) was conducted to compare the four treatments (Neter et al., 1985). In addition, regression analysis was used to test the linear relationships of NDVI values with cumulative cotton fleahopper days and with yield using individual plot means of NDVI across all cotton fleahopper per plant thresholds from the early and late planted plots (Neter et al., 1985).

RESULTS

Cumulative Cotton Fleahopper Days and Cotton Yield. Cotton fleahopper was the primary sucking bug detected. Other sucking insects that injure cotton were absent (spider mites, aphids) or occurred at trace levels (stink bugs or other plant bugs) that never approached economic thresholds. Cotton fleahopper per plant thresholds had a significant effect on the cumulative cotton fleahopper days up to the date of data collection for both early (F=8.36; df =3,16; P < 0.0001) and late plantings (F= 9.55; df =3,16; P < 0.0001) in 2015 (Fig. 1A, 1B). In the early planted plots, cotton fleahopper per plant thresholds decreased cotton fleahopper days in the treated plots (Fig. 1A). Similarly, in the late planted plots, the unsprayed control accumulated significantly more cotton fleahopper days (1.26 ± 0.22) on average compared to the cotton fleahopper per plant threshold treatments (Fig 1B). In 2016, cotton fleahopper per plant thresholds had a marginal (0.05 < P < 0.10) effect on accumulated cotton fleahopper days in the early planted plots (F=2.41; df =3,44; P = 0.0796) and the late-planted plots (F=2.42; df =3,44; P = 0.0791). Compared to 2015, there was a narrower range of cotton fleahopper days in 2016 (2016 data not shown due to lack of significant differences).

Cotton fleahopper per plant thresholds had a significant effect on lint weight for both early (F= 3.94; df =3,16; P = 0.043) and late (F= 5.36; df =3,36; P = 0.0037) planted plots in 2015. The 0.15 cotton fleahopper per plant threshold had the highest yield (255 ± 12g), and the unsprayed control had the lowest yield (216 ± 9g) in the early planted plots. Cotton fleahopper per plant threshold in 2016 had no effect on lint weights in early (F= 1.15; df =3,44; P = 0.22) or late (F= 1.37; df =3,44; P = 0.26) planted plots (2016 data not shown).

Variation in NDVI and Relationship to Cotton Fleahopper. In 2015, NDVI values calculated from the June 23 flight differed across the cotton fleahopper per plant thresholds in the early planting (F=3.135; df =3,16; P = 0.05) (Fig. 1C) and a more significant effect was seen using NDVI values from the July 15 flight (F=5.98; df =3,16; P = 0.006) (Fig. 1E). No differences in NDVI values for all three flights were seen across the cotton fleahopper per plant thresholds in the late plantings or the early planting of the July 28 flight (P > 0.1) (Fig. 1D, 1F-G). In 2016, cotton fleahopper per plant threshold had no significant effect (P > 0.10) on NDVI values calculated from all three flights in both the early and late planted plots (2016 data not shown). This was expected as per plant thresholds had no effect on fleahopper numbers.

We inspected the relationship of the NDVI measures with cumulative cotton fleahopper days with regression. In both early and late plantings, there were varied linear associations between accumulated cotton fleahopper days and NDVI values across the different flights. Across both years, five of 12 regressions were significant, and all five were unexpectedly positive. NDVI values from the flight of July 15, 2015 increased as cumulative cotton fleahopper days increased in early (F= 15.64; df= 1, 16; P= 0.0019) (Fig. 2C) and late plantings (F= 6.04; df= 1, 36; P= 0.018) (Fig. 2C and 2D). There were no linear associations between NDVI values and cumulative cotton fleahopper days in the other two flights across both plantings (Fig. 2A, 2B, 2E, 2F). In 2016, despite no significant effect of cotton fleahopper per plant thresholds on NDVI across all flights, there were three positive linear relationships between NDVI and cumulative cotton fleahopper days. These linear relationships were found in the early plantings of the June 23 (F= 11.675; df= 1, 41; P= 0.0019) (Fig. 3A) and July 23 flights (F= 16.1; df= 1, 41; P < 0.001)(Fig. 3E) and in the late planting of the July 15 flight (F= 3.75; df= 1, 41; P= 0.05). No linear relationships (P > 0.10) were seen in the late plantings of the June 23 (Fig. 3B) and July 23 flights (Fig. 3F) or the early planting of the July 15 flight (Fig. 3C).

