MISSISSIPPI SOYBEAN PROMOTION BOARD
PROJECT NO. 49-2017 (YEAR 10
FINAL REPORT

Title: Investigation and demonstration of the potential for unmanned aerial systems to detect and quantify stressors in soybean production fields

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BACKGROUND AND OBJECTIVES

This research is motivated by a desire to inform producers about advantages and disadvantages of using unmanned aerial vehicle (UAV) technology for farming operations. Adoption of this technology is limited by a lack of information on its value and usefulness. Unmanned aerial vehicles (a.k.a. "drones") offer what University of Nebraska's Dr. Wayne Woldt called "an unparalleled and powerful view of the landscape that would be very difficult to get from the ground when monitoring large parcels of land," and yet for most producers the technology is more of a novelty that, partially due to FAA regulations, has rarely been utilized in their farming operations.

To increase decision making ability, researchers\practitioners must establish that specific stresses are identifiable with a UAV and that the level of stress determined by UAV imagery relates to in-field ground-based stress assessments. Research should also determine the appropriate spectral, spatial, and temporal resolutions for data collection with a UAV to maximize decision making potential. Essentially, this research provides an indication of whether an investment in this technology is warranted, and if so, how to best apply UAV imagery to soybean production systems. This project is a collaboration between research and extension personnel at Mississippi State University, and their colleagues at USDA-ARS in Stoneville, Mississippi.

REPORT OF PROGRESS

In support of this project, we flew approximately 70 UAV missions over soybean research plots. Plots covered research on herbivory, herbicide injury, and herbicide efficacy. Primary unknowns for UAV operations in agriculture relate to appropriate spectral, spatial, and temporal resolutions for enabling decision making by producers. Research is lacking on what equipment is needed, how it should it be used, and when the flight should be conducted, relative to a specific production problem.

Selection of equipment is directly related to cost; best practices for data collection (the how and when) are directly related to decision support. The current market model for UAV services includes a general, one-size-fits-all approach to data collection. The objective of these missions is frequently simple anomaly detection. However, we desired to determine the best practices for identifying specific problems, rather than merely detecting *any* problem. Thus, our missions were conducted with multiple sensor payloads (spectral), at multiple altitudes (spatial), and with high frequency from planting to harvest (temporal) to evaluate the necessary resolutions for detecting our target problems.

For this project, we established two sets of research plots to examine gradients of herbivory damage, one in Starkville and one in Stoneville. Soybeans were planted May 3 (Starkville) and June 12 (Stoneville), 2017. Soybean varieties planted were Terral REV 52A94 (Starkville) and Dyna-gro 31RY45RR (Stoneville). These plots were managed to simulate three levels of herbivory at three growth stages. The selected stages were V3, R1, and R5, and levels were 10, 25, and 50% damage to each plant. Each set of plots also contained 0% damaged control plots. Clipping dates were June 9 (soybeans at V4), June 27, and August 3 in Starkville, and July 12, July 20, and August 24 in Stoneville. Soybean plots were manually clipped to simulate deer browsing at our specified levels.

Soybean plants within a treatment row were measured, the average height taken, and the upper portion of the plant, corresponding to the specified percentage, was stripped of leaves and the meristem removed. This mimics deer browsing in that they generally will only eat the youngest, most tender green portions, with secondary bites only removing leaves and not the entire stem or petioles. To be clear, new plots were selected for each clipping, thus a single plant was clipped only once. Clipped plants were allowed to continue growing unimpeded through the remainder of the growing season. All other plots from which data were collected were established under other research funding and we did not control research within those plots.

The majority of missions were conducted primarily with two sensor payloads. We used the integrated camera in the DJI Phantom 4 Pro and the Parrot Sequoia. Both are easy to obtain and relatively inexpensive ($1300 for the former, and $3500 for the latter), representing products a producer might acquire without much effort or cost. The integrated camera is a standard RGB camera, meaning the resultant image is a composite of red, green, and blue, similar to how human eyes perceive color (Fig. 1).

Remote sensing research indicates that reflectance in the near-infrared portion of the electromagnetic spectrum is useful for evaluating plant health. Because these data cannot be collected with the Phantom camera, we also used the Parrot Sequoia. The Sequoia is a multispectral sensor that collects reflectance in the near-infrared, in addition to other wavelengths (Fig. 1). Most UAV service providers recommend using normalized difference vegetation index (NDVI) maps for crop surveys; the Parrot Sequoia has the necessary components to calculate NDVI (Fig. 1).