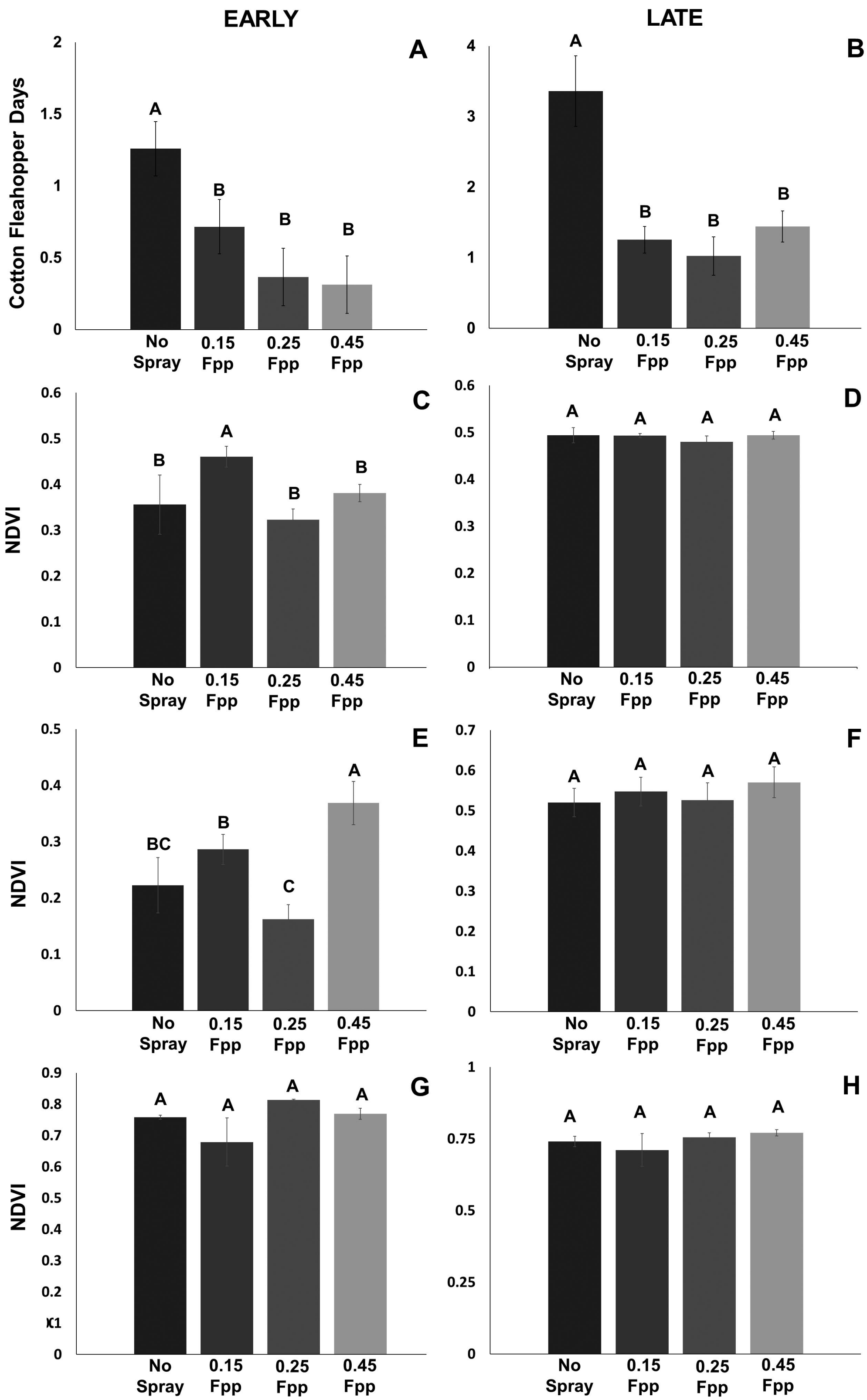

Fig. 1. Cumulative cotton fleahopper days (A, B), and NDVI (C-H) across cotton fleahopper per plant thresholds for 2015 early planted plots (Left column) and late planted plots (Right column). Letters indicate significant differences between means based on Tukey's means separation test (α = 0.05). Treatments are from left to right on the x-axis: unsprayed control, cotton fleahopper per plant thresholds at 0.15, 0.25, and 0.45 cotton fleahoppers per plant (FPP).