Companies such as DroneDeploy create plant health maps using the Visible Atmospherically Resistant Index (VARI), which is derived from UAV-collected RGB images. We also used the Sentera NDVI and the Micasense RedEdge to collect image data on limited occasions. With this arrangement, we were essentially determining if a producer should spend $2,000 more to obtain a sensor capable of providing near infrared reflectance to detect the specific production problems covered in this study.

We used a texture analysis algorithm to evaluate the potential for automation of herbivory damage at the levels used in the study. Plants at the earliest clipping date did not exhibit enough visible difference within the image to assume the algorithm would be successful. The algorithm was, however, applied to R1 and R5 soybean. Representative areas of both clipped and unclipped soybean are selected as training sets for the algorithm. The algorithm then classifies the entire image by evaluating regular sized blocks of pixels and determining if they are more similar to the clipped or unclipped examples that were selected for training.

Output is displayed with overlays in shades of grey to black (Fig. 2). If the block under inspection more closely resembles one class than the other it gives that block a weight, pushing it closer to one end of the spectrum between clipped and unclipped. The blocks that have little to no shading represent the samples of the healthy, unclipped plants. At R1, the algorithm is able detect the 50% clipped row and classify it as one class. The 25% falls in between the clipped and non-clipped, which is not unexpected. The algorithm is not able to detect 10% clip.

At R5, the algorithm is able to detect the 50% clipped row fairly well, but it also selected quite a few other blocks, which are not within the 50% clipped row (Fig. 2). Class confusion is likely due to the visibility of soil background in the heavily clipped rows. This leads the algorithm to also select other areas with high soil visibility, such as alleys, and classify these blocks as clipped soybean. In this case, our results indicate that near infrared image information would have assisted with *automated* detection of herbivory damage as near infrared reflectance is useful for separating plants from soil in an image.

Soybean yield was also collected by plot to determine at what level of damage and at what growth stage no detriment to yield was seen. Yield values ranged from 7 to 65 bu/acre. Not surprisingly, the lowest yielding rows corresponded with those that received significant damage at R5.

Flights were always conducted at two altitudes, 200 and 300 ft (Fig. 1). Spatial resolution and flight altitude are directly related through a linear function; therefore, lower flight altitudes produce more detail within the images collected. With the payload on the Phantom, this results in RGB imagery at approximately 0.65 and 1-inch spatial resolution, respectively. This means one pixel within the image contains what is seen on the ground in 0.65 in^2 and 1 in^2, respectively. With the Sequoia this results in imagery at approximately 2.5- and 3.5-in. spatial resolution. It is however, well known that UAVs suffer from poor battery life. Lower altitude flights often take longer to cover the same area; therefore, it is in the best interest of the operator to conduct UAV missions at the altitude that provides the spatial resolution necessary for detection and nothing lower. This also reduces data volume, which can be a consideration for users uploading data to a cloud environment. Our results indicate that herbivory damage was visible even at the 300 ft. altitude with the Phantom. Even with the coarser resolution of the Sequoia, the damage can be seen. We recommend flying the lower altitude early in the season, but increasing altitude once plants reach V3, as plants can be clearly seen (Fig. 1).

After discussion, the PI and co-PIs determined that naturally occurring populations of weeds were superior to artificially-created weed densities. Thus, during flights, we opportunistically captured and documented prickly sida populations in sample areas within research fields at Stoneville and Starkville. We were able to see weeds with both still images and video footage from the Phantom. Weeds appeared more yellow than soybean in Starkville, but the "greenness" of soybean can vary even by variety. This means that color alone may not be a reliable indicator of weeds. Generally, weeds are located via context clues (e.g., location between rows, increased thickness of rows; Fig. 3). Weeds were less detectable when small, indicating that weeds may be beyond the treatment window before reliably detectable.

We collected imagery from a research project (PI: Reynolds) with gradients of injury from auxin herbicides. Although this is not our study, the images collected show where potential may lie in future endeavors in weed science, as well as in herbivory detection (Fig. 4). Generation of 3D surfaces from aerial imagery is a new area of interest in the UAV industry. Cloud-based processing services such as DroneDeploy can generate this 3D surface automatically if the overlap between UAV flight lines is set sufficiently high (> 70%).

After discussion, the PI and Co-PIs have determined that portions of the experiment will be repeated in the 2018 growing season before considering this as final conclusions. Our lessons learned from the herbivory study have given us insight into how we might improve upon the experimental design. As we already have the necessary equipment, we will establish new plots to repeat the study.

IMPACTS AND BENEFITS TO MISSISSIPPI SOYBEAN PRODUCERS

Our goal is to conduct research and extension necessary for Mississippi soybean producers to understand and take advantage of this new technology to the extent that makes sense for their farming operation. In our preliminary investigation, we have determined that there is potential to detect production problems in soybean with a UAV. However, we have also seen that detection windows may not align with decision windows. While we were unable to automate detection, we were generally able to locate issues by perusing the imagery. This will be a useful starting point for field scouts, who will likely then need to gather supporting information within the field.

In the last year, we have seen dramatic improvements in market offerings for cloud-based data processing. Additional outputs such as 3D surfaces and instant turnaround of imagery and crop health indexes may increase the appeal and value of this new technology to producers.

END PRODUCTS – COMPLETED OR FORTHCOMING

- As we have decided to conduct a second year of data collection, journal article publication will be delayed.

Figure 1. Comparison images of the same area within research plots to show differences in altitude and payload.

A. DJI Phantom 4 RGB imagery collected at 200 ft. altitude at R1
B. DJI Phantom 4 RGB imagery collected at 300ft. altitude at R1
C. Parrot Sequoia imagery, showing color infrared, collected at 300 ft. altitude, at R1
D. Normalized difference vegetation index (NDVI) image, derived from Sequoia imagery, collected at 300 ft. altitude, at R1
E. DJI Phantom 4 RGB collected at 300ft. altitude at V3