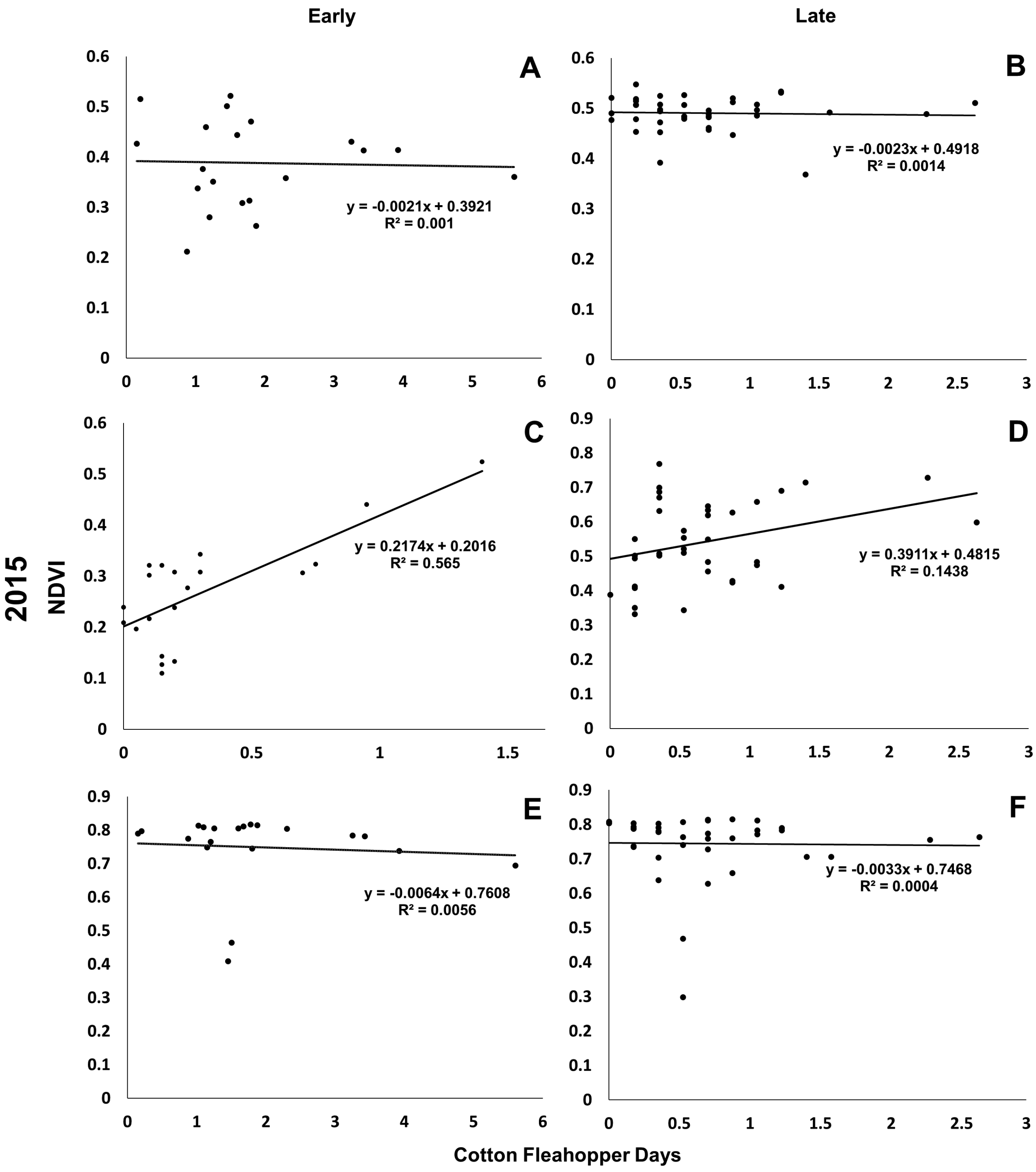

Fig. 2. Linear regressions of NDVI regressed on cumulative cotton fleahopper days (A-F) for early (left column) and late (right column) planted plots for all three 2015 flights. June 23, 2015 (Top Row), July 15, 2015 (Milldle Row) and July 28, 2015 (Bottom Row).