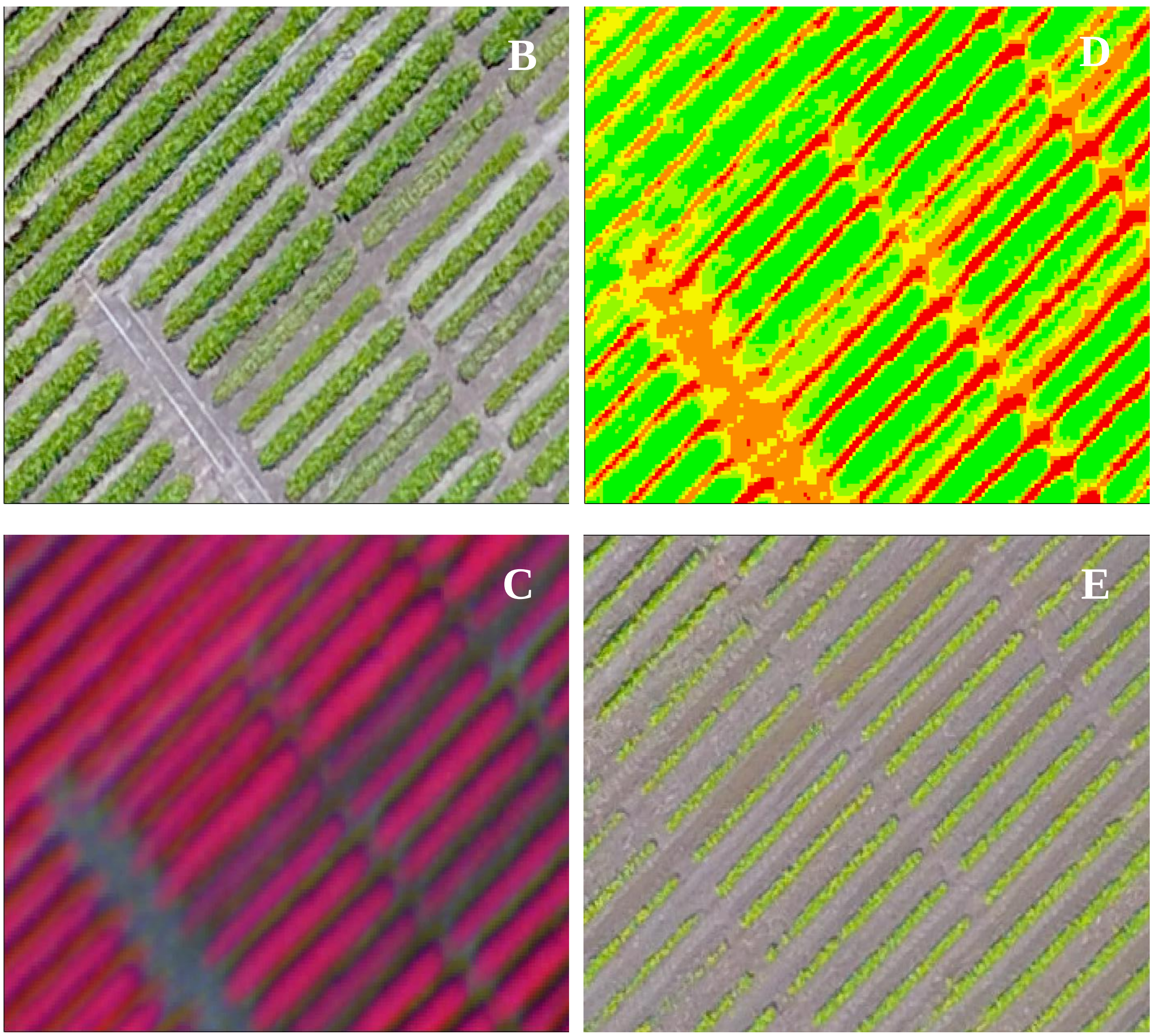
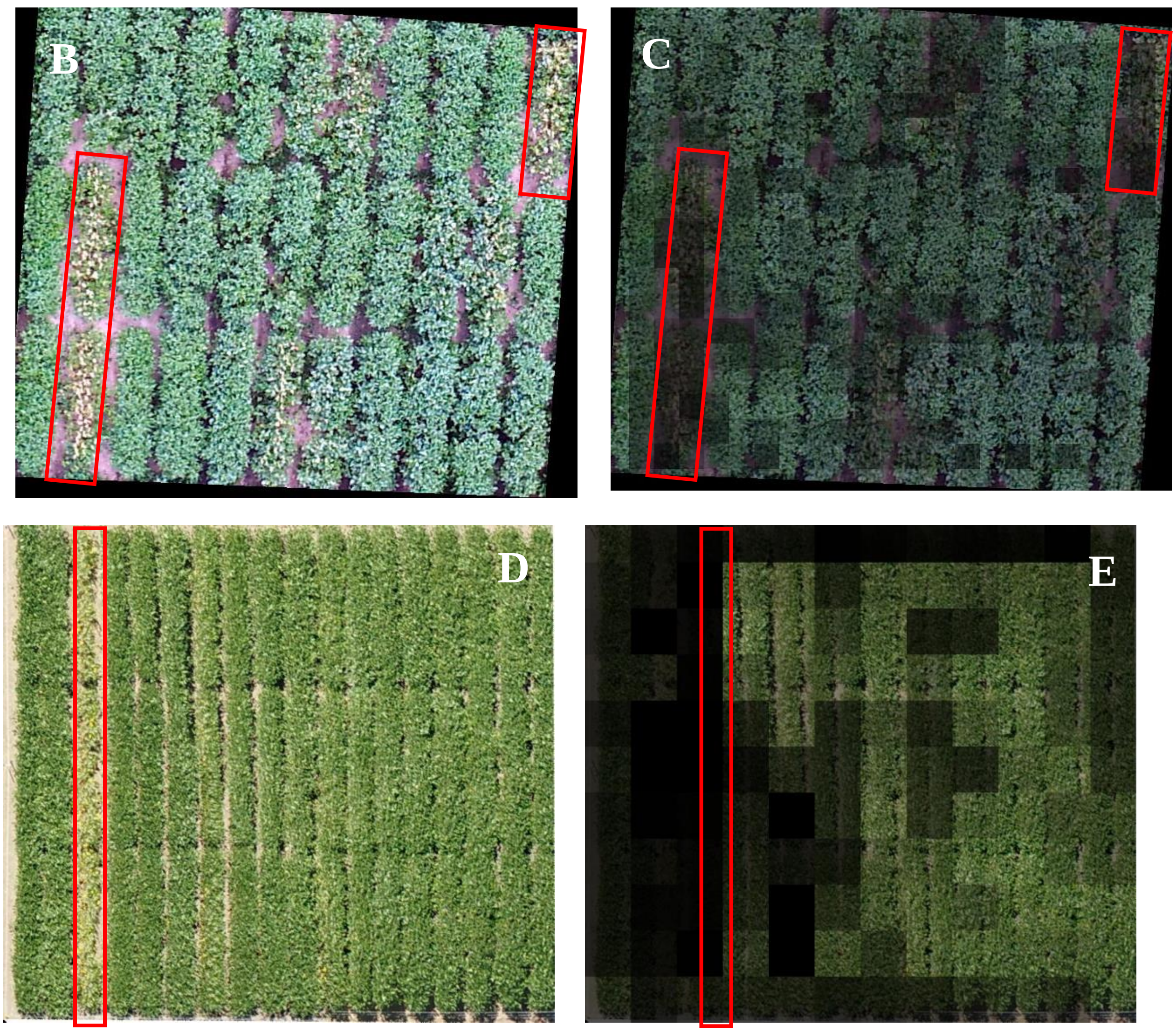


Figure 2. Results of texture analysis at selected maturity stages

A. Soybean plots at V4; differences in clipping levels are difficult to identify
B. Stoneville plots at R5; the red boxes highlight the 50% clip treatment row
C. Output from texture algorithm from R5 image; the darker the tile, the more closely it resembles the 50% clipped samples
D. Starkville plots at R5; the red box highlights the 50% clip treatment row
E. Output from texture algorithm from R5 image; the darker the tile, the more closely it resembles the 50% clipped samples



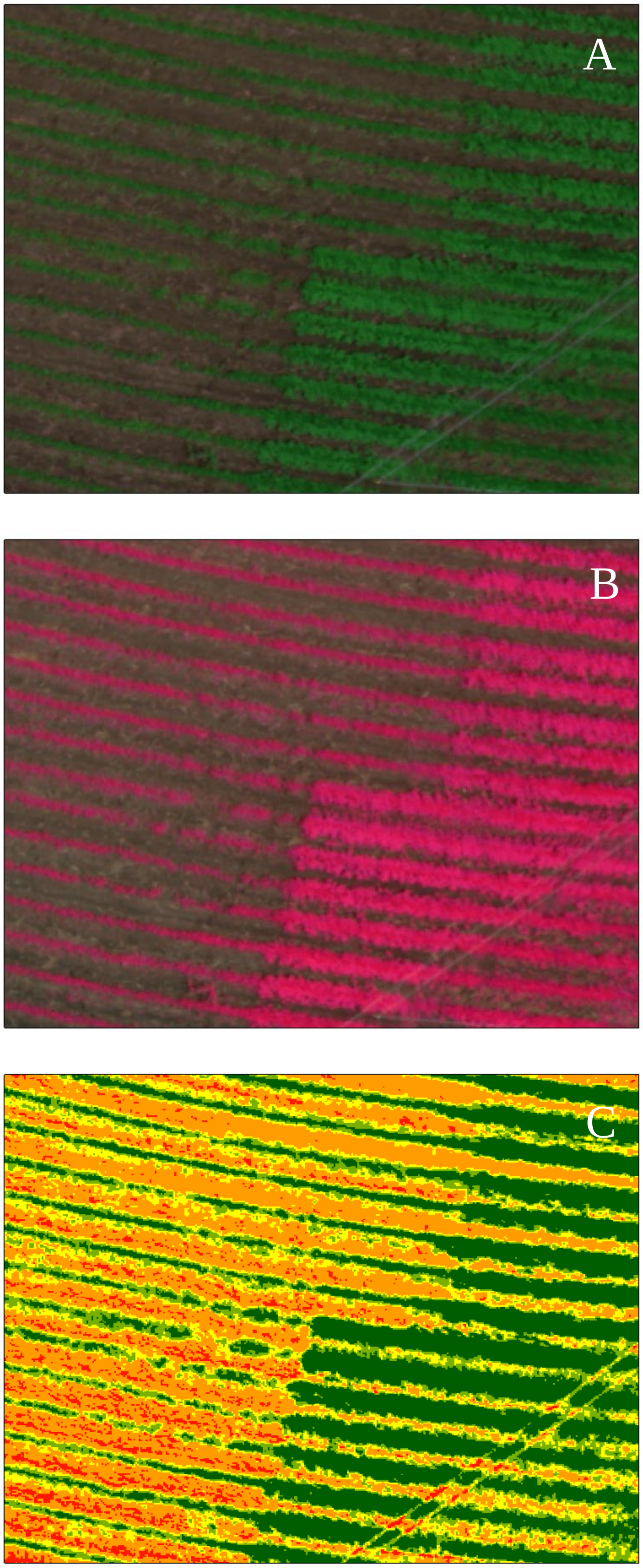
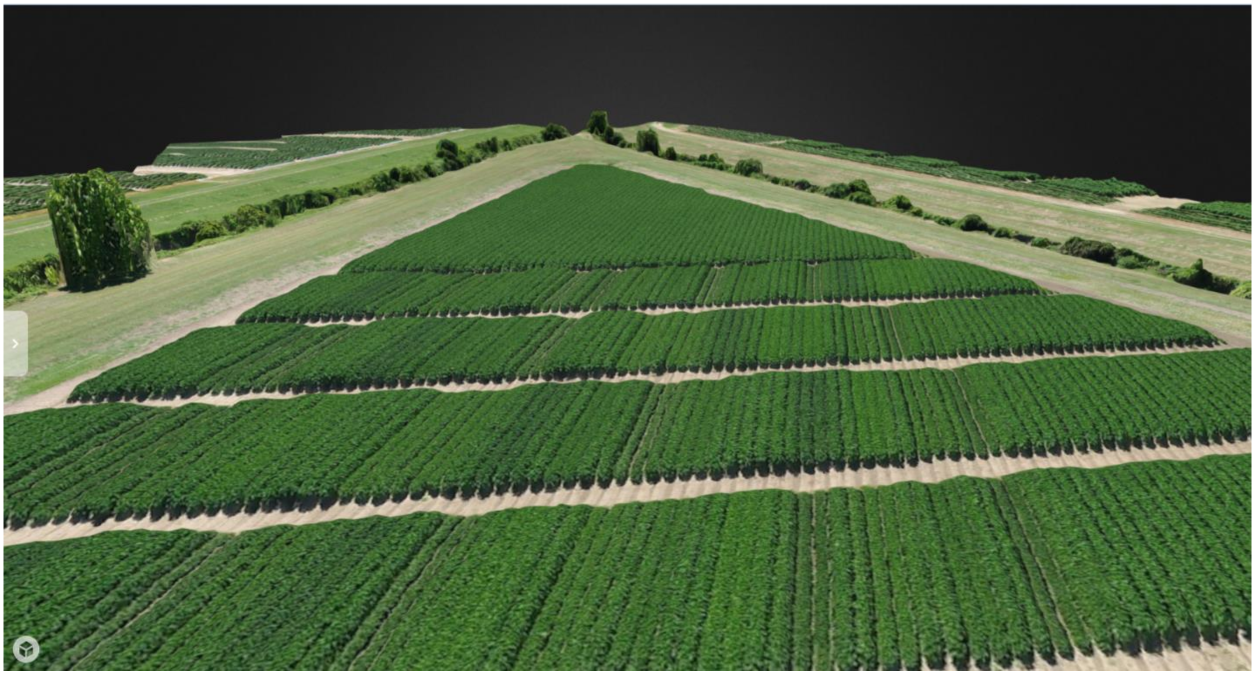