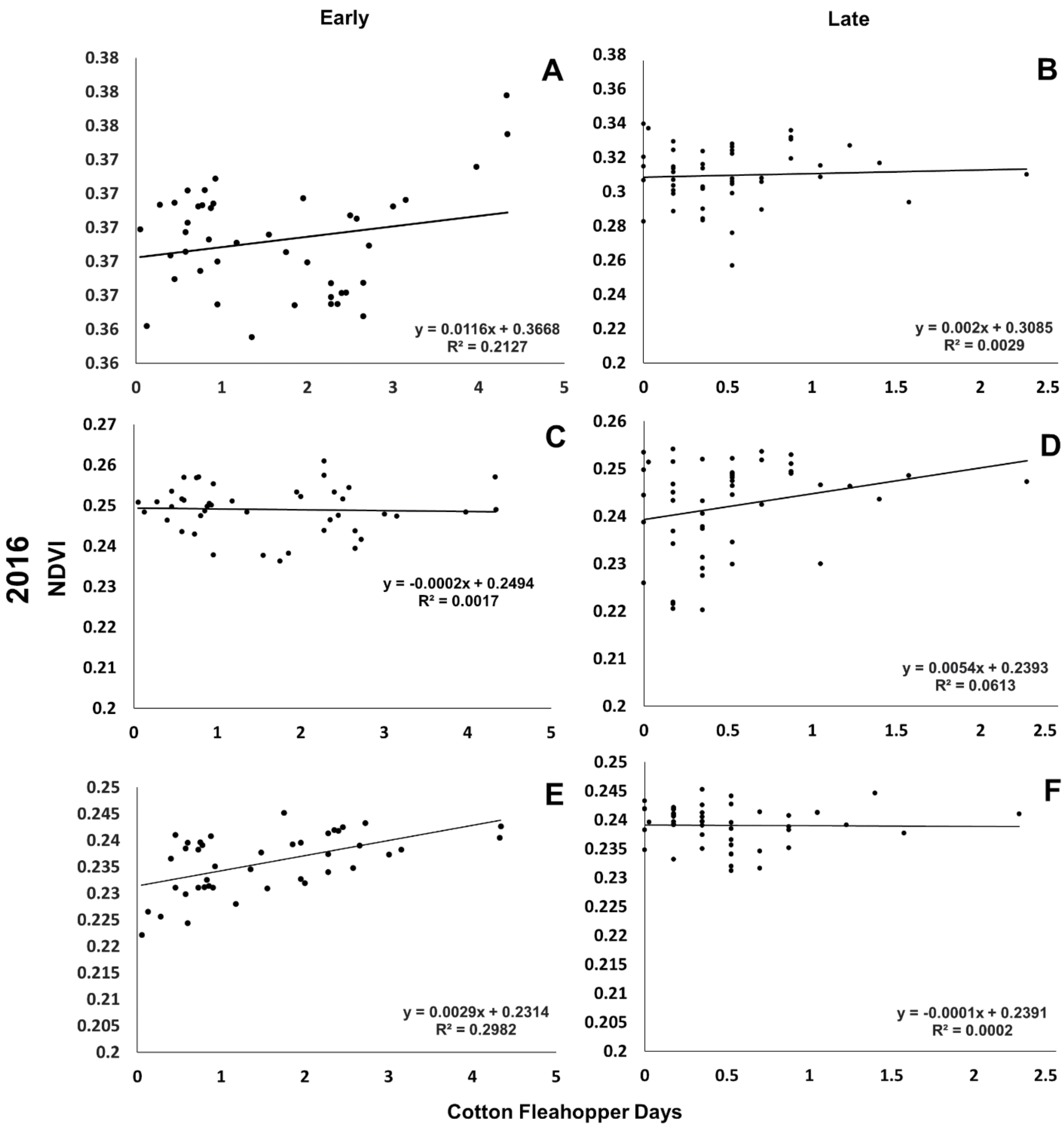

Figure 3. Linear regressions of NDVI regressed on cumulative cotton fleahopper days (A, B) for early (left column) and late (right column) planted plots of all three 2016 flights. June 23, 2016 (Top Row), July 15, 2016 (Milldle Row) and July 23, 2016 (Bottom Row