Figure 3. Soybean rows, with (left side) and without (right side) the presence of prickly sida.

A. Shown as standard RGB
B. Shown as color infrared, where redder hues indicate more green vegetation
C. Shown as NDVI, where greener areas indicate more green biomass

The vegetation shows up more clearly in general in the color infrared. The NDVI obscures the fact that the right half of the field contains many weeds, rather than healthy soybean.



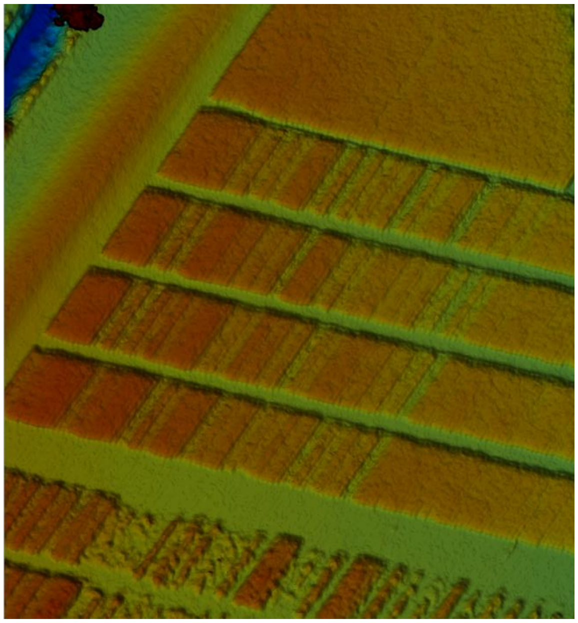


Figure 4. Height differences between treatments detected with the Sentera NDVI sensor. Dr. Reynolds mentioned that he had seen significant height differences between his herbicide treatments, and we worked with him to collect this imagery. As we also noticed clear height differences in our clipped rows, even after regrowth, potential may exist to use this method to monitor herbivory as well.