DISCUSSION

Overall, the experiment of varying cotton fleahopper per plant thresholds on cotton fleahopper was successful in manipulating cotton fleahopper density that led to yield differences in 2015, while 2016 cotton fleahopper data were more variable and did not lead to yield differences. Cotton plant vigor, growing conditions, and cotton development stage may have contributed to year-to-year cotton fleahopper variation (Barman et al., 2012). The relatively high cotton fleahopper day accumulation in the unsprayed control in 2015 compared to 2016 aided the ability to detect differences between the cotton fleahopper per plant thresholds and the unsprayed control in 2015 and may have aided detected difference in subsequent plant response (yield) and NDVI measurements.

Further, cotton fleahopper modestly followed the same trends in the unsprayed and threshold treatments in accumulated cotton fleahopper days, and unexpected and inconsistent trends of increasing NDVI with increasing cotton fleahopper days (five of 12 regressions were significant) were counter to our expectations. Variation of insect activity and its association with yield and NDVI is not uncommon with other pests in cotton. For example, Reisig and Godfrey (2006) detected no differences in insecticide treatment on yield for cotton aphid and spider mite densities but were still able to detect insect-induced damage via reflectance and vegetation indices. The results suggest that NDVI values derived from spectral data acquired by a commercial-grade (modified three-band) camera mounted on a UAS were limited or inadequate in its ability to detect stress by cotton fleahopper where the insect exceeded regional economic thresholds during two years of study. Using reflectance data as a surrogate measure of insect-induced stress may be particulary challenging for insects that feed on reproductive tissue. Additional years of data with economically damaging populations of cotton fleahopper are needed to better resolve the relationships.

There appears to be potential and limits in using UAS imaging drones for insect-induced cotton stress. Overall, it appears difficult to detect insect-induced stress from piercing-sucking insects such as cotton fleahopper (data from our study) and stink bugs (Reay-Jones et al., 2016) that feed on immature fruiting buds and bolls, respectively, using NDVI as estimated from UAS-derived data. We found that as the number of cotton fleahoppers increased, NDVI values also increased, unlike aphid pests in cotton or sorghum, where higher aphid populations led to lower NDVI or NIR values (Reisig and Godfrey, 2007; Stanton et al., 2017). Although successful in using vegetations indices and the NIR-band reflectance values to predict cotton aphid and spider mite infestations on leaves, Reisig and Godfrey (2006) also found unexpected differences in reflectance values across insecticide treatment combinations. Further, Reay-Jones et al. (2016) reported increasing NDVI values were associated with boll injury from stink bug feeding. Again, this is contrary to the expectation of pest-induced stress, in this case stink bugs injuring bolls is associated with decreasing NDVI values.

Since cotton fleahopper feeds on the young fruiting structures of cotton plants (squares) and the injury often leads to square abscission, the plant may compensate for the lack of fruit production by shifting more nutrients to the vegetative growth potentially increasing reflectance values. It has been shown that insect-induced square loss or hand removal of fruiting structures leads to increased vegetative growth and an increase in canopy photosynthesis (Holman and Oosterhuis, 1999; Pettigrew et al., 1992). Further, this has been reported in other studies where insect or human-induced foliage damage lead to increased photosynthetic activity and photosynthates present in leaves (Detling et al., 1979; Fay et al., 1993; Martens and Trumble, 1987)root respiration (RR. In lima beans, rapid structural compensation for leaf mining injury in mature foliage leads to the maintenance of high levels of photosynthetic activity (Martens and Trumble, 1987). This trend should be tested in the future with remote sensing as this may be a way to discern insect-induced damage from insects that do not induce readily visible foliar damage to the plant.

In contrast to our results with cotton fleahopper, NDVI and reflectance values were able to detect cotton aphid and spider mite populations at or above economic thresholds and were found to be moderately accurate predictors of injury of cotton leaves and subsequent yield (Reisig and Godfrey, 2006). While cotton fleahoppers feed on cotton squares, aphids pierce the phloem system and remove nutrients directly affecting leaf and photosynthetic health. Aphids are relatively sessile insects and can reach high numbers on leaves, which can induce reflectance changes in the plant as well as produce an excess of honeydew that may also affect reflectance values. Honeydew covers the plant leaves in a glossy film and is a substrate for sooty mold, which can cause leaves to turn black, making detection via UAS-derived reflectance data more feasible. Spider mites feed by piercing/slashing plant cells and tissue to feed on the nutrients causing chloroplast damage leaving a dead cell that turns brown (Reisig and Godfrey, 2006). In high numbers, spider mites can cause yellowish spots or browning on leaves, making detection with reflectance measurements more viable (Reisig and Godfrey, 2006). Plant bugs are highly mobile, and cotton fleahopper-induced injury is primarily on young fruiting structures; therefore, damage attributed to them may be more difficult to detect in general (Brewer et al., 2016; Ring et al., 1993) and specifically by reflectance measurements.

Constraints and Future Research. Here, a fixed-winged UAS captured three-band (R-G-NIR) imagery from a modified consumer-grade and low-fidelity camera sensor. The camera used a relatively wide bandwidth range that may be prone to errors or insensitivity in detecting cotton fleahopper-derived stress on cotton. Three flights were carried out each year allowing us to only make inferences on insect-induced stress at that point in time corresponding to estimated cotton fleahopper accumulation days. Our goal was to test the feasibility of using commercial grade sensors on readily available UAS platforms however, it appears that there is a need for sensors with higher spatial and spectral resolutions at least at the research stage of investigation as done in remote sensing studies to detect insect-induced plant stress (Nanasen and Elliott, 2016). The unexpected but inconsistent positive trend of cotton fleahopper densities and NDVI, and modest differences between cotton fleahopper per plant thresholds and NDVI, was intriguing. Given past proof-of-concept research using multi-spectral handheld sensors and the applicability to monitoring cotton with UAS for other purposes, we recommend research comparisons of ability to detect insect-induced cotton stress by key pests, including those damaging leaves and reproductive tissue, across a range of sensors and platforms. These may include modified RGB, multi-spectral, and hyperspectral data acquired by hand or tractor-mounted devices and ideally the same or similar quality spectral data acquired by UAS. More comparative research inclusive of other vegetation indices and with higher grade and possibly hyperspectral sensors is warranted to further delineate insect stress.

Alternatively, the lack of correlation to NDVI observed in this study could be due to the increase in cotton fleahoppers not producing detectable levels of plant stress response by the dates of the flights used for the analysis. It could be that the levels of cotton stress during the dates of the flights used in the analysis were inadequate for detection by the NDVI metric derived from the commercial-grade (three-band) camera modified to acquire NIR data. Future experimentation is warranted to better delineate the minimum detectable threshold of cotton fleahopper-induce injury using UAS imaging drones. We suggest it is premature to add insect-induced cotton stress detection to the mission of a UAS with a commercial-grade camera tasked for nutrient and water stress detection (Barbedo, 2019). Future experimentation should include weekly flights from first cotton fleahopper detection until peak bloom. Further, given the variability of cotton fleahopper populations, such as our 2016 experiment, incorporating simulated cotton injury into experiments may be useful. For example, if simulated levels of reproductive tissue feeding by cotton fleahopper leads to detectable increases of NDVI values as our preliminary data suggests, this information can aide in discerning what level of pest pressure leads to this trend.

Specific to cotton that experiences various forms of leaf and reproductive tissue stress caused by insects and other arthropods (Brewer et al., 2012; Reay-Jones et al., 2016; Reisig and Godfrey, 2007), caution is warranted in adapting the current use of imaging drones for mixed applications in nutrient, irrigation, and pest management (Barbedo, 2019). The application of UAS-derived remotely sensed optical data to detect insect-induced plant stress continues to have merit, but a merging of best suited UAS technology to the needs of detecting plant stress will continue to be a research-intensive endeavor (Moses-Gonzales and Brewer, 2021).

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